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Abstract

Mobile indoor localisation has numerous uses for logistics, health, sport and social networking applications. Current wireless localisation systems experience reliability difficulties while operating within indoor environments due to interference caused by the presence of metallic infrastructure. Current position localisation use wireless channel propagation characteristics, such as RF receive signal strength to localise a user's position, which is subject to interference. To overcome this, we developed a Fingerprint Context Aware Partitioning tracking model for tracking people within a building. The Fingerprint Context Aware Partitioning tracking model used received RF signal strength fingerprinting, combined with localised context aware information about the user's immediate indoor environment surroundings. We also present an inexpensive and robust wireless localisation network that can track the location of users in an indoor environment, using the Zigbee/802.15.4 wireless communications protocol. The wireless localisation network used reference nodes placed at known positions in a building. The reference nodes are used by mobile nodes, carried by users to localise their position. We found that the Fingerprint Context Aware Partitioning model had improved performance than using only multilateration, in locations that were not in range of multiple reference nodes. Further work includes investigating how multiple mobile nodes can be used by Fingerprint Context Aware Partition model to improve position accuracy.

Keywords

localisation, indoor, fingerprints, strength, received, aware, signal, context, sub, sorting

Disciplines

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Using Context-Aware Sub Sorting of Received Signal Strength Fingerprints for Indoor Localisation

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Abstract—Mobile indoor localisation has numerous uses for logistics, health, sport and social networking applications. Current wireless localisation systems experience reliability difficulties while operating within indoor environments due to interference caused by the presence of metallic infrastructure. Current position localisation use wireless channel propagation characteristics, such as RF receive signal strength to localise a user's position, which is subject to interference. To overcome this, we developed a Fingerprint Context Aware Partitioning tracking model for tracking people within a building. The Fingerprint Context Aware Partitioning tracking model used received RF signal strength fingerprinting, combined with localised context aware information about the user's immediate indoor environment surroundings. We also present an inexpensive and robust wireless localisation network that can track the location of users in an indoor environment, using the Zigbee/802.15.4 wireless communications protocol. The wireless localisation network used reference nodes placed at known positions in a building. The reference nodes are used by mobile nodes, carried by users to localise their position. We found that the Fingerprint Context Aware Partitioning model had improved performance than using only multilateration, in locations that were not in range of multiple reference nodes. Further work includes investigating how multiple mobile nodes can be used by Fingerprint Context Aware Partition model to improve position accuracy.

I. INTRODUCTION

Real-time position localisation of people is a widely sought after function in numerous applications for emergency services, location based services, social networking and sports and health domains. Commonly used real-time position tracking systems have become popular due to the availability of Global Positioning System (GPS). Indoor localisation tracking of people with unobtrusive, wearable sensors has valuable potential for applications where position tracking and motion activity monitoring is also useful. For example, providing a health-care application in the form of remote monitoring and tracking of aged-care patients can improve their safety and other care aspects. The popular use of GPS has led to a

variety of mobile location based services applications such as social networking, street map guide or asset tracking.

While outdoor localisation in open areas has been largely solved with the advances in satellite-based GPS systems, indoor localisation presents ongoing challenges due to the large range of variables that effect different techniques. There are no widely available or cost-effective and ubiquitous wireless solutions like GPS for indoor localisation which require no prior infrastructure. Indoor localisation systems are available but most have difficulties operating in confined spaces or cannot localise to within small distances in real-time for moving objects as required for sport and health applications.

Current localisation techniques depend on using sensing infrastructure already present in the environment such as visual markers, wireless LAN hotspots, cellular networks or GPS satellite coverage. Indoor environments exhibit multi-path interference to Radio Frequency (RF) wireless technologies because of the presence of physical obstacles such as metal beams or walls. Hence this causes outdoor RF based localisation technologies such as GPS to function inaccurately indoors because of signal degradation. RF localisation methods such as Received Signal Strength Indicator (RSSI) or Time of Arrival also experience inaccuracies and reliability issues when operating indoors. To overcome this, we developed a Fingerprint Context Aware Partitioning (FCAP) tracking model for tracking people within a building.

The FCAP tracking model used a form of RSSI fingerprinting. Fingerprinting is a form of landmark localisation that uses distinct RSSI signatures to estimate a position. The FCAP tracking model extends fingerprinting by using context-aware information, such as a building floorplan. The use of context aware information allowed the FCAP model to improve the reliability of the position accuracy, while depending on varying fingerprint granularity.

Our wireless localisation system used a low powered wireless sensor network infrastructure which consisted of reference nodes placed at predetermined coordinates in a building level. The reference nodes were used to determine the coordinates of

the user within the region covered by the localisation network. Our wireless localisation tracking system consisted of users carrying a mobile node to triangulate their current position. We evaluated the FCAP tracking model in a typical and realistic indoor environment.

This article is organised into the following sections. Section III presents an overview of the wireless localisation network infrastructure used. Sections IV describes the operation of the FCAP tracking model. An evaluation of the FCAP tracking model is discussed in section V. Conclusions and further work are presented in section VI.

II. BACKGROUND LITERATURE

Different types of wireless technologies, such as GPS have been investigated for outdoor and indoor location systems. Unfortunately, GPS is not suitable for indoor use and this has led to research into the use of other wireless technologies including UWB [1], ultrasonic and GSM [2] platforms. Regulations are not clear for the use of UWB, and ultrasonic location detection still requires RF transceivers. GSM uses existing infrastructure, however accurate position resolution indoors is difficult.

Receive Signal Strength Indicators (RSSI) are used for indoor and outdoor localisation, as outlined by Seco et al [3]. The most common RSSI localisation techniques are RSSI fingerprinting, RSSI triangulation and trilateration. RSSI Fingerprinting identifies specific positions with RSSI values, while RSSI triangulation and trilateration associate RSSI with distance or angular trajectory between receiver and known transmitter positions in order to localise [3], [4]. Hightower et al [5] describe the Placelab geophysical location system which users can determine their position in an urban environment. Placelab was an RSSI fingerprinting technique that used wireless LAN hotspots and GSM broadcast towers to determine a user's position. The Placelab software used a database of known wireless LAN hotspots and GSM broadcast towers. The Placelab software can be used with a PDA or laptop with wireless LAN or GSM connectivity. Localisation accuracy is stated as being less than GPS, with 20-25m using wireless LAN and 100m to 150m for GSM broadcast towers. A similar technique of using RSSI is employed by our presented localisation network.

Other RSSI Zigbee based localisation systems include Cho et al [6], who developed the ZiLA algorithm for localisation. The ZiLA algorithm is a maximum likelihood estimator (MLE) used for the ZigBee networks. The ZiLA algorithm was developed using a deployment of cluster-tree Zigbee network topology and derived from the MLE under the log-normal models for the RSSI measurements. The reported average error was 1.8m. Huang et al [7] developed a Zigbee network based mixed centroid localization algorithm using RSSI values for an paint-ball game scenario.

Priwgharm et al [8] compared RSSI range and fingerprint based localisation techniques. They conducted experiments in a typical meeting room. Their results showed that using lateration estimation for localisation gave the best accuracy

and also had a smaller computational time compared to other fingerprint based techniques.

III. INDOOR LOCALISATION NETWORK OVERVIEW

Wireless infrastructure that is currently used for both indoor and outdoor localisation, tends to be computationally intensive with high power consumption. Wireless sensor networks are an alternative form of wireless infrastructure that can be used for localisation but also operate at low power, in comparison. Wireless sensor networks are used for a sensing and actuation applications including smart metering. Wireless sensor network infrastructure can potentially be used for low powered indoor and outdoor localisation. The ZigBee/802.15.4 [9] wireless communications protocol is used by the localisation network. Zigbee is a low data rate wireless communications protocol that can operate on devices with limited computing or power resources and cater for large networks of active devices [9].

Supported Zigbee features include Mesh Networking, 64-bit address, data rates: 20kbps to 250kbps and simple application profiles. Zigbee operates in the unlicensed ISM 2.4GHz or 915MHz frequency band [9]. Current Zigbee protocol radio transceivers have a large indoor range, up to 100m. The availability of RSSI values allowed the Zigbee protocol to be adapted for use in the indoor localisation network. Each Zigbee transceiver has a 64-bit ID address which allows a Zigbee network to handle a large number of active nodes.

The localisation network as seen in Figure 1 consisted of three types of nodes: coordinator, reference meter and mobile. Mobile nodes were carried by users to determine their current location. The reference nodes are used to determine a mobile nodes position via multilateration. The server connected to the coordinator node displays the current positions of the mobile nodes on a building floorplan.

A. Coordinator Node

The coordinator node, seen in Figure 2, is used to receive the location coordinates of each mobile node. The coordinator node communicates with the mobile node via the Zigbee mesh routing connection using the reference nodes. The coordinator node was implemented with a CC2430 Zigbee/802.15.4 module on a SmartRF development board [10]. The coordinator node is connected by a serial connection to a server computer. The server computer tracks the position of the mobile node using the context aware tracking process, as described in later sections. The coordinator node was also powered by standard mains electricity.

B. Reference Node

The reference node, seen in Figure 3, communicates to the coordinator node via a Zigbee network connection. The position of each reference node is known by the coordinator node. The reference nodes are used by the mobile nodes for multilateration. The reference node was implemented using the CC2430 Zigbee/802.15.4 wireless transceiver module from Texas Instruments [10]. Each CC2430 module has a unique 64-bit network address used as the reference node's identifier.

Fig. 1. Overview of Wireless Sensor Network for RSSI Fingerprint Context Aware Partition Tracking Model

Fig. 2. Coordinator Node Platform

Fig. 3. Reference and Mobile Node Platform

C. Mobile Node

The function of a mobile node is to determine a user's position using received signal strength. The mobile node detects reference nodes in near proximity. The mobile node uses the received signal strength from nearby reference nodes to calculate its position. The predicted position is then transmitted to the coordinator nodes via the reference node network. The mobile node was implemented using the CC2431 Zig-

bee/802.15.4 Location Engine Module [10].

D. Network Operation

The range distances are approximated using the radio frequency based Receive Signal Strength Indicator (RSSI) and the coordinates of the reference nodes of the indoor localisation network. Figure 4 shows how the mobile nodes interact with the reference nodes. The mobile node periodically transmitted RSSI Measure messages to the nearest reference nodes in range (Figure 4 A). The reference nodes use the RSSI Measure messages to calculate the receive signal strength indicator value. Five messages are used to calculate an averaged RSSI value.

As seen in Figure 4 B), once a series of RSSI Measure messages has been transmitted, the mobile node will then transmit an RSSI and Position Request message to all reference nodes in range. Each reference node will then respond with its calculated RSSI value and position. It was found that a minimum of three reference nodes must be in range of the mobile node to accurately approximate its position. If more than three reference nodes are detected, the nodes with the strongest RSSI values are used.

IV. FINGERPRINT CONTEXT-AWARE PARTITIONING TRACKING MODEL

The Fingerprint Context Aware Partitioning (FCAP) tracking model estimated a person's position using RSSI fingerprinting. Fingerprints are a set of RF signal strength values, unique to specific locations. The use of fingerprints can determine the likely position of the mobile by estimating which are the nearest reference nodes. However conventional methods using fingerprints can be unreliable due to distortions of measuring RSSI caused by multipath and other forms of RF interference. The use of context-aware information for fingerprint partitioning enables a more reliable means of determining the nearest reference nodes.

Figure 5 shows an overview of the FCAP model. The FCAP model consists of a number of stages used to filter and select the nearest reference nodes to the mobile node. The FCAP

Fig. 4. Mobile Node Receive Signal Strength Measuring Process

Fig. 5. Fingerprint Context Aware Partitioning Tracking Model

model uses the mobile node's RSSI values from the mobile node, RSSI fingerprint database and building floorplan features are used by the FCAP model. First the FCAP model estimates the likely position of the mobile node using circle partitioning. This estimate uses context-aware information provided by the floorplan and subsampling of the RSSI values to refine the likely position. Finally, multilateration is used to estimated the position of the mobile node.

A. Circular Partitioning

The circular partitioning process is used to determine the mobile node's nearest reference nodes within a certain radius. First, the reference node with the highest RSSI fingerprint is used as the centre of a circular area to partition the reference nodes that are within the valid area. The context-information of the building floorplan is then used to reduce which number

Fig. 6. Circular Reference Node Partitioning Example

of RSSI fingerprints that are within the valid area. An example of the circular partitioning process can be seen in Figure 6, where the bounded circle represents the partition encompassing the reference node 5, and the actual mobile node's location. The valid fingerprint set can be reduced to the four fingerprints within the circular partition area.

1) Radius Calculation: The radius of the circular partition area determines the performance and accuracy of the subsequent localisation algorithms. For optimal performance, the selected radius should be as small as possible while still encompassing the mobile node's location. The radius must be defined such that it is equal to or greater than, the distance between the reference and mobile node. As the mobile node's location is unknown, the radius represents a best estimate of the maximum separation.

A logarithmic range radius algorithm was used to calculate

the radius of the circular partitioning area. This algorithm calculates radius by applying fixed path loss logarithmic range. The radius is set to the range calculated between the reference and mobile node. Logarithmic range was found to be well suited to partitioning as it is most accurate for high RSSI values from reference nodes within near proximity. A minimum radius of 2.5m was used to prevent excessive exclusion of neighbouring fingerprints.

B. Context-Aware Partitioning

Indoor environments are characterised by unpredictable radio propagation channel parameters. These unpredictable channel parameters can cause distortion and multipath interference due to the presence of metallic structures within indoor environments. Since the multilateration algorithm, used RSSI for range estimations, wireless channel distortions will cause errors in the predicted position. In order to overcome wireless channel interference induced position errors, we developed a context-aware fingerprint sub sorting process that used the floorplan map.

The floorplan map was used by the context-aware partitioning process to determine the likelihood the RSSI fingerprints to be used. The floorplan consisted of a map with regions mapped with the probability of likely RSSI fingerprints available. Position validity was approximated by detecting if the mobile node's track had to move through a wall or barrier, to its predicted position. Figure 6 shows an overview of the context-aware partitioning process used to check the validity of fingerprints to be used.

C. Fingerprint Sub Sorting

When selecting fingerprints based on a single reference node, observed cases occurred where several fingerprints exhibit similar RSSI. Due to variations in path loss for different locations at fixed node separations, fingerprints with similar RSSI value differences may not be equidistant from the reference node. The RSSI fingerprints were sub sorted based on their path loss exponent, calculated using the RSSI between the reference node and fingerprint. Fingerprints are selected based on a lower path loss exponent. This gives preference to fingerprints with lower attenuating paths, corresponding to those most distant from the reference node.

D. Multilateration Position Calculation

Once the fingerprints have been determined, multilateration is used to calculate the mobile nodes position. The multilateration process used the least squares algorithm to determine the position of the mobile node [4].

E. Fingerprint Collection

RSSI values were collected at various distinct measuring locations in the indoor test environment. These RSSI values were placed into a database and were used to provide a unique fingerprint of each location. In some cases, fingerprint locations were constrained by the presence of immovable obstacles within the environment. The RSSI of all reference

Fig. 7. RSSI Fingerprint Heat Map for Layout 1

Fig. 8. RSSI Fingerprint Heat Map for Layout 2

Fig. 9. Example Walking Path

Fig. 10. Evaluation of FCAP Model with Multilateration

nodes within range was recorded at each fingerprint location. A minimum of three fingerprints were collected for each room, with a spacing of 1m typically maintained between measurements. The mobile node's orientation was constant for all measurements.

Figures 7 and 8 displays an RSSI fingerprint heat map for two different reference node placement layouts, where the measuring locations used are shown as crosses. The reference node locations are discussed in the next section. The coloured circle at each fingerprint represents RSSI value from the reference node at that point, with deep blue through to deep red representing a range of -40 dBm to -90 dBm.

The heat maps show high RSSI over a larger number of fingerprints for Layout 2 (Figure 8) than Layout 1 (Figure 7), due to their closer proximity to the reference node. Two reference node placement layouts were used to test the FCAP model: Layout 1 and 2. Layout 1 consisted of reference nodes placed on along the outer walls (cover area with multiple reference nodes), while Layout 2 consisted of reference nodes placed along the inner walls and did not confine the movement of the mobile node to areas covered by multiple reference nodes.

V. EVALUATION

The FCAP tracking model was tested in an indoor environment shown in Figure 9. The placement of the reference nodes can affect the localisation accuracy using RSSI fingerprints. We tested the FCAP model by having a user walk a known path whilst carrying a mobile node. Testing was carried out for two distinct reference node layouts. Both of these layouts utilised, at most, one reference node per room. The reference node locations are shown in Figure 10 A) and B), for Layouts 1 and 2. Layout 1 places reference nodes adjacent to perimeter walls. Layout 2 places reference nodes adjacent to interior walls. Compared with Layout 1, this decreases separation between reference nodes toward the centre of the building, at the expense of greater separation at its extremities. Layout 2 was designed to test which room the mobile node is in,

where the measured RSSI may be similar on either side of a wall.

RSSI fingerprint measurements was collected for a typical path through the test environment. As shown in Figure 9, the path traversed rooms with and without reference nodes. RSSI was recorded at 14 different locations along the path, each approximately 1m apart. Mobile node orientation matched the direction of travel at each point, which may differ to that used during fingerprint collection.

Both reference node layouts provide different node separation and geometry at the walking path measurement locations. It should be noted that Layout 2 provided significantly lower average distances between the reference nodes and measurement locations than Layout 1. The walking paths average distance from the closest reference node was 2.75m for Layout 1 and 1.33m for Layout 2, while the average separation from all reference nodes was 5.73m and 3.68m for Layouts 1 and 2 respectively.

A. Results

Layout	Average Error (m)	Standard Deviation (m)
Layout 1	2.57	1.62
Layout 2	14.29	24.54
Layout 1 (FCAP)	3.16	2.1
Layout 2 (FCAP)	4.48	4.96

TABLE I
AVERAGE ERROR AND STANDARD DEVIATION FOR LAYOUT 1 AND LAYOUT 2

The placement of the reference nodes can affect the localisation accuracy using RSSI fingerprints. We tested the FCAP model by having a user walk a known path whilst carrying a mobile node. The environment used for testing, showed signs of typical indoor RF interference. Figure 10 A) shows the localisation by multilateration only. Figure 10 B) shows the localisation using the FCAP model. Table I shows the average error and standard deviation measured for both layouts. While the average error was similar for multilateration and the FCAP

model for Layout 1, the FCAP model had less error than the multilateration results for Layout 2.

VI. CONCLUSION AND FURTHER WORK

We presented a wireless indoor localisation system that tracked users in an indoor environment, using the FCAP tracking model. The indoor localisation system used a Zigbee based wireless sensor network. The network consisted of three nodes: coordinator, reference and mobile nodes. The mobile node's RSSI value with respect to the reference node was used by the FCAP model as an RSSI fingerprint. The FCAP model combined the mobile node's RSSI fingerprinting with context-aware information (building floorplan). Through the use of context aware information the FCAP model improved position accuracy of the mobile node.

We evaluated and compared the FCAP model to conventional multilateration RSSI fingerprint based localisation. The FCAP model had a smaller position error when compared to multilateration, where the position of the mobile node was not restricted to areas covered by multiple reference nodes. This was highlighted the advantage of the FCAP model as it unrestricted the placement of the reference nodes. Further work will involve investigating how multiple mobile nodes can use cooperative communications with the FCAP model to improve position accuracy.

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