Unfamiliar facial identity registration and recognition performance enhancement

Unfamiliar Facial Identity Registration and Recognition Performance Enhancement

By

Mohamad Zulkefli Adam

March 2010

Thesis Access Form

Loughborough University

STATEMENT OF ORIGINALITY

This work has not previously been submitted for a degree or diploma in any university. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

…………………………….
Mohamad Zulkefli Adam

March 2010

Unfamiliar Facial Identity Registration and Recognition Performance Enhancement

by

Mohamad Zulkefli Adam

A Doctoral Thesis

Submitted in partial fulfilment of the requirements

for the award of

Doctor of Philosophy in Electronic and Electrical Engineering

of Loughborough University

20 March 2010

Supervisors: Serkharjit Datta, PhD,

Paul Lepper, PhD.

Advanced Signal Processing Research Group

Department of Electronic and Electrical Engineering

Loughborough University, LE11 3TU Leicestershire, UK

In loving memory of loving parents,

*Life is full of variation complexity.
Compensating, extracting and classifying
are truly an awesome journey
of love and honesty.*

*To my wives,
Son and daughters,
Brothers and sisters*

Acknowledgements

The research implemented in this thesis has received invaluable supports professionally and personally from a number of people.

Firstly, I wish to acknowledge and give a very special thanks to my very understanding supervisor, Dr. Sekharjit Datta for his knowledge, experiences and caring towards the completion of the thesis. I also wish to thank to Dr. Paul Lepper for his kind efforts and generous help in the final stage of thesis submission.

I wish to thank the University of Technology Malaysia on behalf of the government of Malaysia for the research funding. I also wish to thank the research group of Applied Signal Processing, Loughborough University for their supports and help.

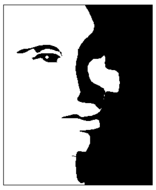
My appreciation also goes to all friends and scholars who are directly or indirectly involved in research resources and knowledge requirement.

Finally, the thesis will never have been completed without the moral supports and understanding from my wives, son and daughters, brothers and sisters.

Mohamad Zulkefli Adam
Loughborough University
United Kingdom
March 2010

ABSTRACT

Unfamiliar Facial Identity Registration and Recognition Performance Enhancement



The work in this thesis aims at studying the problems related to the robustness of a face recognition system where specific attention is given to the issues of handling the image variation complexity and inherent limited Unique Characteristic Information (UCI) within the scope of unfamiliar identity recognition environment. These issues will be the main themes in developing a mutual understanding of extraction and classification tasking strategies and are carried out as a two interdependent but related blocks of research work.

Naturally, the complexity of the image variation problem is built up from factors including the viewing geometry, illumination, occlusion and other kind of intrinsic and extrinsic image variation. Ideally, the recognition performance will be increased whenever the variation is reduced and/or the UCI is increased. However, the variation reduction on 2D facial images may result in loss of important clues or UCI data for a particular face alternatively increasing the UCI may also increase the image variation.

To reduce the lost of information, while reducing or compensating the variation complexity, a hybrid technique is proposed in this thesis. The technique is derived from three conventional approaches for the variation compensation and feature extraction tasks. In this first research block, **transformation, modelling and compensation** *approaches are combined to deal with the variation complexity. The ultimate aim of this combination is to represent (transformation) the UCI without losing the important features by modelling and discard (compensation) and reduce the level of the variation complexity of a given face image. Experimental results have shown that discarding a certain obvious variation will enhance the desired information rather than sceptical in losing the interested UCI. The modelling and compensation stages will benefit both variation reduction and UCI enhancement. Colour, gray level and edge image information are used to manipulate the UCI which involve the analysis on the skin colour, facial texture and features measurement respectively. The Derivative Linear Binary transformation (DLBT) technique is proposed for the features measurement consistency. Prior knowledge of input image with symmetrical properties, the informative region and consistency of some features will be fully utilized in preserving the UCI feature information. As a result, the similarity and dissimilarity representation for identity parameters or classes are obtained from the selected UCI representation which involves the derivative features size and distance measurement, facial texture and skin colour. These are mainly used to accommodate the strategy of unfamiliar identity classification in the second block of the research work.*

Since all faces share similar structure, classification technique should be able to increase the similarities within the class while increase the dissimilarity between the classes. Furthermore, a smaller class will result on less burden on the identification or recognition processes. The proposed method or collateral classification strategy of identity representation introduced in this thesis is by manipulating the availability of the collateral UCI for classifying the identity parameters of regional appearance, gender and age classes. In this regard, the registration of collateral UCI's have been made in such a way to collect more identity information. As a result, the performance of unfamiliar identity recognition positively is upgraded with respect to the special UCI for the class recognition and possibly with the small size of the class. The experiment was done using data from our developed database and open database comprising three different regional appearances, two different age groups and two different genders and is incorporated with pose and illumination image variations.

Unfamiliar Facial Identity Registration and Recognition Performance Enhancement

TABLE OF CONTENTS

List of Figures

List of Tables

List of Notation

α	directly proportional
r	normalized Red colour space
g	normalized Green colour space
b	normalized Blue colour space
H,S,V	Hue, Saturation, Value
Y,Cr,Cb	Luma component, Red-difference, Blue-difference of chroma components
C,M,Y	Cyan, Magenta, Yellow-component of CMYK colour model
C(i,j)	The gray Level Co-occurrence Matrix (GLCM)
I(n,m)	n x m Image
$(\Delta x,\Delta y)$	Offset
μ_i	GLCM mean
σ_i	Standard deviation
σ_i^2	GLCM variance
R_{min}, R_{max}	Minimum and maximum level of RED component in histogram graph.
G_{min}, G_{max}	Minimum and maximum level of GREEN component in histogram graph.
B_{min}, B_{max}	Minimum and maximum level of BLUE component in histogram graph.
D_{TH}	Threshold of difference

List of Acronyms

UCI	Unique Characteristic Information
UCCI	Unique Collateral Characteristics Information
GCV	Geometrical Critical View
PCA	Principle Component Analysis
LDA	Linear Discriminant Analysis
LDA	Linear Discriminant Analysis
SFS	Shape from Surface
SFS	Shape from Shading
DLBT	Derivative Linear Binary Transformation
JAFFE	The Japanese Female Facial Expression Database
2D	Two Dimensional
3D	Three Dimensional
The-ID	Temporary human electronic Identification
RGB	Red, Green, Blue
HSV	Hue, Saturation, Value
LBP	Local Binary Patterns
QGF	Quaternionic Gabor features
2DPCA	Two Dimensional Principle Component Analysis
M2VTS	Multi Modal Verification for Teleservices and Security applications
XM2VTS	The Extended M2VTS Database, University of Surrey
FRGC	Face Recognition Grand Challenge, U.S
VRG	Variation ratio gain
GLCM	Gray Level Co-occurrence Matrix

List of Acronyms (*cont.*)

MDLA	Multi-scale Morphological (dilation-erosion) Dynamic Link Architecture
MMF	Morphological Multi-scale Fingerprints
MQI	Morphological Quotient Image
CMU-PIE	Carnegie Mellon University- Post, Illumination, Expression Database
MSB	Most Significant Bit
LSB	Least Significant Bit
ROI	Region of Interest

CHAPTER ONE

INTRODUCTION

1. INTRODUCTION

The uses and manipulation of information exchange in human interactions has evolved from limited facilities to advanced modern technology of communicating. The level of information important varies accordingly depending on the class of interaction within the community. This has led to a need of information security and privacy in certain application. For instance, accessing a computer or a particular building, talking to one and another, shopping and payment system and many more activities need different levels of information security and privacy. One of the implications of the need for security control and activities observation is a better understanding of environment monitoring involving humans.

As a result, physiological and behavioural characteristics of human being's are being seriously studied. This process is trying to manipulate a pattern that can represent permanent information belonged to a particular person such as his or her identity. In this regards, biometric technology is being widely looked as a promising solution to identification and verification systems. These technologies include finger print, iris scan and facial imaging systems to name a few [1]. A lot of information can be extracted from the properties of human faces and a understanding of the practical aspect of facial actions derived. The study of human facial features includes identity, emotional states or expression, gender, regional appearance, age, attractiveness and other related areas of possible human-computer interaction [1][2].

1.1 3D Human Faces and Unique Collateral Characteristics Information

The structure of a human face is similar to any other. However, the faces are not equal in terms of identity recognition processes. The small differences between facial features reveal the identity. In addition, the collateral characteristics information such as emotional expression, the characteristic of the gender, regional appearance and age contribute to a understanding the information produced by a human face. From the statistical point of view, this collateral information should have its own pattern and analysis.

Figure 1.1 demonstrates (a) the 3D basic structure of human face and (b) various shapes of face actions that invite ((c) and (d)) further analysis and understanding.

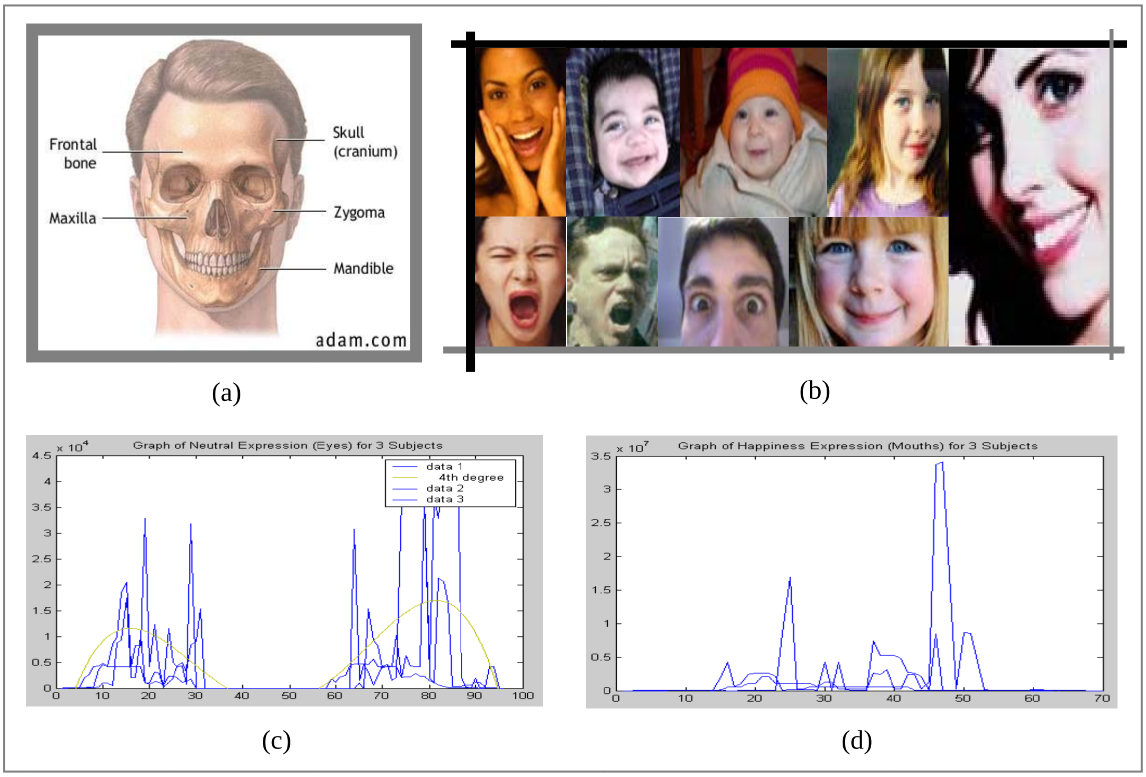


Figure 1.1: Unique facial collateral characteristics and pattern representation. (a) The basic structure of human face. (b) Various face shapes' that carry inherent information and meanings. (c) Samples of pattern shown from the eyes of neutral expression. (d) Samples of pattern shown from the mouths of happiness expression.

All faces share the same basic features such as eyes, nose and mouth. These informative regions and other facial properties such as symmetrical and skin colour are very important factors that contribute to the identity of the person. The shape and texture of these features are counted in most analytical approaches of feature extraction [3]. The understanding of the detailed biology shown in Figure 1.1(a) is not necessary in the area of image processing discussed in this thesis. However, the intrinsic and extrinsic variations such as the viewing geometry, expression, regional appearance, gender, age and illumination impact on 2D images shown in Figure 1.1(b) are what we are going to explore towards the goal of identity recognition. Figure 1.1(c) and 1.1(d) demonstrate the sample patterns of eyes of neutral expression and mouth of happiness expression respectively from five Japanese peoples of JAFFE database [4]. These figures are the graphs of derivative feature measurement versus the discrete region of facial space or matrix. It can be seen from the figure 1.1(c), the patterns of eyes of five different peoples are not exactly the same even they are at the neutral expression. These figures reveal the uniqueness of facial features and deserve the detail analysis and explanation. In the following sections, the face UCI and image variation will be discussed more closely with the feature extraction and classification issues.

1.2 2D Face Images and Variation Complexity

The dimensionality of the face image in two- dimensions (2D) processed by the computer represents the unique collateral characteristic information and the image variations. The complexity of the image variation is comprised of illumination effect, viewing geometry, expression, occlusion and many more. While the 3D information for a human face captured on 2D images is already very challenging, the presence of various types of image variations such as the illumination and viewing geometry further aggravates the analysis difficulty. This is regardless of either the method used has been trained by using a single input image or a sequence of images (video). In any face recognition system, the sensitivity of the methods used is influenced by the existence of the complexity of the image variation where the performance will be degraded during the testing session or real life application. This is due to the fact that only small differences occur among faces where differences may also occurred between faces of the same person in the presence of the image variation. This small differences is a core in the identity information of such person and will cause the automatic processing by a computer is a difficult task where the face may be wrongly classified. One of the simplest ways to confront this problem is by having a controlled environment such as controlled lighting, frontal view, fixed geometry and neutral expression.

Figure 1.2 depicts a typical familiar face recognition system. The information of the features such as eyes, nose and mouth from the original 3D human face may be lost or give incomplete information due to the 2D image variations. From the literature, the conventional approaches in handling this problem can be divided into either feature-based or holistic-based approaches or combination of the two [1]. Feature-based is an analytical approach which analyzes all the possible significant parts of the face images. The holistic-based approach considers the whole face image as a pattern regardless, with or without the image variations. The combination of the two (a hybrid) tries to make use of the advantages of both approaches allowing the recognition performance to be increased.

In this thesis, the conventional approaches are divided into the way the methods extract the unique characteristics information and handling the image variations [5]. The three general categories are variation-modelling, variation-compensation and variation-independent. For instance, variation-modelling approach models all the possible variations before the salient features are extracted. This is different in the case of variation compensation-based approach where the variations are compensated before the extraction of the salient features takes place. In the third category, the variation-independent approaches extract the salient features directly without considering the image variations. These three approaches will be viewed in Chapter Two where the hybrid of these three is extracted and proposed in this thesis.

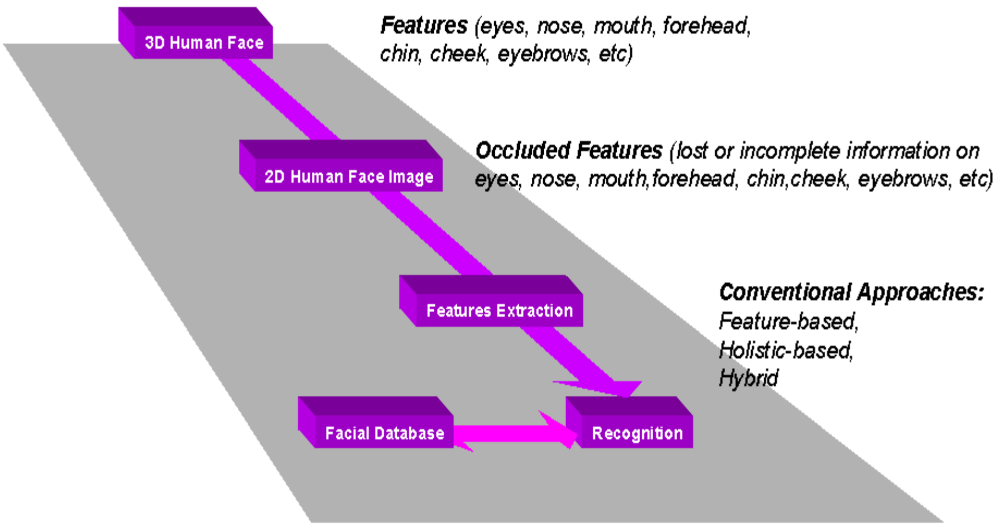


Figure 1.2: Typical familiar facial identity recognition process.

Figure 1.3 illustrates graphically the scenario discussed in this section. The graph of VC versus UCI is plotted conceptually to explore the wanted information, unwanted information and the type of approaches to be considered.

The graph reveals the following facts:

(i) The lower region of the graph is where the low variation image with high unique characteristics information can simply be obtained by conducting a controlled environment.

(ii) In contrast, the unconstrained images from real life normally provide images with high variations and low unique characteristics information as shown in the upper region of the graph.

(iii) More information (VC or UCI) can be collected if more images are available. This is represented in the third dimension of the graph.

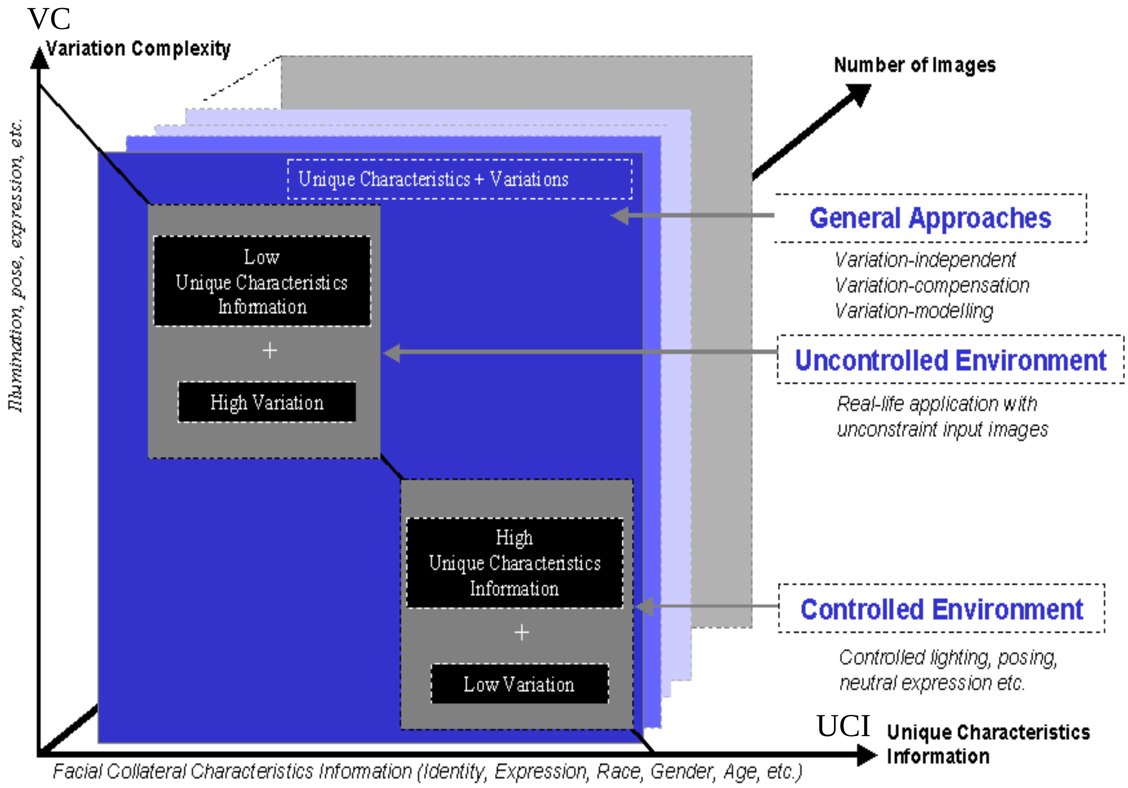


Figure 1.3: Image variation complexity versus unique characteristic information.

Simply, the graph shows that the variation complexity on the 2D facial image is inversely proportional to the unique characteristics information (UCI) extracted from that 2D face images. The relationship between these two types of information can be represented by equation (1) .

$$Variation\ Complexity \quad \alpha \quad \frac{1}{Unique\ Characteristic\ Information\ (UCI)} \quad ....(1)$$

Equation (1) implies that the UCI can only be increased by decreasing the VC which leads to a better recognition performance. This is what commonly happens in the controlled environment such as being practiced in passport application or any other typical identification system. In the case of uncontrolled environment of real-life application, the issue that relates to equation (1) will be greatly challenged. In the case of blurred face images, reducing the VC may reduce or discard the UCI as well. For instance, to compensate (or reduce the VC) the unnecessary dots, lines or curves within the face features on 2D image may also discard the UCI components that belong to the features itself. This issue will be the main theme of the thesis and will be discussed thoroughly throughout the thesis.

1.3 Objectives of Research

The purpose of pursuing this research was to design and test an unfamiliar facial identity recognition system consisting of registration and classification of UCI which can be used to represent the person's temporary identity ready for identification. This is applicable where given the input image, the system will do the searching throughout the registered databases within the predetermined areas of where the databases are located. In other words, the outcome is to answer where the person being looked for is at that particular moment. The detail of this application is explained in the next section.

The objectives of the research are to study the problem of robust facial identification system and propose a comprehensive solution with competitive outcomes within the scope of unfamiliar recognition environment relevant to a computer's perception. The complexity of image variations, the extraction and classification of facial information have been the major focus in the research.

In the case of unfamiliar face recognition environment, given an unknown input, the system must first register the image, representing it in a manner that is ready to be matched in future searches. From the literature [1][5][6][7], this kind of system is normally known as an identification system, but restricted to a specified database and the result dependant on whether the search member exists in the group (database) or not. Some systems simplify the complexity with the requirement of a password or smart card. These systems are normally known as a verification system.

In the proposed case of a unfamiliar face recognition system, the consistency of the identity representation is done through the division of unique collateral characteristics information. It is proposed the regional appearance, gender and age are the three main elements representing the identity, where each of them creates different unique characteristic information or patterns. The details of the system will be discussed in Chapter Two of the thesis.

This thesis focuses on the twofold problems in dealing with the image; variation complexity and optimization of limited collateral UCI availability. The motivation of the study lies on the realisation of some cases where there might be enough information about a person but to what extent the benefit of the available information can be used in searching for that person. Furthermore, the availability of the required information at the end of the process (matching process) may be limited by availability of as few as only a single face image in a the real world situation. This image may be captured with poor illumination and pose variations with non-frontal view where the expression is unknown. The main task is to recover the face images (variation complexity reduction) and representing (collateral UCI) that help the classification task before pursuing the identity recognition. This may involve dealing with the problem of collection of only partial facial information associated with non-frontal geometry but may use the features extraction technique which can also be applied to the illumination problem. The details will be explained in section 1.4 **Problem Formulation and Proposed Approaches** (what problem is to be tackled) and section 1.5 **Scope of the Thesis** (what assumption are to be made). Figure 1.4 illustrates the abstract of the combination of problems discussed previously.

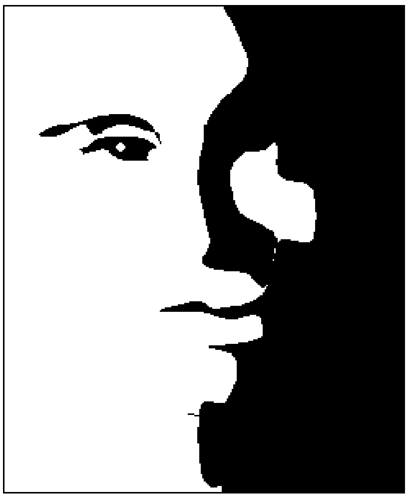
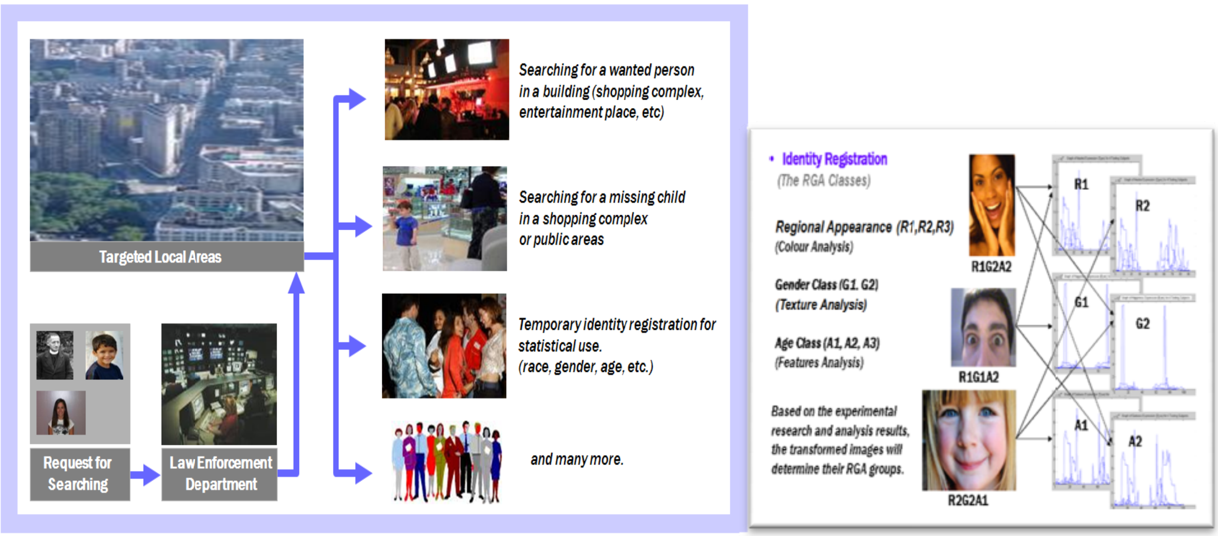


Figure 1.4: **An illustration of 2D face image with huge shadow variation.**
- The viewing geometry, illumination effect and unknown expression state.

1.3.1 System Robustness and Practicality

Unfamiliar faces in the databases are defined and considered from the view of computer perception. Imagine that a building or a public area is attended by hundreds or thousands of peoples in a day and the database might be replaced by different faces the following day. A person might change his or her persona by changing name and appearance. Taking these variables, the proposed system has obtained a searching strategy to take place either by regional appearance, gender or age parameters. The proposed system will try to partitioning the database according to the need of the request. Examples of applications are visualized in figure 1.5. However, it is not only limited to the task of searching for the required person such as a criminal or a child lost from home. The application is also suitable for statistical purposes in a certain area where regional appearance, gender and age information are needed in analysing the crowd for further investigation. This kind of information may be needed by the government, local authority, law enforcement, the shopping complex management, the marketing division and many more.

The final objective is to have a robust system where all the practicalities have been considered. With the aid of this objective, a simple method in estimating the various types of image variations appeared on the face image is specified where these variations give a direct impact to the UCI or identity. There is also a need to design and develop a comprehensive feature extractor and classifier for collecting collateral information that will be useful in enhancing the performance or narrowing the identity search or its components.



(a) (b)

Figure 1.5: (a) Some examples of application. (b) Collateral identity information registration.

1.3.2 Limitations of Existing Matters

Research in this area has received a great deal of attention from scholars and industry practitioners involving multi-disciplines of computer science, electronic engineering, psychology and physiology, mathematics, statistics and many more. In very simple terms, facial recognition systems basically try to determine whether the member belongs to the database or not. But, due to the dynamical characteristics of the 3D human face and the image variations processed by a computer, some research is restricted the work to the controlled environment. Furthermore, in obtaining a precise classification, some researchers have used a number of images per person for training purposes. The image representation approaches invented by the various researches are vary accordingly as to suit the research requirement and intention. There are less studies confronting the large size of the databases where the matching process will be directly affected and can lead to reliability issues in certain application such as the one proposed in this thesis.

In simple terms, most of the previous researches and proposed systems concentrate more on the questions below.

(1.) Who is this person? (*Identification system*)
(2) Is this really the claimed person? (*Verification system*)

In this thesis, we extend the questions by exploring the issues of:
(3) What characteristics of this person? (*Identity parameters: – regional appearance, gender and age*)
(4) Where is this person? (*In which database the person is belonged to*)

Towards the identity recognition, the work in this thesis explored the recognition process by giving more attention to uncontrolled environments, variation complexity (or limited information), combination of all the positive values of the three categories of representation approaches and collateral classification for UCI that will benefit the large size of databases. Figure 1.6 highlights the limitations issues in recognition process.

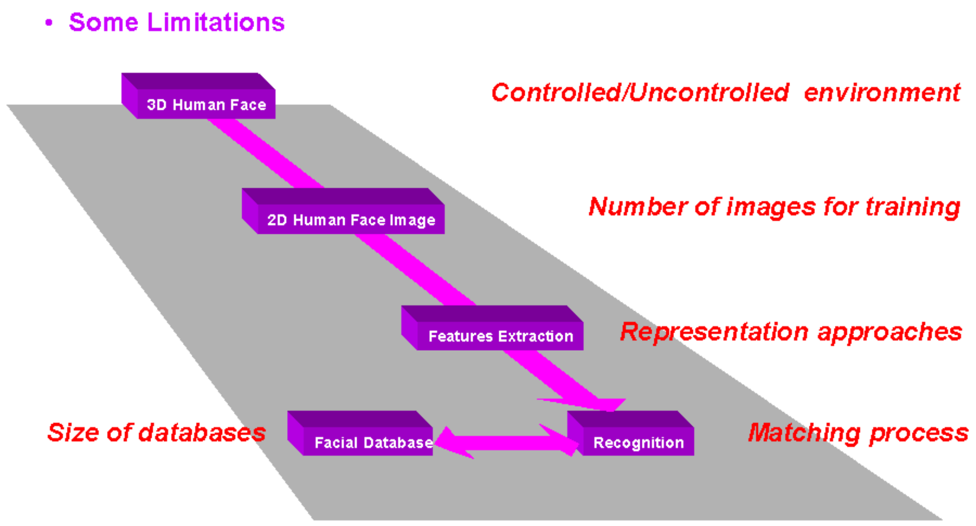


Figure 1.6: Some limitations and issues can be looked into each stage of the recognition process.

1.4 Problem Formulation and Proposed Approaches

Problem formulation is derived from the flow of information transformation as shown in Figure 1.7 considering all stages of the process relevant to the performance of unfamiliar identity recognition.

The detected 2D face image acquired from the large unfamiliar databases available in public areas will be classified into the three important UCI (regional appearance, gender and age). This is done by first applying a hybrid representation technique that incorporates variation complexity reduction and image transformation or signature.

Naturally, the complexity of the image variation problem was built up from the viewing geometry, illumination, occlusion and other kind of intrinsic and extrinsic image variation. Ideally, the recognition performance will be increased whenever the variation is reduced and/or the UCI is increased. However, the variation reduction on a 2D face images might lose important clues or UCI data for a particular face and increasing the UCI may increase the image variation.

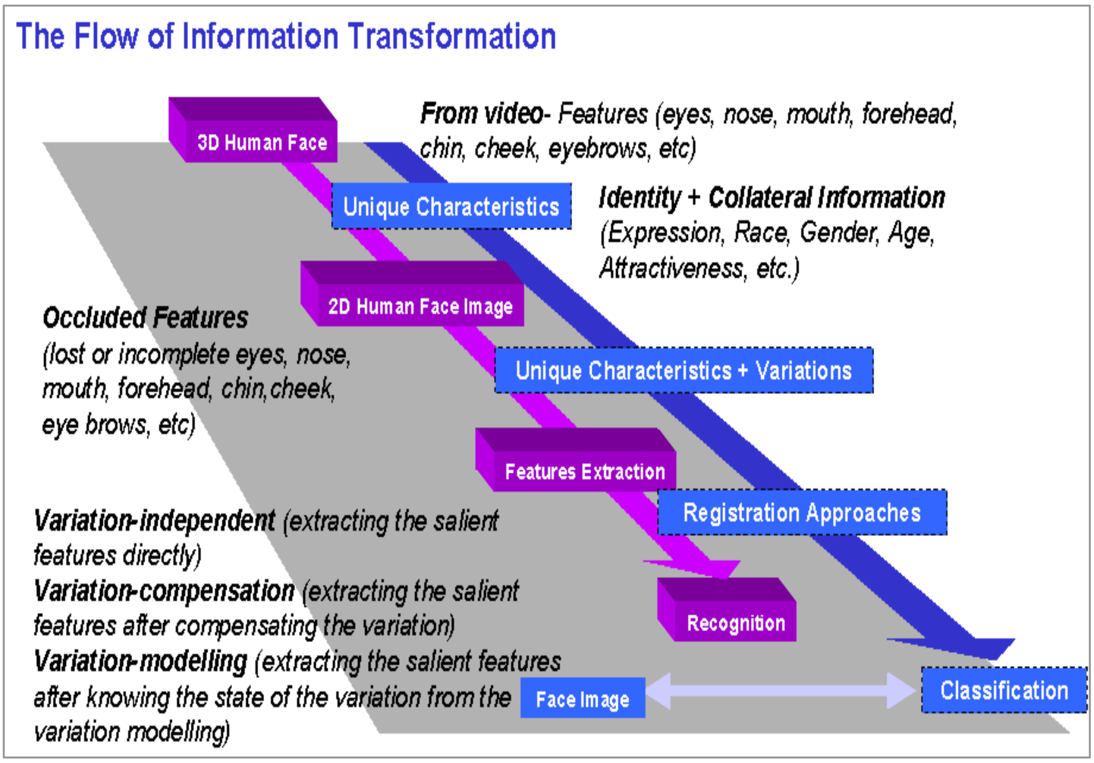


Figure 1.7: The flow of information transformation explains the unfamiliar identity recognition process in identical to the conventional familiar identity recognition process.

To reduce the loss of information while reducing or compensating the variation complexity, a hybrid technique derived from the three ideas of conventional approaches is proposed in this thesis for variation compensation and feature extraction tasks. In this first research block, the ultimate aim of the techniques of transformation, modelling and compensation are combined as to represent (transformation) the UCI without losing the important features by modelling and discard (compensation) and reduce the level of the variation complexity of a given face image. The modelling and compensation stages will benefit both variation reduction and UCI enhancement.

Although the variation compensation has been done successfully, the recognition performance still depends on the classifier efficiency where this is another challenge to the recognition system. This is due to the fact that only small differences exist between the faces. In this regard, classification technique should be able to increase the similarity within the class while increase the dissimilarity between the classes. Furthermore, the smaller the class will resulting the lesser the burdensome of identification or recognition process. This will involves the proposed strategy in classification task in the second block of the research.

Figure 1.8 illustrates the approach conceptually to give some insights to the classification problem and elements that will influent the proposed solution approaches.

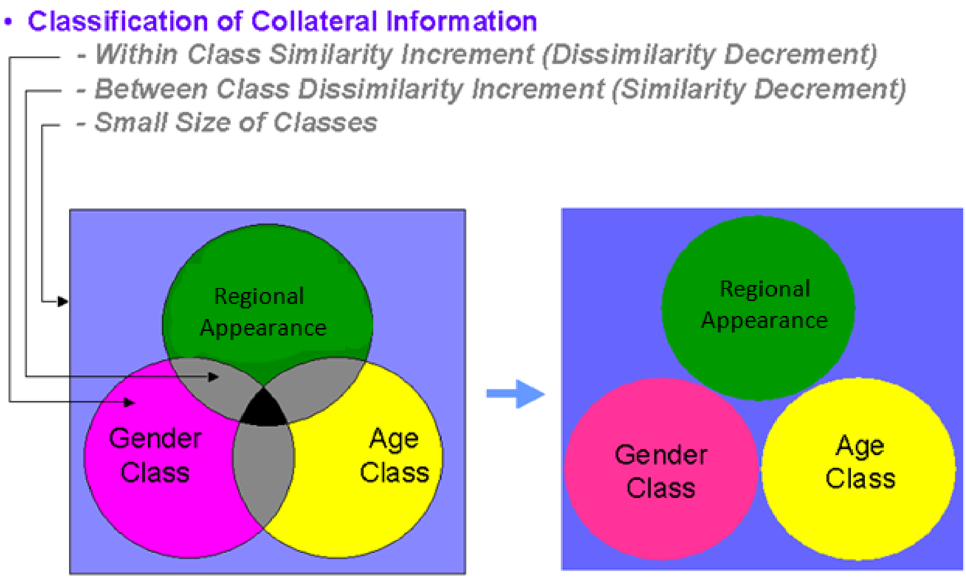


Figure 1.8: Classification of collateral information confronts the similarity and dissimilarity of recognition parameters.

From the equation (1), simply the problem formulation can be derived as,

$$\textit{Variation Complexity} \quad \alpha \quad \frac{1}{\textit{Unique Characteristic Information (UCI)}}$$

And,

$$\textit{Recognition Performance} \quad \alpha \quad UCI$$

Thus,

$$\textit{Recognition Performance} \quad \alpha \quad \frac{UCI}{\textit{Variation Complexity}}$$

Also

$$\textit{Recognition Performance} \quad \alpha \quad \frac{\textit{Number of Input Images (per subject)}}{\textit{Size of Databases}}$$

Therefore,

$$\boldsymbol{\textit{Recognition Performance}} \quad \boldsymbol{\alpha} \quad \frac{\boldsymbol{UCI \;\; X \;\; \textit{Number of Input Images (per subject)}}}{\boldsymbol{\textit{Variation Complexity} \;\; X \;\; \textit{Size of Databases}}} \qquad (2)$$

Equation (2) represents and describes almost all scenarios that happen in a typical face recognition system development and implementation. Indeed, the wanted and unwanted information or components expressed in equation (2) leads to a wide range of research and understanding. As discussed in Section 1.2, the VC compensation for high variation images may also reduce the UCI of the image. However, more UCI can be gained if the number of input images (per subject) is increased or collected. This is the case in a typical face recognition algorithm where the training process is the most important part [2].

On the other hand, the denominator in equation (2) represents the unwanted information or values in the recognition performance. The recognition performance is degraded not only by the existence of the VC but also by the size of databases that are expanded during the system implementation. Generally, in this thesis, the study will focus on how to increase the wanted information (numerator) and how to reduce the unwanted information (denominator) without degrading the recognition performance.

Specifically, from equation (2), the proposed approaches presented in this thesis attempt to answer the following questions.

(1.) How to reduce the complexity of the variation without losing the available unique characteristic information? [*Hybrid Approach*]

(2.) How to enhance the identity information by manipulating the available unique characteristic information? [*Unique Collateral Characteristics Information*]

(3.) How to reduce the burden of databases size which will affect the matching process and performance? [*Collateral UCI Classification*]

(4.) How to get more facial information (input images) for each subject? [*Sequence of images (video) i.e .future work of the thesis.*]

(5) How to make good use the existing system/surveillance facilities for the simplest and cheapest identity searching through the collateral classification and recognition? [*System robustness and practicality i.e. future work of the thesis.*]

Research questions derived in this thesis are not based only on the formulation of equation (2) but also with respect to the relationship with the existing publications as reviewed in Chapter Two (Section 2.1 and 2.2). For simplicity, the thesis has classified the problems and issues tackled by the existing publications into two broad categories or level of research problems. The first one is the issue of handling the variation complexity where various approaches are used towards designing the extractor and classifier. The second level of study deals the face recognition with limited information.

With figure 1.3 as a reference, Figure 1.9 illustrates graphically the formulation of the problems and the step taken in approaching the problems and the solutions proposed for each of them.

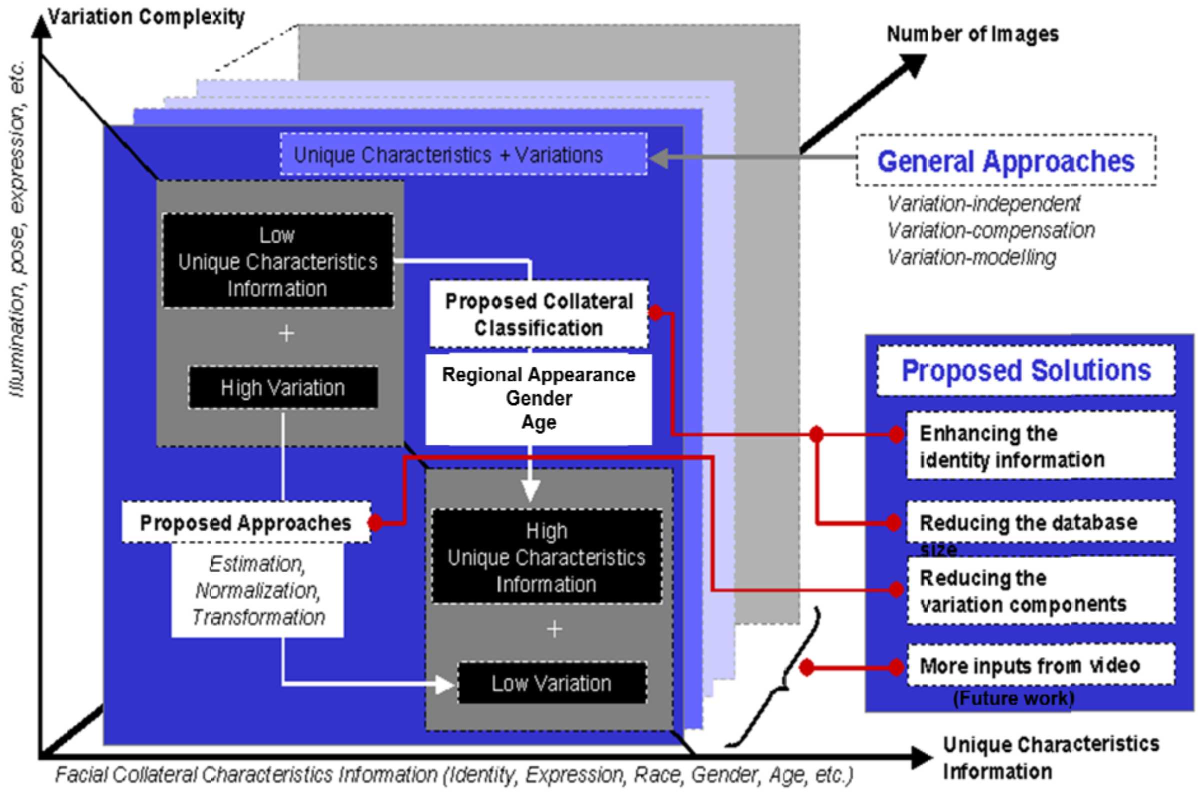


Figure 1.9: Graphical explanation of proposed solutions in handling the image variation complexity while enhancing the unique characteristic information.

Figure 1.10 highlights an overall process flow of the designed system expressing the variation complexity reduction and the identity information enhancement stages. The given face image is first compensated and transformed. The transformation took place into the three different classes (identity elements). The regional appearance element is obtained by using the colour analysis where gender and age classes are done through the texture and features analysis respectively.

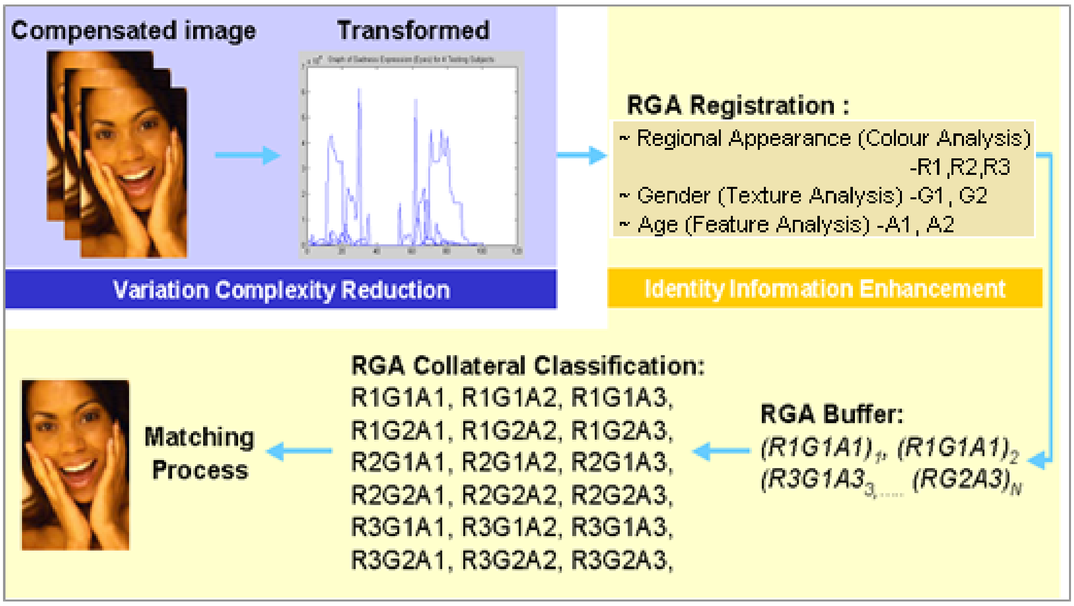


Figure 1.10: An overview of a completed proposed system for unfamiliar identity registration and recognition performance enhancement.

1.5 Scope of the Thesis

Generally, a complete typical face recognition system must consist of acquisition, detection and recognition stages. In most cases, these three stages normally have their own research community. Other tasks such as image filtering and enhancement may be included at any stage to obtain a good quality of the image to work from.

In this thesis, the work is restricted to the recognition stage where feature extraction and classification tasks have been the major focus. The input images are considered to be the detected face images which have been produced by the detection stage. In this regard, the image may be incorporated with large scale variations such as combinations of illumination, pose and expression variations. Figure 1.11 depicts the scope of the work involved in this thesis with respect to the overall process of the identity recognition. The features extractor is designed by incorporating the variation complexity reduction technique and an extraction of unique collateral information. The classifiers of the three identity elements are designed with the aid of colour, texture and feature analysis. This will be the strategy in confronting the large and unknown databases where the matching burden can be reduced for any particular search. The algorithm designed for the classifiers is also being used on the searched databases where matching of input image and the class images is done based on the search requirement. In this case, a multiple searches of different classes may be done in parallel.

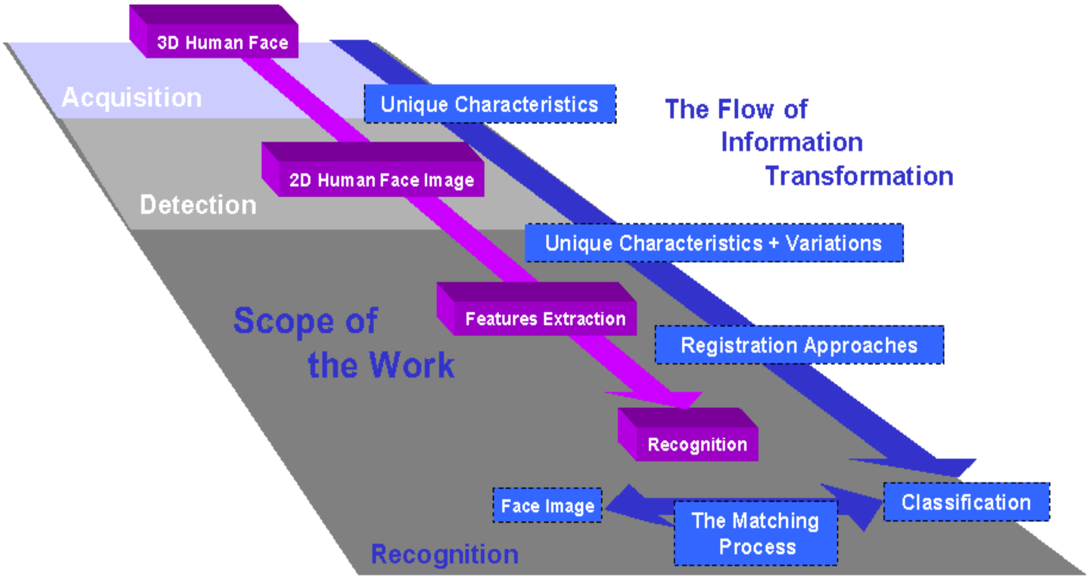


Figure 1.11: The scope of the thesis covers mainly on feature extraction and recognition approaches.

In summary, figure 1.12 shows the overall scope of works which is divided into two blocks of research work. The first and second blocks are named as the variation complexity reduction and the identity information enhancement respectively. In the first block, research has been carried out into the handling the complexity of the image variations whilst not losing the limited UCI of the particular face image. At the end of the block is the outcome of the transformation of the UCI in three different classes (identity elements). The identity representation and enhancement is manipulated in the second block by applying the strategy of determination of three identity elements. This covers the tasks of pattern analysis, classification or matching process and recognition performance analysis.

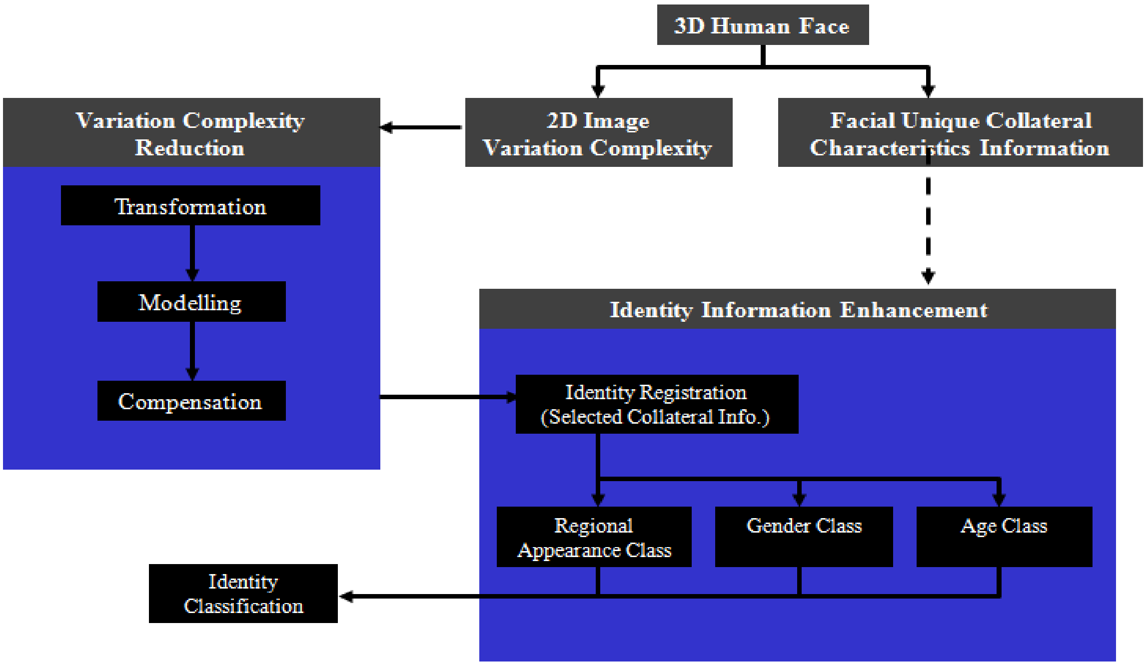


Figure 1.12: The work can be divided into two blocks, variation complexity reduction and identity information enhancement.

1.6 Original Contributions

The work carried out in this thesis is motivated by the intention to contribute to almost all the important aspects that the previous researches have not seriously looked into. There are a number of areas that can be considered for improvement. This includes the problem of dealing with the size of database, number of images that available for training, representation approaches and the matching process or classification approaches. This is easy to understand by going through the processing stages involved in the recognition process such as shown in figure 1.13 as derived from figure 1.6 previously. The problem in dealing with the size of databases can be handled by parallel processing (collateral approach) or by indirectly segmenting the database depending on the searching interest. In addition, the hybrid approach of variation reduction technique proposed in this thesis can be applied to uncontrolled environment where the complexity of the image variation existed. The more input information collected, the better the recognition can be performed. However, by introducing both proposed techniques, the system should be able to search the person's identity even with the limited information such as being given only a single image as an input. A hybrid representation approach allows all the important output for each of the three techniques mentioned earlier to be fully optimized and workable for the feature extraction task. The manipulation of facial unique collateral characteristics information contributed a positive impact to the rest of the processing stages. This includes systematic behaviour of the designed classifier and shortening the matching process in large databases through the division of small classes of identity parameters.

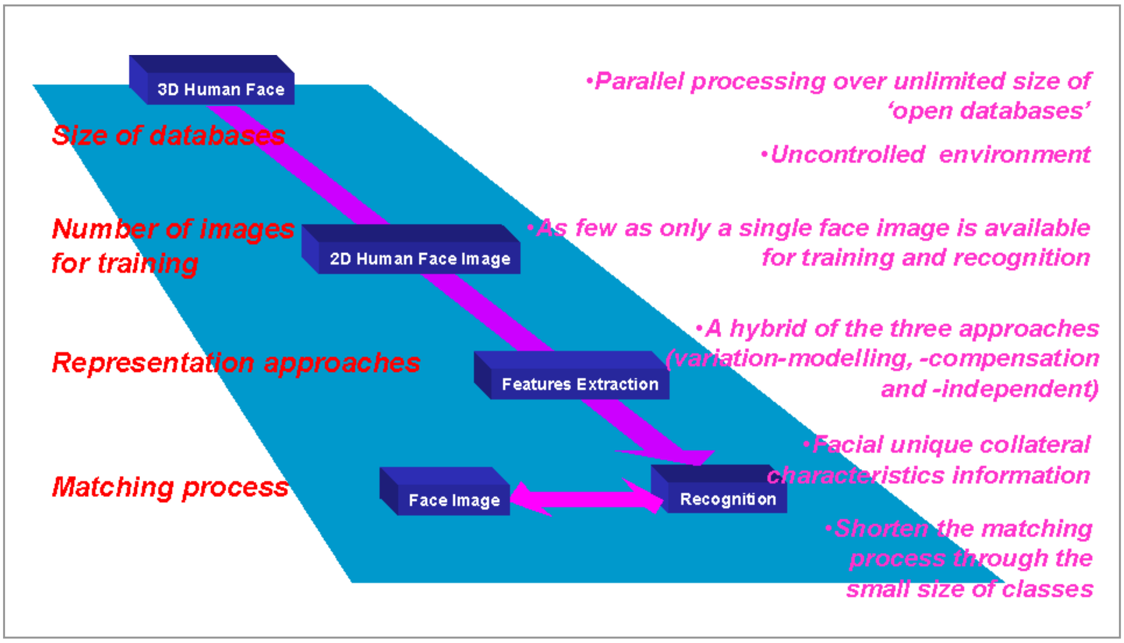


Figure 1.13: The processing stages are devoted and marked by various contributions in the study.

In completion of the theory and system conceptual study, some of the works in this thesis have been published in the following international conference.

1. M.Z. Adam, S. Datta, "*Variation Complexity Compensation in Limited Information Face Expression Recognition*", International Conference on Robotics, Vision, Information and Signal Processing (**ROVISP 2005**): Penang, Malaysia 20-22 July **2005**.

The principal outcomes of the research that have been done in this thesis can be summarized as follows:

- **Image understanding**: The image understanding and the strategy of manipulating the patterns of facial unique collateral characteristics information (UCCI) will lead towards realizing the common factors of identity parameters of regional appearance, gender and age. (Hopefully, this will further lead to the understanding of other derivative facial attributes with respect to the continuity of research behaviour).

- **The UCI extractors**: The problem of variation complexity for 2D face images is handled by a hybrid technique taken from three conventional approaches (variation-transformation, -modelling, and –compensation/independent) where the availability of facial UCCI can be extracted and fully utilized.

- **The classifiers**: The identity information enhancement is done by classifying the facial UCCI based on modelling of RGB skin colour, derivative grey scale texture and derivative edge features for regional appearance, gender and age classes respectively.

- **Recognition performance enhancement**: The database segmentation will help and ease the searching request in typical face recognition system where the matching processing time may reasonably be reduced as the database's size indirectly reduced.

- **Preserving the raw data**: The crowd understanding (attributes) can be done through the scientific analysis and open to wide range of applications (law enforcement, marketing, etc)

1.7 Thesis Structure

At this stage of writing, it is clear that the thesis theme and plot is to reveal the significant characteristics of human faces and how this collateral information can be extracted and grouped into different classes to allow identity recognition optimization. In this regards, this thesis is written in the following manner.

Chapter One: The chapter provides a brief discussion of the relation of a dynamic 3D human face to the static 2D human face images. The important and unnecessary information required for recognizing a person's identity are explained. This covers the problems related to the computer image processing and a short discussion on its conventional solutions. With the understanding of human and computer functions in this task, the research objectives are derived and its motivation is also been explained. The research problem is clearly formulated with the proposed solutions by exploring the phenomena of the elements in the recognition performance and proper approaches that should be taken. In realizing the objectives and carrying out the research on the proposed problem, the scope of the study is explained as the proposed system may involve with a complex system. Finally, the report has been made on to what extent the contribution of the research is being done and as well as the declaration of some works from this dissertation that have been published in international conference.

Chapter Two: Chapter Two is a background or knowledge base of the thesis. This is started with a further explanation into what kind of information or characteristics to be looked at in a face which is the identity and its collateral characteristic information. From here, the explanation is however then limited to the discussion of problems confronted by the features extractor and the classifier. The elements that should be counted in the considered design of a face recognition system are explored by reviewing some previous works which is comprised of the three categories of conventional approaches mentioned earlier. Colour, grey level and edge images techniques are reviewed as these three kinds of image processing that will be used as input to the designed feature extractor explained in Chapter Three. In completion, the explanation is given to the choice of the three parameters of identity (regional appearance, gender and age) that have been applied in the proposed system. This is expressed with respect to the formulated theory that strategizes the classification task at the end of the system. The chapter is ended with a general description of the database development especially created for this thesis.

Chapter Three: In this chapter, the results of the first block (or module) of the research is reported. Variation compensation process and selected UCI representation are reported with the techniques used including a new proposed technique, DLBT. The report also includes the results of skin colour, facial texture and derivative features measurement.

Chapter Four: The second block (or module) of the research is explained in this chapter. The classes of regional appearance, gender and age were formed individually and the detail of analysis results for each class are shown and explained.

Chapter Five: This chapter deals with the explanation of the software development and testing. The software, namely Temporary Human Electronic Identity, abbreviated to ***The-ID*** software is demonstrated in segmenting the given database into the twelve classes, involving the three regional appearances, two gender and two age classes. The results are compared with the PCA-based face recognition algorithm and analysis results are discussed.

Chapter Six: A conclusion for the whole thesis is given. Potential future work is also incorporated at the end of the chapter where discussion is given for both of the two blocks of research in the main thesis.

The thesis includes the MATLAB codes and face image database used in experiments that have been carried out in completion of the thesis. These can be referred to Appendix B and C respectively.

Chapter Two

Background

2. BACKGROUND

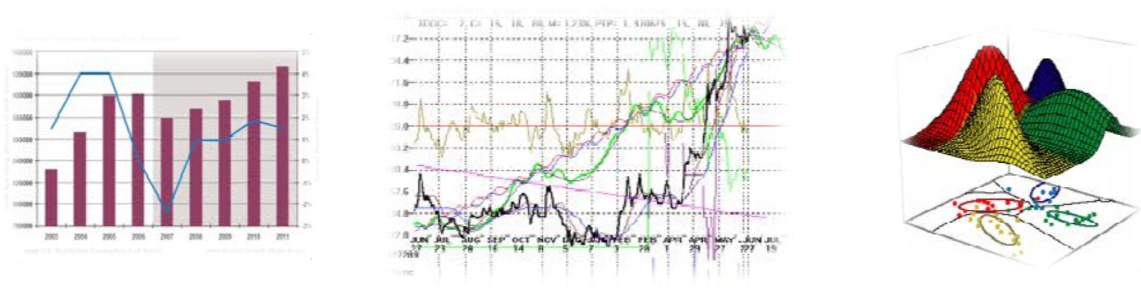
2.1 An Overview of Pattern Recognition

Most of the objects and subjects categorized as living and non-living things in our daily life have their own natural and unnatural patterns. Furthermore, the activities within human interactions and human-object or -machine interaction may reveal inherently the pattern of second order derivative. The study of these phenomena may result in term of shape of the objects, the collection of relational data, the characteristics and behaviour of the matters or context, and the reaction or implication of any evolution, to name a few.

From the digital image processing point of view, a pattern is composed of features or descriptors [3]. In most cases, such as in object recognition, patterns can be classified into a group where they share the most common characteristics. Figure 2.1 illustrates graphically some basic ideas of pattern observation and classification of various objects and phenomena, by virtue of similarity and dissimilarity study.

http://yangkumiesmind.blogspot.com/2011/02

(a) Natural and unnatural patterns.



(b) Modeling, representation and classification of patterns.

Figure 2.1: Various patterns: Nature, representation and classification.

Pattern recognition involves processes such as data acquisition, detection, classification and to the extent of detail pattern understanding. The study covers a range of applications spanning from military equipment and intelligence, medical, business and economical purposes, electronic communication, automation and many more [8]. Pattern recognition has been studied for more than 60 years ago and surveys on pattern recognition researches' work and findings have been made by a number of scholars, where the style of presentation varies accordingly. Most of them reviewed the literatures based on classification approaches or methods and philosophy of study. For instance, in [9], the study focused on bringing up the analytical aspects of the pattern classification problem. The classification decision was then applied in automatic control engineering. They have also outlined the two fundamental problems in pattern classification. The first one, known as characterization problem, is where the real data is transformed into a new set of data where the features are extracted and new representations are obtained. Secondly, the abstraction and generalization problem has been implemented where the decision function will be chosen in deciding the classification result. In [10], a broad discussion and study are reported on the issue of feature extraction technique and pattern recognition. The core part was to explore the method in determining the attributes or features and types of methods that possibly involved in the area of pattern recognition. In general, the authors have divided the methods into microanalysis and macro-analysis.

A very broad of survey has been done as reported in [11], covering the 'research pattern' in pattern recognition works from 1968 to 1974. The main subjects involved were the statistical- and structural-based approaches in pattern recognition field of study, including the contribution on error estimation and classifier methods. Reviews of classical, statistical and learning theory of pattern recognition are reported in [12]. The nearest neighbour, kernel, histogram, Vapnik-Chervonenkis theory and neural networks are discussed thoroughly. Pattern recognition approaches can be categorized into template-matching, decision-theoretic and syntactic approaches [13]. The decision making based on similarity criteria involved direct matching, discriminant function, minimum-distance, maximum-likelihood, minimum-Bayes risk and many more is explained comprehensively. Image segmentation, nevertheless, is important in pattern classification that involved with image processing. The state-of-the-art survey for image segmentation approaches can be referred to [14]. The goal of segmenting the input image is basically to ease the analysis as the image is provided in a very simplified way. The issue of quality and robustness outlined in machine learning, data mining and pattern recognition embedded the main issue of evaluating the predictive performance of classification systems [15].

Many applications of pattern recognition are reported in parallel in the literature since the beginning of the studies in this area. Among them are Real-time recognition of spoken words [16], Vehicle recognition for highway lane [17], Synthetic biometrics [18], Machine recognition of human activities [19], Binarization algorithms on historical documents [20], Audio, visual and spontaneous expressions [21], Pattern recognition in cancer diagnosis [22], Pedestrian detection for advanced driver assistance systems [23], Script recognition [24], Traffic sign recognition [25], Plant recognition method [26], Pattern recognition challenges in data-intensive astronomy [27], Audio-based music classification and annotation [28], and Video-based abnormal human behaviour recognition [29]. All of these applications show that the pattern recognition area of study has been participated by multidiscipline of research groups all over the world.

Pattern recognition demonstrated in face recognition application also receives great responses from scholars, researchers and practitioners in the area of detection, identity recognition and latest in image understanding. A survey of approaches and issues are reported such as approaches applied to three-dimensional face recognition [30], Biometric recognition methods [31], Age synthesis and estimation via faces [32], Local binary patterns and its application to facial image analysis [33], and Multispectral face recognition and multimodal score fusion [34]. The problems involved in classifying and recognizing the pattern of human faces from the given face images certainly similar to other image processing issues and matters. The image variation such as illumination, pose and expression are among the major contribution of the problems to be confronted. Furthermore, classification of face images is basically to classify the images that have the same global characteristics as human faces that are similar but not totally equal. This scenario differs in classifying two different classes of different structure or shape.

The detail of the surveys on face recognition problems and approaches used is discussed in the next following sections. The discussion will begin with matter related to unique characteristics information provided on 2D face images, variation complexity produced by intrinsic and extrinsic variations, approaches and methods, and problems tackled in this thesis and proposed approaches.

2.2 Facial Identity and Collateral Information: Extraction and Classification

A classification task in face recognition is much more difficult compared to the classification task in normal object recognition environment. The challenge of comparing a very similar non rigid object had made face recognition is not of category classification as practised in normal object recognition system [5]. The problem becomes more complicated in the presence of intrinsic and extrinsic variations caused by the face itself or by the external factors or a combination both of them.

This section attempts to discuss (a) the unique characteristics of the facial pattern, (b) the parameters to be considered in measuring and representing that characteristics information and (c) the challenges to be confronted in extracting the uniqueness of facial characteristics. Ideally, the former is crucial to face pattern recognition and the latter is a consideration in developing a very complex intrinsic and extrinsic-invariance model [35]. However, in a practical discussion, these are the factors that need to be considered in developing the classification algorithm that can suit the pre-determined application specification.

Figure 2.2: Some face images of different identity from Yale face database.

From a 2D point of view, the structure of human face as shown in figure 2.2 consists of a number of important parameters or components. This involves the curvature and texture of the features such as eyes, mouth, nose, cheek, chin, forehead and many more. The combination of the properties of curvature characteristics and texture of the features create the unique characteristics information (UCI) or face pattern. This UCI varies from one image to another including the images of the same person (variation complexity). The small differences in the patterns reveal the identity of the person. Pixels intensity on the 2D image represents the surface characteristics and form the curvature or shape of the features. From the curvature of the features, one can analyze its geometry characteristic such as the shape and distance between features. This characteristic can be further derived including the length and area of the region of interest. The informative region is not only restricted to the main features such as eyes, nose and mouth. This group of features have their own response to the intrinsic and extrinsic variations. On the other hand, the consistency of the UCI of some features such as the forehead, nose and chin contributed different forms of data that may reduce the unnecessary response to the image variation due to its more stable information. Furthermore, symmetrical property of the human face and the study of skin colour contribute to the close understanding of the faces unique characteristic information. For instance, the intensity values on a 2D image which representing certain skin colour may be affected by illumination variation and produce incorrect judgement on the exact skin colour for a particular sample.

The UCI discussed thus far needs to be represented by the parameters of measurement where the chosen variables are varied accordingly based on different interest of various researchers. According to [36], the variables can be divided into two categories, namely observed and significant unobserved variables. Given a 2D face image (colour or gray image), the observed variables simply can be viewed and analyzed from its pixel value data. However, the significant unobserved variables are the information inherently delivered by the natural representation of a 3D human face recorded on a 2D image. These variables represent the information such as the expression states of particular faces, type of gender, age, regional appearance or ethnicity and many more. Illumination, geometrical view, orientation (rotation and scaling) and any of its derivatives are grouped as the image variation and unobserved variables. The approaches reported in the literature for extracting the identity of the person can be broadly classified into two categories, namely component-based or feature-based and holistic-based or appearance-based approaches [6], [7], [37]. Holistic-based approach extracts the features of the whole image as one response while the component-based approach is an analytical approach that concentrates on the discrete features of the image. These two approaches will be reviewed later in conjunction with the main theme of the research carried out in this thesis. In this regard, the explanation is classified in the way the problems are perceived, that is the complexity of the image variation in extracting the UCI of a face image.

The challenges in representing the variables mentioned earlier are closely related to the study of image variation that involves intrinsic and extrinsic variations. The performance of the designed features extractor and classifier can be moderately increased by understanding what UCI feature is being looked for and what sources of the variation that effect this the most. The intrinsic variation is observed through the physical nature of the face. This involves identity, sex (gender recognition), age (young or adult), non-rigid movement (such as expression (emotion) and speech), and face changes due to scars, weight and self-occlusion. On the other hand, the changes in extrinsic variation can be caused by changes of viewing geometry, illumination, imaging process, occlusion and rigid movement by head [38]. The illumination problem is observed with the interaction of light with face and the observer. The pose variation is determined from the rigid motion between the observer and the subject. The variation due to facial expression (and speech) is caused by non-rigid motion or changes in 3D shape [35]. Occlusion and accessories (makeup, glasses, beard, etc.) are the sources of variation that can also further impact the recognition performance. Other variations such as changes in weight (expanded face surface) and the presence of scars further challenging the performance of extraction technique.

As mentioned earlier, the classification task is difficult due to inter-personal and intra-personal variation. Obviously, the difference between two images of the same person from different viewpoints is larger than the difference measured for different people viewed from the same view point. This problem has been discussed in [38] and the result is shown in figure 2.3 and figure 2.4.

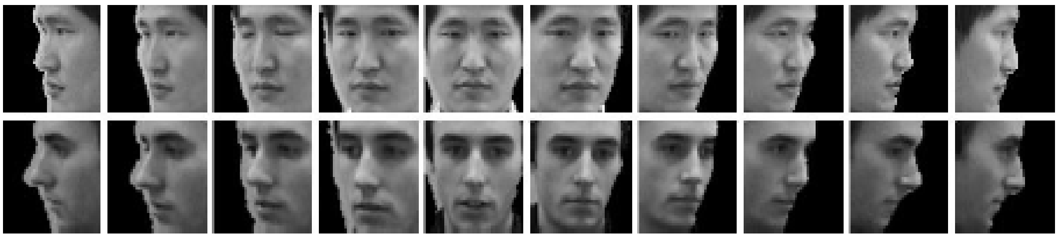


Figure 2.3: The difference between two images of same person with different view point is larger than the difference measured for different people of same view point [14].

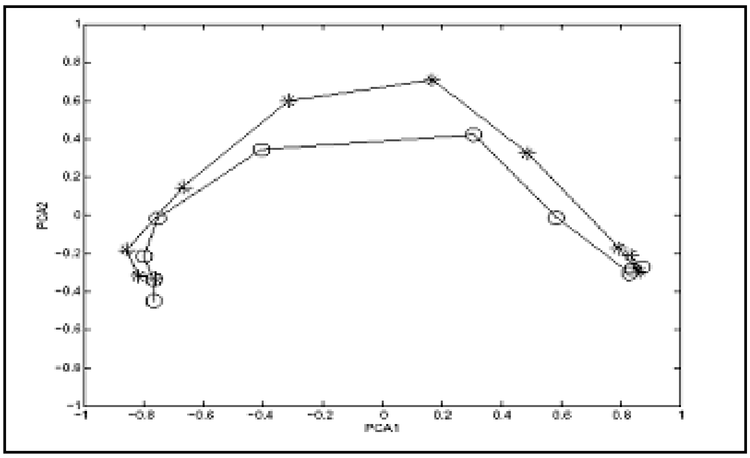


Figure 2.4: Representation of face images from Figure 2.3 in the first two eigenface dimensions [38].

The approach used in a classification task should maximize the intra-personal difference and minimize the inter-personal difference, so that the matching performance can be increased. Ideally, the feature extraction technique used must in some way able to capture the unique characteristic of person's face in the presence of any variation. However, this is not an easy task due to the major variation problems of illumination, pose, expression and occlusion (the dynamic variation of human face). Figure 2.5 demonstrates the various problems of variations and its implication in features extraction and classification tasks. Each of these variations warrants a separate study due to its complexity. A great deal of previous research has been carried out in tackling these variation problems as discussed further in Section 2.3.

Figure 2.5: Facial variation: A model of problems related to face recognition and demonstration of intrinsic and extrinsic variation. (a.) Original face image (frontal view). (b.) Effect of pose variation. (c.) Effect of illumination variation. (d.) Effect of expression variation. (e) Effect of occlusion. (f.) Combination of all.

The second problem is the limitation of UCI due to an increasing level of variation complexity or limited number of images of a particular class that may be available for the training purposes. Furthermore, the images that are used in a training session may cope with the specific application that relate to the training environment but not in other real applications. However, there are fewer studies in the literature tackling this complex problem, due to the limitation of information availability and the high variation complexity or limited image availability.

2.3 Variation Complexity versus Unique Characteristic Information (UCI)

The amount of Unique Characteristic Information (UCI) on a single face image is inversely proportional to its variation complexity. This has been derived and explained in Chapter One. The more the variation complexity, the less the identity information can be observed and extracted. There are two general ways in dealing with these problems. One of them is to reduce the variation sources while collecting more information. This can be done by obtaining the image under a controlled environment condition where controlled lighting could reduce the illumination problem, the user cooperation can helps to solve the viewing problem (giving frontal view) and expression state (normal emotional state) and not allowing occlusion at all. In this regard, almost all of the developed techniques reported in literature may perform precisely [6], [7], [37], [39]. This kind of environment-controlled recognition system is suitable for the application such as security and access control or any other application where the user cooperation can be relied on. Unfortunately, often real-life applications are uncontrolled environments and need a more robust analysis to be carried out. The second way in dealing with the variation complexity is the most challenging one as the recognition performance depends solely on the recognition algorithm. From the literature study, the approaches used for algorithm development in handling the uncontrolled variations can be broadly classified into two categories, image-based and model-based approaches (*variation-modelling*). The first category can further be divided into two approaches; they are *invariant features* and *transformation/normalization* approaches [40]. As most of previous research has focused on the study on specific variation, it is quite difficult to judge the reliability of the techniques when tested on the other type of variation.

In this section, the review on the past and current work focussing on the type of variation components that make the complexity (i.e. illumination, pose, expression and occlusion) and the methods used in handling these variations will be carried out. Secondly, the work on the limited information availability such as using a single face image will be reviewed. Finally, a number of previous research studies that have a similarity in the conceptual problem to the one proposed in this thesis will be discussed.

The illumination impact on the images of same person can be seen in Figure 2.6 [41]. The same features or spot in the image is changes when different illumination impact is given. This non-linear illumination variation is caused by the shape that reflects the light [42]. This variation can make up to 150% changes in original image (i.e. 20% made by pose variation) [36]. Furthermore, a large illumination variation is able to erase the entire features or change the characteristic of features in term of geometry, strength and existence of any given intensity-based features [36]. However, since the face is assumed symmetrical, some parts or erased face features can be compensated by manipulating the other side of symmetrical. This can be seen in figure 2.6 where the spot is represented by the red circle. The study of illumination variation involves the light direction, brightness, contrast, shadow and shading. Work in [40], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52] have demonstrated the handling the problem of illumination variation by the techniques categorized from *invariant features*, *transformation/normalization* and *variation-modelling*. For instance, in [52], the problem of varying illuminations has been tackled by the creation of quotient image based on assumption that all faces fall into a class of object. An appearance-based method discussed in [49] and [50] applied Lambertian reflectance and model the illumination variability. A small set of training images are used to generate the illumination variation representation i.e. the illumination cone. In [48], the gray level histogram of one face was transformed to the histogram of any other face. This is done with the assumption that all faces fall into the same class such as in [52] so that facial pixels modelled by empirical probability distribution can be transformed to normalize the illumination. This is discussed further in [53], [54], [55] and [56].

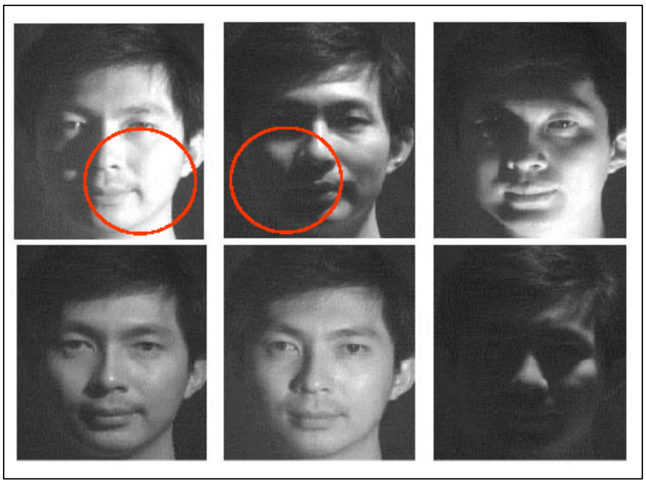


Figure 2.6: Sample images of illumination variation problem.

In [38], pose variation problem has been tackled by the development of dynamic face model. The author had produced a comprehensive approach for face modelling, detection, tracking and dynamic recognition. By using the image sequences (video input), a sparse 3D shape model is developed where several face detectors are constructed choosing the optimum detection that accounts for the accuracy and speed of face image processing. Support Vector Regression, Support Vector Machines and eigenfaces are used and a Kernel Discriminate Analysis technique is developed in this multi-view face recognition. In [57], a multi-view optimization search based on a model and data-driven method is proposed. This is carried out in determine the most suitable views for 3D facial modelling. The simulation of silhouettes images for prototype head/torso using scanned 3D heads are found to be efficient and authors claim the first systematic investigation of optimal views for modelling the 3D face. In [58], with the aid of distribution of needle-map directions on the 2D image, delivered by shape-from-shading technique, the orientation histograms are computed in estimating the facial pose. From the experimental results shown, the authors reported that the method is only effective for the head rotation of less than 40 degrees from the frontal pose. As the method does not rely on the detailed features alignment, the authors suggested that the method to be used for rough pose estimation.

The study of facial expression variation as shown in figure 2.7 have received a great deal of attention in research described in [59][60][61][62][63][64]. A number of references listed in the bibliography suggest the seriousness of this particular study area. [60], [61] are review papers that one can refer to the state-of-the-art in automatic facial expression analysis. In their studies, [60], [65] have reported that facial expression, vocal and verbal carried 55%, 38% and 7% of the message delivery effectiveness respectively.

Figure 2.7: Sample images of common facial expression states from Cohn-Kanade AU-Coded Facial Expression database.

The comparison of performance demonstrated by different methods (Gabor wavelet and Principle Component Analysis) reported in [66] revealed the high achievement (96% accuracy) in classifying 12 facial actions of the upper and lower face. In [67], a similar achievement is also reported for the performance of feature-based method, where 95.4% and 96.7% for upper face action units for (AUs) and lower face AUs respectively. A hybrid approach demonstrated in [68], a result of 92.7% is achieved for the expression recognition performance. It was reported that a combination of the geometric features and regional appearance methods had greater achievement compared with the individual achievement shown by both methods. Results of 89.6% for geometric facial features and 32% for regional appearance pattern are achieved on the test of 514 samples (European, African and Asian ancestry).

Figure 2.8: Sample images from AR database demonstrating face of partially occluded with varying illumination.

The image variation such as those shown in figure 2.8 is another kind of image variation that may greatly influence or degrade the classification performance due to the fact that part of the features is occluded. The study involved the two issues that measure the robustness of the developed system. The first one is the study of the salient features that may exist on the face image and to the extent of which features that may best represent the identity of the person. The second one is the performance of the extractor and which method may provide better extraction. However, fewer studies can be found in the literature for this kind of variation complexity.

There are also studies that investigate use of more than one variation in measuring the robustness of the extractor. [69], [70], [71] and [72] are examples of research works that combined the study of illumination and pose variations in face recognition. The matching between probe and gallery images in [70] is done by the algorithm that estimated the Fisher light-field of the subject's head.

Fisher's Linear Discriminant (or Linear Discriminant Analysis) uses the available class information to compute a projection for discrimination tasks. The work in [69] falls into the category of *invariant features* with the use of identity signature derived from the so called illuminating light field. The method assumed Lambertian reflectance for illumination and light field model for the poses.

There are also various methods applied in tackling the problem of a single face image. Some of this research can be found in [73], [74], [75], [76], [77], [78] and [79]. In [75], the method based on PCA, known as $(PC)^2A$ is proposed. The author has reported that given only a single training image per person, the method has achieved 3-5% higher accuracy as compared to the standard eigenface technique. It is also reported that the method can be performed with less computational cost as well. In [73], the combination of features and holistic approaches is performed through a proposed design procedure. Given a face image of various views, the head model is estimated after allocated 15 feature points on a face. By using geometrical measurements, the rotation of the face can be estimated so that it can be in frontal viewed to compare with the database of 40 frontal-view faces. Secondly, the windows for the eyes, nose and mouth are created and comparison is made between the test image and database using a correlation method. The overall performance rate of over 84% is reported.

Other researchers that have worked on a single image using various methods such as automatic classification, novel views, synthesis of novel views and quadratic approach shape-from-shading can be found in [74], [76], [78] and [79] respectively. Shape-from-shading (SFS) technique is basically measuring the shape gradient on the 2D images from the shading information. In the review papers [80] and [81] the authors have divided the SFS approaches into four categories, these are minimization, propagation, local and linear approaches. The output quality from each category are shown, evaluated and discussed thoroughly although none of them produced good results in term of image recovery. Numerous SFS-based techniques have been developed in [82], [83], [84], [85]. These give examples of the exploration of SFS that use statistical, surface topography information, knowledge-based, adaptive and neural network respectively. The technique of rendering the image for the purpose of obtaining more information has long been used especially in computer science society.

In [86], the variation complexity is restricted to a imprecisely localized image whilst partially occluded and expression variation. The author works on a single image per class for limited information availability. The probabilistic approach (within the appearance-based paradigm) is used, where each of the variations is tackled differently. Studies in [87] investigated the impact of illumination, pose, expression, occlusion and subject gender using two commonly algorithms, template-based and features-based methods. In this study, authors did not propose any new techniques. The objective of their research was to conduct a series of tests on three databases (PIE, Cohn-Kanade and AR) to evaluate the effect of concerned variations. Interestingly, the outcome of their experiment concluded that in natural environment, pose, illumination, expression, occlusion and individual difference among people represent critical challenges to face recognition algorithm [87]. The investigation work described in [88] is similar to [87], except the tests are limited to illumination, occlusion and expression. The comparison of eigenfaces and fisherfaces methods is performed on AR database.

At this stage of discussion, it is clear that the face recognition is an unsolved problem and research to be carried out need to look into the problem complexity with realistic solution.

2.4 Unfamiliar Facial Identity Extraction and Classification

A typical unfamiliar facial identity recognition system has been highlighted in chapter one of this thesis and the main stages occurring in the recognition process shown. The flow of the information transformation is also explored with comparison between familiar and unfamiliar facial identity recognition process with respect to the proposed system and solution in this thesis.

In this section, the detail of the proposed system will be explained from the conceptual overview in relation to the application and the background knowledge involved. The key parameters in the colour, grey level and edge image analysis will be reviewed and the statistical texture analysis and basic operation of morphological approach will also been explained in relation to the background research of the proposed solution.

2.4.1 Conceptual Overview – *The-ID System Overview*

Depending on the search request, figure 2.9 illustrates the flow of the classification process from the image acquisition to the database division of the regional appearance, gender and age classes. However, in this thesis the work is restricted to the extraction, classification and representation of collateral UCI. This means that the input to the developed system is the detected face image. The system works by providing the search request for regional appearance, gender and age classification based on the skin colour, facial texture and features measurement respectively.

For simplicity, the unique identity of a particular person is named as *Temporary Human Electronic Identification,* abbreviated to ***The-ID***. ***The-ID*** represents three identity parameters; they are regional appearance, gender and age. The regional appearance classes are chosen from the three major regional appearances in Malaysia; they are Malay, Chinese and India Malaysian. The gender classes are male and female while the age classes are categorized as child and adult. This chapter expands the explanation of ***The-ID*** determination, the process of collateral classification and recognition results.

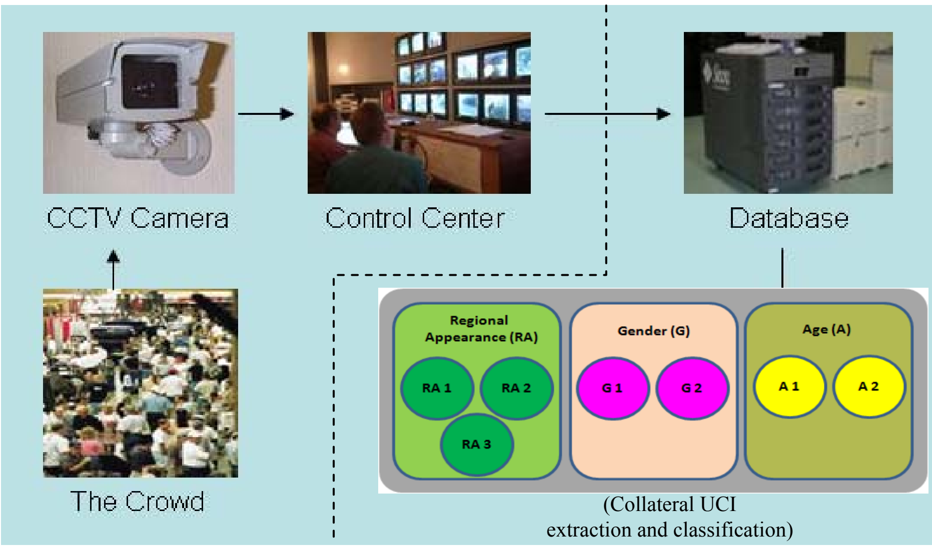


Figure 2.9: The flow of the identity parameters classification from the real life crowd to the database division (regional appearance, gender and age classes).

The challenge confronted in the ***The-ID*** classification task is to isolate and group the classes of regional appearance, gender and age in the manner where each of the class can be either a parent or sub-class. This is important as the ***The-ID*** classifier further needs to classify these classes into sub-classes where each of these sub-classes will have their own independent unique representation. For instance, in the Malay class, there will be Malay-male and Malay-female classes. Furthermore, in these two sub-classes, there can always be Malay-male or female-adult and Malay-male or female-child classes. The same classification hierarchy also applied for Chinese and India classes. In the gender classification, no matter what regional appearance or age the subjects are, the system must capable to classify both male and female classes. For example, no matter whether subject is in male or female class, there will be Malay, Chinese and India subjects where each of them can be further classified their age classes. The same scenario will also happen in the age classification where the sub-classes of regional appearance and gender must be determined. Figure 2.10 illustrates the route of the database division with respect to the searching request.

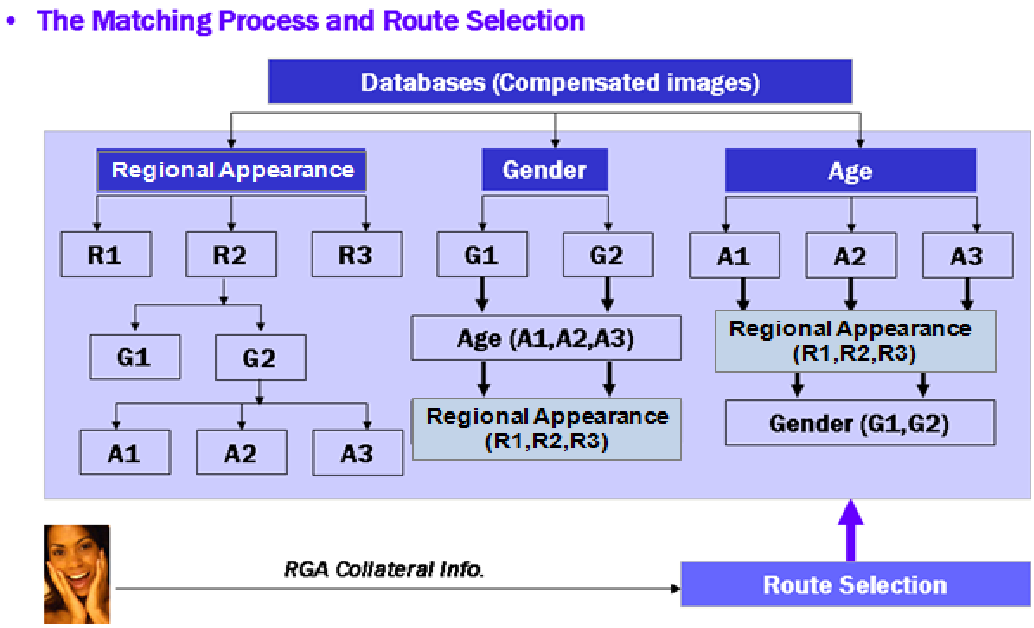


Figure 2.10: Block diagram for the matching process and route selection for identity searching.

The method used in regional appearance recognition must capable to differentiate between the Malay, Chinese and India classes but leave uninterrupted information when differentiating the members within the particular class. The colour analysis is performed to reach this goal as Malay, Chinese and India skin colour are having different characteristics. In this regards, the strategy used has made the rich fullness of the collateral information of the face is not complicated when classifying within the class information as these classes need to be classified into sub-classes of male, female, child and adult classes. Different features of UCI are used to determine these sub-classes. By doing this, the similarity within the class and the dissimilarity between the class can both be increased by not affecting the dissimilarity between the members of a particular class for further classification. For example, the other collateral UCI of the members of the Malay male and female, child and adult class can be extracted from its texture and features sizes and distances (not from the skin colour) by using the proposed DLBT method and creates a signature which then represents a part of the identity. The information included in a completed identity representation is the colour code (regional appearance information), the facial texture (gender information) and derivative of sizes and distances of the features (age information). The vector version of this information measures the identity parameters of a particular person.

The last stage of ***The-ID*** system implementation is to match the criteria of a particular unfamiliar person to the database of detected face images. The term unfamiliar refers to the computer perception and the databases to be searched. These are open databases such as the one in public areas or any other places (shopping complex, private or government building, country border, airport, university campus, school, bus station and many more). This is one of the reasons why ***The-ID*** should have a simple processing approach and be easy to be implemented. As what have been discussed in previous section, face images are full with unique characteristic information. With the rich of information in a particular database, there are many ways of gaining the benefit of the ***The-ID*** classifier. If the ***The-ID*** is applied to the large database such as in the shopping complex or public areas, the ***The-ID*** may generate results of the statistical data of the percentage or fraction of how many Malay, Chinese or Indian are there, which age groups are dominant at that location or which gender is a majority in that area. This statistical data is useful and may be used by an authority body and product development groups for marketing. In the broad area of application, the ***The-ID*** may be used for segmenting the raw data of peoples in any database, such as regional appearance, gender and age classes explained previously, where this data ready to be used for any appropriate purposes.

2.5 Background Knowledge

2.5.1 Colour Image Analysis

Colour cue has been widely used and have been continuously studied in image processing and face detection research communities respectively. This scenario is motivated by the robustness of colour processing with today technology. In face detection, skin colour is considered as robust as viewing geometry, translation, rotation and scaling variation [89]. This statement can be supported by [36] as the main goal in face detection system to extract the face-look object from the scenery that consists of various categories of objects. However, this classification scenario is different in face recognition system as the face is compared to other faces (same category) where the difference is very small. In addition, if the colour characteristics of different peoples are similar, one can only easily judge that they are in the same ethnic group. This means that the facial features are the main UCI that the two peoples are different. Therefore, in this thesis, the colour analysis is chosen to perform the classification of regional appearances groups (Malay, Chinese and India Malaysian).

In this section, we will review the back ground knowledge in performing colour image analysis and reviewing the relevant previous work with respect to the thesis interest.
Figure 2.11 demonstrates the reflectance of the human skin with respect to the wavelength of the light within the visible region from 400 nm to 700 nm [89].

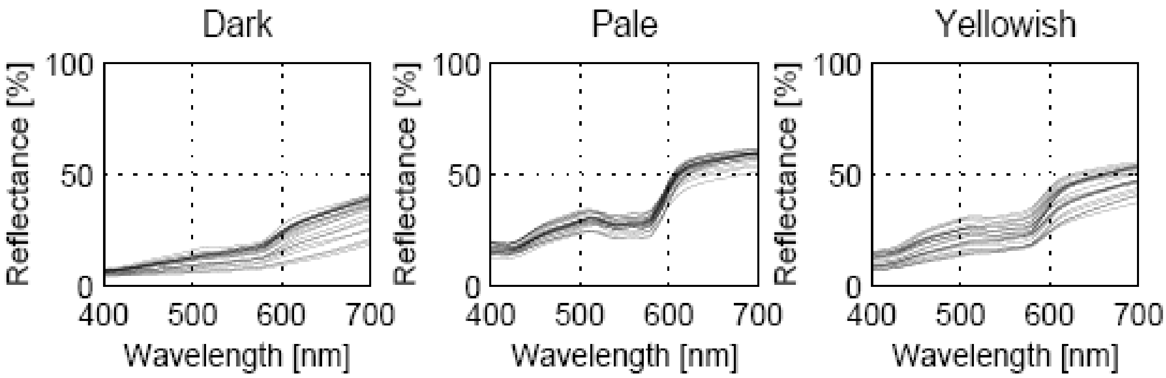


Figure 2.11: Graph of reflectance versus wavelength for the three different groups of human skin (dark, pale and yellowish)[89].

The above results prove that the regional appearance can be classified according to their skin colour. As a matter of fact, these three categories are directly related to the three major regional appearances in Malaysia, they are Malay (pale), Chinese (yellowish) and Indian (dark). The above results can only be referenced from a physics point of view involving the measurement of light wavelength. However, the input of the system proposed in this thesis is dealing with the 2D images where the available information is only the pixel or intensity values. Recalling from [36], the observed variables on the face image are the intensity values that are being used to explore the meaning that is carried by these values, these are the significant unobserved variables (the regional appearance, gender and age).

2.5.1.1 Colour Space

Colour spaces such as RGB (Red, Green, Blue), HSV (Hue, Saturation, Value), YC_rC_b, CMY and many more are used to represent the images in a such way that is perceivable and observable by human eyes. In this section, the discussion of colour spaces will only be focused on the interrelationship between these colour spaces for the image representation purposes. The discussion on the previous research will be made. It is hope that with current technology, colour image analysis should be able to have a place in the image processing although it was known to be processing intensive.

In general the colour that is perceived by human eyes is comprised of white and coloured light. Various amounts of these two make up the variety of colours selection. The dominant wavelength in the coloured light is known as hue. The maximum value of hue is achieved at the level known as saturation (chroma) [89]. HSV colour space is often practiced in commercial applications, such as in illustration application and image programs [90].

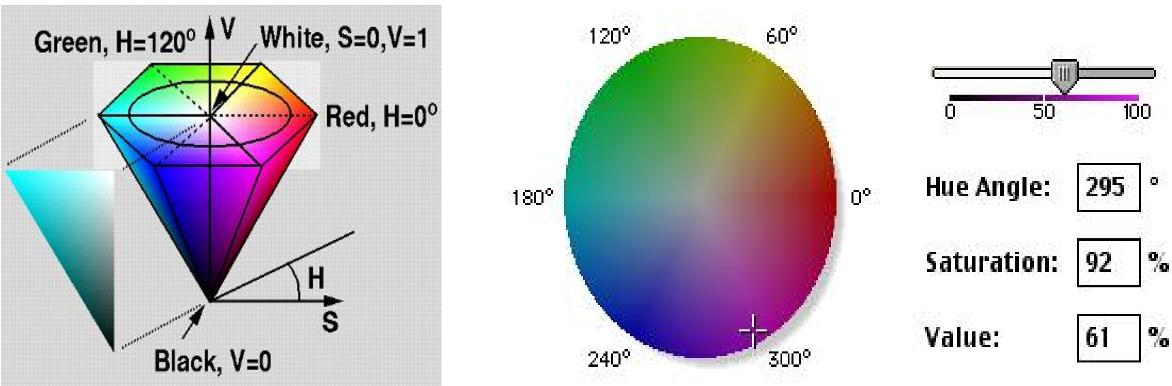


Figure 2.12: Hue, Saturation and Value (HSV) color space or model [179].

Figure 2.12 visualize the HSV colour space showing the direction of hue angle around the vertical axis, the saturation and value in term of percentages on the plane and vertical axis respectively. In [91], the extraction of face regions in a complex background of colour image is reported as successful with the use of YC_rC_b and HSV colour models for skin colour detection. Morphological (opening) operations are then performed to remove small objects in the background area. The decision rule based on shape and size is computed for face regions selection. [92] also used YC_bC_r

and HSV skin colour spaces for segmenting the foreground in their proposed face detection. The opening and closing morphological operations are applied so as to remove the small regions.

The use of AdaBoost algorithm can be found in both [93] and [94] for face recognition and detection respectively. In [93], the AdaBoost learner is integrated with the chromatic information to explore the non-linearity problem and illumination variations in face patterns. In [94], the AdaBoost algorithm is combined with the skin colour segmentation based on YC_bC_r model of chrominance space. Then, they performed morphological operations to remove the unnecessary objects or noise in the image. The face images used in the experiments also incorporated variations of viewing geometry, illumination, expressions and orientation.

One of the latest studies that uses colour for face recognition is [95]. The method is based on the Local Binary Patterns (LBP) of Quaternionic Gabor features (QGF). The QGF is then used to encode the positions and attributes of the face elements. Here the process is reported as being robust to pose, illumination and facial expression variations. [96] also used Gabor features that derive and extended the hyper-complex or quaternion domain. Their work also involved the use of elastic graph which was commonly applied to gray scale images. Performance comparison has been made for both type of input images (colour and gray level) and an improvement of 3% to 17% are reported on the use of colour images. Another recent study on colour face recognition found in [97] is based on a matrix-representation model and a method called 2DPCA. The features extractor computes the colour-Eigenfaces using 2DPCA and a nearest neighbourhood classification approach is adopted to identify the colour face samples [97]. The same category of representation is also demonstrated in [98]. Here they have applied the Linear Discriminate Analysis (LDA) of multispectral LBP histograms to the XM2VTS and FRGC 2.0 databases.

The role of colour image in the case of real life low-resolution image problem has been studied in [99]. Here they have proven improved performance of the colour image compared to the intensity-based images by introducing a new metric so called variation ratio gain (VRG).

2.5.1.2 Relationship of Colour Spaces

Referring to [3] and [89], the relationship between various colours spaces can be shown below. The relationships shown are limited with respect to RGB colour space. For RGB values which are normalized to the range of [0,1], we have:-

(i) ***Normalized RGB:***

$$r = R/(R+G+B),\ g = G/(R+G+B),\ b = B/(R+G+B)$$

(ii) ***HSV:***

$$H = \begin{cases} \theta & \text{if } B \leq G \\ 360 - \theta & \text{if } B > G \end{cases}$$

where,

$$\theta = \cos^{-1}\left\{ \frac{\frac{1}{2}[(R-G) + (R-B)]}{[(R-G)^2 + (R-B)(G-B)]^{1/2}} \right\}$$

$$S = 1 - [(3/(R + G + B))\,[\min(R,G,B)]]$$

$$V = (R + G + B) / 3$$

(iii) ***YC_rC_b:***

$$Y = 0.299R + 0.587G + 0.114B$$

$$C_r = R - Y$$

$$C_b = B - Y$$

(iv) ***CMY and CMYK:***

$$C = 1 - R$$

$$M = 1 - G$$

$$Y = 1 - B$$

2.5.2 Gray Image Analysis

The complexity of the colour images such as RGB format can be reduced to the gray scale with 256 levels for each pixel. Gray image analysis is performed in many classification applications where the desired outcomes can be based on the intensity values. This gray scale images can still provide huge information, but with less processing time as the pixels are only in the range of 256 gray levels.

From a robust computer processing point of view, characterizing the input image must focus on the available information and should not rely on what object should have seen using normal human judgement. This is agreed by many researchers such as the one reported in [100] and [101] to name a few. [101] has provided a unified conceptual framework for various existing theories and techniques in dealing with the gray-scale images. [100] has also demonstrated an example of an application that use gray images for image retrieval. In their study, more than 1000 images have been tested for image retrieval with the use of local gray value invariants technique. There are many other studies in the literature that work on gray scale images with various techniques and application. However, in this section we restrict our review to the texture analysis that works on the gray image with respect to the thesis interests. Furthermore, this current study focuses on the second order statistics, which means dealing with the pixel and its neighbourhood in the form of pairing existence in the image (co-occurrence).

In the next following sub-section, we will review the methods used in the literature for texture analysis and highlights the use of texture as a cue for our proposed method in classifying the gender classes, i.e. male and female classes.

2.5.2.1 Statistical-based Texture Analysis

Texture is one of image primitive cues which describes the depth or 3D information of 2D images. The definition of 'texture' varies accordingly depending on the perception and applications that interest the people who involved in project or algorithm development [89]. Texture analysis is widely used in many applications that are involved with image classification and segmentation from the point of view of the regional texture pattern analysis. Remote sensing and surface inspection are examples of texture applications.

Figure 2.13 demonstrates various kinds of texture (silky, smooth, rough and bumpy) that are typically classified based on human perception, experiences and judgement. Figure 2.14 illustrates one of the examples on how the texture of the image is represented for computer processing. In this example, the rough texture is revealed with the variation of intensity values in 3-by-3 neighbourhood. A simple representation of this regional texture can be made by simply subtracting the minimum value with the maximum value and the judgement can be regarded by setting the threshold value for this rough texture category. In this example, the obvious difference between the maximum and minimum values allows judgments that the texture belongs to the roughness category.

Silky **Smooth** **Rough** **Bumpy**

Figure 2.13: Various kinds of texture.

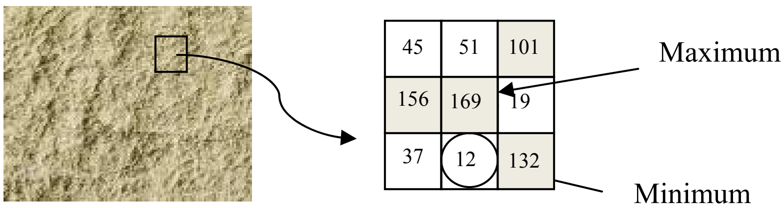


Figure 2.14: Texture observation and representation.

Four main categories of applications that commonly perform the texture analysis are texture classification, segmentation, synthesis and shape from texture. Consequently, methodologies in texture analysis can be categorized into four main approaches, namely geometrical (structural), statistical, model-based and signal processing (transform) [102].

Geometrical methods are the group of methods for analyzing the image texture based on the texture elements which depend on the geometric properties of these elements [102], [103]. The statistical properties and placement rule can be analyzed and decided respectively for the extracted representation. Model-based methods are based on the parameters of texture representation in the form of modelling that can be used to describe and synthesize the texture [102]. In the third category, as the name implies, the signal processing or transformation class methodology uses the frequency domain to represent the texture. This includes techniques such as Fourier transform, Gabor wavelet and many more. In this section, our review is restricted to the statistical texture analysis where we will discuss the important facts around this method and review some other related research work and comments.

The relationship between the pixels can be analyzed from the study of the intensity or gray values and its spatial distribution, which leads to the texture representation and observation. In first order statistics, the pixel is studied individually while the second order statistic try to observe and reveal the relationship between a pixel and its neighbourhood. One of the pioneering pieces of work that applied statistic knowledge is as reported in [104] where the use of co-occurrence matrix was introduced. GLCM, as invented by Haralick *et al*. [142] used a set of offsets of the same distance and computed for four directions, 0, 45, 90 and 135 degrees. With these data, the texture image matrix has been represented with the new form of matrices where a number of statistical analysis methods can be performed.

A co-occurrence matrix is derived as:

$$C(i,j) = \sum_{p=1}^{n}\sum_{q=1}^{m}\begin{cases}1, & if\ I(p,q) = i\ and\ I(p+\Delta x, q+\Delta y) = j\\ 0, & otherwise\end{cases}$$

where,

C(i,j)	=	*The Gray Level Co-occurrence matrix (GLCM),*
I(n,m)	=	*Image I of size n x m.*
(Δx,Δy)	=	*Offset (Direction of performing the pixel pair comparison).*

Suppose the image, *I(n,m)* and a GLCM, *C(i,j)* is defined with matrix size

$$I(n,m) = \begin{bmatrix} a11 & a12 & a13 \\ a21 & a22 & a23 \\ a31 & a32 & a33 \end{bmatrix} \qquad C(i,j) = \begin{bmatrix} (0,0) & (0,1) & (0,2) \\ (1,0) & (1,1) & (1,2) \\ (2,0) & (2,1) & (2,2) \end{bmatrix}$$

The size of *C(i,j)* is determined from the chosen re-quantization level of interest. This gray level is chosen normally with respect to the computation complexity. The higher the level, the more processing time is needed. The above example uses 3 levels of gray scale, from 0 to 2, and as a result, the size of *C(i,j)* is 3 by 3. Comparisons are made between pixels in *I(n,m)* (a reference and neighbour pixel) in a form shown in *C(i,j)*. The entries of *C(i,j)* are the sum of appropriate pixel pair that appear over the image, where the direction (offset) is 0^0 (comparing the pixel with its right neighbour). The process of comparison is repeated with the directions of 45^0, 90^0 and 135^0. For instance, the entry (0,0) is a sum of combination or pair of reference and neighbouring pixel where both pixel values are (0,0). The comparison of this pair is made over the image. Once the completed *C(i,j)* is obtained, the statistical information can be analyzed by using the texture features such as GLCM Mean, Correlation, Energy, Homogeneity and many more.

In short, a few common statistical analysis which can be found in many statistical books or references [3], [102] and [103] are listed below.

***(i)* GLCM Mean,**

$$\mu_i = \sum_{i,j=0}^{N-1} i(P_{i,j}) \qquad \mu_j = \sum_{i,j=0}^{N-1} i(P_{i,j})$$

Both equations represent the GLCM Mean for the horizontal and vertical GLCM respectively. By taking i as a reference pixel while j as a neighbouring pixel, the probability value of GLCM, P_{ij} is elaborated a number of times as a pair of (i,j) appears in the image dimension that have been broken into a single line operation from (i,j) = 1 to N-1.

(ii) GLCM Variance (GLCM Standard Deviation)

$$\sigma_i^2 = \sum_{i,j=0}^{N-1} P_{i,j}\left(i-\mu_i\right)^2 \quad \sigma_j^2 = \sum_{i,j=0}^{N-1} P_{i,j}\left(j-\mu_j\right)^2$$

(iii) Standard deviation equation

$$\sigma_i = \sqrt{\sigma_i^2} \quad \sigma_j = \sqrt{\sigma_j^2}$$

From the equation, the value of GLCM Mean has a direct influence to the GLCM Variance. Indeed, the GLCM parameters inherently affect the variance. As a nature of tabulated pair of (I,j) within the image dimension, the GLCM variance employs the GLCM in such a way of measuring the dispersion values around the mean and its surrounding. GLCM Entropy is similar to GLCM Variance [90].

(iv) GLCM Correlation

$$\sum_{i,j=0}^{N-1} P_{i,j}\left[\frac{\left(i-\mu_i\right)\left(j-\mu_j\right)}{\sqrt{\left(\sigma_i^2\right)\left(\sigma_j^2\right)}}\right]$$

The texture information given by GLCM Correlation is intuitively differed against other GLCM texture measurement. In revealing the linear relationship in pixel neighbourhood, GLCM Correlation may provide a different kind of information as calculated together with other GLCM statistical-based texture measurement [90].

(v) GLCM Energy

$$\sum_{i,j} p(i,j)^2$$

GLCM Energy calculates the sum of squared elements in the GLCM [105].

(vi) GLCM Homogeneity

$$\sum_{i,j} \frac{p(i,j)}{1+|i-j|}$$

The homogeneity in GLCM data is expressed by the measurement of how close the elements in the GLCM have been distributed compared to the one in GLCM diagonal [105].

Texture analysis often leads to a qualitative distinction between micro-textures and macro-textures where the difference between these two classes is based on the size of texture elements [106]. Texture elements in both classes are the factors of shapes, sizes and placement that are analyzed by different observation with respect to the texture class. In this regard, [106] proposed to use the generalized co-occurrence matrices for texture analysis. Another kind of improvement has been made on the way to represent the micro and macro textures are as shown in [107]. They have introduced newly defined spatial size distributions (SSD) in designing the new descriptors for binary and grey-scale images. The comparison between granulometric analysis and granulometric transformation of the image is the main theme in their work where the more complex descriptors derived from the SSD produced more description for the required finer image description.

One of the latest studies as reported in [108] stated that the higher the number of gray-levels used for computing the GLCM, the better is the performance of the GLCM-based features texture analysis, based on their experiments. This statement is agreed conventionally as it reveals more information for texture representation. But, the main problem is to deal with the huge data extracted with higher numbers of grey-level. In this case, they have proposed and studied the effect of grey-level re-quantization on the co-occurrence based texture analysis. In this study the concept and approach is quite similar to the one proposed in this thesis but using different techniques for the image compensation in confronting the problem of image variations. In their study, they have proposed the idea of rescaling the grey values to a particular range in such a way to normalize the pixel values. The approach taken in the current study is discussed further in the following chapter for the gender recognition task with the presentation of results for compensation and recognition.

Colour and grey level image have their own characteristics information depending on the application and approaches that are of interest to researchers and end users. Another important image conversion format is a binary image where the important information remains held in the image but without the illumination influence. Figure 2.15 explains how the grey scale image is represented by the binary image [109].

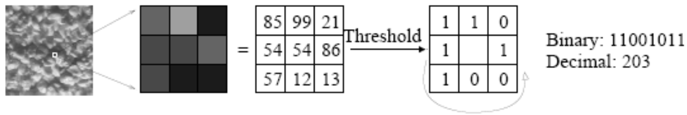


Figure 2.15: The basic operation for binary image representation [134].

A binary image or bi-level image is obtained by threshold the intensity values on a digital image and the outcome is only one of two possible values for each pixel, either ‘0’ or ‘1’. In common practice, the black colour (0) represents the background while the white colour (1) represents the foreground or vice versa.

As discussed in the previous chapter, many images acquired from the real world have variation complexity involving the illumination, viewing angle and other kinds of intrinsic and extrinsic variations. There are many studies in the literature which use binary image to avoid the presence of illumination problem in analyzing the texture. One remarkable piece of work is as reported in [110] and later this approach is applied by many researchers such as in [111]. However, it is believed that there might be some loss in information compared to the original image information. This is the trade off that needs to be considered and the judgement made on the way the information is required for the analysis.

2.5.2.2 Principle Component Analysis (PCA)

As the name implies, PCA is a statistical method employed to perform an analysis on a set of data, possibly with high dimension where the pattern or principle components can be revealed. The fact that the method can be relied on, is the ability to extract the significant factor or pattern characteristics and engage a new representation together with the dimensionality reduction of the original data set.

One of the early works that applied PCA in face recognition system is as reported in [112]. From the mathematical point of view, the PCA method calculates the eigenvectors of the covariance matrix of the set of face images [112].

The steps taken in applying the PCA method in face representation and recognition are generally listed below.

(i) Given a set of face images, the image matrix is first normalized by subtracting the mean from each of matrix element.

(ii) Calculation of covariance matrix is implemented where the eigenvalues and eigenvectors are obtained to represent a new dimension of the data pattern.

The covariance matrix, C_x is defined as [3]:

$$C_x \quad = \quad \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{(n-1)}$$

where,

$$\bar{X} \quad = \quad mean\ of\ matrix\ X.$$

$$\bar{X} \quad = \quad mean\ of\ matrix\ X.$$

In this thesis, PCA-based face recognition algorithm is used and applied. The details of the discussion is reported in Chapter Five where the database is segmented by the ***TheID*** software, (created from the thesis) and searching and classification of face images are done by typical PCA-based FR system. The main purpose of this cooperation is to analyze the performance of ***TheID*** in term of shortening processing time for the face recognition algorithm to classify the subject.

2.5.3 Edge Image Analysis

The complexity of image variation problem is built up from factors including the viewing geometry, illumination, occlusion and other kind of intrinsic and extrinsic image variation. Ideally, the recognition performance will increase whenever the variation is reduced and/or the UCI is increased. However, the variation reduction on 2D face images might lose important clues or UCI data for a particular faces and increasing the UCI may also increase the image variation. This phenomenon has been demonstrated through region characterization shown in the gray and binary image analysis in the previous section.

In this section, we will review another kind of image presentation where only the edges of the objects in the image are to be analyzed. This kind of image simply called edge image is useful in analyzing the characteristics of features in the images such as the shape, size and its derivatives. Figure 2.16 shows a simple and robust edge image conversion using a well known Canny's filter. From the output in the figure, it is clear that the extracted edges have characterized the boundaries and reveals the shape of the object or features in the image. This element of UCI is always confronting the two situations mentioned in the earlier of the section. The output is isolated from the illumination variation, which reduce the dimensionality of the data that needs to be processed.

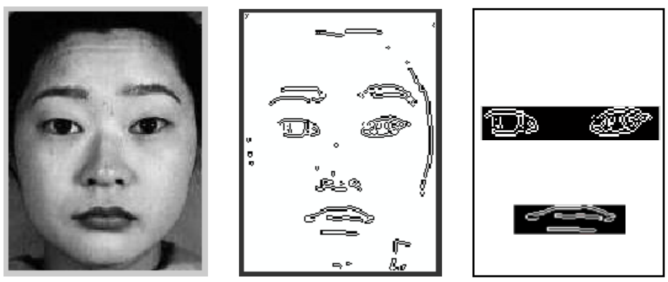


Figure 2.16: Typical edge face image (JAFFE database) produced by Canny filter.

It also reduces the unnecessary data to be analyzed allowing concentration on the remaining data. However, this can only be true if the extracted information is the valid data that is supposed to be extracted. In this regard, the edge detector must play a vital role in detecting a valid situation.

Technically, through the image acquisition system, any 3D real world object may end up on 2D image with various intensity or pixel values representation. The differences between the intensity values may yield the boundaries in term of lines and curves. In other words, these boundaries or simply the 2D shapes (constructed from the combination of lines and curves) of the object on 2D image are characterized by the edges. The edges distinguish the objects from the background. By determining the true edges, one can perform the image segmentation, detection or any relevant image processing task as what is concerned in this thesis.

There are commonly three stages in the process of edge detection. Noise reduction, high-pass filtering and edge localization processes are performed respectively. The principles of edge detection can be explained with the aid of figure 2.17 by observing the cross-sectional or profile view of the intensity changes of an image [113]. There are commonly three types of edges, known as steps ((a) to (b)), lines (c) and junctions (d). The step type can be detected by determining the gradient of intensity function of the image [113] while lines are localized by zero-crossings of the first derivative or local maxima for gray level images. In the case of edge junctions as shown in figure (d), localization can be done such as by a point with great variation in gradient direction. Figure 2.18 illustrates the first and second order derivatives of a one-dimensional function.

A partial derivative for a basic definition of a one-dimensional function, f(x) is given by [3],

$$\frac{\partial f}{\partial x} = f(x+1) - f(x)$$

And a second-order derivative function is given by,

$$\frac{\partial^2 f}{\partial x^2} = f(x+1) + f(x-1) - 2f(x)$$

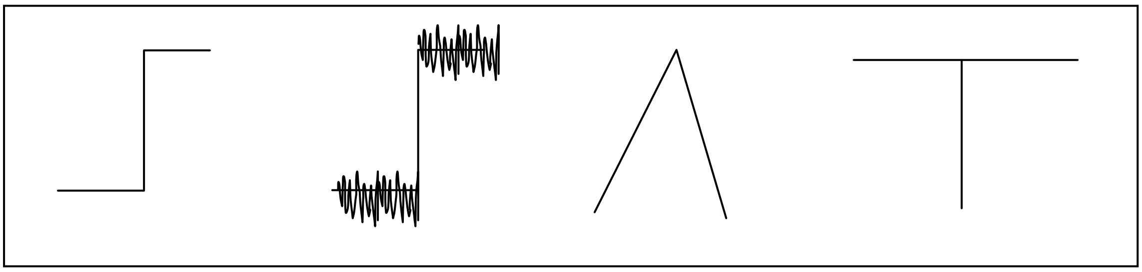
In applying these two functions onto the image, the properties are derived as follows:

(i) Along the ramp, the first order derivative is nonzero. The first order derivative is zero at constant gray level while the second order is zero along the ramp and at constant gray level.

However, in the case of second order derivative, the nonzero only occurs at the onset and the end of the ramp [3].

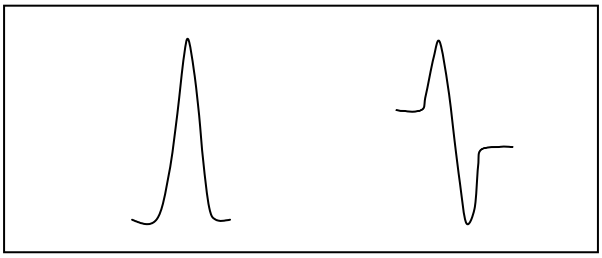
(ii) The edges produced by the first order is thicker compared to the second order derivative.

(iii) The second order derivative yields double response at step changes.



(a) Ideal step edge. (b) Step coupled with noise. (c) Line edge. (d) Junction edge.

Figure 2.17: Profile view of edge gradient.



(e) First order derivative. (f) Second order derivative.

Figure 2.18: First and second order derivatives.

From the understanding of edge principles and properties, it can be seen that the quality of edge detection will have a direct impact in the presence of intrinsic and extrinsic variations. Illumination is a kind of extrinsic variation that will highly influent the quality of edge detection. The intrinsic variation components represented by various level of intensity values within the object boundaries, will directly challenge any edge detection techniques.

There are a number of filters or edge detectors invented and reported in the literature for more than three decades ago. A survey on edge detection methods, among the latest publication can be referred to [113]. In their wide range of edge detection study, the methods are divided into very specific categories of analytic approaches. This includes classical, Gaussian-based, Multi-resolution, non-linear, wavelet-based, statistical, machine learning-based, contextual, line edge and coloured edges methods.

In this thesis, a review on edge detector focuses on Canny filter as its capability is a standard in most industrial application [113]. This is due to the fact that Canny filter has outperformed the classical methods. In [114], the Canny algorithm illustrates that low error rate and precise edge extraction must be the first goal in edge extraction to avoid wrongly analyzing the extracted edges. This statement opens two main issues of extractions i.e. extracting the wrong edges (including the variation) and inability to extract the true edges (discontinuity). These two problems become the motivation for the main criteria in Canny filter or edge detector. Many applications that work on edge images have the benefit of the Canny detector beside other well known edge detectors such as Sobel and Prewitt [114].

Canny has outlined three performance criteria summarized as follows:

(i) A good detection must be able to perform a low failure in marking the real edge points and a low failure in falsely marking non-edge points. These statements direct the derivation to the maximizing signal-to-noise ratio (SNR) which is expressed mathematically

$$\mathrm{SNR}= \frac{\left| \int_{-w}^{+w} G(-x) f(x)\,dx \right|}{n0 \sqrt{\int_{-w}^{+w} f^2(x)\,dx}}$$

where,

$f(x)$ = *Impulse response of the filter.*
$G(x)$ = *Edges of* $f(x)$
n_0 = *Noise amplitude per unit length.*

(ii) The detected edge points must be very close to the centre of the true edge. In this regards, the derivation of good localization is given by:

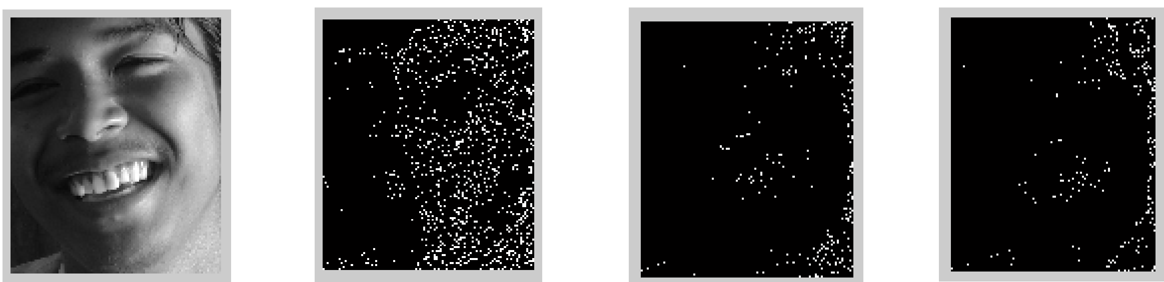
$$Localization = \frac{\left| \int_{-w}^{+w} G'(-x) f'(x) dx \right|}{n_0 \sqrt{\int_{-w}^{+w} f^2(x) dx}}$$

(iii) Eliminating multiple responses so that only one response remains to a single edge. The details of derivation deal with the numerical optimization which can be referred to [114].

In supporting the reasons behind applying the Canny edge detector in this thesis, we have done a sequence of experiments on the selected categories of face images. Face images from controlled and uncontrolled environment have been chosen for these experiments. Figure 2.19 and 2.20 demonstrate the results of Canny filter edge detector against the other two selected edge detectors, the Sobel and Prewitt filters from the classical approaches for a purpose of comparison.

(a) Original image (b) Canny filter (c) Sobel filter (d) Prewitt filter

Figure 2.19: Edge detection results for images of controlled environment.



(a) Original image (b) Canny filter (c) Sobel filter (d) Prewitt filter

Figure 2.20: Edge detection results for images of uncontrolled environment.

The results of both figures show that the Canny filter has outperformed the other filters for both controlled and uncontrolled environment. In this regard, we decide to employ Canny edge detector to extract the face UCI for age estimation and recognition purposes.

The review in this section is limited to the basic understanding of edge images and edge detectors with respect to the advantages and disadvantages as outlined previously. In the next following sub-section, we will review the morphological technique that is applied in this thesis in conjunction with the edge images.

2.5.3.1 Morphological-based Feature Measurement

From linguistic point of view, morphology is a term used to describe the structure of any word of any language. From biology point of view, morphology is a term used to deal with the form or structure of organisms or animals [3]. Mathematical morphology that is based on set theory has long been used in image processing as to describe or represent the characteristics of the features in term of the shape and its derivatives. The motivation of studying and choosing this method is that its characteristics suit the characteristics of proposed approach in solving the image variations and UCI extraction and enhancement. Morphological operations can reduce the dimensionality of image data, represent the features' characteristics while reduce or eliminate the irrelevant objects [115]. We will review this operation directly based on the mechanisms that make it reliable and consistent.

Dilation and erosion are two basic morphological operations. A simple illustrative example is shown in figure 2.21 to demonstrate the dilation operation on the binary image.

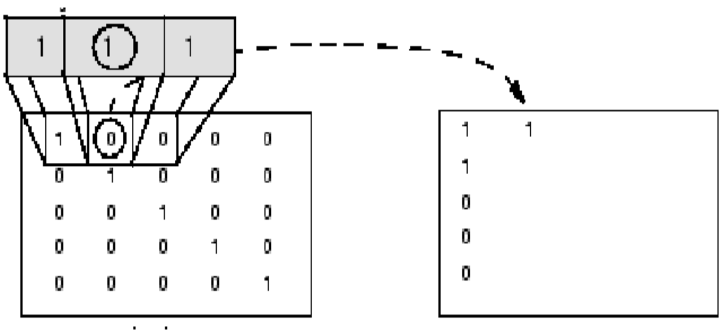


Figure 2.21: Structuring element used in morphological operations [105].

The image is scanned using a small window called a structuring element. In this example, the comparison is been made within 3 neighbourhood pixels and the maximum value (1) is chosen for locating the new value in the corresponding output image. This means, at the end of the process, the dilation operation basically dilates or expand the boundary of the objects in an image. In contrast, the erosion operation will shrink the boundary of the object as a result of setting the minimum value (0) in neighbourhood pixels. Morphological operations can also be applied to gray images with the same concept of local maxima and minima.

There are many operations derived in morphological image processing. Opening, closing and hit-or-miss transformation are among the basic concept in morphological operations. A summary of morphological operations and their properties are discussed in [3].

Morphological-based techniques are used in many research areas in the image processing community, including face detection and face recognition research areas. In both detection and recognition, the common task is to design the feature extractor where the extracted features are derived to be a reliable representation with the limit specified by the approach. A number of research works are reviewed that apply the morphological technique in different ways and with different interest where the reliability of morphology concept in image enhancement and analysis is discussed with the different kinds of technique demonstrated.

In [116], the use of wavelet decomposition and morphological technique are combined to enhance the intrinsic features while reducing both the intrinsic and extrinsic variations. The filtered image is then fed into a neural network of modified high order to allow rapid learning convergence, good generalization properties and a small number of adjustable weights. The authors also combined the information extracted from the face image with signature analysis for their proposed verification system (fusion system) [117]. Wavelet-based morphological approach also can be reviewed in [118] for the proposed face detection based on human skin colour. They have divided the work into two stages, region segmentation and facial region detection. Both results from the wavelet-based morphological approach in segmentation task and skin colour model in face detection task are integrated as to provide the most accurate facial region. In the verification system proposed in [119], the multi-scale morphological dilation-erosion technique which is claimed as novel dynamic link architecture (MDLA) is performed with the substitution of Gabor filters and scaled structuring function. The authors have successfully manipulated the responses of a set of Gabor features and the several structuring functions or elements shape such as hemisphere, the flat and circular parabolic. The same authors have extended their study of MDLA [120], [121] morphological elastic graph matching [122], face authentication [123] and verification [124] that based on morphological shape decomposition as feature extraction mechanism. Similarly, the work in [135] also used a multi-scale morphological dilation-erosion technique for their proposed Morphological Multi-scale Fingerprints (MMF) for face localization. The local maxima and minima are computed in MMF to a certain scale in multi-scale morphological dilation-erosion analysis. The results are compared with the eigenface approach as the proposed technique falls into the same category of global or holistic approach.

In [126], a new method that is claimed to be invariant to illumination in face recognition is introduced with the method so called Morphological Quotient Image (MQI). The MQI is based on the comparison between the morphological close and open operations where the most effective one is chosen. The authors used the Yale database for their training stage and CMU-PIE database for the testing stage. The effect of template size with respect to the recognition rate is also studied and experimental results are reported as encouraging. Another recent study reported in [110], has applied the morphological reconstruction and edge linking to enhance features representation after the edge detection has been performed.

2.5.4 Matching Algorithms

Matching process can be considered as the last stage in recognition module. As a result of matching measurement, similarity or dissimilarity outcomes of the given input image will be judged based on predetermined decision boundary or *thresholding*. Conventionally, there are a few techniques used in pattern recognition system. In this section, we have chosen two famous matching techniques where the motivation and mathematical representation will be explained.

2.5.4.1 Euclidean Distance

The matching process of two images is done by computing the Euclidean distance given as:

$$d_E^2(x,y) = \sum_{k=1}^{MN} (x^k - y^k)^2$$

where,

x and y	=	two images with the size of M x N respectively.
x	=	$(x^1, x^2, \ldots\ldots. x^{MN})$
y	=	$(y^1, y^2, \ldots\ldots. y^{MN})$

Suppose pixels of p, q and z are assigned with the coordinates of (x,y), (s,t) and (v,w) respectively. Thus, the Euclidean distance between p and q is given by:

$$D_e(p,q) \quad = \quad [(x-s)^2 + (y-t)^2]^{1/2}$$

The distance function, D may also be calculated in a number of ways such as "cityblock distance" and "chessboard distance".

2.5.4.2 Correlation

Given two functions, *f(x,y)* and *h(x,y),* the correlation result is defined as [10]:-

$$f(x,y) \circ h(x,y) \quad = \quad \frac{1}{MN}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} f^*(m,n)h(x+m,y+n)$$

where,

f^* = complex conjugate of *f.*

In case of matching the sub-image *w(x,y)* of size J x K within an image *f(x,y)* of size M x N, where $M \geq J$ and $N \geq K$, the correlation between *f(x,y)* and *w(x,y)* can be represented by [3]:-

$$c(x, y) = \sum_{s}\sum_{t} f(s, t)w(x + s, y + t)$$

where,

c(x,y)	=	*Correlation result*
f(s,t)	=	*Image element*

In short, the result is an overlapping of *f(x,y)* and *w(x,y)* through the summation operation in the equation.

2.6 Unique Facial Collateral Characteristics Information: -Extraction, Representation and Classification

2.6.1 Overview

The key to success in recognition task depends on the efficiency of the classifier and the feature extractor. However, the classifier can only work better if the feature extractor helps provide the classifier with all the necessary information and filters out the unnecessary information. The decision of which features must be extracted as required by the classifier further challenges the operation of the extractor. The quality of the feature image will also affect the extractor efficiency especially in the case of high image variation. To this end, the tasks of the registration and recognition demonstrated in this thesis involving with the image transformation, modelling, compensation, feature extraction and classification are discussed.

As introduced in chapter 1, Figure 2.22 shows the proposed collateral classification for enhancing the identity information through the categories of regional appearance, gender and age classes. This figure illustrates variation complexity versus UCI explaining how the low UCI (and high variation) in the image can be brought up to the high UCI (and low variation) by image compensation and manipulation of the meanings of collateral UCI that inherently exist in the facial information

In this chapter, the information that is delivered implicitly by the features extractor will be explored and output to feed the classifier in such a manner that the information is rich of collateral patterns.

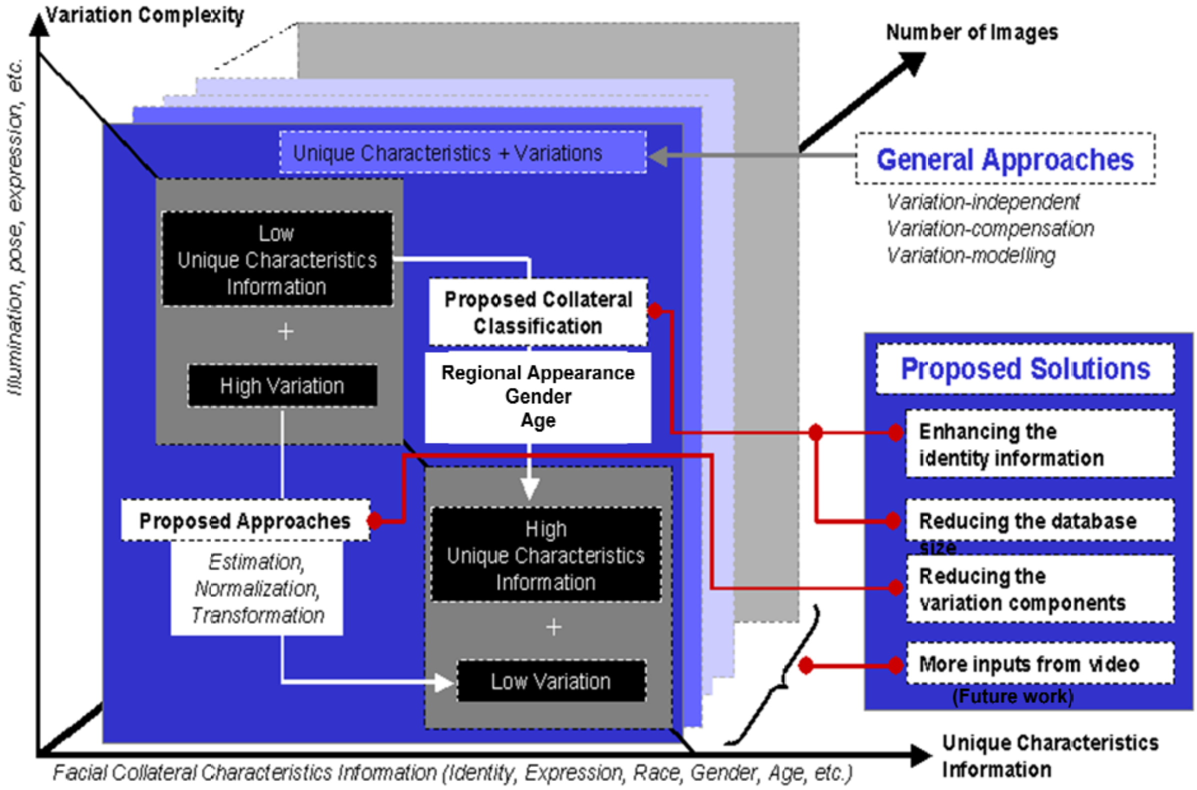


Figure 2.22: Graphical explanation of proposed solutions in handling the image variation complexity while enhancing the unique characteristic information.

The challenges for the extractor are to represent a particular input image with variety of information where different measurement techniques are needed for different UCI classifiers requirement.

The image compensation part is purely the responsibility of the feature extractor (extraction and representation). The outputs from this will be passed to the classifier where the pattern measurement and analysis will take place (classification and recognition).

The process of feature extraction in this chapter is begun with the understanding of what should be looked into in the face image. From here, the features selection criterion specifically for the UCI extractors and the collateral classifiers is identified. However, the extraction of these selected features is not an easy task to be performed as the input images are full of variation. Thus, the study is extended by the proposed variation complexity reduction method where the use of colour, gray level and binary images is explored for the purposes of skin colour analysis, facial texture and features measurement respectively. This involved the transformation, modelling and compensation techniques that will be the mechanism in the extraction process. Results are shown in the end of the

Chapter Three where they are ready for the classifiers (Chapter Four) for further analysis and the classification judgement.

2.6.2 Features Selection Criterion

Generally, features extractors designed and demonstrated in the literature mostly focused their work on the overall necessity of identity representation of a person without being concerned about the type of collateral UCI of the face. In this thesis, we have extended the study on features information manipulation and observed the type of UCI which will contribute to the identity parameters of regional appearance, gender and age. From the overall review, humans can easily justify the major differences between subject facial characteristics. For instance, the difference between regional appearances is based on the skin colour and facial features and the genders are look different because of the facial features and texture characteristics. In addition, the age classes are differed due to features size and distance. For computer image processing, there are a lot more factors to be considered due to the image variation. Generally, it can be summarized that the overall face surface comprises of:

(i.) The face shape (the outer line).
(ii.) The major facial features (eyes, eyebrows, nose and mouth (upper and lower lips))
(iii.) The facial skin colour.
(iv.) The facial texture.

Each of these UCI with the properties such as size, shape and distances and any of its derivatives reveal the unique pattern that can determine what characteristics of the person (regional appearance, gender and age). Figure 2.23(a) illustrates these features location on the 2D image and figure 2.23(b) demonstrates some differences between subjects based on the four characteristics mentioned above. From figure 2.23(a), the information that can be extracted from the face shape (the outer line) can be used for all of the three defined identity parameters (regional appearance, gender and age) concerned in this thesis. However, the validity of this information cannot be relied upon due to the culture practice, life style or even religion matters for some peoples. This can be seen in figure 2.23(b) where the outer line of facial shape is occluded by the scarf wore by the Malay female. In fact, this is common all over the world unrelated to religious matter or as a fashion for a certain occasion. Therefore, we have to ignore this characteristic and no further investigation is taken as we are dealing mostly with the real world images. The only information left is the major facial features (eyes, eyebrows, nose, mouths), the texture and skin colour.

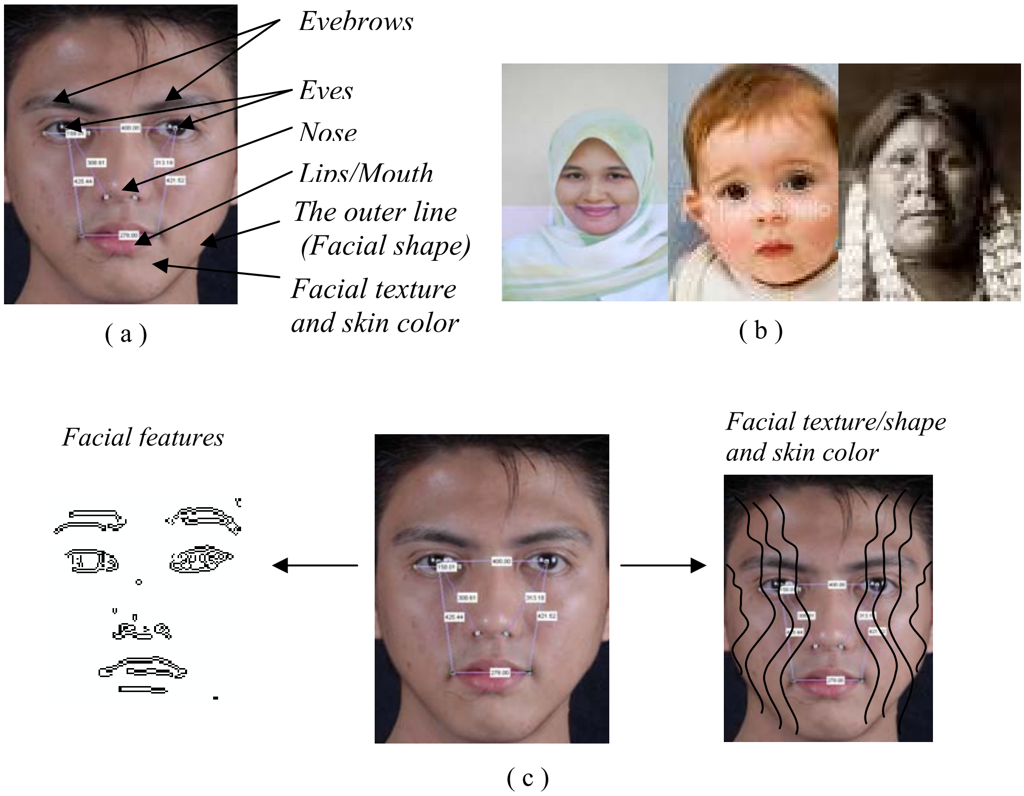


Figure 2.23: Face features selection and groups. (a) Features location. (b) UCI differences. (c) Component of UCI.

Furthermore, the derivative of this characteristic information may further elaborate the type of UCI for a particular subject. For examples, the combination of features size and shape characteristic information will represent the regional appearance and gender classes while the combination of features size and distance information can estimate the age class of a particular subject. In addition, the characteristic of the skin colour information is also useful for regional appearance classification and the texture characteristics can also represent the gender class. From the figure 2.23(b), one can easily classify the regional appearance, gender and age classes of the subjects based on the previously mentioned the facial characteristics. For instance, the baby's features size and distance is different from the adult. It is also can be observed that the features shape and texture of male (figure 2.23(a)) and female (figure 2.23(b)) are different. This shape and size characteristics are also different between different regional appearances (figure 2.23(b)). However, extraction of all of these characteristics is not an easy and the problems are well known among the researchers in this area of study [37]. To accommodate a reasonable classifiers requirement with a compromise of image variation and difficulties, we have proposed three types of UCI to be extracted and three proposed identity parameters. It is proposed the features selection criterion for the proposed collateral representation and classification are as follows.

(i) Skin colour analysis for regional appearance recognition.
(ii) Facial texture analysis for gender recognition.
(iii) Overall facial features size and distance measurement for age recognition.

Figure 2.23(c) illustrates the proposed features to be extracted in visualizing the type of UCI for the collateral representation and classification. The reasons of choosing these characteristics are closely related to the matter of balancing the classifier requirement and the difficulty of handling the image variation. Experiments results have shown that the features are always been distorted by the image variation which result in inconsistency in the facial measurement. Since the actual features are not consistent in extraction results, it is proposed the skin colour is used as the basis of regional appearance recognition. For instance, one of the Chinese regional appearance characteristics is the eyes shape that differs from other regional appearances. However, this unique feature took a very small part of the whole image and is open to a very wide variation exposure. As a result, it is very difficult to extract the shape when working with the real life images.

The features of female such as eyes, nose and mouth are differed from the male. However, these features will also confront the same problem with the regional appearance classification when extracted from the real life images. However, the uniqueness of the male and female gender can also be observed through the facial features as a whole without the need of analyzing every single feature. In this regards, facial texture is proposed to be used for gender classification. The detail explanation on these will be given in the next section including a demonstration of results from the extraction and image compensation processes. A simple manual calculation in estimating the age is by measuring the distance between eyes and the distance between mouth and the two eyes. The ratio of these two distances is calculated where the result can determine the child or the adult class. However, this kind of information and ratio calculation difficult to be done due to the same problem that happen in regional appearance and gender recognition explained previously. In order to optimize the solution, it is proposed the overall facial features are measured in a derivative way to allow the results that are still reliable to a particular classification such as age estimation. The detail explanation will be given in Chapter Three and Four.

2.7 The Developed Database and Open Database

The Malaysian face database developed for this research comprises of the three major regional appearances in the country; Malay, Chinese and India Malaysian. For each of the regional appearances, the database divides it into two categories of the gender i.e. male and female. Each of the gender will then been divided into two categories of the age group; the children and adult classes. The child class is defined as below 12 year old and the adult is above 20 year old. The structure of the database division is depicted in figure 2.24 and some samples of images are shown in figure 2.25.

For each regional appearance class, there are 20 subjects per age class which gives 40 subjects per gender class. This means each of the regional appearance class is has 80 subjects. As a result, the total number of subjects in the database is 240 subjects. There are at least three angles of viewing geometry and four different illumination variations for each of the subjects which give generally seven images per subject. In total, the database comprises of more than 1680 images. The structure of the database and its content are believed to be able to judge the reliability of the system performance testing in the understanding of the objective of the research. For the testing stage, the research used open databases downloaded from the various internet websites where the images are acquired from the real world. This will be explained in the following chapter where the detail of the results is reported.

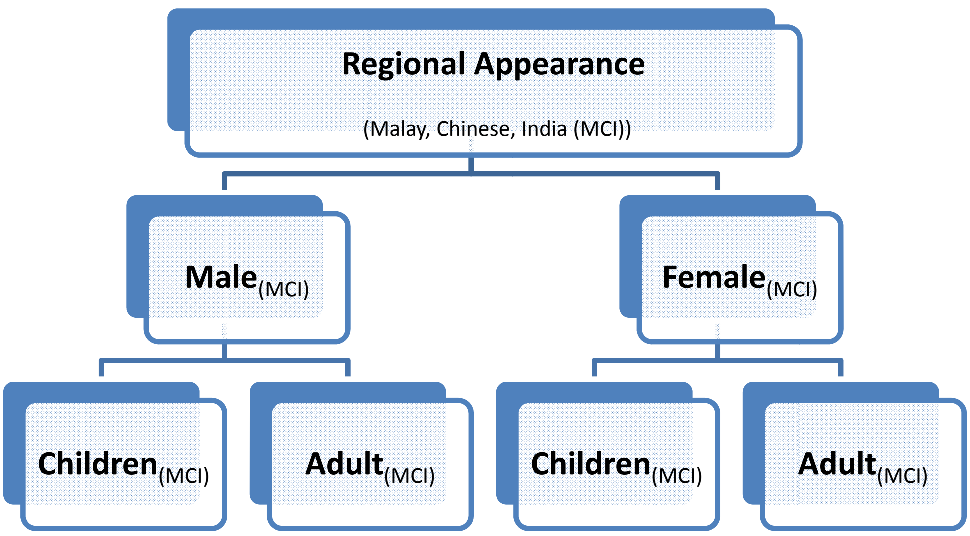


Figure 2.24: The structure of the database division.

(a) Developed database

(b) Open database

Figure 2.25: Some samples from the (a) developed and (b) open databases comprising of Malay, Chinese and India regional appearances including the age (children and adult) and the gender (male and female) for each of the regional appearance.

Chapter Three

Variation Complexity Compensation, UCI Extraction and Representation

3. VARIATION COMPLEXITY COMPENSATION, UCI EXTRACTION AND REPRESENTATION

3.1 Variation Complexity Reduction

3.1.1 Transformation, Modelling and Compensation

To reduce the loss of information while reducing or compensating the variation complexity, a hybrid technique derived from the three conventional approaches is proposed in this thesis for variation compensation and feature extraction tasks. In this first research block (this chapter), the ultimate aim of the techniques of transformation, modelling and compensation are combined to represent (transformation) the UCI without losing the important features by modelling and discarding (compensation) and reducing the level of the variation complexity of a given face image. Experimental results show that discarding a certain obvious variation will enhance the desired information rather than sceptical in losing the interested UCI. The modelling and compensation stages will benefit both variation reduction and UCI enhancement. Colour, gray level and edge image information are used to manipulate the UCI which involves the analysis on the skin colour, facial texture and derivative features measurement respectively. The derivative linear binary transformation (DLBT) technique is proposed for the features measurement consistency. Prior knowledge of input image with symmetrical properties, the informative region and consistency of some features will be fully utilized in preserving the UCI feature information. As a result, the similarity and dissimilarity representation for identity parameters or classes are obtained from the selected UCI representation which involves the derivative features size and distance measurement, facial texture and skin colour, to mainly accommodate the strategy of unfamiliar identity classification in the second block of the research work (Chapter Four).

Figure 3.1 illustrates the block diagram of the process flow involving compensation, transformation and modelling or representation. The compensated image representation will then be used to measure the parameters for classification. The figure also illustrates the structure of this chapter. The colour representation of three regional appearances (Malay, Chinese and India) will be explored followed by the gray level image analysis for finding the facial texture. Results of male and female are shown as to reveal the difference between them based on the texture calculation. Edge image analysis is then follows where the features measurement is obtained. The chapter is ended with the results of facial texture, features measurement and skin colour representation from all classes involved in the research. The classes for Malay regional appearance are Malay male adult, Malay male child, Malay female adult and Malay female child. The other two regional appearances (Chinese and India) follow the same classification. This means that the total of 12 classes of sub-regional appearances needs to be represented and classified.

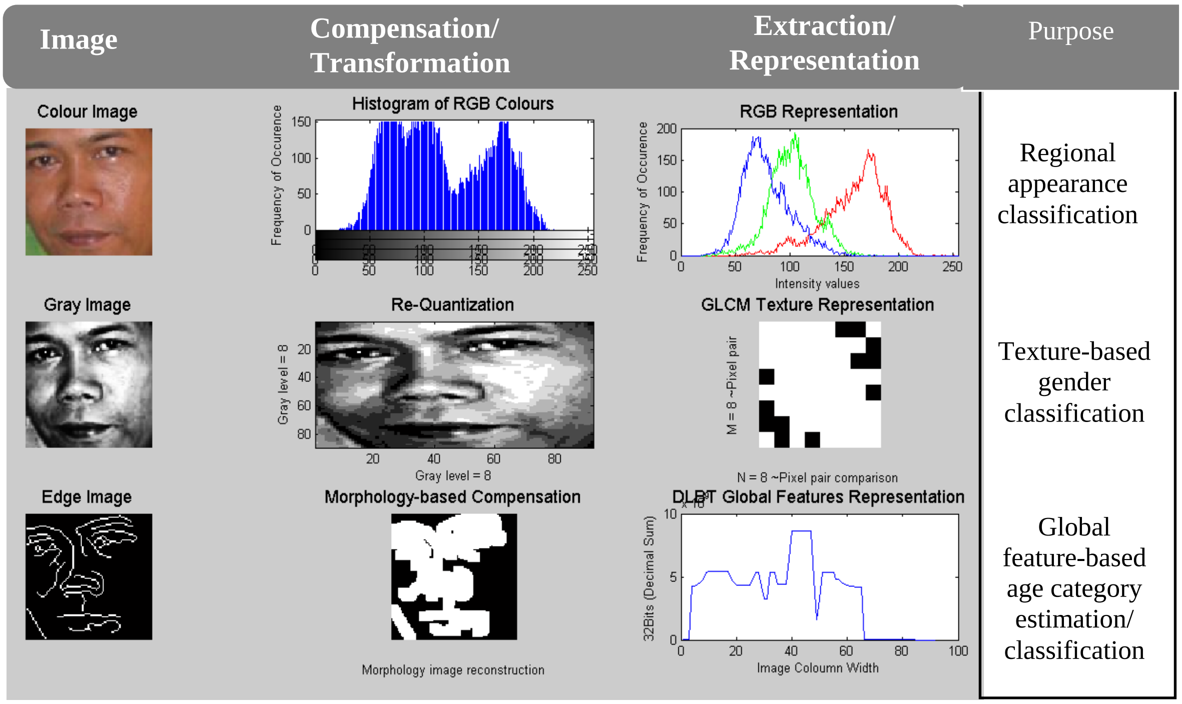


Figure 3.1: Transformation, compensation and modeling (representation) process flow.

3.1.2 Colour Analysis and Skin Colour

The input image to the designed feature extractor is a colour image. The information from the colour image is extracted from the histogram graph as shown in figure 3.2. Using the conventional colour spaces, the calculation of colour spaces is performed and results are recorded as shown in Table 3.1. The pixel values of R, G and B are normalized and are compared with the other two chosen colour spaces, HSV and YC_rC_b. From this transformation, the image will be modelled to observe the variation and the skin colour UCI of a particular person. The compensation can be done based on the collected data and produce a colour representation for the image. At this level, the extraction task is done and this information is next analyzed by the classifier to produce the colour model for each of the regional appearance class. From here, the regional appearance algorithm can be developed and through the experiments, the threshold values can be judged and determined. After the colour information is extracted, the image will be converted to the gray level and edge image for texture and features compensation and representation respectively.

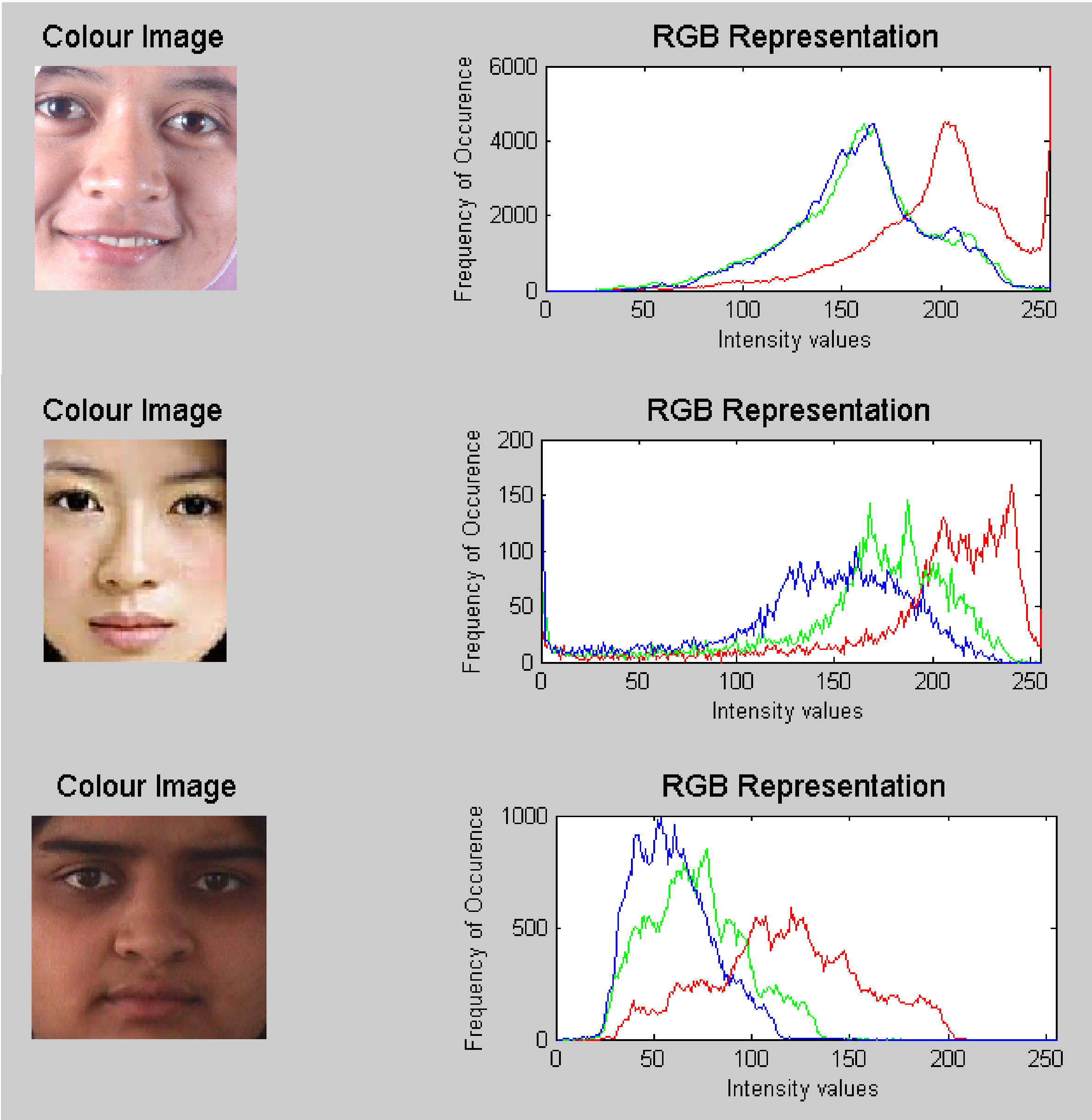


Figure 3.2: The RGB histograms for a sample of Malay, Chinese and India regional appearance classes.

	R	G	B	H	S	V	Y	C_r	C_b
Peak value	**190**	**110**	**82**	**1.51**	**0.36**	**127**	**130.73**	**59.27**	**-48.73**
Minima(Up)	**155**	**60**	**32**	**12.53**	**0.61**	**82.33**	**85.22**	**69.78**	**-53.22**
Maxima(Down)	**230**	**160**	**124**	**-**	**0.28**	**171.33**	**176.83**	**53.17**	**-52.83**

Table 3.1: Sample of color spaces calculation for India regional appearance skin color in comparison of RGB, HSV and YC_rC_b color spaces.

3.1.3 Gray Level Image and Texture Analysis

3.1.3.1 Variation Observation and Histogram Equalization

Figure 3.3 illustrates the 3D surface of face image where this view is meaningless to the human perception in recognizing the identity of this face image. This implies the toughness of the extraction task in extracting the UCI. One of the simplest ways to reduce the variation is by pixels normalization or histogram equalization.

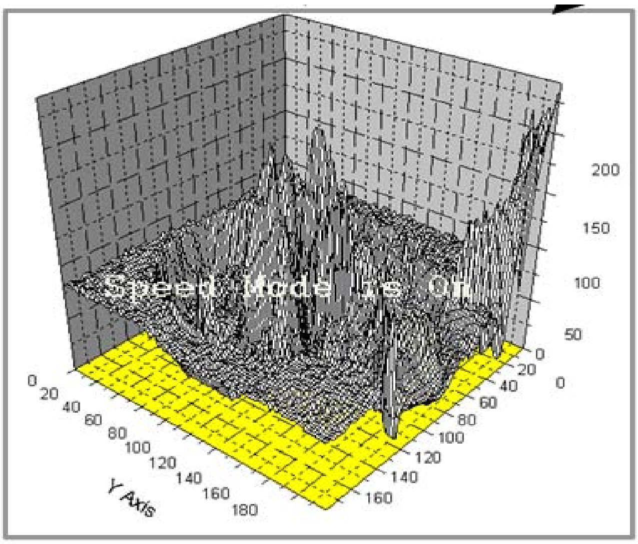
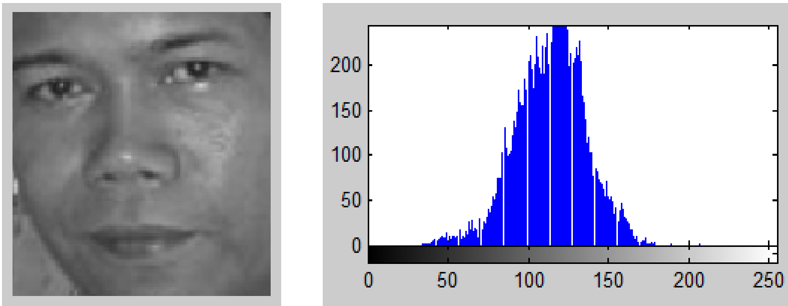
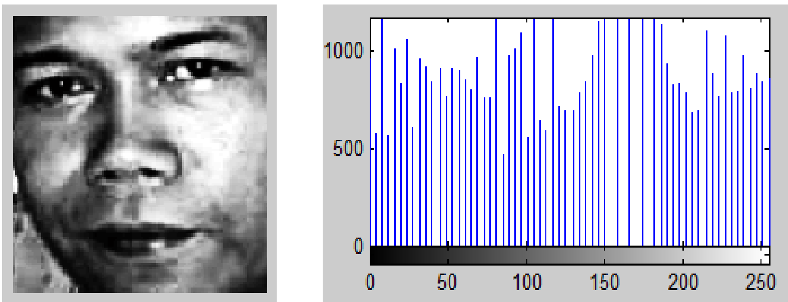


Figure 3.3: Surface display of typical facial image.

Figure 3.4(a) demonstrates the actual pixel distribution of a sample of 2D face image where the histogram shown is before the normalization process. By applying the technique of histogram equalization, the image pixels are evenly distributed within the range of 256 gray levels. This is a simple technique where each pixel of interest in the input image is compared with its neighbours and the average value is calculated and the results are taken to the corresponding output image. Figure 3.4(b) shows the output of this process with its histogram is equalized.



(a)



(b)

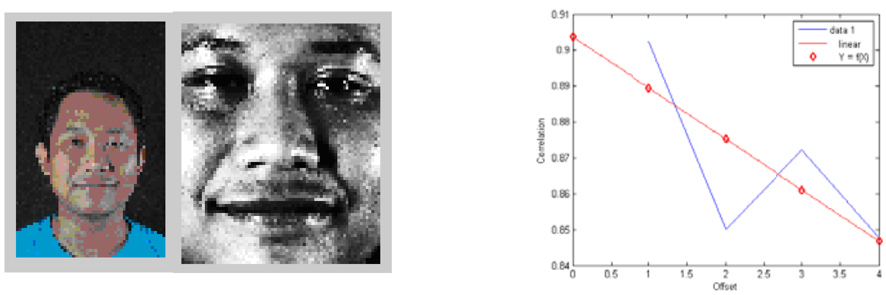
Figure 3.4: Histogram equalization. (a) Original image and its histogram. (b) Image after histogram equalization and its new histogram.

3.1.3.2 Transformation and Texture Representation

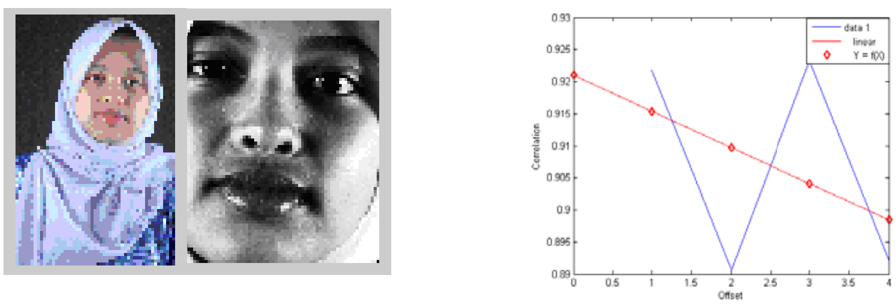
The pixel values on the gray image consist of statistical data that can reveal a lot of information. One piece of information is the uniqueness of the texture of the image or surface. For any of the surface, the texture is a function of interrelation between the local pixels on the image. Since the facial characteristics of male and female classes are different at almost all parts of the face surface including the features, it is proposed the texture measurement for male and female classes are to be based on the whole face region including the major features.

The technique used is based on the conventional approach where the idea is to produce the pattern of the surface shape by observing how frequently the grouping of a pixel and its neighbours appeared in the specified region on the image. The spatial relationship of the pixels within the group can be done in many ways. The calculation of the pixel range, the minimum and maximum values within the group will produce the statistical data such as the mean and standard deviation of localized texture level in the image. Having done this, the analysis can be performed on the new version of data characteristics and the surface can be defined in a very technical way.

In this thesis, the texture measurement of facial surface is used for representing the gender classes such as shown in figure 3.5. Each pixel in the input image is compared with its neighbours by four directions and the corresponding output array is a sum of how many times the pixel pair is exist over the image. The probability of occurrence of each pair in the pixel comparison is correlated and plotted against the number of pixel comparison direction (offset). It can be seen that there is a difference texture level between male and female facial surface. More results are shown in the Chapter Four for classification decision.



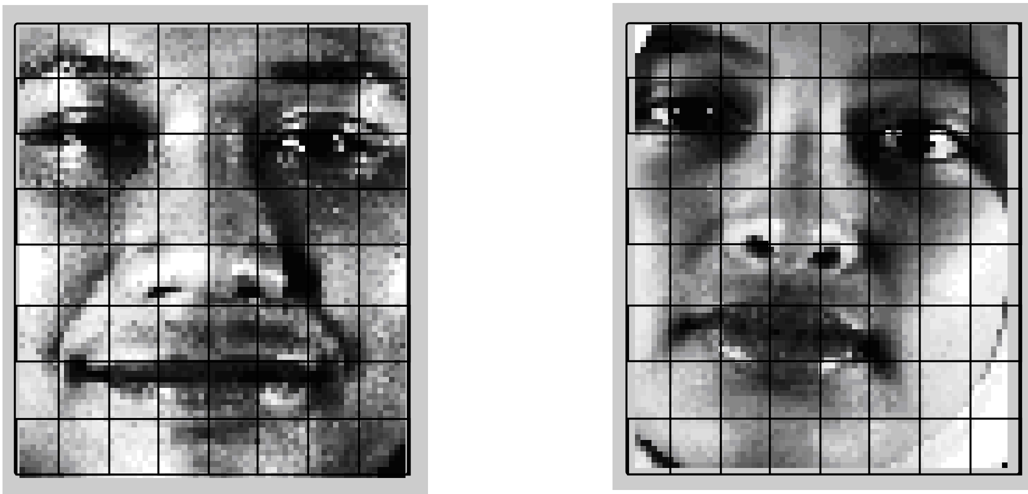
(a) Male class.



(b) Female class.

Figure 3.5: Texture correlation versus offset. (a) Male. (b) Female.

As can be observed from figure 3.6, the male and female classes are distinguished based on their features, mainly eyes, mouth, nose, elbow and overall surface.



(a) Male (b) Female

Figure 3.6: Texture comparison. (a) Male. (b) Female.

The motivation for applying the texture-based technique for representing and classifying the gender is because of: the following reasons-

(i) Features on face surface have their own unique texture pattern where the shape and size are different between features. Thus, face surface and features can be combined and perceived as one region that having one comprehensive texture region. This will justify the uses and credibility of texture-based technique that will be applied on face image surface, which will be explained later in this section.

(ii) Texture for each feature on the same face surface is unique but the location and structure are consistent for all face surfaces. This provides a large scale of texture types and varieties in pattern and will help in increasing the similarity within the class.

(iii) Texture pattern discussed in (i) and (ii) is different between male and female classes. The difference between male and female is not limited to only the main features region of interest, but open surface such as cheek, chin and forehead also reveal the differences in term of texture and shape and possibly the size. This will help the classification task in the context of increasing the dissimilarity between classes.

Based on these reasons and motivation, the GLCM technique applied to the face surface can be accommodated and moderated in analyzing the texture to reveal the difference between classes. The main steps taken are as follows:

(i) Re-quantization is performed on the gray image. In this case, eight (8) gray levels are chosen for the experiments (figure 3.7). Re-quantization needs to be done as to reduce the dimension in calculating the image texture and to normalize the image due to illumination impact.

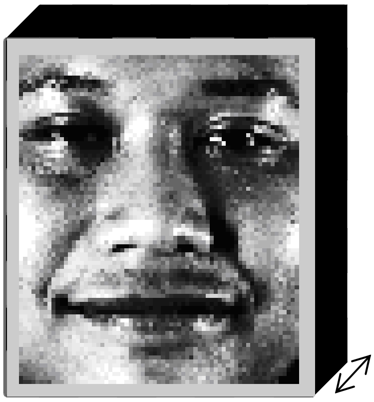


Figure 3.7: Texture comparison of pixels.

(ii) The comparison between two pixels is made as to reveal the difference or gradient in a systematic way as shown in figure 3.8. Notice that the size of the matrix is the same with the gray levels that have been chosen in (i).

(0,0)	(0,1)	(0,2)	(0,3)	(0,4)	(0,5)	(0,6)	(0,7)
(1,0)	(1,1)	(1,2)	(1,3)	(1,4)	(1,5)	(1,6)	(1,7)
(2,0)	(2,1)	(2,2)	(2,3)	(2,4)	(2,5)	(2,6)	(2,7)
(3,0)	(3,1)	(3,2)	(3,3)	(3,4)	(3,5)	(3,6)	(3,7)
(4,0)	(4,1)	(4,2)	(4,3)	(4,4)	(4,5)	(4,6)	(4,7)
(5,0)	(5,1)	(5,2)	(5,3)	(5,4)	(5,5)	(5,6)	(5,7)
(6,0)	(6,1)	(6,2)	(6,3)	(6,4)	(6,5)	(6,6)	(6,7)
(7,0)	(7,1)	(7,2)	(7,3)	(7,4)	(7,5)	(7,6)	(7,7)

Figure 3.8: Texture comparison of pixels.

Each pair of pixel comparison represents a unique pattern in its own and sorted in a proper sequence of gradient. This gradient between pixels can be visualized as illustrated in figure 3.9 below. This agreeas with respect to the first motivation stated previously, that is to reveal the variety of patterns.

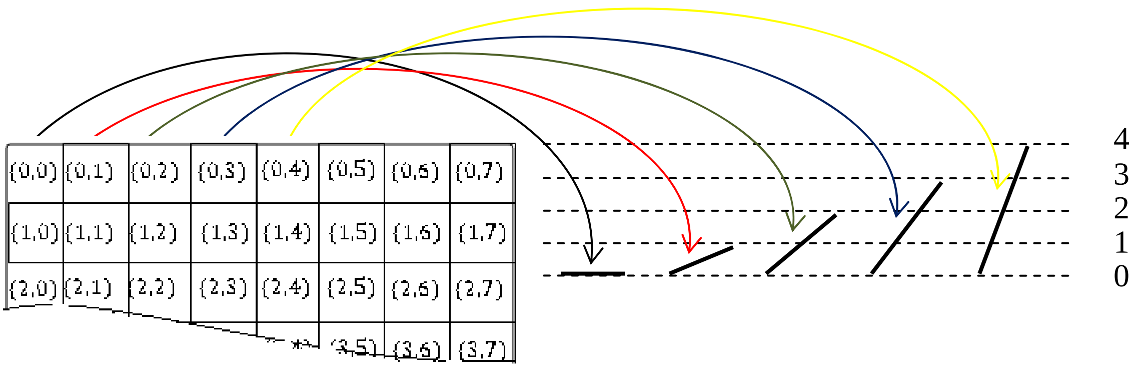
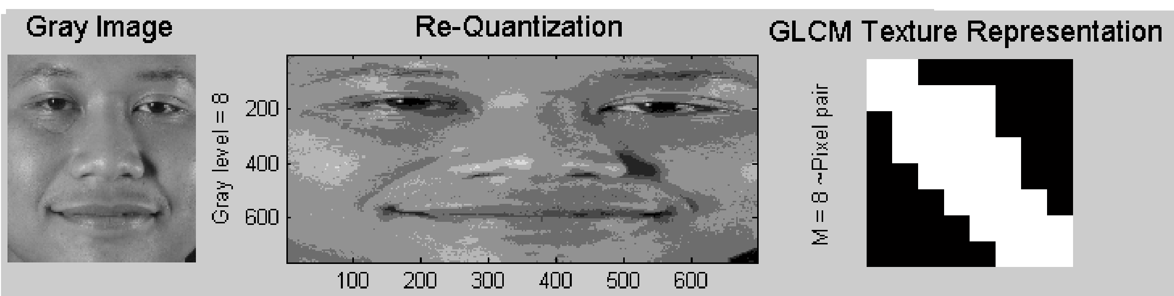


Figure 3.9: Visualization of gradient or pattern differences assigned for each pair of pixels.

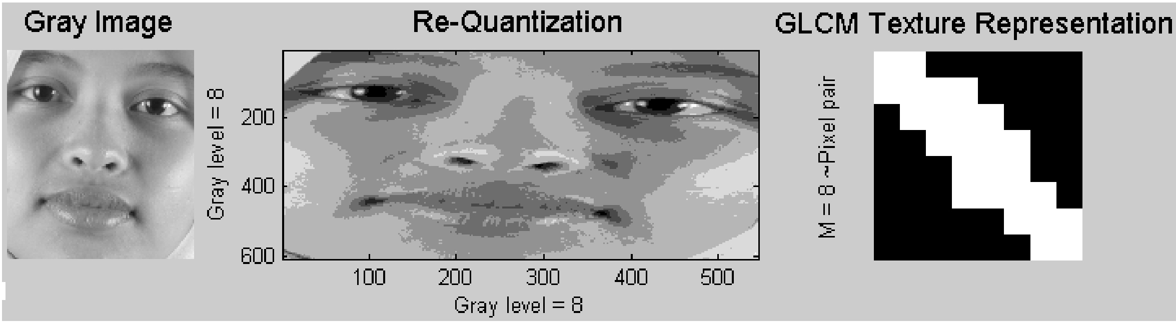
(iii) Since the texture pattern is segmented or sorted in a very systematic way in (i) and (ii) above, even the small differences between features will not be avoided in this kind of texture representation. This complies with the second motivation, that is to increase the similarity within the class.

(iv) Finally, upon the completion of the process, the whole texture of the face surface is represented where the two classes of male and female will be seen such as shown in figures 3.10 (a) and (b) respectively.



(i) Male (ii) Re-quantization (iii) GLCM texture representation

(a) Male class representation.



(i) Female (ii) Re-quantization (iii) GLCM texture representation

(b) Female class representation.

Figure 3.10: Texture comparison and difference between male and female class.

The process of texture realization explained thus far is directed by a comparison between the pixel and its immediate (right hand side) neighbour or simply denoted as zero degree direction (offset (0,1)). The process is repeated with another three directions such as illustrated in figure 3.11 below.

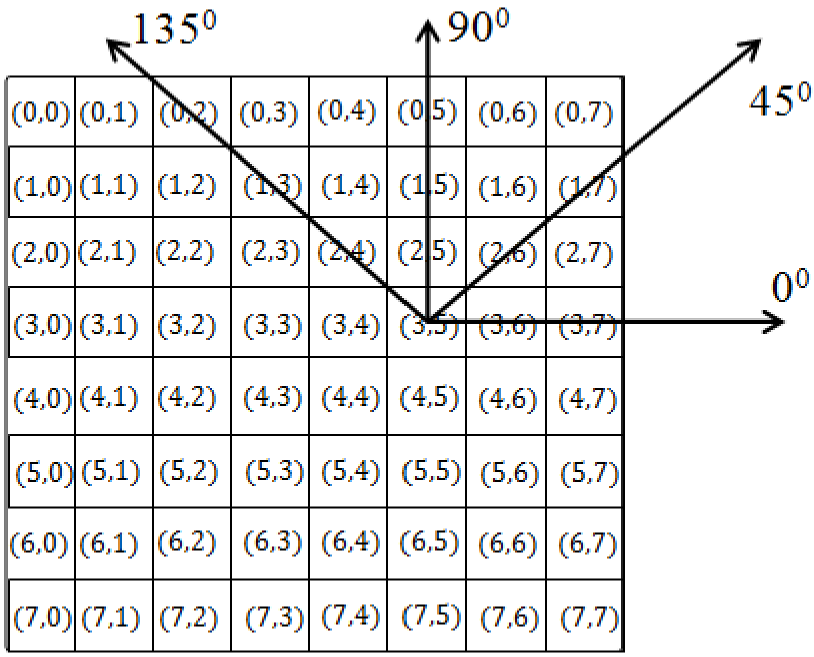


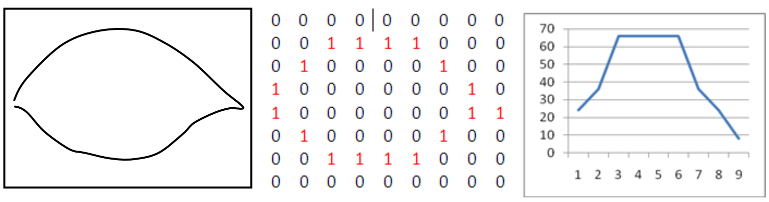
Figure 3.11: Direction (offset) for pixel pair comparison [151].

The GLCM with four directions or offset is calculated where the final output of representation is ready for classification. The use of statistical features, such as GLCM correlation is shown in the next chapter for the purpose of classification judgement. The results are shown and explained from the experiments done using the face database.

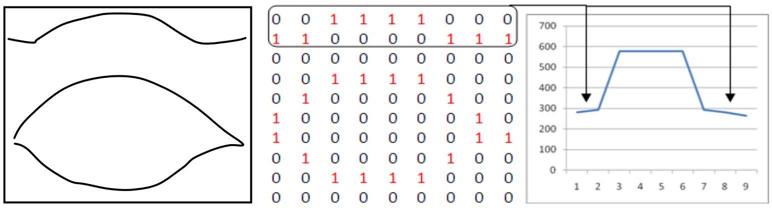
3.1.4 Edge Image and Features Measurement

Edge image analysis is used to visualize only the facial feature edges such as eyes, nose and mouth so that the measurement can be done. The implication of using an edge image is the problem with the possibly wrongly detected edges. The output might include a variation that does not belonged to the extracted features. This problem has been explored and a compromised representation proposed so that the element such as size and distance remain measurable even with high image variation. Since the pixel value of edge image is either 1 or 0, we have created a simple representation to observe some important characteristics which are able to give us the consistency of derivative features size and shape. However, for a high variation image, we might partly lose the shape information but still able to measure the size using the available information.

The transformation of UCI from the edge image to the derivative linear binary transformation (DLBT) form is defined by discretely performing the decimal value calculation for each column of the binary matrix of the image. A sample of eye feature representation is shown in figure 3.12 to demonstrate the transformed outcomes. From the figure 3.12, it can be seen that the DLBT results for eye feature (a) varies accordingly as the eye feature is combined with other components such as eyebrow feature (b) and image variation (c).



(a.) The eye feature, matrix form and DLBT graph.



(b.)The eye and eyebrow features, matrix form and DLBT graph.

(c.) The eye and eyebrow features with the variation, matrix form and DLBT graph.

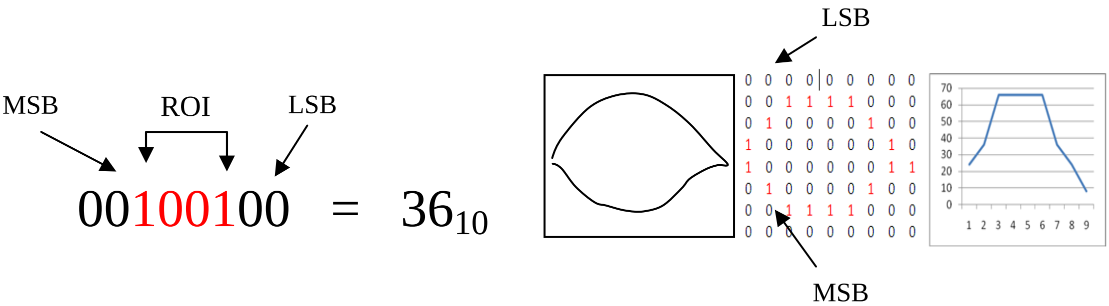
Figure 3.12 : (a), (b) and (c) -The eye and eyebrow features, matrix form and DLBT graph.

There are some important facts that can be explained about the DLBT representation.

(i) Region of interest (ROI).

By the nature of binary number system, the beginning and last points of the measurement region (columns) always referred to the first and the last '1' of the column respectively are where the weight in scalar (decimal) number is calculated. This implies that the measurement is always counting only the region that belonged to the facial features.

Example: Calculation for the second column from the left.



(ii) Handling the image variation.

Suppose the edges detection of a face image is obtained such as shown in the figure 3.13 below. It can be seen that the mouth feature has partly lost the size, shape and length while the existence of unnecessary edges (variation) also unavoidable in the image. This is a typical problem that usually occurs in the edge image.

(i) Gray image (ii) Edge image (iii) DLBT representation

Figure 3.13: Transformation, modeling and compensation for features representation.

From the DLBT representation (Figure 3.13(iii)), notice that each column is calculated including the variation or with the loss of edges belonged to a particular feature. However, this is not the issue as the decimal conversion of each column is calculated by blocks of 32 bits where the sum of blocks will represent the column on the DLBT graph. This means that we have distributed the variation to the segments (blocks) where its impact is been reduced inherently. In this way, we are able to reduce the influence of variation (in the decimal conversion value) on the DLBT graph. The important of this consideration will be revealed in the next section and Chapter Four when the DLBT is used for features measurement for age category estimation or classification.

3.1.4.1 Features Variation Modelling

Figure 3.14 illustrates the observation of the impact of variation complexity on the facial information. The most important things these representations are trying to reveal are the facial features properties such as the size and distance in the presence of the image variation.

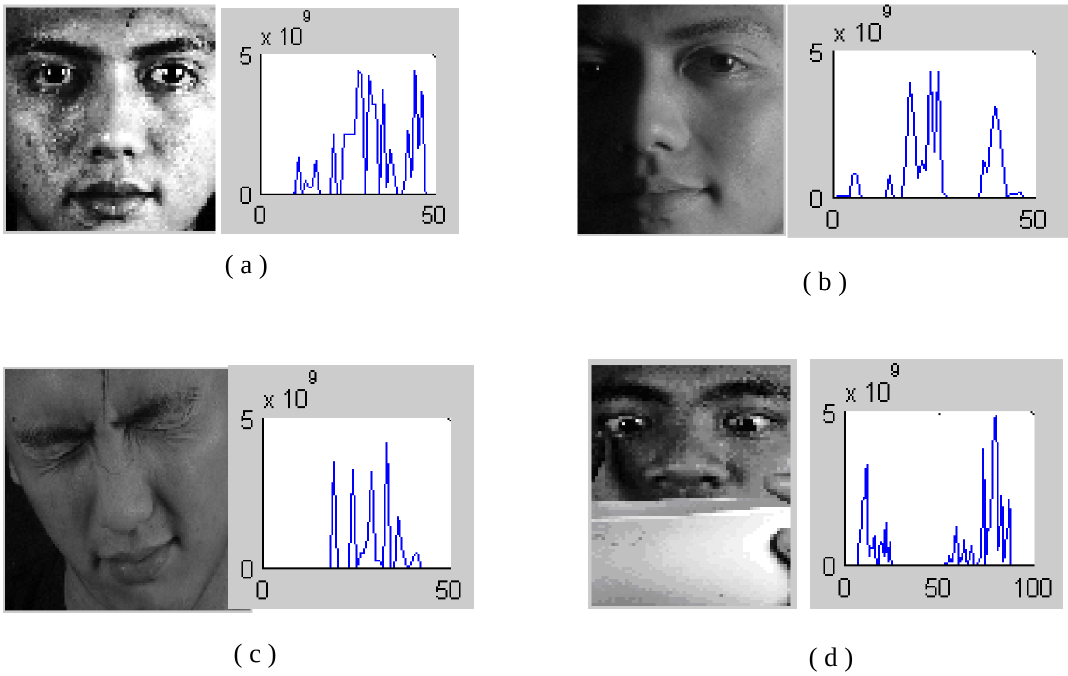


Figure 3.14: Some observation on the impact of variation complexity to the facial features. (a) Frontal view. (b) Illumination effect. (c) Pose effect. (d) Occlusion.

From the figure 3.14(a) to (d) of DLBT graph, notice that the average maximum height is nearly the same for all type of variation involved in the DLBT calculation. In the following section, it will be explained how this property is used to measure the age category estimation of the subject.

Translation, rotation and scaling are other kinds of common problems in image processing that need to be solved before a further analysis can take place. The detection of eyes is very important for feature-based approach to compensate the position of facial features. Intrinsic variation caused by the head movement may occur. Angle calculation can be done with respect to the horizontal axes. In the case of scaling, a simple distance ratios calculation can be applied so that the image size does not matter. This helps the system in confronting real world images. The measurement of distance between eyes and the distance between eyes and mouth are made. The ratio of these two distances is one of the ways to estimate the localization of the overall features which lead to the attention of the region of interest.

The DLBT representation may be extended to confront these problems. However, this current study will not be looking further on this problem instead concentrating more on the illumination and pose variations.

3.1.4.2 Features Variation (Illumination and Pose) Compensation

Some works on illumination and pose variation compensation in this thesis have been published in [136]. In the paper, the method of using a 3D histogram is proposed to further the compensation for illumination and pose variation. The information extracted from the intensity caused by strong illumination will be manipulated to obtain the depth information. Firstly, a 3D view of intensity image is plotted then another four views are determined. Figure 3.15 illustrates the details of these views. By using view 1, the estimation of the pose (face direction) is based on the geometrical location of unique features and symmetrical properties of the face. Symmetrical properties also allow the self-occluded problem to be compensated and reveal the desired features.

This is achieved by using the distance ratios of eyes and mouth location with the face outline (figure 3.15(b)). Indeed, the distance ratios computation will also allow any size of image to be used as the input image. From these views (view 1 to 5), the level of illumination variation can be estimated with the aid of peak values of intensity. This is visualized with the highest values of white (light) located in certain regions on the image.

The shape and depth recovery can be obtained from the analysis of figure 3.15(d). The human eye can see the 2D shape of a face from the view 1. View 2 to 5 is the perceptions of 90 degrees towards the respective image planes where these views are meaningless to the human eye. From the experiment carried out on a number of images, there appear to be a critical range (between 0 to 25 degrees around the vertical axes) of perspective angles within the 90 degrees rotation (e.g. from view 1 to view 2).

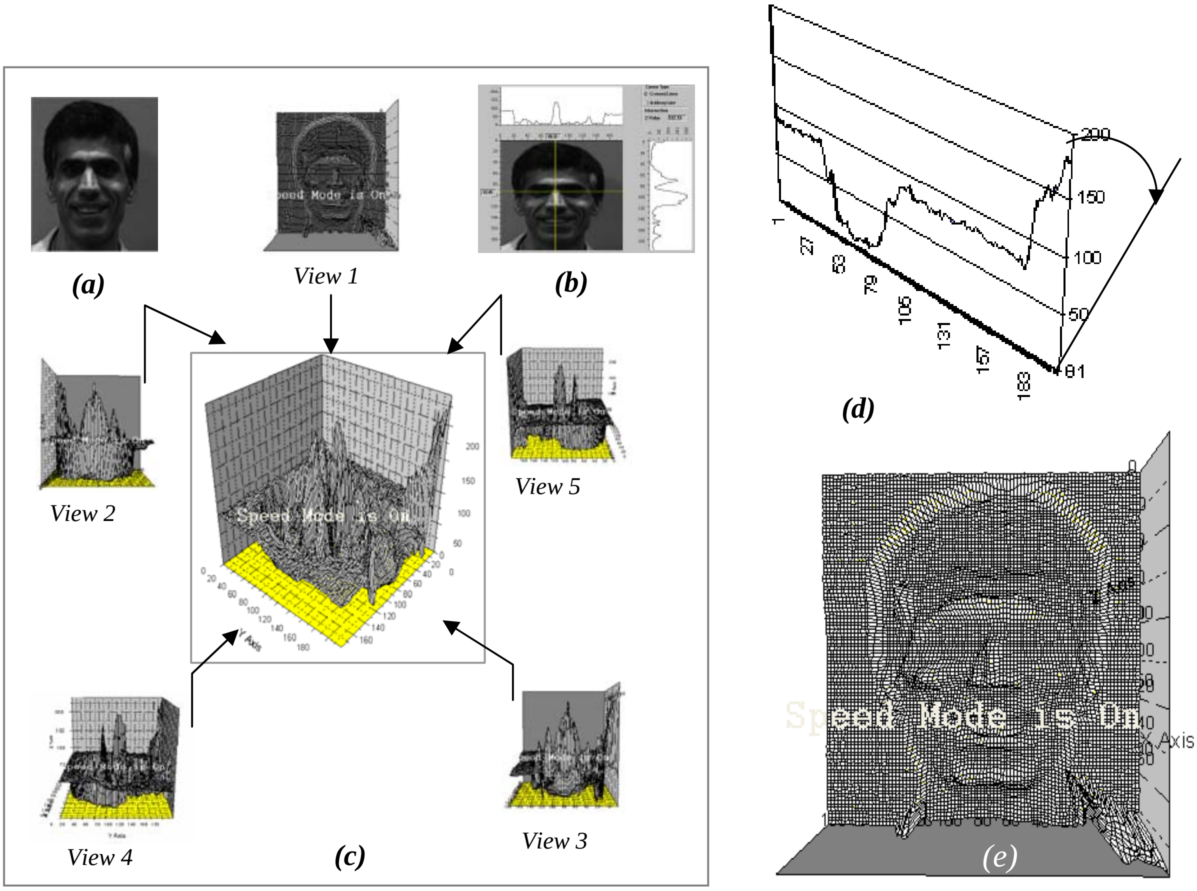


Figure 3.15: Illumination variation compensation: (a) The exploration of views extracted from 2D image planes. (b) Estimation of the eyes region i.e feature location. (c) The five views. (d) Critical rotation angle. (e) A sample of rotated face image where the depth measurement can be calculated.

However, this statement should be supported by a prior knowledge of the perceived object including the information and regional property of the image. In other words, the prior knowledge about the face, such as the symmetrical property and other informative region are still needed in supporting the critical angles mentioned earlier. The key point of shape and/or depth recovery is located at any high point in the pre-determined region. For instance, referring to view 5, notice that the highest and second highest peaks are caused by the impact of the light source on the nose tip and the lower part of the forehead respectively. At an angle of 25 degrees in rotation from view 1 to view 2 will recover the depth of the upper region of the face (above the nose) and the results produced are shown in figure 3.15(e).

In this thesis, the study was extended by focusing more on the ultimate aim of the work on facial features measurement for the classifier to further analyze the age classes. Instead of focusing on the image variation compensation, we have narrowed down the study to the features variation compensation. With the binary image conversion or transformation, we have discarded the illumination problem dealing with view 2, 3, 4 and 5. What is left is view 1. The remaining illumination impact is on the facial features, where the filter has wrongly identified the edges. There are two components that influence the result. The first component is the failure to detect the actual edges that belongs to a particular feature due to the image variation. The second component is caused by wrongly detecting the edges of the features which has been 'confused' by the edges (variation) due to the illumination impact.

These problems are in line with the statement of the problem stated in [151]. By applying the morphological operation with the proposed structuring element, we are able to compensate the features with respect to the aim of type of properties (overall features size) that we are looking for that is the derivative size of the overall facial features. Figure 3.16(a) shows the result of a typical edge image at the worst detection level. Figure 3.16(b) is its DLBT representation graph where the variation can be observed. By applying the morphological operation, the interested features or region of interest can be more visualized in such a manner that the facial features measurement can be done easier. In the meantime, the features variation is inherently reduced with respect to the purpose of compensation. The detail of the measurement technique will be explained in Chapter Four for age category classification. As a result, figure 3.16(c) and (d) are produced and demonstrating the compensated features and DLBT graph respectively.

The same method has also been applied for features pose variation where the facial measurement can be done after the morphological operation takes place. Since we are looking for the size (average height in DLBT graph) of the overall facial features, the problem of viewing geometry or pose variation is not affected much on the UCI property that we are looking for. Figure 3.17 demonstrates the compensation results of the features pose variation. Notice that the average height of both frontal and profile view (non-frontal) of the DLBT representation are between 5 to 10×10^9 decimal value. The detail of analysis results and purpose are explained in Chapter Four.

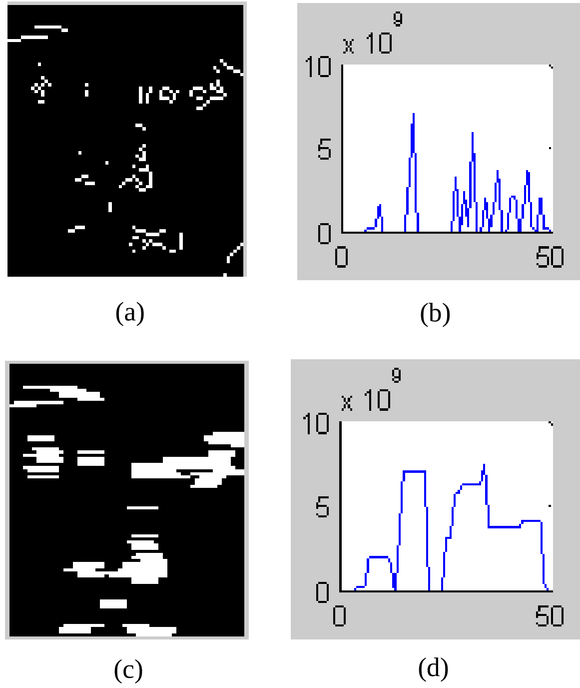


Figure 3.16: (a.) Edge features with the impact of illumination variation. (b.) DLBT representation. (c.) Morphology-compensated features. (d.) DLBT graph representation.

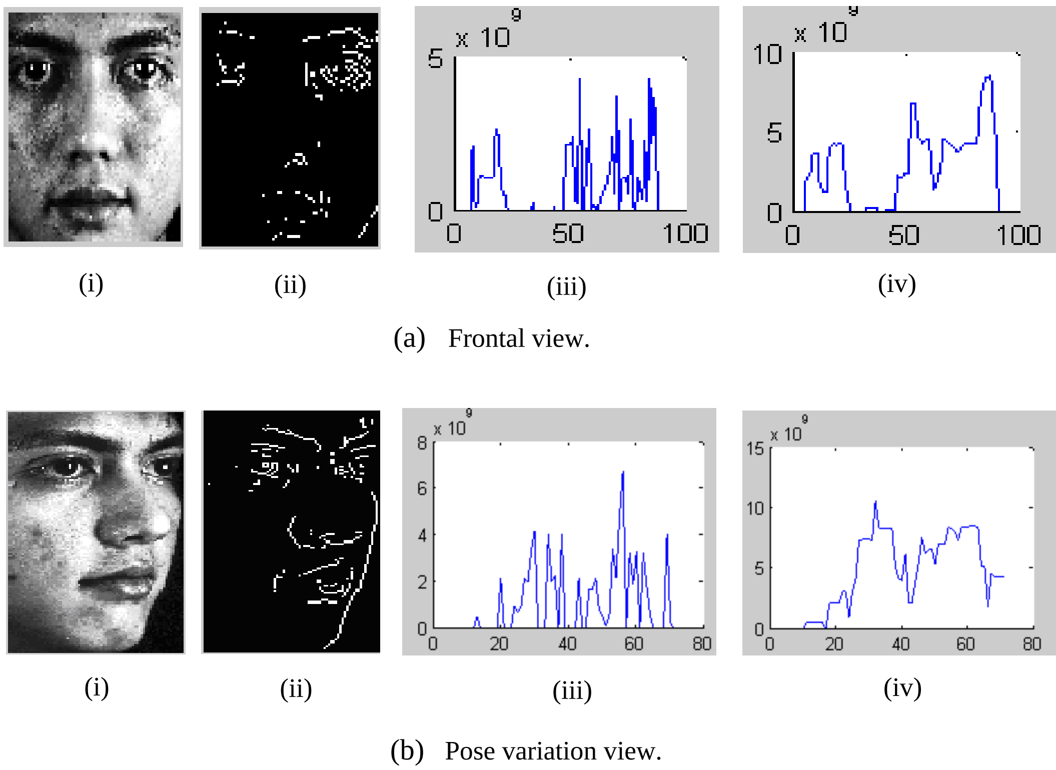


Figure 3.17: Pose variation compensation (independent): (i) Gray face image. (ii) Edge image. (iii) DLBT graph. (iv) Morphological compensated DLBT. graph.

3.2 Similarity and Dissimilarity Representation

3.2.1 Modality Implication

Given the input images where its quality is obtained in a controlled environment such as controlled lighting and pose, most of the algorithms in the literature are able to perform the recognition processes with high performance. In contrast, the performance will be degraded dramatically as the variation is increased. In this thesis, the process of collateral UCI extraction with and without the controlled elements has been demonstrated. The reason is because the objective of the current research was to study and design the unfamiliar identity registration and recognition processes that are robust in real world applications. Although it is very difficult to reach the ultimate goal of the recognition system, we have restricted our research on the identity parameters where the regional appearance, gender and age can be determined from the given face image. This information is still valuable for the most application that are involved in the statistical data collection.

One of the major problems in the process of UCI extraction and representation demonstrated in this thesis is the validity of features edge detection results. The modality implication with respect to the extractor and classifier can thus become a major issue especially on the measurement result validity. This is the main reason that motivated the manipulation of the availability of the detected edges by proposing the DLBT technique. Even with a good edges quality, the measurement results based on the size and area calculation can be confused with a certain natural characteristics of the facial features. For instance, the result of area calculation for Chinese-male eyes and Indian-female child is almost identical. As a result, the threshold value is difficult to be determined. Thus, the measurement of the shape must also be included in this kind of features measurement. Other feature such as mouth and nose may share the same problem. Measuring the size and shape of the features can also determine the three proposed classes; regional appearance, gender and age. However, with the real life image quality, such as blurred or small size of the image, it is very difficult to extract the features with the intention to extract the shape information. For this reason it is proposed that skin colour is the best solution for the regional appearance classification while texture measurement of overall facial surface (including the features) is used for gender representation and classification. Since the age classes of child and adult can be calculated based on the distance ratio of the features without having the detailed shape of the features, it seems to be a reliable method to measure the features using the binary or edge images.

3.2.2 Representation Results

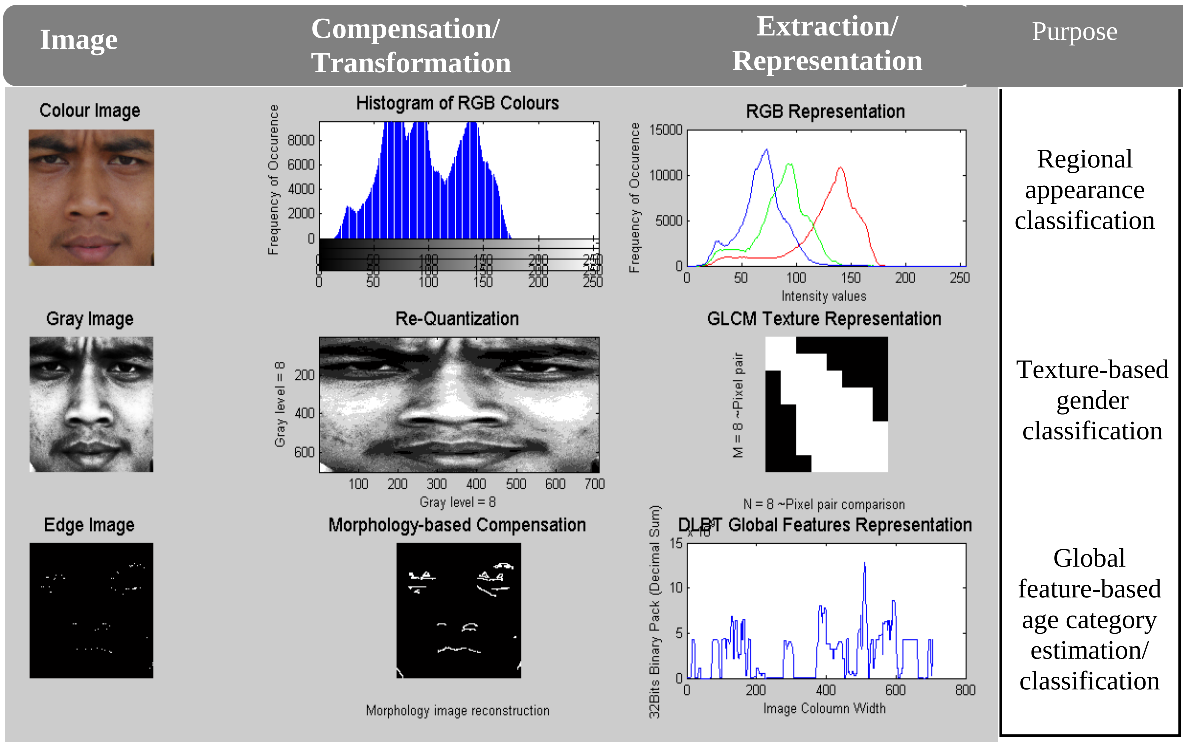
The task of extraction and classification are divided into two blocks of the research work. In this chapter, the results of the UCI representation are given with the general conclusion on the results analysis. The images used in experiments are composed with the illumination and pose variations, where some of them are acquired from the real life environments. The detail of the classification decision will be explained in the next chapter where a proper algorithm is developed and applied to the images of 12 classes as shown in the end of this chapter.

The following section includes samples of the overall results of UCI representation for 12 classes (figure 3.18 to figure 3.23):

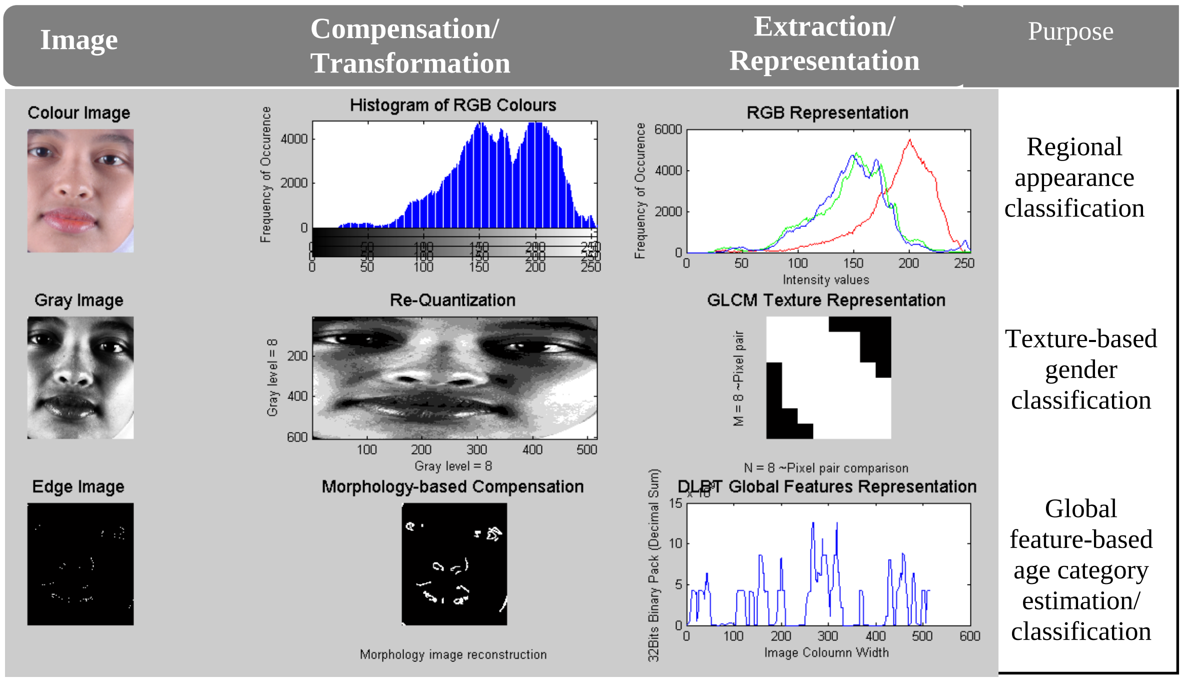
Malay male adult, Malay female adult, Malay male child, Malay female child,
Chinese male adult, Chinese female adult, Chinese male child, Chinese female child,
Indian male adult, Indian female adult, Indian male child, Indian female child,

The results are presented in three columns. In the first column, the image types are displayed for the purpose of references. This is initiated with the input colour image, followed by the gray image and edge images in that order. The second column presents the transformation and compensation that have been done on the image type corresponding to the first column. The colour image is transformed by mapping the three RGB components of red, green and blue. The re-quantization is performed on the gray image as to reduce the gray levels to only 8 levels, so that the calculation complexity is reduced drastically including the illumination variation reduction. Finally, the edge image is compensated by morphology-based method to enhance the links in the edge image for the purpose of plotting the DLBT graph as explained in the previous section. The third column is devoted to the representation results which will be dedicated to the classifier in the next chapter for the purposes of analysis, decision to classify and recognition of identity parameters of regional appearance, gender and age respectively.

3.2.2.1 Skin Colour, Texture and Global Features Representations

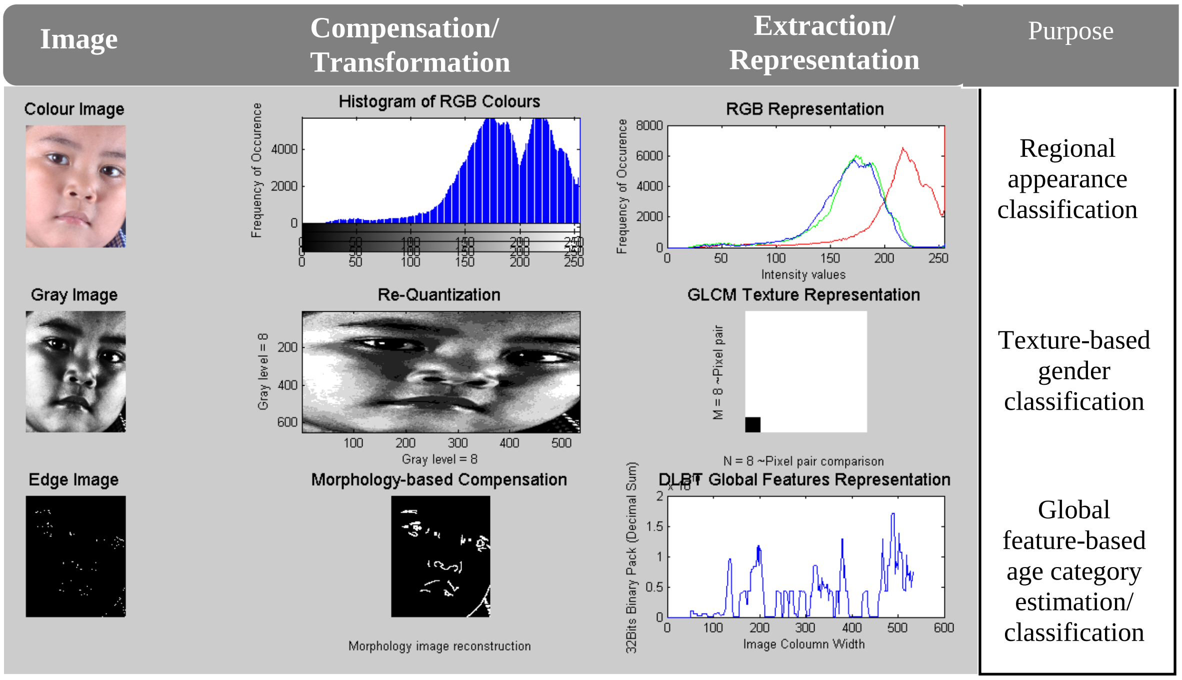


(a) Malay-male-adult.

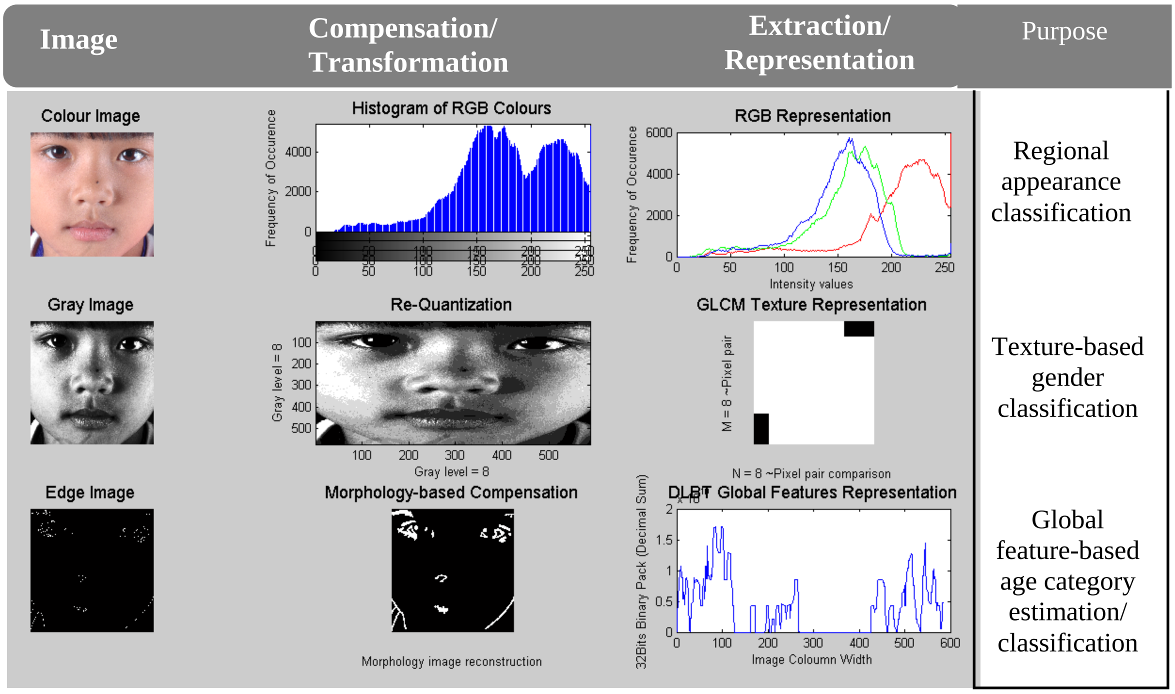


(b) Malay-female-adult.

Figure 3.18: Malay-adult male and female.

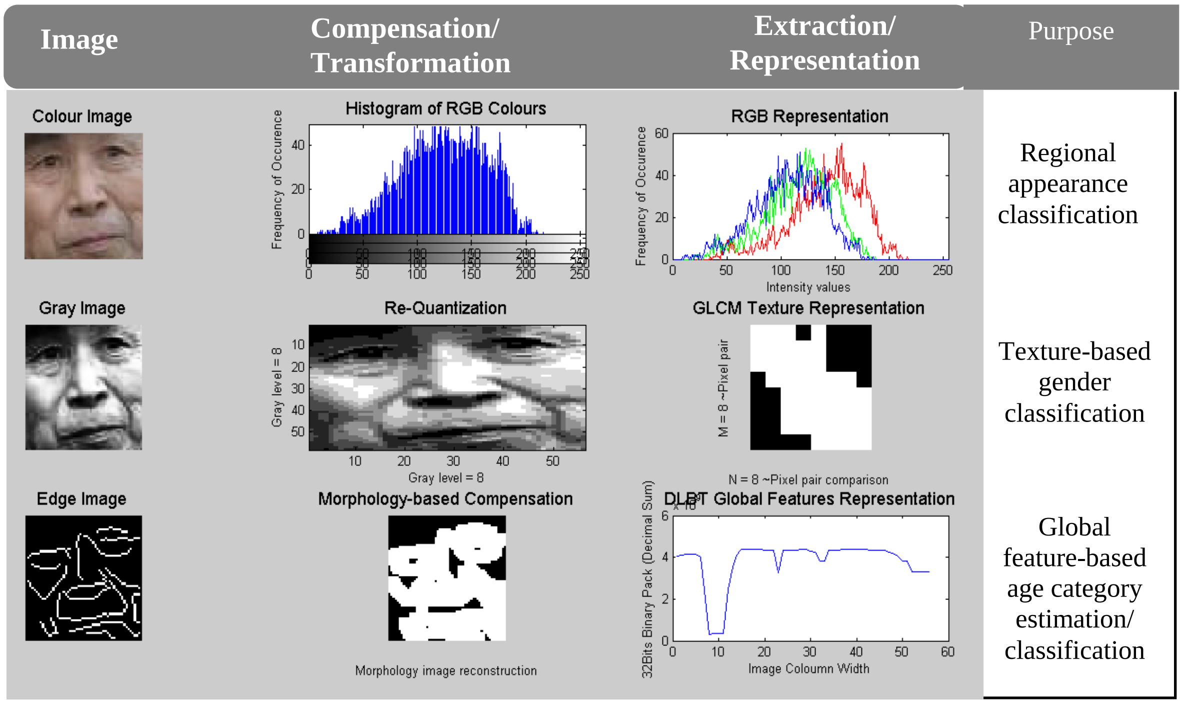


(a) Malay-male-child.

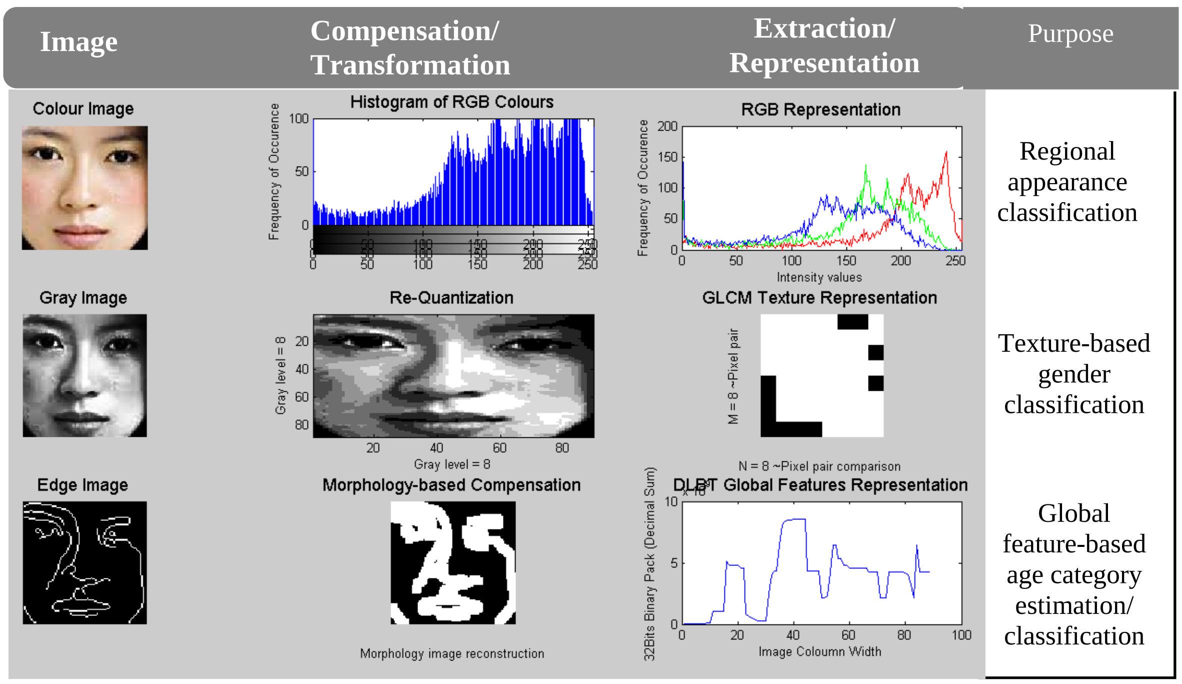


(b) Malay-female-child.

Figure 3.19: Malay-child male and female.

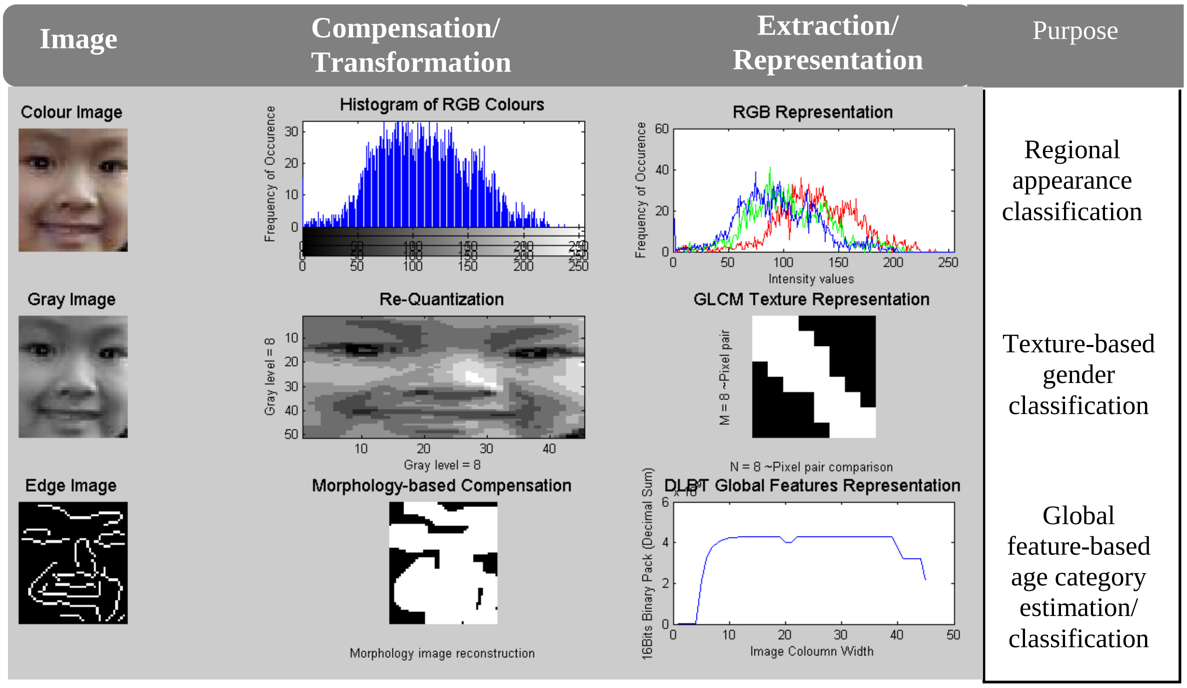


(a) Chinese-male-adult.

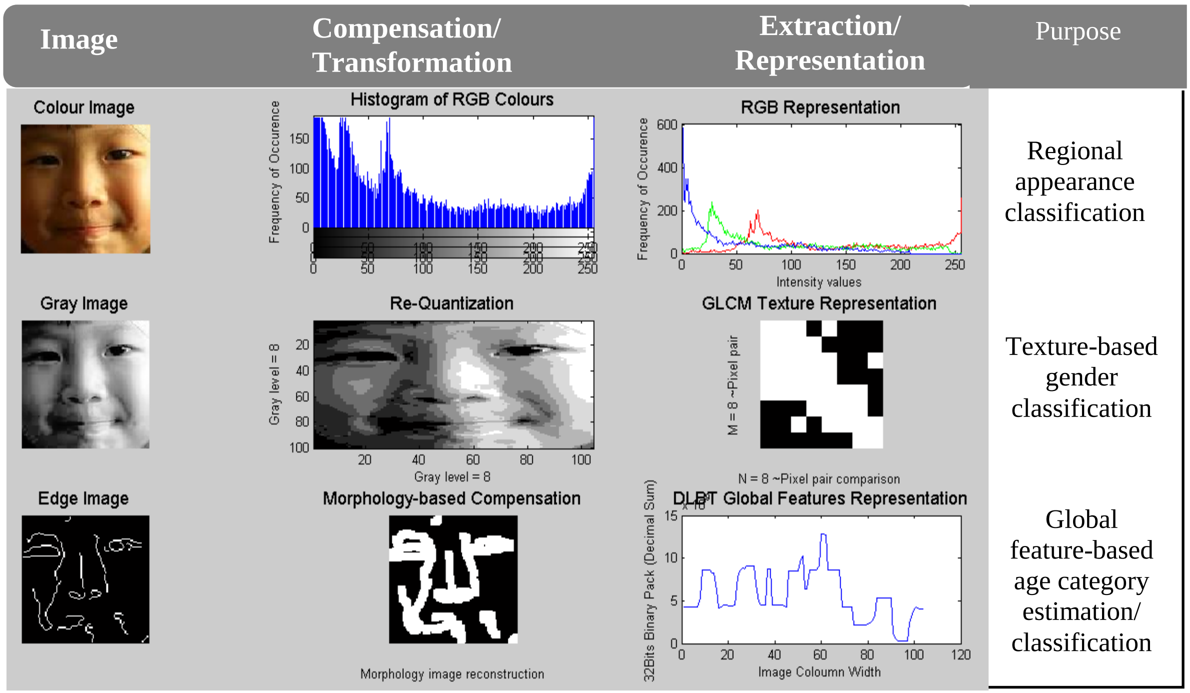


(b) Chinese-female-adult.

Figure 3.20: Chinese-adult male and female.

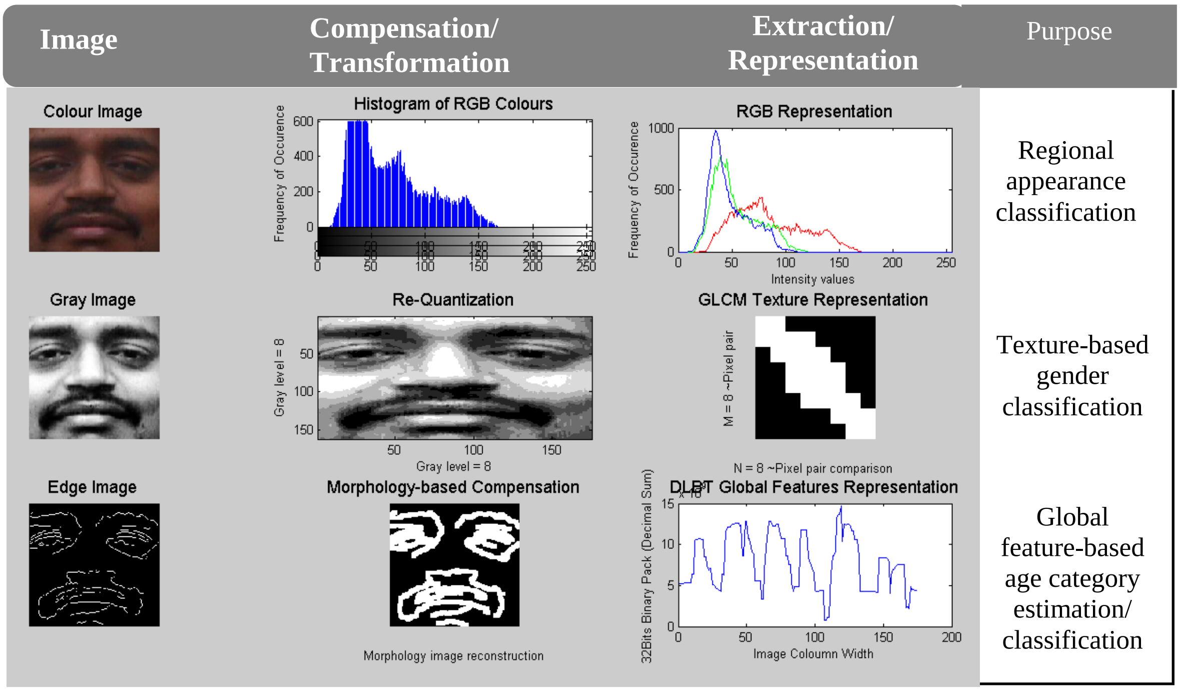


(a) Chinese-male-child.

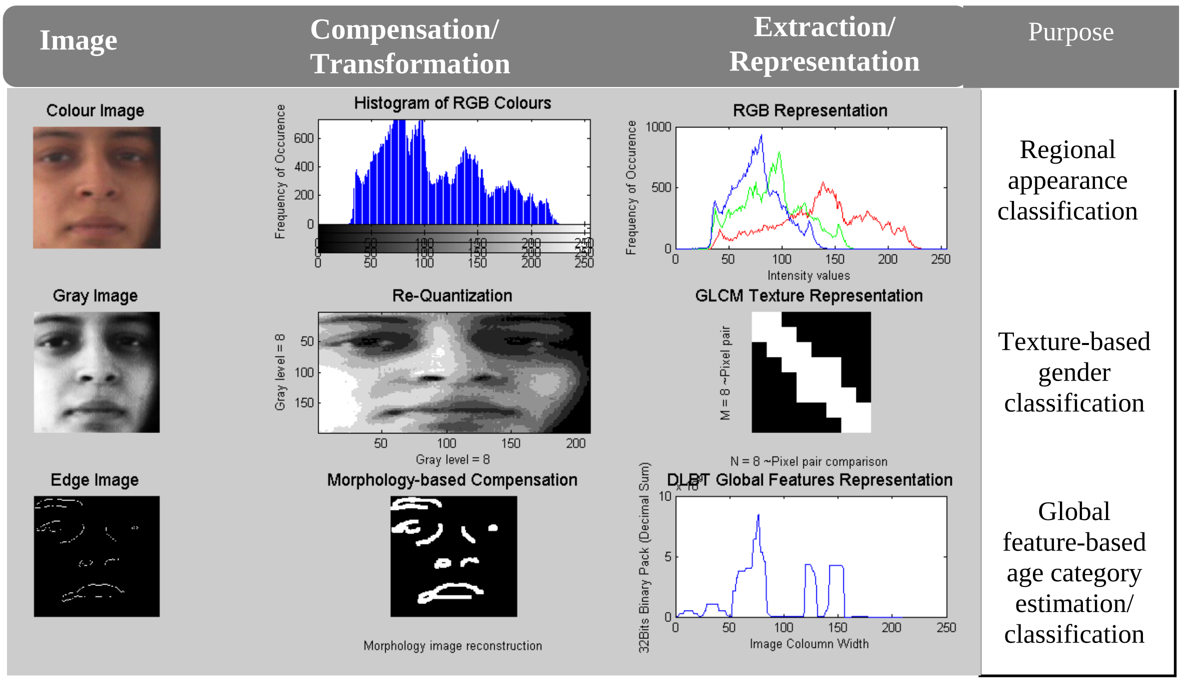


(b) Chinese-female-child.

Figure 3.21: Chinese-child male and female.

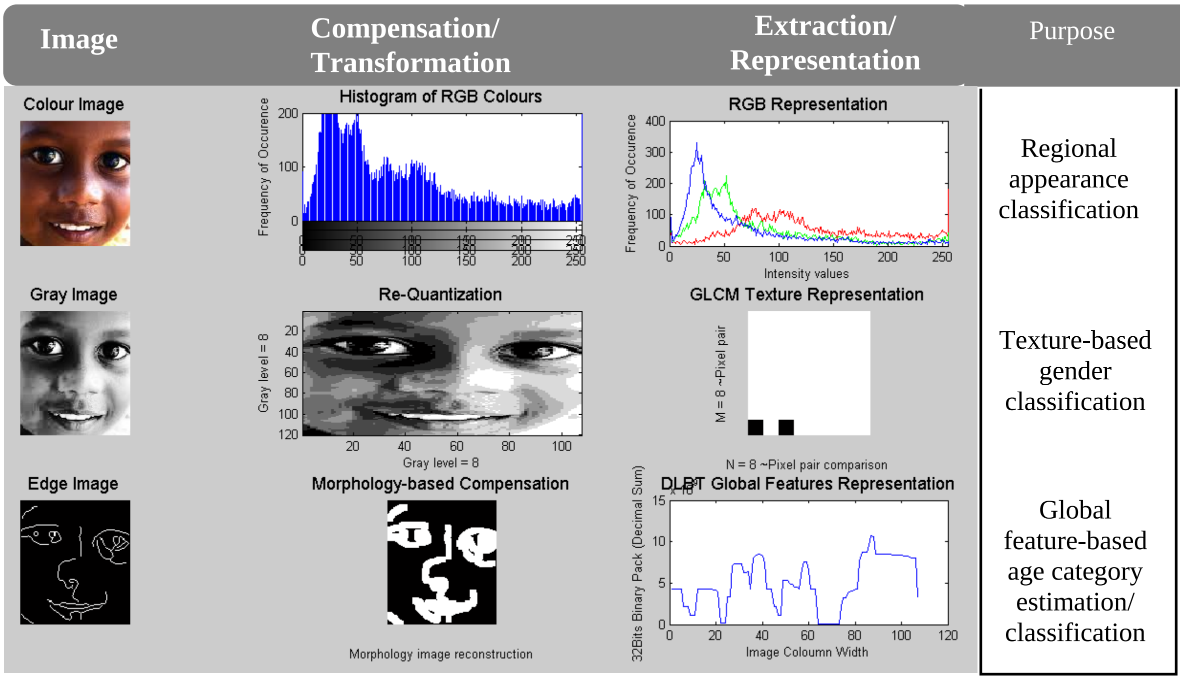


(a) India-male-adult.

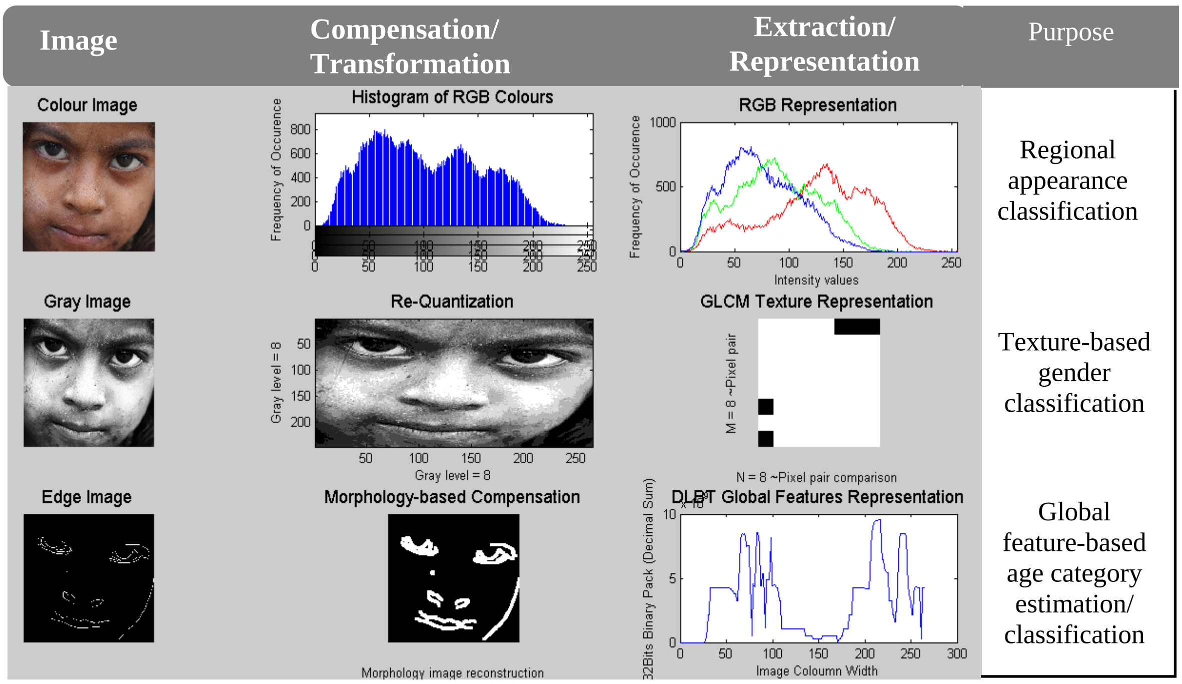


(b) India-female-adult.

Figure 3.22: Indian-adult male and female.



(a) India-male-child.



(b) India-female-child.

Figure 3.23: Indian-child male and female.

Chapter Four

Classification and Recognition of Unique Collateral Characteristics Information (UCCI)

4. CLASSIFICATION AND RECOGNITION OF UCCI

A typical familiar face recognition system classifies the input based on comparison with reference images in a database. A similarity measurement between the input image and reference image is carried out. The outcome from this matching process is either that the subject is a member of the database or not. Unlike familiar face recognition system, unfamiliar facial identity registration and recognition proposed in this thesis is done by identifying the characteristics of the input images. In other words, with an analytical approach, the proposed system has to breakdown the identity parameters of the subject into regional appearance, gender and age classes.

Since all faces share the same structure and only small differences exist between the faces, classification technique should be able to increase the similarity within a class while increase the dissimilarity between the classes. Furthermore, the smaller the class will result in a less burdensome of identification or recognition process. The proposed method or collateral classification strategy of identity representation introduced in this thesis is carried out by manipulating the availability of the collateral UCI for classifying the identity parameters of the regional appearance, gender and age classes. The registration of this collateral UCI has been made in such a way to collect more information of identity. In this manner, classification task will be able to perform better in classifying and enhancing the performance of unfamiliar identity recognition. The special chosen UCI for the different class recognition will not only benefit to the classifier, but also positively contribute to the matching process duration possibly because of the small size of the class. In this regards, the similarity measurement within a particular class is not complicated with the dissimilarity measurement between the classes as a different UCI for a different class was used. An experiment was carried out on the developed Malaysian database and open database comprising three different regional appearances, two different age groups and two different genders and pose and illumination image variations are incorporated.

4.1 The Regional Appearance Class

4.1.1 Malay, Chinese and India Malaysian

Figure 4.1 illustrates various samples of Malay, Chinese and India Malaysian facial images from the developed and open databases. Each of the regional appearance classes has included the male, female, child and adult classes. The illumination and pose variations are also included which have been tested and explained in the previous chapter (extractor).

(a) Malay class

(b) Chinese class

(c) India class

Figure 4.1: Sample of Malay, Chinese and India Malaysian ranging from male, female, child and adult classes.

4.1.2 The Regional appearance UCI Similarity/Dissimilarity Classification

Based on the extraction results, the RGB of the three skin colour classes is further analyzed by performing the experiments on more than 10 subjects per class. In this test stage, the average value of the RGB is calculated and the minimum, maximum and peak values are obtained such as shown in figure 4.2. The minimum (R_{imin}, G_{imin}, B_{imin}) and maximum (R_{imax}, G_{imax}, B_{imax}) values of each RGB component is a range for that RGB component in the scale of 256 intensity levels. Subsequently, the peak values (R_{peak}, G_{peak}, B_{peak}) are the highest point (frequency of occurrence) of each component in the histogram corresponding to their intensity levels (R_{ipeak}, G_{ipeak}, B_{ipeak}) in the histogram.

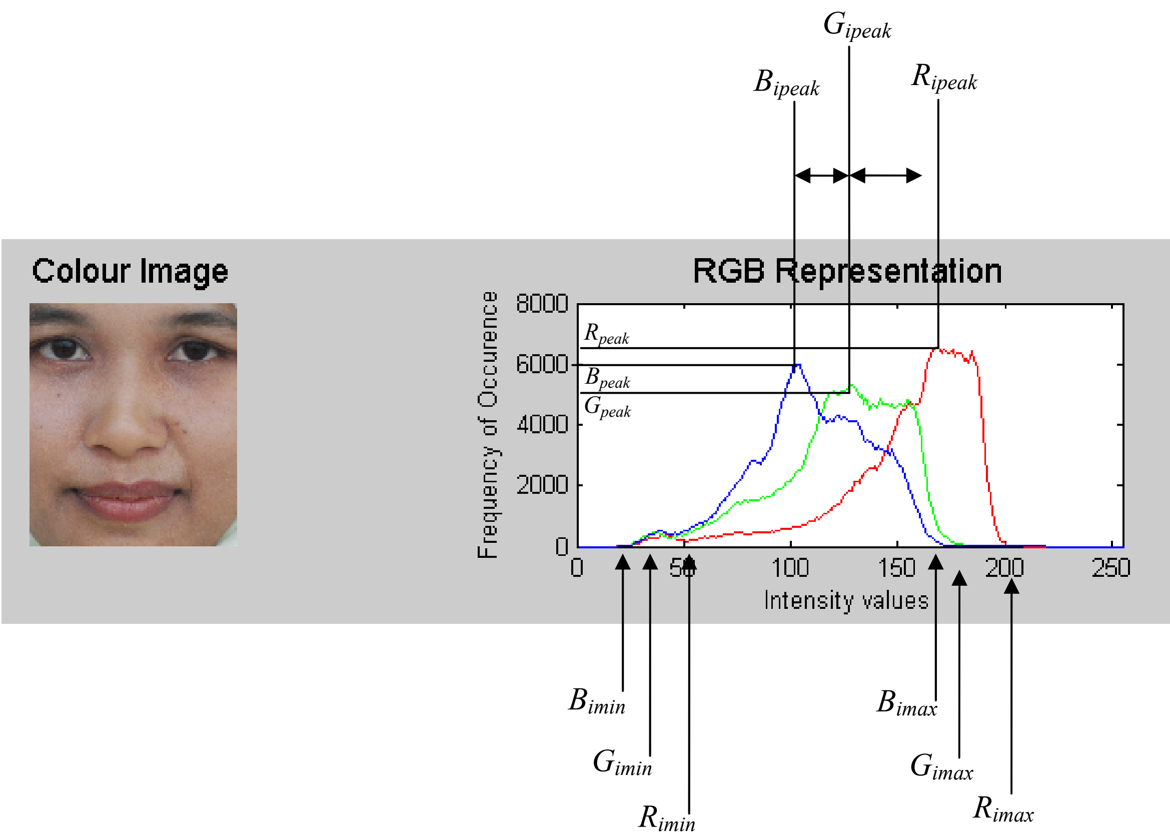
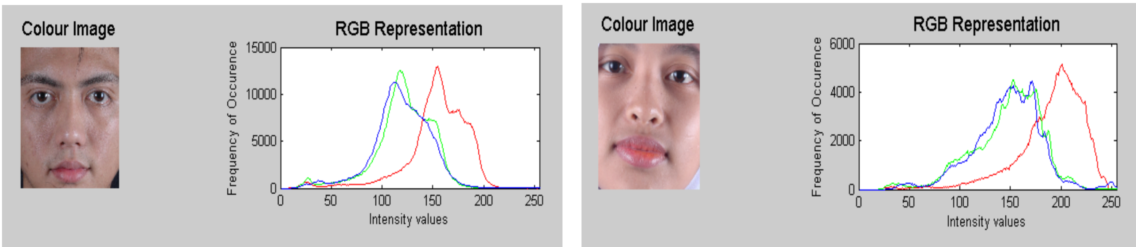


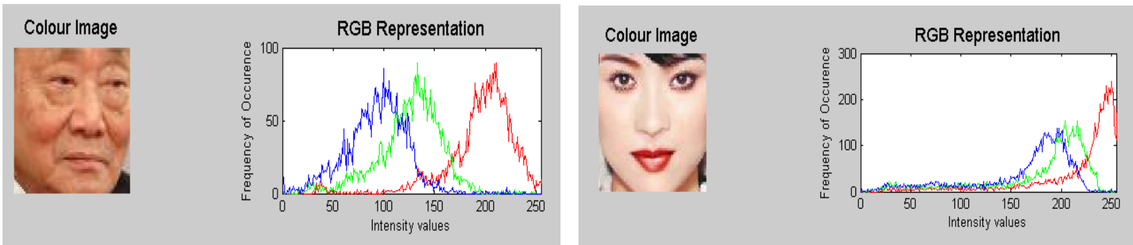
Figure 4.2: RGB property for a typical face image.

The main reason the RGB colour space is used in this classification task is due to its simplicity and reliability. The results shown are able to classify the Malay, Chinese and India classes into the colour category of pale, yellowish and dark respectively.

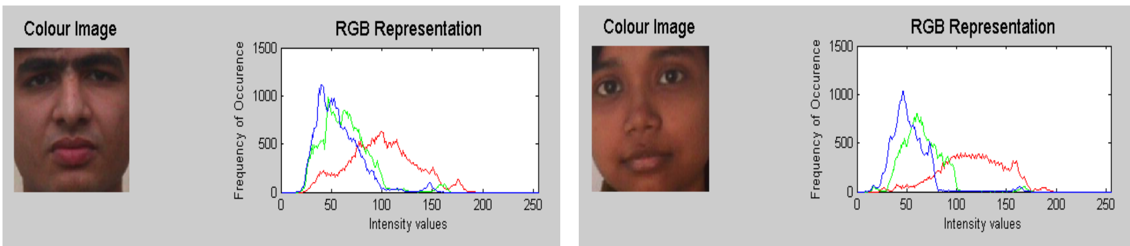
From the representation results produced by the colour extractor discussed in Chapter Three, the class characteristics of regional appearances of Malay, Chinese and India Malaysian can be observed in figure 4.3. For each colour face image, the RGB representation can be obtained where the behaviour of the three colour components is characterized by the classes of regional appearances.



(a) RGB representation of Malay-male and female classes.



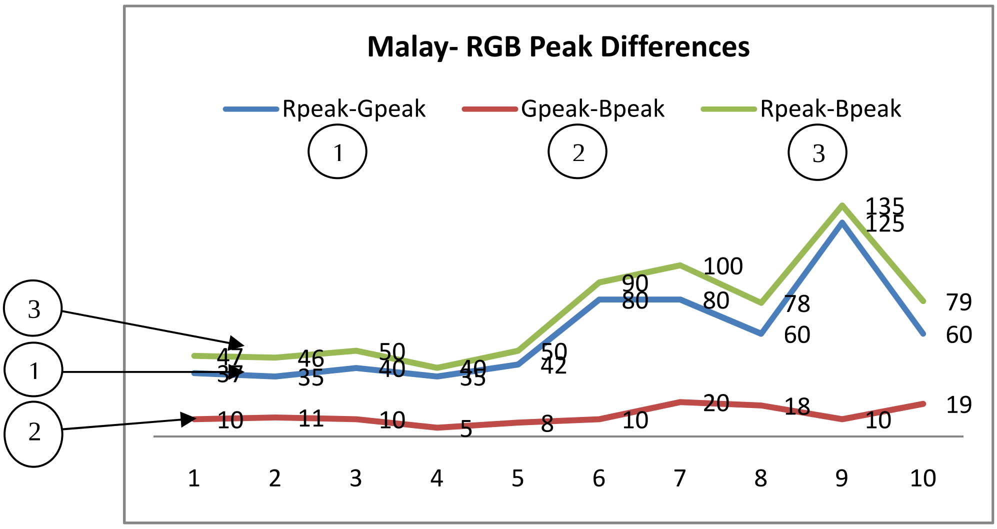
(b) RGB representation of Chinese-male and female classes.



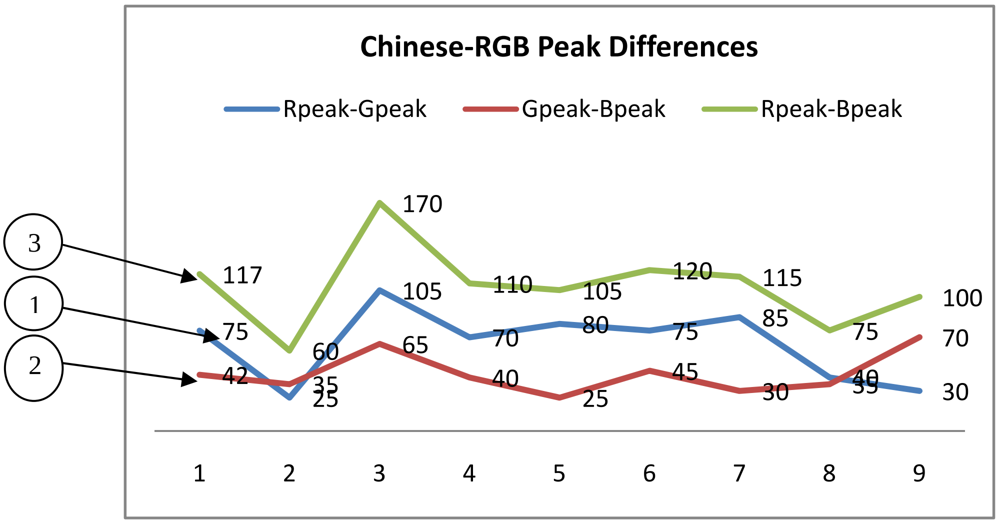
(c) RGB representation of India-male and female classes.

Figure 4.3: RGB representation for typical face images.

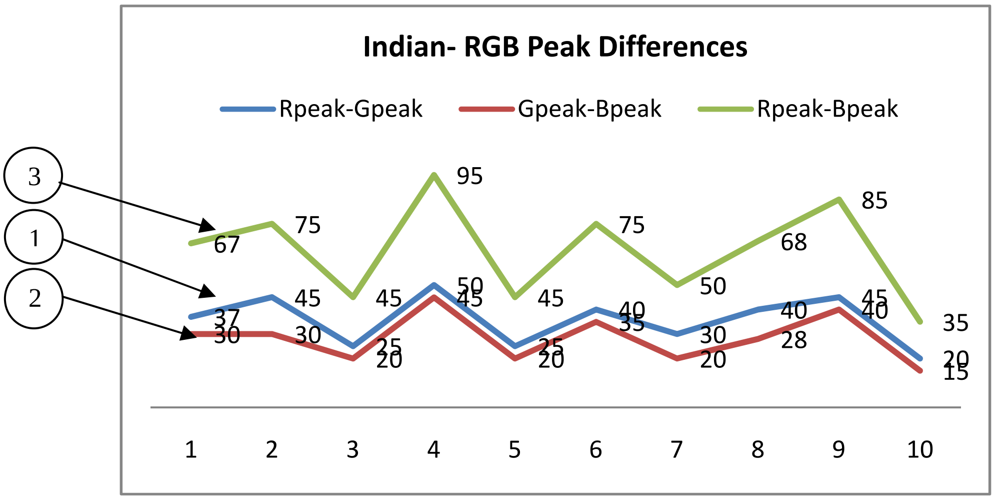
Figure 4.4 demonstrates the category of these classes from the differences between the RGB peak values of the three regional appearance classes.



(a) Malay class (Pale color).



(b) Chinese class (Yellowish color).



(c) India class (Dark color).

Figure 4.4: RGB peak differences for Malay, Chinese and India regional appearances.

From the results shown in Figure 4.4, the colour model of the three regional appearances can be defined as indicated below:

(i) The skin colour is classified as Malay regional appearance if:

$$[(G_{ipeak} - B_{ipeak}) < D_{TH1} * (R_{ipeak} - B_{ipeak})]$$
$$\text{and } [(|B_{peak} - R_{peak}|) < D_{TH2} * B_{peak}],$$
where the threshold of difference:
$$0.0 < D_{TH1} < 0.1 \text{ and } 0.1 < D_{TH2} < 0.2$$

(ii) The skin colour is classified as Chinese regional appearance if:

$$[(G_{ipeak} - B_{ipeak}) < D_{TH1} * (R_{ipeak} - B_{ipeak})]$$
$$\text{and } [(|B_{peak} - R_{peak}|) < D_{TH2} * R_{peak}],$$
where the threshold of difference:
$$0.4 < D_{TH1} < 0.6 \text{ and } 0.3 < D_{TH2} < 0.4$$

(iii) The skin colour is classified as India regional appearance if:

$$[(G_{ipeak} - B_{ipeak}) < D_{TH1} * (R_{ipeak} - B_{ipeak})]$$
$$\text{and } [(|B_{peak} - R_{peak}|) < D_{TH2} * B_{peak}],$$
where the threshold of difference:
$$0.2 < D_{TH1} < 0.4 \text{ and } 0.4 < D_{TH2} < 0.8$$

Where,

$R_{peak}, G_{peak}, B_{peak}$	=	The RGB colour or intensity levels of the highest frequency of occurrence.
$D_{TH1}, D_{TH2}, D_{TH3}, D_{TH4}, D_{TH5}, D_{TH6}$	=	Unique values of percentages of differences between intensity peak values.

In conclusion, the conditions show that the three RGB colour components play an important role in characterizing the classes. For example, from the observation of figure 4.4, it can be said that, when the blue component approached the red component, the image will fall into dark class (India). On the other hand, when the blue component approached the green component, the image will fall into pale class (Malay). Finally, when the colour level of blue component is moderately in between the other two colour components, the image will fall into yellowish class (Chinese).

4.2 The Gender Class

4.2.1 The Male and Female UCI

The objective of the gender recognition is simply to determine or identify for a given image whether the subject is male or female. However, unlike the human capability, the result from the computer classification processing analysis may be conflicted with the face features characteristics information shared by both gender classes. In Chapter Two it is discussed that all the faces no matter whether they are male or female have the same basic structure of features. There are only small differences based on features shape (including the face shape or face outer line) and facial texture. In Chapter Three, we have discussed the features selection criterion and stated the reason that the facial texture is used as the type of UCI chosen for determining the gender class.

Figure 4.5: Some samples of male and female classes comprising of Malay, Chinese and India Malaysian adult and child classes.

Figure 4.5 illustrates some examples of male and female classes. The challenges are to isolate the gender classes where the members of male or female class comprise of all the three regional appearances and all the two age classes. With the aid of texture results information from Chapter Three (extractor), analysis on more than 100 subjects ranging from the different age (child and adult) and different regional appearance classes (Malay, Chinese and India) was conducted. The gender algorithm is developed based on these results and explained in the next section.

4.2.2 The Gender UCI Similarity/Dissimilarity Classification

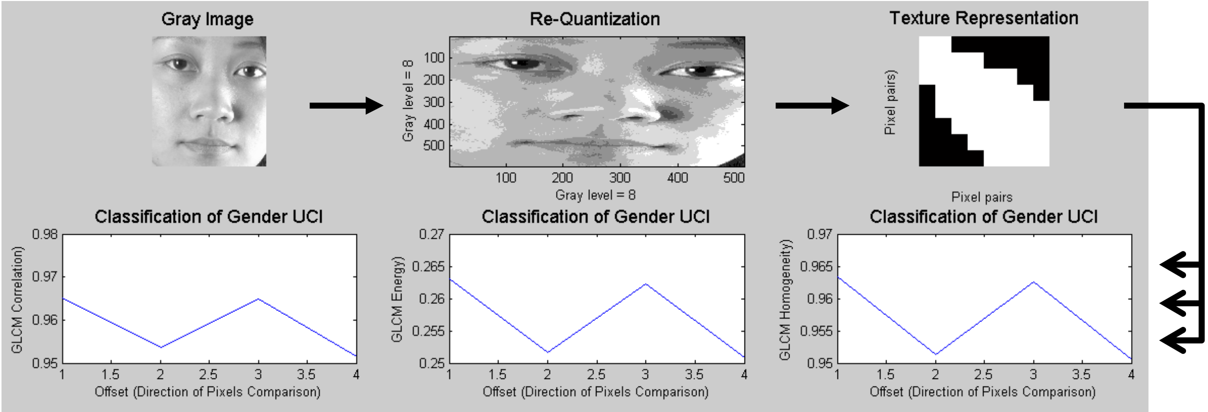
The design of gender classifier is based on facial texture segmentation. The segmentation of texture pattern from 2D face image has been shown graphically with a detail explanation on the experiments result in Chapter Three. Recall that the final outcome from the gender extractor is a GLCM texture representation such as shown in figure 4.6, 4.7, 4.8 and 4.9. In these figures, we have incorporated and demonstrated the statistical analysis results of GLCM texture features by applying the GLCM features of correlation, energy and homogeneity patterns given by:

$$\sum_{i,j} \frac{(i-\mu i)(j-\mu j)p(i,j)}{\sigma_i \sigma_j} \qquad \text{(GLCM Correlation)}$$

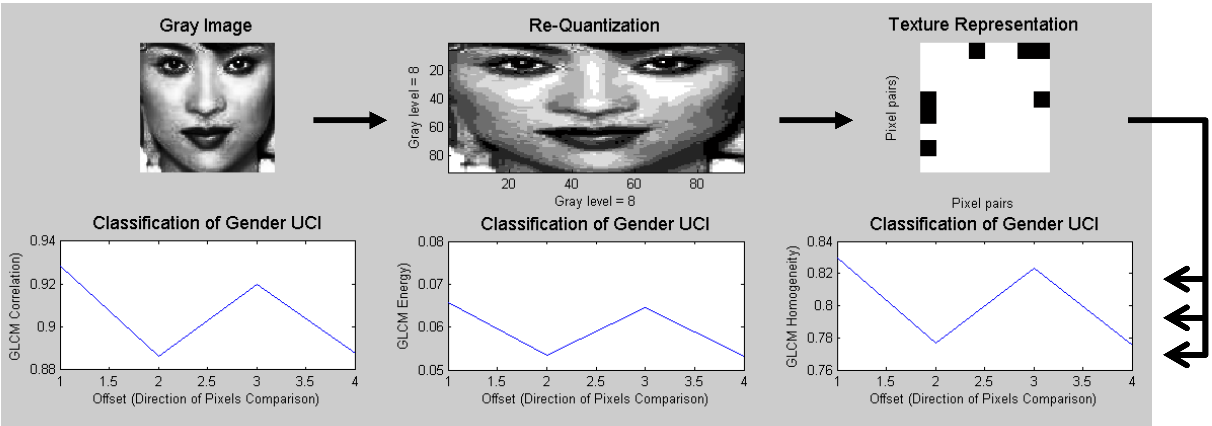
$$\sum_{i,j} p(i,j)^2 \qquad \text{(GLCM Energy)}$$

$$\sum_{i,j} \frac{p(i,j)}{1+|i-j|} \qquad \text{(GLCM Homogeneity)}$$

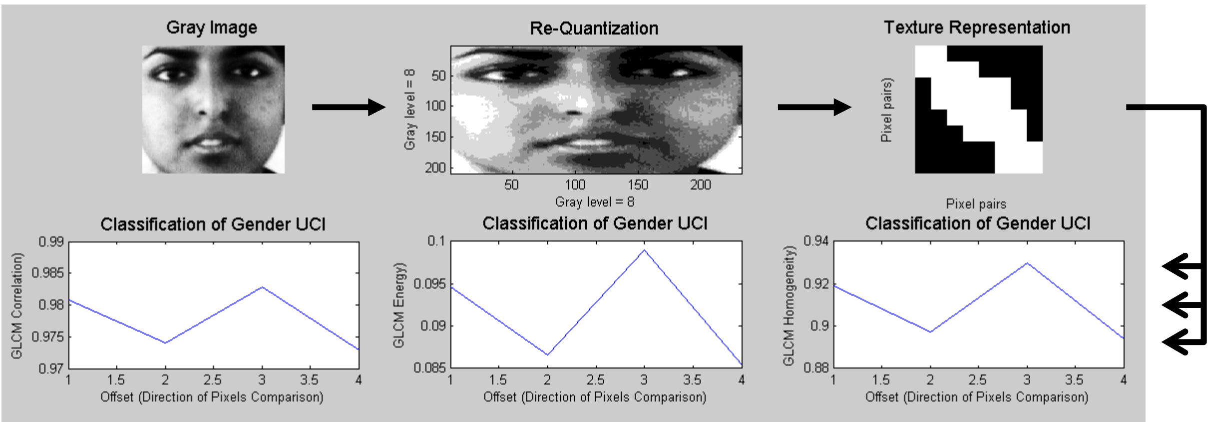
The values of these three features are plotted against the offset or direction of pixel pair-wise comparison. The correlated values, strength of energy over the pattern distribution and the homogeneity features are calculated for the face images. From the results, we have chosen to use the GLCM correlation feature for analysing the texture UCI of the face image by considering the other two features with no noticeble differences.



(a) Malay female adult.

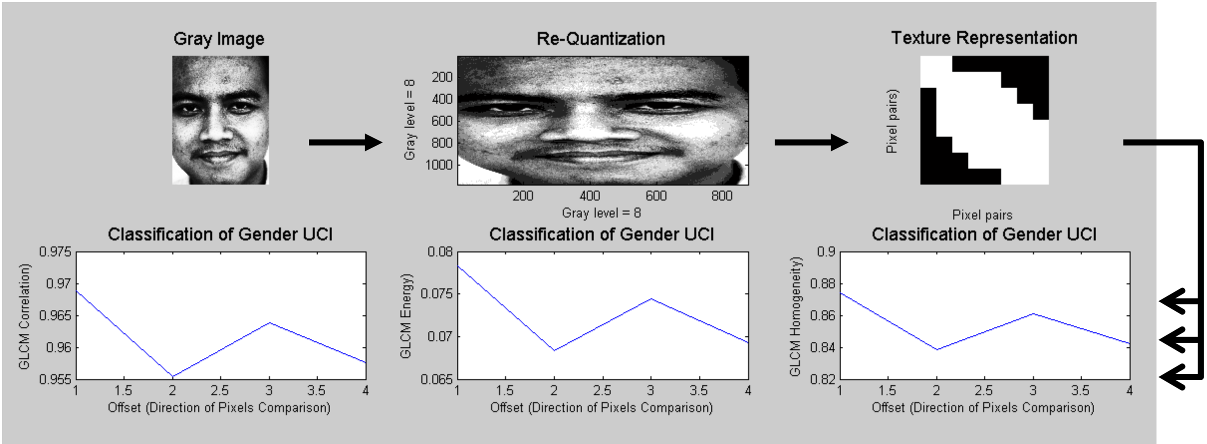


(b) Chinese female adult.

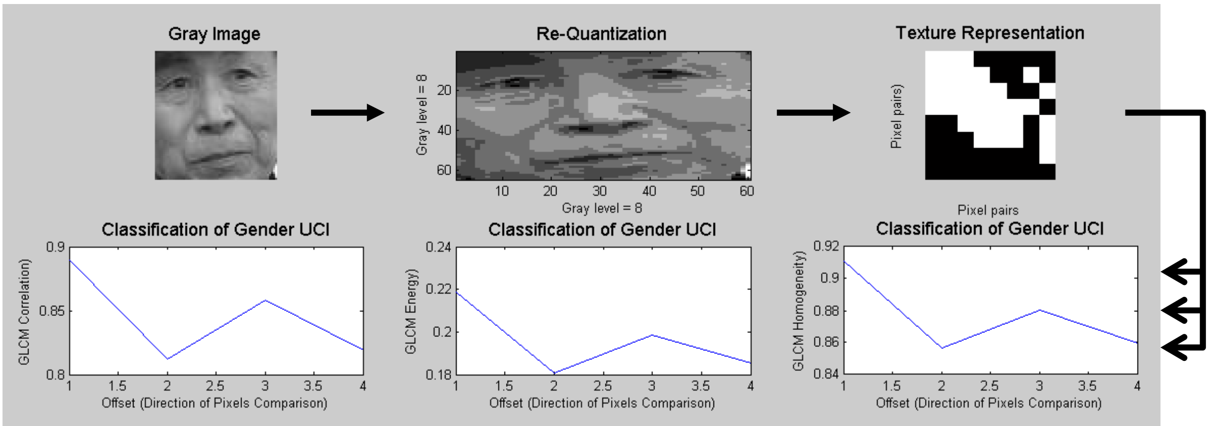


(c) India female adult.

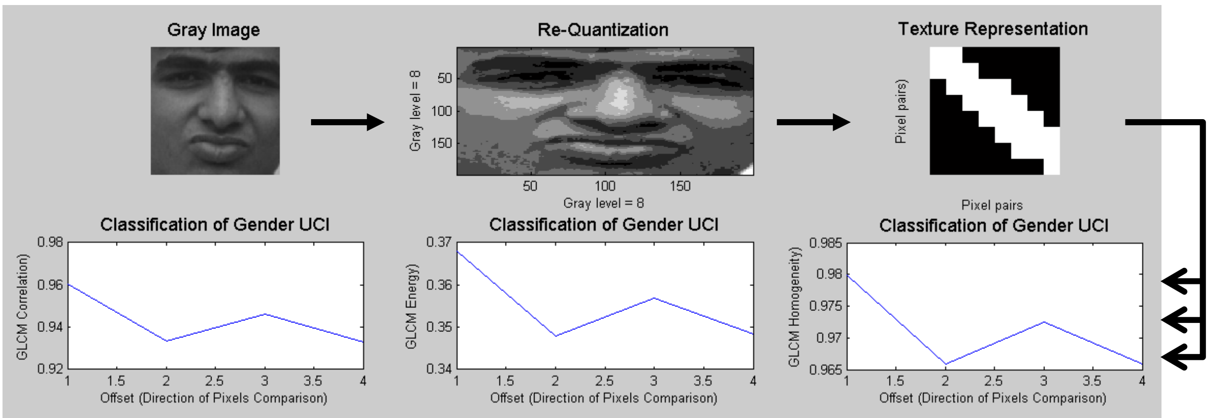
Figure 4.6: Some samples of female adult classification analysis based on GLCM features of correlation, energy and homogeneity calculation.



(a) Malay male adult.

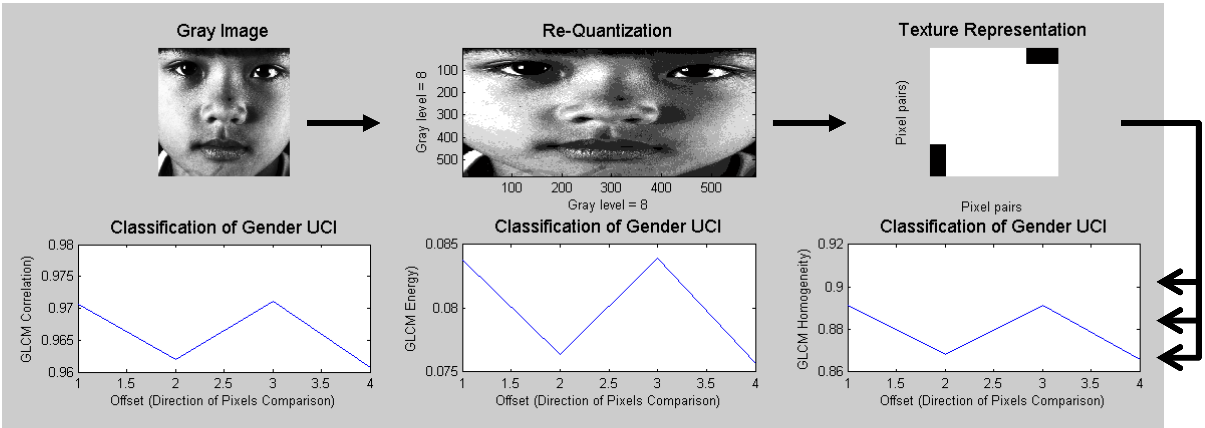


(b) Chinese male adult.

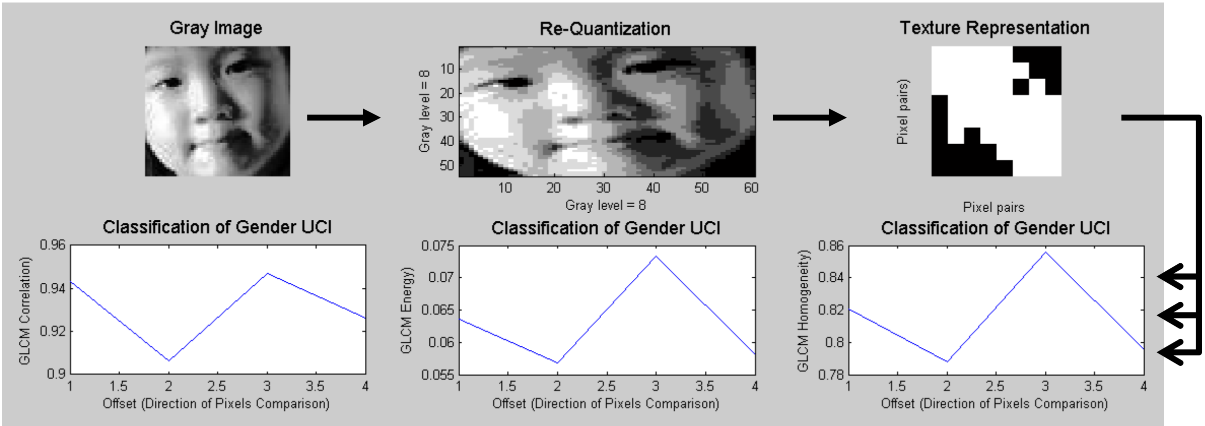


(c) India male adult.

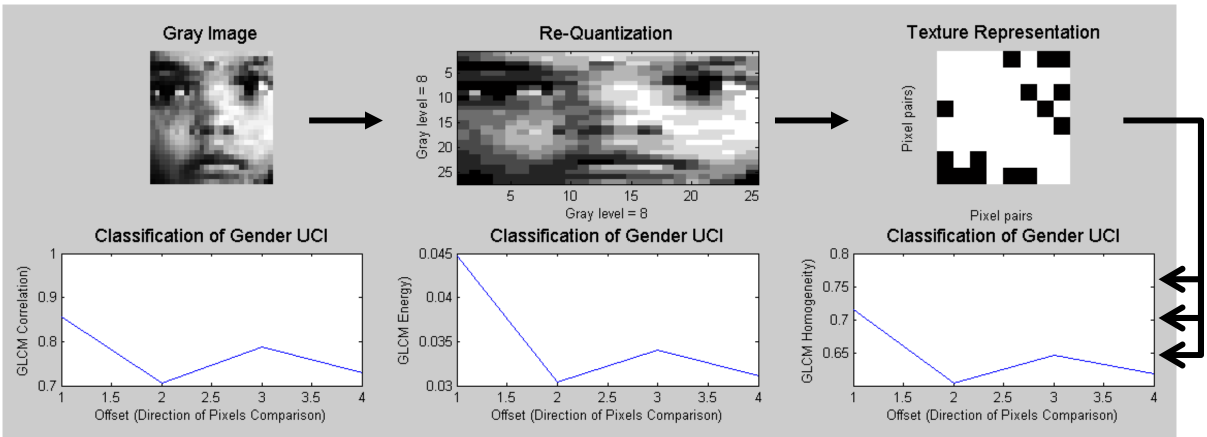
Figure 4.7: Some samples of male adult classification analysis based on GLCM features of correlation, energy and homogeneity calculation.



(a) Malay female child.

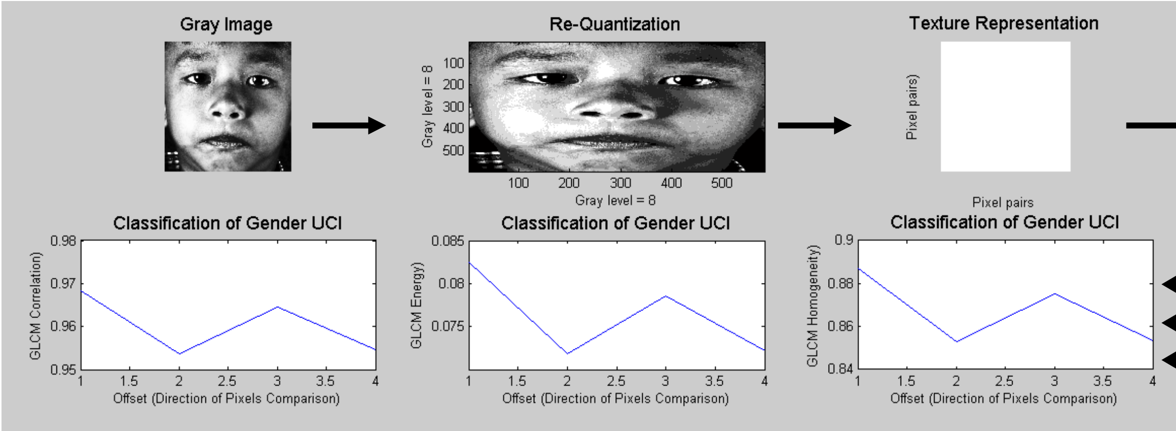


(b) Chinese female child.

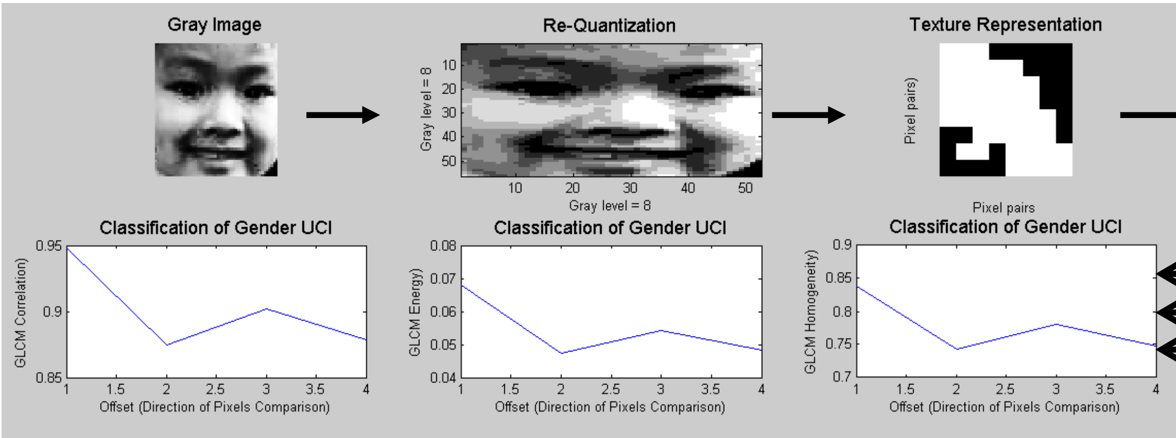


(c) India female child.

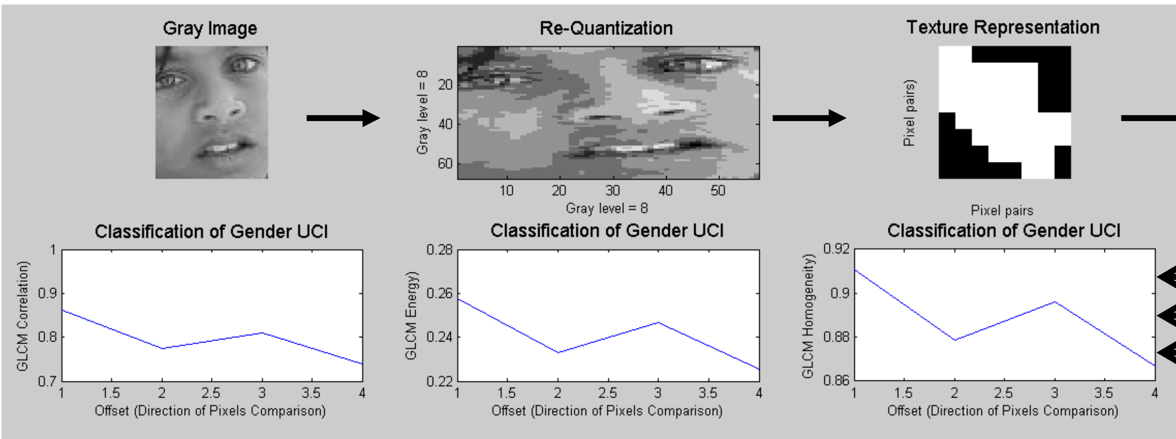
Figure 4.8: Some samples of female child classification analysis based on GLCM features of correlation, energy and homogeneity calculation.



(a) Malay male child.



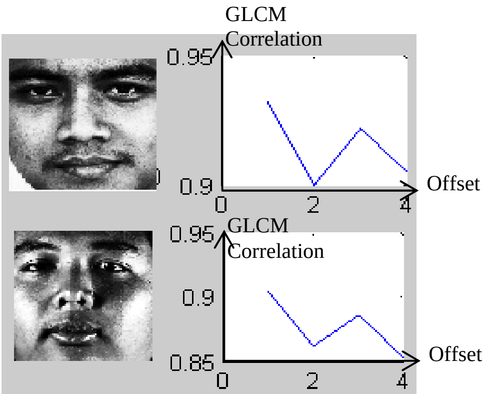
(b) Chinese male child.



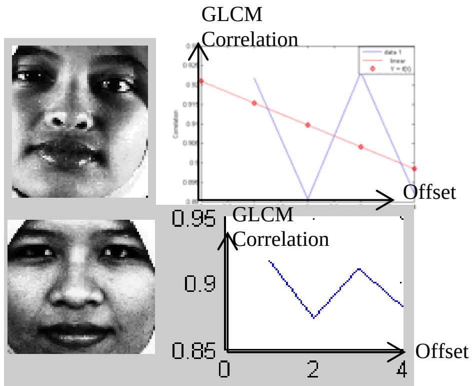
(c) India male child.

Figure 4.9: Some samples of male child classification analysis based on GLCM features of correlation, energy and homogeneity calculation.

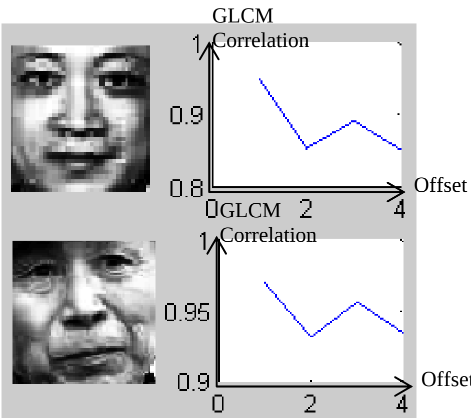
Figure 4.10 shows some outputs (texture correlation versus offset) from the measurement of facial texture for gender recognition. The results comparison can be seen for Malay adult male and female ((a) and (b)), Chinese adult male and female ((c) and (d)) and India adult male and female ((e) and (f)).



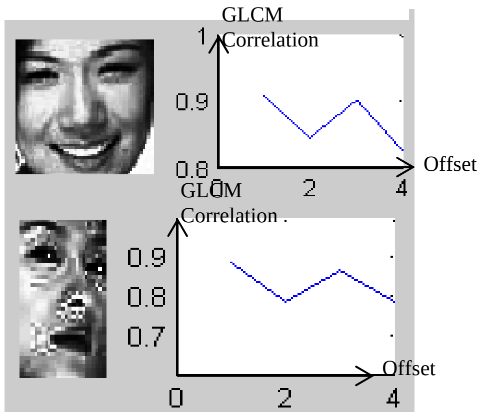
(a) Malay male adult.



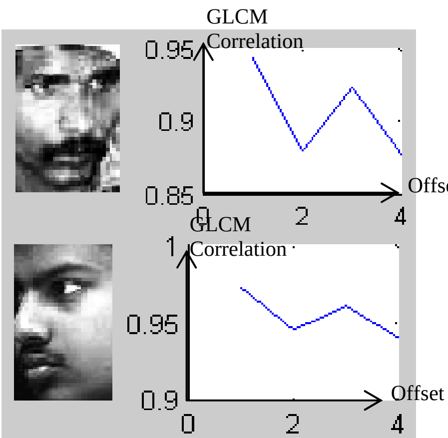
(b) Malay female adult.



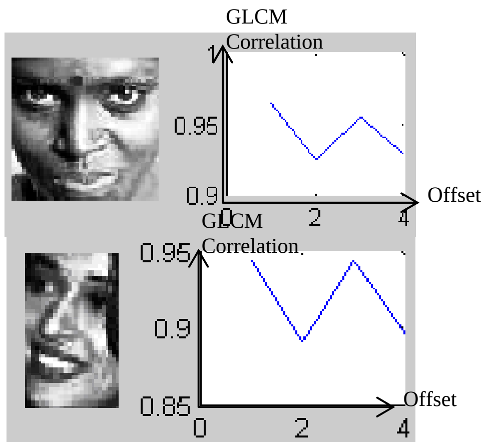
(c) Chinese male adult.



(d) Chinese female adult.



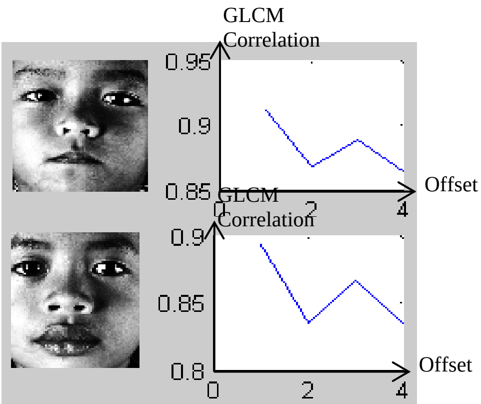
(e) India male adult.



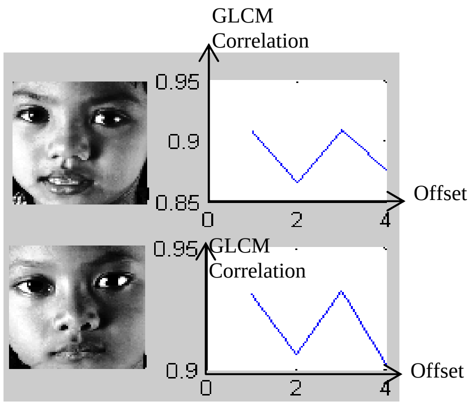
(f) India female adult.

Figure 4.10: Comparison of results between Male and Female classes for all Malay, Chinese, India adult classes - texture correlation versus offset.

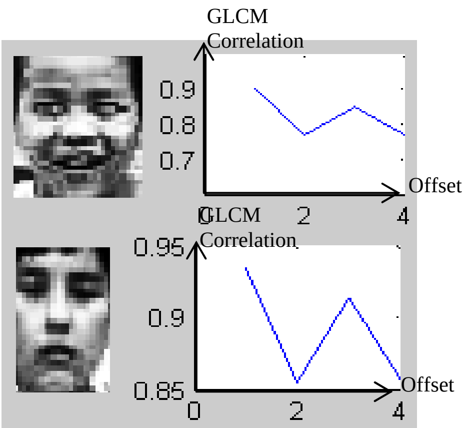
Figure 4.11 shows some outputs from the gender classification for the child classes arranged in the same order as in Figure 4.10 explained previously. The response from the graph of pixel correlation versus offset reveals the difference of the female class compared to the male class.



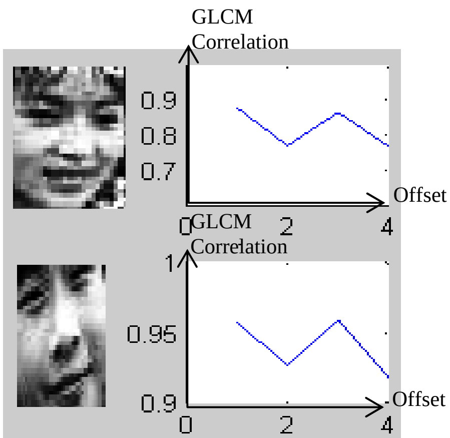
(a) Malay male child.



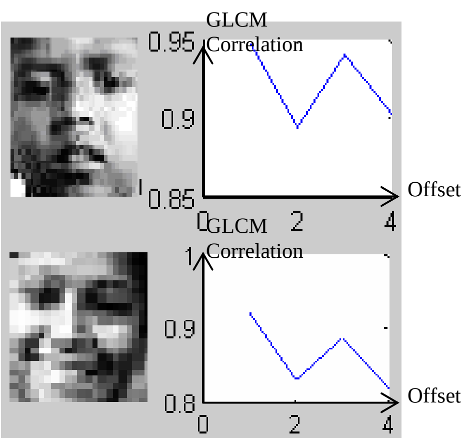
(b) Malay female child.



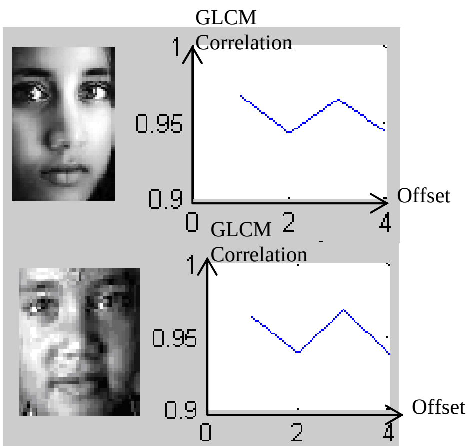
(c) Chinese male child.



(d) Chinese female child.



(e) India male child.



(f) India female child.

Figure 4.11: Comparison of results between Male and Female classes for all Malay, Chinese, India child classes - texture correlation versus offset.

Based on the figures shown, it can be concluded that the facial surface of male and female class is proven to be differed from one to another. The results confirmed the general statement from the human perception that recognition of gender class can be done without knowing the regional appearance or the age of the subject.

We have investigated from the algorithm point of view; that gender recognition can be realized using the developed algorithm based on the 2D image texture analysis. Experiments were done on about 100 subjects involving the three regional appearances (Malay, Chinese and India) with adult and child classes.

Figure 4.12 shows a graph of texture UCI values versus 25 subjects of various classes, giving about 100 subjects.

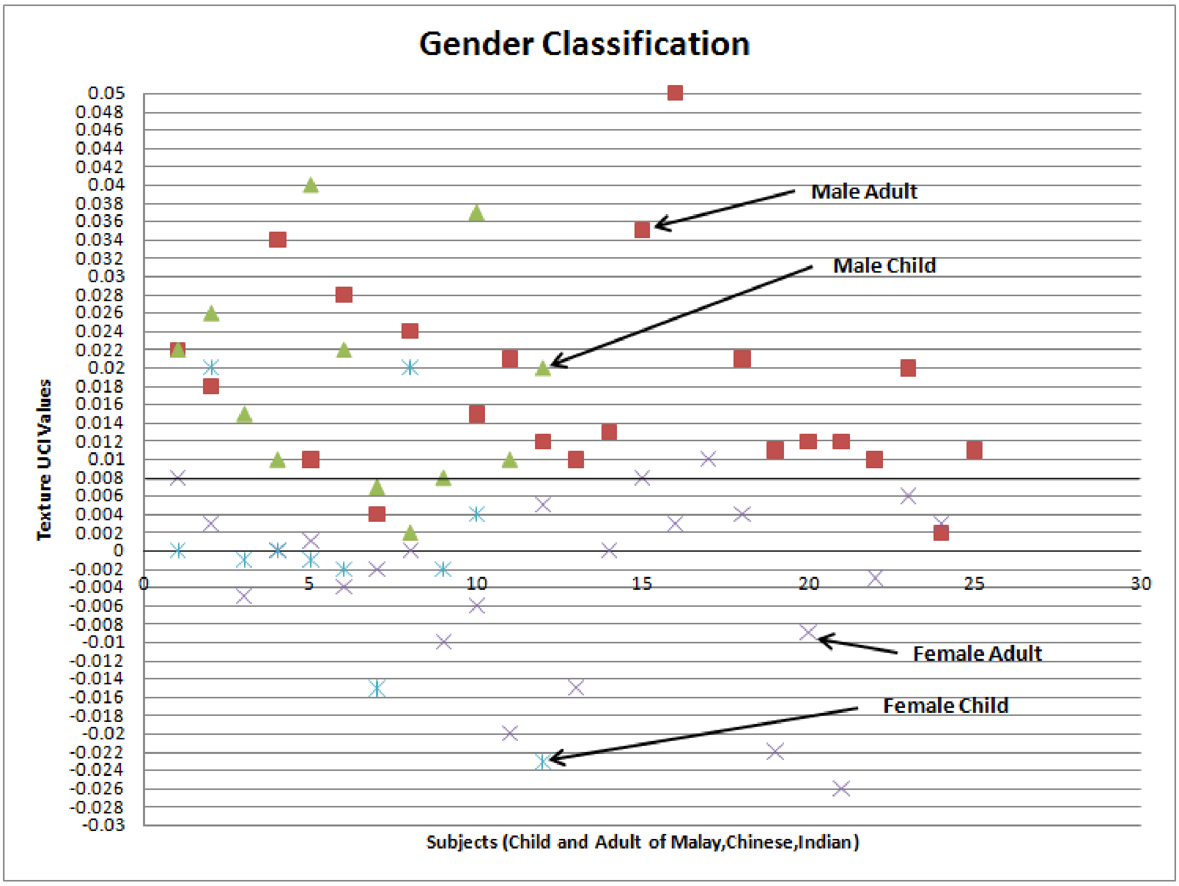


Figure 4.12: Male and female classes (three regional appearances, adult and child classes).

The algorithm for gender recognition can thus be decided as below:

(i) The gender is classified as a male class if:

$$[Offset(1) - Offset(3)] \geq 0.008$$

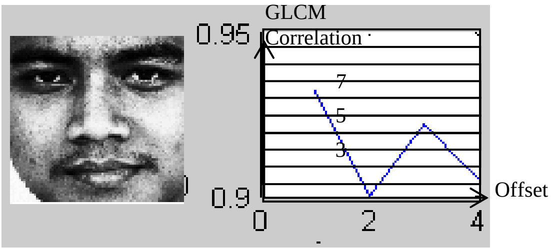
else, (ii) The gender is classified as female class if:

$$[Offset(1) - Offset(3)] < 0.008$$

More results of gender classification and recognition are displayed from Figure 4.13 to Figure 4.26 for adult and child classes of Malay, Chinese and India regional appearances. The texture calculation and results are shown giving the decision of male and female class.

There are 12 classes that have been defined involving hundreds of subjects. These classes are:

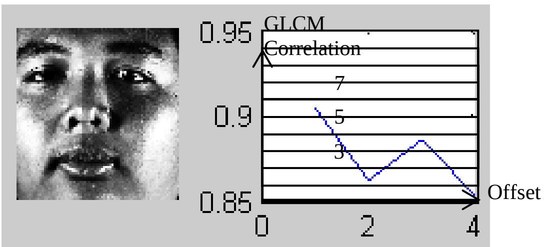
- Male class of Malay adult.
- Male class of Chinese adult.
- Male class of India adult.
- Male class of Malay child.
- Male class of Chinese child.
- Male class of India child.
- Female class of Malay adult.
- Female class of Chinese adult.
- Female class of India adult.
- Female class of Malay child.
- Female class of Chinese child.
- Female class of India child.



Offset	Correlation
1	0.966
2	0.000
3	0.944
4	0.912

Offset 1 – Offset 3 = 0.022

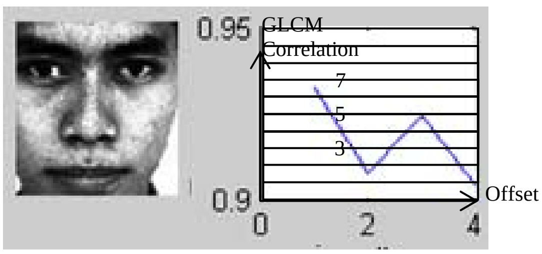
(Male)



Offset	Correlation
1	0.904
2	0.860
3	0.886
4	0.852

Offset 1 – Offset 3 = 0.018

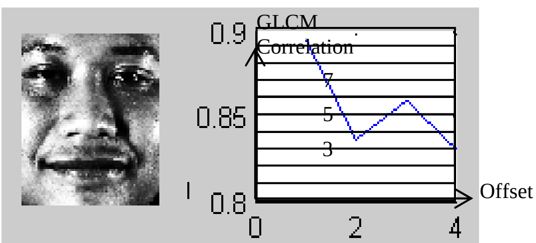
(Male)



Offset	Correlation
1	0.9325
2	0.9075
3	0.9250
4	0.9040

Offset 1 – Offset 3 = 0.075

(Male)

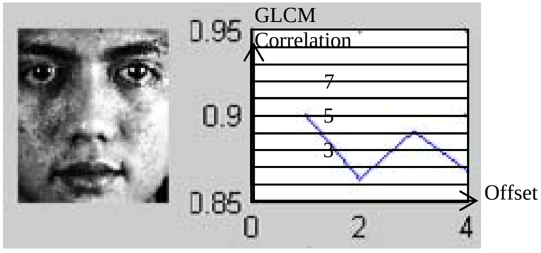


Offset	Correlation
1	0.894
2	0.838
3	0.860
4	0.830

Offset 1 – Offset 3 = 0.034

(Male)

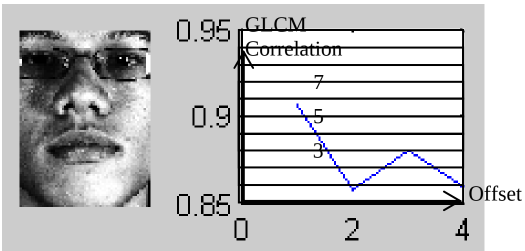
Figure 4.13: Male class of Malay adult.



Offset	Correlation
1	0.901
2	0.863
3	0.891
4	0.868

Offset 1 – Offset 3 = 0.010

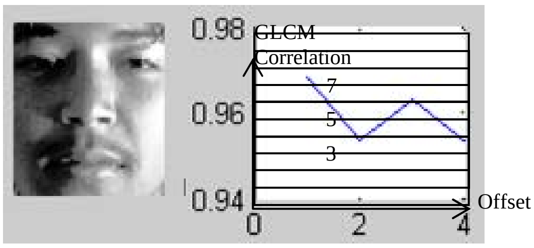
(Male)



Offset	Correlation
1	0.908
2	0.858
3	0.880
4	0.860

Offset 1 – Offset 3 = 0.028

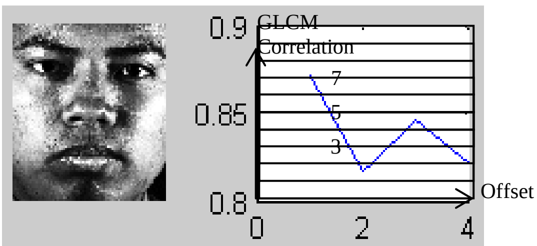
(Male)



Offset	Correlation
1	0.968
2	0.954
3	0.964
4	0.954

Offset 1 – Offset 3 = 0.004

(Male) - *fail*

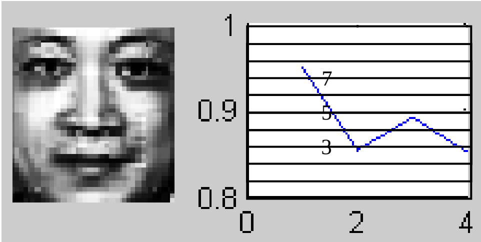


Offset	Correlation
1	0.872
2	0.818
3	0.848
4	0.821

Offset 1 – Offset 3 = 0.024

(Male)

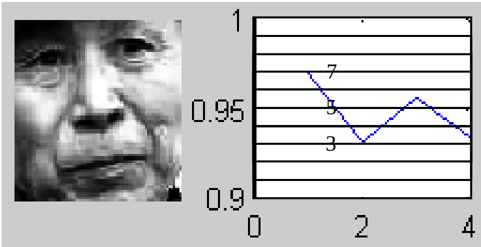
Figure 4.14: Male class of Malay adult.



Offset	Correlation
1	0.950
2	0.860
3	0.890
4	0.860

Offset 1 – Offset 3 = 0.060

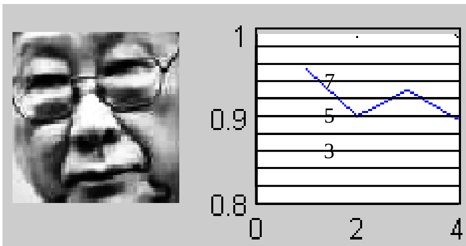
(Male)



Offset	Correlation
1	0.970
2	0.930
3	0.955
4	0.932

Offset 1 – Offset 3 = 0.015

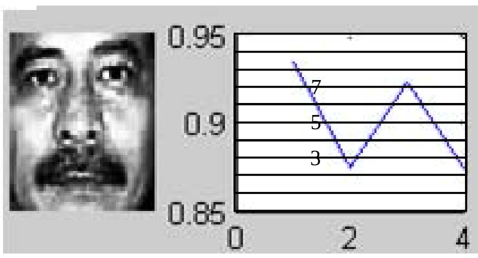
(Male)



Offset	Correlation
1	0.951
2	0.900
3	0.930
4	0.858

Offset 1 – Offset 3 = 0.021

(Male)

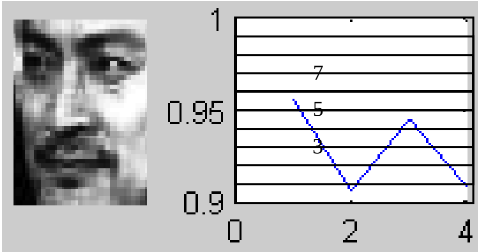


Offset	Correlation
1	0.935
2	0.875
3	0.923
4	0.875

Offset 1 – Offset 3 = 0.012

(Male)

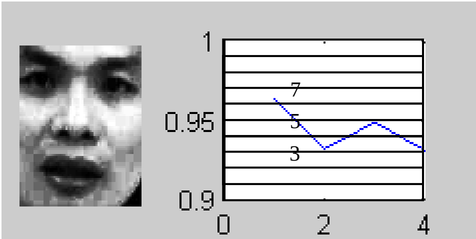
Figure 4.15: Male class of Chinese adult.



Offset	Correlation
1	0.955
2	0.908
3	0.945
4	0.910

Offset 1 – Offset 3 = 0.010

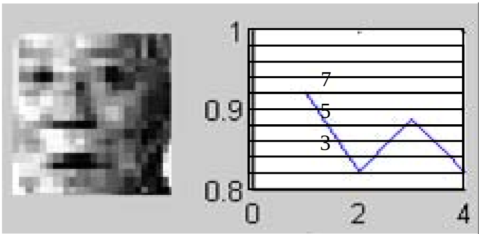
(Male)



Offset	Correlation
1	0.963
2	0.930
3	0.950
4	0.930

Offset 1 – Offset 3 = 0.013

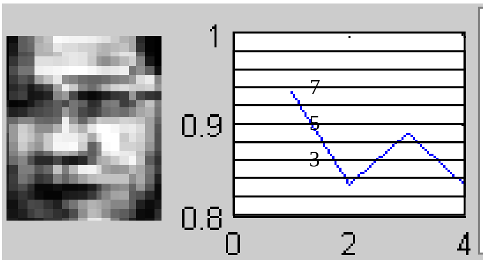
(Male)



Offset	Correlation
1	0.920
2	0.820
3	0.885
4	0.820

Offset 1 – Offset 3 = 0.035

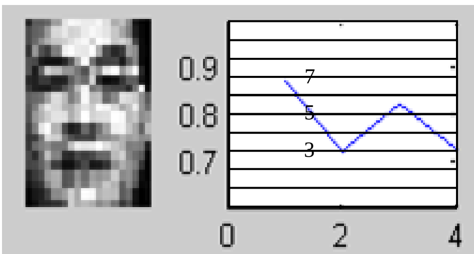
(Male)



Offset	Correlation
1	0.940
2	0.830
3	0.890
4	0.830

Offset 1 – Offset 3 = 0.050

(Male)

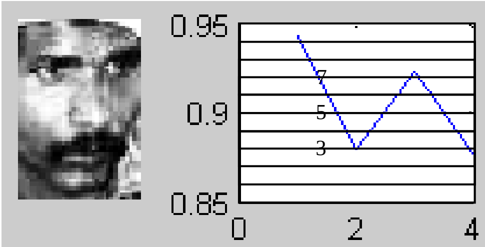


Offset	Correlation
1	0.900
2	0.700
3	0.825
4	0.700

Offset 1 – Offset 3 = 0.075

(Male)

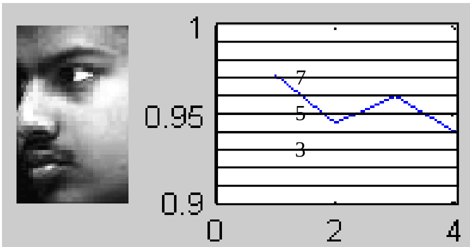
Figure 4.16: Male class of Chinese adult.



Offset	Correlation
1	0.942
2	0.880
3	0.921
4	0.879

Offset 1 – Offset 3 = 0.021

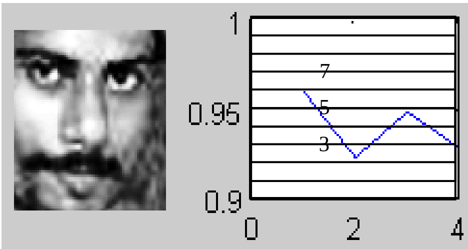
(Male)



Offset	Correlation
1	0.971
2	0.945
3	0.960
4	0.940

Offset 1 – Offset 3 = 0.011

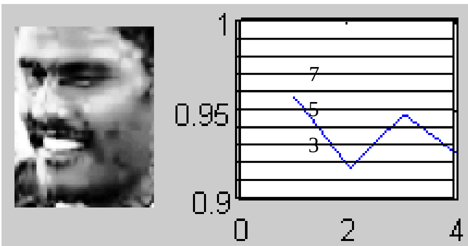
(Male)



Offset	Correlation
1	0.960
2	0.922
3	0.948
4	0.928

Offset 1 – Offset 3 = 0.012

(Male)

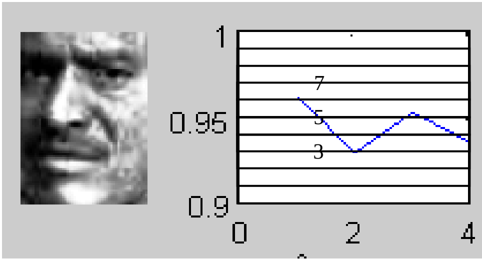


Offset	Correlation
1	0.958
2	0.918
3	0.946
4	0.928

Offset 1 – Offset 3 = 0.012

(Male)

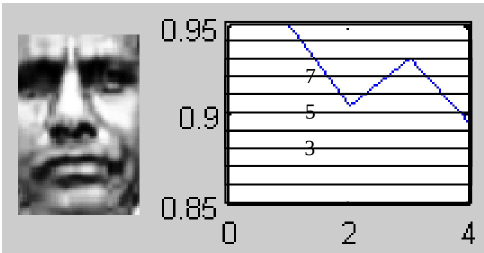
Figure 4.17: Male class of India adult.



Offset	Correlation
1	0.962
2	0.930
3	0.952
4	0.937

Offset 1 – Offset 3 = 0.010

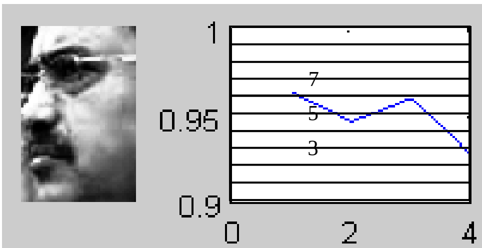
(Male)



Offset	Correlation
1	0.950
2	0.905
3	0.930
4	0.895

Offset 1 – Offset 3 = 0.020

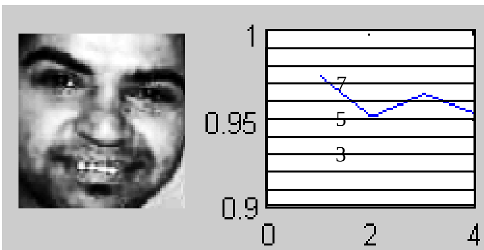
(Male)



Offset	Correlation
1	0.961
2	0.945
3	0.959
4	0.928

Offset 1 – Offset 3 = 0.002

(Male) - *fail*

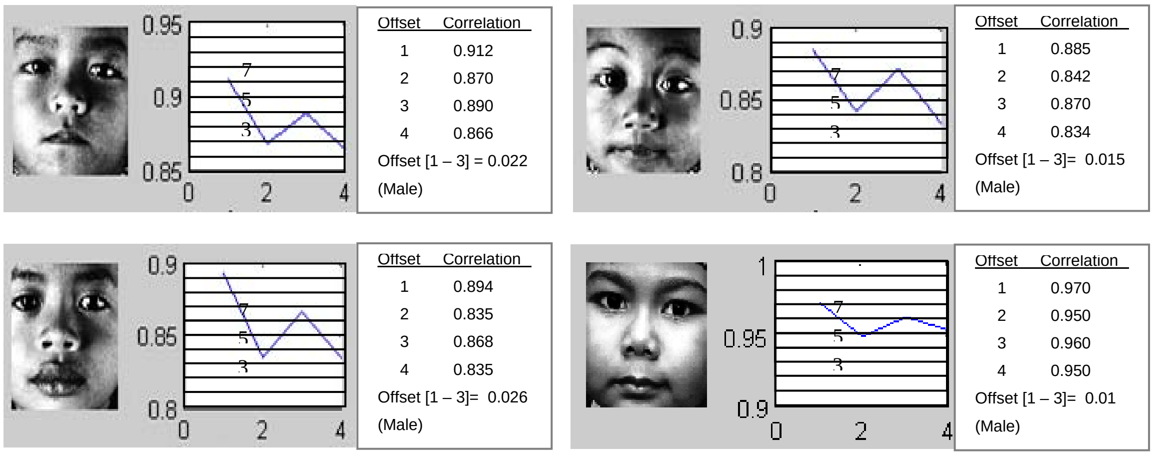


Offset	Correlation
1	0.975
2	0.950
3	0.964
4	0.955

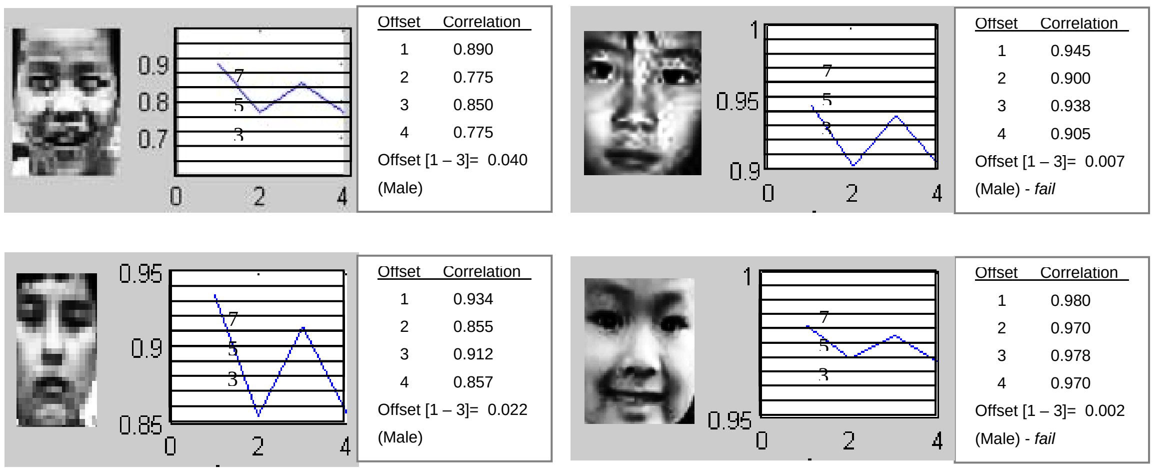
Offset 1 – Offset 3 = 0.011

(Male)

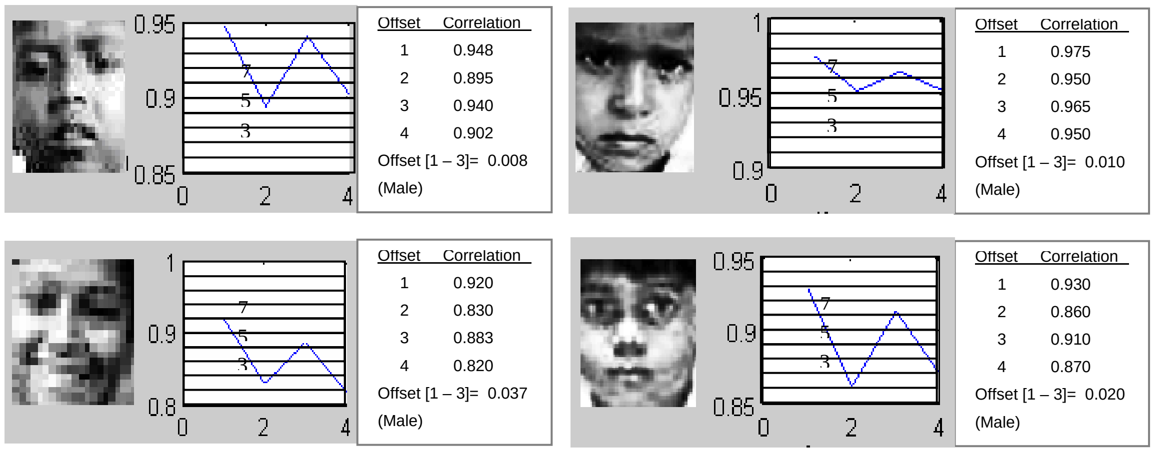
Figure 4.18: Male class of India adult.



(a) Male class of Malay child.

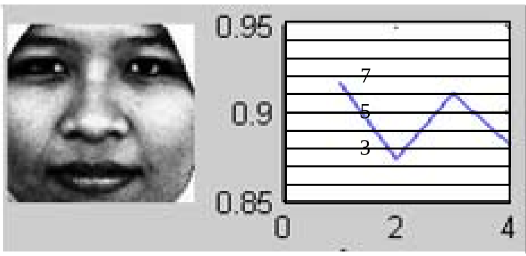


(b) Male class of Chinese child.



(c) Male class of India child.

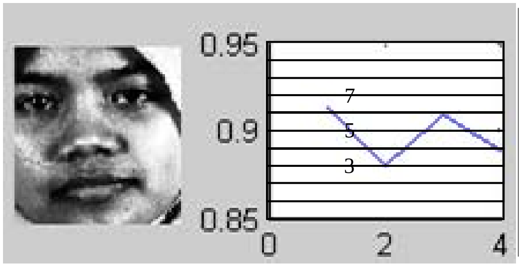
Figure 4.19: Male class of Malay, Chinese and India child.



Offset	Correlation
1	0.918
2	0.874
3	0.910
4	0.880

Offset 1 – Offset 3= 0.008

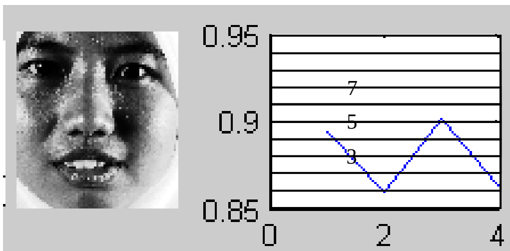
(Female)



Offset	Correlation
1	0.913
2	0.880
3	0.910
4	0.890

Offset 1 – Offset 3 = 0.003

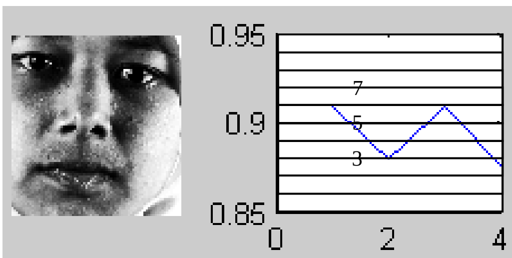
(Female)



Offset	Correlation
1	0.895
2	0.860
3	0.900
4	0.862

Offset 1 – Offset 3 = -0.005

(Female)

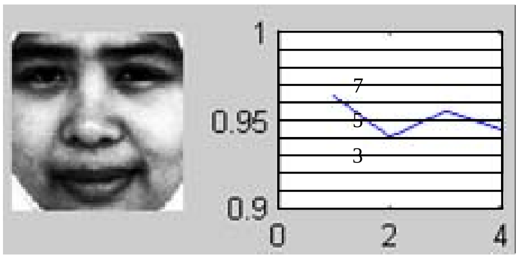


Offset	Correlation
1	0.910
2	0.880
3	0.910
4	0.876

Offset 1 – Offset 3 = 0.000

(Female)

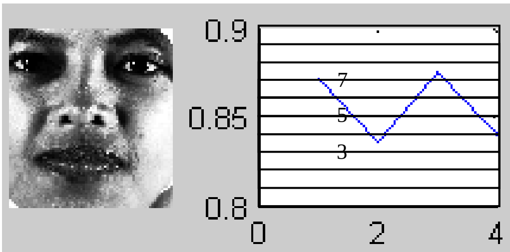
Figure 4.20: Female class of Malay adult.



Offset	Correlation
1	0.965
2	0.940
3	0.955
4	0.945

Offset 1 – Offset 3 = 0.001

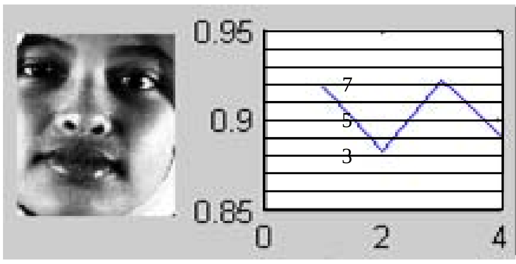
(Female)



Offset	Correlation
1	0.870
2	0.836
3	0.874
4	0.840

Offset 1 – Offset 3 = - 0.004

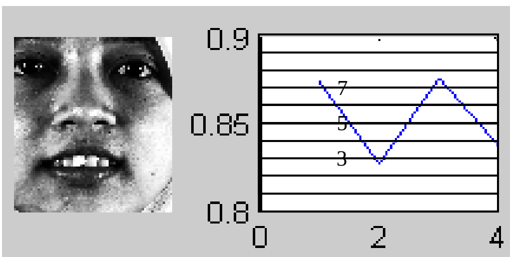
(Female)



Offset	Correlation
1	0.920
2	0.884
3	0.922
4	0.890

Offset 1 – Offset 3 = - 0.002

(Female)



Offset	Correlation
1	0.873
2	0.829
3	0.873
4	0.839

Offset 1 – Offset 3 = 0.000

(Female)

Figure 4.21: Female class of Malay adult.

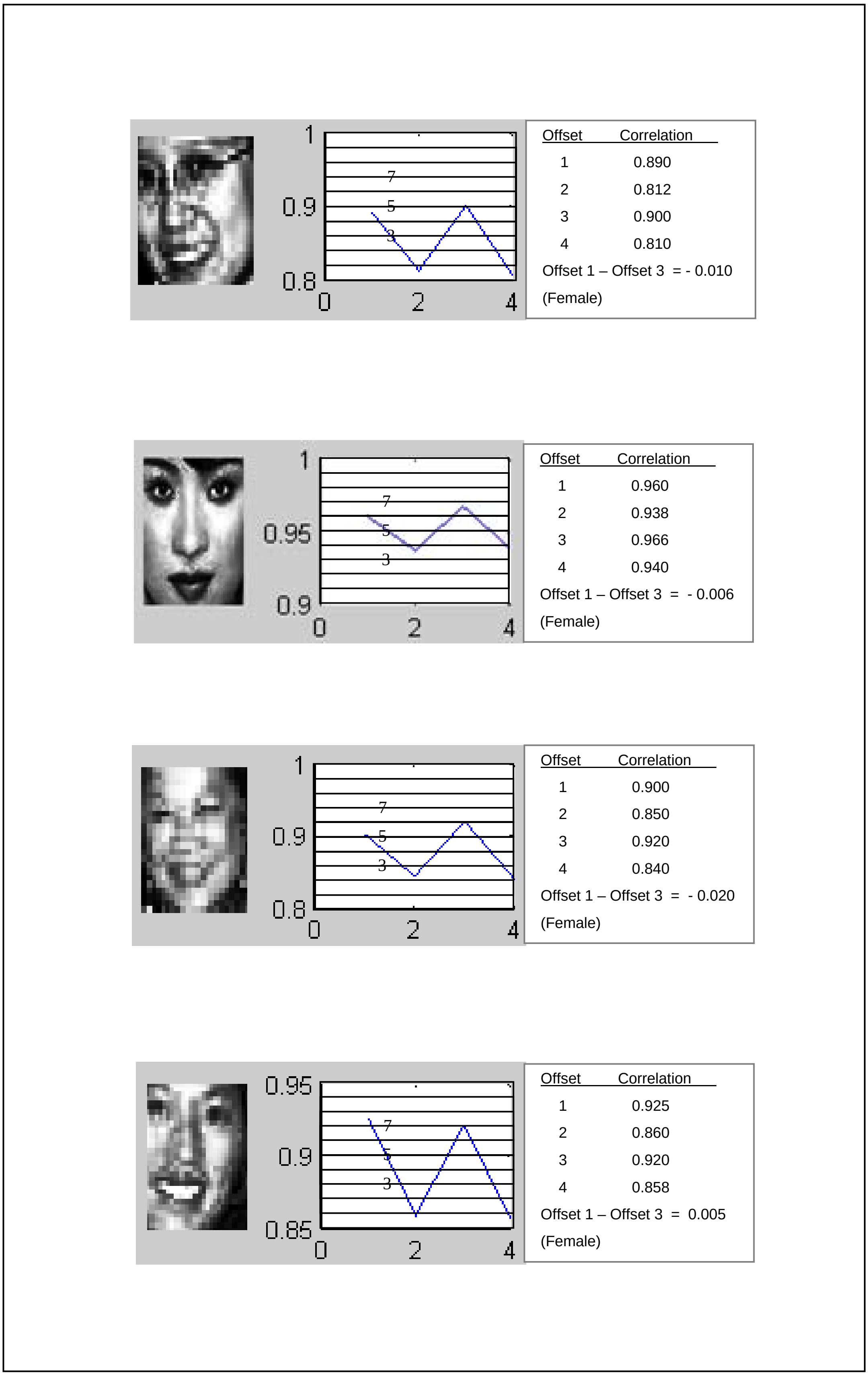


Figure 4.22: Female class of Chinese adult.

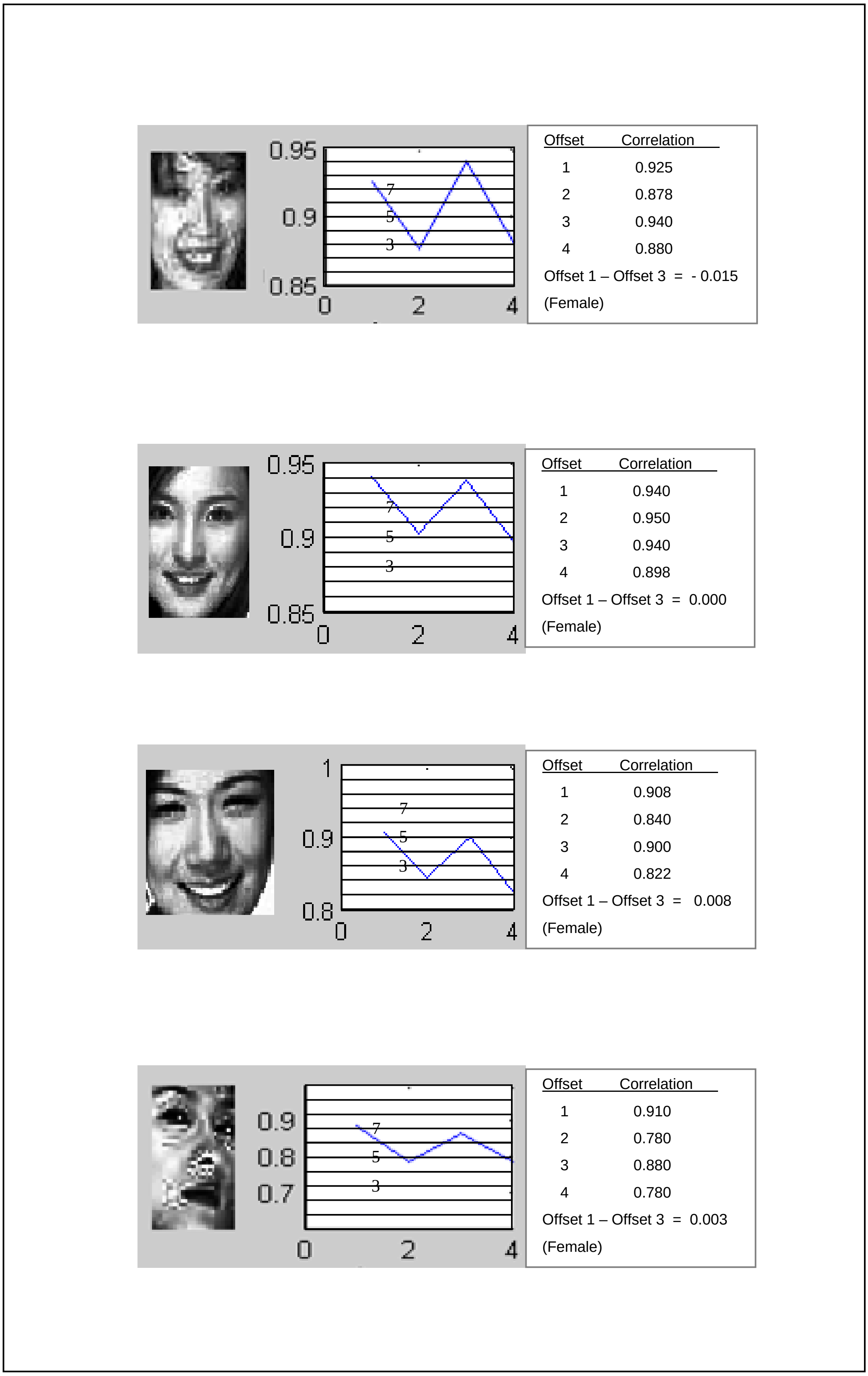
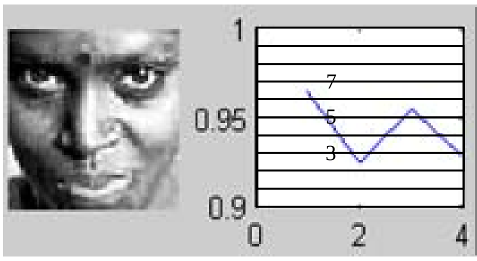


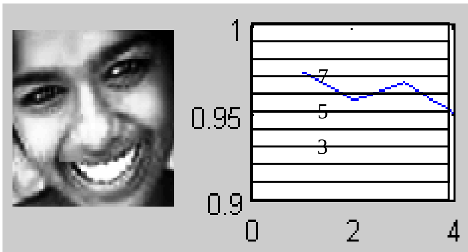
Figure 4.23: Female class of Chinese adult.



Offset	Correlation
1	0.965
2	0.925
3	0.955
4	0.930

Offset 1 – Offset 3 = 0.010

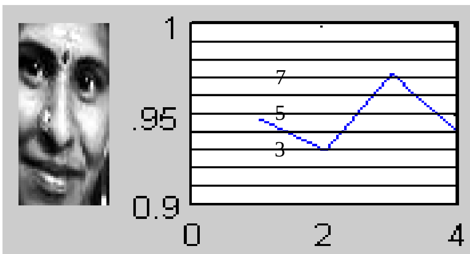
(Female) - *fail*



Offset	Correlation
1	0.972
2	0.957
3	0.968
4	0.950

Offset 1 – Offset 3 = 0.004

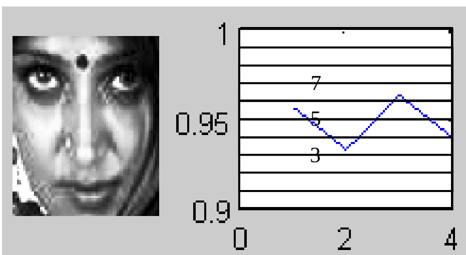
(Female)



Offset	Correlation
1	0.948
2	0.930
3	0.970
4	0.940

Offset 1 – Offset 3 = - 0.022

(Female)

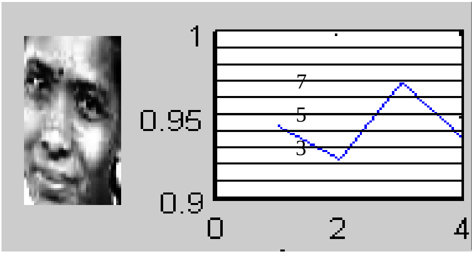


Offset	Correlation
1	0.955
2	0.933
3	0.964
4	0.940

Offset 1 – Offset 3 = - 0.009

(Female)

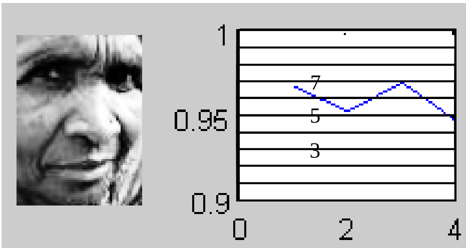
Figure 4.24: Female class of India adult.



Offset	Correlation
1	0.944
2	0.922
3	0.970
4	0.937

Offset 1 – Offset 3 = - 0.026

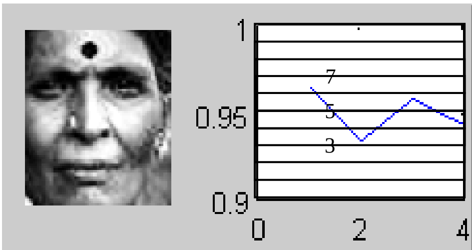
(Female)



Offset	Correlation
1	0.967
2	0.952
3	0.970
4	0.948

Offset 1 – Offset 3 = - 0.003

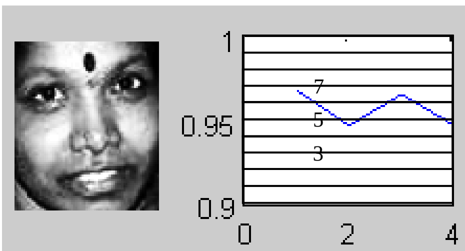
(Female)



Offset	Correlation
1	0.964
2	0.932
3	0.958
4	0.943

Offset 1 – Offset 3 = 0.006

(Female)

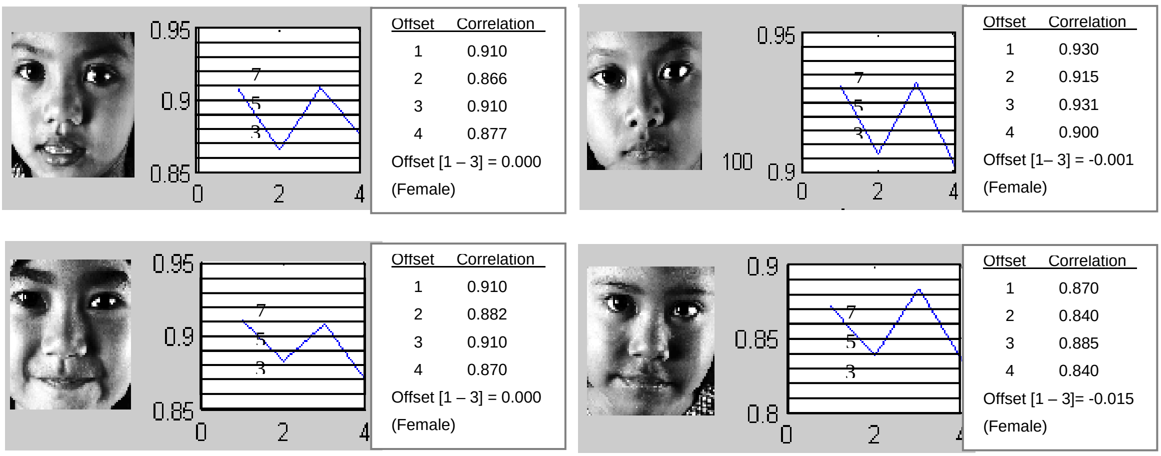


Offset	Correlation
1	0.968
2	0.948
3	0.965
4	0.949

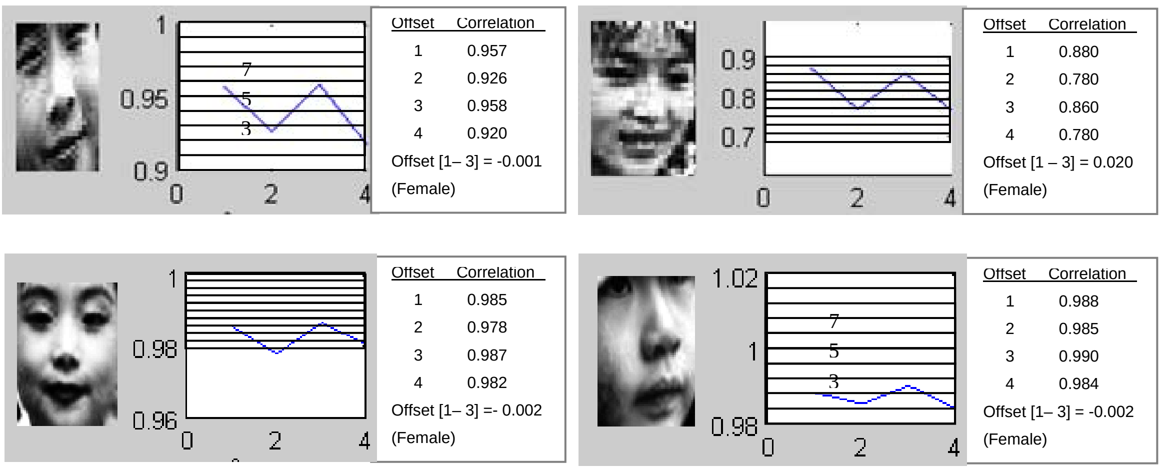
Offset 1 – Offset 3 = 0.003

(Female)

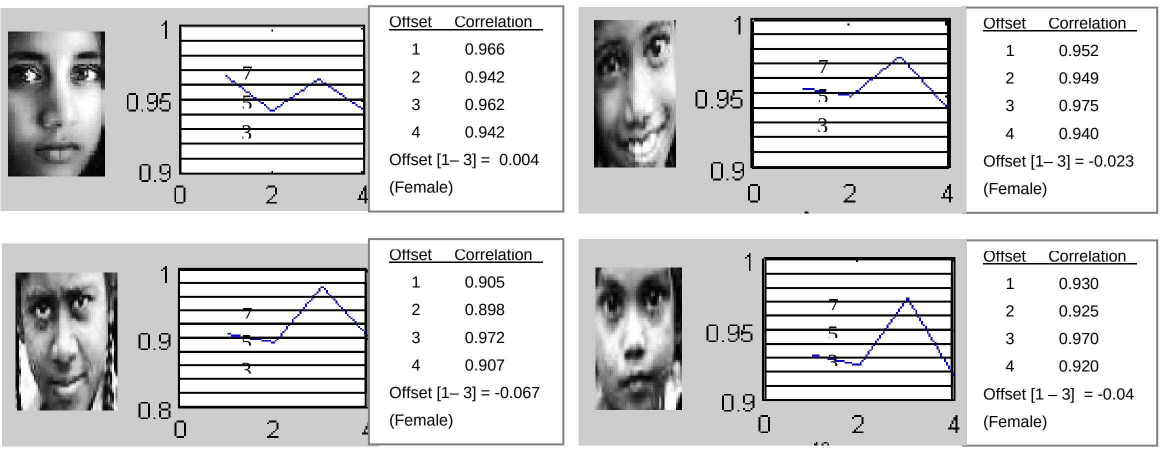
Figure 4.25: Female class of India adult.



(a) Female class of Malay child.



(b) Female class of Chinese child.



(c) Female class of India child.

Figure 4.26: Female class of Malay, Chinese and India child.

4.3 The Age Class

4.3.1 The Age Class Estimation

Figure 4.27 illustrates a variety of face images from the database and where challenges of age category recognition are revealed. In the previous section, the facial texture characteristics information is used and able to classify the gender classes that comprise of different regional appearance and age. In this section, the study have been extended by manipulating the available facial features information and derived its subsequent for classifying two different groups of age; the child and adult classes. The gray level images have been converted to the edge images where the calculation or measurement of feature-based age category estimation can be done automatically.

(a) Child class

(b) Adult class

Figure 4.27: Samples of images from age classes divided into child and adult classes spanning from Malay, Chinese, India male and female classes.

4.3.2 The Age UCI Similarity/Dissimilarity Classification

Conventionally, in the case of facial features measurement for age category recognition, figure 4.28 describes how the measurement should be done. The size, length and shape of each feature are measured where these results are precise and specific to a particular subject. However, this is nearly impossible to do when dealing with a real life images. The problem of image variation complexity and its impact has been explained in the previous chapters.

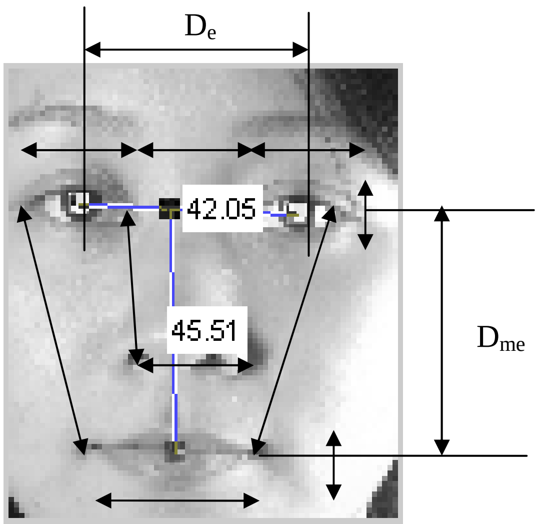


Figure 4.28: Facial features measurement.

In completion, a simple mathematical model that one can derive is as shown below:

(i) The ratio of distances between two eyes, (D_e) and between mouth and eyes (D_{me}).

If (D_{me} / D_e > 1), then
The image is classified as adult class,
Else,
The image is classified as child class.

(ii) The size and shape of the features can be measured classically where an assumption can be made such as the adult features must be greater than the child in term of size or area calculated.

In this thesis, the derivative overall features size and distance are inherently calculated and used to obtain the age classes. Recall from Chapter Three, figure 4.29 which explains how the calculation is done based on the information extracted from the DLBT graph. The average maximum height is taken to represent the age class. The detail of DLBT technique has been explained in Chapter Three.

The calculation of age estimation for classification is then derived as follows.

(a) The measurement of features distance is done inherently by calculating each column of the image as a group of binary number and converted into decimal number representation, where '1' is for white and '0' is for black. In this case, we have manipulated that '1' is basically a marker of feature location on the image. The length of each column is broken into 32 bits block where each block is converted into equivalent decimal number. This is a strategy to reduce the amount of unnecessary data for the large black areas where the values are zero. The group of 32 bits makes it easier to calculate and the sum of corresponding decimal values conversion will be produced and plotted on the graph as shown in figure 4.29(d).

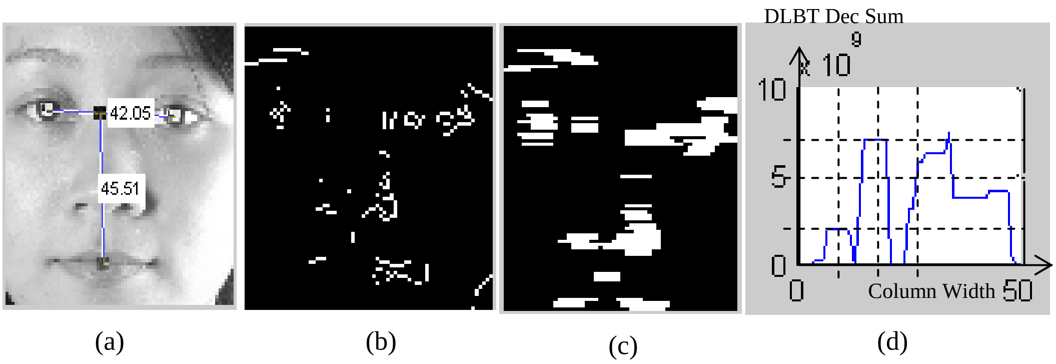


Figure 4.29: Facial features measurement.

(b) By using this method, it can be concluded that,

(i) The analogous calculation of edge point for each column in the image is to measure the features distance such as being done in manual calculation.

(ii) The ratio or correlation between an image and its transpose is analogously trying to obtain the ratio of the features distance as what have been practiced conventionally.

(iii) The combination of (i) and (ii) aggregates the method in performing the age calculation automatically and efficiently.

We have investigated that the age category recognition can be realized using the developed algorithm (DLBT) based on the 2D image global features measurement analysis. The experiments were done on about 100 subjects involving the three regional appearances (Malay, Chinese and India) with adult and child classes.

Figure 4.30 shows a graph of DLBT features UCI values versus 25 subjects of various classes, giving about 100 subjects.

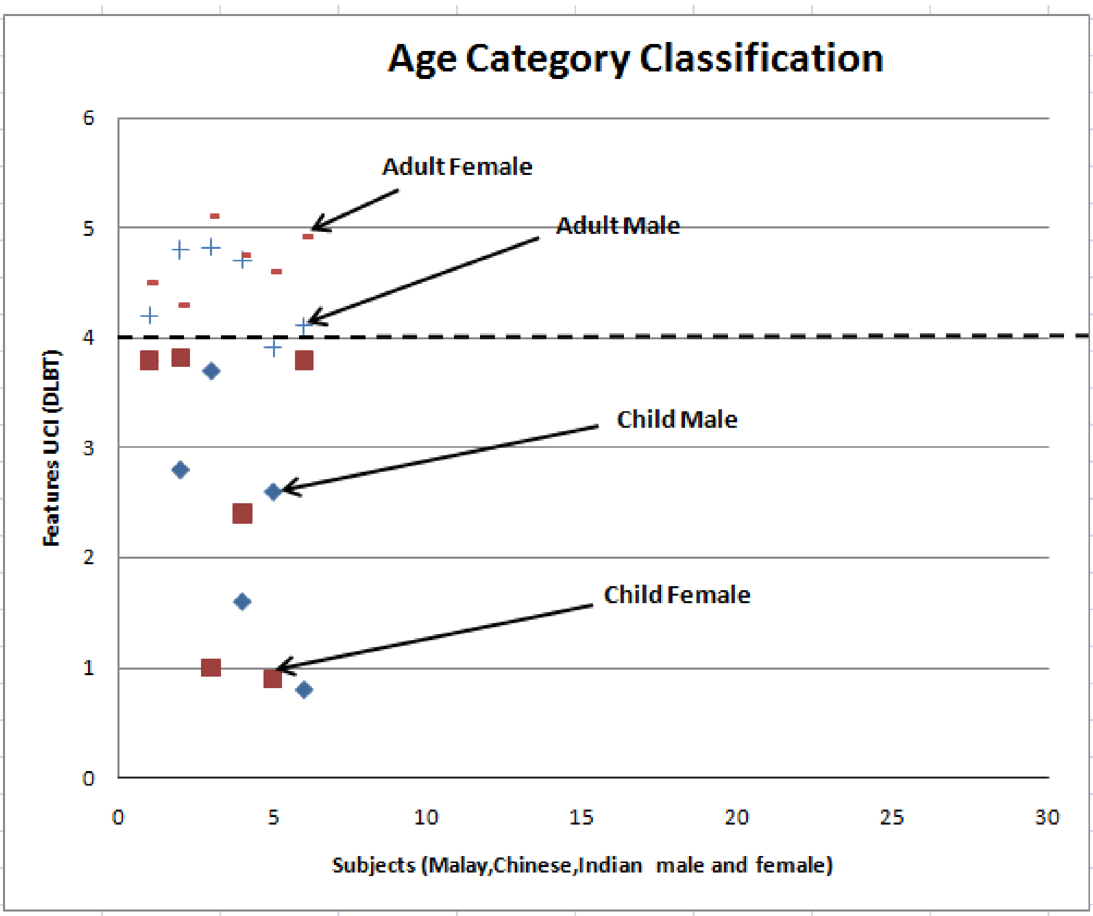


Figure 4.30: Age category classification.

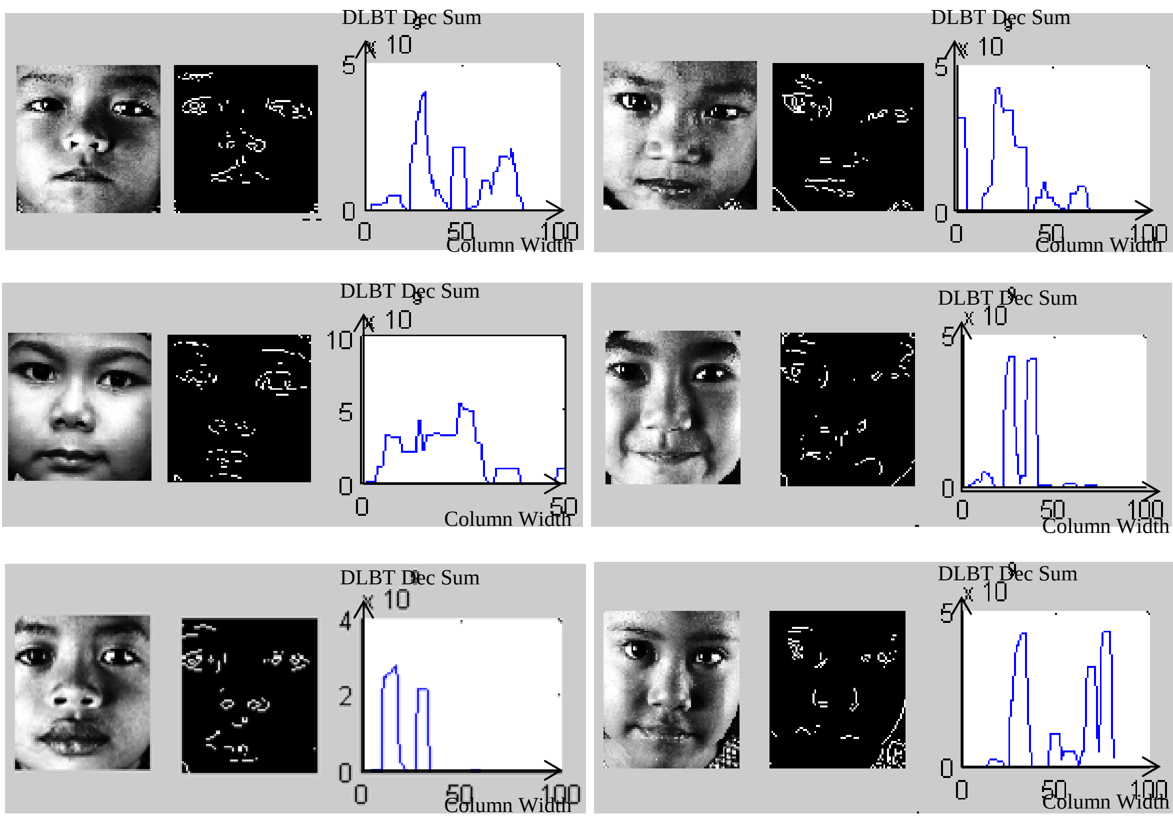
It can be concluded that the age category classification can be implemented based on the algorithm shown below.

(i) The age is classified as **child class** if:

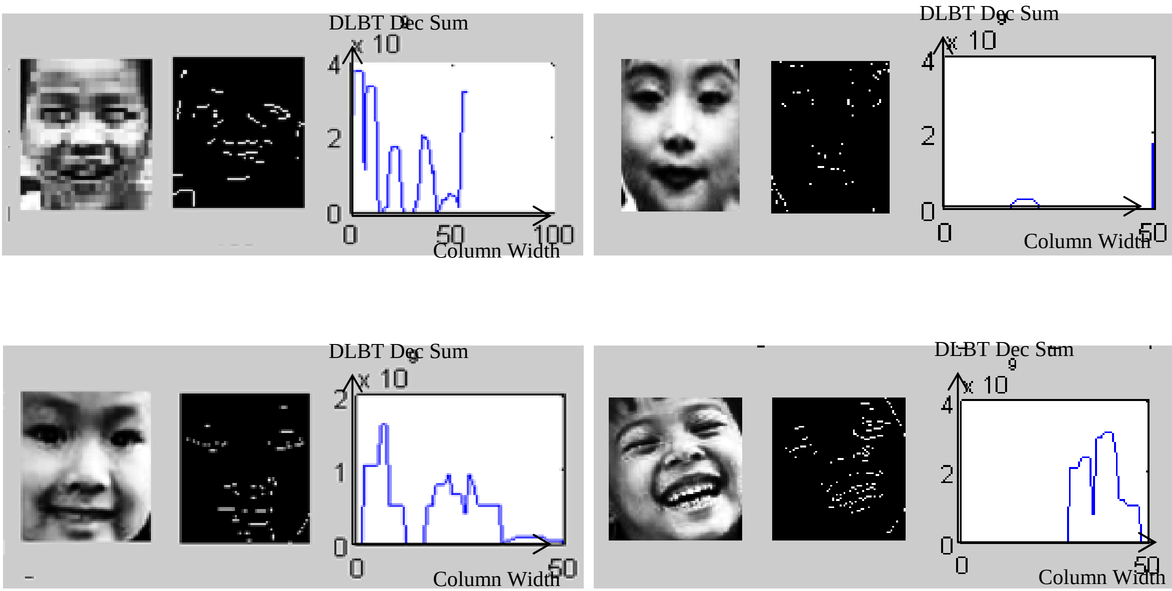
Ratio of edge image and transpose $<$ *7.5 (DLBT unique logarithmic values)*

else, (ii) The age is classified as **adult class**.

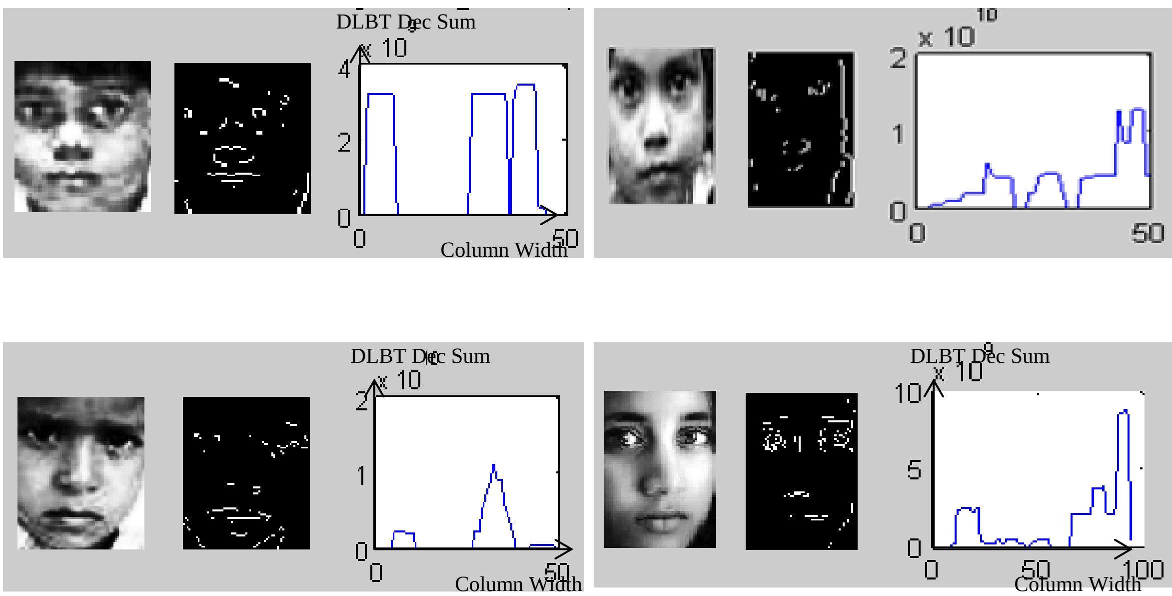
More image results are shown in Figure 4.31 and Figure 4.32 for child and adult classes respectively, comprising their regional appearances and gender classes.



(a) Malay male and female child.

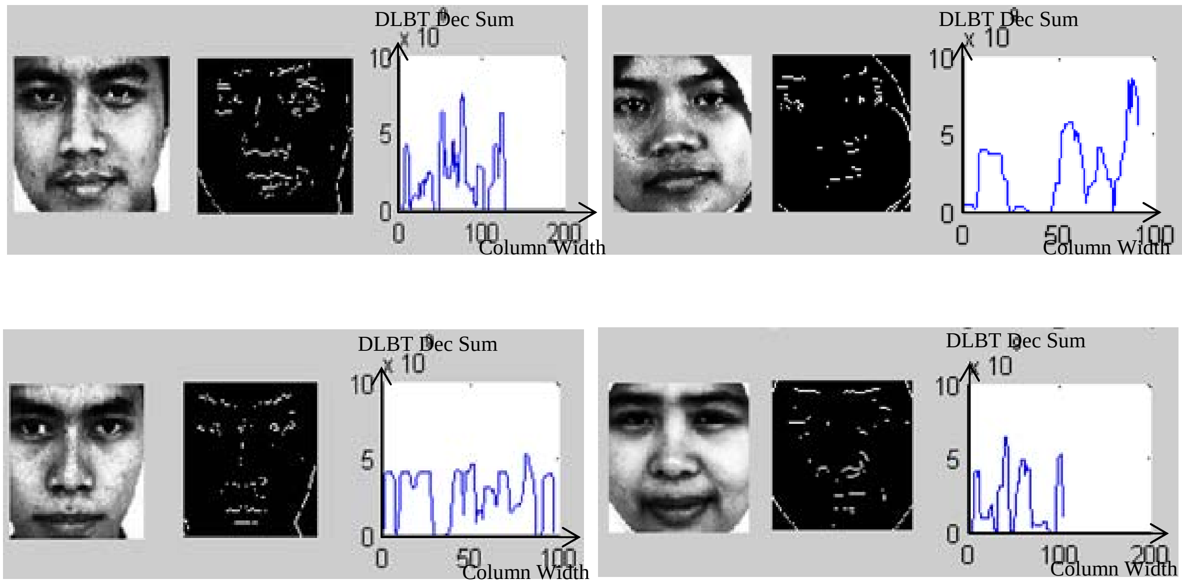


(b) Chinese male and female child.

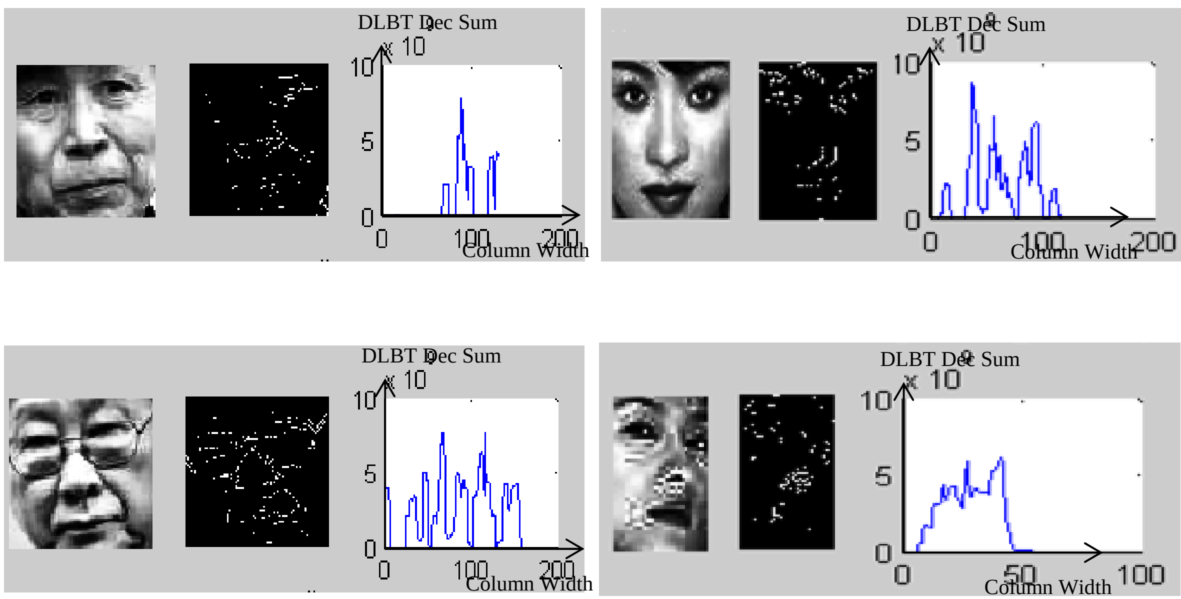


(c) India male and female child.

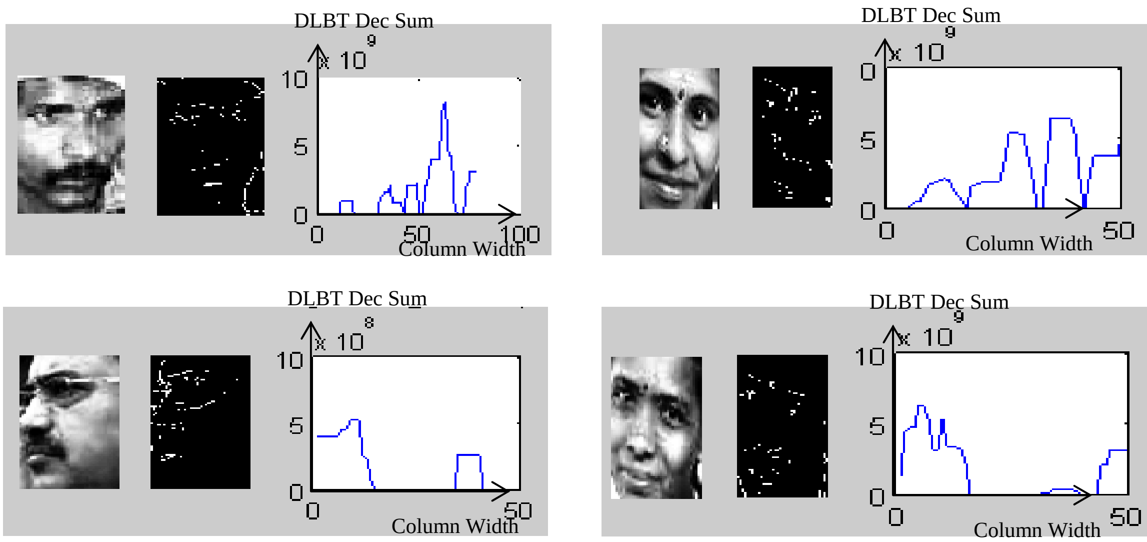
Figure 4.31: Child classes.



(a) Malay male and female adult.



(b) Chinese male and female adult.



(c) India male and female adult.

Figure 4.32: Adult classes.

4.4 Summary of UCCI Extraction and Classification Results

The colour input image represented by RGB components performed by the extractor is fed to the classifier where further analysis is done and the results are shown in this chapter. The colour image is further converted into the gray level format for the purpose of texture calculation. To reduce the dimension of the calculation, quantization is performed on the gray image and GLCM texture approach is applied on the new quantized image. The GLCM correlation performance is revealed by showing the calculated correlation values against the corresponding offset or direction of pixel comparison implemented on the image. The last stage of the process is to obtain the edge image from the gray level image and representing by using the DLBT graph.

The recognition process demonstrated in this thesis is based on the mutual understanding of the extractor and classifier of facial UCI. The image information transformation from the raw input to the extracted features involved a unique pixels manipulation and as an outcome of the unique collateral patterns. These pixels comprises of UCI and image variation components. We have manipulated the pixels values to describe the inherent meanings and perform the classification for three major classes (regional appearance, gender and age) through the three stages of process (transformation, compensation and modelling or representation).

The raw input such as the colour image consists of a lot of information which can uniquely represent the facial identity. The skin colour was chosen to be the basis of regional appearance recognition. The developed algorithm is tested on the developed database and will be implemented on the open database where the performance can be evaluated. It was also demonstrated that the use of gray image could simplify the raw input for facial texture measurement. Experiment results for gender recognition are very convincing based on the texture observation. The manipulation of pixel values differences is achieved from the gray level image through comparison with their neighbourhood in multiple directions for gradient or valley calculation. As a result, the male and female patterns are obtained. The unique representation reveals that all corresponding regional appearances and age differences can be classified under the male and female classes. This is also true in the case of age category recognition where the regional appearances and genders can be classified under the classes of child or adult. The chosen identity parameters for classification are complementary to one and another.

Figure 4.33 is a summary of performance results for regional appearance, gender and age recognition evaluated by applying the developed algorithm on the developed and open databases. More than 100 subjects are used in the experiments but the results shown are based on the 100 subjects comprising of Malay male children and adults, Malay female children and adults, Chinese male children and adults, Chinese female children and adults, India Malaysian male children and adults and India Malaysian female children and adults.

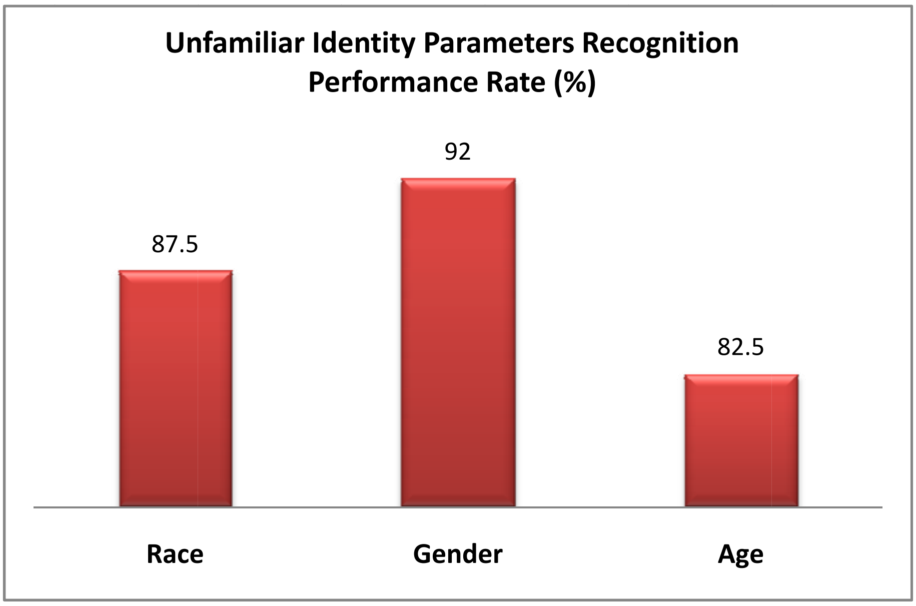


Figure 4. 33: Identity parameters (regional appearance, gender and age) recognition performance result.

The weaknesses of the regional appearance recognition based on the skin colour shown in the results in the figure 4.33 are mostly because of the illumination variation. However there are many problems dealing with the real life images. For instance, the colour images used could be blurred and full of variations. As a result, the regional appearance recognition results that based on the skin colour can be easily influenced by the image variation, especially the illumination effect.

On the other hand, the texture analysis performed on the gray level images produced reasonable results for gender classification. In the presence of illumination and pose variations, the results from the experiments have shown that the facial texture is one of the best UCI that can be relied on. The normalized gray level image (histogram equalization and re-quantization) and GLCM texture representation have provided a tolerable input to a further texture analysis. This is due to the fact that the 3D shape or the depth of each important feature on the 2D face image can be analyzed from the difference between the pixels and its neighbours. The trend of this relationship can be plotted to produce a unique pattern that expresses a unique representation for a particular class.

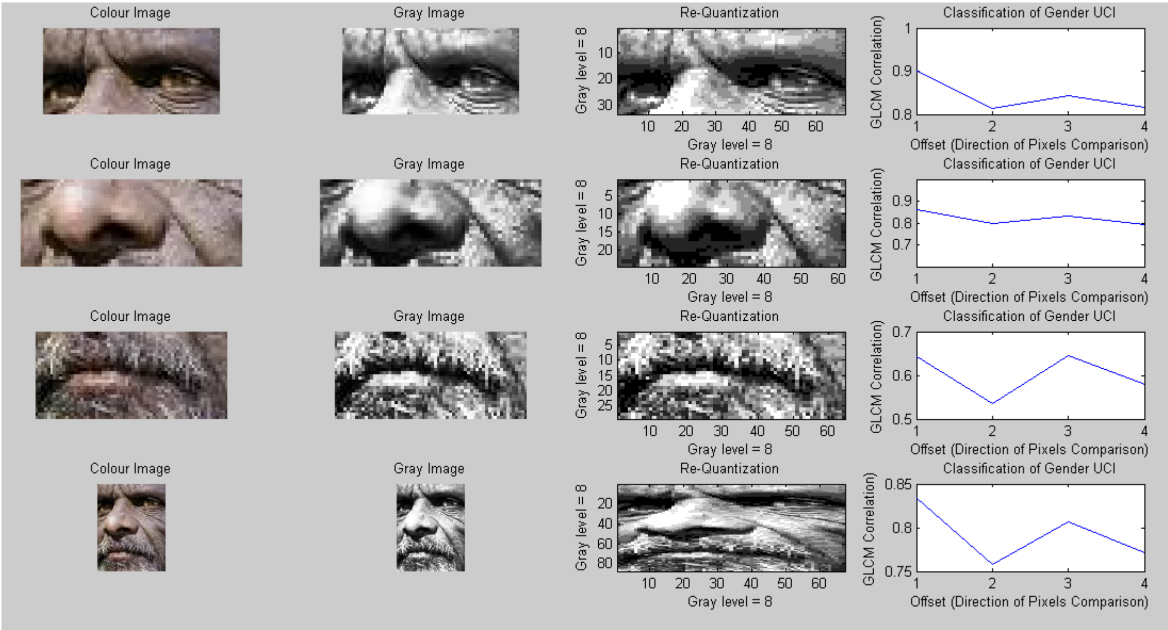
To conclude the study in this section, we are going to explore some facts about the facial features with respect to the classification process and problems determined in this thesis.

(a) The Characteristics and Influences of Facial Features

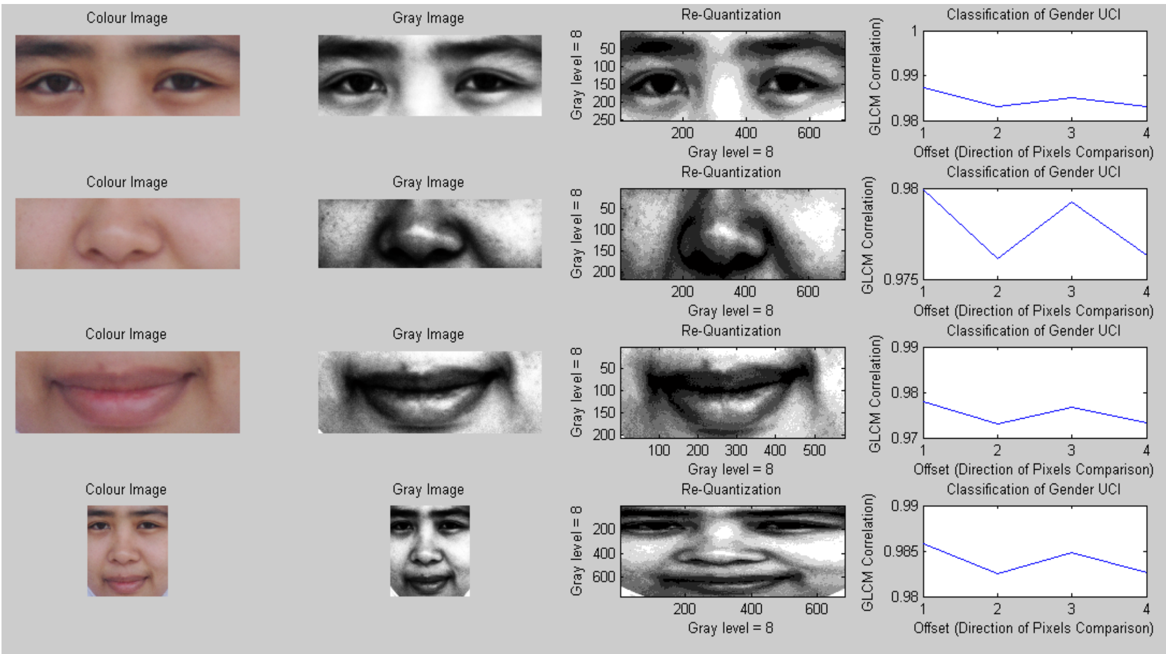
Facial features used in the experiments thus far involved the skin colour, the overall facial surface texture and global facial features. In the following discussion, we will be exploring some facts about what features that contribute more on each classified identity parameters and to what extent these features can be studied and analyzed in promoting more reliable unique characteristics information for future research of the thesis.

The RGB colour used for classifying the regional appearance which is based on skin colour is a good choice as the colour is uniform and consistent throughout the facial surface. However, the classification performance will be degraded in the presence of variation, especially the illumination variation. Results of this condition are shown in the next discussion.

In case of gender classification based on facial texture, figure 4.34 and 4.35 describe the features role in characterizing the gender type of the person. For instance, the eye features in the male class of figure 4.34 (a) have a different pattern influence that makes the overall facial pattern falls into male class.

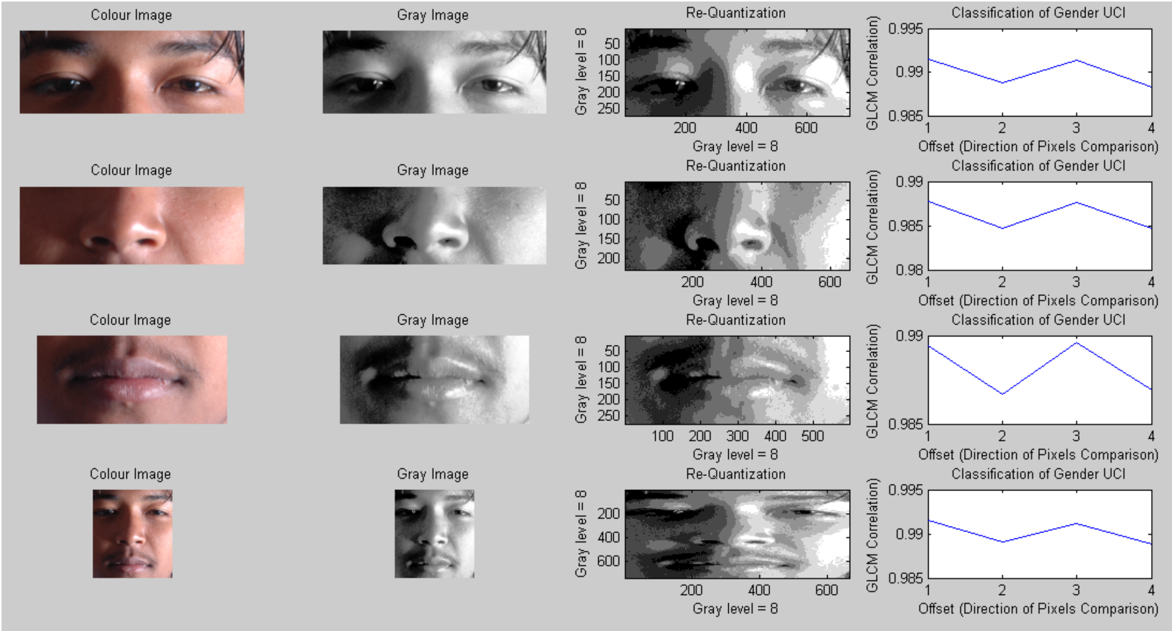


(a) Male features of eyes, nose, mouth and overall region with their corresponding GLCM Correlation vs. Offset direction.

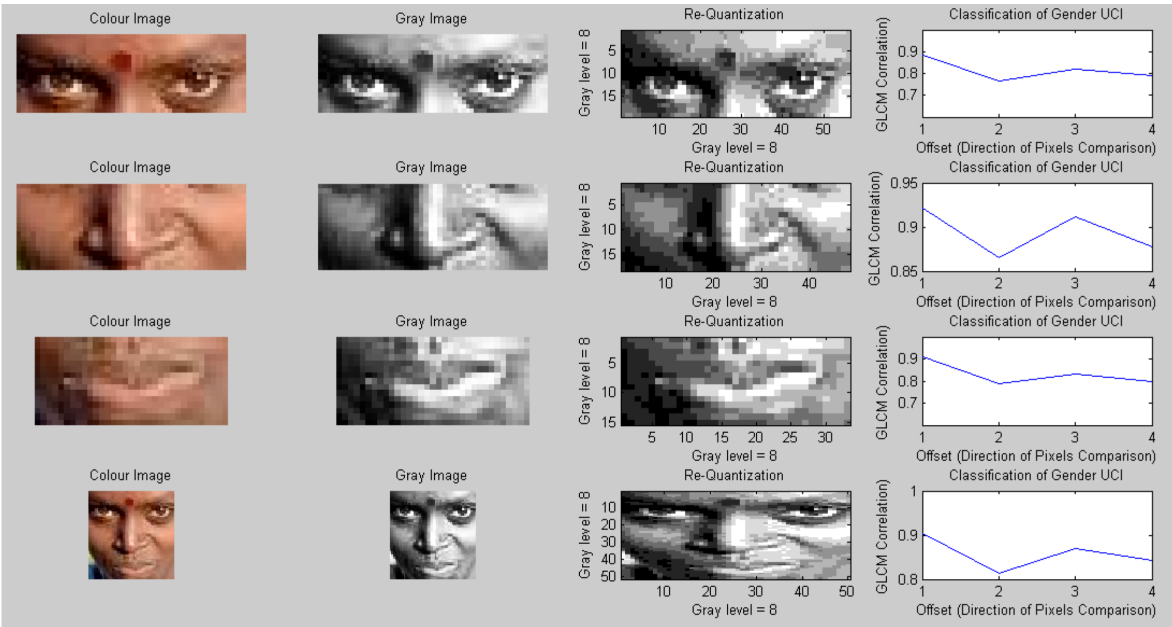


(b) Female features of eyes, nose, mouth and overall region with their corresponding GLCM Correlation vs. Offset direction.

Figure 4.34 (a) and (b): Typical male and female features showing the contribution of texture patterns information.



(a) Male features of eyes, nose, mouth and overall region with their corresponding GLCM Correlation vs. Offset direction which are fall into female class.



(b) Female features of eyes, nose, mouth and overall region with their corresponding GLCM Correlation vs. Offset direction which are fall into male class.

Figure 4.35 (a) and (b): Male and female wrongly classified based on features that fall on opposite class of gender.

On the other hand, figure 4.35(a) and 4.35(b) have shown samples of result where male and female are wrongly classified. This is due to the fact that the characteristics and influences produced by the independent features such as eyes and mouth fall into the opposite classes. The situation is basically not just because of the original unique features that belong to the subjects, but more aggressively have been aggravated by the illumination influence presented in the image.

Another source of performance degradation is as shown in figure 4.36. The presence of intrinsic variation caused by changes made by the subject (facial expression) as demonstrated in the figure, further challenged the classification performance. As a result, the changes in texture orientation of the surface have made the female child class in the figure fell into male class.

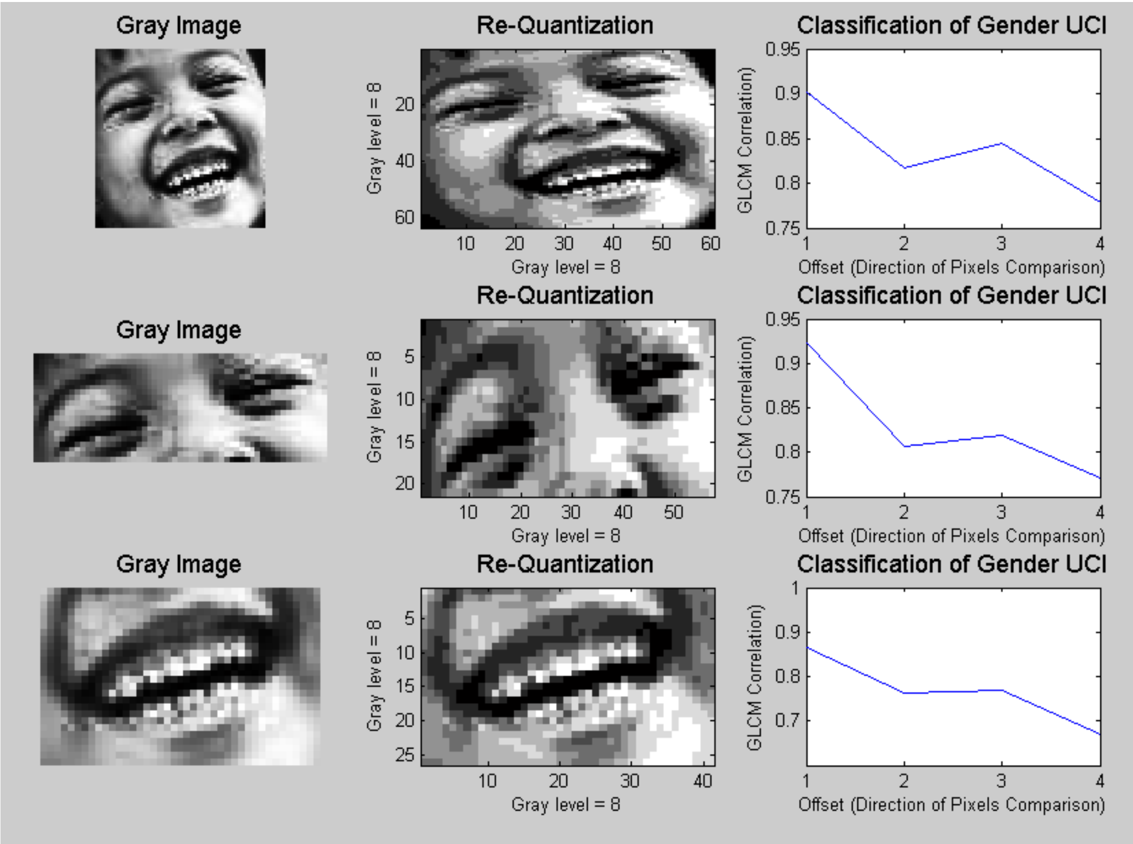
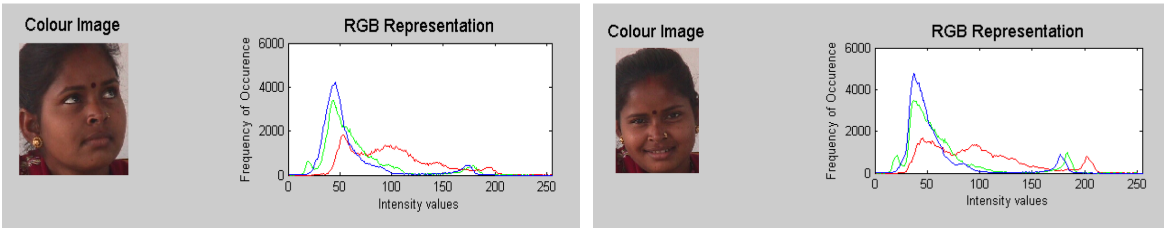


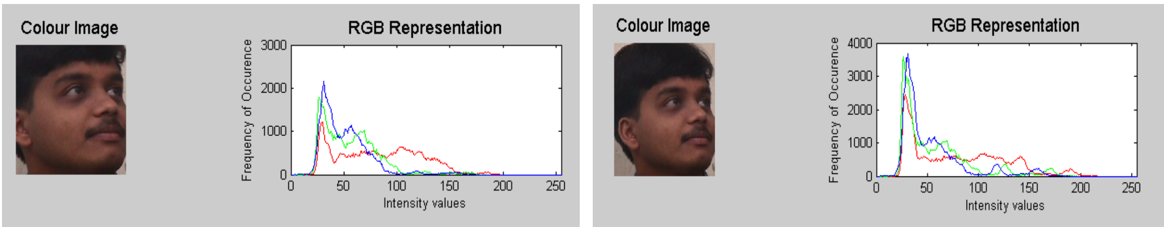
Figure 4. 36: Identity parameters (regional appearance, gender and age) recognition performance result.

(b) The Impact of Auxiliary Features and Face Partly Occluded

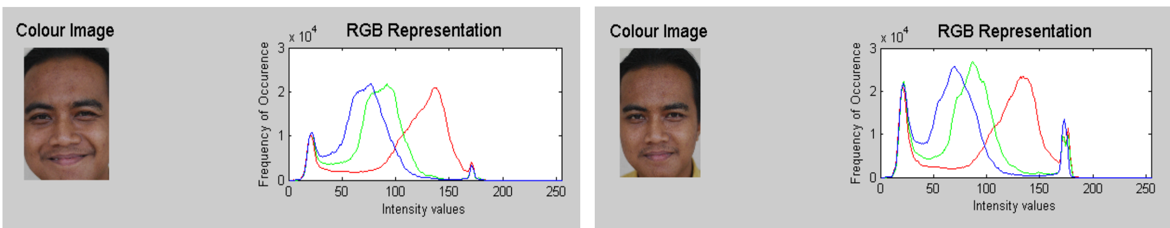
From 2D face image point of view, facial surface is surrounded by hair mostly on the top of the image. Figure 4.37 explores another kind of variation resources which will affect the performance of the developed algorithm. The effect of hair on regional appearance classification can be seen from the additional signal components or noise that is presented in the RGB plot corresponding to the subjects shown. Further research in the future will look into the task of eliminating the noise as the pattern of original UCI have yet to be revealed (from the figure).



(a) Effect of hair on regional appearance (India female).



(b) Effect of hair on regional appearance (India male).



(c) Effect of hair on regional appearance (Malay male).

Figure 4.37: Effect of hair on regional appearances.

The advantages of applying the colour analysis on the skin colour UCI can be seen in figure 4.38. The presence of partial occlusion on the face image has not totally given up the RGB UCI strength and capability. However, an advanced technique needs to be employed as it involves a high variation complexity.

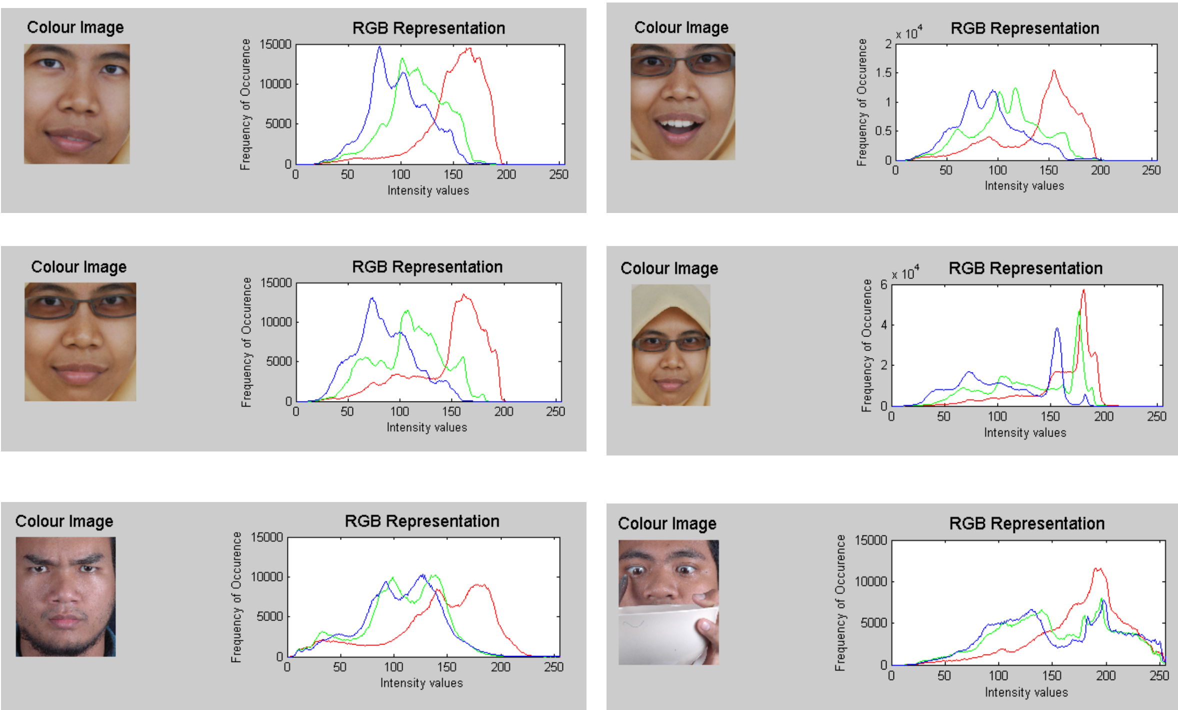


Figure 4.38: Partly occluded for regional appearance (Malay male).

(c) The Impact of Pose and Illumination Variations

(i) Pose Variations in Regional Appearances

As mentioned earlier, the beauty of the skin colour UCI is because of its uniformity and consistency throughout the facial region. Thus, pose variation does not affect much the regional appearance classification. These scenarios are shown in the figure 4.39.

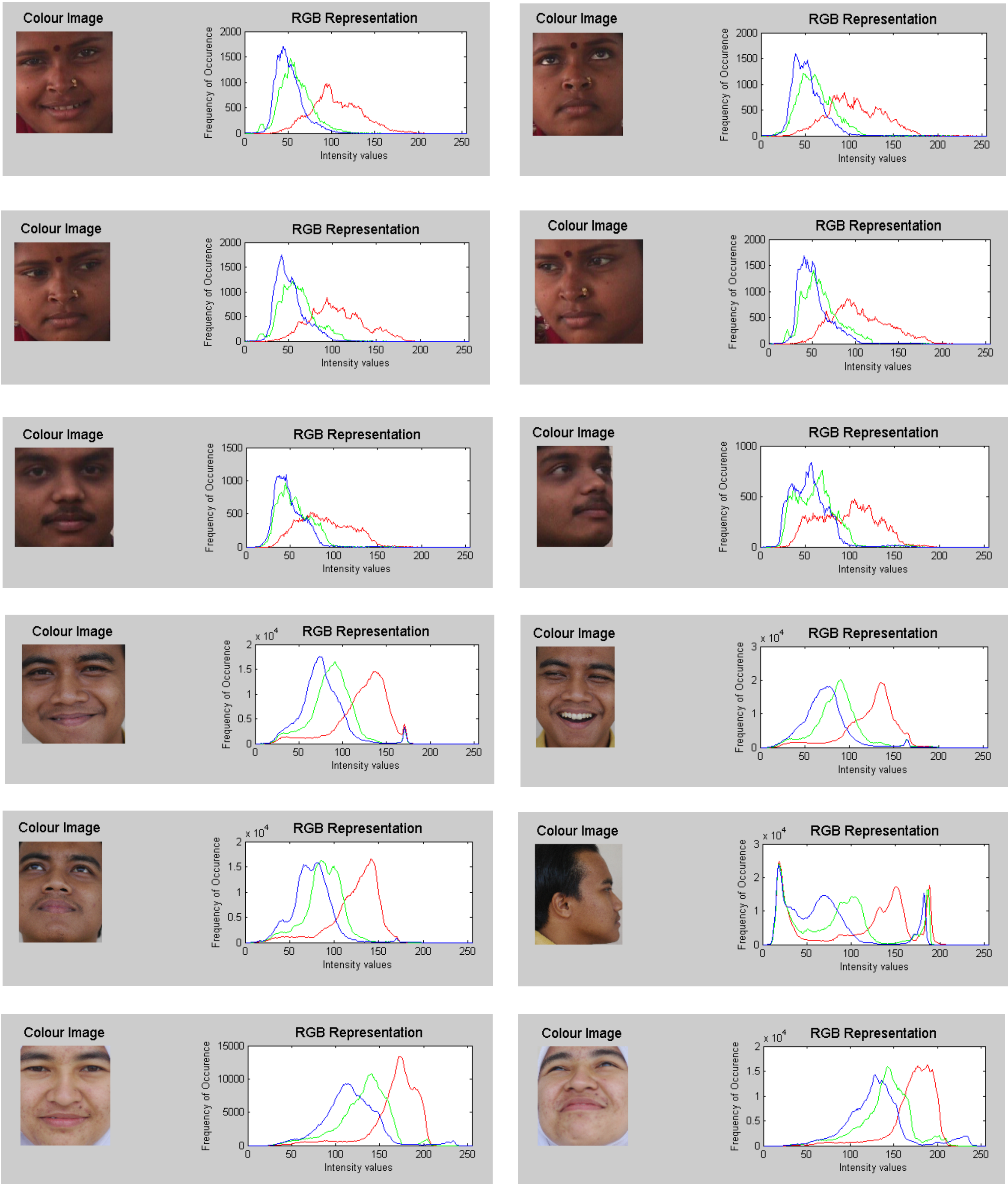


Figure 4. 39: Effect of pose variation in regional appearances.

(ii) Pose Variations in Gender Classification

In the case of gender classification, the pose variation may influence the performance and some results are demonstrated in the figure 4.40. The changes in texture orientation however, have slightly degraded the classification performance where the texture-based technique still can be relied on.

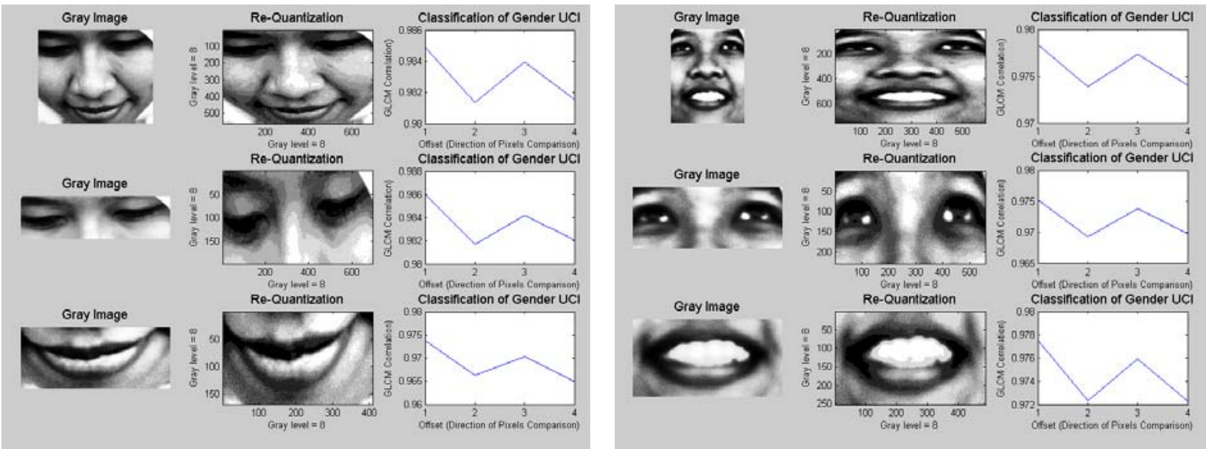


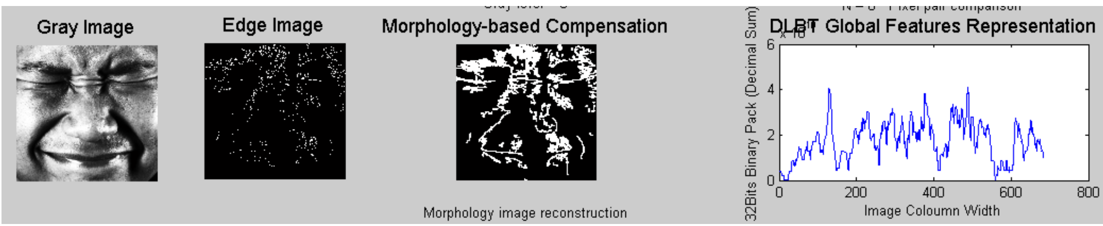
Figure 4. 40: Effect of pose variation in gender classification.

(iii) Pose Variations in Age Estimation

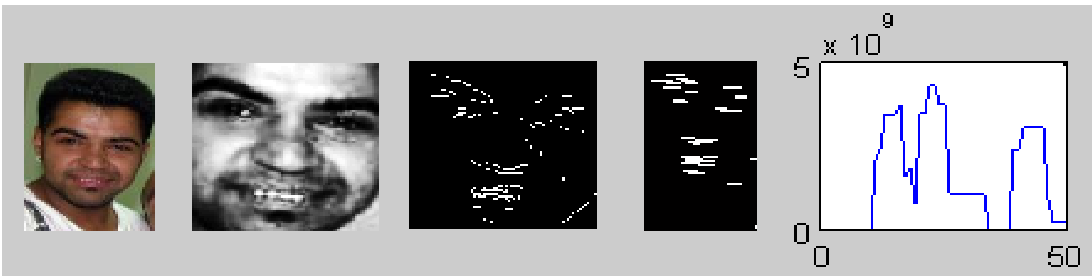
The pose variation has degraded the age classification as shown in figure 4.41(a). This limitation is difficult to overcome even though with the application of direct manual features ratio calculation. The main reason behind this issue is because of the feature distance ratio used is not suitable for the case of pose or geometry variation. The changes in position of mouth feature on 2D face image due to the geometry changes have made the ratio of distance between two eyes and the distance between the eyes and mouth to wrongly calculates and classifies the subject into opposite class.

Texture-based gender recognition is independent of the image variation caused by the changes in the image size either vertically or horizontally, such as shown in Figure 4.41(c) and (d). However, the DLBT applied for age estimation or age category classification will fail whenever the size of the original image has been changed badly. As a result, the adult image (figure 4.41(c)) that has been expanded horizontally has produced the DLBT values below the threshold value which makes it falls into child class. On the other hand, the child image that has been expanded vertically produced the same result as adult class (figure 4.41(d)). There are many more issues that open up to more research works to be carried out..

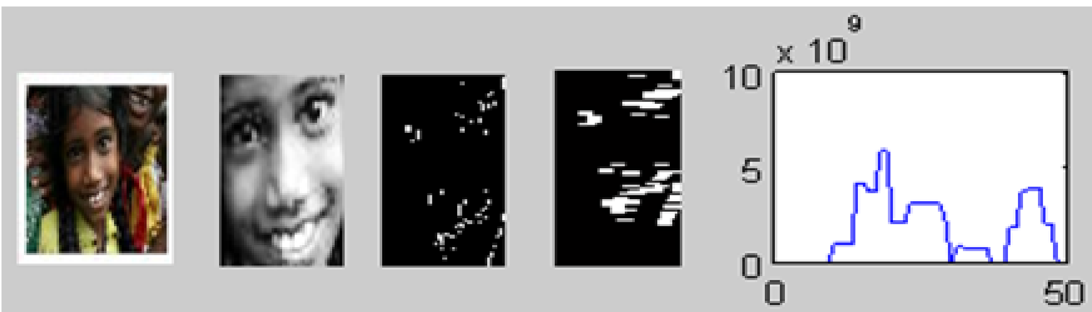
(a) Vertical pose variation, compensation and corresponding DLBT graph representation.



(b) Changes of features orientation and size and its DLBT graph representation.



(c) Effect of 2D image expanded horizontally and its DLBT graph representation.



(d) Effect of 2D image expanded vertically and its DLBT graph representation.

Figure 4. 41: Effect of pose variation and 2D image variation in age classification.

(iv) Illumination Variations in Regional Appearances Classification

In the presence of illumination variation, it can be seen from figure 4.42 that the RGB colour components have been distorted by the noise (illumination effect). As a matter of fact, almost all classes failed to be properly classified. The worst situation has made the classification results no longer valid to be relied on.

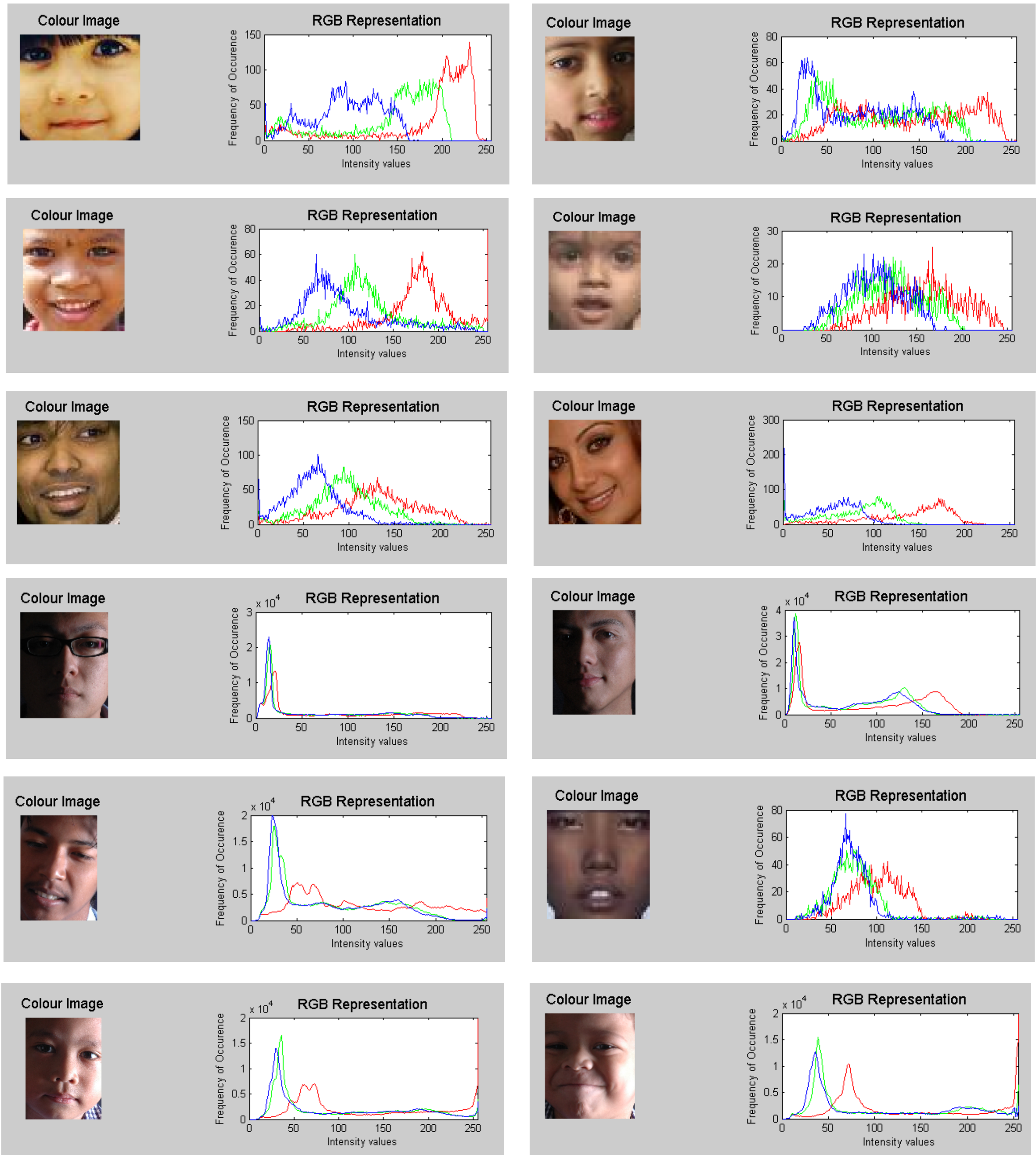


Figure 4.42: Illumination variation has seriously degraded the recognition performance result.

(v) Illumination Variations in Gender Classification

Some of the failures that result in classifying the gender groups in the presence of illumination variation are shown in Figure 4.43. As mentioned previously, the texture-based gender recognition suffers when the facial surface of a particular class has characteristics of opposite class. For instance, the surface of female faces shown in Figure 4.43 is not considered as ‘smooth’ as a whole from the texture-based algorithm aspect. The same failure scenario also happens to the male face surface as shown in the figure. These scenarios are due to the illumination variation where some of the regions are corrupted in term of texture determination. Future works need to look into the analysis of texture of individual features which may gather more information towards the understanding of the unique characteristics of male and female classes.

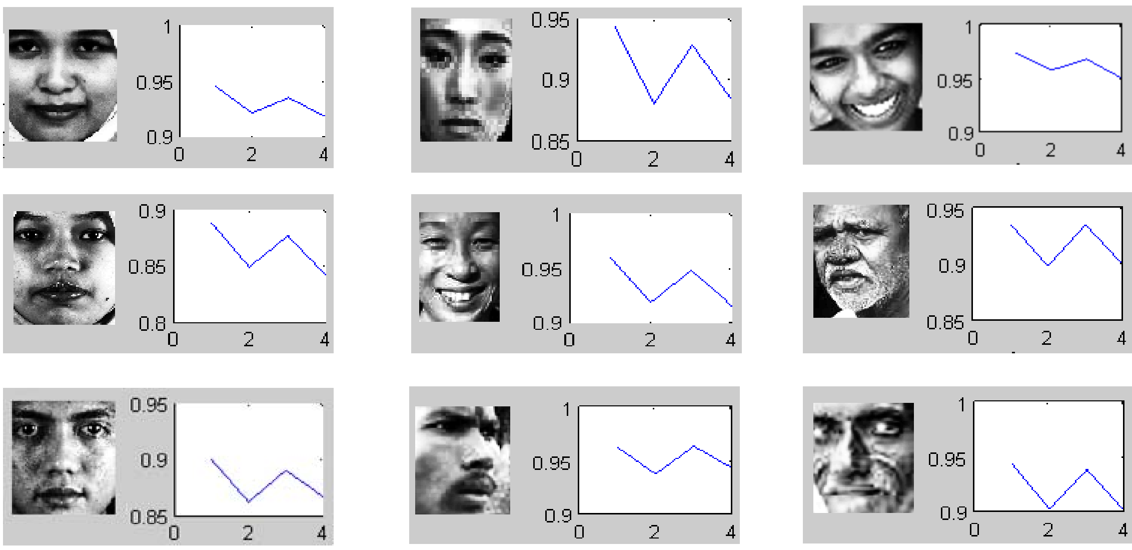


Figure 4. 43: Identity parameters (regional appearance, gender and age) recognition performance result.

(iv) Illumination Variations in Age Estimation

Age estimation that are based on the spatial calculation approach such as proposed in this thesis may not seriously be degraded in the presence of illumination variation depending on the ability of edge extractor performance. Since the technique depends on the edges that represent the features to be calculated, the technique will solely depend on the edge extractor capability. Figure 4.44 shows some results of the scenario discussed.

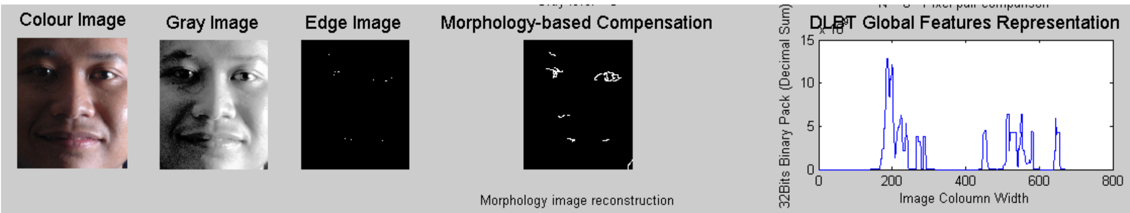


Figure 4. 44: Identity parameters (regional appearance, gender and age) recognition performance result.

With the small amount of edges that belong to the required features, the technique retains its ability to produce the expected outcome.

CHAPTER FIVE

SOFTWARE DEVELOPMENT AND TESTING

5. SOFTWARE DEVELOPMENT AND TESTING

Face images that are available in databases located in areas such as in private or government buildings can be accessed for various purposes. These images are unfamiliar to the typical face recognition system before the algorithm is applied to the databases where each image will then be coded respectively. However, given a face image, most of the system can only identify or verify whether the subject belongs to the database or not. Unfortunately, the system will reject the subject if the image is not in the database. Thus it can be seen that the knowledge provided in the database is not fully utilized for some reason even when the data is freely and readily available every time a new subject appears in the system. From the database usefulness point of view, the UCI (as expressed in this thesis) of face images are not intelligently used in serving the community efficiently. Some examples of extendable application for typical face recognition system are illustrated in figure 5.1. Amongst the application are fast searching for a wanted person (where the characteristics are predetermined) or to the extent of analyzing the crowd where the intelligent estimation can be made possible. This may include the determination of the population behaviour and characteristics where detail statistical information outcomes of group size of regional appearance, gender dominant and age estimation as studied in this thesis can be realized.

The study of handling the knowledge in image processing libraries has long been practiced in industrial applications of machine intelligent and vision system. For instance, the development of software tool reported in [127] is a good example of intelligently handling the knowledge in databases or image libraries for the purpose of building automatic systems. By using artificial intelligence techniques, they have presented knowledge-based pattern recognition software in the field of astronomy to automate the galaxy image processing. The study of pattern recognition software development is not limited to the personalized application. The development of image understanding environment such as in [128] comprehensively set up the goals to serve the research community of image understanding in the context of productivity, technology transfer, education/development and computational models. The work in [129] explained how the software framework for research in image processing, analysis and understanding is designed and developed. The aim of their research is to support research, development and evaluation of components and systems in image processing.

In the case of limited information availability, such as demonstrated in this thesis, the challenges confronted are to exploit the given raw data and to be able to manipulate the data when only a single blurred image is available at any particular time. This is usually the case in any intelligent software as they always work with incomplete and noisy data [130]. A relative objective such as described in [130] where pattern development cycle is introduced through the Link Analysis Workbench (LAW) system and its pattern language, Graph Edit Model (GEM). Among the most important characteristics featured by the LAW system that can be highlighted here for the pattern development cycle is an intuitive pattern language that is based on semantic graphs. Another important characteristic is the way the system is exhibited in the large relational data sets where a simple similarity metric is performed in order to support the retrieval and ranking of inexact matches [130]. One of the latest publications (2011) in dealing with the FR software development is as reported in [131]. In their publication, the study and development of an automated FR system are reported as been implemented for office door access control. The methodology of the developed system is based on the combination of PCA and Neural Network (NN) techniques where the performance of 80% recognition was achieved under predetermined environment and incorporated with image variations for testing.

In the next following sections, the specification required for functional design of ***The-ID*** system proposed in the thesis will be explained. The algorithm development and testing will then be presented in conjunction with the performance evaluation and some facts about practicality and reliability of the system.

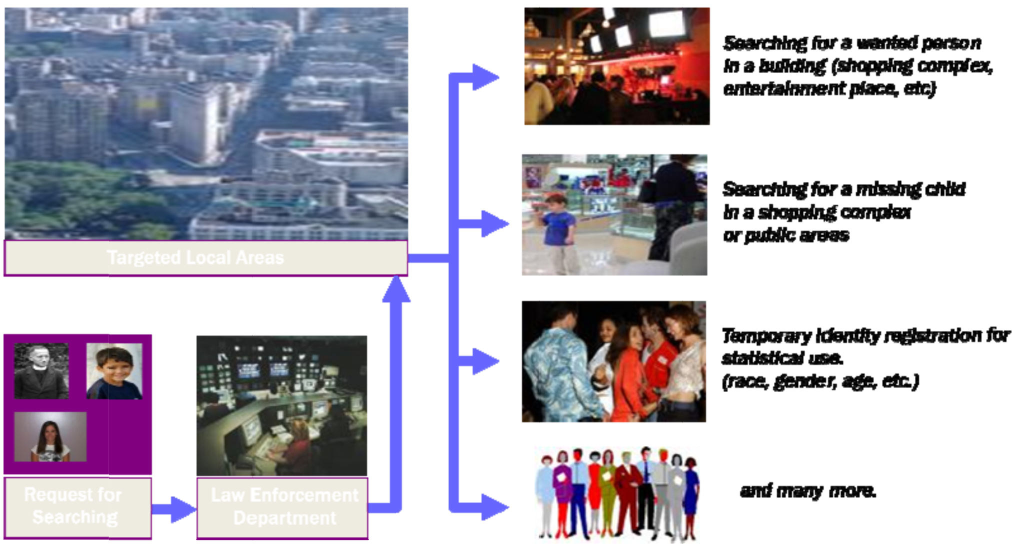


Figure 5.1: Examples of application for unfamiliar facial recognition system.

5.1 Functional Design Specification

The specification and design of unfamiliar facial identity recognition system proposed in this thesis will be described in this section where its purpose, development and practicality will be highlighted. As explained in Chapter Two, for simplicity, the unique identity of a particular person is named as *Temporary Human Electronic Identification,* will be abbreviated as ***The-ID***. ***The-ID*** represents three identity parameters namely regional appearance, gender and age. The regional appearance classes are chosen from the three major regional appearances in Malaysia; they are Malay, Chinese and India Malaysians. The gender classes are male and female while the age classes are categorized as child and adult. This chapter expands the explanation of ***The-ID*** determination, the process of collateral classification and recognition results.

The challenge confronted in the ***The-ID*** classification task is to isolate and group the classes of regional appearance, gender and age in the manner where each of the class can be either a parent or sub-class. This is important as the ***The-ID*** classifier further needs to classify these classes into sub-classes where each of these sub-classes will have their own independent unique representation. For instance, in the Malay class, there will be Malay-male and Malay-female classes. Furthermore, in these two sub-classes, there can always be Malay-male-child and -adult or Malay-female-child and -adult classes respectively. The same classification hierarchy also applies to Chinese and India classes. In the gender classification, no matter what regional appearance or age the subjects are, the system must be capable to classify both male and female classes. For example, no matter whether the subject is in male or female class, there will be Malay, Chinese and India subjects where each of them can be further classified into their age classes. The same scenario will also happen in the age classification where the sub-classes of regional appearance and gender must be determined. Figure 5.2 illustrates the route of the database division with respect to the searching request. The information included in a completed identity representation is the colour code (regional appearance information), the facial texture (gender information) and derivative of sizes and distances of the features (age information). The vector version of this information measures the identity parameters of a particular person.

The core in the ***The–ID*** algorithm is the design of extractors and classifiers for the regional appearance, gender and age recognition. These categories can be breakdown into a specific twelve (12) sub-classes. However, the task of image variation compensation must first seriously be considered as the proposed developed software should deal with the real world images. This includes the pre-processing of the given images involving the size, rotation and scale of the image.

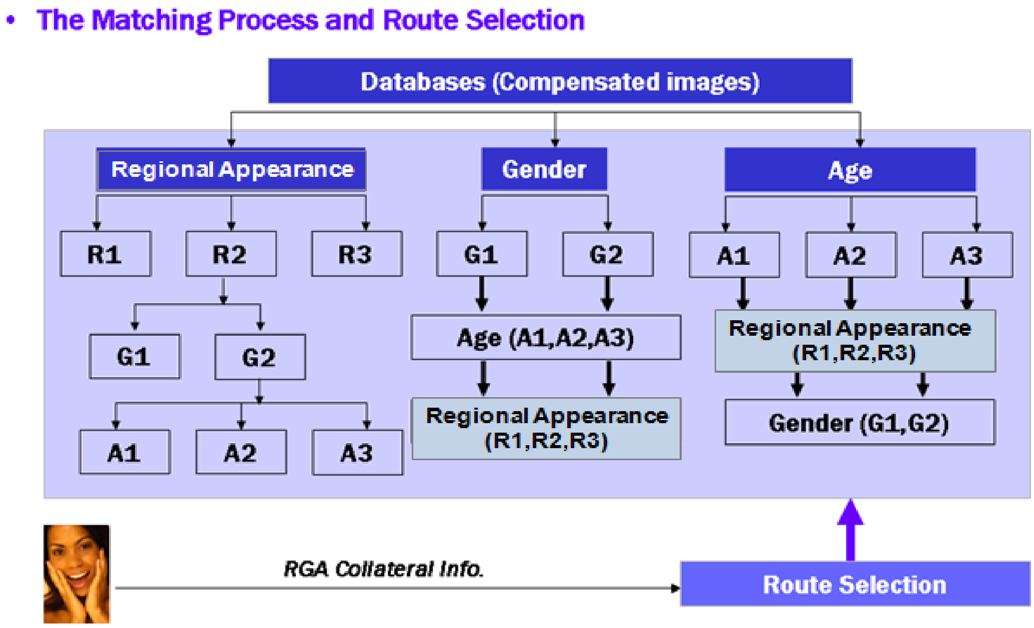


Figure 5.2: Block diagram for the matching process and route selection for identity searching.

The list of extractors, classifiers and corresponding methodologies used are shown in Table 5.1 below:

Context or Identity Parameters	Methodology		
	Feature-based (UCCI) Extractors	**UCCI-based Classifier**	**Key of Input Image Manipulation**
Regional Appearance	Skin colour representation	Statistical RGB components Analysis	RGB colour (.JPG)
Gender	Facial texture representation	GLCM Correlation	Gray level pattern analysis
Age	Global features representation	DLBT	Derivative Linear Binary Transformation (Edge images)

Table 5.1: Extractors, classifiers and methodologies used for the *The-ID* system.

The last stage of ***The-ID*** system implementation is to match the criteria of a particular unfamiliar person to the database of detected face images and classified into appropriate class. The term unfamiliar refers to the computer perception and the databases to be searched. These are open databases such as the one in public areas or any other places (shopping complex, private or government building, country border, airport, university campus, school, bus station and many more). This is one of the reasons why ***The-ID*** should have a simple processing approach and be easy to be implemented. The developed software testing is performed on the databases chosen from a number of locations. The final stage of testing is to compare the performance evaluation between the ***The-ID*** software and typical face recognition system. An illustrative application of this stage can be observed from the figure 5.3. Typical face recognition software will be performed through the process that is coloured in purple. On the other hand, the blue colour is the ***The-ID*** process flow. The detail of the software development is explained in the next section.

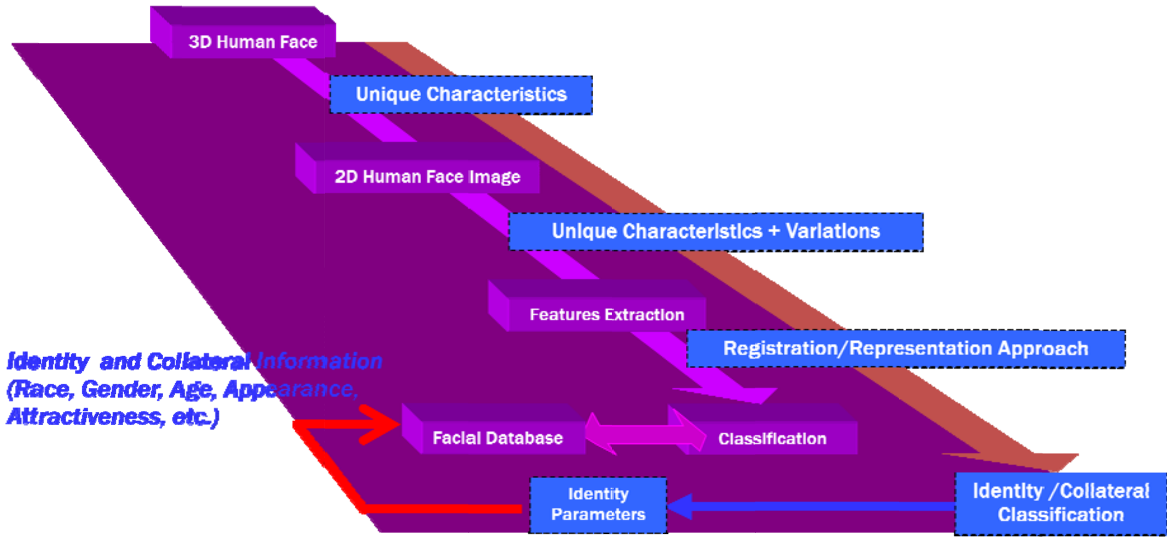


Figure 5.3: Comparison and inter-relation of process flow between independent typical face recognition system and with the aid of the ***The-ID*** system.

5.2 Development and Testing

At this stage of discussion, the specification and design of unfamiliar facial identity registration will be realized through the process of software development and performance evaluation justification. The development of the ***The-ID*** software is best described covering all the stages involved including the stages that are beyond the scope of the thesis. There are five (5) sub-processes identified in the development of the ***The-ID*** system software. However, as stated in Chapter One, the scope of the thesis is limited to the extraction and classification tasks. Image acquisition and face detection are another two important research areas that have their own research community and are beyond the scope of the thesis. In other words, the input to the ***The-ID*** system is a detected face image. Table 5.2 lists the functionality of each sub-process with the conceptual algorithm correspondingly.

Item	Tasks	Functionality	Algorithm
1	Image Acquisition & Detection	Detecting face-like images (from the given databases)	Sub-Program 1
2	Pre-processing	Compensate image variations	Sub-Program 2
3	Transformation	Manipulate the colour, grey and edge images for regional appearance, gender and age classes respectively.	Sub-Program 3
4	Extraction	To extract and represent the UCI of the three classes.	Sub-Program 4
5	Classification	To match the given images with the pre-determined identity parameters based on experiments.	Sub-Program 5

Table 5.2: Sub-processes involved in the ***The-ID*** system.

5.2.1 *The-ID* Algorithm

The-ID algorithm is designed and developed for the purpose of testing and final analysis in the thesis. However, the algorithm can be improved further for commercialization. In this regard, the developed algorithm will focus more on the result obtained and performance of each stage involved in the analysis.

Figure 5.4 illustrates overall process of the ***The-ID*** software. The role of registrar involves two major tasks namely, the extractor and the classifier. The goal in the algorithm is to attempt to reveal the mutual understanding between the extractor and the classifier. The main constraint is identifying which features are the best to be extracted which in turn must be precisely agreed by the classifier to perform further analysis towards producing a reasonable classification results. This is the core of the research in this thesis to the extent of introducing the collateral unique characteristic information (UCI).

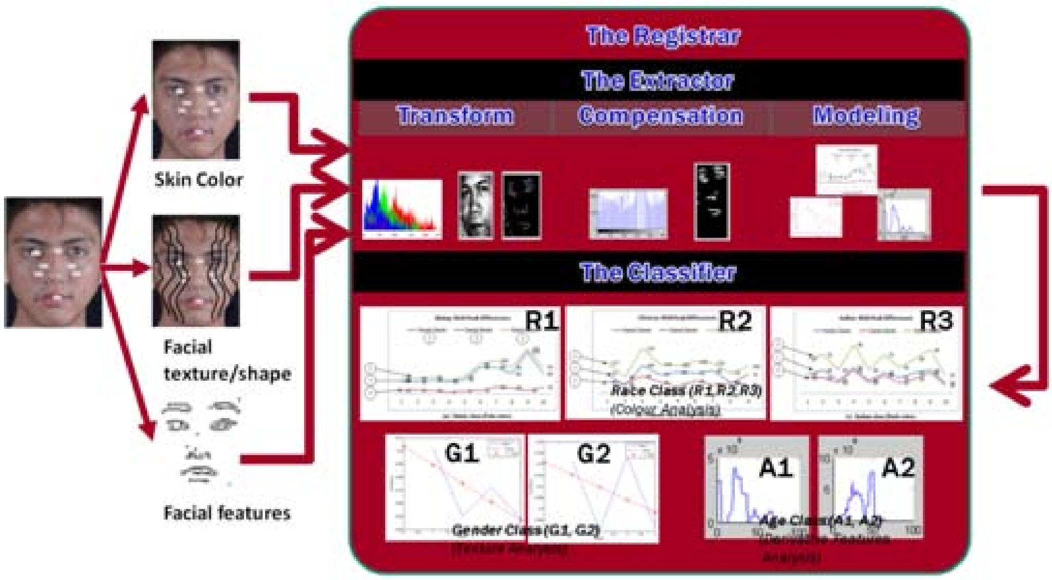


Figure 5.4: The real partnership between the extractors and classifiers.

The detail of the programming codes written in MATLAB software is provided in the Appendix B. In this section, the main coding used and overall output presentation produced by the MATLAB codes will be explained.

The ***The-ID*** software transformed the given input images as follows:-

A. VARIATION COMPLEXITY COMPENSATION, EXTRACTION AND REPRESENTATION

A.1 REGIONAL APPEARANCE EXTRACTION AND REPRESENTATION

The input image is a color image. The image will be loaded into the database where the dimension will be reduced or standardized to a specified size. This input image is assumed to be detected by the Face Detection Algorithm. However, with respect to the scope of the thesis, the detected face image is represented by image cropping. The cropped image will then be compensated by histogram equalization. The final task in this stage is to represent the image whereby the representation is ready for the classifier to perform further analysis.

(a) Face Image Acquisition

The face image is grabbed by using a digital camera with a specified reasonable resolution. The RGB image is then cropped to obtain the face region and then resized. Basically, in real practice, this is done by the face detection algorithm. As mentioned previously, face detection is another area of research community and is beyond the scope of the thesis. Figure 5.5 shows the type of input image (colored face region) which is ready for further analysis.

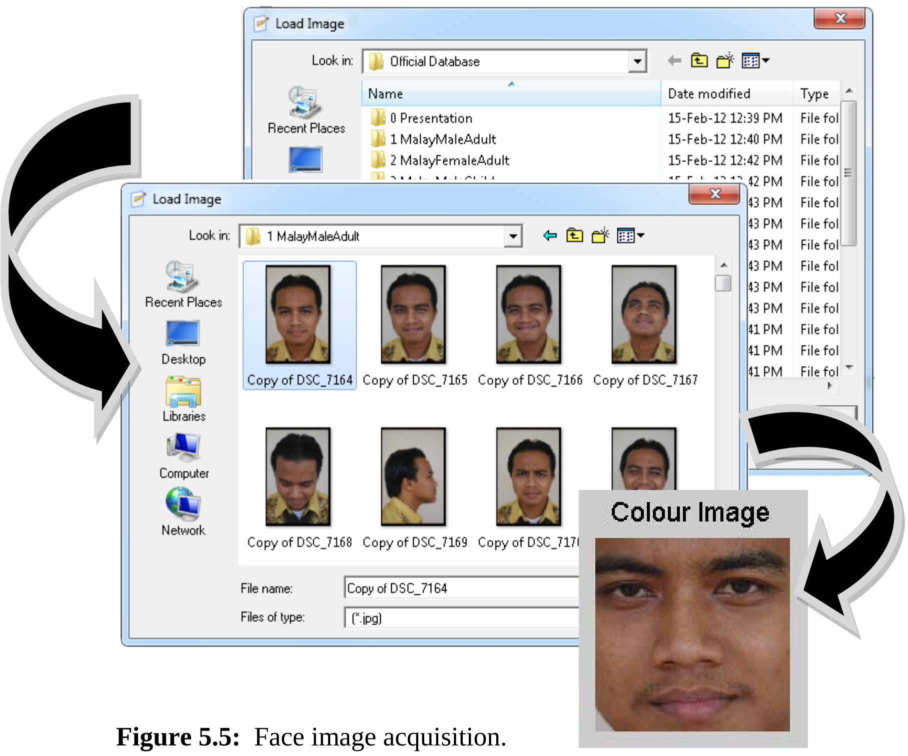


Figure 5.5: Face image acquisition.

The Matlab coding is written as:

rgbImage = imcrop(ColorImage);

(b) Histogram of RGB Colors

The compensation of the cropped image or face region is done by applying the histogram equalization with 256 levels.

The next step is to extract the three components of RGB colors, known as Red, Green and Blue components. The graphs of these three components are plotted as shown in figure 5.6. In representing the RGB components, the vector of intensity values is obtained for each component. Each element in the vector represents the frequency of occurrence sorted from 0 to 255 intensity levels.

The Matlab coding is written as:

```
redPlane = rgbImage(:, :, 1);
greenPlane = rgbImage(:, :, 2);
bluePlane = rgbImage(:, :, 3);
```

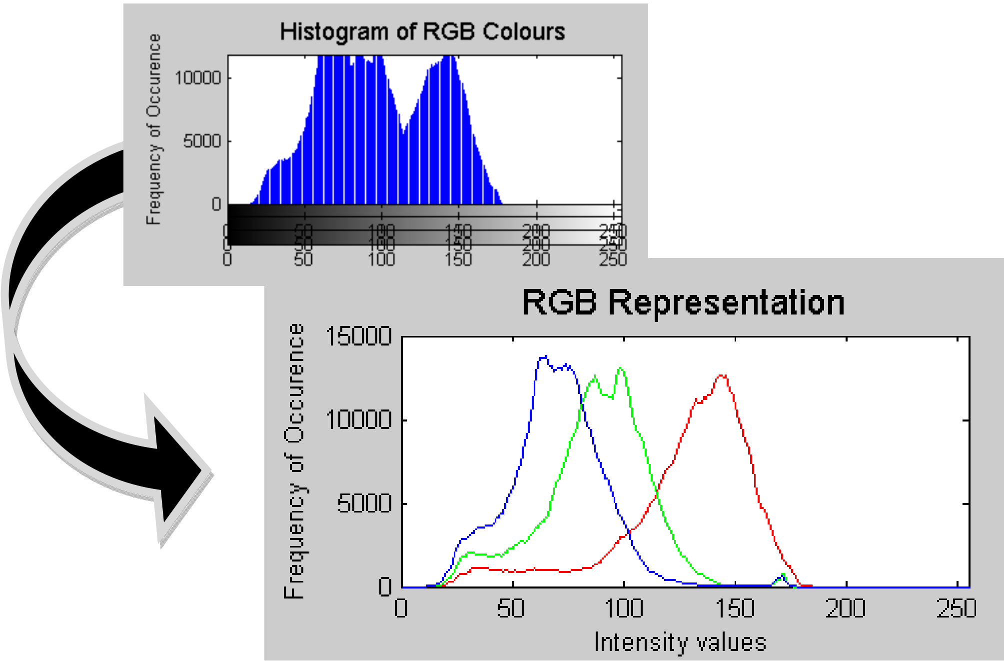


Figure 5.6: Representing RGB components.

(i) Representing Red Component

[pixelCountR grayLevelsR] = imhist(redPlane);

The intensity values of red component are stored in variable **pixelCountR** where the corresponding intensity levels are saved in **grayLevelsR**.

(ii) Representing Green Component

[pixelCountG grayLevelsG] = imhist(greenPlane);

The intensity values of green component are stored in variable **pixelCountG** where the corresponding intensity levels are saved in **grayLevelsG**.

(iii) Representing Yellow Component

[pixelCountB grayLevelsB] = imhist(bluePlane);

The intensity values of yellow component are stored in variable **pixelCountB** where the corresponding intensity levels are saved in **grayLevelsB**.

A.2 TEXTURE-BASED GENDER EXTRACTION AND REPRESENTATION

At this stage, the color image will be transformed into gray level image. The transformed gray image is then compensated by re-quantization where this will reduce the dimension of the image in order to perform the GLCM texture representation. The following steps are taken to illustrate the outcomes.

(i) Gray Image Conversion

The color image is converted to gray image with the following Matlab codes:

GrayImage=rgb2gray(rgbImage);

(ii) Compensation by Histogram Equalization and Re-quantization

The gray image is normalized by histogram equalization so that it may reduce the dimension and illumination impact inherently. The Matlab coding is written as:

GrayEq=histeq(GrayImage,256);

In representing the texture pattern systematically, the GLCM technique is then applied on the equalized gray image, where the Matlab coding is written as follows:

[GLCM1,QuantizedImage] = graycomatrix(GrayEq,'NumLevels',8,'G',[]);

The re-quantized image is saved in variable **QuantizedImage** while the new representation of the texture pattern is saved in variable **GLCM1**. In this case, quantization is limited to eight (8) gray levels in consideration of processing time. This means that the size of matrix of variable GLCM1 is also 8 by 8.

(iii) GLCM Texture Representation

Plotting the variable of **QuantizedImage** and **GLCM1** will yield the image labeled by (ii) and (iii) respectively.

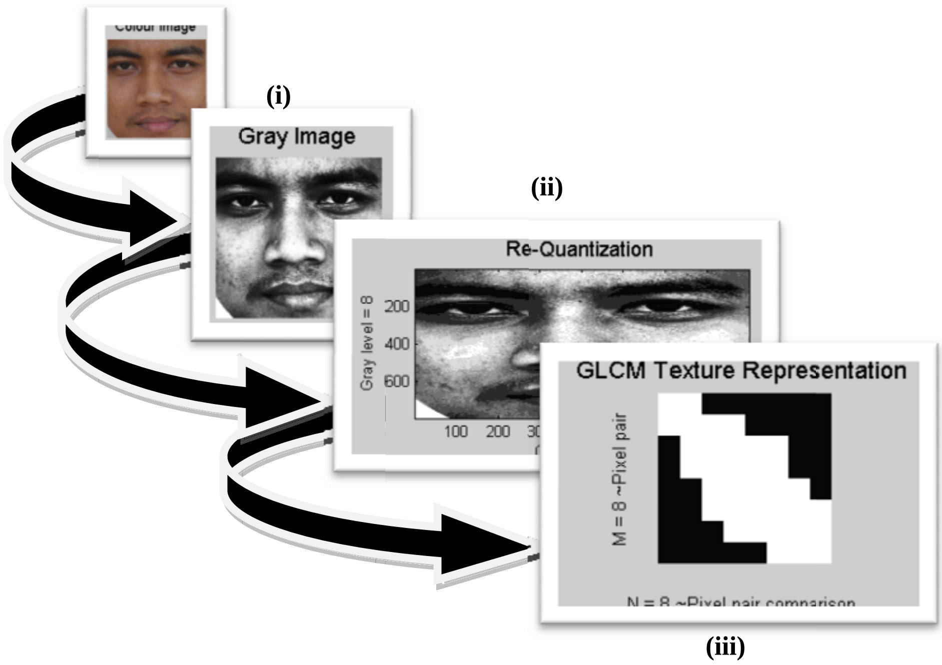


Figure 5.7: Representing RGB components.

A.3 AGE REPRESENTATION

(i) Edge Image Conversion

From the gray image, the edge image is obtained with the following Matlab coding:

```
edgeimage=edge(GrayEq,'canny',0.4);
```

where Canny filter is used with a specified threshold value.

(ii) Morphology-based Compensation

The edge image is compensated by applying the morphology technique with pre-determined structural element of ball shape. Dilation of the edges is performed to enhance the edges. The whole process is written in Matlab coding as follows:

```
DLBT=bwpack(edgeimage);
StrucEle = strel('ball',3,0);
bwp_dilated = imdilate(DLBT,StrucEle,'ispacked');
bw_dilated = bwunpack(bwp_dilated, size(edgeimage,1));
```

(iii) DLBT Global Features Representation

Finally, the DLBT representation of global face features is obtained by packing each column and plotting the graph of equivalent decimal values. The whole process is illustrated in figure 5.8.

```
DLBT2=bwpack(bw_dilated);
V2=sum(DLBT2);
```

The proposed new technique, DLBT is applied to calculate the ratio of vertical and horizontal features. The binary values of each column is summed up and plotted as shown in the figure labeled (iii). The process is repeated for the transposed image. The ratio calculation of the two will be performed by the classifier.

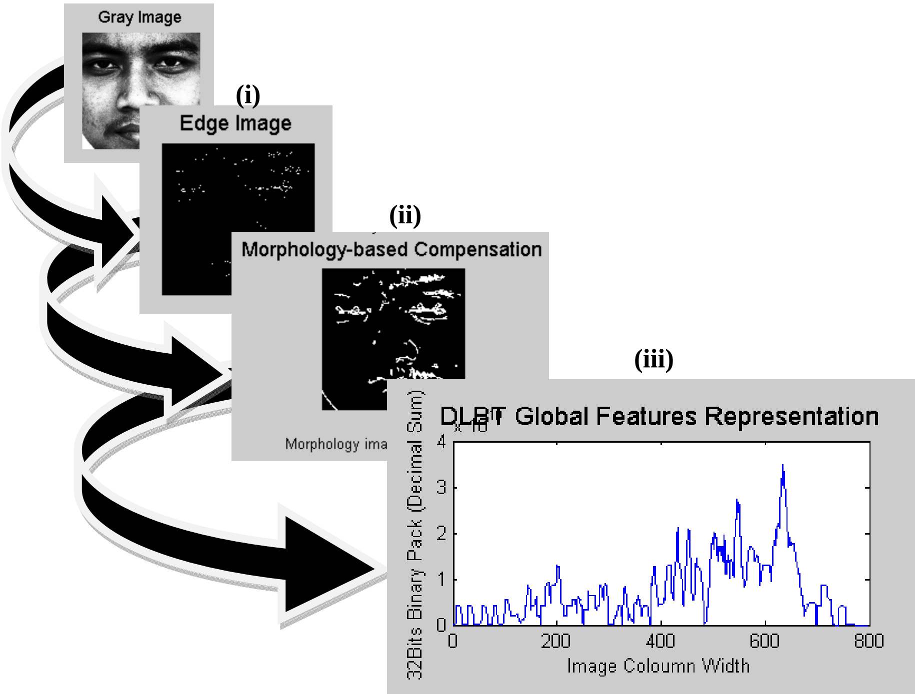


Figure 5.8: Age representation.

B. UCI CLASSIFICATION AND RECOGNITION

In this sub-program, the three classifiers are demonstrated their performance based on the training observation.

B.1 REGIONAL APPEARANCE UCI CLASSIFICATION

The RGB component representations will be analyzed and this leads to the design of the classifier based on statistical approach. The covariance of data set Red, Green and Blue is calculated and judgment is made based on the training observation.

The Matlab coding is written as:

```
% The peak values of frequency of occurrence for three color components are calculated:
maxR = max(pixelCountR);
maxG = max(pixelCountG);
maxB = max(pixelCountB);
```

```
% and the difference between them are determined.

RBpeakDiff = maxR - maxB;
BRpeakDiff = maxB - maxR;
GBpeakDiff = maxG - maxB;

% Corresponding intensity values of distance between peak values for three color components are
% calculated.
GB=Gimax-Bimax;
RG=Rimax-Gimax;
RB=Rimax-Bimax;

PercentGB=GB/RB;
PercentRG=RG/RB;

%  The three regional appearances are classified based on threshold of training results..
if  abs(BRpeakDiff) > (0.01*maxR)
    if abs(BRpeakDiff) < (0.1*maxR)
        if abs(PercentGB) < 0.45
    subplot(3,5,3);plot(BRpeakDiff);
    title('Classification of Malay Regional Appearance UCI','Fontsize',fontSize);
    xlabel('Number of Subjects');ylabel('RGB Differences)');pause(1);
        end
    end
end
if abs(BRpeakDiff) > (0.1*maxR)
    if abs(BRpeakDiff) < (0.3*maxR)
    subplot(3,5,4);plot(BRpeakDiff);
    title('Classification of Chinese Regional Appearance UCI','Fontsize',fontSize);
    xlabel('Number of Subjects');ylabel('RGB Differences)');pause(1);
    end
end
    if abs(PercentGB) > 0.45
     subplot(3,5,4);plot(BRpeakDiff);
    title('Classification of Chinesee Regional Appearance UCI','Fontsize',fontSize);
    xlabel('Number of Subjects');ylabel('RGB Differences)');pause(1);
    end

if abs(BRpeakDiff) > (0.3*maxR)
   % if abs(BRpeakDiff) < (0.9*maxR)
     %   if abs(PercentGB) < 0.45
    subplot(3,5,5);plot(BRpeakDiff);
    title('Classification of India Regional Appearance UCI','Fontsize',fontSize);
    xlabel('Number of Subjects');ylabel('RGB Differences'); pause(1);
      %  end
  %  end
end
```

B.2 GENDER UCI CLASSIFICATION

The gender classifier is designed by firstly, calculating the four directions or offset for the pixel comparison and pattern sorting. Then the GLCM correlation is performed on each of the matrix of different offset. Thus, the final result can be plotted where the GLCM correlation value versus their offsets.

The Matlab coding is written as:

```
offsets0=[0 1;-1 0];
[glcm2, QuantizedImage2]=graycomatrix(GrayEq,'offset',offsets0);
stats=graycoprops(glcm2,'contrast correlation');

GenderRange  = stats.Correlation;
MinGenderRange = min(GenderRange);
MaxGenderRange = max(GenderRange);
DiffGender = MaxGenderRange - MinGenderRange;

if (DiffGender < 0.003)
     subplot(3,5,9);plot(DiffGender);
      title('Gender Classification Result: Female Class','Fontsize',fontSize);
       xlabel('Subjects)');ylabel('Difference Between Offset 1 and 3');pause(1)
else
        subplot(3,5,8);plot(DiffGender);
        title('Gender Classification Result: Male Class','Fontsize',fontSize);
        xlabel('Subjects)');ylabel('Difference Between Offset 1 and 3');pause(1);
end
```

B.3 AGE UCI ESTIMATION/CLASSIFICATION

The calculation of DLBT values is repeated for the transposed image. In this case, the vertical and horizontal of the global face features are considered in calculating the ratio of the two.

The process is written in Matlab coding as follows.

```
HorizontalMeasure = bw_dilated.';
DLBT2=sum(HorizontalMeasure);

DistMth2Eyes = max(DLBT1);
DistEyes = max(DLBT2);
Ratio1 = log10(DistMth2Eyes/DistEyes);
```

```
title('DLBT Global Features Representation','Fontsize',fontSize);
xlabel('Image Coloumn Width');ylabel('DLBT Decimal Summation');pause(1);

if Ratio1 < 7.5
    subplot(3,5,14);plot(Ratio1);
    title('Age Classification Result: Child','Fontsize',fontSize);
    xlabel('Image Column Width');ylabel('DLBT Ratio)');pause(1);
else
    subplot(3,5,13);plot(Ratio1);
    title('Age Classification Result: Adult','Fontsize',fontSize);
    xlabel('Image Column Width');ylabel('DLBT Ratio)');pause(1);
end
```

The detail of Matlab coding is attached in Appendix B of the thesis, while the images used for the training is attached in Appendix C, saved in the CD attached.

Samples of the ***The-ID*** outputs are shown in figure 5.9. The labels represent the sub-classes in classification.

1.- Malay

2.- Chinese

3.- India

4.- Male

5.- Female

6.- Adult

7.- Child

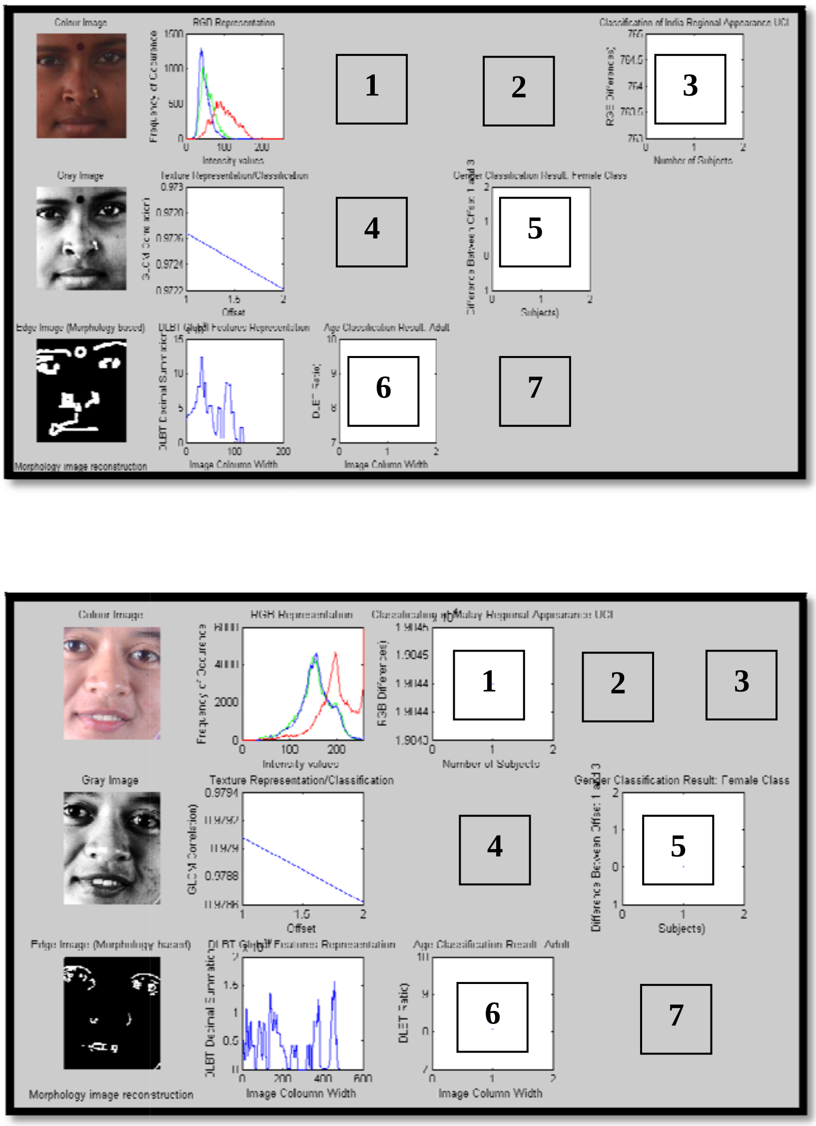


Figure 5.9: Samples of ***The-ID*** outputs.

5.2.2 Software Testing

The software testing conducted in this thesis is based on the procedure listed below:

(1.) The face image database is represented in a form of computer folder. In this folder, the images are composed of various regional appearance, gender and age classes together with image variations.

(2.) Two categories of experiment are chosen to relate with two major applications.

(a) Category 1: Testing of Database Segmentation.

The functionality of the testing is to analyze the characteristics of population in the database. The outcome is the fraction taken by four (4) different options of segmentation. Basically, the role of the ***The-ID*** software is to support the typical FRS in recognizing the subject by segmenting the database based on their identity parameters. The database segmentation can be thought of in various ways.

Option 1: Segmentation by Regional Appearance.

The database is segmented into three (3) classes, where each class is composed of four (4) sub-classes.

Option 2: Segmentation by Gender.

The database is segmented into two (2) classes, where each class is composed of six (6) sub-classes.

Option 3: Segmentation by Age.

The database is segmented into two (2) classes, where each class is composed of six (6) sub-classes.

Option 4: Segmentation by Twelve (12) Specific Classes.

The database is segmented into all possible classes.

(b) Category 2: Testing of Supportiveness of Segmented Database (*The-ID*) in Typical Face Recognition Software (FRS) Application

The functionality of the testing is to perform the fast searching of the wanted person against the large database and possibly to enhance the recognition performance in term of processing time.

In this experiment, the database is firstly coded and segmented by the ***The-ID*** software where given a tested image (wanted person), the ***The-ID*** software will determine to which sub-class the tested image will fall into. Then the PCA-based FRS [150] will be applied and encoded to this sub-class together with the tested image. Matching process will be performed by PCA-based FRS between the tested image and the chosen sub-class. The highest similarity measure will be chosen as a result of recognition.

Figure 5.10 illustrates the possibilities of segmenting and searching as explained in both experiments procedure.

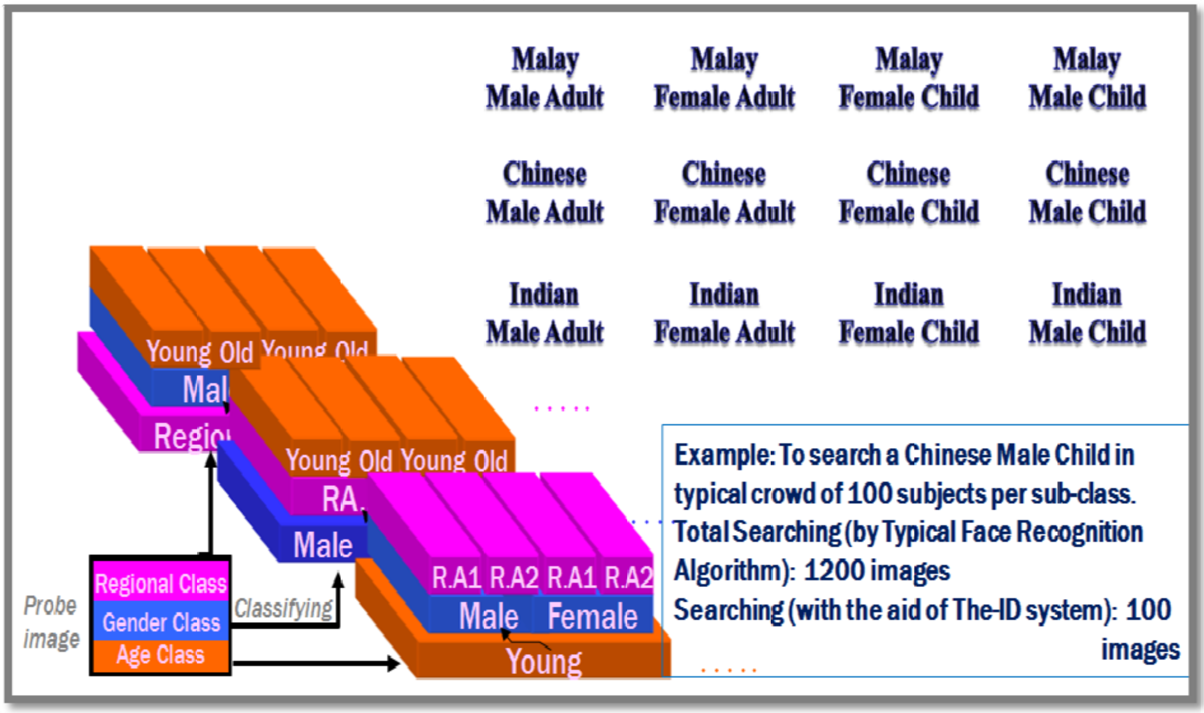


Figure 5.10: Possibility of grouping and searching.

5.2.3 Performance Evaluation

(a) Category 1: Testing of Database Segmentation.

Table 5.3 shows a sample of the ***The-ID*** result based on classification by regional appearance. The parameters of measurement are obtained and performance is calculated for every class involved.

Identity Parameters	Parameters of Measurement							Overall Performance
	Actual	*The-ID*	False Acceptance	False Rejection	Actual *The-ID*	Rate of False Acceptance (%)	Rate of False Rejection	
Malay	29	26	5	8	21	19.23	30.77	72.41
Chinese	33	37	15	11	22	40.54	29.73	66.67
India	39	37	5	7	32	13.51	18.92	82.05
Total	101	100	25	26	75	24.43	26.47	73.71

Table 5.3: Sample of overall result of ***The-ID*** system, classified by regional appearance.

The parameters of measurement are derived as follows:

(i) *Actual*: Actual number of face images in the database with respect to three classes of regional appearance.

(ii) ***The-ID*** Output: The outcomes after running the ***The-ID*** program.

(iii) False Acceptance (F.A): Number of images that have been falsely accepted in a particular class.

(iv) False Rejection (F.R): Number of images that have been falsely rejected from a particular class.

(v) ***The-ID*** Actual: The actual result of running the ***The-ID*** program, which is given by:

The-ID Actual = ***The-ID*** Output - False Acceptance

(vi) Rate of False Acceptance: A measure of failure in accepting a true member of the class, in term of calculating the subject that do not belong to the class.

Percentage Rate of False Acceptance = (False Acceptance/***The-ID*** Output) * 100 %

(vii) Rate of False Rejection: A measure of failure in accepting a true member of the class, in term of calculating the true member(s) of the class that are wrongly rejected.

Percentage Rate of False Rejection = (False Rejection/***The-ID*** Output) * 100 %

(viii) Overall Performance: (***The-ID*** Actual/Actual Segmentation) * 100%

Table 5.4 below shows another way of calculating the ***The-ID*** performance, showing all the three major identity parameters segmentation.

Item	Parameters of Measurement	Actual	*The-ID* Actual	Rate of False Acceptance	Rate of False Rejection	Overall Performance
1	Total Subjects	83	71	10.84 %	14.46 %	74.70 %
2	**Segmentation Results:**					
2.1	**Regional Appearance**	83	71	10.84 %	14.46 %	74.70 %
	Malay,	31	26	12.90 %	16.13 %	70.97 %
	Chinese,	22	18	13.60 %	18.18 %	68.18 %
	India	30	27	6.67 %	10.00 %	83.33 %
2.2	**Gender**	83	71	10.84 %	14.46 %	74.70 %
	Male	38	31	2.63 %	18.42 %	78.95 %
	Female	45	40	17.78 %	11.11 %	71.11 %
2.3	**Age**	83	71	10.84 %	14.46 %	74.70 %
	Child	24	20	16.67 %	16.67 %	66.67 %
	Adult	59	51	8.47 %	13.56 %	77.97 %

Table 5.4: Sample of overall result of the ***The-ID*** system performance, classified by regional appearance, gender and age classes.

From table 5.4, the performance results concluded the ***The-ID*** system is able to segment the database with the overall recognition performance rate of 74.70 %. The rate of false acceptance and false rejection are 10.84 % and 14.46 % respectively.

Various ways can be chosen to determine the segmentation that suit with the application. This is one of the characteristics of ***The-ID*** system where the operator can analyze the database in a few ways so that the outcomes can be relied on.

(b) Category 2: Testing of Supportiveness of Segmented Database (*The-ID*) in Typical Face Recognition Software (FRS) Application

Item	Parameters of Measurement	Actual	*The-ID* Actual	PCA-based Face Recognition (Processing Time in sec.))	Overall Performance (%)
1	Malay Male Adult	23	20	20	(178-20)/178 *100%
2	Malay Male Child	10	7	7	(178 – 7)/178 *100%
3	Malay Female Adult	25	19	19	(178 – 19)/178 *100%
4	Malay Female Child	8	4	4	(178 – 4)/178 *100%
5	Chinese Male Adult	22	18	18	(178 – 18)/178 *100%
6	Chinese Male Child	5	2	2	(178 – 2)/178 *100%
7	Chinese Female Adult	26	17	17	(178 – 17)/178 *100%
8	Chinese Female Child	7	4	4	(178 – 4)/178 *100%
9	India Male Adult	20	15	15	(178 – 15)/178 *100%
10	India Male Child	5	3	3	(178 – 3)/178 *100%
11	India Female Adult	20	16	16	(178 – 16)/178 *100%
12	India Female Child	8	3	3	(178 – 3)/178 *100%
	Total	178	128	128	

Table 5.5: Sample of overall result of the ***The-ID*** system performance in supporting Face Recognition Software.

In understanding the actual scenario of the testing, figure 5.11 illustrates the actual database (before the ***The-ID*** segmentation) and possibility of location or address of the wanted image that needs to be accessed by the matching algorithm. The matching process performed by the PCA-based FRS will initially measure the matching parameters between the probe or tested image and the image at address 0, and followed by address 1 until it comes to the image at address N. The highest score of the matching will be chosen as a result of identified person. This means, the time taken in searching of wanted image depends on the size of the class.

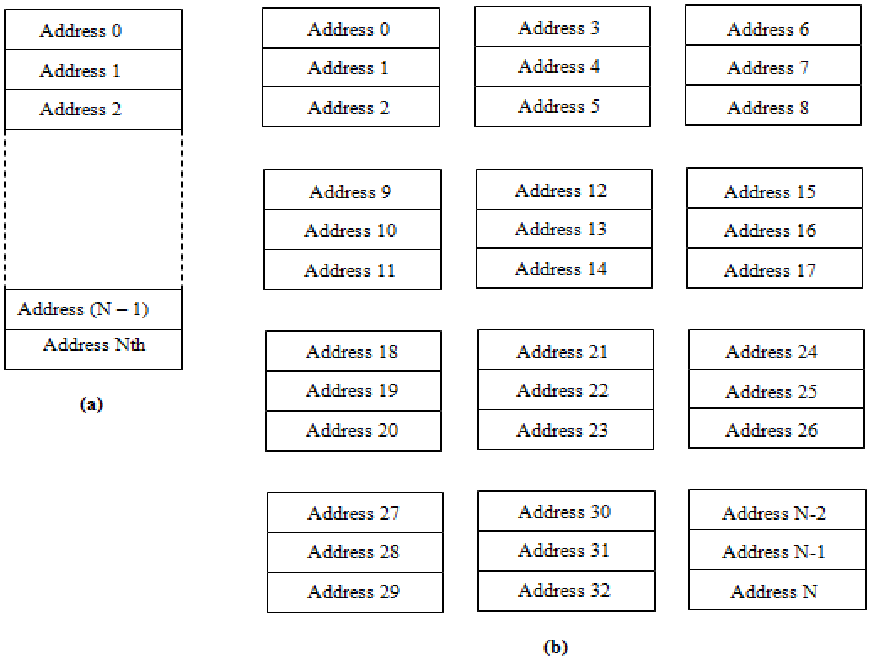


Figure 5.11: Database scenarios (a) without and (b) with the ***The-ID*** system.

The mathematical observation of the real scenario (without ***The-ID*** segmentation) can be derived as follows:

From the figure 5.11(a), suppose N = 100 and the processing time taken by FRS for each image is about 1 second. Then, the total matching processing time needed for 100 images in the database is 100 seconds.

The mathematical observation of the supportiveness of the ***The-ID*** segmentation can be derived as follows:

From the figure 5.11(b), suppose the probe image (wanted person) is classified as Malay Male Adult and the size of this class which is segmented by the ***The-ID*** are 20 images. Then, the total matching processing time needed for 20 images in the class is 20 seconds. However, if the matching result obtained is false, then the second alternative of performing the matching process can be chosen, either by Malay regional appearance, or by Male gender, or by Adult age class. As mentioned previously, the final outcome is always judged by human decision, whether the result is suitable or not and may change the possibility of segmentation.

In conclusion, the overall system performance can be improved further, especially on the methods used for extraction and classification tasks. The system, however, can be reasonably applied in the area of marketing and product acceptance in typical business operation and collecting general information about the population or crowd characteristics. These kinds of application are not categorized as high level information security, but the information obtained from the system will give high benefit to the operator. As a matter of fact, the system reasonably gives an acceptable performance in controlled environment such as shown in figure 5.12 for regional appearance classification. Unfortunately, the illumination effect is a major contribution in performance degradation shown in the region of uncontrolled environment of the figure.

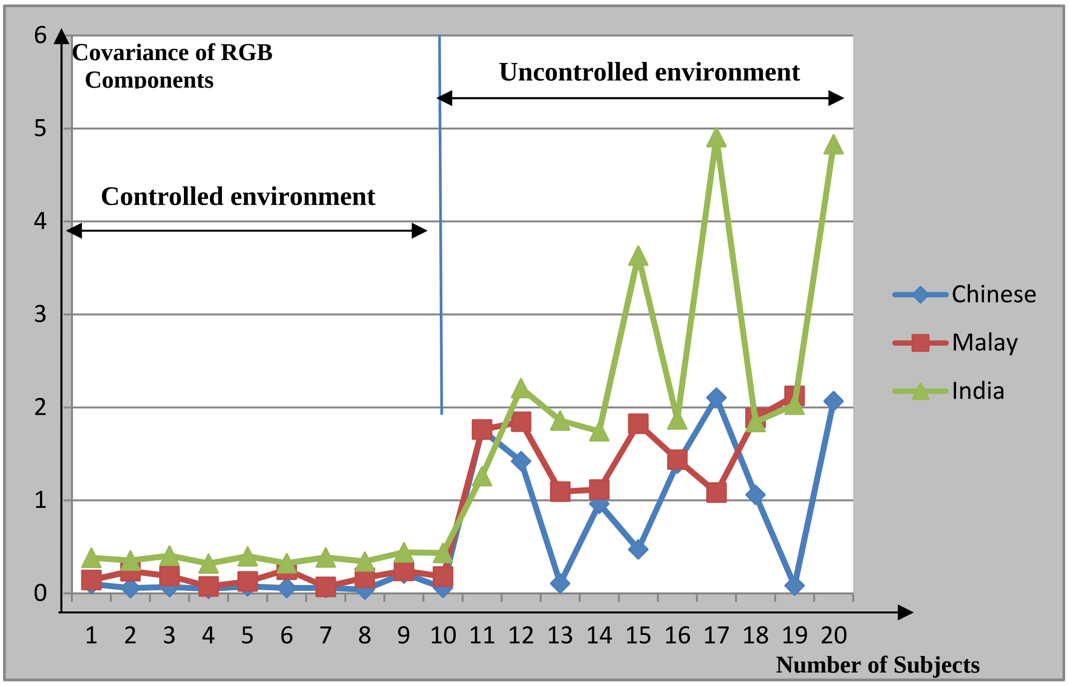


Figure 5.12: Samples of regional appearances classification demonstrating performance in controlled and uncontrolled environment.

The impact of illumination variation also can be seen in the case of gender and age classification, which degraded both classification performance results. These issues have been discussed in Chapter Four where detail parameters of measurement have been explored.

In completion of the section, figure 5.13 shows most of the common images condition (illumination and viewing geometry) provided in the databases that cause performance degradation, whether in regional appearance classification, gender or age classification.

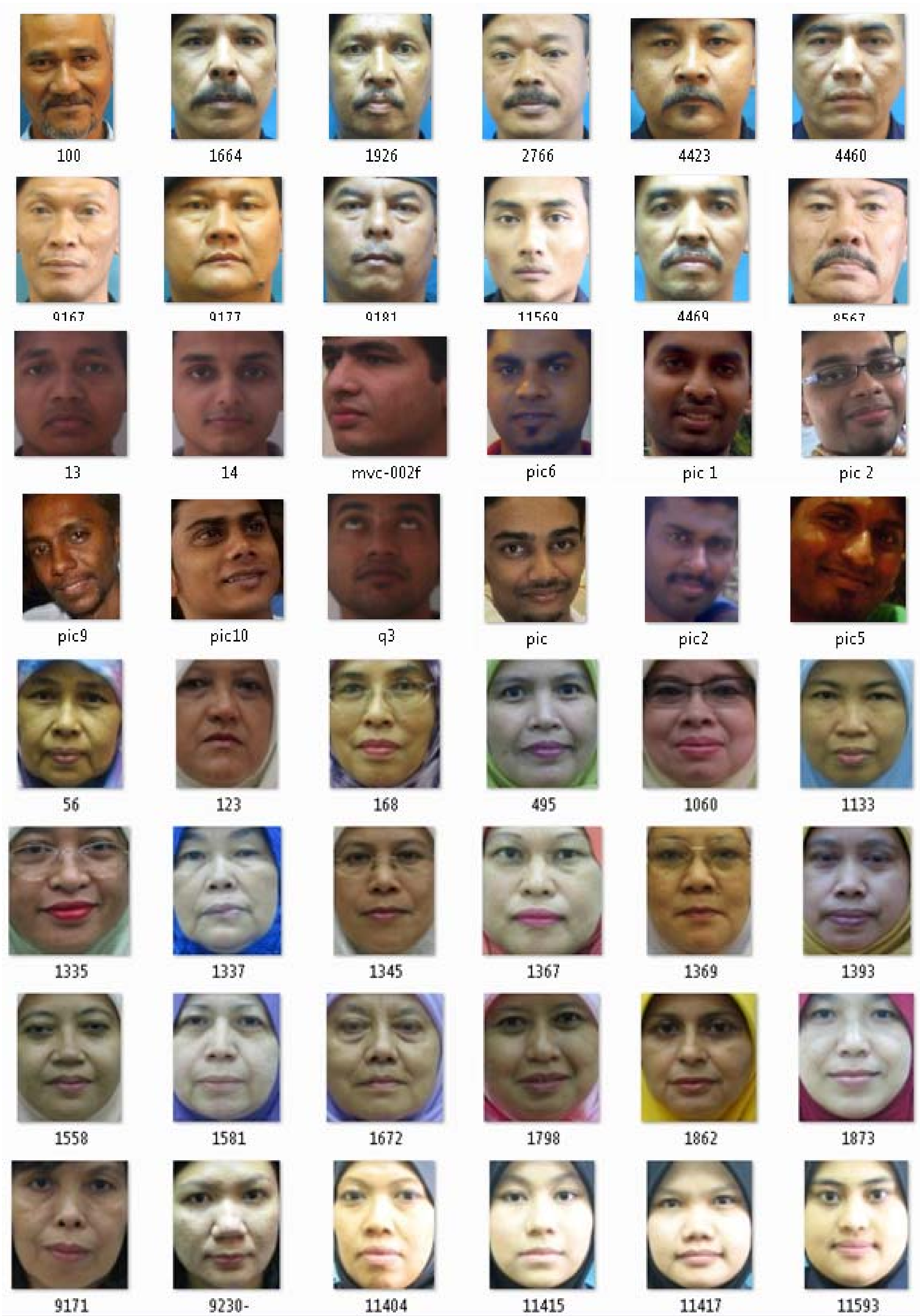


Figure 5.13: Samples of image variations that degraded ***The-ID*** system.

5.3 Practicality and Reliability

As what have been discussed in the previous section, face images are full with unique characteristic information. With the rich of information in a particular database, there are many ways of gaining the benefit of the ***The-ID*** classifier. If the ***The-ID*** is applied to a large database such as in a shopping complex or public areas, the ***The-ID*** may generate results of the statistical data of the percentage or fraction of how many Malay, Chinese or Indian are there, which age groups are dominant at that location or which gender is a majority in that area. However, the goal of ***The-ID*** system is not purely to determine these classes, but, to support or ease the process of face recognition, especially to tackle the understanding of unfamiliar facial recognition environment. On the other hand, the availability of identity statistical data might be useful and may be used such as by an authorized body and product development groups for advanced marketing study. In the broad areas of application, the ***The-ID*** may be used for segmenting the raw data of people in any database, such as regional appearance, gender and age classes as explained previously, where this data is ready to be used for any appropriate purposes. Of main concern, the ***The-ID*** system may also support the typical face recognition software by segmenting the database into small groups or classes where the matching process can be reduced drastically and recognition performance can be enhanced. This scenario can be seen positively in the case of dealing with huge size of database.

The experiments for both situations have been done and the results have been explained in the previous section. The practicality of the ***The-ID*** software can be generalized in any database as its appearance will not negatively influence any cooperation with other face recognition software. The rationale of the ***The-ID*** software integrity lies on the identity parameters (sub-classes) that are supported in the software. This is due to the fact that the recognition process is backed up with three different parameters to be searched for (regional appearance, gender and age). If the recognition result is not appropriate with the given input image, the user may try with the second and third identity parameter of classes. As the final output from the recognition or matching result given by the computer will be judged by human operator, the recognition process can always be repeated with any classes.

There are some facts about the controlled and uncontrolled environment. Indeed, for the purpose of applicable FRS and ***The-ID*** software, the environment can be strategically designed and planned as to create the controlled environment. Any places or spaces that will be occupied by people must have the access or entry point, such as the main entrance of a building. The building in this case may be an office building, commercial or shopping complex, a condominium or flat, an apartment or even a house.

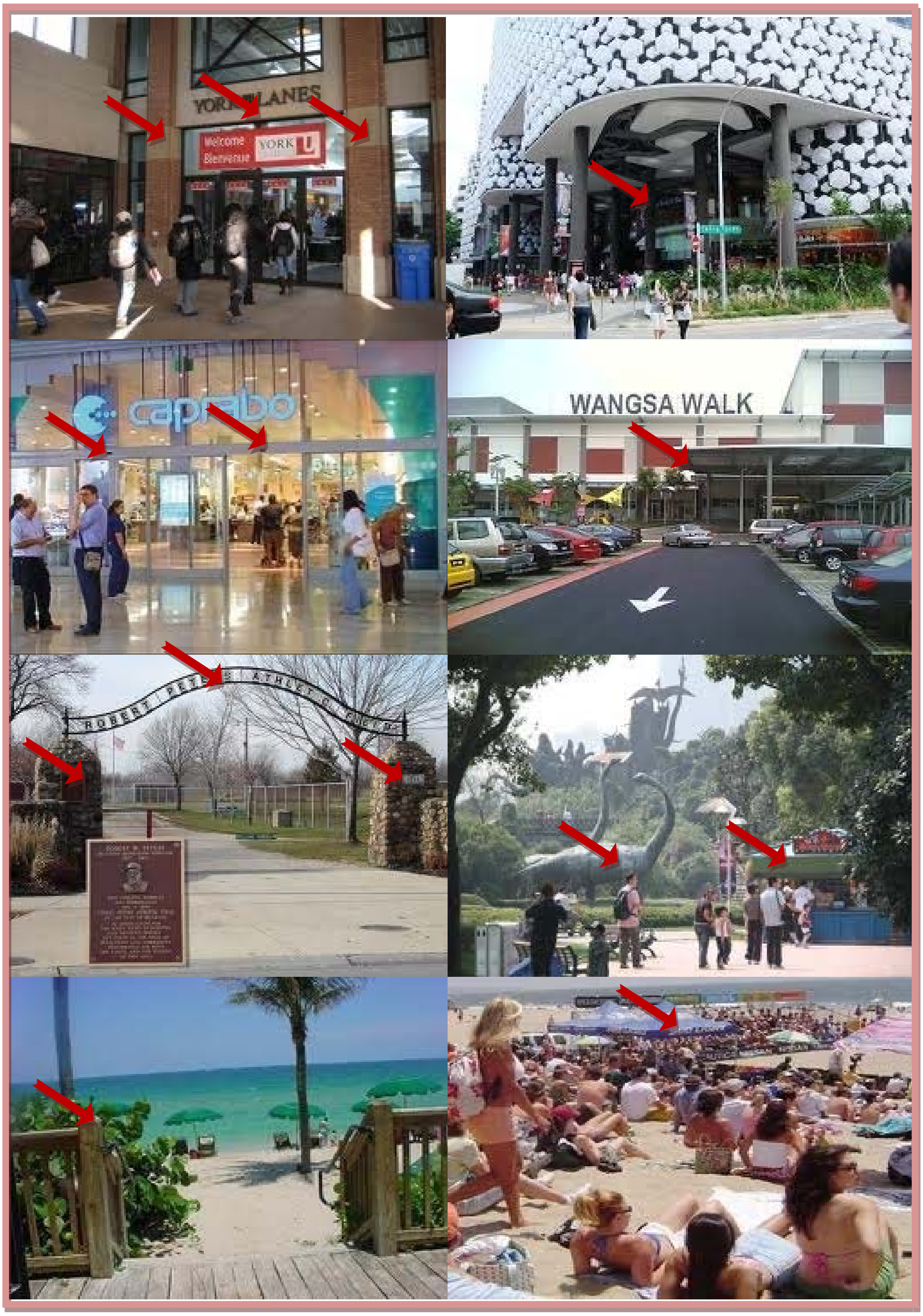


Figure 5.14: Various spaces or places of uncontrolled environment that can be manipulated in having a controlled environment of face recognition system by properly choosing the best spot for camera installation, such as marked by red arrows.

In the case of open spaces such as the park, beaches, or any environment that may allow the presence of crowd, the entrance can still be designed where the access can be managed and monitored systematically. Figure 5.14 explores some basic understanding about the environment discussed where the best spot for cameras installation must be properly chosen and determined, as proposed in the figures, marked by red arrows.

From figure 5.14 and from previous discussions, the design and installation of cameras can be done at an entrance accessible for face image acquisition. In fact this is important as with a proper arrangement of input acquisition, the image variations such as illumination, pose and expression can be reduced extensively. The reliability of the software can be further improved if the image variations can be reduced or managed efficiently.

CHAPTER SIX

CONCLUSIONS AND FUTURE WORKS

6. CONCLUSIONS AND FUTURE WORKS

6.1 Summary and Conclusions

The presence of large image variation problems in imaging process limits the task of vision system such as face recognition system to a specific application where the requirement must be pre-determined. The performance of such algorithm will be degraded dramatically under a different environment compared to the one used during an algorithm development and training.

This leads to the issue of robustness of the system. A robust system is not an easy task to achieve due to the dynamic problem of a 3D human head or face and the imaging process. In achieving reliable performance, the study of the variation problems has received a great deal of attention in developing face recognition algorithm. In general, the challenges can be classified into static and dynamic or video matching where different consideration for image quality, background clutter (from posing challenges to segmentation algorithm), matching criterion and type, amount and nature of user's input [15]. Among the variations, pose and illumination remain as common issues shared by the algorithms developed by system designers. This leads to the implication of application specification, the suitability of the approaches or methods, reliability and many more relevant issues.

Face recognition performed by human brain is far superior. A human can effortlessly judge the another person's face to describe the characteristic of that particular faces. However, in the machine environment this requires systematic processing stages as have been demonstrated in this thesis. The research has employed hierarchy approaches in extracting and classifying the three identity parameters. The uses of colour, grey level and binary images demonstrated in the thesis have shown there is a lot more that can be studied and explored in understanding the information or facial UCI that to be extracted. The outcome from this research could be a grounding for pursuing further study in the unfamiliar facial identity recognition environment.

A summary of what have been done in this thesis is given below.

❖ The comparison between familiar and unfamiliar facial recognition process and the needs for unfamiliar facial identity recognition application.

- ❖ The recognition performance has shown positive and tolerable results in variation complexity compensation and representation for extracting the required identity parameters based on the selected UCI mainly for the proposed unfamiliar facial identity recognition.
- ❖ The identity information enhancement is implicitly done by manipulating the three selected UCI (skin colour, facial texture and features) and breaking down the face classification into three identity parameters classification of regional appearance, gender and age recognition.
- ❖ Proposed hierarchy and hybrid approaches have demonstrated a competitive recognition performance and valuable information on various groups of people.

The novelty of the work contributed can be summarized as below:

(i.) The problem of variation complexity for 2D face images is handled by a hybrid technique taken from three conventional approaches (variation-modelling,-compensation and -independent) where the facial information availability can be fully utilized.

(ii.) The identity information enhancement is carried out by introducing the facial collateral unique characteristics information (UCI) where the proposed three types of UCI can be used and manipulated for regional appearance, gender and age classification (identity parameters) and recognition.

(iii.) The mechanism used in the classification task based on the skin colour, texture and overall features can be applied to all classes and sub-classes of proposed identity parameters where the matching processing time may reasonably be reduced as the classes are complementary.

(iv.) The algorithm is designed for unfamiliar facial registration and recognition performance enhancement where the targeted groups can be segmented based on the search request.

6.2 Proposed Future Works

As mentioned in Chapter One, research carried out in the thesis can be broadly classified into two blocks of experimental work as shown in figure 6.1. The two blocks are variation complexity reduction and identity information enhancement are supposed to have their own research attention with adequate time frames. However, with the scope of the objectives and purposes of the research, these two blocks are included in this thesis and should have been viewed with a reasonable outcomes and open for further research in the areas explained onward.

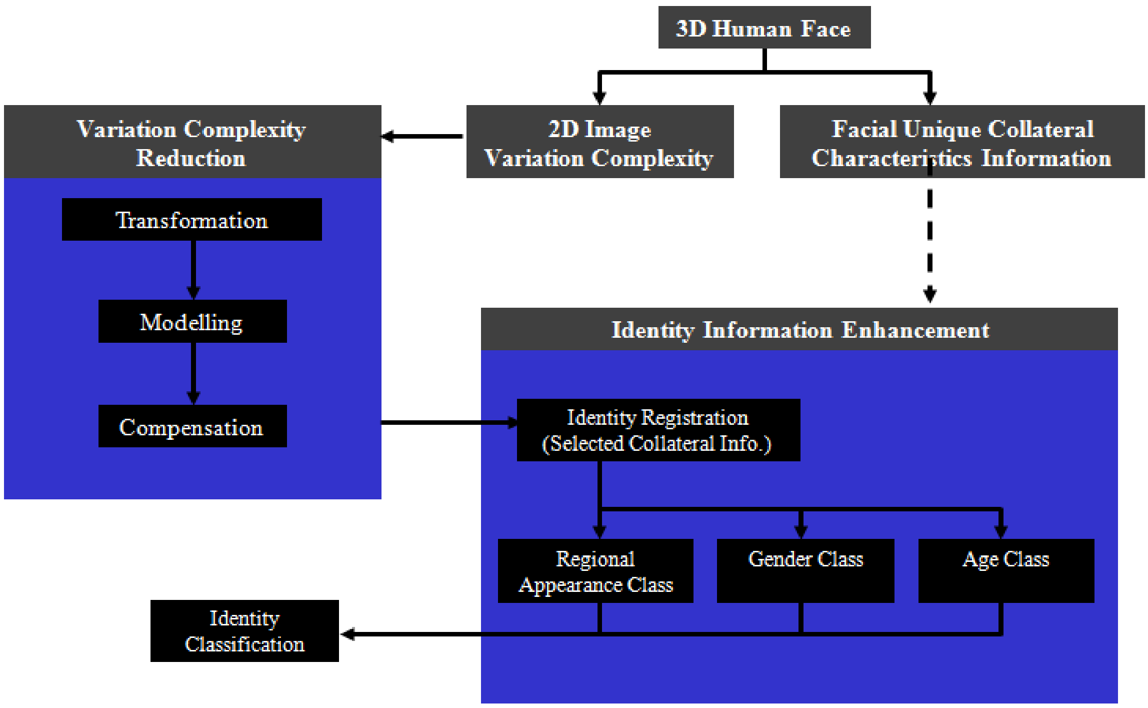


Figure 6.1: The work can be divided into two blocks; variation complexity reduction and identity information enhancement.

Variation complexity reduction has been divided into three consecutive sub-blocks, namely variation estimation (modelling), variation compensation (normalization) and transformation. The main objective of the block is to serve the proposed unfamiliar facial identity registration part. The proposed approach employs some kind of 'image post-mortem' taking into account all of the possibilities in reducing the variation whilst trying to maintain and extract the available UCI of the face image.

It also makes use of the significant factors from the three conventional groups approaches used in this research area. Future research could look into more detailed modelling and transforming of the compensated face image. This is important since the variation varies accordingly from one person to another thus the behaviour of the variation pattern might also reveal the dissimilarity information of a different person. It is hoped that by incorporating large variation complexity into a single face image, the analysis will bring the research up to a certain degree allowing understanding the dynamic of the face image accurately within a simple and realistic computational point of view. This needs further analysis and interpretation in the study such as illumination effect towards realizing the robustness of intelligent unfamiliar facial identity recognition system. The uses of colour, grey level and edge images will also be continuously studied.

In the second block of the research, the identity parameters into three classes (regional appearance, gender and age) from the available facial UCI is broken down. A further investigation into getting the facial UCI could be incorporated with the study of other type of UCI patterns such as the expression states, the level and measure of attractiveness attributes and other dynamic features that human perception always use to interpret any person. Figure 6.2(a) illustrates these issues from a various views of the person and opens a wide discussion.

It has been demonstrated that the availability of the information from the edge image is limited by the credibility of the edge detection. However, it has been shown that the limited UCI can still be used for age category recognition where the proposed measurement has been done. Future research could also focus on the way to extract the characteristic of each facial feature, such as their shape that reveal more meaning. In this case, features variation impact will be investigated seriously to improve the UCI to be represented.

The analysis of the facial UCI will be continuously studied in relation to other kinds of information extraction such as the relation between facial UCI and the weight and height estimation of the particular person where this kind of information may contribute more identity parameters. This is extendable to the selection of the input information to work onto. For instance, the video input might be giving other raw input such as the consistency of the facial movement of the person. All of these are open to the future research including to generate more facial UCI and derive more identity parameters for recognition performance enhancement. Some of these are shown in figure 6.2(a) and (b) for future interest attention.

Finally, the system software developments will also be of future research interest in realizing the outcomes of the current research. This is important and of benefit to the research development in term of continuity of the data collection and is applicable to the new research environment. The application can be implemented for authority and commercial purposes with reasonable expectation.

(a)

(b)

Figure 6.2: The study of UCI similarity and dissimilarity differences and changes. (a) Attractiveness attributes (sexy, cute, handsome, beauty, gentle and many more). (b) The growing of UCI and the prediction of the future changes.

REFERENCES

REFERENCES

[1] Vicki Bruce, Peter J.B. Hancock, and Mike Burton, "Human Face Perception and Identification," in Wechsler, Harry (ed.) et al., *Face recognition. From theory to Applications. Proceedings of the NATO ASI,* Stirling, Scotland, GB, June 23 - July 4, 1997. Berlin: Springer (ISBN 3-540-64410-5). NATO ASI Ser., Ser. F, Computer Syst. Sci. 163, pp. 51-72.

[2] Irving Biederman and Peter Kalocsai, "Neural and Psychophysical Analysis of Object and Face Recognition", in Wechsler, Harry (ed.) et al., *Face recognition. From theory to Applications. Proceedings of the NATO ASI,* Stirling, Scotland, GB, June 23 - July 4, 1997. Berlin: Springer (ISBN 3-540-64410-5). NATO ASI Ser., Ser. F, Computer Syst. Sci. 163, (1998), pp. 3-25.

[3] Rafael C. Gonzalez and Richard E. Woods, "Digital Image Processing", Second Edition, Prentice Hall, 2002.

[4] Michael J. Lyons and Shigeru Akamatsu, "Coding Facial Expressions with Gabor Wavelets", *in Proceedings, Third IEEE International Conference on Automatic Face and Gesture Recognition,* April 4-16, 1998, Nara Japan, IEEE Computer Society, pp. 200-205.

[5] L.C. Jain et al, "Intelligent Biometric Techniques in Fingerprint and Face Recognition", *CRC Press International Series on Computational Intelligence*, 1999.

[6] W. Zhao et al, "Face Recognition: A Literature Survey", Sarnoff Corporation and University of Maryland, 2000.

[7] W. Zhao, R.Chellappa, P.J. Phillips, A. Rosenfeld, "Face Recognition: A Literature Survey", *ACM Computing Surveys, Vol. 35, No. 4,* December 2003, pp 399-458.

[8] King-Sun Fu, and Azriel Rosenfeld, "Pattern Recognition and Image Processing", *IEEE Transactions On Computers,* vol. C-25, No. 12, December, 1976, pp. 1336-1345.

[9] Yu-Chi Ho and Ashok K. Agrawala**, "**On Pattern Classification Algorithms: Introduction and Survey", in *Proc. Of the IEEE.* Vol. ***56.*** NO.12, December 1968, pp. 2101-2114.

[10] Martin D. Levine, "Feature Extraction : A Survey", *Proceedings Of The IEEE.* Vol. 57. No. 8, August 1969, pp. 1391-1407.

[11] Laveen K-Anal, "Patterns in Pattern Recognition : 1968-1974" *IEEE Transaction on Information Theory*, VOL. IT-20, No. 6, November 1974 697 -722.

[12] Sanjeev R. Kulkarni, G´abor Lugosi, and Santosh S. Venkatesh, "Learning Pattern Classification-A Survey", *IEEE Transactions On Information Theory*, Vol. 44, No. 6, October 1998, pp. 2178 – 2206.

[13] King-Sun Fu, "Recent Developments in" Pattern Recognition", *IEEE Transactions On Computers*, Vol. c-29, No. 10, October 1980, pp. 845 – 854.

[14] Shital Raut, M Raghuvanshi, R. Dharaskar, Adarsh Raut, "Image Segmentation – A State-Of-Art Survey for Prediction"**,** *IEEE International Conference on Advanced Computer Control* 2008, pp. 420 – 424.

[15] Ronaldo C. Prati, Gustavo E.A.P.A. Batista, and Maria Carolina Monard," A Survey on Graphical Methods for Classification Predictive Performance Evaluation", *IEEE Transactions On Knowledge And Data Engineering*, Vol. 23, No. 11, November 2011, pp. 1601 – 1618.

[16] Louis C. W. Pols, "Real-Time Recognition of Spoken Words", *IEEE Transactions On Computers*, Vol. C-20, No. 9, September 1971, pp. 972 – 978.

[17] Oliver Sidla, Lucas Paletta, Yuriy Lypetskyy, and Christian Janner, " Vehicle Recognition for Highway Lane Survey", 2004 *IEEE Intelligent Transportation Systems Conference TuB5.3* Washington, D.C., USA, October 34, 2004, pp**.** 531 -536.

[18] S. N. Yanushkevich**, "**Synthetic Biometrics: A Survey", 2006 *International Joint Conference on Neural Network*s, Sheraton Vancouver Wall Centre Hotel, Vancouver, BC, Canada, July 16-21, 2006676 – 683.

[19] Pavan Turaga, Rama Chellappa, V. S. Subrahmanian, and Octavian Udrea, " Machine Recognition of Human Activities: A Survey", *IEEE Transactions On Circuits And Systems For Video Technology*, Vol. 18, No. 11, November 2008, pp. 1473 -1488.

[20] Stathis, P.; Kavallieratou, E.; Papamarkos, N., "An Evaluation Survey of Binarization Algorithms on Historical Documents", *Pattern Recognition, 2008. ICPR 2008. 19th International Conference on*, 2008, pp. 1 – 4.

[21] Zhihong Zeng, Maja Pantic, "A Survey of Affect Recognition Methods: Audio, Visual, and Spontaneous Expressions", *IEEE Transactions On Pattern Analysis And Machine Intelligence*, Vol. 31, No. 1, January 2009 39.

[22] Abarghouei, A.A.; Ghanizadeh, A.; Sinaie, S.; Shamsuddin, S.M. A Survey of Pattern Recognition Applications in Cancer Diagnosis 2009, *International Conference of Soft Computing and Pattern Recognition*, 448 – 453.

[23] David Gero´nimo, Antonio M. Lo´ pez, Angel D. Sappa, and Thorsten "Graf Survey of Pedestrian Detection for Advanced Driver Assistance Systems", *IEEE Transactions On Pattern Analysis And Machine Intelligence*, Vol. 32, No. 7, July 2010 1239-1258.

[24] Debashis Ghosh, Tulika Dube, and Adamane P. Shivaprasad, "Script Recognition - A Review", *IEEE Transactions On Pattern Analysis And Machine Intelligence*, Vol. 32, No. 12, December 2010, pp. 2142 2161.

[25] Meng-Yin Fu and Yuan-Shui Huang, "A Survey Of Traffic Sign Recognition**"** in *Proceedings of the 2010 International Conference on Wavelet Analysis and Pattern Recognition*, Qingdao, 11-14 July 2010, pp. 119 -124.

[26] Juan Zhang and Xin-yuan Huang, "A Survey of Plant Recognition Method Based on Image Processing", 2010 *International Conference on Electrical and Control Engineering*, pp. 4974-4977.

[27] S. G. Djorgovski, C. Donalek, A. Mahabal, R. Williams, A.J. Drake, M.J. Graham, E. Glikman, “Some Pattern Recognition Challenges in Data-Intensive Astronomy”, *Proceedings of the 18th International Conference on Pattern Recognition (ICPR'06),* 2006 , Page(s): 856 - 863

[28] Zhouyu Fu, Guojun Lu, Kai Ming Ting, and Dengsheng Zhang “A Survey of Audio-Based Music Classification and Annotation” IEEE *Transactions On Multimedia*, Vol. 13, No. 2, April 2011 303 – 319.

[29] Oluwatoyin P. Popoola, and Kejun Wang “Video-Based Abnormal Human Behavior Recognition **-** A Review” IEEE *Transactions On Systems, Man, And Cybernetics-Part C: Applications And Reviews,* pp 1 – 14.

[30] Kevin W. Bowyer, Kyong Chang, and Patrick Flynn **“**A Survey Of Approaches To Three-Dimensional Face Recognition” in *Proceedings of the 17th International Conference on Pattern Recognition (ICPR’04)*

[31] Kresimir Delac I **,** Mislav Grgic **“**A Survey Of Biometric Recognition Methods,” *46th International Symposium Electronics in Marine. ELMAR-2004.* 16-18 June 2004. Zadar. Croatia, 184-193.

[32] Yun Fu, Guodong Guo, and Thomas S. Huang, “Age Synthesis and Estimation via Faces: A Survey”, *IEEE Transactions On Pattern Analysis And Machine Intelligence,* Vol. 32, No. 11, November 2010, pp. 1955 -1976.

[33] Di Huang, Caifeng Shan and Mohsen Ardabilian, “Local Binary Patterns and Its Application to Facial Image Analysis: A Survey”, *IEEE Transactions On Systems, Man, And Cybernetics—Part C: Applications And Reviews*, Vol. 41, No. 6, November 2011 765 - 781.

[34] Zheng, Yufeng; Elmaghraby, Adel, “A Brief Survey on Multispectral Face Recognition and Multimodal Score Fusion”, *Signal Processing and Information Technology (ISSPIT), IEEE International Symposium on*, 2011, pp. 543-550.

[35] Shaogang Gong, Stephen J McKenna, Alexandra Psarrou, “Dynamic Vision: From Images to Face Recognition”, Imperial College Press, 2001.

[36] Peter L. Hallinan, Gaile G. Gordon, A.L. Yuille Peter Giblin, David Mumford, “Two-and Three-Dimensional Patterns of the Face”, AK Peters Natick, Massachussets, 1999.

[37] Rama Chellappa et. Al, “Human and Machine Recognition of Faces: A Survey”, *Proceedings of the IEEE Vol. 83, No. 5*, May 1995.

[38] Yongmin Li, “Dynamic Face Models: Construction and Applications”, *PhD Thesis, Depart. of Computer Science Queen Mary, University of Lond*on, 2001.

[39] Julian Ashbourn, “Biometrics: Advanced Identity Verification: The Complete Guide”, Springer, 2000.

[40] Terence Mong-Cheng Sim, “Statistics-Based Face Rendering and Its Application to Face Recognition”, *PhD Thesis, Carnegie Mellon Univ*ersity, (Electrical & Computer Eng), Pittsburgh, Pennsylvania, June 2002.

[41] M.Z. Adam, S. Datta, "*Variation Complexity Compensation in Limited Information Face Expression Recognition*", International Conference on Robotics, Vision, Information and Signal Processing (**ROVISP 2005**): Penang, Malaysia 20-22 July 2005.

[42] W. Zhao and R. Chellappa. "*Image based face recognition, issues and methods*". In B. Javidi, editor, Image Recognition and Classification, pages 375–402.

[43] Aziz Umit Batur, "Illumination-Robust Face Recognition", *PhD Thesis, School of Electrical and Computer Engineering, Georgia Institute of Technology,* July 2003.

[44] W.Zhao, Rama Chellappa, "Robust Face Recognition Using Symmetric Shape-from-Shading", Center for Automation Research and Electrical and Computer Engineering Department, University of Maryland, College Park, 1999.

[45] Terence Sim and Takeo Kanade, "Combining Models and Exemplars for Face Recognition: An Illuminating Example", *Proceedings of Workshop on Models versus Exemplars in Computer Vision, CVPR,* 2001.

[46] Haitao Wang , Stan Z. Li , Yangsheng Wang , Weiwei Zhang, "Illumination Modelling and Normalization for Face Recognition", *Proc.of IEEE Int. Workshop on Analysis and Modeling of Faces and Gestures,2003.*

[47] Jiali Zhao et. al, "Illumination ratio image: synthesizing and recognition with varying illuminations", *Pattern Recognition Letters* 24 (2003) 2703-2710, Elsevier-Science Direct, 2003.

[48] P. Jonathon Phillips et. al, "Efficient Illumination Normalization of Facial Images", *Pattern Recognition Letters 17* (1996) 921-927, Elsevier-Science Direct, 1996.

[49] Athinodoros S. Georghiades et al, "Illumination Cones for Recognition Under Variable Lighting: Faces", *IEEE Conf. On Computer Vision and Pattern Recognition,* 1998.

[50] Jeff Ho and K.C. Lee and David Kriegman, "On Reducing the Complexity of Illumination Cones for Face Recognition", *IEEE CVPR Workshop on Identifying Objects Across Variations in Lighting,* 2001, pp. 56-63.

[51] Wendy L. Braje, "Illumination Encoding in Face Recognition: Effect of Position Shift", *Journal of Vision (2003)* 3, 161-170, 2003.

[52] Amnon Shashua et al, "The Quotient Image: Class-Based Re-Rendering and Recognition With Varying Illuminations", *IEEE Trans. On Pattern Analysis and Machine Intelligence,* Vol. 23, No. 2, Feb 2001.

[53] Athinodoros S. Georghiades, "From Few to Many: Illumination Cone Models for Face Recognition Under Variable Lighting and Pose", *IEEE Trans. On Pattern Analysis and Machine Intelligence, Vol. 23, No 6*, June 2001.

[54] Ronen Basri, "Lambertian Reflectance and Linear Subspaces", *IEEE Trans. On Pattern Analysis and Machine Intelligence, Vol. 25, No 2,* Feb. 2003.

[55] A.U. Batur and M.H. Hayes III, "Segmented Linear Subspaces for Illumination-Robust Face Recognition", *International Journal of Computer Vision 57(1) 49-66, Kluwer Academic Publishers*, 2004.

[56] Horst Bischof, "Illumination Insensitive Recognition Using Eigenspaces", *Computer Vision and Image Understanding, Elsevier,* 2004

[57] Kwang Nam Choi et al, "Estimating facial pose using shape-from-shading", *Pattern Recognition Letters, Elsevier,* 2001.

[58] Jinho Lee, Baback Moghaddam et al, "Finding Optimal Views for 3D Face Shape Modelling", *IEEE AFGR'04, 2004.*

[59] Claude C. Chibelushi et al, "Facial Expression Recognition: A Brief Tutorial Overview", School of Computing, Staffordshire University, UK, 2002.

[60] Maja Pantic & Leon J.M. Rothkrantz, "Automatic Analysis of Facial Expressions: The State of the Art", *IEEE Transactions on Pattern Analysis and Machine Intelligence,* Vol. 22, No. 12, Dec. 2000.

[61] B. Fasel et al, "Automatic Facial Expression Analysis: A Survey", *Pattern Recognition 36 (2003) 259*-275, *Elsevier* 2003.

[62] James Jenn-Jier lien and Takeo kanade, "A Multi-Method Approach for Discriminating Between Similar Facial Expressions, Including Expression Intensity Estimation", *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition,* June 1998.

[63] Lien, Kanade, Cohn & Li, "Detection, Tracking and Classification of Action Units in Facial Expression, Journal of Robotics and Autonomous", *Journal of Robotics and Autonomous Systems,* July 1999.

[64] Karen L. Schmidt and Jeffrey F. Cohn, "Human Facial Expressions as Adaptations: Evolutionary Questions in Facial Expression Research", *Yearbook of Physical Anthropology 44:3-24* (2001).

[65] A. Mehrabian, "Communication Without Words ", *Psychology Today, Vol 2 No 4, pp. 53-56*, 1968.

[66] Gianluca Donata et al, *"Classifying Facial Actions", IEEE Trans. On Pattern Analysis and Machine Intelligence, Vol 21, No 10 Oct. 1999.*

[67] Ying-li Tian, "Recognizing Action Units for Facial Expression Analysis", *IEEE Trans on Pattern Analysis and Machine Intelligence, Vol 23 No 2*, Feb 2001.

[68] Ying-li Tian, Takeo Kanade and Jeffrey F. Cohn, "Recognizing Facial Actions by Combining Geometric Features and Regional Appearance Patterns", Robotics Institute, Carnegie Mellon Uni, 2001.

[69] Shaohua Kevin Zhou and Rama Chellapa, "Image-Based Illumination- and Pose-Invariant Face Recognition: Illuminating Light Field", Center for Automation Research, University of Maryland, College Park, *2004 Optical Society of America*.

[70] Ralph Gross et al, "Fisher Light-Fields for Face Recognition Across Pose and Illumination", The Robotics Institute, Garnegie Mellon University, 2000.

[71] V. Blanz et al, "Face Identification across Different Poses and Illuminations with a 3D Morphable Model",University of Freiburg, Germany, 2000.

[72] Florica Mindru et al, “Moment Invariants for Recognition Under Changing Viewpoint and Illumination”, *Computer Vision and Image Understanding, Elsevier* 2004.

[73] Kin-Man Lam et al. “ An Analytic-to-Holistic Approach for Face Recognition Based on a Single Frontal View”, *IEEE Trans. On Pattern Analysis and Machine Intelligence,* Vol. 20, No. 7, July 1998.

[74] Michael J. Lyons, et al, “Automatic Classification of Single Facial Images”, *IEEE Trans. On Pattern Analysis and Machine Intelligence, Vol. 21, No 12*, Dec. 1999.

[75] Jianxin Wu et al, “Face Recognition With One Training Image Per Person”, *Pattern Recognition Letters 23 (2002)* 1711-1719, Elsevier Science B.V.

[76] Thomas Vetter, “Learning Novel Views to a Single Face Image”, *Proceedings of the second International Conference on Automatic Face and Gesture Recognition* , 1996.

[77] Michael A. Penna, “A Shape from Shading Analysis for a Single Perspective Image of a Polyhedron”, *IEEE Trans on Pattern Analysis and Machine Intelligence, Vol 11 No 6* June 1989.

[78] Thomas Vetter, ”Synthesis of novel views from a single face image”, Technical Report No 26, Max-Planck-Institute, Germany 1996.

[79] Collings, S.; Kozera, R.; Noakes, L, “A Piecewise Quadratic Approach to Single Image Shape from Shading”, *Pattern Recognition, 2002. Proceedings. 16th International Conference on* , pp. 126 - 129 vol.4.

[80] Ruo Zhang; Ping-Sing Tsai; Cryer, J.E.; Shah, M., “Shape from Shading:A Survey”, *Pattern Analysis and Machine Intelligence, IEEE Transactions on,* Volume: 21 , Issue: 8 , 1999 , pp. 690 – 706.

[81] Jean-Denis Durou, “Numerical Methods for Shape from Shading: A Survey with Benchmarks”, Institute de Recherche en Informatique de Toulouse, Universite’ Paul Sabatier, France, 2007.

[82] Joseph J. Atick et al, “Statistical Approach to Shape from Shading: Reconstruction of 3D Face Surfaces from Single 2D Images, Computational Neuroscience Laboratory, The Rockefeller University,NY, 1997.

[83] Philip L. Worthing and Edwin R. Hancock, “Object Recognition Using Shape-from-Shading”, *IEEE Trans. On Pattern Analysis and Machine Intelligence*, Vol. 23, No. 5, May 2001.

[84] Atilla Giiltekin and Muhittin Gokmen, “Adaptive Shape from Shading”, *ELEKTRIK, Vol 6, No 2* 1998

[85] Tianzi Jiang, “A Neural Network Approach to Shape from Shading”, School of Mathematics The University of New South Wales, Sydney, 1999.

[86] Aleix M. Martinez, “Recognizing Imprecisely Localized, Partially Occluded and Expression Variant Faces from a Single Sample per Class”, *IEEE Trans. On Pattern Analysis and Machine Intelligence, Vol 24, No 5*, June 2002.

[87] Ralph Gross, Jianbo Shi, Jeffrey F. Cohn, "Quo vadis Face Recognition", Carnegie Mellon University, 2001.

[88] Betul Karaomeroglu and Reza Hassanpour, "A Comparative Study of Human Face Identification in Presence of Illumination, Occlusion and Expression", *International XII Turkish Symposium on Artificial Intelligence and Neural Networks – TAINN* 2003.

[89] P.Kakumanu et al,"A Survey of Skin-Colour Modeling and Detection Methods", *Pattern Recognition 40 (2007)* 1106-1122, ScienceDirect, Elsevier.

[90] J. D. Foley, A. Van Dam, S. K. Feiner and J. F. Hughes, "Computer Graphics, Principles and Practice", Second edition, Addison-Wesley publishing company, 1990.

[91] Zhi-Ming Liu et al., "Extraction of Face Regions in Color Image*", IEEE Machine Learning and Cybernetics, 2002. Proceedings. 2002 International Conference on* 2002. Volume: 3**,** pp. 1340 - 1343 vol.3

[92] Ming Hu, Qiang Zhang and Zhiping Wang, "Application of Rough Sets to Image Pre-Processing for Face Detection", *Information and Automation, 2008. ICIA 2008. International Conference on*, 2008, pp 545 – 548.

[93] Ganapathi, T.Plataniotis, K.N. Ro, Y.M T., "Boosting Chromatic Information for Face Recognition", *Electrical and Computer Engineering, 2008. CCECE 2008. Canadian Conference on,* 2008 , pp. 000611 – 000614.

[94] Yan-Wen Wu and Xue-Yi Ai, "Face Detection in Color Images Using AdaBoost Algorithm Based on Skin Color Information", *IEEE Workshop on Knowledge Discovery and Data Mining, 2008.*

[95] Wei Lu, Yi Xu, Xiaokang Yang and Li Song, "Local Quaternionic Gabor Binary Patterns for Color Face Recognition", *Acoustics, Speech and Signal Processing, 2008. ICASSP 2008. IEEE International Conference on*, 2008 , pp. 741 – 744.

[96] Jones, C. and Abbott, A.L., "Color Face Recognition by Hypercomplex Gabor Analysis", *Automatic Face and Gesture Recognition, 2006. FGR 2006. 7th International Conference on,* 2006, pp. 6 – 131.

[97] Chengzhang Wang et al., "Color Face Recognition Based on 2DPCA", *IEEE* 2008.

[98] Chi-Ho Chan et al., "Multispectral Local Binary Pattern Histogram for Component-based Color Face Verification", *IEEE* 2007.

[99] Jae Young Choi et al., "Color Effect on the Face Recognition with Spatial Resolution Constraints", *IEEE* 2008.

[100] Cordelia Schmid, Roger Mohr, "Local Gray Value Invariants for Image Retrieval*", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 19, No. 5, May 1997.*

[101] Kuijper, A.; Florack, L.M.J, "The Hierarchical Structure of Images" *Image Processing, IEEE Transactions on,* Volume 12, Issue: 9, 2003, pp. 1067 – 1079.

[102] Mihran Tuceryan and Anil K. Jain,"The Handbook of Pattern Recognition and Computer Vision (2^{nd} Edition)" by C.H. Chen, L.F. Pau, P.S.P. Wang (eds.), *Chapter 2, pp. 207-248, World Scientific Publishing Co., 1998.*

[103] A.Materka and M.Strzelecki, “Texture Analysis Methods – A Review”, *COST B11 report.* Institute of Electronics, Technical University of Lodz, , Brussels 1998.

[104] Robert M. Haralick et al, “Textural Features for Image Classification”, *IEEE Transaction on Systems, Man and Cybernatics, Vol. SMC-3, No. 6, November 1973.*

[105] MATLAB Image Processing Toolbox, User’s Guide, Author, Mathworks, Inc. Publisher, The MathWorks, 2002.

[106] Larry S.Davis et al., “Texture Analysis Using Generalized Co-Occurrence Matrices”, *IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. PAMI-1, No.3, July 1979.*

[107] Guoillermo Ayala, Juan Domingo, “Spatial Size Distributions: Applications to Shape and Texture Analysis”, *IEEE Transactions on Pattern Analysis and Machine Intelligence,* Vol.23, No.12, December 2001.

[108] Patel, M.B.; Rodriguez, J.J.; Gmitro, A.F. “Effect of Gray-Level Re-Quantization on Co-Occurrence Based Texture Analysis”, *Image Processing, 2008. ICIP 2008. 15th IEEE International Conference on,* 2008, pp. 585 – 588.

[109] Ara V. Nefian, “Statistical Approaches To Face Recognition”, *A Qualifying Report of PhD Research,* School of Electrical Eng.,Georgia Institute of Technology, 1996.

[110] Fazhen Yi; Xin Feng; Zhenshen Qu, “Face Features Detection and Representation by Morphological Reconstruction and Linking”, *Systems and Control in Aerospace and Astronautics, 2008. ISSCAA 2008. 2nd International Symposium on,* 2008 , pp. 1- 6.

[111] Guillaume Heusch et al., “Local Binary Patterns as an Image Pre-Processing for Face Authentication”, *Proceedings of the 7th International Conference on Automatic Face and Gesture Recognition (FGR’06), IEEE 2006.*

[113] Mohammadreza Asghari Oskoei and Huosheng Hu, “A Survey on Edge Detection Methods”, *Technical Report: CES-506*, University of Essex, Feb.2010.

[114] John Canny, “A Computational Approach to Edge Detection”, *IEEE Transactions On Pattern Analysis and Machine Intelligence, Vol. PAMI-8, No. 6, November 1986.*

[115] Alessandro Ledda et al., “Quantitative Image Analysis with Mathematical Morphology”, CiteSeer, 2000.

[116] Foltyniewicz, R., “Automatic Face Recognition via Wavelets and Mathematical Morphology”, *Proceedings of the 13th International Conference on Pattern Recognition, 1996*, 1996 , pp. 13 - 17 vol.2.

[117] Foltyniewicz, R.; Sitnik, M. “Verification of Persons via Face and Signature Analysis”, *Image Processing, Proceedings of International Conference on*, 1996, pp. 495 - 498 vol.3.

[118] Jong Bae Kim; Chae Hyun Moon; Hang Joon Kim, “Wavelet-based Morphological Approach for Detection of Human Face Region”, *Pattern Recognition, 2002. Proceedings of 16th International Conference on,* 2002 , pp. 417 - 420 vol.1.

[119] Kotropoulos, C.; Pitas, I., "Face Authentication Based on Morphological Grid Matching", *Image Processing, 1997. Proceedings., International Conference on* Volume: 1, 1997 , pp. 105 - 108 vol.1.

[120] Tefas, A.; Kotropoulos, C.; Pitas, I., "Variants of Dynamic Link Architecture Based on Mathematical Morphology For Frontal Face Authentication", *Computer Vision and Pattern Recognition, 1998. Proceedings of IEEE Computer Society Conference on, pp.* 814 – 819.

[121] Kotropoulos, C.; Tefas, A.; Pitas, I.C.. "Face Authentication Using Variants of Elastic Graph Matching Based on Mathematical Morphology That Incorporate Local Discriminant Coefficients", *Acoustics, Speech and Signal Processing, 1998. Proceedings of the 1998 IEEE International Conference on,* 1998 , pp. 3729 - 3732 vol.6.

[122] C. Kotropoulos et al., "Morphological Elastic Graph Matching Applied to Frontal Face Authentication Under Optimal and Real Conditions", *Multimedia Computing and Systems, 1999. IEEE International Conference on,* 1999, pp. 934 - 938 vol.2.

[123] Kotropoulos, C.; Tefas, A.; Pitas, I., "Face Authentication Based on Morphological Shape Decomposition", *Image Processing and Its Applications, 1997., Sixth International Conference on,* Volume: 2, 1997, pp. 794 - 798 vol.2.

[124] Tefas, A. Kotropoulos, C. and Pitas, I., "Face Verification based on Morphological Shape Decomposition", *Automatic Face and Gesture Recognition, 1998. Proceedings. Third IEEE International Conference on* , 1998 , pp. 36 – 41.

[125] Raducanu B.and Grana, M., "Face localization based on the morphological multi-scale fingerprint ", *Pattern Recognition, 2000. Proceedings. 15th International Conference on Volume: 2,* 2000, pp. 925 - 928 vol.2.

[126] Juanjuan Wang; Lifang Wu; Xiaoguang He, "A New Method of Illumination Invariant Face Recognition", *Innovative Computing, Information and Control, 2007. ICICIC '07. Second International Conference on*, 2007, pp. 139 – 139.

[127] Veronique Clement and Monique Thonnat, "Handling knowledge in image processing libraries to build automatic systems.", *International Workshop on Industrial Applications of Machine Intelligence and Vision (MIV-89),* Tokyo, April 10-12, 1989.

[128] Kohl, C.; Mundy, J., "The Development of the Image Understanding Environment." *Computer Vision and Pattern Recognition, 1994. Proceedings CVPR '94., 1994 IEEE Computer Society Conference on* , 1994 , pp. 443 – 447.

[129] C.Cracknell and A.C.Downton, "TABS: script-based software framework for research in image processing, analysis and understanding." *IPA97 Special Section, 1997.*

[130] Michael Wolverto et.al, "Software Supported Pattern Development in Intelligence Analysis", *IEEE International Conference on Computational Intelligence for Homeland Security and Personal Safety*, Alexandria, VA, USA, 16-17 October 2006.

[131] Ibrahim, R and Zin, Z.M., "Study of Automated Face Recognition System for Office Door Access Control Application", *Communication Software and Networks (ICCSN), 2011 IEEE 3rd International Conference on,* 2011 , pp. 132 – 136.

BIBLIOGRAPHY

BIBLIOGRAPHY

[1] Nello Zuech, “Applying Machine Vision”, *John Wiley & Sons, Inc.*, 1988.

[2] E.R. Davies, “Machine Vision, Theory, Algorithms, Practicalities, 2nd Edition, *Academic Press*, 1997.

[3] Vicki Bruce, “Face Recognition, A Special Issue of the European Journal of Cognitive Psychology”, Lawrence Erlbaun Associates Publishers, 1991.

[4] Gita Sukthankar, “Face Recognition: A Critical Look at Biologically-Inspired Approaches”, The Robotics Institute, Carnegie Mellon University, Pennsylvania, 2000.

[5] Thomas Fromherz, “Face Recognition: A Summary of 1995-1997”, International Computer Science Institute, Berkeley, 1998.

[6] Conrad Sanderson, “Automatic Person Verification Using Speech and Face Information”, PhD Thesis, Faculty of Engineering & Information Technology, Griffith University, Feb. 2003.

[7] Wen Yi Zhao and Rama Chellappa, “SFS Based View Synthesis for Robust Face Recognition”, Center for Automation Research, University of Maryland, 2000.

[8] Terence Sim et. al, “The CMU Pose, Illumination and Expression (PIE) Database”, International Conference on automatic Face and Gesture Recognition, 2002.

[9] Anil K. Jain et al, “Statistical Pattern Recognition: A Review”, *IEEE Trans. On Pattern Analysis and Machine Intelligence, Vol. 22, No 1*, 2000.

[10] P.Jonathon Phillips et. al, “The FERET Evaluation Methodology for Face-Recognition Algorithms”, *IEEE Trans. On Pattern Analysis and Machine Intelligence, Vol 22 No 10* Oct 2000.

[11] Dibyendu Nandy and Jezekiel Ben-Arie, “Shape from Recognition: A Novel Approach for 3D Face Shape Recovery”, *IEEE Trans. On Image Processing, Vol. 10, No 2*, Feb. 2001.

[12] Tirkaz, C. and Albayrak, S., “Face Recognition Using Active Appearance Models”, Signal Processing and Communications Applications Conference, 2009, pp. 940 – 943.

[13] Ralph Gross, “Appearance-based Face Recognition and Light-Fields”, *IEEE Trans. On Pattern Analysis and Machine Intelligence, Vol. 26, No 4*, April 2004.

[14] Syed A. Rizvi, “The FERET Verification Testing Protocol for Face Recognition Algorithms”, *Technical report NISTIR 6281*, Oct. 1998.

[15] D. Bolme, R. Beveridge, M. Teixeira and B. Draper, “The CSU Face Identification Evaluation System: Its Purpose, Features and Structure”, *International Conference on Vision Systems*, Springer-Verlag, pp 304-311, Graz, Austria, April 1-3, 2003.

[16] Conrad Sanderson, Kuldip K. Paliwal, "Fast Features for Face Authentication Under Illumination Direction Changes", *Pattern Recognition Letters, Elsevier*, 2003.

[17] R. Triyogo Atmodipoero et al, "Research on Minimum Illumination as a Function of Visual Performance", *Energy and Buildings Elsevier*, 2004.

[18] Alice J. O'Toole and Herve Abdi, "Models of Face Recognition", *Encyclopedia of the Social and Behavioral Sciences, London Elsevier Science*, 2001.

[19] Terence Sim, Simon Baker and Maan Bsat, "The CMU Pose, Illumination and Expression Database", *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, Volume: 25, Issue: 12, 2003, pp. 1615 – 1618.

[20] Yongsheng Gao et al, "Facial Expression Recognition From Line-based Caricatures", *IEEE Trans on Systems, Man and Cybernetics –Part A: Systems and Humans, Vol 33,* May 2003.

[21] Aleix M. Martinez, "Matching Expression Variant Faces", *Vision Research Elsevier Science*, 2003.

[22] T.Tan, Y.Shi and W. Gao (Eds): ,"Visual Recognition of Emotional States", *ICMI 2000, LNCS 1948, pp 41-48, Springer-Verlag Berlin Heidelberg,* 2000.

[23] Aleix M. Martinez, "Recognizing Expression Variant Faces From a Single Sample Image per Class", *Proceedings of the 2003 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'03)* , 2003.

[24] Tianming Hu et al, "A Hybrid Approach of NN and HMM for Facial Emotion Classification", *Pattern Recognition Letters 23 (2002) 1303-1310*, 2002.

[25] Paola Campadelli et al, "Detection of Facial Features", Springer-Verlag 2002.

[26] Andrew J. Calder, "A Principle Component Analysis of Facial Expressions", *Vision Research-Elsevier Science*, 2001.

[27] Jeffrey F. Cohn et al, "Biomodal Expression of Emotion by Face and Voice", Department of Psychology, University of Pittsburgh,1998.

[28] Kanade,T.; Cohn, J.F.; Yingli Tian, "Comprehensive Database for Facial Expression Analysis", *Automatic Face and Gesture Recognition, 2000. Proceedings. Fourth IEEE International Conference on* , 2000 , pp. 46 – 53.

[29] Irfan A. Essa and Alex P. Pentland, "Coding, Analysis, Interpretation and Recognition of Facial Expressions", *IEEE Trans on Pattern Analysis and Machine Intelligence Vol 19 No 7,* July 1997.

[30] Cohn, J.F.; Schmidt, K.; Gross, R.; Ekman, P., "Individual Differences in Facial Expression: Stability Over Time, Relation to Self-Reported Emotion and Ability to Inform Person Identification", *Multimodal Interfaces, 2002. Proceedings. Fourth IEEE International Conference on*, 2002 , pp. 491 – 496.

[31] James Jenn-Jier Lien and Takeo Kanade, "Subtly Different Facial Expression Recognition and Expression Intensity Estimation", *IEEE Proceedings of CVPR'98,* June 1998

[32] Frederic Pighin et al, “Synthesizing Realistic Facial Expressions from Photographs”, Uni of Washington, Hebrew Uni, Microsoft Research, Association for Computing Machinery, Inc., Copyright@1998.

[33] Michael A. Sayette et al, “A Psychometric Evaluation of the Facial Action Coding System for Assessing Spontaneous Expression”, *Journal of Nonverbal Behavior, pp 167-186,2001.*

[34] Ying-li Tian; Kanade, T.; Cohn, J.F. “Recognizing Lower Face Action Units for Facial Expression Analysis”, *Automatic Face and Gesture Recognition, 2000. Proceedings*. Fourth IEEE International Conference on, 2000, pp. 484 – 490.

[35] Ying-Li Tian; Kanada, T.; Cohn, J.F., “Recognizing Upper Face Action Units for Facial Expression Analysis”, *Computer Vision and Pattern Recognition, 2000. Proceedings. IEEE Conference on* , Volume: 1, 2000, pp. 294 – 301.

[36] Ying-li Tian, Takeo Kanade and Jeffrey F. Cohn, “Evaluation of Gabor-Wavelet-Based Facial Action Unit Recognition in Image Sequences of Increasing Complexity”, *Proceedings of the 5th IEEE International Conference on Automatic Face and Gesture Recognition (FGR’02)*, 2002.

[37] Terzopoulos, D.; Yuencheng Lee; Vasilescu, M.A.O , “Model-based and Image-based Methods for Facial Image Synthesis, Analysis and Recognition”, *Automatic Face and Gesture Recognition, Proceedings. Sixth IEEE International Conference on*, 2004, pp. 3 – 8.

[38] Naiwala P. Chandrasiri et al, “Interactive Analysis and Synthesis of Facial Expressions based on Personal Facial Expression Space”, *IEEE AFGR’04*, 2004.

[39] Bo Gun Park et al, “Recognition of Partially Occluded Objects Using Probabilistic ARG (attributed relational graph)-based matching”, *Computer Vision and Image Understanding, Academic Press Elsevier Science*, 2003.

[40] Jamin Halberstadt et al, “Featural Processing in Face Preferences”, *Journal of Experimental Social Psychology, Academic Press Elsevier Science,* 2003

[41] Ingo Rentschler et al, “Development of Configural 3D Object Recognition”, *Behavioural Brain Research, Elsevier Science*, 2003.

[42] Katja Seitz, “Parts and Wholes in Person Recognition: Developmental Trends”, *Journal of Experimental Child Psychology 82 (2002) 367-381, Academic Press*, 2002.

[43] A. Mike Burton, Vicki Bruce and P.J.B Hancock, “From Pixels to People: A Model of Familiar Face Recognition”, *Cognitive Science Vol 23 (1) pp. 1 –31*, 1999.

[44] Adrian Schwaninger et al, “Configural Information is Processed Differently in Perception and Recognition of Faces”, *Vision Research 43 (2003) 1501-1505, Pergamon Elsevier Science*, 2003.

[45] Paola Campadelli et al, “A Feature-based Face Recognition System”, *IEEE Proceedings of the 12th International Conference on Image Analysis and Processing (ICIAP’03),* 2003.

[46] Jian Yang et al, “Two-Dimensional PCA: A New Approach to Appearance-based Face Representation and Recognition”, *IEEE Trans on Pattern Analysis and Machine Intelligence, Vol 26 No 1*, Jan 2004.

[47] Baback Moghaddam, Tony Jebara, Alex Pentland,”Bayesian Modelling of Facial Similarity”, *Advances in Neural Information Processing 11*, MIT Press, 1999.

[48] Barnes, N.; Zhi-Qiang Liu,” A knowledge based approach to shape from shading”, *Intelligent Processing Systems, 1997. ICIPS '97. 1997 IEEE International Conference on*, Volume: 2, 1997, pp. 1390 – 1394.

[49] Volker Blanz and Thomas Vetter, ”Face Recognition Based on Fitting a 3D Morphable Model”, *IEEE Trans. On Pattern Analysis and Machine Intelligence, Vol. 25, No. 9*, Sept 2003.

[50] Bernd Heisele, Purdy Ho, Jane Wu, Tomaso Poggio, “Face Recognition: Component-based versus global approaches”, Computer Vision and Image Understanding 91(2003) 6-21, Academic Press, Elsevier,2003.

[51] Irfan Aziz Essa, “Analysis, Interpretation and Synthesis of Facial Expressions”, *PhD. Dissertation, Massachusetts Institute of Technology*, Feb 1995.

[52] Gultekin Arabact, “Realistic Rendering of Human Models”, *MSc. Dissertation, Bilkent University*, 2001.

[53] T.F. Cootes and C.J. Taylor, “Statistical Models of Appearance for Computer Vision”, *University of Manchester*, 2004.

[54] Rein-Lien Hsu; Jain, A.K., “Face Modeling For Recognition”, *Image Processing, 2001. Proceedings. 2001 International Conference on*, Volume: 2, 2001, pp. 693 – 696.

[55] Zweitze Houkes, “Estimating 3D Object Parameters From 2D Grey-Level Images, A Model-based Approach”, *PhD Dissertation University of Twente*, 2000.

[56] Turk, M.A.; Pentland, A.P., **“**Face recognition using eigenfaces”, *Computer Vision and Pattern Recognition, 1991. Proceedings CVPR '91., IEEE Computer Society Conference on, 3-6 Pages: 586 – 591*, June 1991

[57] Reisfeld, D.; Yeshurun, Y, “Robust Detection of Facial Features by Generalized Symmetry”, *Pattern Recognition, 1992. Vol.I. Conference A: Computer Vision and Applications, Proceedings., 11th IAPR International Conference on*, 1992 , pp. 117 – 120.

[58] Gordon, G.G, “Face Recognition Based on Depth and Curvature Features”, *Computer Vision and Pattern Recognition, 1992. Proceedings CVPR '92., 1992 IEEE Computer Society Conference on*, 1992, pp. 808 – 810.

[59] Manjunath, B.S.; Chellappa, R.; von der Malsburg, C., “A Feature Based Approach to Face Recognition”, *Computer Vision and Pattern Recognition, 1992. Proceedings CVPR '92., 1992 IEEE Computer Society Conference on*, 1992, pp. 373 – 378.

[60] Roberto Brunelli and Tomaso Poggio, “Face Recognition: Features versus Templates”, *IEEE Trans on Pattern Analysis and Machine Intelligence, Vol 15 No 10 Oct 1993.*

[61] Xiaoguang Jia and Mark S. Nixon, “Extending the Feature Vector for Automatic Face Recognition”, *IEEE Trans on Pattern Analysis and Machine Intelligence, Vol 17 No 12 Oct 1995.*

[62] Cychosz, L.W.; Jun Zhang, "A Face Recognition System Using Holistic Regional Feature Extraction", *Acoustics, Speech, and Signal Processing, 1995. ICASSP-95., 1995 International Conference on* , Volume: 5, 1995 , Page(s): 3431–3434.

[63] Goudail, F.; Lange, E.; Iwamoto, T.; Kyuma, K.; Otsu, N., "Face Recognition System Using Local Autocorrelations and Multiscale Integration", *IEEE Trans on Pattern Analysis and Machine Intelligence, Vol 18 No 10* Oct 1996, pp. 1024 - 1028

[64] Aleix M. Martinez et. al, "Special issue on face recognition", *Computer Vision and Image Understanding 91(2003) 1-5*, Academic Press- Elsevier, 2003.

[65] Biometric Technology Today, "Facial Recognition – Part 1 and 2", Biometric Technology Today, Dec 2003.

[66] Takeo Kanade, "Picture Processing by Computer Complex and Recognition of Human Faces", Ph.D Thesis, Dept. of Information Science, Kyoto University, 1973.

[67] Srinivas Guitta and Harry Wechsler, "Face Recognition Using Hybrid Classifiers", *Pattern Recognition, Vol 30, N0 4 pp 539-553, Elsevier Science*, 1997.

[68] Thomas Heseltine et al, "Face Recognition: A Comparison of Appearance-Based Approaches", *Proc VIIth Digital Image Computing: Techniques and Applications,* Dec 2003.

[69] Argenti, F.; Alparone, L.; Benelli, G., "Fast Algorithms for Texture Analysis Using Co-occurrence Matrices", *Radar and Signal Processing, IEE Proceedings F,* Vol.137, Issue No.6, 1990, pp. 443 – 448.

[70] Lovergine, F.P.; Branca, A.; Attolico, G.; Distante, A., "Leather Inspection By Oriented Texture Analysis With A Morphological Approach", *Image Processing, 1997. Proceedings., International Conference on* , Volume: 2 , 1997 , pp. 669 – 671.

[71] Woods, B.; Clymer, B.; Saltz, J.; Kurc, T., "A parallel Implementation of 4-Dimensional Haralick Texture Analysis for Disk-resident Image Datasets", *Supercomputing, 2004. Proceedings of the ACM/IEEE SC2004 Conference on*, 2004, pp. 48 – 48.

[72] Malik, J.; Belongie, S.; Shi, J.; Leung, T., "Textons, Contours and Regions: Cue Integration in Image Segmentation", *Computer Vision, 1999. The Proceedings of the Seventh IEEE International Conference on,* Volume: 2, 1999, pp. 918 – 925.

[73] H. Kalviainen et al. (Eds.), "Image Analysis with Local Binary Patterns", *SCIA 2005, LNCS 3540, pp.115-118, 2005 (c) Springer-Verlag Berlin Heidelberg 2005.*

[74] Jian Yang; Chengjun Liu, "A General Discriminant Model for Color Face Recognition", *Computer Vision, ICCV 2007. IEEE 11th International Conference on*, 2007, pp. 1–6.

[75] Rajapakse, M.; Tan, J.; Rajapakse, J., "Color Channel Encoding with NMF for Face Recognition", *Image Processing, 2004. ICIP '04. 2004 International Conference on,* Volume: 3, 2004, pp. 2007 – 2010.

[76] Manders, C.; Farbiz, F.; Chong Jyh Herng, "The Effect of Linearization of Range in Skin Detection", *Information, Communications & Signal Processing, 2007 6th International Conference on*, 2007, pp. 1 – 5.

[77] Deng Peng and Pei Mingtao, “Multi-view Face Detection Based on AdaBoost and Skin Color”, *First International Conference on Intelligent Networks and Intelligent Systems on,* ICINIS '08., 2008, pp. 457 – 460.

[78] Yepeng Guan et al., “Efficient and Robust Face Detection from Color Images”, *Proceedings of the 6th World Congress on Intelligent Control and Automation, June 21-23, 2006, Dalian, China.*

[79] Shiguang Shan, Wen Gao, Laiyun Qing, Institute of Computing Technology Chinese Academy of Sciences, *The 4th Chinese Conference on Biometric Recognition, Dec 2003.*

[80] Ganapathi, T.; Plataniotis, K.N., “Color Face Recognition Under Various Learning Scenarios”, *Electrical and Computer Engineering, 2008. CCECE 2008. Canadian Conference on*, 2008, pp. 001549 – 001552.

[81] Tin Kam Ho, “Interactive Tools for Pattern Discovery”, Proceedings of the 17th International Conference on Pattern Recognition (ICPR’04)”, *Pattern Recognition, 2004. ICPR 2004. Proceedings of the 17th International Conference on*, Volume: 2, 2004, pp. 509 – 512.

[82] Cheng He; Chunchun Sui; Jing Chen; Cao Xixin, “Face-Recognition Hardware Implementation Based On SOPC”, *Advanced Communication Technology (ICACT), 2010 The 12th International Conference on* , Volume: 2, 2010 , pp. 1595 – 1599.

Appendix A

Work Published

Variation Complexity Compensation in Limited Information Face Expression Recognition

Mohamad Zulkefli Adam[1], Serkharjit Datta[2]

Applied Signal Processing Research Group, Department of Electronic and Electrical Engineering
Loughborough University, LE113TU Leicestershire, United Kingdom.
Tel: 0044 1509 227037, Fax: 0044 1509 227014, e-mail[1]: M.Z.Adam@lboro.ac.uk e-mail[2]: S.Datta@lboro.ac.uk

Abstract

This paper aims at studying the problems related to the robustness of a face expression recognition system where specific attention is given to the issue of handling the variation complexity with limited information for a single test image. The effect of illumination influences and viewing geometry problem will be tackled and studied on a single face image. In achieving a comparative classification performance, the objective of the proposed method is to compensate for a large-scale image variation before the task of collateral information extraction is performed by a feature extractor. In this manner, a prior knowledge of input image with symmetrical properties, the informative region and consistency of some features will be fully utilized in preserving the unique characteristic feature information. An analysis on 3D histogram of the image is described and a result evaluation concluded the proposed method.

Keywords:

Image processing, face expression, variation complexity, limited information.

Introduction

The similarities of human faces' 3D structure and the image variation complexity have made the machine recognition of faces a difficult task. The problem has remain unsolved in the case of identity, expression, gender and race recognition and other related studies. Face images acquired from the real world are composed of a lot of variations where the major problems are viewing geometry, illumination, expression and occlusion variations. As a result, the task of classification requires the image representation to have a very powerful and robust feature extractor that is invariant to image variations while extracting only the genuine face characteristic information. It is clear that the complexity of the variations is inversely proportional to the amount of face characteristic information on the image.

The simplest way to cater for the problem is having a controlled environment (controlled light, neutral expression, frontal view etc.).

Figure 1 demonstrates the various problems of variations and their implication in classification and feature extraction tasks. Each of these variations devotes a separate study due to its complexity and there are many works in the literature have demonstrated different approaches [1][2]. The images used in training session may cope with a specific application relative to the training environment but largely fail in other real applications. However, there are very few studies in the literature that tackle the second problem due to the limitation of face characteristic information (or number of training images) availability [3]. This kind of problem can be observed in real-life applications where only a single face image is available.

The main issue brought up in this paper is to study and analyse the complexity of these variations on a single face image where the face characteristic information is limited to expression recognition. This provides a framework of proposed novel approach in confronting two challenges (1) variation complexity and (2) limited feature characteristic information. The image was captured with a large illumination variation and non-frontal view where the expression is unknown.

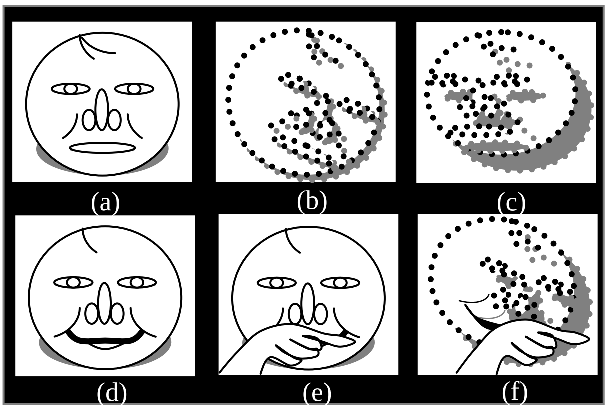


Figure 1 - Facial variations: A model of problems relating to face recognition demonstrating their intrinsic and extrinsic variations. (a.) Original face image (frontal view). (b.) Effect of pose variation. (c.) Effect of illumination variation. (d.) Effect of expression variation. (e) Effect of occlusion.(f.) Combination of all

Basically, the unique characteristics of a face pattern (collateral information) are composed of individual superficial face properties. These features form the shape and texture on 2D images where the symmetrical property, the informative region and consistency of some features can be determined. The proposed approach is to deal with the level of variation complexity that influences the unknown expression state of given a single face image. The information extracted from the 3D histogram of 2D image will be analysed and explained in the following sections.

Figure 2 illustrates the combination of problems that have been discussed.

Figure 2 - Illustration of an illumination and viewing problem with unknown state of facial expression. The large illumination problem can erase some features whereby this becomes closely related to the problem of occlusion [2].

Variation Complexity and Limited Information

The amount of unique characteristic information on a single face image is inversely proportional to its variation complexity. The more the variation complexity, the less the characteristic information can be observed and extracted. There are two general ways in dealing with this twofold problems. One of them is by reducing the variation sources while collecting more information. This can be done by obtaining the image under controlled environment where controlled lighting could reduce the illumination problem, the user cooperation can helps to solve the viewing problem (giving frontal view) and required expression state and no occlusion at all. In this regard, almost all of the invented techniques reported in the literature can perform the classification task precisely. However, in robust system, the implementation is carried out under uncontrolled environment of real-life application. As far as the variation complexity is concerned, this kind of application is the most challenging one as the recognition performance solely depends on the recognition algorithm.

From the literature study, the approaches used for algorithm development in handling the uncontrolled variations can be broadly classified into two categories, namely image-based and model-based approaches (*variation-modelling*). The first category can further be divided into two approaches known as *invariant features* and *transformation/ normalization* approaches [3]. As most of these researches focused on the study on specific variation, it is quite difficult to judge the reliability of the techniques when tested on the other type of variation. In this section, the past/current works will be briefly reviewed on the variation components that make the complexity (i.e. illumination, pose and expression).

The visualization of the illumination impact can be seen in Figure 3. This non-linear illumination variation is caused by the light reflected from the nature of 3D face shape, skin colour and other related factors. This variation can make up to 150% changes in the original image (i.e. 20% made by pose variation) [2]. Furthermore, the large illumination variation is able to erase the entire features or changes the characteristic of the features in term of geometry, strength and existence of any given intensity-based features. The study of illumination variation involves the light direction, brightness, contrast, shadow and shading. For instance, in [4], the problem of varying illuminations has been tackled by the creation of quotient image where the whole idea is based on faces falling into a class of objects. [5][6] are appearance-based method that applied Lambertian reflectance and model the illumination variability where a small set of training images is used to generate a representation that is the illumination cone. In [7], the grey level histogram of one face was transformed to the histogram of some other face. This is done with the assumption that all faces fall into the same class such as in [4] so that facial pixels modelled by empirical probability distribution can be transformed in order to normalize the illumination.

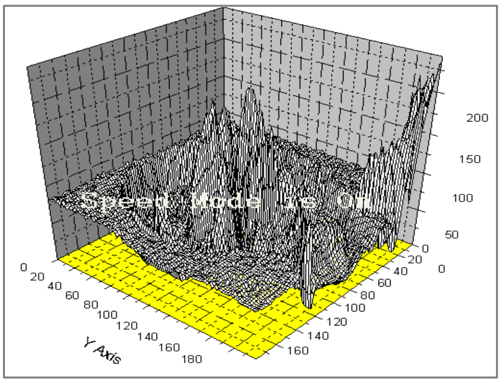


Figure 3 – Illumination visualization observed from 3D intensity graph.

In [8], pose variation problem has been tackled by the development of dynamic face model. The author has produced a comprehensive approach for face modelling, detection, tracking and dynamic recognition. By using the image sequences (video input), a sparse 3D shape model is developed where several face detectors are constructed in choosing the optimum detection that account for accuracy and speed. Support Vector Regression, Support Vector Machines and eigenfaces are used and Kernel Discriminant Analysis technique is developed in this multi-view face recognition. In [10], a multi-view optimisation search that is based on model-based and data-driven method is carried out to determine the most suitable views for 3D face modelling. The simulation of silhouettes images with the use of scanned 3D head for prototype head/torso is found to be efficient and claimed to be the first systematic investigation of optimal views for modelling the 3D face. In [10], with the aid of distribution of needle-map directions on the 2D image delivered by shape-from-shading technique, the orientation histograms are computed in estimating the facial pose. From the experimental results shown, the authors reported that the method is only effective for the head rotation of less than 40 degrees from the frontal pose. As the method does not rely on the detailed features alignment, the authors suggested that the method be used only for rough pose estimation.

In the case of facial expression variations such as the one shown in figure 4, there are a lot of works that can be referred to in the literature. In human interpersonal communication, facial expression contributes to 55% of the effectiveness of the delivered messages, while the verbal (spoken words) and vocal (voice intonation) parts contribute to 7% and 38% respectively [11][12]. The statement revealed the important information that can be extracted from human face for further interpretation and facial analysis in human interaction and activities. Survey papers of [11][13][14] covered a broad discussion in automatic facial expression analysis. In this respect, this paper only focuses on the variation complexity compensation for features extraction and classification in expression recognition. For completeness, some previous works will be reviewed in getting closer to the understanding of facial expression variation problem and proposed solutions. For instance, in [15], the performance of feature-based method developed by the author is reported to be 95.4% for upper face action units (AUs) and 96.7% for lower face AUs.

[16] combined geometric features and regional appearance methods in recognizing facial actions. The average recognition rate for the upper face of 87.6% (using geometric facial features), 32% (using regional appearance pattern), 89.6% (combined methods) and 92.7% (after refinement) are reported on the test of 514 image sequences from 180 adults of European, African and Asian ancestry.

Figure 4 - Sample images of common facial expression states [18]

Another works on comparison of methods' performance also made in [17] where the author reported that both Gabor wavelet and Principle Component representation achieved 96% accuracy for classifying 12 facial actions of the upper and lower face.

In the case of occlusion variation, the challenge is whether the partial information of given face image is enough for the recognition or the features extraction technique used able to perform as the way it should be. Further challenging issue is to investigate which part of the face features that contribute most information or how robust the extractor in dealing with this kind of variation. There are extremely few specific study on this variation as most of the techniques developed in the literature focused on pose, illumination and expression problems.

A lot of great works reported in the literature used frontal images or less variation in challenging the recognition algorithm. In this regard, this paper tried to explore the challenge of variation complexity with limited collateral information.

3D Image Histogram

In face image analysis, it is aggreable that the development of a 3D model can reveal a lot of analytic information. In this paper, the proposed image variation compensation with 3D information extraction process is performed as shown in figure 5 below.

Given a single detected face image, the pre-processing is first performed by using a grey image technique. The illumination normalization is carried out based on the assumption that all faces fall into a class or group. This can be performed by the histogram normalization technique similar to the work in [7].

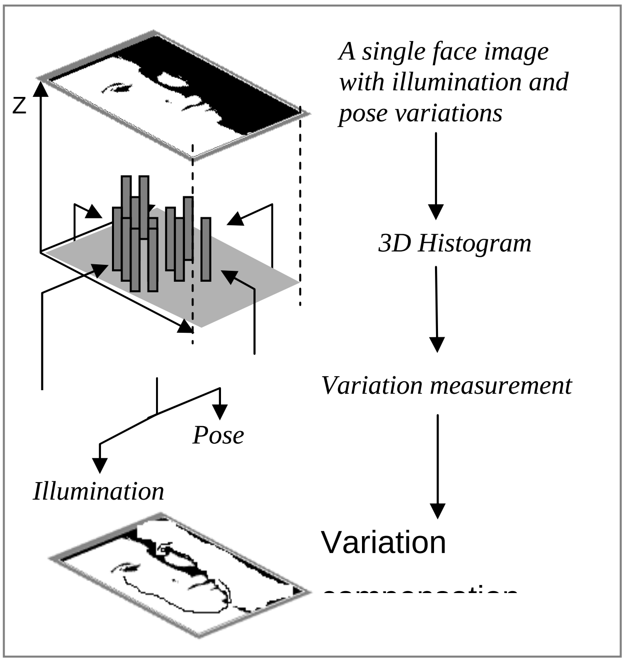


Figure 5 - The proposed process flow for variation compensation and 3D information extraction.

In this paper, the method of 3D histogram is proposed in furthering the compensation for illumination and pose. Furthermore, the information extracted from the intensity caused by the large illumination will be manipulated for obtaining the depth information. Firstly, a 3D view of intensity image will be plotted where another four views can be determined. Figure 6 illustrates the details of these views. By using the view 1, the estimation of the pose (face direction) is based on the geometrical location of unique features and symmetrical property of the face. Symmetrical property also allows the self-occluded problem being compensated and reveals the desired features such as eyes shown in figure 5. This is achieved by the distance ratios of eyes and mouth location with the face outline (figure 6(b)). Indeed, the distance ratios computation will allow any size of the image can be the input image.

From these views (view 1 to 5), the level of illumination variation can be estimated with the aid of peak values of intensity. This is visualized by the highest values of white (light) location in certain region on the image.

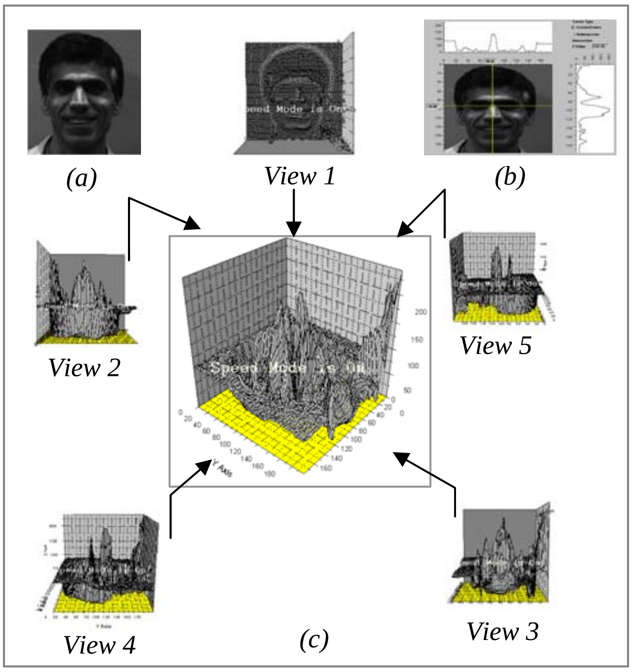


Figure 6 - The exploration of views extracted from 2D image planes. (a) Real image. (b) Estimation of the eyes region i.e feature location (c) The five views.

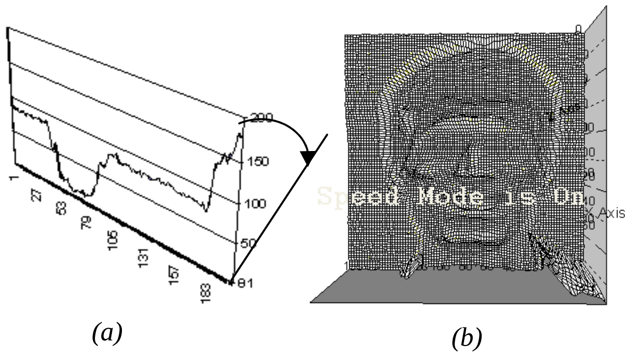


Figure 7 - (a) Critical rotation angle. (b) A sample of compensated face image where the depth measurement can be proceeded.

The shape and depth recovery can be obtained from the undertsanding of figure 7(a). Basically, the human eyes can see the 2D shape of a face from the view 1. View 2 to 5 are the perceptions of 90 degrees towards the respective image planes where these views are meaningless to human eyes. From the experiment carried out on a number of images, there appear to be a critical range (between 0 to 25 degrees around the vertical axes) of perspective angles within the 90 degrees rotation (e.g. from view 1 to view 2). The statement should be supported by a prior knowledge of the perceived object including the informative and regional property of the image. The key point of shape and/or depth recovery is located at any highest point in the pre-determined region. For instance, referring to the view 5, notice that the highest and second highest peaks are the impact of the light source on the nose tip and the lower part of the forehead respectively. At an angle of 25 degrees in rotation from view 1 to view 2 will recover the depth of the upper region of the face (above the nose). As a result, figure 7(b) is produced.

Experiments are still in progress as to test all the possibilities of illumination and pose variations on the face images. From the result of figure 7(b), the current experiment concludes that the variation complexity of the face image can be measured, compensated and analysed in obtaining the depth information with only a single test image.

Conclusion

The presence of large image variation problem in imaging process that limits the task of vision system such as face expression recognition system to a specific application where requirement must be pre-determined. The performance of such algorithm will degrade dramatically under a different environment compared to the one used during an algorithm development and training.

The proposed solution in this paper employed some kind of 'image post-mortem' and taking into account of all the possibilities in getting the unique collateral information of the face. Future research will be looked into expression analysis of this compensated face image and recognition of its expression state. It is hoped that by incorporating large variation complexity into a single face image, the analysis will bring the research up to a certain degree of understanding the dynamic of face image accurately with a simple and realistic computational point of view. These need further analysis and interpretation towards realizing the robustness of intelligent facial expression recognition systems.

References

[1] Zhao, W.; Chellappa, R.; Phillips,P.J; Rosenfeld, A 2003. Face Recognition: A Literature Survey. *ACM Computing Surveys* 35(4): 399-458.

[2] Peter L. Hallinan, Gaile G. Gordon, A.L. Yuille Peter Giblin, and David Mumford, eds. 1999, *Two-and Three-Dimensional Patterns of the Face*, Massachussets,: AK Peters Natick.

[3] Terence Mong-Cheng Sim 2002. Statistics-Based Face Rendering and Its Application to Face Recognition. Ph.D. diss., Dept. of Electrical & Computer Eng., Carnegie Mellon Univ.

[4] Amnon Shashua; and Tammy Riklin-Raviv 2001. The Quotient Image: Class-Based Re-Rendering and Recognition With Varying Illuminations. IEEE Trans. On Pattern Analysis and Machine Intelligence, 23(2): 129-139. IEEE.

[5] Athinodoros S. Georghiades; Peter N. Belhumeur 1998. Illumination Cones for Recognition Under Variable Lighting: Faces. In Proceedings of IEEE Conf. On Computer Vision and Pattern Recognition, 52-59. IEEE.

[6] Jeffrey Ho; Kuang-Chih Lee; David Kriegman 2001. On Reducing the Complexity of Illumination Cones for Face Recognition. IEEE Workshop on Identifying Objects Across Variations in Lighting: Psychophysics and Computation, 56-63. Kauai, Hawai,: IEEE.

[7] P. Jonathon Phillips 1996. Efficient Illumination Normalization of Facial Images. Pattern Recognition Letters 17: *Elsevier*-Science Direct: 921-927.

[8] Yongmin Li 2001. Dynamic Face Models: Construction and Applications. Ph.D. diss., Depart. of Computer Science, Queen Mary, Univ. of London.

[9] Kwang Nam Choi 2001. Estimating facial pose using shape-from-shading. *Elsevier* Pattern Recognition Letters 23:533-548.

[10] Jinho Lee; Baback Moghaddam 2004. Finding Optimal Views for 3D Face Shape Modelling. In Proceedings of the Sixth International Conference on Automatic Face and Gesture Recognition,. Seoul, Korea.: IEEE International Conference on AFGR.

[11] Maja Pantic; Leon, J.M.; Rothkrantz 2000. Automatic Analysis of Facial Expressions: The State of the Art. *IEEE* Transactions on Pattern Analysis and Machine Intelligence 22(12).

[12] A. Mehrabian 1968. Communication Without Words. *Psychology Today* 2(4): 53-56.

[13] B. Fasel 2003. Automatic Facial Expression Analysis: A Survey. Pattern Recognition *Elsevier*: 36: 259-275.

[14] Claude C. Chibelushi 2002. Facial Expression Recognition: A Brief Tutorial Overview, Technical Report, School of Computing, Staffordshire University.

[15] Ying-li Tian 2001. Recognizing Action Units for Facial Expression Analysis. *IEEE* Trans on Pattern Analysis and Machine Intelligence, 23(2).

[16] Ying-li Tia;, Takeo Kanade; and Jeffrey F. Cohn 2001. Recognizing Facial Actions by Combining Geometric Features and Regional Appearance

Patterns. *IEEE Trans. On Pattern Analysis and Machine Intelligence*.

[17] Gianluca Donata 1999. Classifying Facial Actions. *IEEE* Trans. On Pattern Analysis and Machine Intelligence, 21(10).

[18] Kanade, T.; Cohn, J.F.; and Tian, Y. 2000. Comprehensive Database for Facial Expression Analysis. The Fourth IEEE International Conference on Automatic Face and Gesture Recognition (FG'00), France: IEEE.

APPENDIX B

MATLAB CODES

```
function TheID
% TEMPORARY HUMAN ELECTRONIC IDENTIFICATION (The-ID)
%**************************************************************************
% The program is created to ease the analysis work for the thesis of
% "Unfamiliar Facial Identity Registration and Recognition Performance
% Enhancement". The codes are divided into two categories:
% A.  Variation Complexity Compensation, Extraction and Representation.
%     A.1   Colour-based Regional Appearance Extraction and Representation.
%           A.1.1  Face Image Acquisition
%           A.1.2  Histogram of RGB Colors
%                  (i)  Representing Red Component
%                 (ii)  Representing Green Component
%                (iii)  Representing Yellow Component
%     A.2   Texture-based Gender Extraction and Representation.
%           A.2.1  Gray Image Conversion
%           A.2.2  Compensation by Re-quantization
%           A.2.3  GLCM Texture Representation
%     A.3   Global Feature-based Age Extraction and Representation.
%           A.3.1  Edge Image Conversion
%           A.3.2  Morphology-based Compensation
%           A.3.3  DLBT Global Features Representation
%
% B.  UCI Classification and Recognition
%     B.1   Regional Appearance UCI Classification
%     B.2   Gender UCI Classification
%     B.3   Age UCI Classification
%
%**************************************************************************
delete *.mat;
clc;
clear all;

% LOADING THE IMAGES.
buffer=pwd;
[file, pathname] = uigetfile('*.jpg','Load Image');
cd(pathname);
ColorImage=imread(file);
cd(buffer);


%**************************************************************************
% A.   VARIATION COMPLEXITY COMPENSATION, EXTRACTION AND REPRESENTATION
%
% A.1  REGIONAL APPEARANCE EXTRACTION AND REPRESENTATION
%      The input image is a colour image.  The image will be loaded into
%      the database where the dimension will be reduced or standardized to
%      a specified size. This input image supposed to be detected by Face
%      Detection Algorithm. However, with respect to the scope of the
thesis,
%      the detected face image is represented by image cropping. The
cropped
%      image will then been compensated by histogram equalization. The
final
%      task in this stage is to represent the image where the
%      representation is ready for the classifier to perform further
%      analysis.
%
% 1. Face Image Acquisition
[c r B] = size(ColorImage);
```

```
rgbImage=imcrop(ColorImage);
figure,
subplot(3, 3, 1);
imshow(rgbImage, []);
fontSize=13;
title('Colour Image','Fontsize', fontSize);

redPlane = rgbImage(:, :, 1);
greenPlane = rgbImage(:, :, 2);
bluePlane = rgbImage(:, :, 3);

% 2. Histogram of RGB Colors
subplot(3,3,2);imhist(redPlane),hold on;
imhist(greenPlane),hold on;
imhist(bluePlane);
title('Histogram of RGB Colours', 'Fontsize',fontSize);
xlabel('Intensity values');ylabel('Frequency of Occurence');

% 3a. Representing Red Component
[pixelCountR grayLevelsR] = imhist(redPlane);
subplot(3, 3, 3);
plot(pixelCountR, 'r'),hold on;
xlim([0 grayLevelsR(end)]); % Scale x axis manually.

% 3b. Representing Green Component
[pixelCountG grayLevelsG] = imhist(greenPlane);
%subplot(2, 2, 3);
plot(pixelCountG, 'g'),hold on;
%title('Histogram of green plane', 'Fontsize', fontSize);
xlim([0 grayLevelsG(end)]); % Scale x axis manually.

% 3c. Representing Yellow Component
[pixelCountB grayLevelsB] = imhist(bluePlane);
%subplot(2, 2, 4);
plot(pixelCountB, 'b'), hold on;
title('RGB Representation', 'Fontsize', fontSize);
xlim([0 grayLevelsB(end)]); % Scale x axis manually.
xlabel('Intensity values');ylabel('Frequency of Occurence');

% A.2  GENDER EXTRACTION AND REPRESENTATION
%      In this stage, the colour image will be transformed into gray level.
%      The histogram of gray level image is equalized and re-quantization
%      process will be performed for 8 gray levels.  The GLCM is obtained
%      and this new representation for texture pattern of the face image is
%      plotted or demonstrated in the output figure.
%
% 4.  Gray Image Conversion
%
GrayImage=rgb2gray(rgbImage);
GrayEq=histeq(GrayImage,256);
subplot(3,3,4);imshow(GrayEq);
title('Gray Image','Fontsize',fontSize),
%
% 5.  Compensation by Re-quantization (with purpose)
%
[glcm1,SI] = graycomatrix(GrayEq,'NumLevels',8,'G',[]);
subplot(3,3,5),
imagesc(SI);
title('Re-Quantization','Fontsize',fontSize),
```

```
xlabel('Gray level = 8');ylabel('Gray level = 8');
%
% 6.  GLCM Texture Representation
%
subplot(3,3,6); imshow(glcm1);
title('GLCM Texture Representation','Fontsize',fontSize);
xlabel('N = 8 ~Pixel pair comparison');ylabel('M = 8 ~Pixel pair');
%
% A.3  AGE RECOGNITION/ESTIMATION
%      The gray image is transformed into edge image using the Canny filter
%      with the threshold setting.  Morphology is applied to increase the
%      quality of the broken edges and also to enhance the edges.  DLBT is
%      applied by calculating the column by column of the edges occured in
%      the image and the maximum value of the summation vector is obtained.
%      The edge image is transposed and the same process is repeated.
%      The ratio of the two maximum values are calculated and represent the
%      measure of age estimation.
%
% 7.  Edge Image Conversion
edgeimage=edge(GrayEq,'canny',0.4);
subplot(3,3,7);imshow(edgeimage);
title('Edge Image','Fontsize',fontSize);
%
%
% 8.  Morphology-based Compensation
%
DLBT=bwpack(edgeimage);
StrucEle = strel('ball',3,0);
bwp_dilated = imdilate(DLBT,StrucEle,'ispacked');
bw_dilated = bwunpack(bwp_dilated, size(edgeimage,1));
subplot(3,3,8);imshow(bw_dilated);
title('Morphology-based Compensation','Fontsize',fontSize);
xlabel('Morphology image reconstruction');


% 9.  DLBT Global Features Representation
DLBT2=bwpack(bw_dilated);
V2=sum(DLBT2);
subplot(3,3,9);plot(V2);
title('DLBT Global Features Representation','Fontsize',fontSize);
xlabel('Image Coloumn Width');ylabel('32Bits (Decimal Sum)');

%##########################################################################
%##########################################################################
%
%%             B.   UCI CLASSIFICATION AND RECOGNITION
%
% B.1  REGIONAL APPEARANCE UCI CLASSIFICATION

figure,
subplot(3, 5, 1);
imshow(rgbImage, []);
fontSize=10;
title('Colour Image','Fontsize', fontSize);

subplot(3,5,2);
plot(pixelCountR, 'r'),hold on;
xlim([0 grayLevelsR(end)]); % Scale x axis manually.
```

```
plot(pixelCountG, 'g'),hold on;
xlim([0 grayLevelsG(end)]); % Scale x axis manually.

plot(pixelCountB, 'b'), hold on;
xlim([0 grayLevelsB(end)]); % Scale x axis manually.
title('RGB Representation', 'Fontsize', fontSize);
xlabel('Intensity values');ylabel('Frequency of Occurence');

plot(pixelCountR, 'r'),hold on;

maxR = max(pixelCountR);
maxG = max(pixelCountG);
maxB = max(pixelCountB);
RBpeakDiff = maxR - maxB;
BRpeakDiff = maxB - maxR;
GBpeakDiff = maxG - maxB;

if  abs(BRpeakDiff) > (0.01*maxR)
    if abs(BRpeakDiff) < (0.1*maxR)
    subplot(3,5,3);plot(BRpeakDiff);
    title('Classification of Malay Regional Appearance
UCI','Fontsize',fontSize);
    xlabel('Number of Subjects');ylabel('RGB Differences)');pause(1);
    end
end
if abs(BRpeakDiff) > (0.1*maxR)
    if abs(BRpeakDiff) < (0.3*maxR)
    subplot(3,5,4);plot(BRpeakDiff);
    title('Classification of Chinese Regional Appearance
UCI','Fontsize',fontSize);
    xlabel('Number of Subjects');ylabel('RGB Differences)');pause(1);
    end

if abs(BRpeakDiff) > (0.3*maxB)
    if abs(BRpeakDiff) < (0.9*maxB)
    subplot(3,5,5);plot(BRpeakDiff);
    title('Classification of India Regional Appearance
UCI','Fontsize',fontSize);
    xlabel('Number of Subjects');ylabel('RGB Differences'); pause(1);
    end
end
end

% B.2  GENDER UCI CLASSIFICATION

subplot(3,5,6);imshow(GrayEq);
title('Gray Image','Fontsize',fontSize),
offsets0=[0 1;-1 0];
%offsets0=[0 1;-1 1;-1 0;-1 -1];
[glcm2,di]=graycomatrix(GrayEq,'offset',offsets0);
stats=graycoprops(glcm2,'contrast correlation');

subplot(3,5,7);plot(stats.Correlation);
title('Texture Representation/Classification','Fontsize',fontSize);
xlabel('Offset');ylabel('GLCM Correlation)');

GenderRange  = stats.Correlation;
StdGender = std(GenderRange);
```

```
disp(StdGender);
MinGenderRange = min(GenderRange);
MaxGenderRange = max(GenderRange);
DiffGender = MaxGenderRange - MinGenderRange;
disp(DiffGender);

if (DiffGender < 0.003)
            subplot(3,5,9);plot(DiffGender);
            title('Gender Classification Result: Female
Class','Fontsize',fontSize);
            xlabel('Subjects)');ylabel('Difference Between Offset 1 and
3');pause(1)
else
        subplot(3,5,8);plot(DiffGender);
        title('Gender Classification Result: Male
Class','Fontsize',fontSize);
        xlabel('Subjects)');ylabel('Difference Between Offset 1 and
3');pause(1);

end
% B.3  AGE UCI ESTIMATION/CLASSIFICATION

subplot(3,5,11);imshow(bw_dilated);
title('Edge Image (Morphology-based)','Fontsize',fontSize);
%sizebw_dilated=imresize(bw_dilated,[100 50]);
xlabel('Morphology image reconstruction');

T=bw_dilated.';
V3=sum(T);
%V21=size(V2,400);
%V31=size(V3,400);
%Std1 = std(V2);
%Std2 = std(V3);
%Ratio1=log10(Std1/Std2);

DistMth2Eyes = max(V2);
DistEyes = max(V3);
Ratio1 = log10(DistMth2Eyes/DistEyes);
disp(Ratio1);
subplot(3,5,12);plot(V2);
title('DLBT Global Features Representation','Fontsize',fontSize);
xlabel('Image Coloumn Width');ylabel('DLBT Decimal Summation');pause(1);

if Ratio1 < 7.5
    subplot(3,5,14);plot(Ratio1);
    title('Age Classification Result: Child','Fontsize',fontSize);
    xlabel('Image Column Width');ylabel('DLBT Ratio)');pause(1);
else
    subplot(3,5,13);plot(Ratio1);
    title('Age Classification Result: Adult','Fontsize',fontSize);
    xlabel('Image Column Width');ylabel('DLBT Ratio)');pause(1);

end
 %save RBpeakDiff
%save DiffGender
%save Ratio1

end
```

```
%########################################################################
%########################################################################
%
%%                       GENDER ANALYSIS
%           GLCM Correlation, Energy and Homogeneity
%
%;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
%
figure,
%Display Gray Image
subplot(3,3,1);imshow(GrayEq);
title('Gray Image','Fontsize',fontSize),

%Compensation by Re-quantization (with purpose)
[glcm1,SI] = graycomatrix(GrayEq,'NumLevels',8,'G',[]);
subplot(3,3,2),
imagesc(SI);
title('Re-Quantization','Fontsize',fontSize),
xlabel('Gray level = 8');ylabel('Gray level = 8');

%GLCM Texture Representation

offsets00=[0 1;-1 1;-1 0;-1 -1]; %4 directions or angles
[glcm3,dii]=graycomatrix(GrayEq,'offset',offsets00);
stats1=graycoprops(glcm3,'contrast correlation energy homogeneity');

subplot(3,3,3);imshow(glcm1);
title('Texture Representation','Fontsize',fontSize);
xlabel('Pixel pairs');ylabel('Pixel pairs)');

subplot(3,3,4);plot(stats1.Correlation);
title('Classification of Gender UCI','Fontsize',fontSize);
xlabel('Offset (Direction of Pixels Comparison)');ylabel('GLCM
Correlation)');

subplot(3,3,5);plot(stats1.Energy);
title('Classification of Gender UCI','Fontsize',fontSize);
xlabel('Offset (Direction of Pixels Comparison)');ylabel('GLCM Energy)');

subplot(3,3,6);plot(stats1.Homogeneity);
title('Classification of Gender UCI','Fontsize',fontSize);
xlabel('Offset (Direction of Pixels Comparison)');ylabel('GLCM
Homogeneity)');

%;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
%########################################################################
```

APPENDIX C

MALAYSIAN FACE DATABASE

Unfamiliar Facial Identity Registration and Recognition Performance Enhancement

Please find attached CD for the face database used in the thesis. The database comprises of twelve (12) classes listed as follows:

(1) Malay Male Adult
(2) Malay Female Adult
(3) Malay Male Child
(4) Malay Female Child
(5) Chinese Male Adult
(6) Chinese Female Adult
(7) Chinese Male Child
(8) Chinese Female Child
(9) India Male Adult
(10) India Female Adult
(11) India Male Child
(12) India Female Child