An accurate real-time RFID-based location system

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Abstract: Modern applications frequently require the ability to locate objects in real-world environments. This has motivated the development of a number of competing approaches to object localisation, most of which target specific applications. Radio Frequency IDentification (RFID) has emerged as a viable platform for localisation, but due to a number of unresolved challenges with this technology, high levels of performance and wide applicability have remained elusive. In this paper, we outline an RFID-based object localisation framework that addresses these challenges, and propose the use of Received Signal Strength (RSS) to model the behaviour of radio signals decaying over distance in an orientation-agnostic manner to simultaneously locate multiple stationary and mobile objects. The proposed localisation system can operate in a realistically radio-noisy indoor environment, enables design-space trade-offs, is highly extensible, and provides use-case-driven average accuracy as low as 0.15 metres. The proposed localisation system can quickly locate objects with or without the use of reference tags, and illustrates that RSS can be a reliable metric for RFID-based object localisation.

Keywords: RFID; localisation; RSS; empirical power-distance relationship; tag-reader pairs.

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1 Introduction

Modern life has been transformed by the rise of ubiquitous embedded computing devices. These technologies have significantly evolved fields as diverse as manufacturing, energy management, telemedicine, real-time communication, and personal entertainment (Abowd and Mynatt, 2000; Estrin et al., 2002; Liu et al., 2006; Merrell et al., 2005; Satyanarayanan, 2001; Schilit, 2003; Want et al., 2007; Want, 2008). Embedded computing devices are the result of advances in multiple emerging computing paradigms which have introduced fundamentally new requirements and capabilities (IDC Government Insights, 2013). One such requirement is the ability to efficiently and accurately locate objects in any environment (Hightower and Borriello, 2001).

Locating objects is vital to several cross-cutting applications – examples include locating boxes in warehouses, location-based advertising, and equipment tracking, among others (Sweeney, 2005). Consequently, object localisation research is rapidly advancing with approaches based on competing technologies such as Wi-Fi, wireless sensors, lasers, cameras, and ultrasonics, and emerging techniques include signal time of arrival, signal strength, signal phase, etc., have been developed (Bahl and Padmanabhan, 2000; Chae and Han, 2006; Hahnel et al., 2004; He et al., 2005; Mao et al., 2007; Middlebrooks et al., 1991; Montemerlo et al., 2002; Niculescu and Nath, 2002; Priyantha et al., 2000; Otsason et al., 2005).

Originally invented to enable the automatic identification of objects, Radio Frequency IDentification (RFID) technology has since shown potential as a means of locating objects. While RFID technology was not designed for this purpose, it has several key advantages over existing technologies in the context of object localisation. These include operability beyond line of sight, usability in poorly illuminated environments, and easy scalability (Allipi et al., 2006; Milella et al., 2009).

Several RFID-based object localisation approaches targeting indoor environments have been proposed. However, these have tended to provide poor localisation performance and limited applicability (Bechteler and Yenigun, 2003; Bekkali et al., 2007; Choi and Lee, 2009; Wang et al., 2007; Zhang et al., 2007; Zhao et al., 2007). Furthermore, few approaches have addressed the key challenges that preclude high performance, robustness, and scalability, while maintaining reasonable solution cost (Chawla et al., 2010a; Chawla et al., 2010b; Chawla and Robins, 2011a; Chawla and Robins, 2011b; Chawla and Robins, 2012; Chawla et al., 2013; Chawla and Robins, 2013b; Chawla and Robins, 2013c; Chawla, 2014; Chawla and Robins, 2015). Given the current state of the art, there remains significant research work to be done in the utilisation of RFID technology for object localisation.

There are several existing RFID-based object localisation methods. Approaches based on measurements of Received Signal Strength (RSS) measure the variation in an RFID tag's backscattered signal power as the distance between the tag and RFID reader varies to estimate the tag's location (Ni et al., 2003). However, position estimates based on RSS have been generally considered unreliable due to susceptibility to sources of environmental interference such as multipath propagation, occlusion due to metals and liquids, and other sources of spatio-temporal interference (Brchan et al., 2012; Wu et al., 2015).

We show that in addition to such sources of environmental interference, further localisation performance degradation is caused by the highly variable radio sensitivity of tags due to manufacturing inconsistencies. Few RFID-based object localisation approaches currently account for tag sensitivity variation and thus either suffer from low localisation performance, high cost or both (Chawla et al., 2010a; Chawla et al., 2010b; Chawla and Robins, 2011a; Chawla and Robins, 2011b; Chawla et al., 2013; Chawla and Robins, 2013b; Chawla and Robins, 2013c; Chawla, 2014; Chawla and Robins, 2015;

Choi et al., 2009). To mitigate the variability in tags' radio sensitivity, we propose the technique of sorting tags based on detection sensitivity and only using uniformly sensitive tags for localisation.

We propose to locate tags attached to stationary and mobile objects by establishing power-distance relationships correlating the tags' RSS behaviour with tag-reader distance. However, given that radio frequency signal behaviour can vary considerably in a given environment, theoretical power-distance relationships cannot directly be used to reliably locate tags (Chawla et al., 2010a; Chawla et al., 2010b; Chawla and Robins, 2011a; Chawla and Robins, 2011b; Chawla et al., 2013; Chawla and Robins, 2013b; Chawla and Robins, 2013c; Chawla, 2014; Chawla and Robins, 2015; Finkenzeller, 2003). We assume that the average environment-specific impact on a tag's RSS is statistically invariant due to our focus on well-characterised applications. Thus, our proposed approach factors out the interfering environment and utilises uniformly sensitive tags to empirically establish power-distance relationships between a tag's RSS and tag-reader distance by developing several RSS decay models.

A tag's orientation can dramatically impact its detectability and operational performance (Bolotnyy and Robins, 2007). As tags are likely to be arbitrarily oriented in real-world deployments, RSS decay models must account for tag orientation to enable robust and accurate localisation performance. Thus, by using orientation-agnostic RSS decay models, uniformly sensitive tags, and carefully considering the tag-reader distance and operating environment, we dispel the common notion of RSS being an unreliable parameter, and we recommend its possible use for object localisation as well as other applications.

Moreover, we show that by pairing select tags and readers, RSS decay models can be customised to deliver hardware-specific localisation performance (i.e. different tag-reader pairs yield different levels of performance). Thus, models such as these can help improve localisation performance by combining different RFID readers and tags.

Currently, several RFID-based object localisation approaches rely on reference tags to improve their localisation performance (Allipi et al., 2006; Bekkali et al., 2007; Ni et al., 2003; Seo and Lee, 2008). We show that localisation performance can be improved only up to a point using reference tags, identify localisation performance and reference tag density trade-offs, and show that reference tags may be excluded without significantly reducing the localisation performance, thereby considerably improving solution deployment cost.

We experimentally verified that the proposed object localisation framework and system works with commercially available off-the-shelf unmodified RFID hardware and that it is computationally efficient. Thus, by combining the aforementioned insights, we propose a 2D and 3D RFID-based real-time location system for simultaneously locating multiple stationary as well as mobile objects.

This paper is organised as follows: Section 2 provides a brief account of the basics of RFID technology and describes the state-of-the-art of RFID-based object localisation. In Section 3 we make the case for RFID-based object localisation by highlighting key object localisation challenges and their mitigating techniques, define the problem of RFID-based object localisation, and describe our extensible RFID-based object localisation framework. We experimentally evaluate the proposed framework in Section 4, and conclude with future research directions in Section 5.

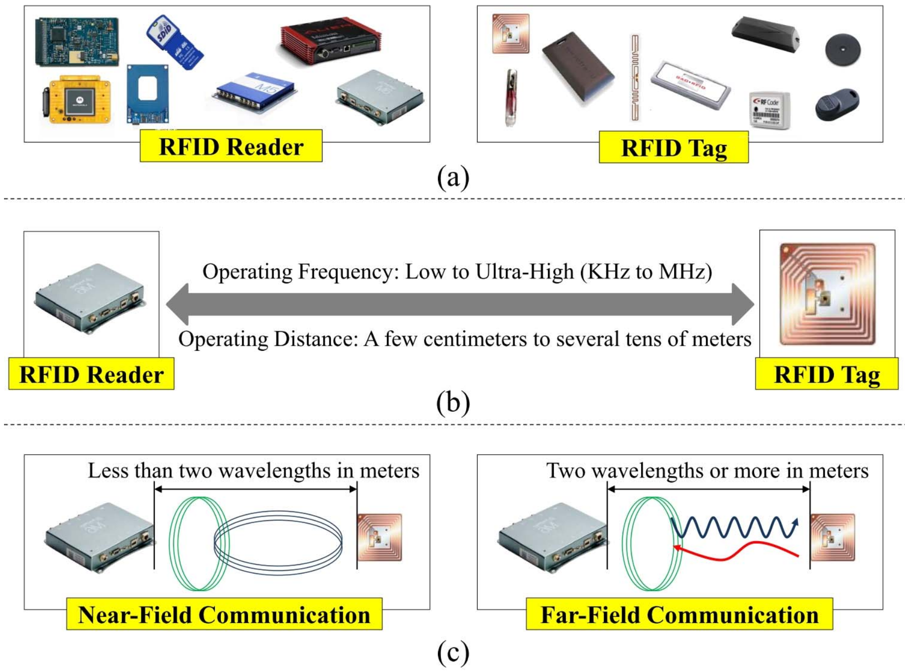
2 Related work

In this section, we briefly discuss the basics of RFID technology and present the state-of-the-art of RFID-based object localisation research.

2.1 Basics of RFID technology

RFID enables the automatic identification of objects and has diverse applications in areas such as livestock tracking, automatic toll collection, warehouse and store checkout automation, theft prevention, and supply chain streamlining (EPCglobal, 2011a; EPCglobal, 2011b; Chawla et al., 2010c; Chawla and Robins, 2013a; Sweeney, 2005; Want, 2004; Want, 2008). It is a wireless technology involving tags and a reader, which use radio frequency signals to communicate. RFID tags and readers are available in a variety of form factors, can utilise two different communication mechanisms, and are operable over a wide range of frequencies and distances (EPCglobal, 2008; EPCglobal, 2011c). Figure 1 illustrates the basics of RFID technology.

Figure 1 RFID tag-reader – (a) form factor, (b) operating frequency and distance, and (c) communication mechanism (see online version for colours)



There are three types of RFID tags - passive, semi-passive, and active tags. Passive tags derive their operational power from and communicate using the incident radio frequency signal emitted by the RFID reader. Semi-passive tags use the reader's radio signal for communication purposes while having an on-board battery for performing computations. Active tags have an on-board battery and can initiate communication on their own (Sweeney, 2005).

The two different tag-reader communication mechanisms utilise the change in temporal radio frequency electromagnetic (EM) fields with respect to tag-reader distance. As shown in Figure 1 (c), when the tag-reader distance is up to two wavelengths of the selected radio frequency signal, a small separation between the charge and current effects of the EM field creates an inductive field which is used for tag-reader communication. This communication mechanism is called ‘near-field communication’. However, as the tag-reader distance increases beyond the two wavelengths span limit, the charge and current effects separate enough to create a radiative field. This radiative field-based tag-reader communication mechanism is called ‘far-field communication’ (Finkenzeller, 2003).

2.2 Object localisation research landscape

The RFID-based object localisation research landscape consists of numerous approaches that utilise techniques such as signal Angle of Arrival (AoA), signal Time of Arrival (ToA), signal Time Difference of Arrival (TDoA), signal phase, and signal strength (Azzouzi et al., 2011; Arumugam and Engels, 2009; Brchan et al., 2012; Chawla et al., 2010a; Chawla et al., 2010b; Chawla and Robins, 2011a; Chawla and Robins, 2011b; Chawla et al., 2013; Chawla and Robins, 2013b; Chawla and Robins, 2013c; Chawla et al., 2014a; Chawla et al., 2014b; Chawla et al., 2014c; Chawla, 2014; Chawla and Robins, 2015; Choi and Lee, 2009; Choi et al., 2009; Hekimian-Williams et al., 2010; Ni et al., 2003). In this paper, we focus primarily on signal strength-based indoor localisation approaches.

Object localisation approaches based on signal strength (and RSS) rely on radio signal propagation behaviour to estimate the tag-reader distance. Theoretically, the Friis transmission equation defines the relationship between the tag-reader signal strength and their respective distance (Finkenzeller, 2003). Numerous signal strength-based localisation approaches have been proposed (Bekkali et al., 2007; Brchan et al., 2012; Choi and Lee, 2009; Choi et al., 2009; Ni et al., 2003; Wu et al., 2015; Zhang et al., 2010; Zhao et al., 2007).

Bekkali et al. (2007) utilise mobile readers and reference tags’ RSS to construct a probabilistic RFID map combined with a Kalman filter to estimate target tags’ locations in indoor environments. The overall localisation accuracy of their approach is in the range of 0.5–1 m. However, their approach is computationally expensive due to the use of probabilistic techniques (i.e. Kalman filter, RFID map, etc.), which precludes locating objects in real-time. Furthermore, due to their dependence on reference tags, the overall cost of their proposed approach is economically prohibitive.

Brchan et al. (2012) propose to combine reference tags with linear RSS-based propagation models and trilateration to locate stationary tags in indoor environments. While the average localisation accuracy of their approach is 1–2 m, it has limited applicability due to the use of unrealistic radio signal propagation models, reliance on reference tags, and expensive active tags.

Choi and Lee (2009) use passive reference tags combined with a *k*-nearest neighbour algorithm to help locate tags with an average localisation error of 0.21 m. However, their approach does not consider environmental interferences, tags’ inherent RSS variability, and tag orientation, thus limiting its scalability. Furthermore, their approach relies on reference tags to improve the target tags’ position estimates, which makes its high localisation performance dependent on the reference tag density.

Choi et al. (2009) utilise a *k*-nearest neighbour algorithm combined with reference tags' RSS to locate objects with accuracy in the range of 0.2–0.3 m. They note that tags have variable RSS behaviour but do not mitigate this issue. Their approach ignores that a tag's axial-radial orientation (i.e. tag orientation on its axis and around the reader) impacts its detection probability and therefore its localisation performance (Bolotnyy and Robins, 2007). Therefore, their proposed approach may not be applicable in real-world deployments.

Ni et al. (2003) develop an RFID-based location system that uses active reference tags combined with *k*-nearest neighbour algorithm to locate tags with an accuracy of up to 2 m. While their approach may be simple, it comes at a very high cost of deploying active reference tags. Furthermore, their approach takes a non-trivial amount of localisation time, making it too slow for applications that require locating objects in real-time.

Wu et al. (2015) utilise reference active and semi-passive tags in combination with *k*-nearest neighbour algorithm, linear RSS-based propagation models, and trilateration to help locate target tags with localisation accuracy in the range of 1.08–2.06 m. While their localisation approach does locate tags in real-time, it may have relatively low localisation accuracy due to the use of linear radio signal propagation models, and high operating cost and scale-resistance due to reliance on active and semi-passive reference tags.

Zhang et al. (2010) correlate variation in the RSS of targeted active tags with that of reference tags and wireless sensors to estimate the positions of the target tags with an average localisation accuracy of 0.45 m. Moreover, in order to improve overall localisation accuracy, a Support Vector Regression (or SVR)-based technique is employed to predict the most likely location of the target tag. This approach is not cost-scalable due its reliance on reference tags and sensors, and requires frequent maintenance due to the use of battery-powered active tags and sensors. Moreover, SVR technique-driven location estimates come at the expense of increased localisation time.

Zhao et al. (2007) introduce the notion of virtual tags and a proximity map, which considers the proximity of actual reference tags to that of virtual tags. A linear interpolation algorithm utilising reference tags' RSS is used to determine the virtual tags' positions. Target tags are localised by intersecting different reader-dependent proximity maps consisting of virtual and reference tags. While the overall localisation accuracy of their approach is in the range of 0.14–0.29 m, the density of reference tags impacts not only the accuracy of virtual tags' position estimates but also their overall performance. Moreover, developing proximity maps for large-scale deployments may be computationally difficult.

3 Real-time RFID-based localisation

In this section, we highlight the key object localisation challenges and their possible mitigation techniques, define the research problem of RFID-based object localisation, and describe our proposed RFID-based localisation framework.

3.1 Object localisation challenges

Tag-reader communication is not only affected by the environmental interferences (e.g. multipath propagation, presence of metal and liquid containers, background noise due to motors, etc.) but more importantly also by the tag's variable radio sensitivity, placement, and orientation. Moreover, the reader's proximity to tags is another important factor affecting object localisation performance. While the impact of environmental interferences on the tag-reader interaction can be factored out, systematic steps must be taken to mitigate such interference, orientation, and placement-related object localisation challenges.

We propose to address aforementioned interference challenges by utilising techniques such as electrostatic shielding, full Faraday cycle analysis, and path loss contour mapping, which can minimise the impact of sources of environmental interference on object localisation performance (Sweeney, 2005). Moreover, by strategically deploying more tags and readers in select regions of interest, adverse interference effects can be minimised. Furthermore, algorithmically modulating the power in the reader-transmitted radio signals can help minimise stray tag read interferences (Chawla and Robins, 2011a; Chawla and Robins, 2011b). While the above techniques can help minimise environmental interferences, hardware-specific interferences such as a tag's variable radio sensitivity must also be carefully addressed.

We note that the tag radio sensitivity is dependent on the tag antenna gain, chip high impedance state, and threshold power sensitivity (Nikitin and Rao (2008). Owing to manufacturing variability, small changes in the circuit components of the tag's hardware (e.g. resistive, capacitive, and inductive components, etc.) lead to significant variability in the tag's radio sensitivity, causing non-uniform tag detectability and unreliable RSS behaviour that impact object localisation performance. To address this issue, we propose a pre-processing step of sorting (i.e. binning) the tags based on their detection sensitivities and RSS behaviour. This step ensures that only uniformly sensitive tags are used in our localisation experiments, leading to more consistent and accurate results.

Placement-related localisation challenges involve issues of tag-reader orientation, relative placement, and proximity which cause delays and errors in locating the tags. For example, several RFID-based object localisation approaches depend on a suitable arrangement of reference tags to enable locating the target tags. Assuming sufficient deployment density of reference tags, we propose that such tags be regularly placed to achieve higher localisation performance (Han et al., 2007). Moreover, tag orientation significantly impacts its detectability and RSS behaviour (Bolotnyy and Robins, 2007; Chawla and Robins, 2011a; Chawla and Robins, 2011b; Chawla et al., 2013). Thus, we propose to characterise the axial-radial orientation of tags when developing RSS decay models, which help mitigate such issues (see Section 3.3.3 regarding empirical power-distance relationships).

Additionally, a variety of other spatio-temporal interference factors affect the practical distance covered by the radio signals. This distance determines the tags' operating region with respect to the reader. Thus, the reader's location and proximity to the tags plays a key role in the tags' localisation performance. We propose utilising long read range passive tags optionally combined with a sufficiently dense deployment of reference tags to improve the object localisation performance.

3.2 Problem definition

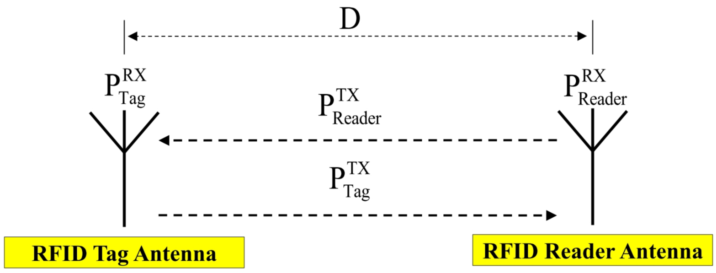
The research problem we seek to solve is to locate objects accurately and efficiently using only standard RFID technology (i.e. locating objects that are affixed with passive tags as oppose to combining more esoteric technologies such as lasers, ultrasonics, etc., with RFID technology in an ad-hoc manner in order to locate objects).

Our proposed object localisation approach relies on the radio signals' power-distance relationship to develop tag orientation-agnostic RSS decay models, which can be optionally combined with reference tags to locate objects. The Friis transmission equation characterises the free-space tag-reader theoretical power-distance relationship as the following (Finkenzeller, 2003; Sample et al., 2007).

$$P_R = P_T G_R G_T \left(\frac{\lambda}{4\pi D} \right)^2 \tag{1}$$

where P_R is the power received at the receiver (e.g. a tag) and P_T is the power transmitted by the transmitter (e.g. a reader). G_R and G_T are respectively the antenna gains for the receiver and transmitter, λ is the radio signal wavelength, and D is the receiver-transmitter distance. Considering the radio signal propagation direction from the reader (i.e. a transmitter) to the tag (i.e. a receiver), as shown in Figure 2, the modified Friis transmission equation is given below.

Figure 2 Tag-reader theoretical power-distance relationship (see online version for colours)



$$P^{RX}_{Tag} = P^{TX}_{Reader} G_{Reader} G_{Tag} \left(\frac{\lambda}{4\pi D} \right)^2 \tag{2}$$

Similarly, considering the radio signal propagation direction from the tag (i.e. a transmitter) to the reader (i.e. receiver), the modified Friis transmission equation is given below.

$$P^{RX}_{Reader} = P^{TX}_{Tag} G_{Reader} G_{Tag} \left(\frac{\lambda}{4\pi D} \right)^2 \tag{3}$$

We note that the free-space radio signal propagation leads to its spatio-temporal decay (i.e. attenuation), which is defined as path loss. Considering the radio signal propagation direction from the tag to reader and adjusting for the path loss we have the following relationship.

$$P^{TX}_{Tag} = P^{RX}_{Tag} PL(D) \tag{4}$$

Substituting equations (4) in (3), we get:

$$P_{Reader}^{RX} = P_{Tag}^{RX} G_{Reader} G_{Tag} \left(\frac{\lambda}{4\pi D} \right)^2 PL(D) \tag{5}$$

Substituting equations (2) in (5), we get:

$$P_{Reader}^{RX} = P_{Reader}^{TX} G_{Reader}^2 G_{Tag}^2 \left(\frac{\lambda}{4\pi D} \right)^4 PL(D) \tag{6}$$

The physical quantity expressed in equation (6) is measured in watts, which could become inconvenient when very small or very large values are involved. Therefore, we simplify calculating the RSS by using a decibel (dB) scale, wherein both sides of equation (6) are multiplied by $10\log_{10}\{\cdot\}$ (expressed here as the operator $[\cdot]_{dB}$). Thus, the scale-adjusted Friis transmission equation is given below.

$$\left[P_{Reader}^{RX}\right]_{dB} = \left[P_{Reader}^{TX}\right]_{dB} + \left[G_{Reader}^2\right]_{dB} + \left[G_{Tag}^2\right]_{dB} + \left[\left(\frac{\lambda}{4\pi D}\right)^4\right]_{dB} + \left[PL(D)\right]_{dB} \tag{7}$$

When locating objects in an indoor environment, the ambient environment's impact on the tag-reader signal strength (and thus the RSS) must also be characterised. While this impact, measured using RSS variability, could be theoretically modelled in a number of ways, the most general way is to model it as a Gaussian random variable (Rappaport, 2002). Thus, the RSS variability-adjusted Friis transmission equation is as follows.

$$\begin{aligned} \left[P_{Reader}^{RX}\right]_{dB} &= \left[P_{Reader}^{TX}\right]_{dB} + \left[G_{Reader}^2\right]_{dB} \\ &\quad + \left[G_{Tag}^2\right]_{dB} + \left[\left(\frac{\lambda}{4\pi D}\right)^4\right]_{dB} + \left[PL(D)\right]_{dB} + \chi_\sigma \end{aligned} \tag{8}$$

We define the symbols used in the aforementioned expression as follows.

$\left[P_{Reader}^{RX}\right]_{dB}$: Power received at the reader (also known as the RSS)

$\left[P_{Reader}^{TX}\right]_{dB}$: Power transmitted by the reader to the tag

$\left[G_{Reader}^2\right]_{dB}$: Reader antenna gain

$\left[G_{Tag}^2\right]_{dB}$: Tag antenna gain

λ: Radio signal wavelength

D: Tag-reader distance

$PL(D)$: Tag-reader path loss

χ_σ: RSS variability modelled as a Gaussian random variable with zero mean and σ^2 variance.

The general definition of the Friis transmission equation (from which equation (1) is derived) suggests that the average ratio of the received power at the tag and transmitted power by the reader is inversely proportional to the N^{th} power of distance between them, where N is in the interval [3, 6]. Such a variation in N accounts for variability in the radio signal's frequency and its propagation losses, among other factors. However, such a characterisation only considers radio signal propagation in the direction of the tag from the reader and may not suitably characterise the amount of power backscattered by the tag to the reader. We provide a possible way, as shown in equation (8), to characterise that behaviour while also making apparent the latent factors in the aforementioned general definition of the Friis transmission equation. In effect, we account for transmitter and receiver-side radio signal strength in the presence of distance-dependent losses (i.e. through $PL(D)$) such as radio signal attenuation due to reflection, polarisation, and absorption.

Assuming all other variables are known a priori, the tag-reader distance can be estimated by measuring the transmitted versus received signal strength at the reader with respect to a given tag, as shown in equation (8). However, in addition to the limitations exhibited by the state-of-the-art signal strength-based RFID object localisation approaches (see Section 2.2 for limitations), a tag's inherent RSS variability and operating environment impact the overall object localisation performance.

While in equation (8) we generally account for the environmental interference sources' impact on the RSS, such theoretical power-distance relationships cannot yield high-performance object localisation due to the various real-world spatio-temporal interferences such as tag's inherent RSS variability, tag orientation, and environment-specific geometry (Choi et al., 2009; Chawla and Robins, 2011a; Chawla and Robins, 2011b; Chawla et al., 2013).

Additionally, modern RFID readers have the capability to measure the tags' RSS, which is utilised to coarsely locate the target mobile tags by integrating their speed over time as shown below (Alien Technology, 2014).

$$D = \int_0^t S(t)\,dt \tag{9}$$

where D is the distance a mobile target tag moves towards or away from the reader starting from a reference location, t is the duration of time the target tag remains mobile, and $S(t)$ is the mobile target tag's speed during that time. However, the above approach cannot determine the target tag's absolute position since the target tag remains mobile during the entire duration of measurements.

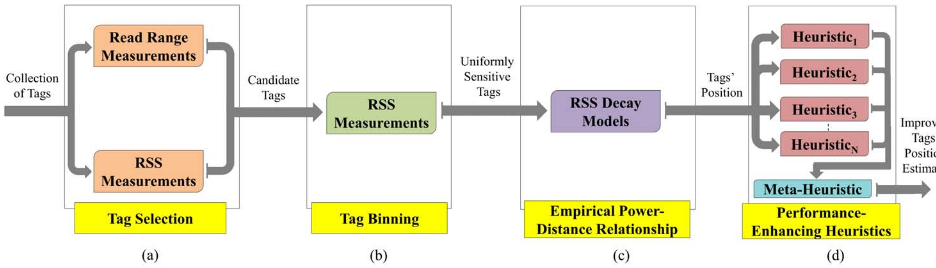
Given this background, our goal is to design a robust and real-time RFID-based object localisation framework and system based on empirical power-distance relationships that utilises the same set of readers' antennas to transmit and receive radio frequency signal, and is agnostic to the environment's geometry, and tag orientations.

3.3 RFID-based object localisation framework

We propose a robust and real-time RFID-based object localisation framework that simultaneously locates multiple objects in a realistically radio-noisy 3D environment. The proposed framework, as illustrated in Figure 3, has several primary components that work together in order to locate objects affixed with passive tags.

The process of locating objects in the proposed framework is initiated by procuring a collection of off-the-shelf passive tags and selecting candidate tags with uniform read range and RSS behaviour. Such candidate tags are potentially of different types (i.e. chipsets, form-factors, etc.). Figure 3 (a) depicts the step of processing a collection of tags to select candidate tags. After carefully selecting different types of candidate tags, a set of candidate tags of a particular type is sorted based on its set-wide RSS behaviour over different combinations of tag-reader distances and reader output power levels.

Figure 3 Main stages of the proposed RFID-based object localisation framework: (a) tag selection, (b) tag binning, (c) empirical power-distance relationship, and (d) performance-enhancing heuristics (see online version for colours)



This process of tag sorting (i.e. binning) yields set-specific uniformly sensitive tags as illustrated in Figure 3 (b). The next step, as shown in Figure 3 (c), is to utilise these uniformly sensitive tags to develop empirical power-distance relationships. In the proposed framework, such empirical power-distance relationships manifest as RSS decay models which match select tags to readers while carefully considering a tag's axial-radial orientation and tag-reader distance. We develop several such models in order to more effectively locate target tags.

While RSS decay models as developed in the previous step can accurately locate target tags, the tags' position estimate can be optionally further improved by utilising reference tags and performance-enhancing heuristics. Several such heuristics can be carefully arranged in a feed-forward network for improved object localisation performance as illustrated in Figure 3 (d). Following this post-processing step, target tags' positions can be visualised via a user interface on a variety of modern platforms (e.g. desktops, laptops, tablets, smartphones, etc.).

We conducted experiments for each step of the proposed framework, in a realistically noisy environment with irregular geometry and having a variety of interfering sources such as overhead metal beams, metal containers filled with liquids, Wi-Fi access points, servo motors, and Bluetooth transceivers. Additionally, we used ThingMagic Mercury6 and Alien ALR 9900+ readers and Electronic Product Code (EPC) compliant generation-2 (Gen2) passive tags operating in the Ultra-High Frequency (UHF) band with far-field tag-reader communication mechanism (ThingMagic, 2014). We describe the proposed framework in detail below.

3.3.1 Tag selection

It is important to note that different types of tags can be read at different maximum distances from the reader (i.e. tags have variable maximum read ranges) and backscatter different amounts of reader-transmitted radio signal power (i.e. tags have variable RSS behaviours) (Choi et al., 2009; Chawla and Robins, 2011a; Chawla and Robins, 2011b). Thus, in order to pragmatically address the problem of object localisation, the aforementioned variabilities must be carefully considered.

We address the above problem by selecting tags from a collection of different tags, which helps in reliably characterising tags' read ranges and RSS behaviours with respect to their distances from readers and reader output power levels.

Figure 4 The 34 EPC Gen2 passive tag types used in the tag selection experiments

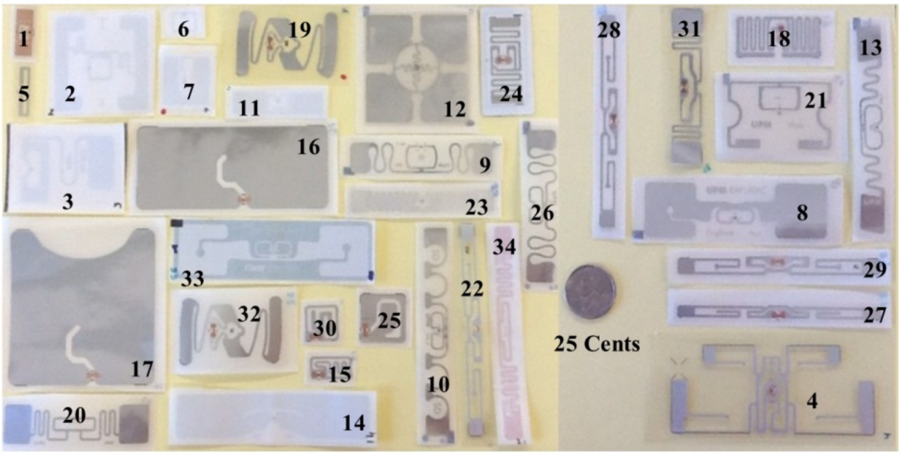


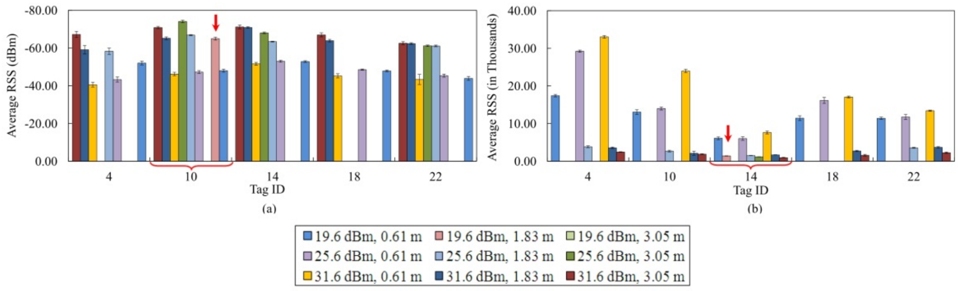
Figure 4 illustrates a collection of 34 EPC Gen2 passive tags with overlaid tag type IDs used in our tag selection experiments that were conducted in the same indoor environment where subsequently the object localisation experiments were also conducted (see Section 4 for more details about our experimental set-up). We selected candidate tags from the above tag collection that had the longest read range and the most uniform RSS behaviour over a combination of tag-reader distances and reader output power levels. Such tags are preferred as they tend to minimise the number of deployed readers, enable graceful RSS decay, provide higher localisation performance, and reduce the overall solution cost.

To effectively select candidate tags, we performed two sets of experiments using ThingMagic and Alien readers. In the first experiment, we measured the longest distance a tag could be read and repeated the experiment for each tag type in the above tag collection using both readers. We found that tags with type IDs {2–4, 8–14, 16–23, 26–29, 31–34} and {2–4, 8–10, 12–14, 16, 19, 20, 22, 23, 26–29, 33, 34} were readable by the ThingMagic and the Alien reader, respectively, at the maximum distance of 9 m.

Only the tags having the longest read ranges were part of the second experiment where we measured such tags' RSS behaviour over different combinations of tag-reader distance and reader output power levels. To draw meaningful inferences quickly, experiments were designed to balance coverage and efficiency, wherein the tag-reader distance and reader output power levels were iterated over the set {0.61, 1.83, 3.05} meters and {19.6, 25.6, 31.6} dBm, respectively.

The average RSS behaviour distribution of the uniformly performing tags for different power-distance combinations using the ThingMagic and the Alien readers is illustrated in Figure 5 (a) and 5 (b). We note that Tag-10 on the ThingMagic reader and Tag-14 on the Alien reader (i.e. tags with type ID 10 and 14 in Figure 4) were the only tags which demonstrated uniform RSS behaviour over different power-distance combinations (e.g. Tag-10 and Tag-14 were the only tags with uniform RSS behaviour at tag-reader distance of 1.83 m and a reader output power level of 19.6 dBm with respect to both the readers).

Figure 5 Average RSS of the selected passive tags using the (a) ThingMagic reader and (b) Alien reader (red arrows show the Tag-10's and Tag-14's RSS at 19.6 dBm and 1.83 m, respectively)



We combined the results from both experiments to determine that Tag-10 and Tag-14 are the best candidate tags for the ThingMagic and Alien reader, respectively. We note that the leftover tags either did not have the uniform RSS behaviour or longer read ranges or both, and while it may be possible to identify a larger set of candidate tags per reader, our experiments only found one such tag type per reader.

3.3.2 Tag binning

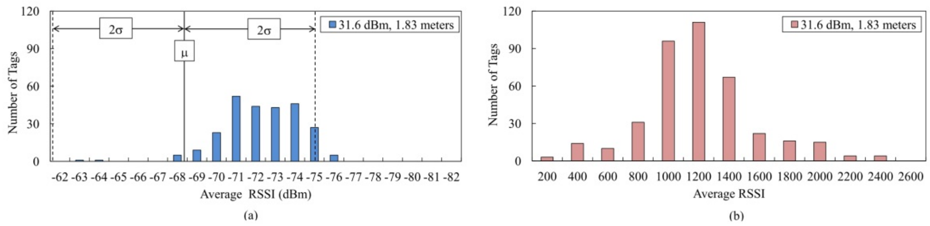
After the tag selection step, the selected types of candidate tags will have the longest read ranges and the most uniform RSS behaviours. However, within each tag type set there still remains radio sensitivity variability (Chawla and Robins, 2011a; Chawla and Robins, 2011b). This is due to the tags' inherent RSS variability which causes two separate tags of the same type to behave differently.

If such variably sensitive tags were used in localisation experiments, it could lead to reduced object localisation accuracy. More precisely, such tags will have non-uniform RSS behaviour that would cause arbitrary RSS decay with respect to tag-reader distance, leading to less accurate position estimates. Alternatively, tags with uniform RSS behaviour will have well-defined RSS decay that will yield improved position estimates.

Thus, to minimise the impact of a tag's inherent RSS variability on its localisation performance, we sort the candidate tags of particular types by their group RSS behaviour and select tags exhibiting uniform RSS behaviour. For example, in the tag selection step, we found that Tag-10 and Tag-14 are the best candidate tags for the ThingMagic and Alien readers, respectively. Thus, we separately characterise the group RSS behaviour of both tag types over their respective readers.

To measure the group RSS behaviour of a particular candidate tag type, we observe their RSS behaviour over a combination of tag-reader distance and reader output power levels. Consequently, we measure the resulting distribution's central tendency and sort the tag types on their RSS behaviour to identify the uniformly sensitive tags. In particular, we measured the group RSS behaviour of 500 tags each for the Tag-10 and Tag-14 types with the ThingMagic and the Alien readers, respectively. Figure 6 shows one such binning distribution for both of the tag-reader pairs.

Figure 6 Tag binning distribution of 500 (a) Tag-10s using the ThingMagic reader, and (b) Tag-14s using the Alien reader at the tag-reader distance of 1.83 meters and reader output power level of 31.6 dBm



We iterated the tag-reader distance and the reader output power level configurations over the set of {0.61, 1.83, 3.05} m and {19.6, 25.6, 31.6} dBm, respectively, thus keeping our set-up consistent with the tag selection step to derive meaningful correlated inferences across the experiments. We note that the tag binning distributions for the [Tag-10, ThingMagic] and the [Tag-14, Alien] tag-reader pairings are a collection of nine power-distance-based distributions with mean μ and standard deviation σ. Table 1 describes overall group RSS behaviours for each tag-reader pairing over the entire tag-reader distance and reader output power level sets. We also project the means from Table 1 for both the tag-reader pairs. Figure 6 (a) shows the mean and two standard deviations using the black (solid and dashed) markers, respectively.

Table 1 Group RSS behaviour of candidate tag types for different power-distance combinations

Mean and standard deviation of the selected tag-reader pairs		
Statistics, pairs	*[Tag-10, ThingMagic]*	*[Tag-14, Alien]*
($\mu_{0.61}$, $\sigma_{0.61}$)	(–59.02, 0.56)	(5076.84, 272.74)
($\mu_{1.83}$, $\sigma_{1.83}$)	(–68.22, 3.46)	(882.66, 796.77)
($\mu_{3.05}$, $\sigma_{3.05}$)	(–24.29, 42.08)	(739.98, 650.88)

To select uniformly sensitive tags from each of the power-distance-based tag binning distributions, we utilise a filtering window of width 2σ (i.e. twice the standard deviation) about the mean per distribution. For example, considering the [Tag-10, ThingMagic] tag-reader pair, the filtering window of width 2σ at 1.83 meters is 6.92 about the mean of –68.22 dBm. Thus, Tag-10 type tags selected from the RSS interval of [–75.14, –61.30] dBm would account for 95.45% of the uniformly sensitive tags for the 1.83 m distribution at the 31.6 dBm power level.

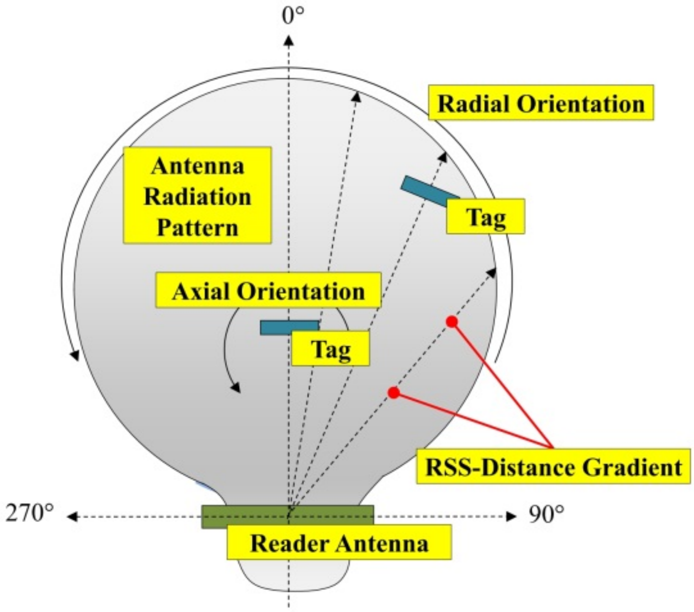
We apply the above filtering window to all the power-distance-based tag binning distributions per tag-reader pair and eliminate the duplicates to determine that 66% of the tags (330 out of 500) of the Tag-10 type and 69.8% of the tags (349 out of 500) of the Tag-14 type are uniformly sensitive for the ThingMagic and Alien readers, respectively. We utilise these tags in the subsequent steps.

The width of the filtering window can be adjusted to balance the quality of tags' RSS behaviour with the quantity of tags needed for various application-specific trade-offs (e.g. restricting the filtering window to 1σ selects fewer tags with more uniform RSS behaviour, while relaxing the filtering window's width to 3σ selects more tags with less uniform RSS behaviour).

3.3.3 Empirical power-distance relationship

After carefully sorting the candidate tags of selected type, tag-reader power-distance relationships must be established for the purpose of object localisation. However, theoretical tag-reader power-distance relationships such as described in equation (8) cannot be used in practice due to a variety of environmental interferences and occlusions, the operating environment's geometry, a tag's inherent RSS variability, and its axial-radial orientation (Arumugam and Engels, 2009; Chawla and Robins, 2011a; Chawla and Robins, 2011b; Saarinen et al., 2012). Thus, empirical tag-reader power-distance relationships are needed to enable high-accuracy object localisation.

Figure 7 Measuring tag's RSS using the reader antenna's radiation pattern and the tag's axial-radial orientation (see online version for colours)

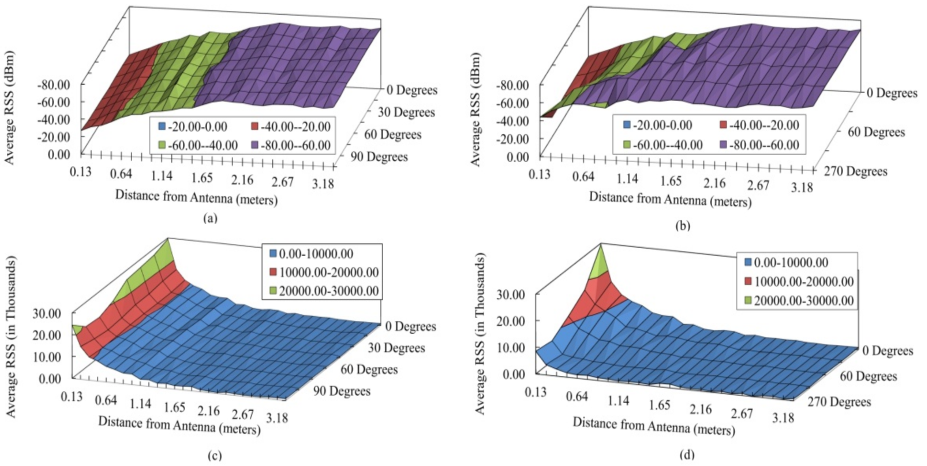


We note that such empirical tag-reader power-distance relationships can be established by modelling a tag's RSS decay over a range of tag-reader distances, while assuming the environmental impact on the tag's RSS to be statistically invariant and carefully considering the tag's axial-radial orientation. While it may seem counter-intuitive to assume the environment's impact on a tag's RSS to be statistically invariant, careful selection of application scenarios, wherein the operating environment may not change significantly, enables minimising its average-case spatio-temporal impact on the tag-reader RSS decay models.

For the development of the RSS decay models we considered the reader antenna's radiation pattern, the gradient relationship between the tag-reader distance and the tag's RSS, and the tag's axial-radial orientation as shown in Figure 7. While it's possible that different reader antennas have different radiation patterns, we preferred spherical-ellipsoidal shaped radiation patterns as they provide broader radio signal coverage and lower overall solution deployment cost. Subsequently, we varied the tag-reader distance over the range [0, 3.30] m in steps of 0.127 m while keeping the reader's output power level constant at 31.6 dBm.

To measure the impact of the tag's axial-radial orientation on its RSS, we planar-rotated the tag on its axis and around the reader over the interval [0°, 90°] in steps of 15° and 30°, respectively (the other half of the radial coverage is similar by symmetry). The need for efficiently covering larger radial area compared to smaller axial area requires a small disparity between the axial and radial rotation step sizes. We also measured the tag's RSS at 270° to ensure complete coverage of the reader antenna's radiation pattern. Figure 8 shows the tag's axial-radial orientation-based RSS behaviour for both tag-reader pairs.

Figure 8 RSS decay for (a) [Tag-10, ThingMagic Reader, Axial Orientation], (b) [Tag-10, ThingMagic Reader, Radial Orientation], (c) [Tag-14, Alien Reader, Axial Orientation], and (d) [Tag-14, Alien Reader, Radial Orientation]



We note that the well-defined RSS behaviours shown above are the result of the tag selection and binning steps. Thus, based on the above methodology, we have developed several RSS decay models having the following general expression:

$$RSS = C \cdot D^{E} \tag{10}$$

where RSS, C, D, and E are the tag's RSS (provided by the reader), coefficient, tag-reader distance, and exponent, respectively. Furthermore, we utilised two separate goodness-of-fit measures, R^2 and Normalised Root Mean Square Error (NRMSE), to select curves with reasonably good fit for the tag's axial-radial orientation-specific RSS behaviours.

To mitigate the radial gap introduced by the axial-radial orientation step size disparity, we interleaved the RSS-distance radial orientation data gathered at 30° intervals with the values generated from the coefficient and exponent-based interpolating functions at 15°, 45°, and 75°, respectively. Thus, we efficiently radial-cover the radiation pattern while bringing axial-radial orientation step sizes on par with each other. Interpolating functions for the [Tag-10, ThingMagic] tag-reader pair are shown in equation (11).

$$\begin{aligned} C(\theta) &= a_1 \cdot \sin\left[\pi\left(\frac{\theta - a_2}{a_3}\right)\right], \\ E(\theta) &= a_4 \cdot \cosh\left[\pi\left(\frac{\theta - a_5}{a_6}\right)\right] \end{aligned} \tag{11}$$

Equations (12) gives the interpolating functions for the [Tag-14, Alien] tag-reader pair.

$$\begin{aligned} C(\theta) &= a_7 \cdot \cosh(\theta) + a_8 \\ E(\theta) &= a_9 \cdot \sin(a_{10} \cdot \theta) + a_{11} \end{aligned} \tag{12}$$

where θ, $C(\theta)$, $E(\theta)$, and $\{a_1 \dots a_{11}\}$ are the radial orientation measured in degrees, the coefficients, the exponents, and the constants, respectively. We describe the average-case (i.e. an average of axial-radial orientation data and values derived from the interpolation functions) RSS decay models for both the tag-reader pairs in Table 2.

Table 2 RSS decay models

Average RSS decay model for the [Tag-10, ThingMagic] pair				
Degree[a]	*C*[b]	*E*[c]	R^{2d}	*NRMSE*[e]
0°–270°	–53.17	0.29	0.91	0.07
Average RSS decay model for the [Tag-14, Alien] pair				
Degree	*C*	*E*	R^2	*NRMSE*
0°–270°	3246.17	–0.89	0.96	0.04

Note: [a] Inclusive of tag axial-radial orientations
[b] Coefficient
[c] Exponent
[d] $R^2 \in [0.0, 1.0]$, values closer to 1 indicate better fit
[e] $NRMSE \in [0.0, 1.0]$, values closer to 0 indicate better fit.

We note that, in the above table, different readers may return the tag's RSS values in different units (e.g. the ThingMagic reader returns RSS values in dBm units while the Alien reader provides unitless absolute RSS values). Post-development of the RSS decay models, several stationary and mobile objects affixed with target tags can be located by combining the target tag's real-time RSS values, translated into distance measurements by applying equation (10), with planar-spatial trilateration (Yang and Liu, 2010).

The proposed real-time location system based on the above principles can exhibit spatio-temporal drifts, which require performing either periodic or on-demand in-situ calibrations to correct the drifted RSS decay model parameters. This observation is consistent with our overall design philosophy for the proposed real-time localisation framework and system that focuses on robustness through need-based calibration. To mitigate such drifts and further improve the object localisation performance, uniformly sensitive reference tags can be combined with the *k*-nearest neighbour algorithm to estimate the model parameters. Furthermore, the RSS decay model parameters can evolve in the different ambient physical conditions by employing modern sensor tags (RFCode, 2014).

3.3.4 Performance-enhancing heuristics

In the previous section, we outlined our proposed object localisation approach, capable of simultaneously locating multiple objects with high accuracy in real-time (see Section 4.2 for experimental results).

We note that by relaxing the constraint that the objects be located in real-time, the proposed approach's localisation accuracy can be further improved by optionally utilising reference tags, *k*-nearest neighbour algorithm, and heuristics that determine nearest neighbour reference tags.

However, as reference tags are used to further improve the target tags' position estimates, their placement and density, as well as the heuristics used to select them as the nearest neighbours, has an impact on the overall localisation accuracy (Chawla and Robins, 2011a; Chawla and Robins, 2011b). More precisely, the ability of a heuristic to select the nearest neighbour reference tags determines the localisation accuracy improvements in our object localisation approach.

Figure 9 Manifestation of localisation errors through the use of reference tags and *k*-nearest neighbour algorithm (see online version for colours)

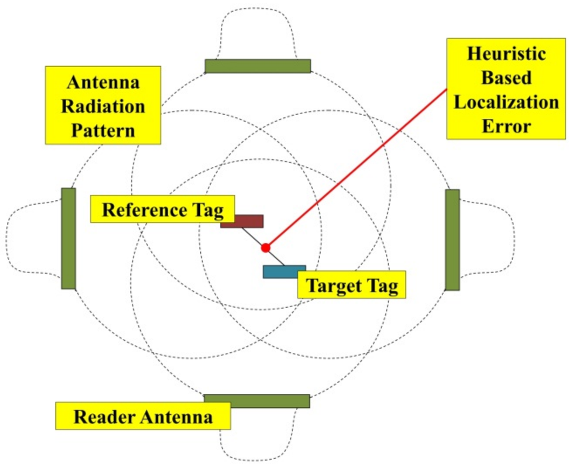


Figure 9 illustrates this issue, which we address by developing a number of performance-enhancing heuristics. For example, in equation (13) we propose a heuristic which computes the average over *k*-nearest neighbour reference tags' positions and treats that as the position of the target tag.

$$H_1 : \underset{\forall d \in (X,Y,Z)}{Heuristic}[d] = \frac{1}{K}\sum_{n=1}^{K} RT_{n,d} \tag{13}$$

Alternatively, in equation (14) we propose a heuristic which computes a weighted sum over three nearest neighbour reference tags' positions and utilises that as the position of target tag. Weights (i.e. c_n) are determined based on the need to better distinguish the individual reference tags' position-error contributions.

$$H_2 : \underset{\forall d \in (X,Y,Z)}{Heuristic}\left[d\right] = \sum_{n=1}^{3} C_n \cdot RT_{n,d} \tag{14}$$

The weights in the above heuristic are empirically determined and thus may require manual calibration. Moreover, for the sake of clarity and ease of overall computation, the nearest neighbour reference tags were ranked prior to applying the heuristics. While the previous two heuristics, also known as primary heuristics, were designed to provide the target tags' position estimates through the use of reference tags and *k*-nearest neighbour algorithm, our next heuristic, also known as the *meta-heuristic*, has a broader goal of balancing the need to maximise the object localisation accuracy with the design philosophy of future extensibility.

The meta-heuristic selects a primary heuristic which meets a specific objective measure while allowing for continual localisation performance improvements through the future development of new primary heuristics (e.g. applications which need quick and reasonably accurate object position estimates can utilise the proposed meta-heuristic to select primary heuristics that provide the desired accuracy quickly). In equation (15) we provide such a meta-heuristic that minimises the Euclidean distance between the target tags' position estimates derived from several primary heuristics and RSS decay models.

$$H_{meta} : \underset{\forall d \in (X,Y,Z)}{\arg\min} = \left(\left\lfloor \sqrt{E_{i,X}^2 + E_{i,Y}^2 + E_{i,Z}^2} \right\rfloor\right) \tag{15}$$

Note that the meta-heuristic returns an optimal primary heuristic, unlike the primary heuristics that return target tags' position estimates. We define the symbols used in the above expressions as follows.

$\{a, i, j, m, n, K, X, Y, Z\}$: Assorted variables

c_n: Series of weight coefficients such that $\Sigma c_n = 1.0$

d: Axis in the Euclidean space $\Re^{3+}$

RT: Reference tag

H_{meta}: Meta heuristic

$\hat{H}$: Set of heuristics

$E_{i,m}$: Error metric $(H_{i,m} - I_m)$

$H_{i,m}$: Heuristic i based tag distance along the axis m

I_{m}: RSS decay models based inferred tag distance along the axis m

We also note that by using the above optional post-processing heuristics to improve upon the RSS decay model-based target tag position estimates, the proposed approach may no longer be able to locate objects in real-time. Intuitively, utilising reference tags creates a trade-off between localisation accuracy versus execution time, in order to meet different application-specific needs.

4 Experimental evaluation

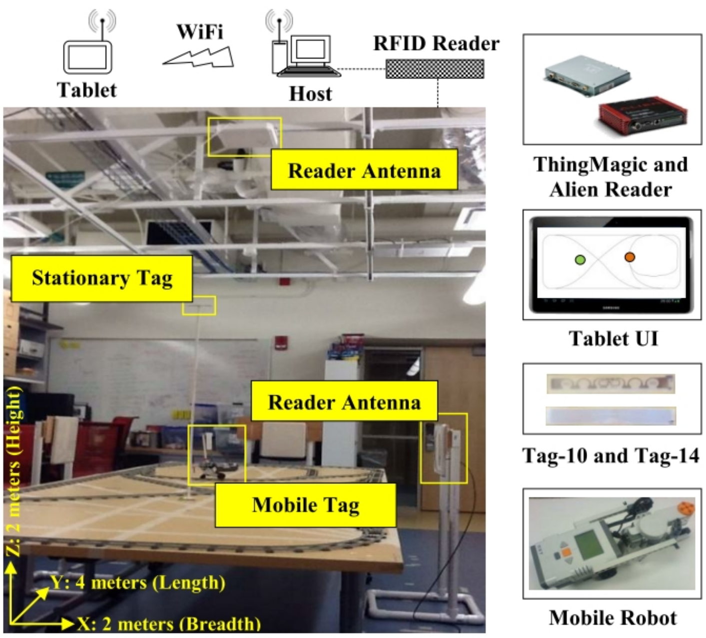
In this section, we present the experimental set-up used by our object localisation approach for locating objects, as well as several key object localisation results. In particular, we evaluate our object localisation approach in locating several stationary and mobile objects in 2D and 3D environments, measure their object localisation performance (both separately and combined) using RSS decay models and reference tags, study the impact of reference tag density on our approach's localisation performance, and compare our approach to other state-of-the-art RFID-based object localisation approaches.

4.1 Experimental set-up

To evaluate the proposed real-time location system, we selected a realistically noisy experimental region having a volume of 16 cubic-metres which contained a Lego Mindstorms-based track-driven mobile robot system (see Section 3.3 for details on noise sources).

A host machine having an AMD Athlon 64 processor operating at 2 GHz with 1 GB RAM and 100 GB hard disk space wirelessly controlled moving robots with on-board target-tags. We also used this host machine for interacting with both the RFID readers, for implementing RSS decay models, converting the reader-provided real-time RSS values to target tag distance estimates, and computing planar-spatial trilateration for determining target tag position estimates. Consequently, these position estimates were wirelessly routed to tablet computers (e.g. an Apple iPad, a Samsung Galaxy Tab, etc.) that used a graphical user interface to display the localisation results visually. Figure 10 illustrates our experimental set-up.

Figure 10 Experimental set-up with readers and tags (see online version for colours)



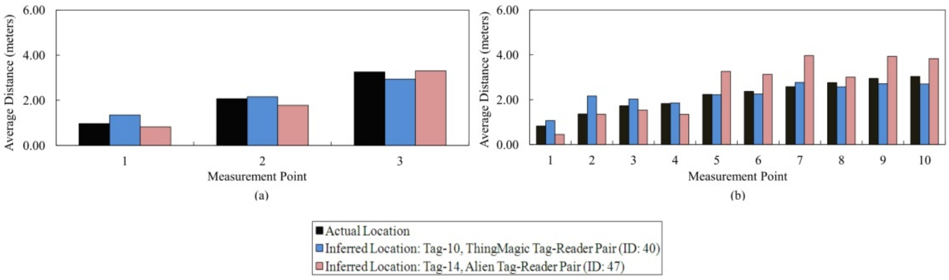
We note that in order to meet the real-time object localisation requirements the mobile robot's speed was bounded at 0.2 metres per second to allow for computational delays in determining the target tag's location and in processing other relevant steps (e.g. visualising the target tag's location).

4.2 Results and analyses

We deployed the proposed system to locate several of the aforementioned robots, acting as stationary and mobile objects in a 2D plane across the experimental region. Figure 11 shows the overall object localisation accuracy for one such stationary and mobile object. As shown in Figure 11, the actual and inferred points 2 and 3 are higher than 1 because these tags are placed further away from the reference origin location, which is one of the edges of the table-top set-up (shown in Figure 10). It is evident that the actual locations of stationary and mobile objects are closely matched by their inferred location estimates over both of the tag-reader pairs.

However, there are a few locations (e.g. Figure 11 (b): measurement points 5 and 7) where the inferred location estimates are less accurate than the rest of the locations. We note that such outcomes are due to limited availability of the radio signals provided by the Alien reader's antenna radiation pattern at those locations.

Figure 11 Overall object localisation accuracy in 2D for (a) stationary and (b) mobile objects



We also tested the proposed location system with mobile objects in a 3D space across the experimental region.

Figure 12 Overall object localisation accuracy in 3D for (a) stationary and (b) mobile objects

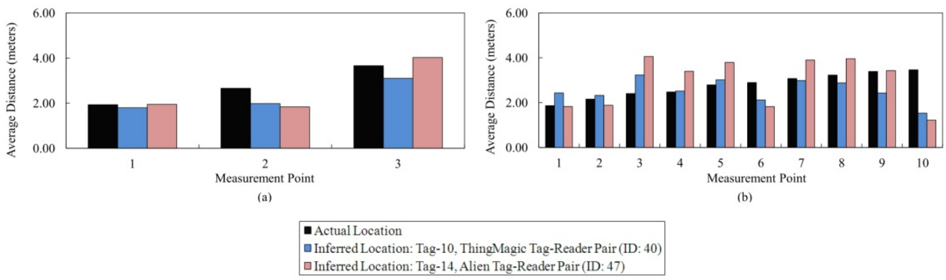


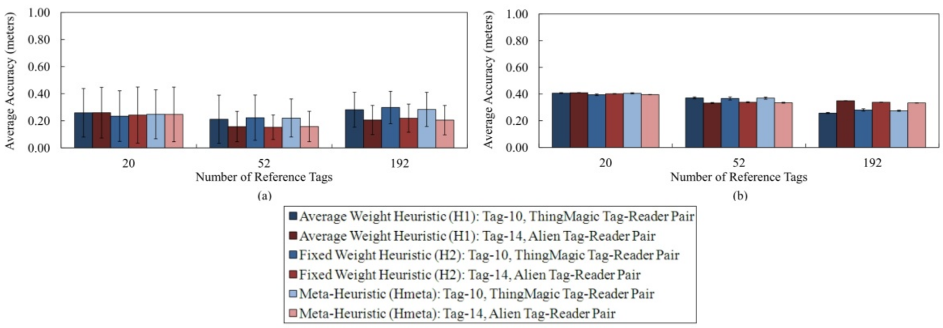
Figure 12 illustrates the overall object localisation accuracy for both objects. We note that the inferred location estimates closely follow their actual locations except at a few locations (e.g. Figure 12 (b): measurement points 3 and 10) where the placement of *Z*-axis reader antenna limited the availability of radio signals for both the readers, leading to comparatively lower object localisation accuracy.

We note that the 2D and 3D overall object localisation accuracy results described above were obtained without using reference tags as shown in Table 3 (Section: RSS Decay Models and Planar-Spatial Trilateration – Without Reference Tags). It is evident that the overall localisation accuracy in a 3D space is lower than in a 2D plane. This is due to having fewer spatial reader antennas (compared to planar readers) available in our particular experimental set-up, meaning that it is harder to balance any overshooting of localisation errors in a 3D space.

Our 2D object localisation resulting error rates are evidently lower than the error rates of other state-of-the-art RFID-based object localisation approaches, while our system offers the added ability of real-time localisation. For example, compared to Zhao et al. (2007), our combined 2D object localisation accuracy range of 0.22–0.70 m is slightly less accurate; however, unlike them, we were able to locate both stationary and mobile objects with that accuracy in real-time. Furthermore, with the exception of Wu et al. (2015), other state-of-the-art object localisation approaches have only demonstrated their ability to locate objects in 2D environments, while our proposed approach can locate objects in both 2D and 3D scenarios. Moreover, our combined 3D object localisation accuracy range of 0.34–1.09 m compares favourably to the 2D and 3D object localisation results of other state-of-the-art object localisation approaches as shown in Table 3.

We also combined reference tags and performance-enhancing heuristics with our proposed approach to determine their impact on overall object localisation performance. Figure 13 shows our overall object localisation accuracy for stationary and mobile objects over different combinations of reference tag density and performance-enhancing heuristics in the 2D plane. As the reference tag density increases, the overall object localisation accuracy of our approach either remains constant or improves.

Figure 13 Overall 2D object localisation accuracy with different reference tag densities and performance-enhancing heuristics for (a) stationary and (b) mobile objects



Moreover, the meta-heuristic does seem to provide marginally better localisation accuracy than the two primary heuristics over both the tag-reader pairs and different reference tag densities. The above reference tag and performance-enhancing heuristic-based experiments were limited to the 2D plane only (by keeping the *Z*-axis constant in the heuristics) to show the emergence of a trade-off between the localisation accuracy and execution time (i.e. higher accuracy requires longer run times while lower accuracy can be achieved faster). We compute the average distance in 2D plane and 3D space using the Euclidean distance. Thus, the tags' actual locations in 2D plane and 3D space are subsumed by the pertinent distance metrics. Such metrics subsequently help in ranking the different tags based on their actual and inferred locations, as illustrated above.

Table 3 Comparative evaluation

State-of-the-art RFID-based object localisation approaches					
Approach	*Technique*	*Time*	*Accuracy*	*Operating region*	*Reference tag*
Ni et al. (2003)	kNN[a]	Not real-time	2 m	2D, 20 m^2	Active
Bekkali et al. (2007)	Kalman Filter	Not real-time	0.5–1 m	2D, 9 m^2	Passive
Zhao et al. (2007)	Proximity map	Not real-time	0.14–0.29 m	2D, 20 m^2	Passive
Choi and Lee (2009)	kNN	Not real-time	0.21 m	2D, 14 m^2	Passive
Choi et al. (2009)	kNN	Not real-time	0.2–0.3 m	2D, 3 m^2	Passive
Zhang et al. (2010)	SVR[b]	Not real-time	0.45 m	2D, 36 m^2	Active
Brchan et al. (2012)	LPM[c]	Real-time	1–2 m	2D, 22 m^2	Active
Wu et al. (2015)	kNN and LPM	Real-time	1.08–2.06 m	3D, 108 m^3	Active/semi-passive
Our localisation approach: RSS decay models and planar-spatial trilateration – without reference tags					
Type	*Tag-reader pair*	*Time*	*Accuracy*	*Operating region*	*Reference tag*
Stationary (2D)	[Tag-10, TM[d]]	Real-time	0.22–0.40 m	2D, 8 m^2	Not required
Stationary (2D)	[Tag-14, AL[e]]	Real-time	0.42–0.60 m	2D, 8 m^2	Not required
Mobile (2D)	[Tag-10, TM]	Real-time	0.69–0.70 m	2D, 8 m^2	Not required
Mobile (2D)	[Tag-14, AL]	Real-time	0.68 m	2D, 8 m^2	Not required
Stationary (3D)	[Tag-10, TM]	Real-time	0.34–0.66 m	3D, 16 m^3	Not required
Stationary (3D)	[Tag-14, AL]	Real-time	0.69–1.09 m	3D, 16 m^3	Not required
Mobile (3D)	[Tag-10, TM]	Real-time	0.70–0.91 m	3D, 16 m^3	Not required
Mobile (3D)	[Tag-14, AL]	Real-time	0.78–1.02 m	3D, 16 m^3	Not required

Table 3 Comparative evaluation (continued)

Our localisation approach: RSS decay models and planar-spatial trilateration – with reference tags					
Type	*Tag-reader pair*	*Time*	*Accuracy*	*Operating region*	*Reference tag*
Stationary (2D)	[Tag-10, TM]	Not real-time	0.21–0.30 m	2D, 8 m^2	Passive
Stationary (2D)	[Tag-14, AL]	Not real-time	0.15–0.26 m	2D, 8 m^2	Passive
Mobile (2D)	[Tag-10, TM]	Not real-time	0.26–0.41 m	2D, 8 m^2	Passive
Mobile (2D)	[Tag-14, AL]	Not real-time	0.33–0.41 m	2D, 8 m^2	Passive

Note: [a] *k*-Nearest Neighbour Algorithm
[b] Support Vector Regression Algorithm
[c] Linear Propagation Models
[d] ThingMagic Reader
[e] Alien Reader.

Table 3 (Section: RSS Decay Models and Planar-Spatial Trilateration – With Reference Tags) shows our 2D object localisation accuracy results using the reference tags and meta-heuristic. The combined 2D overall object localisation accuracy range of 0.15–0.41 m is better than our 2D object localisation accuracy results of 0.22–0.70 m that was obtained without using reference tags, and is also a considerable improvement over the other state-of-the-art object localisation approaches. However, this improved localisation accuracy comes at the cost of increased execution time.

Our localisation results were presented with and without the use of reference tags in order to showcase the subtle trade-off that exists between the localisation accuracy and execution time. In particular, the variant of our localisation approach that relies on reference tags is not real-time, although it offers the highest localisation accuracy. On the other hand, by not using reference tags, we admit a small amount of localisation error while ensuring that localisation time is real-time. Our comparisons to other object localisation approaches highlight the trade-offs, assumptions made, and results obtained. Thus, our proposed approach is low-cost, highly accurate, and simultaneously locates multiple stationary and mobile objects in real-time, while offering a trade-off between localisation accuracy, execution time, and operational cost.

5 Conclusions and future work

In this paper, we proposed an approach to locate objects in 2D and 3D environments using only standard RFID technology. The proposed approach models RSS decay with respect to varying tag-reader distance and tag axial-radial orientation in order to accurately locate multiple stationary and mobile objects in real-time. We developed methods for binning and selecting tags based on the inherent variability in their radio sensitivity, which improves the accuracy of object localisation. We proposed several empirically derived RSS decay models, which utilised the uniformly sensitive tags. We suggested techniques to calibrate the RSS decay models in order to mitigate spatio-temporal drifts, and used heuristics and optional reference tags to further improve performance. Our tablet-based visualisation tools enable users to track the objects' positions and motions in real-time.

Future research directions include studying how scaling up the operating environment (i.e. area covered and number of objects) impacts localisation performance, developing additional families of RSS decay models for various tag-reader pairs, designing new performance-enhancing heuristics that further leverage RFID hardware capabilities, locating objects in real-time while using reference tags, and locating faster moving objects.

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