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HYBRID FINGERPRINTING AND PEDESTRIAN DEAD RECKONING USING MACHINE LEARNING FOR INDOOR POSITIONING SYSTEM

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ABSTRACT

Indoor Positioning System is one of the hot research topics in the last years for it gives opportunity to be used in many business platform. BLE technology is used for indoor positioning system to reduce material and energy cost over time compared to other technologies which cost more. There has been a lot of study to increase positioning accuracy. One of the latest improvements is to use hybrid approach which combines the results of two methods. In this study, we propose a positioning algorithm for indoor positioning system using fingerprinting approach using two machine learning: Artificial Neural Network (ANN) and Support Vector Regression (SVR), and a hybrid of fingerprinting and Pedestrian Dead Reckoning (PDR) using ANN and SVR. Hybrid fingerprinting using Weighted K-Nearest Neighbor (W-KNN) and PDR is used as benchmark of this experiment. ANN and SVR are proposed as the machine learning used for both fingerprinting and hybrid method to combine with PDR. On benchmark, hybrid fingerprinting KNN using ANN achieve positioning root-mean-squared error 147.94 cm. The proposed hybrid fingerprinting ANN achieved 103.29 cm using ANN and 160.86 cm using SVR.
Keywords: *Indoor Positioning System, Fingerprinting Methods, Pedestrian Dead Reckoning, Hybrid Method, Machine Learning*

1. INTRODUCTION

Indoor positioning system (IPS) is a user positioning mapping technique that works indoor. IPS is different with Outdoor Positioning System, like GPS which cannot work well in indoor environment because it's difficult for signal to penetrate building [1]. There are already some research related to IPS technologies, like using Radio Frequency Identification (RFID) [2, 3], infrared [4, 5], Bluetooth [6, 7], Wi-Fi [8, 9], Inertial Measurement Unit (IMU) [10, 11], and some other technologies. A survey conducted in 2017 shows that BLE has good potential to develop an indoor positioning system [1, 8].

Indoor positioning system is used in navigation and monitoring activities. It is already expanded to many functions, like as a navigation system in a hospital [12], navigation system in a mall [13], and many more. By using this system, it is hoped that a navigation system can be applied in various places, especially in environments that require high accuracy in the navigation system to get the minimum error possible.

There are already some techniques used to determine user's position in a room. One of the method is by using geometry method, like trilateration [14], that uses three BLE signal strength (RSSI) to determine the estimated position. Other method is by using fingerprinting method that applies machine learning for fingerprinting to estimate user's position using five BLE RSSI [15, 16]. Other method is by using fusion technique by combining some estimations using two or more IPS technique to increase accuracy [7].

There are many factors that affect BLE radio signal in indoor environment, like multipath effect, random behaviour from Received Signal Strength caused by reflection, receiver movement rate, and others [1]. To solve these issues, fingerprinting method is developed. Fingerprinting collects data such as the strength of a radio signal with respect to

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a certain position and stored in a database to be able to estimate the position when a device is used to predict the position using a radio signal by calculating the distance from the approximate five closest positions taken from the comparison of signal strength during data collection [16]. This makes the errors mentioned above already included in the measurement at the data collection stage.

Machine learning techniques used in the fingerprinting affects the result accuracy. There are several fingerprinting methods, including regression-based fingerprinting methods, such as SVR, ANN, RF, MLR, and CNN [15, 16] and weighted sum-based fingerprinting, such as KNN [7, 17].

Many researches were made to improve the performance of the indoor positioning system, especially in dynamic locations. Some applies filters like Extended Kalman Filter (EKF) to filter noise from the obtained RSSI [18]. Some use hybrid approach by using fusion algorithm to combine two or more positions to increase accuracy [7, 19, 20].

Research conducted in 2021 combined fingerprinting and pedestrian dead reckoning (PDR) methods using machine learning ANN which resulted in better accuracy [7]. This research achieved a quite good accuracy, but the fingerprinting method used weighted KNN for the machine learning. Based on literature review [15], regression-based fingerprinting gave better result than weighted-sum one.

The main focus of this research is to compare some fingerprinting and hybrid methods, then compare the results using the method used by previous researcher [7]. The fingerprinting methods used in this research are regression-based fingerprinting using ANN and SVR. Fingerprinting using KNN will be used as the benchmark. Each of the fingerprinting results then combined with PDR using machine learning ANN and SVR. This research is intended to improve the accuracy of indoor positioning, especially SVR or ANN fingerprinting when combined with PDR using machine learning ANN or SVR.

The remainder of this paper is organized as follows: Section 2 explains existing relevant studies on Indoor Positioning System along with brief explanation. The proposed Fingerprinting, PDR, and Fusion methods are explained in Section 3. Section 4 explains the dataset, experimental design, and the result and analysis of the experiment while Section 5 will conclude this research.

2. RELATED WORKS

As what has been established in Section 1, previous research already reached a good accuracy, but the fingerprinting method can be improved. Therefore, most related works discussed will be more focused on BLE fingerprint approach.

Fingerprinting algorithm can be classified into deterministic algorithm and probabilistic algorithm [21]. Deterministic algorithm finds the best match between RSS and radio map, then estimates position based on distance between each reference point. Probabilistic fingerprinting represents RSS values as probabilistic distribution, then estimates position using Bayes rule, likelihood estimator, or other probability functions.

One of popular deterministic algorithm is nearest neighbour algorithm, such as KNN. The main idea of KNN is to select k calibration points, which are the nearest neighbours, then calculate the estimation by using distance estimation method, like Euclidean distance and Manhattan distance.

One of probabilistic algorithm is coverage area (CA) model. Coverage area estimates user's position by matching fingerprint location density and user location density. CA models user's location probabilities within access point reception range. However, based on survey conducted by Davidson [20], probabilistic algorithm has lower accuracy than deterministic algorithm.

Fingerprinting needs to match the measured RSS with radio map. The matching algorithm can use machine learning to do pattern recognition. Many research already conducted to improve position accuracy by applying different machine learning, such as Artificial Neural Network Regression (ANN), Support Vector Regression (SVR), Convolution Neural Network (CNN), and other methods [15, 16].

Another research tried to improve accuracy by doing a hybrid between BLE positioning and IMU-based positioning [7]. The researcher used machine learning ANN and Kalman Filter as the fusion algorithm to fuse fingerprinting estimation and pedestrian dead reckoning estimation.

3. PROPOSED METHOD

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3.1 Fingerprinting Methods

In this paper, we proposed fingerprinting method to estimate position from RSS. Fingerprinting consists of an offline phase and an online phase as shown in Figure 1. In the offline phase, the RSS value received from a set of devices is related to a certain position. This relation will be stored in a database called radio map which will store all positions and RSS values of each transmitter. Each data in radio map consists of coordinate (x, y) of the reference point and RSS value of each BLE transmitter.

In the online phase, the retrieved RSS value will be compared with the signature in the database using the localization method to estimate the position of the closest reference associated with the reference point. There are two approaches used in this research: KNN and machine learning using ANN and SVR.

3.1.1 K-Nearest neighbour

KNN calculates the distance by using Euclidean Distance between reference points and measured RSS. The distance is calculated using (1).

$$D(mp, rp) = \sqrt{\sum_{i=1}^{23} (RSS_i^{mp} - RSS_i^{rp})^2} \quad (1)$$

After all the distances are calculated, k number of reference points with smallest distance are selected. After k reference points are selected, the estimation (x, y) position are calculated using (2) and (3) where the weight is calculated using (4).

$$\hat{x} = \sum_{i=1}^{k} (W_i x_i^{rp}) \quad (2)$$
$$\hat{y} = \sum_{i=1}^{k} (W_i y_i^{rp}) \quad (3)$$

$$W_i = \frac{D_i}{\sum_{i=1}^{k} D_i} \quad (4)$$

Where x_i^{rp} and y_i^{rp} are the x and y value of i^{th} nearest reference point. $\hat{x}$ and $\hat{y}$ is the estimated x and y position.

3.1.2 Machine learning

This research will use two machine learning methods: ANN and SVR for fingerprinting methods. The input for the machine learning will be the RSSI distances to all reference points. The input then will be processed with respective machine learning method. This will result the estimated x and y position. The deep learning architecture proposed is illustrated in Figure 2.

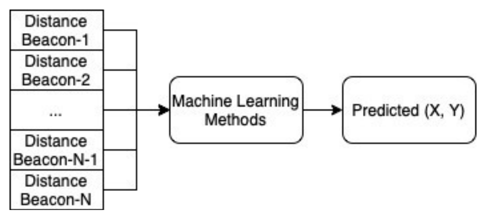

Figure 2. Proposed Fingerprinting Machine Learning Model

RSSI data is used to train the machine learning regression model. Training model is later used to determine the most optimum model for each machine learning regression model through parameter tuning.

3.1.2.1 Artificial neural network

Artificial Neural Network (ANN) consists of three layer: input layer, hidden layer, and output layer. Input layer is used to receive input data, hidden layer is used to process the data, and output

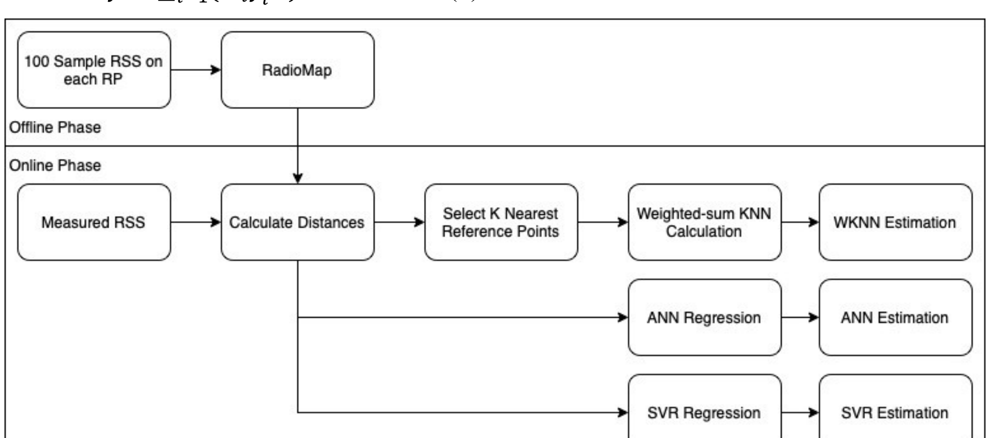

Figure 1. Phase of Fingerprinting

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layer is used to produce the predictive result [15]. ANN is strong against noise and interference which are one of the major factors affecting the accuracy of IPS [22].

In this experiment, hidden layer size, solver for weight estimation, activation function, and number of epochs will be tuned by using validation data to reach the optimal configuration for better accuracy.

3.1.2.2 Support vector regression

SVR defines the hyperplane to maximizes the margin of error tolerance to minimize error [23]. Therefore, the error tolerance (C) will be tuned to reach the optimal configuration. Besides error tolerance, the value of ε (epsilon) that determines the width of the tube around the hyperplane also needs to be tuned [24].

Some other parameters to be tuned are the kernel function and the degree of the polynomial kernel function. Therefore, the value of C and ε will be tuned for both kernel functions. For polynomial kernel, there will be an additional degree parameter to be tuned.

3.2 Pedestrian Dead Reckoning

Pedestrian Dead Reckoning calculates current position by using previous position and determined speed over elapsed time. The movement speed and heading direction can be detected by using smartphone sensors like accelerometer, gyroscope, and magnetometer. The transition can be represented by equation (5) and (6).

$$v_t^x = S_t . \sin \theta_t \quad (5)$$
$$v_t^y = S_t . \cos \theta_t \quad (6)$$

Where t is the timestamp. (v_t^x, v_t^y) is the transition vector on x and y axes. S_t is the step length from previous timestamp to current timestamp. θ_t is the angle of heading on current timestamp.

There are three main phases in PDR: step detection, heading estimation, and step length determination. Figure 3 illustrates the overview of PDR method.

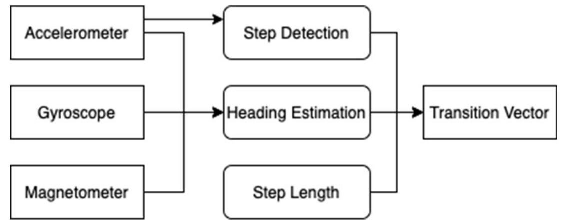

Figure 3. PDR Method Overview

3.2.1 Step detection

Step detection is measured using accelerometer sensor. Accelerometer will detect acceleration on three axes (x, y, z). The root mean square of the reading values (a_x, a_y, a_z) will be represented as waveform of the acceleration (a).

One of the detection algorithm to identify a step is by calculating a high peak using equation (7). But, using high peak is not reliable enough due to the multiple peaks and amplitude variation of measurement.

$$\sqrt{a_x^2 + a_y^2 + a_z^2} \geq a_{th} \quad (7)$$

Where a_{th} is the peak threshold value. (a_x, a_y, a_z) are the acceleration values on each axes read from accelerometer.

To reduce unintended high peaks, time threshold between each step will need to be set to reduce the detection error of total step count. The time threshold validation is represented in equation (8).

$$\Delta t > t_{th} \quad (8)$$

Where Δt is the timespan between each step. t_{th} is the timestamp threshold value.

3.2.2 Heading estimation

Heading estimation is measured using accelerometer, gyroscope, and magnetometer sensor. Direction and changes of direction can be determined by using the initial heading direction. Azimuth will be calculated based on rotation matrix built by accelerometer and magnetometer reading. The progressive heading direction change will be determined by using quaternion and gyroscope.

3.3 Hybrid methods

This research will use two machine learning methods: ANN and SVR for hybrid methods. The

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input for the machine learning will be the estimated fingerprinting position $(\tilde{x}_t, \tilde{y}_t)$, estimated transition vector using PDR (v_t^x, v_t^y), and previous estimated position $(\bar{x}_{t-1}, \bar{y}_{t-1})$. The input then will be processed with respective machine learning method. This will result the estimated x and y position $(\bar{x}_t, \bar{y}_t)$. The deep learning architecture proposed is illustrated in Figure 4.

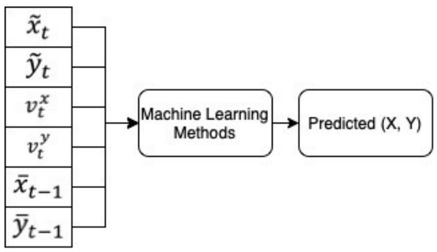

Figure 4. Proposed Hybrid Machine Learning Model

Same as the machine learning used for fingerprinting, the parameters to be tuned for ANN will be hidden layer size, solver for weight estimation, activation function, and number of epochs. For SVR, the parameters are error tolerance (C), ε (epsilon), kernel functions, and degree of the polynomial kernel function.

4. EXPERIMENTS

4.1 Dataset

The experiment will use dataset from [7] that contains 5 route data that was taken using 5 routes as shown in Figure 5. Each dataset contains RSSI reading and IMU reading. The dataset also contains 100 RSSI reading from each beacon at every reference point. There are 54 reference points and 23 beacons spread as shown in Figure 5.

4.2 Experimental Design

Reference point data is used to generate radio map for fingerprinting offline phase. Radio map is generated by averaging RSSI reading for each beacon at each reference point.

Route data will be split into three datasets: training dataset, validation dataset, and testing dataset. Training dataset will be used to train the

Figure 5. Route Taken

machine learning model. Validation dataset will be used to tune the parameters of each method. Testing dataset will be used to evaluate the model performance.

Route 5 is used for testing data for it is the longest distance treaded between each route. Route 2 is used as validation dataset for it is the second-longest distance. The rest of the routes are used for training.

IMU data is used for PDR method. All the fingerprinting and PDR results are combined using machine learning methods to produce the final predicted location to be evaluated.

In this experiment, model is evaluated using Mean Positioning Error (MPE) where the error is measured using Root Mean Squared Error (RMSE) metrics which are defined by equation (9) and (10).

$$Error = \sqrt{\left(x - x_p\right)^2 + \left(y - y_p\right)^2} \quad (9)$$

$$MPE = \frac{1}{n}\sum_{i=1}^{n} Error_i \quad (10)$$

Where (x, y) is the ground truth of actual position. (x_p, y_p) is the predicted position. n is the total number of position detected from fingerprinting method.

For KNN fingerprinting and PDR method, all the parameters to be tuned will follow the same parameter as author [7]. For ANN fingerprinting and hybrid method, the hidden layer size, solver for weight estimation, activation function, and number of epochs will be tuned according to the lowest RMSE. For SVR fingerprinting and hybrid method, value of C, ε, and degree will also be tuned according to the lowest RMSE. The summary of explored parameter can be referenced in Table 1.

Table 1. List of Explored Parameters

	Explored Parameter
Fingerprint KNN	Number of selected BLE (i) Number of selected RP (k)
PDR	Step detection peak threshold (a_{th}) Step length
ANN (hybrid and fingerprint)	Hidden layer size Number of epoch Solver for weight estimation (lbfgs, sgd, adam) Activation function (identity, logistic, tanh, relu)
SVR (hybrid and fingerprint)	Kernel (linear, polynomial) Tolerance (C) Epsilon (ε) Degree

4.3 Experimental Results

For the experimental results, the discussion will be started from the parameters being used. This discussion will start with carried over parameters from paper [7]. Each other methods will have its own subsection, starting from fingerprinting ANN tuning, fingerprinting SVR tuning, and hybrid SVR tuning. The discussion will be closed with experimental results.

4.3.1 Carried over parameter

The tuning configuration for fingerprinting KNN, PDR, and hybrid ANN will be based on the configuration used in paper [7]. Fingerprint KNN will use $i = 23$ and $k = 8$. PDR will use $a_{th} = 10.5$ and Step Length = 34 cm. Hybrid ANN will use 5 hidden layer for X model and 9 hidden layer for Y model, number of epoch 7000, solver lbfgs, and activation function relu.

4.3.2 Fingerprinting ANN tuning

Fingerprinting ANN is fine-tuned using training data and validation data. The result shows that the best solver is adam with activation function relu. Optimal hidden layer size is 2 for x axis and 9 for y axis. Number of epoch used is 4000.

4.3.3 Fingerprinting SVR tuning

Fingerprinting SVR is fine-tuned using training data and validation data. The result shows that the best kernel is polynomial with degree 3. Optimal tolerance is 10 for x axis and 45 for y axis. Optimal epsilon is 0.001 for x axis and 35 for y axis.

4.3.4 Hybrid SVR tuning

Hybrid SVR is fine-tuned using training data and validation data. The result shows that the best kernel is linear. Optimal tolerance is 1 for x axis and 10 for y axis. Optimal epsilon is 70 for x axis and 0.001 for y axis. The summary of all the parameter used can be seen in table 2.

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Table 2. Parameter Configuration

Parameter Configuration		
Fingerprint	KNN	i = 23 and k = 8
	ANN	Solver = adam Activation = relu Epoch = 4000 Hidden layer size x = 2 Hidden layer size y = 9
	SVR	Kernel = polynomial Degree = 3 Cx = 10 Cy = 45 εx = 0.001 εy = 35
PDR		a_{th} = 10.5 Step Length = 34 cm
Hybrid	ANN	Solver = lbfgs Activation = relu Epoch = 7000 Hidden layer size x = 5 Hidden layer size y = 9
	SVR	Kernel = linear Cx = 1 Cy = 10 εx = 70 εy = 0.001

4.3.5 Result

After all the parameters have been explored using validation data, the testing is done using testing data. All the combination results in testing dataset are shown in Table 3 and 4. Table 3 shows the result for each individual method and Table 4 shows the result for each hybrid method.

Performance Measure (cm)	Testing Result			
	W-KNN	SVR	ANN	PDR
Mean of Error	280.86	372.42	238.90	219.84
Min	62.50	37.64	52.75	27.022
Max	481.22	657.18	499.06	419.84
Median	327.58	434.90	212.64	217.06
90th Percentile	399.29	599.57	403.42	338.31

Table 3. Individual Testing Performance

Both tables show that the hybrid method improves the accuracy compared to the individual one. Both tables show that the improvement of hybrid accuracy is related to the fingerprinting accuracy. Fingerprinting W-KNN with mean of error 280.86 cm when combined using ANN resulted mean of error 147.94 cm. But, when fingerprinting ANN with mean of error 238.90 cm is combined using ANN, the result mean of error is also improved into 103.29 cm. When a worse fingerprinting method, in this case SVR with mean of error 372.42 cm, combined using the same method, the mean of error is also worsened into 219.78 cm.

As shown in table 4, better fingerprinting used in the hybrid improve the accuracy. The proposed fingerprinting ANN improved the accuracy by 30.18% (44.65 cm). But, the proposed SVR fingerprinting reduced the accuracy. This improvement is also consistently shown in CDF in Figure 6.

Table 4. Hybrid Testing Performance

Performance Measure (cm)	Testing Result					
	Fingerprint W-KNN + PDR + ANN	Fingerprint W-KNN + PDR + SVR	Fingerprint SVR + PDR + ANN	Fingerprint SVR + PDR + SVR	Fingerprint ANN + PDR + ANN	Fingerprint ANN + PDR + SVR
Mean of Error	147.94	209.29	219.78	300.89	103.29	160.86
Min	17.68	37.37	61.59	193.95	22.06	14.78
Max	256.57	535.46	523.43	602.80	263.09	402.07
Median	138.17	218.61	216.91	265.64	91.25	130.66
90th Percentile	239.29	371.04	359.80	409.99	173.70	337.85

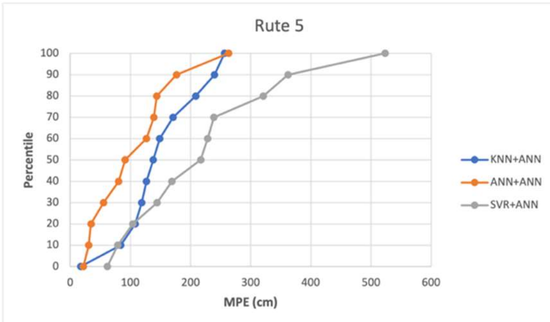

Figure 6. Cumulative Distribution Function (CDF) of Hybrid ANN

5. CONCLUSION AND FUTURE WORK

We tested hybrid of Regression-based Fingerprint and PDR using various machine learning methods to find a better machine learning fusion method to improve the accuracy of positioning. The experiment was designed to compare the proposed ANN and SVR model to the benchmark of W-KNN Fingerprinting method when combined using machine learning. Result of the experiment proves that by utilizing training datasets, more accurate positioning can be achieved by up to 30.18% using proposed ANN model compared to the W-KNN Fingerprinting method.

For further study, an investigation on various hybrid method may be interesting. Also, an investigation on various IMU-based positioning to be combined is another interesting topic.

CONFLICT OF INTEREST:

The authors declare that there is no conflict of interest regarding the publication of this paper.

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