A Novel Approach for Addressing Wandering Off Elderly Using Low Cost Passive RFID Tags

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Abstract. Wandering (e.g. elopement) by elderly persons at acute hospitals and nursing homes poses a significant problem to providing patient care as such incidents can lead to injury and even accidental morbidity. These problems are particularly serious given aging populations around the world. While various technologies exit (such as door alarms), they are expensive and the reliability of such systems have not been evaluated in the past. In this article we propose two novel methods for a very low cost solution to address the problem of wandering off patients using body worn low cost passive Radio Frequency Identification (RFID) tags using phase based measurements. Our approach requires no modification to the air interface protocols, firmware or hardware. Results from extensive experiments show that: i) the proposed algorithms can accurately identify whether a person is moving into or out of, for example, a room; and ii) it can be implemented in real-time to develop a low cost wandering off alarm.

Keywords: Passive RFID, Wandering off, walking direction detection

1 Introduction

Acute hospital patients as well as residents at nursing homes, especially those with Alzheimer's disease, dementia and cognitive impairments, may be injured as a result of wandering off [1] (e.g. elopement) around facilities or leaving cared areas [2]. There are serious consequences arising from wandering to elderly, care givers and care providers such as mortality (colliding with a vehicle from wandering outside care facilities), complete disappearances and litigations [3]. As a consequence of an ageing world population, the cohort of elderly with wandering behavior is expected to increase, for example, it is estimated that by 2050 the incidence of Alzheimer's disease will approach 11 to 16 million people in the U.S. alone [4]. Monitoring elderly and recognizing when they are leaving facilities (hospital rooms, nursing homes) in real time provide an opportunity to intervene and prevent occurrences of wandering off.

Although boundary alarms ('buzzers') based on battery powered wrist worn bracelets[1] are employed to prevent or deter elderly from wandering off, these devices are simple proximity based sensors. A recent study has used a battery powered Wifi tag [5] on a wheel chair and localization methods while in [6] researchers have

1 example: http://alert.com.au/index_files/W101TX.htm

proposed a method of localizing individuals by highly instrumenting the subject with multiple battery powered devices (e.g. an audio recorder, wireless sensor node, an RFID wristband reader). Other researchers, for example in [7], have proposed using mobile phone devices to address wandering off. These devices cost in the range of hundreds of dollars and are battery powered and therefore require maintenance and care. Furthermore the solution to instrument wheel chairs does not address the need to monitor elderly that do not require such an aid. The other central drawback with battery powered devices is that either carers or elderly uses must remember to replace batteries and to carry a bulky device. This is a significant issue for dementia sufferers or cognitively impaired patients.

The ability by modern RFID (Radio Frequency Identification) readers to obtain phase information from passive (batteryless) tag responses is creating new possibilities to detect the direction of motion of tags in an unsupervised manner. In this paper we evaluate the performance of two methods based on estimating the direction of travel of batteryless, lost cost, lightweight RFID tags to detect wandering off patients in hospital and nursing home settings. In particular we make the following contributions:

- We propose a novel approach, for the first time (to the best of our knowledge), for determining elderly wandering off supervised areas such as hospital rooms and nursing care facilities based on them wearing a low cost passive sensor enabled RFID tag over their attire.
- We develop two algorithms using tag phase information to identify the direction of traversal of a person wearing an RFID tag to accurately determine persons attempting to travel beyond a threshold.
- We evaluate the performance of our proposed algorithms by conducting extensive experiments.

The following sections of the paper are organised as follows: in Section 2 we discuss related works in tag direction estimation; Section 3 describes our approach, tag phase and theoretical aspects of the proposed methodologies; Section 3 outlines the two unsupervised algorithms for estimating direction of tag traversal; and Section 4 presents results of our experiments. Finally discussion, limitations and conclusions are in Section 5.

2 Related Works

Although we have not found literature on the use of passive RFID tags to determine the direction of traversal of a person, a limited number of published methodologies for determining tag direction exist [8, 9, 10, 11]. However, experimental evidence to support such methods are limited [8, 9] while performance evaluation of proposed methods are non-existent.

Nevertheless, a number of existing localization methods for spatial identification of active transmitters have been applied for tracking the direction of objects tagged with active tags. Active tags employ an active transmitter with extended tag logic and therefore can generate a strong signal back to a reader over a long distance. By contrast, the performance of passive RFID tags is affected by additional noise sources, which makes accurate spatial identification of a tagged object difficult in real-world situations. Sources of noise can be as a result of the limited working range of modulated backscatter Ultra High Frequency (UHF) RFID, noise in the received signal, multi-path effects, tag incident power, fading and scattering [12, 13]. Existing RFID based spatial identification methods can be categorized into the following two approaches [13, 14]:

- **Scene analysis** with extra reference nodes. This approach uses statistical algorithms such as *k*-nearest neighbour (kNN) and probabilistic methods for spatial identification, according to the measured RSS (Received Signal Strength) of a tag response.
- **Continuous measurement of connectivity information**, i.e. distance can be estimated by using RSS, time of arrival (ToA), angle of arrival (AoA), time difference of arrival (TDoA), and phase difference of arrival (PDoA).

Typical scene analysis, such as LANDMARC [15], determines the spatial position of a tag by comparing the signal strength between reference nodes deployed in the environment, and then uses statistical algorithms to improve localization accuracy. In [16] Kalman filtering is used improve the accuracy of localization based on RSS measurements from two antennas. Overall, RSS based spatial identification methods are feasible for motion tracking, however, due to the limited working range and the noise in backscattered UHF RFID systems, these RFID localization techniques have only been successfully used to track active tags. Meanwhile, deployment of proposed infrastructure can be rather expensive due to the requirement of multiple readers and reference tags. Moreover, such approaches have only been evaluated in the determination of static tags as opposed to determining the direction of traversal (DoT) of tags, for example in or out of a hospital room.

Connectivity information based schemes have been applied for tag direction of arrival (DoA) estimation. Oikawa [8] proposed a method using time difference of signal arrival, which is measured by the strength of the received signal at two antennas, to estimate the tag DoA. Consequently, the accuracy of DoT information is deteriorated due to multipath affects [12]. Other researchers have also focused on using DoA estimation for tag localization [10, 11]. However, the accuracy of their methods decreases as a result of tag readings in overlapping reader antenna zones and the work in [10] is only theoretical and experiments to evaluate the performance of proposed approaches are absent.

Passive RFID tags have greater advantages than active tags or current battery powered proximity sensors used for determining wandering off patients because of significantly lower cost, compact form, lightweight and batteryless nature requiring no maintenance while providing disposability for reasons such as infection control. Consequently, our research focuses on estimating the direction of traversal of passive RFID tags through door thresholds (e.g. patient rooms in acute hospitals, nursing homes) to determine whether a patient wearing an RFID tag is moving *in* or *out* of a room. Furthermore, developments in wearable RFID tags [17] and commercial washable RFID tags [18] have made it possible to develop extremely lightweight tags suitable for patient monitoring. In this paper we develop and evaluate two methods to determine the direction of movement of patients out of clinical areas (such as exit doors, doors leading out of hospital rooms).

2 Systems Overview and Models

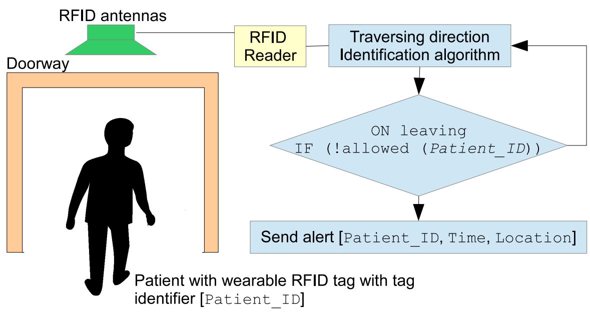


Fig. 1. Systems overview of the proposed patient wandering off alarm system where an alert can be sent to a caregiver using, for example a nurse call system, to alert them of an elderly leaving a care facility

We propose a wandering off alarm system based on using four components: i) RFID reader; ii) two RFID reader antennas connected to a reader; iii) wearable RFID tag; and iv) a patient traversing direction identification algorithm as illustrated in Fig. 1.

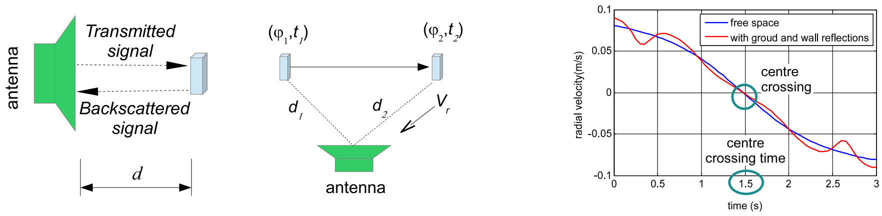
RFID readers interrogate tags to obtain electronically stored information such as a unique identification code, for example, an EPC (electronic product code). The two RFID antennas both provide power to the passive tags and also collect tag responses (i.e. passive tags rely on the carrier wave received from the reader antenna to power the tag and backscatter a response as oppose to actively transmitting a signal). Passive RFID tags are low cost mostly due to their batteryless nature. Therefore our focus is on using such low cost passive tags to develop a wandering off alarm. The patient traversing direction identification algorithm considers an input sequence of observations as a time series of tuples [*time of read*, *antenna identifier*, *tag radial velocity*] to determine if the patient is walking out of a doorway or threshold. Although *time of read* and *antenna identifier* are directly reported by RFID readers, *tag radial velocity* must be estimated first using tag phase reported by the reader.

2.3 Tag phase

Fig. 2(a) provides an overview of radio wave propagation between a reader antenna and a passive RFID tag. It can be seen from Fig. 2(a) that a signal to a tag travels across two links: i) forward reader-tag link; and ii) return tag-reader link. Therefore, the total distance travelled by a radio wave is $2d$ m. Then the total phase reported by RFID readers for each tag read in any prorogation environment is $\varphi = \varphi_r + \varphi_o + \varphi_{BS}$ where φ_r is the phase rotation over distance $2d$, φ_o is the phase offset due to the reader's transmit circuits and tag's reflection characteristics, φ_{BS} is the backscatter phase of the tag [12]. In free space, the phase rotation of the radio wave over a distance $2d$ can be expressed as:

$$\varphi_r = -2\pi(\frac{2d}{\lambda}) \tag{1}$$

where λ is the wavelength. It can be observed that the phase in (1) is dependent on the distance between the tag and the reader. Meanwhile, the variation of tag backscatter phase due to varying power of the transmitted radio wave is very small (less than ten degrees) compared to phase changes due to tag motion. Hence, the total phase is highly dependent on φ_r [12]. Then the phase of tag signal (backscattered response) is directly proportional to the distance d between the tag and reader (assuming phase offset and tag backscatter phase do not change considerably).



(a) (b) (c)

Fig. 2. (a) Illustration of radio wave propagation between a tag and antenna; (b) an iillustration of radial velocity estimation; and (c) simulation obtained using the model in [9] for the tag traversal illustrated in (b)

2.3 Tag radial velocity

The projection of the tag velocity vector on to the line of sight between the tag and the reader, as shown in Fig. 2(b), can be estimated by measuring the phase difference $\varphi_2 - \varphi_1$ of a tag at two different time instances t_1 and t_2 at a fixed frequency. Then by attributing the phase difference $\varphi_2 - \varphi_1$ to the path difference $d_2 - d_1$ resulting from the motion of a tag, the difference in distance between $d_1$and $d_2$can be obtained as:

$$d_2 - d_1 = \frac{1}{2}(\frac{\varphi_2 - \varphi_1}{2\pi}\lambda).$$

The radial velocity of the tag can then be expressed as

$$V_r = -\frac{d_2 - d_1}{t_2 - t_1}$$ and substituting $\lambda = c/f$ gives,

$$\mathrm{V_r} = -\frac{\frac{1}{2}(\frac{\varphi_2 - \varphi_1}{2\pi}\lambda)}{t_2 - t_1} = -\frac{c}{4\pi \mathrm{f}}\frac{\Delta\varphi}{\Delta t}. \tag{2}$$

Consider a tag traversing on a path in front of an antenna (Fig. 2(b)). Then the difference in distances d between the tag and the antenna is decreasing when the tag is moving towards the antenna from the left while the difference is increasing as the tag moves away to the right of the antenna. Therefore, a positive radial velocity implies that the tag is moving towards to the antenna and a negative velocity implies that the tag is moving away from antenna as illustrated in Fig 2(c). Theoretically, we call the time-space coordinate of when a tag's velocity changes direction (e.g. from positive to negative) the *centre crossing* and the time coordinate as the *centre crossing time* (as shown in Fig 2(c)).

3 Traversing Direction Identification Methods

In this section we propose two tag traversing direction identification (TDI) methods: i) center crossing time estimation method; and ii) radial velocity distribution estimation method. Both of these methods are based on analyzing the radial velocity of a passive RFID tag worn by a person, to enable us to determine if a person wearing the tag is entering (*moving in*) or leaving (*moving out*) a doorway (Fig. 1).

Our proposed reader antenna arrangement for both methods is shown in Fig. 3. The reader antennas are arranged at a 45 degree angle to the vertical axis (maximize the velocity based information available, read zones and minimize read zone overlap). Here both antennas are installed opposite to each other and at the same height.

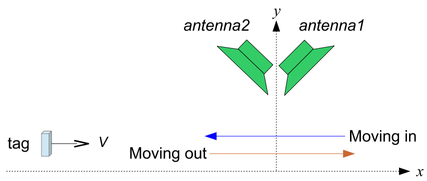


Fig. 3. Antenna configuration for the TDI methods

Algorithm: ***cct_detect***

Input: Tag reads (time, radial velocity) in time $\in [t_{start}, t_{end}]$for a given antenna
Output: Estimated center crossing time vector CCT.

$t \leftarrow t_{start}$ and $CCT \leftarrow 0$ //center crossing time vector.
do
  $m \leftarrow 0$ //count of positive velocity estimates
  $n \leftarrow 0$ // count of negative velocity estimates
  update m and n in time $\in [t, t+1]$
  if $m < n$ and $n \geq 2$, **then** //filtering noisy velocity estimations
    $CCT \leftarrow t$.
  else $t \leftarrow t + 1$
while $t < t_{end}$
return CCT.

Fig. 4. Algorithm for detecting centre crossing time

3.1 Center Crossing Time Estimation Method

Considering the arrangement in Fig 3, if the tag *moves out* (traverses from left to right), it will pass through *antenna2* and *antenna1* in succession. Therefore, the center crossing time of radial velocity at *antenna2* can be expected to be earlier than at *antenna1*. Similarity, when tag *moves in*, the center crossing time at *antenna1* can be expected be earlier than that at *antenna2*. Hence, the tag traversing direction can be identified by comparing center crossing times at the two antennas. Assuming CCT_1 and CCT_2 are centre crossing times at *antenna1* and *antenna2*, the first TDI method can be illustrated as:

- If $CCT_1 - CCT_2 < 0$ then tag is moving from *antenna1* to *antenna2* (*move in*)
- If $CCT_1 - CCT_2 > 0$ then tag moving from *antenna2* to *antenna1* (*move out*)

However, for real-time application, we should consider an algorithm to detect the centre crossing time automatically and estimate whether a person is moving in or moving out. Shown in Fig. 4 is the algorithm developed for estimating centre crossing times, while the proposed algorithm for detecting the direction of travel is in Fig. 5.

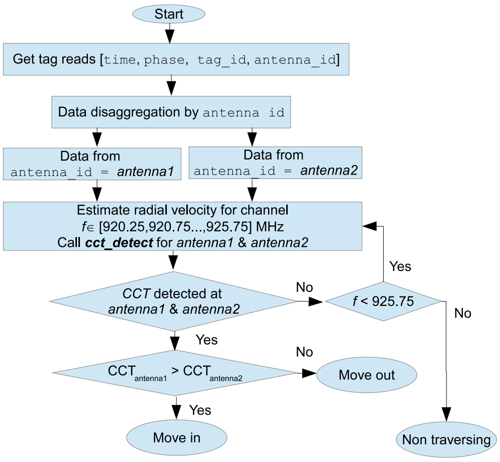


Fig. 5. TDI method using CCT

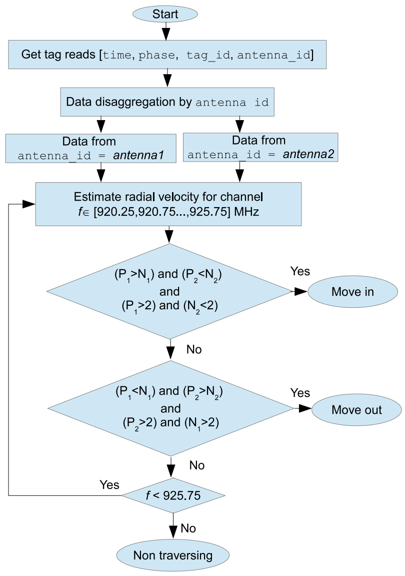


Fig. 6. TDI based on velocity distribution

3.2 Radial Velocity Distribution Estimation Method

The second TDI method proposed is based on using the information from changing read zones of the tag in addition to its radial velocity. When a tag is moving in (see Fig. 3), because of the different coverage of the two antennas, it will mainly be detected by *antenna1* as approaching, and then by *antenna2* as departing. As a result, the distribution of radial velocity estimates is skewed towards positive velocities rather than negative velocities at *antenna1* and negative velocities at *antenna2*. Similarity, when a tag is moving out, distribution of velocities will be mostly positive at *antenna2* and negative for *antenna1*. Based on this theory, an alternative approach to detecting tag direction can be derived by observing the distribution of radial velocities at the two antennas. Then, using $P_1$and $N_1$to represent the quantity of positive and negative radial velocities at *antenna1*, P_2 and N_2 represents the positive and negative velocity quantities at *antenna2*, the second method can be illustrated as:

- If $P_1 > N_1$ & $P_2 < N_2$ then tag is moving from *antenna1* to *antenna2* (moving in).
- If $P_1 < N_1$ & $P_2 > N_2$ then tag is moving from *antenna2* to *antenna1* (moving out)

The algorithm based on the distribution of positive and negative velocities as a result of differing coverage of a moving tag at the two antennas is outlined in Fig. 6. Here we do not rely on evaluating the CCT for any of the antennas and has the ability to overcome errors in CCT detection that may results as a consequence of measurement error (for example in phase estimated by the reader).

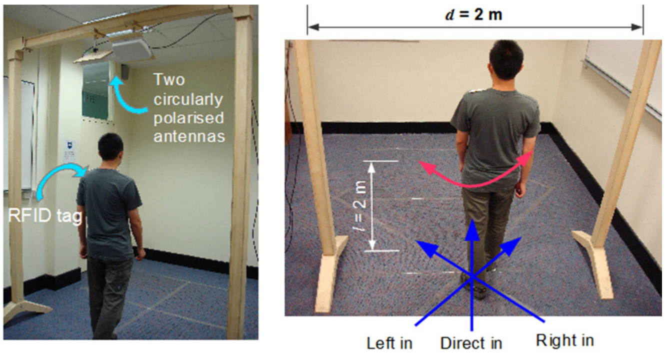


Fig. 7. Laboratory experimental environment setup for evaluating TDI algorithms

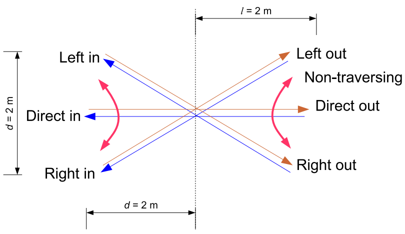


Fig. 8. Traversal paths considered in the laboratory experiments

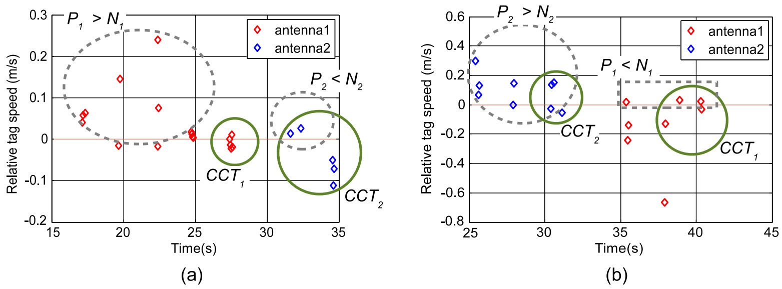


Fig. 9. Radial velocity at the two antennas depicting the center crossing times and the distribution of velocities: (a) when a person is *moving in*; and (b) when a person is *moving out*

4 Experiments

In order to evaluate the performance of the two proposed algorithms, we conducted detailed and extensive experiments in a laboratory environment under real world conditions. We evaluated the ability of the algorithms to to identify the traversing direction of a person through a threshold at, for example, a critical exit at a nursing home or an acute hospital.

Although modern RFID readers can perform fully coherent detection and report the phase of the backscattered signal, as a result of phase estimation techniques used [12], π radians of ambiguity is introduced to phase measurements such that the reported phase can be the estimated phase (θ) or the estimated phase combined with a multiplicity of π radians ($\theta + k\pi$) [19]. The readers used in our experiments (Section 4.1) were observed to randomly flip the phase π radians. Consequently, the measured backscatter signal phase cannot be directly used for phase based measures of spatial and temporal dimensions of tags (such as radial velocity). Therefore we limited the range of phase measurements to $[0, \pi]$ by taking modulo π radians of phase measurements prior to estimating velocity.

4.1 Settings

The experiment scenario is shown in Fig. 7. The reader antennas were located 2.6 m above ground level and in order to obtain accurate measurements, the cables connected with two antennas had the same length and the two antennas employed are also of the same model (two circularly polarised antennas, model no: Impinj IPJ-A1000-USA). We used an Impinj Speedway Revolution UHF (Ultra High Frequency) RFID reader (R420) and 'Squiggle' passive tags (using an Alien Higgs 3 Integrated Circuit manufactured by Alien Technology) encased in a rubber packaging that is 3 mm thick. The equipment operated under Australian Electromagnetic Compatibility Regulations (4 W Equivalent Isotropic Radiated Power, frequency range from 920 MHz to 926 MHz, 12 channels).

4.2 Statistical Analysis

In this study, we evaluated: i) Sensitivity = *True Positives* / (*True Positives* + *False Negatives*) and ii) Specificity = *True Negatives* / (*True Negatives* + *False Positives*); and iii) Accuracy = *True Positives* + *True Negatives* / (*True Negatives* + *True Positives*+ *False Positives* + *False Negatives*). Here true positives (TP) were correctly identified movements (e.g. moving in). True negatives (TN) were movements of no-interest that were correctly identified (e.g. non-traversing). False negatives (FN) were movements (e.g. moving in) that were not identified (i.e. misses). False positives (FP) are other movements that were identified as a moving direction of interest.

4.3 Results

Two healthy, young adults (one female and one male) participated in the study. The RFID tag (Fig. 7) was attached over clothing using double sided tape onto the shoulder of the person (Fig. 7). The two persons were not instructed to walk at a certain speed but asked to walk at their normal walking speed. We considered eight paths with an approximate length of 4 m as shown in Fig. 8 for the study where Right In, Direct In, Left In were considered as *moving in* paths (as depicted in Fig.3) while Right Out, Direct Out and Left Out were considered as *moving out* paths.

In particular, we included two non-traversing paths to consider situations where elderly simply walked parallel to or walk towards and then away from a threshold of a doorway. The study participants performed a scripted routine of 45 moving in path trials (the script consisted of a list of 45 moving paths randomly selected from direct in, left in and right in paths), a scripted routine of 45 moving out path (45 randomly selected from direct out, left out, right out paths) and 90 trials for non-traversing paths.

Center Crossing Time Estimation Method (CCT-TDI): Fig. 9 shows an example of the radial velocity estimated at the two antennas for a trial where a participant moved along the direct in path and direct out path (shown in Fig. 8). We can observe the change in radial velocity from positive to negative at both antennas and the center crossing times successfully detected by the algorithms. In Fig. 9(a) we can see that the centre crossing time at *antenna1* (CCT_1) identified is smaller than centre crossing time at *antenna2* (CCT_2) when the person is moving along the direct in path, while CCT_1 is greater than CCT_2 when the person is moving along the direct out path (Fig. 9(b)).

Radial Velocity Distribution Estimation Method (RV-TDI): Fig. 9 also illustrates the distribution of positive and negative velocities at both antennas for direct in path (*moving in*) and direct out (*moving out*) path traversals. When the participant is moving in, we can reach a consensus that the distribution of positive radial velocities is larger than the negative velocities at *antenna1* while at *antenna2* the distribution of positive radial velocities is smaller than the negative velocities. Similarly, when the participant is *moving out*, we can observe more positive estimations at *antenna2* and less positive velocity estimates at *antenna1*.

Table 1. Performance of the two proposed algorithms

Algorithm	Path	TP	FN	FP	TN	Sensitivity	Specificity	Accuracy
CCT-TDI	*Move In*	38	7	8	37	84.4%	82.2%	84.4%
	Move Out	39	6	9	36	86.7%	80.0%	83.3%
RV-TDI	*Move In*	41	4	5	40	91.1%	88.9%	90.0%
	Move Out	40	5	6	39	88.9%	86.7%	87.8%

Table 1 outlines the results of our laboratory trials. Although both algorithms provide good accuracy, sensitivity and specificity, RV-TDI algorithm performs better on all three metrics. Sensitivity results (≥ 88%) for RV-TDI is noticeably higher than CCT-TDI indicating a very low (≤12%) miss rate (missing that a person moved through a monitored threshold). Similarly specificity results (≥ 86%) for RV-TDI is also higher than for CCT-TDI indicating relatively lower (≤14%) false alarm rates (detecting that a person has traversed through when they have not). The low error rates of our proposed algorithms are likely to be translated to higher levels of acceptance of the system by caregivers as they are less likely to be frustrated by false alarms and more likely to observe the benefits of the system to provide safe care.

The reason for lower performance is of CCT-TDI algorithm is because of its reliance on estimating the center crossing time. Due to the noise in phase measurements and the speed at which a participant walks across the threshold, the center crossing algorithm (*cct_detect* in Fig. 4) can fail to detect a *CCT*.

5 Conclusions and Future Work

The main finding of our study was that a single RFID tag placed over the shoulder accurately identified *moving in* and *moving out* of a threshold to address eloping in elderly in an ageing population context. The small, battery free and low cost nature of RFID tags are an advantage, especially in settings where there is significant risk of infection such as hospitals where the device offers both disposability and user-friendliness. Comparing our approach to existing wandering off alarms, the use of simple passive device as opposed to presently used expensive battery powered devices is a key advantage. Although our approach does required RFID readers, current solutions also require a powered transceiver and associated antennae at each threshold. The RV-TDI method performed better with few false negatives and false positives. These low error rates can lead to higher levels of acceptance of the system by care givers.

Although both algorithms performed well, there are a number of limitations. Firstly, we have not investigated the effect of antenna orientations other than 45 degrees (Fig. 3) on the performance of the algorithms. Clearly reducing the angle will diminish the difference between the center crossing time at the two antennas and we can expect the CCT-TDI algorithm performance to reduce.

Secondly, the traversing speed of the tag presents an upper bound on walking speed beyond which it is not possible to distinguish center crossings. In particular, reader frequency randomly hops between 12 channels (under Australian regulations) during interrogations and maximally 2 seconds are required to hop back to the same channel. If a person travels at high speed, inadequate readings can be obtained from the reader at a fixed frequency to evaluate radial velocity V_r. Hence, the accuracy of our algorithms decreases as the walking speed of a person increases due to the absence of enough radial velocity information.

However, we can evaluate an upper bound for walking speed. For each antenna, at least four phase measurements are needed for the proposed CCT-TDI (Section 3.1). In the worst case, 8 seconds are required to obtain four phase measurements. Then algorithm performance can be expected to deteriorate if walking speed exceeds $d_{path}/8$ (m/s) where d_{path} is the distance over which each antenna can successfully read a tag. Taking a nominal reading rage of 5 m from an antenna, the upper bound on velocity is approximately 4.5 (km/h) which, according to mean gait speeds reported in [20] is adequate for monitoring elderly over the age of 70 years, the target population for our algorithms.

Since RV-TDI method (Section 3.2) relies on reaching consensus on positive and negative samples, algorithm performance can be expected to deteriorate if walking speed of a tag wearer exceeds 9 (km/h) where we assume only two phase measurements are needed within 2 seconds but over a d_{path} of 5 m. It is also important to note that the ability to detect walking direction at significantly higher walking speeds also relates to the better performance observed with this approach (Table 1).

Furthermore, we hope our results will serve as a benchmark for wandering off detection methods in the future as well as TDI estimation methods. We are currently looking at applying filters and pattern recognition algorithms on phase measurements, velocity and return signal strength to improve the estimation of traversal direction as well as using multiple frequencies as opposed to a single frequency and using mean radial speeds to estimate TDI to overcome the limitation posed by walking speed. Finally, we plan to evaluate our approaches on a larger cohort of older volunteers.

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