Predicting Indoor Position Using Bluetooth Low Energy And Machine Learning

Ivan Alexander, Gede Putra Kusuma

Abstract: Many people spend most of their time indoors.Providing localization services indoor will have many potential applications, such as navigation, requesting help and asset tracking.There are manyexistingpositioning techniques for indoor positioning system such as multilateration, trilateration and least square estimation.But theweakness of this existing positioning technique is that the results of predictionerrors are still very large. With the development of machine learning technique, many researchers had used machine learning techniquesfor indoor positioning system.However, the existing research still uses location classification, even though machine learning can be used as regression to predict location. In this study, we propose a positioning algorithm forindoor positioning system using Bluetooth Low Energy (BLE), fingerprinting approach and four machine learning regression: Artificial Neural Network Regression (ANN), Multiple Linear Regression (MLR), Random Forest Regression (RF) and Support Vector Regression (SVR). We compare theperformance in term of Mean of Error, Min of Error, Max of Error, Median of Error and 90th Percentile of Error between four machine learning regression and the weighted sum method as a benchmark. The results obtained that allmachine learning regression has lowerMean of errorcompared to the weighted sum method. The SVR model has the best performance amongthemachine learning regression,whichyields134.92 cmofMean of error, 18.39cm ofMin of Error, 336.29 cmofMax of Error, 125.54cm ofMedian of Error and 216.65 cm of 90th Percentile of Error.

Index Terms:Localization, Bluetooth Low Energy, Machine Learning, Fingerprinting, Indoor Position System, Wireless technology, Sensor networks

1. INTRODUCTION

Localization is a process to obtain information on the location of a person or an object in connection with a set of reference positions in a predetermined location. Localization is divided into two groups: indoor and outdoor [1]. The most popular technology for outdoors is the Global Positioning System (GPS). Unfortunately, GPS has proven ineffective for indoor positioning due to the lack of signal coverage. Because many people spend most of their time indoors, providing localization services indoor will have many potential applications such as advertising/marketing, road search/navigation, search/requesting help and asset tracking/people [2]. There are already several solutions and alternative for indoor localization by using wireless technology, such as Radio-frequency identification (RFID), Wi-Fi Wireless Local Area Networks (WLAN) and Bluetooth [3]. However, each of them has disadvantages.For example, Wi-Fi hasa limitation due to limited numbers of access points and difficult installation. RFID has the best accuracy among all technology, but RFID has a short-range (below 1m)and the installation of RFIDisvery expensive. Most of the research and applications refer to systems using Bluetooth since it performed better in terms of quality and cost[4].Bluetooth is a standard wireless technology that is used to exchange data at close range.The new generation of Bluetooth, namely Bluetooth 4.0, is made to increase efficiency.The name of this new Bluetooth technology is Bluetooth Low Energy (BLE). BLE has excellent specifications for low power wireless communications [5]. BLE acts as a continuous signal for Bluetooth broadcasting; each signal contains a Universal Unique Identifier (UUID) information. With the UUID, each BLE can be seen where it is placed [6]. Therefore, Bluetooth Low Energy (BLE) devices have recently been considered as a potential wireless technology for indoor positioning devices. Low-cost and easy to develop causes the use of BLE technology becomes popular. Therefore, in this study, we used BLE (Cubeacon Card) as the main signal transmitter [7].Positioning techniquessuch as Multilateration,Trilateration and Least Square Estimation [8]areexisting techniquesthat are often used in indoor positioning system.Thesetechniqueshave aweakness, that is the error results of prediction are very large, due to this weakness, many researchers had used machine learning technique for indoor positioning systemusing K-Nearest Neighbors algorithm (kNN) algorithm, Discriminant analysis classifier (Dac) and Support vector machine (SVM)[9]. But the existing research for indoor positioning system still uses location classification.What interesting here is machine learning can be used as regression to predictuser location as in the existing positioning technique.Moreover with the use of machine learning regressionit is expected to increase the performanceof prediction. In this study, BLE, fingerprinting approach and machine learning regression model will be usedto create positioning algorithm. Four machine learning regression: Artificial Neural Network Regression (ANN), Multiple Linear Regression (MLR), Random Forest Regression (RF) and Support Vector Regression (SVR) will be used and theperformancefor each machine learning regression model will be compared to the weighted summethod as a benchmark.

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2 RELATED WORKS

Research conducted by Qais Ahmed Habash[10] has succeeded in conducting an indoor positioning system using nRF51822 BLE module as the main signal transmitter and Beacon which is the slave. The purpose of this study is to help hospital staff find their patients quickly both through the main server and the staff's smartphone. To detect the presence of someone, BLE is placed in a predetermined room and connected to microcontroller module. What is interesting in this study is that there is an alarm feature that gives alerts to the server, if the patient enters a forbidden place in the hospital. In this study BLE and beacons were only used to determine the localization of patients.Research conducted by Ankush A. Kalbandhe and Shailaja.C.Patil[11]measured Received signal strength indication (RSSI) from BLE tags to smartphone applications using a positioning algorithm based on measurements of RSSI values and transmission power to determine the distance in meter. On the smartphone will appear the distance from the smartphone to the BLE tag that is connected, an experiment is carried out to measure the distance from the BLE tag to the smartphone. This study only measures the distance from the BLE tag to the smartphone.The research conducted by Sugandh Memon[12]does as Ankush did, but the difference is there are advertising intervals on beacons that are tested. The interval value used are 100ms, 500ms and 1000ms. 100% accuracy were obtained for 100ms and 500ms intervals, while 94% accuracy obtained for 1000ms interval.The research conducted by Quang Huy Nguyen [8]took an approach of indoor positioning system thatoptimized by using BLE to detect the location of smart devices in a room (Static device). The first stage of the experiment is the calibration stage to measure RSSI. The second step is cleaning the RSSI value by using three different filter types, namely the Gaussian filter, Feedback filter and Kalman filter, the best result is Kalman filter, therefore the result of cleaning Kalman filter is used for the next stage, which is estimating the position results with using three different methods, namely Trilateration-weighted Centroid, Least Square Estimation (LSE) and Improved LSE. The results with the highest accuracy are using Improved LSE with a difference of 0.2 - 0.35m with the real position. The difference obtained in this study is still very large.The research conducted by GokhanŞengül(Karakaya & Sengul, 2017)using machine learning technique and classification of locations with a size of 1x1 meters. The algorithm used in this study is supervised learning, namely K-Nearest Neighbors algorithm (kNN) and Discriminant analysis classifier (Dac). The first experiment was carried out only by using 1 BLE to find out whether by increasing the number of BLE the results would be better. The next experiment used 2 BLE and the results of each algorithm, namely kNN and Dac are both good, which is above 90% and these two algorithms can be used for indoor positioning. The disadvantage of this research is that the location classification will be better if the results that appear are in the form of x and y coordinates.Research conducted by Jes´usLov´on-Melgarejo[13]uses kNN machine learning techniques and Support Vector Machine (SVM) in conducting indoor positioning systems, the level of Tx in BLE is set, 0x06, 0x07 and 0x08. The results obtained are pretty good is to use the kNN technique at Tx0x06. This research also uses location classification.Some studies had proposed indoor positioning system with the use of machine learning technique, but the machine learning technique used is only for location classification. In this study we use machine learning technique as a regression to predict user location.

3 PROPOSED METHOD

In this study used fingerprinting approach used to predictuser location.The predicted location will include X coordinateand Y coordinate of user location. There will be two phases, offline fingerprinting approach and online fingerprinting approach as shown in fig. 1.

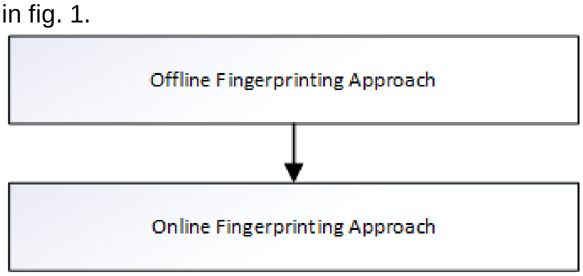

Fig. 1. *Fingerprinting Approach*

The first phaseis Offline fingerprinting approach, whereradio maps data is collected. Radio maps is a collection of data of reference points.The collection of radio maps data containsBLE$\overrightarrow{\mathrm{RSSI}}$value, X coordinate and Y coordinateas a reference point (RP).After radio maps has been made, the next step is collecting training data which contains BLE $\overrightarrow{\mathrm{RSSI}}$value, X coordinate and Y coordinate nearest the reference point as a training point (TP), both of these data will be used to find k-nearest reference based on RSSI distance ($RSSI_d$)for each X and Y coordinate.$RSSI_d$calculation based onL2-normEquation as shown in Equation(1) andwill be used to trainthe machine learning regression model.Fig. 2. is the block diagram for offline Fingerprinting approach.

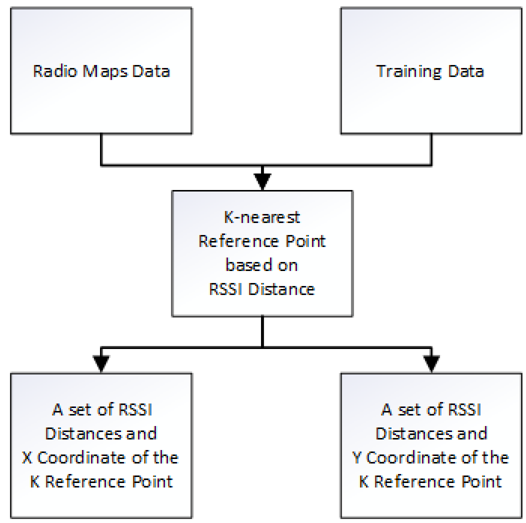

Fig. 2*. Offline Fingerprinting Approach*

$$\mathrm{RSSI\ Distance}_{(\mathrm{TP,RP})} = \sqrt{\sum_{i=4}^{4} (\mathrm{RSSI}_i^{\mathrm{TP}} - \mathrm{RSSI}_i^{\mathrm{RP}})^2} \quad (1)$$

The next step is training the machine learning regression model. There are four machine learningregression used:

1. Artificial Neural Network Regression (ANN)

ANNisa methodology of machine learning that developed based on the principle of the human brain[14]. ANN methodcan solve complex problems. There are three main elements in ANN, neurons, connections, and training rules (learning rates).ANN consists of three layers,input layer to receive the input data, hidden layer to process the input data in order way and output layer to produce predictive results. Layersin ANN used to interconnect neuron.In this study will be usedFeed-forward network based on the back propagation.Two steps are involved in the training process of Feed-forward ANN: The first step is the feed-forward procedure where the data is delivered fromthe input layer to the output layer via the hidden layers. The second stepis where the derivatives ofthe objective function in terms of weights are spread among all the nodes of the network,where it means that the weight and bias of all nodes are adjusted based on the errorbetween the simulated values and the desired target output.The transfer function is used to obtain the accumulated result by calculating the inner product of theinput data and the weight factor for the node layer.

1. Multiple Linear Regression (MLR)

MLRcalculates a linear regression model from the input.The MLR regression based on the linear correlation between dam effect quantities and environmental variables[15]. The goal of the MLR regression is to model the linear relationship between the independent variables and the dependent variable. Equation (2) is the MLR equation.

$$Y = W_1X_1 + W_2X_2 + W_3X_3 + \cdots + W_nX_n + b \qquad (2)$$

2. Random Forest Regression (RF)

RFis a classification and regression algorithm based on the bagging [16] and random subspace methods [17]. Random forests are built by combining the predictions ofvarious trees. To construct a random tree, there are three considerations to look. First is the method for splitting trees, secondis the type of predictor to use in each of leaf and the last is the method to injecting randomness in thetrees[18].The prediction of the ensemble is constructed from the separate decisions by majority voting for the classification and averagefor the regression. Bagging will reduce the variance in the final model when compared to the first model and it also can avoid overfitting.

3. Support Vector Regression (SVR)

SVR takes input data and predicts, for each given input, which of the two possible classes comprises theinput.This makes SVR as a non-probabilistic binary linear classifier[19].The main idea of SVR is to minimize error, individualizing the hyperplane which maximizes the margin.The advantages of SVR is that the computational complexity does not depend on the input space dimensionality.$RSSI_d$ dataused to train the machine learning regression model.In the training process, K-fold Cross Validation method will be used. The purpose of the training model is to determine the most optimummodelfor each machine learning regression model throughparameter tuning. Fig. 3. isthe block diagram forMachine Learning Regression Models Training for each X and Y coordinate.

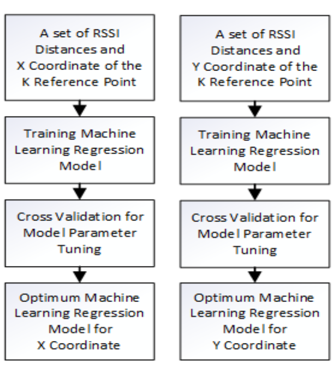

Fig. 3. *Machine Learning Regression Models Training*

The next step isan online Fingerprinting approach.The online fingerprinting approach is used to find a set of RSSI distance and coordinate data which is used to testing the optimum machine learning regression model, the difference is in the data(Test Data).Fig. 4. Is the block diagram for online Fingerprinting approach.

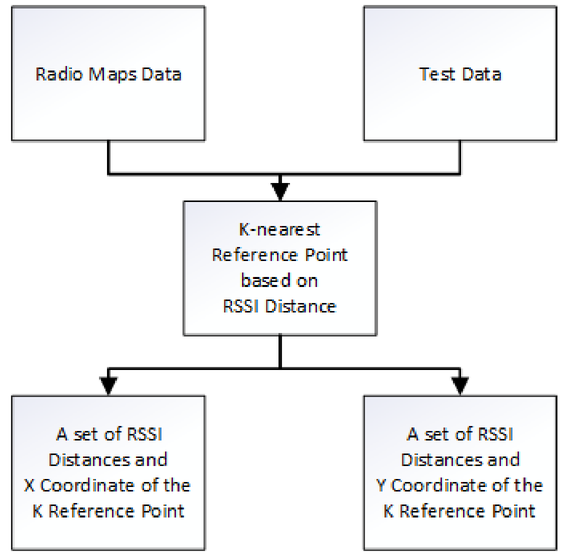

Fig. 4. *Online Fingerprinting Approach*

The optimum machine learning regression model which is founded from offline Fingerprinting approach will be used to testing the performanceof the model by predicting user location using $RSSI_d$data obtained through the online Fingerprinting approach. The performance of machine learning regression model for each predicted user location will be combined and evaluated. Fig. 5. Is the block diagram for predicting user location.

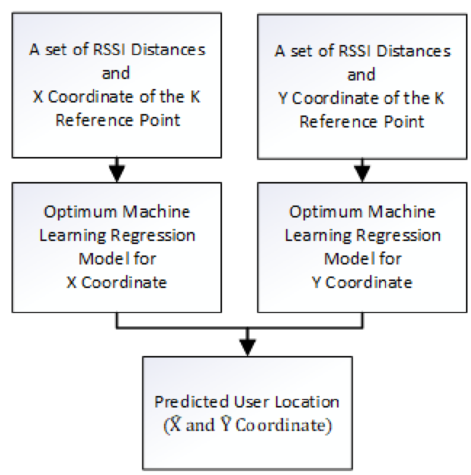

Fig. 5. *Predicting User Location*

4 EXPERIMENTS

4.1 Dataset Collection

Radio Maps data collection conducted in 400 cm x 600 cm room. There are 4 BLE pieces placed at a height of 1.25 meters in the room as shown in Fig.6. The BLE configuration used is TX Power 6 100ms with broadcast interval.

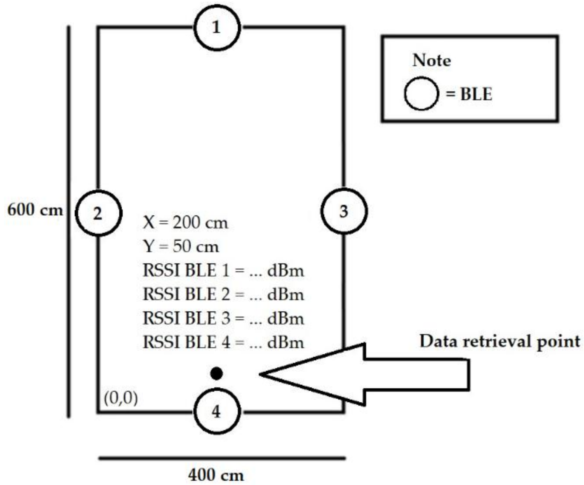

Fig. 6. *Data Collection Room and The Radio Maps Data Collection Scheme*

The data collected for radio maps are four$\overrightarrow{RSSI}$value of each BLE, X coordinate and Y coordinate. The coordinate positionsampled every 50cm distance in 400 cm x 600 cm room. Data was collected at a height of 1.25 meters from the floor using a smartphone, the application used is BLE RSSI Application that created using Android Studio. For each position, 100 sample datawerecollected, one sample datawere collected every 200ms. There are 77sampled position points in the room, so total data for radio maps are 7700 data. Theradio maps data for each positionare averaged, so the total data forradio maps are 77 datathat contains BLE $\overrightarrow{\widetilde{RSSI}}$, X coordinate and Y coordinate. The next collected data istraining and testing data. The datawere taken four points at each intersection of sampledcoordinate position points, for each position of intersection there were10 data collected. There are 308 positions in total, so total data are3080.The data for each positionare averaged, so the total data are 308 that contains BLE $\overrightarrow{\widetilde{RSSI}}$, X coordinate and Y coordinate.Fig.7. is the scheme of data collection for training and testing data.

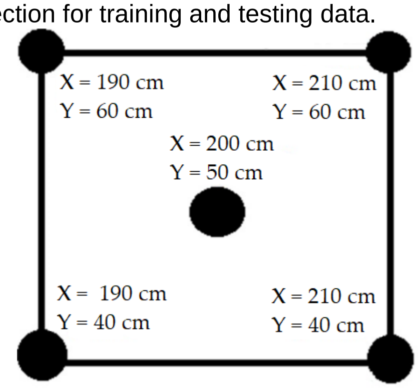

Fig. 7. *Training and Testing Data Collection Scheme*

The X and Y coordinate of radio maps used as a reference point (RP) while the X and Y coordinate of training and testing data used as a label to be predicted. After collected,radio maps, training, and testing data are used to find k-nearest based on RSSI distance ($RSSI_d$) with a total of 308 data for each X and Y coordinate.In this experiment we use the k value is 4, so the best four $RSSI_d$ data are taken.There are 9 data component for each$RSSI_d$ data, for $RSSI_d$X coordinate it contains X label, four best $\overrightarrow{\text{distance}}$data and four $\overrightarrow{\text{X coordinate reference point}}$as well for$RSSI_d$Y coordinate.The best distance and reference pointdata will beused as input fortraining the machine learning regression model.

4.2 Experimental Design

There area total of308$RSSI_d$data for eachcoordinate, 308 $RSSI_d$data for X coordinateand 308 $RSSI_d$data for Y coordinate. The $RSSI_d$data is randomly separated with a ratio of 80:20. Total of244 data usedto trainthe machine learning regression model and 64 data used for testing the optimummachine learning regression model.Four-fold cross-validation is used to train the machine learning regression model, therefore 244 data are divided into four folds, with a total of61 data for each fold.Before the process begins, the 244 data randomly separated with a total of 183 data for the training set anda total of 61 data forthe validation set. Based on the four foldsit means there are3 folds containing61training set dataand 1fold containing 61validation set data.Then, the process using data that already dividedby folds typeis repeated 4 times (K = 4). The position of the validation setfold is different in each iteration. Fig 8. Is the process of four-fold cross-validation.

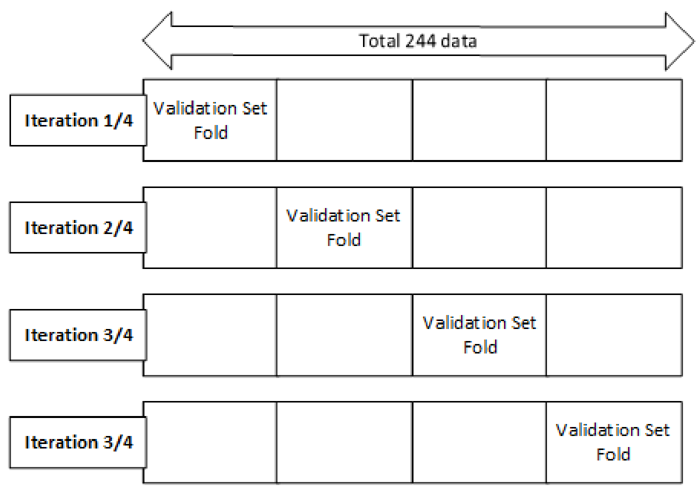

Fig. 8. *Four-Fold Cross Validation Process*

Four-fold cross-validation usedfor model parameter tuning.TheRoot Mean Square Error (RMSE) results of cross-validationused as validation, the lower the RMSE result, the better the model becomes.The next step is applying64 test data in machine learning regression models that have been trained. The predicted results of user location will be combined for each position and evaluated as shown in Fig.9.The first step of performance evaluation is calculating the error between actual user location (X, Y) and predicted user position $(\hat{X}, \hat{Y})$ by using Euclidean distance equation (4), after calculated,the error results will be averagedto find the Mean of error results.Besides Mean of Error,Min of Error,Max of Error, Median of Error,and 90^{th}Percentile ofError results arealso calculated. The lower the results, the better the performance becomes. Each trained machine learning regression modelperformance resultswillbe compared.

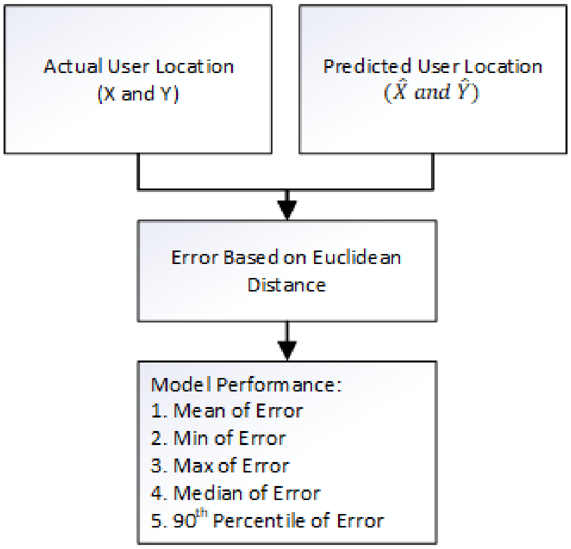

Fig. 9. *Model Performance Evaluation*

$$\text{Euclidean Distance} = \sqrt{(X - \hat{X})^2 + (Y - \hat{Y})^2} \qquad (2)$$

The evaluation plan that will be carried out is evaluating the proposed Indoor Positioning System method compared to the fingerprinting approach that Yuan Zhuang did [20]. The difference is in the positioning algorithm method, Yuan Zhuang's method used Weighted Sum method. Weighted sum method calculationis simply to add the multiplication result of an alternative value with weighted criteria[21],whilethepositioning algorithm method proposed is using Fingerprinting approach and four machine learning regression, ANN, MLR, RF, and SVR.

4.3 Experimental Results

For the experimental results, the discussion will be started from the machine learning parameter being used. For the parameter tuning it has been done for each model and the parameter listed here already the best parameter for themachine learning regression model used.Machine learning regression parameter used for X position are:

1. ANN for X Position
   - Activation Function : Sigmoid
   - Hidden Layers (HL) : 2
   - Neuron of each HL : 6
   - Learning Rates : 0.01
   - Momentum : 0.01
2. MLR for X Position
   - Feature Selection : M5 Prime
   - Min Tolerance : 0.05
3. RF for X Position
   - Number of trees : 500
   - Criterion : Least Square
   - Maximal Depth : 25
   - Prepruning : On
     - Min Gain : 0.01
     - Min Leaf Size : 2
     - Min Size Split : 4
     - Prepruning : 5
4. SVR for X Position
   - Kernel Type : Anova
   - Kernel Gamma : 1.0
   - Kernel Degree : 2.0
   - C : 0.5
   - Convergence Epsilon: 0.001

Next is the machine learning parameter used for Y position:

1. ANN for Y Position
   - Activation Function : Sigmoid
   - Hidden Layers : 2
   - Neuron of each HL : 6
   - Learning Rates : 0.008
   - Momentum : 0.008
2. MLR for Y Position
   - Feature Selection : Iterative T-Test
   - Max Iterations : 100
   - Forward Alpha : 0.01
   - Backward Alpha : 0.01
   - Min Tolerance : 0.05
3. RF for Y Position
   - Number of trees : 500
   - Criterion : Least Square
   - Maximal Depth : 5
   - Prepruning : Off
4. SVR for Y Position
   - Kernel Type : Dot
   - C : 0.5
   - Convergence Epsilon: 0.001

For the next discussion is the Validation RMSE results. Table 1. Is the Validation RMSE results for training model.This results already provided the best Validation RMSE for each model used.

TABLE 1

VALIDATION RMSE RESULTS

Model	Position	RMSE (cm)
ANN	X	93.78 +/- 7.01
ANN	Y	130.81 +/- 9.24
MLR	X	94.70 +/- 8.83
MLR	Y	133.94 +/- 8.23
RF	X	93.11 +/- 7.31
RF	Y	130.09 +/- 6.45
SVR	X	92.30 +/- 7.64
SVR	Y	133.29 +/- 5.68

For X coordinate,the SVR model has the smallest validation RMSE results in 92.30 cm, while the RF model has the smallest results in 130.09 cm for Y coordinate.Next is the performanceresults for each trained machine learning regression modeland the weighted sum method. Table 2. is the performance results ofthe trainedmachine learning regression model and the weighted sum method.

TABLE 2
PERFORMANCE RESULTS FOR ALL MODELS

Model and Method	Performance				
	Mean of Error (cm)	Min of Error (cm)	Max of Error (cm)	Median of Error (cm)	90^{th} percentile of Error(cm)
ANN	138.80	19.38	311.37	128.13	228.41
MLR	142.22	31.28	309.38	137.16	229.42
RF	137.87	19.52	340.50	133.48	215.48
SVR	134.92	18.38	336.29	125.54	216.65
Weighted Sum	146.47	18.39	379.88	137.68	241.83

First let's see the Mean of Error results column, the smallest Mean of Error result is the SVR model with result in134.92cm, while the weighted sum method has the biggestMean of Error resultin 146.47cm, aside from that, ANN, MLR, and RF model also has smaller results of Mean of Error than the weighted sum method.Next is the Min ofError results column, in herethe SVRmodel also has the smallest result in18.38cm.For the next column isMax of Error results, the MLR model has the smallest Maxof Error result in309.38cm. Next, let's see the Median of Error results column, 125.5 cm is the smallest result for this column, produced with the SVR model, the biggest result is the weighted sum method in 137.68 cm. The last column is 90^{th}Percentile of Error, the RF model has the smallest result in 215.48 cm, the SVR model is the second smallest result in 216.65cmof 90^{th}Percentile of error result. The weighted sum method also has the biggest result in 241.83 cm of 90^{th}Percentile of Error. The discussion and rank performance for the machine learning regression model and weighted sum method summarized in Table 3 below.

TABLE 3
RANK PERFORMANCE

Rank	Mean of Error	Min of Error	Max of Error	Median of Error	90^{th} percentile of Error
1	SVR	SVR	MLR	SVR	RF
2	RF	Weighted Sum	ANN	ANN	SVR
3	ANN	ANN	SVR	RF	ANN
4	MLR	RF	RF	MLR	MLR
5	Weighted Sum	MLR	Weighted Sum	Weighted Sum	Weighted Sum

From Table 3. we can see that the SVR model has the best performanceamong the machine learning regression model, SVR has the best performancein term ofMean of error, Min of error and Median of error. The test performancefor the SVR modelis consistent with the validation RMSE result. The weighted sum method did not perform very well interm of Mean of Error, Max of Error, Median of Error and 90^{th} Percentile of Errorcompared to allmachine learning regression model.The evaluation plan carried has been successful to compare the performance of four machine learning regression with weighted sum method.

5 CONCLUSION AND FUTURE WORKS

In this paper, proposed a positioning algorithm using fingerprinting approach and four machine learning regression: ANN, MLR, RF, and SVR.Our positioning algorithm has lower Mean of error result compared to the weighted sum method, it means allfourmachine learning regression model that has been trained has better performance than the weighted sum method. The SVR model has the best performance among the machine learning regression modelwith results in 134.92 cm ofMean of error. Besides that,the SVR model also has better performance in term ofMin of Error in 18.39 cm and Median of Error in 125.54 cm. For the next study,a bigger room will be used to do the experiment.With the bigger size room, the more difficult it will be,so the amount of BLE used will be increased and more machine learning regression model will be used.Besides than machine learning regression model, deep learning model also will be used to predict user location.

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