Multiple Target Localization Using Artificial Neural Network

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***Abstract*—We are considering energy based, received signal strength indication (RSSI), target localization in a wireless sensor network. This paper includes the solutions to many problems such as multiple-target tracking, how many targets are in an area, trajectory analysis, indoor navigation, location detection of a fireman in a building on fire, etc. The proposed method uses the RSSI to find the location of targets. This paper presents the localization problem as classification problem in which target position is defined as a grid number that is being estimated using a vector containing the RSSI value received from the wireless access point at a location. The monitoring region was divided into a large number of small grids. Sensors and targets are placed in some random location $i.e.$ grid. We implemented a simple neural network model to estimate the target location. The reason of using the neural network is its accurate and robust estimation against highly nonlinear and noisy sensor measurement.**

Keywords*—*Neural Network, RSSI,Target tracking, Wireless Sensor Network

I. Introduction

Global positioning system (GPS) is the most broadly used outdoor location measuring technology, but there are several hindrances which make GPS impossible to be used for the indoor positioning system. Because of several reasons like the line of sight demand between satellite and receiver, it has poor coverage and insufficient accuracy.

In recent years, localization has been recognized as an important supporting technology for wireless sensor networks (WSNs). Localization has demonstrated a wide range of application such as indoor navigation, object tracking, trajectory analysis, location detection of a fireman in a building on fire, target counting within an area or finding the place with less crowd, equipment monitoring in wireless sensor networks, etc. With recent advancements in wireless communication and electronics, localization using the RSSI has gained a lot of attention. Current, literature shows a growing interest in using localization techniques based on the received signal strength (RSS) because they can be applied to almost any radio device. As RSSI measurements are highly non-linear and noisy, we can use machine learning model based on neural network can be used for supervised learning to achieve good estimation. As the machine learning method requires a large amount of labeled data for high accuracy, the significant efforts such as time and human skill are needed. For instance, GPS (Global Positioning System) signal is not available indoors, the only solution in collecting the labeled training data points is to collect them manually. Collecting the training labeled data involves repeatedly placing a target and measuring the RSSI from the sensor nodes in the known location while unlabeled data can be collected by recording RSSI without knowing the target location. The multipath effect is significant in indoors because of signal reflection from walls, furniture, and some other obstacles and the signal attenuation is higher for the high density of obstacles which leads to non-linearity in the RSSI measurement data. Therefore, indoor localization with high accuracy remains a challenging research problem to be solved.

The main contribution of this paper is as follow: (1). We proposed a simple yet efficient method for this problem with greater accuracy. (2). We offer a system that anyone can deploy with a slight change as according to their indoor location.

We formulated the localization problem as a classification problem. We divide the whole monitoring area in N grids, and each grid represents a class s(for more detail see the section 4-Experimental setup). And while training we have the labeled data associated with each class. In our case, the total number of classes/grids are 1268. Now the challenge is to build a neural network model that will accurately classify these many classes.

The rest of the paper is organized as follows: Sect. II summarize the related work, Sect. 3 presents the overview of our system, Sect.4 describes the proposed method and system work flow, Sect. 5 provides the experimental setup, Sect. 6 shows the result of the proposed method, and Finally Sec. 7 conclude the paper and talk about future work.

II. Related Work/ Literature Survey

Several types of sensing modalities of the wireless signal have been used for the indoor localization such as time of flight(TOF), the angle of arrival (AOV), received signal strength indication (RSSI). RSSI does not need any addition hardware to quantify it thus it is one of the most common modalities. But its values are affected by obstructions like walls, furniture and other obstacles which may reflect or propagate the signals. A non-linear conversion between the RSSI values and the location is offered as a result. Many of the previous localization approaches have been used the RSSI as measurement metric for location determination.

A lot of algorithms and techniques have been developed and applied for the localization such time difference of arrival, manifold learning algorithm and the angle of arrival etc.

The localization system based on time difference of arrival [1] require cooperation with tracked device with localization server and optimization of access point distribution. This method need a calibration procedure in the entire monitoring area to achieve a high accuracy. But the calibration data are extremely sensitive to the instantaneous position of the various object in the area including persons, furniture, etc. That is why real case accuracy of this system varies in the range of 10m to 100m.

In manifold learning algorithm [2], [3], localization problem was formulated from the pairwise measurement as dimensionality reduction on a Riemann manifold. But the sparsity of wireless sensor network affects the accuracy of this technique. In a dense wireless sensor network, this method achieves a good accuracy while its accuracy decreases sharply in a sparse wireless sensor network. This method exhibits a high communication cost in term of bandwidth and energy because it needs continuous communication between each sensor node. It also requires a center node to transmit pairwise measurement which also increases the communication cost.

The direction of arrival methodology [4] can be applied only in the area where there is a straight line of sight between the mobile user and reference point. Location estimation is done by measuring the angle between a line from a reference point (RP) to the mobile target and a line from RP to a predefined direction. The biggest disadvantage of this technique is the need of special RP that can precisely measure the direction of received signal.

Received signal strength indication is an indoor localization methodology based on WLAN. Many technologies had been developed that uses fingerprinting approach with RSSI based technique such as k-nearest neighbor method, compressive sensing, neural network etc. Fingerprinting based approach primarily creates a map of RSSI vector. Each vector belongs to the coordinate of the measurement taken in a particular area. The benefit of this technique is that the target location can be estimated without knowing the location ofA access point's (AP).

The k-nearest neighbour [5] method uses RSSI data to calculate a distance vector and estimate the target location by comparing its RSSI measurement vector to other vectors. After that, the signal space distance(SSD) are sorted. Then the k-samples with smallest SSD will be selected as k-nearest neighbour. In this, SSD can be calculated by various pattern classification technique like euclidean distance, Manhattan distance, Spearman distance [6] etc. And the location associated with the fingerprint which has smallest SSD will be selected as object location. The accuracy of this algorithm is highly dependent on the choice of k-value.

Based on the previous research in the field of compressive sensing theory, one can recover sparse or compressible signal from fewer samples than that are actually needed by Nyquist sampling theorem. In this, technique [7], the target locations are represented as a sparse matrix in the discrete spatial domain. And with the use of minimization technique like $l1$ target location is recovered by measuring only a small number of signal from the target. This method is best suited in a small area where number of grids are small but in the larger area estimating the target location becomes costly in term of computation.

Artificial neural network model [8] uses the training data as input. In this approach, an artificial neural network is constructed and is used to estimate the location of the target. The artificial neural network works like the way biological nervous system work. Here, training data is used to teach the model the relation between input vector and the target location. Once the neural network has been trained then it can be used to predict by detecting similar pattern of the input data even if the data has not been seen by the network previously. While location estimation RSSI vector will be given as input and the target's location is expected as the output.

III. System Architecture

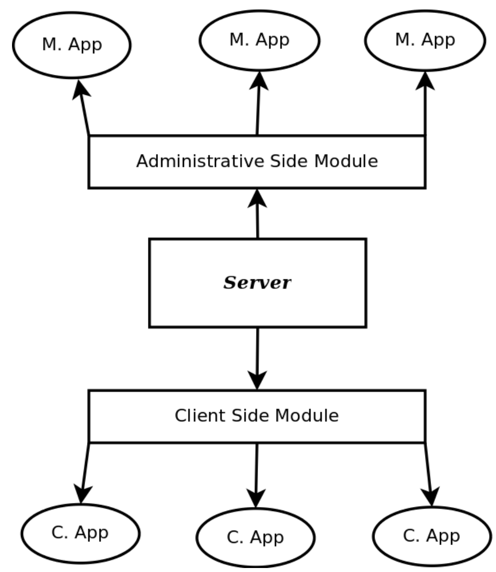

Fig. 1. System Overview

Here, **M. App** is Master android application that will be used for collecting data and to train the model on server. Only administrative people should use this application. And, **C. App** is the client android application that will be used by each target.

IV. Proposed Method and Work flow of the system

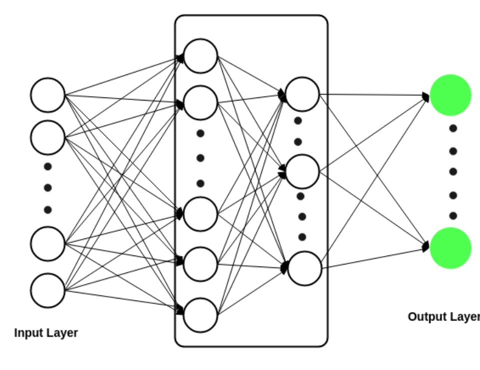

Fig. 2. Neural Network Architecture

Fig. 2. shows the basic workflow of our system. To collect the data, we build an Android App (M. App) that will record the RSSI reading from each access point and send it to the

server where it will get stored in the database. After collecting the labeled data, we import the data from database in CSV format. Once the training data is ready, we can teach the neural network to learn these inputs. After learning, we will save the neural network model and will convert in into dl4j [9] format. Before locating yourself, you have to use the C. app which will download the trained model from the server. After downloading the model, you can get you location using C. app which will read the RSSI and compute the location.

Fig. 3. shows the neural network architecture. The model has 26 neurons in input layer $i.e$ size of RSSI vector. **There are two hidden layer one have 100 neurons and second have 80 neuron**. And last is output layer which has 1268 number of node $i.e$ number of grids.

V. Experimental Setup

This section describes the problem formulation including the experimental setup with data collection and localization structure. For experimental setup, we choose our college campus in which we selected the ground floor and first floor as monitoring area. The size of the chosen area is 6780×7080 cm^2. Refer Fig. 5 to see the actual map.

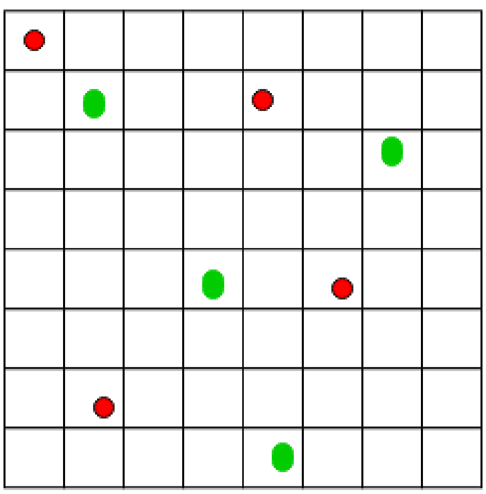

Fig. 3. Monitoring area

Here, green points represent the WIFI access point, and the red-dot represent the target randomly distributed over the area.

We conducted the experiment in the area of size 67.8m×77.8m. We divide the monitoring area in a large number of small grids. Here the ground floor area is divided into 624 grids. Similarly, the first floor is also divided in 644 number of grids. figure 2. shows the localization setup of the ground floor. In this area, 13 wifi access points are placed all over the area. And we follow the same setup for the first floor. For uniquely identifying the target location we assign a unique number to each grid in the map. And the target location is defined as grid number. So, one grid is considered as one location. And, more than one target can be present in one grid.

A. Data Acquisition

For obtaining the labeled training data, we repeatedly collect the RSSI measurements of the mobile target from different locations. Data is represented as:
labeled data = (Y, X)
where , $Y \in N$, grid number
X $\in \mathbb{R}^n$ RSSI measurement vector

While collecting the data, Y (grid number) is the input by human operator and X (RSSI measurement vector) is obtained by the mobile device. We note that the training data set does not include the positions of the sensor nodes. Therefore, our algorithm does not need the locations of the sensor nodes.

B. Learning phase

Our algorithm for localization is consist of three steps *i.e.* offline learning phase, test phase and on-line learning phase.

1) Offline learning phase: Given the labeled training data, the major output of the training phase is a neural network model that maps the RSSI measurement vector to grid number. This can be considered as regression scheme which maps the input RSSI vector to a location.

2) Test Phase : Test data $x \in \mathbb{R}^n$ are defined as the RSSI measurement set obtained from all n sensor nodes or WIFI access points. Then we estimate the target location using test data by using trained model.

3) On-line learning phase: We consider a situation when new labeled data is available after the offline learning. For example, when one of the sensor nodes is not working. So, the purpose of on-line learning is to update the model when new labeled data comes.

As stated earlier, the monitoring area is divided in large number of small grid and labeled data is collected from each tile. Now, the problem becomes a classification problem in which target location is one of the 1268 grid.

VI. Results

A. Target localization

We place the same target on different locations and estimate the location using client app. Fig. 5 shows the estimated location as green grid and the actual location is red dot. In some cases, when target is located on the boundary of two grids then our model estimate the location as one of the two adjacent class but when the target is inside a grid then the model will correctly estimate the target location as the actual location/grid.

Fig. 4 shows the localization result collected using the client app on Xiomi redmi note 3 device. But these result may vary with the change of device as different device may have different NIC configuration. As we cannot do the testing on all different type of device, we added some noise to the data collected by Xiomi redmi note 3. Below is the result with change in noise level.

noise	$\sigma = 1$	$\sigma = 2$	$\sigma = 3$	$\sigma = 4$
Accuracy (%)	95.8	91.09	76.56	61.40

Here, each cell RSSI value is perturbed by adding Gaussian noise of different σ.

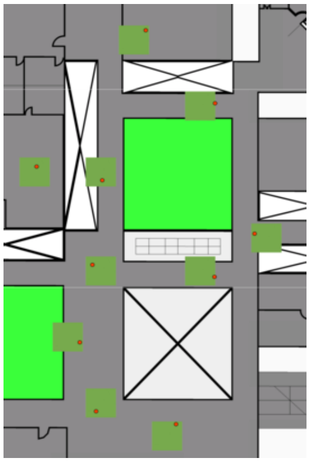

Fig. 4. Part of the map

B. Failure of AP's

We have considered the situation when some AP's failed. In that case, the location (cells) in the coverage of that AP's will me classified wrongly but all other location (cells) will be classified correctly.

# failed AP's	$n = 1$	$n = 2$	$n = 3$	$n = 4$	$n = 5$
Accuracy (%)	74.20	57.74	39.10	28.48	19.39

VII. Conclusion and Future Work

This paper present a very simple but efficient way to deal with localization problem as a classification problem. We have developed a system that can be deployed anywhere with some slight modification in the code. We have proposed a method which gives high accuracy with minimal computation. We deployed the trained neural network on android device as to reduce the computation on central server. But while tracking, the target location is estimated on central server because it need continuous predication of target location which makes it difficult to compute on mobile device.

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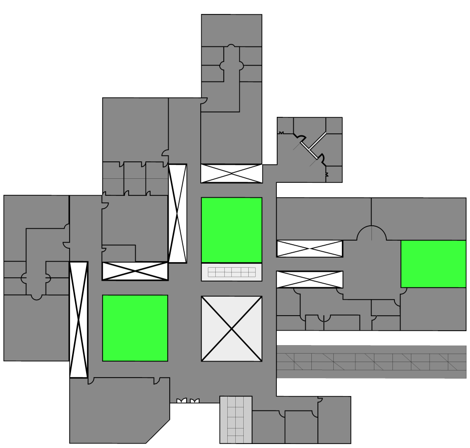

Fig. 5. Ground Floor Map

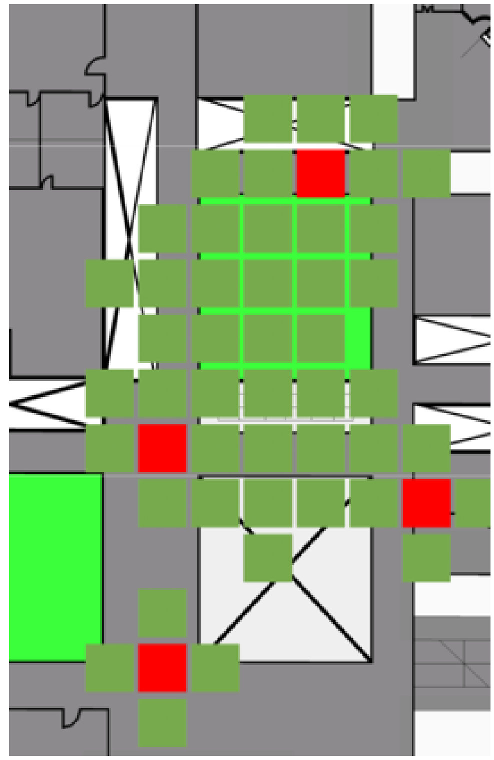

Fig. 6. This is how we divided the whole map into grids.

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