COMBINED TECHNIQUES OF INDOOR POSITIONING SYSTEM USING BLUETOOTH LOW ENERGY

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ABSTRACT

This study tried a combination of several methods for the Indoor Positioning System covering all stages, RSSI Filtering, BLE Selection, and Location Estimation, where the fingerprinting approach used by most other studies is partial. In the RSSI Filtering stage, Kalman Filter and Autoencoder methods are used, BLE Selection stage using Strongest Signal and Fisher Criterion. Position estimation uses the WKNN algorithm and the Kalman Filter. Two static and dynamic datasets (including the movement of an object) are used to measure the accuracy of these combined methods. Overall, the best combination on the static dataset is the Kalman filter and the Strongest Signal Criterion which results in an accuracy of 2.44m, and for the dynamic dataset is the Strongest Signal and WKNN + Kalman Filter with an accuracy of 1.91m.

Keywords: *Fingerprint-Based Algorithm, Indoor Positioning Accuracy, RSSI Filtering, BLE Beacon Selection, Location Estimation*

1. INTRODUCTION

Bluetooth Low Energy (BLE) technology is growing rapidly nowadays, in line with the increasing market demand for smart systems based on the Internet of Things (IoT). The lower price of BLE devices opens up opportunities for what possibilities can be maximized on this device, including its use in the field of Indoor Positioning Systems (IPS).

IPS will affect human interaction in a room. Visitors can map their location [1] from an area (room). Apart from determining the location in an area, it is hoped that this system can help many other things. In the building area, for example, visitors can be guided by the system to a certain location. If something goes wrong, the building can find out the position of a visitor. Visitor location-based advertising is a growing marketing service. For persons with disabilities, it will be very helpful to get to a location through guidance from the system. At the international airport building [2] visitors will no longer have trouble finding flight gates, restrooms, parking areas, and other places to go. In the field of sports, IPS can assist the training process, for example, the coach can evaluate the movements of the players, whether it is according to the strategy applied by the coach or not. The training technique will be highly developed to the level of detail, the player's running speed can be measured and the technique of kicking a ball can be analyzed by foot movements to the ball. IPS technology will be very much needed in the robotics field [3], mapping the location of a room will help the movement of the robot to a certain location even though there are many obstacles. Improving location prediction accuracy is expected to make a lot of contributions to humans. In a study conducted [4] in the field of sports, Ultra-wideband technology (UWB) can detect locations and limb movements properly. The number of studies related to IPS produces many methods used to improve accuracy, for example, signal smoothing and channel separation [5]–[8], signal clustering [9]–[11], machine learning methods [3], [12]–[14]. The results of the analysis from the literature study, in general, to estimate the position of a receiver against the surrounding beacons will go through several stages, filtering of the RSSI signal, beacon selection stage to be processed, and the location estimation calculation stage. The purpose of the stages is to increase accuracy and reduce unnecessary computation. The proposed solutions vary widely but there is no one has yet discussed a combination of these stages that can produce the best accuracy performance. This research will try to combine the methods at each stage to find the most accurate combination of methods. The RSSI Filtering stages will use the Kalman Filter and Autoencoder algorithm, the BLE Selection stage will use Strongest Signal and Fisher Criterion, and the location estimation stages will use the Weighted K-Nearest Neighbor and Trilateration algorithms. Research including all of these stages is expected to be able to analyze the influence of each stage in producing predictive values, whether at a certain stage there are things that become important for further analysis.

A literature study was carried out to determine the extent of the accuracy produced and methods in the Indoor Positioning System, literature review was carried out on international journals related to this research topic. Then to have detailed theories related to the Indoor Positioning System, further study was carried out from various sources such as scientific papers, journals, books, videos, etc. At the implementation stage, a fingerprint-based model will be designed related to the methods being used, namely RSSI Filtering, BLE Selection, and location estimation then evaluate each of the proposed combinations. The last step of this research is to summarize reports up to the conclusion.

2. RELATED WORKS

Preprocessing with the clustering method was used in the study [15], the fingerprint data will be grouped using the K-Means algorithm. After that, modeling with Artificial Neural Networks in each group was carried out. This modeling implementation uses the Scikit-Learn library in a Python environment with the ANN Regression MLPRegressor algorithm. Then, Multi-objective optimization (MOP) is carried out to reduce the use of data storage on the smartphone used in this study. Experiments using the proposed model Multi-Objective Optimization Radiomap Modeling (MOO-RM) resulted in an error value of 4.55m, 54% better than the ANN model. In the offline phase carried out in the study [7], for each location on the fingerprint 20 RSSI data per beacon were taken. This stage is repeated 10 times using a round-robin technique resulting in 200 entries per beacon. The expected result is to minimize the effect of the instability of the RSSI value. This study achieved an accuracy value of 2m using the median value of the resulting distribution data.

In a study conducted by [16], to improve accuracy in detecting a location while reducing implementation costs, 3 (three) techniques were used, namely: channel diversity, Kalman Filtering, and weighted trilateration techniques. The main purpose of using channel diversity techniques is to reduce the spread of RSSI measurements. Then the use of Kalman Filtering was carried out to improve the accuracy due to errors in RSSI measurements. The last technique, which is an extension of the basic trilateration algorithm, is carried out to ensure the measurement results in a point location. The study resulted in a 43.47% increase in accuracy for medium-sized rooms and 38.33% for large rooms, compared to other techniques. Although the results of other studies have a higher level of accuracy, more resource requirements will require greater costs. So the approach in this study is carried out in terms of using fewer resource costs.

A study conducted by [1], examined BLE technology in replacing traditional technology for detecting location such as Wi-Fi or GPS. The study proposes a framework for indoor location detection using BLE tags and signals strength-based distance measurement (RSSI). The proposed system has 3 main components, namely: BLE tags, an indoor positioning application installed on the smartphone, and a communication interface system. The resulting level of accuracy reaches 4m. Accuracy is claimed to be better than Wi-Fi and trilateration techniques.

This study [17], proposed an indoor positioning system based on Bluetooth low energy technology and the MQTT protocol. To detect the location of a mobile device, this study uses the RSSI technique combined with the trilateration technique and is based on a 2-parts linearization algorithm. Several experiments were carried out to analyze the level of accuracy and efficiency of the trilateration technique using BLE-GeoMarkers. From the experimental results, the location detection accuracy rate is <1.5m. Next, the study will try to experiment using RSSI filtering techniques such as Kalman and Chebychev theorem.

Another technique that can be used in this study is the fingerprinting technique. Studies related to this technique conducted by [18] resulted in an accuracy rate of <2.6m as much as 95% with scattered beacons (1 beacon per 30m^2) and <4.8m as much as 95% with more scattered beacons. meetings (1 beacon per 100m^2), compared to Wi-Fi technology which only yields an accuracy of <8.5m at 95%. A summary of several previous studies can be seen in Table 1.

Table 1: Summary of Literature Review in Previous Research.

Research	Method	Results
[6]	Using 10Hz beaconing batch filtering and 1s batch processing of the median/mean value	Accuracy increases with 6-8 beacons/fingerprinting combinations
[15]	Using data clustering, modeling (ANN), then multi-objective optimization.	Accuracy close to the WKNN standard used with fewer data storage usage on smartphones
[7]	Using round-robin to retrieve 20 RSSI data per beacon for 10 iterations.	The median value in the distribution produces an accuracy of up to 2m.

[8]	The localization process (radio map) is carried out using the separation of 3 advertising channels.	Accuracy results are claimed to increase 12% from conventional methods (Wi-Fi).
[19]	Using the SSD algorithm in the online phase	Accuracy with the proposed method has a figure of 96.6% on the correct location prediction
[20]	Combining fingerprinting generated by Wi-Fi and BLE using i-KNN filtering	Accuracy increased from 4.05m to 2.33m and dataset size was reduced from 12% to 37%.
[21]	Using histogram-based algorithm on fingerprinting data to determine the relationship between the number of bins, bin separation, the direction of measurement on the radio map to the level of detection accuracy.	Bin values < 7 or 8 give better accuracy values. Separation of bin values and measurement directions does not provide increased accuracy.
[16]	Using techniques: channel diversity, KF, and weighted trilateration techniques	43.47% for medium-sized rooms and 38.33% for large-sized rooms.
[22]	Using techniques: channel-separate polynomial regression model (PRM), channel-separate fingerprinting, and EKF	< 2.56m accuracy rate is 90% (1 beacon per 9m). accuracy rate < 3.88m by 90% (1 beacon per 18m).
[23]	The interactive smart museum uses BLE Beacons for indoor positioning.	Museum visitors will get a more interactive experience.
[1]	IPS using BLE	Accuracy reaches 4m and is claimed to be better than Wi-Fi
[17]	Using technique: RSSI combined with trilateration technique and 2-parts linearization algorithm	Accuracy rate < 1.5m
[24]	Using technique: RSSI shifting to stabilize the signal measurement results	The resulting signal graph is more stable.
[25]	InLoc system guides the user to a location in the room. The techniques used are RSSI and LST as well as machine learning.	The designed system can be used to guide the user in the room with the shortest path.
[26]	Using technique: RSSI to detect human location in room.	By using the KF technique, better accuracy can be obtained.
[18]	Using technique: RSSI-based fingerprinting to detect location.	Accuracy rate < 2.6m 95% (1 beacon/30m2) and < 4.8m 95% (1 beacon per 100m2)
[5]	To increase accuracy, the number of advertising channels is increased.	The accuracy rate is better when increasing/decreasing other parameters: number of beacons, channel, beacon signal strength.

The development of the Indoor Positioning System using Bluetooth low energy is still growing to produce a better level of accuracy. The RSSI technique is very commonly used in determining location, but the level of accuracy depends on the combination of the number of beacons, beacon placement, signal strength, channel usage, filtering algorithms, and so on. Although the price of BLE beacons is relatively low, researchers should also consider the signal strength settings to maximize battery usage in the beacons. For this reason, further studies are needed to look for combinations, how to select the beacons to be used, and related filtering techniques in determining the parameters to be used to improve the level of accuracy while still not requiring large costs and too many beacons.

Many studies related to this field have been carried out, various methods have been used to improve accuracy, starting from the selection of BLE beacons to be processed, filtering techniques for highly unstable RSSI signals, machine learning approaches to reducing noise, using fingerprinting as a representation of the observation environment, and other mathematical approaches related to signal processing. The results level of accuracy varies widely, several examples can be seen in Table 1, but the method is carried out partially, no research tries to combine the methods at each stage of the IPS to find the best combination to produce the best accuracy. This paper will examine the combination of beacon selection (BLE Selection) to be processed, namely based on the strongest signal (Strongest RSS) and Fisher Criterion, and RSSI Filtering using Kalman Filter and Autoencoder. Performance evaluation will be carried out using the Weighted K-Nearest Neighbor (WKNN). For dynamic datasets; datasets that have movement routes; the Kalman Filter will be added to improve accuracy at the final stage. Several combinations will be tested to find which one produces the best to estimate location. The level of accuracy that is closest to the actual location (ground truth).

3. THEORY AND METHODS

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Indoor Positioning System (IPS) is a system designed to locate a position in a room. The working principle is like the technology used by the Global Positioning System (GPS), where several transmitters try to map a certain position based on the signal. GPS signal is very good for open spaces (outdoor), but if the object you want to recognize is in a building or a room where there is no signal, the detection process will not be accurate. For indoor detection, a new mechanism is needed similar to GPS but more suitable for the room environment. The equipment used must be more efficient in terms of energy, price, and quantity. The increasing need for IPS technology produces many new technological devices that can accommodate it. Wi-Fi technology, Bluetooth [27], and Zigbee [28] are mostly used in IPS with 2D modeling, while in 3D modeling, using infrared technology [29], ultra-wideband (UWB) [30], and ultrasonic [31]. Compared to 3D-based models, the devices used in 2D models are much cheaper. 3D-based technology mostly uses the TOA (Time of Arrival), AOA (Angle of Arrival) method, and other methods related to time and space. For 2D-based models, the method commonly used is fingerprinting (FP). This method is divided into 3 types, namely: visual fingerprinting that uses image data, motion fingerprinting that uses motion sensor data such as accelerometer, electric compass, and so on, and signal fingerprinting that uses Received Signal Strength Indication (RSSI) data.

Detecting a location in a room has its challenges, the signal strength is not always stable, there is a lot of interference and a reduction in quality due to the object/layout of the room. Walls, partitions, glass, and other materials will greatly affect the signal quality in the measurement. At the beginning of a study related to IPS, adding a transmitter (beacon) to a room was expected to solve the signal strength problem, but the results did not solve the problem. The increasing number of transmitters does not guarantee the accuracy of the detection of a location, even though very cheap BLE devices have been used.

3.1 Bluetooth Low Energy (BLE)

BLE is a small wireless transmitter with a battery power source [32]. BLE is a new standard for wireless technology which is developed from conventional Bluetooth technology. The technology used still carries the frequency band at 2.4GHz. This BLE has a different function from the conventional Bluetooth 4.0 standard, which is a lower throughput value of up to 7x but has a more endurance level of about 100x than the standard [33].

BLE works by using 40 radio channels at a frequency of 2.4 GHz, each of which has a width of 2 MHz. Each channel is given an index. 3 channels are used for advertising channels (37, 38, 39) and the remaining 37 channels are used for data (0 - 36) as in Figure 1.

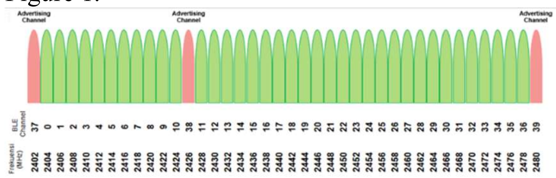

Figure 1: Bluetooth Low Energy Channels

The purpose of placing advertising channels far apart is to prevent interference from other devices working on the same spectrum, for example, Wi-Fi. Advertising channels are used to transmit advertising data, scan response/packet requests, and indication of connection packets. BLE is very popular in the Internet of Things (IoT) devices because of its low price and low power usage. The BLE 4.0 technology can reach speeds of 25Mbit/s over a distance of 60m. One of the factors that affect the performance of BLE is transmission power. As a wireless device, transmission power greatly affects the transmission range. Although the reachable distance is 60m, this will greatly reduce battery life and also interfere with other beacon signals. The time lag between each transmission (advertising interval) also affects battery life. When an object to be detected (receiver) moves, a small advertising interval is needed, but the resulting signal will be very unstable. Slower advertising intervals will make the signal more stable and save battery life [32], this is something that must be considered.

3.2 Received Signal Strength Indication (RSSI)

RSSI of a beacon can be used to estimate the distance from the receiver. As long as conditions permit, distances can be calculated using the inverse-square law. This method is very popularly used to determine position. To calculate the distance, the path-loss model is used as in formula (1)

$$RSSI = -10n\log_{10} d + A \tag{1}$$

Where n is the signal propagation constant which is influenced by the surrounding environment, d is the distance, and A is the received signal strength at a distance of 1m. Based on this traditional model, the formula for a noisy environment [34] is:

$$RSSI = RSSI_0 - 10n\log_{10}\left(\frac{d}{d_0}\right) + v \tag{2}$$

So the formula for calculating distance regardless of RSSI noise:

$$d_{noiseless} = d_0 10^{\left(\frac{RSSI_0 - RSSI}{10n}\right)} \tag{3}$$

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While the formula for calculating the distance with RSSI noise:

$$d = d_{noiseless} \, exp^{-0.5\left(\frac{\sigma_{RSSI} \ln 10}{10n}\right)^2} \quad (4)$$

3.3 Indoor Positioning System Flow Process

In general, IPS works as in Figure 2. A series of transmitters that transmit signals (beacons/access points) will be used to estimate the location of the user (receiver) at a location using a positioning algorithm. RSSI received at the receiver can be processed into a coordinate representation of the surrounding environment. Because this system uses RSSI which is susceptible to signal fluctuations, many factors will affect the quality in predicting the location of the receiver. Optimization can be done from an early stage including beacon placement, number of beacons, beacon specifications used, beacon parameters, beacon placement, and so on. Then, at the positioning stage or predicting the location, many approaches are taken to improve accuracy. These include signal filtering, selecting beacons to input into computations, and other signal-related optimization techniques. Algorithms for calculating location predictions being the last part of this process involve many mathematical approaches as well as machine learning. Until now, no model has an accuracy rate of 100%.

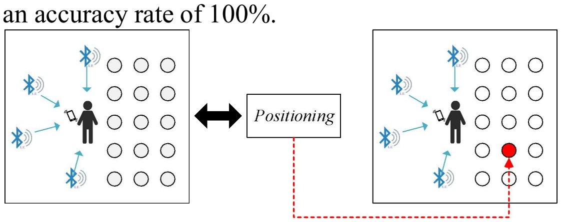

Figure 2: Indoor Positioning System Flow Process

3.4 RSSI Filtering

RSSI Filtering is done to improve accuracy by reducing the selection of noise-containing and unstable signals. There are various algorithms used, one of the simplest is Thresholding [35], where the unselected RSS value will not be used. A study conducted by [14] proposes Thresholding on the Signal Tendency Index (STI) compared to the RSS value, RSS is transformed into a standard fingerprint based on Procrustes analysis, then a similarity metric called STI is formed. Its purpose is to match the characters of the different devices and adapt to changes in the observation environment. This method is claimed to be better in accuracy than RSS. The Threshold method is also used in conjunction with the Gaussian Filter on training data [36], the accepted RSSI value is between μ + σ and μ-σ, where μ and σ are the mean values of the standard deviation of the RSS at the reference point.

3.4.1 Kalman Filter

The Kalman Filter (KF) is a filter developed by Rudolf Kalman in 1960 to remove noise from a group of data. KF is widely used in the world of control systems to estimate the state of a process related to a noisy environment where the state is always changing under dynamic conditions. KF can predict the next situation and perform a correlation analysis of various related parameters. This estimation is done by minimizing the Mean Square Error value from the ideal state to the actual (noisy) state. This process is carried out in 2 stages, time update (prediction) and measurement update (correction). The time-invariant linear equation is written as [37]:

$$X_{t+1} = Fx_t + noise(Q), \quad (5)$$

$$Y_t = Hx_t + noise(R), \quad (6)$$

Where F and H are the system matrix, X represents the state at time t, and Y represents the time t at observation, Q and R are the covariances of the noise measurement. Suppose an object is moving at a constant speed, its estimated position is the previous position plus the velocity and noise. Matrices that can be formed such as:

$$F = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \quad (7)$$

The position of the target is estimated using spatial orientation, with a matrix size of 4 and an observation matrix of size 2. The measurement parameters (Q and R) are determined by finding the correct value to minimize the error in estimating the position. Kalman Filter Algorithm as illustrated in Figure 3.

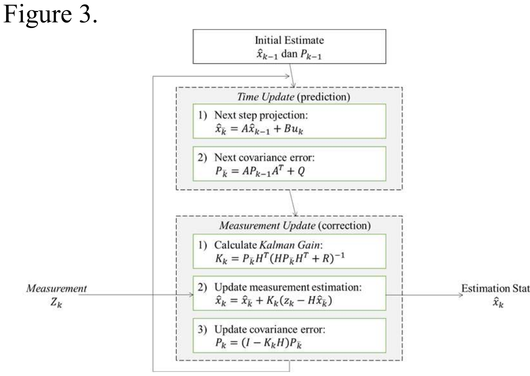

Figure 3: Kalman Filter Algorithm

3.4.2 Autoencoder

Autoencoder is a neural network model that has input and output that is similar to the input.

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Autoencoders are trained to be able to reconstruct data. It is included in the unsupervised category in machine learning because the training process uses data without labels. The purpose of the autoencoder is to reduce the dimensions of a feature. The autoencoder architecture is shown in Figure 4.

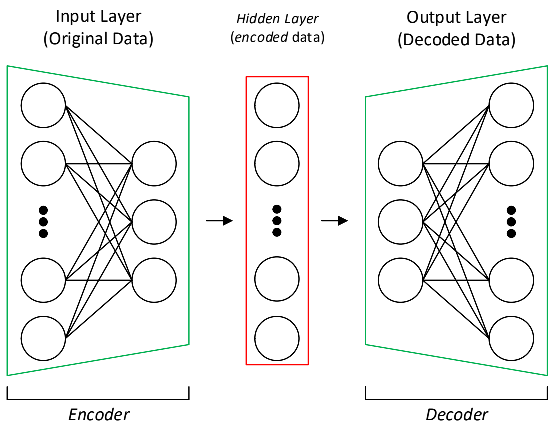

Figure 4: Autoencoder

The middle part of the autoencoder is a vector of a group of neurons that is less in number than the encoder and decoder layers. If the model can be trained properly, this middle section becomes a simple representation of the inputs. The right side is the process of reconstructing the data so that it is similar to the original data. The training flow is carried out by forwarding propagation until the data is successfully reconstructed by the decoder then the error is calculated from the difference in value difference with the original data using the Mean Square Error formula. The formula used is [13]:

$$z = \phi(x) \qquad x' = \psi(z) \tag{8}$$

Where ϕ is the encoding function, ψ is the decoding function, x' 'is the reconstructed result from the input. To minimize the difference between the input and the reconstruction result, it is described by the equation $\min_{\phi,\psi}\|x - \psi(\phi(x))\|^2$, where x is an input vector containing the RSSI values of the beacons at a reference point$x = [r_1, r_2, \dots, r_m]^T$. The thing that must be considered is that the activation function will determine the final value of the model. For example, the decoder should use the Sigmoid or Tanh activation function in the last layer. So that the output can be mapped into a range of values, for example between 0 and 1.

3.5 BLE Selection

Increasing the number of beacons processed corrects errors in the detection of a location. However, there is a limit to the number of beacons used which no longer improves accuracy [33]. Limiting the number of beacons used will make the computation process more efficient and optimal. Likewise in BLE selection, the selection process is expected to eliminate unnecessary computation. For example, ignoring noisy beacons. A study conducted by [35], proposed 3 criteria based on the strongest signal (strongest RSS), Fisher Criterion, and random combination. In simple terms, the strongest signal will be close to the receiver, the closest beacons should be selected. Meanwhile, Fisher Criterion will represent the ratio between data and noise. Fisher values are calculated from RSS on fingerprinting against all reference points (RPs). The higher the index, meaning that the beacon will be unique to other reference points, this beacon should be selected.

3.5.1 Strongest Signal

The selection of beacons is made on several L beacon subsets that have the strongest RSS in the online phase. The strongest RSS beacons provide a constant good range possibility. A subset of beacons can be obtained by sorting the RSSI into a vector V in descending order, and selecting the top K beacon where K <L. The fingerprint index of the radio map is sorted when there is an unknown location [38].

3.5.2 Fisher Criterion

In the offline phase, Fisher Criterion utilized the statistical properties approach of the radio map to select more informative beacons in detecting locations. The distinguishing values of the beacons against their RP are calculated and arranged in descending order. A total of K beacons with the highest discrimination and signal stability were selected as informative beacons. The value is given for each beacon as in the (9) [38]:

$$\zeta^i = \frac{\sum_{j=1}^{M}\left(\psi_j^i - \bar{\psi}^i\right)^2}{\frac{1}{T-1}\sum_{l=1}^{T}\sum_{j=1}^{M}\left(r_j^i(t_l) - \psi_j^i\right)^2}, \quad i = 1,2,\dots,L \tag{9}$$

Where $\bar{\psi}^i = \frac{1}{M}\sum_{j=1}^{M}\psi_j^i$, M is the number of RPs on the radio map, r is the provisional vector for each RP, and T is the number of time samples at each reference point.

3.6 Location Estimation

To estimate the position of a receiver, the most common method is based on the RSSI value. This study uses fingerprinting method, which is by first making a map of the observation environment. The

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beacon will be positioned at certain distances, then the RSSI value is recorded against the reference points as a representation of the RSSI value in a position. This data set will later be matched with RSSI measurements when predicting a location.

In the online phase, the location estimation process will match the RSSI on the receiver with the radio map to determine the location of the receiver, therefore a positioning algorithm is needed. Until now, there are 2 categories of positioning algorithms, namely the deterministic and probabilistic approaches. A deterministic-based positioning algorithm will carry out the matching process in real-time during the online phase. As with machine learning algorithms that are based on RSSI measurements, the accuracy depends on the fingerprint data in the offline phase. K-Nearest Neighbor (KNN) is a machine learning algorithm. KNN and its variations are widely used in fingerprinting-based IPS because of its uncomplicated implementation and good performance. The basic idea of the KNN is to compare RSSI with radio map data. The formula (10) used is [14]:

$$d_q(V_a, V_i) = \left(\sum_{j=1}^{n} \left| v_j - v_{ij} \right|^q \right)^{\frac{1}{q}} \qquad (10)$$

with $V_a = (V_1, V_2, \dots, V_n)$ is an RSS signal intensity vector on the receiver. q = 1 when using Manhattan Distance, and q = 2 when using Euclidean Distance. After calculating the similarity, the k fingerprint data will be determined based on the similarity. Calculating the mean value of the k fingerprint data will increase the accuracy. The average value is the location of the receiver.

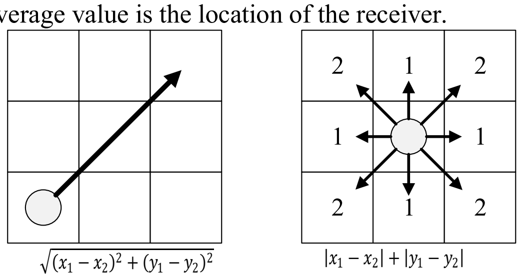
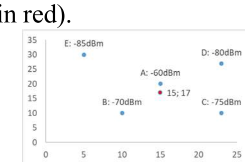


Figure 5: Euclidean (left) and Manhattan (right) Distance

WKNN is a development of the KNN algorithm where the weighting of the nearest neighbor is given through the distance function (for example Euclidean or Manhattan Distance in Figure 5) between the training data and the test data. This algorithm has the same principles as the KNN. The WKNN algorithm can be implemented with pseudo [12]:

The example in Figure 6, consists of 5 beacons (in blue), the RSSI value, and the location of the receiver (in red).



beacon	X	Y	Weight	Weighted X	Weighted Y
A: -60dBm	15	20	25	375	500
B: -70dBm	10	10	15	150	150
C: -75dBm	23	10	10	230	100
D: -80dBm	23	27	5	115	135
E: -85dBm	5	30	-	-	-
		total	55	870	885
			final	15.818	16.091

Figure 6: WKNN Example

Equation (11) is the weight calculation for all k beacons. Equation (12) is the approximate location on the coordinates (X, Y).

$$W_t = \sum_{n=1}^{k-1} W_n \qquad (11)$$

$$(x, y) = \frac{\sum_{n=1}^{k-1} [W_n * (x_n, y_n)]}{W_t} \qquad (12)$$

4. RESEARCH METHODOLOGY

4.1 Data Collection

Data collection in the offline phase in this study will use radio map data that is already available at Bina Nusantara University. Radio map data obtained from previous studies using the fingerprinting method. This radio map will be used as reference location data based on signal strength. The dataset used is a static dataset with stationary users and a dynamic dataset with users moving along a route. the size of the room used is 21m x 12m.

4.1.1 Static dataset

This dataset has 24 beacons, total reference on the radio map approximately ±167,040 data. For each reference point, the radio map database will contain the RSSI values from the measurement results at that reference point. An example database with 15 beacons is shown in Figure 7.

The static dataset consists of training data, validation data, and testing data. The training data consists of 54 reference points scattered in a room with a distance of ±200cm, each reference point consists of 24 beacons and each beacon has 100 RSSI samples, this data is used to calculate the Fisher Index which will be used in the BLE Selection stage. The validation data consists of 117 reference points with each have 24 beacons and each beacon have 10 RSSI samples, this validation dataset is used for tuning the best parameter to represent the environment with minimum distance error from the ground truth. The testing dataset is used to evaluate the performance of the estimation method proposed. The testing data

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consists of 39 test points with each have 24 beacons and each beacon have 10 RSSI samples.

ID	X	Y	RSSI 1	RSSI 2	RSSI 3	RSSI 4	RSSI 5	RSSI 6	RSSI 7	RSSI 8	RSSI 9	RSSI 10	RSSI 11	RSSI 12	RSSI 13	RSSI 14	RSSI 15
1	0,5 m	0,5 m	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm
2	1 m	0,5 m	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm
3	1,5 m	0,5 m	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm
4	1,5 m	1 m	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm
5	1,5 m	1,5 m	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm
6	2 m	1 m	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm
7	3 m	2 m	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm
…	x m	x m	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm
1000	21 m	12 m	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm	x dbm

Figure 7: Dataset Example

Each beacon in Figure 8 will send a signal to the receiver (Python-based application), then the signal strength value will be stored along with the coordinates of the location in the room. X symbol is the reference point and dot symbol is BLE Beacon location. This radio map will later become a reference for predicting the actual location of the receiver during the online phase.

The layout for validation data and testing data for this static dataset is in Figure 9 and Figure 10.

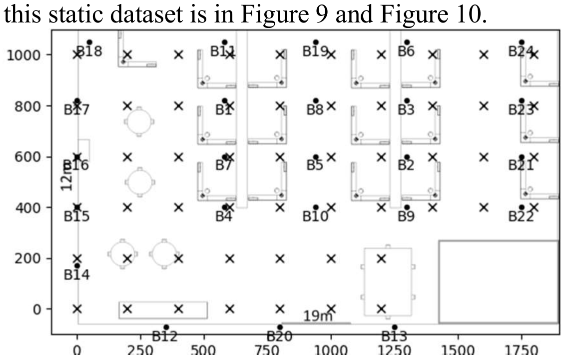

Figure 8: BLE Beacon Location and Reference Point (Train Data)

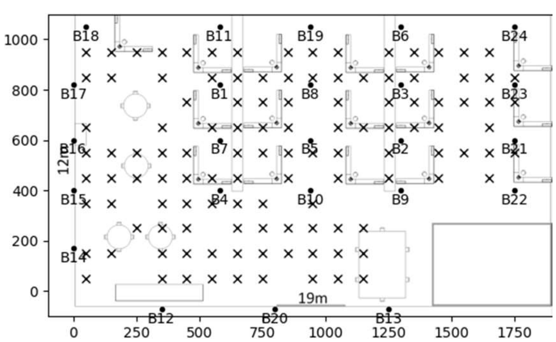

Figure 9: BLE Beacon Location and Reference Point (Validation Data)

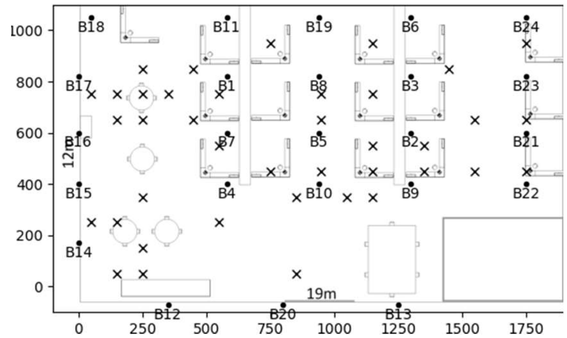

Figure 10: BLE Beacon Location and Reference Point (Test Data)

4.1.2 Dynamic Dataset

This dataset has 23 beacons and its coordinates, total reference on the radio map approximately ±126,360 data. This dataset consists of training data with 54 reference points and each beacon has 100 RSSI samples which are used to calculate the Fisher Index for the next stage, validation data which consists of 3 routes; with route 1, route 2, route 3, have 13, 16, and 17 reference points, and testing data which consists of 2 routes; with route 1, route 2 have 21 and 23 reference points. Each of the validation and testing datasets has time data when the RSSI is recorded. The routes for validation data are in Figure 11, Figure 12, and Figure 13.

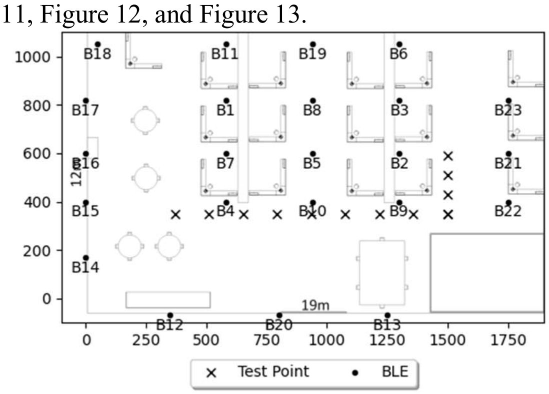

Figure 11: Route 1 of The Validation Dataset

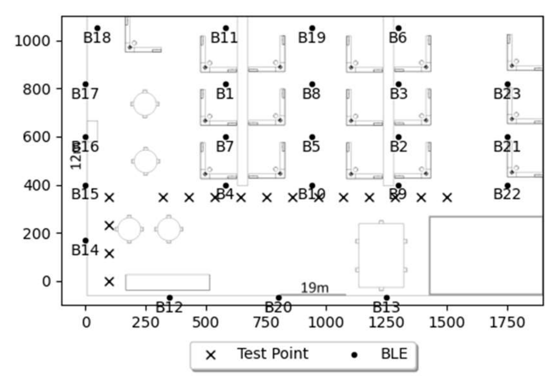

Figure 12: Route 2 of The Validation Dataset

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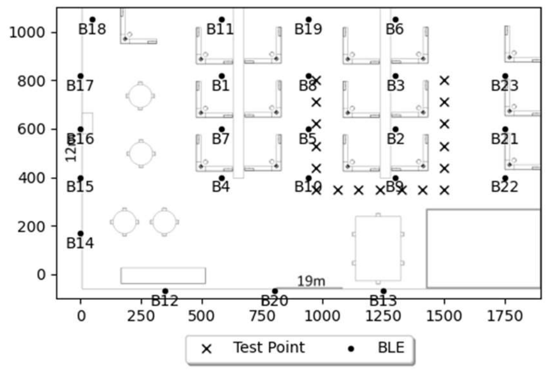

Figure 13: Route 3 of The Validation Dataset

The routes for the testing dataset are in Figure 14 and Figure 15:

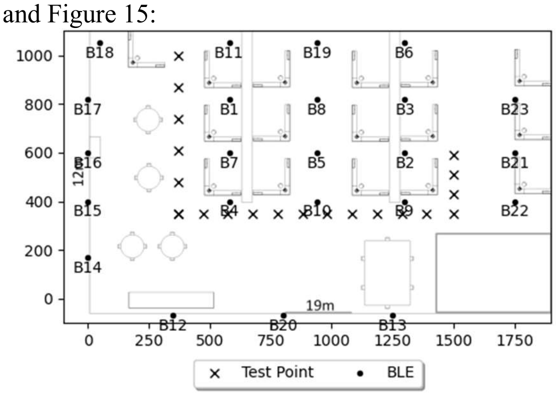

Figure 14: Route 1 of the testing dataset

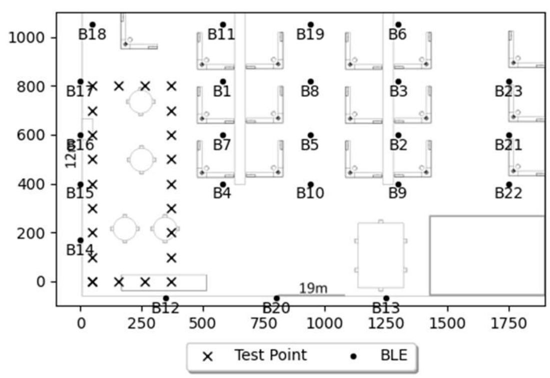

Figure 15: Route 2 of The Testing Dataset

4.2 Position Estimation Method

In this paper, the authors proposed a Position Estimation Method (PEM) model with a fingerprinting approach as describes in Figure 16. Hardware used is BLE beacon and cellular phone. BLE beacon with nRF51822 as signal transmitter and Bluetooth-embedded phone as the signal receiver.

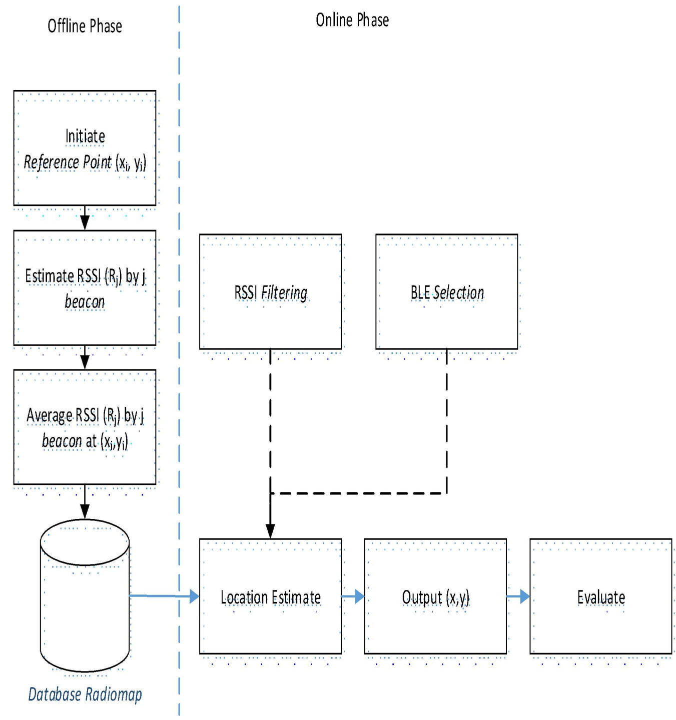

Figure 16: Position Estimation Method

The existing fingerprint dataset is used to implement the PEM method. The measurement value of each reference point will be used to predict location on the online phase. The method will be used are RSSI Filtering (Kalman Filter and Autoencoder) and BLE Selection (Strongest RSSI and Fisher Criterion). The next step is to estimate location, WKNN algorithm will be used to output the coordinate of the receiver. Then the estimated locations of the combined method will be evaluated to the ground truth resulting error value of the accuracy.

The first step is RSSI Filtering, this step is to reduce signal noise. When the user does not move at a reference point, the RSSI value on the beacons varies because of the signal propagation, this affects the calculation which reduces accuracy. This filtering process will output 1 RSSI value representing RSSI samples from each beacon. Two algorithms Kalman Filter and Denoising Autoencoder will be used at this stage for the static dataset. This study uses an autoencoder as a denoising signal. The input layer will contain RSSI values that have been added with random noise for the model to learn a certain noise pattern. It is expected that the output will produce a signal with minimal noise.

The RSSI Filtering is not required on a dynamic dataset (validation and testing) because it only consists of 1 sample of data for each beacon.

After the signal noise is reduced, the next step is to choose which beacons will be used as a benchmark for measuring their location predictions. At one reference point, there are 24 RSSI (static dataset) and 23 (dynamic dataset) values of beacons. Only several beacons based on the selection algorithm will be used. The selection of beacons will be carried out using the Strongest Signal and Fisher Criterion algorithms. The Strongest Signal Selection method will select several highest RSSI values. This indicates that the reference point is supposed to be close or in between the selected beacons. This selection will be done in the online phase, it needs to compute in every reference point. Meanwhile, the Fisher Criterion will select several beacons with a larger Fisher Index. This method works on the fingerprinting level in the offline phase, thus the computation process in the online phase will be faster. The purpose of this criterion is to describe the discriminability across all reference points by selecting the ideal beacons for the environment. The selected beacons remain the same in the online phase on every reference point.

The last stage is location prediction, using the WKNN algorithms, the location prediction will be estimated. For the dynamic dataset, Kalman Filter as a tracking algorithm will be used to improve the accuracy. The combination is as shown in Table 2.

Table 2: Combined Techniques

Dataset	RSSI Filtering	BLE Selection	Location Estimate Algorithm
Static	Kalman Filter	Strongest RSSI	WKNN
	Kalman Filter	Fisher Criterion	WKNN
	Autoencoder	Strongest RSSI	WKNN
	Autoencoder	Fisher Criterion	WKNN
Dynamic	-	Strongest RSSI	WKNN + Kalman Filter
	-	Fisher Criterion	WKNN + Kalman Filter

The results of the location predictions from each experiment will be compared with the actual location (ground truth) to evaluate the accuracy performance.

4.3 Experimental Design

The use of the validation dataset is to find the best parameters presenting the research environment. These parameters will be used in the testing data to compare their accuracy. WKNN Tuning is done by looking for the most appropriate value of K, to represent the best parameter for the environment. This K value is related to how many beacons will be selected in the estimation stage.

For the dynamic dataset, the tuned Kalman Filter parameters are process errors in the process covariance matrix (distance ΔP_x and velocity ΔP_{v_x}) and observation errors (distance Δx and velocity Δv_x). Following the equation in Figure 3, the process covariance matrix $P_{k-1} = \begin{bmatrix} \Delta P_x{}^2 & 0 \\ 0 & \Delta P_{v_x}{}^2 \end{bmatrix}$ and observation errors matrix; also known as noise(R) in Kalman Gain equation; R = $\begin{bmatrix} \Delta x^2 & 0 \\ 0 & \Delta v_x{}^2 \end{bmatrix}$. To support Kalman Filter algorithm for tracking objects, velocity and direction of motion on the x-axis and y-axis are obtained from calculating the time difference at each test point on the route. $\hat{X}_{k-1} = \begin{bmatrix} distance \\ velocity \end{bmatrix}$

After tuning is done during the validation process, performance will be measured against each combination of methods using the testing dataset. The results are the best combination with the smallest error.

4.4 Performance Measure

For each location prediction result, there will be a difference to the original expected value (ground truth), in this case, the coordinates of the testing point. To measure how accurate the prediction to the original value, the error value that occurs is used. Since the observation environment is represented by 2-dimensional coordinates, the Euclidean Distance function can be used as in (13).

$$error(p,r) = \sqrt{(r_x - p_x)^2 + (r_y - p_y)^2} \quad (13)$$

Where p is the predicted location on the coordinates (p_x, p_y) and r is the actual location (ground truth) at the coordinates (r_x, r_y).

Furthermore, using the Cumulative Distribution Function (CDF), statistical analysis will be generated on the mean, minimum, median, 90th percentile, and maximum.

5. RESULTS AND DISCUSSION

The best parameters used for the validation dataset are shown in Table 3.

Table 3: Best Tuned Parameters

Dataset	Parameters	Best Combination
Static	K = 4	RSSI Filtering: Kalman Filter BLE Selection: Strongest Signal Average Error WKNN: 2.08m
Dynamic	K = 3 ΔP_x = 3 cm ΔP_{v_x}= 2 cm/sec Δx = 5 cm ΔP_{v_x} = 3 cm/sec	BLE Selection: Strongest Signal Average Error WKNN: 2.13m Average Error WKNN+KF: 1.70m

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5.1 Results on Static Dataset

The combination of methods used on the Testing Dataset using parameters from Table 3 resulting in a Euclidean Distance Error as shown in Figure 17. Cumulative Distribution Function (CDF) as shown in Figure 18.

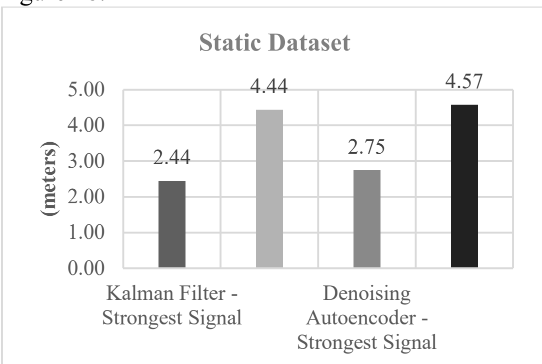

Figure 17: Average Error Static Dataset

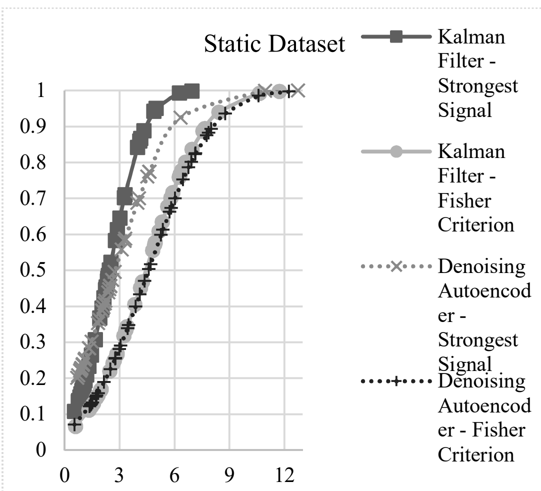

Figure 18: Cumulative Distribution Function Static Dataset

Table 4 shows the combination of Kalman Filter and Strongest Signal (error = 2.44m) has the highest accuracy based on the dataset used and room environment.

Table 4: Cumulative Distribution Static Dataset

meter	Kalman Filter – Strongest Signal	Kalman Filter – Fisher Criterion	Denoising Autoencoder – Strongest Signal	Denoising Autoencoder – Fisher Criterion
Mean	2.44	4.44	2.75	4.57
Min	0.54	0.59	0.67	0.53
Median	2.24	4.13	2.17	4.11
90th	4.87	7.64	4.62	8.00
Max	6.95	11.71	12.74	12.24

The result of Denoising Autoencoder as an RSSI filter of a noise-added signal is in the following Figure 19, it can be seen that the filter results should represent the varied RSSI value of a beacon due to propagation.

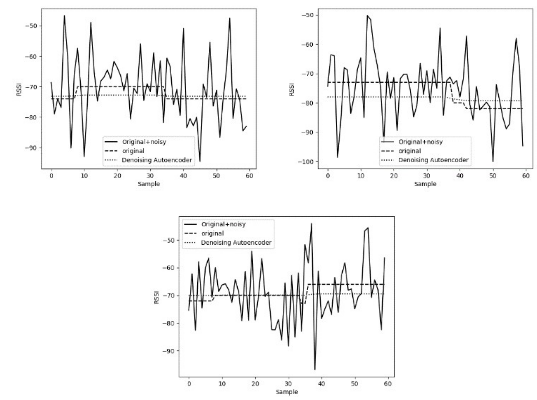

Figure 19: Example of Denoising Autoencoder

The comparison of the filter results from Kalman and Denoising Autoencoder is shown in the following Figure 20. Kalman Filter has a smoother change in value than Denoising Autoencoder in terms of representing signal fluctuations.

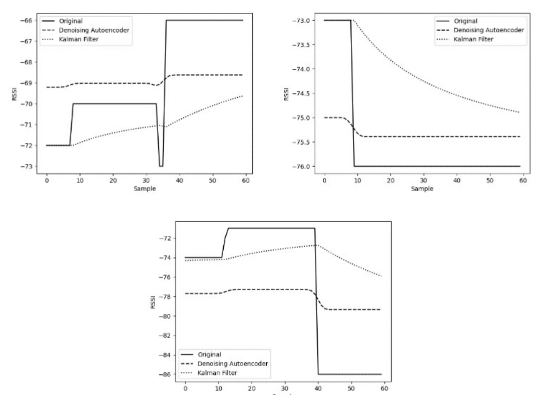

Figure 20: Example of Kalman Filter and Denoising Autoencoder in the same beacon at a Reference Point

The difference in filter results is not significant, only around ±5db. However, the computation required by Denoising Autoencoder is more excessive than the Kalman Filter. More data samples will increase the time and computational process even this stage is done in the offline phase. The following Figure 21 is a comparison at a test point of 24 beacons.

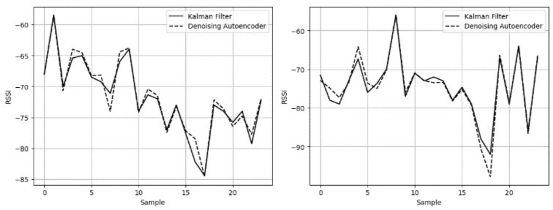

Figure 21: Example of Kalman Filter and Denoising Autoencoder in all beacons at a Reference Point

The BLE Selection of the 4th and 28th reference points in the testing dataset is shown in Figure 22, the selected beacons not representing an ideal condition. Although the Strongest Signal has better accuracy, the selected beacons may be located at a larger distance from the reference point, whereas the expected is to select the closest beacons. The example on the lower-left Figure 22, B9 (-70db) which is the next nearest beacon is supposed to be selected than B23 (-68db), similar on the upper left figure, B14 (-79.07db) and B12 (-75.75db) need to be selected instead of B16 (-57.5db) and B7 (-66.3db). Adjusting the selection will result in better location prediction.

Fisher Criterion which tends to choose the most ideal beacon representing the room conditions has the highest error result due to the same thing, the ideal condition near the reference point is the RSSI value getting higher, but the selected beacon by Fisher Criterion which is the farthest have RSSI value B18 (-72.08db) which should be getting smaller than the nearest B7 (-82.8db). Thus, the estimation predicted the position to be closer to the B18 than the ground truth position (lower-right Figure 22). In the upper-right figure, B14 (-81.0db) should have a higher RSSI value than B18 (-72.0db), B2 (-72.0db), and B20 (-71.0db). This path loss (signal propagation) is very affecting the result of position estimation

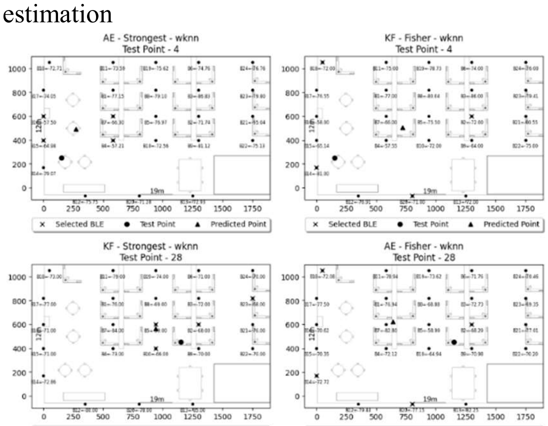

Figure 22: Illustration of BLE Selection Strongest Signal (left) and Fisher Criterion (right)

As discussed earlier, the WKNN algorithm, which relies on the RSSI value, must be supported by a more appropriate RSSI value.

5.2 Results on Dynamic Dataset

The combination of methods used on the Testing Dataset using parameters from Table 3 resulting in a Euclidean Distance Error as shown in Figure 23. Cumulative Distribution Function (CDF) as shown in Figure 24.

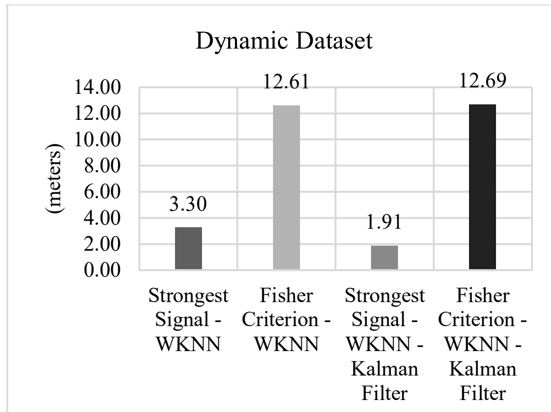

Figure 23: Average Error Dynamic Dataset

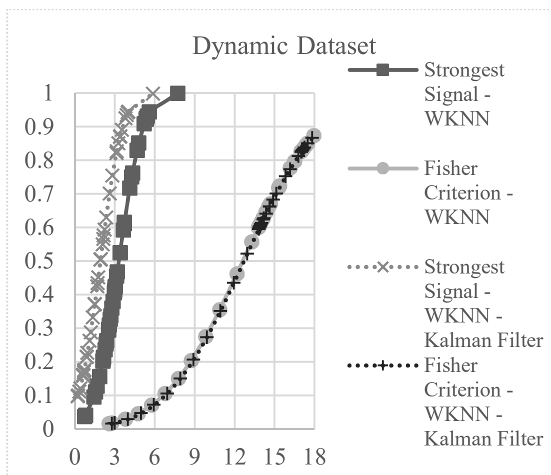

Figure 24: Cumulative Distribution Function Dynamic Dataset

Table 5 shows the combination of Strongest Signal and WKNN+Kalman Filter (error = 1.91m) has the highest accuracy based on the dataset used and room environment.

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Table 5: Cumulative Distribution Dynamic Dataset

(meter)	Strongest Signal - WKNN	Fisher Criterion - WKNN	Strongest Signal – WKNN – Kalman Filter	Fisher Criterion – WKNN – Kalman Filter
Mean	3.30	12.61	1.91	12.69
Min	0.73	2.56	0.21	2.77
Median	3.00	13.88	1.72	13.98
90th	5.36	17.25	3.83	17.21
Max	7.72	17.96	5.85	17.84

This dynamic dataset is used to measure the accuracy of the proposed method in the prediction of the object movement at a certain route.

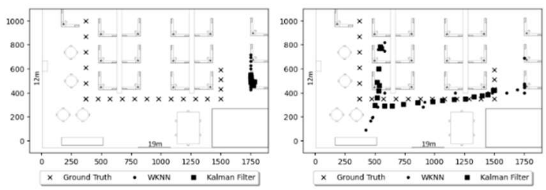

Figure 25: Illustration of BLE Selection Fisher Criterion (left) and Strongest Signal (right) on Route 1 with WKNN+Kalman Filter

On the 1st route (Figure 25), the combination of Fisher Criterion and WKNN+Kalman Filter cannot recognize the route due to the RSSI itself not represent the ideal condition as mentioned on the static dataset. This method estimates the location on every reference point with large errors.

Strongest Signal and WKNN+Kalman Filter, on the other hand, can recognize the route better. Although the estimation of WKNN could not recognize the route, applying Kalman Filter as a tracking method can help improve the accuracy average from 2.91m to 1.08m.

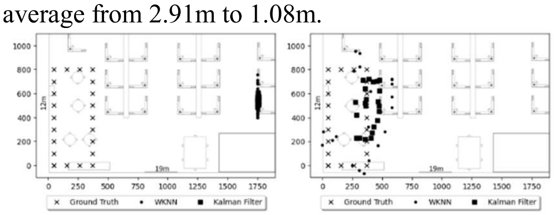

Figure 26: Illustration of BLE Selection Fisher Criterion (left) and Strongest Signal (right) on Route 2 with WKNN+Kalman Filter

The 2nd route has similar results (Figure 26), Fisher Criterion as a BLE Selection cannot identify the route. With average errors of 15.76m and even worst after applying Kalman Filter, the errors become 15.85m. This is considered a failure. Meanwhile, the Strongest Criterion and WKNN have average errors of 3.65m and improves to 2.66m as Kalman Filter applied.

Kalman Filter improves the accuracy for the 1st route by about 63% (2.91m to 1.08m) and the 2nd route about 27% (3.65m to 2.66m). The overall average error against all reference points of these 2 routes is 1.91m, which means by applying the Kalman Filter, around 42% of accuracy is improved (from 3.3m). If the error at each reference point can be corrected, the route can be more accurately recognized.

6. CONCLUSION AND FUTURE WORKS

The proposed methods used in each stage (RSSI Filtering, BLE Selection, and Location Estimate) show variations in the accuracy of IPS in predicting indoor locations. This proves how the approach of each method in generating predictions can improve accuracy. Two datasets have been used in this study to measure the level of accuracy, a static dataset with stationary objects and a dynamic dataset with objects moving along the route.

The results of this study conclude that the combination of Strongest - WKNN and Kalman Filter as both Filtering and object tracking has the best level of accuracy in predicting the location of the reference point. This result is limited to the room environment of the Binus Graduate Program (BGP) lecturer room based on the radio map dataset with the size of the room used is 21m x 12m. The room is representing a complex wireless environment filled with desks, chairs, tables, partitions, glass, and concretes. The best combination for the static dataset is Kalman Filter and Strongest Signal with an average error of 2.44m and for the dynamic dataset is Strongest Signal and WKNN+Kalman Filter with an average error of 1.91m.

This study also concludes that the RSSI value greatly affects the estimation results, no matter how good the BLE Selection method is used, if the RSSI value still does not reflect ideal conditions due to signal propagation caused by reduction in power density, the accuracy will not be optimal.

Kalman Filter as a tracking object can compensate for the prediction errors of the WKNN algorithm by calculating direction and velocity. However, if a large error occurring from the beginning of the prediction, this method still has difficulty recognizing routes with short distances and directions changing.

Finally, there is still much that can be done to improve the accuracy, such as:

- Other BLE Selection methods like Random Combination or Eisa's 3 Criterions could be explored, RSSI Filtering / Processing like Signal Tendency Index (STI), Gaussian Filter, or Procrustes Analysis which can approach more ideal conditions, and other estimation algorithms like Enhanced Weighted K-Nearest Neighbor

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(EWKNN), Gaussian Distribution or PSO+BPNN.
- Furthermore, future studies can add signal measurement data such as Time Difference of Arrival (TDOA) and Angle of Arrival (AOA).
- Machine Learning approach at the RSSI Filtering / Preprocessing stage which involves all RSSI samples from all beacons at the same reference point, this study only covers RSSI samples per-beacon at the same reference point.
- Analysis of reducing the number of beacons on radio map data.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

ACKNOWLEDGMENT

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