



A Novel Probabilistic Algorithm for Indoor WLAN Fingerprinting System

Mrindoko R. Nicholaus¹, Edephonc N. Nfuka² and Kenedy Aliila Greyson³

^{1,2} Dept of ICT, The open University of Tanzania, Tanzania

³ Dept of Electronics and Telecoms Eng, Dar es Salaam Institute of Technology, Tanzania

¹nicholausmrindoko@gmail.com, ²edephonce.nfuka@out.ac.tz, ³kenedyaliila@yahoo.com

ABSTRACT

Location-based systems for indoor positioning have been examined generally inferable from their application in different fields and simple deployment. However, it requires a database containing the distribution of received signal strength (RSS) of the area of interest, called radio map. The computational time of Wi-Fi indoor localization needs to be reduced meet the demand of viable mobile applications. The Probabilistic fingerprinting algorithm uses a compound probability density function (PDF) to estimate the best location which increases the positioning time. This paper proposes a novel fingerprinting algorithm, the enhanced probabilistic algorithm, which reduces positioning time by introducing mean filter prior to PDF. Experimental results show that the proposed algorithm has improved positioning time.

Keywords: Probabilistic fingerprinting algorithm, Indoor positioning, Probability density function, Received signal strength, Computational time.

1. INTRODUCTION

With the growing interest in localization services, indoor positioning estimation has drawn a significant concentration during the recent years [1]. Global Positioning System (GPS) admirably for an outside localization; yet it doesn't perform viably in indoor conditions as a result of the incapacity of GPS signal to infiltrate the building. Thusly, an extraordinary number of researches have been done to address the indoor restriction issue. On account of the least cost and unpredictability, the greater part of the current radio frequency constructs indoor limitations are situated in light of the RSS [2].

Numerous fingerprint-based positioning algorithms, employ the RSS offered by the surrounding wireless devices, have been proposed to meet the progressions of the indoor condition [3]. In a practice fingerprint-based

RSS localization, a lay down of training points is to be chosen in the zone area. Amid the offline training stage, position-dependent RSS parameters, are determined and recorded at each unique training point as the unique fingerprint for the particular position. Amid the online localization stage, the position of the question object device is evaluated through coordinating between the radio unique fingerprint and immediate RSS [4].

However, a positioning system that relies solely on RSS to define location fingerprints is still suffered from accuracy and computational time overhead required to meet viable mobile application. Furthermore, the computational time may change based on different RSS indoor parameters such sample density and number of access points (APs). Establishing indoor localization fingerprints which reduce computational overhead is important for the sustainability of viable mobile application and indoor positioning in general [5].

In this paper, the novel location fingerprint algorithm based on combination of MF and PDF is proposed to reduce computational time overheard of RSS based indoor fingerprints. Firstly, a MF algorithm is proposed to reduce to select three reference points smallest aggregate mean. Selected aggregate mean might evaluated from different reference points. Secondly, PDF equation is applied to calculate the probability of each selected reference point. Lastly, the reference point high probability is selected as the best user location.

The rest of the paper is planned as follows. The next section 2 highlights an overview on the related works. Experimental study and results verification is detailed in Section 3. Finally, Section 4 concludes this paper.

2. RELATED WORK

In improving localization algorithms, the preceding researches mostly focused on improving the quality of the radio fingerprints. Currently [6] suggested that while collecting Wi-Fi signal strengths, the beacons that have the best distinguishing results and stability also has to be considered. Authors in [7] proposed an extension Weighted K-Nearest Neighbor (WKNN) by varying the number of considered neighbours. The main idea of authors remains on accuracy improvement only rather than computation time.

Author in [8] proposed an approach of environment adaptability for building database of fingerprints. In their research, they administered to figure out on how to improve the efficiency of algorithms using predictive model during data collection, but they could not consider the positioning time. Furthermore, authors in [9] said, integrates received and transmitted RSSI signals, would raise the performance of localization. Author in [10] proposed a moving average filter fingerprinting method to improve accuracy of indoor localization. Similarly, the author anticipated new positioning algorithms incorporating traditional algorithms which based on accuracy improvement rather than computation time.

3. EXPERIMENT STUDY

The fingerprint-based location implemented to evaluate the computation time performance of positioning based on the mean filter. The points of interest of the examination are depicted as takes after.

3.1 Experimental Environment

Experiment testbed is located around the Computer laboratory of the Mbeya University of Science and Technology main corridor. During the testbeds, there are 74 training locations consistently distributed in the room and corridor. The training process involves placing the mobile device at each training location and collecting data. Three base stations are manually placed in the study area.

Fingerprints are collected 20 samples at each reference point for each beacon and are averaged for radio map establishments. Experiment covers an area of 350 m². It is consists of two separate rooms (divided by walls) and one air corridor.

3.2 Modelling Distributions of Wi-Fi Received Signal Strength

Fingerprint maps generally store only the mean value of RSSI over time without fully exploiting information about RSSI characteristics in the environment. In practice, the

probability of continuous signal is zero. Therefore it is important to model and understand the characteristics of RSSI under the environment before constructing the radio map and introducing errors during position estimation. For the probabilistic algorithm, two main parameters named mean (μ) and standard deviation (σ) for the RSSI fingerprints are keys in position estimation. These parameters investigated to understand their effects on the radio map as transmitter height varies while the number of samples, APs and transmitter power kept constant.

3.2.1. Probabilistic method

The method normally considers positioning as a classification problem. Assuming that there are n reference points: L1, L2, L3...Ln and S is the examined signal strength vector. Define $P((L_j|S))$ as the probability of the user in location L_i , the decision rule can be obtained:

Choose L_1 , if $P((L_1|S)) > P((L_j|S))$, for $j = 1, 2, \dots, n, j \neq 1$

(1)

According to Bayes rule, it is known that $P((L_j|S)) = \frac{P((S|L_j)) P(S)}{P(L_j)}$. If believing all the test points have equal chance to be accessed and there is no prior knowledge about whether they are available $P(L_i) = P(L_j)$ for $i, j = 1, 2, 3, \dots, n$, the decision rule can be transformed to:

Choose L_i , if $P((S|L_i)) > P((S|L_j))$, $>$, for $j = 1, 2, \dots, n, j \neq i$

(2)

Localization probabilistic approach utilized as part of our experiment relies on normal difference probability density function (PDF) prior with the mean filter. It finds reference points with the smallest mean before it calculates the probability density function values of each common relation that is found between user retrieved beacons and database beacons. Then for every position, it sums up that probability density function values and divides it with the amount of relations. The resultant value is not the probability per se, because in continuous normal distribution, the probability of a single point is zero. Equation 3 to 5 demonstrates probabilistic mathematical formulae utilized for this study.

Let $\mu_{x1}, \mu_{x2}, \mu_{x3}, \dots, \mu_{xn}$ = Offline RSSI Mean at Reference Point 1 for different APs and $\mu_{y1}, \mu_{y2}, \mu_{y3}, \dots, \mu_{yn}$ = Online RSSI Mean at Reference Point 1 for different APs

Then Mean filter (MF) from Reference Point 1 for three APs is given by equation 3

$$MF = (\mu_{x1} - \mu_{y1}) + (\mu_{x2} - \mu_{y2}) + (\mu_{x3} - \mu_{y3}) \quad (3)$$

Then from the radio map best three K with the lowest MF are selected to apply equation 4 and finally equation 5

$$F(z) = \frac{e^{-\left(\frac{(\mu_x - \mu_y)}{2(\delta_x^2 + \delta_y^2)}\right)^2}}{\sqrt{2\pi(\delta_x^2 + \delta_y^2)}} \quad (4)$$

$$P(L) = \frac{\sum_{i=1}^n F(z_i)}{n} \quad (5)$$

3.3. Experiment results and analysis

3.3.1 The effect of transmitter height

The beacon height influences the location algorithms, which might affect the performance of RSSI location fingerprints. As shown in Figure 1, the RSSI mean of the localization system is slightly improved when the height of transmitter decreased from 2 to 1 m, particularly if the error is within the range of 10 dBm. However, the labour of the training data and the computational overhead are remains the same. It was noted in the experiment that, the entire mean variation in all height range from 17 to 18 dBm, this implies that, there is no possibility of having zero standard deviation which can lead to the unknown location in the proposed algorithm as shown in figure 2.

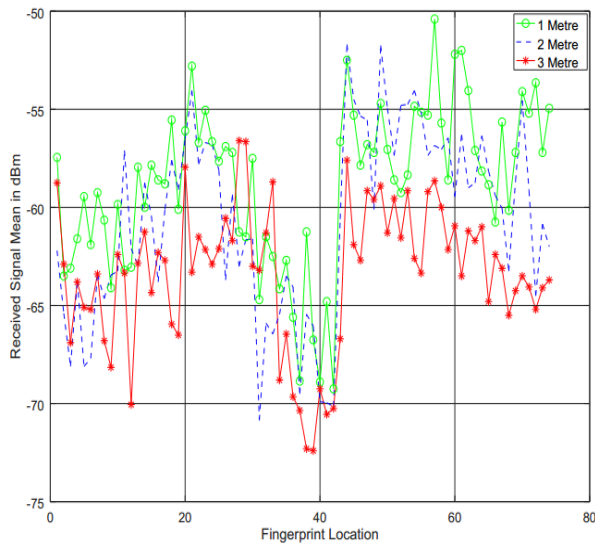


Fig. 1. Received Signal Strength (Rss) Against Fingerprint Location For 20 Samples

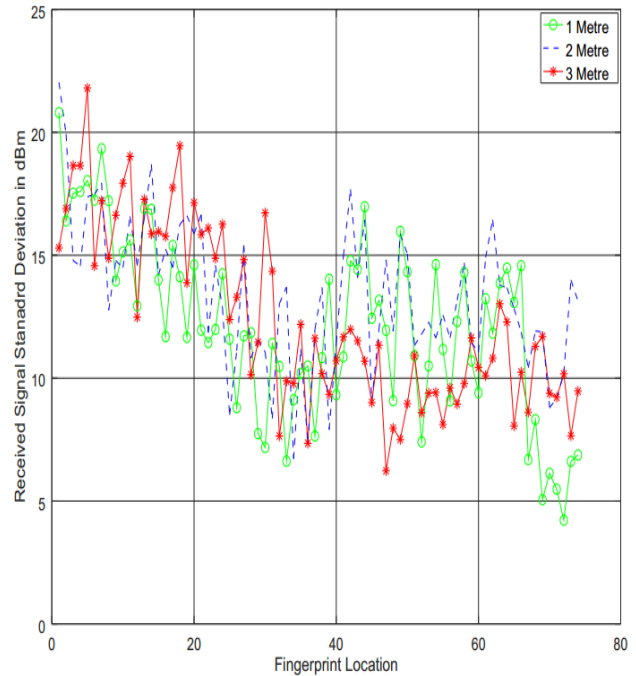


Fig. 2. Standard Deviation Against fingerprint Location For 20 Samples

3.3.2 Computational Comparisons

For this experiment, the same data has used to calculate user position for both algorithms. For conciseness, Experiment has only utilized the PDF without MF and with MF method for computational performance comparison. The procedure repeated for more than 10 times in order to obtain all the times in second (s) for different location. Finally obtain the time computational graph of Figure 3. As can be observed, PDF with MF-based algorithm has much better computational time than PDF without MF algorithm with high transmitter power and 20 training samples in the presence of transmitter height variations. This implies that PDF with MF -based algorithm can improve computational time up to 40%, regardless of RSSI mean and standard deviation variations.

From the investigation, it is also examined that in spite of the fact that, even though localization time improved the accuracy was not influenced and sustained as before in the two situations as exhibited in Figure 4 whereby PDF with MF algorithm computed only the accuracy of best three point when K= 3.

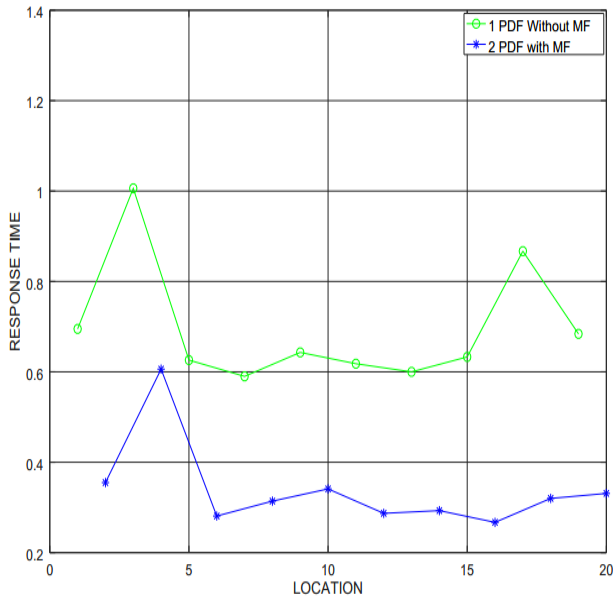


Fig. 3. Response Time Against Its Location

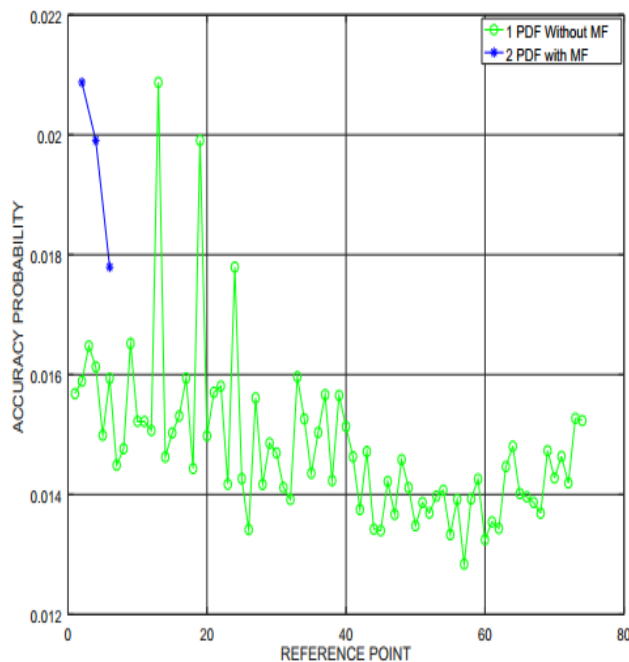


Fig. 4. Location Accuracy Based On Probability Functions

5. CONCLUSIONS

In this paper, a novel probabilistic positioning algorithm based on mean filter prior to PDF is presented. The height of the transmitter has an influence to the indoor signals fingerprints. The RSSI mean of the localization system is slightly improved when the height of transmitter decreased. The mean and standard deviation are not

identical through the entire reference points as height varies which eliminate the possibility of unknown location to the proposed algorithm. The proposed algorithm has shown an improvement in computational time overhead which localization accuracy remains unaffected. Incorporating accuracy improvement into the proposed algorithm considered to be the future direction of this research work.

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