# Indoor Positioning Using WiFi Fingerprint

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***Abstract*— Indoor Positioning System helps to locate, monitor and track the devices using the radio signals. This can be used to find the people who are trapped inside a building. Outdoor localization problems can be solved by using Global Positioning System (GPS). Since GPS signals are lost inside the buildings, Indoor Positioning still remains a problem. This paper provides a technique for indoor positioning by using WiFi fingerprint. The intensity of the received signal is measured and is stored in a database. The database consists of the list of signal strength and their corresponding locations. The similarity of the signal detected and those stored in the database can used to detect the position of the user. The prevailing WiFi infrastructure can be used for this purpose. We use deep neural network with stacked autoencoders to determine the floor and building. The classifier is used to detect the building and the floor level .**

***Keywords—Indoor Positioning System, WiFi, Fingerprinting, stacked autoencoder, deep neural network***

## I. INTRODUCTION

The growth of mobile and other smart devices has created wide applications in tracking and monitoring the people and objects. Specially, this can be used to check the employee occupancy in offices. This also helps to know the working patterns of the employees which further helps to improve the productivity of the company[1].

In order to provide their services, many applications require the localization of a person or object. Global Positioning system solves the problems of outdoor localization. Indoor positioning still remains a problem because GPS signals are lost in indoors. Indoor positioning systems can be used to track and locate the people or objects in buildings or any other places by using the magnetic fields, radio signals or other sensory information. They can be used to find people who are trapped inside a building or any other places, monitor patients in a hospital, track employees inside an office[10]. Indoor positioning has become an important task and there is no global solution for all the applications. In large buildings and offices, large scanners are used for position estimates[8]. In limited areas, the networked cameras can be used[9]. There are many methods for indoor positioning. One of them is by capturing 802.11 radio signals. Mobile devices scans 802.11 signal periodically for access points. This require transmission of messages or sometimes data frames are send. These signals are collected by central monitor[3]. Fingerprinting is also used as WiFi signals are usually available indoors and can provide rough initial position estimate or can be used together with other positioning systems.

## II. LITERATURE SURVEY

The Indoor Positioning System have wide scale applications in today's world. The tremendous developments in mobile and smart devices has increased the attention to the IPS. There are many methods proposed by different authors for the purpose of indoor positioning.

R.Want [2] uses an Active Badge for indoor positioning. This Active Badge which is worn by persons or attached to objects emits a unique code identifier every 15 seconds. Network of IR sensors in building detects these transmissions. This data is collected by the central server and gather it to a central data bank. Thus the location of badge can be determined.

In [4], Hazas provides a method that use Ultrasonic tags called bats that emit periodic signal to receivers mounted across ceiling. The disadvantage of this method is that it requires large number of receivers across ceilings.

John Krumm [5] provides a system that uses two sets of stereo colour cameras to track multi persons in rooms. Stereo images are used to locate the people and colour images are used to maintain their identities. The disadvantages is that it can be expensive because it uses multiple cameras.

Another method proposed by D.Harmer explains an Ultra wide band technology in which the system estimates the Time of Arrival(ToA) of received pulse signals. These signals were transferred to a server computer where the location of transmitter was calculated. The indoor object will be equipped with an active tag and provided accurate information[6].

P. Bahl provides a Finger printing method, in which there are two stages: Off-line stage and On-line stage. In off-line stage, RSS values and physical coordinates are collected from RF transmitters at a reference point and stored in a database. In the On-line stage, mobile user samples the RSS pattern and searches for similar pattern in off-line database to find best possible position[7].

## III. IMPLEMENTATION

Indoor Positioning has become a challenging task in today's world. The GPS can be used for outdoor localisation. Since GPS signals are lost inside the building, the indoor positioning remains as a problem. In our system, WiFi signals are used for indoor localization. The captured WiFi signals

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can provide a rough estimation of the position of the devices. The system uses WiFi fingerprinting which consists of Access points and Received Signal Strength(RSSI). When the Access points are detected, the intensity values are shown as negative values. The positive values show when access points are not detected. The data is split into two and given to training and testing phase.

### A. Registration

First, the signals from the access points are registered. Signal strength of each position is estimated and recorded. When a user with the device comes to a particular position, based on the RSSI value previously recorded, the relative position is determined.

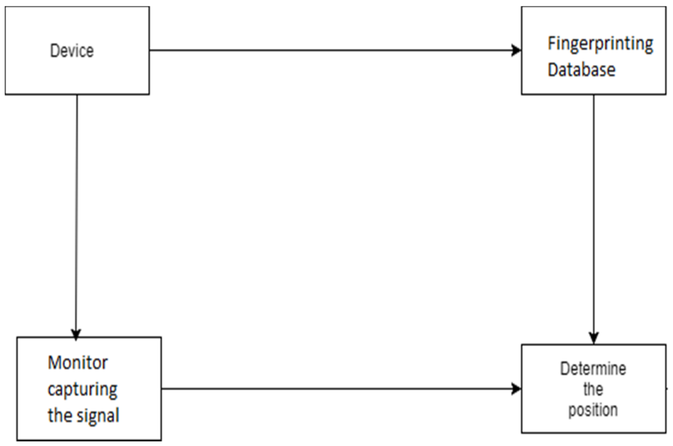


Figure 1: Architecture of the system

### B. Deep Neural Network

Deep Neural Network consists of an input layer, output layer and many hidden layers in between them. Here Stacked auto encoder(SAE) is used in deep neural network to determine the position. So that the input data's dimensionality is reduced. The input to the encoder is the received signal strength values of WiFi network. The output of decoder is the reconstructed RSSI of the input values. During the unsupervised training, the encoder is learnt and the encoder and decoder should be trained so that the output obtained is same as the input provided. After the unsupervised learning is performed, the decoder part is removed and the encoder part is connected to the classifier. The classifier predicts the probabilities of the signals being detected from different floors and buildings. The data used for the learning is divided into training and validation set. The learning of the neural network is done on training set and the validation data is used to check performance.

### C. Dataset

The dataset used for our system is UJIIndoorLoc dataset[10] which consists of the measurements of WiFi. It consits of 21048 WiFi measurements in which there are 19937 training data and 1111 validation data. The data is created using 25 Android devices. The dataset consists of 529 attributes of the WiFi fingerprint. In these 529 attributes , the first 520 attributes denotes the signal strength of the Wireless Access Points. The siganal strength vary from 0dBm to -104dBm. The positive value 100 denote the WAP is not detected.

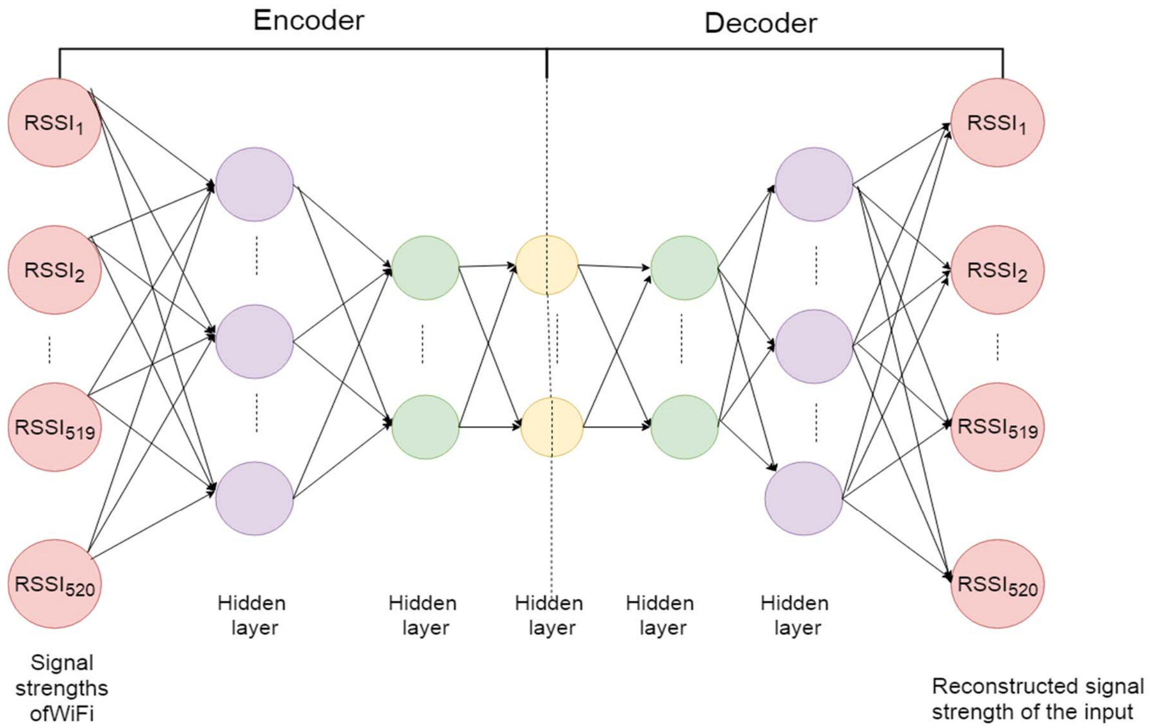


Figure 1: Architecture of autoencoder

The negative vlues are the intensity values, ranging from 104dBm(poor signal) to 0dBm. There are remaining 9 attributes. These attributes denote longitude and latitude of measurement, floor, building ID, space ID, relative position. The attributes also include user ID, phone ID and timestamp. The UJIIndoorLoc dataset does not contain testing data. So we divide the dataset into training and validation data.

## III. RESULTS AND DISCUSSIONS

The input to the encoder part is received signal strength values(WAP to WAP520). The output of decoder is reconstructed RSSI of input values. The table shows the loss and accuracy of training data at each iteration.

TABLE 1: LOSS AND ACCURACY OF THE NETWORK

| Epoch | Loss | Accuracy |
|---|---|---|
| 1 | 0.3145 | 0.8850 |
| 2 | 0.1361 | 0.9541 |
| 3 | 0.1056 | 0.9640 |
| ..<br>.. | ..<br>.. | ..<br>.. |
| 19 | 0.0361 | 0.9870 |
| 20 | 0.0389 | 0.9868 |

The overall network performs with an accuracy of about 93% over 20 epochs.

## III. CONCLUSION

We have come across the estimation of the position of the person by identifying the device position. This can used to determine the track and monitor the persons inside a buildings. The system uses the fingerprinting method for RSSI of each Access Points. This can be used to track the locations of objects. The system provides the relative position of the object or device. As a future work, the accurate position of the user can be determined.

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