Indoor Positioning System using Regression-based Fingerprint Method

Reginald Putra Ghozali[1], Gede Putra Kusuma[2]
Computer Science Department, BINUS Graduate Program–Master of Computer Science
Bina Nusantara University, Jakarta, Indonesia, 11480

***Abstract*—Indoor Positioning System has opportunity to be used in different business platform. Based on past research, optimized localization method for Bluetooth Low Energy (BLE) to predict position of person or object with high accuracy has not been found yet. Most recent research that have solve Received Signal Strength (RSS) inconsistent value is using fingerprint method. This paper proposed a deep regression machine learning using convolutional neural network (CNN) with regression-based fingerprint model to estimate real position. The model used 5 nearest fingerprints as reference RSS values with their location (x or y) label as inputs to produce output of single value position (x or y), then repeat the process to produce second value of position to create complete coordinate of estimated position. To evaluate the proposed model, a comparison between training data with validation data using Root Mean Squared Error (RMSE) is used. The comparisons are with Multilayer Perceptron model and with the weighted sum method as benchmark. The experiment Gave results of mean distance and 90th percentile distance between proposed model with the benchmark. CNN model achieved accuracies of lower than 330cm at 90th percentile with mean distance lower than 185cm. Weighted sum model achieved accuracies lower than 360cm at 90th percentile with mean distance higher than 185cm, and MLP is in between them. The result demonstrates that the proposed method outperformed the benchmark methods.**

Keywords*—Indoor positioning system; fingerprinting; regression machine learning; convolutional neural network

I. Introduction

Indoor Positioning System (IPS) has been a trend in research even until now. The system is capable of diverse purposes. Different from Global Positioning System (GPS) that optimized for outdoor environment where mostly no significant obstructions, IPS needs to work for indoor environment that have significant obstructions like walls, roof, and every room object including human itself. There are more demands of accurate position for IPS.

Various surveys already written for IPS related topics [1] [2] from outdated methods are still used to more recent methods and most of them did not differentiate the methods for Wi-Fi or Bluetooth Low Energy (BLE). While they use similar bandwidth (2.4GHz radio frequency), the actual systems have different computing capabilities and availability. Among them, BLE has been used frequently by reasons of low cost, very low battery consumption, and high availability as supported by most modern smartphones.

BLE used 2.4 GHz unlicensed frequency (2402 to 2480 MHz) with total of 40 channels (2 MHz for each channel width). And using 3 channels for discovery services (channel 37, 38, 39) [3] [4]. Many algorithms have been used for optimizing accuracy of the system. Such as multilateration and fingerprinting. Even so, there is not yet optimized solutions for high accuracy using BLE technology [1].

There are many factor that affect the BLE radio propagation of the signals in indoor environments as BLE using radio signals, e.g., multipath effect, causing a random behavior in the Received Signal Strength (RSS) measurements caused by reflection [5], movement rate of human [6], and fast fading when measuring within a little time [7]. To solve these problems, fingerprinting method is needed to estimate indoor position that needs estimation algorithm to ensure accuracy of position.

To get object's location based on received signal strength from BLE, certain measurement method is needed. Current popular method is fingerprinting. Where localization algorithms used for measure or estimate location. It consists at least 2 steps: Offline step and Online step. Offline step used to create a radio mapping of possible location from given signal strength received. While online step [1] will match the received signals during online moments with radio mapping from previous step to determine object's location. Method to determine estimated position will affect the accuracy of estimated real position of an object. Different methods have been used, started from K-Nearest Neighbor (KNN) to using machine learning.

Current state-of-the-art [8] is using Polynomial regression to calculate distance as propagation model. Where RSS received processed using weighted centroid localization or weighted sum to get coordinate and using polynomial regression model to get distance. Both are calculated using RSS signal from 3 advertisement channels of each beacon. Then both results filtered using outlier detection to clean the result, by combine fingerprinting with polynomial regression model distance into combined distance. This filtered result will be processed using extended Kalman filtering using filtered distance from first outlier detection. Result from extended Kalman filtering will be filtered again using outlier detection to remove false measurement. This result then processed again with extended Kalman filtering into estimated position that will be compared with radio map to get the real position. This method is using distance-based measurement. Where the error rate is pretty high, caused by multipath effect and person movement rate, which is why the distance is filtered through many processes mentioned in the method. Other weakness is it takes lots of calculation time.

This paper intended to implement probabilistic method of fingerprinting using Deep Learning Convolutional Neural Networks Regression Model to estimate position of a person. The proposed method is expected to improve accuracy of estimated position. The design consists of BLE beacons as signal transmitter, and mobile smartphone as signal receiver. Signal received in the device will be processed using fingerprinting method, then estimated by Convolutional Neural Networks (CNN) with self-designed architecture, resulting an estimated position of a person.

This paper is divided into 8 sections, starting with introduction. Section 2 provides overview of related works from past to current state-of-the-art. Section 3 describes detail of proposed method. Section 4 describes experimental design and data collection method. Section 5 presents the experimental results and comparison with other methods. Section 6 provides discussion on limitations and complexity issues. Section 7 summarizes our works. Suggestions of further research are provided in Section 8.

II. Related Works

Indoor positioning Systems have been made using different methods. A review paper [1] describes lots of technologies and techniques used in developing indoor positioning system. Most used technologies until now is radio frequency-based technology using BLE. On the techniques side, most used until now is fingerprinting. Fingerprinting consist of two phases: offline phase, where a method of “training” to create possible mapping of estimated position that called as radio map from RSS. And online phase, where real position of an object is estimated by matching the received RSS with radio map using localization algorithms. At this phase, different kind of methods are used to optimize the estimated position. Few examples that described in this paper are summarized in Table I.

TABLE I. Summary of Recent Studies on Indoor Positioning Fingerprinting

Authors (Year)	Inputs Variable(s)	Output	Method(s)	Performance	Result(s)
Yu, et al. (2014)	5 WiFi RSS	Estimated position (x,y)	Cluster K-nearest Neighbor Manhattan Distance	Localization accuracy Between 2.4G and 5G WiFi signal.	1.4700 for 2.4G 1.1500 for 5G
Li, et al. (2016)	8 WiFi RSS	Estimated position (x,y)	Weighted K-nearest Neighbor Improved Manhattan Distance	Cummulative Distributive Error at 80th percentile.	2.10m for Euclidean distance 1.88m for Manhattan distance 1.48m for improved Manhattan distance
Faragher, R., & Harle, R. (2014)	19 BLE RSS	Estimated position (x,y)	Gaussian Process Regression Bayesian Likelihood Function Maximum a posteriori probability Euclidean Distance	Cumulative Probability / Distributive Error Between WiFi and BLE	8.5m at 95th percentile of the time for WiFi 2.6m at 95th percentile of the time for BLE
Faragher, R., & Harle, R. (2015)	19 RSS from BLE and 3 RSS from WiFi	Estimated position (x,y)	Proximity algorithm Weighted KNN Gaussian Process Regression Euclidean Distance	Cumulative Probability / Distributive Error Between WiFi and BLE	<3m at 95th percentile of the time for BLE <6m at 95th percentile of the time for WiFi
Zhuang, Yang, Li, Qi, & El-Sheimy, (2016)	20 BLE RSS	Estimated position (x,y)	Weighted Centroid Localization Algorithm Polynomial Regression Model Propagation Model Outlier Detection Extended Kalmann Filtering	Cumulative Distributive Error Between Propagation Model and Regression Model	3.1m at 90th percentile for Regression Model 3.8m at 90th percentile for Propagation Model
Tuncer & Tuncer, (2015)	3 RSS and 3 ID from 4 BLE	Estimated position (x,y)	Artificial Neural Network (ANN) Centroid Localization Algorithm (CLA)	Hyperbolic Tangent Sigmoid and Linear Transfer Function for Cost Function. Root Mean Squared Error for performance.	Training: 22m for ANN 58.24m for CLA Testing: 33.26m for ANN 108.15m for CLA
Xu, Wu, Li, Zhu, & Wang, (2018)	49 RFID RSS	Estimated position (x,y)	Support Vector Regression-LANDMARC algorithm	Root Mean Squared Error	35.532m for LANDMARC 27.226m for SA-SVR-LANDMARC 26.936m for BP-LANDMARC 20.243m for SVR-LANDMARC

Localization algorithms in fingerprinting for indoor positioning system are used to determine a position of a person or object. Based on [9], localization algorithms can be divided into deterministic and probabilistic method. Deterministic methods use metric to measure signal and fingerprint location based on the data. Some advantages using these methods are easy to implement and usually low computation. However, as the accuracy can be improved using complex measurement and many access points, the computation can take longer. Most traditional method is K-nearest neighbor (KNN). Author in [10] using modified KNN called cluster-KNN with three nearest Manhattan distances from BLE signals estimate position. KNN use received signal strength indicator received from fingerprinting during offline phase of detecting signal to produce fingerprint map. These signals then processed with the algorithm using either Manhattan distance or Euclidean distance to classify nearest access point that can represent the person's or object's position who brought the emitter devices. While the algorithm itself is not too much complex, making computation far faster, it sacrificed accuracy of the positioning by taking access point location as the detected person's location. The research used 2.4G and 5G WiFi signal to compare localization accuracy from Manhattan distance of RSS average error, resulting 1.4700 for 2.4G and 1.1500 for 5G. Other KNN method used by [11] is called weighted-KNN. Where a parameter called weight assigned to every coordinate according to the value of distance. This paper used improved Manhattan distance, where certain constant used as threshold to consider increment of distance difference. This research used comparison between Manhattan distance and Euclidean distance using simulation software that simulate an office room with 8 rooms with an access point placed at innermost of the room and a corridor, resulting 1.88m positioning error at 80th percentile for Manhattan distance, and 2.10m positioning error at 80th percentile for Euclidean distance, and 1.48m at 80th percentile for improved Euclidean distance.

Probabilistic methods use estimation to determine position based on training set of signal data, and then choosing the most likely position of the target. Example of probabilistic methods is: Gaussian process [3] [4]. Gaussian Process in indoor positioning system used to estimate possibility from Bayes rule. Author in [3] used Gaussian process to point location based on uncertainty of Bayes rule estimation of received signal strength. Using 19 BLE beacons, they received accuracy of error rate around 2.6m in 95%, compared with WiFi, the accuracy of 8.5m in 95%. Author in [4] continues research of [3], with detailed and motivating reasons to use BLE for indoor positioning.

Author in [8] is using polynomial regression model to estimate cumulative distribution methods of average distance errors for each BLE beacon, then compare the result with same data using propagation model. The RSS data came from three advertisement channels processed through model using Fingerprinting for location and Polynomial Regression Model for distance resulting three different locations and three different distances. Then, each of them improved the distance estimation by using statistical method from first Outlier Detection. This improved distance estimation processed with Extended Kalman Filtering resulting estimated current target location. This result processed in second Outlier Detection to remove outliers and the outputs will be compared with RSS mapping database to select most appropriate location. Polynomial Regression Model used to calculate distance (1).

$$^{d}PRM = \sum_{i=0}^{n} c_i \, . RSS^i \qquad (1)$$

Where c_i is coefficient from n-degree polynomial, then multiplied by RSS value. They use 20 beacons with 3 advertisement channels, resulting total of 60 average distance errors. The polynomial degree is 5. The result is, polynomial degree 2 through 5 have similar result and better than first polynomial and propagation model. With polynomial degree 2 has fastest computation than other. This paper stated that at 90% estimated error of used data using polynomial regression model is 3.1m, while using propagation model is 3.8m. Based from this paper, assumed that polynomial regression at degree 2 has high accuracy and fast computation.

Machine learning can be used on either classification problem or regression problem. One kind of machine learning type is Artificial Neural Network (ANN). ANN work similarly like human brain, just like neuron interconnected each other inside brain. The neuron part gives brain capability to learning, prediction, and recognition. This means ANN can be trained to learn something. Author in [12] used ANN for localization compared with centroid localization algorithm. Location of the user is estimated by using coordinates of at least three anchor points to calculate the central point, then using the distance between central point and location of user to find location error. They proposed three layers ANN model (input, hidden, output) using hyperbolic tangent sigmoid and linear transfer functions, with backpropagation algorithm for network training. Results of the RMSE from training are 22m for ANN and 58.24m for centroid localization algorithm. For testing results, 33.26m for ANN and 108.15m for centroid localization algorithm. Another kind of regression is Support Vector Regression (SVR) that uses supervised learning model to analyze a regression line model that represent all data closest to the plane. Author in [13] used SVR to improve RFID-based indoor positioning system. Using vector of RSS values read from single tag and reference position to train model using linear regression. The research compared RMSE results from different kind of LANDMARC algorithm, which is reference-tag based positioning system using RFID. This method consists of reference label matrix for positioning label in space, RSSI values from unknown position and reference labels, and KNN algorithm for positioning. The research resulted 25.532m for non-customized LANDMARC, 27.226m for SA-SVR-LANDMARC, 26.936m for BP-LANDMARC, and 20.243m for SVR-LANDMARC.

Most of the machine learning referred before only solve linear problem. There are deeper methods in machine learning to solve non-linear problem, called deep learning. Author in [14] defines deep learning as a technique that uses many non-linear information for execute either supervised or unsupervised of feature extraction, transformation, pattern analysis, and classification. There are two key aspects in deep learning: 1) The models consists of many non-linear information processing. 2) The methods for either supervised or unsupervised learning of feature extraction. Reasons that deep learning gains popularity in recent research are increased capability of GPU, lowered cost of computer hardware, and recent advances in signal processing.

Based on review of above papers, Bluetooth low energy has high chance become best candidate for indoor positioning, because low energy consumption that made devices usable longer, low cost in either installation or maintenance, has high update rates in receiving signal, and supported by modern smartphones. For estimation algorithm, regression using Deep Learning Convolutional Neural Networks (CNN) method is proposed to research if deep learning model is capable to increase positioning accuracy.

The proposed method is using BLE as signal transmitter and receiver. Current bluetooth technology (bluetooth 4.1) provides BLE with small, cost effectiveness, and lower energy consumption device that allows BLE to run for several years and designed for machine-to-machine communication. The optimized result of RSS signal is around radius 2-3 meters [15]. Fingerprinting is the state-of-the-art method. This method removes multipath effect and human movement problem from BLE radio signal weaknesses by collecting multiple samples and uses the average from samples [9]. A method of interval sampling also removed fast fading problem by increasing time interval to receive BLE RSS signal [3] [4].

The machine learning model used to predict estimated position is using CNN. The model estimates x position and y position separately which mean there are two models of machine learning with similar architecture. To train these models, RMSE is used as cost function. Results from these models are mean of distance and cumulative distribution function that represent the distances produced by these models.

III. Regression based Fingerprint Method

Design proposed in this paper is indoor positioning using BLE with deep learning CNN regression model for fingerprinting. Where The proposed method is based on fingerprinting that consist of two phases. Offline phase to create radio map database. A reference point will be assigned in the map. By standing at the point, the smartphone will receive RSS values from all of the BLE beacons. these RSS values will be stored together with the reference point as a single data in database. This step will be repeated until each reference point in the map has RSS values stored within the database.

Online phase estimate position using the CNN model. Position of a person will be estimated using localization algorithm. First, the smartphone receiver will receive RSS values within an interval of 5 seconds. The RSS values will be measured with Euclidean distance (2) with all reference points and then ranked using k-Nearest Neighbor to find five nearest reference points with estimated position.

There are two models of deep learning used to estimate x position and y position that trained separately. By using these distances, together with x position of the reference point related with the distance, feed them as inputs of the Deep learning machine. Resulting the estimated x position of the smartphone. These distances will be used again in estimating y position. The deep learning architecture in proposed method's illustration is represented in Fig. 1.

The model used to predict estimated position is using CNN. CNN used to process a grid-like data or matrix that can be applied with mathematical operation called convolution and modified the output using pooling function. Convolution operation is commutative way for giving weight to the measurement to provide a smoother measurement, resulting multidimensional array of data called feature map. Convolution involves three important ideas to improve machine learning. Sparse interactions using kernel smaller than the input, parameter sharing that uses same kernel parameter in more than one input functions. And equivariant representations that present the output changes in same way the input changes [16].

Pooling function replaces output at certain location with a summary statistic of nearby outputs. The purpose is to make representation of output approximately invariant to small translation of the input, so the feature placed exactly where it is unaffected by small transformation. Method of pooling used in this research is cross-channel pooling [17] to merges multiple feature maps into single feature map to reduce number of parameters needed.

The CNN architecture proposed is inspired by AlexNet [18] deep learning architecture as base principle as AlexNet is suited for small scale training datasets. Using 10x1 matrix contains RSS Euclidean distance and position (either x or y) from five best ranked reference points as input. The CNN starts with the input go through convolution by 3x1 kernel with one padding, so the output of convolution will not change either row or column of kernel matrix. Convolution is done using Rectified Linear Unit (ReLU) as activation function to produce five feature maps from a convolution. These results will go through cross-channels pooling layer to combine them into single 10x1 matrix. These processes are be called as convolution-pooling layer and modified to prove difference of accuracy of CNN model. This process will be repeated according to needs of research, resulting 10x1 matrix that will go through two fully connected layers. The fully connected layers are using ReLU method so the output can be either positive infinite or zero. Finally, the output layer is a neuron that produce 1 value of estimated position (either x or y). The CNN will be repeated for estimating another value of estimated position that has not through CNN process yet.

The fingerprinting method from the model will be trained using Root Mean Square Error (RMSE) [19], where real position will be subtracted by estimated position then find mean value from distance values, and square root the mean value. RMSE used for lost function, by comparing cost between two datasets (training and validation) from a model. The calculation will be done using (3) and Equation (4) Where (x, y) is real position and (xp, yp) is predicted position. Both trained models were compared with weighted sum or weighted centroid method to measure the performance using mean of Euclidean distance (5) and cumulative distributive function of estimated distances. The cumulative distribution is to find accuracy at certain percentile.

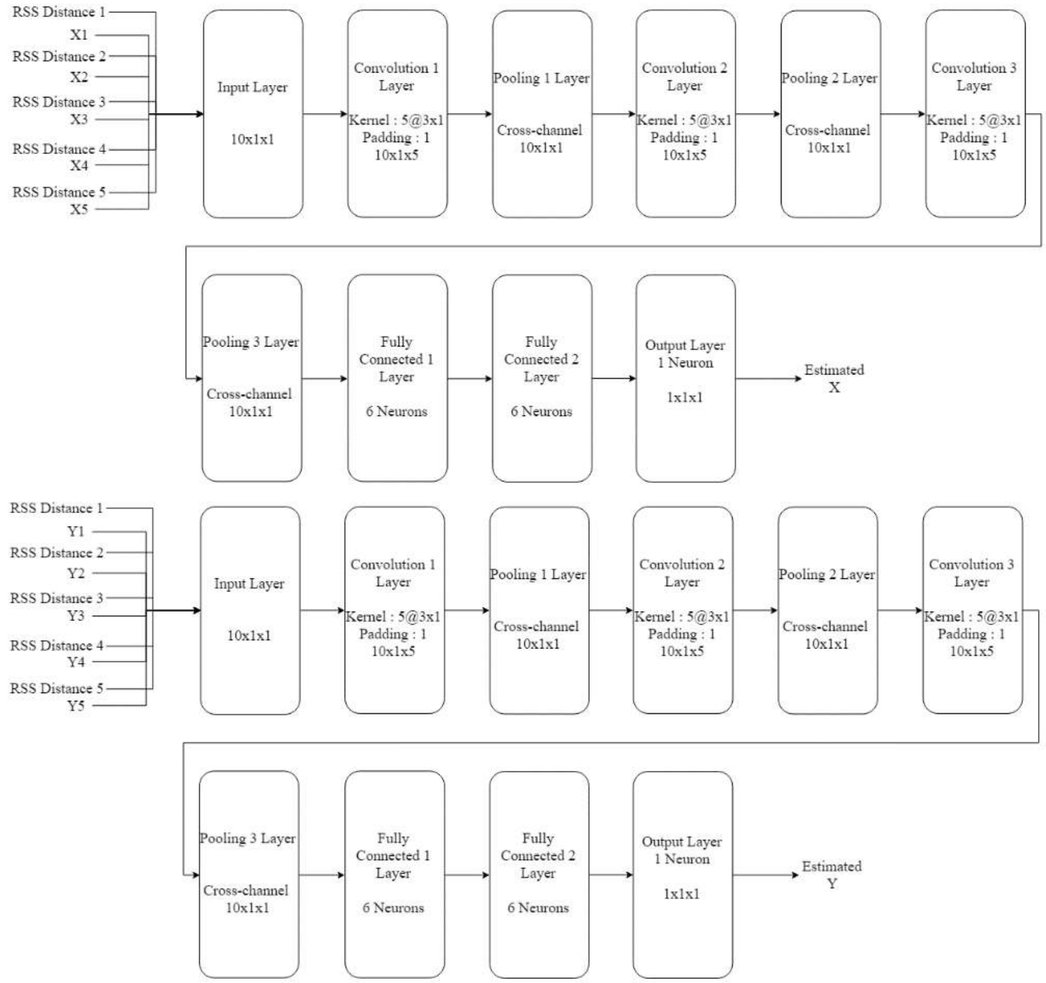

Fig. 1. CNN Model (with 3 Convolution-Pooling Layers).

IV. Experimental Design

BLE beacons used in this research are Nordic Semiconductor nRF51822 Bluetooth Smart Beacon that shown in Fig. 2. Each of them configured with 0 dBm transmit power and with 200 milliseconds of refresh rate. The beacons used highest possible settings to achieve maximum potential that can be predicted. 24 BLE beacons used in this research and each of them placed according to coordinate map based on their BLE ID. All BLE beacons attached at height around 1.2 meters.

Data used in the research are based on reference points and testing points in the coordinate map shown in Fig. 3. Sampling data are done in an office room with size of 12m x 19m with all office room properties. A total of 54 reference points used with 100 samples for each reference point and 156 testing points used with 10 samples for each of testing point. Reference points placed with gap of 2 meters and testing points placed with gap of 1 meter. Data sampling is done by standing on the point with a smartphone installed with RSS signal receiver application for few minutes. After all RSS values from each beacon received, the application starts to store the sample and repeat sampling with 1 second interval of each sampling to avoid zero value from a beacon. There are three sessions of data sampling separated in range of a week because of the limitation of building operational time, different amount of time to stabilize and receive all RSS signal from 24 beacons, and inferences by amount of people going around the moment of sampling.

Fig. 2. Nordic Semiconductor nRF51822 Bluetooth Smart Beacon.

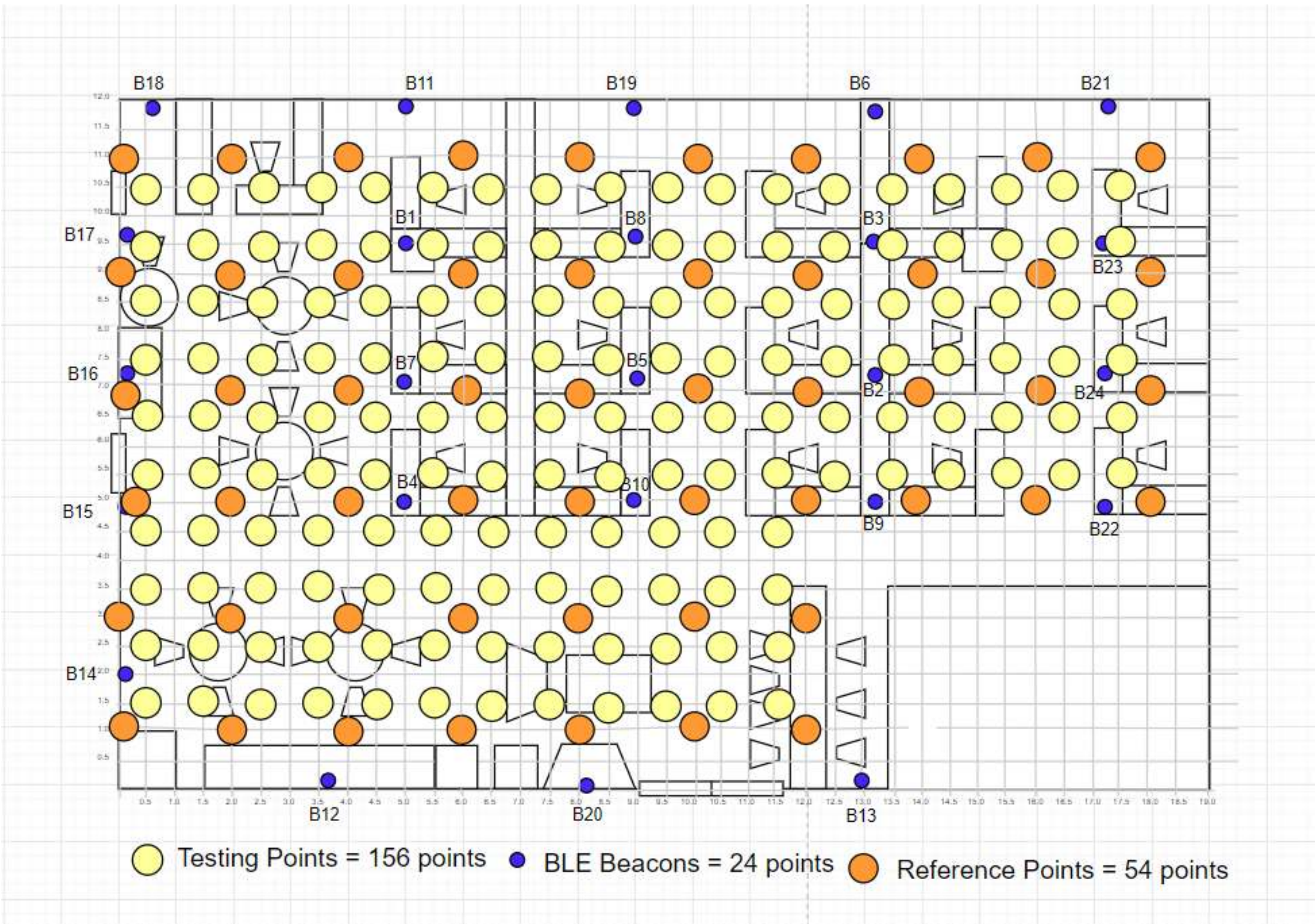

Fig. 3. Coordinate Map and BLE Beacons' Position.

Reference Points: RSS values from 100 samples will be averaged into single RSS for each beacon, producing 24 averaged RSS values for each reference point. Each RSS value from the reference point will be determined the distance with each testing points using Euclidean distance (2).

$$d_{ij} = \sqrt{\sum_{k=1}^{n}\left(RSS_{ik} - RSS_{jk}\right)^2} \tag{2}$$

This process results in 1560 data that ready to be used. The data separated into 1040 training data, 260 validation data, and 260 testing data by random sampling. Training data will be fed into the deep learning model (Convolutional Neural Network) for training and finally evaluated with validating data. Result from the training and validation will be measured using Root Mean Squared Error (RMSE) of predicted position with label position as the lost function. Both x and y RMSE value will be measured separately as (3) and (4).

$$RMSE_x = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[\left(x - x_p\right)\right]_i^2} \tag{3}$$

$$RMSE_y = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[\left(y - y_p\right)\right]_i^2} \tag{4}$$

Finally, by using testing data, the performance of the model is calculated using mean of distance (5) and cumulative distribution function (CDF). Using both combined result of distance from both x and y value predicted with their labels calculated using Pythagoras rule. The sum of combined result from each estimated position is divided by n-number of samples, producing the mean of distance.

$$Mean\ of\ Distance = \frac{1}{n}\sqrt{\sum_{i=1}^{n} d_i} \tag{5}$$

CDF calculated using the sorted combined result of estimated position. Then, separate the value by ranking them into n-percentile. The percentiles are based on sample rank position divided by n-number of samples. Which mean lowest percentile is called minimum distance and highest percentile is called maximum distance. To clarify the results, a set of minimum distance, median distance, 90th percentile distance, and maximum distance are used. Results from research are shown in Fig. 4.

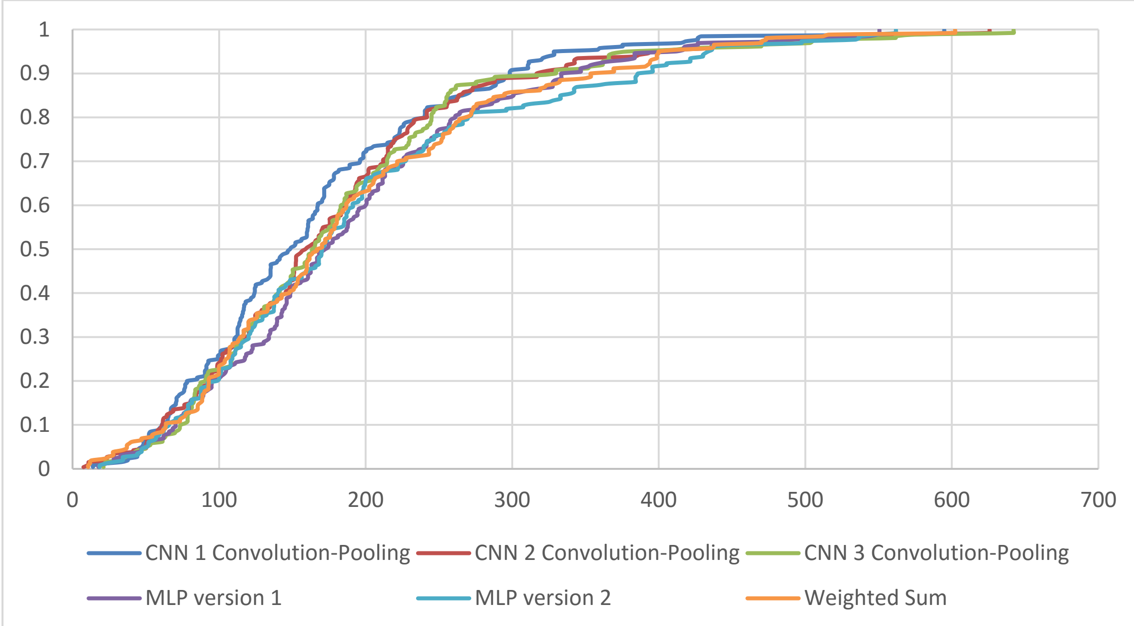

Fig. 4. Cumulative Distributive Function for Distance Accuracies.

V. Result

The experiment conducted using 1560 data collected. The data separated as described in previous section and randomized for each training epoch using random sampling, with exception for testing data. These data used to feed both CNN models, Multilayer Perceptron (MLP) models, and weighted sum method. Few variations of models are tried to prove accuracy of the method. The first CNN model used 1 convolution-pooling layer; second CNN model used 2 convolution-pooling layers; and the third one using 3 convolution-pooling layers. Then after the convolution-pooling process, the result went through 2 fully-connected layers with 6 neurons each fully-connected layer. For the MLP models, 2 variations are used. The first one is using 2 layers with 6 neurons each. This one is similar with CNN models but without convolution-pooling layers. The second one is using 6 neurons on first layer, then 3 neurons on second layer.

The training and validation result for CNN models shown on Fig. 5 and Fig. 6, while MLP models shown on Fig. 7 and Fig. 8. The RMSE cost results from last epoch of model x are 137.13cm for training and 127.92cm for validate. For model y, it was 163.39cm for training and 156.67cm for validate. For MLP Models, the RMSE cost results for model x are 150.59cm for training and 161.42cm for validate. The model y gave 181.61cm for training and 171.67cm for validate. Based from RMSE results, the CNN models give better cost reduction compared with MLP. Then, the models were measured for performance using 260 random testing data. Both value x and value y of position combined to calculate the distance. Results from comparing mean of distance are shown in Table II, which consisting of 167.49cm from first CNN model, 179.96cm for second CNN model, and 183.40cm for third CNN model. The MLP first model gave 192.22cm and second model gave 195.95cm. The weighted sum gave 189.50cm. From mean of distances, the CNN models gave better results compared with MLP models and weighted sum.

From the training and validate results of CNN and MLP, CNN model shown faster learning rate on both model x and model y compared with MLP model.

Cumulative distributive function from both model's distances are shown in Fig. 4. First model of CNN gave 298.36cm at 90th percentile. This model gave the highest performance compared with other models. Second model of CNN gave 316.69cm at 90th percentile, while third model gave 329.81cm at 90th percentile. The MLP models did not outperform the CNN models. MLP first model gave 333.50cm at 90th percentile and second model gave 385.79cm at 90th percentile. The benchmark weighted sum model gave 353.57cm at 90th percentile, which in between the MLP models.

The experiment shows that CNN model achieved accuracies of < 330cm at 90th percentile. Weighted sum model achieved accuracies of < 360cm at 90th percentile. The MLP models are in between the benchmark method but could not outperform CNN models. In Fig. 4, it was shown that CNN models performed slightly better than MLP models and weighted sum. Table III shown cumulative distribution for certain percentile from all models used.

TABLE II. Mean of Distance in CM

Model	Mean of Distance
CNN model 1 Convolution-Pooling	167.49
CNN model 2 Convolution-Pooling	179.96
CNN model 3 Convolution-Pooling	183.40
MLP Version 1	192.22
MLP Version 2	195.95
Weighted Sum	189.50

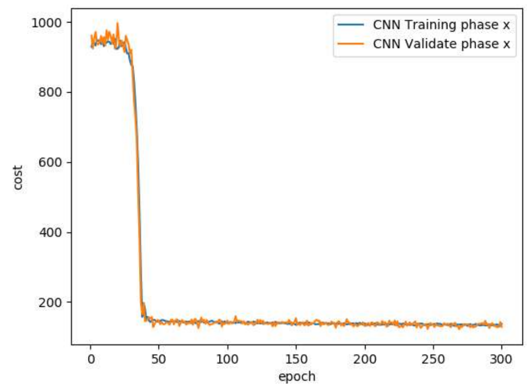

Fig. 5. Training and Validate for CNN Model x.

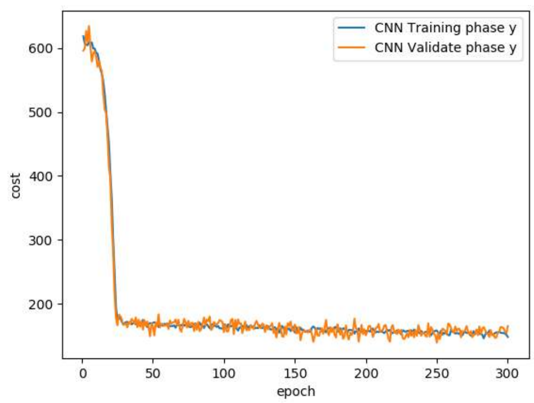

Fig. 6. Training and Validate for CNN Model y.

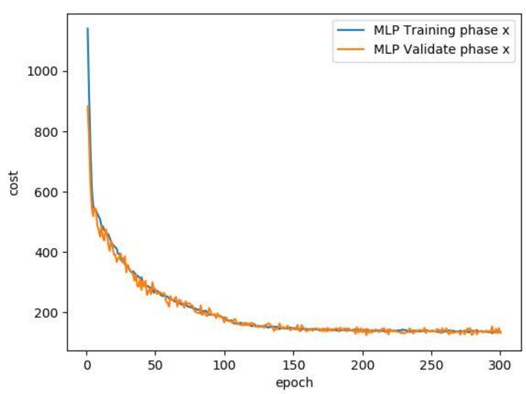

Fig. 7. Training and Validate for MLP Model x.

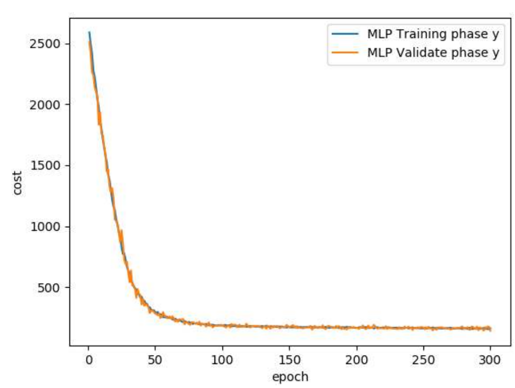

Fig. 8. Training and Validate for MLP Model y.

TABLE III. CUMULATIVE DISTRIBUTION OF DISTANCE IN CM

Percentile	Min distance	Median distance	90th percentile distance	Max distance
CNN model 1 Convolution-Pooling	13.93	148.41	298.36	594.79
CNN model 2 Convolution-Pooling	7.414	158.85	316.69	625.73
CNN model 3 Convolution-Pooling	21.11	163.38	329.81	642.11
MLP Version 1	17.69	172.40	333.50	550.57
MLP Version 2	18.44	170.21	385.79	561.83
Weighted Sum	10.60	166.77	353.57	602.20

VI. DISCUSSION

With the limitation of data collection time, the amount of data used in this research is pretty low for a CNN model. The proposed method might be not the most optimal model designed. The model needs to be analyzed and optimized with the principle of Deep Neural Network (DNN) [20] to further increase the accuracy.

Another problem in data collection is the battery capacity. As it is using button battery, the BLE could stay active at least six months to two years with relatively stable signal power [21]. However, the BLEs used in this research can only stay active for not more than one month. This means that current BLE beacons' setting is using too much battery power.

This research used averaging method to solve unstable RSS values received from each BLE. There are large fluctuations of data received caused by large amounts of people and obstacles in the office room. The placement of BLE beacons could affect the positioning error resulted from prediction [22]. More localization model could also be tried to improve the quality of RSS values. As this model affect the coverage area of the BLE beacons placed in the office room [23].

VII. CONCLUSION

This paper proposed CNN architecture to estimate position. The experiment showed that proposed CNN model surpassed MLP models and weighted sum method. The CNN models gave accuracies of < 330cm at 90th percentile, while the weighted sum gave accuracies of < 360cm at 90th percentile while MLP models in between CNN models and weighted sum. However, the CNN model has not been modified with optimum configuration and not yet implemented with different environments. This research is executed with maximum capability from BLE beacons used, which is significantly reducing BLEs' battery lifetime. The extensive time of sampling data should be reduced to improve accuracies.

VIII. FUTURE RESEARCH

For future researches, different CNN architectures should be tested and compared. These models should be tested on different indoor environments and room shapes. Another point to be researched is the validity of CNN model for predicting position. More researches should be done to prove it.

Different BLE placements could also be interesting future topic to analyze changes. The optimum setting for BLE beacons used in this research is not yet to be defined as the current setting gave high battery power usage but provide maximum capabilities from the BLE beacon.

References

[1] R. F. Brena, J. P. García-Vázquez, C. E. Galván-Tejada, D. Muñoz-Rodriguez, C. Vargas-Rosales and J. Fangmeyer, "Evolution of indoor positioning technologies: A survey.," Journal of Sensors,2017, 2017.

[2] D. Čabarkapa, I. Grujić and P. Pavlović, "Comparative analysis of the bluetooth low-energy indoor positioning systems," in 2015 12th International Conference on Telecommunication in Modern Satellite, Cable and Broadcasting Services (TELSIKS), 2015.

[3] R. Faragher and R. Harle, "An analysis of the accuracy of bluetooth low energy for indoor positioning applications," in Proceedings of the 27th International Technical Meeting of the Satellite Division of the Institute of Navigation (ION GNSS+'14), 2014.

[4] R. Faragher and R. Harle, "Location fingerprinting with bluetooth low energy beacons," IEEE journal on Selected Areas in Communications, vol. 33, no. 11, pp. 2418-2428, 2015.

[5] M. Terán, J. Aranda, H. Carrillo, D. Mendez and C. Parra, "IoT-based system for indoor location using bluetooth low energy," in Communications and Computing (COLCOM), 2017 IEEE Colombian Conference, 2017.

[6] F. Topak, M. K. Pekeriçli and A. M. Tanyer, "Technological Viability Assessment of Bluetooth Low Energy Technology for Indoor Localization," Journal of Computing in Civil Engineering, vol. 32, no. 5, p. 04018034, 2018.

[7] D. Contreras, M. Castro and D. S. de la Torre, "Performance evaluation of bluetooth low energy in indoor positioning systems," Transactions on Emerging Telecommunications Technologies, vol. 28, no. 1, p. e2864, 2017.

[8] Y. Zhuang, J. Yang, Y. Li, L. Qi and N. El-Sheimy, "Smartphone-based indoor localization with bluetooth low energy beacons," Sensors, vol. 16, no. 5, p. 596, 2016.

[9] S. He and S. H. G. Chan, "Wi-Fi fingerprint-based indoor positioning: Recent advances and comparisons," IEEE Communications Surveys & Tutorials, vol. 18, no. 1, pp. 466-490, 2016.

[10] F. Yu, M. Jiang, J. Liang, X. Qin, M. Hu, T. Peng and X. Hu, "5 G WiFi Signal-Based Indoor Localization System Using Cluster k-Nearest Neighbor Algorithm," International journal of distributed sensor networks, vol. 10, no. 12, p. 247525, 2014.

[11] C. Li, Z. Qiu and C. Liu, "An improved weighted k-nearest neighbor algorithm for indoor positioning," Wireless Personal Communications, vol. 96, no. 2, pp. 2239-2251, 2017.

[12] S. Tuncer and T. Tuncer, "Indoor localization with bluetooth technology using artificial neural networks," in Intelligent Engineering Systems (INES), 2015 IEEE 19th International Conference, 2015.

[13] H. Xu, M. Wu, P. Li, F. Zhu and R. Wang, "An RFID Indoor Positioning Algorithm Based on Support Vector Regression," Sensors, vol. 18, no. 5, p. 1504, 2018.

[14] L. Deng and D. Yu, "Deep learning: methods and applications," Foundations and Trends® in Signal Processing, vol. 7, no. 3-4, pp. 197-387, 2014.

[15] K. Townsend, C. Cufí and R. Davidson, Getting started with Bluetooth low energy: tools and techniques for low-power networking, O'Reilly Media, Inc., 2014.

[16] I. Goodfellow, Y. Bengio, A. Courville and Y. Bengio, Deep learning, vol. 1, Cambridge: MIT press., 2016.

[17] I. J. Goodfellow, D. Warde-Farley, M. Mirza, A. Courville and Y. Bengio, "Maxout networks," in arXiv preprint arXiv:1302.4389, 2013.

[18] S. Hoo-Chang, H. R. Roth, M. Gao, L. Lu, Z. Xu, I. Nogues, J. Yao, D. Mollura and R. M. Summers, "Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning," IEEE transactions on medical imaging, vol. 35, no. 5, p. 1285, 2016.

[19] T. Chai and R. R. Draxler, "Root mean square error (RMSE) or mean absolute error (MAE)?–Arguments against avoiding RMSE in the literature," Geoscientific model development, vol. 7, no. 3, pp. 1247-1250, 2014.

[20] N. Tishby and N. Zaslavsky, "Deep learning and the information bottleneck principle," in *2015 IEEE Information Theory Workshop (ITW)*, Jerusalem, 2015.

[21] Y. Wang, Q. Yang, G. Zhang and P. Zhang, "Indoor positioning system using Euclidean distance correction algorithm with bluetooth low energy beacon," in *2016 International Conference on Internet of Things and Applications (IOTA)*, Pune, 2016.

[22] W. Nakai, Y. Kawahama and R. Katsuma, "Reducing error of positioning based on unstable rssi of short range communication," in *2018 IEEE 32nd International Conference on Advanced Information Networking and Applications (AINA)*, Krakow, 2018.

[23] C. Liu, D. Fang, Z. Yang, H. Jiang, X. Chen, W. Wang, T. Xing and L. Cai, "RSS distribution-based passive localization and its application in sensor networks," *IEEE Transactions on Wireless Communications,* vol. 15, no. 4, pp. 2883-2895, 2015.