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Ultimate Indoor Navigation: A Low Cost Indoor Positioning and Intelligent Path Finding

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Abstract

Despite the rapid improvement in mobile devices, overall gradual growth in the ubiquitous computing field, the wide applicability, more usefulness of location based services in general and indoor navigation. The Global Positioning System (GPS) has undergone tremendous improvement since the 1900s and it, indeed is considered one of the most successful navigation systems known to date. However, it is still inefficient for sufficiently accurate positioning in both indoor environments and environments with many tall buildings such as skyscrapers since such buildings block or interfere with its signal transmissions. In particular, building a sufficiently accurate, efficient and relatively cheap indoor navigation system in a GPS-free environment is still a challenging task with a lot of tradeoffs and constraints to put into consideration. In this paper, a simple yet robust, low-cost, context-aware user-interactive, user-friendly hybrid of fingerprinting and dead reckoning indoor navigation system suitable for both the visually and the physically disabled as well that takes advantage of the results yielded by sensor fusion is proposed. The presented system is also designed to allow for efficient evacuation of users in cases of emergences. The prototype is made majorly of the following parts; user tracking, optimal, context-aware and dynamic route calculation and planning and dynamic route representation with an upper bound of 2m and an average of 0.8-1.3m accuracy. All that is required from the user is a smart phone without installation of extra hardware.

Keywords

Indoor Navigation,

Tracking Algorithm,

Fingerprinting,

Visually Impaired,

Dead Reckoning

1. Introduction

The Global Positioning System (GPS) has undergone tremendous improvement since the 1900s and it, indeed is considered one of the most successful navigation systems known to date. However, it is still inefficient for sufficiently accurate positioning in both indoor environments and environments with many tall buildings such as skyscrapers since such buildings block or interfere with its signal transmissions. It is a

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satellite navigation and navigation system with a network of at least 24 satellites. These satellites were commissioned by the US Department of Defense and placed in Earth's orbit. The poles of the earth's magnetic field will gradually give way to GPS receivers; GPS is a system that is navigated by a group of satellites. The satellites that circle around Earth in their orbits; these satellites are in contact with special stations on the ground, and their position in space is always clear. Your GPS receiver, by communicating with a number of these satellites, sets the distance to them, and then your exact position is obtained on the ground. The GPS Global Positioning System consists of 24 satellites that are located at an altitude of 20,000 km from the ground, and in 6 circuits, each of which has four satellites, and has a circle of 55 degrees and a 12-hour period. Each GPS satellite sends two waves with two frequencies in the electromagnetic waves (L1, L2). The L1 wave is powered by a frequency of 1575 MHz and a L2 wave with a frequency of 1227 MHz.

The ubiquity of mobile devices (such as cell phones) has led to the introduction of Location Based Services (LBS), or Location-Aware Services. LBS aim at providing information/services relevant to the current location and context of a mobile user. One of the first several LBS applications, named Active Badge Location System, was introduced in R. Want et al. [1]. This system employed infrared technology for tracking a user’s current location and used this location to forward phone calls to a telephone close to the user. Since then, many researchers have studied this topic and as such many LB applications have emerged over time because of the increased market of both outdoor and indoor location based services and applications.

Recent technological advance such as the gradual maturation of ubiquitous computing M. Weiser series [2], or pervasive computing, and the evolution of mobile devices (such as PDAs, cell phones, etc.) and wireless communication (3G, Wireless LAN, Wireless Sensor Network, IoT [37], etc.) has further increased the pace of progress A. Butz et al [3]. They also make an overview about map-based mobile guides using the dimensions of Positioning (either GPS, WiFi, UMTS, or other), Situational factors (user or context-related), Adaptation capabilities, interface/use interaction (multi-model or others), Use of maps (2D vector, 2D bitmap, 3D model etc.), and Architecture (client-server, interacting, multi-blackboard or multi-agent system). These dimensions are roughly defined, and some of these dimensions need to be further subdivided. Raper et al. [4] developed a much more complete classification which used the axes of Application (tourism, recreation, transport, and museum), Positioning, Architecture, Presentation, Context relevance, Delivery (pull or push), Use case, and Adaptively (resource adapted, resource adaptive, resource adapting), and then made a research about LBS applications in the published literature. However, these researches are mainly for outdoor applications cases in indoor cases have various requirements that they can be solved by different positioning algorithms and technologies. As a result, more detailed dimensions on positioning, such as signal (infrared, ultrasonic, radio signals, etc.) and signal metrics (Cell of Origin, Time of Arrival, Time Difference of Arrival, Angle of Arrival, to mention but a few), are needed to evaluate the various positioning technologies. Because context-aware is very important for LBS systems, there should be some dimensions that assess the context awareness of these indoor applications due to the fact that the correct user is not easy to monitor [5].

Still the serious participation of well-known firms’ sectors such as Bing maps and Google maps in [6] and [7] as well as the steady show of interest of companies such as [8] and many more, further stresses the importance and potential of indoor navigation. However, even for such powerful companies accurately mapping all buildings and provided precise navigation is still very hard, if not impossible due to the continuous growth of the construction and business industries. It is simply hard to keep up. As the range of LBS applications is vast, it is practically impossible to introduce all of them here due to brevity. Mobile navigation systems, which aim at providing wayfinding services and tracking to the user, are the most important applications of LBS. However, in indoor navigation and localization, accurately pinpointing the location of a user and correctly and optimally guiding the user to the desired destination is pretty challenging. Till to date, available techniques and attempts at indoor mapping and/or localization can be distinctly categorized in two major groups; those that employ fingerprinting [9] and those that do not [10, 11, 12]. Humans to generating discriminative signatures for the access points (APs) face most fingerprinting based techniques with the problems ranging from susceptibility to intervention. Also, the Received Signal Strength Indicator (RSSI) varies over time due to noise, multipath, reflection off and absorption by surfaces and other objects.

The fingerprinting [9, 34] techniques include Wi-Fi RSSI and FM broadcast fingerprints to help map the indoor environment in question. Indoor locations are attached to signal strength values thereby mapping the environment. Techniques that do not involve finger printing generally the dead reckoning technique to calculate the user's current position in reference to pre-known values. There is also the issue of presenting the route to the user in the most efficient way possible. So, the users do not understand signal strengths in decibels (say -45dB) or coordinates in form of (x, y) or (x, y, z) and instead objective descriptions such as "to the left of the canteen right in front you" or suitable graphical presentation and so on and so forth are much easier to understand and hence make more sense. All these and many more problems are considered and addressed in our paper.

The rest of this paper is organized as follows. Section 2 presents related works, section 3 introduces the methodology used in this work and the model of the proposed prototype, section 4 shows the field experiments and results performed and discussions concerning the results. Section 5 presents the future works, possible improvements to the proposed system and conclusion.

2. Related Work

In our lives, the importance of machine learning and intelligent systems are increasing day by day. In recent years, many valuable studies have emerged in the literature and in practice such as [35, 36]. Indoor navigation has become a serious and popular field of interest owing to its wide applicability, usefulness and the improvement in ubiquitous computing and the development of mobile devices in general and hand held smart phones in particular. As mentioned above, previous attempts to map indoor environments can be generalized in two main categories; those that employ Wi-Fi-fingerprinting and those that do not. Those that do not use fingerprinting exploit techniques such as crowdsourcing [13], triangulation and trilateration. This can be more broadly categorized in two again those that use wireless and sensor technologies (such as most of those discussed later on) and those that use image recognition and processing [14].

In [15] is proposed an enhanced form of GPS for indoors and urban area usage. However, the accuracy attained was still not impressive as GPS signals were still being lost through absorption or reflection from walls and other objects – the so-called multipath problem. This coupled with other GPS related issues on its application indoors render it not the best of choices. The complex nature and structure of the indoor environment, however, still poses a practical solution to the indoor navigation problem using GPS – even with the Chinese Satellite system [16] cooperating with the recent Galileo Positioning System, despite the potential they present. We bypass GPS related issues by not relying on the GPS system for positioning or user tracking. Instead, we use Wi-Fi fingerprinting coupled with dead reckoning techniques.

In [17] is suggest a Kalman filter based Wi-Fi fingerprinting and dead reckoning indoor navigation system as well. The major differences between their work and ours includes is first, they highlight their usage of a Kalman filter. As pointed out by most studies, a Kalman filter is not suitable for this kind of work; we use a low pass filter. We also use a text based feedback relay approach coupled with audio feedback. This is in order to make the application helpful during emergence situations and emergence evacuation scenarios and furthermore take the visually impaired and blind into consideration.

In [18], they proposed pressure sensitive floors whereas [19] proposed pressure sensitive shoes. These systems may be able to solve the indoor positioning and tracking problem but not only do they not offer a means for navigation, they are also extremely expensive to setup especially for mass deployment, not to mention the necessity to track the weight of each of person in case of pressure sensitive floors. Setting up these requirements for pressure sensitive floors and shoes can barely be categorized as low-cost. Besides, this system can only provide tracking, not navigation in best scenario.

In [13] is suggested an approach that does not require the use of Wi-Fi signals at all. They simply use a crowdsourcing approach based on sensor data and a step detection algorithm to determine the position of the user. This different approach is not suited for emergence situations.

In [20], the steps to deal with varying position-tracking accuracy in mobile augmented reality systems are discussed. They argue that neither the problem nor the solution is limited to only augmented reality problems but to all systems that require relatively accurate position tracking – which our system qualifies to be.

In [21] a time dependent optimal routing model for emergency evacuations in which the route is made basing on the position of the sensors and not the architecture of the structure itself is proposed. In the model, the geometry of the structure in question is ignored and all operations and algorithms developed depending on the available sensors. Hence a change or misread from the sensors could easily lead to significantly flawed navigation and routing service results. As it was designed to handle emergence situations, such potential sources of errors should best be avoided. Furthermore, their system is specifically designed for micro-scale temporary emergence evacuation. Therefore, their simulations included human detection with 5-10 second intervals. Our proposed system is a multi-purpose prototype that provides navigation and optimal path routing no matter the situation.

One of the difficulties faced throughout recent research is the accurate prediction of signal propagation. This can be approached using a technique called Location fingerprinting, that is based on measuring actual signal strengths from surrounding access points [22, 23, 24]. Furthermore, [24] provides a purely Wi-Fi fingerprinting based approach to localization and indoor navigation. They directly perform scans and store the RSSI with the corresponding MAC addresses into the databases without further processing and simply read and compare the obtained RSSI from the user with the pre-stored values. If the RSSI is within a given range (in their case a $+4 \geq RSS \geq -4$), then the user is at a correct location. In addition, they thus let the users know so. Else, they are at a wrong location. Major drawbacks to this approach, however, include; requirement of constant database update due to temporal variation in RSS over time and incase of change of the environment. In addition, sometimes the variation n RSS is much greater or less than the (+4, -4) given interval. Under such circumstances (especially for very large or very small roomed buildings), erroneous navigation is inevitable. We apply dead reckoning using filtered data to overcome and minimize the effect of temporal variation of RSS. There is also the issue of latency caused by such variations and multipath. Since calculations are performed much faster, the dead reckoning branch of the algorithm also minimizes this.

An indoor navigation model that supports optimal length-dependent routing is suggested in [26]. It, however, is limited to PCs, uses a server client model and necessitates extra plugin installation thereby barely qualifying as cost efficient. One needs to have at least a laptop to use the application. This is very inconvenient for navigating indoors especially nowadays that mobile phones provide pretty much all the basic functionality sufficient to facilitate navigation.

The CricketNav project [5] proposed the design and implementation of an indoor mobile navigation system using the cricket infrastructure developed in MIT labs. Their project requires installation of hardware developed in MIT labs. They also developed special Cricket beacons and Cricket listeners to aid their cause.

In [25] is proposed a resource-adaptive mobile navigation system (REAL). Their complete project had three major components; an information booth that had a 3D graphics workstation, an indoor navigation system based on strong infrared signal transmitters planted into ceilings and PDAs used for presentation and finally a head-set laptop combination for outdoor navigation. The routing information is presented depending on the kind of device used. Route optimization is also dependent on the resources available on the device being used.

Cyberguide [26] is among the first systems that employed location aware information to aid tourists. The project was designed to help tourists both indoors and outdoors. It comprised of two major components; an indoor and outdoor component. This project’s indoor component depended on beacons that broadcast unique ID using infrared signals from infrared beacons. On the other hand, the outdoor system used GPS. Both components functioned independently from each other.

In [27] a probabilistic navigation system for pedestrians based on mainly inertial sensors found in a specially made device [28] is presented whereas The NEXUS system also tries to provide a general framework for mobile and location aware computing. The concept of an augmented world is used to keep information necessary for a user’s location. It is the basis model for the virtual information towers that it can connect information objects.

In this paper, we present a user-interactive context-aware hybrid system of dead reckoning and fingerprinting that provides navigation services to users. It also puts into consideration visually impaired and physically incapacitated users by provided audio directives and a list of options that are aimed to make the user’s navigation experience less troublesome and onto the point. For example, a user on a wheel chair can set the system such that stairs are excluded from path/route presented to the user.

3. Ultimate Indoor Navigation: A Low Cost Indoor Positioning and Intelligent Path Finding (UIN)

In this section, the methodology and architecture of Ultimate Indoor Navigation (UIN) are descripted.

3.1. Methodology in UIN

Given the attention Indoor navigation has attracted, so many studies about and around the topic have been carried out. Alongside these studies, a plethora of approaches to achieve this feat has been presented in previous literature. In this section, we present the complete methodology that we propose, accompanied with the more important algorithms involved.

3.1.1. Tools Used

Wi-Fi fingerprinting and smartphone's inbuilt inertial sensors are used in our paper. This choice is made because Wi-Fi Access Points (APs) are readily available and are already installed throughout not only the school campus (the test case in this paper) but also in most indoor facilities nowadays such as industries, airports, hospitals to mention but a few and pretty much everyone owns a smartphone. Given these conditions, a low cost functioning, robust navigation system can be built.

The smartphone's accelerometer provides x, y and z coordinate values that, with data processing, can not only provide a lot of information but also provide pretty amazing results. Information it can provide ranges from the relative position of a user in general and the user's device in particular, the distance travelled over time and so forth. However, the accelerometer values are not used to determine the distance travelled by the user in this application because that would require double integration of the achieved values whose error bounds increase tremendously with the operation. We instead use fingerprinting, dead reckoning whilst employing the classic Euclidean distance formula in equation (3) below to estimate the distance travelled by the user to a sufficiently estimate the pose of the navigator. Using the magnetometer and gyroscope, the user's orientation and direction can be and are determined and it is much easier to determine whether the user is on or off track as smartphones have Wi-Fi receivers and scanners. It should also be pointed out at this point that smartphone technology nowadays has improved significantly. Therefore, smartphones are capable of carrying out computation tasks of this scale without negatively affecting the phone's daily/expected tasks.

3.1.2. Sensors

In this section, a brief overview of the sensors most relevant to the paper will be made.

<u>Accelerometer</u>

The acceleration in smartest phone devices is basically related to the phenomenon of weight experienced by a test mass that's found on the reference frame of the accelerometer (device). An accelerometer is thus a device that measures this proper acceleration and hence, this acceleration is not necessarily the change of velocity of the smart phone in space/coordinate acceleration. Given the general structure of this accelerometer, a device at rest relative to the earth's surface would show roughly 1g upwards due to its weight. Where g is the gravitational force, whose unit is m/s2. The accelerometer of a smartphone measures both dynamic motions such as movement, phone tilting in the x and y-axes and static forces such as the gravitation force (in the z-axis).

<u>Gyroscope</u>

A gyroscope is a device that, according to the principles of angular momentum, sensors, measures orientation. A mechanical gyroscope which consists of three two gimbals onto which a spinning a wheel that resists changes in orientation is attached. Unlike it, conventional gyroscopes in smart phones generally are made of Micro Electro-Mechanical Systems that measure angular rate, hence the name rate-gyros, while mechanical gyroscopes observe the change in the angle of adjacent gimbals as the spinning wheel remains at a constant global orientation.

<u>Magnetometer</u>

Magnetometer is a device designed to measure changes in the strength of the Earth's magnetic field. Some of the spacecraft carry magnetometers to measure the magnetic field of other planets. The magnetometer shows that the shape and strength of the Earth's magnetic field is constantly changing.

3.1.3. Steps Involved

The system's fingerprinting mechanism set up was made in phases, an online phase and an offline. During the online phase, fingerprints were recorded and stored for reference. It is of paramount importance that all stored fingerprints have distinct values from each other. Fingerprints have signal strength value at a given location. This is coupled with a short vivid description of the location (referred to as node during route planning and calculation) for assistance in routing. For example; to the left of the canteen right ahead of you, since indoors mere signal strength values (say -75dB) or coordinates such as (x, y, z) carry no comprehensible meaning to the user who may be a temporary guest at the institution in question. An appropriate floor identification (floor id) value is also added to the AP's identifiers. This is very useful for multi floor buildings. It helps to distinguish one floor from another with ease. Assigning a value of say 11 to the first floor, 22 to the second floor, 33 to the third floor and so on and so forth, helps distinguish floors that receive sufficiently strong signals from identical APs since the height from one floor to the other is significantly.

After data collection, then we can go onto navigating the user(s). An instance of the node's coordinates is also stored – this is mainly for usage by the dead-reckoning algorithm as explained later. The dead reckoning service runs in background and, basing on the user's concurrent location, the user's entered parameters (main source and destination), aids in the timely warning of the user in case the user is off route. In addition, furthermore, triggers route dynamic recalculation thereby reducing the delay these operations would cause in real time.

3.1.4. Data Acquisition

One of the most challenging and time consuming tasks in any fingerprint based approach of indoor mapping is the generation of discriminate fingerprints for given points of interests (POIs/nodes). This process is not only time consuming but also requires that empirical results be obtained a couple of times due to signal instability of the Wi-Fi networks resulting from interference, multipath and so on and so forth. As such, we felt the need to develop, as part of the paper, an application that will aid to ease the process. This we believe will not only benefit us, but also future researchers in the field.

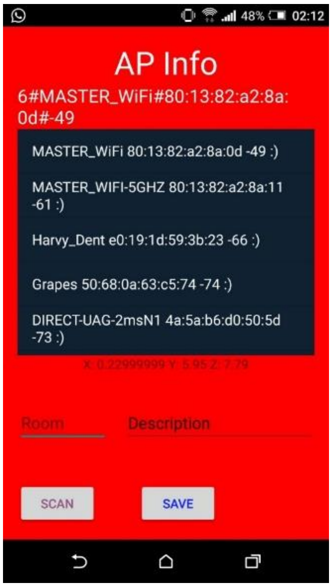

Fig. 1. Data Acquisition and Configuration Assisting Application.

The Figure 1 is part of the smart system that helps in the data acquisition process. The system keeps scanning the environment at a constant pre-specified interval – the default is 2 seconds. The user only needs to walk through the indoor environment while stopping at significant POIs (nodes). If the user stops at a place for a period greater or equal to 3 seconds, the system will automatically save the place in the application database. Saved will be the relevant information for both the dead reckoning and fingerprinting algorithms. Such information includes filtered sensor data, room name, ranked RSS (Received Signal Strength) from nearby Access Points (APs) and a short description of the node. This data is displayed to the user before it is actually used in the auto Graph (to be described later) generation phase. This gives the user time to make necessary changes to the data before it is saved. The user (one doing the mapping) then presses the saved button if he/she is satisfied with the current information. The saved information is then used in the generation of an undirected connected graph [29] used in route calculation and path presentation.

3.2. Route Calculation and Planning

A modified and optimized form of Dijkstra's shortest path algorithm is used to generate an optimal route from the user's current position to the desired destination. We modified Dijkstra's algorithm to suit our needs in various ways, ranging from enabling physically challenged users to dodge staircases in tall buildings to being able to evacuate as fast and safely as possible through emergency exits. Most path planning algorithms and applications use mainly either graph-based approaches or cell-based approaches [30]. Our system belongs to the former. Dijkstra algorithm basically finds the short path, given a graph G comprising of a set of Vertices, V and a set of Edges, E so that the graph can mathematically be represented as G = {V, E}. Attached to each edge, E is a weight w. A special vertex s can be fixed and considered as the source. The algorithm then finds the shortest path from s to each v Є V. We modified the algorithm such that the shortest path is found from a specified source to a specified destination. Extra parameters are also fed to the algorithm so that directions such as left & right are catered for depending on the user's current location and the desired destination. If the user digresses from the right path, the system automatically notifies the user and recalculates the route/path updating the source as the user's current position whilst keeping the destination fixed.

3.2.1. Route Representation

After successfully calculating an optimal route from the user's current location to the desired destination, it is very crucial that this information be clearly presented to the user in the simplest way possible. Visually impaired and physically challenged users should also be put into consideration while choosing the display mechanism of the route information to the user. Either a dynamically updated visual 2D or 3D map-model or simple precise list directives in form of text instructions coupled with audio assistance would do just fine. This is because we would not want the user to always be locked on to the screen while travelling, but the updated information should be always available when needed, say for consultation. We therefore integrate text instructions in our system with audio assistance to the users. The instructions/directives are kept as precise, accurate and understandable as possible (Figure 2.).

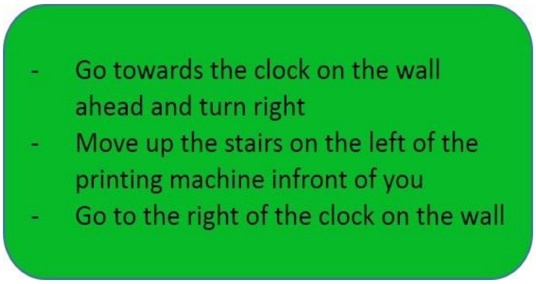

Fig. 2. Route representation as simple precise textual directives.

In this paper, we choose the later because it is easier to comprehend and follow. Some people are biased towards map reading. Furthermore, we think it is easier to listen to directives or quickly comprehend written directives during an emergence than try to understand and follow a map in an unfamiliar environment.

3.2.2. Position and Tracking

Signal strength received from the APs (RSS) and data received from the sensor fusion operations are used for user positioning and tracking. Whichever set yields the least error compared to the values stored in our database is considered as the current user position. This is done in order to compensate for temporal variations in signal strength or random noise received from the smartphone's inertial sensors – though most of the time the two are used to support each other.

Detecting User's Steps (The algorithm)

Recent versions android (4.4 and later) support the step-counting feature that can easily be used to detect user steps. However, the accuracy of the API used varies greatly from device to device. During the course of this paper, it was found to be more accurate while using Google's nexus 5 phone than with the HTC M8S phone. Occasionally the step detection was delayed in the nexus device as well. This delay was more pronounced in the HTC device rendering the current API alone unusable for our purposes. Need for a more consistent, faster algorithm arose. The approach for step detection in this paper is similar to that employed in [13] and [31]. By applying a few operations on the accelerometer readings, we can get the user's steps.

The algorithm to detect the user's steps is as follows. Empirically determine a suitable window to pass over filtered sensor readings to categorize them as either a step or not. When a user takes a step, the accelerometer magnitude values show a peak. This window's value is of paramount importance to the accuracy of the results yielded as a very small value gives too many steps since noisy data or even slighter motions can be detected as steps and, conversely, an extra-large window will give less steps than those actually taken by the user.

Let R_a represent accelerometer readings, W be the chosen window, $M(R_a)$ be the median accelerometer reading, T_{elap} be the elapsed time value, $D(W)_{cur}$ be the current standard deviation of the window and D_{thres} be the standard deviation threshold value of the window.

We say the window represents a step if;

$Max|R_a| = M(R_a) \forall R_a \in W$ and

$$D(W)_{cur} \geq D_{thres} \quad (1)$$

Over a given time T_{elap} for any two successive steps. With most Points of Interest (POI) being fingerprinted studies, find it sufficient to use the fingerprints to estimate the user's current location. In this paper, we further supplement this practice with a dead-reckoning service to improve accuracy and performance of the application.

For example assuming a user moves from a start position to a point $p(x_1, y_1)$, his position can be defined in terms of the distance (d_1) travelled and the direction (α) can be easily determined using the Magnetometer sensor. Now, if the user moves to point $q(x_2, y_2)$. The successive position can be obtained using the dead-reckoning technique as follows:

$$y_1 = d_1 \sin\alpha$$

$$x_1 = d_1 \cos\alpha$$

$$y_2 = y_1 + d_1 \sin\beta$$

$$x_2 = x_1 + d_1 \cos\beta \quad \ldots\ldots(2)$$

The Euclidean distance, d, between the two points can be obtained using the equation;

$$d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \quad (3)$$

Dead reckoning requires the starting position, the change in direction/orientation and the actual or an estimate of the distance travelled by the navigator. If, however, any of these parameters is not sufficiently accurate, dead reckoning yields accumulative errors [32].

The gained results from the dead reckoning algorithm are always check and compare with the results of the fingerprinting based algorithm and the least error is considered the true result. Thus correcting and updating the algorithm of the more erratic algorithm – assuming that the result return by the more erratic algorithm is catastrophic, else no need to update the parameters. Say if there is a difference greater than 2 meters between the returned results.

Filtering Sensor Data

Raw sensor readings can yield disastrous results. This is because the data obtained by these sensors contains noise. It is thus necessary to filter the data before usage in the algorithms to avoid errors.

Below formula is the first-order discrete low-pass filter applied to the sensor data. It is a recursive filter and can easily be implemented (in Java for this paper):

$$y(t) = y(t_{-1}) + \mu(x(t) - y(t_{-1}))$$

$$\text{s.t:} \qquad \mu = \frac{dt}{TC+dt} \tag{4}$$

Where, dt: is the period of sampling the sensor. TC: cutoff frequency or time constant. Doing this yields relatively smoother less noise readings as shown in Figure 3 and Figure 4.

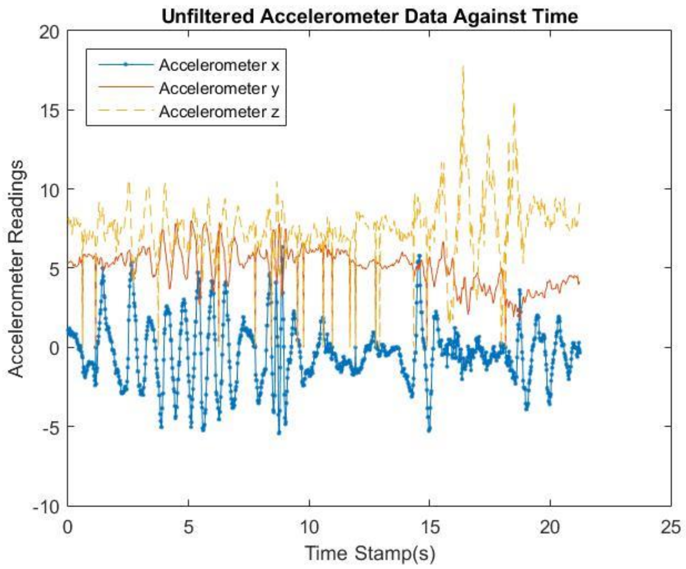

Fig. 3. Unfiltered Accelerometer Readings

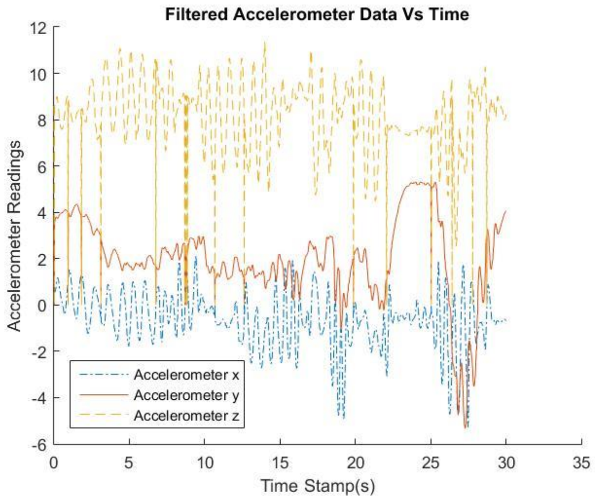

Fig. 4. Filtered Accelerometer Readings using a low pass filter.

The figures 3 and 4 are shown the behavior of accelerometer data against time in unfiltered and filtered reading method, respectively.

3.2.3. Route Confirmation and Context Awareness during Navigation

Indoor navigation can be tricky sometimes as the app user can either easily miss the destination or go off track. It is, thus of paramount importance to let the user know once they are off the right track. As soon as the route has been calculated, the user is constantly notified whether they are on or off the right track. In this paper, fingerprinted nodes and the results from dead-reckoning are used to determine whether the user is on or off the right track. If the user is not on the right track, an appropriate notice is issued and the route is re-calculated. A few of the advantages of the fingerprinting, dead reckoning hybrid algorithm are briefly described below;

1. If an AP breaks down or is changed/replaced, the fingerprinting algorithm will give erroneous results. The dead-reckoning algorithm compensates for this.
2. RSS varies over time. This could lead to errors in the routing algorithm. In such cases, the dead reckoning algorithm backs up the fingerprinting algorithm. Likewise, dead-reckoning results are prone to error accumulation as stated above. Periodic comparison of results from both algorithms helps address this issue. Since some rooms/nodes use one AP, if there happens to be a temporary significant variation in RSS, the navigator may easily be routed to the wrong location.

For example, our assuming is the navigator was wishing to move from TD006 with AP E to TD005 with AP A. Where A and E are the base nodes for the Wi-Fi fingerprints stored in the knowledge base. If AP B happens to be disabled, or replaced or breakdown -depicted by the Red Cross in the Figure 5- the situation described above would arise in which case the results from dead reckoning would be more than sufficient to seamlessly rectify the issue without troubling the navigator.

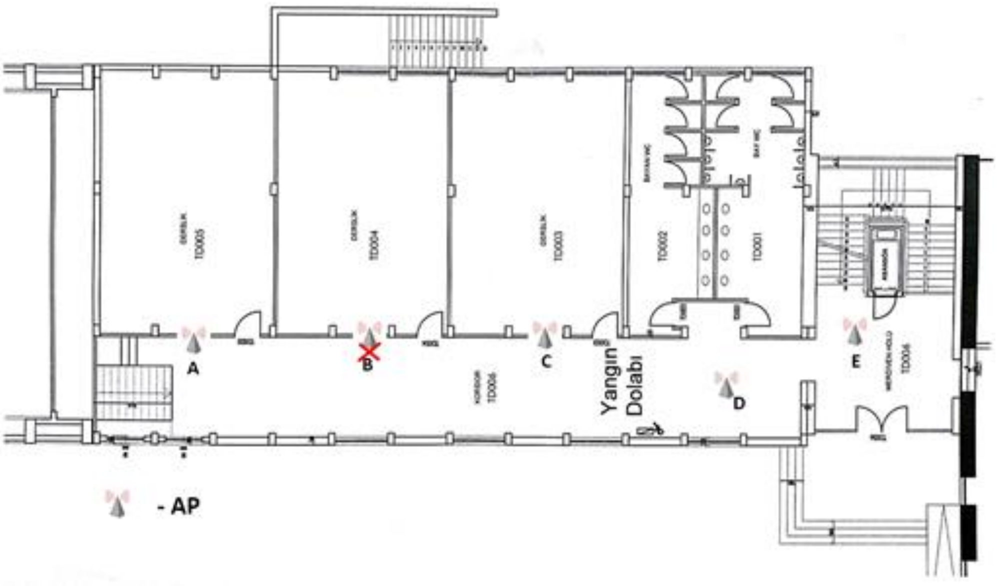

Fig. 5. A demonstration of algorithm compensation.

4. Architecture of the UIN

In this section, the architecture of the proposed system is presented. It explains how the major components of the entire system are linked to and interact with one another. The system comprises mainly of receivers, transmitters, a knowledge base (database) and a processing unit. The navigator's smart phone works as a transmitter, receiver, processing unit and contains the knowledge base. The APs are receivers as well. They receive signals transmitted by the smart phone. Then they in turn also transmit data to the smart phones. As mentioned section 3, the architecture set up is in two main phases; the offline and online phases of the Wi-Fi fingerprinting. During the offline phase, reference data is acquired, processed and added to the knowledge base. During the online phase, a user unfamiliar with the environment or wishing to do navigation to a certain location within the environment simply queries the system for a route from a given location to a desired destination.

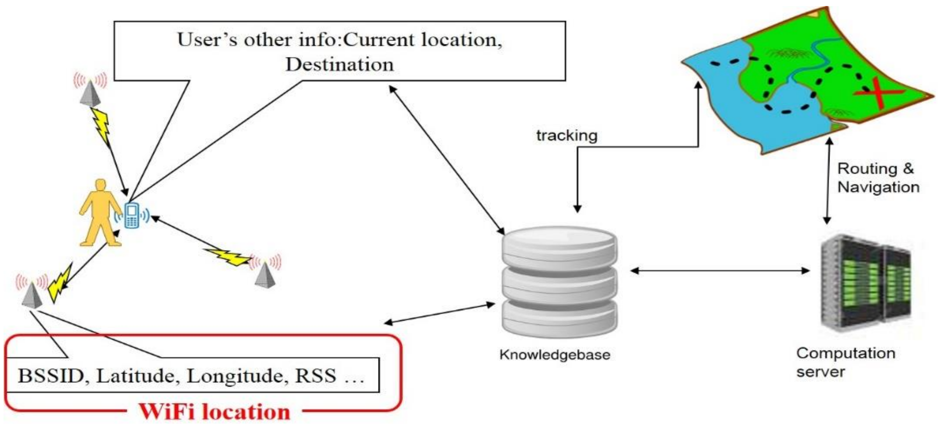

Fig. 6. Model of the proposed system.

Generally, as shown in the Figure 6, the navigator first provides the current position of the location from which they wish to start the navigation guidance to their desired destination and provides the optimal route according to the navigator's configurations. Among the options the navigator has are:

- Whether they wish to use stairs or elevators.
- The rate (in seconds) over which the audio directions are given. This is set to 10 seconds by default.
- Whether they are physically disabled …

Then as the navigator moves, the system keeps on periodically calculating and updating the route according to the user's current location in real-time whilst providing notifications whether or not they are on the right track or not. Figure 7 shows the simple choice screen of the prototype.

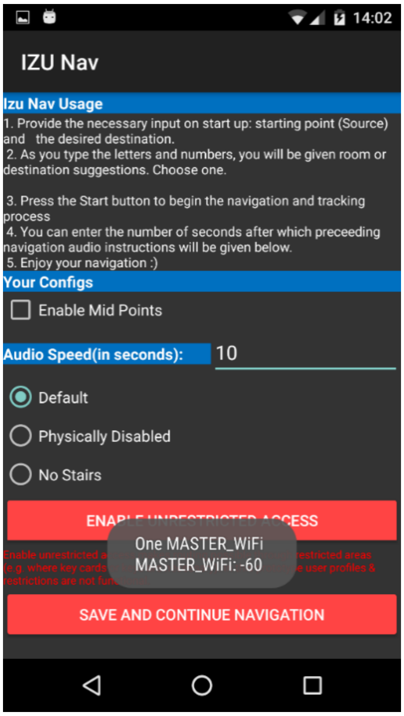

Fig. 7. Simplified Choice Screen of prototype.

The message in the toast is of no significant importance. It is simply a message meant for debug purposes and it displays the strongest received signal now the screenshot was taken.

5. Experimental Results

In this section, the experiment tests carried out to test the suggested prototype are explained. Empirical results obtained when testing the system described above are displayed. A Google Nexus 5 using android version 6.0.1 was used throughout the testing procedure at the Istanbul Sabahattin Zaim Campus (Figure 8). These results include the accuracy level, success and the failures with corresponding failure levels.

Satisfying as the results may be, there is still a lot of room for improvement and development. Both as far as performance and providing a much better user experience are concerned. This section covers such areas that can be improved or enhanced are presented. Android Studio [33] was used as the Integrated Development Environment.

5.1. Tests and results

The following scenarios were tested;

1. User at the very entrance of the floor provided both source and destination. In addition, the user can follows instructions from the application in an unbiased way.

2. User provided both source and destination, and then followed the instructions while intentionally getting off the suggested route.
3. User provided wrong position as the current location (Check whether and, if so, how fast the program will update the current location).

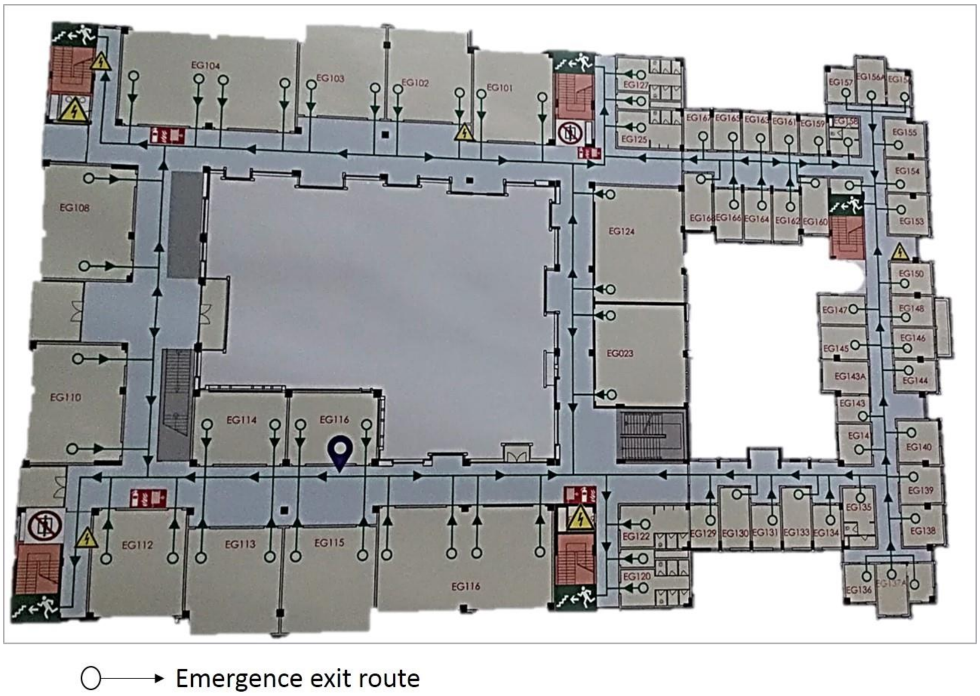

Fig.8. A simplified version of the used map in the paper prototype of the first floor of the Education blocks left wing.

As shown in Table 1, some results denote failures. These errors are obtained when the paper prototype gives a wrong node at a given point/node, say if Class EG117 is shown as EG116. Every correctly identified significant node on the path calculated and presented to the navigator is considered as success. The values in the brackets show how far off the yielded results actually are from the intended location. Using the analogy above, this corresponds to how far the user was taken from EG117. As for the case of the route from EG110-EG108, it is because both room EG110 and room EG108 share the same node and were assigned the same node value. Hence an empty list of results is returned since it was, for test purposes, was configured to do so. The same behavior will also be exhibited in case we try to navigate towards a disconnected node in a disconnected graph. There are so many choices for handling these situations, in this case since the two rooms are right adjacent to one another so we chose to simply let the user know that they have already arrived at their desired destination and add a direction they should turn to depending on their orientation. Given that, all the failures are with ≤2m range or less – with 2m being the upper bound. The descriptive navigation instructions accurately and very efficiently rectify this offset since all the intended targets are within eye sight so considering the whole system has an average accuracy of about 0.8-1.3m. This is sufficiently accurate for indoor building even those with small rooms since room level (~2m) accuracy is just sufficient. The average of ~0.8m was observed for standard sized rooms (~4m3) such as student laboratories or even larger whilst that of 1.3m was observed for relatively small rooms (~2.1m3) for example, the rest rooms.

Table 1. Sample results table.

Current Location	Input Location	Destination	Time to calculate route(ms)	Average Update Time If required(ms)	Success	Failure (Deviation in meters)
EG123	EG123	EG110	16	Null	5	0
EG110	EG110	EG104	27	Null	4	0
EG110	EG110	EG108	5	Null	1	1(~1.2m)
EG113	EG113	EG101	27	Null	6	2(~≤1.33m, *0.4m*)
EG124	EG117	EG104	20	46	5	1(≤*1.5m*)
EG104	EG101	EG122	25	37	7	1(≤*1.28m*)

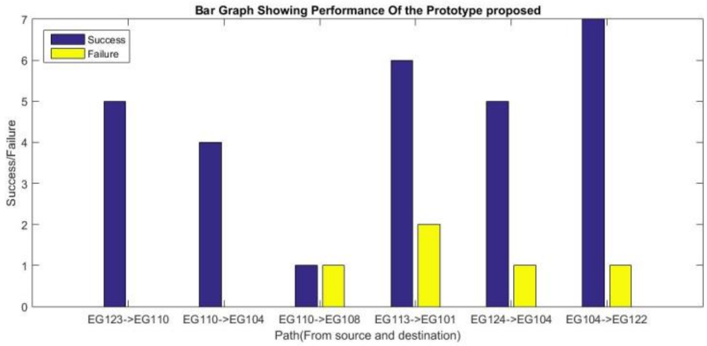

Fig. 9. Bar graph reflecting the performance of the suggested prototype.

Figure 9 shows the performance of the proposed prototype. The overall accuracy of the system, let alone the fast response time, is sufficiently accurate at room level - which is approximately less than (in most cases) or equal to 2m (~ ≤ 2m). This accuracy, however, drops drastically if there happens to be a disconnected node in the graph. Hence, paramount attention must be paid whilst creating the graph. The graph should not be disconnected. The effects of a disconnected graph on the performance and accuracy of the proposed prototype are demonstrated in Figure 10 and Figure 11.

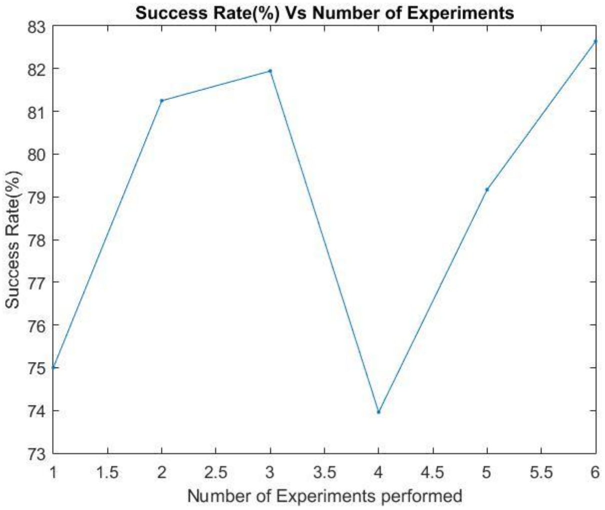

Fig. 10. Average success rate of a disconnected graph

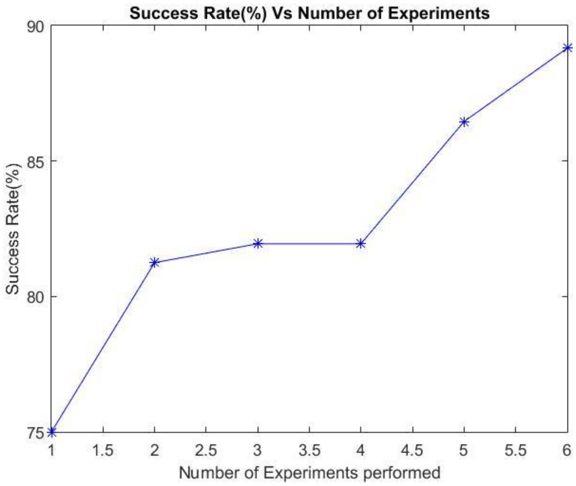

Fig. 11. Average success rate of a connected graph.

In the disconnected graph that is shown in Figure 10, a single classroom was not connected to any other room/node in the graph whilst in Figure 11. This node was not put into consideration.

Furthermore, the prototype scales with building room or node number size. Latency or calculation delays do not get worse with increasing number of node points. This is clearer shown in Figure 12. This Figure shows the scalability of the suggested prototype. The number of nodes in the map does not have a significant negative effect on the time take to calculate a route.

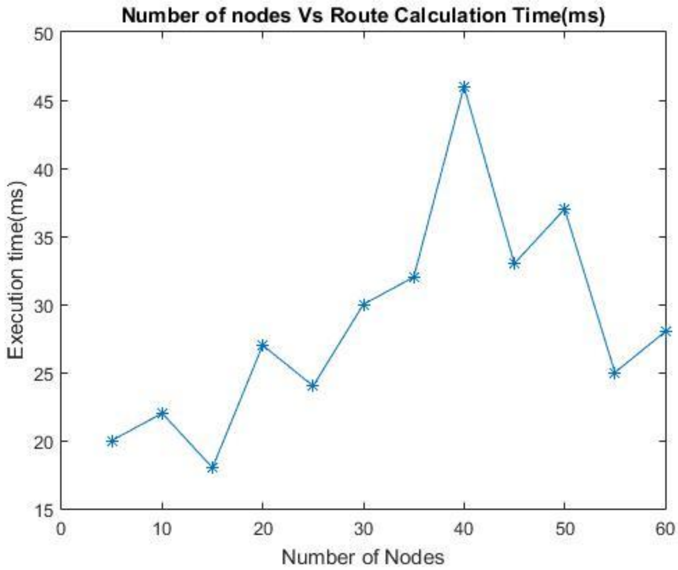

Fig. 12. Number of nodes Against Route Calculation time (ms).

5.2. General Comparison with trending approaches

In this section, we briefly show how UIN fairs with other trending approaches from related works performance wise. On top of providing an optimal route and navigation services for users – including the visually impaired and the physically disabled, UIN performs rather well performance wise as shown in Figure 13.

Method / Approach	Average Accuracy (m)
KNN	4.37
Probabilistic	2.78
Fingerprinting	2-3
Probabilistic and particle filter	1.96
ALPCIPIPF	0.8 – 1.3

Fig. 13. General Performance Comparison.

6. Conclusion and Future Work

In this paper, a cost efficient user interactive indoor navigation system using Wi-Fi fingerprinting and sensor fusion that requires no installation of extra hardware or third-party software is proposed. The system offers optimal navigation to the user with an upper bound of 2m and an average of 0.8-1.3m accuracy. The proposed prototype is also suitable for the visually impaired and physically challenged as it enables the user to choose the kind of configuration they prefer. In any case, the most efficient route is always suggested and presented to the navigator. The system implementation is a hybrid of Wi-Fi fingerprinting and dead reckoning performed using resultant data from the application of a filter on sensor data so as to reduce noise. Prototype test cases were carried out on the Education block of IZU campus. This prototype is of an indoor navigation system that runs on a user's smart phone device and requires nothing else. The suggested prototype is suitable for navigation and emergence evacuation for both normal, visually impaired and physically challenged users. Audio support is included into the system so users are able to get voice directions as they navigate throughout an unfamiliar indoor environment.

In this section, future works for this paper are presented and possible improvements are suggested. The system is likely to suffer serious accuracy issues if any AP is taken down, removed or changed especially, assuming the node(s) associated with the AP have not multiple AP access but single or two AP access are connected to many other nodes. Worst-case scenario is if the other APs are also experiencing non-insignificant RSS variations. This would throw both the fingerprinting and the DR algorithms off track. This means that periodic checkup of the APs would be in our best interest or constant communication with the ones responsible with AP setup in the facility in case of any changes. Furthermore, environmental changes such as infrastructural renovations also have an impact on the accuracy, but not the performance of the application. We therefore plan to implement automatic AP update or leave it up as a significant future work.

This prototype was designed basing mainly on only one building or infrastructure - from the building/infrastructure's management's point of view (say a university campus such as ours). However, we would also like to think from the users /navigators' point of view. If the users install this software from a given building, it also implies that they would have to re-install the software when they go to another infrastructure (again say, university) that uses the same software. Hence, with a little finance or support we would like to set the system up such that users install the software once and can use the finished paper in any place that uses the same software. Seamless integration with google maps so that the navigator seamlessly travels not only from building block to building block, but can also easily and comfortably use the app outdoors. Multi-language support. In this prototype, due to brevity, only the English language is supported. However, in the later versions, a wider range of language choices for example French, Turkish, Arabic, Spanish, to mention but a few will be implemented. A more locale language based implementation is not a big challenge. We plan to give the user a choice of the route/path representation in the future. A 3D/2D dynamic map such the one used by Google maps or the textual representation as shown here.

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