WIFI indoor location optimization method based on position fingerprint algorithm

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***Abstract*—GPS based location technologies can achieve high accuracy on meter level in outdoor environments, however, it cannot obtain high level position accuracy in the indoor environment. Therefore, in this paper, we propose a novel WIFI indoor location optimization approach based on position fingerprint algorithm. Each fingerprint contains a set of intensity values of the detected WAPs, and then it is defined as a vector with fixed size. The proposed location fingerprinting algorithm is made up of online and offline phase, in which generating the location fingerprint database is a crucial issue. Particularly, at the end of training process, a probabilistic map is generated for the interest area, and a single probability density function for the access point and the reference point are defined as well. Finally, we choose three smartphones with different hardware configurations on Android OS to conduct an experiment. Experimental results show that the proposed algorithm can effectively optimize the WIFI indoor location.**

Keywords- WIFI, Indoor location optimization, Position fingerprint, Received signal strength, Access points.

I. INTRODUCTION

Existing GPS and related location technologies can obtain high accuracy on meter level in outdoor environments [1,2]. However, for indoor environment, they can't obtain high level position accuracy. With the fast development of WiFi technology and its rapid coverage rate, the study on WiFi indoor positioning has attracted many researchers [3-5]. Moreover, there are many indoor positioning algorithm been proposed. In recently years, with the rapid development of wireless communication and computer technology, indoor positioning technology has attracted more and more attention [6,7]. The utilization of WIFI hotspots indoor is extensive and intensive, and exploiting the WIFI network to location has been a key method to achieve the indoor positioning [8]. WIFI positioning approach based on the position fingerprint algorithm needs little hardware resource, and low computation cost and higher positioning accuracy [9].

Particularly, location based services have extended from outdoor scene to indoor environment. Hence, this technology has a brilliant prospect. High performance positioning technology has great significance [10,11]. With the rapid development of wireless LANs, WLAN based positioning method has been widely used. This is due to the fact that WiFi indoor positioning technology is an effective indoor positioning technology, and WiFi indoor positioning technology based location fingerprint is simple, low cost, accuracy, robustness, scalability, and so on [12,13].

Wireless Local Area Networks have widely been used for indoor location fingerprinting technology which is suitable to be used in indoor positioning [14,15]. Fingerprinting is regarded as an estimator which uses the received signal strength measurements to compute the most likely position of the user [16,17].

In this paper, we propose a novel WIFI indoor location optimization method based on position fingerprint algorithm. The rest of the paper is organized as follows. We explain overview of the indoor location fingerprinting in section 2. In Section 3, we illustrate the proposed WIFI indoor location optimization method. In section 4, experiments are conducted to prove the effectiveness of the proposed algorithm. Finally, we conclude the whole paper in section 5.

II. OVERVIEW OF THE INDOOR LOCATION FINGERPRINTING

Each fingerprint is made up of a set of intensity values of the detected WAPs, and then fingerprint is defined as a vector with fixed size. Assume that there are P access points at location $\{\phi_1,\phi_2,\cdots,\phi_P\}$ and R reference points with known location $\{\theta_1,\theta_2,\cdots,\theta_R\}$ in two-dimensional area, and the following two conditions are satisfied.

$$\phi_i=\left[x_i^{AP},y_i^{AP}\right]^T \tag{1}$$

$$\theta_r=\left[x_r^{AP},y_r^{AP}\right]^T \tag{2}$$

We suppose that there W collected fingerprinting measurements of all access points memorized in database, and the fingerprint vector related to the r^{th} reference point is represented as follows.

$$S_{RP}^{r}(h)=\left[s_1^r(h),s_2^r(h),\cdots,s_q^r(h)\right] \tag{3}$$

978-1-5386-2813-3/17 $31.00 © 2017 IEEE
DOI 10.1109/ICSGEA.2017.123

where $s_i^r(h)$ is the h^{th} measured received signal strength at the r^{th} reference point from i^{th} access point.

Afterwards, the mean received signal strength vector at the location θ_r is defined as follows.

$$S_{RP}^{r} = \left[\hat{s}_1^{r}, \hat{s}_2^{r}, \cdots, \hat{s}_h^{r}\right] \quad (4)$$

$$\hat{s}_i^{r} = \frac{1}{J}\sum_{j=1}^{J} s_i^r(j) \quad (5)$$

Based on the above analysis, location fingerprint database generation is shown in Fig. 1.

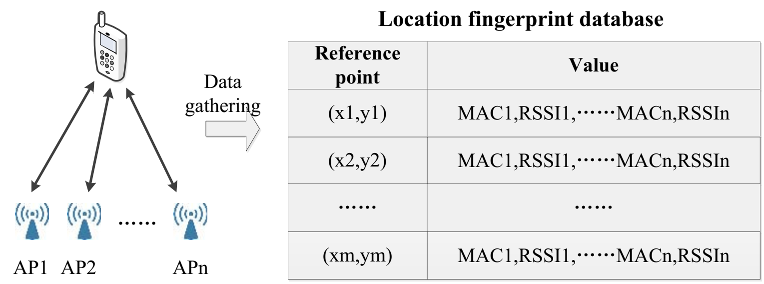

Figure 1. Location fingerprint database generation

III. THE PROPOSED WIFI INDOOR LOCATION OPTIMIZATION METHOD

In this work, we optimize WIFI indoor location via the location fingerprinting algorithm, and flowchart of the location fingerprinting algorithm is shown in Fig. 2.

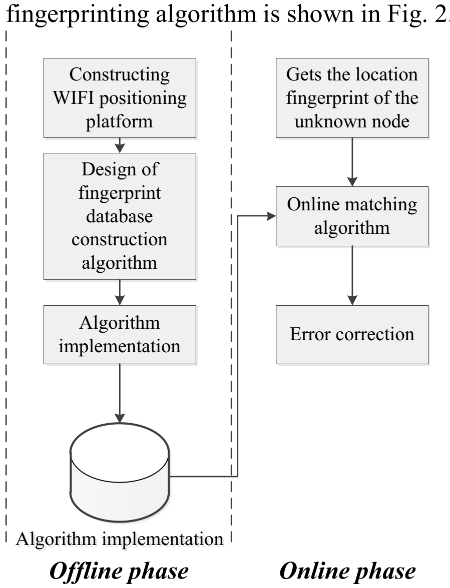

Figure 2. Flowchart of the location fingerprinting algorithm

The proposed location fingerprinting algorithm is made up of online and offline phase. Suppose that L, M refer to the number of exploited reference points and access points, and the l^{th} reference point and m^{th} access points are represented as RP_l and AP_m, where $1 \le l \le L$ and $1 \le m \le M$ are satisfied. Furthermore, RP_l is represented as the coordinate $d_l = (x_l, y_l)$ related to a 2D Cartesian reference system.

In the training process, a 3D observation matrix M is made up of R rows and C columns with K elements. The element $E_{c,r,k}, r \in [1,R], c \in [1,C], k \in [1,K]$ of matrix M refers to the single Received Signal Strength value which is received from the c^{th} access point, and sensed at the r^{th} reference point in the k^{th} signal strength measure.

The radio fingerprint of each reference point is represented as follows.

$$\begin{cases} \mu_{c,r} = \dfrac{1}{K}\sum_{k=1}^{K} E_{c,r,k} \\ \sigma_{c,r}^2 = \dfrac{1}{K}\sum_{k=1}^{K}\left(E_{c,r,k} - \mu_{c,r}\right) \end{cases} \quad (6)$$

where $\mu_{c,r}$ and $\sigma_{c,r}^2$ refer to the mean and variance of observations for the c^{th} access point, and sensed at the r^{th} reference point

At the end of training process, a probabilistic map is generated for the interest field. The single probability density function for the c^{th} access point and the r^{th} reference point are defined as follows.

$$N\left(\mu_{c,r},\sigma_{c,r}^{2}\right)=\frac{1}{\sqrt{2\pi\sigma_{c,r}^{2}}}e^{-\frac{\left(v_c-\mu_{c,r}\right)^2}{2\sigma_{c,r}^2}} \quad (7)$$

where $v=\left[v_1,v_2,\cdots,v_c\right]$ is the observation vector, and the quantity $p\left(c\middle|v\right)$ is computed using Bayes formula as follows.

$$p\left(c\middle|v\right)=\frac{p\left(v\middle|c\right)\cdot p\left(c\right)}{p\left(v\right)} \quad (8)$$

where $p\left(v\middle|c\right)$ is calculated as follows.

$$p\left(v\middle|c\right)=\prod_{c=1}^{C}\frac{1}{\sqrt{2\pi\sigma_{c,r}^{2}}}e^{-\frac{\left(v_c-\mu_{c,r}\right)^2}{2\sigma_{c,r}^2}},\forall r\in\left[1,R\right] \quad (9)$$

IV. EXPERIMENT

In this section, we conduct an experiment to test the performance of the proposed algorithm. Particularly, we choose three smartphones which are represented as $SP1, SP2, SP3$ respectively, and all these smartphones are installed the Android operating system. Hardware settings of these three smartphones are shown in Table. 1 as follows.

Table. 1 Hardware settings of smartphones used in this experiment

Parameter	SP1	SP2	SP3
Processor	Cortex-A8 (1GHz)	MSM8255T (1.4GHz)	ARM 11 (528MHz)
Memory	8GB	4GB	512MB
WIFI	802.11b/g/n	802.11b/g/n	802.11b/g/n
Operating system	Android v2.1	Android v2.3	Android v1.6

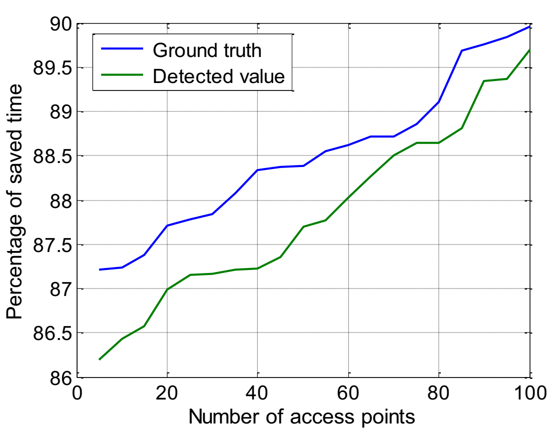

Figure 3. Percentage of saved time for SP1 with different number of access points

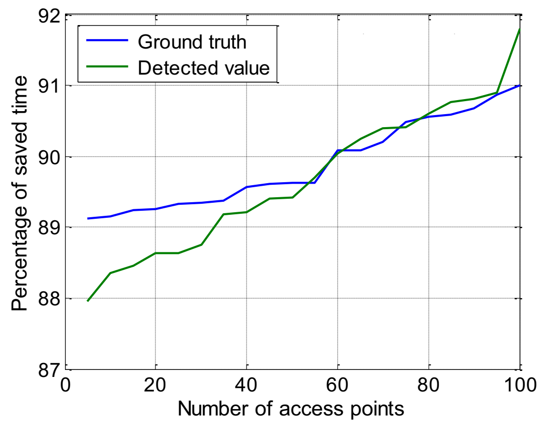

Figure 4. Percentage of saved time for SP2 with different number of access points

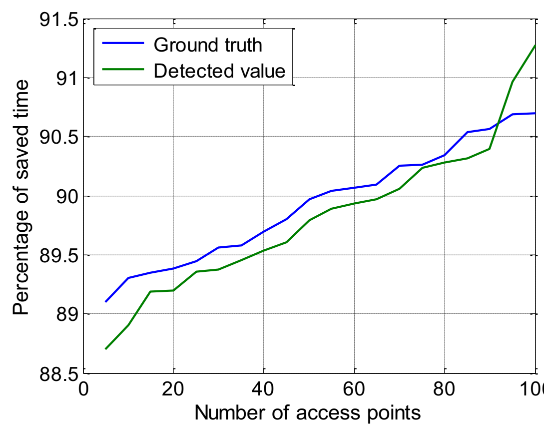

Figure 5. Percentage of saved time for SP3 with different number of access points

Integrating experimental results from Fig. 3 to Fig. 5, it can be seen that for all these three smartphones the detected value is very close to the ground truth. In the following part, we show positioning error and consumed energy under various number of access points.

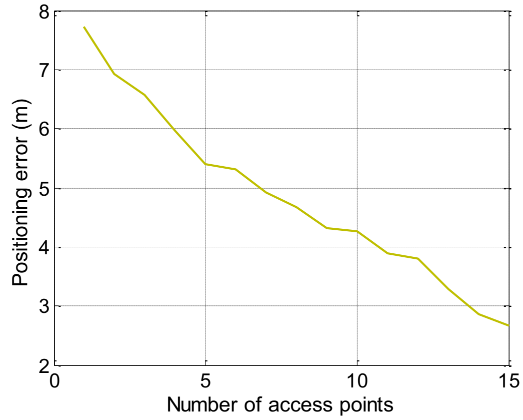

Figure 6. Positioning error with different number of access points

Fig. 6 shows that utilizing the proposed WIFI indoor location optimization method, positioning error decreases with the number of access points increasing.

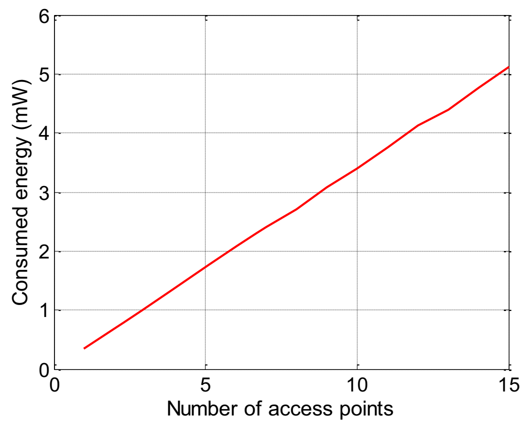

Figure 7. Consumed energy with different number of access points

Fig. 7 demonstrates that consumed energy linearly increases with number of access points increasing. Integrating all experimental results, it can be observed that the proposed algorithm is able to effectively optimize the WIFI indoor location.

V. Conclusion

This paper presents a new WIFI indoor location optimization approach based on position fingerprint algorithm. In particular, the proposed location fingerprinting algorithm contains online phase and offline phase. At the end of training process, a probabilistic map is generated for the interest area, and then a single probability density function for the access point and the reference point are defined. In the end, experimental results prove the effectiveness of the proposed algorithm.

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