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Hybrid ToF and RSSI real-time semantic tracking with an adaptive industrial internet of things architecture

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ABSTRACT

Real-time asset tracking in indoor mass production manufacturing environments can reduce losses associated with pausing a production line to locate an asset. Complemented by monitored contextual information, e.g. machine power usage, it can provide smart information, such as which components have been machined by a worn or damaged tool. Although sensor based Internet of Things (IoT) positioning has been developed, there are still key challenges when benchmarked approaches concentrate on precision, using computationally expensive filtering and iterative statistical or heuristic algorithms, as a trade-off for timeliness and scalability. Precise but high-cost hardware systems and invasive infrastructures of wired devices also pose implementation issues in the Industrial IoT (IIoT). Wireless, self-powered sensors are integrated in this paper, using a novel, communication-economical RSSI/ToF ranging method in a proposed semantic IIoT architecture. Annotated data collection ensures accessibility, scalable knowledge discovery and flexibility to changes in consumer and business requirements. Deployed at a working indoor industrial facility the system demonstrated comparable RMS ranging accuracy (ToF 6 m and RSSI 5.1 m with 40 m range) to existing systems tested in non-industrial environments and a 12.6–13.8 m mean positioning accuracy.

1. Introduction

Mass production in manufacturing puts greater emphasis on real-time asset location monitoring: pausing a production line to locate an asset can lead to significant losses when, for example, an engine is produced every 30 s at the Ford factory in Dagenham (Ford, 2014). Additionally, manufacturing agility and resilience increases if supply chain tracking can extend the scope of trusted suppliers and foundries (Collier et al., 2015). When location information can be associated with monitored contextual information, e.g. machine power usage and vibration, it can be used to provide smart monitoring information, such as which components have been machined by a worn or damaged tool. The corollary of this is that sensor data without timely positioning has limited use (Liu et al., 2010).

Indoor positioning systems have not taken a semantic web or future-proofed IoT approach: services and algorithms are embedded on devices and limited to unconventional architectures that are inflexible to business requirements and technological progress (Liu et al., 2007; Xu et al., 2014; Miorandi et al, 2012). To ensure that accuracy and precision are not trade-offs for scalability and interoperability, semantic technologies offer service-agnostic resource sharing (Holtewert et al., 2013; Famaey et al., 2010; Hachem et al., 2011; Roda and Musulin, 2014).

The IoT supports resource sharing through a global network infrastructure of interconnected, intelligent devices for environmental, healthcare, military and industrial monitoring (Xu et al., 2014), often in the form of low-cost and easily deployed WSN. These necessitate solutions to integrate common functionality and the large amounts of data output by these devices. This can be met by both the use of structured, machine processable data and standardised, semantic access to algorithms and toolsets used to sanitise noisy, incomplete datasets.

WSN positioning exploits the capabilities of fixed anchor devices, or nodes, to locate mobile ones. The communications of fixed devices, used for contextual IoT monitoring, can be reused to track nearby moving assets. A stimulus, such as the detection of movement with accelerometers (Goswami, 2013), initiates communication with the purpose of localising an asset. Ranging data are collated from multiple nodes and passed to filtering and positioning algorithms. Frequent communications, calls to computationally expensive recursive functions (Lau and Chung, 2007) e.g. Particle Filters (Davies et al., 2011), and storage directly affect system timeliness and usefulness.

Large-scale manufacturing also puts greater emphasis on non-intrusive technologies as pausing a production line to maintain or

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scale infrastructure represents high productivity losses. Low powered WSN devices with long lifetimes can meet industrial user-requirements of scalability and limited intrusion on supply chains and existing communications infrastructure (Shen and Norrie, 1999; Miorandi et al., 2012; Xu et al., 2014). Systems considered state of the art in precision tracking, such as UWB, intrude on industrial power and network infrastructure and rely on high granularity of anchors, limited re-usability of software processes and functions and are susceptible to long range and metal obstacles (Section 2).

Validation of indoor industrial positioning approaches must be undertaken subject to realistic spatially, temporally and frequency varying multipath propagation effects of wireless signals that occur in the presence of mobile, dense and metallic obstacles and the consequently dynamic floor-plans of industry (Wylie and Holtzman, 1996; Puccinelli and Haenggi, 2006; Tang et al., 2007). Resulting signal corruption increases the likelihood that the direct path, LoS signal is lost and that ranging is derived from a NLoS signal.

LoS signals are characterized by LoS propagation as well as the absence of obstacles, with dimensions larger than the signal wavelength, within the 1st Fresnel volume (Savazzi et al., 2017; Lee and Lee, 2000). Obstacles may occupy the 2nd Fresnel volume. A NLoS signal is characterized by obstacles completely obstructing the direct path between transmitter and receiver, but leaving a clearance zone inside the first Fresnel area (Savazzi et al., 2017). However, existing network validation approaches do not address issues of complex and harsh environments that are typical in industry and many are still untested in real indoor environments (Halder and Ghosal, 2015; Souza et al., 2015) (Tables 4–5).

The highest measurement accuracy shown by WSN ranging approaches tested indoors has been 4–6 m in office environments with static floor-plans and no significant obstacles (Pettinato et al., 2012; Mazomenos et al., 2011) and on a small scale with toy car tracking (Blumrosen et al., 2013). These approaches have used software, as opposed to precision hardware acknowledgement and time stamping, and large numbers of ranging measurements (1000–5000 per location at 250 kbps (Mazomenos et al., 2013) – 500 kbps (Pettinato et al., 2012)). Economical communication is a critical consideration for IoT devices, which should be capable of monitoring in real-time, without overloading shared network resources (Xu et al., 2014).

A novel representation ontology-driven IIoT solution that comprises four contributions, is proposed as a solution in this paper:

1. A hybrid positioning approach using short-range RSSI ranging and long-range ToF ranging data, based on clock errors and the increase in RSSI path loss exponent with distance (Pu et al., 2012), as discussed in Sections 3 and 2.1. Measurement uncertainty is reduced using hardware interrupt metering and calibration of RTT and propagation delay, RSSI and distance (Section 3.3.1).
2. Design and development of a scalable semantic service and IIoT network architecture that supports distributed, intelligent services and communications in indoor environments (Section 3).
3. Implementation of the architecture in a reasoned RDF/OWL ontology defining service inputs, outputs, requirements and relationships of each component of the architecture and the middleware for annotated abstraction of cross-layer parameters (Section 3.1).
4. Demonstration of the capabilities of the architecture through deployment and remote querying linked-dataset real-time positioning. Ranging in a real industrial environment showed 5.1–6 m RMS accuracy and large-scale positioning, 12.6–13.8 m mean accuracy (Section 4), comparable with the accuracy of state-of-the-art systems evaluated in Section 2.

2. Related work

Positioning consists of assorted stages aimed at improving the accuracy of measured distance data, and converting this to a location coordinate. Filtering, based on probability, can be used to reduce errors in results and positioning is conducted with lateration, angulation or location fingerprinting. Industrial environments are characterised by lack of reliable existing infrastructure and detrimental wireless dynamics as a result of metal obstacles and competing RF signals (Savazzi et al., 2017). For both RSSI and ToF measurements multipath propagation effects introduce ranging errors, while clock precision and bias impact on the usefulness of ToF measurements. Thus, an accurate ranging measurement phase is key in reducing error propagation into subsequent phases.

Based on a number of considerations we chose to use an ontology to investigate the development of a semantic architecture, as it is ontologies that describe service implementation and data access in the semantic web. The architecture design can be fully represented in an ontology. Additionally, an RDF representation of linked data can be stored on the web, validated and accessed remotely through the use of the SPARQL query and update languages.

2.1. Ranging communications

Calibration of RSSI extends from short-range measurements to attenuation maps for a known environment, to which real-time RSSI results are compared. RSSI ranging with LQI and attenuation modelling have shown ranging errors as low as 3.8% of propagation distance (Lai and Cheng, 2013). However, map creation entails an extensive and intrusive calibration phase and they become unreliable in dynamic floor-plan conditions Table 1.

Time-based ranging offers a linear relationship between LoS distance and signal propagation time. ToF offers a synchronisation free approach (Goswami, 2013) by measuring the time taken for the signal to propagate across the wireless medium. The distance, d is found as a product of propagation time (ToF) and c, the speed of light. Measurement errors may arise from additional distances (d') travelled by the signal, as a result of multipath propagation.

ToF is measured as a component of the RTT, the time taken to send a packet and receive an ACK. Measured RTT consists of transmission ($T_{tx/rx}$), propagation (ToF) and processing (T_p) delays, interrupt latency

Table 1
List of Acronyms.

Expansion	Acronym
Wireless Sensor Networks	WSN
eXtensible Stylesheet Language Transformations	XSLT
Geometric Dilution Of Precision	GDOP
Industrial Internet of Things	IIoT
Internet of Things	IoT
Line-of-Sight	LoS
Link Quality Indicator	LQI
Non-Line-of-Sight	NLoS
Notation3	N3
Radio Frequency	RF
RDF Schema	RDFS
Real Time Location System	RTLS
Received Signal Strength Indicator	RSSI
Resource Description Framework	RDF
Round Trip Time	RTT
Routing Protocol for Low-Power and Lossy Networks	RPL
Semantic Communication Bus	SCB
Service Oriented Architectures	SOA
Simple Common Logic	SCL
Symmetrical Double-Sided Two-Way Ranging	SDS-TWR
Texas Instruments	TI
Time of Flight	ToF
Ultra-wideband	UWB
W3C Web Ontology Language	OWL
Web Services Description Language	WSDL
Yet Another Sparql GUI	YASGUI

($T_{interrupt}$, a sub-clock-tick value) and multipath propagation errors d'/c (given in Eq. (1)). The processing component is the RX/TX turn-around, the time between the radio receiving and changing to transmit. It is given in the transceiver data sheet of our devices as 192 μs (Texas Instruments, 2013).

$$RTT = 2ToF + T_p + 2(d'/c + T_{tx/rx} + T_{interrupt}) \quad (1)$$

In the ToF ranging implemented, each node measured the two-way RTT from the last bit of data transmission to the time of radio interrupt, on receipt of the ACK packet. To reduce sources of uncertainty, constant packet length was used in all deployments. Transmission delay, the time taken to push the packet onto the channel, is difficult to measure accurately. A timing offset (T_{Off}), equivalent to $d'/c + T_{tx/rx} + T_{interrupt}$, was calculated within the calibration phase (Section 3.3.1). ToF measurements are subject to the varying clock bias of each node, resulting from gradual drift in clock-tick length. SDS-TWR (Fig. 3) is used to reduce the impact of imprecision and tick-length drift in the clock oscillator.

2.2. Positioning services

RSSI tracking using iterative trilateration has demonstrated a 1.7 m average error, for a linear trajectory moving from an outdoor environment into a building corridor, with six anchor nodes outlining a 47.5 × 3 m test area (Lau and Chung, 2007). Using RSSI to correct ToF readings in a particle filter has previously been demonstrated to give a mean error of 10.7 m, with up to a 12 m range (Davies et al., 2011).

A small scale deployment of a range-only ToF scheme, by the authors in (Mazomenos et al., 2011), has demonstrated an RMS error of 2.23 m (outdoors) to 4 m (in-building corridor) for 200 measurements per location in a 15 × 15 m area.

While these approaches have shown a sub-5 m LoS accuracy this has been demonstrated in environments that are substantially different from a typical industrial harsh environment. There was an absence of obstacles such as pipes, metal structures, walkways, valves within the second Fresnel volume and no changing LoS and NLoS environmental conditions.

The highest level of positioning accuracy is offered by commercially available, precision UWB hardware architectures (Zebra Technologies, 2012; Ubisense, 2014): to centimetre level in outdoor and urban environments (Liu et al., 2007). However, UWB requires a wired infrastructure and high granularity of anchors, has limited re-usability of software processes and functions and is susceptible to long range and metal obstacles. Low cost, self-powered sensor networks have drawn particular interest in the IIoT as these offer distributed systems with limited infrastructure intrusion. Although self-powering offers both scalability and low cost, this is at the expense of reduced communication and processing overheads of the system (Alrajeh et al., 2013).

2.3. The semantic IIoT

Semantic web architectures have developed as a subset of SOA. In SOAs application components commonly expose service access via APIs, enabling cooperation, scalability and interoperability between multiple software components. SOAs comprise consumer facing, business process, functional and technical libraries and systems components. Through the addition of semantic technologies, agents can autonomously engage with common interfaces or service functionality. Offering machine-interpretable annotations also aims to disconnect the meaning of data and the vast quantity of heterogeneous, distributed data produced by IoT systems (Aggarwal et al., 2013).

Multi-layer semantic architectures have been suggested for the IoT, to ensure interoperability between devices and scalability of services. These architectures propose sensing layers of identifiable devices, networking layers for interconnectivity and discovery of services, middleware service layers and interface layers (Xu et al., 2014).

Semantic technologies were applied in a client-server tracking architecture, using OpenStreetMap to export XML coordinate data and transform this to N3 with XSLT (Matuszka et al., 2013). An ontology determined locations that could be reached, according to the map and SPARQL CONSTRUCT queries calculated distances between locations. The client then relied on accelerometer, compass and QR code information to navigate within a small indoor area.

Service buses have been proposed as middleware layers for the semantic web; they generalise interface access to services and provide necessary functionality such as discovery, routing, mapping and parsing. This extends the functionality of traditional publish-subscribe approaches to the dynamic identification of redundant functionality and offering services independent of interface and type specification. This independence enables flexibility of the architecture to the addition of new services. Functionality is advertised rather than interfaces, such as a WSDL descriptor (Karastoyanova et al., 2007; Famaey et al., 2010). Ontology representation of service functionality is therefore key to accessing this knowledge. The ontology can be tasked with defining inputs, outputs, requirements, invocation processes and mapping services to WSDL (Karastoyanova et al., 2007).

Virtual Fort Knox is a manufacturing service bus to manage cyber-physical systems on production lines (Holtewert et al., 2013). This allows businesses to use a third party IT infrastructure, while accessing data and controlling systems through a platform of applications. The autonomic SCB, similarly, uses an ontology to allow service-users to access and create multiple message types to identify functions, variables and entities (Famaey et al., 2010). These messages facilitate functionality discovery and subscriber notification.

An IoT middleware has been proposed that is made responsible for service discovery as well as estimation tools (Hachem et al., 2011). The middleware contains a knowledge base of multiple ontologies bringing together methods, analytical models and expected distributions with which to complete partial datasets. In this approach the ontologies themselves contain the mathematical models required by service requesters.

An ontology framework for intelligent data analysis has been proposed to manage validation, representation and interpretation of data (Roda and Musulin, 2014). Observed data are first sanitised for noise, outliers and input errors and then stored. Metadata is then attached, including recorded precision and range of the devices used. A temporal model alongside a reasoner can then identify particular qualitative states of a system.

3. Semantic IIoT architecture

The proposed semantic service bus architecture is designed and developed in consideration of the requirements of an asset tracking system and to be extensible to other systems in the IIoT (Fig. 1). It builds on existing (Holtewert et al., 2013; Roda and Musulin, 2014) and conceptual (Xu et al., 2014) architectures, adding new industry-specific structure and services defined according to business process requirements, client needs, low level systems and tool sharing and extensibility (via an RDF Schema/SCL semantic service bus). This is then built as a comprehensive RDF/OWL ontology that will support the advertisement of service functionality.

The embedded knowledge includes the requirements and relationships of each component, used for collation of tracking data and by a WSN infrastructure of embedded devices using cross-layer middleware to calibrate and abstract ranging data. The middleware forms an initial implementation for the service bus, as this provides generic infrastructure service access to functionality through mediation, orchestration, routing and abstraction of information and messages (Section 2.3). It has been created such that numerous, varied outputs from embedded device implementations are accessible to an interface-agnostic service layer, providing functionality to client applications,

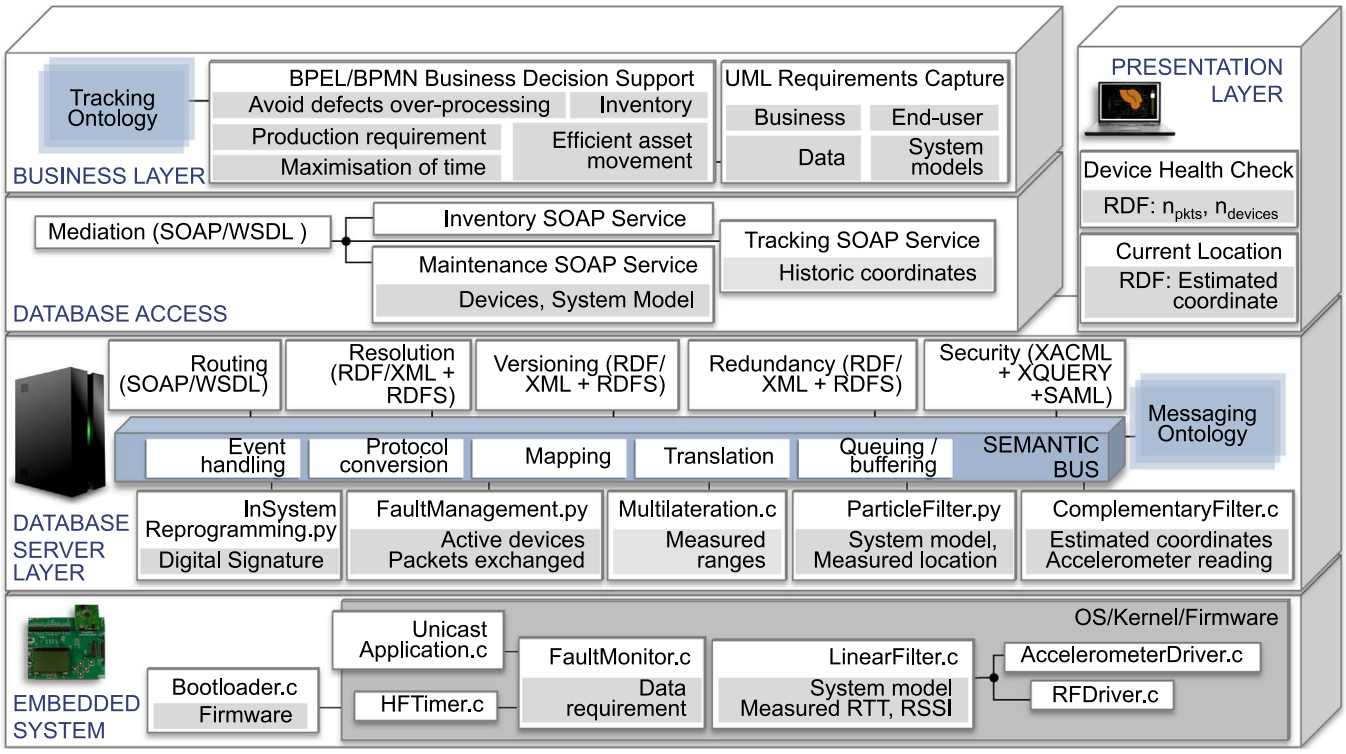


Fig. 1. Semantic IIoT architecture.

manufacturing service users and administrators. Reasoning and SPARQL queries are used to classify additional knowledge from the linked position data and support service-agnostic use of linked functionality.

The architecture proposed is more scalable than previous proposals (Pettinato et al., 2012; Mazomenos et al., 2013) as network resource consuming communications are bounded to 100, instead of the 1000–5000, packet transmissions per location. Non-real time recursive particle or Kalman filter algorithms for node ranging and high anchor infrastructure granularity are avoided (Lau and Chung, 2007; Davies et al., 2011) and through the use of semantic technologies, the knowledge acquired by the system becomes reusable and distinct from the data produced.

3.1. IIoT ontology

The proposed approach uses RDF and OWL for knowledge engineering (Horridge et al., 2011). The class 'Thing' is the predefined top level class and Fig. 2 demonstrates the top level sub-classes and relationships of the knowledge base. Cardinality restrictions (Minimum, Maximum and Exactly) were used to define the sets and relationships between individuals for each ontological property. Objects and individuals could easily be related to business process decisions e.g. for asset tracking the number of packets transmitted and communication rate selected. The ontology was initially logically validated using the HermiT and Pellet OWL reasoners and made remotely accessible, with version control, on GitHub. Pellet uses description logic to check the soundness and completeness of the OWL code while HermiT parses hierarchical relationships to check consistency across the ontology (Khamparia and Pandey, 2017).

Under the OSI architecture, applications do not address devices, therefore the tracking ontology class IndoorTrackingDevices was used to link device type to service, for service functionality discovery. The Device subclass was extended to further subclasses: Portal and RTLS. This in turn was extended to a *MovingTag* type, of which there can be more than three unique servers. The individual positions of the assets being tracked can be pushed to a subclass of IndoorTrackingDevices as these were independent of the sensors used to track them.

The tracking devices were classed according to the sensor type *(MotionSensor)* used to determine an asset location; *AccelerometerReading* or *ZigbeePacket* (used for *TimeofFlight* or RSSI). The device analytics were classed according to method used rather than chip type, to accommodate flexibility of the low level systems .

The IndoorTrackingDevices class captured information about the positioning sensors used (see Fig. 4): commercial device name, functionality, capabilities and measurements. Some of these were subclasses of the BusinessDecisionSupport class and device selection, thus functionality could be modified with flexible, high-level client or business requirements.

The *SemanticBusServices* class enables extensible access via predefined Messaging. This supports access to data-set sanitisation services, such as filters and analytical models and device specific services for tuning parameters e.g. total packets used for ranging (further discussed in Section 3.3). The functionality is made accessible via PHP scripts in the Gateway devices. *InSystemProgramming* services support secure, reliable transmission of firmware for reprogramming devices.

The Client Presentation class encapsulates the access provided to users via user interfaces, to monitor the location of all tagged assets within a supply chain and the Device Health GUI to flag up fault management information on devices that have lost power or network connectivity. Finally, the *ManufacturingApplication* class supports accessibility to services by system providers. A Mediation service enables *TrackingMaintenance* of device firmware and parameters, Inventory of assets located, as required by the BusinessDecisionSupport service and historic positioning from the *TrackingService*. The *GDOPValuePartition* enables quantitative evaluation of GDOP measurement errors.

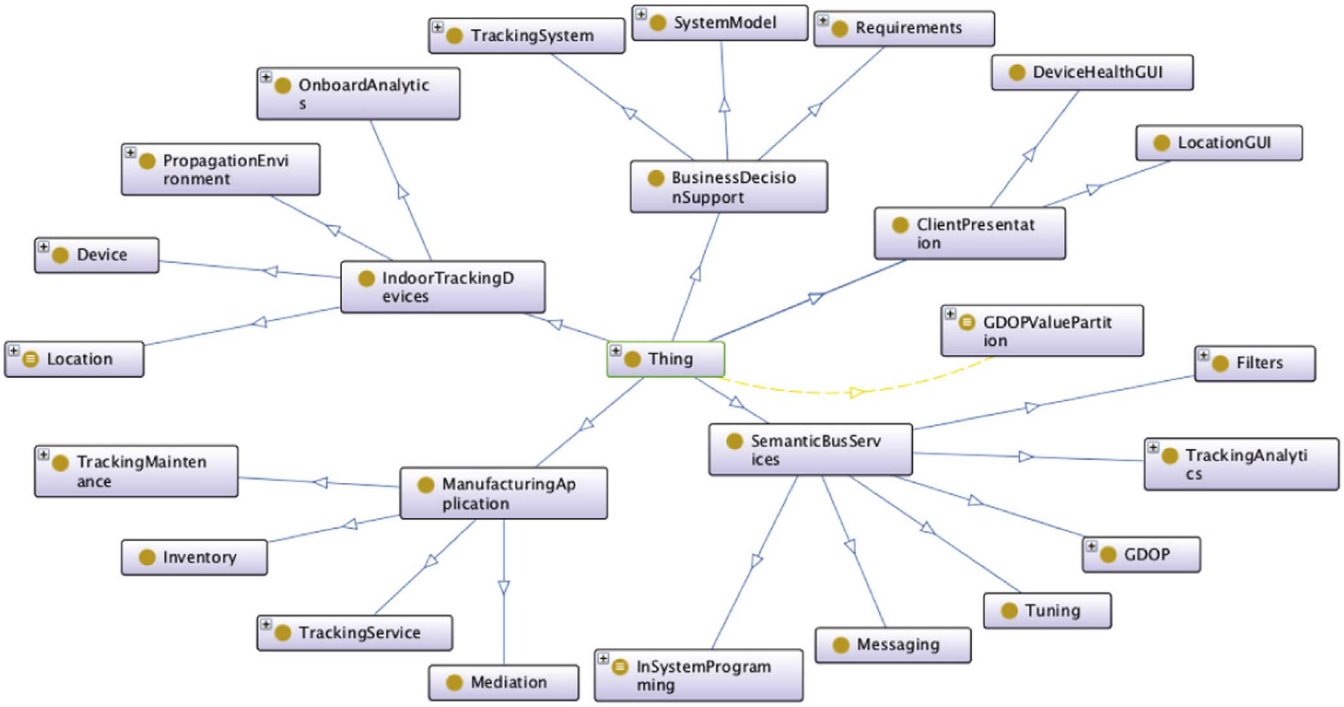


Fig. 2. Tracking Ontology: Top Level Classes.

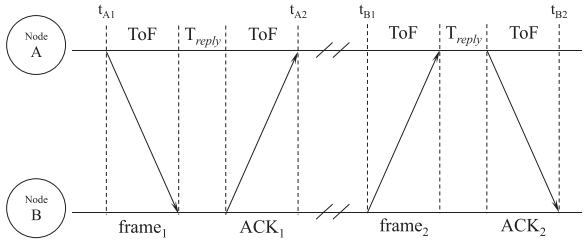


Fig. 3. SDS-TWR.

3.2. IoT infrastructure

In the proposed architecture, every device has a unique IPv6 address and is connected to the Internet, for reliable and secure, seamless service provisioning. All our devices are equipped with wireless interfaces and anchor devices, via Ethernet interface. Gathered data are stored and analysed in remote servers, and local servers are used to avoid data loss on connectivity failure. An overview of the system is provided in Fig. 5.

RPL has been used as it is designed to stabilise and avoid flooding in lossy wireless conditions (Winter et al., 2012). However, as RPL does not respond well under rapid link tear-down and setup, tracking is initialised only during periods of low accelerometer-measured mobility. This is arbitrarily based on the maximum factory vehicle speeds of 2.5 m/s of our industry partner. Economy of communication is a critical consideration for IoT devices, which should be capable of real-time monitoring, without undermining shared network resources, system timeliness and usefulness (Xu et al., 2014; Goswami, 2013).

Anchor devices route traffic onwards based on LAN routing protocols. Background control plane traffic, including IPv6 neighbour discovery solicitations, advertisements and RPL packets, enables the WSN to be self-configuring. IP, ICMP and UDP are used at the transport and network layers (Vasseur and Dunkels, 2010).

3.3. ToF and RSSI ranging

The devices used are custom designed versions based on TI CC2538+CC1200 (Texas Instruments, 2013; TI, SimpleLink). A dual IEEE 802.15.4 RF interface supports low-power communications, for short-range 2.4 GHz and long-range sub-GHz frequencies. A Cortex-M3 MCU and 32 MHz crystal oscillator are key components used for ranging. The oscillator has ± 40 ppm drift, meaning that a 40 ppm error in 1 ms would be a 40 ns error. Measurement of timing from

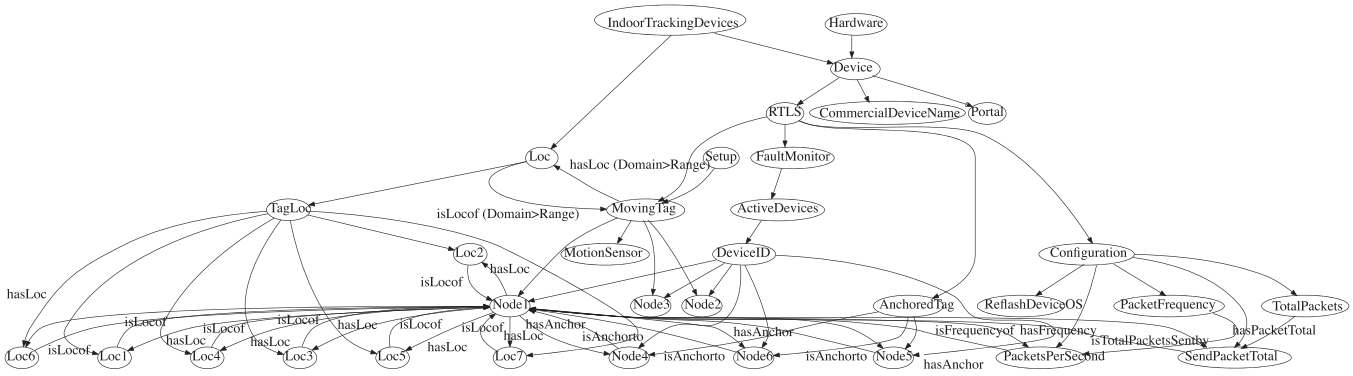


Fig. 4. Tracking Ontology: Devices Class with Individuals.

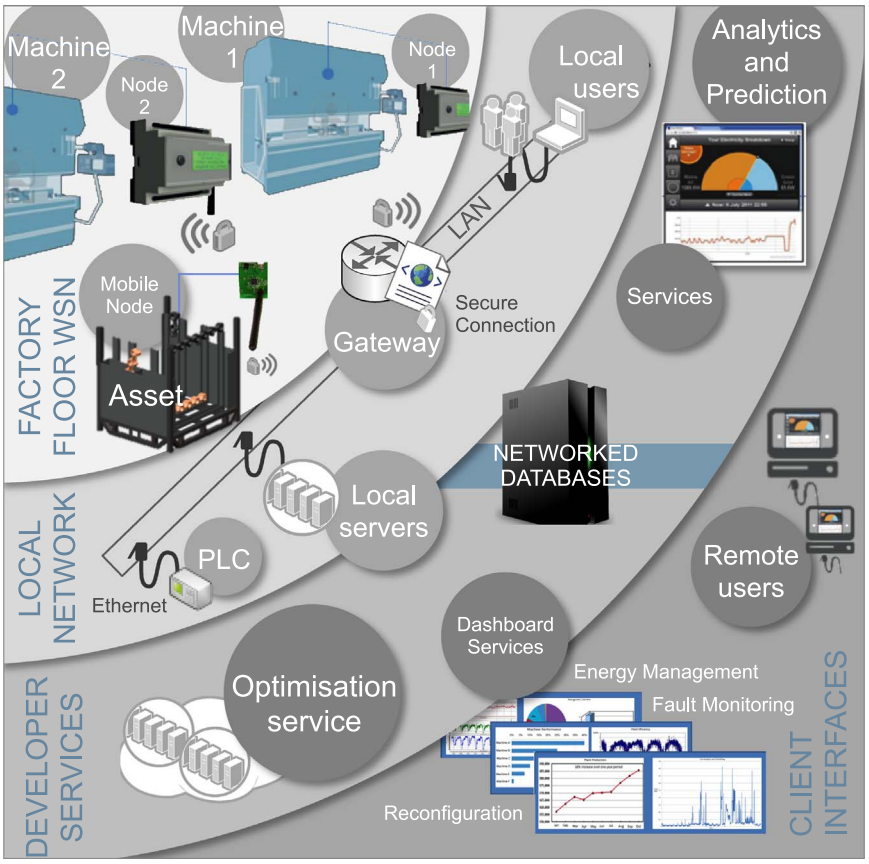


Fig. 5. Network Infrastructure.

hardware interrupts and the hardware acknowledgement on the receiver side of the device communications are used to limit timing error.

ToF and RSSI are metrics used to measure the distance between nodes. The proposed hybrid ranging uses SDS-TWR (Goswami, 2013) where each node measures the RTT from its own clock and calculates ToF and then distance, following the method shown in Section 2.1. To reduce communications overheads in our approach, we take 50 measurements per node at 250kbps, when accelerometer-measured mobility is low.

Wasteful battery consumption is avoided by reducing the communications requirement and making it event-driven. This enables the application to operate with an on-demand duty cycle where a node will only need to be active for a minimum amount of time. Additionally, communications redundancy is reduced by transmitting only a single mean distance estimate to the sink for every 50 SDS-TWR packets exchanged (Anastasi et al., 2009).

Radio transceivers can report RF signal power (RSSI) in dBm that can be used to calculate the propagation distance of a signal, using a log-attenuation model (Benkic et al., 2008; Whitehouse et al., 2007). The accuracy of ranging, based on this multi-parameter statistical model, rapidly decreases with distance (Pu et al., 2012; Liu et al., 2007) and needs to be calibrated to environment. RSSI ranging does not require any extra transmissions as distance can be measured using the same packets sent in SDS-TWR.

In the proposed system both RTT and RSSI readings are used for positioning, as described in Section 3.4. Least squares exponential regression is then used to calibrate measured RTT and RSSI to produce a ranging distance estimate .

3.3.1. Calibration phase

To calibrate the ranging algorithm, measurements were taken by a pair of nodes conducting the SDS-TWR method in an automotive manufacturing plant. The method is described in Section 3.3, where a single estimate is produced from the pairwise measurements. This enabled calibration of the timing offset (T_{Off}) and RSSI to actual internodal distance, d (Figs. 7–8). Least squares exponential regression was then used to fit RTT to a timing offset (T_p) and RSSI to distance for the estimate at each location.

Jackknife re-sampling cross-validation is used to evaluate the

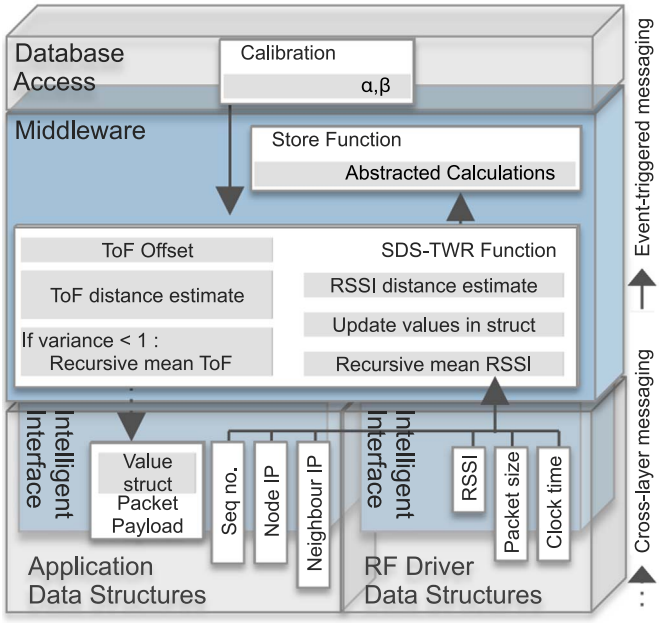


Fig. 6. Cross-layer middleware abstraction.

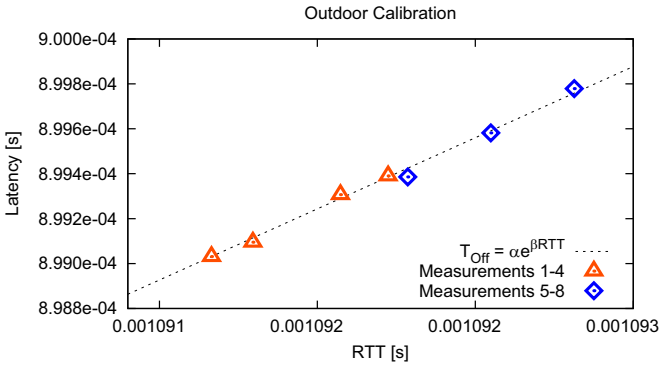


Fig. 7. Indoor Calibration: ToF Offset and RTT.

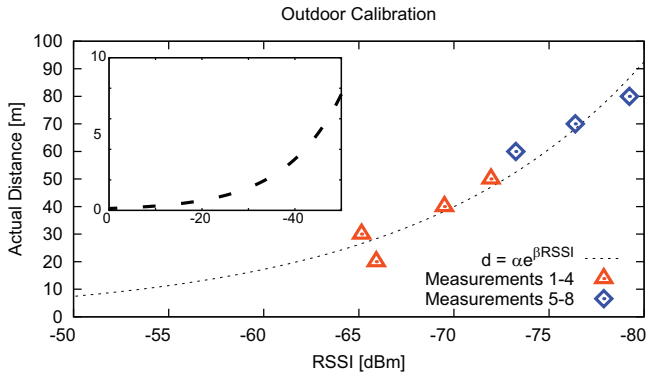


Fig. 8. Calibration: RSSI and Distance (with Zoomed view of 0–10 m).

accuracy of calibration. Measurements were taken at four and eight distances and data from measurements 5–8 were used to validate the calibration from measurements 1–4. All results regarding our estimation method were obtained using this jackknife re-sampling if not mentioned otherwise.

Equation $d = (1/2RTT - 1/2T_p - \alpha \cdot \beta^{RTT})c$ has been used to estimate distance from RTT and $d = \alpha \cdot \beta^{RSSI}$ from RSSI, in all deployments. To ensure the re-usability of the system, calibration was carried out using a different set of nodes on a different day from the ranging and positioning experiments in Section 4.

3.4. Hybrid semantic positioning

This hybrid approach is based on the clock precision problem that can result from the use of RTT alone for ranging and the difficulty in calibrating RSSI at long range. With an oscillator resolution of $c/32\,MHz$, a single clock-tick error in ToF would result in a 9.37 m ranging error. Thus this hybrid system sets the threshold at 10 m, using RSSI measurements for short-range positioning and ToF for long range positioning (Section 4.2). While the impact of the exponentially increasing path loss exponent reduces the accuracy of any RSSI calibration with distance (Pu et al., 2012). Thus, if SDS-TWR or RSSI ranging produces a value of less than 10 m, then the RSSI ranging output is input into the positioning service.

The positioning algorithm then takes three distance estimates to identify a Cartesian coordinate for a known mapped area, within a geographical coordinate system. However, the errors within these multiple ranging estimates are then propagated into a larger positioning error. Thus, sub-5 m NLoS ranging errors (Table 4) can cause wide fluctuations in distance estimates (Wylie and Holtzman, 1996; Puccinelli and Haenggi, 2006; Tang et al., 2007). To reduce the number of NLoS errors included in the ranging estimate, large variance (more than one deviation) from the running mean is used to exclude erroneous results.

In this paper, a trilateration service (Zhang et al., 2010) is used for positioning. Trilateration is used to determine the intersection of more than three lines, each corresponding to ranging distance estimates. These lines form the radii of three spheres, where the sphere centres are the known locations of fixed nodes. To improve the capability of the algorithm to stabilise, each of the six anchor-order permutations are used. This is because errors in the ranging estimates may mean that the algorithm cannot converge on any coordinate. To reduce this risk, the algorithm performs a search to ensure that the spheres formed by each of these six anchor ranging calculations are not collinear or concentric. In its entirety the algorithm takes on average 1.33 ms to run.

3.5. Cross-layer middleware

While the application is responsible for the unicast exchange of packets required for tracking, it cannot access RF driver parameters in an OSI stack. The OSI paradigm of withholding internal parameters from other layers facilitates fast development of interoperable systems and can be preserved with parameter monitoring in cross-layer middleware (Sharma et al., 2012).

The middleware functionality is shown in Fig. 6. Packet size, sequence number and receiver IP are abstracted at the application layer and associated with triggered *clocktime* abstraction from the RF driver. RSSI is also abstracted within the RF driver and *clocktime*, within the interrupt service routine, on receipt of the hardware acknowledgement of SDS-TWR.

In order to economise communication overheads, our middleware calculates recursive mean values for RTT and RSSI and associates these with next hop IP. To reduce NLoS errors, filtering outside one standard deviation of the mean is used. A timing offset, T_{Off}, and distance are also estimated in middleware using methods discussed in Section 2.1. RTT is measured, filtered and ToF calculated on a distributed basis within the nodes and mean data from one SDS-TWR exchange are then sent via a Gateway to a database.

4. Experimental evaluation

The capabilities of the proposed architecture and the ranging and positioning phases in numerous LoS and NLoS conditions and update and querying of the instantiated ontology have been validated in this section. This was conducted around automotive manufacturing stacks of steel racks, some full of assets and some of which were being moved around a plant by forklift traffic. All of these create complex network dynamics due to attenuation, reflection, refraction, diffraction and other multipath propagation effects (Wylie and Holtzman, 1996); Puccinelli and Haenggi, 2006); Tang et al., 2007). Mobility-induced reconfiguration of the network topology leads to greater rate of change in channel quality as nodes rapidly lose and gain wireless LoS.

In all deployments the devices were elevated on tripods to 1.4 m. This was to enable LoS testing in the absence of obstacles, with dimensions larger than the signal wavelength, in the 1st Fresnel volume around the automotive racks.

The instantiated positioning output was queried as a remotely accessed ontology set from a public SPARQL endpoint, created using an Apache Jena-Fuseki server (Fuseki). Queries were tested using both Fuseki and YASGUI, a web application for querying SPARQL endpoints (Rietveld and Hoekstra (2013).

4.1. LoS ranging

The SDS-TWR ranging approach was tested in three LoS environments, (1) The indoor plant environment of a UK based automotive collaborator, in a 5 × 40 m area surrounded by stacked, full metal racks of engine components, (2) A busy multi-storey car park provided a second complex LoS environment, combining concrete walls, metal beams and metal obstacles with exposed sides, (3) Ranging was

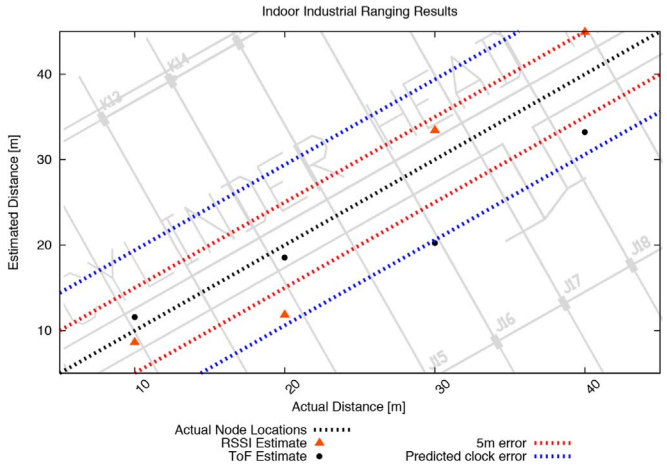


Fig. 9. LoS Ranging in Industrial Environment.

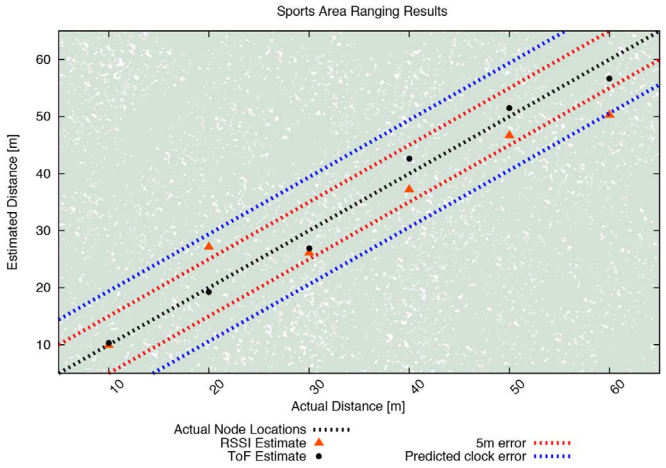


Fig. 11. LoS Ranging in Sports Area.

conducted in a sports area, with metal and human obstacles and fences but no obstacle mobility.

In the two indoor settings, a dense population of moving obstacles created rapidly changing network dynamics. Thus architecture performance was also dependant on timely processing. In both environments the maximum possible testing range was limited, therefore internodal distances could not extend beyond 40 m.

While the hybrid tracking system uses short-range RSSI ranging and long range ToF ranging, ToF and RSSI are compared at all distances in this section. In Figs. 9–11 the black dotted lines indicate the actual node locations and the blue lines the error which might be expected in the case of maximum clock drift (discussed in Section 3.3).

In the real industrial environment the Tof ranging error was 6.0 m but 3.2 m in the multi-storey car park (Table 2). In contrast RSSI ranging error went from 5.1 m in the factory to 8.9 m in the car park. From Fig. 10 it can be seen that ToF error stayed within reasonable bounds while RSSI error increased with internodal distance.

The plant environment presented a much more uniform distribution of obstacles, with forklifts moving on defined pathways, whereas obstacles (cars) were densely parked and regularly mobile throughout the test area in the car park. This had a greater impact on RSSI ranging where accuracy of the calibration strongly depends on path length.

However, the multistorey car park created worst-case conditions due to the density of parked cars and regular movement of vehicles, with a significant impact on RSSI. This pushed the ranging errors beyond 10 m at internodal distances of greater than 30 m (Fig. 10). The results still demonstrate that a high level of accuracy (5–6 m RMS) can be provided by both methods of ranging in a real industrial environment.

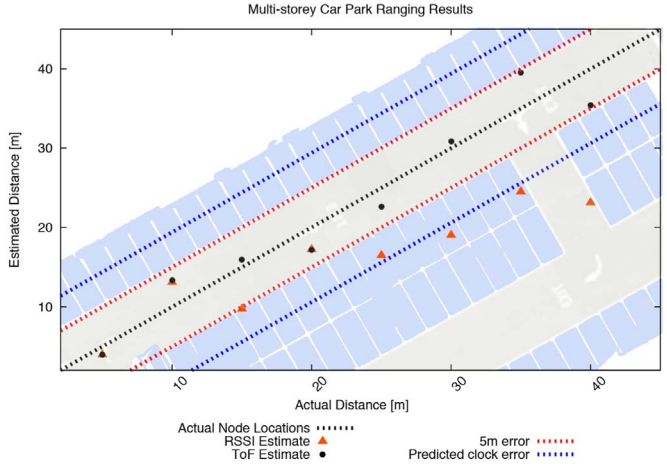


Fig. 10. LoS Ranging in Multistorey.

Table 2
RMS Ranging Error.

	RMS error		
Ranging	ToF [m]	RSSI [m]	Range [m]
Industrial LoS	6.03	5.11	40
Industrial NLoS	11.32	16.05	15
Multi-storey	3.20	8.89	40
Sports Area	2.24	5.48	60

Higher channel quality and link availability result when the granularity and mobility of obstacles are low. With improved propagation conditions it was more likely that the LoS signal arrived at the receiver. Thus in the open sports area, (Fig. 11) the RMS ranging error when ToF was used was the lowest of all scenarios at 2.2 m (Table 2).

As link length increases, network congestion and collision thresholds reduce, pushing protocols into error recovery. Again, the longer paths (up to 60 m) had a greater impact on the RSSI accuracy, resulting in an RMS error of 5.5 m, comparable to previous experiments, notwithstanding the improved multipath conditions .

In Table 4 the ranging system is compared to contemporary systems that have been validated in indoor environments. The approaches evidently produce varying results according to the range of office test environments (Cheon et al., 2016; Mazomenos et al., 2011; Pettinato et al., 2012). However, the proposed system produces a comparable RMS error to contemporary RSSI and ToF ranging solutions, while demonstrating robustness to a harsh industrial environment.

4.2. LoS positioning

Obtaining accurate positioning information on the basis of three or more sets of ranging data is key to real-time tracking of assets. While ranging can provide a circular or spherical area within which an asset can be located, positioning produces a specific coordinate location. The positioning approach was validated on a different day from the ranging test, three nodes were deployed in the open sports area and a fourth was carried across an eight point trajectory between these anchors, as indicated in Figs. 13–14.

The real world objects instantiated in the ontology, were then associated with location instances using OWL object properties (*hasLocation*, *isLocationof*) and data properties (*TimeStamp*, *UID*, *XCoordinate*, *YCoordinate*, *ZCoordinate*, *SystemNoiseVar* and *TransmitRate*.)

Figs. 13–14 demonstrate the system estimation versus actual

```
PREFIX ontoloc: <https://raw.githubusercontent.com/[redacted]
SELECT ?Location ?Time ?X ?Y ?Z ?PacketsSent ?Rate ?Anchors WHERE { ?Location ontoloc:isLocof ontoloc:Server1 .
  ?Location ontoloc:TimeValue ?Time .
  ?Location ontoloc:XValue ?X .
  ?Location ontoloc:YValue ?Y .
  ?Location ontoloc:ZValue ?Z .
  ?SendPacketTotal ontoloc:isTotalPacketsSentby ontoloc:Server1 .
  ?SendPacketTotal ontoloc:PacketTotalValue ?PacketsSent .
  ?PacketsPerSecond ontoloc:isFrequencyof ontoloc:Server1 .
  ?PacketsPerSecond ontoloc:PacketsPerSecondValue ?Rate .
{ SELECT (count(?AnchoredTag) as ?Anchors) WHERE {
  ?AnchoredTag ontoloc:isAnchorto ontoloc:Server1 . }
GROUP BY ?MovingTag } }
ORDER BY ASC(?TimeValue)
```

QUERY RESULTS

Raw Response | Table

Search: Show 10 entries

	Location	Time	X	Y	Z	PacketsSent	Rate	NumberOfAnchors
1	ontoloc:Location1	2014-11-06T13:22:06	0.01	-0.04	1.4	50	5	3
2	ontoloc:Location2	2014-11-06T13:23:33	1.26	7.97	1.4	50	5	3
3	ontoloc:Location3	2014-11-06T13:24:59	0.1	21.14	1.4	50	5	3
4	ontoloc:Location4	2014-11-06T13:27:52	12.69	17.58	1.4	50	5	3
5	ontoloc:Location5	2014-11-06T13:28:55	8.68	12.9	1.4	50	5	3
6	ontoloc:Location6	2014-11-06T13:33:25	11.32	3.5	1.4	50	5	3
7	ontoloc:Location7	2014-11-06T13:34:43	16.45	2.67	1.4	50	5	3

Fig. 12. Remote Querying Semantic Position.

position of the nodes. Table 3 compares the hybrid approach to positioning with that based purely on RSSI or ToF data. RMS error shed little light on the benefit of the hybrid approach over the other two. The maximum errors for the ToF and hybrid approaches were comparable at 21.7 and 21.2 m, but the RSSI error was significantly higher at 30.4 m.

With the ToF and hybrid approaches the algorithm converged on a coordinate for all location. In this experiment nodes were subject to the shortest internodal distances of only 28 m. However RSSI ranging still performed poorly and the positioning algorithm could not converge on a location in all cases. Ranging errors from each of the fixed nodes propagated into the subsequent positioning phase, resulting in large positioning errors (Table 3).

Fig. 12 shows the remote update and querying of the rich tracking data. Here, the system outputs are *Time*, *X*, *Y* and *Z*. Whereas, *Anchors*, *PacketsSent* and *Rate* are variables that have been reasoned from these data. These variables provide useful knowledge that can be used for fault management, on anchors in range of the assets and packet loss (channel busy periods and packet arrival rate), without requiring redundant reporting by the nodes themselves .

The highest level of positioning performance was gained by combining RSSI measurements for short-range and ToF for long range with a threshold set at 10 m. RMS errors, mean and maximum errors were the lowest with this approach. Table 5 shows that the mean error of the proposed tracking system (up to 4.2 m) is comparable to the mean error of contemporary RSSI and ToF tracking systems reported in the literature.

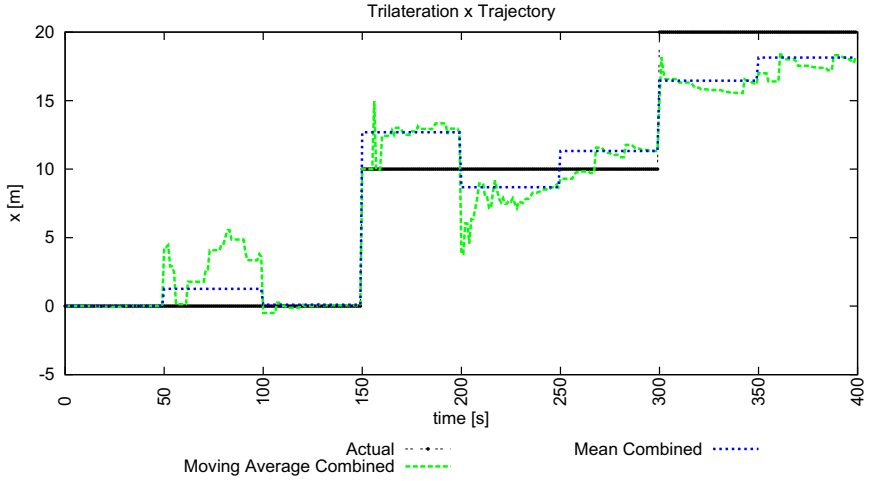


Fig. 13. X Trajectory Estimate.

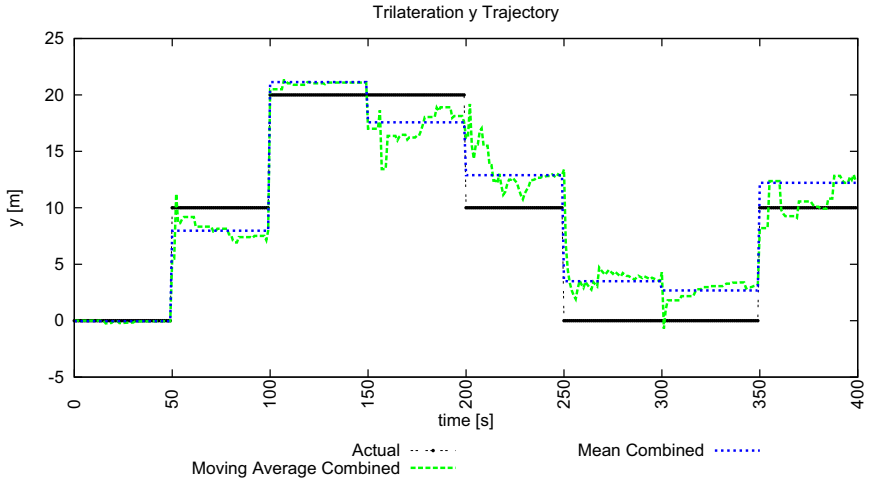


Fig. 14. Y Trajectory Estimate.

Table 3
Hybrid Positioning Error.

	RMS error		
Positioning	x [m]	y [m]	Convergence [%]
ToF	11.16	9.26	100
RSSI	6.45	15.36	87.5
Hybrid	10.48	8.55	100

Table 4
Validation of Potential Ranging Systems.

Environment	Ranging	RMS Error	Comms
Industrial	Proposed	5–6 m	250kbps
Office	WSN RSSI Zanella and Bardella (2014)	4.6 m	N/A
Office	WSN ToF Mazomenos et al. (2011); Pettinato et al. (2012)	<5 *m*	250–500 kbps
WiFi-free Office	Zigbee ToF Cheon et al. (2016)	0.5 m	N/A

Table 5
Validation of Potential WSN Location Systems.

Environment	Ranging	Mean Error	Comms
Industrial	Proposed	<4.2 *m*	250kbps
Outdoor/Office	RSSI Lau and Chung (2007)	<2 *m*	0.76 Hz
Office	ToF Mazomenos et al. (2013); Hartmann et al. (2016)	<3 *m*, <5.9 *m*	2 Hz

4.3. Non-line of sight conditions

A second bank of ranging tests was conducted, across varying obstacles for the same internodal distance. Results were collected in five conditions: (1) both nodes in LoS, (2) 5 m depth of metal obstacles with LoS, (3) 5 m depth of metal obstacles with NLoS, (4) 10 m depth of metal obstacles with LoS and (5) 10 m depth of metal obstacles with NLoS. The obstacles as seen from both nodes is illustrated in Figs. 15. For all LoS cases, obstacles were present in the second Fresnel volume and for NLoS cases in the first Fresnel volume.

This test area was surrounded by metal racks, beams and columns, thus the overall RMS error was significantly higher than in previous environments, exceeding 10 m with all ranging methods. However,

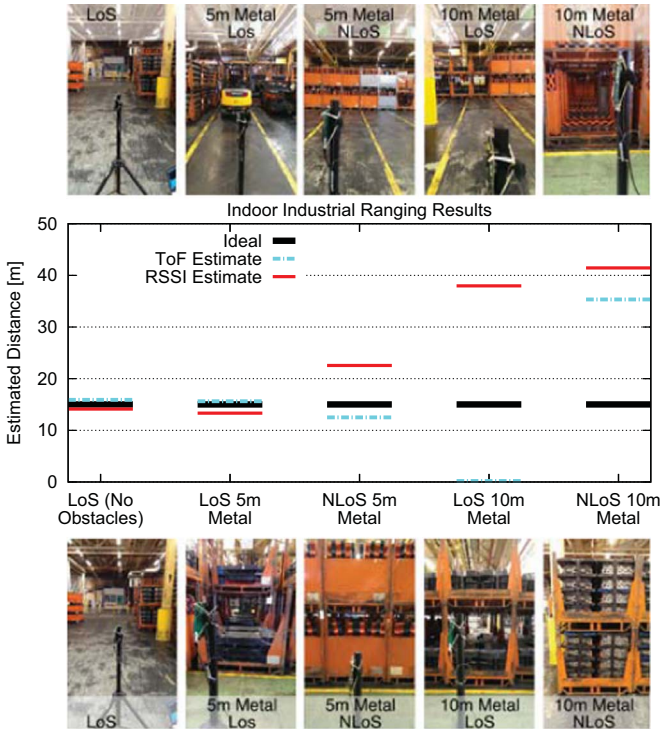


Fig. 15. Ranging in LoS/NLoS with Metal Obstacles.

actual ranging accuracy varied in each location and decreased, as expected, with the depth and density of the obstacles, as shown in Fig. 15(b).

The ToF distance was within 1 m of the true range for the full LoS case and for LoS with a 5 m depth of metal obstacles. This accuracy reduced to 2.5 m with NLoS and 5 m of obstacles. The RSSI ranging achieved a more consistently increasing error with obstacle density than ToF. However, with 10 m of full racks and NLoS between devices, errors of more than 20 m occurred for all approaches. Evidently, both ToF and RSSI ranging can offer a reasonable degree of ranging accuracy with up to 5 m of metal obstacles in the first Fresnel zone. Assuming that some LoS signals are received, filtering can be used to ignore distance estimates with high variance.

5. Conclusions and future work

This paper has presented the design, implementation and proof of concept evaluation of an industrial, semantic Internet of Things

positioning architecture, using low-power embedded wireless sensors. The proposed architecture deployed wired nodes at known locations in order to execute real-time locations of moving assets, without reliance on high processor and power overheads. Performance evaluation has shown comparable RMS ranging accuracy (ToF 6 m and RSSI 5.1 m, with 40 m range in an indoor industrial location) to existing systems tested in non-industrial environments and a 12.6–13.8 m mean positioning accuracy.

Future work will extend the architecture to further develop the middleware into a full semantic service bus and its interfaces linked to additional services to access information from accelerometer and gyroscope drivers and to correct ranging results using a complementary filter. The SPARQL endpoint will be used for rapid ontology reasoning. The positioning system is also to be tested in the industrial environment, with devices attached to mobile automotive racks and a fourth anchor in a different plane (Zhang et al., 2010) to increase the capability of the trilateration algorithm to converge. Finally, the positioning system will be tested under NLoS conditions, similar to those considered for ranging in Section 4.3.

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