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SSD BASED LOCATION IDENTIFICATION USING FINGERPRINT BASED APPROACH

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ABSTRACT: *Fingerprint-based methods are widely adopted for indoor localization purpose because of their cost-effectiveness compared to other infrastructure-based positioning systems. However, the popular location fingerprint, Received Signal Strength (RSS), is observed to differ significantly across different devices' hardware even under the same wireless conditions. We derive analytically a robust location fingerprint definition, the Signal Strength Difference (SSD), and verify its performance experimentally using a number of different mobile devices with heterogeneous hardware. Our experiments have also considered both Wi-Fi and Bluetooth devices, as well as both Access-Point (AP)-based localization and Mobile-Node (MN)-assisted localization. Also compare these SSD-based localization algorithms' performance against that of two other approaches in the literature that are designed to mitigate the effects of mobile node hardware variations, and show that SSD-based algorithms have better accuracy. To justify this we make a data transfer between the nodes using the SSD-based and it proves the accuracy.*

I. INTRODUCTION

Accurate indoor location determination is an indispensable building block of various context-aware services and ubiquitous environments. Geometric approaches require Antenna arrays with large number of array elements on transceivers to achieve good accuracy, which incur high hardware cost. On the other hand, fingerprint-based approaches, utilizing signal parameters provided by off the- shelf wireless devices, are widely adopted for indoor Localization purpose for their cost-effectiveness. In a typical fingerprint-based system, a set of "training locations" are chosen in the service area. During an offline "training phase," location-dependent signal parameters, most commonly Received Signal Strength (RSS) values are measured and recorded at each training location as the fingerprint for that particular location. During the online localization phase, various methods utilizing the recorded data can be applied to estimate the target device's location when the online RSS values of the device are collected.

1.1 Robust RF Location Fingerprint:

In a typical fingerprint-based system, a set of "training locations" are chosen in the service area. During an offline "training phase," location-dependent signal parameters, most commonly Received Signal Strength (RSS) values are measured and recorded at each training location as the fingerprint for that particular location. During the online localization phase, various methods utilizing the recorded data can be applied to estimate the target device's location when the online RSS values of the de RSS is the most common RF signal parameter used as location fingerprints for Wi-Fi s . For Bluetooth, both "Received Signal Strength Indicator (RSSI)" and "Link Quality (LQ)" have been previously used as location fingerprints vice are collected. Based on their analysis, it is apparent that all these signal parameters have specific usage according to their own respective technologies, which may render them inappropriate as location fingerprints. Among all the signal parameters available, RSS is argued to be the most viable option as location fingerprint for both Wi-Fi and Bluetooth.

1.2 Signal Strength Difference (SSD)

By comparing the two types of signal strength ,the signal strength differences are analyzed Signal Strength Difference (SSD), which was shown to outperform the traditional RSS fingerprint in terms of robustness across heterogeneous mobile devices, both analytically and experimentally they analyze the robustness of SSD more elaborately, In existing localization literature, they usually encounter two different approaches to collect the signal strength samples, namely, AP-based, where the RSS is measured at the AP, and MN-assisted, where the RSS is actually measured at the MN itself. In order to verify SSD's robustness, here by considering both of these scenarios. Using several off-the-shelf Wi-Fi and Bluetooth devices they derive analytically a robust location fingerprint definition, the Signal Strength Difference (SSD), and verify its performance experimentally using a number of different mobile devices with heterogeneous hardware.

II. PROBLEM DESCRIPTION

2.1 Existing System:

Most of the indoor location determination is an indispensable building block of various context-aware services and ubiquitous environments. Geometric approaches require antenna arrays with large number of array elements on transceivers to achieve good accuracy, which incur high hardware cost. On the other hand, fingerprint-based approaches, utilizing signal parameters provided by off the- shelf wireless devices, are widely adopted for indoor localization purpose for their cost-effectiveness. In a typical fingerprint-based system, a set of "training locations" are chosen in the service area. During an offline "training phase," location-dependent signal parameters, most commonly Received Signal Strength (RSS) values are measured and recorded at each training location as the fingerprint for that particular location. During the online localization phase, various methods utilizing the recorded data can be applied to estimate the target device's location when the online RSS values of the device are collected. Various commercially available hand-held devices and wireless Access Points (APs) are capable of reporting RSS. In general, the RSSs are mostly reported in dBm values. However, these devices usually come with many different hardware solutions, even for the same wireless technology. Regardless of whether a device's signal strengths as perceived by the APs are used to denote the device's location fingerprint, or the reverse approach in which the APs' signal strengths as perceived by the device (i.e., Mobile Node (MN)) are used, such fingerprints may differ significantly with the device's hardware, even under the same Wireless. This is often observed in existing popular wireless technologies, such as Wi-Fi or Bluetooth.

2.2 Major Issues:

Received signal strength (RSS), Network topology will haven't stable it may be differ according to the hardware variation whether a device's signal strengths as Perceived by the APs are used to denote the device's Location fingerprint, or the reverse approach in which the APs' signal strengths as perceived by the device Mobile Node (MN)) are used, such fingerprints may differ Significantly with the device's hardware even under the Same wireless conditions. This is often observed in existing popular wireless technologies, such as Wi-Fi or Bluetooth and the presence of power control feature in some mobile devices further complicates the issue. As a result, a positioning system that relies solely on RSS to define location fingerprints generally does not perform well across heterogeneous devices

III. PROPOSED WORK

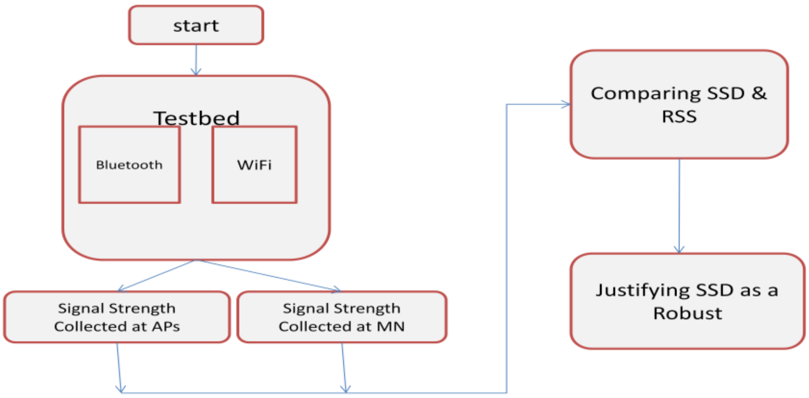

Fig 1: Proposed work Flow of Robust Location using SSD.

The need for a robust location fingerprint is obligatory for any fingerprint-based localization algorithm; a robust location fingerprint is proposed, namely, Signal Strength Difference (SSD). SSD was shown to outperform the traditional RSS fingerprint in terms of robustness across Heterogeneous mobile devices. **(**Fig 1: shows the) Proposed work Flow of Robust Location using SSD. The signal strength samples are collected at the APs or at the MN, SSD is a more robust location fingerprint compared to the traditional RSS.

IV. RELATED WORK

4.1 Setting up the testbed

The two experimental Testbed 1 and Testbed 2 are created in here; these testbed located inside a laboratory in real time environment, but here due to high cost of setting these Testbeds, the two Testbeds are created with the help of Netbeans Java Tool. Testbed 1 is AP (Access point) Wi-Fi Testbed located inside a laboratory; Here the nodes are created and they are going to act between the Access point and Mobile node(Shown in Fig.2) and here the two more are AP' are created. Testbed 2 is a MN (Mobile node) Bluetooth Testbed located within another laboratory. Due to widespread availability of Wi-Fi and Bluetooth networks within buildings, then choose both of these RF wireless technologies for the analysis and experiments the testbed 1 emulates the AP-based positioning system where the signal strengths are actually measured at the AP side. The testbed 2 follows an MN-assisted approach where the MN itself retrieves the signal strength information.

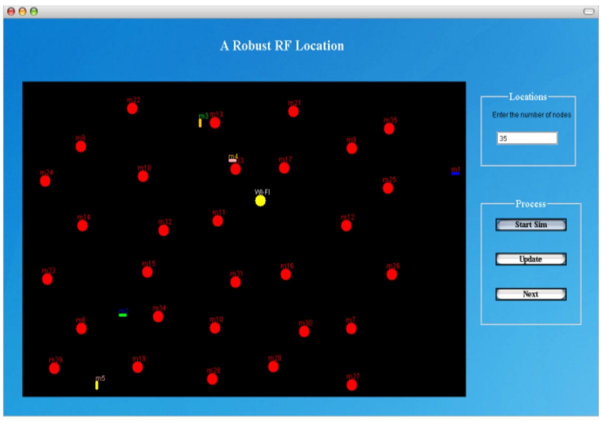

Fig. 2: AP based Localization.

4.2 Establishing Front End (GUI):

In two testbeds the training process involves placing the mobile device at each training point, and collecting data. Our front-end of the signal strength collection program has a Java Graphical User Interface (GUI).That graphical user inter face allows the user to load the map, location, distance to be trained conveniently. Normally the tcp dump is used to capture the signal strength at the MN. The Bluetooth signal strength information retrieval program is written utilizing the protocol stack. The central server is also responsible for calculating the location during the testing phase, and the distance for robust location is estimated here with the help of following equations suppose P (d) and P (d_0) denote the received signal strengths at an arbitrary from the transmitter,

$$\left[\frac{P(d)}{P(d_0)}\right]_{dB} = -10\beta\log\left(\frac{d}{d_0}\right) + X_{dB} \qquad (1)$$

The first term on the Right Hand Side (RHS) of (1) defines the path loss component (β is the path loss exponent), while the second term reflects the variation of the received power at a certain distance ($X_{dB} \sim N(0, \sigma_{dB}^2)$).Equation (1) can be rewritten as

$$P(d)|_{dBm} = P(d_0)|_{dBm} - 10\beta\log\left(\frac{d}{d_0}\right) + X_{dB} \qquad (2)$$

Depending on the hardware used at both the AP and the MN, the perceived power at a reference distance (i.e., P (d_0)) varies, as a result of hardware-specific parameters, such as Antenna gains. Therefore, the perceived RSS at a distance d is also hardware-dependent. This explains why RSS is not a robust location fingerprint, although it is commonly used in the existing literature. To simplify first focus on the AP based approach, where the MN is the transmitter, while the AP is the receiver. Rather than using absolute RSS values as location fingerprints, the difference of the RSS values observed by two APs (i.e., SSD) can be used to define a more robust signature for a transmitting mobile device. In order to explain analytically, let P(d_1)and P(d_2)denote the RSSs of a mobile device's transmitted signal as perceived at two different APs (AP1 and AP2) which are at distances $d_1$and $d_2$from the mobile device, respectively. Assume that all the APs have the same hardware properties, since it is quite common for an institution to choose the same brand and model for all their APs in the building. Consequently, using (2) write the following for AP1 and AP2,

$$P(d_1)|_{dBm} = P(d_0)|_{dBm} - 10\beta_1\log\left(\frac{d_1}{d_0}\right) + [X_1]_{dB} \qquad (3)$$

$$P(d_2)|_{dBm} = P(d_0)|_{dBm} - 10\beta_2\log\left(\frac{d_2}{d_0}\right) + [X_2]_{dB} \qquad (4)$$

$$\left[\frac{P(d_1)}{P(d_2)}\right]_{dB} = -10\beta_1\log\left(\frac{d_1}{d_0}\right) + 10\beta_2\log\left(\frac{d_2}{d_0}\right) + [X_1 - X_2]_{dB} \qquad (5)$$

Equation (5) denotes SSD's expression, which is free from P (d_0). Based on the above analysis, that claims the SSD is more robust against device hardware variations, Fig.4.5: Estimated SSD location using Access points compared to traditional RSS in denoting the location fingerprint. In the following sections, this was explained in a more detailed way. Also inspect the case of MN-assisted localization where the signal strength samples are actually collected at the MN. Here, the shadowing model of RF propagation analysis is applied, which is a common practice in existing indoor localization literature for the sake of analytical tractability. The shadowing model has also been used to model indoor RF propagation in popular "Wireless Communications" textbooks.

Nevertheless, also provide an alternative analysis using multipath propagation channel model in Appendix. Note that, although it is common for Wi-Fi communication infrastructure in most campus and industrial buildings to have APs with the same brand and model, it is not a mandatory condition for the proposed SSD fingerprint to Work in practice. This will show in the following analysis, as long as each AP remains constant for both the training Phase and the localization phase, the proposed scheme is able to eliminate the hardware differences caused by device heterogeneity.

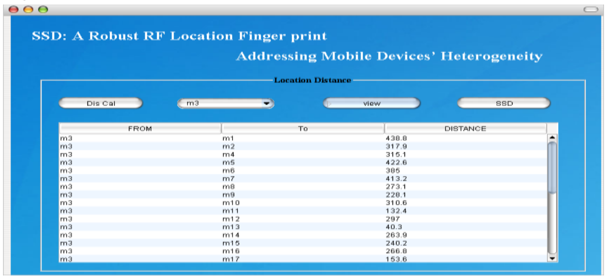

Fig.3: Calculated Distance between the Nodes.

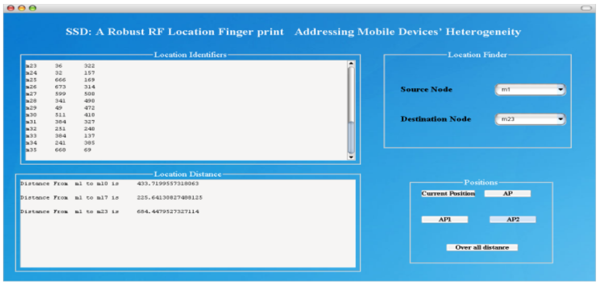

Fig.4: Distance between the AP'S

4.3 Gathering RSS and SSD Information:

The Received signal strength (RSS) and signal strength difference are collected with the help of location and signal strength, by using the different RSS from many AP's the heterogeneity may get differ to prove the Robustness we use here the SSD based approach is used, the d_1 and d2 as a different signal strength and comparing this two (3) and (4). We derive the SSd based expression (6),this will prove the traditional RSS and device hetroginity. P (d_1) and P (d_2) - RSSs of a mobile device's transmitted signal.d_1 - Received signal strengths at an arbitrary distance d and d_0 - Reference distance from the transmitter. β - Path loss exponent, $G_{AP}-$ is the (i^{th}) AP's antenna gain. L - System loss factor. λ_{MN} - transmitted carrier's wavelength. To prove this SSD in some more detailed and to rectify some issues like antenna gain and power variation this SSD's are compared with other two approaches AP- based and MN- based approach by these two approaches , and the signal strength difference (SSD) is analyzed, And here all information's are gathered and calculated with the following equations.

Fig.5: RSS and SSD's are analyzed from AP's.

4.3.1 AP-based method:

Consider the same scenario as above but with the assumption that the reference power, i.e., P (d_0) of (2), can be evaluated using the free space propagation model and this is the AP based approach

$$\boldsymbol{P(d_0)|_{dBm} = 10\log\left(\frac{P_{MN}G_{MN}G_{AP_i}\lambda_{MN}^2}{16\pi^2 d_0^2 L}\right)} \qquad (6)$$

Where $P_{MN}$is the MN's transmitted power, G_{MN} is the MN's antenna gain, P_{MN} is the AP's antenna gain, L is the System loss factor, and G_{AP_i} is the transmitted carrier's Wavelength.

$$\boldsymbol{P(d_1)|_{dBm} = 10\log\left(\frac{P_{MN}G_{MN}G_{AP_1}\lambda_{MN}^2}{16\pi^2 d_0^2 L_1}\right) - 10\beta_1\log\left(\frac{d_1}{d_0}\right) + [X_1]_{dB}} \qquad (7)$$

$$\boldsymbol{P(d_2)|_{dBm} = 10\log\left(\frac{P_{MN}G_{MN}G_{AP_2}\lambda_{MN}^2}{16\pi^2 d_0^2 L_2}\right) - 10\beta_2\log\left(\frac{d_2}{d_0}\right) + [X_2]_{dB}} \qquad (8)$$

$$\boldsymbol{\left[\frac{P(d_1)}{P(d_2)}\right]_{dB} = 10\log\left(\frac{G_{AP_1}L_2}{G_{AP_2}L_1}\right) - 10\beta_1\log\left(\frac{d_1}{d_0}\right) + 10\beta_2\log\left(\frac{d_2}{d_0}\right) + [X_1 - X_2]_{dB}} \qquad (9)$$

Subtract (8) from (7), the expression of SSD for the AP-based approach in (9),this may not prove the Robust due to some issues because of MN, It does not contain any MN-dependent term Fig.6:Signal Strength difference for AP-based Approach. Therefore, the SSD would be entirely free from any influence caused by the MNs' hardware variations. Moreover, even if different APs have different antenna gains and system loss factors, as long as these settings for each individual AP remain consistent across both training and localization, SSD will achieve consistency between the offline and online fingerprints.

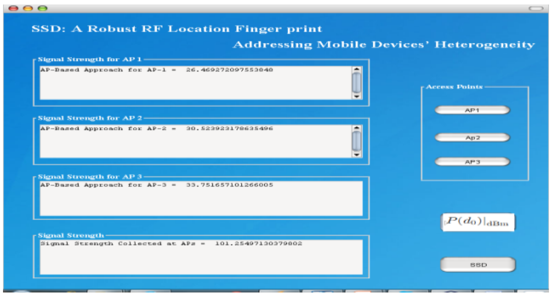

Fig.6: Received signal strength from different AP's

Fig.7: Signal strength difference for AP-based

4.3.2 MN-based method:

The same scenario as above was considered, and the signal strength is now measured at the MN rather than at the APs Fig.7: Signal Strength for Mobile Node. Subsequently, (7) and (8) take the following forms, respectively,

$$\boldsymbol{P(d_1)|_{dBm} = 10\log\left(\frac{P_{AP_1}G_{AP_1}G_{MN}\lambda^2{}_{AP_1}}{16\pi^2 d_0^2 L_1}\right) - 10\beta_1 \log\left(\frac{d_1}{d_0}\right) + \ [X_1]_{dB}} \quad (\mathbf{10})$$

$$\boldsymbol{P(d_2)|_{dBm} = 10\log\left(\frac{P_{AP_2}G_{AP_2}G_{MN}\lambda^2{}_{AP_2}}{16\pi^2 d_0^2 L_2}\right) - 10\beta_2 \log\left(\frac{d_2}{d_0}\right) + \ [X_2]_{dB}} \quad (\mathbf{11})$$

In order to compute SSD in this scenario, subtract (11) from (10),

$$\boldsymbol{\left[\frac{P(d_1)}{P(d_2)}\right]_{dB} = 10\log\left(\frac{P_{AP_1}G_{AP_1}\lambda^2{}_{AP_1}L_2}{P_{AP_2}G_{AP_2}\lambda^2{}_{AP_2}L_1}\right) - 10\beta_1 \log\left(\frac{d_1}{d_0}\right) + \log\left(\frac{d_2}{d_0}\right) + \ [X_1 - X_2]_{dB}} \quad (\mathbf{12})$$

Again, in the MN-assisted approach Fig.7: Signal Strength for Mobile Node Actually Measured from Access point, the SSD is entirely free from the influence caused by MNs' hardware variations. Although the SSD expression is affected by different APs' configurations such as power settings, antenna characteristics, and operated channels, as long as the configuration for each individual AP remains consistent across both training and localization phases, the SSD will achieve consistency between the offline and online fingerprints. Furthermore, even if the APs were to switch to different channels from the training phase, the changes in the λ's of (12) will not be significant. It should also be noted that, the samples gathered at the MN can be derived from the beacon frames that come from the APs. Since these Frames are generally sent using some default power setting.$P_{AP_1} \approx P_{AP_2}$Disadvantage compared to an RSS that, if the same device were to be used for both training and online localization phases, then the use of RSS fingerprint vectors could yield better localization accuracy than SSD fingerprint vectors. Nevertheless, that when N is large (N >5), an increase in RSS fingerprint vector's dimensionality no longer results in any significant improvement of the localization accuracy. Therefore, the effect arising from the slightly smaller dimensionality of the SSD fingerprint vector should also become insignificant when N is large. In many practical scenarios, a localization system is intended to track heterogeneous devices, and hence, expect the user devices to be frequently different from the training device. The different devices tend to report quite different RSS values at the same location. Under such circumstances, the use of RSS as a location fingerprint usually results in significant deterioration of the localization accuracy. The SSD, in contrast, is able to maintain its good localization accuracy across heterogeneous devices. With four APs, it is observed that the localization accuracy obtained from using SSD fingerprints is only slightly lower than using RSS Fingerprints when the same device is used for both training and online localization phases. However, in the more practical case in which different devices are used for training and online localization

Respectively, the SSD outperforms RSS significantly even though the SSD fingerprint vector has a smaller dimensionality Fig.:8 Signal Strength Difference (SSD).

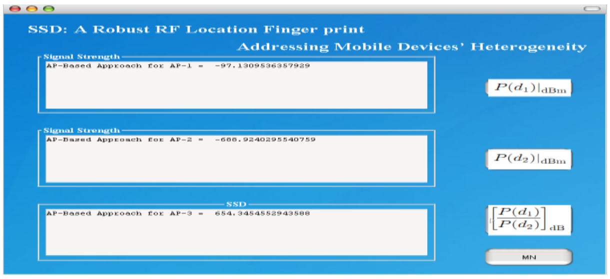

Fig.8: Signal strength difference for MN-based Approach

4.4 Comparison between SSD and RSS:

A robust location fingerprint definition is derived analytically, the Signal Strength Difference (SSD). The SSD, which provides a more robust location signature compared to the traditional RSS in the presence of mobile node hardware heterogeneity. To investigate further, the experiments inside both AP based Wi-Fi (Testbed 1) and MN-assisted Bluetooth (Testbed 2) testbeds to visualize the effects of MN's hardware variations. In order to inspect the "same device" effect, among these user fixed nodes the test is undergone. Then run the algorithms (i.e., KNN and Bayesian) to obtain the localization errors. Repeat this procedure for 101 times in order to obtain all the errors for different combinations of training and testing samples. The results obtained using the KNN algorithms have demonstrated similar trends. In order to inspect the "different device" effect, the two different Wi-Fi NICs as localization, the error performance when using the same device for both training and testing, In this case, the RSS-based algorithms perform slightly better than its SSD counterparts. As explained earlier in Section 2, the SSD fingerprint vector has a smaller dimensionality compared to the RSS fingerprint vector. This puts SSD at a slight disadvantage when the same device is used for both training and online localization. Moreover, one may also argue that SSD has higher variance than RSS. Using (2) and (5), and assuming that X1 and X2 are independent and identically distributed Gaussian with variance σ_{dB}^2 RSS and SSD are distributed as

$$\boldsymbol{N\left(P(d_0)|_{dBm} - 10\beta \log\left(\frac{d}{d_0}\right), \sigma_{dB}^2\right)} \qquad \mathbf{(12)}$$

And

$$\boldsymbol{N\left(-10\beta_1 \log\left(\frac{d_1}{d_0}\right) + 10\beta_2 \log\left(\frac{d_2}{d_0}\right), 2\sigma_{dB}^2\right)} \qquad \mathbf{(13)}$$

For the same device, both RSS and SSD do not change, and the variance of RSS is actually lower than that of SSD. However, in practical scenarios, a localization system is usually intended to track heterogeneous devices, and hence, the better performance of RSS only occurs occasionally when the user device happens to be the same as the device used for training. In practice, it is more often for the users to carry different devices from the training device. It can be easily seen from the Gaussian approximations of RSS and SSD that the mean of RSS varies depending on different MNs' hardware since it includes P (d_0), while SSD's mean still remains the same Fig.10:Signal Strength Difference (SSD). As the practical hardware dependency issue overshadows the disadvantage of the larger variance and smaller dimensionality of the SSD fingerprint, based on our experimental results shown below Fig.9: Performance for Wi-Fi RSS and Bluetooth RSS, using commonly found commercial devices. It is apparent that the hardware variations of the MN have adverse effects on RSS-based localization's performance for both Bluetooth and Wi-Fi. We further notice that, this issue is prevalent regardless of or at the MN for MN-assisted localization. On the contrary, SSD based localization has much better accuracy than RSS-based localization in the presence of hardware variations in both Wi-Fi and Bluetooth experiments. As can be seen, the accuracy of SSD based localization remains almost the same in the respective comparisons Fig.8: Performance for Wi-Fi SSD and Bluetooth SSD Using Bayesian Inference. This implies that

SSD-based localization is invariant to the mobile device being used, regardless of whether it is the same as the training device or not. This agrees with the analysis in Section 2 that SSD is free from Hardware-dependent effects.

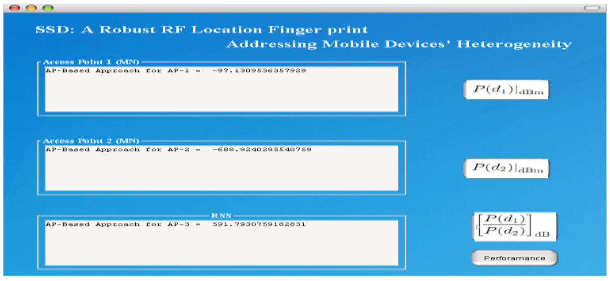

Fig.9: Comparison between SSD and RSS

4.4.1Comparison Results:

We present the results of both the performance analysis by using the different combinations of training and testing samples, and finally obtain the cumulative probability graph of
Wi-Fi-RSS and Bluetooth-RSS this shows its performance is uneven and it shows that the signal strength if not much robustness

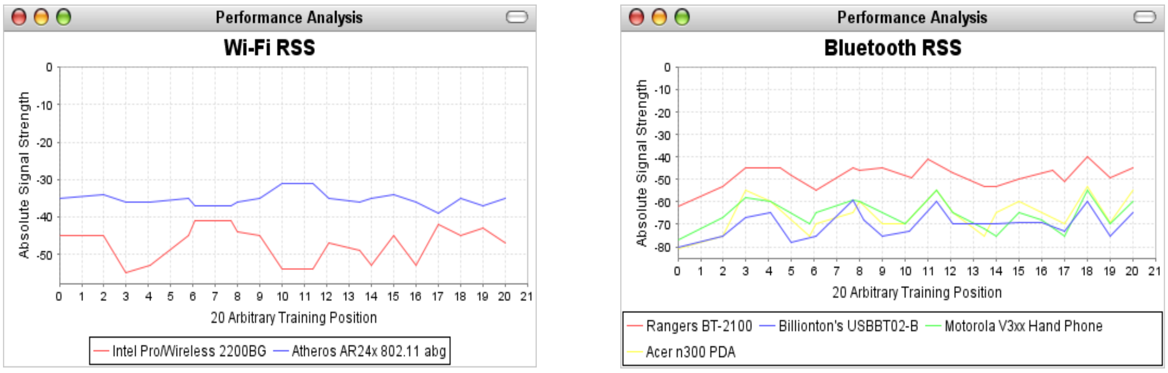

Fig.10: Performance for Wi-Fi RSS and Bluetooth RSS

We present the results of two well-known localization algorithms (K Nearest Neighbor and Bayesian Inference). And then run the algorithms to obtain the localization errors in order to obtain all the errors for different combinations of training and testing samples, and finally obtain the cumulative probability graph of 6.2. Show the Wi-Fi – SSD and Bluetooth – SSD. Hence proved, as that the SSD-based algorithms have better accuracy.

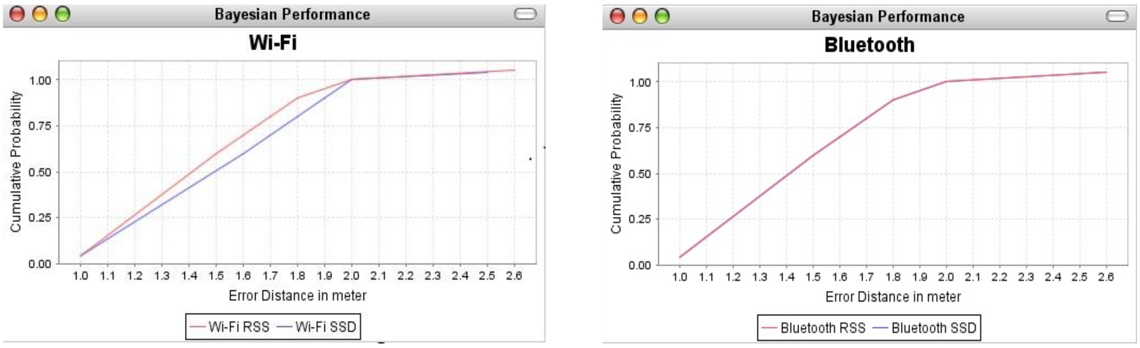

Fig.11: Performance for Wi-Fi SSD and Bluetooth SSD

V. RESULT

Fingerprint-based methods are widely adopted for indoor localization purpose because of their cost-effectiveness compared to other infrastructure-based positioning systems. Here the popular location fingerprints are collected and Received Signal Strength (RSS) is observed to differ significantly across different devices' hardware even under the same wireless conditions. Analytically a robust location fingerprint definition, the Signal Strength Difference (SSD), and verify its performance experimentally using a number of different mobile devices nodes with the help of NETBEANS 7.3.1 with the supporting language as JAVA (JDK 7.1) to prove the experiment as heterogeneous. Experiments are happened in both Wi-Fi and Bluetooth devices, as well as both Access-Point (AP)-based localization and Mobile-Node (MN)-assisted localization. The location and nearest node and the distance between the nearest nodes are analyzed with the help of references and above equations to find the signal strength of the signals between the nodes and the AP (Access Point) and MN (Mobile Node). By these signal strength RSS (Received Signal Strength) and the SSD based approach we analyzed the performance of RSS for (Wi-Fi and Bluetooth) and result as the probability of graph and to justify the SSD the data's are transferred and it proves Robustness and accuracy in my future work.

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