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Analysis of three indoor localization technologies to support facility management field activities

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Abstract

Facility management (FM) related field activities often involve accessing and reading manuals/specifications/drawings and exchanging information about a specific building element that is being worked on among different FM personnel (Lee et al. 2009). Such information retrieval and exchange is referred to as contextual retrieval and exchange in this paper because it is contingent upon accurate knowledge of: 1) the activity (task) being performed; and 2) the location of person/object in the facility. Assisting retrieval of contextual information requires determining the granularity (i.e., accuracy) of the location information, which is needed by FM personnel. The authors identified three main requirements for determining FM personnel location information using localization technology: 1) sub-room level (2-3m) accuracy; 2) greater than 95% precision; and 3) no-line-of-sight required to deploy transmitters/receivers for localization. Three technologies were selected for evaluating their capabilities in fulfilling the requirements identified for indoor localization to support facility management related field activities: 1) Radio Frequency Identification Tags (RFID); 2) Wireless LAN (WLAN); and 3) Inertial Measurement Units (IMUs). These three localization technologies were selected based on the fact that they do not require line of sight, are scalable and low cost. The authors used a fingerprinting approach, which involves creation of a signal strength map for localization, and the k-Nearest Neighbor (kNN) algorithm for location determination. Several Experiments were carried out to evaluate, for each of these technologies, accuracy and precision. These experiments also helped in assessing the reliability of received signal strengths over two variables: 1) time; and 2) direction/orientation for the same point/location. All of the technologies have been tested on the same floor of an actively used university building, following the same path on different days. The paper concludes with the comparison of performance of the three selected technologies over the requirements identified for indoor localization.

Keywords: indoor localization, fingerprinting, kNN, RFID, WLAN, IMUs

1 Introduction

Operations and maintenance (O&M) related activities constitute a major part of facility management (FM) to ensure effective functioning of facilities. O&M is the longest phase in the building lifecycle and consequently approximately 85% of the total building lifecycle cost is spent in O&M (Liu et al. 1994; Teicholz, 2004). Several researchers have worked on providing computational/mobile support to O&M activities, such as asset management, preventive maintenance and maintenance history tracking to reduce facility lifecycle O&M cost (Wing, 2006; Junghanns et al., 2009; Legner and

Thiesse, 2006; Ko, 2009; Ergen et al., 2007; Motamedi and Hammad, 2009). Many of these applications involve utilizing location information for equipment and component tracking. At the same time, little work has been done to evaluate indoor localization technologies to assess their applicability in supporting the above-mentioned applications. In addition, FM personnel carrying out field activities, such as accessing and reading manuals/specifications/drawings, getting information on necessary materials/tools, documentation, and arranging collaboration with co-workers/subcontractors, require interaction with actors/systems that are not located at the activity site (Lee et al. 2009). The actors/systems, not located at the activity site, require field personnel location information in appropriate detail (accuracy) to support the O&M personnel carrying out their field activity (Hammad et al., 2004) for example for locating a shut-off valve in a mechanical room and guiding the user to the right location, a navigation system might require to know user position at 2-3m accuracy level.

This paper evaluates indoor localization technologies against the requirements identified for supporting facility management field activities. Indoor localization is the process of determining the location of a person/object in an indoor environment (Hightower and Borriello, 2001). The authors observed staff at a regional hospital and identified three metrics for evaluating of indoor localization technologies: 1) accuracy; 2) precision; and 3) no-line-of-sight requirement, i.e., the ability of a sensing technology to localize a person/object even when the person/object is not in the line of sight of any sensor. The authors have defined the accuracy requirement as the ability of a localization technology to localize the user within a certain distance and precision requirement as the ability to reproduce the required accuracy over time.

Section 2 of this paper overviews some major requirements of localization technologies to support field O&M activities, Section 3 provides an overview of the background research on indoor localization, Section 4 describes the details of the research approach and Section 5 contains the description of the test-bed, experimentation methodology and results.

2 Detailed requirements

O&M field activities often involve working in dense mechanical environments and locating the desired object/equipment on the site. These field activities might also require identification of object/equipment obscured by false ceiling tiles or other objects. Visual search and identification consumes a great deal of time on site. Hence, there is a need to present the field personnel with location information, corresponding to a particular sub-space in a particular room, in which the field personnel has to perform his/her task. We refer to such location information as sub-room level (2-3m accuracy) and it can reduce the time spent by field personnel by guiding him/her to the right location. Dense mechanical environments also present a limitation on placing many transmitters that require line-of-sight for localization. Hence, a localization technology that provides sub-room level (2-3m) accuracy with no line-of-sight requirement is needed. O&M field activities, just like other industrial processes, also need to implement quality control to improve services delivered to occupants (Holtz and Campbell, 2004). Hence the selected localization technology should be able to provide sub-room level accuracy at 95% precision to ensure smooth execution of O&M tasks most of the time.

3 Background research

This section provides a brief overview of the various sensing technologies available for localization and the various algorithms available for analysing the sensed data (i.e., algorithms for localization).

3.1 *Indoor localization technologies*

Current sensing technology for indoor localization can be broadly classified into three categories based on the physical principle involved for sensing: 1) Wave propagation based technologies; 2) Digital imaging based technologies; and 3) Motion sensing based technologies. Wave propagation sensing exploits various properties of waves, such as phase and angle of waves, and covers a wide range of frequencies of electromagnetic and sound waves, such as radio waves (300 kHz to 3 GHz), infra-red waves (300 GHz to 300 TeraHertz), sound waves (frequencies greater than 20kHz) and ultrasonic waves (Finkenzeller, 2003; Miller et al., 2006; Want et al., 1992; Skibniewski and Jang 2007; Kim and Choi, 2007). Amongst all ranges of frequencies, radio waves are the most widely used for localization since they have a longer range and are relatively less costly (Hightower and Borriello 2001).

Image based localization involves image-matching and digital image processing techniques. Usually, a database of visual characteristics of an indoor environment is created by capturing digital images and then the images collected by a mobile agent carrying an image capture device are matched to the stored images to determine the current location of the user (Ferdaus et al. 2008). This approach is susceptible to changes in indoor environments as well as occlusions in a scene at a given point in time.

Motion sensing is based on detecting human motion through accelerometers and gyroscope. Coupling a magnetometer along with accelerometer and gyroscope can provide rate and direction of movement (Fraden, 2003). This is the principle involved in an Inertial Measurement Unit (IMU) and is called the Dead Reckoning (DR) technique. DR involves fusing current movement rate, motion type (walking or running), and direction of motion with the known location at previous time step, to determine how far and in what direction the user has moved in the current time step. IMUs are susceptible to drift errors and require correction points along the user's path (Pradhan et al., 2009a).

3.2 *Techniques for localization*

The techniques for indoor localization are mainly classified into three broad categories: 1) Range-based; 2) Range-free; and 3) Fingerprinting (Biaz and Ji, 2005). Range-based techniques calculate distances between receivers and transmitters and may include time-of-flight, time-delay-of-flight, time-of-arrival and angle-of-arrival calculations (Liu et al., 2009). Range-based techniques usually involve placing the transmitters in the line-of-sight of the mobile receivers, as the reflection from the indoor environment can cause a change in wave properties, such as time, angle or phase of arrival. Range-free techniques include the use of proximity to associate the position of a user with the location of the transmitter that is the most strongly read by the user's receiver/tag/mobile device. The third type of broad technique, called fingerprinting, involves creating a map of signal strength of the transmitters beforehand and then matching the received signal strength characteristics to the created signal strength map for location determination. The following section describes the technologies and techniques selected in this research for evaluation against the requirements identified for localization for fieldwork in operations and maintenance.

4 Research approach

This section provides the description of the process of selecting several indoor localization technologies and techniques, and specific algorithms for localization for further evaluation.

4.1 *Selected localization technology*

Indoor environments can be dense, hence they might present a challenge to range-based localization as this technique usually requires line-of-sight to accurately calculate wave propagation time, angle or phase (Liu et al., 2009). Providing the sub-room level accuracy desired by O&M personnel by using range-based methods might require installing a large number of transmitters or receivers throughout a facility to ensure that there are no blind spots. This might turn out to be costly. Hence, we decided not to include the range-based technologies, such as Ultra-Sonic, Ultra-Wide band and indoor GPS, which require line-of-sight, in our evaluation. Some non-range-based technologies, such as GSM, infrared, TV signals and Bluetooth, were also not selected since previous research studies reported low accuracies for these technologies (Rabinowitz and Spilker, 2005; Otsason et al, 2005; Bruno and Delmastro, 2005; Want et al, 1992). Based on the background research, the authors selected Radio Frequency (RFID), wifi (WLAN) and Inertial Measurement unit (IMU) for evaluation considering the requirements identified in Section 2. None of the above-mentioned three technologies requires line-of-sight for localization. Previous research studies have reported the localization accuracy of RF-based technologies to be around 10 meters (Bahl and Padmanabhan 2000; Elnahrawy et al. 2004). IMU is also selected as it is infrastructure independent and can function even if there is a power outage.

4.2 Selected localization technique

The authors chose fingerprinting (signal strength map creation) over range-based (time-of-flight, angle-of-arrival, time-of-arrival, time-delay-of-arrival) and range free (proximity based) methods for WLAN and RFID technology. Fingerprinting involves using received signal strength (RSS) measurements for localizing the receiver of these signals, which can be done even when the wave propagation characteristics of the indoor environment are not known. Moreover, fingerprinting approach does not require line-of-sight, and hence can perform well with a limited number of transmitters in dense environments, such as mechanical rooms. The third selected technology, IMU, requires implementation of the Dead Reckoning technique, because it is a motion-based localization technology as compared to WLAN and RFID, which are wave-propagation based technologies.

4.3 Selected algorithm for fingerprinting

The authors selected the k-Nearest Neighbor (kNN) algorithm for determining location from a fingerprint map. kNN belongs to the set of deterministic fingerprinting algorithms, whereas algorithms like the Bayes Classifier belong to the set of probabilistic fingerprinting algorithms. With limited training data, deterministic classifiers, having fewer parameters to configure, perform better than probabilistic classifiers (Hossain et al. 2007). The next section describes the details of the test-bed and implementation of the algorithms for fingerprinting, as well as the results of evaluation of the three selected technologies.

5 Test-bed description and results

This section provides the details of the test-bed and experimentation procedure to evaluate WLAN, RFID and IMU technologies against the requirements identified for supporting facility management field activities.

5.1 Test-bed description

All the selected technologies were evaluated in the basement of a building with concrete walls, metallic environment (lockers, artifacts hanging from walls etc.) and many overhead pipes. The test-bed for WLAN and RFID consists of a 270 ft long hallway on which signal strengths of Wireless Access Points and RFID tags were measured every 1.52m or 5 ft, which corresponds to two human strides (Ladetto et al. 2000) and this distance provides the necessary granularity to achieve the required accuracy without making the user collect data at a large number of points. Existing wireless infrastructure was used for testing WLAN. A freely available wireless signal strength measurement software, NetStumbler (http://www.netstumbler.com/), was utilized for measuring signal strengths of different access points. Figure 1 depicts the test-bed with the position of some access points located near the test-bed, as well as the location of RFID tags and the test-path for IMU. The selection and placement of RFID tags were done in a previous research project (Pradhan et al. 2009b) and RFID data was analyzed to study the variation of RFID signal strength over longer time spans. Pradhan et al (2009b) placed the RFID tags strategically so that the user could collect signal strength data from at least two different tags at every point. The RFID tags are ultrahigh frequency (915Mhz) passive tags with long non-directional reading range (30-90m) and have a battery life of 5-6 years but the battery is non-rechargeable. IMU data was collected over three different routes in the same test-bed. The lengths of the IMU test-paths are 250m, 160m and 157m. The first and the second routes are highlighted in Figure 1 and the third route is a route similar in shape to route 1, located in a different section of the same floor on which the test-bed is located.

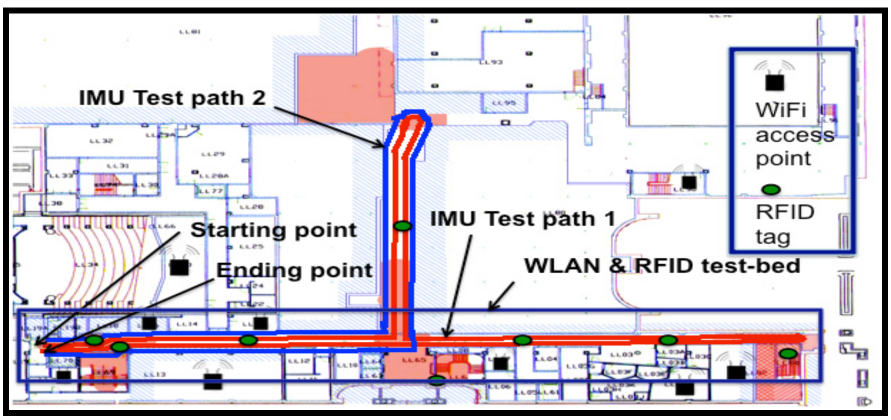

Figure 1. Description of the test-bed for the evaluation of WLAN, RFID and IMU

5.2 Details of the experiment

Signal strength data for WLAN and RFID signals were collected for 55 points, along the hallway, separated 1.52m (5ft) apart; signals were collected in all four directions at each point. WLAN and RFID data were collected in two phases. In the first phase, WLAN data was collected by a handheld portable computer on 5 different days; in the second phase, conducted recently, three months after the first phase, the WLAN data was collected by a laptop over 6 days. The first phase of RFID data was collected and analyzed by Pradhan et al. (2009b); the second phase was collected recently over 6 days. A laptop was used for collecting data in both phases of RFID data collection using the software supplied by the RFID device vendor and a PCMCIA card. The analysis of the collected data for WLAN and RFID signals was done using the kNN algorithm for fingerprinting. The kNN algorithm has been implemented for 10 different cases for each day of data collection (Table 1); the implementation details for different cases of kNN are described in Pradhan et al. (2009b). For the IMU data, a portable handheld computer was used to link to the IMU and data from the IMU was collected using the software provided by the IMU manufacturer. IMU data was collected over three routes, visited eight times each and the device itself gave as output the coordinates of every time point with respect to the starting point, which were plotted to find the route calculated by the IMU.

5.3 Results

The results of fingerprinting using WLAN and RFID signals were analyzed based on the percentage of time the algorithm could identify the actual location of the user within a certain distance. The accuracy of the IMU approach was assessed as the difference between the starting point and the ending point (drift error) when a user closed the loop. Figure 2 shows the resulting accuracy using

WLAN data collected by the handheld computer in phase one of data collection. The best result is obtained in case 1 of kNN implementation where the algorithm is able to identify the location of the user within 1.52m (5ft) of the correct location, 95% of time. The second phase of WLAN data collection was carried out using a laptop and retrieved a duplicate Wifi access point for every room, which caused the accuracy of the approach to decrease. We are currently investigating the reason for reading duplicate access points. The analysis of RFID data in the second phase carried out in this research study resulted in poor accuracies. Pradhan et al (2009b) had reported accuracies of around 10.7m for greater than 93% confidence in best case during the first phase but due to the reduced signal strength of most of the installed RFID tags read in this phase of data collection, the accuracies of localization went down. The authors are currently investigating the cause of the reduced readings of signal strength values from RFID tags installed four years ago. For the IMU data, it was observed that there was a very high error for route one (13.1m) whereas the error observed for route two was 5.18m and route three was 2.89m. We are currently investigating the features of route one that could have caused a high error in the case of route one. Table 2 summarizes the accuracy and precision of the three evaluated technologies.

Table 1 Different case for implementation of kNN algorithm

Case #	Case name	Training data set creation (SS=signal strength)	Test data set creation
1	Avgof4Dir	Average of SS for all directions	Average of SS for all directions
2	Avgof4Dir(South)	Average of SS for all directions	Average of SS for south direction
3	AvgofSouthDir(South)	Average of SS for South direction	Average of SS for south direction
4	Avgof4Dir(Random)	Average of SS for all directions	Average of SS for a random
5	AvgofRandomDir(Random)	Average of SS for a random direction	Average of SS for a random direction
6	Maxof4Dir	Max of SS among all directions	Max of SS among all directions
7	Maxof4Dir(Random)	Max of SS among all directions	Max of SS in a random direction
8	Maxof4Dir(South)	Max of SS among all directions	Max of SS in south direction
9	MaxofSouthDir(South)	Max of SS in south direction	Max of SS in south direction
10	MaxofRandomDir	Max of SS in a random direction	Max of SS in a random direction

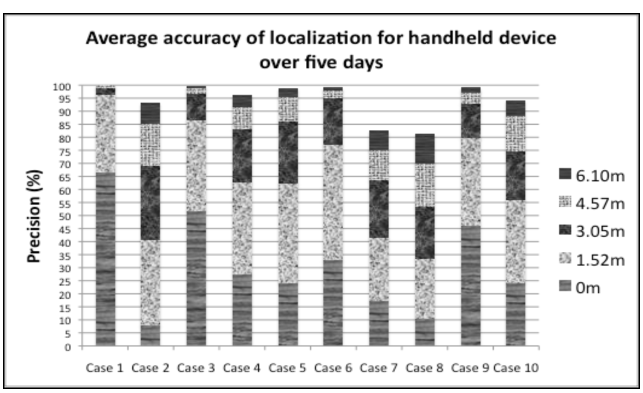

Figure 2: Accuracy of WLAN for different cases of kNN

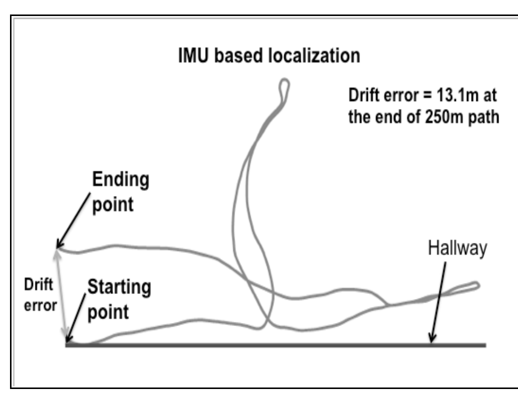

Figure 3: Accuracy of IMU for route one

Table 2: Summary of accuracies of the three technologies based on experiments done till date

Technology	Average accuracy of 5 samples	95 percentile accuracy
WLAN	0.58m (Best case kNN)	1.52m (Best case kNN)
RFID	11.9m (Best case kNN)	>30m
IMU	13.1m drift error at the end of 250m route 1	18.6m

6 Conclusions and discussion

WLAN satisfied all the requirements of indoor localization technology identified in this paper. Even when we reduced the density of wifi access points from 32 different access points to only 9 different access points read in the test-bed, the accuracy fell only to 3.05m, for 95% confidence. RFID technology based localization had poor results in our implementation. One of the possible reasons can be the fact that the RFID tags, which were installed four years ago, are being read only at close range in the current phase of data collection. The reason for decreased transmission power of these RFID tags is yet unknown but needs to be inspected in detail. The IMU data showed a varying trend of accuracy, which can be dependent on the indoor environment features that can cause the magnetometer to output erroneous readings. One way of determining this environment dependent IMU error might be to utilize Building Information Models (BIM) to identify properties of spaces and materials that can cause a high magnetometer error. If the sources of errors can be accurately identified, IMU can be an effective means of localization along with WLAN, especially when the WLAN or other sensor infrastructure is down.

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