Activity Recognition Based on Array Sensor

Tomoaki Ohtsuki and Jihoon Hong
Keio University
Graduate School of Science and Technology
3-14-1 Hiyoshi, Kouhoku-ku, Yokohama, Japan
Email: ohtsuki@ics.keio.ac.jp, jihoon.hong@gmail.com

***Abstract*—This paper introduces activity recognition based on our proposed array sensor. The array sensor consists of an antenna array on the receiver side and decomposes received signals into eigenvectors and eigenvalues. It exploits these components depending on its applications, such as activity recognition. When an event occurs, the propagation environment changes, and thus the eigenvector and eigenvalue change. Eigenvector and corresponding eigenvalue are inherent to their propagation environments so that to activity as well. Based on the change of these components, we can detect an activity accurately. In addition, using machine learning based on these components, the proposed array sensor can classify several more complex states and activities. This paper also introduces various applications of array sensor.**

I. Introduction

It is well-known that Japan is the fastest aging society in the world. In Japan there are a lot of elderly persons living at home alone [1]. They need to be monitored for their safety. Video cameras is one way to monitor persons accurately. However, of course, people do not want to be monitored even by their children or relatives; people do not want surveillance cameras to be installed in their home. In addition, information obtained from one sensor or camera is local. Therefore, we need a way that can monitor people without invading their privacy. In house one of the places where an accident occurs most and need to be monitored is bathroom. We need to monitor person's activities, such as falling and drowning in bathroom. As we can easily imagine, however, one of the places where it is difficult to install camera is bathroom. In addition infrared sensors cannot work correctly in bathroom.

For the above application, monitoring, we often want to know not only whether it happens but also where it does. Thus, localization is also important. Localization techniques are roughly classified into two classes, active localization and passive localization. Majority of localization techniques is active localization 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 of stress brought on by carrying tags/devices. In addition it can extend the application such as localization in a bathroom. However, localization accuracy of passive localization is lower than that of active one in general.

As event detection systems, several electrical wave-based systems are reported in [2][3][4] where an event such as intrusion is detected based on the change of received signal strength (RSS). Electrical waves arrive every corner, and thus wide sensing range is expected. The electrical wave-based security system has no need to be worried about privacy invasion by images. However, RSS suffers from the effects of noise and fluctuates even in static conditions. Thus, a detection error occurs.

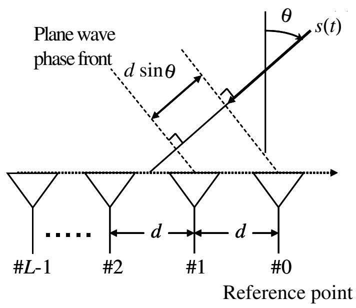

Fig. 1. L-element uniform linear array with source signal $s(t)$ from DOA θ

We have proposed an event detection system using the signal subspace spanned by eigenvector [5]–[8]. This system uses antenna array as receiver to obtain direction of arrivals (DOAs) of incident signals (i.e. the signal subspace spanned by eigenvector). Eigenvector is based on not RSSs but DOAs. The subspace changes only when the indoor environment of interest changes intermittently, and statically or dynamically because the array signal processing removes the effects of fading and noise. Thus, the systems is referred to as array sensor. We reported the principle of our array sensor and some of fundamental detection performance of the system using dipole antennas arranged linearly or circularly as the receiver, although they are not necessarily arranged regularly.

This paper introduces activity recognition based on our proposed array sensor. Using machine learning based on eigenvector and eigenvalue components obtained by array sensor with array signal processing, the proposed array sensor can classify several more complex states and activities. This paper also introduces various applications of array sensor.

II. Array Data Model

Consider the L-element circular linear array for simplicity of explanation. Note that any type of array antennas can be used in array sensor, even the precise alignment of antenna elements is not required. The angle of elevation of DOA has only 90 degree, because the each element used in this experiment is dipole antenna. There is one source signal $s(t)$ shown in Fig. 1. DOA θ is defined clockwise relative to the Broadside. The source signal $s(t)$ is a plane wave owing to the far field assumption. The noise $\mathbf{n}(t)$ is an additive white Gaussian noise (AWGN) of zero mean and variance σ^2. The received signal vector $\mathbf{x}(t)$ from DOA θ is represented as

$$\mathbf{x}(t) = \mathbf{a}(\theta)s(t) + \mathbf{n}(t) \tag{1}$$

where $\mathbf{a}(\theta)$ is referred to as a steering vector, which is a complex vector denoting a phase shift of a source signal at each antenna relative to the first antenna (reference point). In the uniform linear array, the steering vector is represented as

$$\mathbf{a}(\theta) = \left[1, \mathrm{e}^{-j\frac{2\pi}{\nu}d\sin\theta}, \ldots, \mathrm{e}^{-j\frac{2\pi}{\nu}(L-1)d\sin\theta}\right]^T \tag{2}$$

where ν is wavelength and $[\cdot]^T$ is transposition. In the indoor wireless scenario, the antenna array receives not only signals from direct path but also many reflected multipath components with different DOAs [9]. Therefore, we represent the received signal vector that includes the total signal picked up by the antenna array as follows.

$$\mathbf{x}(t) = \sum_{i=1}^{M} \alpha_i \mathbf{a}(\theta_i)s(t) + \mathbf{n}(t) = \mathbf{a}'s(t) + \mathbf{n}(t) \tag{3}$$

$$\tag{4}$$

where M is the total number of direct and multipath components, and α_i is the phase difference and amplitude decay between the direct path and the ith multipath. $\mathbf{a}'$ is a new steering vector, which consists of the linear coupling of the incident signals.

To analyze wave propagation, we use the data correlation matrix estimated from the received signal vector. The data correlation matrix $\mathbf{R}_{xx}$ is defined as follows.

$$\mathbf{R}_{xx} = E[\mathbf{x}(t)\mathbf{x}(t)^H] \tag{5}$$

where $E[\cdot]$ is ensemble average and $[\cdot]^H$ is conjugate transpose. In general, additive noise is uncorrelated with the source signal. The noise is independent in each element Therefore, the data correlation matrix can be simplified as follows.

$$\begin{aligned}\mathbf{R}_{xx} &= E[\mathbf{a}'s(t)s(t)^H\mathbf{a}'^H] + \\ &\quad \underbrace{E[\mathbf{a}'s(t)\mathbf{n}(t)^H] + E[\mathbf{n}(t)\mathbf{a}'^H s(t)^H]}_{\to 0} + E[\mathbf{n}(t)\mathbf{n}(t)^H] \\ &= \mathbf{a}'S\mathbf{a}'^H + \sigma^2\mathbf{I}\end{aligned} \tag{6}$$

where $S = E[s(t)s(t)^H]$ and $\mathbf{I}$ is the identity matrix. However, the data correlation matrix $\mathbf{R}_{xx}$ cannot be strictly obtained. In effect, on the basis of ergodic hypothesis, ensemble average of eq. (3) is replaced with time average. The estimated data correlation matrix $\hat{\mathbf{R}}_{xx}$ is written for time $t = t_1, t_2, \ldots, t_{N_s}$

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

where N_s is the number of snapshots. In this paper, we treat $\hat{\mathbf{R}}_{xx}$ as $\mathbf{R}_{xx}$.

III. Subspace-Based Method

Subspace-based method [10] decomposes the data correlation matrix into orthogonal signal and noise subspaces via the eigenvalue decomposition (EVD). In this paper, signal subspace spanned by eigenvector is proportional to $\mathbf{a}'$ of eq. (4).

By the EVD of $\mathbf{R}_{xx}$, we obtain eigenvalue λ_i and eigenvector $\mathbf{v}_i$, which satisfy the following equation:

$$\mathbf{R}_{xx}\mathbf{v}_i = (\mathbf{a}'S\mathbf{a}'^H + \sigma^2\mathbf{I})\mathbf{v}_i = \lambda_i\mathbf{v}_i, \ i = 1, 2, \cdots, L \tag{8}$$

EVD of the L-element data correlation matrix $\mathbf{R}_{xx}$ is as follows.

$$\begin{aligned}\mathbf{R}_{xx} &= \mathbf{a}'S\mathbf{a}'^H + \sigma^2\mathbf{I} \\ &= \sum_{i=1}^{L} \lambda_i \mathbf{v}_i \mathbf{v}_i^H &(9)\\ &= \mathbf{V}\mathbf{\Lambda}\mathbf{V}^H &(10)\\ \mathbf{V} &= [\mathbf{v}_1, \mathbf{v}_2, \cdots, \mathbf{v}_L] &(11)\\ \mathbf{\Lambda} &= \mathrm{diag}\{\lambda_1, \lambda_2, \cdots, \lambda_L\} &(12)\end{aligned}$$

where λ_i and $\mathbf{v}_i$ are respectively eigenvalue and eigenvector, which satisfy the following equation: Since $\mathbf{R}_{xx}$ is a positive definite Hermitian matrix, the eigenvalue λ is nonnegative real number and is sorted in the descending order: $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_L (> 0)$. Then, we can write

$$\begin{aligned}\mathbf{a}'S\mathbf{a}'^H\mathbf{v}_i &= (\lambda_i - \sigma^2)\mathbf{v}_i = \lambda_i'\mathbf{v}_i, \ i = 1, 2, \cdots, L &(13)\\ \lambda_i' &= \lambda_i - \sigma^2 &(14)\end{aligned}$$

where, because $\mathrm{rank}[\mathbf{a}'S\mathbf{a}'^H] = 1$,

$$\lambda_1' > \lambda_2' = \cdots = \lambda_L' = 0. \tag{15}$$

Thus, eigenvalue distribution of the data correlation matrix is

$$\lambda_1 > \lambda_2 = \cdots = \lambda_L = \sigma^2. \tag{16}$$

Therefore, the eigenvalue matrix $\mathbf{\Lambda}$ is decomposed into signal and noise eigenvalues. However, the eigenvalue distribution is ideal, and in fact some errors are observed owing to using the estimated correlation matrix $\hat{\mathbf{R}}_{xx}$.

We can write

$$\mathbf{a}'^H\mathbf{v}_i = 0, \ i = 2, 3, \cdots, L. \tag{17}$$

Therefore, the space spanned by the eigenvector matrix $\mathbf{V}$ is decomposed into the orthogonal signal and noise subspaces via the EVD. The first eigenvector $\mathbf{v}_1$ spans signal subspace and is proportional to $\mathbf{a}'$, because all the eigenvectors are mutually orthogonal.

IV. Detection Method

The signal subspace spanned by eigenvector is stable when the environment of interest does not change, while it changes when the environment changes. For detecting simple events, such as intrusion, we can use a simple threshold-based detection based on change of first eigenvector [5]. 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 array sensor in the following.

A signal subspace spanned by an eigenvector is obtained as the first eigenvector by EVD of the data correlation matrix and is proportional to $\mathbf{a}'$. Thus, the signal subspace spanned by eigenvector consists of the linear coupling of the steering vectors from incident multipath signals as follows.

$$\mathbf{v}_1 = \mathrm{span}\{\mathbf{a}(\theta_1), \ldots, \mathbf{a}(\theta_M)\} \tag{18}$$

where $\mathrm{span}\{\cdot\}$ represents the linear coupling of vectors. The incident multipath signals go through indoor everywhere of interest. Therefore, the signal subspace spanned by an eigenvector represents a wave propagation. When the environment of interest changes, the wave propagation changes and thus the signal subspace spanned by an eigenvector changes. Consequently, the signal subspace spanned by an eigenvector is inherent to each environment of interest.

In the array sensor, we use cost functions based on eigenvector and eigenvalue to detect events, depending on what we want to detect. Each cost function is obtained from N_t received signal vectors. The cost function $P(u)$ based on the eigenvector is defined as

$$P(u) = |\mathbf{v}_1(u_{\mathrm{no}})^H \mathbf{v}_1(u)|, \qquad (0 \leq P(u) \leq 1), \tag{19}$$

where $\mathbf{v}_1(u_{\mathrm{no}})$ is the first eigenvector obtained in advance, the reference vector, and $\mathbf{v}_1(u)$ is the first eigenvector obtained at the observation time u. Both eigenvectors are normalized to unity. $P(u)$ means the correlation between the indoor environment at the reference time and the observation time u. Therefore, the closer $P(u)$ to one, the smaller the change of environment is, and the smaller $P(u)$ is, the larger the change of environment is. The eigenvector is stationary even in the noise and fading environment because it does not include received signal strength (RSS) information.

The cost function $Q(u)$ based on the eigenvalue is defined as

$$Q(u) = 1 - \frac{|\lambda_1(u) - \lambda_1(u_{\mathrm{no}})|}{\lambda_1(u_{\mathrm{no}})}, \qquad (Q(u) \leq 1), \tag{20}$$

where $\lambda_1(u_{\mathrm{no}})$ is the first eigenvalue obtained in advance, the reference value, and $\lambda_1(u)$ is the first eigenvalue obtained at the observation time u. Like $P(u)$, the closer $Q(u)$ is 1, the smaller the change of environment is, and the smaller $Q(u)$ is, the larger the change of environment is. The eigenvalue is less stationary than the eigenvector, but $Q(u)$ can detect even for the small events. Then, we use both $P(u)$ and $Q(u)$ as the situation demands [8].

To detect simple events we just set the threshold P_{th} to the cost function to detect an event. For detecting and classifying more complex states and activities, such as sitting in a bathtub and falling in a bathroom, we use SVM. SVM is one of the most attractive machine learning [11]. SVM has shown several advantages in prediction, regression, and estimation over some of the classical approaches in a wide range of applications owing to their excellent generalization capabilities. For instance, SVM is used for image processing, natural language processing, and various antenna processings such as beamforming, DOA estimation, and sidelobe suppression [12]. SVM is a supervised computer learning method that exploits prior knowledge of similar scenarios and functions to identify unknown (never experienced before) cases or similar functions. Once the SVM has been trained, then all future unknown samples can be classified in real time. If we use machine learning for the safety system like array sensor, there are some essential points as follows; detect in real time or semi-real time; work on nonlinear problem; use as many features as possible. SVM meets the above conditions and then, it is suitable for localization based on array sensor system. One of the attractive kernel used as a mapping function is radial basis function (RBF) kernel, because it has less numerical difficulties. 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 [11]. Moreover, we use cost functions based on the eigenvector and eigenvalue for the features of SVM.

V. Localization Using Array Sensor

The proposed array sensor can localize a person's position.

A. Training Model

Assume that we classify N_p positions. In the training phase, we get the received signals $\mathbf{x}_p(t)$ $(p = 1, \ldots, N_P)$ when a person stands at position p for T_N observation times. From the signals, we compute the cost functions $P_i(u), Q_i(u)$, where $u = 1, \ldots, T_N$. That is, we have $N_P T_N$ training samples. When we need more features for better classification performance based on SVM, we also compute the cost functions based on eigenvectors and eigenvalues with spatial smoothing processing (SSP) $P_j^{\mathrm{SSP}}(u), Q_j^{\mathrm{SSP}}(u)$ for each data. Next, the necessary cost functions are combined to one feature vector, such as

$$\begin{aligned} \mathbf{z}_p \quad = \quad & [P_1(u), \ldots, P_L(u), Q_1(u), \ldots, Q_L(u), P_1^{\mathrm{SSP}}(u), \\ & \ldots, P_{D_S}^{\mathrm{SSP}}(u), Q_1^{\mathrm{SSP}}(u), \ldots, Q_{D_S}^{\mathrm{SSP}}(u)]^T. \end{aligned} \tag{21}$$

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

B. Localization for Testing Data

The proposed localization algorithm is shown in Fig. 2. In the testing 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 position of standing person based on above algorithm.

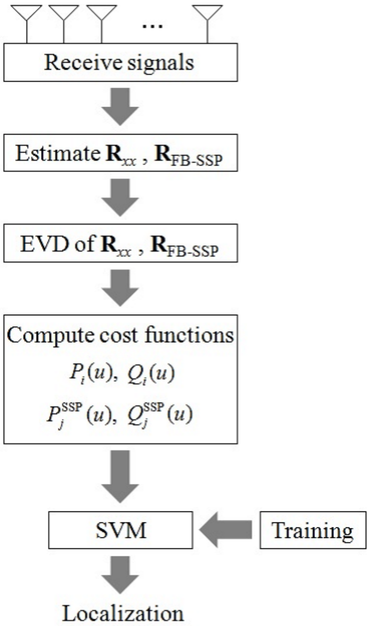

Fig. 2. Localization algorithm using array sensor

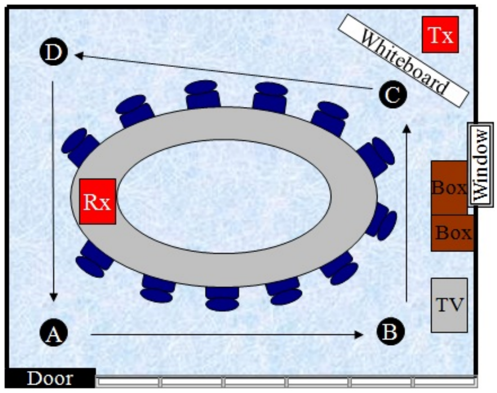

Fig. 3. The room used for experiment 1

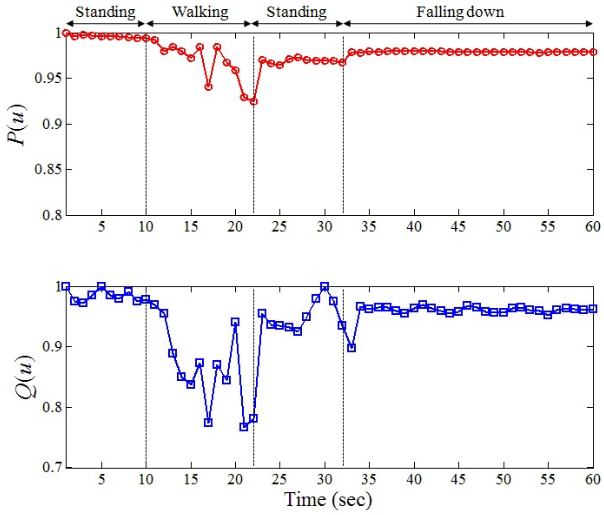

Fig. 4. Change of cost functions: $P(u)$ and $Q(u)$

VI. Experimental Results

A. Experiment 1: Detection of Person's activities, Standing, Walking, and Falling down

We show one of our experimental results obtained in the room with concrete walls and glass walls shown in Fig. 3. One transmitter and one receiver are fixed in non-line-of-sight (NLOS) so that the signal subspace spanned by eigenvector captures sharply the change of the propagation environment. 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. The experimental parameters are listed in Table I. The proposed system does not use accurate DOA information of received signals. Thus, different from general array applications, such as DOA estimation, the proposed system can use array antenna where each antenna element is placed in arbitrarily. In addition no array antenna calibration is needed. Thus, array antenna can be simple and cost-effective. In addition installation of array antenna can be easy and simple in practical environments.

Figure 4 shows change of cost functions $P(u)$ and $Q(u)$ for a series of person's activities, standing, walking, standing, and falling down. In this experiment, the person is first at the point B for 10 seconds and goes through the points C, D, and A as shown in Fig. 3. Between the points D and A, the person stops for 10 seconds. For each activity, we can see the different change of cost functions. Using SVM, we can classify each activity with high probability. For instance, the classification probability of activities between falling down and others is 93.3 $\%$ without filtering and higher than 98 $\%$ with filtering, where filtering removes sudden changes of activity that is not possible for people.

B. Experiment 2: Localization Using Array Sensor

We show one of experimental results of localization using array sensor. Experimental parameters are listed in Table I. Localization system is composed of the 2.4 GHz band transmitter like WLAN and the receiver with 8-element linear array without calibration. Experimental room is shown in Fig. 5. It is a general class room constructed of ferro-concrete walls and glass windows. There are obstacles in front of each transmitter, and then the transmitters and receiver are set on NLOS.

We define root mean square error (RMSE) as the distance

TABLE I
Experimental parameters

Transmission frequency	2484, 2467 GHz
Transmission power	-10 dBm
Modulation method	No modulation
Transmitter	Dipole antenna
Receiver	8-element linear array
Sampling rate	20, 60 MHz
Number of snapshots	8192, 1024

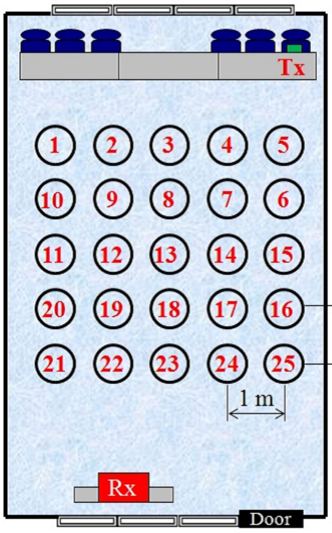

Fig. 5. The room used for experiment 2

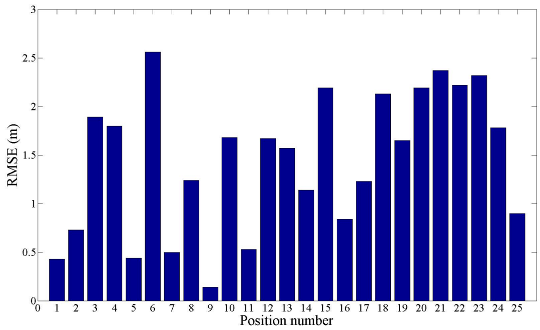

Fig. 6. RMSE at each position

error between true position and estimated position. 16 features obtained by array signal processing are used for SVM.

In the training phase, we obtained the data when a person stands at each position for 100 observation numbers (approximately 15 seconds) and experimented for three persons. Thus, the number of training samples is $25 \times 100 \times 3 = 7500$. Then, the SVM separates $1800 \times 3 \times 2 = 10800$ testing samples into 25 classes.

Figs. 6 and 7 show RMSE at each position in the room in Fig. 5 in two ways. We can see that the proposed localization using array sensor can achieve good RMSE performance smaller than 2.5 m. We can also see that RMSE at near the receiver is relatively large, though it is still smaller than 2.5 m.

VII. Conclusion

This paper introduces activity recognition based on our proposed array sensor. The proposed system exploits an antenna array on the receiver side and decomposes received signals into eigenvectors and eigenvalues. The proposed system exploits these components depending on its applications, such as intrusion detection, monitoring, and passive localization. Using

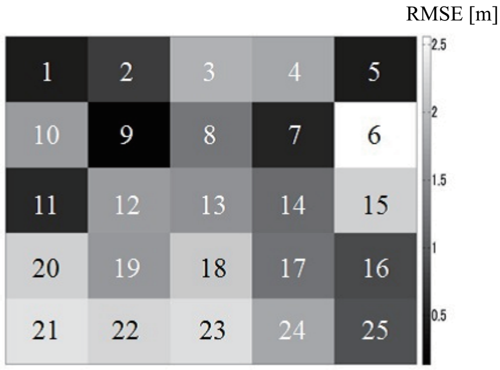

Fig. 7. RMSE at each position

machine learning based on these components, the proposed array sensor can classify several more complex states and activities. We presented some of our experimental results, such as detecting person's activities in office environment and localization performance of person's position. The proposed array sensor can be useful for monitoring without invading privacy, such as monitoring elderly person living alone, monitoring person in bathroom and restroom.

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