INDOOR LOCALISATION USING SINGLE ACCESS POINT

THESIS

submitted by

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CERTIFICATE

This is to certify that the thesis entitled **"Indoor Localization using single access point"** submitted by **Tejavath Sai Tejaswi** to the Indian Institute of Technology, Madras for the award of the degree of **Bachelor of Technology,** is a bona fide record of research work carried out by her under our supervision. The contents of this thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

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ABSTRACT

Smartphones are mobile embedded devices with advanced capabilities beyond ordinary mobile phones. Smartphones have gone from becoming a luxury to becoming a necessity these days. The advancement of smartphone devices equipped with Wi-Fi has led to a new generation of new applications and solutions. These devices give away a great deal of information about the user (location, posture, communication patterns, etc.), which helps in capturing the user's context. Such information can be utilized to create smarter apps from which the user can benefit. A challenging new area that is receiving a lot of attention in indoor localization as interest in location-based services is also rising. Indoor localization has recently witnessed an increase in interest, due to potential wide range of services it can provide by leveraging Internet of Things (IoT), and ubiquitous connectivity. In this thesis, we propose innovative technique based on machine learning algorithms for Indoor Localization. In this work, we propose a technique based on machine learning algorithms and classify the location of the user without using any sensors and extreme mathematical equations which are used in inertial measurement unit (IMU), monocular camera simultaneous localization and mapping (SLAM) and Wi-Fi SLAM. The only factor which we take into consideration is the variation of Received Signal Strength Indicator (RSSI) with time.

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CHAPTER 1
INTRODUCTION

1.1. INTRODUCTION

GPS works extremely well for localization in an outdoor environment. Unfortunately, due to the signal attenuation caused by construction materials, the satellite based Global Positioning System (GPS) loses significant power indoors affecting the required coverage for receivers by at least four satellites. In addition, the multiple reflections at surfaces cause multi-path propagation serving for uncontrollable errors. These very same effects are degrading all known solutions for indoor locating which uses electromagnetic waves from indoor transmitters to indoor receivers.

1.2. OBJECTIVE OF THE WORK

The objective of the work is to predict the location of the user without using any sensors and extreme mathematical equations. As there is only one access point available, it is quite different to predict the location of the user. The main attribute that contributes to determine the position of the user is RSSI. So with the help of one access point, we should be able to predict the location of the user

1.3. SCOPE OF THE THESIS

This thesis is an attempt to present the understandings developed from various experimental observations. With the help of this thesis we will be able to predict the zone of the user with the help of one access point as mentioned above.

The literature review part explains the theoretical concepts and the research behind the experiment. In chapter 3, experiment details give the environment and the procedure followed in the experiment. Chapter 4 tells us to modify the data in the required form and then building the models. Chapter 5 discusses about results and discussions. Chapter 6 on conclusions.

CHAPTER 2
LITERATURE REVIEW

2.1. BACKGROUND

Due to their proliferation in modern technology and society, radio frequency (RF) signals have been the target of numerous studies, and their general behavior in idealistic cases has been understood. These properties have been exploited in technologies prominent today, ranging from localization by triangulation in Global Positioning Systems (GPS) to mobile communications through cellular networks. Fingerprinting methods are used to determine the location in the indoor environment[5]. The indoor localization method in this paper specifically rely Wi-Fi power distributions in indoor environments, as explained in the following sections.

2.2. RECEIVED SIGNAL STRENGTH INDICATOR

Received Signal Strength Indication (RSSI) is one of the most commonly used characteristics for indoor localization. It is the measure of the power present in a signal sent from an access point to a client device or vice-versa. As radio waves attenuate according to the inverse-square law, the distance can be approximated based on the relationship between the transmitted and received signal strengths, as long as no other errors contribute to incorrect measurements. The combination of this information with a propagation model can help to determine the distance between the two devices [4].

It can be assumed that a greater amount of information can be collected as the number of available access points increases. Hence, the accuracy could be increased if relevant information is obtained. However, this also works as a trade-off. An increase in the number of access points thereby would increase the interference between different signals. A key challenge in wireless localization systems is that the range measurements are often associated with errors. RSSI techniques are among the cheapest and easiest methods to implement, but they do not provide the best accuracy. Filtering is necessary to improve system accuracy using RSSI-based localization.

2.3. SELECTION OF THE SIGNAL

As mentioned, the primary data source for this paper will be ambient RF signals. It was decided that out of the RF signals accessible to Android (Wi-Fi 802.11x, Bluetooth, GPS, Cellular, and sometimes FM), Wi-Fi would be the principal source of signal data for current system iteration.

This was due to its balance of reliable, stationary node positioning (that act as" beacons" to guide the system in indoor navigation) and its significant correlation of power with proximity (so that different distances from the source could be more easily distinguished). Other RF signals collected by Android, even if capable in staticity, perform poorly in RSSI variability, and vice versa [3].

2.4. PROBLEM DEFINITION AND APPROACH

The present work focuses on Indoor Localization using RSSI. RSSI is collected at different locations by dividing the room in several zones. So RSSI is the only input which we are dealing with. But the RSSI significantly varies in short range of time, it is not possible to predict the location of the single RSSI value (having the RSSI value alone). Hence, we take the pattern of RSSI values as the features and proceed by building a machine learning model to the dataset.

CHAPTER 3

EXPERIMENTAL DETAILS

3.1. ENVIRONMENT

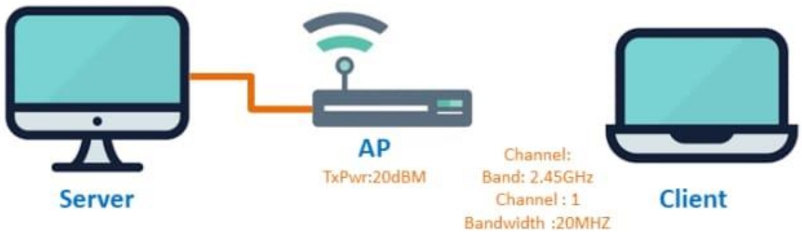


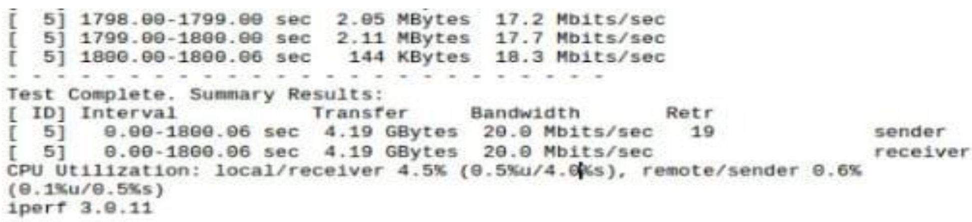
Figure 1. Experimental setup

The server is connected to the router via LAN whereas the client is connected to the router via Wi-Fi. The experiment was conducted in two different rooms. The first room is a lab with multiple cabins while the second room is a conference room.

3.2. SOFTWARES USED

To establish a connection between server and client using TCP and measure various parameters various tools are used. They are listed below.

1. iPerf3: To establish connection and generate traffic. A sample output of iperf application is shown below which indicates TCP file transfer.



```
[  5] 1798.00-1799.00 sec  2.05 MBytes  17.2 Mbits/sec
[  5] 1799.00-1800.00 sec  2.11 MBytes  17.7 Mbits/sec
[  5] 1800.00-1800.06 sec   144 KBytes  18.3 Mbits/sec
- - - - - - - - - - - - - - - - - - - - - - - - -
Test Complete. Summary Results:
[ ID] Interval           Transfer     Bandwidth       Retr
[  5]   0.00-1800.06 sec  4.19 GBytes  20.0 Mbits/sec   19             sender
[  5]   0.00-1800.06 sec  4.19 GBytes  20.0 Mbits/sec                  receiver
CPU Utilization: local/receiver 4.5% (0.5%u/4.0%s), remote/sender 0.6%
(0.1%u/0.5%s)
iperf 3.0.11
```

Figure 2. Sample of traffic generated from server to client

2. netcat : To transfer and store measurements from AP to local server. The below figure shows

```
        wiphy 1
        channel 52 (5260 MHz), width: 20 MHz, center1: 5260 MHz
        txpower 20.00 dBm
Station d0:53:49:60:a3:a1 (on phy0-wlan0)
        inactive time:   9830 ms
        rx bytes:   139679
        rx packets: 1741
        tx bytes:   140509
        tx packets: 949
        tx retries: 0
        tx failed:  40
        rx drop misc:     10
        signal:     -47 [-53, -49, -95, -95] dBm
        signal avg: -53 [-58, -54, -95, -95] dBm
        tx bitrate: 150.0 MBit/s MCS 7 40MHz short GI
        rx bitrate: 1.0 MBit/s
        rx duration:      206153 us
        authorized: yes
        authenticated:    yes
        associated: yes
        preamble:   short
        WMM/WME:    yes
        MFP:        no
        TDLS peer:  no
        DTIM period:      2
        beacon interval:100
        short preamble:   yes
        short slot time:yes
        connected time:   4549 seconds
```

Figure 3. Several parameter values stored using netcat

3. Rsyslog: To store logs of the AP

3.3. HARDWARE COMPONENTS

The components required in this experiment are one access point, one server and one client. The access point used in this experiment is Asus RT-AC58U and conducted experiments in 2.4GHz. The channel allocation is dynamic.

3.4. EXPERIMENT METHODOLOGY

The first experiment was conducted in a lab with multiple cabins which causes interference of signals. RSSI values are taken at different positions in Line-of-Sight and Non-Line-of-Sight to observe the effect of RSSI based on distance parameter and also an initiation step to find location of the user.

The same experiment is repeated in conference room. The room is divided into two zones namely Location 1 and Location 2 as shown below. Each of the zone is further divided into four sub-zones as location 1, location 2 and so on as shown below. The x variables of the data conducted will be RSSI whereas the y variable of the data will be location (zone) number.

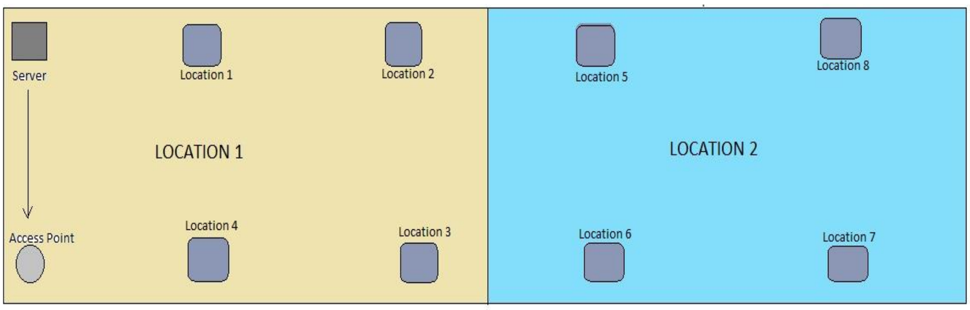


Figure 4. Partition of zones in a room.

CHAPTER 4

DATA REPRESENTATION AND BUILDING MACHINE LEARNING MODELS

As the RSSI value varies significantly vary within a small change in time as mentioned above, it is not possible to train a single RSSI value. So I took RSSI patterns as variables against the location. In this experiment, approximately 3600 RSSI values are there for a single location. So, I reframed it into 60X60, where each data point is a 60 values of RSSI and trained this dataset via machine learning model to predict the location given the pattern of RSSI values. One model is built considering 2 locations whereas the other is built considering 8 locations.

	0	1	2	3	4	5	6	7	8	9	...	52	53	54	55	56	57	58	59	60	61
0	-53	-74	-53	-74	-53	-74	-53	-74	-53	-74	...	-52	-50	-52	-50	-52	-50	-52	-50	1	1
1	-52	-50	-52	-51	-52	-50	-52	-50	-52	-49	...	-52	-50	-52	-50	-52	-50	-52	-50	1	1
2	-52	-50	-52	-50	-52	-50	-52	-50	-52	-49	...	-54	-51	-54	-51	-54	-51	-54	-51	1	1
3	-54	-51	-54	-51	-54	-50	-54	-51	-54	-51	...	-54	-49	-54	-49	-54	-49	-54	-50	1	1
4	-54	-50	-54	-49	-54	-49	-54	-49	-54	-50	...	-53	-50	-53	-50	-53	-50	-53	-50	1	1
5	-53	-49	-53	-51	-53	-49	-53	-49	-53	-49	...	-56	-50	-56	-50	-56	-50	-56	-50	1	1
6	-56	-50	-56	-50	-56	-50	-56	-50	-56	-50	...	-56	-50	-56	-50	-56	-51	-56	-52	1	1

Figure 5. Sample of dataset of location1.

Our main goal is to predict the location of the user. In order to predict the location zone of the user, the model should be trained by the data and later test the data to check the accuracy. Since it is a classification problem, supervised learning is used (like Linear Discriminant Analysis, Random Forests, kNN etc.). Deep learning techniques like Encoder Decoder, LSTM predict the location zones more accurately.

CHAPTER 5

RESULTS AND DISCUSSION

The below given plot is the variation of RSSI with time of different locations for a small duration. As the distance increases the RSSI value decreases (location 8 is far away from access point compared with other locations)

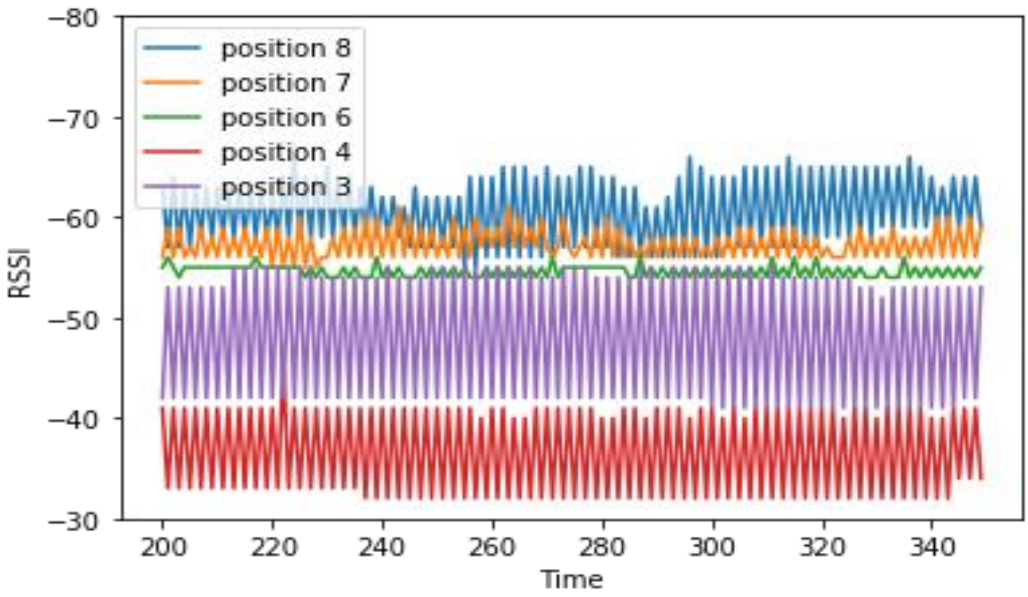


Figure 6. Received Signal Strength Indicator vs Time in various locations.

Boxplot is a standard way of representing the distribution of data based on 5 number summary. They are minimum, first quartile (Q1), median, third quartile (Q2), maximum.

Interquartile range (IQR) = Q3-Q1

minimum = Q1-1.5*IQR

maximum = Q3+1.5*IQR

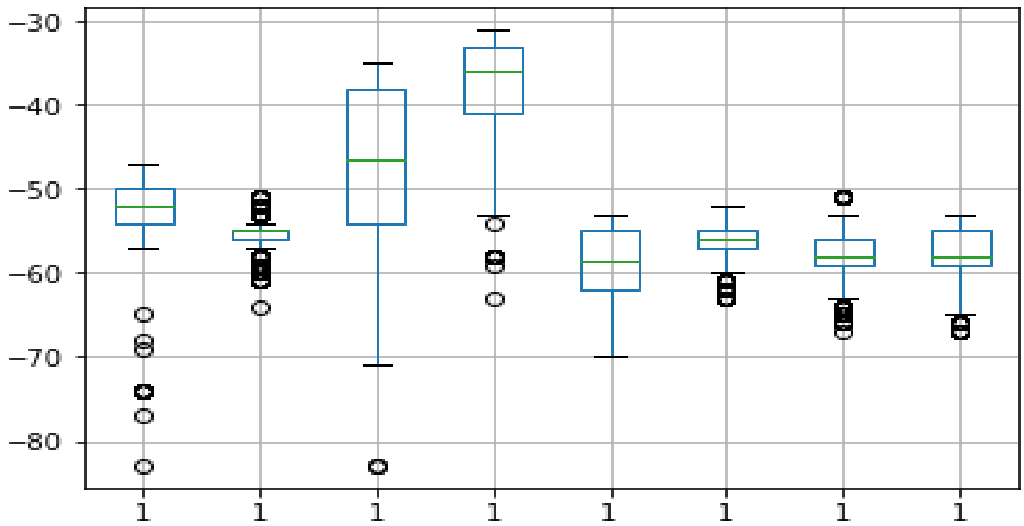


Figure 7. Boxplot of the RSSI signals in various zones

From the box plot we can conclude that no two locations have same mean and are not identical distributions. They do not vary in the same manner which can be taken as a advantage in determining the location

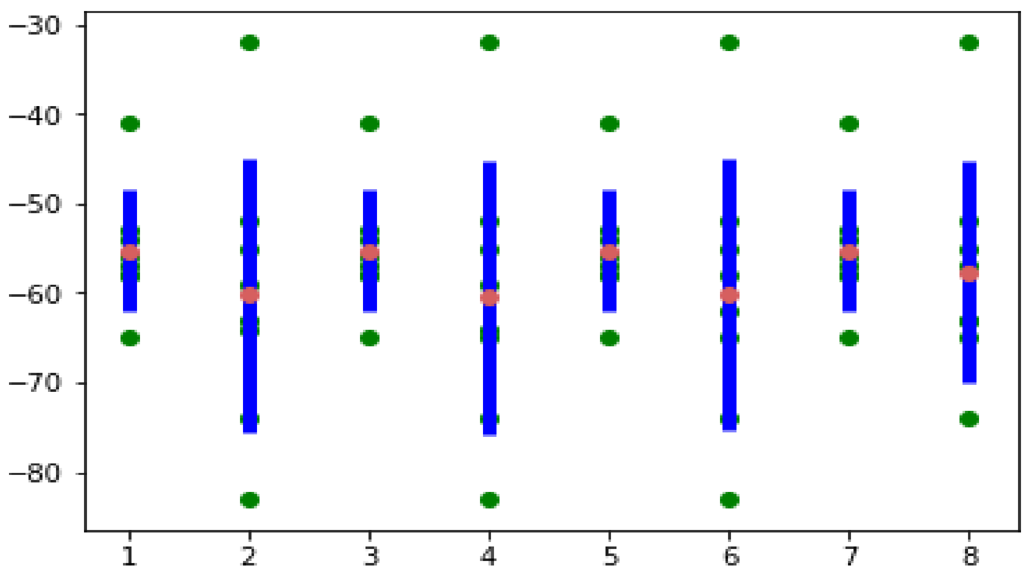


Figure 8. Error bar plot in various zones

Accuracy for two location based model is 97.87 using KNN algorithm

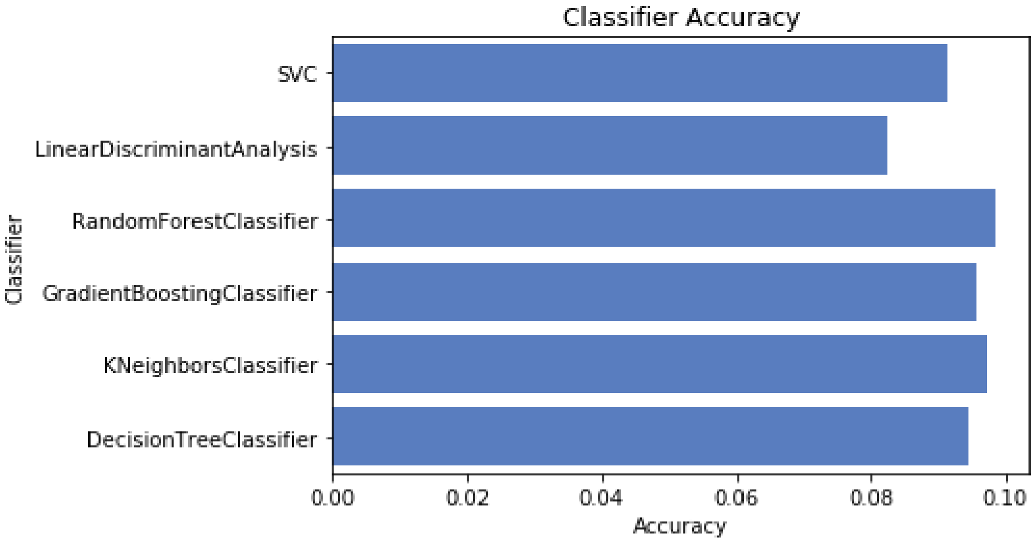


Figure 9. Classifier vs Accuracy in 2 location based model

Accuracy for eight location based model is 94.33 using KNN algorithm

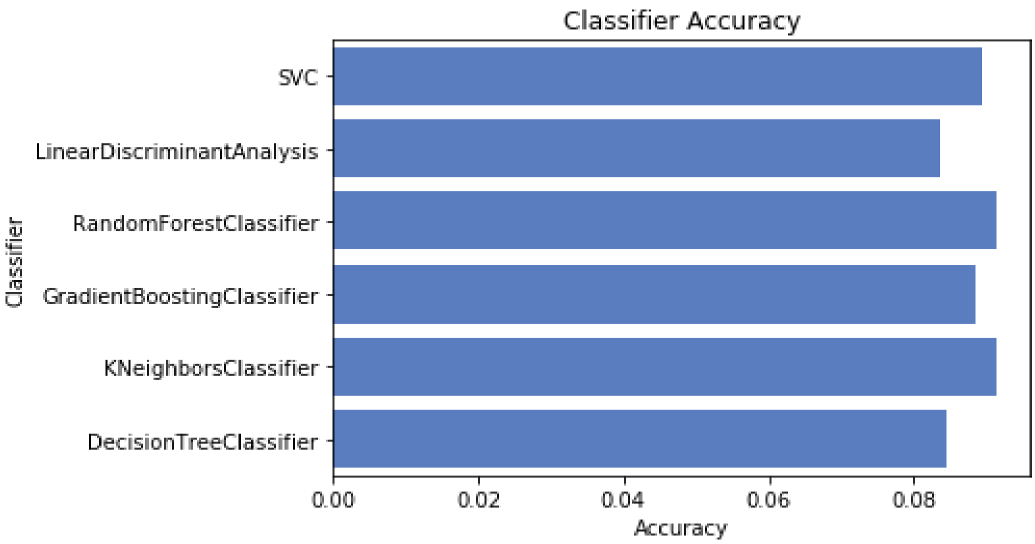


Figure 10. Classifier vs Accuracy in 8 location based mode

CHAPTER 6

CONCLUSIONS

The following are the conclusions drawn from the above results: -

- RSSI vary significantly in a given amount of time at the fixed location due to several factors.
- Environment dependent errors in RSSI measurements are caused by shadowing, i.e., the attenuation of a signal due to obstructions (furniture, walls, trees, buildings, and more) that a signal must pass through or diffract around in its path between the transmitter and receiver. Shadowing is also called medium-scale fading.
- Multiple signals with different amplitudes and phases arrive at the receiver, and these signals add constructively or destructively as a function of the frequency, causing frequency-selective fading.
- The accuracy reduces as the number of locations (zones) increases. This can be overcome by considering other factors as well.
- Determining the position of the user when the difference between two zones is identical is very difficult.

RECOMMENDATIONS FOR THE FUTURE WORK

The following are the things that can be worked upon in the future: -

- Accuracy of the position system may be still improved by the appropriate deployment and proper number of fixed wireless receivers. As mentioned above there will be a tradeoff between number of wireless devices and channel conditions.
- Predicting the location of the user can be done by having much more information about the environment rather than classifying them into zones.

- Attaining high level of accuracy with precision is one of the most important thing.

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