INTEGRATED ALGORITHMS FOR RFID-BASED MULTI-SENSOR INDOOR/OUTDOOR POSITIONING SOLUTIONS

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ABSTRACT: Position information is very important as people need it almost everywhere all the time. However, it is a challenging task to provide precise positions indoor/outdoor seamlessly. Outdoor positioning has been widely studied and accurate positions can usually be achieved by well developed GPS techniques but these techniques are difficult to be used indoors since GPS signal reception is limited. The alternative techniques that can be used for indoor positioning include, to name a few, Wireless Local Area Network (WLAN), bluetooth and Ultra Wideband (UWB) etc.. However, all of these have limitations. The main objectives of this paper are to investigate and develop algorithms for a low-cost and portable indoor personal positioning system using Radio Frequency Identification (RFID) and its integration with other positioning systems. An RFID system consists of three components, namely a control unit, an interrogator and a transponder that transmits data and communicates with the reader. An RFID tag can be incorporated into a product, animal or person for the purpose of identification and tracking using radio waves. In general, for RFID positioning in urban and indoor environments three different methods can be used, including cellular positioning, trilateration and location fingerprinting. In addition, the integration of RFID with other technologies is also discussed in this paper. A typical combination is to integrate RFID with relative positioning technologies such as MEMS INS to bridge the gaps between RFID tags for continuous positioning applications. Experiments are shown to demonstrate the improvements of integrating multiple sensors with RFID which can be employed successfully for personal positioning.

1. INTRODUCTION

The demand for positioning information has significantly increased due the rapid development of ICT technologies. Typical personal positioning applications are for example tracking miners underground (Zhang *et al.*, 2009), monitoring athletes (Wu *et al.*, 2007), locating first responders (Miller *et al.*, 2006), guiding the disabled and providing other general Location Based Services (LBS) (Retscher *et al.*, 2005). Visitors often need guidance and positional information support especially in complex buildings. Studies have showed that people tend to lose orientation a lot easier within buildings than outdoors. However, it is a challenging task to provide precise positions indoor/outdoor seamlessly. Outdoor positioning has been widely studied and accurate positions can usually be achieved by well developed GPS techniques (Misra & Enge, 2006) but these techniques are difficult to be used indoors since GPS signals are either blocked completely or too weak to be received. A number of alternative techniques can be used for indoor positioning. Popular

techniques include radio-based pseudolites (Barnes *et al.*, 2003), Wireless Local Area Network (WLAN) (Li *et al.*, 2006), Bluetooth and Ultra Wideband (UWB) (Yan & Bellusci, 2009), infrared (Arc Second, 2002) and ultrasonic positioning systems (Priyantha, 2005) as well as inertial sensors but all of them have limitations. For example, inertial sensors usually suffer from drifting problems caused by the accumulating errors of both acceleration and angular velocity measurements (Titterton & Weston, 2004) and the radio-based techniques are prone to the obstructions and multipath effects of the transmitted signals (Lehner & Steingaß, 2003). It is therefore necessary to develop improved methods for minimising the limitations of the current indoor positioning techniques and providing an adequately precise solution for indoor positioning and seamless indoor/outdoor positioning. The main objectives of this paper are to investigate and develop novel algorithms for a low-cost and portable indoor personal positioning system using Radio Frequency Identification (RFID) and its integration with other positioning systems.

2. RFID TECHNIQUES

RFID describes the use of radio frequency signals to provide automatic identification of items. A RFID system consists of three components: a control unit, an interrogator (RFID reader) and a transponder (RFID tag) that transmits data and communicates with the reader (Finkenzeller, 2003). An RFID tag can be incorporated into a product, animal or person for the purpose of identification and tracking using radio waves.

2.1 The RFID System Used

Fig. 1.   RFID interrogator and transponder used in the research (*i-Card III* interrogator (left) and *i-Q* transponder (right) of the *Identec Solutions* long range active RFID system)

The RFID system used in this research was an intelligent long range system produced by *Identec Solutions*. It consists of an *i-Card III* reader and *i-Q* tags (see Figure 1). The system is working on 915MHz in Australia and claims 100m reading range in free space (Identec Solutions, 2004). In practice, the maximum reading range is about 30m due to the effects from the surrounding environments (reflections and obstructions).

2.2 Characteristics of RFID Signal Propagation

In positioning applications, the Received Signal Strength (RSS) is the major observation component in RFID systems. It can be used to determine either the appearance of a mobile user in the reading range or the distance between the reader and the tag. However, in

practice, modelling the relationship between this value and the distance may be affected by various factors. Four major potential effects are listed below:

1. Environmental dynamics
2. Path loss patterns
3. Directional patterns
4. Multipath effects

2.2.1 Environmental Dynamics: The RSS values are very stable in static environments. The average value of the RSS variations at a fixed position is approximately ±0.8dBm at a 95% confidence interval. This value does not change much with different environments and different distances between the RFID readers and tags. However, RSS can be dramatically changeable in dynamic environments. Figure 2 shows the RSS measured at the same position in different contexts (i.e., static indoor environments and dynamic indoor environments). In the static environment, the distribution of RSS aligned well with the associated Gaussian distribution but in the dynamic environment, the distribution is disturbed and several peaks are observed. The mean RSS value also shifts away from the one measured in the static environment. This is caused by moving obstacles and reflectors, such as the people passing through the areas between the RFID reader and the tag scanned, during the surveying process.
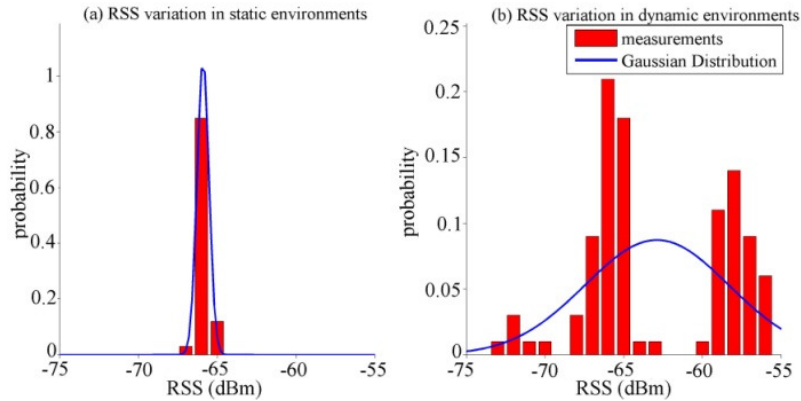

Fig. 2. Comparisons of the RSS values in both static and dynamic environments (The bars show the probabilities of observing certain values of RSS and the lines are the associated Gaussian distributions with the same means and variations of the measurements.)

2.2.2 Path Loss Patterns: In general, the power of the RF signals decreases when it propagates into space (Rappaport, 1996). The trend of this process can be mathematically modelled. One of the simplest models, which describes the decreasing trend without the effects from reflections and obstructions, is presented as the log-distance path loss model (see Equation 1).

$$PL(d) = PL(d_0) + 10 \cdot \gamma \cdot \lg(\frac{d_0}{d}), d \geq d_0 \geq d_f \tag{1}$$

where d = the distance between the transmitter and the receiver

$PL(d)$ = the path loss at d

d_0 = the reference distance

d_f = the Fraunhofer distance

γ = the path loss exponent

In reality, the RF signal strength is affected significantly by the propagation media and the surrounding environments and it may not exactly follow the trend described in the log-distance path loss model above. Figure 3 shows comparisons of the RFID RSS measurements in both outdoor and indoor environments. It indicates that the path loss pattern in the outdoor experiments is close to the log-distance pattern. In contrast, the results in the indoor environments show a linear pattern. This is mainly due to the differences in the environments. In the indoor environments, the walls, ceilings and floors can form a structure, called waveguide. This structure forces the RF signals to propagate in particular directions (e.g. the two directions along an indoor corridor) and, consequently, changes the path loss patterns of the signal propagation and increases the errors distance estimation using RSS.
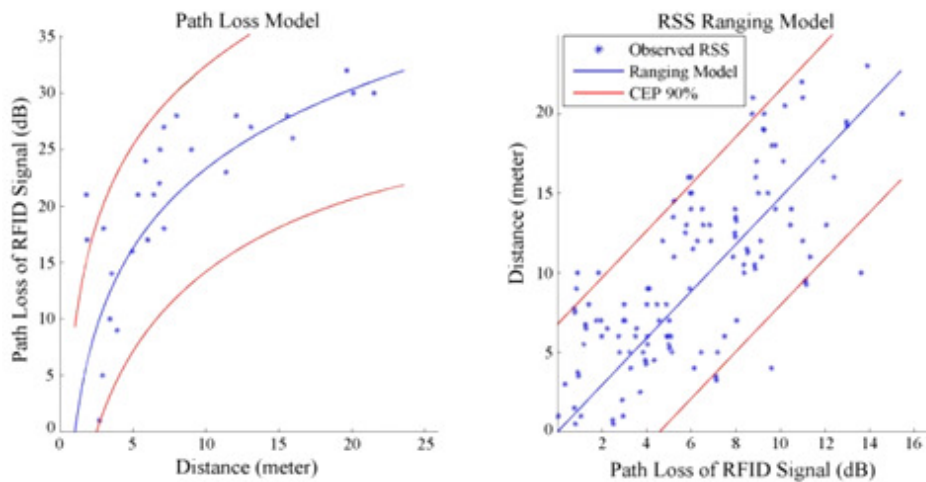

Fig. 3. Comparisons of path loss patterns in various environments (The left plot shows a log-distance pattern of the RSS in outdoor open areas. The right plot shows an approximate linear pattern in a corridor indoor.)

2.2.3 Directional Patterns: As noted from the observations, the RSS measured can be very different due to the relative directions between the transmitter and the receiver. Theoretically, the major causes of this are the antenna gain patters, obstructions and reflections between the transmitters and receivers in different directions. In practice, the antenna gain patterns can be precisely measured in a laboratory but the exact effects from the environment between the transmitters and receivers are not easy to be modelled and separated from the RSS directional patterns. Figure 4 shows an example of the directional patterns measured indoors with different distances (1.5m, 2.5m, 3.5m, 4.5m and 5.4m) between the RFID reader and tag from eight orientations (0°, 45°, 90°, 135°, 180°, 225°, 270° and 315°) respectively. The result shows that RSS variations due to directional patterns can be up to 20dB and the patterns vary from one position to another.
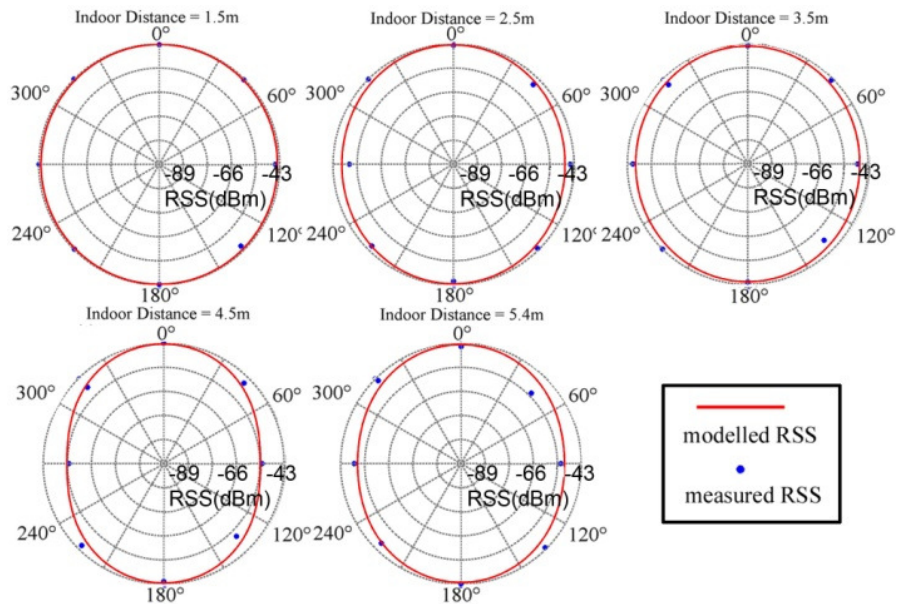

Fig. 4. The directional patterns and the models used to represent the patterns of RSS in indoor environments with different distances between the RFID reader and tag (The RSS from eight relative directions (0°, 45°, 90°, 135°, 180°, 225°, 270° and 315°) and five distances (1.5m, 2.5m, 3.5m, 4.5m and 5.4m) between the reader and tag were measured in indoor environments.)

2.2.4 Multipath Effects: Another detrimental effect on the RSS-based positioning methods is the variations of RSS caused by multipath effects. This phenomenon is mainly caused by reflections of the RF signals, which make the received signals a combination of signals from both direct and indirect paths (see Figure 5). The combination of the signals will lead to an unpredictable variation of signal strength in the space since the paths are site-specific.
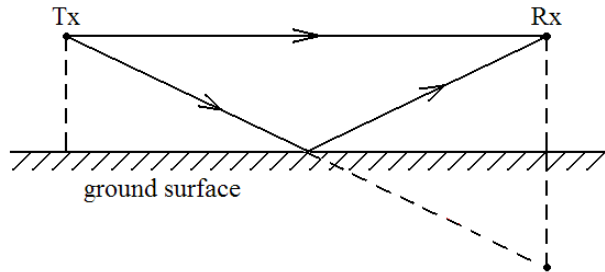
Fig. 5. A schematic plot of the ground reflection model (Tx refers to the RFID tag; Rx refers to the RFID reader and the arrow lines refer to RF propagation paths.)
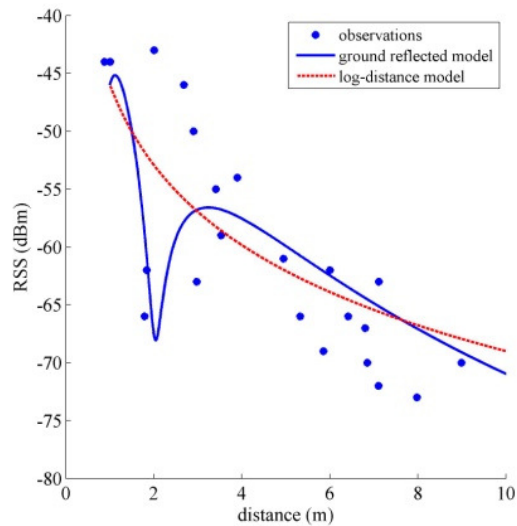

Figure 6.The comparison of the log-distance path loss model, the ground reflected model and the observations in outdoor environments (The RSS is measured in the open areas outdoor within 10m from the transmitter. The log-distance path loss model (red line) and the ground reflected model (blue line) are generated using the same dataset.)

Figure 6 shows a comparison of propagation models and outdoor observations in the open areas. The log-distance model and the ground reflected model are generated based on observations. It shows that the RSS observations are scattered around the estimated values of the log-distance model (red line) but have a significant drop between 2m and 3m. The variations of the RSS observations also show a similarity with the ground reflected model since the conditions in the outdoor open areas are similar with that of the ground reflected model. However, in the metropolitan areas or indoors, the number of RF reflectors can be enormous and the conditions of the environments can be very complex. This will make the RSS estimation very difficult.

3. RFID POSITIONING ALGORITHMS

For location determination one conventional strategy is that RFID tags are placed as active landmarks or at known locations in the surrounding environment. If the user passes by with an RFID reader the tag ID and additional information (e.g. the 3-D coordinates of the tag) are retrieved. Thereby the range between the tag and the reader in which a connection between the two devices can be established depends on the type of the tag. Another strategy used for RFID positioning is that readers are installed at certain waypoints in the surrounding environment (e.g. entrances of buildings, storage rooms, shops, etc.) to detect an object when passing by. For that purpose an RFID tag is attached to or incorporated in the object to be located. This approach is widely used in warehouse management and logistics as well as in theft protection of goods in shops and for the tracking of containers and goods.

In general, for RFID positioning in urban and indoor environments three different methods can be used.

1. Cellular Positioning
2. Trilateration
3. Location Fingerprinting

3.1 Cellular Positioning

Cellular positioning (i.e. RFID Cell of Origin (CoO)) is defined by Equations (2) and (3). When the mobile user observes the RFID signals from a cell, the position of the cell centre will be assigned to the user as its approximated position (Zhu, 2008). It can be employed in areas where the positioning accuracy requirement is not that high, e.g. in outdoor environments. For CoO the positioning accuracy depends on the size of the cells which is given by the defined reading range of the RFID systems.

$$Z(p_0) = Z(p_c), \, p_c \in \{p_1, \ldots, p_n\} \tag{2}$$

$$\hat{p}_0 = p_c \tag{3}$$

where p_0 = the true position of the mobile user

$Z(p_0)$ = the mobile user's observed signal

p_c = the centre's position of the cell c

$Z(p_c)$ = the signal transmitted from the cell c

$\hat{p}_0$ = the estimated position of the mobile user

3.2 Trilateration

Another method is trilateration using ranges to the surrounding RFID tags to determine the mobile user's positions (see Equation (4)). This method can be used to achieve medium range positioning accuracy levels of a few metres (Retscher & Fu, 2008). Therefore it may

be employed in areas where the accuracy requirement is higher than in open outdoor environment such as in the transition zone between outdoor to indoor environments.

$$d_{io} = \sqrt{(p_{x,i} - p_{x,0})^2 + (p_{y,i} - p_{y,0})^2 + (p_{z,i} - p_{z,0})^2} + \varepsilon_{i0} \ i = 1,\dots,n, \varepsilon_{i0} \sim N(0, R_{i0}) \quad (4)$$

where d_{i0} = the distance between the mobile user and the i th transmitter

$p_{x,0}$, $p_{y,0}$ and $p_{z,0}$ = the position of the mobile user

$p_{x,i}$, $p_{y,i}$ and $p_{z,i}$ = the position of the i th transmitter

ε_{i0} = the associated measurement noise with zero-mean normal distribution

3.3 Location Fingerprinting

The third method is location fingerprinting which may be used in areas where high positioning accuracies of one to few metre level is required, e.g. for navigation indoors. In this case, two phases, the training phase and the positioning phase, are required. In a training phase RSS values at certain positions are obtained and stored in a database. Then in the positioning phase the current observed RSS values are matched with the values in the database and the position of the user is determined. The positioning phase can be implemented via two approaches. One is the deterministic approach and the other is the probabilistic approach.

3.3.1 Deterministic Approach: The deterministic approach was developed for the first RF-based location fingerprinting system, RADAR (Bahl & Padmanabhan, 2000). It is to find the position in the defined area, which has the minimum distance between the vector of observations in positioning phase and the vector of observations in training phase (see Equations (5) and (6)).

$$\|Z(p_0) - Z(p_c)\| \le \|Z(p_0) - Z(p_i)\|, p_c \in \{p_1, \dots, p_n\},$$
$$\forall p_i \in \{p_1, \dots, p_n\} \quad (5)$$
$$\hat{p}_0 = p_c \quad (6)$$

where $Z(p_0)$ = the mobile user's observed signals

p_c and p_i = the positions in the defined area

$Z(p_c)$ and $Z(p_i)$ = the signals vectors measured in the training phase at positions

p_c and p_i respectively

3.3.2 Probabilistic Approach: The probabilistic approach was introduced by Castro *et al.* (2001) using a Bayesian network to find the most possible location according to the received signals. This approach was further developed by Roos *et al.* (2002) The statistical model, which includes the probabilistic approach was used instead of the empirical models (see Equation (7)). It is superior to the deterministic approach in dealing with the small amount of RSS variations caused by the environmental dynamics.

$$P(p_i|Z) = \frac{P(p_i \cap Z)}{P(Z)} = \frac{P(p_i) \cdot P(Z|p_i)}{P(Z)}$$

$$p_i \in \{p_1, \ldots, p_n\} \tag{7}$$

where $P(p_i|Z)$ = a conditional probability of the mobile user at position p_i when he/she observes signal Z

$P(p_i)$ = a prior probability of the mobile user at position p_i

$P(Z|p_i)$ = a conditional probability of the mobile user observing signal Z at position p_i

$P(Z)$ = a probability of the mobile user observing signal Z

4. MULTI-SENSOR INTEGRATED TECHNIQUES USING RFID

According to current research (Grejner-Brzezinska *et al.*, 2007), multi-sensor integrations can provide more accurate and reliable estimations by constraining the results with redundant observations. It can also significantly reduce the cost and volume of the entire positioning system. In this research, a Micro-Electro-Mechanical System (MEMS) Inertial Navigation System (INS), *MinimaxX*, is combined with RFID to enhance the accuracy and reliability of the RFID positioning. This device is a portable athlete tracking system (Wu *et al.*, 2007). It contains a tri-axis accelerometer, a tri-axis gyroscope and three magnetometers. Two integrated methods are developed. One is the integrated INS/RFID probabilistic CoO algorithm and the other is the integrated INS/RFID location fingerprinting algorithm.

4.1 Integrated INS/RFID Probabilistic CoO Algorithm:

In order to improve the continuity and the positioning accuracy of the conventional RFID CoO algorithms an integrated INS/RFID probabilistic CoO algorithm is developed. Rather than using a fixed solid cell in the deterministic CoO, an adjustable ring-shaped cell is developed (see Figure 7) (Zhu, 2008). The radius of the ring is determined by a RSS-based ranging model. The probability of the mobile user's position is given by the joint probability of the mobile user at position p and the distance from the mobile user to the transmitter equals d_0 (see Equation (8)).

$$P(p_0 = p) = P(p \cap (d_0 = d)) = P(p) \cdot P(d_0 = d)$$

$$P(d_0 = d) \sim N(d, \sigma^2) \tag{8}$$

where $P(p_0 = p)$ = the probability of the mobile user's position

$P(p)$ = the probability of the mobile user at position p

$P(d_0 = d)$ = the probability of the distance from the mobile user to the transmitter equalling d_0

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4.2 Integrated INS/RFID Location Fingerprinting Algorithm

For RFID location fingerprinting algorithms, the instability of RSS is a major error source in positioning. It is mainly caused by environmental dynamics, path loss patterns, directional patterns and multipath effects and can lead to the uncertainty of the solutions in RFID location fingerprinting algorithms. Therefore, a method using additional observations or constraints to select the correct solution is required.
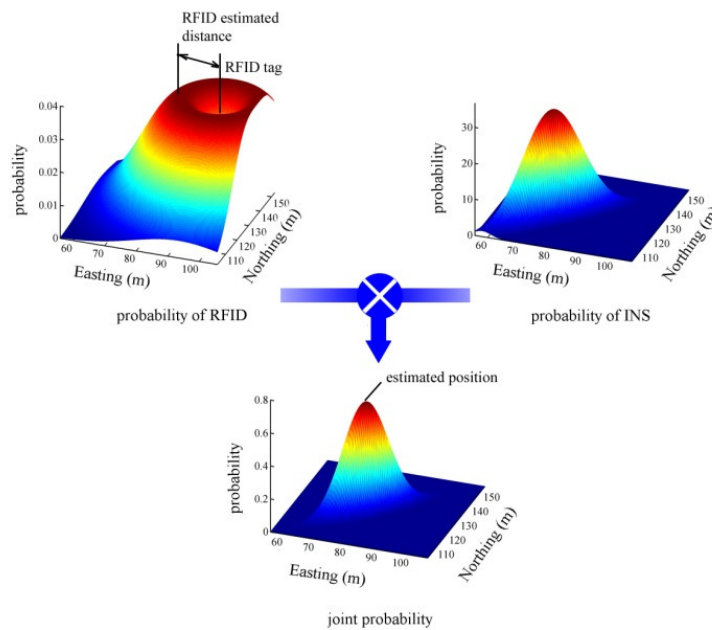

Fig. 7.   A schematic plot of the probabilistic CoO algorithm (The probability of RFID probabilistic CoO algorithm is a round-shape distribution with the radius of the distance estimated by RFID and centre of the RFID tag. The position is determined by the joint probability with the observations from other sensors, such as INS.)

In the probabilistic approach, a normal distribution is used to replace the uniform distribution of the prior probability $P(p_i)$, of the mobile user's position in the RFID stand-alone techniques (see Equation (7)). The mean and the variance of this normal distribution are estimated according to the INS predicted position and its predicting uncertainty. Consequently, the probabilities near the short-term predicted position are amplified and the positioning uncertainty caused by the instability of RSS in RFID system is constrained (Zhang *et al.*, 2008).

5. EXPERIMENTS AND RESULTS

Experiments for evaluating the RFID positioning algorithms developed for indoor and outdoor positioning are conducted at Yarra Bend Park and a building at RMIT University's

City Campus, Melbourne, Australia. The integrated MEMS INS/RFID system using *MinimaxX* and *Identec Solution*'s RFID is used for implementations.

5.1 Outdoor Experiments

The outdoor experiments are conducted to evaluate the RFID CoO algorithms and the integrated INS/RFID CoO algorithms at Yarra Bend Park. Seven RFID tags are placed in a U-shape trajectory in outdoor open areas. The cell centres are placed with different intervals (20m intervals in the east part and 50m intervals in the west part of the trajectory) (see Figure 8). A GPS Real Time Kinematic (RTK) system (*Trimble R8*) is mounted on the mobile user to provide the centimetre-level reference positions for comparison purpose.
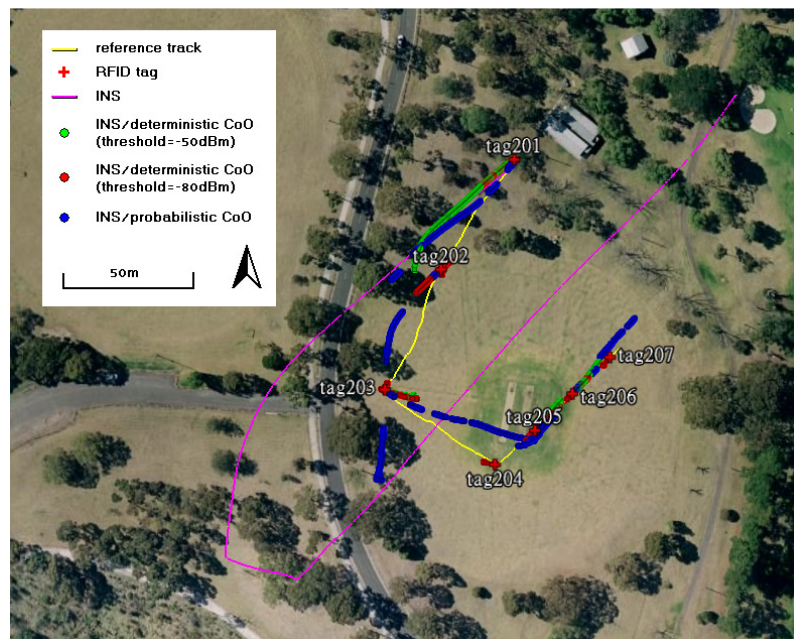

Fig. 8.The experimental site for the evaluations if the integrated INS/RFID CoO algorithms (The satellite image in the background comes from *GoogleEarth*
(URL: http://www.google.com/earth/index.html Access date: 28 Jul 2010).)

Four algorithms are evaluated, including:
1. The 2-D reduced INS algorithm
2. The integrated INS/RFID deterministic CoO algorithm with small cell size (RSS threshold = -50dBm)
3. The integrated INS/RFID deterministic CoO algorithm with large cell size (RSS threshold = -80dBm)
4. The integrated INS/RFID probabilistic CoO algorithm

The results (see Table 1) show that all of the integrated INS/RFID CoO algorithms constrain INS drifts significantly. The accuracy of integrated INS/RFID deterministic CoO algorithms is highly dependent on the size and distribution of the cell. The accurate positions of the cell centres can be used to constrain INS drifts when suing small cells (e.g. RSS threshold = -50dBm). However, the cells have to be densely distributed to provide frequent corrections (at least 0.2Hz) to the MEMS INS sensors. Otherwise, the dramatic drifts of INS can significantly degrade the positioning accuracy of the integrated algorithm with large spacing between cells. An alternative is to use large cells (e.g. RSS threshold = -80dBm) to provide continuous cell coverage and, consequently, the frequent corrections to INS. However, the limitation of this approach is that large cells cannot provide corrections as accurately as small cells. It is a great challenge to compromise between accuracy, continuity and the number of cells for deterministic CoO algorithms. In contrast, the integrated INS/RFID probabilistic CoO algorithm overcomes this limitation and provides more accurate positioning by introducing a flexible cell size according to the RSS. This provides continuous trajectories and it is more accurate than the integrated INS/RFID deterministic CoO algorithms.

Tab. 1.   The positioning errors of the integrated INS/RFID CoO algorithms (RMSE: Root Mean Square Error)

Method	RMSE (m)
INS/Probabilistic CoO	15.4
INS/Deterministic CoO (-80dBm)	19.6
INS/Deterministic CoO (-50dBm)	28.1
INS	67.7

5.2 Indoor Experiments

The indoor experiments are conducted to evaluate the RFID location fingerprinting algorithms and the integrated INS/RFID location fingerprinting algorithms in a building at RMIT University's City Campus. A series of experiments are conducted at the known positions in an 8m×10m room for evaluating the RFID location fingerprinting algorithms. Four approaches are used, including using single, two and six measurement(s) of the RSS vector at one direction at each point to estimate position respectively and using four directions' measurements to estimate position. The results (see Table 2) show that a positioning accuracy, better than 2.5m, can be achieved using RFID location fingerprinting algorithms. By using multiple scans both in number and in directions, accuracy can be improved. However, the methods using multiple observations at a single position is only practicable for static positioning applications. It is impracticable when the mobile user is moving in real-time.

Tab. 2. RMSE of the static indoor positioning tests using RFID location fingerprinting algorithms

Method	RMSE (m)
Single scan in one direction	2.3
Two scans in one direction	1.8
Six scans in one direction	1.5
Single scan in four directions	1.5

Four trajectories between level 9 and 11 of the building are also used for the evaluations of 3-D integrate INS/RFID location fingerprinting algorithm for dynamic positioning. The results show that mobile user movements between the levels can be clearly mapped using the algorithm developed. The RMSE of the experiments are 3.7m, 3.4m, 4.2m and 4.0m respectively (see Figure 9). The drifts in INS can be constrained and the integrated algorithm can provide a continuous trajectory for dynamic positioning.

6. CONCLUSIONS

In summary, three typical positioning methods can be used for RFID positioning (i.e., cellular positioning, trilateration and location fingerprinting). All of them are affected by the RSS instabilities, which are mainly caused by the environmental dynamics, path loss patterns of the signals, directional patterns of the signals and multipath effects. The experiments conducted at Yarra Bend Park and a building at RMIT University's City Campus, Melbourne, Australia show that multiple observations and multi-sensor integrations can both increase the positioning accuracy. The multi-sensor integrated techniques using RFID and MEMS INS are superior in their portable volume, low-cost and metre-level positioning accuracy by using the algorithms developed. It indicates that these techniques can be successfully employed for LBS and personal positioning.
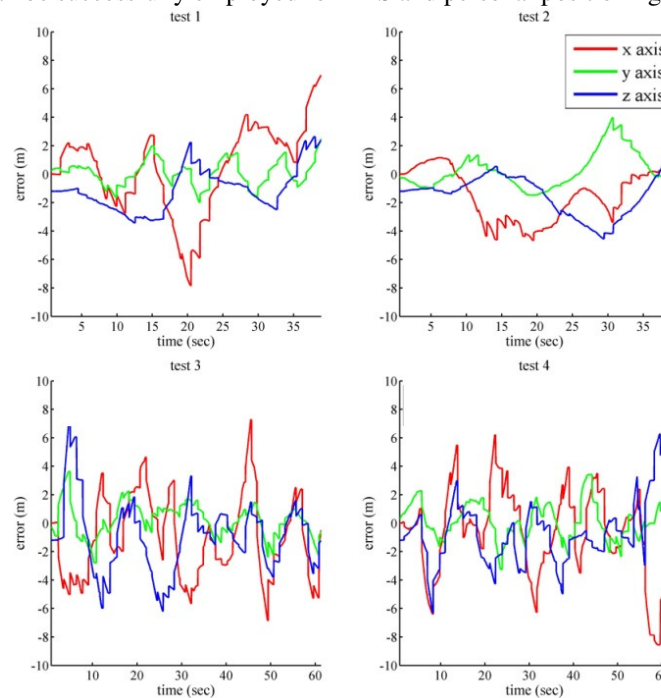

Fig. 9.Positioning errors for the 3-D integrated INS/RFID location fingerprinting algorithms (Test 1: the trajectory from levels 11 to 10. Test 2: the trajectory in test 1, travelling in the opposite direction. Test 3: the trajectory from the intermediate level between levels 10 and 11 to the intermediate part between levels 9 and 10. Test 4: trajectory in test 3, travelling in the opposite direction.)

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