Array Antenna based Localization Using Spatial Smoothing Processing

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***Abstract*— An array antenna based localization using spatial smoothing processing (SSP) is proposed for wireless security and monitoring, referred to as array sensor. The proposed method is based on the array sensor that exploits an array antenna at the receiver to detect the propagation environment of interest. If an event occurs, e.g., human motion, the propagation environment is changed. Thus the eigenvector and eigenvalue spanning the signal subspace that is inherent to its environment changes as well. Using a machine learning technique based on the eigenvector and eigenvalue, we can detect the event accurately. The proposed method is improved from our previous work which uses only a limited number of signal subspace features. The basic idea of this work is the extension of the dimension of the signal subspace by using SSP without increasing the number of array element. In addition, this work investigates the impact of the array antenna placement on localization performance. The experimental results show that the proposed SSP based method achieves a 41.83 % improvement in localization accuracy, and a 1.24 m improvement in root mean square error (RMSE) compared to the previous method.**

***Index Terms*— localization, monitoring, array antenna, spatial smoothing processing**

I. Introduction

Indoor localization technologies have become one of the major techniques for many applications such as intruder detection in office/home, and finding people in emergency situations, and healthcare monitoring for the elderly people who are living alone [1][2]. With a camera such as a closed-circuit television (CCTV) [3], we can significantly know the target location. One of the problems, however, is that it comes at the expense of user privacy. For instance, it is difficult to install in a private area such as in a house. Another problem is that the detection area is limited, and it cannot locate positions behind obstacles.

Recently, electrical wave-based localization techniques have attracted attention [4]–[7]. Typically, there are two kinds of techniques: active localization and passive localization. The majority of localization techniques fall in the active class, where a person being localized and/or tracked, needs to carry tags/electric devices. In passive localization, a person is localized and/or tracked without the need of tags/electric devices being carried by him. In general, passive localization is preferred owing to relief from stress brought in by carrying tags/devices; this makes this kind of localization feasible in a bathroom environment. However, localization accuracy of passive localization techniques is generally lower than that of active ones.

Several electrical wave-based security systems are reported in [8]–[12], where an event such as intrusion is detected based on the change of received signal strength (RSS). Electrical waves arrive in every corner of the area of interest, and thus wide sensing range is achieved. In addition, there is no need to worry about privacy invasion in these systems. However, RSS suffers from the effects of noise and fluctuates even in static conditions. Thus, a detection error occurs.

A passive sensing system using an array antenna, referred to as array sensor, for monitoring and security is proposed in [13]. The array sensor is based on the change of signal subspace of interest. The array sensor uses only an array antenna without calibration [15] as the receiver and observes wide range with high accuracy. The array signal processing decomposes the received signals into eigenvectors corresponding to direction of arrival (DOA) and eigenvalues corresponding to RSS. Unlike the aforementioned systems, it can mitigate the effect of noise because it uses only the signal subspace. Using a machine learning technique, support vector machine (SVM), based on the eigenvector and eigenvalue, we can detect an event accurately [16].

This paper explains the array antenna based localization using spatial smoothing processing (SSP). Although the conventional method [13] can detect human activities, it cannot determine the position of the human being in detail because the number of features (i.e., eigenvector and eigenvalue) is limited. Furthermore, it is dependent on the number of array elements. The proposed method is improved from our previous work which uses only a limited number of signal subspace features (up to the number of array elements). In addition, this paper investigates the impact of array antenna placement on localization performance. The experimental results show that the proposed SSP based method improves the localization accuracy and root mean square error (RMSE) compared to the previous method.

The rest of this paper is organized as follows: Section

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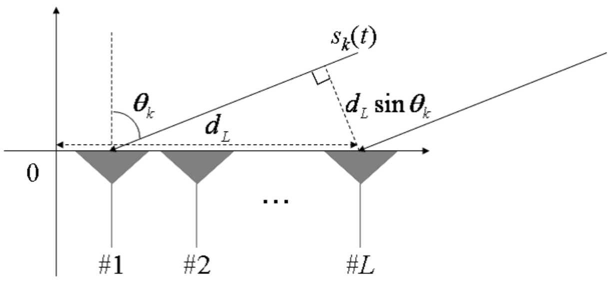

Figure 1. L-element array antenna

II explains array data model. Section III introduces detection methods, and Section IV presents the proposed localization method. We show the experiment results in Section V. Finally, we conclude the paper in Section VI.

II. Array Data Model

A. Data Model

Consider the L-element linear array and the K narrow band signals as shown in Fig. 1. In the proposed system, there is no need to consider a specific array deployment because the idea of our system is to use the eigenvector changes by the propagation environment of interest changes. The signal $s_k(u)$ $(k = 1, \cdots, K)$ is received by the array antenna from direction θ_k at time u as a plane wave owing to the far field assumption. The received signal vector is represented as

$$\mathbf{x}(u) = \sum_{k=1}^{K} \mathbf{a}(\theta_k) s_k(u) + \mathbf{n}(u) \tag{1}$$

$$= \mathbf{A}\mathbf{s}(u) + \mathbf{n}(u), \tag{2}$$

$$\mathbf{A} = [\mathbf{a}(\theta_1), \dots, \mathbf{a}(\theta_K)], \tag{3}$$

$$\mathbf{s}(u) = [s_1(u), \dots, s_K(u)]^T \tag{4}$$

where $[\cdot]^T$ is the transpose operator, and $\mathbf{n}(u)$ is an additive white Gaussian noise (AWGN) of zero mean and variance σ^2. The steering vector $\mathbf{a}(\theta_k)$ is the complex vector including a phase shift of a source signal at the lth element $d_l, (1 \le l \le L)$ away from the reference point, it is represented as

$$\mathbf{a}(\theta_k) = [e^{-j\frac{2\pi}{\lambda} d_1 \sin\theta_k}, \dots, e^{-j\frac{2\pi}{\lambda} d_L \sin\theta_k}]^T \tag{5}$$

where λ is the wavelength of the source signal.

To analyze wave propagation, we use the data correlation matrix obtained by the received signal vector $\mathbf{s}(u)$. The data correlation matrix $\mathbf{R}_{xx}$ is defined as

$$\mathbf{R}_{xx} = E[\mathbf{x}(u)\mathbf{x}(u)^H] \tag{6}$$

where $E[\cdot]$ and $[\cdot]^H$ denote the ensemble average and the conjugate transpose of vector $[\cdot]$, respectively. The $\mathbf{R}_{xx}$ cannot be obtained properly. Therefore we measure an ensemble average of eq. (4) based on the basis of ergodic hypothesis. The estimated $\hat{\mathbf{R}}_{xx}$ is sampled for the number of snapshots N_s as follows

$$\hat{\mathbf{R}}_{xx} = \frac{1}{N_s} \sum_{u=1}^{N_s} \mathbf{x}(u)\mathbf{x}(u)^H. \tag{7}$$

In this paper, we treat the estimated $\hat{\mathbf{R}}_{xx}$ as $\mathbf{R}_{xx}$.

B. Subspace Based Method

Subspace based method [17] decomposes $\mathbf{R}_{xx}$ into the orthogonal signal and noise subspaces via the eigenvalue decomposition (EVD). We can compute the L-dimension data correlation matrix $\mathbf{R}_{xx}$ with the EVD as follows.

$$\mathbf{R}_{xx} = \sum_{l=1}^{L} \lambda_l \mathbf{v}_l \mathbf{v}_l^H = \mathbf{V}\mathbf{\Lambda}\mathbf{V}^H, \tag{8}$$

$$\mathbf{V} = [\mathbf{v}_1, \mathbf{v}_2, \cdots, \mathbf{v}_L], \tag{9}$$

$$\mathbf{\Lambda} = \mathrm{diag}\{\lambda_1, \lambda_2, \cdots, \lambda_\mathrm{L}\}, \tag{10}$$

where $\mathrm{diag}\{\cdot\}$ is a diagonal matrix, λ_l and $\mathbf{v}_l$ are the lth eigenvalue and eigenvector, respectively. When the L-element array antenna receives K signals, the dimension of the signal subspace $\mathbf{V}_S$ and noise subspace $\mathbf{V}_N$ is K and $L - K$, and then $\mathbf{V}_S$ and $\mathbf{V}_N$ are written as follows.

$$\mathbf{V}_S = [\mathbf{v}_1, \dots, \mathbf{v}_K], \tag{11}$$

$$\mathbf{V}_N = [\mathbf{v}_{K+1}, \dots, \mathbf{v}_L], \tag{12}$$

where

$$\lambda_1 \ge \cdots \ge \lambda_K \ge \lambda_{K+1} \approx \cdots \approx \lambda_L \approx \sigma^2. \tag{13}$$

Therefore, the eigenvalue matrix $\mathbf{\Lambda}$ is decomposed into signal and noise eigenvalues. We use these components, eigenvector and its eigenvalue spanning signal subspace, to detect the change of propagation environment of interest.

III. Detection Method

When a pair of transmitter and receiver are fixed, the signal subspace spanned by eigenvector changes when the indoor environment of interest changes. For detecting simple events, such as intrusion, we can use a simple threshold-based detection based on change of first eigenvector. For detecting and classifying more complex states and activities, such as sitting in a bathtub and falling in a bathroom, we use support vector machine (SVM). We explain detection methods used in the array sensor.

A. Cost Function

We use cost functions based on signal eigenvectors and its eigenvalues to detect events. The cost function based on the eigenvector is defined as

$$P_i(u) = |\mathbf{v}_i^H(u_{\mathrm{no}})\mathbf{v}_i(u)| \qquad (0 \le P_i(u) \le 1) \tag{14}$$

where $\mathbf{v}_i(u_{\mathrm{no}})$, the reference vector, is the ith eigenvector obtained in advance. And $\mathbf{v}_i(u)$ is the ith eigenvector obtained at the observation time u. Thus, the larger the value of $P_i(u)$, the smaller the change of the environment is, and the smaller $P_i(u)$ is, the larger the change of the environment is. The eigenvector is stationary even in noise and fading environment, because it does not include RSS information.

The cost function based on the eigenvalue is defined as

$$Q_i(u) = 1 - \frac{|\lambda_i(u) - \lambda_i(u_{\rm no})|}{\lambda_i(u_{\rm no})} \qquad (Q_i(u) \leq 1) \quad (15)$$

where $\lambda_i(u_{\rm no})$ is the ith eigenvalue obtained in advance, that is the reference value, and $\lambda_i(u)$ is the ith eigenvalue obtained at the observation time u. Like $P_i(u)$, the larger the value of $Q_i(u)$, the smaller the change of the environment is, and the smaller the value of $Q_i(u)$, the larger the change of the environment. The eigenvalue is less stationary than the eigenvector, however, $Q_i(u)$ can detect even the smallest changes. Therefore, we use both $P_i(u)$ and $Q_i(u)$ as situation demands [15].

B. SVM

As mentioned above, in order to detect and classify more complex states and activities, such as sitting in a bathtub and falling in a bathroom, we use SVM [22]. SVM is one of the most attractive machine learning techniques. SVM has shown several advantages in prediction, regression, and estimation over some of the classical approaches in a wide range of applications owing to its improved generalization capabilities. Once the SVM has been trained, then all future unknown samples can be classified in real time.

In general, the larger the number of training samples becomes, the more difficult the linear separability becomes, and the larger the dimension of the feature space, the easier the classification process. However, mapping into high dimensional feature space causes high complexity. Kernel trick maps the feature vector into high dimensional feature space without computing features in the mapped space. Although the dimension of the feature space transformed with non-linear mapping function becomes very large, the complexity of SVM does not increase because the objective function in the SVM depends on the inner product of input patterns only.

In order to use machine learning for a safety system like an array sensor, the following essential points must be considered: detection in real time or semi-real time; work on a non-linear problem; use of as many features as possible. Therefore, we use radial basis function (RBF) kernel for the mapping function, because it has less numerical difficulties [23]. The number of kernel parameters that influences the complexity of model selection is small and the other kernel functions have more kernel parameters than the RBF kernel. Moreover, we use cost functions based on the eigenvector and eigenvalue for the features of SVM.

IV. Localization Method Using Array Sensor

A. Multiple Signals

If there are I uncorrelated sources and K_i multipath signals from the ith transmitter in the indoor environment,

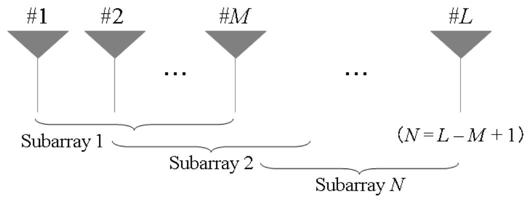

Figure 2. L-element array divided into M-element subarray

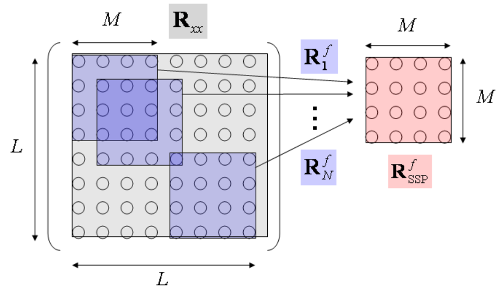

Figure 3. $L \times L$ correlation matrix and $M \times M$ sub-correlation matrix

the received signal vector is represented as

$$\begin{aligned} \mathbf{x}(u) &= \sum_{i=1}^{I} \sum_{k=1}^{K_i} \alpha_{ik} \mathbf{a}(\theta_{ik}) s_i(t - \beta_{ik}) + \mathbf{n}(u) && (16) \\ &= \tilde{\mathbf{A}} \tilde{\mathbf{s}}(u) + \mathbf{n}(u), && (17) \\ \tilde{\mathbf{A}} &= [\mathbf{a}(\theta_{11}), \ldots, \mathbf{a}(\theta_{1K_I}), && (18) \\ & \quad \mathbf{a}(\theta_{21}), \ldots, \mathbf{a}(\theta_{IK_I})] && (19) \end{aligned}$$

where α_{ik} is the complex attenuation coefficient and β_{ik} is the reference delay for the kth path from the source i, with $\alpha_{ik} \neq 0$, $\alpha_{i1} = 1$, and $\beta_{ik} \neq 0$. In the indoor environment, the difference of propagation delay among multipath waves is negligibly small, that is $\beta_{ik} \approx \beta$. Therefore, the rank of $\tilde{\mathbf{S}} = E[\tilde{\mathbf{s}}(u)\tilde{\mathbf{s}}(u)^H]$ is I and the dimension of the signal subspace D_S equals to I.

B. SSP

Spatial smoothing processing (SSP) is the method that separates coherent signals [20]. It does not need to increase transmitters and receivers to use uncorrelated signals. The fundamental theory of SSP is that the phase relationships among coherent signals are different from one element to another, and the cross-correlation value becomes small owing to average effect by parallel shift of the receiving position. Thus, we do not need to increase the number of array elements.

If the L-element linear array is divided into M-element subarrays, we get N subarrays, where $N = L - M + 1$, as shown in Fig. 2. The received signal vector in the nth subarray is obtained by

$$\begin{aligned} \mathbf{x}_n^f(u) &= [x_n(u), \ldots, x_{n+M-1}(u)]^T && (20) \\ n &= 1, \ldots, N. && (21) \end{aligned}$$

The new M-dimension correlation matrix is obtained by the spatial average of the N sub-matrices as shown in

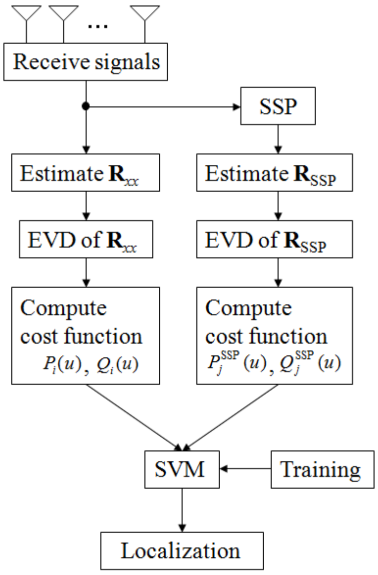

Figure 4. Localization algorithm

Fig. 3.

$$\mathbf{R}_{\mathrm{SSP}}^{f} = \frac{1}{N}\sum_{n=1}^{N}\mathbf{R}_{n}^{f} \tag{22}$$

$$\mathbf{R}_{n}^{f} = E[\mathbf{x}_{n}^{f}(u)\mathbf{x}_{n}^{f}(u)^{H}] \tag{23}$$

There is an improved method, called the forward-backward SSP (FB-SSP) [21]. The correlation matrix obtained by FB-SSP is represented as follows.

$$\mathbf{R}_{\mathrm{FB-SSP}} = \frac{\mathbf{R}_{\mathrm{SSP}}^{f} + \mathbf{R}_{\mathrm{SSP}}^{b}}{2} \tag{24}$$

where $\mathbf{R}_{\mathrm{SSP}}^{b}$ is the backward correlation matrix obtained by $\mathbf{x}_{n}^{b}(u) = [x_{n+L-1}(u), \ldots, x_{1}(u)]^{T}$.

However, in real multipath environments, there are many incoming signals and it is difficult for a few elements to separate all coherent signals. The FB-SSP can separate $2N$ signals per group of coherent signals and the dimension of whole subspace is M corresponding to the rank of $\mathbf{R}_{\mathrm{FB-SSP}}$. Then, the dimension of the signal subspace D_S is extended as

$$D_S = \min\{2NI, M\}. \tag{25}$$

The proposed method uses the FB-SSP to separate coherent signals and extend the dimension of signal subspace. From here, we describe FB-SSP simply as SSP.

C. Algorithm

The proposed localization algorithm is shown in Figure 4.

1) Training Phase: If the dimension of the signal subspace is extended, we can use many cost functions as features of SVM. Assume that we classify N_p positions. In the training phase, we get the received signals $\mathbf{x}_p(u)$ $(p = 1, \ldots, N_P)$ when a person stands at position p for U_N observation times. From the signals, we compute the cost functions without SSP, $P_i(u), Q_i(u)$, and those with SSP, $P_j^{\mathrm{SSP}}(u), Q_j^{\mathrm{SSP}}(u)$ for each data, where $u = 1, \ldots, U_N$. That is, we have $N_P U_N$ training samples. Next, all the cost functions are combined to one feature vector as

$$\begin{aligned}\mathbf{z}_p = {} & [P_1(u), \ldots, P_I(u), Q_1(u), \ldots, Q_I(u), P_1^{\mathrm{SSP}}(u), \\ & \ldots, P_{D_S}^{\mathrm{SSP}}(u), Q_1^{\mathrm{SSP}}(u), \ldots, Q_{D_S}^{\mathrm{SSP}}(u)]^T.\end{aligned} \tag{26}$$

The dimension of $\mathbf{z}_p$ (the number of features) is

$$F = \begin{cases} 2I, & \text{w/o SSP} \\ 2D_S, & \text{with SSP} \\ 2(I + D_S). & \text{w/o SSP} \cup \text{with SSP} \end{cases} \tag{27}$$

Then, $\mathbf{z}_p$ is mapped into a high dimensional space by RBF kernel and the training model is obtained.

2) Localization Phase: In the localization phase, although we get cost functions and the feature vector in the same way as in the training phase, we do not know what position this feature vector is classified to. However, once the SVM has been trained, then all future unknown samples can be classified in real time. We localize the unknown position of standing person based on the algorithm.

V. Experimental Results

In this section, we show three experimental results obtained in different environments under various scenarios. Before introducing experimental results for localization, we first introduce an experimental result for the person intruding, stopping, or moving. All experiments are conducted in a non-line-of-sight (NLOS) condition. In NLOS there is no direct-path signal that is dominant over the signal subspace spanned by eigenvector and thus the signal subspace spanned by eigenvector enhances the impact of multipath signals that capture the change of environment.

A. Experiment 1: Detection of Person's Activities, Intruding, Walking, and Stopping

We show one of our experimental results obtained in the room shown in Fig. 5. We use a transmitter and its transmission frequency is 2.484 GHz. The size of array antenna is $9.0 \times 9.0 \times 7.3\ \mathrm{cm}^3$ and the number of array elements is 8.

Fig. 6 shows an experimental result for the person intruding, stopping, or moving. In this experiment, a person opens the door and intrudes, and passes through points A, B, C, and goes through the door as shown in Fig. 5. The person stops for 20 seconds at each point, A, B, C. The cost function $P(u)$ changes significantly when the door opens. $P(u)$ also fluctuates significantly when the person moves and fluctuates moderately when the person stops. This happens because the change of environment, such as the door opening, the existence of the person, and the person's motion, changes the propagation of the radio waves and thus the first eigenvector as well. Therefore, the cost function, that is the correlation of the first eigenvector

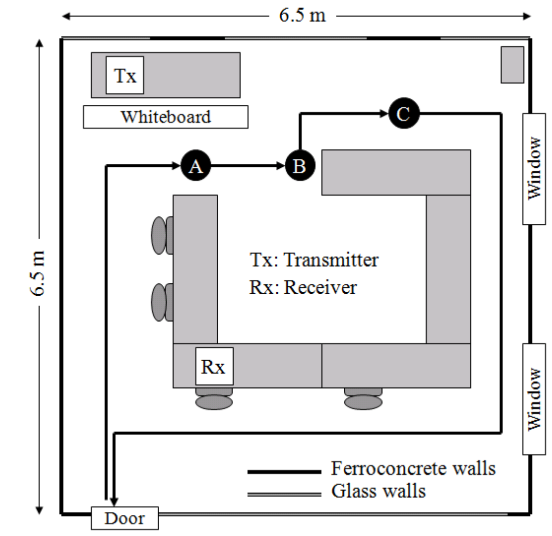

Figure 5. The room used for experiment 1

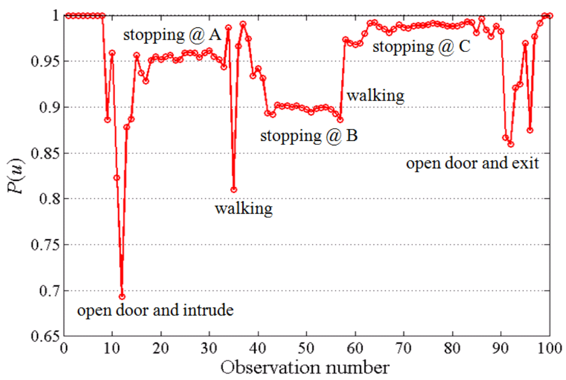

Figure 6. Detection performance of person's activities, intruding, walking, and stopping

between in the reference and in the observation, also changes. From this result, we can easily see the person's movement; intruding, stopping or moving.

B. Experiment 2: Localization with SSP

We show the experimental results using multiple coherent signals to improve localization accuracy. Fig. 7 shows this experimental environment. We use three transmitters (Tx1, Tx2, and Tx3) in this experiment. Experimental parameters are listed in Table I. Each transmitter transmits signal with different frequencies as described in Table II. Three transmitters were set up on the windows side, and

TABLE I.
EXPERIMENTAL PARAMETERS

Transmission power	-10 dBm
Modulation method	No modulation
Transmitter	Dipole antenna
Receiver	8-element linear array
Sampling rate	60 MHz
Number of snapshots	1024

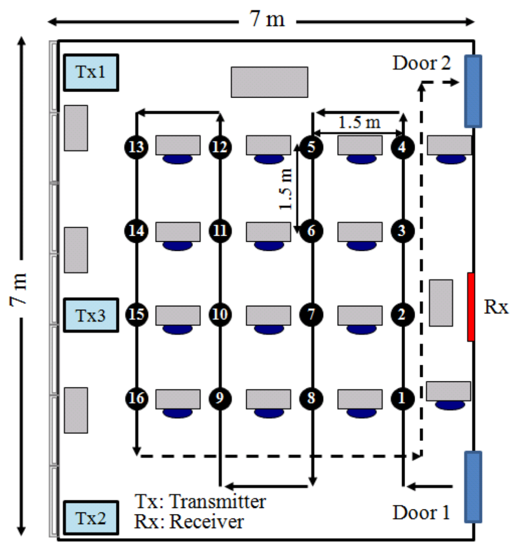

Figure 7. The room used for the experiment 2

TABLE II.
TRANSMISSION FREQUENCIES

Transmitter	Frequency
Tx1	2.412 GHz
Tx2	2.417 GHz
Tx3	2.422 GHz

a receiver (Rx) was set up on the wall side. There are also some obstacles between the transmitters and the receiver to make NLOS situation.

In total, 16 points are selected as candidate points shown as in Fig. 7. In the training phase, we obtained 100 observation data (approximately 15 seconds) when a person stands at each position. Five persons participated in the experiment. In total 8000 $(= 100 \times 16 \times 5)$ data are collected, then trained by the SVM. We use $\mathbf{z}_p = [P_1(u), \ldots, P_{Ds}(u), Q_1(u), \ldots, Q_{Ds}(u)]$ as the feature vector of the conventional method and eq. (26) as that of the proposed method.

In the testing phase, a person enters the room from the door 1, walks from point 1 to 16 in the route indicated by solid arrows, stands at each position for 10 seconds, walks from position 16 to the door 2 in the route indicated by dot arrows, and exits from the room. The testing data can be obtained in real time and we localize the person in a continuous way with SVM.

1) Cost Function in the Testing Phase: Fig. 8 shows the change of cost function $P_i(u)$ $(i = 1, 2, 3)$ without SSP. The reference eigenvectors are obtained in advance when there is no person in the room. The dimension of the signal subspace is three and we can use those cost functions, that is $i = 1, 2, 3$, because there are three uncorrelated transmitters in the room. From this figure, we can see that the proposed method can observe a whole room same as the conventional method.

Fig. 9 shows the change of cost function $P_i(u)$ $(i = 4, 5, 6)$ without SSP. These cost functions cannot detect

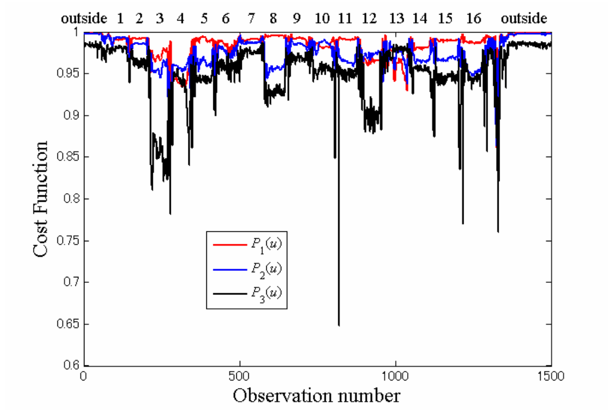

Figure 8. The change of cost function $P_i(u)$ $(i = 1, 2, 3)$ without SSP

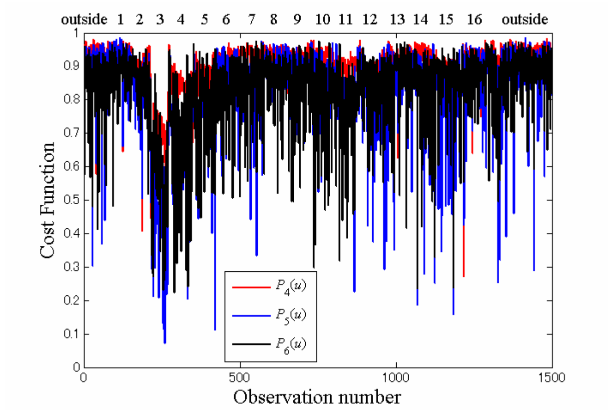

Figure 9. The change of cost function $P_i(u)$ $(i = 4, 5, 6)$ without SSP

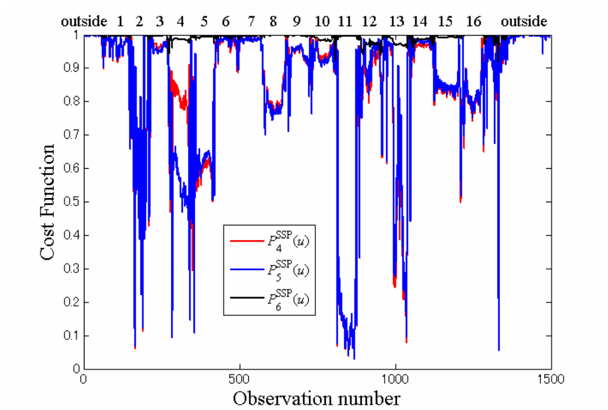

Figure 10. The change of cost function $P_i^{\mathrm{SSP}}(u)$ $(i = 4, 5, 6)$ with SSP $(N = 3, M = 6)$

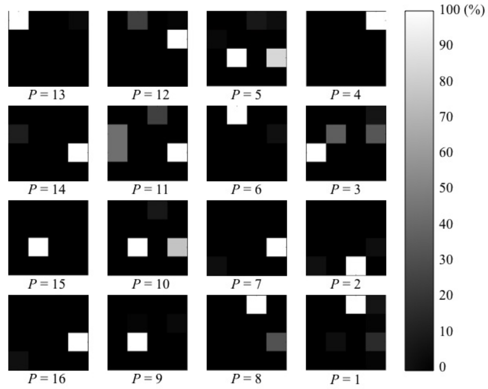

Figure 11. Localization accuracy without SSP $(F = 2)$

any events because the 4th, 5th, and 6th eigenvectors are the basis vectors of the noise subspace. Thus, we can see that the cost function $P_i(u)$ $(i = 4, 5, 6)$ includes noise information. Therefore, the dimension of the signal subspace is three, we can use only $P_i(u)$ $(i = 1, 2, 3)$ as features.

Fig. 10 shows the change of $P_i^{\mathrm{SSP}}(u)$ $(i = 4, 5, 6)$ with SSP $(N = 3, M = 6)$. The dimension of the signal subspace is extended to six as in eq. (25). These cost functions can also be used as features of SVM, because the SSP can separate coherent signals into multiple uncorrelated signals.

2) Comparison of Localization Accuracy and RMSE: Table III shows the localization accuracy and root mean square error (RMSE) of the conventional method (w/o SSP) and proposed method (w/o SSP ∪ w/ SSP). We define the accuracy as the correct probability that the estimated position is p when the person stands at position p, and RMSE as the distance error between true position and estimated position. D_S is the dimension of the signal subspace used for cost function, N is the number of subarrays used for SSP, and F is the number of features used for SVM.

From these results in each method, we can see that the larger F shows the higher localization accuracy and lower RMSE. This happens because SVM learning ability is improved by increasing the number of features. We can also see that in the same condition $(F = 6)$, the "w/o SSP" achives higher accuracy than "w/ SSP". This happens because SSP reduces the effective aperture of the array antenna. Compared to "w/ SSP" and "w/o SSP ∪ w/ SSP", (g), (h) and (i), (j), "w/o SSP ∪ w/ SSP" shows higher accuracy than "w/ SSP". This happens because we can observe multiple path. The proposed method achieves higher accuracy than all the other methods. This happens because SVM learning ability is improved by increasing the number of features.

3) Probability Map: Figs. 11 and 12 show one example of the estimation probability map for the method without SSP and the method with SSP, respectively. In the figures, each small map is divided into 16 blocks

TABLE III.
COMPARISON OF LOCALIZATION ACCURACY AND RMSE.
D_s = DIMENSION OF THE SIGNAL SUBSPACE, N = NUMBER OF SUBARRAYS, F = NUMBER OF FEATURES

	Method	D_S	N	F	Accuracy (%)	RMSE (m)
(a)	w/o SSP	1	0	2	25.69	2.71
(b)	w/o SSP	2	0	4	41.60	2.40
(c)	w/o SSP	3	0	6	52.70	1.92
(d)	w/ SSP	3	6	6	12.10	3.22
(e)	w/ SSP	4	5	8	41.32	2.11
(f)	w/ SSP	5	4	10	48.85	2.16
(g)	w/ SSP	6	3	12	54.28	2.06
(h)	w/ SSP	7	2	14	48.16	2.29
(i)	w/o SSP ∪ w/ SSP	3	6	12	59.89	1.67
(j)	w/o SSP ∪ w/ SSP	4	5	14	56.50	1.63
(k)	w/o SSP ∪ w/ SSP	5	4	16	62.33	1.66
(l)	w/o SSP ∪ w/ SSP	6	3	18	61.47	1.71
(m)	w/o SSP ∪ w/ SSP	7	2	20	67.52	1.47

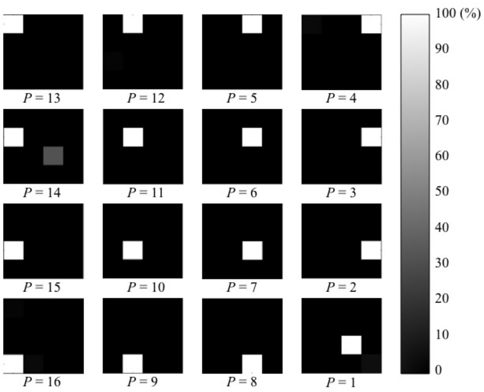

Figure 12. Localization accuracy with SSP ($F = 20$)

related to 16 positions in Fig. 7. Fig. 11 shows the result of localization using only $P_1(u)$ and $Q_1(u)$. From this figure, the method without SSP can hardly localize the position of the standing person. We can see high localization accuracies at only three points ($p = 4, p = 10, p = 13$).

Fig. 12 shows the result of localization using twenty cost functions $P_i(u)$, $Q_i(u)$ $(1 \leq i \leq 3)$ and $P_j^{\mathrm{SSP}}(u)$, $Q_j^{\mathrm{SSP}}(u)$ $(1 \leq j \leq 7)$. This method uses two subarrays of SSP ($N = 2$). The accuracies of all points except at the $p = 1$ are higher than 80 %. Thus, we can see that the proposed method that uses with SSP, shows better localization performance than the other one.

C. Experiment 3: Impact of the Array Antenna Placement on Localization Performance

We investigate the impact of the array antenna placement on localization performance. If the receiver and/or transmitter placed on higher than the target object, the change of propagation by the target is small. Thus, it may affect the localization performance of array sensor. Therefore, this experiment 3 attempts to find out the impact of array antenna placement on localization performance. Fig. 13 shows the experimental environment of the experiment 3. Experimental parameters are listed in Table I which

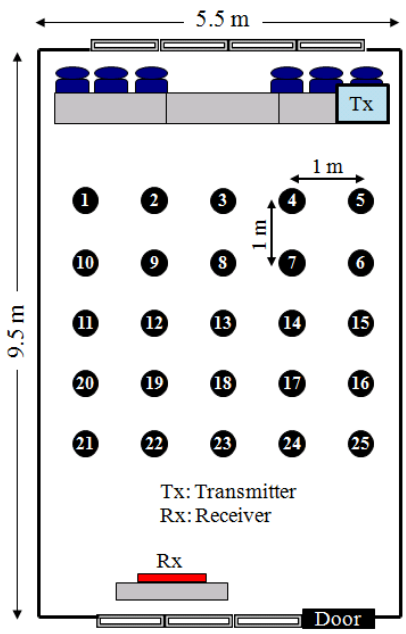

Figure 13. The room used for the experiment 3. The numbers in circle show the points to localize human's position.

is same as the experiment 2. The transmitter (Tx) is placed on the chair of 0.4 m height from the floor. To evaluate localization performance of receiver position, we conducted two types of experiments; the receiver (Rx) is placed on the desk of 2.6 m (A) and 0.7 m (B) height. (A) means that higher than a target object's height, and (B) means that the lower than the target.

We collected training data for three persons. In the training phase, we obtained the data for each position when a person stands at each position for 15 seconds. The training data were labeled 25 classes. In the testing phase, a person moves from point 1 to 25, standing at each position for 10 seconds.

We compare the RMSE of the two types of Rx heights, (A) and (B). The localization RMSE results are summarized in Table IV. From these results, we can see that the (B)'s results show higher localization performance than (A). This happens because target object

TABLE IV.
RMSE RESULTS

Method	F	RMSE (m) (A) Rx: 2.3 m	RMSE (m) (B) Rx: 0.7 m
w/o SSP	2	2.74	2.53
w/o SSP	4	2.77	2.40
w/o SSP	6	2.83	2.43
w/o SSP ∪ w/ SSP	16	2.48	1.85
w/o SSP ∪ w/ SSP	18	2.44	1.86
w/o SSP ∪ w/ SSP	20	2.45	1.85

can impact the eigenvector and eigenvalue spanning the signal subspace, when the antenna height is lower than the target object. This happens because the change of signal subspace feature (i.e., eigenvector and eigenvalue spanning the signal subspace) is affected by the target object in the transmission path. Thus, the change of propagation environment of interest affects by the target object.

VI. Conclusions

In this paper, we propose a method that uses SSP to increase signal subspace feature for passive localization using array sensor. We show that signal subspace features, which include the eigenvector and its corresponding eigenvalue, can be increased by using the SSP. We apply the features to a new localization algorithm on array sensor. The experimental results show that the proposed SSP based method achieves a 41.83 % improvement in localization accuracy, and a 1.24 m improvement in root mean square error (RMSE) compared to the previous method. We further discuss the impact of the array antenna placement on localization performance. We find the array antenna placed lower than the target object can improve the localization performance.

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References

[1] C. H. Lu and L. C. Fu, "Robust location-aware activity recognition using wireless sensor network in an attentive home," *IEEE Trans. on Autom. Sci. and Eng.*, vol. 6, no. 4, pp. 598-609, Oct. 2009.
[2] C. Fischer and H. Gellersen, "Location and navigation support for emergency responders: A survey," *IEEE Pervasive Comput.*, vol. 9, no. 1, pp. 38–47, Jan.-March 2010.
[3] B. Song, A. T. Kamal, C. Soto, C. Ding, J. A. Farrell, and A. K. Roy-Chowdhury, "Tracking and activity recognition through consensus in distributed camera networks," *IEEE Trans. on Image Proc.*, vol. 19, no. 10, June 2010.
[4] S. A. Golden and S. S. Bateman, "Sensor measurements for Wi-Fi location with emphasis on time-of-arrival ranging," *IEEE Trans. Mobile Computing*, vol. 6, no. 10, pp. 1185-1198, Oct. 2007.
[5] D. J. Geiger, "High resolution time difference of arrival using timestamps for localization in 802.11b/g wireless networks," *Wireless Comm. and Net. Conf. (WCNC), 2010 IEEE*, pp. 1–6, Apr. 2010.
[6] C. Wong, R. Klukas, and G. Messier, "Using WLAN infrastructure for angle-of-arrival indoor user location," *Vehicular Tech. Conf., VTC 2008-Fall. IEEE 68th*, pp. 1–5, Sept. 2008.
[7] A. Hatami and K. Pahlavan, "In-building intruder detection for WLAN access," *IEEE Pos., Loc. and Nav. Symp.*, pp. 592-597, Apr. 2004.
[8] L. M. Ni, D. Zhang, and M. R. Souryal, "RFID-based localization and tracking technologies," *Wireless Communications, IEEE*, vol. 18, no. 2, pp. 45–51, Apr. 2011.
[9] J. Koo and H. Cha, "Localizing WiFi access points using signal strength," *Communications Letters, IEEE*, vol. 15, no. 2, pp. 187–189, Feb. 2011.
[10] M. Youssef, M. Mah, and A. Agrawala, "Challenges: Device-free passive localization for wireless environments," *Proc. ACM MobiCom*, pp. 222-229, Sept. 2007.
[11] J. Wilson and N. Patwari, "Radio tomographic imaging with wireless networks," *IEEE Trans. Mobile Computing*, vol. 9, no. 5, pp. 621-632, Jan. 2010.
[12] D. Zhang, J. Zhou, M. Guo, J. Cao, and T. Li, "TASA: Tag-free activity sensing using RFID tag arrays," *IEEE Trans. Parallel and Distributed Systems*, vol. 22, no. 4, pp. 558-570, Apr. 2011.
[13] S. Ikeda, H. Tsuji, and T. Ohtsuki, "Indoor event detection with eigenvector spanning signal subspace for home or office security," *IEEE 68th Vehicular Tech. Conf.*, pp. 1–5, Sept. 2008.
[14] S. Ikeda, H. Tsuji, and T. Ohtsuki, "Indoor event detection with eigenvector spanning signal subspace for home or office security," *Trans. of IEICE*, E92-B, no. 7, pp. 2406-2412, July 2009.
[15] S. Kawakami, K. Okane, and T. Ohtsuki, "Detection performance of security system using radio waves based on space-time signal processing," *Procedia - Social and Behavioral Sciences*, vol. 2, pp. 171-178, Jan. 2010.
[16] J. Hong and T. Ohtsuki, "A state classification method based on space-time signal processing using SVM for wireless monitoring systems, " *IEEE Int. Symp. on Personal Indoor and Mobile Radio Commun. (PIMRC2011)*, pp. 2229-2233, Sept. 2011.
[17] H. Krim and M. Viberg, "Two decades of array signal processing research," *IEEE Sig. Proc. Mag.*, vol. 13, no. 4, pp. 67-94, July 1996.
[18] H. Yan and H. H. Fan, "On source association of DOA estimation under multipath propagation," *IEEE Sig. Proc. Letters*, vol. 12, no. 10, pp. 710-712, Oct. 2005.
[19] S. S. Jeng, G. Xu, H. P. Lin, and W. J. Vogel, "Experimental study of antenna arrays in indoor wireless applications," *IEEE 29th Asilomar Conf. on Sig. Syst. and Comput.*, vol. 2, pp. 766-770, Oct. 1995.
[20] T. J. Shan and T. Kailath, "Adaptive beamforming for coherent signals and interference," *IEEE Trans. Acoust., Speech, Signal Processing*, vol. 33, no. 3, pp. 527-536, June 1985.
[21] S. U. Pillai and B. H. Kwon, "Forward/backward spatial smoothing techniques for coherent signal identification," *IEEE Trans. Acoust., Speech, Signal Processing*, vol. 37, no. 1, pp. 8–15, Jan. 1989.
[22] V. Vapnik, *Statistical Learning Theory*. New York: Wiley, 1998.
[23] C. J. C. Burges, "A tutorial on support vector machines for pattern recognition," *Data Mining Knowl. Disc.*, vol. 2, no. 2, pp. 1–47, 1998.
[24] C. W. Hsu and C. J. Lin, "A comparison of methods for multiclass support vector machines," *IEEE Trans. Neural Netw.*, vol. 13, no. 2, pp. 415-425, Mar. 2002.

[25] C. C. Chang and C. J. Lin, “LIBSVM: A library for support vector machines,” *ACM Trans. Int. Syst. and Tech. (TIST)*, vol. 2, no. 3, pp. 1–27, Apr. 2011.

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