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DL-IPS: Deep Learning Based Indoor Positioning System for Improved Accuracy

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Abstract*: *Indoor tracking has evolved with various methods and well known these days. There are diverse types of solutions that concentrate on exactness, low cost, and control utilization within the field. Particularly in recent years, Received Signal Strength Indicator based positioning estimation have been getting popular. Still, the accuracy are not adequate, and there's no correct way chosen to overcome this issue. In this paper, we propose a strategy that leverage Deep Learning and Wi-Fi/BLE (Bluetooth Low Energy) Fingerprinting strategy to produce superior precise accuracy.

Keywords* : *Deep learning, Fingerprinting, indoors positioning, localization, Wi-Fi positioning, BLE, Machine learning

I. INTRODUCTION

In today's world, the smartphone-based indoor positioning technic has an enormous amount of applications benefiting from location detection, Hospital routing, food delivery, travel booking, personalized ads, emergency evacuation management, inhouse stock navigation, etc.

Wi-Fi/BLE based received signal strength measuring technic of the indoor positioning system is popular among other methods.

Positioning technologies, which are regularly utilized nowadays, change, and make our lives simpler. GPS is the foremost commonly used technology for following displacement units such as persons and vehicles within the open zone. Due to the shortcoming of the GPS signals inside in an indoor environment, GPS technology cannot work at the specified precision. For this reason, indoor positioning frameworks are a hot topic that's being considered both in scholastic and industrial professional areas [1]. Also, this issue is exceptionally imperative, given that 87% of people's lives are thought to go through in closed spaces such as schools, houses, shopping centers, and working environments [2].

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Wi-Fi technology is the foremost commonly utilized technology for indoor area detection. In any case, this technology consumes a lot of power and incorporates an absolute precision within the range of 2 to 3 meters [3]. As an alternative to Wi-Fi, Bluetooth Low Energy is a cheap

innovation with moo control utilization that can be utilized for this reason. It is found in gadgets commonly used by individuals such as keen phones, tablets, shrewd TVs, and its predominance is expanding day by day [4]. They can work for a few months with a battery due to low energy utilization, are secluded, and straightforward to introduce [5]. Since of all these focal points, the utilize of Bluetooth Low Energy (BLE) in indoor situating is getting to be progressively common.

Received Signal Strength Indicator (RSSI), a signal received by the mobile unit indicates the current strength of any Wi-Fi/BLE access point. It can be utilized to discover the separation between the smartphone unit and the access point/indicator device [14]. There are different approaches to deciding the position using this data. The foremost commonly utilized methods are Triangle-˙processing, Trilateration, and Fingerprint strategies. All these methods position of the portable unit or the fixed position of the Bluetooth transmitting unit / Wi-Fi access point.˙The signals gotten are based on the RSSI information.

The fingerprint in a certain position (x, y) is expressed as shown in Eq. (1),

$$RSSI(x,y) = [RSSI1-1, RSSI1-2, \ldots, RSSI1-M1, RSSI2-1, RSSI2-2, \ldots, RSSI2-M2, \ldots, RSSIN-1, RSSIN-2, \ldots, RSSIN-MN] \quad (1)$$

Where M1 = M2 = . . . = MN = M, implies the number of RSSI utilized in a fingerprint is equal for all of the grapples. This presumption is reasonable since in a BLE5.0 based framework, the broadcast interims of grapples are set to be the same, and the number of RSSI been seen is nearly equal.

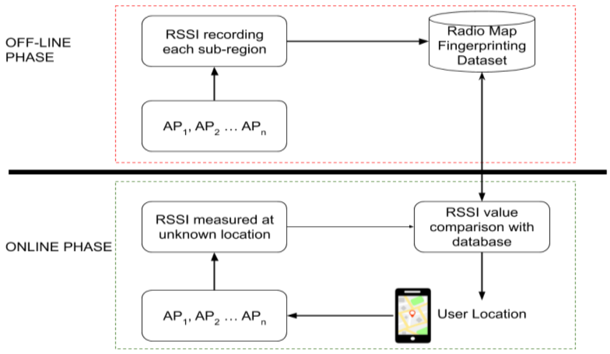

Fig. 1. Wi-Fi Fingerprinting positioning method

Fingerprint method, environmental pointers at the time of operation. The acquired RSSI data is the strategy of comparing the sub-region where the foremost fitting coordinate is gotten by comparing the information with the prepared information set. It comprises of 2 phases, online and offline. The offline phase is used as a recording of access point (AP) RSSI from each sub-region values are saved within the database and online as scanned RSSI value comparison with this database, as shown in Fig. 1.

II. MOTIVATION

The fingerprint-based positioning technic compares the unique finger impression of Wi-Fi access point or Bluetooth technology RSSI. In this approach, it was found that as it were 2 - 7 meters exactness can be accomplished in indoor situating [7]. This exactness rate is very inadequately when observing the area enclosed zones, particularly in limit zones such as hallways [3]. In this study, the Fingerprint Learning, using the standard unique mark method, it is expecting to attain way better comes about over the time.

III. PROPOSED METHOD AND ALGORITHM

To apply the Fingerprint method, the position required adequate RSSI in the area where the analysis will be made data have to be collected, and a test area has been established for this purpose. When creating the test area with 4 standard Beacon [8], which are frequently used for indoor positioning in the market, were used. These are point-to-point devices with Bluetooth Low Energy (BLE) technology that can be installed by building, working with the battery for a long time. The following are the specification of the Beacon markers are used in the following structure in our tests; Firmware: 6.7.3 • Location Information Signal Strength: 4dBm • Location Information Propagation Period: 200ms

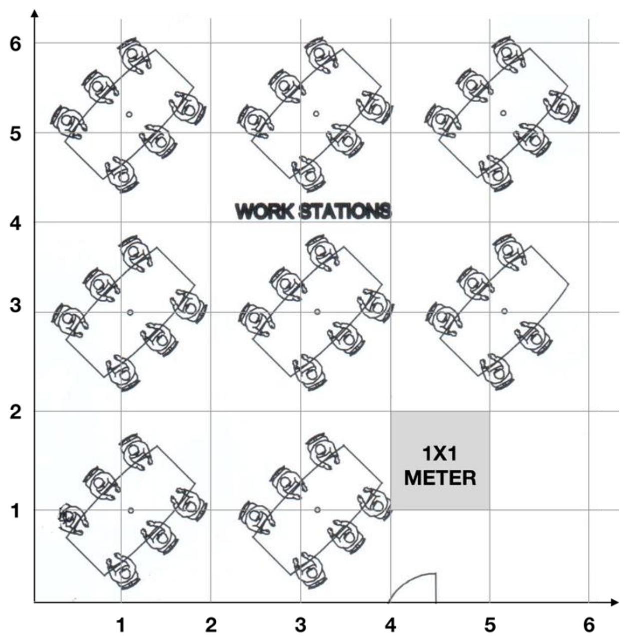

Fig. 2. Collecting of RSSI Data Area

Signal Strength Indicator information database of every 1 square meter in the test area as shown in Fig. 2.

In addition, these Beacon markers are located in the topology of the corners of the rectangular test area for accessible real-life applications. The distance between the markers in the knit topology is positioned to be 5 meters or closer to minimize the estimated error rate [9]. As a result, a test area S was created in Fig. 2, divided into 6 square meters and 6 square meters.

It is positioned in 4 corners through 36 sub-regions of Signal Strength Indicator after each of the is filer markers information has been read and saved in the database. Usually, locating takes place online.

The RSSI value measured are prone to have error and noise. It is essential to do pre-treatment to remove the noise, and then these values are compared to the data set previously saved in the database, which corresponds to the sub-region located. But the problem here is that the RSSI can be matched to more than one sub-region due to environmental effects such as signal mixing and signal reflection. In such cases, methods such as mathematical modeling of RSSI values, and the use of speed and gyroscope information with the Extended Kalman Filter [10] can be applied [5]. But in this study, the database recorded, Signal Strength Indicator raw data, generated, and Deep Learning will be used as an education set of learning structures.

Deep Learning; regression, classification, and forecasting are the powerful machine learning approach [3]. In this study, for each sub-region RSSI value acquired. We use machine learning approach to classify that, is the indicator data included in this subgroup or not? To respond to this, the classification approach of Deep Learning will be utilized.

We have a total of 4800 lines of data, 250 of each sub-region, taken from 6X6 meter of the test area with 4 pointer devices. There are 520 different data sets. Then, this data will be used in the training of the Deep Learning model, which will be 20% for verification and 80% for educational purposes.

Our Deep learning Neural Network model is designed to include 2 hidden layers, which are the entry-level of Deep Learning. In addition, since there are no standards available, the number of nodes to be found in the hidden layers is determined to be half of the sum of the generally accepted input and output nodes, i.e., 3. Among the hidden layers, Rectifier function (as shown in Eq. (2)) ReLU and Sigmoid Function (as shown in Eq. (3)) was used in the output layer as shown in fig. 3. The reason for using ReLU is that, due to the definition of the function, it tends to obtain the least sparse vector by excluding weights less than zero. This reduces the processing load [11]. In addition, Sigmoid Function is Signal Strength Indicator

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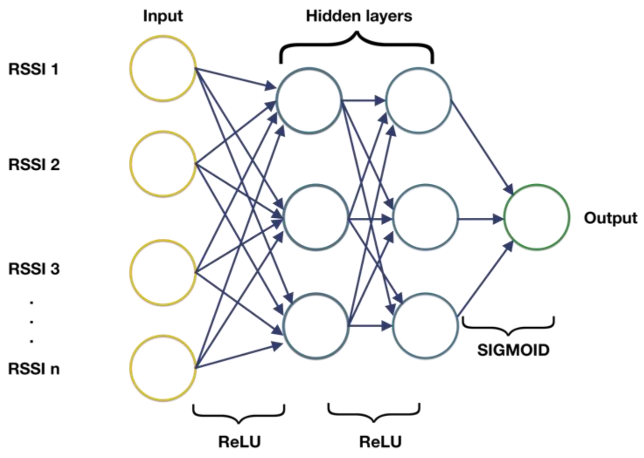

Fig. 3. Deep Learning Model Layer with Knot

How much data is included in this sub-region? It also gives the probability value. Advancing Algorithm as¸ stages, collected online¸ Signal Strength Indicator Accuracy ratio for each sub-region will be calculated using the samples, and the most appropriate sub-region will be selected.

$$\sigma R(z) = \max(0, z) \quad (2)$$

$$y(x) = (1 + e^{-x})^{-1} \quad (3)$$

After the model is created, the parameters that will be used in the machine learning process; Parameter adjustment was performed for the Grid Search method to obtain the best output for lot size, several training rounds, and optimizer function.

- Number of Batch Size: 4, 10, 16, 25, 32, 64
- Number of training tours: 25, 50, 100, 200

Table- I: Deep learning network parameters for Optimized Test environment

Parameters	Values
Number of Party Size	64
Number of Training Tours	400
Optimizer	ReLU Function
Loss Function	Binary cross entropy

As a result of this process, ¸parameter values decided to be used as in Table I. Then, in line with this structure, the data sets available for each sub-region were used for educational purposes. At the end of education, accuracy rates were found for each sub-region separately. Table II contains the maximum and minimum values of the predicted accuracy rates for each sub-region.

Table- II: Projected Accuracy for the sub-regions – Maximum and Minimum value

Min-Max Accuracy Ratio	Value
Maximum	0.991
Minimum	0.938

In this process, the K-Layer Cross-Verification method was used to avoid being affected by the over-learning problem. As a result of this method, it was observed that the educational outcomes for each sub-region were not significantly affected by the excessive learning problem. As the output of this test, the maximum and minimum values of the standard deviations of accuracy rates obtained from successive calculations in each sub-region education are given in Table III.

Table III: Cross verification for each sub-region using proposed method – Average standard deviation maximum and minimum values

Min-Max Standard Deviation	Value
Maximum	0.028 6
Minimum	0.010 9

As a result, after Deep Learning education, the minimum accuracy rate of 0.931, which is the calculated accuracy rate for each sub-region, was accepted as the overall accuracy value of the whole system.

IV. EXPERIMENT

The experiment is performed at the start of the Fingerprint method in the test area. The data obtained from the data collection process and our computer-generated environment were performed using a new test dataset. When creating this test dataset, G separately collected for the lower region RSSI values , and standard deviation values used. This set of tests indicates the signal strength of each subregion. The mean values of the indicator values are the standard deviation of randomly generated RSSI values comprising.

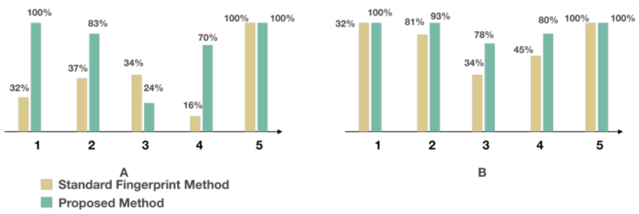

Fig. 4. Standard Fingerprint method Vs Proposed method

The test data set, which consists of a total of 3000 data, 150 of which are produced for each sub-region, was created. We give a label for each sub-region of build using standard Fingerprint and. The outputs obtained by using Deep Learning structure were observed. Accuracy percentages of the outputs obtained for the same test input were calculated and is shown in Fig. 4. which illustrates that in some subregions, the proposed method gives better results than the Fingerprint method, but the accuracy rates are still not sufficient. For improving the accuracy, the additional study has increased the number of hidden layers in the model.

The number of changes in the hidden layers of the model and the parameters mentioned in Table 1 was kept constant, and the accuracy ratios were calculated for each sub-region by changing the model so that the number of hidden layers was 1, 2, 3, 4, 5 and 6. The correlation between the minimum values of the subregions obtained at each step and the numbers of the imprecise coefficients can be observed in Fig. 4.

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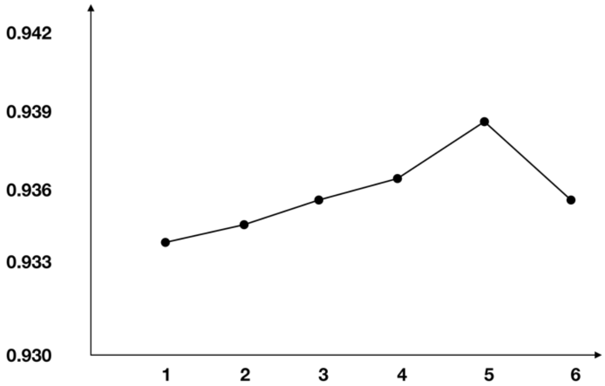

Fig. 5. Number of Hidden Layers Vs Accuracy Ratio

As shown in Fig. 5., the accuracy rate obtained by increasing the number of hidden layers used in the model increases linearly, and it is seen that the 5 hidden layer models have the best accuracy ratio. It was observed that the development of the model in this way provided an improvement throughout the system. In addition, education for the sub-region when the data of the cluster is examined, the pointing device signal strength indicator.

The standard deviation value of the flow rate is quite significant processes. Therefore, the signal strength of this field is produced Test inputs randomly generated using indicator information. The range is extensive, and the ratio of matching to the sub-region decreases. The reason why the standard deviation is so significant is considered to be a experienced test environmental impact in the field of testing when training data are collected.

V. EXPERIMENT RESULT AND CONCLUSION

In this paper, Bluetooth Low Energy technology and Deep Learning with Strength Indicator-based Fingerprint Method is used to improve the accuracy of finding indoor position. A Deep Learning structure with the parameters mentioned in Table I has been established, and the tests have been observed, and the results have been observed.

According to the outputs in Fig. 3. ; Except for the subregion with the' A2' label, it was observed that the position finding dog increased for all remaining subregions — one in other words; our algorithm, Fingerprint direction-better results than supply. Besides, when the whole system is evaluated, locating the position with the last method result in 79.7%. Besides, since the sub-regions in the test environment are set up to be 1 square meter, the accuracy rate of 79.7%, calculated for the whole system, is 1 meter and below for position Standard deviation using Fingerprint. The position error of the method is between 2 and 3 meters. Also, the standard fingerprint method was observed with a rate of 18.3% and it is known that the position deviation of the standard Fingerprint method has been improved by 3 times with the approach mentioned in this paper.

In future studies, some sub-regions (see Fig. 3, A2 region) will be examined in more detail to determine why this method has less accuracy and improvement studies will be conducted in this direction.

REFERENCES

1. Joseph R, Sasi SB. Indoor Positioning Using WiFi Fingerprint. In2018 International Conference on Circuits and Systems in Digital Enterprise Technology (ICCSDET) 2018 Dec 21 (pp. 1-3). IEEE.
2. Hameed A, Ahmed HA. Survey on indoor positioning applications based on different technologies. In2018 12th International Conference on Mathematics, Actuarial Science, Computer Science and Statistics (MACS) 2018 Nov 24 (pp. 1-5). IEEE.
3. Ma Z, Wu B, Poslad S. A WiFi RSSI ranking fingerprint positioning system and its application to indoor activities of daily living recognition. International Journal of Distributed Sensor Networks. 2019 Apr;15(4):1550147719837916.
4. Jallow B, Hong WT. Evaluation of Indoor Positioning Based on iBeacon and Pi-Beacon. In2018 International Conference on System Science and Engineering (ICSSE) 2018 Jun 28 (pp. 1-4). IEEE.
5. Li X, Wang Y, Khoshelham K. Comparative analysis of robust extended Kalman filter and incremental smoothing for UWB/PDR fusion positioning in NLOS environments. Acta Geodaetica et Geophysica. 2019 Jun 15;54(2):157-79.
6. Liu H, Darabi H, Banerjee P, Liu J. Survey of wireless indoor positioning techniques and systems. IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews). 2007 Oct 22;37(6):1067-80.
7. Pu YC, You PC. Indoor positioning system based on BLE location fingerprinting with classification approach. Applied Mathematical Modelling. 2018 Oct 1;62:654-63.
8. Jürgens M, Meis D, Möllers D, Nolte F, Stork E, Vossen G, Werner C, Winkelmann H. Bluetooth Mesh Networks for Indoor Localization. In2019 20th IEEE International Conference on Mobile Data Management (MDM) 2019 Jun 10 (pp. 397-402). IEEE.
9. Mendoza-Silva GM, Matey-Sanz M, Torres-Sospedra J, Huerta J. BLE RSS Measurements Dataset for Research on Accurate Indoor Positioning. Data. 2019 Mar;4(1):12.
10. Xia L, Geng J, Wu D, Peng Q. Attitude Heading Estimation of Indoor Moving Object Based on Extended Kalman Filter Algorithm. In2018 Ubiquitous Positioning, Indoor Navigation and Location-Based Services (UPINLBS) 2018 Mar 22 (pp. 1-7). IEEE.
11. Zhang C, Woodland PC. Parameterised sigmoid and ReLU hidden activation functions for DNN acoustic modelling. InSixteenth Annual Conference of the International Speech Communication Association 2015..
12. Xiao C, Yang D, Chen Z, Tan G. 3-D BLE indoor localization based on denoising autoencoder. IEEE Access. 2017 Jun 27;5:127
13. Huang B, Liu M, Xu Z, Jia B. On the performance analysis of wifi based localization. In2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) 2018 Apr 15 (pp. 4369-4373). IEEE.
14. Arif SA, Niaz MH, Shabbir N, Zafar MH, Hassan SR, ur Rehman A. RSSI Based Trilatertion for Outdoor Localization in Zigbee based Wireless Sensor Networks (WSNs). In2018 10th International Conference on Computational Intelligence and Communication Networks (CICN) 2018 Aug 17 (pp. 1-5). IEEE.
15. Yüksel KD, Töreyin BU. A deep learning and RSSI based approach for indoor positioning. In2018 26th Signal Processing and Communications Applications Conference (SIU) 2018 May 2 (pp. 1-4). IEEE.
16. Xu B, Zhu X, Zhu H. An Efficient Indoor Localization Method Based on the Long Short-Term Memory Recurrent Neuron Network. IEEE Access. 2019 Aug 27;7:123912-21.

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