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A REVIEW OF INDOOR POSITIONING SYSTEM TECHNIQUES USING BLUETOOTH LOW ENERGY

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Abstract. *Indoor Positioning System (IPS) provides the geo-location of a receiver in an indoor environment, which becomes the prerequisite for any indoor Location-Based Service (LBS) applications. Researchers have worked out many different transmitters as well as several positioning algorithms to improve the IPS. In 2012, Bluetooth Low Energy (BLE) was started to become publicly available and become one of the potential transmitters in IPS. Since then, researchers have proposed many positioning methods specifically for BLE. However, there has been no recent review on IPS techniques using BLE. Therefore, this review was made in order to serve a comprehensive understanding of the different positioning methods, by focusing on BLE. Based on the literature study, four future research directions on IPS using BLE are also provided in this review.*
Keywords: Indoor positioning system, Indoor location-based service, Bluetooth low energy, Positioning techniques, Fingerprint-based algorithm

1. **Introduction.** Location-Based Service (LBS) has a huge role in nowadays life, such as tracking, navigation, targeted advertisement [1], and entertainment. Global Positioning System (GPS) provided the geographical location of the receiver, relying on the GPS signal propagated from the GPS satellite. Unfortunately, GPS is less accurate whenever used in the indoor environment [2]. Therefore, more reliable sources are needed in order to provide indoor LBS. Several sources such as radio, infrared [3], ultrasound [4], camera [5], and geomagnetic field [6] have been proposed to be used for an Indoor Positioning System (IPS).

The major challenges in indoor LBS include the availability, accuracy, and cost of the system [7]. There is no perfect system in IPS, as there is a trade-off between requirements. IPS using ultrasound with sub-centimeter accuracy [4] may exist, but the transmitter is not commonly installed. Meanwhile, the more available Radio Frequency (RF) transmitter such as a Wi-Fi Access Point (AP), RFID, and Bluetooth Low Energy (BLE) has lesser accuracy. Moreover, different sources will be susceptive to different kinds of noises. RF signal is affected by object obstruction [8]; meanwhile, ultrasound is affected by high-frequency noises [9].

BLE provides several advantages such as lower power consumption, lower network latency, and higher sampling rate [10,11]. However, one of the main challenges in using BLE for IPS is the signal fluctuation. It has been shown that the signal fluctuation in BLE is much larger than Wi-Fi [12]. A hardware solution to reduce the fluctuation in BLE is by using other BLE channels such as the advertisement channels (Channel 37-39) [13]. This is similar to Channel State Information (CSI) in Wi-Fi, which is the subcarrier channel in Wi-Fi [14]. It has been shown that using CSI in IPS is better than the regular Wi-Fi signal [15,16].

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Despite signal fluctuations, some researches have shown that BLE provides better accuracy compared to Wi-Fi [17]. Research [18] explained that due to the higher sampling rate, a large number of samplings are enough to average out the fluctuations. Since there is no recent review that focused on IPS using BLE, this becomes the main motivation of making this review. The aim of this review is to provide a further explanation of different positioning techniques on BLE. By understanding IPS using BLE, several future research directions are also provided to improve this research topic, thus the full potential of BLE in IPS can be explored.

The structure of this paper is organized as follows. Section 2 explains the methodology of the review and the statistical narrative of the references. Different positioning techniques will be discussed and compared in Section 3. Then, based on the discussion, several future research directions are compiled in Section 4. Finally, this review will be concluded in Section 5.

2. **Review Methodology.** All of the literature used in this review was searched from an online search engine such as Google Scholar and Science Direct. Journal articles and conference proceedings are prioritized. The literature is all related to at least one of these topics: Indoor Positioning/Localization/Tracking System, Bluetooth Low Energy, and Indoor Location-based Service. Although IPS is a relatively old problem, BLE as well as Bluetooth 4.0 was publicly available since 2012. This makes the literature in the topic of IPS using Bluetooth before the year 2012 less relevant. Therefore, the chosen literature is mostly published in the range of year 2012 to 2019. This also makes IPS research on BLE less often and less mature. Fortunately, Wi-Fi has the same wavelength as Bluetooth, thus sharing a lot of similarity between both of them. In this review, there will be some studies on Wi-Fi IPS in order to support what is lacking in Bluetooth IPS, especially using BLE.

The literature was narrowed down even further into 48 publications, by considering some factors such as the number of citations and the content of the literature itself. The distribution between the published year is shown in Figure 1. Among these 48

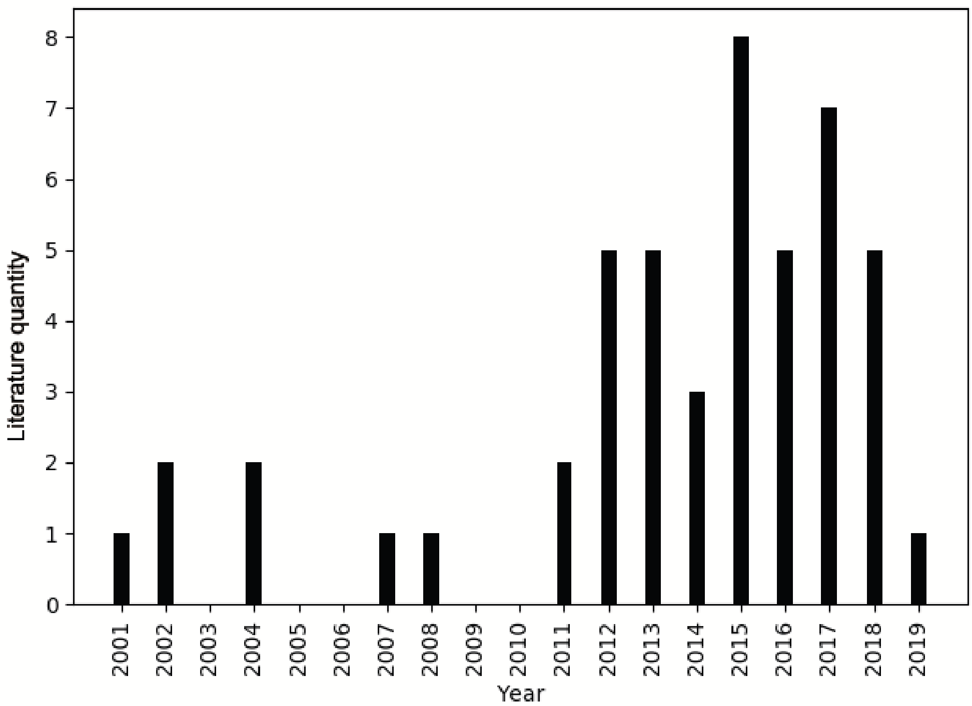

Figure 1. The literature quantity used, based on the published year

TABLE 1. Overview of different IPS methods used in Section 3

Classification	Positioning algorithm	Advantages	Disadvantages
BLE selection	Strongest RSS [20]	–	Reduce positioning accuracy
	Fisher criterion [20]	Provide high accuracy	Require more computing power
	Random combination [20]	Require least amount of computing power with reasonable accuracy	Might be unreliable due to its randomness
	Eisa's 3 criteria [21]	Reduce computational loads with having similar accuracy	Disadvantages have not been explored yet
RSS pre-processing	Thresholding [20]	Versatile and necessary	–
	Signal Tendency Index (STI) [22]	Better performance than thresholding on RSS	–
	Gaussian filter [23]	Reduce noises based on actual data	Require larger samplings to form the distribution accurately
	Procrustes Analysis (PA) [22]	Handle device heterogeneity	–
	Signal strength difference [24]	Handle device heterogeneity	It has been shown that PA is better
	Average value [18]	Easy to implement	The value might not be that representative
	Kalman filter [25]	Better on reaching steady RSS	Work better over time
Fingerprint-based positioning	Weighted average [26-32]	Commonly used, easy to implement, versatile	Only cover the area inside of the convex hull of the RPs
	K-nearest neighbour (KNN) [26,27]	Versatile, good for removing unwanted RPs	–
	Enhanced weighted k-nearest neighbour [28]	Good for complex room architecture	–
	Gaussian distribution [29]	Robust for data with unstable RSS	Require larger sampling for better accuracy
	DeepFi architecture [30]	Provide one of the highest accuracy	More computing power for deep learning
	Gaussian mixture model [31,32]	Robust for data with unstable RSS	Require larger sampling for better accuracy
	Weighted extreme learning machine [22]	Faster training and testing time with better accuracy	–
	PSO + BPNN [33]	Provide lower standard deviation on positioning error	–
Calibration-free positioning	Trilateration/Multilateration [34]	Commonly used, easy to implement	Susceptible by object obstruction
	Heron-Bilateration [25]	Only require 2 transmitters	Susceptible by object obstruction
Tracking algorithm	Kalman filter/Extended Kalman filter [13,35]	Commonly used even in GPS	Require additional hardware, i.e., accelerometer
	Recurrent neural network [36]	Faster converges towards the ground truth location	Require training data, which includes moving receiver

publications, 20 of them are focused on positioning technique, as mentioned in Table 1. The majority of the publications are fingerprint-based positioning. The reason is that fingerprint-based positioning generally has higher accuracy. The fingerprint can represent a different kind of wireless environment, thus showing its versatility. A lot of fingerprint-based positioning techniques have been proposed over the years, which explains why fingerprints IPS publications are more variative compared to the other methods. The positioning techniques will be explained further in Section 3.

3. **BLE Positioning Techniques.** There are several different algorithms that can be applied in an IPS using BLE. In this review, these algorithms are classified based on their purpose. The different classifications are such as BLE selection, BLE signal pre-processing, fingerprint-based positioning, calibration-free positioning and tracking algorithm. The combination between methods in different classification can be used in order to achieve the best performance possible. All of the methods used in this section are compiled in Table 1.

3.1. **BLE selection.** One of the benefits of using BLE in IPS is that BLE has cheaper price compared to other transmitters. Therefore, an array of BLE can be used in order to increase the accuracy even further. Instead of using a single RSS value, we can use a vector of RSS values, termed RSS vector. Research showed us that the positioning error is getting smaller as we increase the number of BLE beacons [19]. However, it will reach a certain point where the additional beacons are less impactful to the improvement of the positioning.

Increasing the number of BLE used also means that it provides a larger coverage area. This might also lead to a higher number of detectable BLEs compared to the actually required for positioning. When noises are considered, some of the RSS might be unreliable and better to be removed [20]. Another benefit of BLE selection is to reduce the number of RSS in the vector, thus decreasing the computational load.

There are several criteria for choosing the more informative RSS values in the RSS vector. Research [20] proposed 3 different criteria: strongest RSS, Fisher criterion, and random combination. Strongest RSS means choosing the most likely closest BLE to the receiver, with the argument of having the highest probability of coverage over time. Fisher criterion is a representation of signal-to-noise ratio to ensure that the BLE with higher ratio has more ability to discriminate between reference points in a fingerprint-based algorithm. The random combination is simply picking random BLE, with the benefit of having the least amount of computation.

Research [21] proposed a threshold over 3 combinations of criteria: number of distinct RSS values, percentage of missing RSS values, and overall standard deviation. A large number of distinct RSS means the BLE is able to propagate the signal across the room very well. Percentage of missing RSS value describes the area of coverage; lower percentage of missing RSS is more preferable. Standard deviation of the RSS describes the fluctuation of the BLE.

3.2. **RSS pre-processing.** This step is important to reduce noises from the RSS data. The simplest pre-processing method is thresholding; RSS values outside the threshold will be ignored. Another method of thresholding is to use Signal Tendency Index (STI) [22] of the RSS, instead of the RSS itself. Other than the unwanted RSS values, there might also be some missing RSS values due to signal loss. These missing values can be replaced by an insignificant value, such as less than -100 dBm [20]. Research [23] on BLE fingerprint uses Gaussian filter on the training data. The RSS value will be accepted if the value is inside $\mu \pm \sigma$, where μ and σ are the mean and statndard deviation of the Gaussian.

Another problem that is better to be addressed is device heterogeneity. Even at the same wireless environment, different devices' hardware might receive different RSS values [37]. This directly impacts the accuracy of the positioning, especially for fingerprint methods. A method of using Signal Strength Difference (SSD) instead of RSS, was proposed [24]. It has shown to have better performance on both Wi-Fi and Bluetooth, regardless of the device variety. Another research [22] showed us that despite the difference RSS value received on different devices, it still resembles a similarity in shape. Thus, in the experiment, Procrustes Analysis (PA) was used on Wi-Fi signal. It was shown that using PA provides lower distance error compared to both the traditional RSS values and the previously proposed SSD.

Another pre-processing method that can be done is noise filtering on the RSS value. The most common method of noise filtering is simply using statistical analysis such as average. By using a large number of samplings, the correct RSS value should appear more often than the noise, thus averaging out the noise [18]. Research [25] also proposes using Kalman Filter (KF) to filter the noise. A stable transmitter should have steady RSS value over time; therefore, KF can be used to reduce the noise by considering the previous RSS value. The experiment also shows that KF is able to filter noise better than the conventional statistic method.

3.3. **Fingerprint-based positioning.** The fingerprint represents the wireless environment; it contains a set of predetermined Reference Points (RPs) with a number of samplings taken from each point. The process of gathering the fingerprint is called the calibration step. Then the positioning can be achieved based on the gathered fingerprint. The set of RPs may vary and it will determine how discriminative the RPs are [38]. Generally, the fingerprint-based algorithm will be involving a weighted average of the RPs. Each RP will be assigned with a weight that described how likely the ground truth location is on that point. There are 2 ways to determine the weight: Deterministic Fingerprint (DF) and Probabilistic Fingerprint (PF).

In DF, a degree of similarity between the RSS on ground truth location and RSS on the RPs will be used, because the neighbouring area should have similar RSS. Research [26] used Euclidean distance between the RSS vectors. Meanwhile, in a newer research [27], it has been shown that using Chebyshev distance achieved better accuracy. Another improvement that can be made is to pick some of the best RPs instead of all of them using K-Nearest Neighbour (KNN) [39,40]. Another method named Enhanced Weighted K-Nearest Neighbour (EWKNN) was proposed, capable of dynamically changing the number of neighbours to achieve lower positioning error [28].

In PF, the probability will be used to determine how likely the ground truth location is on the given RP. Generally, PF will have better performance compared to DF [30]. Research [29] uses the Gaussian distribution on the RSS distance. Nowadays PF is related to posterior probability and Bayesian statistic. The weight used in an RP is the posterior probability of that RP becoming the ground truth location given the RSS value ($P(RP|RSS)$). This probability can be calculated using Bayes' Theorem (1). Furthermore, the value of $P(RSS|RP)$ can be calculated by data through different algorithms. A research [30,41] on Wi-Fi CSI uses Gaussian Radial Basis Function (RBF) between the CSI and the reconstructed CSI using deep learning. Another research [31,32] on Wi-Fi fingerprints uses Gaussian Mixture Model (GMM) as the Probability Distribution Function (PDF) of the RSS value given certain RPs. Our previous research uses GMM on BLE fingerprint, and it performs well under signal fluctuation.

$$P(RP|RSS) = \frac{P(RP)P(RSS|RP)}{\sum P(RP_i)P(RSS|RP_i)} \tag{1}$$

The fingerprint is also suitable for supervised learning algorithm since the fingerprint can be used as the training data. Research [22] uses Weighted Extreme Learning Machine (WELM) by using the fingerprint as the training data. The trained model will be used in the online phase, and the experiment shows that WELM performs better than KNN. Another research [33] uses Particle Swarm Optimization (PSO) on Back Propagation Neural Network (BPNN) showing that the proposed method provides lower standard deviation of positioning error, which implies to better stability.

The benefit of using fingerprint is that it can represent any kind of wireless environment if it is designed to do so. This includes complex room design with a lot of object obstruction. Research [8] on Wi-Fi fingerprint tried to include dynamic human intervention in the fingerprint. However, fingerprint requires the calibration step in order to gather the fingerprint, which is very time consuming and labor intensive. Moreover, it also scales with what the fingerprint wants to represent [42]. The amount of effort spent on calibration will be based on the number of RPs and the number of sampling on each point.

3.4. **Calibration-free positioning.** Calibration-free algorithm refers to the non-fingerprint algorithm. Therefore, the positioning should be done by using other measurements, such as Time of Arrival (ToA), Time Difference of Arrival (TDoA), Angle of Arrival (AoA), and RSS. Therefore, these algorithms do not require a calibration process, which becomes one of the main advantages of using a non-fingerprint algorithm.

Bluetooth does not provide accurate time synchronization, and it is also hard to measure the angle using Bluetooth [34]. IPS using BLE usually relies on RSS, with the help of propagation loss model (2) to determine the distance between the transmitter and the receiver [43]. The variable d represents the distance between the receiver and the transmitter. Meanwhile d_0 is a pre-determined variable that represents the anchor distance used as a reference. Variable n is a constant, usually $n = 1$. This distance value can be used in different algorithms. Research [34] used trilateration or multi-lateration algorithm, which requires at least 3 distance values to do an estimation. Research [25] on RFID proposed a method termed Heron-Bilateration. It requires only 2 distance values, making it faster to compute and has lower positioning error.

$$RSS_d = RSS_{d_0} - 10n\log\left(\frac{d}{d_0}\right) \tag{2}$$

Unfortunately, due to object obstruction, the propagation loss model only works in a perfect environment. This makes the fingerprint-based algorithm generally having better accuracy than the calibration-free algorithm. Research [44] proposed a machine learning algorithm that can learn the propagation model on different shape of room. However, it requires the data collection for the training data, thus eliminating the convenience of not required to do calibration.

3.5. **Tracking algorithm.** By doing the positioning in a real-time, it introduces a new aspect of time-series to the problem that allows more algorithms to smoothen the positioning over time. Kalman Filter (KF) or Extended Kalman Filter (EKF) is a common tracking algorithm to be used in GPS [45], and it can be adapted to IPS as well. Research [35] on Wi-Fi IPS uses the velocity and acceleration of the receiver in both x and y axes in addition to the previous location as the input of the EKF. The positioning itself is handled using weighted trilateration. Similar uses of KF are also applied on BLE sub-channels, with weighted trilateration as the main positioning algorithm [13]. Another algorithm that can be used on a real-time positioning is Recurrent Neural Network (RNN), which allows the neural network to include the previous estimation to be used on the current estimation. Research [36] simulated the real-time positioning using RNN, and showed us that it is an effective method to be used in tracking problem.

4. **Future Research Directions.** By analyzing the current existing IPS research, authors have compiled several topics on IPS using BLE that might be relevant in the near future. Several topics are more common in another transmitter such as Wi-Fi, since BLE is a relatively new technology. There is still a lot of room for improvement to show the potential of BLE.

a) Advance fingerprint-based algorithm to handle complex and dynamic wireless environment. Almost all of the IPS research on BLE was held in an empty room with several static object obstruction such as walls and furniture. However, in real scenario, there will be a lot of changes in its wireless environment. While non-fingerprint algorithm suffers even more from the fluctuation, fingerprint-based algorithm also requires a more advanced fingerprint that can represent the dynamic environment. There is a small number of IPS researches [8] that include dynamic human intervention, but none of them are using BLE.

b) Utilize Channel Diversity instead of the single RSS value. Similar to CSI in Wi-Fi, BLE also has its sub-channel termed Channel Diversity. It has been shown that both CSI [30] and Channel Diversity [13] provide higher accuracy compared to the regular RSS value, even if tested on a similar algorithm. Unfortunately, there are only a small number of researches utilizing Channel Diversity. It is possible that Channel Diversity might not be as promising as we think. It might work well on the previously proposed method [13], but it does not guarantee that all positioning techniques that work in RSS will perform better if applied on Channel Diversity. Further research on Channel Diversity and its positioning techniques are required.

c) IPS using multiple different kinds of transmitters. While each transmitter has its own advantages and disadvantages, using multiple kind of transmitters might be the solution. Research [20] proposed a coarse-to-fine approach on the combination of Wi-Fi and BLE. As BLE has lower coverage area compared to Wi-Fi, the Wi-Fi will be used as the coarse estimation to roughly estimate the ground truth location. Then the fine estimation will be done using multiple BLEs near the rough estimation, thus improving the accuracy of the positioning.

d) BLE fingerprint public dataset. Public dataset is very important as it will become easier to compare the performance between methods. This is not a problem on Wi-Fi fingerprint as there are public datasets of Wi-Fi fingerprint [46-48]. Despite the importance of public dataset, there has not been any public dataset for BLE fingerprint so far. Each BLE device has different parameters on its setting, and different brand may produce a different result too. Having a public dataset will be a reliable way to compare the performance of each method.

5. **Conclusion.** In this paper, the authors reviewed recent IPS techniques, especially on BLE. Recent studies on IPS using BLE has been focusing on improving the accuracy due to the signal fluctuation. Twenty papers about different positioning techniques have been selected to be discussed thoroughly, and they were grouped into 5 classifications based on the task they want to achieve. The techniques are compared towards each other to pinpoint the advantages and disadvantages of each technique. Between categories, fingerprint-based algorithm is the most popular research these days due to the versatility of what the fingerprint wants to represent. The more sophisticated fingerprint-based algorithm has also been proposed to increase the accuracy even in the harsh wireless environment. Based on the literature review, 4 future research directions are provided in order to improve the research topic of IPS using BLE.

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