EVALUATION OF LOCALIZATION ALGORITHMS FOR WLAN-BASED TRACKING TO SUPPORT FACILITY MANAGEMENT FIELD ACTIVITIES

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ABSTRACT

Facility management activities often require the capability to track and guide field personnel during routine and corrective maintenance tasks in dense indoor environments and large facilities. For example, during a water leak, a facility maintenance employee might need guidance to the nearest valve in a mechanical room. Such guidance requires accurate localization and tracking of mobile maintenance personnel in the field. The objective of this research paper is to evaluate various localization algorithms for WLAN-based tracking of maintenance personnel in terms of accuracy and precision. Accuracy has been defined as the ability of a localization approach to track a person within a certain distance and precision has been defined as the ability to reproduce the required accuracy over time. The research described in this paper builds on the previous work of the authors on evaluating different localization technologies and utilizes the same test bed for evaluating the performance of different algorithms for supporting stationary and mobile personnel localization. The main motivation behind using the same test bed, which is an actively utilized building in Pittsburgh, PA, is to have the same baseline for evaluation. WLAN technology has been selected as the localization technology as it achieved good results in the previous research work. The authors have evaluated deterministic and probabilistic algorithms based on the fingerprinting approach for localization. Fingerprinting approach has been selected, as it does not require line-of-sight between localization technology transmitters and mobile receivers, which has been identified as a requirement in the previous research work. The previously developed fingerprinting approach is further augmented by adding filtering methods to evaluate the impact of incorporating the motion characteristics of humans on the accuracy and precision of the implemented algorithms. Initial assessment of the results indicate that deterministic algorithms perform better than probabilistic approaches when fingerprint data is limited, and implementing filtering methods, increases the accuracy and precision of mobile personnel tracking.

Keywords: Facility Management, Mobile Tracking, Indoor Positioning, WLAN, Fingerprinting

1. INTRODUCTION

Facility management field activities entail routine operations and maintenance of building components as well as planned and requested repair activities. Facility management constitutes the longest phase in building lifecycle and costs incurred during this period can amount up to 85% of the total lifecycle cost (Liu et al. 1994). Field activities, such as maintenance and repair, form a major part of the facility management domain and constitute a hefty chunk of the operating budget of buildings (Lai 2010). Lee and Akin (2009) observed maintenance personnel during fieldwork and identified various inefficiencies in the work processes during maintenance and repair activities. The authors state that the process of locating the exact component that needs to be worked upon in the field takes 8-10% of additional time after the maintenance worker has reached the location of maintenance/repair. Similarly, the authors in the current study, carried out interviews with maintenance staff at a major international hospital and discovered that maintenance personnel spend a lot of time in travelling between the site of work request and the location where building blueprints are kept, trying to find out the details of the work site or just locating the place of work request. Such non-value adding activities waste a lot of time and money during building lifecycle and hence there is a need to assist field workers while they carry out their activities in field through innovations in Information Technology (IT) (Bowden et al. 2004, Skattor et al. 2007). Han et al. (2007) stated that a lot of non-value adding activities can be removed from field work by retrieving context specific information on site. Kunze et al. (2009) also demonstrated the benefits of using context for delivery of information in maintenance scenarios over traditional paper-based documentation by observing a 50% improvement in efficiency when using context to retrieve and exchange information. Researchers have also worked on developing context-aware systems for applications in AEC domain (Anumba and Aziz 2006, Behzadan et al. 2008, Khoury and Kamat 2009).

This paper presents results of a study that is part of a larger research project aimed at creating a framework for contextual information exchange, called Context-Aware Building Information Model (BIM), to support field activities in facility maintenance and repair. In order to create such a framework, the research team has evaluated indoor localization technologies to provide location information. Location information constitutes the most important part of the context (Schilit et al. 1994), hence it becomes necessary to ascertain user location for contextual information retrieval and exchange. This research paper builds off from previous work done by some members of the same research team in which three different indoor localization technologies were evaluated in their support for the creation of Context-Aware BIM framework for facility operations (Taneja et al. 2010a). In the present research study, the authors have evaluated the utility of various deterministic and probabilistic position tracking fingerprinting algorithms for WLAN-based tracking of maintenance personnel. WLAN technology has been selected as it achieved good results for stationary personnel localization in the previous research work (Taneja et al. 2010a). The fingerprinting algorithms that were developed previously (Bahl and Padmanabhan 2000, Roos et al. 2002) have been further augmented by adding several filtering methods to evaluate the impact of incorporating the motion characteristics of humans on the accuracy and precision of the implemented algorithms.

We have evaluated the long-term stability of WLAN-based stationary user localization accuracy, obtained through different fingerprinting algorithms, by collecting signal strength data in two phases separated eleven months apart. These two data sets have been evaluated using deterministic algorithms such as k-Nearest Neighbor (kNN) as well as probabilistic algorithms such as Naïve Bayes. We also evaluated black-box approaches like Neural Networks. Results show that kNN based approach performed better than Naïve Bayes algorithm whereas due to limited data the Neural Network could not be trained for location determination. Upon establishment of long-term stability of WLAN signals for stationary user location determination, we also evaluated the capability of kNN and Naïve Bayes algorithm for mobile user tracking. The results depicted that kNN and Naïve Bayes performed poorly for moving user localization although subsequent application of filtering techniques, such as Bayesian filter, upon the results obtained from Naïve Bayes algorithms, improved the moving user localization accuracy.

Section 2 of this paper present an overview of the context-aware BIM framework for contextual information exchange, section 3 presents the background research on the techniques and algorithms for indoor localization, section 4 contains the description of the research approach including the details of implemented algorithms followed by a description of the test bed and experimentation procedure in section 5. Section 6 contains the results of the implemented algorithms and section 7 presents the conclusions and findings.

2. CONTEXT-AWARE BIM

Context-awareness is the understanding of the conditions surrounding a situation or task whose knowledge can support better execution of the task or improvement in the situation for a user. Dey and Abowd (2000) state that “a system is context-aware if it uses context to provide relevant information and/or services to the user, where relevancy depends on the user’s task”. Khoury (2009) states that context-aware information access can assist on-site decision making in construction operations and inspection of facilities by providing necessary and required information rapidly based on the current context of the user. Similarly, To improve situational awareness during facility operations and maintenance field activities and to reduce operating costs of the facilities, this paper authors’s are trying to create a framework, called the Context-Aware BIM, which aims to assist in contextual retrieval and exchange of building information during field activities. Retrieval and exchange of contextual building information is contingent upon the knowledge of location information as location information represents the most critical piece of a user’s context (Schilit et al. 1994). Contextual information retrieval and exchange also requires the existence of a data repository, which should contain the necessary pieces of information required to support and facility operations field activities. Context-Aware BIM is a framework that entails tracking the location of a field personnel for determining the context of a maintenance field worker as well as integrating the current context in the field with relevant facility operations and maintenance data. Context-Aware BIM aims at providing a platform to plug-in different indoor localization technologies and algorithms as well as facility information for realizing different categories of use-cases in facility operations and maintenance phase of a building. Context-Aware BIM also aims at fusing location data with building information using map-matching algorithms for improving accuracies of various indoor localization technologies. The authors of this paper are currently working on developing such a framework that can assist in fusing location data with building information from BIM using novel amp-matching fusion algorithms for realizing different categories of use-cases.

In the current research work, the authors interacted with facility personnel at an international hospital and identified various use-cases that support the creation of contextual retrieval and exchange of information framework. The authors utilized the use-cases to identify the requirements for indoor localization technologies. Taneja et al. (2010a) state that sub-room level (2-3m) accuracy, 95% precision and no need for line-of-sight are the major requirements of indoor localization technologies for supporting facility maintenance and operations fieldwork. Accuracy has been defined in this research as the ability of a localization approach to track a person within a certain distance and precision has been defined as the ability to reproduce the required accuracy over time. The present research study builds on the previous work of the same authors by evaluating various indoor localization algorithms for WLAN- based tracking. The next section presents the background research on the existing techniques and algorithms for indoor localization

3. BACKGROUND RESEARCH: TECHNIQUES AND ALGORITHMS FOR INDOOR LOCALIZATION

Biaz and Ji (2005) surveyed the techniques and algorithms for indoor localization and they state that here are three main techniques for indoor localization: 1) Range-based; 2) Range-free; and 3) Fingerprinting. Range-based approaches for localization involve absolute point-to-point distance (range) calculation, a process known as Lateration, or estimation of angle for calculating location, a method called Angulation. Range-based techniques utilize the following features of the received signal to calculate distances between the receivers and the transmitters for localization (Liu et al. 2007):

- Angle of Arrival (AoA): This technique involves estimation of relative angles between the transmitters and using trigonometry to obtain the range information.
- Received Signal Strength Indicator (RSSI)/Attenuation: This technique involves utilization of a signal strength propagation model (e.g., a path-loss model) in the indoor environment to map the received signal strength at the receiver to the distance from the transmitter (Hightower and Borriello 2001).
- Time of Arrival (ToA): This technique involves utilization of the measurement of signal propagation time from multiple transmitters (at least three) to a receiver to obtain the range information (Liu et al. 2007).
- Time Difference of Arrival (TDoA): This technique involves utilization of the difference in time at which a signal arrives at multiple stationary receiving units to determine the relative position of a mobile transmitter (Liu et al. 2007).

- Roundtrip time of flight (RTOF): This technique involves measurement of the time-of-flight of the signal traveling from the transmitter to a receiver unit and back to the transmitter to estimate the range.
- Received Signal Phase Method (RSPM): This technique involves measurement of the phase difference between the emitted signal and the received signal, to estimate the range.

Range-based techniques require simultaneous measurements of signal characteristics at multiple transmitters/receivers hence care must be taken to synchronize the signals or time stamp them properly. Range-based techniques provide fine grained (sub-meter level) accuracy, especially for technologies such as ultra wide band and ultrasonic, but they require placement of transmitters in the line-of-sight of the mobile receivers, as multi-path reflection and absorption from the indoor environment can cause a change in wave properties, such as time, angle or phase of arrival (Hightower and Borriello 2001).

The second approach is called range-free approach. It provides symbolic relative location information in indoor environments and collocates a mobile transmitter with a fixed receiver. A mobile target is considered to be associated with the antenna that receives the strongest signal from a mobile transmitter (Liu et al. 2007). Since Range-free approaches do not require synchronization of signals at multiple transmitters and receivers hence they are easier to configure and operate than Range-based approaches (Hightower and Borriello 2001), but because these approaches involve localization of a mobile transmitter by association, the accuracy of range-free approaches is less than the range-based approaches (Liu et al. 2007).

Another technique for localization is scene analysis or fingerprinting. It consists of collecting some signal strength footprints or signatures that characterize the WiFi signal strength received at different locations in the environment. A mobile device collects the received signal strength data from different access points at different locations and stores it as the Wifi signature of those locations in a database. The location of a user is then estimated by matching current time signal strength measurements with the closest *a priori* collected Wifi signatures. There are mainly two kinds of scene matching algorithms: 1) Point-based algorithms; and 2) Area-based algorithms. In point-based algorithms, the signal strength is measured at a specific point and the location is determined as one of the measured points (Bahl and Padmanabhan 2000). In area-based algorithms, location is determined by combining signal strength readings from different points and forming a probabilistic area. Fingerprinting technique is the most suitable technique for indoor environments since indoor environments present obstructions to the propagation of signal strength and present various obstacles to the placement of transmitters in the line-of-sight of receivers (Lin and Lin 2005). The next section presents the details of the research approach adopted by the authors.

4. RESEARCH APPROACH

The authors selected WLAN localization technology for evaluation of the indoor localization algorithms. WLAN was selected as it does not require line-of-sight for placement of transmitters in indoor environments, it is low-cost and requires minimal maintenance overhead, and it had the best results for stationary user localization among WLAN, Radio Frequency Identification (RFID) tags and Inertial Measurement Units (IMU) determined in a previous research study conducted by the authors (Taneja et al. 2010a). The authors selected fingerprinting approach for determining location from WLAN signal strength data. Fingerprinting technique was selected as unlike Range-based techniques it does not require placement of transmitters in line-of-sight of the receivers. Moreover, fingerprinting does not require installation of large number of transmitters for sub-room level accuracy, as is in the case for range-free methods (Liu et al. 2007). WLAN has long range (~100m) in indoor environments and therefore, even without the installation of a large number of WLAN access points, good localization accuracies can be obtained by recording signal strength characteristics at different locations and performing fingerprinting.

The authors selected k-Nearest Neighbor (kNN), Naïve Bayes and Neural Network as the algorithms for fingerprinting. The kNN algorithm uses Euclidian distance to find out the k closest matches in the WLAN signal strength signature database to the current time signal strength measurement. The location of the user is then determined by averaging the location of the k closest matches obtained from fingerprinting. In the present study, the authors have used k=1, as sensitivity analysis of the localization accuracy to the number of nearest neighbors conducted by the authors in a previous work suggested k=1 as the best value (Taneja et al. 2010b). The second approach, called the Naïve Bayes classifier, involves modeling signal strength as Gaussian distribution and using the collected signal strength to learn the parameters of Gaussian distribution, which are the 'mean' and the 'variance'. Instead of calculating the Euclidian distance, as in the case of kNN algorithm, this method requires calculation of posterior probability P(S|l), which is the probability of observing signal strength vector S at location l. In equation 1, S_i is the observed signal strength from i^{th} access point at location l, M_i^l is the mean of signal strength of the i^{th} access point at location l calculated from the fingerprinting data, D_i^l is the standard deviation of the i^{th} access point at location l calculated from the fingerprinting data and |A| is the number of access points visible at location l. When a signal strength vector S is obtained from the current time measurements of signal strength in the field then the probability P(S|l) is calculated for all the locations in the field where signal strength has been measured during signal strength database creation. The location l which has the highest probability P(S|l) for the current time signal strength vector is classified as the location of the user in field at the current time point.

$$P(S/l) = \prod_{i=1, S_i \neq 0}^{i=|A|} \left(\frac{2\varepsilon}{\sqrt{2\pi} d_{xi}} \exp \frac{(S_i - M_i^l)^2}{2(D_i^l)^2} \right) \quad \text{(1) (Ferris et al. 2006)}$$

The authors also selected Neural Networks, which are considered as a special class of deterministic algorithms called black-box approaches. Unlike kNN algorithm, which involves calculating Euclidian distance from every stored data point, Neural Networks learn a network structure from stored data points to predict the location of users. These are called black-box approaches as the relationship of the inputs, i.e. the signal strengths in this case, to the outputs, i.e. the location of the user in this case, is unknown to the user. This is not the case in kNN and Naïve Bayes where the inputs are related to the output either through Euclidian distance or Gaussian probabilities. Neural Networks use hidden layer perceptrons or neurons to transform an input to an output using a transfer function which is generally sigmoidal. Due to the complex structure of neural networks, this approach requires a lot of stored data points to learn the structure of the network so that it can predict correct locations in future.

The authors also selected a filtering algorithm to evaluate the effect of filters on the location estimates of fingerprinting algorithms. Filters are algorithms that have been used in the process industry where dynamic systems need to be identified. Filters, as the name suggests, filter out improbable states of a dynamic system based on two apriori defined models namely process model and measurement model. The process model transforms the state from one time step to another and at each time step a sensor measurement confirms the state of the process. Filters, such as Bayesian filter, Kalman filter, and Particle filter, have also been utilized for location estimation of robots by utilizing a robot motion model and a sensor model (usually a video camera sensor or laser installed on the robot) (Thrun et al. 2005). The authors selected Bayesian filter for improving the moving user localization accuracies (Ferris et al. 2006). Bayesian filter provides a convenient method of incorporating the Naïve Bayes algorithm. Equation 2 represents the formula used to calculate the belief or the probability of the presence of a mobile user at a particular location on time step t. $B(l_t)$ represents the belief of the user to be present at location l at time point t, $P(S|l_t)$ is the probability calculated by Naïve Bayes formula, $P(l_t|l_{t-1},u_{t-1})$ is the motion model or the probability of the movement of the user to location l_t at time point t if the user was at location l_{t-1} at time point t-1.

$$B(l_t) = \eta P(S \mid l_t) \int P(l_t \mid l_{t-1}, u_{t-1}) B(l_{t-1}) dl_{t-1} \quad \text{(2) (Ferris et al. 2006)}$$

As stated earlier, in this paper the authors have evalauted the capability of the selected algorithms to provide WLAN-based indoor localization that confirms to the requirements identified by Taneja et al. (2010a). These requirements are: 1) sub-room level (2-3m) accuracy, and 2) 95% precision. Next section presents the details of the testbed and the experimentation procedure.

5. TEST BED AND EXPERIMENTATION PROCEDURE

WLAN-based localization was evaluated in the basement of a heavily utilized academic building in Pittsburgh, PA with concrete walls, metallic environment (lockers, artifacts hanging from walls etc.) and many overhead pipes. The test-bed consists of a 270 ft long hallway on which signal strengths of existing WLAN access points were collected on 55 points each separated by 1.52m or 5 ft, which corresponds to two human strides. 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 some RFID tags. WLAN data was collected in two phases. In the first phase, data was collected by a handheld portable computer on 5 different days; in the second phase, which was conducted eleven months after the first phase, the data was collected by the same handheld computer over 3 days. The kNN and Naïve Bayes algorithms have been implemented for 10 different cases for each day of data collection (Table 1); the implementation details for different cases are described in Pradhan et al. (2009).

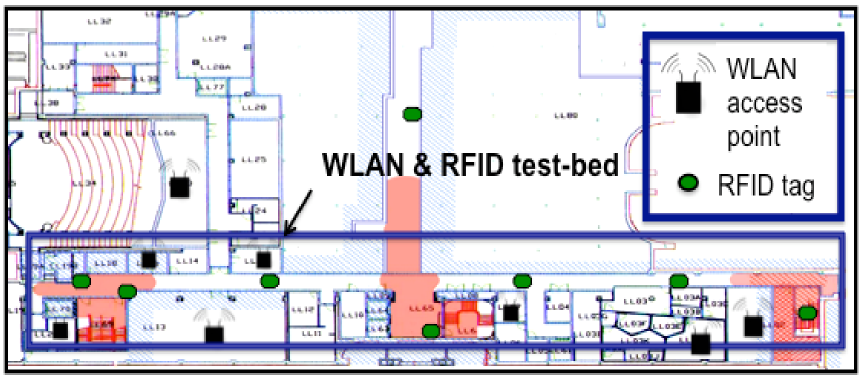

Figure 1: Test-bed for the evaluation of algorithms for WLAN-based localization

Table 1 Different case for implementation of kNN algorithm (Pradhan et al. 2009)

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

6. RESULTS

The results of WLAN-based localization using fingerprinting algorithms have been presented based on the percentage of time the algorithm could identify the actual location of the user within a certain distance. Apart from figure 2, which was a result of the previous work (Taneja et al. 2010a) and is included here for comparison purposes, all other figures depict results of the present study. Figures 2 and 3 show accuracy and precision of WLAN-based localization using kNN algorithm in phase one and phase two of data collection respectively. For the kNN algorithm, the best result is obtained in case 1 of implementation (Table 1) in both the phases where the accuracy of localization is atleast 1.5m with 95% precision in phase one and 3.0m accuracy with 95% precision in phase two.

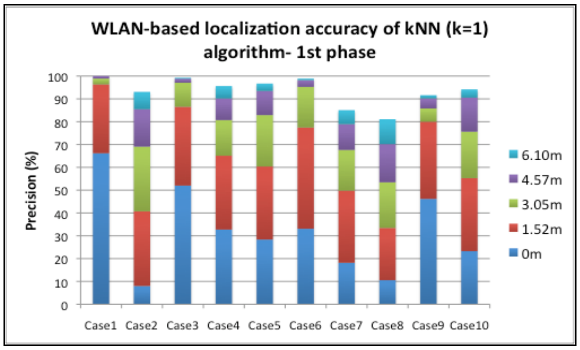

Figure 2: Accuracy of kNN in first phase

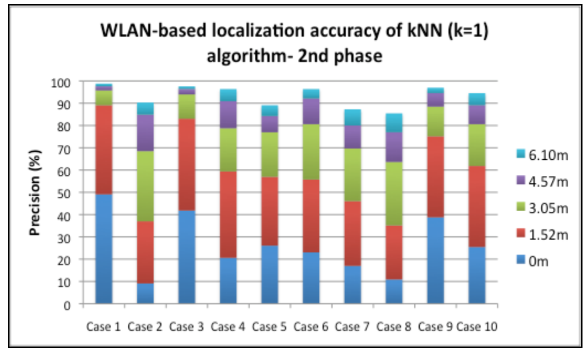

Figure 3: Accuracy of kNN in second phase

For the Naïve Bayes algorithm, the best case is again obtained in case 1 of implementation (Table 1) with the accuracy of localization as 3.0m for 95% precision in both phases of data collection (Figure 4 and 5). The accuracy and precision values from both kNN and Naïve Bayes algorithm confirm with the requirements of accuracy and precision identified in a previous paper (Taneja et al. 2010). For moving user localization analysis, the Naïve Bayes algorithm obtained an accuracy of 10.7m for precision less than 90% (Figure 6). This accuracy was improved by using Bayes filtering algorithm to 7.6m for greater than 95% confidence (Figure 7). The authors observed very low accuracies, around 10m for 50% precision, for neural network-based fingerprinting approach.

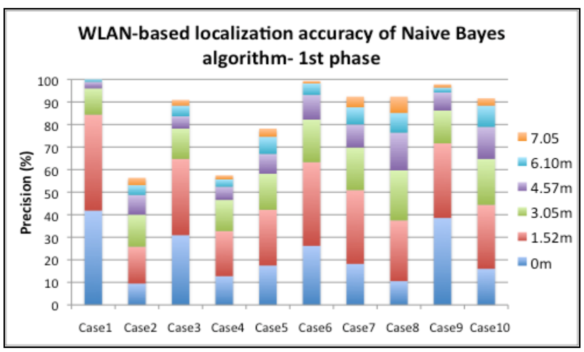

Figure 4: Accuracy of Naïve Bayes in first phase

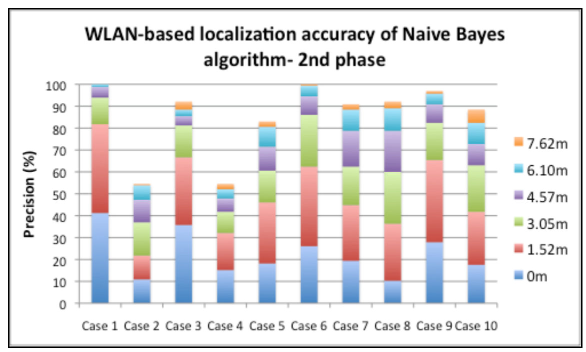

Figure 5: Accuracy of Naïve Bayes in second phase

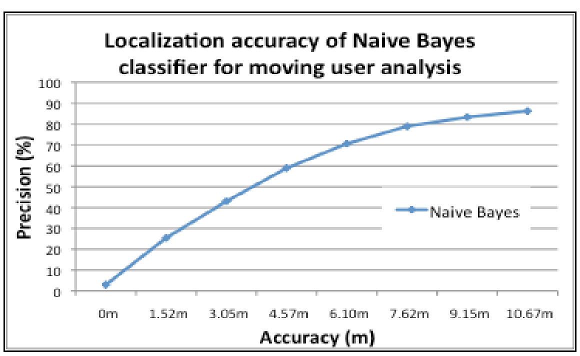

Figure 6: Accuracy of Naïve Bayes for moving user analysis

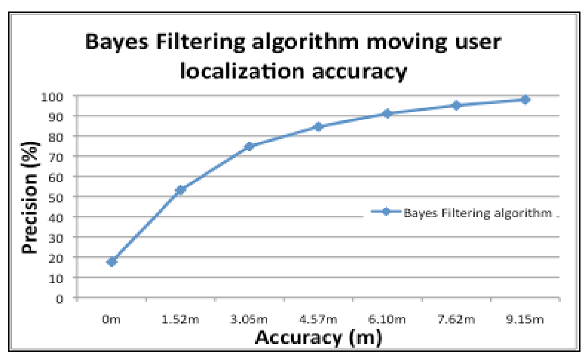

Figure 7: Accuracy of Bayes Filtering for moving user analysis

7. CONCLUSIONS AND DISCUSSIONS

WLAN-based localization using kNN and Naïve Bayes algorithm for fingerprinting satisfies the accuracy and precision requirements of indoor localization technologies stated earlier. kNN, which is a deterministic algorithm, performs better than Naïve Bayes, which is a probabilistic algorithm, as kNN algorithm does not assume Gaussian distribution of signal strength data and does not involve estimation of Gaussian parameters namely 'mean' and 'variance' (Lin and Lin 2005, Hossain et al. 2007). kNN based results had higher precision values for the same accuracy level in both the phases of data collection as compared to Naïve Bayes alogirthm. For the moving user localization analysis, the accuracy obtained were significantly lower than the requirements of localization stated earlier although filtering technique did demonstrate an improvement in accuracy level for same the precision value. One possible reason for low accuracy levels obtained in moving user analysis is the low rate of data acquisition (1Hz). Increasing data acquisition rates can improve localization accuracies. The authors also observed poor accuracies using neural networks for fingerprinting. Neural networks are black boxes and require learning of a large number of network parameters for predicting user locations. With limited number of data points (five and three days of data in first and second phase respectively), neural networks could not be trained to achieve the desired accuracy.

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