High Performance Indoor Location Wi-Fi Fingerprinting using Invariant Received Signal Strength

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ABSTRACT

The instability of Wi-Fi received signal strength (RSS) incurred by mutable channel characteristics hampers a wide-spread adoption of RSS based location fingerprinting to real world indoor localization applications. To overcome RSS instability, we propose a new approach based on the concept of "invariant RSS statistics". By invariant RSS statistics, we mean the RSS samples collected at each calibration location, especially, under minimal random spatiotemporal disturbances. The proposed method forms the reference pattern classes for individual calibration locations with the invariant RSS statistics thus obtained. Fingerprinting is done by identifying the reference pattern class that maximally supports the RSS readings collected at an unknown location for available Wi-Fi sources. The support of RSS readings is defined here as the sum of the likelihood probabilities of individual RSS readings. Unlike conventional methods, the proposed method allows only those readings high in statistical confidence to participate in the sum, while excluding other readings. This is to screen out the influence of those readings contaminated by time-varying disturbances on classification. Experimental results show that the proposed method provides superior performance to conventional ones with the success rate higher by 17%, the printing resolution finer by 30% and, naturally, no performance degradation in time without recalibration.

Categories and Subject Descriptors

A.0 [**General**]; C.2.1 [**Network Architecture and Design**]: Wireless communication; H.3.4 [**Systems and Software**]: Information networks; H.5.2 [**User Interfaces**]: Interaction styles

General Terms

Performance, Experimentation, Human Factors.

Keywords

Wi-Fi Fingerprinting, Indoor Localization, Indoor Positioning System, Wi-Fi received signal strength, IEEE 802.11 technology, Human-Robot Interaction, RSSI Fingerprinting

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1. INTRODUCTION

The use of Wi-Fi received signal strength (RSS) for location fingerprinting in indoor environments has drawn attention as an enabler of various location based personal services with handheld/wearable communication devices. Applications of these services to the fields of robotics, logistics, medicine and entertainment are expected to grow in the coming years. However, the instability of RSS incurred by highly mutable channel characteristics, due to random spatiotemporal disturbances, hampers a wide-spread adoption of RSS based location fingerprinting to real world applications [1]. Conventional approaches adopt the framework of multi-class pattern classification for location fingerprinting, where the RSS readings from available Wi-Fi sources are collected at each calibration location as statistical samples to form a pattern class. Fingerprinting is then performed by deriving the decision boundaries that provide minimum-error classification [2-4]. The problem is that the random spatiotemporal disturbances associated with RSS make class patterns heavily overlapped and time varying, causing significant classification errors while requiring frequent offline recalibration. Increasing the number of available Wi-Fi sources and/or decreasing the number of calibration locations may help reduce the problem somewhat but at the cost of efficiency and/or fingerprinting resolution. Although Wi-Fi sources ineffective for classification can be identified and removed offline for improved efficiency [5], the problem described above is remained fundamentally unchanged.

This paper presents a novel approach to cope with the RSS instability, using the concept of "the minimally disturbed invariant RSS statistics," or, simply, "the invariant RSS statistics." The invariant RSS statistics introduced here is intended not only for enhancing the classification accuracy but also for eliminating the need for offline recalibration without scarifying efficiency and resolution. As such, the proposed method is especially suited for smartphone based location fingerprinting where only the Wi-Fi sources existing in the environment are to be utilized. In what follows, we introduce more details of the proposed method.

The outcome of this work is aimed to be applied on localizing humans or robots equipped with a smartphone in a multiple room's indoor environment. A human may call a robot using a smartphone application by automatically sending his location information to the robot during the calling process, and then the robot which knows its own location (by using the same application from its side) may approach the caller based on the location received.

The rest of the paper is organized as follows: In Section 2, we review existing works in indoor localization and Wi-Fi fingerprinting. Section 3 elaborated the Wi-Fi RSS model. We continue by enlightening our proposed approach in Section 4. Then, we clarifying the experimentation that we conducted in Section 5. Consequently, the experimental results are presented in Section 6. Finally, Section 7 concludes the paper with pointers to future works.

2. RELATED WORK

The RADAR system which was developed by Microsoft Research [6] is one of the first works that make use of WiFi-based network to produce location fingerprints. In their training phase, an area is divided into a 1x1 meter grid where the signal strength measurements of the access points are taken at each intersection. The mean of the signal strengths which have been obtained, is recorded to create a radio map to be used in the online phase. In the online phase, when the user looks for its location, the mobile station will detect and record the signal strength from as many access points as possible. Then, the signal strength received will be compared to the radio maps to determine the location of the user. Although the authors assume that the radio map is always stable, there is an issue that it is not always the case [3]. Furthermore, by picking the access points' signal strength arbitrarily, it is hard to get the optimum location estimation.

Bolliger [7] has developed an indoor positioning system named Redpin by exploring the issue of localization accuracy using WLAN fingerprinting to improve the radio map precision in the database. There is also a method using signal strength ratios between pairs of base stations [8]. They claim that this method is more stable among Wi-Fi clients than absolute signal strength. This approach however will increase the computational time. There are also other similar works [9, 10] trying to use Wi-Fi RSS in the fingerprinting process.

Recently, research in WiFi-based indoor localization explored its feasibility using smartphones [3, 5, 11-16]. In choosing the Wi-Fi signals to be used to uniquely classify a location, different authors used different approaches in their methods. However, none of them have yet successfully create a stable location fingerprint database because of the nature of Wi-Fi signals that fluctuates over time depending on environment disturbance.

Martin *et. al.* [11] claim that they are the first to implement localization application using Received Signal Strength (RSS) of Wi-Fi signals in a smartphone. The authors apply deterministic method in their work. They take all signals above -80 dBm, and used their mean values in their location fingerprint database formation. A similar approach is also implemented by Shin *et. al.* [13]. They developed an indoor Wi-Fi positioning system for Android-based smartphone and collecting Wi-Fi access points RSS indiscriminately. By this approach, the localization process suffering from a good accuracy because instability to the location fingerprints due to signal fluctuations.

Another approach in the selection of Wi-Fi signals is using a *predetermined number* of "first-come-first-get" signals [16]. By setting up a predetermined number (e.g. 8), they will compare the online measured first eight detected signals to the location fingerprint database to estimate the location. The authors apply probabilistic method in this work. Although this approach will slightly increase the computational time, again it will suffer from instability of accuracy.

Meanwhile, Chen [12] use Received Signal Strength (RSS) relations instead of RSS mean values. They claim that although RSS fluctuates, relations between values are more stable. Their approach is setting up rules at each reference location such as *"less than"*, *"equal to"*, or *"greater than"* between two related signals. Another method [15] proposed a way to improve location estimation by penalizes signals from unstable access points and signifies strong signals compared to weak signals. They criticized the use of Euclidean distance in nearest neighbor approach. However, all these approaches still will lead to the same problem where variation is too high when time varying is included during data collection, which will lead to unavoidable large overlaps in location classification.

The key to formulate a stable location fingerprint is selecting the best appropriate signals. Samih Eisa *et. al.* [5] has made an effort in this matter by removing useless signals. However, their approach still lacks in producing highly stable location fingerprints because the authors definition and identification methods of useless signals is not enough to select the best signals to form a good location fingerprints. Our earlier work [4] focusing on orientation-based indoor localization using smartphones. We managed to localized the smartphone by location and orientation. However, there is still rooms for improvements in the calibration phase.

In this paper, we introduce a novel approach to formulate a highly stable indoor location fingerprints by eliminating offline recalibration to produce an accurate and robust indoor localization system.

3. WI-FI RECEIVED SIGNAL STRENGTH MODEL

The m dimensional Received Signal Strength (RSS) vector, $\{\mathbf{s}_i(t)\}_j$, at time t at a particular calibration location j due to m Wi-Fi sources, i=1, …, m, is represented as

$$\{\boldsymbol{s}_i(t)\}_j = \{\boldsymbol{s}_{1,j}(t), \boldsymbol{s}_{2,j}(t), \dots, \boldsymbol{s}_{i,j}(t), \dots, \boldsymbol{s}_{m,j}(t)\}, \quad j = 1, \dots, n \tag{1}$$

where the bold-face letter, $\mathbf{s}$, is to represent it as a random variable.

Here, we model $\mathbf{s}_{i,j}(t)$, the RSS from the i^{th} Wi-Fi source at the j^{th} calibration location, as

$$\boldsymbol{s}_{i,j}(t) = \boldsymbol{\alpha}_{i,j}(t) \times r_{i,j} + \boldsymbol{\delta}_{i,j} \tag{2}$$

where $r_{i,j}$ represents the time-invariant RSS with no spatiotemporal disturbances present, $\boldsymbol{\alpha}_{i,j}(t)$ the multiplicative signal alteration factor due to the spatiotemporal disturbances of $r_{i,j}$, and $\boldsymbol{\delta}_{i,j}$ the sensor noise. Note that we introduce $r_{i,j}$ as the ideal time-invariant signal attenuated by the distance from the Wi-Fi signal source i to the location j through the invariant channel characteristics, taking only fixed building infrastructure and furniture layout into consideration. The actual signal, $\mathbf{s}_{i,j}(t)$, is then considered as the alteration of $r_{i,j}$ by $\boldsymbol{\alpha}_{i,j}(t)$, $0 < \boldsymbol{\alpha}_{i,j} \leq 1$, reflecting the stochastic channel characteristics due to randomly moving people and/or objects as well as due to random orientation of the smartphone user which blocks the channel during RSS measurement. Note that $\mathbf{s}_{i,j}(t)$ with minimal random spatiotemporal disturbances implies $\boldsymbol{\alpha}_{i,j}$ to be equal or close to 1.

4. INVARIANT RECEIVED SIGNAL STRENGTH STATISTICS APPROACH

The invariant RSS statistics are defined at individual calibration locations as the statistics of the particular RSS readings collected with minimal, if not free of, random spatiotemporal disturbances using smartphone or any handheld/wearable devices. Figure 1 depicts the whole process of the proposed approach, and the explanation is detailed in the following paragraph.

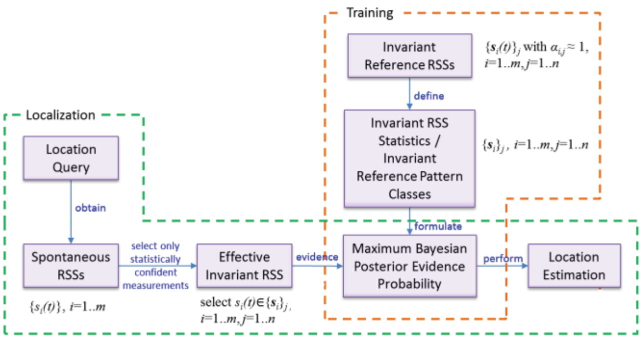


Figure 1. Block diagram of proposed smartphone-based invariant Wi-Fi RSS approach.

The invariant RSS statistics, $\mathbf{s}_{i,j}$, represents $\mathbf{s}_{i,j}$(t) with $\boldsymbol{\alpha}_{i,j} \approx 1$, i.e., from equation (2)

$$\boldsymbol{s}_{i,j} \approx r_{i,j} + \boldsymbol{\delta}_{i,j} \qquad (3)$$

Equation (3) indicates that the randomness of $\mathbf{s}_{i,j}$ comes mostly from sensor noise. Applying (3) to available Wi-Fi sources, i=1..m, an m dimensional invariant RSS statistics vector, $\{\mathbf{s}_i\}_j$, is obtained at the calibration location j. For pattern classification, $\{\mathbf{s}_i\}_j$ forms the j^{th} reference pattern class in the m dimensional Wi-Fi source space.

Figure 2 schematically represents three reference pattern classes, $\{\mathbf{s}_i\}_j$, j=1..3, of small blue ellipses in two dimensional Wi-Fi source space i=1,2. The larger solid or dotted red circles surrounding blue ellipses represent the distribution of spatiotemporally disturbed RSS vector, $\{\mathbf{s}_i(t)\}_j$.

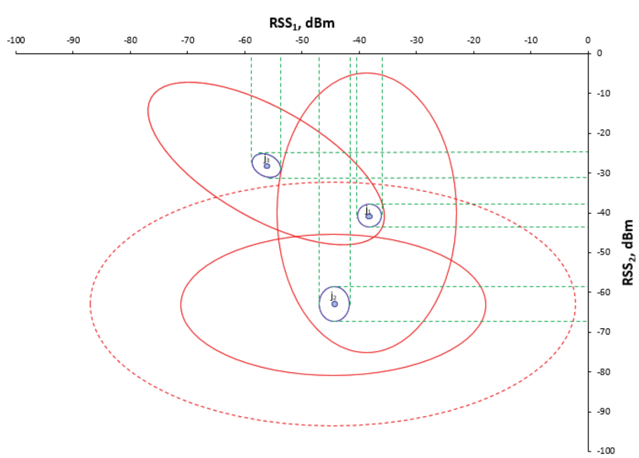


Figure 2. Schematic representation of three reference pattern classes (small blue ellipses) and distribution of spatiotemporally disturbed RSS vector (larger red ellipses), in two dimensional Wi-Fi source space.

Fingerprinting of the RSS vector, $\{s_i(t)\}$, captured at an unknown location is done by identifying the reference pattern class among $\{\mathbf{s}_i\}_j$, j=1, …, n, that maximally support $\{s_i(t)\}$. The support of $\{s_i(t)\}$ by the reference pattern class j is defined here as the number of $s_i(t)$ that fall in $\mathbf{s}_{i,j}$ for i=1, …, m, or the sum of the likelihood probabilities of $s_i(t)$ to belong to $\mathbf{s}_{i,j}$, for i=1 …, m. Note that, in counting the number or summing the likelihood probabilities, only those $s_i(t)$ having a sufficiently high level of statistical confidence as a member of $\mathbf{s}_{i,j}$ are allowed to participate in the sum, while excluding others.

Formally, fingerprinting is done based on the following pattern classification rule:

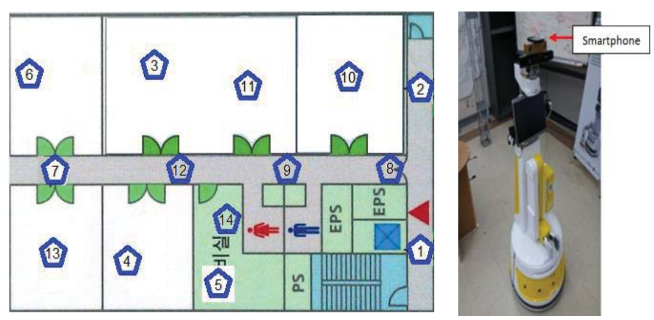
> Find j for all j such that Max(j) Sum$_i$ 1/0 ($s_i(t) \in [\mathbf{s}_{i,j}]$) for all i or Find j for all j such that Max(j) Sum$_i$ Pr($s_i(t)$/ $\mathbf{s}_{i,j}$) for $s_i(t) \in [\mathbf{s}_{i,j}]$, for all i, where 1/0 (x) = 1/0 if x is true/false and $[\mathbf{s}_{i,j}]$ implies the lower and upper bounds of $\mathbf{s}_{i,j}$.

5. EXPERIMENTATION

We conducted experimental investigation to show the efficiency of our approach and compare the performance with existing approach.

5.1 Experimental Setup

The location of the experimentation is in the 6th floor of Research Complex 2, Sungkyunkwan University, South Korea. The experimentation area is approximately 350 square meters, which consists of a few rooms and hallway. We preset seven calibration locations to begin with (we add more calibration locations as the research progresses), where it is the spot that has been used to collect the readings of the Wi-Fi RSS data. Figure 3(a) depicts the floor map of the experimental area with 14 calibration locations (Loc. 1 to Loc. 14).



(a) (b)

Figure 3. (a) The experiment floor map area with marked calibration locations (b) The robot attached with a smartphone used in invariant RSS data collection

5.2 Data Collection

The invariant RSSs are collected with very minimal random spatiotemporal disturbances. To achieve that, we carry out the data collection after midnight in avoiding human presence into the experimental area. Furthermore, a robot is used to collect data rather than a human in avoiding body disturbance effect and information error. A smartphone is placed on top of the robot and the robot is tele-operated through each calibration location. The smartphone collects Wi-Fi RSS in a particular calibration location and the RSS data is sent to a server, and the readings are tag to the location associated to it. Figure 3(b) illustrates the robot that has been used during data collection. A total of 100 reading samples are taken at each calibration location with four different orientations. Then, the reference pattern classes are defined based on the invariant RSS statistics.

5.3 Performance Evaluation

We evaluate the performance of our proposed approach by a few evaluation procedures and make comparison with existing approaches [3][5]. We begin the evaluation by determining the success rate, followed by the time-based performance. Then, we evaluate the success rate at different resolutions. Finally, we compare the performance based on invariant RSS statistics from different length of time. The results of all the experimental investigations are elaborated in the following section.

6. RESULTS AND DISCUSSION

We evaluate the performance of our proposed approach and the conventional indoor localization method by running both algorithms in a smartphone which embedded to an autonomous robot. The robot then relocated to a particular location for testing purposes.

6.1 Localization Success Rate

The test is carried out at each calibration location with four different orientations (0°, 90°, 180°, and 270°). The reason to include different orientations in the testing procedure is to see whether performance is uniformed in all orientations or certain orientation give better/worse accuracy than the others. A total of 120 tests have been performed at each calibration location to identify the success rate of both our proposed approach and conventional approach. We begin the experimentation with seven calibration locations (Loc.1 to Loc.7). Figure 4 shows our approach performs superior results with 93% average success rate in comparison to 76% by conventional approach. We observed from the success rate that stable results are achieved in our invariant RSS approach regardless of the orientation, meanwhile conventional approach shows large difference from one orientation to another.

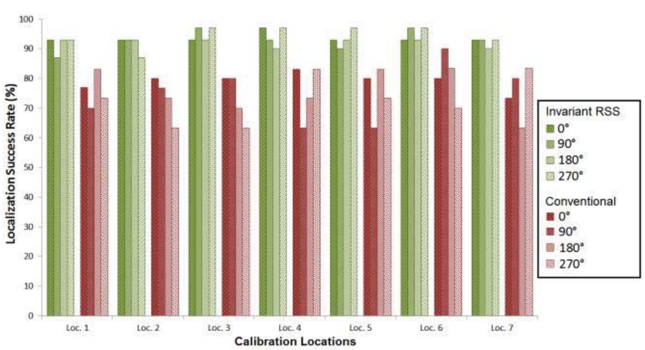


Figure 4. Comparison of localization success rate between the proposed invariant RSS approach and conventional approach at 7 calibration locations with 4 different orientations.

Next, we apply the algorithm to a different set of seven calibration locations (Loc.8 to Loc.14). The reason is to see whether different set of calibration locations would produce similar results or not. We train a new set of seven calibration locations with similar location tabularization distance to the earlier set. It is observed that the result is similar to the earlier set of calibration locations. These identical results verify the validity of the results.

6.2 Time-based Performance

We conducted the comparison of time-based performance of both approaches. The aim is to see whether there is any degradation of performance in our approach as normally hinders conventional approach after some lapse of time, which requires recalibration need to be carried out, in order to get a good reasonable success rate again. Same calibration locations are used for both approaches. The test has been conducted continuously in 18 weeks. We performed all tests by maintaining a similar environment disturbance condition, i.e. a normal office hour environment.

The result as depicted in Figure 5 shows that after 18 weeks, the conventional approach degrades 14% in success rate, while our approach maintains the identical performance. In between week 12 and 13, we recalibrate location fingerprint of the conventional approach and create a new database out of it, at the same time we still keep the older database. After week 12, we observed that our approach still conserve high performance results. On the contrary, the success rate of the older location fingerprint of conventional approach continues to deteriorate further. As for the new location fingerprint after recalibration of the conventional approach, although the success rate rise to 77%, it is still significantly lower than the proposed approach, and continues to deteriorate in the following weeks. We conclude that our approach performs not only better in performance, but also stable as time goes by.

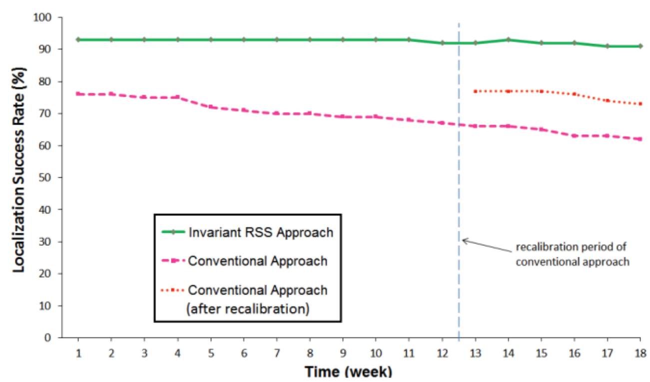


Figure 5. Time-based performance comparison with recalibration applied to conventional approach.

6.3 Performance at Different Resolutions

We performed localization test with different resolutions to find the optimal resolution that supported our approach. We setup dedicated calibration locations with distance resolutions between 1 and 5 meters as depicted in Figure 6 in order to perform this investigation. Four calibration locations for each resolution are pre-identified, and invariant RSS statistics are defined. Then, we tested the success rate for each resolution at each its calibration location. The average success rates for all resolutions are tabulated in Figure 7. We also perform and compare the results with conventional approach and another existing approach [5].

The results as shown in Figure 7 illustrates that our invariant RSS approach supports higher resolution than the conventional and *remove useless Wi-Fi sources* [5] approach. We achieve 85% success rate at 3 meters resolution and around 3.7 meters resolution to get a 90% success rate. On the contrary, the existing approaches did not manage to perform 90% success rate with below 5 meter resolution.

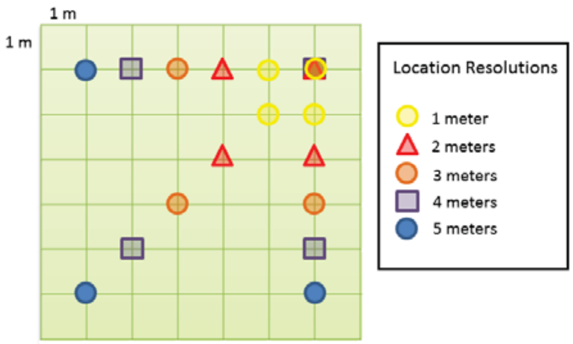


Figure 6. Calibration locations setup map for optimal resolution investigation.

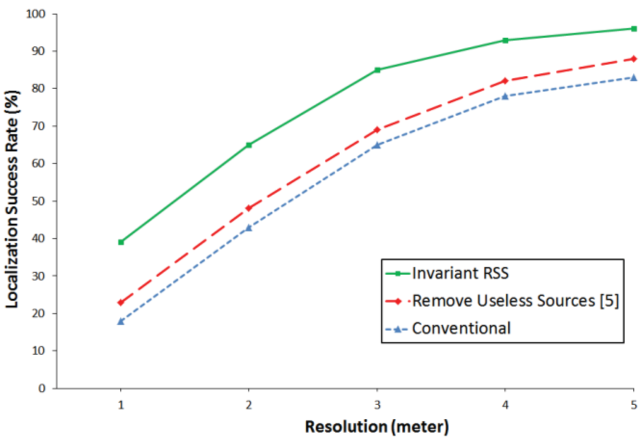


Figure 7. Comparison of localization success rate at different resolutions

Based on the discovery of the optimum resolution as above, we will increase the number of calibration locations to reflect our experimental area as our succeeding work.

6.4 Performance from Samples Collected over Different Length of Time

In the preceding experiments, we used the same number of samples (n=100) which was taken in a period of approximately 2 hours in the formation of all invariant reference pattern classes. Our next investigation is to apply an increased number of samples from a longer period of time for all approaches to check whether time length of collecting samples affecting the localization success rate. We continue our investigation with n=200 and n=300 which was collected dispersedly in one week and two weeks respectively.

Figure 8 illustrates the comparison results to the existing approaches. We observed that our invariant RSS approach produced a higher success rate and stable regardless of the number of samples over different length of time. On the contrary, the conventional approach and the *remove useless Wi-Fi sources* approach [5] suffers from success rate degradation as the number of samples increased over time. From our analysis, the reason behind this result is our approach only takes invariant RSS which maintain low variance although as time increased, as opposed to existing approaches that takes all available RSS which increased the variance by longer time.

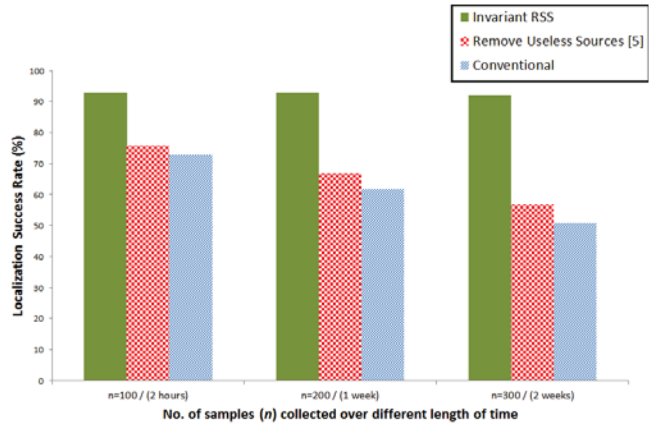


Figure 8. Performance comparison with different number of samples collected over different time length.

Figure 9 illustrates the example of output from the smartphone application that has been used throughout this work. The application showing the location of the smartphone based on the invariant reference pattern classes of the calibrated locations.

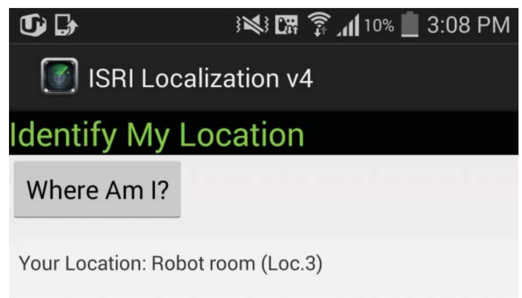


Figure 9. Example output of the smartphone application.

7. CONCLUSION AND FUTURE WORK

The results from the experimental study shows that our invariant RSS approach performs not only better in performance, but also stable as time increased, with finer resolution than the conventional and existing improved approach. Our approach performs 17% better in localization success rate and 90% recognition rate at 3.7 meters resolution.

The proposed method offers not only a reliable but also an efficient solution for the RSS instability problem, making it viable for many real-world applications: 1) Resorting to invariant RSS statistics as the reference in fingerprinting, together with the effective RSS readings chosen as input data, make the proposed fingerprinting accurate and robust against random spatiotemporal disturbances. Unlike conventional methods, it requires no or minimum recalibration once the invariant RSS statistics are set initially. 2) The automatic removal of ineffective Wi-Fi sources in the process of soliciting effective RSS readings makes the proposed method efficient in fingerprinting with the in-situ reduction in the dimension of decision space.

The outcome of this paper will allow us to continue our work further by increasing the number of calibration locations so that it is reflecting the resolutions that we accomplished with regard to the experimental area that we have.

8. ACKNOWLEDGEMENT

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