Indoor Localization for Mobile Devices Using Bluetooth Low Energy Beacons and Wi-Fi Access Points

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***Abstract*—Lorem ipsum dolor sit amet, consectetur adipiscing elit. Cras dictum vestibulum libero, non ultricies est tempus quis. Cras ultrices lacinia iaculis. Quisque facilisis mi sed libero mollis, dignissim finibus massa porta. Quisque eget fermentum massa. Donec pulvinar quam sapien, non interdum nulla pellentesque vel. Nullam lacinia eros arcu, ut volutpat quam congue eu. Sed eget tincidunt risus. Curabitur sodales rhoncus nibh vitae pellentesque. Quisque urna nisi, maximus eget urna et, faucibus egestas ligula. Maecenas sit amet accumsan tellus. Proin vulputate felis ut risus commodo convallis. Aliquam eu venenatis mi, vitae facilisis arcu. Maecenas faucibus, odio non faucibus tincidunt, erat lectus vestibulum purus, sed vulputate turpis augue a lectus. Vestibulum ante ipsum primis in faucibus orci luctus et ultrices posuere cubilia Curae; Maecenas dolor dui, blandit sit amet nulla egestas, feugiat malesuada quam. Praesent vel posuere libero.**

I. Introduction

Indoor navigation systems have been in increasing demand since the introduction of smart-phone technology. The sensors in smart-phones can be used to provide accurate localization in an outdoor environment by using the Global Position System, but so far, no standard indoor localization system has been commercialized.

The problem with such a system pertains to localizing and tracking the user in an indoor space. This issue has many challenges that must be faced that are highlighted in [**?**], as including: the loss of signal precision of wireless systems due to Non-Line-of-Sight (NLOS) conditions and multipath effect, scaling the system for large spaces, complex environments, and the nonstatic nature of persons and obstacles in indoor settings.

A practical, accurate and cost-efficient indoor navigation system that solves these challenges has many beneficial applications such as assisting firemen to navigate a burning, smoke-filled building, locating people in danger in emergency situations, and navigation of public spaces such as malls, airports, and university buildings.

One important but unconsidered application of an indoor navigation system is assistance for the visually impaired. In 2013, there was a reported 7.3 million people in the United States with some form of visual impairment [1]. With no form of eletronic navigation assistance when in an indoor setting, these individuals are hindered when traversing public spaces, such as malls, universities, airports and bus or train stations, among others. This would mean these individuals will need some form of help to locate his or her desired destination in such structures.

Many methods of indoor localization systems have been explored. Previous methods that have been tested use technologies such as GSM (the current global mobile communication standard), radio frequency identification tags (RFID), infrared beacons and receivers, and ultrasonic sensors [**?**], [**?**], [**?**], [**?**], [**?**]. Unfortunately, none of these approaches were adopted because of different drawbacks such as short detection ranges, high installation costs, unsuitable levels of accuracy, and little space for improvement.

Other more practical solutions to the localization problem use the Wi-Fi infrastructure that is available in most buildings to reduce cost and installation times. The signal of the Wi-Fi Access Points (AP) can be used to approximate location using the Received Signal Strength Indicator (RSSI). However, These techniques alone are usually not enough to provide acceptable accuracy.

More recently, approaches that use Bluetooth Low Energy (BLE) have been tested. BLE is a technology that has recently surfaced that is used by many devices, including smart-phones. BLE beacons are a great candidate for implementing indoor localization due to their low energy consumption, compact size and affordability.

Recently, Google released Eddystone, an open BLE beacon format that can be configured to send several different types of payloads using the same packet format [**?**]. Before Eddystone, iBeacon, a proprietary protocol developed by Apple, was the standard format for BLE beacons. Eddystone is much more developer friendly and is becoming very popular due to its compatability with both Android and Apple mobile devices. The format can be used to create a contextually aware experience for users by delivering proximity event-triggered attachments.

Our proposed system, BluNavi, localizes the user by fusing data provided by Inertial Measurement Units (IMUs) and distance approximations calculated from BLE signals. To further increase accuracy, the system is complemented by Wi-Fi fingerprinting , a method which makes use of APs by mapping their RSSI values to absolute locations. Eddystone configured beacons will be used to drive our mobile, context based, indoor navigation application. The system will communicate with the user and the beacons/access points through an Android application to provide accurate, real-time indoor navigation. With this approach we aim to provide a low-cost, widely deployable system while still maintaining a high-level of accuracy.

The rest of this paper is organized as follows: Section II describes current indoor localization research. Section III explains the methodology behind our approach and section IV contains the evaluation of the experimental results. Lastly, Section V details our conclusions and future work.

II. Related Work

Wi-Fi based indoor localization has been a widely researched topic due to its availability, and the recent surge of BLE beacons has also spurred an interest in applying previous methods used in Wi-Fi and other technologies to the advantages of BLE. Most of these approaches use the RSSI of the wireless signal to approximate the location of the device.

Wi-Fi Fingerprinting is a highly popular technique in indoor localization [**?**], [**?**]. This technique focuses on building a signal strength map of a given area by creating reference points around it. In each of these reference points, RSSI values are gathered for each available access point found. These values are stored in a database and identified by the reference point in which they were gathered. Localization is achieved by obtaining the signal strengths of all available APs at the time of a scan and matching the current values to the ones in the pre-existing database. This method has many advantages due to the system being fully based on previously installed Wi-Fi APs and not inccuring any extra hardware costs. Fingerprinting also eliminates the need of using noisy wireless signals for distance approximation. In addition, algorithms such as Nearest Neighbor or the Hidden Markov Model can be applied to the current scans to improve accuracy. However, fingerprinting also has its shortcomings such as long scan times and similar fingerprints.

An improvement on Wi-Fi fingerprinting is examined in [**?**]. A Particle Filter (PF) is used to fuse location estimations provided by a dead reckoning model and Wi-Fi fingerprinting to provide a higher localization accuracy. The PF is initialized using a Random Sample Consensus model which filters out the outliers of the Wi-Fi fingerprinting algorithm by comparing the estimations to the dead reckoning model, thus reducing the chance of the PF initializing in the wrong location. For the fingerprinting, two methods are examined. The first is a probabilistic approach using a Gaussian distribution to approximate the distribution of RSSI values of an AP. The second approach is deterministic using a Support Vector Machine (SVM) for pattern recognition of online readings to the database values. The reported accuracy of the approach was less than 2.9 (m) with an average error distance of 1.2 (m). This approach has good accuracy while not requiring any additional hardware, but it also requires a lengthy off-line training phase for the fingerprint database.

BLE signal fingerprinting is an alternative to Wi-Fi AP fingerprinting. Using BLE over Wi-Fi has the advantages of faster scan times and lower power consumption. In [**?**], a grid was established and probabilities were distributed into cells using a Bayesian likelihood function based on the results of a K-Nearest-Neighbor location estimation. Accuracies of less than 2.6m at 90% of the time were reported with a deployment of 1 beacon per $30m^2$. This accuracy is better than Wi-Fi fingerprinting and uses less power, however the system requires a dense deployment of beacons to achieve medium levels of accuracies.

BLE beacon fingerprinting can be combined with a radio frequency propagation model to increase the accuracy of a system. The model is built by using the relationship between signal strength and distance. Because of the large levels of noise in the signal strength, the distance approximation is subject to high levels of volatility. [**?**] uses an outlier detection system along with an Extended Kalman Filter (EKF) on the fingerprint and propagation model estimations to reduce noise and improve accuracy. An improved approach to building the radio map by updating the data while the system is online to reduce time of off-line training was also used by this approach. This system achieved distance estimations of less than 2.5m at 90% of the time for a dense deployment of beacons at 1 beacon per 9m.

III. Methodology

[INTRO PARAGRAPH TO DESCRIBE SYSTEM]

When developing the Wi-Fi fingerprinting system, a signal strength heat map of our testbed, the 3rd Floor of the Engineering Building B in the University of South Florida, was created. The map was created using the Ekahau HeatMapper application. The high availability of access points, as seen in the map, shows the high probabilities of an accurate implementation for this setting.

Fig 1. Radio Signal Strength radio map of of the ENB 3rd Floor, USF. (The heat mapping software used also marks the name of each access point in the area. Due to the large amount of APs in range, the text overlaps.)

[Rough First Draft] For the fingerprinting implementation, a reference point map is created. At every reference point, RSSI data for every available access point are collected. In each location, 25 scans are performed and the signal strength values of each run are saved in the RSSI database. When the system tries to locate the user, it scans for the signal strengths from all available access points. The system then compares this list of values by matching the access points to the ones in the pre-recorded database. Comparisons are made with the mean of the signal strength values of each access point per

Data: Wi-Fi Scans Data
Result: Fingerprint Database
for $i = 0$ **to** N **do**
    scan for access points;
    for *for each available AP* **do**
        store AP's MAC address;
        store AP's RSSI;
        store reference point;
    end
end

Algorithm 1: Creating Fingerprint Database

location. If the difference between a current value and a mean value is within a certain threshold, which is decided based on how much the signal strengths varied, the probability weight of the user being in the corresponding location is increased. At the end of these calculations, the location with the highest weight is returned as the location of the user.

A. Pedestrian Dead Reckoning Model

BluNavi uses a Dead Reckoning (DR) model to track two key localization components: displacement (movement) and orientation. Displacement occurs when the user of the system takes a step. Changes in orientation result from the user turning to face a new direction. The IMU's available in most mobile devices are used to track both components.

Displacement of the user is estimated by calculating the length of the current step. BluNavi's DR model uses measurements provided by an accelerometer to calculate step length. The data is passed through a low-pass filter to remove noise and smooth the curve. The filtered values are then used in the formula presented in [**?**] which can be seen in Eq. 1

$$s_n = K\sqrt[4]{a_h - a_l} \tag{1}$$

where n is the current step, s_n is the length of step n, and a_h and a_l are the high (maximum) and low (minimum) values of the accelerometer's vertical axis during step n, respectively. K is a constant that expresses the leg length of the user and is determined through training.

Step length is estimated upon completion of the step. Two methods can be used to determine when a step has been taken. If a step detector is available in the mobile device, then the information provided from it is used for step detection. Otherwise, a step detection process begins when the vertical values of the accelerometer pass a set threshold. [GRAPH OF ACC. DATA TO HELP EXPLAIN?]

The values used are derived from raw accelerometer data that is passed into a low-pass filter to reduce noise and smooth the functions peaks and valleys. Orientation, which will be converted to an azimuth angle, is tracked using a gryoscope and magnetometer.

[Propagation Model] Distance from device to beacon is approximated using a radio frequency propagation model that relies on the relationship between RSS and distance. A commonly used model for such purposes as BluNavis is the free-space path loss model which can be seen in equation [x] [ADD EQUATION]. This equation has acceptable accuracy in open, line of sight environments but suffers from signal fluctuations caused by indoor environments.

[Extended Kalman Filter] The Extended Kalman Filter (EKF) is used in BluNavi to increase the localization accuracy of the system by fusing sensor information provided by the fingerprinting algorithm, the dead reckoning model, and the propagation model. The filter works in two steps: a prediction step and an update step. The prediction step works by a process model that estimates the devices movement (or non-movement) through the indoor environment. The model is given by [PROCESS MODEL] where the state vector is defined as [STATE VECTOR]. Next, after sensor data is collected at time (t), a measurement model is used to record the observations: [MEASUREMENT MODEL].

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References