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INDOOR POSITIONING SYSTEM USING COMBINED METHOD OF FINGERPRINTING AND DEAD RECKONING

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ABSTRACT

The development of technology to determine the position of an object is very helpful and widely used, such as the technology of the Global Positioning System (GPS). However, GPS technology can only be used to see the position of an object outdoors at an accurate level that is still far from the indoor positioning technology known as the Indoor Positioning System (IPS). This research will discuss IPS technology which is very useful for several things. One of the benefits that can be applied to student attendance systems using smartphones, which generally already have Bluetooth technology. IPS technology currently has several methods and hardware used, one of which is Bluetooth Low Energy (BLE). BLE issues a signal that is lower than Wi-fi so that in a room several BLEs can be placed which will later be taken by the Received Signal Strength Indicator (RSSI) from the specified Reference Point (RP). One RSSI from each RP is the offline data retrieval phase from the Fingerprinting method. The next step is online data collection and will use the Weighted Sum approach to calculate the second fingerprint data and combine it with the Dead Reckoning method. Where the Dead Reckoning method takes advantage of the accelerometer and gyroscope features found on smartphone devices. To produce a stable Final Location from both methods will use the Kalman Filter formula. When these two methods are combined, the results show that the Fingerprinting method has higher accuracy than the Dead Reckoning method.

Keywords: *Indoor Positioning System, Bluetooth Low Energy, Fingerprinting, Dead Reckoning*

1. INTRODUCTION

Technology to determine the position of an object at this time shows very rapid progress and is approaching very good position accuracy and helps us in many ways for example helping people with disabilities [1], tracking humans [2]. One of them is an objective determination technology that is known as GPS (Global Positioning System). But GPS technology cannot be used to determine the position of an object in a room, so technology is needed to determine the position of objects in a room known as IPS (Indoor Positioning System).

There are several technologies used to determine the position of an object in a room which according to him includes using Infrared (IR) [3], Wifi [4], RADAR, ZigBee, and Bluetooth Low Energy (BLE) technology [5], [6] Faragher in research this states that the accuracy of positioning with BLE devices is 95% more accurate than using Wifi with the fingerprint method [7].

A fingerprint is a method for mapping by utilizing measurements from RSSI. In the process of mapping closed space is divided into several lattices/sections, then place the device that functions as an Access Point (AP) or transmitter that emits RSSI signals, then the receiver RSSI signal is measured to determine its strength in dB units. There are two phases in the fingerprint method, the online phase, and the offline phase, of the two phases that spend time, is the offline phase. The disadvantage of fingerprints is the influence of mapped environments, such as physical barriers/barriers, other signal disturbances [8].

In addition to the fingerprinting method that focuses on working on BLE devices, there is also the Dead Reckoning method which focuses on working on smartphone devices by utilizing sensors found on smartphone devices, including accelerometer and gyroscope sensors. Cellphones such as smartphones and tablets are widely used. All of these devices are equipped with common sensors devices such as magnetic fields, accelerometers, gyroscopes, and sound sensors [10].

Therefore, the development of sensor-based positioning system technology is practical and easy

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to implement, whereas GPS does not work accurately in indoor environments. The proposed system uses only a few available smartphone sensor technologies: accelerometer sensor, gyroscope sensor, and gravity sensor for Pedestrian Dead Reckoning (PDR) which detects steps and measure the length and orientation of the stairs and then calculate their location. As mentioned above, positioning using the Pedestrian Dead Reckoning (PDR) approach and orientation is a simple and effective way to find the user's location.

Pedestrian Dead Reckoning (PDR) can be used easily only with a smartphone or tablet, it does not require infrastructure that has a lot of resources. In this method every time the user takes a step, the step will be automatically detected by the system, having already determined the stride length of the user and orientation then calculated to give the user's initial position. To ensure interactions that result in good accuracy, we only estimate where the user is holding their phone when the user is looking at the surface of the phone.

Of the several existing methods, combining research has been carried out both technologically and by existing methods, including: has combined the positioning system with PDR technology (sensors found on smartphones), WiFi and BLE iBeacon [11]; using BLE technology with the Trilateration and Dead Reckoning methods [12]; the technology and methods used to have many similarities with the research of Ke Huang, et al [13]. The only difference is the method used, namely using KNN for the basic position of BLE and also using Bayesian Estimation to estimate the average position of the objects that exist.

Based on the results of previous research, the fingerprinting method has a higher level of accuracy compared to other methods so that in this study the method chosen is a combination of the fingerprinting method and Dead Reckoning for indoor positioning. While the Dead Reckoning method was chosen because from several previous studies this method was good enough to determine the position of objects that were dynamic or moving. Whether by combining the two existing methods can produce this research, it is hoped that it can provide an academic contribution, namely providing an understanding of the effect of combining the PDR and Fingerprinting methods and making practical contributions in the development of the IPS method that can be used to support indoor positioning applications.

2. RELATED WORKS

The method of determining indoor position has been carried out by many studies, one of which is the fingerprinting method [12]-[14], trilateration [12], [16], the combination of methods between trilateration and dead reckoning [16] and also the combination of methods between fingerprinting and Pedestrian Dead Reckoning (PDR) [17], [18]. For the fingerprinting method, two stages are carried out, namely the first collection of offline data or offline training where in this phase the Received Signal Strength Indicator (RSSI) sample is taken from each reference point (RP) and the second stage is taking online data or data testing which will be the second stage. this will be calculated using the Weighted K-Nearest Neighbor (WKNN) Technique [15]. For methods that combine both the trilateration method with dead reckoning [16], as well as between the fingerprinting method and the Pedestrian dead reckoning [17] for final position determination using the Kalman filter theory consisting of predict and update positions. Some of the results of the research that have been carried out can be seen in Table 1.

Table 1: Summary of Literature Review Results from Previous Research

Research	Year	Technology / Method	Conclusion
Ramsey Faragher, et al	2015	Wifi and BLE	BLE is better than Wifi
Danijel, et al	2015	BLE, *Fingerprinting*	The Fingerprinting method requires a combination of several algorithms
Luka, et al	2018	Wifi and BLE	Has a low cost compared to other methods
Han Zou, et al	2017	PDR, Wifi and iBeacon	0,59 Meter
Azhar, et al	2018	Fingerprint	0,2 – 0,4 Meter
Sugandh, et al	2018	Fingerprint	96%
Umair, et al	2019	Wifi and BLE	Wifi is more accurate than BLE
Taiga Arai, et al	2019	Infrared Beacon	122 – 147 millimeters
Ke Huang, et al	2019	BLE, accelerometer, and magnetometer	0,757 Meter

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Research	Year	Technology / Method	Conclusion
Rohan, et al	2019	Bayesian, K neighbors and PDR	0,65 – 0,85 Meter
Han Jun Bae, et al	2019	*Fingerprinting* (BLE) and PDR (smartphone)	new fingerprint technique called reverse fingerprint (Inv-FP)

Based on the results of the literature study, it can be seen in Table 1 that for the best method the accuracy value is the Fingerprinting method performed by Azhar, et al. However, this research was carried out on objects with a fixed or immovable position, while for the moving position the Fingerprinting method did not produce good accuracy so that it needed to be combined with the Dead Reckoning method which had high accuracy for positioning the moving object in the room so that at This research will research the system of determining the position of an object in the room using the Dead Reckoning method to determine the position of a dynamic or moving object and combine it with the Fingerprinting Weighted Sum method from the nearest RP where based on several previous studies stated that the Fingerprinting method has a higher level of accuracy.

For methods that have been done using the same technology even though they use different methods and there are also some using different technologies with the same method. The technologies used include RADAR, Wi-Fi, ZigBee, and Bluetooth Low Energy (BLE). From several technologies that have been used in previous studies, based on the results in Table 1, the technology used to support research on indoor positioning systems is a combination of fingerprinting and dead reckoning methods using BLE.

3. BACKGROUND THEORIES

3.1 Indoor Positioning System

Indoor Positioning System methods is the determination of position in an indoor environment that is often achieved using radio frequency reference points [19]. The development of indoor positioning technology is diverse. The main technologies include infrared, ultrasonic, computer vision, Zigbee, RFID, Wi-Fi, Bluetooth, LED visible light, and Ultra-Wideband (UWB). Traditional positioning methods include seven main principles such as triangulation, fingerprints, closeness, positioning of the center of mass, pole method, multilateral positioning methods, and Dead Reckoning [20].

In the technique of determining the Indoor Positioning System, there are several techniques used to determine the position of an object and are broadly divided into two approaches, namely the Geometric approach which consists of triangulation, scene analysis, and statistical approaches consisting of the KF algorithm, EKF, Gradient Filters. In triangulation techniques can be divided into two, namely Lateration and Angulation. The lateration technique consists of several methods, namely Receiver Signal Strength Indicator (RSSI), Time of Arrival (ToA) & Difference in arrival time (TDoA), Round Trip of Flight (RToF), and Received signal phase method (RSPM). Whereas the Scene approach consists of the fingerprint method and k-Nearest Neighbor [8].

3.2 Bluetooth Low Energy

BLE Beacon is a small Bluetooth radio transmitter, which is powered by batteries. Flares are similar to lighthouses in function. This small hardware continuously sends Bluetooth Low Energy (BLE) signals. This Bluetooth enabled smartphone can scan and display these signals [21].

BLE is a widely available technology that offers inexpensive battery-powered equipment. BLE emits a weaker signal strength than Wi-Fi, so greater consideration must be taken to where the BLE reference node is placed. Poorly positioned reference points can be considered useless because they do not provide significant signal propagation [18].

Figure 1: BLE iBeacon

For this research, researchers used the Bluetooth BLE 4.0 series can be seen in Figure 1. Wireless Module for DOTT iBeacon Base Station Intelligent Control System Beacon Module with Case. Some of the BLE 4.0 series are the CC2640 beacon module which supports Bluetooth Energy Saving single-mode operation, and the output power can support class 2. This module provides the ability to load your entire application into the integrated ARM Cortex M3 microcontroller or use the module in Network Processor mode. along with the microcontroller of your choice. ARM Cortex M0 dedicated RF Core improves system performance and frees up FLASH memory for special applications. The beacon has a shrapnel battery in it and is easy to test with the CR2032 button battery. Features: Built-in CC2640F128 Bluetooth Smart System-On-Chip (SOC), 128 kB Flash / 20 kBSRAM, RF Output Power: +5 dBm, RF Receiving Sensitivity: -96 dBm, Operating Voltage: 1.8V to 3.8V, Operating Temperature: -40 to + 85C, Transmit Mode 8.4 mA, Receive Mode 7.4 mA, Standby Mode 1A with fast start-up 100, Shutdown 200nA, Active CPU Current 61A / MHz, Driver, Bluetooth Energy Saving, Controller, and bootloader on ROM, Flexible peripheral devices, Onboard 32 kHz and 24 MHz Crystals. Application: In-store navigation mobile payment specialist flow analysis for iBeacon Description Run standalone as iBeacon, No external host required. Application for advertising and location. Support customize your own for iBeacon configuration including UUID etc. Built-in JTAG port for other customizations [22].

3.3 Fingerprinting Method

A fingerprint is a method for mapping by utilizing measurements from RSSI. In the process of mapping closed space is divided into several lattices/sections, then place the device that functions as an Access Point (AP) or transmitter that emits RSSI signals, then the receiver RSSI signal is measured to determine its strength in dB units. There are two phases in the fingerprint method, the online phase, and the offline phase, of the two phases that spend time, is the offline phase. The disadvantage of fingerprints is the influence of mapped environments, such as physical barriers/barriers, other signal disturbances [8].

The fingerprint method with BLE uses RSSI for the Indoor Positioning System which consists of two phases, namely in the offline phase an accurate model is adopted for Radio Map construction, whereas in the online phase, a deterministic positioning algorithm is applied to place the receiver in the test area [21], [23].

One of the most effective KNN variants is Weighted K-Nearest Neighbor (WKNN). KNN estimates the average closest K neighbor is chosen while WKNN assigns the appropriate weight to each chosen neighbor. Therefore, WKNN has been widely used in indoor positioning. Here, the Euclidean distance used in the algorithm represents the physical distance between the receiver and the reference point [24], [25].

The application fingerprinting method used is Scan BLE & Record can be seen in Figure 2. This application will store RSSI data from several active BLEs around the research room. The results of retrieval of stored data facilitate research that must run 2 applications at once in online data retrieval. To find out the position in online data retrieval, a note is made every time it passes a predetermined alphabet point.

Figure 2: BLE and Record Application

3.4 Dead Reckoning Method

Dead Reckoning is the process of calculating the current position from a given initial position by estimating the movement of pedestrians. More specifically, PDR estimates the number of steps, step length, and orientation of the movement by using an IMU sensor with smart devices such as smartphones. It usually determines the steps by analyzing the accelerometer sensor data pattern and estimating the direction of the user's movement by analyzing the IMU sensor data, namely the gyroscope signal, magnetometer, and the device's accelerometer sensor. Compared to the RF fingerprint scheme, this is a relative positioning scheme because it calculates the next position relative to the current position by estimating the relative user's movement. This leads to tracking adjacent locations which are not possible with current RF signal-based localization schemes.

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However, it can only give relative position results [26]-[28].

For this method, data collection uses an existing application, namely the Dead Reckoning application from Nisarg Patel can be seen in Figure 3, where this application produces data in the form of a gravity table, Gyroscope, Initial_Orentation, Linear_Acceleration, Magnetic_Field, and XY_Data_Set. For some of the tables generated, this research takes data from this application for the result of the Dead Reckoning method.

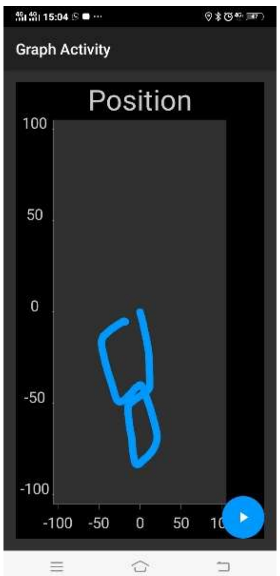

Figure 3: Dead Reckoning Application

3.5 Kalman Filter

The Kalman filter algorithm consists of two processes namely the Predict and Update processes with the following equation:

Predict:

$$L_t = AL_{t-1} + BU_t \quad (1)$$

$$P_{t|t-1} = AP_{t|t-1}A^T + Q \quad (2)$$

Update:

$$K_t = P_{t|t-1}C^T(CP_{t|t-1}C^T + R)^{-1} \quad (3)$$

$$L_{t|t} = L_{t|t-1} + K_t(Z_t - CL_{t|t-1}) \quad (4)$$

$$P_{t|t} = (1 - K_tC)P_{t|t-1} \quad (5)$$

where, A, B, and C are the identity matrices; P is a process covariance matrix that represents an estimation error; and K is the Kalman gain of the system, which ranges from 0 to 1. When the Kalman gain is higher, the measurements are more accurate, and the estimates are unstable. When Kalman's profits are lower, estimates are more accurate, and his measurements are unstable [16], [28].

4. PROPOSED INDOOR POSITIONING SYSTEM

The proposed method is a merger between the fingerprint method and Dead Reckoning to determine the position in the room because according to the results of previous studies the fingerprint method has a higher level of accuracy compared to other methods such as the trilateration method [29].

In the fingerprint method, data collected in the online phase is divided into two: training data and testing data. Existing training data is used to train and determine the optimal parameters of the system that is made, and testing data is used to measure the performance of the system that is made [30].

While the Dead Reckoning method was chosen because from previous studies this method is good enough to position dynamic or moving objects. This method can be done with the help of the Inertial Measurement Unit (IMU) which is already owned by most smartphones, namely the accelerometer and gyroscope sensors.

The final step is to determine the final location using The Kalman Filter. The Kalman filter is an optimal recursive data processing algorithm that provides estimates of linear, unbiased, and minimum error variance from the unknown state vector [31]. This method will be generated later from several parts contained in a cellular device, namely the accelerometer and the gyroscope [32] as a predictive value and the fingerprint method as an update value as depicted in Figure 4.

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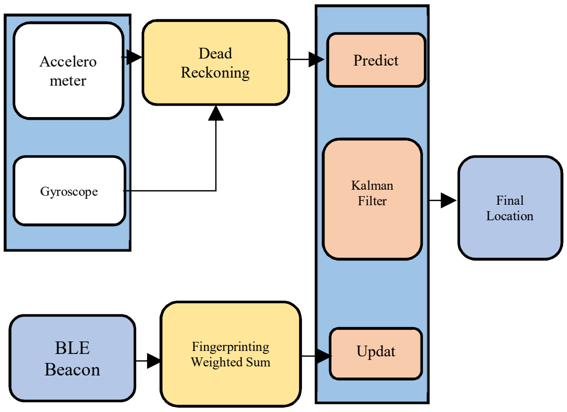

Figure 4: Flowchart of System Design


Figure 6: RPL Lab Room SMKN 1 Sorong

5. EXPERIMENTS

5.1. Experimental Design

For the fingerprinting method, two data will be taken, namely: RSSI data from 36 RPs can be seen in Figure 5 that have been determined in the lab room. RPL SMKN 1 Sorong is the place where this research was conducted which is the training data.

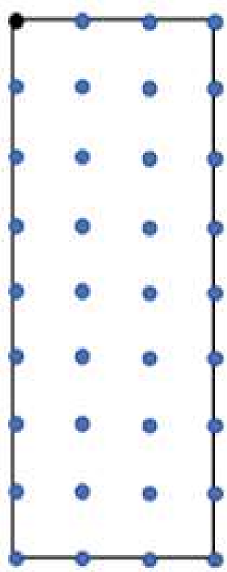
Figure 5: Reference Points

Determination of the RP location is done randomly by making a space grid, namely, the distance between RPs is approximately 2 meters can be seen in Figure 5. The black dot is the point (0, 0) or RP1.

This research was conducted in the lab room. RPL SMKN 1 Sorong can be seen in Figure 6 with a room size of 16 meters x 4.8 meters. Where on the long side of the room, each side of the 3 pieces of BLE is placed and on the wide side of room 1 BLE is placed with a height from the floor which is 1.5 meters can be seen in Figure 7 and Table 2.

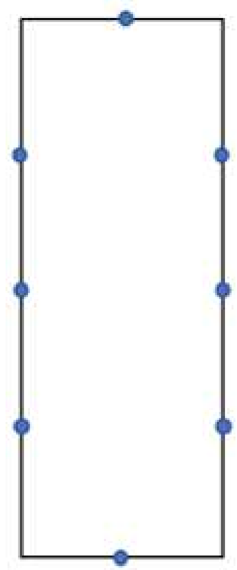
Figure 7: BLE Position

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Table 2: BLE coordinates

No.	BLE	x	y	unit
1	Beacon1	240	0	cm
2	Beacon2	0	400	cm
3	Beacon3	0	780	cm
4	Beacon4	0	1230	cm
5	Beacon5	1200	240	cm
6	Beacon6	480	1190	cm
7	Beacon7	480	740	cm
8	Beacon8	480	350	cm

For online data retrieval, 5 routes have been determined where the routes to be traversed are marked in the alphabet from A to F. The routes are as follows with the coordinates of the route are summarized in Table 3:

1. A→B→D→F→E→C→A
2. B→D→C→E→F→D→C→A→B
3. E→C→D→B→A→C→D→F→E
4. F→D→B→A→C→E→F
5. F→E→C→A→B→D→F

Table 3: Route Alphabet Coordinates

Route Coordinate				
NO	Point	x	y	unit
1	A	40	320	cm
2	B	440	320	cm
3	C	40	840	cm
4	D	440	840	cm
5	E	40	1320	cm
6	F	440	1320	cm

For the determination of Reference Points, BLE positions and route coordinates in online data collection can be seen in Figure 8.

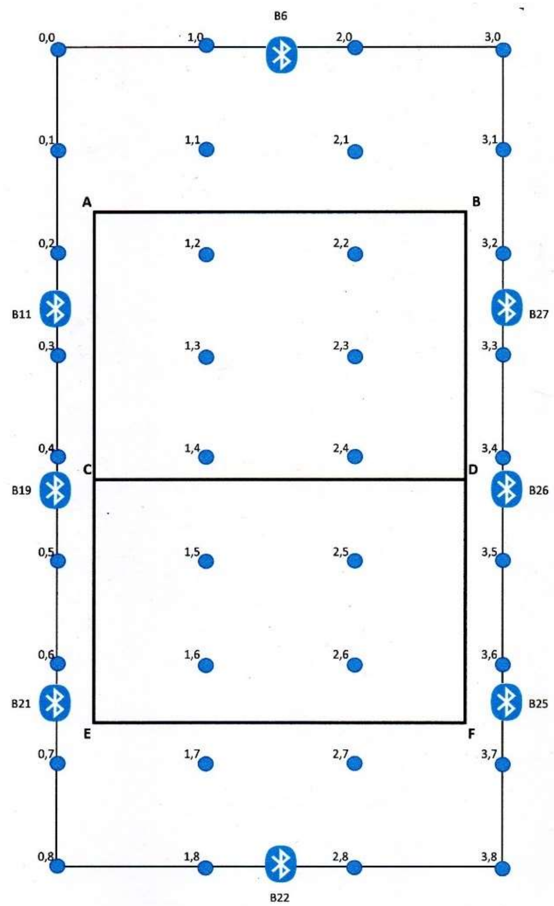

Figure 8: RPs, BLE Position, and Route Coordinates

In Figure 8, the BLE naming is adjusted to the device name detected in the BLE and Record application. Meanwhile, thick lines are the paths that are traversed in online data retrieval that pass through predetermined coordinate points.

After determining the coordinates of the location of the BLE, the reference point, and the coordinates of the route to be passed for online data collection, the next step is to calculate the Weighted Sum value for the fingerprinting method using the Weighted Sum formula:

$$x_w = \sum_{i=1}^{m} x_i \times \frac{w_i}{\sum_{i=1}^{m} w_i} \quad (6)$$

$$y_w = \sum_{i=1}^{m} y_i \times \frac{w_i}{\sum_{i=1}^{m} w_i} \quad (7)$$

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to use the Weighted Sum formula, the Euclidean Distance formula is also needed:

$$w_i = \sqrt{\sum_{i=1}^{m}\left(RSSI_{i_{testing}} - RSSI_{i_{reference}}\right)^2} \quad (8)$$

where w_i is the weight to be searched from RSSI RP.

For the Dead Reckoning Method, the initial position can be obtained from RSSI-based positioning. The accelerometer is used to calculate step detection and stride length, while the heading direction is determined by the gyroscope. Assuming the starting position with the equation (x^k, y^k); then the next position becomes the equation (x^{k+1}, y^{k+1}) with the following calculations:

$$x^{k+1} = x^k + SL^k \cos\theta^k \quad (9)$$

$$y^{k+1} = y^k + SL^k \sin\theta^k \quad (10)$$

where SL^k is the length of the stride in the step k, and θ^k is the heading angle in step k [15].

5.2. Step Detection Result

Step Detection is a process that is needed to determine the displacement of an object. To detect steps, you can use accelerometer data. For the step detection method, the peak point detection method is a fundamental way to achieve a good step detection performance using an accelerometer. This method involves the vertical acceleration generated by a vertical blow when the foot hits the floor. Since vertical acceleration is affected by the tilt of the smartphone, we took the magnitude of acceleration into account (a_{mag}). A step is detected if it meets the following two conditions:

$$|a_{mag} - g| \geq a_{th} \quad (11)$$

$$Timestamp\ \Delta t \geq t_{th} \quad (12)$$

where g is the gravity of the earth, a_{th} is threshold acceleration, and t_{th} is the threshold time for the acceleration measurement period Δt. threshold acceleration a_{th} used to limit the detection of false steps, and the time threshold t_{th} limit step detection to a limited time duration. The acceleration threshold level can be seen in Figure 9.

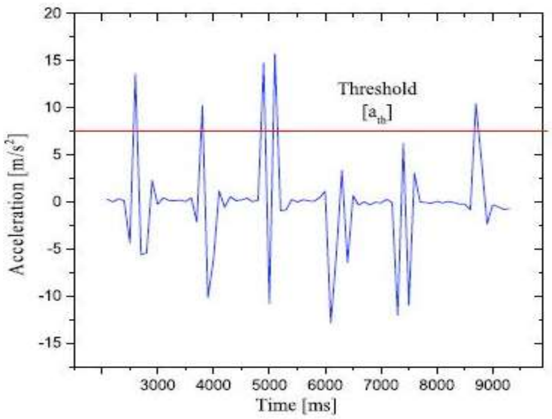

Figure 9: Acceleration and Threshold

5.3. Step Length Estimation Result

Each person's stride length is different and when stepping does not always have a constant and changing stride length, it is very difficult to estimate the exact stride length. There are several methods for estimating stride length. In general, there are two methods, namely the static method, the dynamic method. The static method assumes that every step a person takes is the same length, which can be determined by the equation:

$$SL = height * K \quad (13)$$

where k is a constant value, 0.415 for men and 0.413 for women.

The dynamic method for estimating the stride length that allows different stride lengths at each step is the Weinberg approach used in research with equations:

$$SL = K\sqrt[4]{a_{max} - a_{min}} \quad (14)$$

$$a = \sqrt{x^2 + y^2 + z^2} \quad (15)$$

where a_{max} and a_{min} is the maximum value and the minimum value of vertical acceleration. In this study, the k value obtained based on trials was 0.43 [32].

5.4. Heading Estimation Result

Determining the heading is the most difficult part of the calculation of death, to determine the heading of the tool used is the gyroscope on a smartphone device. For the Gyroscope, only values are taken y-axis (y_g) and z-axis(z_g) because when the user rotates the smartphone device in front of the chest, the x-axis data is mostly zero. So that the equation used is as follows:

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$$Gyr = \sqrt{y_g{}^2 + z_g{}^2} \quad (16)$$

To calculate the change in direction based on the value generated in Equation 16, the following equation is used:

$$Ori = \sum(Gyr * Time * 57.29578) \quad (17)$$

where the orientation (change in direction) can be determined by multiplying the combined gyroscope data from Equation 16, time interval, and parameter 57.29578. The parameter changes the orientation from radians to degrees (180 / 2π) [32].

The two methods above will be combined using the Kalman Filter algorithm. The Kalman filter algorithm consists of two processes, namely predicting and updating, where the predicting process is the result of the Dead Reckoning method, which is in the updating process based on the results of the Fingerprinting Weighted Sum method. If L is the variable x or y, the Kalman Filter algorithm can be written as follows:

Predict:

$$L_{t|t-1} = L_{t-1} + U_t \quad (18)$$

$$P_{t|t-1} = P_{t|t-1} + Q_t \quad (19)$$

Update:

$$L_{t|t} = L_{t|t-1} + K_t \times L - L_{t|t-1}) \quad (20)$$

$$K_t = P_{t|t-1} \times (P_{t|t-1} + R)^{-1} \quad (21)$$

$$P_{t|t} = (1 - K_t) \times P_{t|t-1} \quad (22)$$

where U_t is the change in position value x^k see Equation 9 or y^k see Equation 10. For the predictive value of the Dead Reckoning method and L is the x or y value for the updated value of the Fingerprinting Weighted Sum method and the value taken from the two combined methods is the value $L_{t|t}$ as the result value of the combined method of Fingerprinting and Dead Reckoning with a value of Q and R is 0.01.

The final step of the three steps above is to determine the mean of error, Min, Max, Median, and 90th Percentile values of the three methods above using the Euclidean Distance formula to compare the predicted value of each method with the existing ground truth.

5.5. Location Estimation Results

From the data that has been taken, the first calculation is the calculation for the first method, namely fingerprinting using the Weighted Sum formula, the second for Dead Reckoning data generated through the Dead Reckoning application. The two methods are combined with the Kalman Filter method so that the overall data results are described in Table 4.

Table 4: Average Result for Each Route

Route	Metrics	Weighted Sum (cm)	Dead Reckoning (cm)	Combined (cm)
1	Mean of Error	346.89	444.65	372.43
	MIN	90.73	45.63	107.73
	MAX	860.24	1,049.23	899.91
	Median	307.51	418.39	326.04
	90th Percentile	619.35	849.30	683.77
2	Mean of Error	446.33	540.24	526.31
	MIN	56.53	43.03	48.57
	MAX	1,419.24	1,249.59	1,125.86
	Median	348.31	507.68	503.31
	90th Percentile	869.31	946.35	895.31
3	Mean of Error	291.96	546.36	538.60
	MIN	63.59	25.25	36.11
	MAX	672.51	1,091.23	1,047.54
	Median	282.24	530.09	522.22
	90th Percentile	443.61	947.04	918.17
4	Mean of Error	258.46	589.94	589.92
	MIN	57.35	0.68	0.84
	MAX	667.47	1,081.12	1,080.05
	Median	239.52	578.01	577.89
	90th Percentile	436.41	1,016.57	1,016.82
5	Mean of Error	359.21	588.29	588.30
	MIN	43.53	1.06	1.15
	MAX	1,155.80	1,077.98	1,078.29
	Median	317.94	558.23	558.64
	90th Percentile	583.00	1,023.67	1,023.66

Table 4 shows the average results of taking each route where each route was taken 5 times. The average results displayed consist of 3 methods where the third method is a combination of the two proposed methods, namely the Fingerprinting Weighted Sum method and the Dead Reckoning method. The result of the average of each route shows that the value of the combined method is between the two values of the two combined methods. From the five average results for each route, the overall average value is taken and can be seen in Table 5.

Table 5: Average Result

Metrics	Weighted Sum (cm)	Dead Reckoning (cm)	Combined (cm)
Mean of Error	333,56	543,84	533,92
MIN	63,98	16,73	24,38
MAX	968,66	1.161,43	1.069,38
Median	288,99	519,95	515,45
90^{th} Percentile	573,26	965,73	921,45

Overall average data results in Table 5 show that the existing data has a very far data range where the minimum data value is very low and the maximum data value is very high so that it gets a median value and a 90^{th} percentile value between the Weighted Sum approach and The Dead Reckoning method has a far-reaching value so that the Mean of Error value is very far from the accuracy value.

Based on the final average result. the value of the Mean of Error which is small so that it can be said to have a high accuracy value is the Fingerprinting method with the Weighted Sum approach and after combining these two methods, the combined result value is between the values of the two methods that have been combined with the Kalman Filter algorithm.

However, in this research, the final value has a higher level of accuracy than previous studies using a combination of fingerprinting and dead reckoning methods, Rohan, et al, 2019, in the Bayesian journal, K neighbors and PDR with an accuracy of 0, 65 - 0.85 meters [18] and Han Zou, et al, 2017, in the journal PDR, Wifi and iBeacon with an accuracy rate of 0.59 meters [11]. And in this research, the accuracy rate reaches 0.53 meters.

6. CONCLUSION AND FUTURE WORK

Based on existing reference sources, research on indoor sequence systems using a combined method that can produce high accuracy is a combined method of the Fingerprinting method and the Dead Reckoning method. This study tries to combine the Dead Reckoning and Fingerprinting methods according to the original purpose of this study.

The results showed that the method that has high performance or level of accuracy is the Fingerprinting method using the Weighted Sum formula, while for the Dead Reckoning method the results obtained have a low level of accuracy compared to the Fingerprinting method. Same as in previous studies where the fingerprinting method can have an accuracy value of 0.2 - 04 meters [22]. Likewise, in this research based on Table 4 where the fingerprint method has a Mean Error value of 0.258 - 0.446. So, from the final results of the research that has been done, it can be concluded that this research has carried out a hybrid method or a combination of the Dead Reckoning method and the Fingerprinting method. The final result of this research shows that the method that has the highest performance is the Fingerprint method.

Each of the existing methods in determining the position of the room has advantages and disadvantages so that to get maximum results, several methods can be combined to determine the position in the room. In this research, the combined method that has been carried out by utilizing several existing technologies and applications can produce a higher level of accuracy than the previous research which is summarized in Table 1. So, it is hoped that this research can contribute to further research using the Fingerprinting and Dead Reckoning methods.

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