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A Low Cost Indoor Positioning System Using Bluetooth Low Energy

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ABSTRACT In this paper, we present a Bluetooth Low Energy (BLE) based indoor positioning system developed for monitoring the daily living pattern of old people (e.g. people living with dementia) or individuals with disabilities. The proposed sensing system is composed of multiple sensors that are installed in different locations in a home environment. The specific location of the user in the building has been pre-recorded into the proposed sensing system that captures the raw Received Signal Strength Indicator (RSSI) from the BLE beacon that is attached on the user. Two methods are proposed to determine the indoor location and the tracking of the users: a trilateration-based method and fingerprinting-based method. Experiments have been carried out in different home environments to verify the proposed system and methods. The results show that our system is able to accurately track the user location in home environments and can track the living patterns of the user which, in turn, may be used to infer the health status of the user. Our results also show that the positions of the BLE beacons on the user and different quality of BLE beacons do not affect the tracking accuracy.

INDEX TERMS Bluetooth low energy, living patterns, indoor localization, received signal strength indicator

I. INTRODUCTION

In the past few years, we have witnessed considerable BLE progress in localization systems relying on wireless sensing technologies, which have been applied in areas including navigation, human mobility, life pattern mining and location-based services. Moreover, with the increased growth of ubiquitous smart sensing, both human mobility pattern and trajectory mining are becoming popular research areas for learning and discovering human activities and living patterns [1]. GPS technologies [2] accurately geolocate users and can also provide a level of accuracy for outdoor activity recognition. A number of studies have been carried out to analyze outdoor lifestyle activities [1], [3]. However, GPS technologies cannot be used for assessing indoor activities given that the GPS signal is not able to penetrate buildings.

More importantly, an aging population is becoming a global challenge and there is a growing interest in monitoring and assisting people living with dementia and people with disabilities in indoor environments [4], [5]. Over recent decades, the number of old people has increased significantly. The European Commission had predicted that between 1995 and 2025 the UK alone will see a 44% rise in people over 60 years old [6]. An aging and disabled population presents a significant challenge for the health care systems [7]. There is an increasing need for home rehabilitation to understand the needs of older users, carers and clinicians [8]. In addition, people spend most of their time (~90%) indoors, e.g. at a work place or at home according to a National Human Activity Pattern Survey [9]. Therefore, indoor tracking is in great demand for all kinds of people. Understanding the indoor patterns of users (especially for frail people and/or people living with dementia) will help detect any anomaly event (e.g. fall at home, and epileptic seizure) of the user. Moreover, the long-term monitoring of an occupant's use of their home will help with clinical decision making and diagnostics whilst also providing a deeper understanding of chronic conditions such as dementia, and neurological conditions.

Considerable research effort has been spent to explore indoor location tracking technologies including the use of cameras [10], ultrasound [11], RF [12], infrared [13], Wi-Fi [14], [15], Bluetooth [16] and etc. Among these technologies, Wi-Fi and Bluetooth based methods have been prominently

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used for indoor positioning. Moreover, there has been extensive work carried out on Bluetooth and iBeacons based indoor localization systems [17], [18]. In the iBeacon-based methods, a user's mobile phone is localized by the iBeacons installed at different afore-known locations in a test environment. However, these methods are based on a proxy by localizing the user's mobile phone to determine the location of the user. In real-world cases, people tend not to keep their phones on their physical body at all times in an indoor environment, especially in home environments. Therefore, the location of the phone may not indicate the location of the user. In order to accurately monitor the location of the user in an indoor environment, a tracker or sensing object which can be attached/worn by the user is needed. There are existing studies for detecting the user's activity and location at home with a body attached sensor [8], but the battery of the sensor is a critical issue in these sensing scenarios. Longer term research in indoor localization needs a tracker, the size of which is suitable to carry long hours and with a long battery usage, e.g. longer than a month.

The aim of this study is to develop a low-cost indoor localization system that is able to monitor the user's location patterns in a home setting for long term use. In this paper, we present our indoor localization system using BLE based method. BLE beacons are used as the tracking object carried by the user. The proposed indoor localization system is developed based on BLE technologies integrating Raspberry Pis (RPi) and BLE beacons. In our evaluation scenarios, the BLE beacons can be sewed into the clothes of the users or can be worn on the wrist of the users or placed in their pockets. Two algorithms in indoor localization of the tracking object are proposed including trilateration and fingerprinting. Considering the potential noise and obstacles in an indoor environment, Kalman filter and Particle filter-based noise reduction methods have been used to smooth the collected raw RSSI values.

The rest of paper is organized as follows. Section II presents a literature review of the related work in indoor localization. Section III presents the system design including the hardware and software of our developed BLE based indoor localization system. Section IV discusses the methods used in localization based on the developed system. Section V presents our Experimental results. Section VI concludes the paper.

II. RELATED WORK

Our work is related to a range of areas including human tracking and indoor localization. In the recent years, various solutions have been developed for indoor tracking e.g. camera based method [10], [19], inertial sensing based method [20], sound based method [11], [21] and RSSI based method [22]–[24]. Combining two or more sensing technologies can provide better positioning accuracy.

Radio-frequency identification (RFID) is a wireless technology has been used in indoor localization [25] and there are two main categories: tag-oriented and reader-oriented. Though the RFID is flexible in tag size, the cost of the RFID reader and unstable received signal strength make it unmatured for the indoor localization applications. Besides, other types of RFID evolutions including millimeter wave and THz passive tags are emerging [26].

With the increasing use of smartphones, the method of integrating inertial sensing methods and Wi-Fi based methods has become a popular method for indoor positioning [27]. In the area of Wi-Fi based localization, both device-based [28] and device-free [15] solutions have been developed. The device-free based method has the advantage where a device does not need to be carried by the user, but the disadvantage is the complexity of the system and that the system normally only works with and for one user.

A number of research studies focused on using Wi-Fi based positioning method in large buildings [29]–[31] for mobile device users. More recently, researchers started to use BLE based positioning method [32], [33] in indoor localization. Researchers [34] have also combined Wi-Fi fingerprinting and BLE trilateration. Most of the recent works focus on tracking the user's location via locating the smartphones [35]–[37]. In [38], indoor localization has been tracked by fusing the information from analysis of RSSI from BLE beacons and inertial sensor data from a smartphone. Similarly, in [39] probabilistic localization algorithm has been proposed to employ both inertial sensor from smartphones and BLE beacons. However, the disadvantage of these system is that the phone is required to be with the tracking object at all times, which is not realistic in real indoor environment especially for occupant with long term chronic conditions and users who do not own a smartphone. The current commercial indoor localization systems are very expensive e.g. Infsoft [40] locator node is around £150 per device. Our proposed system provides a low-cost solution and it is feasible for real world deployment. In this study, we focus on exploring the location of interest based approach for indoor localization instead of grid based approach [41], [42] as the user's use of their home is our main concern. The location of interest-based approach simplifies the procedure of labelling in a home environment. Furthermore, in this study, a number of different BLE beacons including tracker beacon and smart wearables are evaluated.

In our previous study [43], we had used Wi-Fi and Bluetooth sensing technologies to monitor bus occupancy. The technologies have been further extended in this work, in particular, focusing on the issue of performing tracking of the occupant's locations in home settings for low cost long-term use. In this work, we present the detailed development of a localization system using an RSSI based method and discuss the related work on RSSI based methods using Wi-Fi or Bluetooth sensing.

When considering the different obstructions within indoor settings, it is difficult to develop a suitable radio propagation model. Traditionally, trilateration and triangulation methods are used as positioning algorithms. In this work, trilateration is

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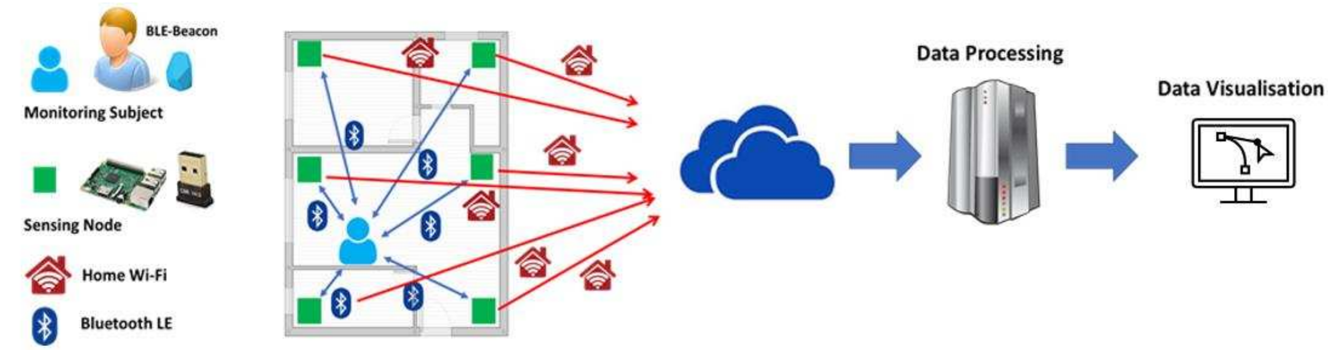

FIGURE 1. System Overview

FIGURE 2. Sensing node & Screenshot of BlueZ BLE sensing

used and methods to mitigate the measurement errors are developed. In [44], Running Average, Kalman Filter and cascaded Kalman Filter-Particle Filter algorithms had been explored to improve proximity detection accuracy. In our work, in order to improve the accuracy in trilateration, Kalman filter is applied to reduce the measurement error of RSSI.

III. SYSTEM DESIGN

We propose an approach to monitor a user's location automatically in an indoor environment. A low cost BLE beacon is worn by the user and worked as a tracking target. The BLE beacon broadcasts regularly (every 100millis to 1000millis). The sensing system is composed of a few BLE enabled Raspberry Pis that are strategically positioned around the home to maximize detection and triangulation/ fingerprinting. The BLE antennas mounted on the Raspberry Pis are used as the sensing module that are used to detect the BLE packets that are sent periodically from the BLE beacons. In the sensing stage, there is no operation needed from the user given that the sensors automatically sense the BLE beacon worn by the user and record the sensed raw data (the MAC address of the BLE beacons and its corresponding RSSI) to the Raspberry Pi which is then uploaded to a server. Initial data processing is done on the Raspberry Pi and processed data will be sent to the server for further analysis including the training of a machine learning classifier to recognize the location of the tracking object. The overall framework of the system is illustrated in Fig. 1.

A. BLE Beacons

A series of different types of BLE beacons have been used in the study as the tracking targets. The tracker beacons used in this study include the Estimote beacons [45] and JAALEE beacons [46]. These beacons are designed for the purpose of indoor localization and proximity detection related purposes. The broadcast intervals of these beacons are around 1 second (1Hz) which can be modified through a mobile application. The advantage of these beacons is the battery can last for a few months, up to several years.

Nevertheless, there is an increasing popularity for smart watches and wristbands. Most of these bands use BLE technology to communicate with a smart phone. Unlike the tracker BLE beacons, the broadcasting frequency of some smart wearables are not changeable and are usually lower than that of the tracker BLE beacons. This can be an issue if the aim of a study is to monitor the trajectory of the user in an indoor environment and in real time however these wristbands can still be used in detecting the stay points in the indoor environment. In this work, experiments have been carried out on different types of currently available commercial BLE wearables on their broadcasting frequency and detection accuracy, which will benefit the future work related to BLE beacons based low cost indoor positioning system (See Section V.B.3).

B. Raspberry Pis

To sense the Bluetooth packets sent by the BLE beacons, a Bluetooth 4.0 LE module (BLE CSR 4.0) is attached to a Raspberry PI via a USB interface as shown in Fig. 2. The Raspberry Pi uses the BlueZ package [47] to sense the raw RSSI data from the BLE beacons. Data is saved locally to the Pi and then regularly uploaded to a web server. An example of the sensed raw data is shown in Fig. 2. Only the MAC address used to identify the beacon and its corresponding RSSI value were saved in this study.

IV. Methodology

A. Position Calculation

1) RSSI & DISTANCE

To localize the user, the first proposed method uses the changes in RSSI signal with respect to the signal propagation distance. The relationship between the RSSI and distance is

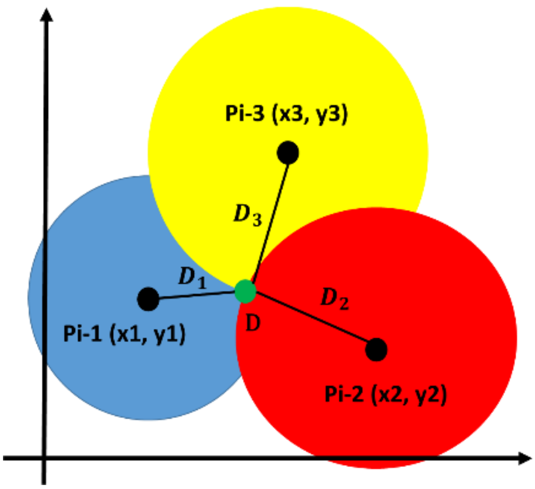

FIGURE 3. Trilateration used in our sensing system

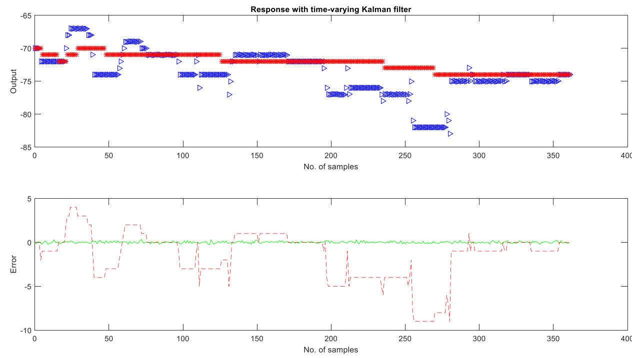

FIGURE 4. Raw RSSI values and RSSI values filtered by Kalman filter (the blue plot is the raw RSSI values while the red plot is the filtered results)

modelled by using a path loss model as the equation below [48].

$$RSSI = -10 * m * lgD + A \tag{1}$$

$$D = 10^{[(A-RSSI)/(10*m)]} \tag{2}$$

where D is the distance. The parameters m and A are determined in real field tests. Line of sight experiments have been done to calculate these parameters (See Section V.A.1).

2) TRILATERATION

We also implemented a trilateration-based algorithm which is illustrated in Fig. 3. Based on the known location of the three reference sensors (Pi-1, Pi-2, and Pi-3), equations (3) and (4) are used to calculate the position of the beacon. In the Cartesian coordinate system, the coordinates of the three sensors Pi-1, Pi-2, and Pi-3 are (x1, y1), (x2, y2) and (x3, y3). The distance between the beacon (green dot D (x, y) in Fig. 3) and three sensors (D1, D2, and D3) can be determined by the Euclidian distance equations shown below:

$$\begin{cases} D_1 = \sqrt{(x-x_1)^2 + (y-y_1)^2} \\ D_2 = \sqrt{(x-x_2)^2 + (y-y_2)^2} \\ D_3 = \sqrt{(x-x_3)^2 + (y-y_3)^2} \end{cases} \tag{3}$$

To simplify the equations, the location of the sensor Pi-1 (x1, y1) is chosen as the origin point (0,0). The simplified equation is as below:

$$\begin{cases} x = \frac{{D_1}^2 - {D_2}^2 + {x_2}^2}{2*x_2} \\ y = \frac{{D_1}^2 - {D_3}^2 - 2*x_3*x + {y_3}^2 + {x_3}^2}{2*y_3} \end{cases} \tag{4}$$

3) KALMAN FILTER BASED RSSI NOISE SMOOTHER

Due to different obstructions in an indoor environment, the raw RSSI can be very noisy. Even at a fixed location, the RSSI values may vary significantly (See Section V.B.1). Therefore, a Kalman filter is used to smooth the raw RSSI values. In this case, the estimation of the state is based on the estimation of the previous state A=1. In the measurement process H=1. The equations for state process and measurement process are as follows:

State process:

$$x_k = x_{k-1} + w_k \tag{5}$$

Measurement Process:

$$z_k = x_k + v_k \tag{6}$$

Process noise covariance is Q and sensor noise covariance is R.

Time update equation:

$$\hat{x}_k^{\,-} = \hat{x}_{k-1} \tag{7}$$

$$P_k^{\,-} = P_{k-1} + Q \tag{8}$$

Measurement update equation:

$$K_k = P_k^{\,-}(P_k^{\,-} + R)^{-1} \tag{9}$$

$$\hat{x}_k = \hat{x}_k^{\,-} + K_k(z_k - \hat{x}_k^{\,-}) \tag{10}$$

$$P_k = (I - K_k)P_k^{\,-} \tag{11}$$

Parameters tuning the Kalman filter [49] were performed based on a trial and error basis. In this study the selected parameters are as shown below. Process noise covariance Q = 1*e-5, Sensor noise covariance R = (0.1)^2, and $P_0^{\,-}$=1. As it can be seen in the Fig. 4, the fluctuation of the Raw RSSI values have been significantly decreased after applying the Kalman filter. After smoothing of the raw RSSI values, the smoothed values are fed to the loss path model to calculate the distance between the beacons and the sensors. Then the calculated distance is used in the above trilateration algorithm Eq. (3) and Eq. (4) to locate the user's position.

B. Fingerprinting for Indoor Localization - Position Calculation

We tested another approach based on fingerprinting which usually comprises of two-phase training and predication (Fig. 5). The first phase is training using the features created from the raw sensed RSSI signals together with known locations

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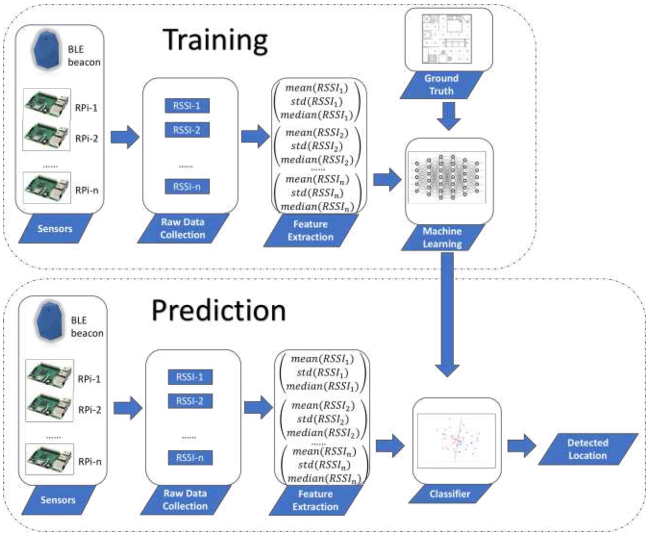
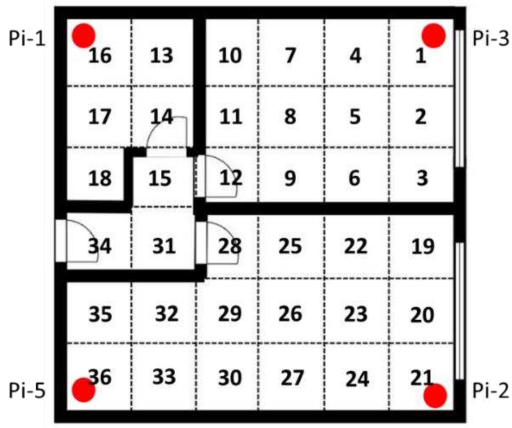
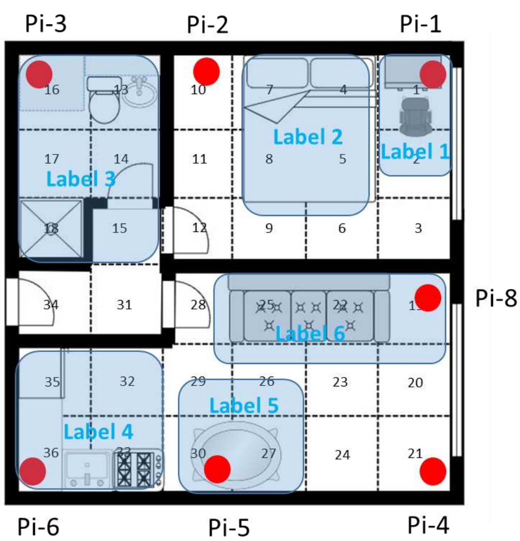


FIGURE 5. Overview of the Fingerprinting based method in our system.



(a) Grid (1m*1m) Based, location of 36 grids



(b) LoI based, location of 6 interest areas

FIGURE 6. Grid and LoI based classification – indoor map view (in (b) the blue circles are the locations of labeled LoI).

(ground truth). Ground truth was manually labelled by the user. The user was asked to record the start and end time at each stayed area (evaluation point) in the tracking environment. Raw data collection is carried out by the RPi sensors. The RSSI values collected by different RPi sensors were used to generate the features. For each of the RPi sensors, the mean, standard deviation and median of the RSSI values were used as features for classification. In the training phase, all the collected data were labelled with ground truth in order to train classifiers. The labelling was generated when the beacons had been placed in the home-setting environment. Different classifiers were used in this work including (i) Naïve Bayes (ii) SMO (iii) Random Forests (iv) BayesNet and (v) J48. For data segmentation, a non-overlapping windowing method was selected. Window intervals between 1 and 10 seconds were analysed. In the prediction phase, the BLE beacon was localised by using the sensed RSSI values to and the built classifiers.

For the fingerprinting method, two types of scenarios were proposed.

1) GRID BASED CLASSIFICATION

A rectangular area of 36 m^2 was selected and divided into 36 grids, each grid was 1m×1m as shown in Fig. 6 (a), where four Raspberry Pi based sensors were installed. The data collected from all the RPis were used to create the features for each of the grids. In order to train the classifier, experiments had been done to collect data from all the 36 grids (locations). Features were extracted from processed RSSI signals including mean and standard deviation.

2) LOCATION-OF-INTEREST (LOI) BASED CLASSIFICATION

Only certain locations in a home were of interest, for example, beds (Label1), desks (Label2), toilets (Label3), hobs (Label4), tables (Label5), couches (Label6) (Fig. 6 (b)), where seven Raspberry Pi based sensors were installed. The ground truth for these locations were collected to train classifiers and the trained classifiers were used to predict the locations in unseen cases. This method simplified the procedure of the ground truth collection and in this case, the collection of the ground truth could be done by a final user using a simple annotation mobile app allowing them to annotate the different locations, increasing the wide applicability of the method. The selection of the LoI was based on the areas of interest and the socket availability in a home are considered.

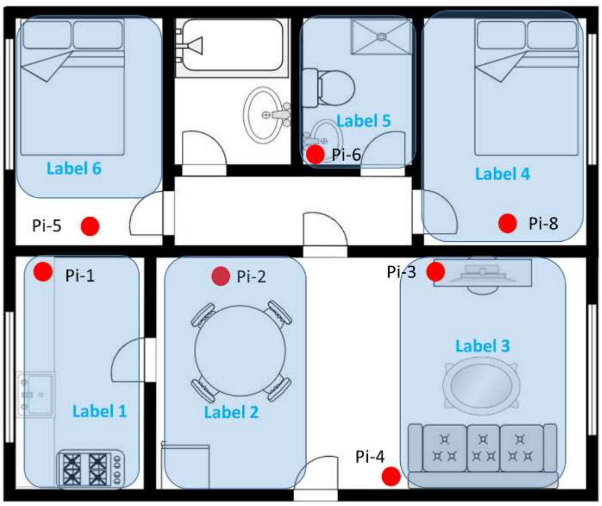
V. EXPERIMENTAL SETUP AND RESULTS

Experiments were carried out in order to assess the accuracy of the different approaches. They were carried out in realistic conditions in an inhabited flat to evaluate the detection accuracy of the two proposed sensing methods.

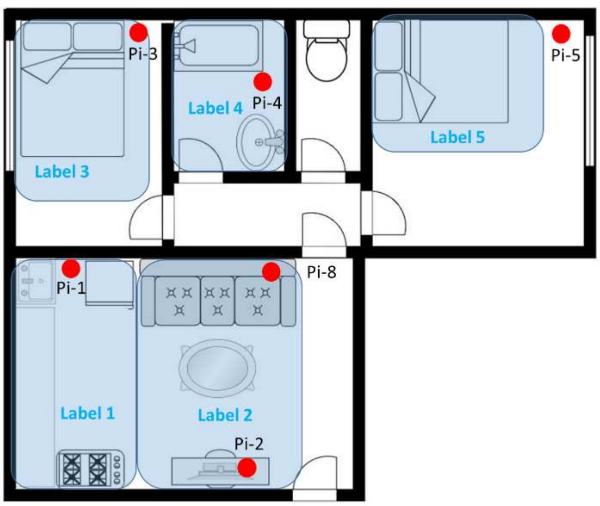
A. Experiment Set-Up

1) LINE OF SIGHT EXPERIMENT.

FIGURE 7. **Line of sight experiment set-up.**



(a) Home #2



(b) Home #3

FIGURE 8. **Floor Plan of Home #2 and #3 with the sensors' location.**

FIGURE 9. **Different commercial wearables used as the BLE beacons.**

TABLE I
EXPERIMENT HOME SETTINGS

Home #	Home Type	No. of Installed Sensors	Area (m^2)	Testing days
#1	One-bed Flat	6	36	7
#2	Two-bed Flat	6	58	1
#3	Two-bed Flat	6	108	1

Experiments have been carried out in different homes.

In order to calculate the path loss model as describe in Section IV.A.1, we have carried out a line of sight experiment to calculate its unknown parameters: We installed the sensors and BLE beacons in an empty corridor. The sensors were left in fixed positions. Then we changed the position of the BLE beacons for various distances between 0 and 14 meters, in one-meter steps (See Fig. 7). At every position, we collected data for two minutes, provided an average of 120 RSSI samples per RPi.

2) INDOOR LOCALISATION EXPERIMENT.

The experiments were done in three different home settings as described in Table I. Only one user was involved in the tracking for all three different homes in this study. The sensing system and tracking object set-up is shown in Fig. 6 (b) (Home #1) and Fig. 8 (Home #2 and 3). The location of the sensors (red dot) were restricted by the location of the power sockets. The experiments had been mainly done in Home #1 and different experiments had been done by implementing the proposed sensing system in two different classification scenarios – grid based and LoI based. Results from these two scenarios are presented in Section V.B.2.

For the experiments done in Home #1, both tracker beacons and smart wearables (Fig. 9) were tested. Experiments were carried out in two ways: static tests and dynamic tests. For the static tests, the beacons were placed in a fixed location at each labelled location (e.g. Label 1, Label 2 etc. in Fig. 8) during the testing period. For the dynamic tests, the beacons were worn by the user and movement of the user was within 1 square meter around the center of labelled location. For example, during the dynamic testing, the user was asked to work on a laptop at the desk, watch movies on the couch, and cook in the kitchen etc.

B. Experiment Results

1) LINE OF SIGHT EXPERIMENT.

The raw RSSI values were collected in order to analyze value changes against the distance. Our experiments showed that the broadcasting intervals of the beacons were not fixed. Multiple

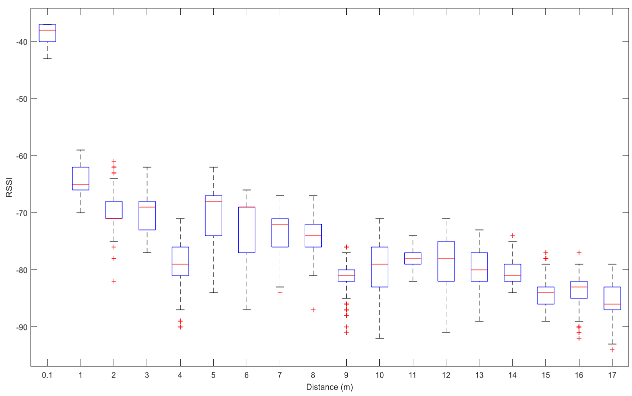


FIGURE 10. **A box plot of raw RSSI values collected at different locations in a line of sight experiment.**

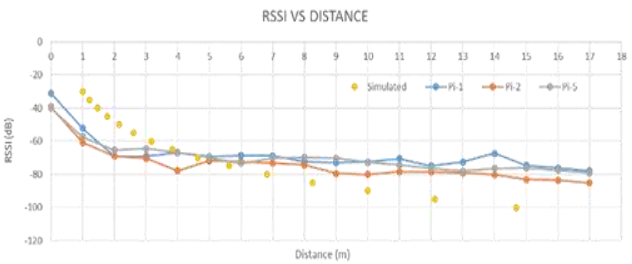


FIGURE 11. **Curve fitting for RSSI values at different distance for different sensors of one beacon (for different BLE beacons sensed by three RPis).**

TABLE II
PARAMETERS OBTAINED FROM CURVE FITTING

Tracker BLE Beacon1:			Tracker BLE Beacon2		
Parameters	Value	95% CI	Parameters	Value	95% CI
m	1.876	(1.644, 2.109)	M	2.119	(1.895, 2.343)
A	-60.17	(-62.31, -58.02)	A	-60.80	(-62.88, -58.73)
R^2	0.948		R^2	0.968	

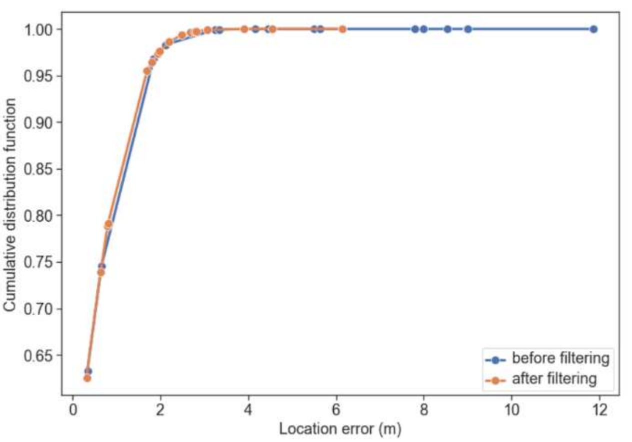


FIGURE 12. **CDF comparison of location errors before and after filtering for line of sight experiment.**

RSSI readings were recorded within one second and sometimes only one RSSI reading was recorded every few seconds. It also differed from beacon to beacon. More importantly, the raw RSSI values can vary significantly even at fixed locations. A box plot (Fig. 10) is used to illustrate the changes of the RSSI at different fixed locations for the line of sight experiment. Therefore, the smoothing method for RSSI is proposed as descried in Section IV.A.3.

Data collected from the line of sight experiment was used to model the path loss model as described in Section IV.A.1. The data from different sensors and curve fitting result are as shown in Fig. 11. In order to determine the parameters in Eq. (2), the curve fitting was applied on the raw data from the in line experimental tests. The pass loss model parameters obtained through the curve fitting tool in MATLAB are shown in Table II.

To evaluate the path loss model, the estimation of the error was calculated based on the line of sight experiment. The errors were obtained by comparing the actual distance with the calculated distance from the path loss model. In addition, Kalman filer was used to smooth the noise from the raw RSSI. Table III shows the actual distance and computed distance from the path loss model before and after the Kalman filtering. According to the results from line of sight experiment in Table III, the average location error is 0.6 within 3 meters. Fig. 12 shows the comparison of cumulative distribution functions (CDF) of the location errors both before the filtering and after filtering and it can be clearly seen that after filtering reaches high probability faster.

2) INDOOR LOCALISATION EXPERIMENT - FINGERPRINTING BASED METHOD.

Grid based classification.

The floor plan was divided into 36 grids, each grid 1m*1m. The averaged RSSI for each of the 36 grids were calculated. A heat map was created to show the change in RSSI in the home setting. The location of the Pi is shown in Fig. 13. A 10 cross-fold validation was used to assess the performance of a range of selected classifiers, including BayesNet, Naïve Bayes, Random Forest, SMO and J48, and the average accuracy is 95.94%. The classifications were implemented using WEKA. The error rate for each of the grid is shown in the Fig. 14, and it can be seen that 90% of the grids have error rates under 0.1.

Location-of-interest based classification.

The grid-based classification method presents good accuracy; however, it is very complicated to obtain the ground truth. As our requirement is to provide a self-installable technology, obtaining the ground truth for every grid for a user would be challenging. Furthermore, we are only interested in users' location for context awareness. The locations in a home setting for example, bed, couch, dining table, hob and toilet are the locations of interest. Therefore, by using the location-of-interest based method, we only need to collect the ground truth in these key locations. In Home #1, we carried out experiments

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TABLE III LINE OF SIGHT ENVIRONMENT – EMPTY CORRIDOR

Beacon 1: (CE:14:C8:E6:B3:FC) before filtering				Beacon 1: (CE:14:C8:E6:B3:FC) after filtering			
Averaged RSSI	Actual Distance (m)	Computed distance (m)	Error (m)	Averaged RSSI	Actual Distance (m)	Computed distance (m)	Error (m)
-60.74	1	0.34	0.66	-64.65	1	1.64	0.64
-69.04	2	2.66	0.66	-68.92	2	2.81	0.81
-70.30	3	2.66	0.34	-70.23	3	3.32	0.32
-77.82	4	2.15	1.85	-79.05	4	10.14	6.14
-71.86	5	2.88	2.12	-69.94	5	3.20	1.80
-72.31	6	2.66	3.34	-71.73	6	4.02	1.98
-73.24	7	2.84	4.16	-73.56	7	5.06	1.94
-74.35	8	4.75	3.25	-73.96	8	5.32	2.68
-79.57	9	4.55	4.45	-81.34	9	13.55	4.55
-80.01	10	4.36	5.64	-79.55	10	10.80	0.80
-78.48	11	3.21	7.79	-77.67	11	8.52	2.48
-78.67	12	6.49	5.51	-79.17	12	10.30	1.70
-79.22	13	4.02	8.98	-79.08	13	10.18	2.82
-80.28	14	2.14	11.86	-79.86	14	11.23	2.77
-83.22	15	7.01	7.99	-83.97	15	18.90	3.90
-83.59	16	6.99	9.01	-83.67	16	18.20	2.20
-85.26	17	8.47	8.53	-84.44	17	20.07	3.07

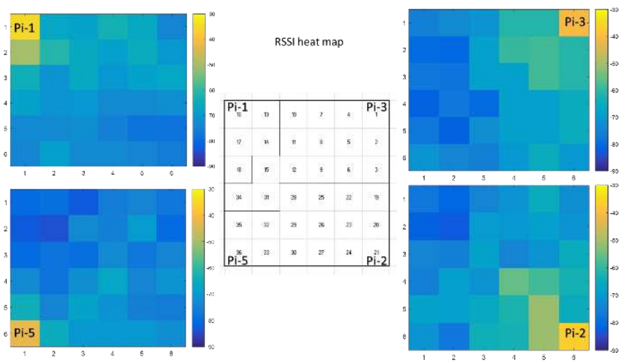

FIGURE 13. Heat map of different sensors in grid-based scenario in Home #1.

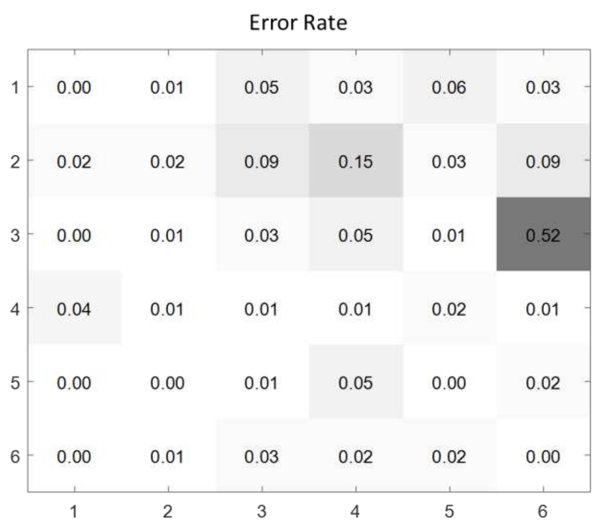

FIGURE 14. Error rates of each grid in grid-based scenario in Home #1

TABLE IV
STATIC EXPERIMENTAL RESULT
(AT HOME #1, TRACKER BLE BEACON2)

Classifier	Precision	Recall	F-Measure
BayesNet	96.1%	96.1%	96.1%
NaiveBayes	92.9%	92.7%	92.7%
SMO	93.7%	93.6%	93.7%
J48	98.3%	98.3%	98.3%
RandomForest	**99.4%**	**99.4%**	**99.4%**

TABLE V
STATIC EXPERIMENTAL RESULT
(AT HOME #1, TRACKER BLE BEACON2)
(1% TRAINING DATA, 99% TEST DATA)

Classifier	Precision	Recall	F-Measure
BayesNet	92.7%	92.6%	92.6%
NaiveBayes	92.4%	92.3%	92.3%
SMO	92.5%	92.3%	92.3%
J48	89.4%	89.3%	89.3%
RandomForest	**95.3%**	**95.2%**	**95.2%**

over multiple days including both static tests and dynamic tests. During the static tests, the sensors were kept stationary during the tests and in total 78440 samples had been collected. The experimental results for different classifiers are presented in Table IV. In our dataset, we have partitioned 80% as the training datasets and 20% as the testing datasets. In real world scenario, it may not be feasible to collect so many samples, therefore, we had also trained the classifiers using only 1% of the total collected samples for static tests in Home #1. As shown in Table V, the random forest classifier had the best performance with precision and recall above 95%. It only takes two minutes at each LoI to collect the data to train the classifiers in a new environment.

From Table IV, it can be seen that accuracy is higher than 99% for a tracker BLE beacon in a static scenario. However, in the real-world scenarios, the devices will be worn by users rather than being positioned on a flat surface. Therefore, we

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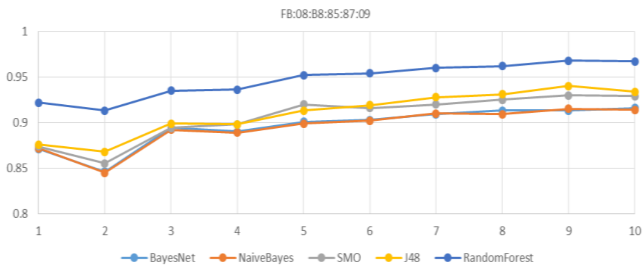

FIGURE 15. System performance under different feature selection window by using a tracker BLE beacon.

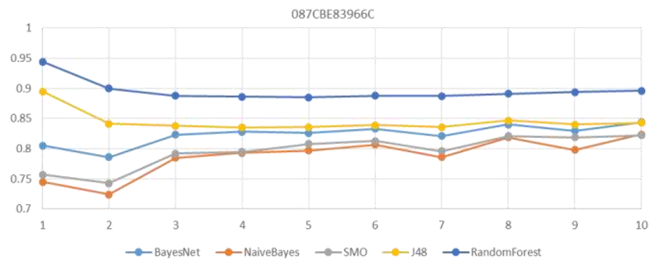

FIGURE 16. System performance under different feature selection window by using a smart wearable.

TABLE VII
DYNAMIC EXPERIMENTAL RESULT (AT HOME #1) (5% TRAINING DATA, 95% TEST DATA)

Beacon Type	Classifiers	Precision	Recall	F-Measure
Jaalee		91.3%	91.2%	91.2%
Estimote1		89.1%	89.1%	89.1%
Estimote2		90.2%	90.2%	90.1%
Estimote3	Random Forest	89.8%	89.6%	89.6%
Mi band1		84.2%	84.2%	84.1%
Mi band2		87.4%	87.1%	87.1%
Lem basic		82.8%	82.7%	82.7%
Lem advance		82.6%	82.5%	82.5%

TABLE VIII
EXPERIMENT RESULTS OF BLE BEACONS ON DIFFERENT LIMB SEGMENTS OF A SUBJECT

Location of the sensor	Classifier	Precision	Recall	F-Measure
Tracker Beacon 1 (Left Leg)	BayesNet	99.7%	99.7%	99.7%
	NaiveBayes	99.7%	99.7%	99.7%
	Kstar	**99.8%**	**99.8%**	**99.8%**
	J48	98.5%	98.5%	98.5%
	RandomForest	99.7%	99.7%	99.7%
Tracker Beacon 2 (Right Leg)	BayesNet	97.0%	97.0%	97.0%
	NaiveBayes	95.8%	95.8%	95.8%
	Kstar	97.0%	97.0%	97.0%
	J48	96.2%	96.2%	96.2%
	RandomForest	**97.9%**	**97.9%**	**97.9%**
Tracker Beacon 4 (Left Arm)	BayesNet	94.5%	94.5%	94.5%
	NaiveBayes	92.2%	92.1%	92.1%
	Kstar	93.9%	93.7%	93.7%
	J48	91.1%	91.1%	91.1%
	RandomForest	**96.1%**	**96.1%**	**96.1%**
Tracker Beacon5 (Trunk)	BayesNet	95.7%	95.7%	95.7%
	NaiveBayes	93.7%	93.7%	93.6%
	Kstar	95.7%	95.7%	95.7%
	J48	93.1%	93.1%	93.1%
	RandomForest	**96.3%**	**96.3%**	**96.3%**

TABLE VI
DYNAMIC EXPERIMENTAL RESULT (AT HOME #1) (80% TRAINING DATA, 20% TEST DATA)

Beacon Type	Classifiers	Precision	Recall	F-Measure
Jaalee	BayesNet	91.5%	91.4%	91.4%
	NaiveBayes	91.7%	91.5%	91.5%
	SMO	93.0%	92.9%	92.9%
	J48	93.5%	93.5%	93.5%
	RandomForest	**96.7%**	**96.7%**	**96.7%**
Estimote1	BayesNet	88.1%	87.9%	87.9%
	NaiveBayes	86.8%	86.6%	86.6%
	SMO	89.3%	89.2%	89.2%
	J48	90.4%	90.4%	90.4%
	RandomForest	**96.1%**	**96.0%**	**96.0%**
Estimote2	BayesNet	89.3%	89.3%	89.3%
	NaiveBayes	88.6%	88.5%	88.5%
	SMO	91.5%	91.4%	91.4%
	J48	92.3%	92.3%	92.3%
	RandomForest	**95.1%**	**95.1%**	**95.1%**
Estimote3	BayesNet	87.9%	87.7%	87.7%
	NaiveBayes	85.4%	84.9%	84.9%
	SMO	88.5%	88.5%	88.5%
	J48	90.5%	90.5%	90.5%
	RandomForest	**96.4%**	**96.3%**	**96.3%**
Mi band1	BayesNet	81.0%	81.0%	80.9%
	NaiveBayes	74.5%	74.6%	74.3%
	SMO	75.8%	75.5%	75.4%
	J48	90.1%	90.1%	90.1%
	RandomForest	**95.4%**	**95.3%**	**95.4%**
Mi band2	BayesNet	85.2%	85.2%	85.2%
	NaiveBayes	81.1%	81.1%	81.1%
	SMO	81.2%	81.1%	81.1%
	J48	94.9%	94.9%	94.9%
	RandomForest	**98.0%**	**98.0%**	**98.0%**
Lem basic	BayesNet	81.0%	81.0%	80.9%
	NaiveBayes	74.5%	74.6%	74.3%
	SMO	75.8%	75.5%	75.4%
	J48	89.6%	89.6%	89.6%
	RandomForest	**94.8%**	**94.8%**	**94.8%**
Lem advance	BayesNet	78.9%	78.8%	78.8%
	NaiveBayes	74.8%	74.7%	74.7%
	SMO	74.2%	73.9%	73.9%
	J48	89.7%	89.7%	89.7%
	RandomForest	**95.1%**	**95.0%**	**95.0%**

tested accuracy in a dynamic experimental scenario where all the tracker beacons were placed in the pocket of a person and all the smart wearables were worn by the human subject. The dataset was split again into 80% as training data and 20% as testing data. In addition, the dynamic experimental tests were carried out over four consecutive days in order to explore the relationship between window size and classification accuracy. Performance was tested with different window sizes. As shown in Fig. 15 & 16, the tracker BLE beacon and smart wearable behaved differently when the window size was changed. In Fig. 15, for example, the selection of the window size can affect the performance of the classifier for the Jaalee beacon: for all classifiers, a maximum precision is achieved with a window size of 9 sec. For other beacons e.g. the smart wearables, the best results are achieved with a window size of 1 sec (see Fig. 16, the classifiers J48 and the Random Forest classifiers obtain the highest precision with a window size of 1 sec). The classification results of different beacons are shown in Table VI. Samples collected for the dynamic experimental tests were 59520 for each BLE beacon and eight

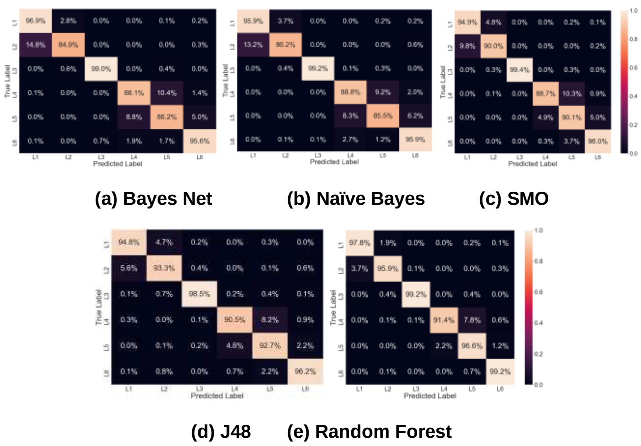

FIGURE 17. **Confusion matrix for a tracker beacon using a window size of 9 sec.**

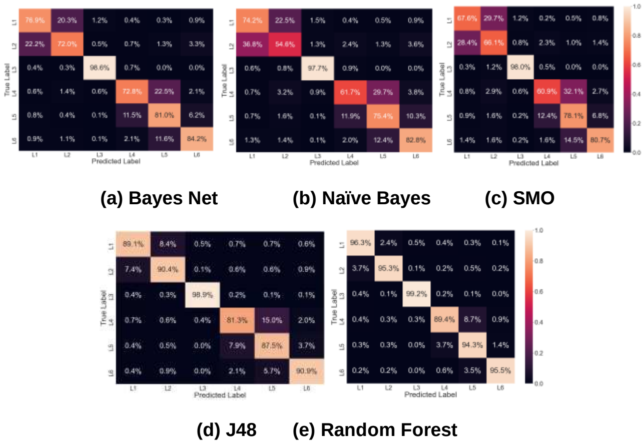

FIGURE 18. **Confusion matrix for a smart wearable beacon using a window size of 9 sec.**

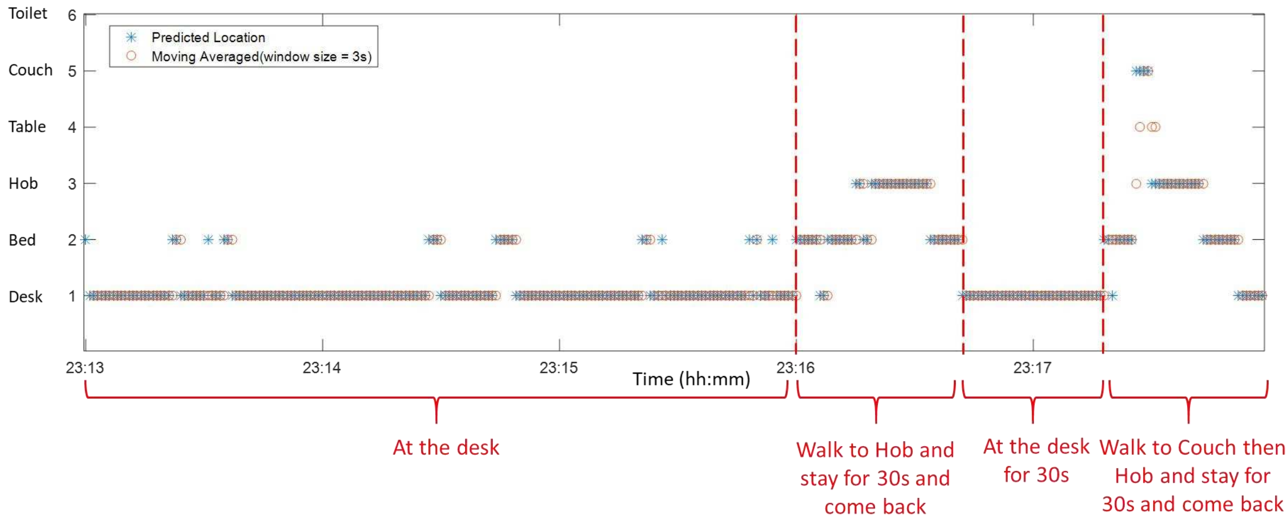

FIGURE 19. **Location Prediction of a dynamic walking test**

beacons were tested. However, we only need very small number of samples to build a classifier which is able to generalize on future data. In Table VII, we built a classifier using only 5% data and the precision and recall can both achieve above 90%.

The normalized confusion matrix of both tracker beacon and smart wearable beacon are shown in Fig. 17 and Fig. 18 respectively. It can be seen that by using classifiers J48 and Random Forest, all the labels achieved classification accuracies over 90%. Label 2 and Label 4 proved more challenging in correctly classification since that fact that Label 1 is close to Label 2 and Label 4 is very close to Label 5 (see Fig. 6 (b)).

In order to select the best position to attach the BLE beacon on a human subject, different BLE beacons have been attached on different parts of the body to explore how the location of the BLE beacons affect the positioning accuracy. The results in Table VIII shows that localization accuracy is above 90% regardless of the attachment location of the BLE Beacons. Therefore, the sensing system accuracy is not significantly affected by the location of the BLE beacons. The Beacons can be attached on different segments of the body according to the need of the application. For example, for people living with dementia or those with significant physical disability, the BLE beacon can be attached onto clothing.

Fig. 19 shows the results of another dynamic test at Home #1, of which the user was asked to follow a known path. The user sat in front of the desk for 3 minutes and walked to the hob in the kitchen and stayed there for 30 seconds and came back to the desk for another 30 seconds. Then the user walked to the couch in the living room and then walked to the hob in the kitchen and stayed there for 30 seconds and came back to the desk at the end of the test. It can be seen from Fig. 19, the dynamic change of the position can be tracked accurately most of the time. There is some error in the previous 3 mins where the location of desk has been misclassified as bed, it is mainly because the desk is so close to the bed as seen in the floor plan

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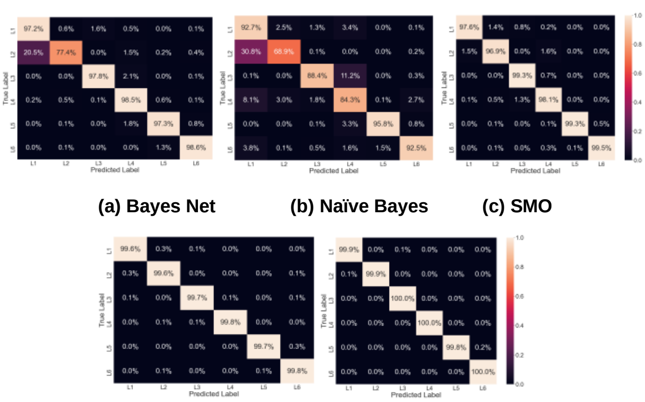
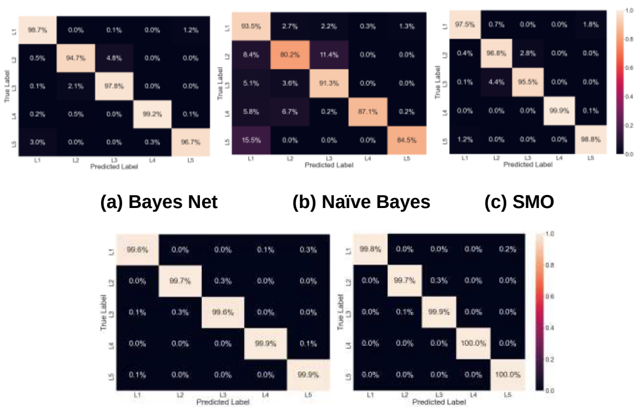


(a) Bayes Net (b) Naïve Bayes (c) SMO

(d) J48 (e) Random Forest

FIGURE 20. Normalized confusion matrix of different classifiers in Experimental home #2



(a) Bayes Net (b) Naïve Bayes (c) SMO

(d) J48 (e) Random Forest

FIGURE 21. Normalized confusion matrix of different classifiers in Experimental home #3

TABLE IX
EXPERIMENT RESULTS IN HOME #2 & HOME #3 (80% TRAINING, 20% TEST)

Home #2			
Classifier	Precision	Recall	F-Measure
BayesNet	95.1%	94.6%	94.5%
NaiveBayes	89.4%	87.8%	88.0%
SMO	98.6%	98.6%	98.6%
J48	99.8%	99.8%	99.8%
Random Forest	**99.9%**	**99.9%**	**99.9%**
Home #3			
Classifier	Precision	Recall	F-Measure
BayesNet	97.2%	97.1%	97.1%
NaiveBayes	89.2%	87.5%	87.9%
SMO	97.5%	97.5%	97.5%
J48	99.7%	99.7%	99.7%
Random Forest	**99.9%**	**99.9%**	**99.9%**

TABLE X
EXPERIMENT RESULTS IN HOME #2 & HOME #3 (1% TRAINING, 99% TEST)

Home #2			
Classifier	Precision	Recall	F-Measure
BayesNet	89.9%	89.6%	89.6%
NaiveBayes	86.9%	86.0%	86.2%
SMO	94.9%	94.8%	94.8%
J48	94.3%	94.2%	94.2%
Random Forest	**98.1%**	**98.1%**	**98.1%**
Home #3			
Classifier	Precision	Recall	F-Measure
BayesNet	88.8%	87.9%	88.1%
NaiveBayes	88.6%	85.8%	86.4%
SMO	95.1%	94.8%	94.8%
J48	94.5%	94.5%	94.5%
Random Forest	**98.8%**	**98.8%**	**98.8%**

TABLE XI
COMPARISON BETWEEN DIFFERENT WEARABLES

Beacon Type	Average Advertising Intervals (s)	Cost (£)	Accuracy (in positioning)	Battery Life
Jalee Beacon (black)	2.24	£10	96.7%	About 1 year
Estimote (Beacon Mint)	1.80	£15	96.3%	About 2 year
Estimote (Beacon ICE)	1.79	£15	96.0%	About 2 year
Estimote (Beacon Blueberry)	1.80	£15	95.1%	About 2 year
Lem wrist band (basic version)	4.03	£2	94.8%	15 days
Lem wrist band (Advanced version)	3.86	£4	95.0%	7 days
Mi band 1	4.11	£8	95.3%	30 days
Mi band 2	6.04	£16	99.74%	20 days
Fitbit Surge	2.72	£145	88.17%	7 days

in Fig. 6 (b). This type of error can be reduced by applying a moving average method. When the user walked to the hob in the kitchen, the user would need to pass the bed area, which can also be observed from Fig. 19.

In addition, as described in section V.A.2, the system was tested in two other homes which are different in floorplan and floor size to investigate accuracy in different home layouts. Similar as Home #1, the same number of the sensors were used in Home #2 and Home #3. In Home #2 and Home #3, only static tests had been carried out. For Home #2, 45227 samples had been collected from 8 beacons. For Home #3, 61933 samples had been collected from eight different types of BLE beacons. The datasets had been split into training dataset (80%) and test dataset (20%), and the details of the experimental results are shown in Table IX. The confusion matrix of two Homes are presented in Fig. 20 and Fig. 21 respectively. Additionally, we had built classifiers using only 1% samples from the collected dataset and the precision and recall of Random Forest model can still achieve above 95% as in Table X.

3) TEST RESULTS ON DIFFERENT WEARABLE SENSORS.

Experiments were carried out to test different commercial smart wearables in Home #1 using the classifier J48. Our results indicate that these wearables are good enough to be used as the object tracker to track the people for the purpose of indoor localization (Table XI). It is interesting to see that high accuracy is achieved with very cheap devices (e.g. The LEM wrist band can be bought for GBP£5, around USD $10). Wearable sensors should be selected according to the user case. For example, in an application for real-time indoor localisation, a wearable sensor with a small advertising interval should be selected while for long-term indoor life pattern analysis, a wearable sensor with long battery life should be chosen.

VI. CONCLUSIONS

In this work, we proposed a low cost BLE sensing based system for person localization in the home. A BLE beacon is used as the tracking object that attached on the target user. Our BLE sensing based system localizes the position of the BLE beacon through two proposed algorithms. One method used the trilateration algorithm to track the position of the BLE beacon in a known coordinate reference frame. Another method used the fingerprinting-based method to locate the BLE beacon in one of the 36 $1m^2$ grids or one of Location-of-Interest. The smoothing method has been proposed in order to remove the noise of from the raw RSSI values. Our experimental results have shown good accuracy in indoor positioning. From our results, it can be seen that high accuracy can be obtained in localizing around key areas/stay points (table, bed, etc.). Our fingerprinting based method demonstrated that as even with low cost sensors, a high accuracy (>90%) achieved. Our results have shown this is consistently true for different devices in different home settings. In our experiments, we had collected large datasets for evaluation. However, in real world testing, there is no need to collect so many samples. Based on our results from dynamic testing, only 5mins data collection at each labelled location will suffice.

The cost of the overall system is around USD$200 making it scalable for a wide range of people who would benefit from monitoring even if they are only mildly at risk (e.g. people at the early stages of dementia). This may enable longer independent living with beneficial impact to both the individual, their relatives, and the national health system.

In addition, Wi-Fi passive sensing approaches shares the similar working principle with the above BLE sensing approach. It locates the target by tracking the RSSI changes in the tracked object (a Wi-Fi device, usually a smartphone). It can be useful if the mobile phone is the tracked object. There are Wi-Fi modules available that have a smaller size and can be attached to human body as that of a BLE beacon. However, a Wi-Fi device usually consumes more battery than a BLE device (a BLE beacon or a smart watch).

As for future work, we will implement our system in real world applications to investigate the indoor pattern for people with significant physical disabilities and for those with neurological conditions e.g. people living with dementia, people affected by stroke, Parkinson’s disease, epilepsy, etc. This could help the clinicians and doctors understand and diagnose the individuals in home rehabilitation.

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