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Wi-Fi fingerprint and pedestrian dead reckoning-based indoor localization with supervised learning

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ABSTRACT

The Global Positioning System is not suitable for indoor localization due to signal loss in enclosed environments. Hence, this research designed and developed a hybrid indoor localization approach by integrating the Wi-Fi fingerprinting approach with the pedestrian dead reckoning. Limitations of the Wi-Fi fingerprinting-based localization are compensated by the pedestrian dead reckoning approach which is implemented on the mobile platform. Supervised learning models such as artificial neural networks and K- nearest neighbors have been used to map offline and online datasets. The predicted locations obtained through the hybrid localization approach are compared with the true locations via Euclidean and Manhattan distance calculations. The results prove that the Wi-Fi Fingerprinting and Pedestrian Dead Reckoning together has given promising results for localization than using them alone.

Keywords: Wi-Fi, Indoor localization, Pedestrian Dead Reckoning, Artificial Neural Network, K-Nearest Neighbor

INTRODUCTION

The new trends in localization-based technologies and the cutting-edge technologies of ubiquitous computing have gained significant advancements today. Unlike in enclosed environments, the global positioning system (GPS) plays a vital role in outdoor environments. The satellite signals are broken due to the shadowing effect in indoor environments is the main problem which restricts the use of GPS inside(Yassin, 2017). Therefore, over two decades, indoor localization has been a vital topic for many researchers which address the insufficiency of global positioning systems for indoor environments.

Although a lot of studies have been done but have yet to develop a fully featured effective and accurate indoor positioning system (IPS). Indoor positioning has numerous applications, for example, giving indoor route frameworks to dazzle and outwardly hindered individuals, finding gadgets through structures, helping travellers in large unfamiliar places like mega malls, finding a crisis exit in a smoky climate, following children in packed places, etc. Indoor positioning applications might require different quality credits, and hence IPSs ought to be painstakingly chosen to meet the pre-defined need of the application. IPSs utilize various positioning components that change immensely concerning cost, accuracy, technology, adaptability, and security (Alarifi A.,et al., 2016).

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BACKGROUND

Some of the most often studied IPS technologies are; RFID, UWB , Infrared , Ultrasonic , Zigbee, Wi-Fi , Cellular Based , Bluetooth , Dead Reckoning, and Image-based Technologies (Obeidat, Shuaieb, & Obeidat, 2021).

Wi-Fi

Wi-Fi technology is selected as one of the localization methods in this research because Wi-Fi is: (1) can be accessed easily, (2) available at a low cost, (3) can be easily found in every building, (4) used in existing communication networks, (5) signals penetrate walls more than GPS. (6) existing networks cover more than one building. (7) most types of equipment are compatible and operate with Wi-Fi.

Wireless local area networks (WLANs) are now common in many places, including both homes and workplaces. These networks use variants of the IEEE (Institute of Electrical and Electronics Engineers) 802.11 standard, better known in the market as Wi-Fi. Wi-Fi stands for "wireless fidelity". These devices transmit using relatively low power in the ISM (industrial, scientific and medical) band at 2.4 GHz or 5GHz.(Malone & Malone, 2010) Wi-Fi is a high-speed internet connection and network connection without the use of any cables or wires. The wireless network is operating three essential elements that are radio signals, antenna, and router. The radio waves are keys that make Wi-Fi networking possible. (Elprocus, What is a WiFi Technology & How Does It Work?, 2023) Wi-Fi positioning is a positioning system that uses several techniques to locate a connected object or device. Wi-Fi location uses already existing infrastructure and Wi-Fi access points (APs) to calculate where a device is located. The device needs to be able to listen to the Wi-Fi AP but does not need to connect to it. Wi-Fi has a short range, but the signal can extend up to 150 meters. The accuracy generally depends on how many APs are nearby and the environment in which they are deployed. The more APs in a given area and the more precisely their position is known, the more accurate the location will be. (Jones, 2020)

RSSI (Receive Signal Strength Indicator) is an indicator and RSS (Receive Signal Strength) is the real value. Indicators mean it can be a relative value and RSSI is always a positive value and there is no unit for the RSSI. RSS can be easily obtained by common wireless devices (e.g., wireless sensors, mobile phones) without additional hardware. However, RSS are apt to be affected by indoor environments, since radio signal is easily reflected, refracted, and scattered by various indoor objects. Many RSSI purification technologies are widely used in many studies to cancel the error. Such filters are the Gaussian filter (Wang, Hwang, Peng, Park, & Park, 2021), Kalman filter(Lee, Lim, & Lee, 2016), and particle filters(Shen, Hwang, & Jeong, 2020) are typically designed to mitigate either linear or non-linear noise through smoothing.

RF values are always told in dBm and the values are negative values most of the time. Both dBm and RSSI represent signal strength where RSSI is a relative index, while dBm is an absolute number representing power levels in mW (milliwatts). RSSI is a term used to measure the relative quality of a received signal to a client device but has no absolute value.

RSSI-based indoor positioning using WLAN can be categorized into three: Trilateration, Approximate perception and Fingerprinting.

Trilateration is a mathematical method used for determining the position of an object based on measurements of the distances between the object and three or more known reference points. In

indoor localization, trilateration is used to estimate the position of a device based on the measurements of the distances between the device and a set of reference points, such as beacons or access points. The trilateration process involves calculating the intersection of the spheres centred at each reference point and having a radius equal to the measured distance between the reference point and the device. The position of the device can then be estimated by finding the intersection of the spheres, which is typically done using iterative numerical methods. Trilateration is widely used in indoor localization due to its simplicity and robustness, and it can be combined with other techniques, such as Kalman filtering, to further improve the accuracy of the localization estimate(ilçi, Gülal, Alkan, & Cizmeci, 2015)(Din, Jamil, Maniam, & Mohamed, 2018). Triangulation is a mathematical method used for determining the location of an object based on measurements from multiple reference points. In indoor localization, triangulation is used to estimate the position of a device based on the measured angles between the device and a set of reference points, such as beacons or access points. The triangulation process involves using the angles and the known positions of the reference points to calculate the position of the device. This can be done by constructing a series of triangles between the reference points and the device and using trigonometric relationships to determine the position of the device. Triangulation is commonly used in combination with other methods, such as trilateration, to provide a more accurate estimate of the device's position. It can also be used in environments where distance measurements are unreliable, such as when there is interference from other devices or physical obstacles.
When the accuracy needed is not extremely high, the propagation model approach is generally easy to use and effective. However, due to wireless signal noise and interference from indoor impediments such as multi-storey floors, doors, and walls, it is still challenging to measure the distance properly using signal attenuation(Din, Jamil, Maniam, & Mohamed, 2018)(Javed, Khan, & Asif, 2019).

Fingerprinting is the most popular method of localization because of its high accuracy compared to other methods. It does not require line-of-sight measurements of APs, has low complexity, and gains high applicability in the complex indoor environment. Fingerprinting-based localization usually consists of two main phases: offline (training) and online (test)(Subedi & Pyun, 2017).

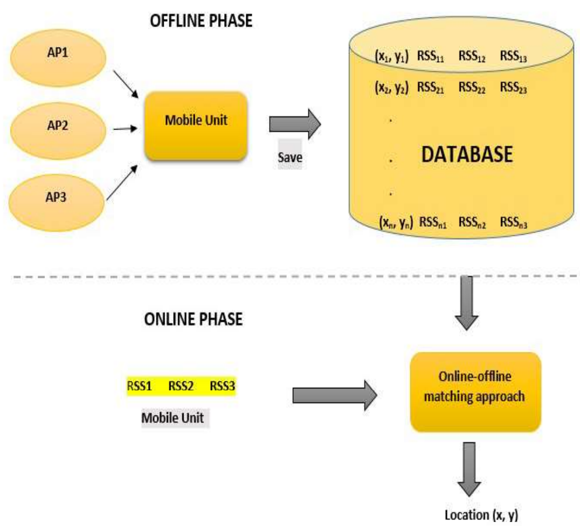

Figure 1. Two phases of fingerprinting-based localization

Offline phase-A radio map database is constructed in the offline phase by collecting the fingerprints at each location (reference points) which depends on the indoor map of the site. This fingerprint represents RSS readings from the Wi-Fi access points.

The majority of the currently accessible fingerprint database construction techniques are time- and labour-consuming. Due to the radio signal propagation impact brought on by environmental changes, the non-stationarity of Wi-Fi signal distribution poses a further hurdle that needs periodic fingerprint database updates to improve position prediction. It often takes surveying every reference point and recording fingerprints at each location to develop a Wi-Fi fingerprint database. By averaging the RSS at each reference point and providing a sense of orientation, this method enhances the dependability of a fingerprint database. However, if reference points must cover a large region and surveyors must manually label reference sites, this method is exceedingly labour- and time-intensive(Ahmad A. , Claudio, Naeini, & Sohn, 2020).

Another effort makes use of a crowdsourced fingerprint-gathering technique to reduce collection time to address this issue. Many techniques rely on sensors or input from outside sources. These outside sensors are expensive, challenging to set up and require constant upkeep(Zegeye, Amsalu, Astatke, & Moazzami, 2016).

Numerous studies have been conducted to speed up the site survey procedure(Zhuang, Syed, Li, & El-Sheimy, 2016)(Wang, Chen, Yang, & Chao, 2016). RSS prediction using interpolation or signal propagation modelling is one of the most often used techniques. Simultaneous Localization and Mapping, or Wi-Fi SLAM, is another well-liked method for building radio maps with cheap survey costs, but because of its high computing load, it is not suited for use on handheld devices with limited resources, such as smartphones. Intrusive/explicit user feedback is used in active crowdsourcing techniques to create a radio map. Although active crowdsourcing replaces the need for professional surveyors, it still requires user engagement and may be subject to deliberate deception. It has been suggested to use passive fingerprint crowdsourcing in place of active user participation. Using smartphone inertial sensors, passive crowdsourcing links fingerprints to relevant RPs. While passive crowdsourcing systems have made fingerprinting more realistic than before, they still have several drawbacks, including the necessity for GPS, a narrow range of applications, and poor accuracy(Gu, Ramezani, Khoshelham, & Zheng, 2020). Although many efforts have been made to decrease the labour and time needed to create a radio map, they have several drawbacks, including the need for active user engagement, being computationally expensive, having a limited range of applications, and having low accuracy.

Online phase-In this phase after constructing the radio map, the location of a mobile device inside a building is estimated by matching the online fingerprints of the mobile device with the corresponding fingerprints of the offline radio map database. Matching the database entries with dynamic RSS is performed using a positioning algorithm, which returns the approximate location of the mobile device. The approximated location is then displayed on an indoor map of the building which could be 2D or 3D.

Supervised Learning Methods

In the literature, several fingerprint localization algorithms have been proposed to find the best matching algorithm and try to improve the localization accuracy, many researchers propose the nearest neighbor (NN), K-nearest neighbor (KNN) (Torteeka & Chundi, 2014), weighted K-nearest neighbor (WKNN) (Shin, Lee, Lee, & Kim, 2012), Bayesian probabilistic model (BPM), and artificial neural network (ANN)(M. Zhou, 2010).

KNN

The k-Nearest Neighbor rule (k-NN) is a distance-based classifier which compares a current sample to all the labelled samples from a database. To select the K that's right for the collected data, the KNN algorithm was executed several times with different values of K and choose the K that reduces the number of errors encountered while maintaining the algorithm's ability to accurately make predictions.

ANN

ANN can be utilized for indoor positioning due to their robustness against noise and interference which are one of the major factors affecting the accuracy of IPS. The main advantage of using ANNs is that the system doesn't need prior awareness of the surroundings or noise distribution. A widely used ANN structure among modellers is the feed-forward back-propagation neural network. It is also considered one of the simplest and most general methods used for supervised training. The aim of this research is to perform indoor localization based on ANN using Wi-Fi fingerprint.

PDR for Indoor Localization

Pedestrian Dead Reckoning (PDR) is the process of calculating one's current location by using the previously known position and advancing that position over time using established or estimated speeds and trajectories (or stride lengths and directions) (Hou & Bergmann, 2017).

PDR is broadly embraced in the field of the pedestrian route with handheld gadgets such as mobile smartphones. It is specially adjusted to cell phone-based confinement as inertial sensors can be planned in a MEMS (Microelectromechanical Sensors) technology, empowering them to be implanted in lightweight gadgets(Yu, Na, Liu, & Deng, 2019). However, because of gyro float and step identification constraints, extra data is expected to help the PDR positioning cycle. For foot-mounted sensors, zero speed update (ZUPT) alignment is taken advantage of to change the positioning boundaries by identifying position stages inside the stride cycle (static stage), however, this adjustment is preposterous with handheld gadgets as a result of free hand movement and expanded trouble to distinguish the positioning stage.

Distance Matrices

Several distance metrics have been often used by researchers such as Euclidean(Wang S. , 2020), Manhattan (*Njima, et al, 2017*), Minkowski (*Jiang et al, 2020*), and Hamming (Mosleh *et al 2019*) distance. Out of these, both Manhattan and Euclidean distance methods are considered in this research**.**

Manhattan distance

Distance between two points in a grid-like path.

$d = \sum_{i=1}^{n} |x_i - y_i|$……………………… Eq: 01(Gohrani, 2019)

Euclidean distance

This is the straight line distance between the two datapoints.

$d = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$……………………Eq: 02 (Gohrani, 2019)

METHODOLOGY

Wi-Fi Fingerprinting based Localization

Fingerprinting is the most well-known strategy for Wi-Fi-based localization due to its high precision contrasted with different strategies. Fingerprinting-based localization is implemented in two stages: offline (preparing) and online (testing).

Stage 01: Offline phase

Figure 2. Process of the offline phase

Selection of test environment, identification of reference points and placements of APs

In this study, a vacant room with a dimension of 10m x 8m is selected as the test environment. The signal emitting from APs needs to be strong and steady. Therefore, the testing environment is selected such that it needs to be barrier-free and noise free for as much as it can. The layout of the experimental area with pre-defined reference points (RPs)and three APs is shown in figure 3. There are 25 reference points and each point was 1 m apart from the other.

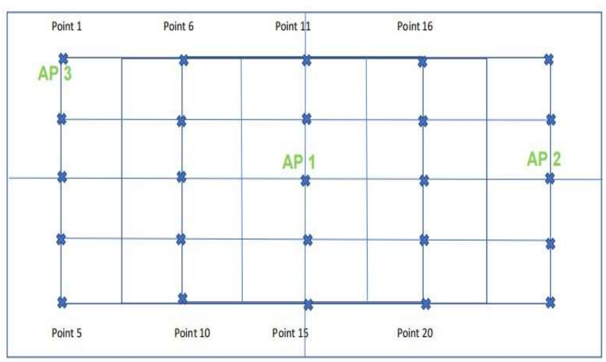

Figure 3. Experimental area including 25 reference points with 3 WAPs

In this study, indoor true locations are estimated based on the nearby outdoor GPS coordinates gained from Google Maps. First, mark the points which are outside the test area. Then, the GPS location reading corresponding to the outdoor points is obtained using Google maps. Next, the location measurements in line with the border and the middle of the test area are calculated. As the location coordinates latitude and longitude are provided by the GPS sensor. All these coordinates are converted to their respective (x, y) coordinates.

The actual coordinates of the test environment (12 points (in black) in the outer limit of the test environment) are calculated based on coordinates obtained by the Google map of outer points beyond the blue region (16 points (in blue) outside the structure of the building) as shown in figure 4.

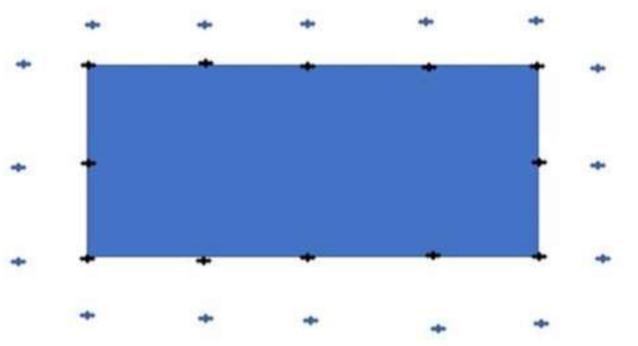

Figure 4. Calculations of true points based on Google map

Recording the RSS values and construction of the offline database

Once the coordinates of each reference point are gained the next task was to record the RSS values for the new test area with pre-defined names(labels). RSS values are calculated with the help of the Wi-Fi scanner smartphone application developed in this research as shown in the figure 8 and figure 9.The data is recorded 03 times per day, for 03 days using three APs.

There are many off-the-shelf applications are available to measure the Wi-Fi RSS in the indoor environment. However, most of the applications are unable to access more than one access point. Some smartphone applications are designed specifically for cellular networks and do not provide information about Wi-Fi networks. The accuracy of the information provided by some other smartphone applications depends on the quality and compatibility of the device's cellular hardware, which may not be reliable for all devices. The signal strength of a few applications can vary greatly in different locations and at different times, making it difficult to get a consistent measurement of network quality. Some mobile applications are typically designed to work with specific router brands and models, which means they may not be compatible with all routers. Therefore there is a need for a reliable, accurate scanner to measure more than 1 APs.

Development of a Wi-Fi Scanner Application

A high number of networks detected can indicate a congested wireless environment, which can lead to interference and slow performance. This can be particularly problematic in densely populated areas where many wireless networks are competing for the same bandwidth.

A smartphone application is developed to scan RSS of Wi-Fi signals indoors which provides details of the wireless networks in a specific area. The output of this app can provide information about the network's name (SSID), and signal strength. This app can detect the RSS of more than one AP available at a given time in the target area which is one of the key features when compared with the existing RSS readers which can provide the reading of only one AP.

The filtering option in a scanner allows network administrators to filter the results of a scan and display only the information that is relevant to their needs. This option can be particularly useful when a large number of wireless networks are present in an area, as it helps to simplify the results and make it easier to identify specific networks.

Another important aspect of the result of a Wi-Fi scanner is the signal strength of each network. The signal strength indicates the quality of the connection between the device and the network. A weak signal can indicate that the network is far away, or that physical obstructions are blocking the signal.

Android Studio is used to develop the application from the java language. The first step was to get all the available Wi-Fi SSIDs onto a listview. By using the Wi-Fi manager, available Wi-Fi was displayed on the listview. A button was created to send the required RSS value at the RP to the database. By using the button, the application can send only the required RSS value from AP to the reference point. The Android Runtime Permissions API is used to request permissions at runtime to handle the necessary user permissions to access the location and Wi-Fi state. Then the results can be displayed on the user interface, such as a list or a table, by looping through the scan.

Stage 02: Online stage

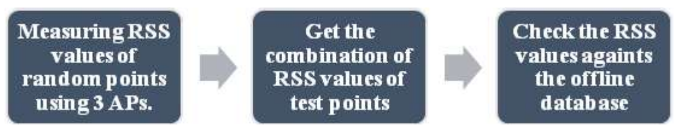

Figure 5. Online stage

According to figure 5, the online RSS values of a particular RPs are mapped against the offline database.

Selection of appropriate mapping method

ANN Model

The location of an object is determined by applying an ANN to map the real-time (online) measurements of RSS with the closest location that can be found in the radio map database (offline). In this work, a two-layer artificial neural network with gradient descent with a momentum back-propagation learning algorithm was used. The network configuration consists of three inputs from three access points and outputs with two neurons corresponding to the position of the user (x, y) and one hidden layer with ten neurons in MATLAB.

However, several shortcomings of Wi-Fi-based indoor localization are identified. The instability of RSS signals may be caused by people moving around, the material of objects inside the building, changing the order and arrangement of indoor furniture, and other disturbances such as other radio inferences, Bluetooth signals, etc. (Thewan, Ismail, Panya, & Terashima, 2016).Interference of Wi-Fi signals with other electronic devices, a limited range that may not penetrate walls or other obstructions, makes it difficult to locate devices in some areas of a building. The accuracy of the Wi-Fi signals degrades when the distance increase from the access points. Due to these reasons, the measurement accuracy of RSS signals is less. Therefore, there is a need of combining Wi-Fi-based localization with another localization technique.

Hybrid Localization

The proposed hybrid model as shown in figure 6, consists of Wi-Fi and PDR-based localization to upgrade the position exactness for indoor localization. Figure 6 shows the overall architecture of the proposed approach.

Figure 6. Proposed hybrid IP system.

PDR-based localization is implemented as a smartphone application. A walking person can monitor the step count from the source and the location coordinates of the current position. Moreover, this smartphone application can compare the position estimation of the PDR method along with the Wi-Fi method and ensures accurate localization. The user will be notified of his current location once the real-time coordinates tally with the offline coordinates of the Wi-Fi fingerprinting database. This smartphone application is personalized by including the age, height, weight and gender of the user which inturn assists to calculate the step count accurately.

Android Studio is used to develop this smartphone application along with the embedded motion sensors such as the accelerometer and attitude composite sensor in a smartphone. Based on the count and number of turns (to left or right) the PDR position is calculated. When the user is taking a turn the user needs to tilt the phone so the sensors could understand the change in the direction of the motion.

RESULTS AND DISCUSSION

Results Wi-Fi RSS Fingerprint-based Localization

Results of Wi-Fi Scanner

During the offline phase of the Wi-Fi fingerprinting, the RSS of each AP at a given reference point has to be stored in the database. The filtering options in a scanner include the ability to filter by network name (SSID), and signal strength as shown in figure 7.

The “Sort By” option in a WLAN scanner allows you to sort the results of a scan based on various criteria. This feature can be useful for quickly finding specific information or for analysing the data in a meaningful way. Some common “Sort By” options in WLAN scanners include SSID and strength of the signal as shown in figure 8.

The signal strength that we got to the list view was divided into five categories according to the quality levels of the Wi-Fi RSS. The colour codes are shown in table 1 corresponding to the dBm.

Figure 7. Filtered result

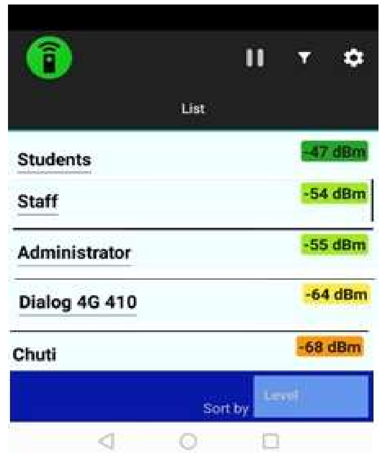

Figure 8. Sorted by level

Table 1. Signal strength vs color

dBm	Interpretation
-30dBm	Perfect Signal
-50dBm	Excellent Signal
-60dBm	Good Reliable Signal
-80dBm	Unstable Connection
-90dBm	Unlikely Connection

Figure 9. shows the location difference between the true location points and the predicted location points of a separate test set which consists of four random reference points. Arrows are points from true locations to predicted locations.

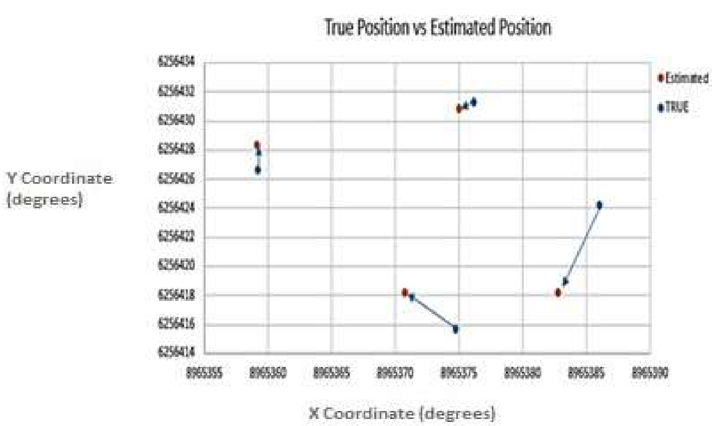

Figure 9. True vspredicted location points

It can observe that the length of the error line (arrow) is different from each other that is because of the fluctuations of the RSS signals.

Results of the ANN Model

The learning curve can determine the minimum required number of training trajectory samples and training epochs for the proposed ANN model. Figure 10 illustrates the relationship between the training and cross-validation errors vs. the number of running epochs. The number of running epochs is approximately 12.

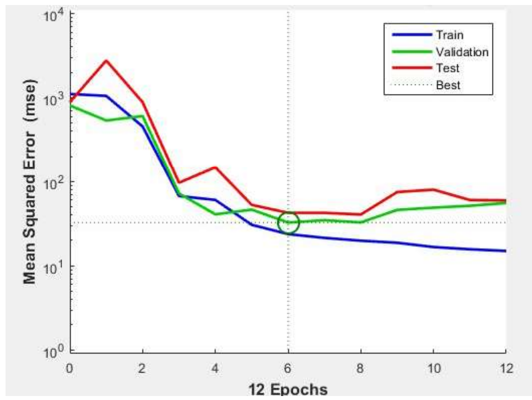

Fig. 10. Mean Squared Error vs. Epochs

The regression R-value measures the correlation between predicted locations and true locations. An R-value of 1 means a close relationship, and 0 is a random relationship. In this research 0.7996 of R is obtained which proves that there is an approximately close relationship between the true and predicted values.

Results of the KNN Model

In this experiment, the K value was kept on increasing from 1- 4 for each AP and check the way it affect the error.

Table 2. K value vs error

	K=1	K=2	K=3	K=4
Mean Absolute Error	1.0633	1.0433	1.2007	1.242
Root Mean Square Error	1.3785	1.3154	1.5434	1.653
Relative Absolute Error	26.1752	25.6829	29.5558	27.895
Root Relative Square Error	28.3402	27.0429	31.7305	31.847

After studying all these values, it is identified that the best value for K is 2 based on the reduction of errors.

Result of the Distance Matrices

By considering the gained values we calculated the following results:

- Mean Euclidean Distance: 3.067227636
- Mean Manhattan Distance: 3.356666667

Therefore, Euclidean distance matric performed well when compared with the Manhattan distance.

Results of hybrid localization

Individual factors such as age, height and weight are taken as inputs to personalize the smartphone application and to calculate the step count as shown in figure 11 (a). Whenever a user comes across a coordinate of a reference point a pop-up dialogue box will open and will notify the user of his current locationas shown in figure 11 (b).

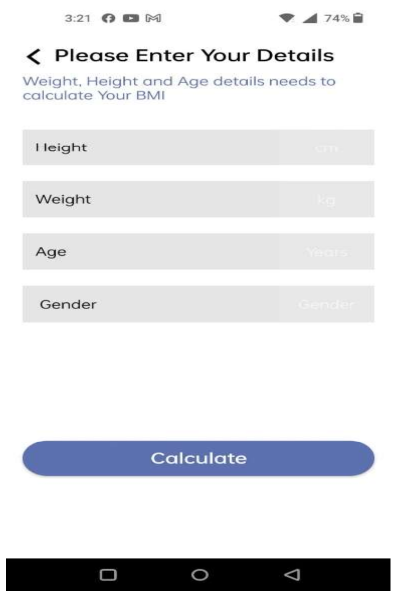

Figure 11 (a). Personalization UI

Figure. 11 (b). Step Count based on inertial sensor measurements

CONCLUTION

In this research, Wi-Fi and PDR are selected for indoor localization. Wi-Fi with RSS fingerprinting was used which was mainly implemented in two steps: online phase and offline phase. The smartphone application called WLAN scanner was developed to measure the Wi-Fi signal strength to build the offline training RSS database. KNN was implemented to match the offline and online phases of Wi-Fi RSS-based localization. Moreover, a feed-forward back-propagation neural network is developed and trained using the RSS measurements collected during the offline phase as the training data. ANN was tested against the test RSSI data collected during the online phase. PDR is the other localization used to fuse with Wi-Fi-based localization. The use of the smartphone to implement the PDR seems a better option as the smartphone itself comes with various useful inertial sensors. A novel app was developed which is capable to track the step count and the turns taken by the user to calculate the PDR. Both Euclidean and Manhattan Distance was calculated to benchmark the estimated hybrid localization points against the actual location points and Euclidean was selected as the best. Evaluation results were benchmarked against the same localization approaches in the literature. In the future, the proposed hybrid localization method can be further extended to create a map just like Google maps for the localization of unknown indoor locations such as airports, shopping malls, etc. Moreover, this app can be introduced to blind people if we could add voice feedback assistance in the future.

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I. GENERAL INSTRUCTIONS

1) Research presented in the manuscript could be in any field of science. 2) The research work should not have been published or submitted for publication elsewhere. 3) A corresponding author who will be responsible for all communications with the SLAAS Office should be identified. 4) Submission of manuscripts: Manuscripts can be submitted online https://journal.slaas.lk/. 5) Certificate of authenticity: Declaration form should be duly filled, signed by all authors and attach separately. 6) Submissions that involve human or animal trials should provide evidence of approval obtained by an ethics review committee.

II. SPECIFIC INSTRUCTIONS TO AUTHORS

1. Document to be submitted: Manuscript in MS Word format.

2. Format for typesetting
    - Paper size: A4 (210 x 297) typed single sided only.
    - Margins: Top, bottom and right margins of 25 mm and a left margin of 30 mm. 2
    - Line spacing: 1.5 (18 points) throughout the text.
    - Length: Length of the manuscript including text, tables, figures and references should not exceed 15 typed pages.
    - Page and line numbering: All pages should be sequentially numbered using Arabic Numbers. All lines should also be numbered sequentially starting from the top to the bottom of each page.
    - Font: Arial font, size 12. ! Language/spelling: UK English only.
    - Software: Authors may use either MS Word for Windows or the Macintosh equivalent.
3. Title Page: Title page should include the following Information;
    - Title and running title (less than 25 Characters). They should be in bold faced letters
    - Name/s and affiliation/s of author/s
    - Email address, mailing address and contact numbers of the corresponding author. Note: Identified the corresponding author by placing an asterisk after the name.
4. Abstract
    - Should be limited to a maximum of 250 words.
    - Up to a maximum of the five (05) key word should be identified, arranged in alphabetical order, included immediately after the abstract.
    - Abstract should be typed in italics. Scientific names in the abstract should be underlined.
    - No reference, tables, or figures should be included in the abstract.
5. Body
    - Introduction: Justification of the research work, objectives and hypotheses should be included in the introduction.
    - Methods and Materials/ Methodology: All materials, chemicals, clinical, subjects and samples used should be identified. Analytical, survey and statistical method should be explained concisely. Common analytical methods need not be elaborated.
    - Results and Discussion: Can be combined.
    - Conclusions: Should be concise.
    - Headings: All headings should be in bold capital and centered, e.g., INTRODUCTION
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6. Table and Figures
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7. Units
    - SI units should be used.
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8. Acronyms and Abbreviations
    - All acronyms should be written in full at the first time of appearance. Abbreviations can be used subsequently.

- The full stop should not be included in abbreviations. Where abbreviations are likely to cause ambiguity or may not be readily understood by readers, the units should be mentioned in full.

9. On being informed of the acceptance, the manuscripts should be revised as per the reviewers' suggestions and re-submitted to the Editor – SLAAS. The accepted manuscripts will be published in the inaugural Journal of the SLAAS. Manuscripts that do not confirm to the above guidelines will not be accepted.
10. Acknowledgements Only the essential individuals and/or organizations/institutes should be include
11. Need to attach the manuscripts both as 1. with names and affiliations of the author and 2. Without with names and affiliations of the author

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