Knowledge Aided Adaptive Localization via Global Fusion Profile

Xiansheng Guo, *Member, IEEE*, Lin Li, *Student Member, IEEE*, Nirwan Ansari, *Fellow, IEEE*, and Bin Liao, *Senior Member, IEEE*

***Abstract*—Indoor localization is becoming critical to empower Internet of Things for various applications, such as asset tracking, geolocation, and smart cities. Wi-Fi-based indoor localization using received signal strength (RSS) has drawn much attention over the past decade because it does not require extra infrastructure and specialized hardware. It is well known that the localization accuracy using RSS is rather susceptible to the changing environment. Localization by fusing multiple fingerprint functions of RSS is a promising strategy to overcome the above drawback. However, the existing fusion techniques cannot make full use of the intrinsic complementarity among multiple fingerprint functions. It also fails to exploit the knowledge obtained in the offline phase and thus shows low accuracy in the complex environment. This paper proposes a knowledge aided adaptive localization (KAAL) approach by using a global fusion profile (GFP) to mitigate the above shortcomings. First, we propose a GFP construction algorithm by minimizing position errors over all fingerprint functions with weight constraints in the offline phase. Based on the knowledge from GFP and the trained multiple fingerprint models, we then derive two KAAL algorithms, namely, multiple function averaging and optimal function selection, to achieve highly accurate localization results. Experimental results demonstrate that our proposed localization approach is superior to the existing methods both in simulated and real environments.**

***Index Terms*—Global fusion profile (GFP), indoor localization, knowledge aided adaptive localization (KAAL), received signal strength (RSS), Wi-Fi.**

I. Introduction

INDOOR positioning has received great attention recently because position information is essential for providing location-based services [1]–[3], which enable intelligent services in various fields in the context of Internet of Things (IoT) [4]–[6]. Although space-based satellite navigation systems, such as GPS offer high outdoor localization accuracy, the poor connectivity between satellites and end-devices render them ineffective indoor, thus triggering further research on indoor localization [7], [8].

Received signal strength (RSS)-based Wi-Fi indoor localization has become one of the most attractive solutions owing to the wide deployment and availability of Wi-Fi infrastructures [9]–[12]. These Wi-Fi infrastructures can readily provision RSS without any hardware modification. However, the RSS-based localization system is not accurate and robust because the RSS of Wi-Fi is known to be vulnerable to an unpredictable changing environment [5]. Recently, channel state information (CSI) [13] was proposed to improve the accuracy of Wi-Fi localization, which requires the specific hardware, i.e., Intel 5300 Wi-Fi network interface card to extract the CSI, and thus is not applicable for most of exsiting commodity Wi-Fi infrastructures [14], [15].

To improve the accuracy and robustness of the RSS-based Wi-Fi localization system, several advanced techniques were proposed, such as fingerprint calibration [16], fingerprint transformation [2], and machine learning [6], among which the machine learning can improve the accuracy and robustness of the RSS-based localization significantly [2], as it localizes targets by constructing the relationship between RSS measurements and the locations of targets [17]. However, most of the existing machine learning localization methods are based on some single fingerprint functions, which do not exploit the superiority of machine learning methods [6].

Recently, information fusion has attracted more attention in indoor localization [18]. By fusing some single fingerprint functions (including machine learning methods and the conventional localization methods, such as least squares (LSs), and weighted LS), one can exploit the complementarity among fingerprint functions and improve the localization accuracy significantly. The existing fusion methods can be categorized as two groups: one is based on a grid dependent fusion profile (GDFP), such as dynamic fingerprint combining (DFC) and its variants [17], [19]–[21], and the other is based on a grid independent fusion profile (GIFP), such as minimum mean square error (MMSE) based location estimation [22]. In a nutshell, the former constructs different fusion profiles at different grids, while the latter trains one fusion profile (FP) for all grids. Therefore, GDFP belongs to adaptive localization framework and is superior to GIFP in a complex environment. In general, the existing fusion techniques cannot make full use of the intrinsic complementarity among multiple fingerprint functions when constructing the FP; furthermore, the weights

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selection strategies of the existing fusion techniques just uses an RSS direct matching, which fails to exploit the knowledge obtained in the offline phase. The wrong weights selection by the direct RSS matching will lead to a large location error in a complex environment.

In this paper, we propose a knowledge aided adaptive localization (KAAL) approach by using a global FP (GFP) to overcome the above drawbacks. In the offline phase, we first construct a GFP by minimizing the global position errors over all fingerprint functions. Unlike the existing FP construction strategy, which optimizes the weight for each fingerprint function sequentially, our proposed GFP is the optimal solution in the whole fingerprint function space, i.e., we jointly optimize all fingerprint functions with weights normalization constraint by using some offline training data. As compared with the existing FP, GFP can fully excavate the intrinsic complementarity among fingerprint functions, and thus yields a more accurate location estimate.

Based on the knowledge from the multiple functions trained in the offline phase, we further propose two knowledge aided weights selection algorithms for the online phase, namely, multiple functions averaging (MFA), and optimal function selection (OFS), instead of the RSS matching. MFA chooses the weights according to the average of the outputs of multiple fingerprint functions, while OFS tries to obtain weights based on the output of the best fingerprint function. The knowledge aided weights selection strategies can better exploit the knowledge of multiple functions and GFP to increase the success probability of weights selection and thus improve the fusion localization accuracy, which is more attractive in a complex indoor environment.

Below are the main contributions of this paper.

1) We propose a GFP construction algorithm by minimizing global position error over all fingerprint functions. Our proposed GFP can fully excavate the intrinsic complementarity between each fingerprint function as compared with the existing FP. The computational complexity is also reduced significantly as compared with the FP construction strategy.
2) We propose a KAAL framework to fully exploit the knowledge about fingerprint functions and GFP obtained in the offline phase. As compared with the RSS direct matching, the knowledge from multiple fingerprint functions make MFA and OFS more robust against some changing environments.
3) We implement our proposed localization in both a real office environment and a simulation environment. Experimental results show that the KAAL framework outperforms the existing fusion methods in localization accuracy. The more complex the indoor environment is, the more superior our proposed approach will be. Hence, KAAL is very suitable for complex indoor environments.

The remaining paper is organized as follows. Section II introduces the proposed localization framework. Our proposed GFP construction algorithm and two KAAL algorithms, MFA and OFS, are detailed in Section III. Additionally, algorithm complexity and accuracy are also analyzed in Section III. Section IV describes the experimental setup and presents extensive results in both simulated and real office environments for performance evaluation. Finally, conclusions are drawn in Section V.

II. Proposed Localization Framework

Suppose that a location area can be divided into K grid points, each numbered by a label, and the area is covered by L Wi-Fi APs. Assume that we can construct two databases $\boldsymbol{D}$ and $\boldsymbol{D'}$ from the fingerprints collected at all grid points. Among them, $\boldsymbol{D} = \left[\boldsymbol{D}_1\ \boldsymbol{D}_2 \cdots \boldsymbol{D}_K\right] \in \mathcal{R}^{L\times M\times K}$ is used for training multiple fingerprint functions with M being the number of corresponding training samples, while $\boldsymbol{D'} = \left[\boldsymbol{D}'_1\ \boldsymbol{D}'_2 \cdots \boldsymbol{D}'_K\right] \in \mathcal{R}^{L\times N\times K}$ is collected for GFP construction with N being the number of corresponding training samples. At the kth grid point, the submatrices $\boldsymbol{D}_k$ and $\boldsymbol{D}'_k$ are

$$\boldsymbol{D}_k = \begin{bmatrix} r_k^1(1) & r_k^1(2) & \cdots & r_k^1(M) \\ r_k^2(1) & r_k^2(2) & \cdots & r_k^2(M) \\ \vdots & \vdots & \ddots & \vdots \\ r_k^L(1) & r_k^L(2) & \cdots & r_k^L(M) \end{bmatrix} \tag{1}$$

and

$$\boldsymbol{D}'_k = \begin{bmatrix} r_k^1(M+1) & r_k^1(M+2) & \cdots & r_k^1(N+M) \\ r_k^2(M+1) & r_k^2(M+2) & \cdots & r_k^2(N+M) \\ \vdots & \vdots & \ddots & \vdots \\ r_k^L(M+1) & r_k^L(M+2) & \cdots & r_k^L(N+M) \end{bmatrix} \tag{2}$$

respectively, where $r_k^l(n)$ is the RSS value collected at the nth time index, at the kth grid point, and from the lth AP.

Our proposed KAAL framework consists of an online phase and an offline phase, as depicted in Fig. 1. In the offline phase, we need to first obatin a knowledge database, which includes two modules: 1) building the models, i.e., obtaining the multiple fingerprint functions trained by the offline training data $\boldsymbol{D}$ and 2) constructing the GFP with $\boldsymbol{D}'$. Each model $f_h(\boldsymbol{D})$ is trained from the hth fingerprint function f_h and it maps from an RSS vector to a corresponding label (i.e., grid position/location). GFP $\in \mathcal{R}^{K\times H}$ is constructed by minimizing the global position errors in the whole fingerprint function space, which can be expressed as

$$\text{GFP} = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1H} \\ w_{21} & w_{22} & \cdots & w_{2H} \\ \vdots & \vdots & \ddots & \vdots \\ w_{K1} & w_{K2} & \cdots & w_{KH} \end{bmatrix} \tag{3}$$

where H is the number of fingerprint functions. The kth row in GFP denotes the weights of multiple fingerprint functions at the kth grid point, i.e., the FP of the kth grid point.

In the online phase, to fully leverage the knowledge database trained in the offline phase, we derive two KAAL algorithms, namely, MFA and OFS, to improve the accuracy of weights selection. After having obtained the weights to be fused, the location estimate $\hat{\boldsymbol{p}} = [\hat{x}, \hat{y}]^T$ of a user at an unknow location $\boldsymbol{p} = [x, y]^T$ with the RSS $\tilde{\boldsymbol{r}}$ is

$$\hat{\boldsymbol{p}} = \sum_{h=1}^{H} w_{\hat{k}h}\big(\tilde{\boldsymbol{r}}, \text{GFP}\big) g\big(f_h\big(\tilde{\boldsymbol{r}}, \boldsymbol{D}\big)\big) \tag{4}$$

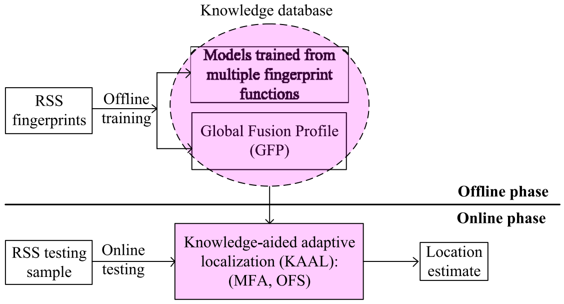


Fig. 1. Overview of the proposed KAAL framework.

where $w_{\hat{k}h}(\tilde{\boldsymbol{r}}, \text{GFP})$ is the selected weight from GFP by using MFA or OFS when the testing RSS sample $\tilde{\boldsymbol{r}}$ is given. $\hat{k}$ is the estimated grid point index. $g(\cdot) : \mathcal{R}^1 \rightarrow \mathcal{R}^2$ maps a label to a 2-D coordinate. In summary, the key problems of accurate localization are: 1) how to construct a robust GFP when several fingerprint functions are given and 2) how to choose the optimum weight or set of weights for fusion from the constructed GFP for the online testing sample $\tilde{\boldsymbol{r}}$, i.e., how to calculate $\hat{k}$ in (4). We will discuss these two key problems in the next section.

III. Proposed Algorithm

A. Knowledge Database Construction

1) Models and Fingerprint Functions: As mentioned above, the models $f_h(\boldsymbol{D})$ $(h = 1, 2, \ldots, H)$ are trained from multiple fingerprint functions f_h by using $\boldsymbol{D}$. Hence, we need to choose some fingerprint functions for training in the offline phase. Given an online testing sample, some of the fingerprint functions may have large localization errors, while others have small localization errors. Hence, a fingerprint function with higher accuracy may still exploit the complementarity of others to yield an enhanced location estimate. In other words, a fingerprint function with poor performance still can contribute to the final location estimate for some certain testing samples. In this paper, we test the fusion performance by using four typical fingerprint functions: 1) neural network (NN) [23]; 2) K-NN (KNN) [24]; 3) extreme learning machine (ELM) [25]; and 4) random forests (RFs) [26]. For the consideration of the limited space, we will not discuss each fingerprint function in detail. However, how to choose a set of fingerprint functions to yield a more accurate localization result is the key problem of ensemble learning. In summary, we should try our best to select the fingerprint functions with good diversities and low average generalization errors [27] for a high accurate localization.

2) Global Fingerprint Profile Construction: At the kth grid point, we can obtain the predictions by using the trained models of multiple fingerprint functions and $\boldsymbol{D}'$ as

$$\hat{z}_h = f_h\left(\boldsymbol{D}'_k, \boldsymbol{D}\right) \tag{5}$$

where $\hat{z}_h$ is an $N \times 1$ vector with the ith entry being the prediction $f_h(\boldsymbol{r}_k(i), \boldsymbol{D})$, $(M + 1 \leq i \leq M + N)$ given by the hth model $f_h(\boldsymbol{D})$ when inputting the offline sample $\boldsymbol{r}_k \subset \boldsymbol{D}'$, i.e.,

$$\hat{z}_h(i) = f_h(\boldsymbol{r}_k(i), \boldsymbol{D}). \tag{6}$$

For the ith sample $\boldsymbol{r}(i)$, the predictions of models can be written as

$$\boldsymbol{z}(i) = \left[\hat{z}_1(i), \hat{z}_2(i), \ldots, \hat{z}_H(i)\right]^T. \tag{7}$$

FP was first proposed in [17] and it is a weight matrix trained by using $\boldsymbol{D}'$. FP evaluates the performances of fingerprint functions by assigning different weights. As mentioned earlier, FP includes GIFP and GDFP. The former uses a unique weight vector to fuse a localization result at all grid points, while the latter adopts different weights to fuse a location estimate. As compared with GIFP, GDFP shows good adaptivity and is more accurate in complex environments. Using the GDFP approach, DFC tries to determine the weight w_{kh} for the hth fingerprint function at the kth grid point by minimizing the average position errors over N RSS samples as

$$\hat{w}_{kh} = \underset{0 \leq w_{kh} \leq 1}{\arg\min} \frac{1}{N} \sum_{i=M+1}^{N+M} e(\boldsymbol{r}_k(i)|w_{kh}) \tag{8}$$

where $e(\boldsymbol{r}_k(i)|w_{kh})$ is the localization error for the ith RSS sample at the kth grid point with the weight w_{kh}, that is,

$$e(\boldsymbol{r}_k(i)|w_{kh}) = \left\| w_{kh} \times g(f_h(\boldsymbol{r}_k(i), \boldsymbol{D})) - \boldsymbol{p}_k \right\|_2 \tag{9}$$

where $\|\cdot\|_2$ is the ℓ_2-norm and $\boldsymbol{p}_k = [x_k, y_k]^T$ is the known location of the kth grid point.

After having obtained all weights of multiple fingerprint functions *sequentially*, the normalized operator is given by

$$\sum_{h=1}^{H} \hat{w}_{kh} = 1, \quad k = 1, \ldots, K. \tag{10}$$

Note that the weights searching strategy using (8)–(10) is just the optimization for each fingerprint function over all N RSS samples. It cannot fully excavate the intrinsic complementarity among fingerprint functions. Therefore, the FP of DFC is not a global optimum solution. To mitigate the above shortcoming, we construct GFP by minimizing the global position errors over all fingerprint functions as follows.

Let the GFP $\boldsymbol{w}_k$ at the kth grid point being $\boldsymbol{w}_k = [w_{k1}, w_{k2}, \ldots, w_{kH}]^T$, which can be obtained by

$$\begin{aligned} \hat{\boldsymbol{w}}_k = \underset{\boldsymbol{w}_k}{\arg\min} \quad & \frac{1}{N} \sum_{i=M+1}^{N+M} e'(\boldsymbol{r}_k(i)|\boldsymbol{w}_k) \\ \text{s.t.} \quad & \boldsymbol{w}_k^T \mathbf{1} = 1 \\ & w_{kh} \geq 0, \quad h = 1, 2, \ldots, H \end{aligned} \tag{11}$$

where $\mathbf{1}$ is an $H \times 1$ all one vector. The localization error $e'(\boldsymbol{r}_k(i)|\boldsymbol{w}_k)$ for the ith RSS vector with global weights $\boldsymbol{w}_k$ at the kth grid point is

$$e'(\boldsymbol{r}_k(i)|\boldsymbol{w}_k) = \left\| \boldsymbol{w}_k^T g(\boldsymbol{z}(i)) - \boldsymbol{p}_k \right\|_2 \tag{12}$$

where $\boldsymbol{z}(i)$ is given by (6) and (7). After having obtained $\hat{\boldsymbol{w}}_k$, the GFP matrix is given by

$$\boldsymbol{W} = \left[\hat{\boldsymbol{w}}_1 \ \hat{\boldsymbol{w}}_2 \ \ldots \ \hat{\boldsymbol{w}}_K\right]^T. \tag{13}$$

Our proposed GFP can be obtained by solving the optimization problem depicted in (11) and (12), which is a joint optimization of multiple fingerprint functions. It can excavate the

Algorithm 1 GFP Construction

Input: 1) The number of grid points K; 2) The number of fingerprint functions H; 3) The offline training fingerprints $\boldsymbol{D}$; 4) The offline testing fingerprints $\boldsymbol{D}'$

Output: The GFP maxtrix $\boldsymbol{W}$.

for $h = \{1, 2, \cdots, H\}$ **do**
  Train the model $f_h(\boldsymbol{D})$ by using $\boldsymbol{D}$
end for
for $k = \{1, 2, \cdots, K\}$ **do**
  for $i = \{M+1, M+2, \cdots, M+N\}$ **do**
    Compute $\boldsymbol{z}(i)$ by using Eqs. (6) and (7)
    Compute $e'(\boldsymbol{r}_k(i)|\boldsymbol{w}_k)$ by using Eq. (12)
  end for
  Compute $\hat{\boldsymbol{w}}_k$ by using Eq. (11)
end for
$\boldsymbol{W} = \left[\hat{\boldsymbol{w}}_1 \ \hat{\boldsymbol{w}}_2 \ \cdots \ \hat{\boldsymbol{w}}_K\right]^T$
return $\boldsymbol{W}$

complementary of multiple fingerprint functions. As compared with the FP constructed from DFC, GFP can offer more knowledge for KAAL. We summarize the procedure of constructing GFP in Algorithm 1.

B. Knowledge Aided Adaptive Localization

Given the knowledge database, another key problem for accurate fusion localization is how to choose the optimum weights for fusion given a testing sample $\tilde{\boldsymbol{r}}$ in the online phase, i.e., how to estimate a suitable grid index $\hat{k}$ for $\tilde{\boldsymbol{r}}$? The existing $\hat{k}$ estimation method is the RSS direct matching between the testing sample $\tilde{\boldsymbol{r}}$ and the training fingerprints $\boldsymbol{D}$, that is,

$$\hat{k} = \arg\min_{k} \|\tilde{\boldsymbol{r}} - \boldsymbol{D}(k,:)\|_2. \tag{14}$$

Apparently, this strategy is not intelligent because it could be affected by the fluctuation of the RSS in complex indoor environments. To fully leverage the knowledge from the offline phase, we propose the following two KAAL algorithms.

1) Multiple Functions Average: Multiple functions average algorithm obtains the fusion result by averaging the location estimates of multiple models. As compared with the direct RSS matching method, it can exploit the merits of multiple models in the knowledge database. The weights selection is based on the following grid index estimate:

$$\hat{k}_j = f_h\big(\tilde{\boldsymbol{r}}, \boldsymbol{D}\big). \tag{15}$$

The KAAL result based on MFA is given by

$$\hat{\boldsymbol{p}} = \frac{1}{H}\sum_{j=1}^{H}\left(\sum_{h=1}^{H}\hat{w}_{\hat{k}_j h}\, g\big(f_h\big(\tilde{\boldsymbol{r}}, \boldsymbol{D}\big)\big)\right). \tag{16}$$

MFA uses the knowledge of all models. It can yield more accurate estimate when all fingerprint functions show good performances. However, it may show poor performance if one of the fingerprint function models degenerates seriously.

Algorithm 2 MFA

Input: 1) The number of fingerprint functions H; 2) The trained models $f_h(\boldsymbol{D})$; 3) The online testing sample $\tilde{\boldsymbol{r}}$

Output: The final location estimate $\hat{p}$

for $j = \{1, 2, \cdots, H\}$ **do**
  Compute the matched grid point $\hat{k}_j$ by using Eq. (15)
end for
Compute the final location estimate $\hat{\boldsymbol{p}}$ by using Eq. (16)
return $\hat{\boldsymbol{p}}$

Algorithm 3 OFS

Input: 1) The number of fingerprint functions H; 2) The trained models $f_h(\boldsymbol{D}), (h = 1, 2, \cdots, H)$; 3) The offline testing fingerprint database $\boldsymbol{D}'$; 4) The online testing sample $\tilde{\boldsymbol{r}}$

Output: The final location estimate $\hat{p}$

for $k = \{1, 2, \cdots, K\}$ **do**
  for $i = \{M+1, M+2, \cdots, M+N\}$ **do**
    Compute $\boldsymbol{z}(i)$ by using Eqs. (6) and (7)
  end for
end for
Estimate $\hat{h}$ by using Eq. (17)
Compute the matched grid point $\hat{k}$ by using Eq. (18)
Compute $\hat{\boldsymbol{p}}$ by using Eq. (19)
return $\hat{\boldsymbol{p}}$

2) Optimal Function Selection: This matching strategy first finds the optimal model by using offline testing fingerprints $\boldsymbol{D}'$, that is,

$$\hat{h} = \arg\min_{h}\sum_{k=1}^{K}\sum_{i=M+1}^{N+M}\left\|g\big(\hat{z}_h(i)\big) - \boldsymbol{p}_k\right\|_2 \tag{17}$$

where $\hat{z}_h(i)$ is given by (6). Equation (17) can yield the index estimate of the optimal model.

In the online phase, assume that we can obtain a matching grid point according to the prediction of the optimal model when inputting the testing sample $\tilde{\boldsymbol{r}}$

$$\hat{k} = f_{\hat{h}}\big(\tilde{\boldsymbol{r}}, \boldsymbol{D}\big). \tag{18}$$

Then, the optimum weights $\boldsymbol{w}_{\hat{k}}$ at the estimated grid point $\hat{k}$ will be selected from the GFP matrix $\boldsymbol{W}$, which yields the final location estimate

$$\hat{\boldsymbol{p}} = \sum_{h=1}^{H} w_{\hat{k}h}\, g\big(f_h\big(\tilde{\boldsymbol{r}}, \boldsymbol{D}\big)\big). \tag{19}$$

OFS could choose the weights based on the output of the optimal model; in other words, it selects the optimal weights by resorting to the knowledge of the trained model. So, it is smarter than MFA. We summarize the procedures of our proposed two KAAL algorithms in Algorithms 2 and 3.

C. Performance Analysis

1) Complexity: The computational complexity of our proposed KAAL framework is mainly composed of two parts: 1) GFP construction and 2) the online matching, i.e., MFA

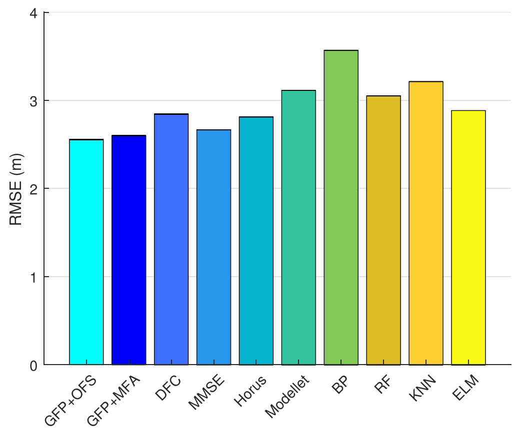


Fig. 2. RMSEs of different algorithms.

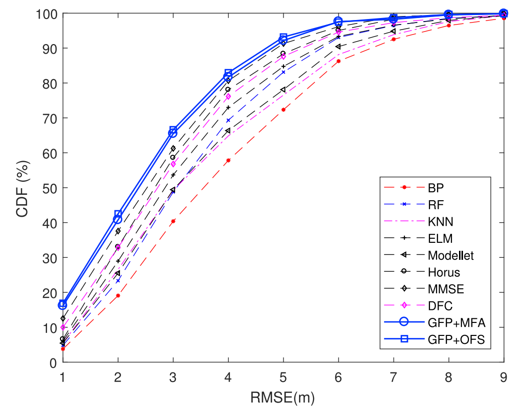


Fig. 3. CDFs of different localization algorithms.

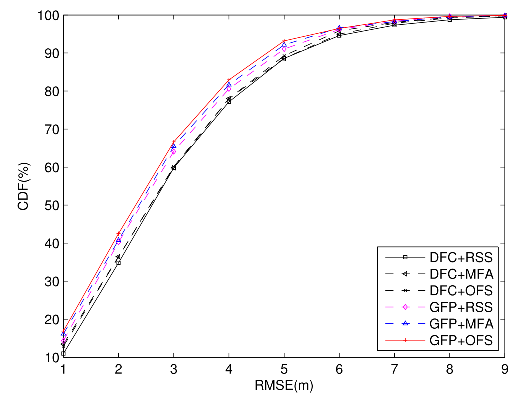


Fig. 4. CDFs of different matching strategies of two GDFP approaches.

or OFS. In comparing with the sequentially weights computing strategy used in FP construction (see (8) and (10) for reference), the weights obtained according to (11) in GFP construction are done in parallel, thus reducing the computational complexity efficiently especially when the number of fingerprint functions is large. As compared with the RSS direct matching used by DFC, MFA is simpler by averaging the outputs of multiple models. OFS needs to estimate the optimum model before localization, and thus slightly increases the computational complexity. Fortunately, it is done in the offline phase. Meanwhile, unlike MFA, OFS does not need to average the outputs of multiple models, and thus has the lowest complexity in the online phase.

Fingerprint construction is also a time consuming task for fingerprint-based localization approaches including DFC, MMSE, and our methods. Fortunately, it is done in the offline phase and has little impact on the complexity of online localization. How to decrease the budern of fingerprint construction without remarkable performance loss in localization accuracy is a well-pursued topic in indoor localization fields [12], [16], [28], and we can use some of these strategies to tradeoff the burden of the fingerprint database construction and localization accuracy [28].

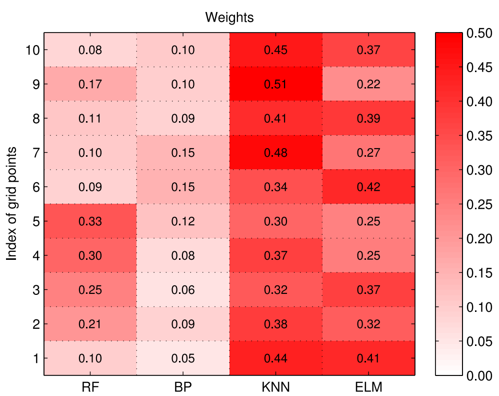
2) Accuracy: As compared with DFC and MMSE, our proposed GFP and KAAL can enhance accuracy well. First, the weights constructed from GFP can fully excavate the intrinsic complementarity among multiple fingerprint functions. The accuracy can be improved by fusing these weights. Second, our two proposed MFA and OFS algorithms can further improve the accuracy by decreasing the weight selection errors induced by the RSS direct matching. The accuracy improvement will be more remarkable as the number and performance differences of fingerprint functions increase. Furthermore, the superiority of our approach in localization accuracy will be strengthened when the environment becomes more complex, as shown in the subsequent experimental results.

IV. Experimental Setup and Results

To evaluate the effectiveness of the proposed algorithm, we have designed two experimental scenarios using simulation data and real data, respectively. We compare the performance of our methods with two existing fusion methods and two typical fingerprint-based methods.

1) *Two Fusion Methods:*
   a) *DFC [17]:* A representative approach of GDFP which optimizes the weight for each fingerprint function sequentially at different grid points.
   b) *MMSE [22]:* A representative approach of GIFP which trains one FP for all grid points.
2) *Two Fingerprint-Based Methods:*
   a) *Horus [11]:* A classical probabilistic algorithm that calculates the probability distribution of the received RSS at each grid point in the offline phase. In the online phase, Horus obtains the final location using maximum likelihood estimate.
   b) *Modellet [12]:* A virtual fingerprints aided fingerprint-based method in which virtual fingerprints are generated by applying the local log-distance path loss model trained from some limited real fingerprints. In the online phase, Modellet uses a location inference algorithm, such as KNN, to yield a location estimate. In our experiments, the distances between two adjacent grid points for generating virtual fingerprints are set to 2 and 3 m in simulation and real scenarios, respectively.

(a)



(b)

Fig. 5. Fusion weights comparison assigned by (a) FP and (b) GFP.

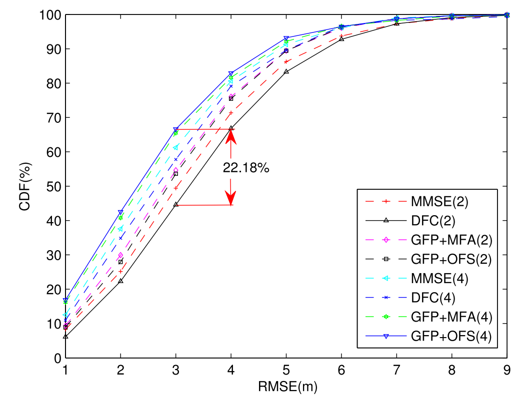


Fig. 6. CDFs versus RMSEs with different number of fingerprint functions.

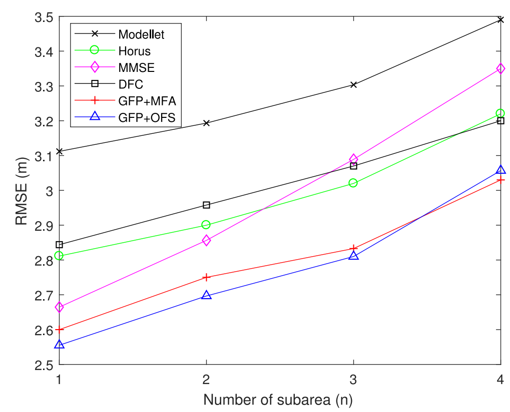


Fig. 7. RMSEs versus the number of subareas.

A. Simulation Experiment

In the first experiment, we construct the Wi-Fi fingerprints by using the RSS model [29]. Four APs are placed at the four corners of a room of size 140 m^2 with positions $z_1 = [0\text{ m}, 0\text{ m}]^T$, $z_2 = [0\text{ m}, 14\text{ m}]^T$, $z_3 = [14\text{ m}, 0\text{ m}]^T$, $z_4 = [14\text{ m}, 14\text{ m}]^T$, respectively. There are 144 grid points and the distance between two adjacent grid points is 1 m. Four fingerprint functions including RF, BP NN, KNN, and ELM are considered. The root mean square error (RMSE) is defined as

$$\text{RMSE} = \sqrt{\frac{1}{J}\sum_{n=1}^{J}\left[\left(\hat{x}_n - x\right)^2 + \left(\hat{y}_n - y\right)^2\right]} \tag{20}$$

where $[\hat{x}_n, \hat{y}_n]^T$ represents the nth location estimate, and $[x, y]^T$ is the true location of the source. J is the number of experiment trials.

First, we show the RMSEs of these algorithms in Fig. 2. It is found that the RMSE of DFC is 2.84 m, close to that of ELM, because DFC cannot fully exploit the intrinsic complementarity among fingerprint functions. This drawback aggravates when different fingerprint functions have different performances. Note that MMSE is better than DFC in this case. However, the performance of MMSE degrades seriously when the indoor environment becomes complex, as shall be shown latter. The RMSE of Modellet is 3.11 m, performing worse than any fusion method, because Modellet severely depends on the quality of generated virtual fingerprints. Generally, the localization performance of virtual fingerprints is worse than that of real measurements because the trained parameters are not accurate in a complex environment. Horus achieves RMSE of 2.81 m, which is slightly better the optimal fingerprint function but worse than our methods. Our proposed GFP+OFS and GFP+MFA lead to 2.55 and 2.6 m localization errors, respectively, which demonstrate the effectiveness of the proposed KAAL strategy.

As shown in Fig. 3, GFP+OFS outperforms the other methods, reducing the RMSE by 1.7%, 4.1%, 10.2%, 9.2%, 17.8%, 16.3%, 28.4%, 20.5%, and 11.4%, as compared with GFP+MFA, MMSE, DFC, Horus, Modellet, RF, BP, KNN, and ELM, respectively. The probability of DFC in acquiring RMSE of less than 2 m is 34%, while GFP+OFS is up to 42%. This improvement comes from the joint utilization of GFP and OFS, as compared with DFC, which uses FP and the direct RSS matching.

To reveal the merits of KAAL, we detail the influence of GFP, MFA, and OFS on RMSEs. Fig. 4 shows that the performance improvements achieved by different combinations, including DFC (i.e., the RSS direct matching), DFC+MFA, DFC+OFS, GFP+RSS (i.e., the RSS direct matching), GFP+MFA, and GFP+OFS. Note that the performance differences among DFC+RSS, DFC+MFA, and DFC+OFS are insignificant. As compared with DFC, the proposed GFP, MFA, and OFS can improve the performance to some extent.

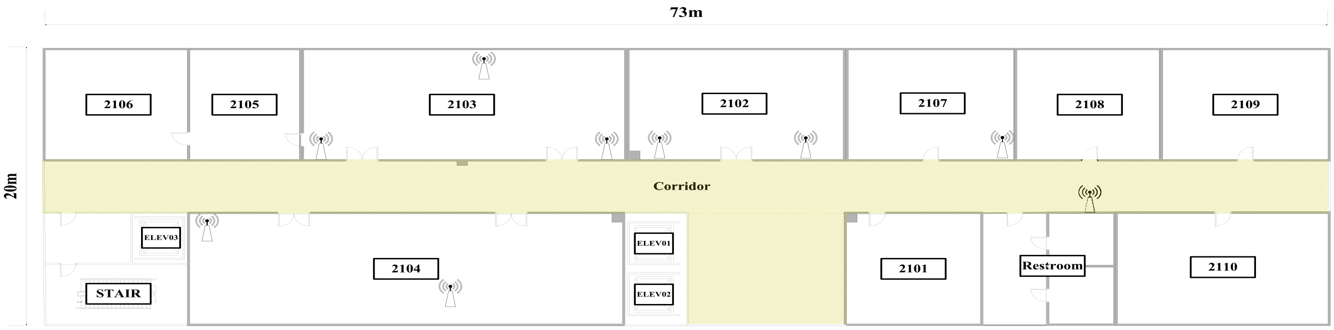


Fig. 8. Layout of the 21st floor in our experimental study.

TABLE I
DIFFERENT PATH LOSS FACTORS USED IN OUR SIMULATION

Path loss factor	**The number of subareas**			
	$n=1$	$n=2$	$n=3$	$n=4$
γ	$\gamma_1=2$	$\gamma_1=2$ $\gamma_2=3$	$\gamma_1=2$ $\gamma_2=3$ $\gamma_3=4$	$\gamma_1=2$ $\gamma_2=3$ $\gamma_3=4$ $\gamma_4=5$

To clarify the differences between our proposed GFP and FP, we illustrate the weights assignments by GFP and FP in Fig. 5. Owing to the limited space, we only list the weights of ten grid points for comparison. In Fig. 5, the number in each box is the weight of a single algorithm at each grid point with deeper color representing a larger weight. Fig. 5(a) shows that the weights assigned by DFC are close to each other at all grid points. These weights cannot reflect the differences between fingerprint functions. In Fig. 5(b), KNN and ELM functions play a greater role in the fusion in most cases in our constructed GFP, and hence, they are assigned some larger weights. Although the other two functions have lower weights, they still contribute to the final location estimate, as shown at the fifth grid point. By comparing Fig. 5(a) with Fig. 5(b), we can draw a conclusion that GFP can better exploit the complementarity among multiple fingerprint functions.

Theoretically, the superiority of our KAAL framework becomes more noticeable as the number of fingerprint functions increases. That is the motivation why we develop the KAAL framework. Fig. 6 illustrates the influence of the number of fingerprint functions on RMSEs. Here, we consider two cases: 1) two fingerprint functions and 2) four fingerprint functions. Our proposed GFP+OFS obtains 22.18% improvement of RMSE of less than 3 m, as compared with DFC with two fingerprint functions, as shown in Fig. 6.

Finally, we evaluate the adaptive abilities of these algorithms to a changing environment. To elicit the numerical analysis, we partition the indoor environment from one to four subareas with different γ. In Table I, $n=1$ means that the path loss constant $\gamma_1=2$ in the RSS model, i.e., the indoor environment does not change, and $n=2$ means that we use two different path loss factors $\gamma_1=2, \gamma_2=3$ to model the indoor environment. The different γ's for $n=3$ and $n=4$ are also listed in Table I. Fig. 7 depicts the RMSEs versus the number of subareas. Note that the performance of MMSE degrades faster than other algorithms as the complexity of environment increases because MMSE adopts GIFP for fusion. Although DFC is an adaptive one, the FP and matching strategies of DFC degenerate its performance. Thus, the RMSE of DFC increases faster than our approach. The performance of Modellet also degrades fast as the complexity of environment increases; this is also due to the bad quality of generated virtual fingerprints. Horus performs better than DFC in the case of $n=1, 2, 3$ and degenerates slowly as compared with MMSE. Comparatively, our proposed KAAL framework is more robust to the complexity of indoor environment. The more complex the indoor environment is, the more superior our proposed approach will be. Hence, our KAAL framework is more suitable for real applications than the other two methods.

Fig. 9. Interior environment and AP in our experimental study.

B. Real Environment Experiment

We conducted an experiment in a real office environment located on the 21st floor of the innovation building on the campus of University of Electronic Science and Technology of China. The area is about $73\ \text{m} \times 20$ m, i.e., 1460 m^2. It mainly includes ten offices and one corridor. Nine AIROCOV 6260 APs are sparsely deployed, as shown in Fig. 8. AIROCOV 6260 uses special probe frame technology and is more suitable

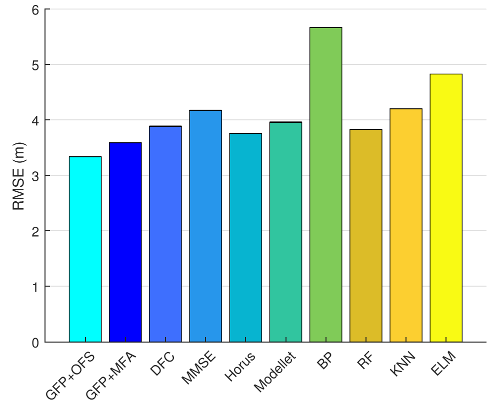


Fig. 10. Histogram of average RMSEs of different localization algorithms.

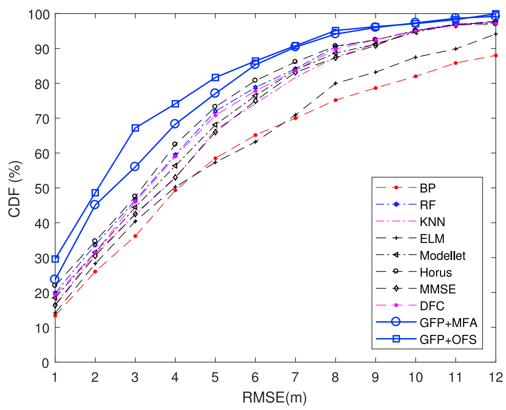


Fig. 11. RMSEs of different localization algorithms.

for IoT applications [30]. The AP and interior environment are shown in Fig. 9.

Specifically, we first divide the whole area into many grid points and the distance between two adjacent grid points is 0.8 m. We construct RSS fingerprints with an Android smartphone, and the RSS fingerprints construction, storage, and localization algorithms are all run in a server to decide the location of the smartphone. Hence, the energy consumption in smartphone is little. At each grid point, we collect 20 and 10 RSS measurements for $\boldsymbol{D}$ and $\boldsymbol{D}'$, respectively. Then, we construct GFP by using Algorithm 1. In the online phase, we collect 1200 RSS testing samples at 80 different grid points on different days. Based on GFP, we compute the final location estimates by using Algorithms 2 and 3. The average RMSE is calculated to evaluate the performance of localization.

Fig. 10 shows the histogram of average RMSEs of different localization algorithms. Note that the average MMSE is 4.18 m, while DFC is 3.89 m. As mentioned above, MMSE cannot give an accurate location estimate when the differences between the training data and the testing data increase. Hence, MMSE is not suitable for the complex environment. As compared with our proposed algorithm, DFC shows low accuracy because it cannot adequately exploit the complementary of multiple fingerprint functions. The RMSE of Modellet is 3.96 m, performing worse than any fusion method. Horus achieves RMSE of 3.76 m, and is better than MMSE, DFC and other algorithms, thus demonstrating the effectiveness of probabilistic methods. Our proposed GFP+OFS and GFP+MFA can achieve RMSEs of 3.33 and 3.59 m, respectively, which are smaller than other fusion strategies.

Fig. 11 shows the CDFs of the average RMSEs of different localization algorithms. Our proposed GFP+OFS outperforms the other methods in terms of the reduction of the average localization error by 7.1%, 14.2%, 20.1%, 11.3%, 15.8%, 41.2%, 12.9%, 20.7%, and 30.9%, in comparing with GFP+MFA, DFC, MMSE, Horus, Modellet, BP, RF, KNN, and ELM, respectively. The probability of DFC in acquiring a localization error of less than 2 m is 32%, and our proposed GFP+OFS algorithm can go up to 48% under the same condition. The proposed method performs better than any other algorithms we tested.

V. Conclusion

In this paper, we have proposed a KAAL framework for indoor Wi-Fi environment. To overcome the drawbacks of existing fusion localization methods, we have first proposed a GFP construction algorithm to fully exploit the complementarity among multiple fingerprint functions. GFP outperforms the conventional FP both in localization accuracy and computational complexity. Then, based on the knowledge database of GFP and the trained models, we have derived two KAAL algorithms, namely, MFA and OFS, to overcome the drawback of the RSS direct matching. These two algorithms can improve the localization accuracy in a complex indoor environment significantly. Our proposed localization approach has been validated for both simulated and real indoor environments.

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