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Bluetooth Low Energy (BLE) and Feed Forward Neural Network (FFNN) Based Indoor Positioning for Location-based IoT Applications

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Abstract: In the recent development of the Internet of Things (IoT), Artificial Intelligence (AI) plays a significant role in enabling cognitive IoT applications. Among popular IoT applications, location-based services are considered one of the primary applications where the real-time location of a moving object is estimated. In recent works, AI-based techniques have been investigated to the indoor localization problem, showing significant advantages over deterministic and probabilistic algorithms used for indoor localization. This paper presents a feasibility study of using Bluetooth Low Energy (BLE) and Feed Forward Neural Networks (FFNN) for indoor localization applications. The signal strength values received from thirteen different BLE ibeacon nodes placed in an indoor environment were trained using a Feed-Forward Neural Network (FFNN). The FFNN was tested under other hyper-parameter conditions. The prediction model provides reasonably good accuracy in classifying the correct zone of 86% when batch size is 100 under the learning rate of 0.01.Hence the FFNN could be used to implement on location-based IoT applications.

Index Terms: Indoor Localization, Internet of Things (IoT), Feed Forward Neural Network (FFNN), Artificial Intelligence (AI)

1. Introduction

Researchers and developers are motivated to design IoT and AI-based novel applications in smart cities, transportation, intelligent buildings, smart agriculture, and other areas due to the rapid growth of the Internet of Things (IoT) and Artificial Intelligence (AI) blended technologies. Among these applications, location-based services are considered essential applications that enable many innovative IoT-AI blended applications. People nowadays spend most of their daily lives indoors, for their works, education, shopping, etc. Hence, developing location-based IoT services is playing a significant role in this era. Furthermore, for intelligent applications such as buildings, identifying users in indoor spaces is critical since it serves as the link that allows users to collaborate with other IoT services. The indoor localization has been done using several deterministic and probabilistic algorithms in the past. However, these algorithms are inefficient and very difficult to implement on real IoT systems.

The recent developments of AI enable its applications in every domain. One of the strong branches of AI is Artificial Neural Networks(ANN). As a sub-type of ANN, Feed Forward Neural Network (FFNN) is a powerful machine learning technique used for regression and classification problems. Though many works exist on applying machine learning techniques for indoor localization problems as a regression problem, there is less work on using machine learning classifiers for indoor localization problems. Machine learning regressor provides the geographical coordinates as a numerical value, and the classifiers give the specific location as a zone. Such classification-based approach could enable many smart IoT localization applications such as predicting the location of an older person living alone in a home, the person in a specific block or floor in a building or animals within a particular area in an animal farm, location of an autonomous robot in a factory floor, etc.

The existing works on machine learning-indoor localization mainly consider the localization problem a regression-type machine learning problem.However, to identify a specific area in the indoor environment, we can formulate it as a machine learning regressor type problem. The objective of this research was to investigate FFNN for indoor localization.In this work, we have used a publicly available Received Signal Strength Indicator(RSSI) data set collected from BLE ibeacon nodes [1]. There were thirteen ibeacon nodes on the first floor of Waldo Library, Western Michigan University. Data was collected using iPhone 6S. The library area is virtually divided into four zones. FFNN was used to train the data and tested the classification accuracy under several conditions of the neural network.

2. Related Works

Researchers have contributed towards machine learning-based indoor localization problems. In [2-8], the indoor localization problem has been investigated as a regression problem where the estimated x and y coordinates provided by the supervised regressors such as Random Forest Regression (RFR), Decision Tree Regression, Support Vector Regression (SVR)algorithm and experimental setups were based on Wi-Fi. This method can be used any number of beacon nodes in the system. Moreover, the prediction accuracy will significantly increase when increasing the number of beacon nodes [2]. Indoor localization using neural networks has received little attention. [6-8] for Wi-Fi-based systems. Furthermore, because IoT devices create a vast amount of data, neural networks outperform other classifiers in these cases. [9-13].

All the above works contributed towards neural network-based indoor localization is considered a regression problem where numerical predictions are provided as the output. In this work, we approach indoor localization as a classification problem, and it gives the estimated location as a zone. And model evaluations are also evaluated as a classification problem.

3. Background

3.1 RSS Based Indoor Localization

Received Signal Strength(RSS) based localization outperformed compared to the other available signal measurement techniques. Yet, there is no proper and generalized model for indoor localization due to potential obstacles, floor layouts, and multipath propagation. Arrival angle (AoA), arrival time (ToA), the Time Difference of Arrival (TDoA), and received signal strength indicators(RSSI) are the most popular models used in positioning systems. The AoA system uses an antenna array to determine the angle of signal propagation. Then, to place the receiver, utilize triangulation and the geometric principles of the angle of the triangle. AoA technology usually requires complex hardware and needs to be calibrated to get the correct position. ToA is one of the most accurate techniques available [9]. Synchronous clocks can be used to determine the signal propagation time between the transmitter and receiver. TDoA is similar to ToA in that it requires a synchronous clock, but it finds the absolute signal propagation time by combining the signal propagation times of many receivers. The time delay between the arrival of data packets at different receivers can measure the distance. [9].

One of the most effective methods for indoor localization is RSSI. RSSI's popularity stems from the fact that it does not necessitate any additional apparatus for measurement. The RSSI is a signal intensity metric that estimates the signal intensity of data packets received by a receiver. It is frequently used to calculate the distance between a transmitter and a receiver since the signal strength reduces as the signal radiates outward from the transmitter. RSSIs generally result in erroneous readings and mistakes in positioning systems because the propagated signal is vulnerable to external noise. Equation 1 expresses the link between distance and RSSI. [6-10].

$$RSSI = -(10n)log10(d) + A, \tag{1}$$

Where A is the offset RSSI reading at 1 meter from the transmitter, n is the signal propagation constant, d is the distance in meters, and n is the signal propagation constant. As per figure 1, it is required to keep multiple Beacon nodes at fixed places to receive the RSSI from the target sensor node, which we need to estimate the location.

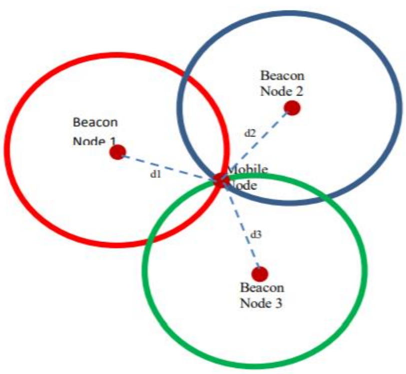

Fig.1. RSS Based localization

3.2 Feed Forward Neural Network (FFNN)

There are several layers in a Multilayer Feedforward Neural Network. Input Layer: It's the layer where the various input parameters go to be processed. The ReLU activation function is used in the input layer of our experiment. It's the layer where the different input parameters go to be processed. The ReLU activation function is used in the input layer of our investigation.

Hidden Layer*:* It performs intermediate computations as the middle layer between the input and output layers. There could be one hidden layer or many, with the number of concealed nodes variable.

Output Layer: It's the layer that comes after the hidden one. This layer generates the final output. The softmax function is commonly used for classifications.

The neuron is the most fundamental component of a neural network that takes inputs. These inputs are used in conjunction with the changeable parameters, covered in more detail in a subsequent subtopic. A neuron's fundamental aim is to change the learning rule's adjustable parameters based on its inputs to uncover important qualities unique to a class and then send the calculated output to the neurons in the next layer. The neuron in a neural network is modeled after a neuron in the human brain. In neural networks, inputs take the place of dendrites, and inputs are processed by learning rules and other mathematical calculations rather than the cell body. The axons of a human neuron are in neural networks, and the outputs are substituted.

Each of these tiers may contain one or more artificial neurons. Every neuron in one layer also communicates with every other neuron in the following layer. Every neuron in the input layer is connected to every neuron in the hidden layer, in other words. Depending on the nature of the chosen architecture, every neuron in the hidden layer will connect to neurons in the next layer that follows this hidden layer, another hidden layer(s), or an output layer. An activation function may exist between these levels to speed up or slow down the signal to the next layer. An activation function may exist between distinct layers, such as the input and hidden layers or the hidden and output layers. Additionally, these activation functions may or may not be the same. [14-16].

Fully linked layers are those in which all inputs from one layer of a neural network are attached to each activation unit of its next layer. Just the last few layers of the most common models are fully attached, and the characteristics retrieved by the previous levels are assembled to the final output. Fully connected layers take a long time to complete. To minimize computing time and prevent losses, all layers are not entirely connected.

3.3 Bluetooth Low Energy (BLE)

Bluetooth Low Energy (BLE) is a low-power wireless communication technology that can be utilized for short-range communication. BLE is used to establish a seamless experience across smart wireless devices used every day (smartphones, smartwatches, fitness trackers, wireless headphones, PCs, and so on). The BLE technology is highly recommended for IoT design as it consumes less energy [8]. Moreover, LBE is ideal for short-range indoor applications where sensing ranges below 60m.

Gimbal Beacon was used to design all the beacon nodes for the experimental testbed. The Apple iBeacon protocol is used to create the Gimbal Beacon. The universal unique identifier (UUID), a 16-byte lot used to identify a collection of beacons, is one of three fields defined in the IBeacon data packet structure. The "main" and "secondary" values are in the second and third fields, respectively.

4. Experimental Setup and Dataset

The dataset used in this experiment was taken from [1]. The RSSI readings of an array of 13 ibeacons on the first floor of Western Michigan University's Waldo Library were used to produce the dataset, as shown in figure 2. The information was gathered using an iPhone 6S. The dataset contains both a labeled (1420 instances) and an unlabeled (1420 instances) dataset. The recording took place within the library's usual business hours. Closer proximity to an iBeacon is indicated by higher RSSI values. The RSSI is displayed by -200 for iBeacons that are out of range. Figure 2 depicts the layout of the arrangement of iBeacons in green color circles. This experiment has only used the labeled data. Further, in the original data set, a location labeled includes the number of rows and columns. However, as per the zone classification approach, we have re-labeled the ibecon dataset by dividing it into four zones: A, B, C, and D.

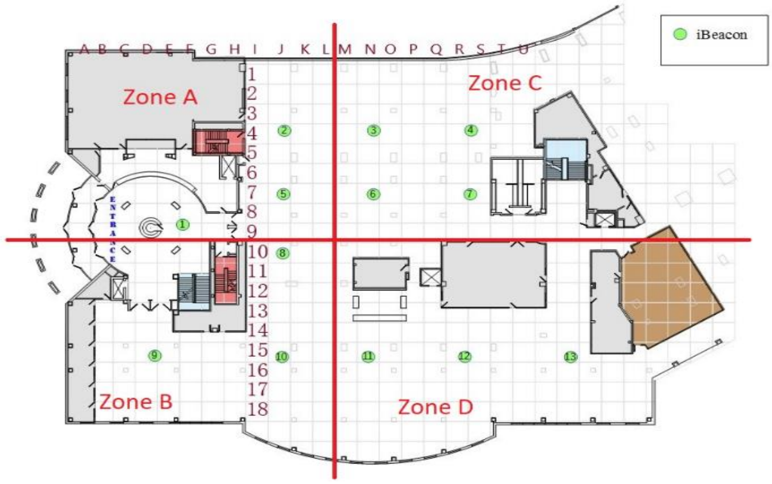

Fig.2. Experimental Setup [1]

5. Model Development and Training

The proposed FFNN consists of two fully connected layers and one output layer. There are thirteen inputs at the input layer as it has thirteen beacons node inputs. The first fully connected layer has 20 neurons, and the second fully connected layer has 17 neurons, as shown in figure 3. The models were trained on Jupiter Notebook using Python3. TensorFlow 2.0 was used to prepare the FFNN. 70% of the dataset was used for training and 30% for the testing during training. Models were trained under three different hyper-parameters values of Learning Rate (LR), batch size, and epochs. Network architecture consisted of four fully connected layers and one classification layer for all simulations. The ReLU activation function was used during the simulations in fully connected layers and the SoftMax function in the last layer [17-18].

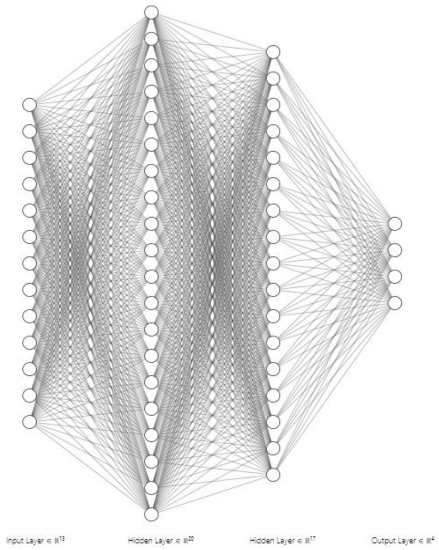

Fig.3. The network architecture of the FFNN

6. Model Evaluation

Implemented FFNN was tested by tuning hyper-parameters, learning rate, batch size, and the number of epochs. The training accuracy and testing accuracy were tested under the different epochs from 0 to 100 and under three different batch sizes, 10,50, and 100. It observed that training accuracy is always a high value compared to the testing accuracy. The results are shown in Figures 4 and 5.

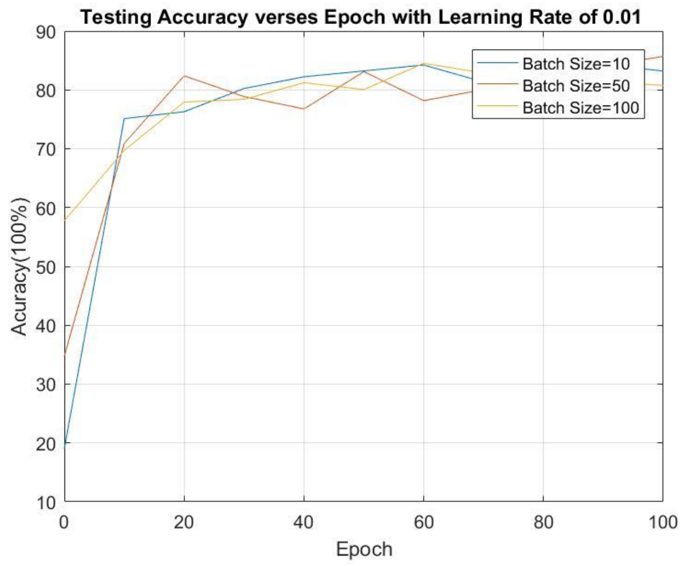

Fig.4. Testing accuracy versus no. of epoch

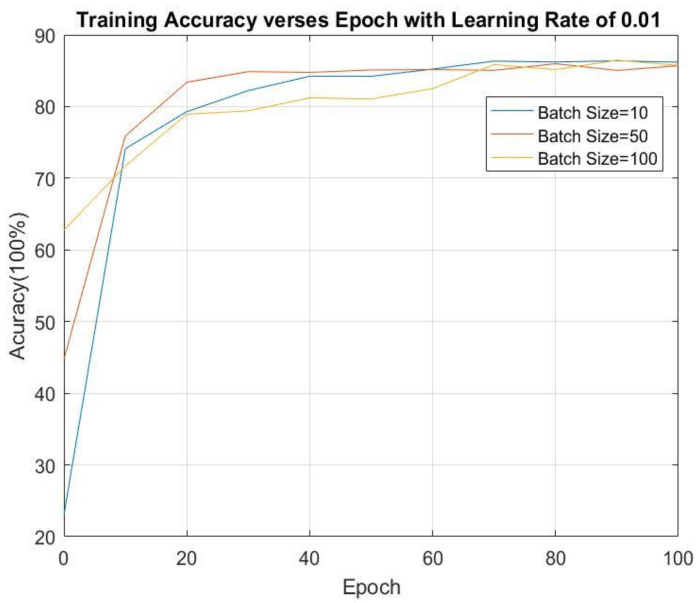

Fig.5. Training accuracy versus no. of epoch

Table 1. Confusion Matrix

	Zone A	*Zone B*	*Zone C*	*Zone D*
Zone A	143	8	0	0
Zone B	7	187	9	4
Zone C	2	3	523	4
Zone D	1	0	11	518

Table 2. Model evaluation matrix

Zone	*Accuracy*	*Precision*	*Recall*	*F1 Score*
Zone A	98.73%	0.95	0.93	0.94
Zone B	97.82%	0.90	0.94	0.92
Zone C	97.96%	0.98	0.96	0.97
Zone D	98.59%	0.98	0.98	0.98

7. Conclusions

This paper presents a novel indoor localization method that can be used for location-based services in IoT. This method is BLE and FFNN based model for location-based IoT applications to estimate a person's location or any other object. This model predicts the location as a classification problem. Using FFNN, we could able to achieve pretty good accuracy in location classification. The RSSI values received from thirteen different iBeacon nodes were trained under a four-layered FFNN. The hyperparameters were tuned and observed the change of accuracy in each condition. The prediction model provides reasonably good accuracy in classifying the correct zone of 86% when batch size is 100 under the learning rate of 0.01.

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