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Full Length Research Paper

Filtering Effect on RSSI-Based Indoor Localization Methods

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ABSTRACT

Indoor positioning systems are used to locate and track objects in an indoor environment. Distance estimation is done using received signal strength indicator (RSSI) of radio frequency signals. However, RSSI is prone to noise and interference which can greatly affect the accuracy performance of the system. In this paper Internet of Things (IoT) technologies like low energy Bluetooth (BLE), WiFi, LoRaWAN and ZigBee are used to obtain indoor positioning. Adopting the existing trilateration and positioning algorithms, the Kalman, Fast Fourier Transform (FFT) and Particle filtering methods are employed to denoise the received RSSI signals to improve positioning accuracy. Experimental results show that choice of filtering method is of significance in improving the positioning accuracy. While FFT and Particle methods had no significant effect on the positioning accuracy, Kalman filter has proved to be the method of choice for BLE, WiFi, LoRaWAN and ZigBee. Compared with unfiltered RSSI, results showed that accuracy was improved by 2% in BLE, 3% in WiFi, 22% in LoRaWAN and 17% in ZigBee technology for Kalman filtering method.

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INTRODUCTION

The advancement of technology has brought forth the generation of digital natives with gadgets and devices always connected and sharing information. These devices are embedded with sensors wirelessly connected to improve users' experience (Sadowski & Spachos, 2018). The interconnectedness of these sensors forms a wireless sensor network (WSN). Through development of the Internet of Things (IoT), low cost and energy efficient devices embedded with the sensors have been developed. In smart buildings, warehouses, museums, hospitals, airports, parking lots or shopping malls, it is of importance that all devices can determine their location in real-time for efficient sorting, delivering and management (Sangthong et al., 2020). The WSN has been extensively used to develop indoor positioning systems using different technologies. It is however, observed that in designing the indoor positioning systems, there is no standard set of specifications or protocols used to guide the localization process (Pande & Ibwe, 2021). Different localization techniques, signal metrics and wireless technologies are used with no single parameter being globally accepted as international localization standard. Likewise, the wireless and IoT technologies currently used were not primarily intended for localization purposes (El-Absi et al., 2020).

To locate objects in a building, indoor positioning is performed. Indoor positioning is used inside an environment where Global Positioning System (GPS) fails. GPS is one of the most commonly used positioning systems. In GPS, satellites orbiting the Earth send time-stamped signals to a receiver which is used to estimate the position. However, it provides a maximum accuracy of five meters, making it challenging to use for effective indoor positioning (Zhang et al., 2017). It also consumes a large amount of energy and can be expensive to implement for every node in a large network (Al-hadhrami et al., 2016). Due to a dependency on Line-of-Sight (LoS) between GPS satellites and receivers, GPS cannot be used indoors. Therefore, when performing indoor positioning, an accuracy of less than one meter is required for a proper positioning system. Hence, other methods need to be used in order to determine a device's position in indoor environments (Pande & Ibwe, 2021).

To implement indoor positioning system that can accurately track targeted devices, WSN is a solution that is often applied. WSN consist of dispersed sensors that collect environmental information, share the collected data with nearby device or aggregate to a central location. One advantage that WSN has for indoor positioning is the portability of the sensor nodes (Sadowski & Spachos, 2018). Batteries are often used to power the nodes which allows them to be placed anywhere. The other advantage is the scalability of WSN. Using a standard number of nodes to achieve positioning is usually not possible due to the varying shapes and sizes of environments. Using a larger number of nodes can often provide increased accuracy requiring extra hardware while producing additional interference in the area (Kim et al., 2017).

Implementing an indoor positioning system has many uses in a variety of areas (Pu et al., 2011). It provides the added benefit of safety and security and also improve efficiency in the working environment. In hospitals, the indoor positioning can be used to track patients and enable doctors and medical personnel to know their exact locations inside the building without needing to provide constant supervision (Tsang et al., 2015). Likewise, in emergency situations, stress prevention and management are critical for responders to stay well and to continue to help in the situation. Responders could use indoor localization to help quickly guide them to anyone who is in distress without needing to know the exact layout of the building (El-Absi et al., 2020).

The indoor positioning, however, suffers from several challenges that are not present when performing positioning outdoors. The obstacles in the indoor environment including furniture, walls, and people, which can reflect the signals produced and increasing multipath effects (Njima et al., 2019). The different wireless technologies currently used in communication affect the performance of the indoor positioning systems through noise and interference. The interference distorts the quality of signals received by the objects and compromise the positioning accuracy. The most common technologies used in indoor positioning include WiFi, Bluetooth, Radio Frequency Identification (RFID) (Deng et al., 2018), Ultra-Wide Band (UWB) and cellular (Singh et al., 2021). However, each of the aforementioned technologies have their strengths and weaknesses when used indifferent environments. The abundance of WiFi access points in many buildings, has made WiFi the simplest indoor positioning option, as any additional hardware that is needed is minimal. However, the WiFi access points are often placed to maximize signal coverage, not for indoor positioning. WiFi consumes large amount of power, which could easily deplete battery powered devices, hence, not ideal for positioning systems (Sadowski & Spachos, 2018). The emergency of inexpensive IoT devices and applications like Bluetooth Low Energy

(BLE) (Luo et al., 2018), Zigbee and beacons, has made it easy to arrange the devices for indoor positioning. The Bluetooth beacons are battery powered hence limiting their service time. Nevertheless, the mentioned wireless technologies can be configured to follow the same algorithm in localizing objects in given environments.

The indoor positioning system has three parts in deriving the object's location information. These are physical quantity measured, measurement method and the extraction of useful location information based on the measurements (Dolha et al., 2019). The sensing devices make use of any of signals like ultrasonic, radio frequency, infrared or vision to measure physical quantity for location. These signals travel between transmitters and receivers and also carry coordinate information of reference nodes. The physical quantity are measured as time of arrival (TOA), time different of arrival (TDOA), angle of arrival (AOA) and received signal strength indicator (RSSI) (Singh et al., 2021). With the raw information of a physical quantity measured, various techniques and algorithms are used which transform raw data into usable position information. Techniques have been classified as triangulation/trilateration, Scene Analysis, Proximity (Tsang et al., 2015) and fingerprinting. Position estimated by algorithms may be relative or absolute and it varies from system to system like GPS estimates absolute positioning for every located device.

TOA is among the most accurate techniques which estimate the signal propagation time between a source and receiver using the synchronized clocks (Njima et al., 2019). It the receiver. It is often used for finding the distance between the transmitter and the receiver, since the signal strength decreases as the signal propagates outward from the transmitter. Since propagating signals are greatly susceptible to noise in the environment, RSSI often leads to inaccurate values that can cause errors in the uses time stamps embedded in transmitted packets along with the received time to determine how far the packet had to travel to reach the destination. However, when using a TOA set up, devices in the network need synchronized clocks, which requires additional hardware, thus increasing the cost of the system. TDOA is similar to TOA in that it requires that devices to be synchronized in time, but it uses the signal propagation time to multiple receivers to find the absolute signal propagation time (Sadowski & Spachos, 2018). The distance can then be calculated by the differences in arrival time of the packet to the different receivers. AOA systems use an array of antennae to determine the angle, from which the signal propagated (Liu et al., 2021). It is based on the principle of measuring angular directions (Azimuth and Elevation) from a device placed at a known location. With angle it is meant the angle in which the signal meets the receiver. The angle is measured by computing the phase of the receiving radio signals. Triangulation is then used along with the geometric principle of angles of triangles to determine the position of the receiver. AOA techniques often require complex hardware and must be calibrated in order for an accurate position to be obtained. RSSI is one of the most popular and simplest methods for localization (Pande & Ibwe, 2021). The main reason for its popularity is that finding the RSSI requires no additional hardware and can be found on any device utilizing almost any type of wireless communication technology. These technologies could be BLE, ultrasonic, Zigbee, WiFi, RFID, LoRaWAN, UWB and cellular (Sadowski & Spachos, 2018). RSSI works by measuring the signal strength of packets on positioning system. To improve estimation accuracy, the received RSSI signals should be filtered to remove noise (Liu et al., 2021).

In this paper, through experimentation, a filtering comparison between the positioning accuracy of WiFi, BLE, Zigbee, and LoRaWAN is performed. The wireless technologies were chosen based on public availability, easily connected to one another and use in the IoT. Zigbee is also a popular low power technology, often used in IoT applications. BLE and WiFi are both heavily present in society. Most devices are able to connect with at least one or both of the mentioned technologies, allowing creation of WSN. LoRaWAN is a novel technology that is not as prevalent as the BLE, Zigbee and WiFi. LoraWAN operates at 915 MHz with nodes that can reach distances of 15000 meters. The tests were performed using a trilateration technique where the RSSI values were utilized in determining the approximate distances between the transmitting nodes and the receiver. Two different environments were used for experimentation as discussed in (Sadowski & Spachos, 2018) . In particular, the paper presents, analyses, and quantitatively compares the effect of different techniques such as Fourier Transform, Discrete Kalman, and Particle for filtering RSSI fluctuations due to signal noise, by pointing out how filtering can impact on RSSI-based indoor positioning system performance. This work uses the RSSI data set which is available online[1]. The distance error performance is assessed in terms of number of meters. These results are obtained using PYTHON® simulation platform.

METHODS AND MATERIALS

RSSI Filtering Methods

RSSI fluctuations due to signal noise significantly affect both stability and efficiency of the estimation process. For instance, in mobile beacons when the RSSI value of the target reader or tag is interfered or corrupted by noise, even small RSSI fluctuations can produce significant distance estimation changes, thus relevantly reducing the accuracy. In addition, in those conditions RSSI over/under-estimation may trigger unnecessary predictions, thus lowering efficiency. The section presents three different filtering components that are implemented to mitigate RSSI fluctuations. These are Fourier Transform, Discrete Kalman and Particle.

Fourier Transform Filtering

For a given access point, the set of its actual RSSI discrete values measured at the receiver side is represented as:

$$R_o = \{r_o(1), r_o(2), r_o(3), \ldots, r_o(n)\} \tag{1}$$

where $r_o(i)$ is the RSSI value at discrete time *i*. It is also possible to estimate $R_1 = \{r_1(1), r_1(2), r_1(3), \ldots, r_1(n)\}$

where

$$r_1 = \sum_{j=1}^{i} r_o(j) \tag{2}$$

The proposed Discrete Fourier Transform (DFT) filter module extract from R_o, a Fourier coefficient set (A_i and B_i) representing the RSSI sequence in the frequency domain. In a time window of duration (*Ro size*)*(RSSI *Sampling Period*). The coefficient set is extracted with usual Fourier equations as:

$$A_o = \frac{1}{N}\sum_{n=1}^{N} y(n\Delta t) = \frac{1}{N}\sum_{k}^{N} y_k \;; \qquad B_o = B_{\frac{N}{2}} = 0\;;\; A_{\frac{N}{2}} = \frac{1}{N}\sum_{k}^{N} y_k \cos(k\pi) \tag{3}$$

$$A_p = \frac{2}{N}\sum_{n=1}^{N} y(n\Delta t) = \frac{2}{N}\sum_{k=1}^{N} y_k \cos\left(\frac{2\pi pk}{N}\right) \tag{4}$$

$$B_p = \frac{2}{N}\sum_{n=1}^{N} y(n\Delta t) = \frac{2}{N}\sum_{k=1}^{N} y_k \cos\left(\frac{2\pi pk}{N}\right) \tag{5}$$

where $p = 1\ldots N/2\text{-}1$, $\Delta t = T/N$, and N is the size of R_o.

The Fourier coefficient set is the basis to define an Inverse Discrete Fourier Transform (IDFT) to regenerate the RSSI signal given as:

$$f_k = \frac{A_o}{2} + \sum_{p=1}^{M}\left[A_p \cos\left(\frac{2\pi pk}{N}\right) + B_p \sin\left(\frac{2\pi pk}{N}\right)\right] \tag{6}$$

when IDFT exploits only a subset of the series terms in Equation (6), the generated RSSI sequence do not exhibit its high frequency components and show a more regular trend like a low pass filter. In this case, the optimal number of *N* and *M* are 4 and 1 respectively.

Discrete Kalman Filter

The Kalman filter addresses the general problem of trying to estimate the state $x = \Re^n$ of a discrete-time controlled process that is governed by the linear stochastic difference equation as:

$$x_k = Ax_{k-1} + Bu_k + \omega_{k-1} \tag{7}$$

with a measurement $y = \Re^n$ that is

$$y_k = Hx_k + \psi_k \tag{8}$$

The random variables ω_k and ψ_k represent the process and measurement noise respectively (Park et al., 2019). They are assumed to be independent of each other, white and with normal probability distributions

$$p(\omega) = N(0,Q) \tag{9}$$

$$p(\psi) = N(0,R) \tag{10}$$

The *nxn* matrix *A* relates the state at the previous time step to the state at the current step, in the absence of either a driving function or process noise. The $n\times 1$ matrix *B* relates the optional control input $y \in \Re^n$ to the state *x*. The $m\times n$ matrix H in the measurement equation relates the state to the measurement y_k.

In this case, the discrete Kalman filtering module will be estimating RSSI values by representing the RSSI time evolution as a combination of signal noise measurement noise and maximum signal evolving process noise (Park et al., 2019). The filter works by minimizing process noise (ω) through a two-phase algorithm: first, a predictor performs next RSSI estimation (Equations (11) and (12)); then, a corrector improves the RSSI estimation by exploiting current RSSI measurement (Equations (13), (14) and (15)). Therefore, an iteration of the proposed Discrete Kalman filtering module processes:

$$\hat{x}_k^- = A\hat{x}_{k-1} + \omega_{k-1} \tag{11}$$

$$P_k^- = AP_{k-1}A^T + Q \tag{12}$$

$$K_k = P^-{}_k H^T (HP^-{}_k H^T + R)^{-1} \tag{13}$$

$$\hat{x}_k = \hat{x}_k^- + K_k(z_k - H\hat{x}_k) \tag{14}$$

$$P_k = (1 - K_k H)P_k^- \tag{15}$$

x and *z* are RSSI values, the state coincides with the output (*A* is a $n\times n$ identity matrix) and the estimation of the next state estimate is equal to the current state (*H* is a *mxn* matrix). After running several tests, the good trade-off between RSSI fluctuation mitigation and filtered to actual RSSI delay by setting $Q = 1.6$ and $R = 6$.

Particle Filtering

Particle filtering uses a set of samples to represent the posterior distribution of a stochastic process given the noisy and/or partial observations. The state-space model can be nonlinear and the initial state and noise distributions can take any form required. Particle filter techniques provide a well-established methodology for generating samples from the required distribution without requiring assumptions about the state-space model or the state distributions (Ata-Ur-Rehman et al., 2021). Particle filters update their prediction in an approximate manner. The samples from the distribution are represented by a set of particles; each particle has a likelihood weight assigned to it that represents the probability of that particle being sampled from the probability density function. Weight disparity leading to weight collapse is a common issue encountered in these filtering algorithms, however, it is mitigated by including a resampling step before the weights become uneven.

In this case, like the Discrete Kalman, the proposed Particle filtering module tries to estimate RSSI by minimizing measurement and process noise, but without imposing a linear equation modeling and without imposing normal distribution for signal noise in the deployment stage. The main idea at its basis is for the algorithm to compute, at each step, several possible filtered RSSI values for each measured RSSI; then associates each candidate value with a weight and choose the most promising values from the new measured RSSI values as described in (Bellavista et al., 2006). It then perturbs the candidate values according to the rules described in (Bellavista et al., 2006) to obtain a new filtered average RSSI value.

To illustrate Particle filtering, this work adopts the example in the work of (Bellavista et al., 2006) for the algorithm iteration with 10 particles, which represents 10 possible filtered RSSI values as shown in Figure 1. The setup starts with 10 possible filtered RSSI values (light circles), all with the same weight. Then, the state estimate probability is exploited which has been obtained from RSSI measurement. The next step is to assign a weight at each filtered RSSI value (dark circles) and spread the heavy RSSI points in different RSSI values with the same weight (light circles), while discarding the light RSSI values. Lastly, the filtered RSSI are randomly perturbed (light circles). The number of particles strongly influences the Particle filter performance; in general, greater is the particle number, better the filtered RSSI follows the actual RSSI sequence.

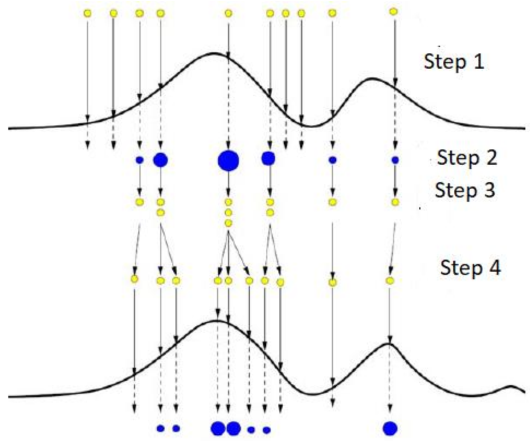

Figure 1: Particle Filtering Steps (Bellavista et al., 2006).

Trilateration Algorithm

The trilateration algorithm uses measurements of the RSSI values to estimate the distance between reference node and targeted node reader (Pu et al., 2011). The distances between reference locations and the target location can be considered as the radii of many circles with centers at every reference location. Hence, the target location is the intersection of all the sphere surfaces. This work adopts the tags' distance relations derivations in (Pande and Ibwe, 2021). Figure 2 shows the arrangement of reference (readers) and target (Tag) nodes in a simplified fashion. The reference sensor nodes are located at the corners of the triangular area. This technique requires three reference nodes to achieve trilateration. Node A(x_1,y_1) and B(x_2,y_2) are taken to achieve x value while C(x_3,y_3) and A(x_1,y_1) are used to get y value, hence (x,y). The distances among sensor nodes/readers (d_1, d_2 and d_3) are obtained using a log-distance path loss model to convert RSSI values to distances from the previous process. The theoretical model used in indoor propagation for RSSI ranging is called log-normal propagation model presented in (Zou et al 2013). The model is presented as:

$$P_{RX}[\mathrm{dB}] = PL(d_o) - 10\eta \log_{10}\frac{d}{d_o} + X_\sigma \quad (16)$$

where $P_{RX}[dB]$ is the received RSSI value, $PL(d_0)$ is the path loss value for a reference distance d_0, η is the path loss exponent, and X_σ is a Gaussian random variable with zero mean and variance, σ_2, that models the random variation of the RSSI value. The received signal power is affected by attenuation, multipath, reflection, fading, interference, noise and shadowing (Luo et al., 2018). The position of the tag is likely to be erroneous in this way because the point of intersection is affected by the RSS value. Due to the multipath, interference and noise the three circles may not intersect with a common point. The algorithm presented in (Pande & Ibwe, 2021) is adopted in this work for the best position estimation of the target node.

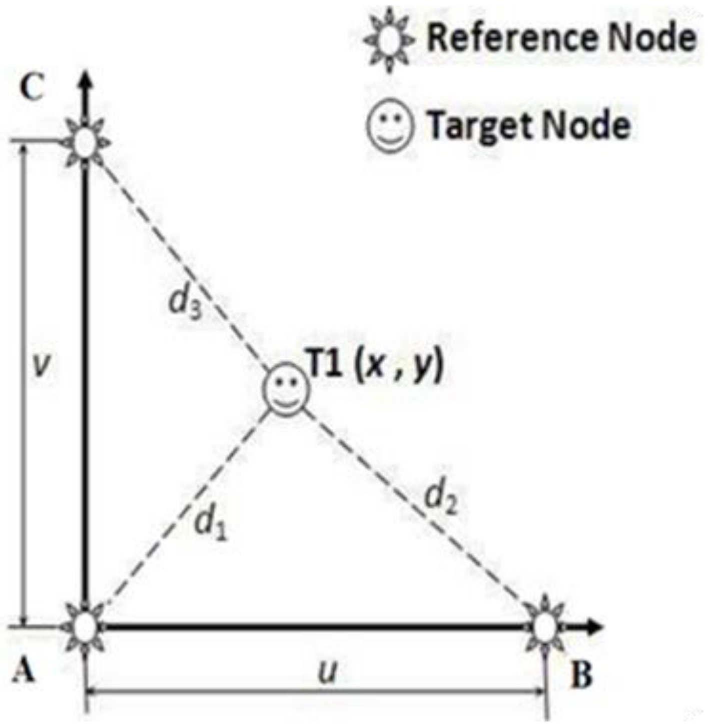

Figure 2: Tags and readers arrangement.

Adopting the values $x_1 = 0$, $x_2 = u$, $x_3 = 0$, $y_1 = 0$, $y_2 = 0$, $y_3 = v$ gives

$$x = \frac{u^2 + (d_1^2 - d_3^2)}{2u} \tag{17}$$

$$y = \frac{v^2 + (d_1^2 + d_3^2)}{2v} \tag{18}$$

Environmental Modeling

The primary goal of RSSI filtering in this work is to mitigate RSSI fluctuations due to signal noise in order to primarily improve indoor positioning accuracy, with simultaneous acceptable values for efficiency and stability for the selected wireless technologies WiFi, BLE, ZigB and LoRaWAN. Therefore, to evaluate the performance of each wireless technology, two environments were built as described in (Sadowski & Spachos, 2018). The first environment was selected to be a typical research lab with dimensions 10.8 m × 7.3 m. The environment was selected due to the large size with large numbers of equipment, computers, WiFi and BLE devices that could impose interference, mimicking a very noisy environment for experimenting. The second selected environment had dimensions of 5.6 m × 5.9 m representing a small meeting room. The second environment was a perfect testing area as it demonstrated conditions contrasting those in the first environment. The second environment had much smaller space that contained only tables and chairs. No equipment, devices or computers were present in the environment that could cause significant interference in the area, creating a low-noise environment for testing. The parameters used for environment 1 and environment 2 are shown in Table 1 and Table 2, respectively.

To set up for the experiments of the two environments, the arrangement in Figure 3 was set up. The right-angle triangle was created between the nodes. The distances of the triangle, *d* meters, between nodes A, B and C, were set to be equal. The actual coordinates of point A, B and C are (0,0), (*d*,0) and (*d*,*d*) respectively. The experiments used three selected distances for testing at 1, 3 and 5 meters. The receiver was set to one of three positions: in the center between nodes A and B (*D*1), in the center between nodes A and C (*D*2), and in the centroid of the triangle (*D*3). The target locations are given in Table 3. The three distances were tested using the different wireless technologies, WiFi, BLE, ZigBee and LoRaWAN, while keeping the same arrangement and adjusted target positions *D1*, *D2* and *D3*.

Table 1: Parameters used in environment 1

	WiFi	BLE	ZigBee	LoRaWAN
η	2.013	2.511	2.261	1.246
X_σ	-49.990	-75.540	-51.100	-31.380

Table 2: Parameters used in environment 2

	WiFi	BLE	ZigBee	LoRaWAN
η	2.162	2.271	1.653	0.519
X_σ	-45.730	-75.480	-51.010	-33.440

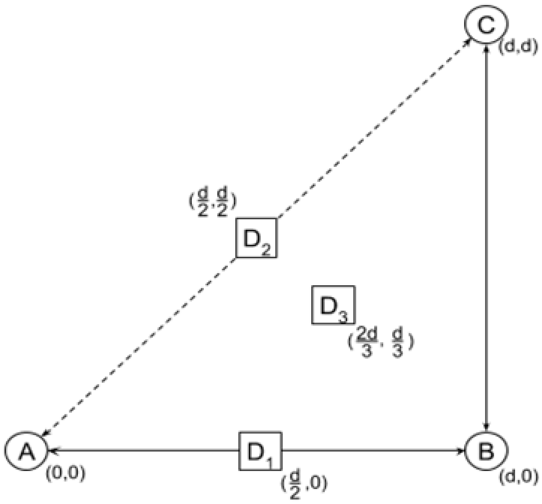

Figure 3: Experimental Setup.

Table 3: Targets Location at Given Distances

Location (m)	Test Points Coordinates		
	D1 (m)	D2 (m)	D3 (m)
1	(0.500,0.000)	(0.500, 0.500)	(0.667, 0.333)
3	(1.500,0.000)	(1.500, 1.500)	(2.000, 1.000)
5	(2.500,0.000)	(2.500, 2.500)	(3.333, 1.667)

The theoretical propagation models were developed and simulated in PYTHON using equation 16 and the parameters given in Table 1 and Table 2. The channel models were developed for each wireless technology using the publicly available RSSI dataset[2]. Nine tests were done for each wireless technology based on varying the distances in Table 3. In each of the test, the location of all the nodes was recorded along with the measured RSSI values. The measured RSSI values were used to approximate the position of the receiver with respect to reference nodes. To evaluate the accuracy of the filtering technique in each wireless technology used, the mean squared error (MSE) of the actual and approximate distance was used. The MSE is measured as

$$MSE = \frac{1}{K}\sum_{i}^{K}\sqrt{(x-x_i)^2+(y-y_i)^2} \qquad (19)$$

where, K is the number of nodes. x and y are the actual and x_i and y_i are the estimated coordinates of the target node. These results were then passed to Microsoft Excel for data analysis. The MSE in each environment were estimated and analyzed. To demonstrate filtering effect, the filtered RSSI has to show smaller MSE compared to the unfiltered RSSI with respect to environment changes.

RESULTS AND DISCUSSION

The filtering accuracy evaluation between the wireless technologies, based on minimum MSE given in Equation (19), was performed. The results for FFT filtering in environment 1 and environment 2 are shown in Table 4 and Table 5, respectively.

In environment 1, the BLE produced an average error of 0.655 meters while in environment 2 the average error 0.834 meters. Using the FFT filtering method, BLE has demonstrated to have the best error performance in environment 1 with 0.654 meters. However, its overall performance for both environments of 0.744 meters ranks second of the four technologies. WiFi has demonstrated to be the second-best technology in environment 1 with 0.795 meters and the best technology in environment 2 with 0.662 meters when FFT filtering was used. The overall performance of WiFi still places it to the first place with 0.728 meters. ZigBee is the least performing in environment 1 with 0.889 meters and third in environment 2 with 0.939 meters. It is also demonstrated to be the third best in overall performance with 0.914 meters.

Table 4: MSE values with distances in Environment 1 for FFT Filtering

Distance (m)	Test Point	Actual Coordinates (m)		Error (m)			
		M	N	BLE	WiFi	LoRaWAN	ZigBee
1	D1	0.500	0.000	0.134	0.135	0.349	0.339
	D2	0.500	0.500	0.011	0.116	0.506	0.351
	D3	0.670	0.330	0.186	0.773	0.755	1.765
	Average			**0.110**	**0.341**	**0.537**	**0.818**
3	D1	1.500	0.000	1.183	1.169	0.247	1.273
	D2	1.500	1.500	0.048	0.174	0.268	1.230
	D3	2.000	1.000	0.787	0.730	0.917	0.677
	Average			**0.673**	**0.691**	**0.477**	**1.060**
5	D1	2.500	0.000	2.351	2.772	1.803	0.178
	D2	2.500	2.500	0.098	0.559	0.847	0.355
	D3	3.330	1.670	1.094	0.726	1.148	1.837
	Average			**1.181**	**1.352**	**1.266**	**0.790**

Table 5: MSE values with distances in Environment 2 for FFT Filtering

Distance(m)	Test Point	Actual Coordinates (m)		Error (m)			
		M	N	BLE	WiFi	LoRaWAN	ZigBee
1	D1	0.500	0.000	0.464	0.276	0.492	0.376
	D2	0.500	0.500	0.853	0.313	0.001	0.350
	D3	0.670	0.330	0.312	0.772	0.236	0.226
	Average			**0.543**	**0.454**	**0.243**	**0.317**
3	D1	1.500	0.000	1.468	1.051	1.498	1.383
	D2	1.500	1.500	0.507	1.157	0.126	0.630
	D3	2.000	1.000	0.590	0.583	2.900	0.610
	Average			**0.855**	**0.930**	**1.508**	**0.874**
5	D1	2.500	0.000	2.222	0.599	2.430	1.843
	D2	2.500	2.500	0.054	1.123	0.507	1.578

	D3	3.330	1.670	1.032	0.081	2.313	1.456
	Average			**1.103**	**0.601**	**1.750**	**1.626**

The results for Kalman filtering in environment 1 and environment 2 are shown in Table 6 and Table 7, respectively. In environment 1, the BLE is the best performing with an average error of 0.681 meters while in environment 2, it ranks third with the average error 0.800 meters. Using the Kalman filtering method, WiFi has demonstrated to have the best error performance in environment 2 with 0.476 meters. However, its overall performance for both environments of 0.740 meters ranks third of the four technologies. ZigBee has demonstrated to be the second-best technology in environment 1 with 0.691 meters and the in environment 2 with 0.754 meters when Kalman filtering was used. The overall performance of WiFi still places it to the first place with 0.623 meters. LoRaWAN is the least performing with an overall error performance of 0.769 meters.

Table 6: MSE values with distances in Environment 1 for Kalman Filtering

Distance (m)	Test Point	Actual Coordinates (m)		Error (m)			
		M	**N**	**BLE**	**WiFi**	**LoRaWAN**	**ZigBee**
1	D1	0.500	-	0.2334	0.1812	0.3789	0.2378
	D2	0.500	0.500	0.0075	0.0905	0.3992	0.2804
	D3	0.670	0.330	0.1892	0.7007	0.6471	1.3459
	Average			**0.143**	**0.324**	**0.475**	**0.621**
3	D1	1.500	-	1.2727	2.3621	0.2406	0.5693
	D2	1.500	1.500	0.0408	0.256	0.2054	0.5518
	D3	2.000	1.000	0.7625	0.3905	0.6528	0.6014
	Average			**0.692**	**1.003**	**0.366**	**0.574**
5	D1	2.500	-	2.4348	1.6278	2.1485	0.7623
	D2	2.500	2.500	0.0736	0.3184	0.62	0.276
	D3	3.330	1.670	1.1131	0.9986	1.1327	1.5979
	Average			**1.207**	**0.982**	**1.300**	**0.879**

Table 7: MSE values with distance in Environment 2 for Kalman Filtering

Distance (m)	Test Point	Actual Coordinates (m)		Error (m)			
		M	**N**	**BLE**	**WiFi**	**LoRaWAN**	**ZigBee**
1	D1	0.500	-	0.478	0.198	0.495	0.428
	D2	0.500	0.500	0.591	0.141	0.032	0.264
	D3	0.670	0.330	0.209	0.031	0.236	0.421
	Average			**0.426**	**0.123**	**0.254**	**0.371**
3	D1	1.500	-	1.455	0.203	1.494	1.343
	D2	1.500	1.500	0.355	0.366	0.071	0.401
	D3	2.000	1.000	0.665	0.924	1.285	0.837
	Average			**0.825**	**0.498**	**0.950**	**0.860**
5	D1	2.500	-	2.321	1.208	2.469	1.026
	D2	2.500	2.500	0.015	0.615	0.448	1.129

	D3	3.330	1.670	1.114	0.600	0.886	0.944
	Average			**1.150**	**0.808**	**1.268**	**1.033**

The results for Particle filtering in environment 1 and environment 2 are shown in Table 8 and Table 9, respectively. In environment 1, still the BLE is the best performing with an average error of 0.659 meters while in environment 2, it ranks second with the average error 0.843 meters. Particle filtering method has enabled WiFi to demonstrated the best error performance in environment 2 with 0.474 meters. Likewise, its overall performance for both environments of 0.652 meters ranks first of the four wireless technologies. ZigBee has demonstrated to be the third-best technology with an overall average error performance of 0.864 meters when Particle filtering was used. The overall performance of WiFi still places it to the first place with 0.623 meters. LoRaWAN is the least performing in with an overall error performance of 1.001 meters when Particle filtering was used.

Table 8: MSE values with distance in Environment 1 for Particle Filtering

Distance (m)	Test Point	Actual Coordinates (m)		Error (m)			
		M	**N**	**BLE**	**WiFi**	**LoRaWAN**	**ZigBee**
1	D1	0.500	-	0.114	0.135	0.334	0.354
	D2	0.500	0.500	0.007	0.120	0.490	0.303
	D3	0.670	0.330	0.182	0.976	0.765	1.764
	Average			**0.101**	**0.410**	**0.529**	**0.807**
3	D1	1.500	-	1.224	2.681	0.350	1.170
	D2	1.500	1.500	0.035	0.322	0.279	0.708
	D3	2.000	1.000	0.756	0.492	1.077	0.618
	Average			**0.672**	**1.165**	**0.569**	**0.832**
5	D1	2.500	-	2.427	1.355	2.114	0.109
	D2	2.500	2.500	0.094	0.439	0.895	0.349
	D3	3.330	1.670	1.090	0.944	1.117	1.844
	Average			**1.204**	**0.913**	**1.375**	**0.768**

Table 9: MSE values with distance in Environment 2 for Particle Filtering

Distance (m)	Test Point	Actual Coordinates (m)		Error (m)			
		M	**N**	**BLE**	**WiFi**	**LoRaWAN**	**ZigBee**
1	D1	0.500	-	0.540	0.117	0.492	0.402
	D2	0.500	0.500	0.959	0.177	0.053	0.338
	D3	0.670	0.330	0.183	0.122	0.236	0.481
	Average			**0.561**	**0.139**	**0.260**	**0.407**
3	D1	1.500	-	1.458	0.284	1.494	1.355
	D2	1.500	1.500	0.413	0.448	0.107	0.531
	D3	2.000	1.000	0.673	0.967	2.565	1.004
	Average			**0.848**	**0.566**	**1.389**	**0.963**
5	D1	2.500	-	2.249	0.890	2.431	1.361
	D2	2.500	2.500	0.015	0.799	1.004	1.533

	D3	3.330	1.670	1.096	0.463	2.297	1.328
	Average			**1.120**	**0.717**	**1.911**	**1.407**

It is observed that environment 1 had a better advantage to ZigBee and LoRaWAN technologies whose signals could travel farther distances with less obstructions, reflections and diffractions. In environment 2, the LoRaWAN deteriorated due to an increased number of objects in the room. It is also observed that WiFi has the best performance in both environments at all distances of 1, 3 and 5 meters at test points D2, because of lower amount of interference. However, at the edges of the triangle as shown in Figure 3, the devices experienced high interference level hence degrading the estimation accuracy.

In Figure 4, the comparison of filtering performance is done with the unfiltered for BLE, WiFi, LoRaWAN and ZigBee technologies. It is observed in Figure 4 that FFT filtering has no significant improvement on the error performance in both environmets for all the wireless technologies used. In particular, the ZigBee and WiFi FFT filtered error performance is is outperformed with the unfiltered. This is due to the fact that the approximations made in the design of the FFT filter cannot cope with the differences in reflected signal frequencies as the WiFi signal travels across multiple objects. As the WiFi signal

the average better error performance of WiFi technology, BLE could be the technology of choice due to portability and battery

reflections of different objects have different frequencies; the fluctuations of different frequencies are separable in the frequency domain. Thus, the approximated FFT filter does not perform well on the altered frequencies.

The performance of Particle filtering is also the same as the unfiltered for all wireless technologies used. This is due to the fact that the window size of the selected particles of reference were limited to 10. This number was limited by the computer resources used of 1024 MB memory space and 2.12 GHz. This influenced the Particle filter performance; in general, greater is the particle number, better the filtered RSSI follows the actual RSSI sequence. It is observed that the Kalman filtering method outperforms all filtering methods used. It improves overall estimation accuracy by 2% in BLE, 3% in WiFi, 22% in LoRaWAN and 17% in ZigBee as shown in Figure 4. The Kalman adaptation has revealed useful insights in this study. LoRaWAN works well in long distance open spaces with less interfering objects. Overall, it has been observed that error performance improved for both wireless technologies used in this study when Kalman filtering was used. The experimental results confirm that despite powering ability. But, the WiFi and LoRaWAN are ideal for medium and longer ranges respectively.

Figure 4: Comparison of average position error

CONCLUSION

It has been shown that modelling an indoor environment has been tedious due to the nature of it. This is because of the presence of walls, furniture, electronics devices and movement of people and objects in small confined space unlike outdoor. This forces indoor positioning systems to be specific for a given environment to cope with interference. This research work tries to improve positioning accuracy by filtering the received RSSI using FFT, Kalman and Particle methods. To achieve this existing trilateration and positioning algorithms have been used with BLE, WiFi, LoRaWAN and ZigBee technologies. Kalman filtering method has shown greater improvement in achieving accurate position coordinates with all wireless technologies used. However, WiFi demonstrated the lowest overall average error of 0.639 meters followed by BLE, which produced an error of 0.748 meters. ZigBee followed with an error of 0.845 meters and the least performing was LoRaWAN with an average error of 0.943 meters. Furthermore, these findings were compared with unfiltered RSSI and showed that accuracy was improved accuracy by 2% in BLE, 3% in WiFi, 22% in LoRaWAN and 17% in ZigBee technology for Kalman filtering method. These results have shown that improved position accuracy could be obtained if the RSSI are filtered before processing to remove the interference and noise. Likewise, the results have given further insights on the selection of the filtering methods for different types of wireless technologies.

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