Indoor Positioning and Navigation System for Interior Design Augmented Reality

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Abstract—**The problem of indoor localization and navigation has become increasingly important for a range of different applications. One of these applications is interior design augmented reality. Due to the inability of the global positioning system (GPS) to navigate indoors, and the lack of any global indoor localization scheme, research has turned to develop several approaches and solutions to indoor localization. Accuracy of these techniques ranges from few centimeters to few meters depending on the technology used. High accuracy is achieved through special hardware equipment. For interior design applications, users are interested in getting high accuracy in certain positions depending on the design layout. It is also desirable to use market tablets and mobile phones rather than special hardware for such applications. In this paper, a hybrid WiFi fingerprinting - sensor fusion scheme is proposed to achieve accurate indoor positioning and navigation using Android tablets. Moreover, an algorithm has been developed to determine the WiFi Access Points (APs) positions given the apartment layout. Results show high accuracy for both the positioning and navigation parts.**

Keywords–Indoor positioning; Indoor navigation; WiFi fingerprinting; Sensor fusion; Interior design augmented reality.

I. INTRODUCTION

Indoor localization systems work to locate and track objects within a closed environment such as a building or an office. Sample applications in such systems include positioning patients in hospitals, objects within a warehouse, employees in an office, customers in malls or locating people within a burning building. Indoor localization systems can also be used to enhance the clients experience in applications like Interior Design Augmented Reality. Indoor localization systems typically require a carefully planned environment involving Access Points (APs), sensors or other stationary or mobile equipment. Furthermore, there has been an increased demand on these systems to deliver high-accuracy with minimal cost and initial set-up.

Previous researches concerning this topic have achieved good results using WiFi fingerprinting, dead reckoning, camera-based techniques. Furthermore, integrated approaches have been developed to combine two or more techniques together. However, most of the proposed techniques do not target specific application scenario and hence, the resulted accuracy was not enough to be used in various applications that require very high accuracy, e.g., augmented reality applications. As we are biased towards low cost and high accuracy systems, we have been investigating the use of a hybrid system that combines the WiFi fingerprinting technique with the step detection technique to achieve better accuracy for interior design augmented reality applications.

This paper provides a number of contributions focusing on Interior Design Augmented Reality applications. Firstly, an algorithm is developed to determine the adequate number and locations for the APs used for the WiFi-Fingerprinting in order to differentiate easily between different Points of Interests (positions users are likely to stop at to view the interior design model). Secondly, to tackle the problem of different signal strengths in different cardinal directions, a map for each direction was used. Moreover, the orientation detection module was enhanced using an algorithm that estimates the step angle using the last five angles while excluding outlier values. Finally, a hybrid WiFi fingerprinting - sensor fusion scheme is developed to achieve accurate indoor positioning and navigation using Android tablets.

The remainder of this paper is organized as follows: In Section II, related work of research of high-accuracy indoor localization systems is surveyed. The problem assumptions adopted in this work are listed in Section III. The proposed solution for the automatic selection of the APs positions is presented in Section IV. In Section V, the proposed indoor positioning and navigation hybrid scheme for the interior design augmented reality application is presented. Performance evaluation details and results are discussed in Section VI. The paper is concluded in Section VII.

II. RELATED WORK

Related work in indoor localization systems have achieved good results using WiFi fingerprinting, dead reckoning, camera-based techniques. Furthermore, integrated approaches have been developed to combine two or more techniques together. Various methods rely on multi-lateration of radio waves and location fingerprinting [1][2][3]. However, methods relying solely on multi-lateration usually provide relatively low accuracy (within 1-3 meter) as well as being dependent on existing infrastructure and often involve calibration. Methods relying on location fingerprinting usually provide slightly better accuracy than multi-lateration methods while also providing better opportunity for integration with other localization methods (e.g., dead reckoning) [4].

Shih et al. [5] attempt to deal with problems for fingerprint differences due to environment changes (weather changes, doors opening and closing, etc.). The main idea in the work is the clustering of reference points (RPs) based on the similarity of the path-loss exponent values and then uses the path loss propagation model to calculate RSS fingerprints dynamically in these RP clusters or regions. This calculation is achieved via sensors that re-measure the RSS value for each cluster. The work also contributes an algorithm to calculate accurate placement of these sensors. The work maintains a higher accuracy of 0-2 meters but incurs additional computational cost for the initial k-means clustering which also adds cost to the calibration phase.

The problem of noisy data (from sudden movements, band interference, etc.) has been tackled by Zhao et al. [6]. The system introduces three signal strength filters: the max filter, the limit filter and the move average filter. It was found that two of these filters (max filter and limit filter) provide higher accuracy to the k-NN algorithm employed for location estimation; increasing accuracy in 2.5 m range of error to 96% and reaching 98% in an error range of 3 m. The work also introduces a path tracking assistance that prunes the search space for the forecasted location to a predetermined subspace. This requires a stage whereby these subspaces are defined before real-time location determination but significantly lessens the localization execution time. Although the work by Zhao et al. [6] provided interesting insights, it failed to tackle heightened accuracy (less than 1 m) and also did not incorporate any smartphone sensor data into its localization algorithm.

So et al. [7] discuss a novel method to compare the run-time fingerprint to the patterns in the fingerprint data set instead of the Euclidean and probabilistic approaches. The authors propose two schemes to replace the Euclidean distance approach. The first scheme filters out large Received Signal Strength Indicator (RSSI) differences and hence when a difference increases beyond a certain threshold, the distance is no longer increased. The second scheme reduces the distance coefficient to 1 (instead of 2 as in Euclidean distance). This results in reducing the effect of large RSSI differences and give higher value to the exact match. The proposed schemes achieve a much better accuracy than the Euclidean distance metric. However, they also introduce additional problems of determining the proper threshold in the first scheme. Another problem is that it increases the sensitivity to small RSS differences (which is likely occurring due to fading).

Another category depends on device sensors, called dead reckoning, has shown promise in several approaches. Alzantot and Youssef [8] recognize and solve some of the problems of estimating motion based on accelerometer. The presented approach uses Support Vector Machine (SVM) to detect gait (walk, jog, etc.) and calculates displacement based on step count and step length estimations (derived from the gait). One of the work novel contributions is that its step detection (and hence count) is done via a Finite State Machine (FSM) that models the various states in an acceleration signal during a step. This removes problems of the smartphone changing the orientation as well as removes any need of preprocessing the accelerometer signal. Accuracy of navigation is about 4 m and 97% accuracy on the SVM classifier. Yim [9] presents a system designed to handle users walking around in large exhibition spaces. Its main contributions are improvements on the FSM proposed by Alzantot and Youssef in [8] as well as periodically assessing if the user is standing to watch a particular exhibit (via assessing the accelerometer y-axis magnitudes standard deviation). The system however, depends on the observation that users in exhibition spaces moved very slowly; an assumption that is not safe to make for other environments.

Integrated methods often utilize sensor fusion to combine inputs from multiple sensors in the Inertial Navigation System (INS) and RSSI for room-level navigation. The approach proposed by Holčík [10] uses sensor fusion to combine heading information from gyroscope and accelerometer sensors and utilizes a state model to model transition from one state to another based on three factors: the RSSI probability map, step length and stride length. This achieves a relatively bad accuracy of 2.3 meters. Chai et al. [11] combine inputs from barometer, WiFi fingerprinting and accelerometer. The proposed approach uses an Adaptive Kalman Filter (AKF) to incorporate measurement with the proposed state model. Although it achieves a slightly better accuracy at 1.65 meters, it also has the disadvantage of using individual sensors rather than smartphone ones. Le [12] uses a probabilistic model to combine RSSI and INS information. The model relies on a combination of likelihoods, i.e., the likelihood that location is accurate given RSS information and Previous location from INS, is equivalent to the probability of WiFi positioning based on RSS * probability of current location given the previous location, calculated according to a likelihood function. This is one of the best accuracies recorded for integrated systems and achieves an accuracy of 0.7 m.

Aside from the popular approaches discussed so far, other techniques have also been suggested in the literature for the localization problem that do not involve location fingerprinting or an integration of location fingerprinting and dead reckoning. For example, Filonenko et al. [13] provide 0.1 meter accuracy but changes the regular hardware used for localization to use four ultrasound microphones to provide for ultrasound (and inaudible) multi-lateration.

Previous work either uses special hardware to achieve high accuracy or cannot achieve the required accuracy for intrior design augmeneted reality applications. Our focus is to achieve high accuracy using commercially available Android tablets depending on the assumption that users of such applications will likely stop at certain positions to view the design and navigate between these positions. The next section presents our system assumptions.

III. System Assumptions

In our work, it is assumed that the location/apartment map with dimensions and the positions where the user will like to stop and view the interior design is known; we call these positions the Points of Interests (PoIs). The positioning and navigation module shall utilize this information to choose the number and positions of the WiFi APs and then builds a Radio Map of the signal strengths at each of the PoIs in an offline phase. Using the WiFi fingerprinting techniques, the positioning and navigation will map the user position to the nearest PoI when the module detects that the user has stopped, otherwise the step detection and counting module along with the orientation/heading direction are used to update the user position while moving from one PoI towards another one. It is also assumed that the user's direction is the same as the tablet's heading direction which is compatible with interior design applications needs. Finally, a subset of the corners will be chosen as the positions of the APs based on the algorithm described in Algorithm1 in the next section. Positioning the APs in corners limits the search space to a finite number of combinations. The following sections describe the system architecture and its main building blocks in more details.

IV. Determination of number of APs and their locations

The overall algorithm steps are described in Algorithm 1. At the beginning, PoIs are manually placed on the location map. The coordinates of these PoIs and the coordinates of the corners of the location are the inputs of the algorithm which determines the minimum number of APs and the best locations for them. This algorithm will differentiate between PoIs based on readings of the signals strength of the APs.

Algorithm 1 Determination of number of APs and their locations

Data: n(initial number of APs) = area / coverage area
Result: optimal number of APs and their locations
while *true* **do**
    c = get all combination of 'n' corners;
    for *each combination* **do**
        for *each PoI* **do**
            estimate the RSS from each AP;
        end
        if *no more than 2 PoIs have the same RSSs range* **then**
            return this combination;
        end
    end
    n++;
end

For a significant reduction in the processing time and resources, a mapping between signals strength and distance is used. It takes into consideration, other factors that affect the signal strength such as walls, doors, ceilings and floors. Thus, what are processed through the algorithm are Euclidean distances between each PoI and every corner, added to them the effects of the previously mentioned factors. Then, a distinct byte value is given for each range of distances. These values are then used to fill a 2D array where first dimension is number of PoIs and the second dimension is the number of corners that can be nominated to be the APs locations. Each step is explained in details, in the following sections.

A. Inputs and Combinations of corners

The inputs are the coordinates of the PoIs and the coordinates of the corners of the location as mentioned earlier. After this step, the corners will undergo enumeration process and get stored in an array. An initial number of APs needed, is calculated by dividing area of the location over the average coverage distance of the APs used. Each AP can be located in one of the corners. Thus, a combination module is developed to output all the possible combinations of corners (possible locations of the APs) to be used in the following step.

B. Calculating distances between PoIs and indexed Corners

Using the coordinates of the corners and the coordinates of the PoIs, the distance between each PoI and each corner is calculated and mapped to a byte value depending on its range from each AP location using the following ranges with gaps ([0m, 1m], [1.5m, 3.5m], [4.5m, 7.5m], $>$ 8.5m) that have been determined through evaluation of different types and different brands of access points.

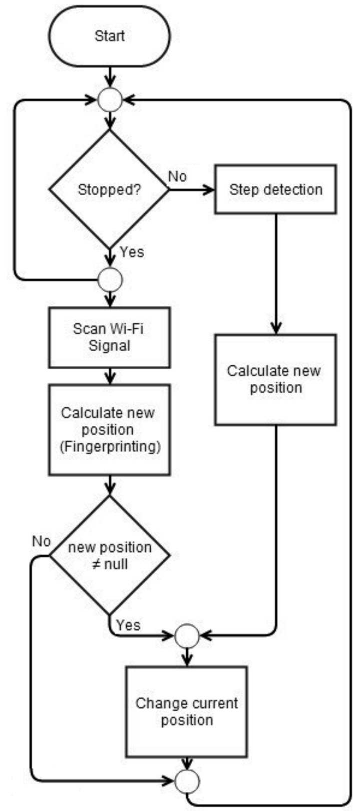

Figure 1. Overall System modules and interactions among them

C. Bitwise pattern and the Output

The 2D array is then filled where the elements in each row are the Byte-values resulting from the calculated distances that have been mapped to Bytes. Thus, each row is the bitwise pattern for the respective PoI. Each bitwise pattern of a PoI is XORed with the rest of the bitwise patterns of the rest of the PoIs. If any XOR operation resulted in a value equals zero (There are two PoIs that couldn't be differentiated from each other), this means that another combination needs to be tested. If all combinations failed for the current number of APs, the number of APs will be incremented and the new combinations that include the additional AP will be tested. Otherwise, if all the XOR operations for a combination resulted in a non-zero value this means that the corners in this combinations can be selected as the locations for the APs and can be successfully used to differentiate between all PoIs. Finally, the outputs are the number of APs needed and their locations.

V. Proposed Indoor Positioning and Navigation Scheme

The proposed hybrid scheme is depicted in Figure 1. The scheme consists of two main modules: Step detection and counting using Mobile Inertial Sensors and Localization using WiFi fingerprinting. The WiFi fingerprinting Localization is responsible for determining the user's location according to

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the nearest PoI ***where the PoI are predefined points provided by the Interior Designer (based on the developed design)***.

The WiFi fingerprinting module consists of two phases:

- Offline Phase: where the Radio Map is being built.
- Online Phase: where the user location is estimated.

On the other hand, the Step Detection and Counting module using the Inertial Sensors is responsible for determining the user's location while moving between PoIs. It contains two sub modules:

- The Step Detection Sub Module which determines the step boundaries based on the raw sensor values.
- The Orientation Detection Sub Module that estimates the user orientation/heading direction.

The two modules, the WiFi fingerprinting and Step detection and counting, will then be integrated to construct our Localization System.

A. Localization using the Inertial Sensors

This module determines the user's location while moving between PoIs. It contains two sub modules. The Step Detection Module which determines the step boundaries based on the raw sensor values and the Orientation Detection Module which estimates the user orientation/heading direction.

1) Step Detection Module: This module has three main components: the step sensitivity algorithm that is developed to estimate the user's step shape, the stop detection algorithm that is used to detect the stopping event of the user, and the step detection algorithm that is used to detect the steps of the user. The following subsections describe each component in details.

a) Step Sensitivity Algorithm: The basic idea behind this algorithm is to get estimation for the user's step shape (range of positive and negative accelerometer peaks). The user starts walking 20 steps during which the accelerometer values are being stored. Then, the positive and negative peaks are calculated with the average accelerometer values and are used to calculate a certain threshold that is used during the user's movement (in Section V-A1c) to estimate if the current accelerometer values represent a step or not.

b) Detect Stop Algorithm: In order to use the step detection algorithm in the hybrid system (in Section V-B2), the user's stopping event has to be detected. This algorithm depends on a simple check that verifies if the difference between the current time and the last step time is higher than a certain threshold (2 sec for example), which indicates that the user must have stopped.

c) Step Detection Algorithm: This algorithm is used to detect each step the user performs while he is moving. It simply searches in the current accelerometer values for a positive peak that is higher than the positive peak threshold specified previously during the Step Sensitivity process (in Section V-A1a), then the algorithm searches for a matching negative peak that is less than the negative peak threshold specified previously (in Section V-A1a). It then checks if the difference between those two peaks is less than a certain threshold and that the difference between the current time and the last step time is higher than 0.5 s, then it is considered as a step.

2) Orientation Detection Module: The aim of this module is to get the most accurate direction of the user during each step performed in order to determine the distance in the X direction and the Y direction after each step. First, the direction relative to the north is calculated using the magnetometer and accelerometer values. Each time the magnetometer and accelerometer values are renewed, a new direction is calculated and added to the angle list. When a step is detected, the last five angles in the angle list are retrieved and an algorithm is used to exclude two outlier angles (out of 5 angles) and get the average of the remaining 3 angles representing the step's angle.

3) Step Length: In our work, there different ways to estimate the user's step length have been investigated that range from the simplest to the most accurate.

- Put an average step length for all users (around 0.7m).
- Let the user enter his height as an input and use the Height-Step Length equation to get the corresponding step length
$$step\,length = 0.42 \times height$$
- Let the user walk a specified number of steps, then divide the distance travelled by that number to get the average step length for that specific user.

Finally, in order to determine the current user's location, first, we calculate Δx and Δy, which represent the change in location, and then add these values to the previous location. Δx = Lsinθ and Δy = Lcosθ where L represents the average step length and (θ) is the orientation angle, which is defined from the Orientation Detection Module (in Section V-A2).

B. WiFi Localization

There are generally two phases for location fingerprinting. First one is the offline phase in which AP' Received Signal Strength (RSS) samples are collected at RPs to build the Radio Map. Second one is the online phase in which the user location is estimated based on the RSS from each AP and the Radio Map prepared in the offline phase.

1) Offline Phase- Building the Radio Map: There are two steps to build the Radio Map. First, identify the RPs, then collect the RSS samples at each RP. In our system, we treat the PoI as the RPs, at which we collect the RSS samples. To build the Radio Map, fingerprints are collected at each RP. For each RP the user has to wait around 25 seconds for the system to collect 5 RSS samples. These values are then averaged to get one fingerprint for each RP and save it in the Radio Map. The user has to repeat this step for all the specified RPs. At first, all samples were collected in one direction. This results in low accuracy if the user stops at any PoI with a direction different than the one used in collecting RSS samples. To solve this problem, the radio map is built with samples in 4 main directions (North, South, East, and West). Four maps are generated from the radio map builder and used to locate the user while stopping at one of the PoIs. This approach increases the time needed to build the radio map(s) in the offline stage but increases the accuracy of the localization system in the online stage as well. ***The current orientation of the user when stopping at one of the PoIs is mapped to the nearest map.***

2) *Online Phase- Estimating the user location:* Fingerprinting algorithm works as follows; when the user stops, three APs' RSS readings are taken. After the first reading, a short list of the nearest PoIs (estimated by the Inertial Sensors Localization module in Section V-A) is constructed. Euclidean distances between the RSS and each fingerprint of this short list (stored in the Radio Map with the corresponding direction, mentioned in Section V-B1) are calculated. If the Euclidean distance of the Nearest Neighbor (NN) is less than a specific threshold, the current estimated position is set to the NN's location. After the third reading, a short list of the PoIs locating in specific covered range (calculated from the number of estimated steps and the average error per step) is constructed. Euclidean distances between RSS of each reading and each fingerprint of this short list are calculated to determine the NN from each reading. Then, a voting method is used to obtain the best candidate. If the Euclidean distance between the winning candidate and the RSS is less than a specific threshold, the current estimated position is modified by the candidate's location. The last PoI detected is not included in the short lists if the user takes a few steps away from the PoI and doesn't return back to prevent the fingerprinting from resetting the current position to the last PoI. Therefore a condition is added to check if the difference between the numbers of steps taken in opposite directions is smaller than certain value before adding the last PoI in the short list.

VI. Performance Evaluation

The testing environment is a location of $91m^2$ in area. It consists of 2 rooms and a hall. The first room is $33.5m^2$, the second is $22.5m^2$, while the hall is $35m^2$ in area. The location has 12 corners in total. Six points in this location are chosen to be the PoIs marked by symbol "'O'" in Figure 2. The coordinates of these corners and these PoIs are stored in a file to be used in the following scenarios.

A. Determination of number of APs and their locations

The file is then used as the input to the algorithm that was explained in Section IV. After testing the corner combinations, 2 APs can differentiate between all PoIs, and their locations are the corners marked by symbol "'X'" in Figure 2.

B. WiFi Localization

The WiFi fingerprinting map is then created using the 2 APs determined in the previous step and the wifi online phase is tested by standing at a each PoI and verifying the correctness of the detction. This experiment is repeated several times for all the PoIs to get an estimated average of the WiFi fingerprinting module accuracy. These experiments resulted in an average accuracy of 93%.

C. Step detection module

To evaluate the performance of the step detection module. A certain number of steps are performed, then the actual number of steps is compared with the number of steps detected by the developed navigation module. This experiment is repeated several times to get an estimated average of the step detection module accuracy. It can be stated that 90% of the steps are correctly detected by the step detection algorithm.

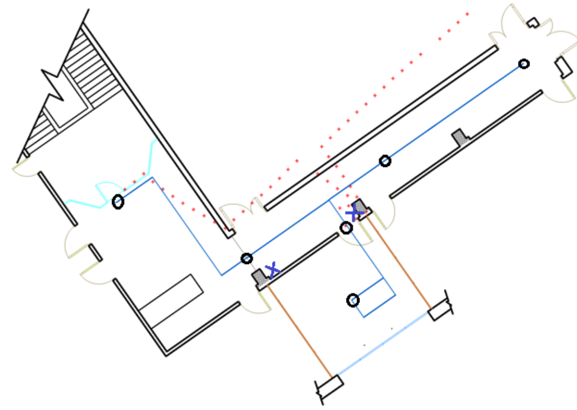

Figure 2. Test results of Localization using the Inertial Sensors

D. Orientation detection module

Testing scenario: Angles from a real compass were compared with angles provided by the sensors fusion. This experiment was repeated several times in different cardinal directions in order to calculate an approximate estimate of the Orientation detection module accuracy. The maximum angle deviation was in the range of -7 to +7 degrees with an average around 2 degrees.

E. Localization using the Inertial Sensors

The localization system using the inertial sensors is then tested without the integration with the WiFi fingerprinting. A certain number of steps is performed to get from a starting position to ending position and the difference between the actual ending position and the position given by the application is calculated. This experiment is repeated several times to get an estimated average of the step and orientation modules accuracy. The red dots in Figure 2 represent the actual positions of the user while the blue dots represent the estimated positions. The accumulated step detection error was up to 2.6m, which is a relatively low accuracy, as it can be seen in Figure 2.

F. Overall Hybrid Localization System

The previous testing scenario is repeated for the integrated hybrid WiFi fingerprinting and sensor fusion system. The red dots in Figure 3 represent the actual positions of the user while the blue dots represent the estimated positions. Using the integrated system, the step detection error was corrected constantly each time the user stopped (using the Wifi fingerprinting module), which led to a less localization error ranging from 0.5 m to 0.7 m.

The overall integrated system accuracy was acceptable to the interior design augmented reality applications where the user is likely need to view the design at the PoIs with high accuracy and can accept slightly less accurate view while moving among PoIs.

VII. Conclusion and Future Work

In this paper, a hybrid WiFi fingerprinting - sensor fusion scheme was presented to achieve accurate indoor positioning and navigation using Android tablets. The target application for our system is the interior design augmented reality applications where users are interested in getting high accuracy in certain positions depending on the design layout and can accept less accuracy while moving among these positions. An algorithm

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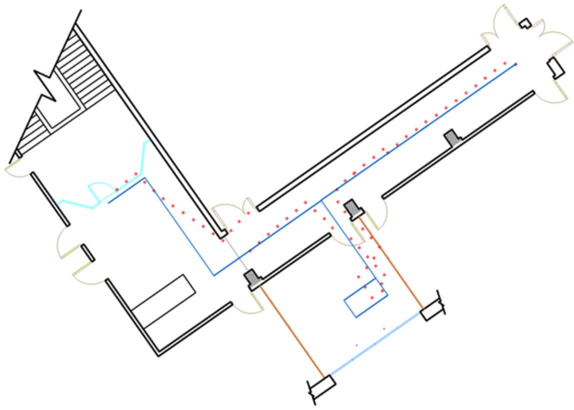

Figure 3. Test results of Localization using the Hybrid System

has been developed to determine the WiFi Access Points (APs) positions given the apartment layout. The hybrid localization system uses WiFi fingerprinting to cancel the sensor fusion-based navigation error at certain posistions. Results show high accuracy of 90% for less than 0.7m for the hybrid integrated system.

Future extensions of this work include the comparison with other related techniques in the same environment and with the same system assumptions. The replacement of the WiFi access points with beacons is currently investigated as promising cheaper alternative. Better integration with the augmented reality part through the utilization of the tablet's multiple cores is also of interest.

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