Hybrid Indoor Localization Method Based on Signal Subspace Fingerprint Database

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***Abstract*—To solve the localization problem of multipath propagation in complex indoor circumstance, a localization method of signal subspace matching based on fingerprint database is proposed by using small antenna array in the indoor environment. Compared to the RSSI, the signal subspace fingerprint can obtain better effect by utilizing more space information. The received signal from each array is firstly processed with self-correlation and it's eigenvalue decomposed to create the signal subspace fingerprint. Location is then determined by the smallest angle between the received signal subspace and the fingerprint database. Simulation results show that the proposed algorithm has made a great improvement in localization accuracy.**

Keywords-indoor localization; fingerprint database; subspace matching; hybrid localization

I. INTRODUCTION

There have recently been many studies on the localization of terminals because the location information is important for providing valuable applications and is critical to several new services such as ubiquitous network systems [1, 2]. Localization techniques can be classified into several categories, such as using received signal strength (RSS), time of arrival (TOA), time difference of arrival (TDOA), angle of arrival (AOA), location fingerprint, and combinations thereof [3].

Conventional localization techniques using AOA, TDOA, and AOA often fail when estimating locations of indoor transmitters because of complex radio wave propagation [4]. Therefore, the location fingerprint technique, which generally uses RSS, is attractive for indoor localization [5, 6]. The basic idea of the fingerprint approach is matching patterns based on a location technique. A multipath delay profile can also be used to locate a mobile terminal with pattern matching. Although there are many studies that use the fingerprint technique, they do not take advantage of the spatial information of the received signal effectively [7]. The traditional fingerprint database is only set up by RSS. Additionally, there are some existing source localization techniques obtain the location of sources by estimating distance r and DOA θ of targets [8, 9]. The performance of localization will degrade in presence of multipath or non-line-of-sight (NLOS) propagation [10].

In this paper, we propose a method that uses both spatial and conventional fingerprint information. We use the signal subspace of the received signal at an array antenna, which includes both spatial and fingerprint information, and a subspace matching approach to identify the location of the indoor terminal. This method can not only add auxiliary information that can be used for indoor mobile terminal location but also reduce localization error.

II. SIGNAL SUBSPACE FOR LOCALIZATION

A. Signal Model and Subspace

Consider a linear array of b sensors uniformly spaced at distance d and signals emitting narrow-band plane waves L, which impinge on the array from distinct directions $\theta_k, k=1,\ldots,L$. The linear array is illustrated in Figure 1. We use AP represent access point to transmit signal, use T_M represent antenna array to receive signal.

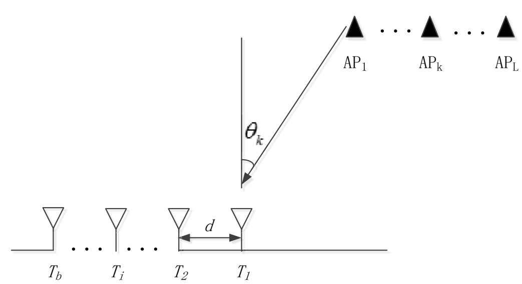


Figure 1. Linear array for receiving signal.

The steering vector is defined as

$$a(\theta_K)=[1,\exp(-j2\pi\frac{d}{c}\sin\theta_K),\ldots,\exp(-j2\pi(b-1)\frac{d}{c}\sin\theta_K)] \quad (1)$$

Select the first array as the reference point, where c is the wavelength of transmitted signal, and θ_L is the angle of arrival of L-th signal. The steering matrix is defined as

$$A = [a(\theta_1), \ldots, a(\theta_k), \ldots, a(\theta_L)]$$

$$= \begin{bmatrix} 1 & \cdots & 1 & \cdots & 1 \\ e^{-j2\pi \frac{d}{c}\sin\theta_1} & \cdots & e^{-j2\pi \frac{d}{c}\sin\theta_k} & \cdots & e^{-j2\pi \frac{d}{c}\sin\theta_L} \\ \vdots & & \vdots & \cdots & \vdots \\ e^{-j2\pi \frac{d}{c} i \sin\theta_1} & \cdots & e^{-j2\pi \frac{d}{c} i \sin\theta_k} & \cdots & e^{-j2\pi \frac{d}{c} i \sin\theta_L} \\ \vdots & & \vdots & \ddots & \vdots \\ e^{-j2\pi (b-1)\frac{d}{c}\sin\theta_1} & \cdots & e^{-j2\pi (b-1)\frac{d}{c}\sin\theta_k} & \cdots & e^{-j2\pi (b-1)\frac{d}{c}\sin\theta_L} \end{bmatrix} \quad (2)$$

The received signal can be represented as

$$x(t) = As(t) + n(t) \quad (3)$$

$$n(t) = [n_1(t), \ldots, n_L(t)]^T$$

where T denotes the transpose operation, $x(t) = [x_1(t), \ldots, x_i(t), \ldots, x_b(t)]^T$ is an $b \times 1$ vector of the complex envelopes of the observed signals. In addition $s(t) = [s_1(t), \ldots, s_k(t), \ldots, s_L(t)]^T$ [11].

The co-variance matrix of the received signal vector is defined as

$$R = E\{x(t)x(t)^H\} \quad (4)$$

where $E\{.\}$ implies the expected value and H denotes the conjugate transpose operation. The estimation of the co-variance matrix can be calculated by

$$\hat{R} = \frac{1}{N}\sum_{t=1}^{N} x(t)x^H(t) \quad (5)$$

where N is the number of snapshots. For simplicity, let us assume that the observation noise is Gaussian white noise with a variance σ^2, which has no correlation with the signal sources. In addition, the number of impinging signals P is less than the number of antenna elements M. Therefore, the co-variance matrices are defined as

$$S \equiv E\{s(t)s^H(t)\}, \quad E\{n(t)n^H(t)\} = \sigma^2 I \quad (6)$$

Finally, we get the following equation.

$$R = ASA^H + \sigma^2 I \quad (7)$$

By applying spectral factorization, this equation can be written as

$$R = ASA^H + \sigma^2 I = U\Lambda U^H \quad (8)$$

where U is the unitary matrix, and Λ is the diagonal matrix of the real eigenvalues having an order of $\lambda_1 \geq \cdots \geq \lambda_i \geq \cdots \geq \lambda_b > 0$. Each matrix is represented as

$$\Lambda = \begin{bmatrix} \lambda_1 & 0 & \cdots & & 0 \\ 0 & \ddots & & & \vdots \\ 0 & \cdots & \lambda_i & \cdots & 0 \\ \vdots & & & \ddots & \vdots \\ 0 & \cdots & & & \lambda_b \end{bmatrix}, \quad U = [v_1, \cdots, v_i, \cdots, v_b]$$

Here, the eigenvalue λ_i and eigenvector v_i satisfy the relationship $Rv_i = \lambda_i v_i$. The eigenvalue-eigenvector pair can be used to separate the signal space from the noise space. Then, the equation (8) can be rewritten as

$$R = U_s \Lambda_s U_s^H + U_n \Lambda_n U_n^H \quad (9)$$

where $\Lambda_s = \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \lambda_L \end{bmatrix}$, $\Lambda_n = \begin{bmatrix} \lambda_{L+1} & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \lambda_b \end{bmatrix}$,

$$U_s = [v_1, \cdots, v_L], V_n = [v_{L+1}, \cdots, v_b]$$

where Λ_s represent for signal eigenvalue, and U_s represent for signal eigenvector accordingly, $v_{L+1} = \cdots = v_b = \sigma^2$. Since span$\{U_s\}$ = span$\{\Lambda\}$, we use span$\{\Lambda\}$ to represent signal subspace. The signal subspace can be used in the fingerprint for localization.

After above steps, the signal subspace fingerprint databases can be obtained, we get the Table I as following.

TABLE I. SIGNAL SUBSPACE FINGERPRINT DATABASES

coordinate		***subspace fingerprint***
X	***Y***	
X_1	Y_1	$U_{1,1}$
X_1	Y_2	$U_{1,2}$
$\vdots$	$\vdots$	$\vdots$
X_m	Y_n	$U_{m,n}$

B. *Signal Subspace Based Localization Algorithm*

The main idea of signal subspace for localization algorithm is to build a fingerprint of signal subspace, which is calculated from the decomposition of co-variance matrix. In off-line phase, we store the eigenvector corresponding to the largest eigenvalue of co-variance matrix, each grid has signal subspace fingerprint U_s. The on-line signal subspace is calculated by the same method, which is denoted as $U_s^{'}$, then the subspace matching technique can be demonstrated as follows:

Let U_s and $U_s^{'}$ be signal subspace in $b \times L$ dimensions. The angles $\alpha_1, \ldots, \alpha_q \in [0, \pi/2]$ between U_s and $U_s^{'}$ are defined recursively as follows. For $\|u\| = \|v\| = 1$, we define

$$\alpha_k\left(U_s, U_s^{'}\right) = \arccos\left(\max_{u \in U_s} \max_{v \in U_s^{'}} \left(u^H v\right)\right) \qquad (10)$$
$$= \arccos\left(u_k^H v_k\right), \quad k = 1, 2, \cdots, L$$

where $u^H u = v^H v = 1$, $u^H u_j = 0, \quad j = 1, \cdots, k-1$, $v^H v_j = 0, \quad j = 1, \cdots, k-1$.

In this equation, α_k represents the kth largest deviation of U_s from $U_s^{'}$, it is called the kth principal angle between U_s and $U_s^{'}$. If $U_s = U_s^{'}$, then $\alpha_k = 0$. We compare each set of the fingerprint with the observed set and pick the maximum value of α as the receiver location.

Based on the above demonstration, we proposed an algorithm of hybrid localization named subspace knn (SKNN). It inherits the advantages of KNN algorithm and provides an enhanced performance by making using of the signal subspace is proposed.

Algorithm 1 SKNN algorithm

Input: Received RSSI vector $\boldsymbol{v}$ and $U_s^{'}$

Locations and signal vectors of all APs.

Output: Location estimation $\left(\hat{x}, \hat{y}\right)$

for i = {1, ... , m} **do**
  for j = {1, ... , n} **do**
    Calculate co-variance matrix by using Eq. (5)
    eigenvalue decomposition by using Eq. (8)
    Calculate $\hat{U}_s$ by using Eq. (9)
    $\boldsymbol{U_s} = \boldsymbol{U_s} \cup \hat{U}_s$
  end for
end for
Using KNN to obtain k indexes of locations
Calculate angle by using Eq. (10) with $U_s^{'}$
pick the maximum value of α whose location as the receiver location.
$\left(\hat{x}, \hat{y}\right)$

III. SIMULATION ANALYSIS

Simulations are conducted in a zone of size 6 ×10 × 3m in 3D coordinate. The indexes of reference locations are shown in Figure 2. The access point device is placed at floor. Adjacent receiver terminal locations are setted in 1 m apart [12].

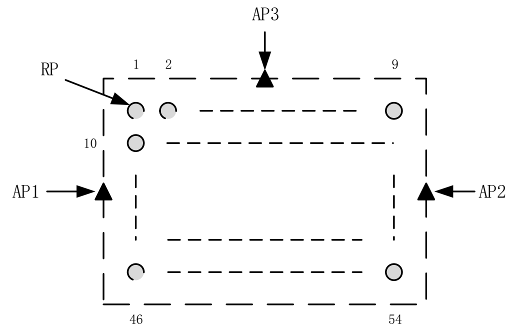


Figure 2. The indexes of reference location in database

In our experiment, an 8-elements linear array with $d = c/2$ and $L = 3$ are employed to localize a signal source with multipath signals in additive Gaussian noise. The receiver's location is indicated by "RP" in Fig.2. The black triangle represent access point (AP) which is 2m above the ground. These multipath is obtained by Ray-tracing method. 1000 Monte Carlo simulations are performed to compare the performance of NN, KNN and SKNN algorithm. The test points were selected by random shifts from the database points. Five-hundred data is sampled to estimate the array output co-variance matrix.

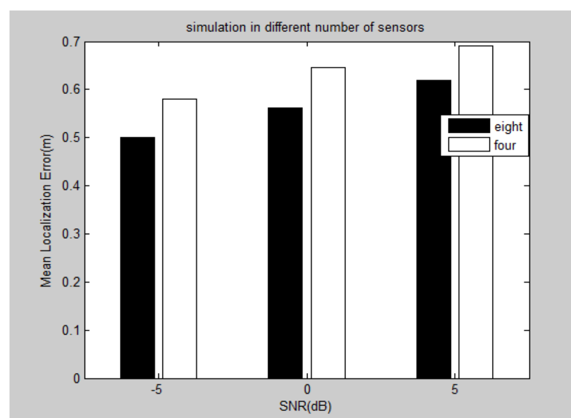
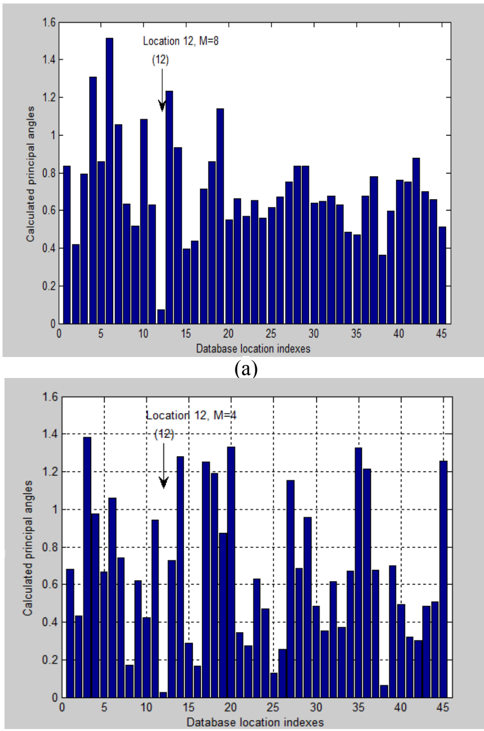


Figure 3. The mean localization error compared in different number of sensors

As seen in Fig. 3, with the increase of the sensors number, the antenna receives more data, gets higher robustness and lower root mean localization error.

Next, Fig. 4 shows the calculated principal angles at location 12 where the sensors number is 4 and 8. This method also succeeded in estimating location of the receiver even though the number of sensors was decreased.



(a)

(b)

Figure 4. Calculated principal angles between signal subspace of database and measured signals (for receiver located at 12)

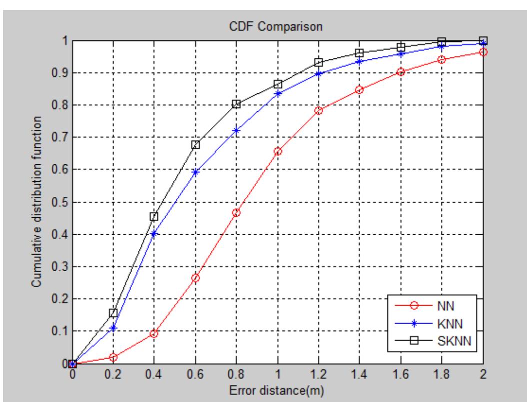


Figure 5. The succeed probability of NN, KNN and SKNN algorithm

In order to compare the algorithms, we did another experiment. The cumulative distribution function is compared while the Error distance increased. The results in Fig. 5 clearly show that the performance of the SKNN algorithm is better than NN and KNN.

IV. CONCLUSION

In this paper, we proposed a hybrid indoor localization method based on signal subspace fingerprint database. This method uses spatial and signal strength fingerprint information of received signals at an array antenna. The simulation results showed the effectiveness of our SKNN algorithm.

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