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Indoor Positioning System using Pedestrian Dead Reckoning and Bluetooth Beacon

Graduate School of Chosun University

Department of Information and Communication Engineering

Rohan Kumar Yadav

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보행자 추측 항법과 블루투스 비컨을 활용한 실내 측위 시스템

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Graduate School of Chosun University

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Advisor: Prof. Jae-Young Pyun

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Table of Contents

List of Figures

List of Tables

Acronyms

IPS	Indoor Position System
IMU	Inertial Measurement Unit
UWB	Ultra Wide Band
RSS	Radios Signal Strength
BLE	Bluetooth Low Energy
TKBE	Trusted K nearest Bayesian Estimation
KNN	K-Nearest Neighbors
GPS	Global Positioning System
IoT	Internet of Thing
RFID	Radio Frequency Identification
PDR	Pedestrian Dead Reckoning
LBS	Location Based Services
WSN	Wireless Local Area Network
RSSI	Received Signal Strength Indicator
AP	Access Point
MMSE	Minimum Mean Square Error
MAP	Maximum a Posteriori
MAVE	Minimum Mean Absolute Value of Error
TCPF	Trust Chain Positioning Fusion
LOS	Line of Sight

Abstract

Integration of Trusted K nearest Bayesian Estimation and Pedestrian Dead Reckoning for Indoor Positioning System

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Location based services are emerging as an important aspect of modern civilization. GPS technology has embraced many areas to provide navigation in outdoor environment, but it has not been quite accepted in the indoor environment due to the interference of the signal. Hence, indoor positioning systems have got more attention because of its wide range of applications. However, this positioning system also suffers from huge error in localization and has less solidity. The main approaches widely used for indoor localization are based on Inertial Measurement Unit (IMU), Bluetooth, Wi-Fi, and Ultra Wide Band (UWB). Specifically among them, the major problem with Bluetooth based fingerprinting is inconsistency in radios signal

strength (RSS), while IMU based localization has drift error that accumulates with time.

To overcome these shortcomings, we concentrate on enhancing the accuracy of the indoor positioning system with integration of two positioning algorithms. This thesis introduces a novel positioning system that integrates IMU sensors and Bluetooth Low Energy (BLE) beacon using fuzzy logic Kalman Filter named Trusted K nearest Bayesian Estimation (TKBE). We propose BLE beacon based positioning using K nearest neighbor (KNN) and Bayesian Estimation where as IMU based positioning uses Pedestrian Dead Reckoning.

Our experiment shows that the proposed BLE beacon based positioning increases the accuracy by 25% as compared to existing KNN based positioning and proposed fuzzy logic based Kalman Filter additionally enhances the accuracy by 15%. Overall, the proposed TKBE gives error less than a meter in our experimental environments.

한글요약

보행자 추측 항법과 블루투스 비컨을 활용한 실내 측위 시스템

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위치 기반 서비스는 현대 사회에서 중요한 기술로 자리잡고 있다. GPS 기술은 야외 환경에서 내비게이션 서비스를 비롯한 다양한 분야에서 활용되어 왔으나, 신호의 간섭과 수신 제한으로 인해 실내 환경에서는 사용이 제한되어 왔다. 때문에, 실내 측위 시스템이 실내 환경에서 다양하게 응용될 수 있는 대안으로 주목받고 있다. 그러나, 실내 측위 시스템 또한 높은 측위 오차와 낮은 신뢰성이라는 문제로부터 자유롭지 못하다. 오늘날 실내 측위에서 주로 사용되고 있는 접근법으로 관성 측정장치 (IMU), 블루투스, 와이파이, 초광대역 무선기술(UWB) 등이 있다. 이들 중에서 블루투스를 기반으로 하는

핑거프린팅 측위 방식은 일정치 않은 무선 신호 세기에 의한 문제점을, IMU 기반의 측위 방식은 시간이 지나면서 누적되는 드리프트 오차에 의한 문제점을 지니고 있다.

이러한 단점들을 극복하기 위해, 우리는 두 가지 측위 알고리즘을 결합하여 실내 측위 시스템의 정확도를 향상시키는 방법에 주목하였다. 본 논문에서는 TKBE (Trusted K nearest Bayesian Estimation)라는 퍼지 로직 칼만 필터를 사용하여 IMU 센서와 저전력 블루투스 (BLE) 기반의 비콘을 결합한 새로운 측위 시스템을 제안한다. 제안 시스템은 BLE 비콘 기반 측위에 K-최근접 이웃(KNN)과 베이지안 추정을 이용하고 IMU 기반 측위에는 보행자 추측 항법을 이용한다.

본 논문에서는 실험을 통해 제안 된 BLE 비콘 기반 측위가 기존 KNN 기반 위치 인식과 비교할 때 정확도를 25% 가량 증가시키고 제안 된 퍼지 로직 기반 칼만 필터는 정확도를 15% 가량 향상시킴을 보여주고 있다. 전반적으로, 제안 된 TKBE 는 실험 환경에서 1 미터 미만의 측위 오차를 보이고 있음을 알 수 있었다.

1. Introduction

1.1 Motivation

Indoor Positioning System (IPS) is a technology used to locate the user in the indoor environment. Unlike Global Positioning System (GPS) that works in outdoor navigation, it is suitable for indoor localization where GPS is unable to track the target due to signal blockade. The extensive use of indoor positioning system in smart buildings, shopping mall, indoor parking, airports, and hospitals has made it quite popular technology in recent market.

People spend their most of the time in indoor environment thus it becomes an important factor for Internet of Thing (IoT) era. Various research has been carried out to provide better performance of IPS using Wi-Fi[1][2], Bluetooth Low Energy (BLE)[3][4], ultra wideband (UWB)[5], Inertial Measurement Unit (IMU)[6] and radio frequency identification (RFID)[7] and many more.

Although, various technologies have come up to refine and stable the performance of indoor positioning system, there still exists some drawbacks due to some trade off considered during designing the model. There is still not ideal indoor localization technique that locates user flawlessly and with better stability. Hence, it is always desirable to improve the positioning performance by exploring various machine learning techniques.

1.2 Objectives

The major objective of this research is to study the conventional methods used in indoor positioning system and identify potentials for improvements. We also aim to discuss various smartphone based sensors used in IPS.

Additionally, we propose novel integration algorithm that can improve the overall accuracy and performance of IPS.

1.3 Contributions

In this thesis, we design an indoor positioning system with Bluetooth Low Energy (BLE) beacons and IMU sensors of the smartphone which are based on probabilistic approach of fingerprinting technique and Pedestrian Dead Reckoning (PDR) respectively. These two methods are combined together through fuzzy logic Kalman filter called Trusted K nearest Bayesian Estimation (TKBE) algorithm.

1.4 Thesis Layout

The reminder of this thesis is organized as follows. Chapter 2 provides the theory and background overview sensors used as well as algorithms associated with it. Chapter 3 discusses relevant previous work in the field of IPS. Chapter 4 describe the algorithms of our proposed IPS independently for each sensors and its fusion. Chapter 5 provides an overview of the experimental setup in the testbeds and its performance evaluation based on obtained results to evaluate our proposed algorithm. Finally, chapter 6 concludes the thesis and presents summary of further research based on the presented work.

2. Theory and Background

2.1 Indoor Positioning System

The market for location-based services (LBSs) has expanded in recent times. Because global positioning system technology cannot play the vital role in indoor environments owing to complications in the line of sight (LOS), many technologies have been proposed to overcome such adverse effects, e.g., Bluetooth, RFID, ultra-wideband (UWB), ZigBee, the wireless local area network, and the inertial measurement unit (IMU) [1], [2]. These techniques make use of wireless signals for location extraction. Some of the methods for extracting the distance of the user are the Time of Flight, Time of Arrival (ToA), and received signal strength indicator (RSSI). For example, ToA uses the packet transmission to estimate the time lags between wireless devices. This method has high precision, but its high hardware costs and implementation difficulties limit its applications. On the other hand, the RSSI usually depends on the environment and surrounding structure and has limited accuracy. Because there is always a tradeoff between accuracy and practicability in designing an LBS, the RSSI, being a very cost-effective method with reasonable accuracy, is currently the most widely used technique for indoor positioning systems.

RSSI-based position estimation for an indoor tracking system is designed using propagation models to estimate the distance between devices [3], [4]. Usually, the propagation models do not take obstacles into consideration; hence, this is not considered an effective method for obtaining the position. However, this problem can be rectified by using fingerprinting techniques, i.e., by matching the trained positioning data with the real-time observed data. In the fingerprinting method, reference points are assigned with the collection of unique signal strengths called fingerprints. The fingerprints are stored in a database and used in the localization phase through pattern recognition and machine-learning algorithms. These techniques can be useful for both deterministic and probabilistic methods [12]. A most common approach like K nearest neighbor can be used as a deterministic approach for indoor positioning system, which is enhanced using the variance in RSSI [13]. Generally, the probabilistic approach introduces mathematical analysis considering the variance of the signal strength to obtain a better result than the deterministic approach.

Another approach for enhancing the indoor positioning system employs IMUs, which consist of an accelerometer, a gyroscope, a magnetometer, and a barometer. The most common approach using IMU sensors for navigation is pedestrian dead reckoning (PDR). Here, the accelerometer is used to estimate the displacement of the user, while the gyroscope and magnetometer are used to calculate the heading direction. PDR is a very low-cost system and does not require additional devices. However, there are drawbacks; e.g., the initial position of the user is required, and the drift error accumulates with time.

To overcome these obstacles, RSSI fingerprinting and IMU-assisted positioning can be combined to eliminate the drawbacks of each method. There are various filtration methods, e.g., the Kalman filter, the Particle filter, and their variants [6], [7]. The Kalman filter is generally used with linear and Gaussian models, whereas the particle filter is used with nonlinear models. The particle filter provides significantly better estimation of the position in noisy and inaccurate measurements. However, it requires higher computation power and is more complex than the Kalman filter [16]. Because minimum computation and complexity are preferred in smartphone environments, considering the memory use and power consumption, the Kalman filter is widely used for removing noise and accurately estimating the location.

2.2 Sensors

Features of smartphones have been improved continuously. Most of them are embedded with multiple sensors that provides various facilities required in daily life. Inertial Measurement Unit (IMU) sensors are essential sensors present in recent smartphones. It helps to estimate the motion and the position of the device that can be used for IPS. These IMU sensors are worth mentioning in this thesis. IMU consist of Accelerometer, Gyroscope, and Magnetic field sensor.

2.2.1 Accelerometer

Accelerometer is one of the IMU sensors and almost all the android devices are provided with three-axis accelerometers. The copious availability of such sensors makes it captivating sensor to consider in various navigation techniques. Accelerometer measures data with respect to its device. An output pattern of accelerometer is shown in Figure 1. The measurement of accelerometer is along x, y and z–axis. Despite of its dependency on orientation of device, there is gravitational force of approximately 9.81 m/s^2 that remains similar in any orientation. Accelerometer has various application like measuring orientation of the phone, obtain speed and distance travelled by integrating the accelerometer value double over time.

2.2.2 Gyroscope

A gyroscope is another IMU sensor that is embedded in most of the android devices. It measures the angular velocity and can be valuable along with the accelerometer and magnetic field sensors to obtain high accurate motion information. It measures the three-axial data which measures the angular velocity in all three axes along the device. Its unit is radians per second (*rad/s*) with respect to its device coordinate system.

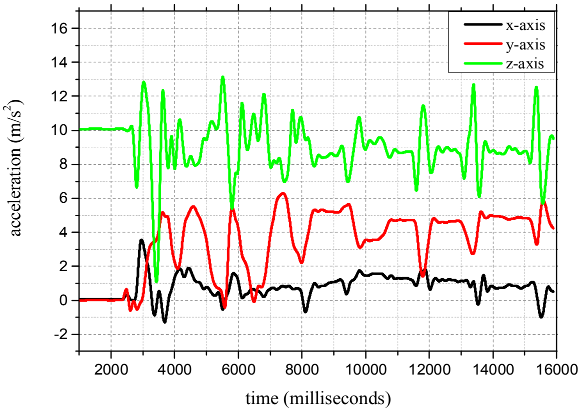


Figure 1. Accelerometer data obtained from Samsung Note 8 by randomly moving device.

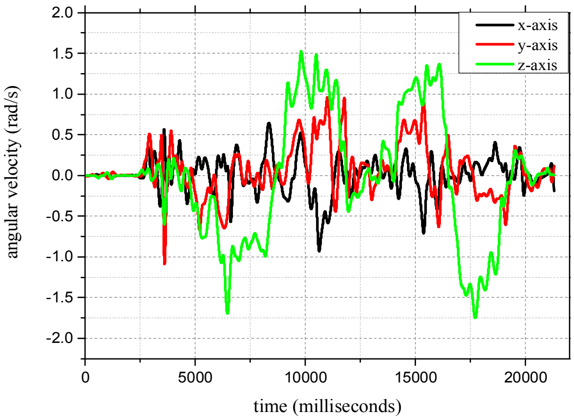


Figure 2. Gyroscope data obtained from Samsung Note 8 by randomly changing its orientation.

Gyroscope is important sensors if used along with magnetic field sensor to detect the change in rotation of device. Gyroscope cannot provide the initial orientation hence cannot replace the magnetic field sensor. For this both has to be utilized to get long term overall orientation of the device. The typical output of the gyroscope is given in Figure 2.

2.2.3 Magnetic Field

A magnetic field sensor is one of IMU sensors that measures the orientation of the device with respect to the magnetic north. Values measured using this sensors are in Earth's magnetic field in each direction namely *x, y,* and *z-axis*. These axes are used to detect the orientation of device with respect to the Earth's surface. Its unit is μT (micro-Tesla). The magnetic sensor of smartphones is very sensitive to the disturbances in the environment which can be unstable and unreliable. Several electronic devices and structural part of the buildings can disturb the pattern of magnetic field. Such disturbances can be used in localization [17]. This sensors is useful factor that provides necessary input during Pedestrian Dead Reckoning (PDR) system.

2.3 Wireless Technologies

Communication through wireless technologies are ruling the world and is most fundamental need of current development. As of many applications, IPS also depends on the wireless communication technologies. These technologies are principally designed for communication between various technologies and has various use in academic and industries. However, these characteristics are now frequently used in indoor positioning techniques. Each technologies has its own advantages of localization. Recently, some of the technologies used in IPS are Wi-Fi, BLE, and UWB. These are briefly explained in this section.

2.3.1 Wi-Fi

Wi-Fi is most commonly used local area networking techniques around the globe. Wireless Access Point (AP) establishes a local network that connects different devices on the network. In terms of LBS, Wi-Fi makes use of either RSSI or angle of arrival (AOA). Commonly, RSSI based positioning is used as wireless positioning techniques[18]. There exists a relation between RSSI and the distance between transmitter and receiver as shown in Figure 3. It states that signal strength decreases with the increase in distance. This relation is known as path loss model and is given by

$$RSSI = PL(d_0) - 10\eta \log_{10}\frac{d}{d_0} + A \ , \tag{1}$$

where $PL(d_0)$ is the path loss at particular reference distance (normally d_0 = 1m), d is distance from the sensor, η is path loss exponent, and A is a Gaussian random variable with zero mean and variance σ^2 [19].

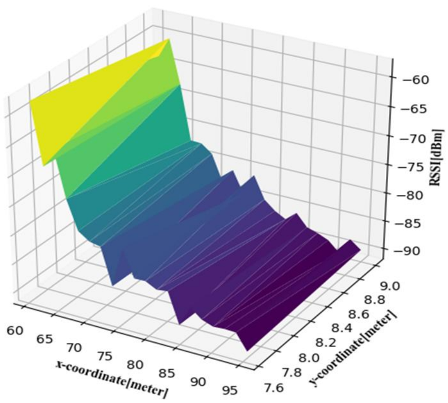


Figure 3. Relationship between RSSI and distance measured.

2.3.2 BLE

Bluetooth Low Energy has evolved from Bluetooth technology precisely to provide service with low energy consumption than the classic Bluetooth. Specifically, it is designed to be applicable in wearable technology, IoT and beacons. Its main function is to broadcast short messages to the nearby Bluetooth enabled devices. Due to its low power consumption and longer battery life, it has become quite popular choice for IPS[20]. Although Wi-Fi are easily available in public areas, it is quite tough to get the location of access points that limits the indoor localization techniques. Hence, the use of BLE based beacons are growing in recent market since, it can be installed in desired place with minimal effort of installation.

2.3.3 UWB

Ultra wideband radio is one of the technology that has capabilities of high bandwidth communication over short distances. It is also very low energy consuming technology that is used in many applications that require high bit rate at short range. Its main benefit is that it transmits the short pulses with the sharp transition without any carrier or baseband. A carrier is modulated by a conventional radio giving a narrow spectral peak. However, it can also be used at medium to long ranges which require low bit rate due to its power characteristics. UWB makes use of short pulse over spectrum of large frequency to send the data. This characteristics have been proven to be very useful for high precision data. UWB is popular because of its less vulnerability to reflections when passing through the obstacles compared to other technologies using smaller bandwidth[21].

2.4 Estimation Techniques

IPS has various estimation techniques based on RSSI. Some of them are trilateration, proximity, and fingerprinting. Most of them are based on calculating distance of the user to various APs whereas fingerprinting approach is carried on by pattern recognition and machine learning techniques.

2.4.1 Trilateration

Trilateration method uses the RSSI, frequency, MAC address and real coordinates of APs. The RSSI obtained from APs are used to calculate distance between the receiver and the AP. Since, the signal strength decreases exponentially with increase in distance, this property can be considered for trilateration based positioning. The distance obtained from RSSI is represented as a circle with radius around the AP. Hence, the trilateration refers to the intersection of three such circle from three different APs. So at least three APs are needed for trilateration. This can be shown by equations given below

$$d_1^2 = (x - x_1)^2 + (y - y_1)^2 \tag{2}$$

$$d_2^2 = (x - x_2)^2 + (y - y_2)^2 \tag{3}$$

$$d_3^2 = (x - x_3)^2 + (y - y_3)^2, \tag{4}$$

where (x_1, y_1), (x_2, y_2), and (x_3, y_3) are the coordinates of AP1, AP2, and AP3 where as d_1, d_2, and d_3 are the estimated distance. The model of trilateration is shown in Figure 4.

Wi-Fi and BLE based beacons are most commonly used technologies for trilateration based indoor localization. Recently, LTE has been approached for using trilateration but it lacks the precision because of the long distance between the base stations.

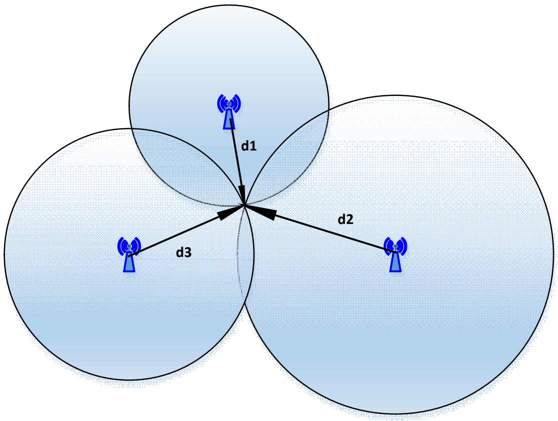


Figure 4. Concept of trilateration, position estimation using intersection of three circle created by the distance between receiver and APs.

2.4.2 Proximity

It is a technique that is used to estimate the device's location as the same location of AP that it receives. It gives the position as the location of AP rather than providing the location in coordinates. It is only preferred to locate an object because of its low accuracy. Various Wi-Fi, Bluetooth, BLE beacons can be used to estimate the position of object near its AP using proximity [22]. Actually, fingerprinting can be considered as the approach for proximity based positioning. Hence, acoustic sound can be used as information in some indoor localization as shown in [23].

2.4.3 Fingerprinting

The fingerprinting technique is widely used approach in IPS. It is based on two phases: offline phase and online phase[24].

Offline phase: RSSI along with various distinctive features are measured at referenced positions and these measured value and the location of its referenced position are stored in the database. This stored database is called as fingerprinting map.

Online Phase: In this phase, the localization of the target takes place. The target at any location sends the current measured RSSI along the distinctive features to the database and then various machine learning algorithms are used to estimate the current location based on how close the measured value are with compared to stored fingerprinting map [25]. The procedure of fingerprinting is shown in Figure 5.

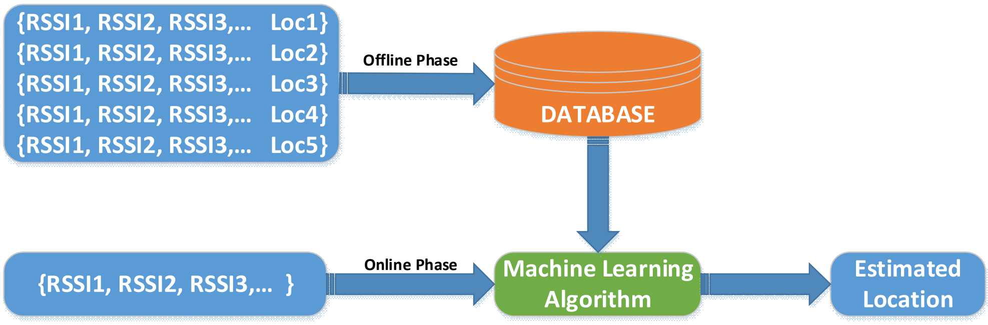


Figure 5. Procedure of fingerprinting technique.

Recently, there are various kinds of machine learning algorithms that are used for estimating the positon of the target. Mostly these matching algorithms can be classified into two methods. They are deterministic approach and probabilistic approach.

2.4.4 Pedestrian Dead Reckoning (PDR)

Pedestrian Dead Reckoning, also referred as PDR, is a navigation technique that estimates the position of the user obtained from the data of IMU sensors. The IMU sensors like accelerometer, gyroscope and magnetic field sensors are utilized to calculate the current position of the user. It is based on step detection, step length and heading estimation. Step detection and step length is estimated by accelerometer data and heading is estimated using gyroscope and magnetic field data.

2.5 Estimation Methods

IPS has been adapted in various industries as well as academic field. Hence, various approaches have been developed to achieve better accuracy day by day. These approaches are divided into two categories. They are probabilistic and deterministic approaches. Deterministic approach deals with the pattern matching algorithms to estimate the location whereas the probabilistic approach deals with finding the occurrence probability of the target based on its stored data as well as its variance.

2.5.1 K nearest Neighbor (KNN)

A KNN is probably the most common and straight forward method of indoor localization one can use. It can have very good results in the environment where dense amount of AP are installed. The KNN is basically a nearest neighbor (NN) when K =1. It shows the user's location is at one of the reference points of AP. It is based on the characteristics of RSSI since, RSSI degrades with distance.

This methods has been quite popular since it does not need any kind of signal modelling but other techniques like trilateration which estimate distance between transmitter and receiver for location estimation requires the signal modelling. However, KNN's performance is deteriorated with decreasing number of APs. If the number of APs are limited, it does not provide reasonable accuracy. The number of K in KNN depends on the number of APs available. Since, both less and more number of K can swing the accuracy both ways.

2.5.2 Bayesian Estimation

Bayesian estimation is foundation of formulation of statistical inference issue. It combines the evidence accommodates in the signal with knowledge of prior probability distribution to estimate the random process in an observation signal. This methodology consists of classical estimators like minimum mean square error (MMSE), maximum a posteriori (MAP), maximum likelihood (ML) and minimum mean absolute value of error (MAVE). One of the example of Bayesian model is hidden Markov model that is used widely in statistical signal processing. It depends on the available information and on the estimator's efficiency.

Estimation theory deals with the determination of unknown parameter vector and its best estimation from observation signal. While estimating or predicting the state of the process, Bayesian estimation involves both prior probability of the process and information in the observation signal. Let us consider the value of random parameter vector, given observation vector x. Then, according to Bayes' rule, the posterior probability density function of φ given x, $f_{\varphi|x}(\varphi \mid x)$ is expressed as

$$f_{\varphi|x}(\varphi \mid x) = \frac{f_{\varphi|x}(x \mid \varphi) f_{\varphi}(\varphi)}{f_x(x)}, \tag{5}$$

where $f_x(x)$ is a constant and only responsible for normalizing effect. $f_{\varphi|x}(x \mid \varphi)$ is the likelihood of the signal x was generated by the vector φ and

$f_{\varphi}(\varphi)$ is the prior probability of the vector having value φ. The likelihood $f_{\varphi|x}(x|\varphi)$ and prior probability $f_{\varphi}(\varphi)$ effects the posteriori probability density function $f_{\varphi|x}(\varphi|x)$ on the basis of the shape of the function.

2.6 Kalman Filter

The Kalman filter is one of the most successful implementation of a Bayesian filter and often used as estimation method of a state [26]. This filter provides prediction and correction in an alternate step. Kalman filter is regarded as the method to represent an estimation problem by using predictor and corrector structure. In the prediction system also known as the time update is estimated using the previous known system and properties of state transition. In the correction system also known as measurement update, the weighted observation is used to correct the predicted values. The state equation y_k and measurement model z_k are given by

$$y_k = Ay_{k-1} + Bu_k + w_{k-1} \tag{6}$$

$$z_k = Hy_k + v_k, \tag{7}$$

where w_{k-1} and v_k are represented as process and measurement noise respectively and are assumed to be independent of each other having the normal probability distributions as given below in equations 8 and 9.

$$p(w) \sim N(0,Q) \tag{8}$$

$$p(v) \sim N(0,R). \tag{9}$$

Generally, the process noise covariance Q and measurement noise covariance R changes with the time of measurement step. The matrix A, B, and H are state transition matrix. Mostly matrix A is considered as constant or can be changed with respect to time. Matrix B is the component that is related to control input u at time $k-1$. The overall process of Kalman filter is shown in Figure 6.

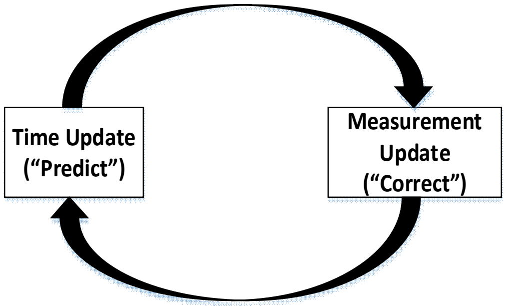


Figure 6. Kalman Filter cycle which shows the time update projects the current state estimation ahead on time. The measurement update adjusts the projected estimate by an actual measurement at that time.

2.7 Related Works

In this section, we examine the various existing indoor positioning techniques, among which fingerprinting is the most common and favored [5]. Two types of approaches—deterministic and probabilistic—are the major methods using pre-assembled RSSI fingerprints to estimate the current location. Santosh et al. identified the important factor for reducing the number of reference points using fingerprinting and weighted centroid localization [27]. In another study, the recent methods of localization using probabilistic methods were demonstrated to be more efficient than the orthodox techniques, such as trilateration [28]. Rui et al. used weighted fusion with a probabilistic approach [29]. Because the fingerprint dataset can be large for an extensive environment, Loizos et al. showed an efficient way of filtering initial fingerprints with respect to the BLE devices [30]. Zhiliang et al. proposed an algorithm that minimizes the computation complexity and does not require an optimization search using the Gaussian radial function in a support vector machine [31]. Recent advances in indoor positioning with Wi-Fi were reported in [32]. An error of approximately 2 m can be obtained in Wi-Fi/BLE-based localization.

Another very popular technique of indoor positioning is PDR using an IMU for the navigation. This is a relative navigation process that predicts the position of the user according to the previous location. It does not require extra devices and is thus considered as the most simple and effective navigation method. However, this method has the drawback of locating the initial position of the user. Pavel et al. presented the various methods of navigation using PDR [33]. In another study, PDR navigation was performed by enhancing the heading estimation [34]. Additionally, a map-matching algorithm for improving the performance was reported [35]. A SmartPDR-based localization technique was implemented in a real-time scenario by combining a magnetometer and a gyroscope to obtain a more accurate heading direction [36].

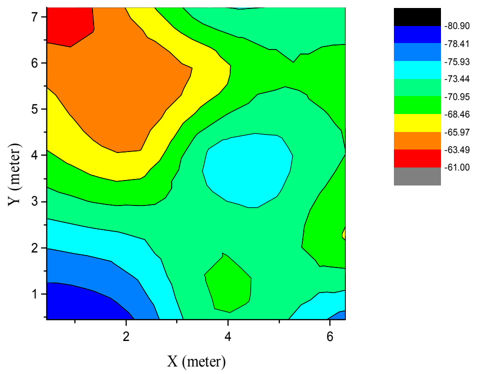
Integrated positioning algorithms have been introduced for improving the accuracy in indoor positioning. Various algorithms have been derived for the integration of PDR, Wi-Fi, and UWB. Linear and nonlinear filtration methods, such as the Kalman filter, particle filter, and extended Kalman filter, are the most widely used approaches for removing noise and enhancing the localization accuracy. PDR and Wi-Fi were combined with the Kalman filter [37], where weighted centroid localization was used for Wi-Fi, which eliminates the burden of fingerprint training data. The particle filter, which uses a probabilistic approach for estimating the position, is another choice for data fusion. The complexity and performance of the particle filter were examined in [38]. Another probabilistic approach also involves non-parametric analysis of the RSSI for indoor positioning [21]–[23]. Trust Chain Positioning Fusion (TCPF), which eliminates the Wi-Fi interference by using Trust State and Trust Point Determination, was detailed in [41]. In this study, we use BLE beacons for the RSSI-based positioning because it makes the installation and operation stable for a long period of time and is considered to be efficient with regard to power consumption.

3. Proposed algorithm for IPS

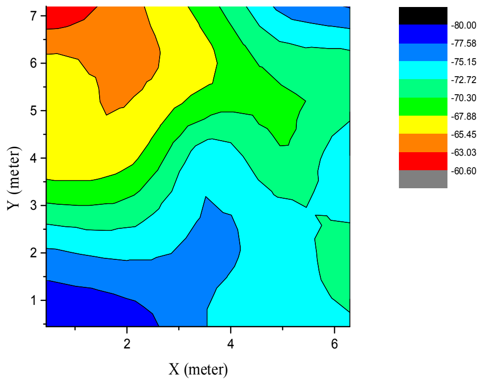
Different localization techniques have different drawbacks in real environments. RSSI-based localization has a performance limitation due to its signal fluctuation, depending on the environment. Its accuracy decreases with the change of the environment and the fading effect. On the other hand, localization using PDR is precise in a short range, provided the initial position. However, as the distance increases, the location from PDR drifts from the walking path. Hence, we propose a TKBE algorithm that handles the signal fluctuations and drift errors using a fuzzy-logic Kalman filter.

3.1 Enhanced BLE based positioning

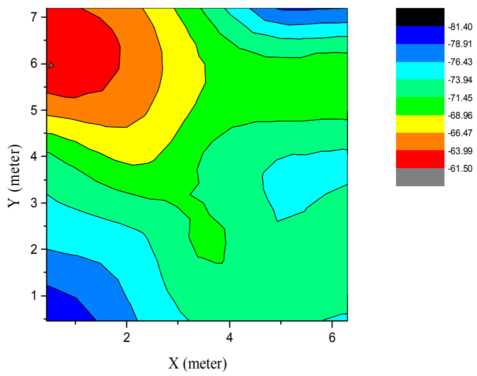
Fingerprinting techniques usually consist of two stages: the offline phase and the online phase. Although this approach is considered as time-consuming, it has been widely used owing to its higher accuracy compared with other techniques. This algorithm surpasses the performance of various techniques, such as trilateration and weighted centroid localization. The effect of RSSI fluctuation in localization can be reduced by using the K-nearest neighbor (KNN) to some extent. [42]. The KNN works in a deterministic way and is based on the shortest physical distance between the reference points and the target position. However, it does not consider the variance of the RSSI. Large variance of the RSSI cannot be ignored for positioning, necessitating a probabilistic approach. The RSSI varies with changes in the surroundings, LOS, and antenna orientation. This limits the localization performance. Owing to these features, the fluctuation in RSSI is seen even at the same location with different points of time. Figure 7 (a) shows the variation of the RSSI at different locations of the room, where one BLE beacon is installed at one corner of the room at a particular point of time t_1. Figure 7 (b) and (c) show the variations of the RSSI of the same beacon at two different points of time: t_2 and t_3, respectively



(a)



(b)



(c)

Figure 7. RSSI variation with respect to time (a) at time t_1, (b) at time t_2, and (c) at time t_3.

From the above figures, we observe that the RSSI at several locations may be indistinguishable or heterogeneous [43]. It is complicated to find the occurrence of reference points based on the given RSSI. Additionally, if the test corridor is large and a large number of training data are present, the Bayesian estimation can be groundless because the prior probabilities of all the reference points are considered to be the same throughout the positioning. However, the priori probabilities of all the reference points are not the same in real time. This can be overcome by applying the KNN for selecting the nearest reference points in terms of the signal strength for the Bayesian estimation, which helps to select a favorable number of reference points whose prior probability is considered as 1; the rest are ignored. This approach deals with the uncertain behavior of the signal strength at various locations.

3.1.1 K nearest Neighbor (KNN)

Let N be the number of reference point in the test area. Each reference points is denoted with where i =(1, 2, 3, 4, 5…… N). Here represents 2-dimensional location of the reference point, i.e. $X_i = [x_i, y_i]^T$. There are total M numbers of BLE beacons used in the testbed. In offline phase, a radio map is constructed and stored in the Database. The radio map is given by equation 10.

$$R_i = [X_i, S_{ij}, \sigma_j] \;, \tag{10}$$

where S_{ij} is the mean of RSSI obtained from the j^{th} BLE beacons at i^{th} reference point and σ_j is the standard deviation of measurement noise of each BLE beacon M is the number of BLE beacons.

During the online phase, Euclidean distance between the target position and the reference points is calculated by equation 11.

$$Euclidean\,Distance(E_i) = \sqrt{\sum_{j=1}^{M} (S_j - S_{ij})^2} \;, \tag{11}$$

where S_j is the RSS vector obtained from j^{th} BLE beacon at the online phase. The Euclidean distance is sorted in ascending order. In conclusion, a reference point closer to the online target position has a smaller Euclidean distance. In this study, 15 neighboring reference points that have a small Euclidean distance are taken for further estimation (K=15).

3.1.2 Bayesian Estimation

Bayes' theorem is the outcome in probability theory that shows the connection among conditional probabilities. It is considered as an effective structure for reasoning and decision making under variability. The probability $P(A \mid B)$ represents the likelihood of event B occurring given that A is true and the individual probabilities of A and B. It is given by

$$P(A \mid B) = \frac{P(A)P(B \mid A)}{P(B)} \quad . \tag{12}$$

This conditional probability can be used to find the probability of the location based on the given set of RSSI as explained in Xu et al. [44]. Generally, in probabilistic approach, the location of the target is computed by maximizing the conditional posterior probabilities given by $P(R_i \mid S_j)$.

The posterior probability of being at location X_i given the RSSI obtained in the online phase is given by equation 13.

$$P(R_i \mid S_j) = \frac{P(S_j \mid R_i)P(R_i)}{\int P(S_j \mid R_i)P(R_i)d(R_i)}. \tag{13}$$

Because the RSSI signals are obtained from different BLE beacons, they are considered as independent random variables; hence, their probabilities $P(S_j \mid R_i)$ can be multiplied. $P(R_i)$ is the prior probability of reference points, which is generally considered to be the same for all reference points, but this is not applicable in the real environment. To deal with this, a certain number of reference points are selected using the KNN, and the prior probability of these points is considered as 1, neglecting other points that are distant from the user. This eliminates the other reference points from consideration in Bayesian estimation and increases the likelihood of the nearest points. Thus equation 13 becomes

$$P(R_i \mid S_j) = \frac{\prod_{j=1}^{M} P(S_j \mid R_i)}{\int P(S_j \mid R_i) d(R_i)}. \tag{14}$$

The distribution of RSS measurement is considered as Gaussian which can be observed at any particular point of location. This is shown by Kolmogorov Smirnov test [45]. This test gives the means of comparison of the sample distribution and theoretical distribution. It is used as test of good fit and is best suited for small sample of data. It helps to compare the cumulative distribution function for RSSI with specific distribution. The value of test statistic D is calculated by

$$D = Maximum \mid F_o(S) - F(s) \mid , \tag{15}$$

where

- $F_o(S)$ = cumulative distribution observed from a random samples of 100 RSSI observation.

- $F_o(S) = \frac{k}{n} = (number\ of\ observation \leq S)/(Total\ number\ of\ observation)$
- $F(S)$ = the theoretical frequency distribution.

The critical value of D is obtained from the K-S table for one sample test. There are two conditions for K-S test. They are

- Acceptance Condition: $D_{calculated} < D_{critical}$
- Rejection Condition: $D_{calculated} > D_{critical}$

Here, D is calculated by collecting 100 samples of RSSI and evaluating the cumulative frequencies. From equation 15,

$$D = Maximum\,|F_o(S) - F(s)|$$
$$D = 0.104236$$

The table of D at 5% significance level is given by

$$D_{0.05} = \frac{1.36}{\sqrt{n}},\ where\ \ n = 100$$
$$D_{0.05} = 0.136$$

Since $D < D_{0.05}$, it fails to reject the null hypothesis, we conclude that the data is a reasonably good fit with Gaussian distribution.

number of samples (n)	**100**
mean	**-66.21**
standard deviation	**2.6791187**
D_{max}	**0.1042362**
$D_{critical}$	**0.13581**

Here, the distribution of 100 samples of RSSI is evaluated and plotted the in Figure 8.

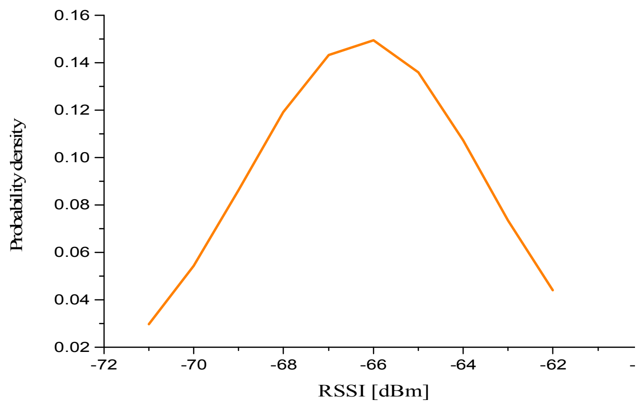


Figure 8. Gaussian distribution of the RSSI.

By using Gaussian distribution, the probability $P(S_j \mid R_i)$ can be calculated from equation 16.

$$P(S_j \mid R_i) = \frac{1}{\sqrt{2\pi\sigma_j^2}} \exp^{-\frac{(S_j - S_{ij})^2}{2\sigma_j^2}} , \tag{16}$$

Using (14), $P(R_i \mid S_j)$ is obtained. Minimum mean square error is applied over the conditional density probability that is acquired from Bayes theorem to achieve the location of the target X_{ble}. This is demonstrate as equation 17.

$$X_{ble} = E[R_i \mid S_j] = \int X_i \cdot P(R_i \mid S_j) d(R_i) . \tag{17}$$

The proposed algorithm limits the number of reference points with the KNN and maximizes the location probabilities around the true position. Figure 9 shows the step of the proposed BLE beacon-based positioning with the KNN and Bayesian estimation. The performance of different methods—BLE beacon-based positioning with only the KNN, with only Bayesian estimation, and with the KNN and Bayesian estimation—is shown in Figure 10.

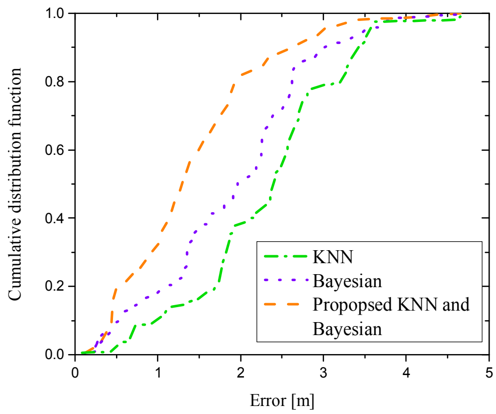


Figure 9. Performance of various BLE beacon-based positioning algorithms.

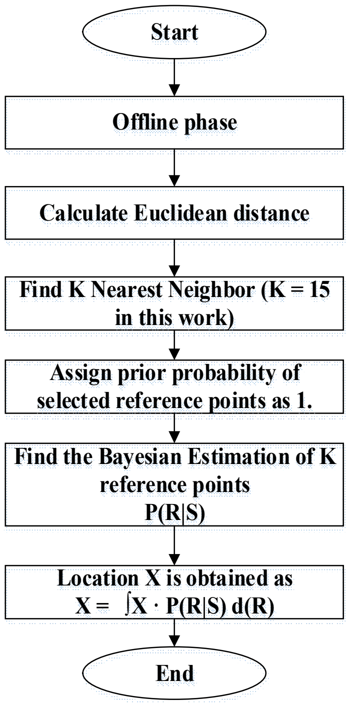


Figure 10. Proposed BLE beacon-based positioning algorithm with KNN and Bayesian Estimation.

3.2 Pedestrian Dead Reckoning Based Localization

PDR is the method of tracking the current position of a pedestrian by using previously determined position. In the PDR, the initial position can be obtained from the RSSI based positioning. There are three components for target navigation i.e., step detection, step length, and heading direction. These fundamental components are obtained by three sensors of the smartphone. An accelerometer is used for computing the step detection and step length, whereas the heading direction is acquired by magnetometer and gyroscope. Let us assume the initial position (x^k, y^k), then the position after a step (x^{k+1}, y^{k+1}) is calculated by:

$$x^{k+1} = x^k + SL^k \cos\theta^k \tag{18}$$

$$y^{k+1} = y^k + SL^k \sin\theta^k \ , \tag{19}$$

where SL^k is the step length at step k and θ^k is the heading angle at k^{th} step. Since PDR is effectively applicable for short distance, it can be combined with other approaches for full area positioning.

3.2.1 Step Detection

Among the methods for detecting steps, peak detection is a fundamental way to achieve good step-detection performance by using the accelerometer. This method involves the vertical acceleration generated by the vertical strike when the foot hits the floor. Because the vertical acceleration is affected by the tilting of the smartphone, we consider the magnitude of the acceleration (a_{mag}). A step is detected when it satisfies the following two conditions:

$$| a_{mag} - g | \geq a_{th}$$

$$Time\,stamp\,\Delta t \geq t_{th}\ ,$$

where g is the gravity of Earth, a_{th} is the threshold acceleration, and t_{th} is the time threshold for the acceleration measurement time period Δt . The acceleration threshold a_{th} is used to restrict the false step detection, and the time threshold t_{th} restricts the detection of steps to a finite duration of time. The acceleration and threshold level are shown in Figure 11.

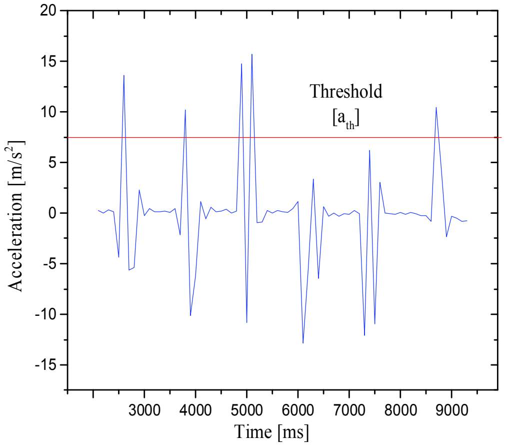


Figure 11. Acceleration and its threshold for step detection.

3.2.2 Step Length Estimation

Step length alters from individual to individual. Moreover, some individuals may have different step length while walking. Therefore, it is very hard to estimate a precise step length. There are various forms of step length calculation [46]. They can be classified into static and dynamic estimations. The static method usually assumes the length of the step is constant throughout the process and only variable based on individual feature as follows:

$$SL = height * k\ , \tag{20}$$

where k is fixed for the men or women and height is adjusted according to each individual.

Dynamic methods are popular because they allow a different step length in every step. A dynamic approach called the Weinberg approach is used in this study for estimating the step length [47]. This method uses the vertical acceleration due to the impact of running or walking. The value of the vertical acceleration is obtained from the accelerometer. Then, the step length is given as

$$SL = k\sqrt[4]{a_{\max} - a_{\min}} \quad , \tag{21}$$

where $a_{\max}$ and $a_{\min}$ are maximum and minimum vertical accelerations, respectively. In our experiment, the value of k is obtained as 0.35 by testing people with different heights.

3.2.3 Heading Estimation

The most common method for determining the heading direction is by using the magnetometer readings, but the magnetometer is easily affected by other metals and electronic devices present in the environment. Hence, another approach is considered, which employs the angular velocity obtained from the gyroscope. However, the gyroscope suffers from the problem of sensor noise that accumulates with the integration. To eliminate this drift, a Kalman filter is used with magnetometer and gyroscope readings [48]. The heading estimate is converted into the coordinate system of the testbed. It is assumed that the user holds the smartphone in the hand while walking.

The proposed state transition and measurement equation for Kalman Filter are given by:

$$\alpha_t = \alpha_{t-1} + \Delta t V_t + \varphi \tag{22}$$

$$Z_t = \alpha_t + \theta \ , \tag{23}$$

Here, α_t is the walking direction, V_t is the gyroscope reading, Z_t is the direction of the heading obtained from the magnetometer, Δt is the time index for the gyroscope measurement, φ is the Gaussian error with zero mean and variance *P*, and θ is the Gaussian error with zero mean and variance *Q*. Figure 12 shows the turns observed in our experiment via the proposed heading estimation.

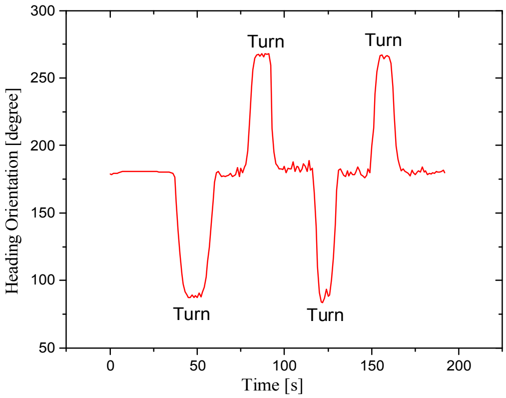


Figure 12. Heading direction estimation using magnetometer and gyroscope.

3.3 Proposed Trusted K nearest Bayesian Estimation (TKBE) Algorithm

In this section, the proposed fusion algorithm is explained. The method obtains the locations from the BLE beacon and PDR-based positioning and then combines them using a fuzzy-logic Kalman filter for estimation of the position. The fusion process is composed of three sections: the fuzzy-logic Kalman filter, clustering of next reference points, and PDR drift elimination. The framework of the proposed method is shown in Figure 13.

3.3.1 Integration with Fuzzy Logic based Kalman Filter

The Kalman filter is the most widely used filter for sensor fusion and position estimation. It keeps track of the estimated state of the system and the variance. Additionally, it yields rigorous results compared with other filters used in recent times, with reasonable computational power. The Kalman filter is based on the estimation of the process and the measurement noises [49].

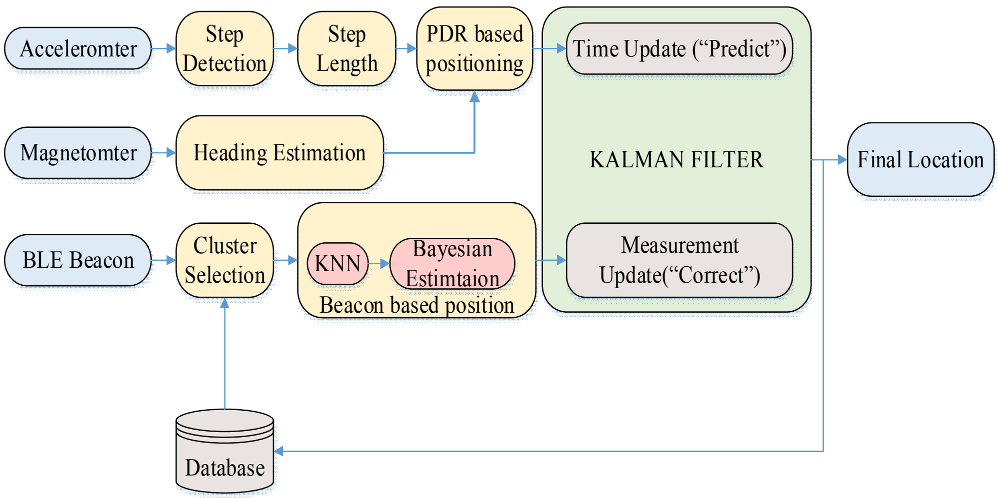


Figure 13. Framework of the Proposed Trusted K Nearest Bayesian Estimation (TKBE) algorithm.

Let L_t be the 2 dimension coordinate expressed as $[x,y]^T$. Also, the state transition and measurement function are given by:

$$L_t = AL_{t-1} + Bu_t + w \tag{24}$$

$$Z_t = CL_t + v \ , \tag{25}$$

where $u_t = SL^k[\cos\theta^k \ \sin\theta^k]^T$ obtained from step estimations of PDR based positioning and Z_t is the 2-dimensional coordinate obtained from beacon based positioning. A, B and C are the identity matrix. The variables w and v symbolize the process and measurement noises with normal probability distributions.

$$p(w) \sim N(0,Q) \tag{26}$$

$$p(w) \sim N(0,Q)\ . \tag{27}$$

Here, Q is the covariance matrix of the Gaussian noise of the PDR approach with zero mean, and R is the covariance matrix of the Gaussian noise of the BLE beacon-based algorithm with zero mean. The Kalman filter algorithm consists of the following two processes.

Predicting:

$$L_t = AL_{t-1} + Bu_t \tag{28}$$

$$P_{t|t-1} = AP_{t|t-1}A^T + Q\ . \tag{29}$$

Updating:

$$K_t = P_{t|t-1}C^T(CP_{t|t-1}C^T + R)^{-1} \tag{30}$$

$$L_{t|t} = L_{t|t-1} + K_t(Z_t - CL_{t|t-1}) \tag{31}$$

$$P_{t|t} = (I - K_tC)P_{t|t-1}\ . \tag{32}$$

Here, A, B, and C are the identity matrix; P is the process covariance matrix which represents the estimation error; and K is the Kalman gain of the system, which ranges from 0 to 1. When the Kalman gain is higher, the measurements are more accurate, and the estimates are unstable. When the Kalman gain is lower, the estimates are more accurate, and the measurement are unstable. There are two estimation errors: the priori estimation error and the posterior estimation error. These errors are the difference between the estimated value and the actual value and are given as follows:

$$\text{Priori estimate error } (E_k^-) = L_k - \hat{L}_k^- \tag{33}$$

$$\text{Posteriori estimate error } (E_k) = L_k - \hat{L}_k \ , \tag{34}$$

where L_k is actual value, $\hat{L}_k^-$ is priori estimated value, and $\hat{L}_k$ is posteriori estimated value. The priori estimate error covariance P_k^- and posteriori estimate error covariance P_k are given as:

$$P_k^- = E[E_k^- E_k^{-T}] \tag{35}$$

$$P_k = E[E_k E_k^T] \, . \tag{36}$$

Let the priori estimated value be the 2D location from the PDR approach and the posteriori measured value be the 2D location from the BLE beacon-based positioning. If these two values are close to the actual value (true position), the estimated error is small. In our experiment, the priori estimated value is assumed to be close to the actual value $(L_k \approx \hat{L}_k^-)$ because if the initial position is provided correctly, the PDR shows the minimum drift in a short distance. We see from 31 that the difference between the priori estimated and measured values, along with the Kalman gain, affects the estimation of the location. The process and measurement noises are considered as a constant in real-time application [50]. As the Kalman gain eventually depends on both the process and measurement noises, assuming that both parameters are constant throughout the process does not yield correct estimation, because of the difference between the actual and estimated values. For any sensor, if the noise covariance is unknown, i.e., Q = 0 and R = 0, the Kalman filter returns an optimal estimate of L_t , which minimizes the mean of the squared error.

However, if the noise covariance is assumed to be constant throughout the process, Kalman filter provides the estimate according to A, B, and C, which are identity matrices in this system. We attempt to compensate for the uncertainty in the process and measurement noise for each step of estimation. $P_{t|t-1}$ is initial process covariance matrix and is computed only once because the priori estimated value is assumed to be the actual value. We experimentally initialize the process noise matrix with small value, $Q = \begin{pmatrix} 0.225 & 0 \\ 0 & 0.225 \end{pmatrix}$, and the initial process covariance matrix, $P_{t-1|t-1} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$.

PDR based tracking system lacks the detection of initial positioning and suffers from the heading error which cannot be fully recovered using any optimization techniques. However if the initial position is precise and heading drift error is eliminated using Kalman Filter, the PDR can assure better relative positioning for shorter period of time. Hence if RSSI based approach can provide the initial position to PDR and be used for short period of time, it yields better result of positioning.

The role of measurement noise matrix R and process noise matrix Q is to adjust the gain of the filter in a way which controls bandwidth as the state and varies the measurement error. During updating process of Kalman filtering, we design measurement update that continuously changes the measurement noise matrix R according to the value of posteriori estimate error E_k. Therefore, matrix R is defined by:

$$R = \begin{pmatrix} y & 0 \\ 0 & y \end{pmatrix}, \tag{37}$$

where y is a variable obtained from set of basic fuzzy logic system designed to assign R to the measurement update of Kalman Filter which is given by

$$y = \begin{cases} 0.675 & if\ 0 \leq |\mathrm{E}_k| < 1 \quad \text{(Low Error)} \\ 1.125 & if \leq |\mathrm{E}_k| < 2 \quad \text{(Medium Error)} \\ 1.575 & if\ |\mathrm{E}_k| \geq 2 \quad \text{(High Error)} \end{cases}. \tag{38}$$

There are three conditions of E_k obtained from fuzzy logic system:

- Low Error: Estimated and measurement values are close and reliable. Hence, R is less.
- Medium Error: Estimated and measurement values are apart by more than 2 units and less than 4 units. In this case both value are equally likely. Hence R is slightly higher.
- High Error: Estimated and measurement values are apart by more than 4 units. In this case measurement value is less reliable than estimated value. Hence, R is higher which shifts the calculation towards estimated value.

Experimentally, the matrix $R = \begin{pmatrix} 0.675 & 0 \\ 0 & 0.675 \end{pmatrix}$ gives the fair estimation of the system but varying the measurement noise R in accordance with the posteriori estimate error E_k yields better result overall.

3.3.2 Clustering of next reference points

Owing to the large number of reference points and the unpredicted behavior of the RSSI, the measured Euclidean distance between radiofrequency devices may not yield the desired reference points that need to be selected for positioning. However, this issue can be alleviated by creating a cluster of reference points as candidates for the next step of positioning. The area is created by feeding back the final position to the database and creating a trusted zone [51]. If $[x, y]$ is the final location, it is fed to the database, and $[(x-n) \le x \le (x+n), (y-n) \le y \le (y+n)]$ is the bounded area for the next step of positioning, where n = 9 m in our testbed. This prevents the selection of false reference points in the KNN due to interference.

3.3.3 PDR drift elimination

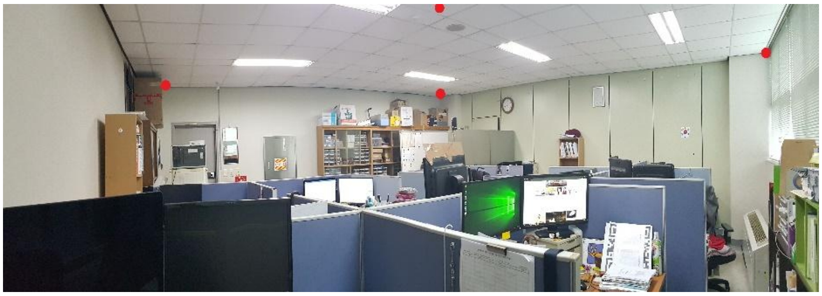
Generally, the PDR error drifts with distance owing to the integration process of the acceleration signal. However, the PDR positioning error can be reduced by resetting the current location with the location obtained from the RSSI approach. In this work, the location of PDR is reset every 10 steps.

4. Experimental results and performance evaluation

4.1 Experimental Setup

Two experiments were conducted in the computer laboratory and the corridor of the 8th floor of the IT Building of Chosun University in South Korea. The corridor had dimensions of 100×2.25 m^2, and the laboratory had dimensions of 7×7 m^2. The beacons were placed with a distance of 6.75 m between them and at a height of 2.6 m in both the testbeds. The experiments were performed using Estimote iBeacons, and the application was developed on the Android platform. The device used for the positioning was a Samsung Galaxy Note 8 (API 27).

Figure 14 (a) and (b) show the corridor and the computer laboratory, respectively. The red circles indicate the positions where the beacons were installed. The beacons were placed at opposite sides along the corridor and in the four corners of the laboratory. A total of 35 beacons were used for the positioning. In the testbeds, 100 RSSI samples were collected at each reference point in four directions. The reference points were assigned at a distance of 1.8 m for both the testbeds. The information of the collected RSSIs was stored in a SQLite database on the Android device during the offline phase. We used two sets of fingerprint data for both the computer laboratory and the corridor.



(a)

(b)

Figure 14. Testbed for experiments of (a) Computer Laboratory, (b) Corridor

4.2 Initial Location of BLE based positioning/PDR initialization

The initial position is a major factor giving a big impact on the localizing the target. As PDR is a relative navigation based on the previous location, the initial position should be more accurate to carry the position accuracy throughout the process. When the initial position obtained from RSSI positioning with KNN and Bayesian estimation is given, several test were done and checked the average error between the real locations and obtained the location in both laboratory and corridor as shown in Figure 15 and 16.

From the result, it was found that the average error while obtaining initial position was below 2 meters in the computer laboratory and the corridor.

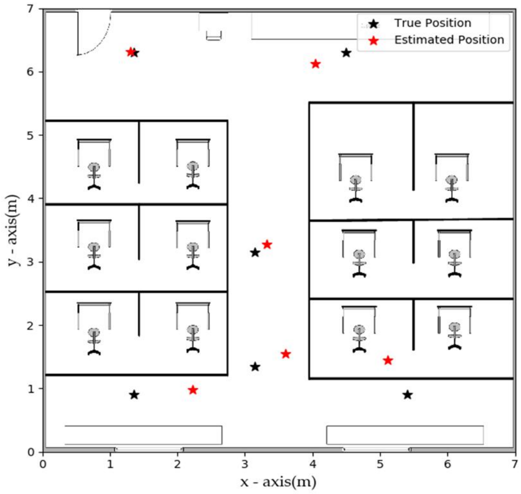


Figure 15. Performance of initial position in coordinate system of computer laboratory.

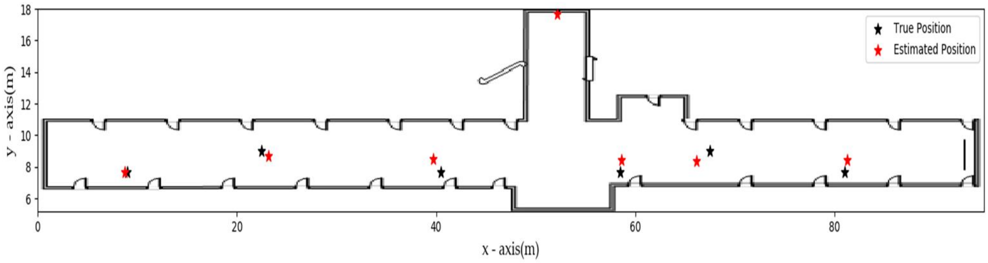


Figure 16. Performance of initial position in coordinate system of corridor.

4.3 Positioning Error and Cumulative Distribution Function

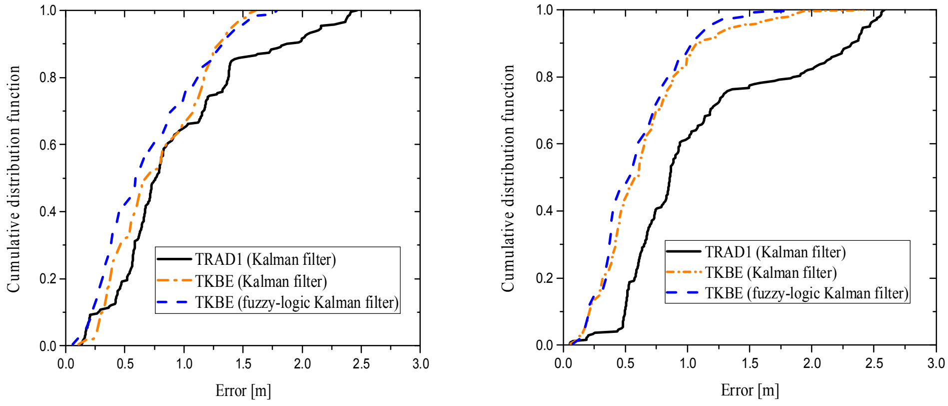
An experiment was performed in the testbed to evaluate the cumulative distribution function of the error. The target stood still in several locations, and >50 location samples were collected. Figure 17 shows the cumulative distribution of the error in the computer laboratory, and Figure 18 shows that in the corridor. Here, the solid line indicates the error of the traditional positioning algorithm using both BLE with KNN and PDR (called TRAD1). The dashed dotted line indicates the error of TKBE positioning with the conventional Kalman filter, and the dashed line indicates the error of TKBE positioning with the fuzzy-logic Kalman filter. In all the cases, we observe that the proposed positioning method yields a better result than the TRAD1 using the conventional Kalman filter. We also observe that the variable measurement noise matrix reduces the error rather than keeping it constant throughout the process. The error of the proposed algorithm was <1 m for 80% of the experiment time.

Table 1. Comparison of positioning methods in a computer laboratory

Fingerprint Database Set	**Algorithm**	**Average Error**	**Standard Deviation**
1	TRAD1 (Kalman filter)	1.09	0.670
	TRAD2 (Kalman filter)	0.85	0.623
	TKBE(Kalman filter)	0.65	0.423
	TKBE (fuzzy-logic Kalman filter)	0.55	0.327
2	TRAD1 (Kalman filter)	1.29	0.486
	TRAD2 (Kalman filter)	1.11	0.484
	TKBE(Kalman filter)	0.85	0.453
	TKBE (fuzzy-logic Kalman filter)	0.70	0.444

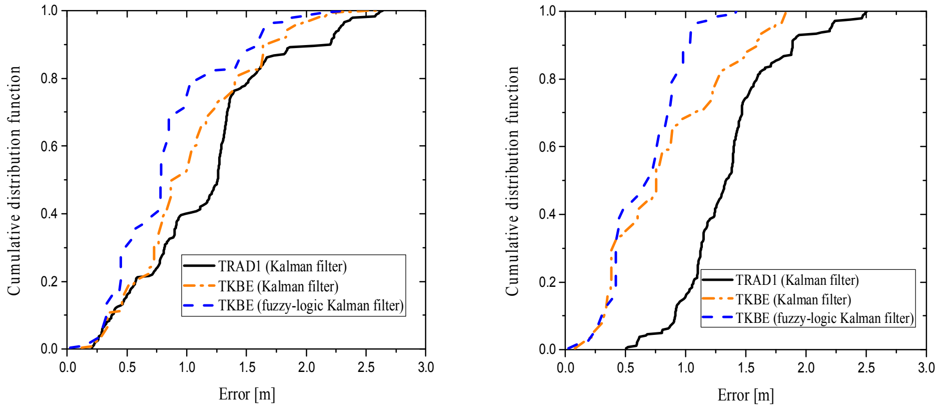
Table 2. Comparison of positioning methods in a corridor

Fingerprint Database Set	**Algorithm**	**Mean**	**Standard Deviation**
1	TRAD1 (Kalman filter)	1.16	0.577
	TRAD2 (Kalman filter)	1.10	0.556
	TKBE(Kalman filter)	1.01	0.490
	TKBE (fuzzy-logic Kalman filter)	0.82	0.453
2	TRAD1 (Kalman filter)	1.35	0.398
	TRAD2 (Kalman filter)	1.15	0.452
	TKBE(Kalman filter)	0.82	0.475
	TKBE (fuzzy-logic Kalman filter)	0.65	0.286



(a) (b)

Figure 17. Comparison of cumulative distribution function of the error for Computer Laboratory (a) data set 1, (b) data set 2.



(a) (b)

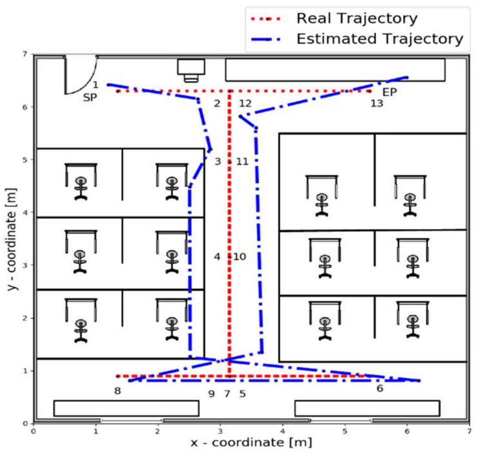
Figure 18. Comparison of cumulative distribution function of the error for the corridor (a) data set 1, (b) data set 2.

Tables 1 and 2 show the results of the performance comparison between the algorithms. In the computer laboratory, the proposed TKBE algorithm had an average error of 0.65 m, whereas TRAD1 exhibited an error of 1.09 m. In the corridor, TKBE and TRAD1 had mean errors of 0.82 and 1.16 m, respectively.

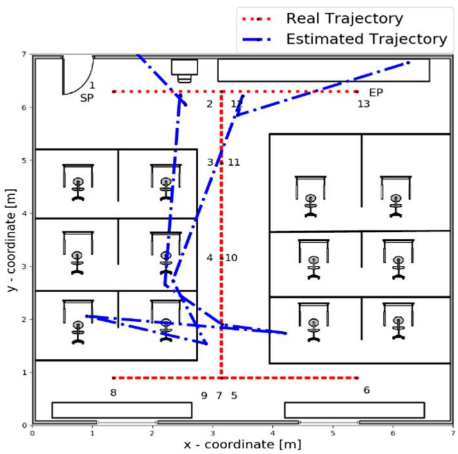
Under the same conditions, the traditional positioning algorithm using both BLE with Bayesian estimation and PDR (called TRAD2) exhibited slightly better performance than TRAD1 but worse performance than the proposed TKBE method. The positioning of the proposed algorithm was further enhanced by the changing measurement noise R with respect to the posteriori estimation error, yielding slightly better performance than a constant R. Hence, we can obtain approximately 25% better performance than existing algorithms by using the TKBE algorithm.

4.4 Walking Trajectory Performance Analysis

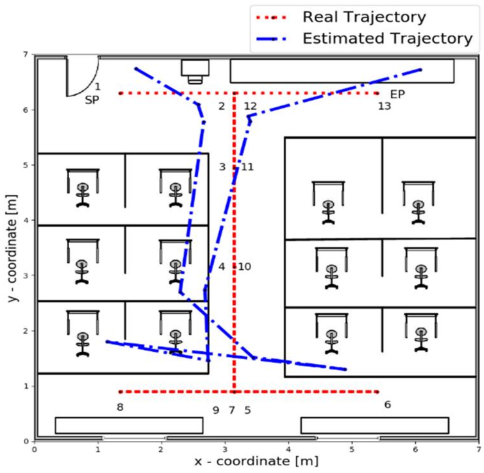
This result was obtained by measuring the location of the user walking through the testbed. The experiment was performed in both the computer laboratory and the corridor. The location of the user was stored every 5 s. In Figure 19 and 20, SP and EP denote the starting point and end point, respectively. The user moved in the order of 1 to 13 in the computer lab and in the order of 1 to 18 in the corridor. The red dotted line and blue dashed dotted line indicate the real and estimated trajectories, respectively.



(a)

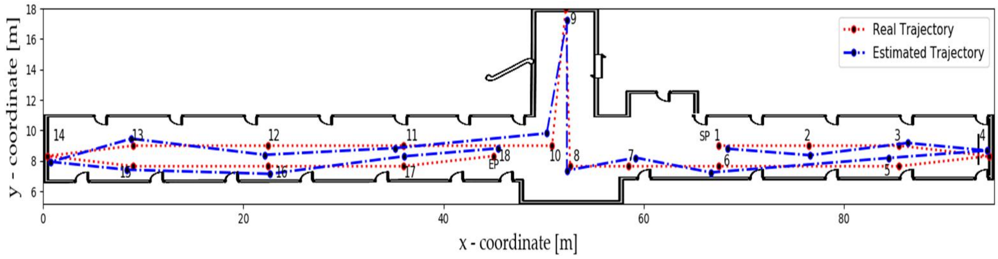


(b)

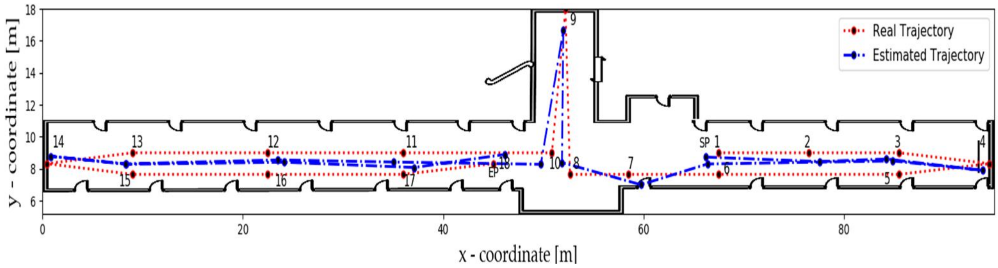


(c)

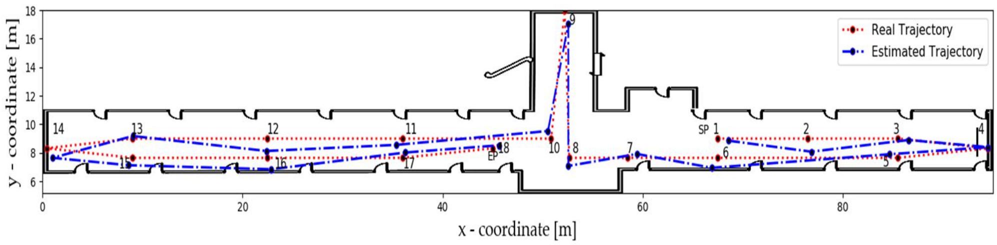
Figure 19. Performance comparison of the positioning algorithms for the computer laboratory, when a person moves along the path. (a) TKBE, (b) TRAD1, and (c) TRAD2



(a)



(b)



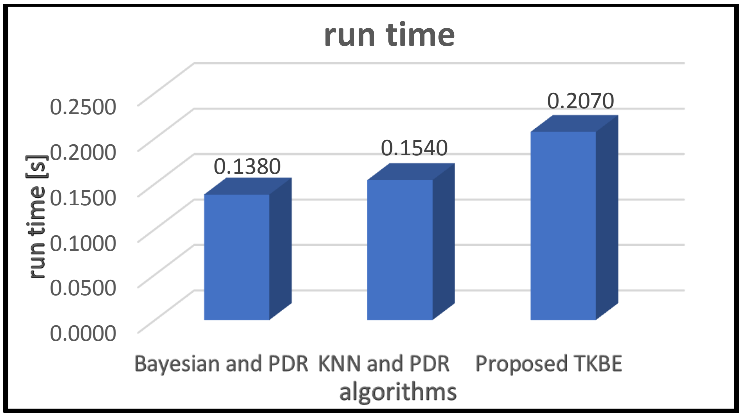
(c)

Figure 20. Performance comparison of the positioning algorithms for the corridor, when a person moves along the path. (a) TKBE, (b) TRAD1, and (c) TRAD2

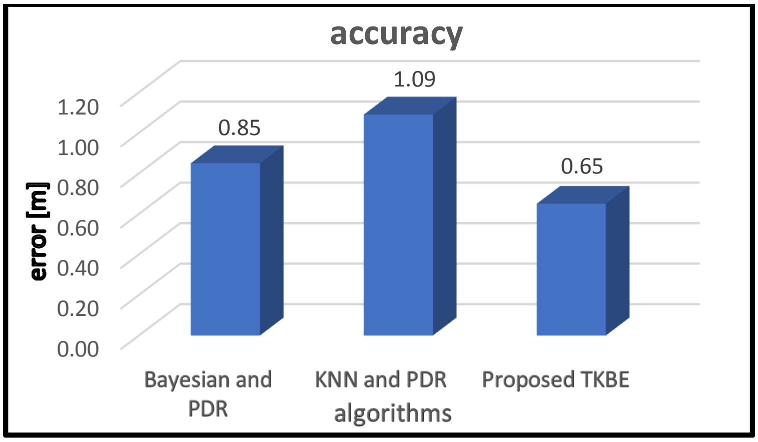
4.5 Computational Complexity Analysis

The experiments were performed using an Android application (Java) running on a Samsung Galaxy Note 8 with Samsung Exynos 9 octa 8895 and a 1.7-GHz octa-core processor. Because the processing time of any algorithm depends on the processor specifications, we computed the runtime of various algorithms on the same device to compare the computational complexity.

As shown in Figure 21 (a), the runtime of the TRAD1 algorithm was slightly longer than that of TRAD2. Therefore, it is clear that the Bayesian estimation is preferred over the KNN because of its high accuracy and lower computational complexity. The proposed TKBE algorithm had a slightly longer computational time than the TRAD1 and TRAD2 algorithms. Because the TKBE combines the KNN and Bayesian methods, it exhibited higher performance than each of these two methods, with slightly higher computational complexity, as shown in Figure 21 (b). The proposed TKBE algorithm had approximately 30% longer computational runtime than other two. However, the accuracy of the TKBE method was more than 25% higher than those of the other algorithms. This tradeoff appears to be acceptable, as the runtime of the algorithm depends on the size of the fingerprinting database.



(a)



(b)

Figure 21. Comparison of (a) run time and (b) error of the algorithms.

5. Conclusion

A method for enhancing the accuracy of indoor localization based on BLE beacons and IMUs is proposed and localization algorithm with BLE beacon is designed using KNN-based Bayesian estimation, whereas IMUs employ PDR. The BLE based positioning and PDR based positioning were combined using fuzzy-logic Kalman Filter. The proposed TKBE algorithm consists of three components: enhanced positioning using BLE beacons, PDR, and fusion performed by the fuzzy-logic Kalman filter. The BLE-based positioning is enhanced by selecting KNNs and then estimating its probability density function. This minimizes the error in the estimation caused by the unstable RSSI in a large testbed and enhances the accuracy of the existing basic KNN and PDR algorithms by ≥25%. A fuzzy logic-based Kalman filter was designed using a fuzzy-logic set of values assigned to the measurement update based on the posteriori estimation error E_k . This set of values adjusts the Kalman gain toward either prior estimated values or the posteriori measured value. The proposed algorithm exhibited accuracy improvements of by 15% to 20% compared with the conventional Kalman filter. The error of the proposed algorithm was <1 m for most of the experiments (>80%). Moreover, although this algorithm had slightly longer runtime than the TRAD1 and TRAD2 algorithms, it is feasible for a real-time smartphone-based application and provides higher accuracy by mitigating the effects of the RSSI instability and the PDR drift error.

As this paper uses KNN for selecting most probable reference points whose prior probability is considered as 1, it can be made more accurate by calculating exact prior probability of nearest reference points. But, this can cause the complexity to increase in smartphone based LBS. Hence we will be working on efficient algorithm to calculate more accurate prior probability. As the computational running time is slightly higher, we will continue to work on reducing it to make indoor positioning system reliable and effective for daily uses for the people.

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