Ambient Intelligence Sensing using Array Sensor: Device-Free Radio based Approach

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Abstract
In this paper we introduce a novel device-free radio based activity recognition with localization method with various applications, such as e-Healthcare and security. Our method uses the properties of the signal subspace, which are estimated using signal eigenvectors of the covariance matrix obtained from an antenna array (array sensor) at the receiver side. To classify human activities (e.g., standing and moving) and/or positions, we apply a machine learning method with support vector machines (SVM). We compare the classification accuracy of the proposed method with signal subspace features and received signal strength (RSS). We analyze the impact of antenna deployment on classification accuracy in non-line-of-sight (NLOS) environments to prove the effectiveness of the proposed method. In addition, we compare our classification method with k-Nearest Neighbor (KNN). The experimental results show that the proposed method with signal subspace features provides accuracy improvements over the RSS-based method.

Author Keywords
Device-free sensing, antenna array, activity recognition, localization

ACM Classification Keywords
I.5.4 [Applications]: Signal processing.

Introduction

Ambient intelligence sensing has become an important line of research in recent years. Vision based sensing systems (e.g., video camera) are commonly used for monitoring owing to their price and ease of use. However, a significant problem is the invasion of user's privacy. Thus, it is difficult to install in private areas, such as a bathroom. Wearable sensor-based systems are the other attractive technology for e-Healthcare. This is because the sensor can obtain user information without user privacy concerns. Unfortunately, the limitation of the wearable sensor-based system is inconvenience because users have to always wear devices/tags to be monitored.

Recently, device-free radio based systems have received attention because they provide less stress from carrying devices/tags to users. The device-free radio based systems use radio wave characteristics such as reflection, diffraction and scattering by objects. Broadcasting waves such as FM and TV, can be used for detecting human movements by using the changes of received signal strength (RSS) of broadcasting waves from outside [12, 15]. The main advantage of broadcasting based systems is that there is no need to install a transmitter. The systems need only a receiver to detect human movements, thus the cost for installation of the system is lower than that of transmitter-receiver pair systems. However, the changes of RSS over time are large due to fading and noise. Therefore, it is necessary to increase the number of RSS samples to improve the detection performance, which causes the latency issue.

Using micro-Doppler features, an approach for human activity classification was proposed [11]. The approach uses micro-Doppler radar to measure human activities by extracting features from the Doppler spectrogram. To classify human activities, a support vector machine (SVM) is adopted. The classification accuracy of the approach was found to be above 90 %. However, the detection range of the micro-Doppler radar is narrow to cover all the area of interest. In addition, better hardware is needed for non-line-of-sight (NLOS) environment.

For device-free radio based localization, many previous researches considered using RSS [14, 16, 17]. These systems measure RSS values between transmitter and receiver, and use a radio tomographic imaging (RTI) technique [16] or a fingerprinting based technique [17] for localization. As aforementioned above, RSS is very sensitive to fading and noise. Furthermore, natural conditions such as the temperature and humidity may also affect RSS variance. Moreover, the conventional systems require a number of sensing devices to improve localization accuracy and to cover sensing area.

We have proposed a monitoring system which uses an antenna array at the receiver side, referred to as array sensor [7, 8, 6, 10, 4, 13, 3, 5, 9]. The system uses the change of signal subspace spanned by signal eigenvectors of covariance matrix from array sensor. For example, when a human enters the room where the system is installed, the signal subspace in the room changes by the human. Unlike the general applications for direction of arrival (DOA) of transmitted signals using antenna array, the array sensor does not require DOA estimation. The array sensor also uses any frequency band on the application in use. Main advantage over the conventional RSS-based systems is the noise mitigation. Based on a subspace based method, received waves can be divided into signal subspace and noise subspace spanned by eigenvector and its corresponding eigenvalue. Since the array sensor uses only the eigenvector spanning signal subspace as a signal feature, it is more robust to noise than RSS.

In this paper, we present a device-free radio based ambient intelligence sensing for not only activity recognition but also localization using array sensor. We apply a machine learning method with SVM for activity and location classification. Moreover, we evaluate the performance of the signal subspace features compared with that of RSS. We also analyze the impacts of antenna deployment on the enhancements of classification accuracy in NLOS environments to prove the effectiveness of the proposed method. In addition, we compare our classification method with k-Nearest Neighbor (KNN). The experimental results show that the proposed method with signal subspace features outperfomrs the RSS-based method.

The rest of the paper is organized as follows. We first explain the system model and then introduce the proposed classification method. Next, we show the experimental evaluation. Finally, we summarize the main contributions in the conclusion.

System Model

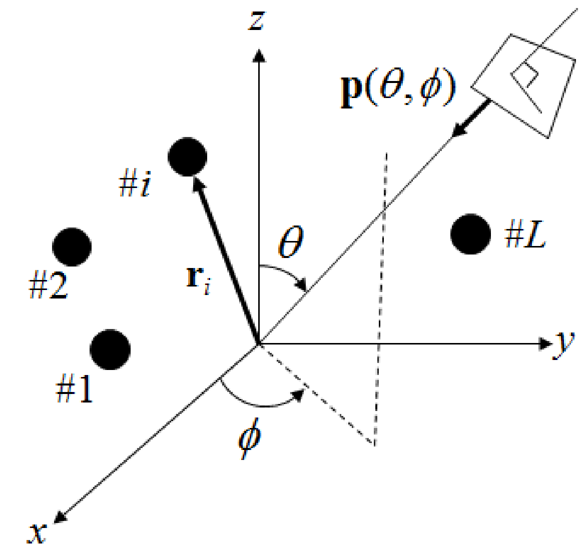


Figure 1: L-element three dimensional antenna array. At time t, the transmitted signal $s(t)$ from direction of arrival (DOA) θ, ϕ is a plane wave owing to the far field assumption. [10]

This model refers to the case when a single transmitter transmits the signal and it is received at a receiver with an antenna array. Let us consider an antenna array deployed at different points in three dimensional space as shown in Fig. 1. The received signal vector $x(t)$ arriving at time t from direction (θ, ϕ) is represented as

$$\mathbf{x}(t) = \sum_{z=1}^{Z} \alpha_i \mathbf{a}(\theta_z, \phi_z) s(t) + \mathbf{n}(t) = \mathbf{A}\mathbf{s}(t) + \mathbf{n}(t) \quad (1)$$

where $\mathbf{a}(\theta_z, \phi_z)$ is a steering vector including the phase difference between reference point and each element. M

is the number of received signals and α_z includes the delay and strength of z-th multipath signal. $\mathbf{A}$ is a new steering vector composed of a linear combination of each signal steering vector, and depends on direction, power, and phase.

We can estimate the data correlation matrix $\mathbf{R}_{xx}$ from (1) as follows:

$$\mathbf{R}_{xx} = E[\mathbf{x}(t)\mathbf{x}(t)^H] \quad (2)$$

where $E[\cdot]$ and $[\cdot]^H$ denote the ensemble average and the conjugate transpose of vector $[\cdot]$, respectively. In general, additive noise is uncorrelated with the source signal. Therefore, the data correlation matrix can be simplified as follows:

$$\begin{aligned} \mathbf{R}_{xx} &= E[\mathbf{A}\mathbf{s}(t)\mathbf{s}(t)^H\mathbf{A}^H] + E[\mathbf{n}(t)\mathbf{n}(t)^H] \\ &\quad + \underbrace{E[\mathbf{A}\mathbf{s}(t)\mathbf{n}(t)^H] + E[\mathbf{n}(t)\mathbf{s}(t)^H\mathbf{A}^H]}_{\to 0} \\ &= \mathbf{A}\mathbf{S}\mathbf{A}^H + \sigma^2\mathbf{I} \end{aligned} \quad (3)$$

where $\mathbf{S} = E[\mathbf{s}(t)\mathbf{s}(t)^H]$ and $\mathbf{I}$ is the identity matrix. Assuming the noise is independent in each element, $E[\mathbf{n}(t)\mathbf{n}(t)^H] = \sigma^2\mathbf{I}$.

In practical use, the data correlation matrix $\mathbf{R}_{xx}$ can be approximated by the estimated data correlation matrix $\hat{\mathbf{R}}_{xx}$. Because of the ergodicity hypothesis (i.e., ensemble average is equal to time average), the ensemble average of (2) can be replaced with the time average. The estimated data correlation matrix $\hat{\mathbf{R}}_{xx}$ is then written for time $t = t_1, t_2, \ldots, t_{N_s}$,

$$\hat{\mathbf{R}}_{xx} = \frac{1}{N_s}\sum_{k=1}^{N_s} \mathbf{x}(t_k)\mathbf{x}(t_k)^H \quad (4)$$

where N_s is the number of snapshots. As $N_s \to \infty$, we can obtain the better estimation accuracy of $\hat{\mathbf{R}}_{xx}$.

Activity and Location Classification Method

Radio Wave Feature

The received signal is extracted from the received waves of interest at time t. We extract the correlation between two signal eigenvectors. The correlation between two signal eigenvectors is expressed as

$$P_m(t) = \left|\mathbf{v}_1^H \mathbf{v}_m(t)\right|, \quad m = 1, 2, \cdots, M \quad (5)$$

where $\mathbf{v}_1$ is the first signal eigenvector of default antenna set and $\mathbf{v_m}(t)$ is the signal eigenvector obtained from the m-th antenna set at time t.

We also use variance of $P_m(t)$ as a feature for classifying between movement and no movement.

$$\mathrm{var}(P_m(t)) = \frac{1}{N}\sum_{i=1}^{N}(P_m(i) - \mu)^2 \quad (6)$$

where N is the number of observation data and μ is the average value of $P_m(t)$ on the interval $[1, N]$.

Another feature for classification is differences between each $P_m(t)$.

$$\mathrm{diff}(P_m(t)) = |(P_m(t) - P_{m-1}(t))| \quad (7)$$

In comparison, the conventional RSS based method, we use average of RSS values from each element i of antenna array at time t is expressed as follows.

$$\mathrm{avg}(RSS_i(t)) = \frac{1}{M}\frac{1}{N_s}\sum_{i=1}^{M}\sum_{j=1}^{N_s} RSS_i(j) \quad (8)$$

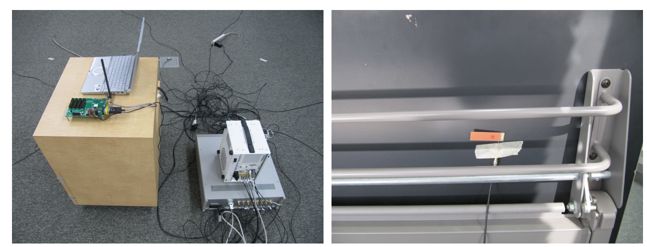
where M and N_s are the number of antenna elements and the number of snapshots, respectively. In this paper, we replace $RSS_i(t)$ with $\mathrm{avg}(RSS_i(t))$.

Multiclass Support Vector Machines for Classification
We use SVM for classification of activities and locations, based on signal subspace features. SVM can be used for not only two-class classification but also multiclass classification, named multiclass support vector machines. In general, there are two major methods to solve multiclass classification problems: "one-against-all" and "one-against-one" approaches. The "one-against-all" approach constructs μ SVM models where μ is the number of classes. The l-th SVM is trained using all of the data in the l-th class with positive labels, and all other data with negative labels. The "one-against-one" approach trains a two-class SVM model for any two classes from the training set, which for a μ-class problem results in $\mu(\mu-1)/2$ SVM models. In the cross-validation phase, a voting procedure assigns the class of the classification pattern to the class with the maximum number of votes [1]. In this paper, we use "one-against-one" approach for multiclass SVMs, because its performance including time cost is better than that of "one-against-all" approach [1].

Experimental Results

Experimental Setup

Figure 2: Experiment environment



(a) **(b)**

Figure 3: (a) a transmitter and (b) a patch antenna for array sensor.

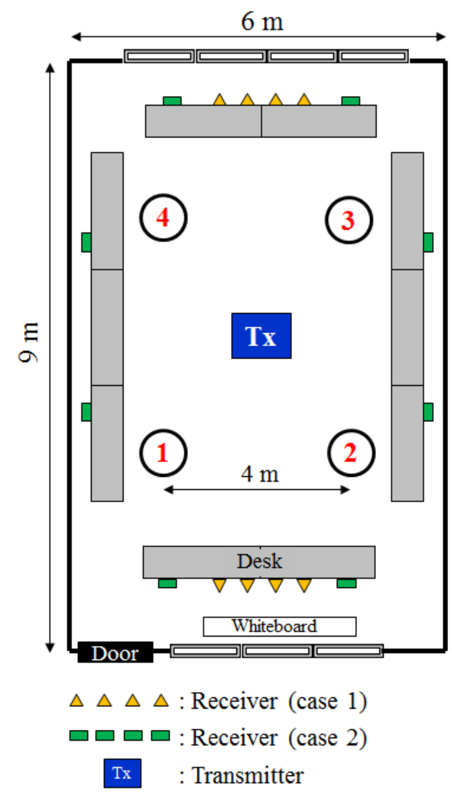


Figure 4: Experiment layout

Table 1: Experimental Parameters

Transmitter antenna	Dipole antenna
Transmitter frequency	2.484 GHz
Number of transmitter antennas	1
Number of receiver antennas (M)	8
Sampling frequency	60 MHz
Number of snapshots (N_s)	1000

In this section, we show the experimental setup and results with a comparison of classification performance. Fig. 2 shows the experimental environment, where the transmitter (Tx) is placed on the center of the room (see Fig. 3 (a)) and the antennas of the array sensor (Rx) are patched on the back of the tables (see Fig. 3 (b)). The experiments were conducted in a room as shown in Fig. 4. In this figure, each number in circles represents a person's standing location. The transmitter uses one single dipole antenna, which transmits continuous waves in the 2.4 GHz frequency band. The antenna array has 8-element antennas and all antenna elements are fixed in an NLOS condition. To evaluate receiver antenna's deployment, we set up two types of antenna array, shown as the yellow triangles (Case 1: front-back) and the green squares (Case 2: square) in Fig. 4.

We obtained 600 observation data while a person enters the room from the door, walks from location 1 to 4, stands at each location for 10 seconds, walks from position 4 to the door, and exits from the room. Three persons participated in the experiment, and repeated the scenario. We labeled the scenario when the room is empty as "No event, that when the person is walking as "Moving", and that when the person is standing at each location as "Loc. 1", "Loc. 2", "Loc. 3", and "Loc. 4". We performed three-fold cross validation in which the data from two persons used for training and then the data from the other one used for testing. For example, the data from person A and B are used for training data, while the data from person C are used for test data.

We use MATLAB 7.12.0 to compute features from the received data. To implement SVMs with MATLAB, we use *LIBSVM*, which is a SVM library developed by Chang and Lin [2]. We summarize the experimental parameters in Table 1.

Performance Metric
To evaluate the performance of our proposed method, we show our experimental results obtained in different antenna setups (Case 1 and Case 2 as shown in Fig. 4). We also compare the classification performance of the proposed system with different feature vectors as shown in Table 2. Last but not least, we show the comparison results with KNN and SVM classifiers. In this paper, we define classification accuracy as

$$\frac{\text{The number of correctly classified data}}{\text{The number of total data}} \times 100\ \%. \quad (9)$$

Feature Analysis

Table 2: Summary of the used feature vectors.

Name	Features
Feature A (conventional)	$RSS_i(t)$
Feature B (proposed)	$P_m(t)$, $\mathrm{var}(P_m(t))$
Feature C (proposed)	$P_m(t)$, $\mathrm{var}(P_m(t))$, $\mathrm{diff}(P_m(t))$

We summarize the used feature vectors for comparison between RSS (i.e., Feature A) and signal subspace features (i.e., Feature B and C), as given in Table 2. Fig. 5 shows an example of the each feature we used over observation numbers in Case 2. As we can see from Fig. 5 (a), RSS values fluctuate over observation numbers even while no event occurs. In contrast, $P_m(t),\ \{m = 1, 2, \cdots, 8\}$, values are stable during no event and a person standing shown in Fig. 5 (b), (c), and (d). Moreover, we can see each $P_m(t)$ from a different antenna set has different level at all locations. From Fig. 5 (c), variance of $P_m(t)$, we can easily see the difference between movement and no movement. Thus, we can use signal subspace features for activity and location classifications. We will discuss the comparison of the three feature vectors in the next subsection.

Comparison of results
Fig.6 and Table 3 show the classification results from different persons, and the confusion matrix of the three-fold cross validation result, respectively, using Feature C with SVM in Case 2. Although there are some classification errors on the Person A data shown in Fig. 6 (a), the classified activities and locations of Person B and C are classified correctly shown in Fig.6 (b) and (c).

Table 4 shows the classification accuracy of the KNN and SVM methods with three feature vectors for a front-back (Case 1) and square (Case 2) antenna deployments. From these results, we can see that the SVM method outperforms the KNN method in classification accuracy. This happens because SVM learning ability is improved by increasing the number of features. We can also see that the proposed signal subspace-based features (Feature B and C) achieves higher classification accuracy than the conventional RSS-based feature (Feature A). This is because the signal eigenvectors spanning the signal subspace are more robust to noise than RSS. In two antenna deployment cases, we can see that a square deployment (Case 2) has a much higher classification accuracy than a front-back deployment (Case 1).

Conclusion
In this paper, we proposed an activity recognition with localization method based on signal subspace using array sensor. We extracted the signal subspace features

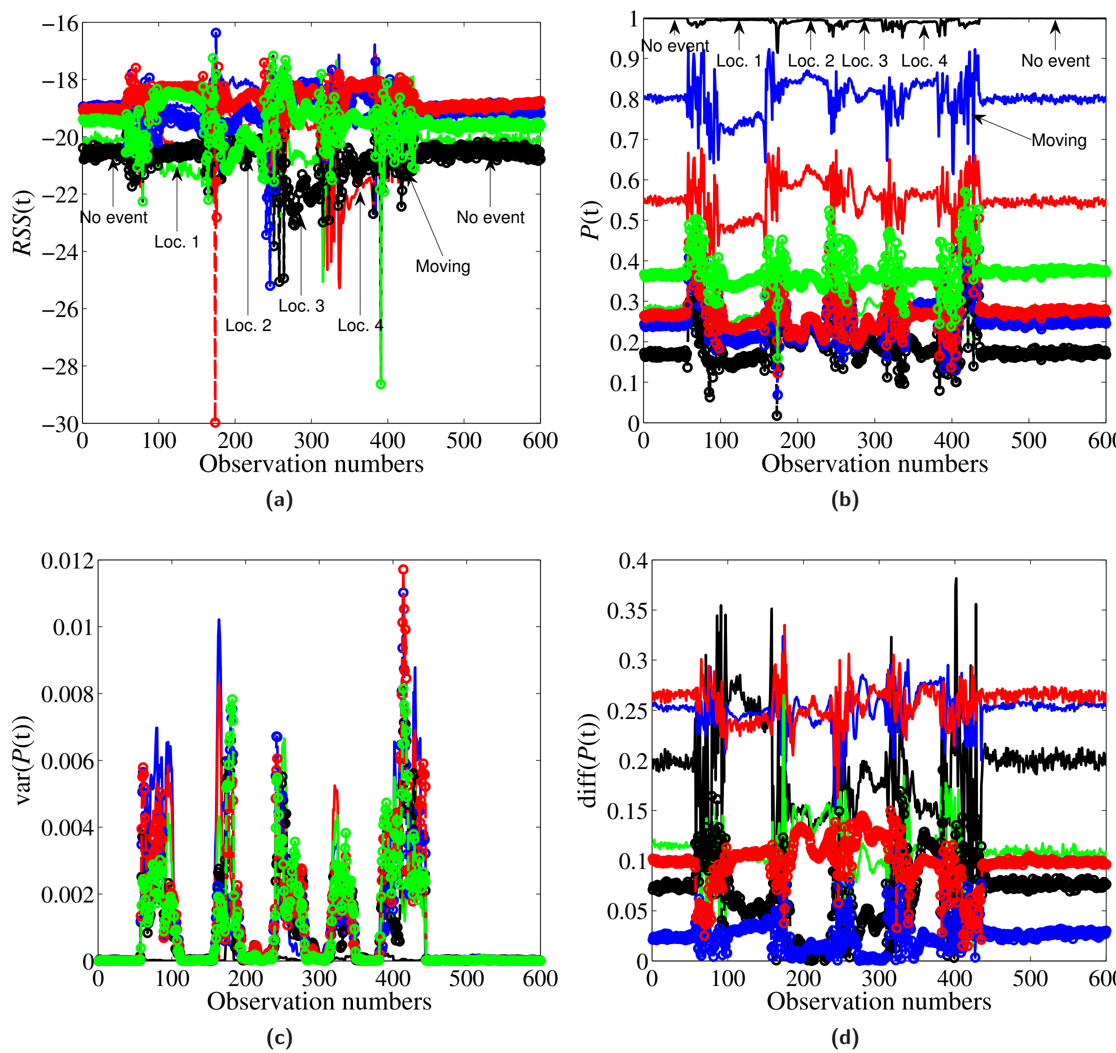
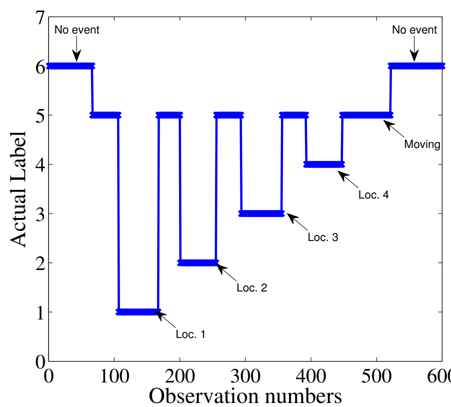
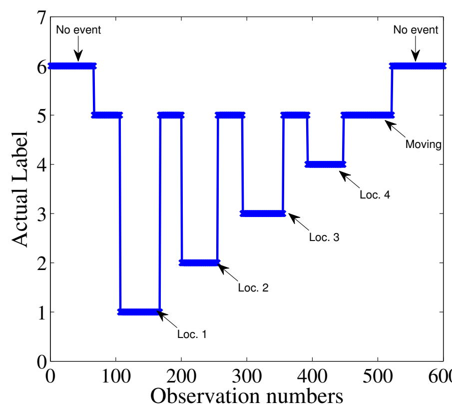


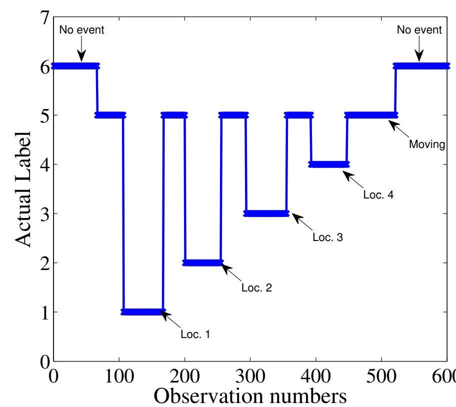
Figure 5: Examples of array sensor measurements. (a) $RSS(t)$, (b) $P(t)$, (c) $\mathrm{var}(P(t))$, (d) $\mathrm{diff}(P(t))$. In (a), the lines show RSS values from antenna elements 1 to 8. In (b)-(d), the lines show values from different antenna set. A person stands at each location from Loc. 1 to 4 shown in Fig. 4.



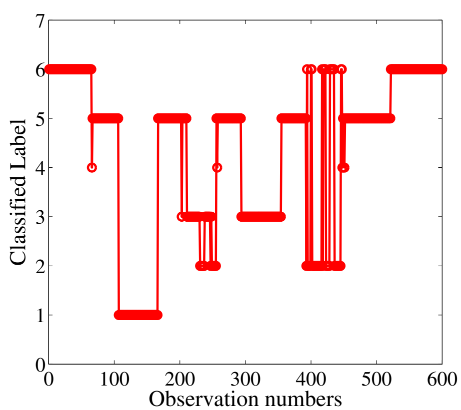
(a) Person A



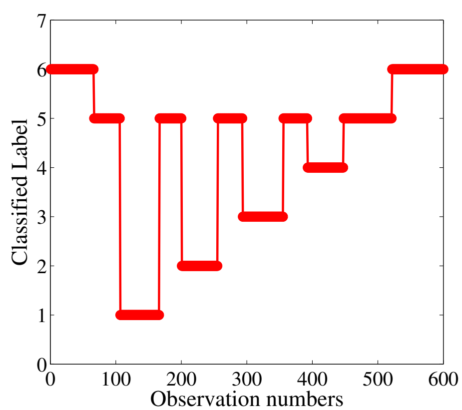
(b) Person B



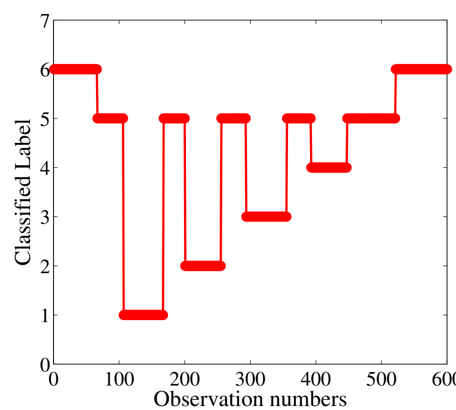
(c) Person C



(d) Person A



(e) Person B



(f) Person C

Figure 6: Actual labels (top) and the corresponding classified labels (bottom) of Case 2. Label 1: Loc. 1. Label 2: Loc. 2. Label 3: Loc. 3. Label 4: Loc. 4. Label 5: Moving. Label 6: No event.

Table 3: Confusion matrix of classification results of Feature C with SVM in Case 2. The diagonal shows corrected classified data. Overall accuracy is 87.06 %.

	Classified labels					
	Loc. 1	Loc. 2	Loc. 3	Loc. 4	Moving	No event
Loc. 1 (actual)	149	0	0	0	6	3
Loc. 2 (actual)	0	59	31	26	11	21
Loc. 3 (actual)	1	62	87	0	2	2
Loc. 4 (actual)	0	38	0	83	1	17
Moving (actual)	1	3	2	4	644	1
No event (actual)	0	0	0	1	0	545
Accuracy	94.30 %	39.86 %	56.49 %	59.71 %	98.32 %	99.82 %

Table 4: Comparison of the classification accuracy of the KNN (K = 3) and SVM methods with three feature vectors for a front-back (Case 1) and square (Case 2) antenna deployments.

	Case 1			Case 2		
	Feature A	Feature B	Feature C	Feature A	Feature B	Feature C
KNN	64.94 %	71.61 %	75.44 %	64.39 %	73.39 %	82.83 %
SVM	62.83 %	72.83 %	78.11 %	64.06 %	73.61 %	87.06 %

measured from an antenna array. Then we used a machine learning method with SVM for activity and location classification. We conducted experiments to evaluate the classification accuracy of the proposed method with the signal subspace features and RSS in NLOS. We also analyzed the impacts of antenna placement on classification accuracy to prove the effectiveness of the proposed method. In addition, we compared our classification method with KNN method. The results presented in this paper show that the signal subspace features could improve the activity and location classification accuracy compared with the RSS-based method.

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