

Device-free Human Activity Recognition Based on Random Subspace Classifier Ensemble

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Abstract—In recent years, Channel State Information (CSI)-based Human activity recognition (HAR) has received extensive attention for its low cost and privacy protection property. Existing CSI-based HAR systems utilize single classifier to accomplish recognition, which results in poor robustness and relatively low recognition accuracy. In this paper, a random subspace classifier ensemble method is proposed for classification, which utilizes the frequency domain feature instead of the time domain feature and each kind of feature is selected in the same amount. We evaluate its performance both in typical indoor and outdoor environment. Our results show, the recognition accuracy can reach 91.2% and 90.2% in outdoor and indoor environment, respectively.

Index Terms—Device-free, channel state information, activity recognition

I. INTRODUCTION

Existing HAR systems ignore frequency domain feature, which is a kind of key parameter for recognition. What's more, previous HAR systems mainly utilize the limited single classifier with poor robustness and low recognition rate to complete the recognition [1-2]. In this paper, we propose a random subspace classifier ensemble method for classification, which utilizes frequency domain feature instead of time domain feature and each kind of feature is selected in the same amount. Experiments show that it enjoys higher recognition accuracy over existing HAR systems.

II. RANDOM SUBSPACE CLASSIFIER ENSEMBLE

The obtained activity data form a matrix $\mathbf{H}$ with 30 rows and T columns, where T represents the durations of one activity and 30 represents the number of subcarrier. First, Principal Component Analysis (PCA) [3] is adopted and the second to fourth principal components are chosen in this paper. The number of principle components $k = 3$. The matrix $\mathbf{H}_r$ is obtained after the PCA of $\mathbf{H}$. Afterwards, $\mathbf{H}_d$ is obtained after the q -layer Discrete Wavelet Transform (DWT) [4] of $\mathbf{H}_r$.

The statistical information of $\mathbf{H}_d$ is extracted to reduce the length of features. The statistical features selected in this paper are mean, standard deviation, interquartile range, the 50th percentile, the 68.3th percentile and the 95th percentile. Suppose there are N

activities and they can form a matrix $\mathbf{H}_e$ with N rows and $6 \times k \times (q + 1)$ columns. $\mathbf{H}_e$ is standardized by

$$\mathbf{H}_f(i, j) = \frac{\mathbf{H}_e(i, j) - S_j}{\sigma_j} \quad (1)$$

where $S_j = \text{mean}(\mathbf{H}_e(\cdot, j))$ and $\sigma_j = \text{std}(\mathbf{H}_e(\cdot, j))$. It should be noted that $\text{mean}(\cdot)$ denotes the mean of $(\cdot)$, and $\text{std}(\cdot)$ represent the standard deviation of $(\cdot)$.

The space composed by all matrix elements is termed full space, which is denoted as $\mathbf{V}$. We select x subsets from $\mathbf{V}$ to construct the subspaces. x is set to be $x = \text{lcm}(6, k, q + 1)$, where $\text{lcm}(\cdot)$ denotes the lowest common multiple of $(\cdot)$. The subsets selection approach of subsets is conducted by following steps:

- Step1: Divide $\mathbf{V}$ into $k \times (q + 1)$ groups, each of them is made up by 6 kinds of statistical features of one frequency component in a principal component.
- Step2: Initialize the candidate set $\mathbf{U} = [1, 2, \dots, x]$, the subset $\mathbf{S} = \emptyset$ and the index of the i th statistical feature $i = 1$.
- Step3: Initialize the set $\mathbf{S}_i' = \emptyset$ and the times of sampling $\text{time} = 0$.
- Step4: Randomly extract a number z from $\mathbf{U}$ and conduct $z' = \text{mod}(z, k \times (q + 1))$. If $z' \notin \mathbf{S}_i'$, add the i th statistical feature of group z' to $\mathbf{S}$ and z' to $\mathbf{S}_i'$, remove z from $\mathbf{U}$, $\text{time} = \text{time} + 1$; otherwise, repeat step4.
- Step5: If $\text{time} = \frac{x}{6}$, $i = i + 1$; otherwise, go back to step 4.
- Step6: If $i \leq 6$, go back to step 3.
- Step7: If $i > 6$, end.

The subsets $\{\mathbf{S}_1, \mathbf{S}_2, \dots, \mathbf{S}_c\}$ that construct the feature subspaces can be obtained, and SVM is conducted to generate the classifiers $\{\text{model}_1, \text{model}_2, \dots, \text{model}_c\}$, where c represents repeat times. Since the performance of classifiers that consist of some specific features will be better, these classifiers should be given larger weight. The Pseudo-code of the proposed weight assignment method is shown below.

Algorithm 1 Pseudo-code of weight vector calculation process

Input: $\mathbf{H}_f$, the number of activity N , $\{\mathbf{S}_1, \mathbf{S}_2, \dots, \mathbf{S}_c\}$

Output: Weight vector $\mathbf{w}$

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1: Initialize the weight vector as  $\mathbf{w} = \{w(p) = 0 | p = 1, 2, \dots, c\}$ ;
2: do
3:   for  $y = 1$  to  $N$  do
4:     for  $p = 1$  to  $c$  do
5:       Extract features from  $\mathbf{H}_f$  to get  $\mathbf{H}_f'$  by  $\mathbf{S}_p$ ;
6:       Remove the  $y$ th activity from  $\mathbf{H}_f'$  to get  $\mathbf{H}_f''$ ;
7:       Utilize SVM to train  $\mathbf{H}_f''$  to get  $model_p'$ ;
8:       Utilize  $model_p'$  to classify the  $y$ th sample;
9:       if The recognition result is correct then
          $w(p) = w(p) + 1$ ;
10:      end if
11:    end for
12:  end do

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Then the set of results $\{b_1, b_2, \dots, b_c\}$ by classifying each of group in corresponding classifier can be obtained, and the recognition results are combined by Eq.2 and Eq.3.

$$J(i) = \sum_{j=1}^c w(j) \times u(i, j) \quad (2)$$

$$u(i, j) = \begin{cases} 1, & b_j = i \\ 0, & \text{others} \end{cases}$$

$$opt = \arg \max_i J(i) \quad (3)$$

where i denotes the activity index of the i th activity in $\{b_1, b_2, \dots, b_c\}$, $J(i)$ represents the weighted sum of classifier whose recognition result is i , and opt indicates the activity index of final recognition result.

III. IMPLEMENTATION AND EVALUATION

We test activities in typical outdoor and indoor environment, respectively. The signal is captured by Intel 5300 network card. During the experiments, 5 common activities are tested in this paper.

We analyze the performance of DWT after PCA. The time-frequency component graphs are shown in Fig. 1. Results show that the time-frequency component can feature each activity well.

We compare the proposed algorithm with common recognition algorithms to analyze the recognition performance of it by using the same data. From Fig. 2 we know, the recognition rate of the proposed algorithm is slightly higher than conventional recognition methods which are widely used in HAR existing systems.

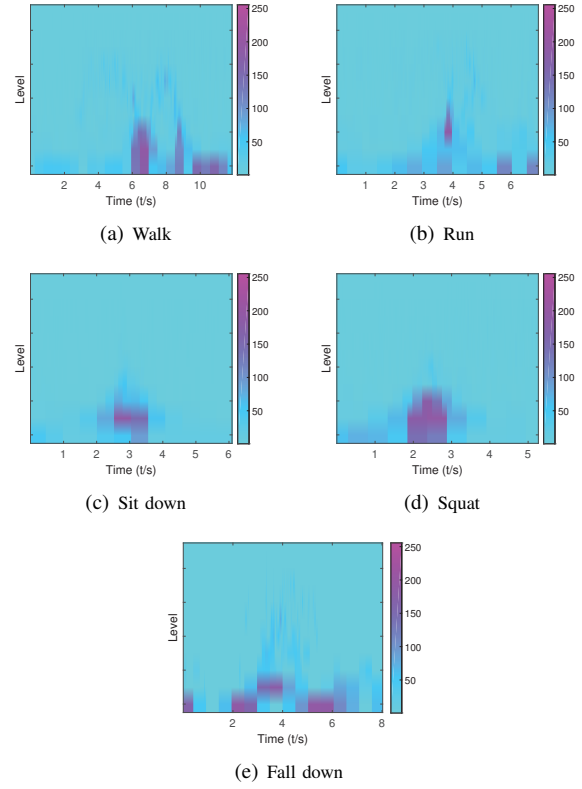


Fig. 1. Time-frequency component graphs of each activity in indoor environment after DWT.

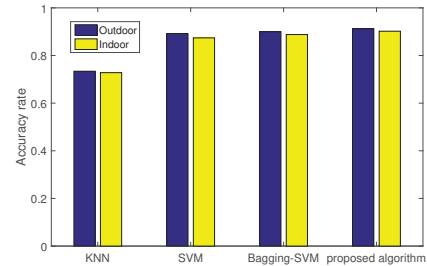


Fig. 2. The recognition results of the four recognition algorithms in two environments.

REFERENCES

- [1] G. M. Jeong, P. H. Truong and S. I. Choi, "Classification of Three Types of Walking Activities Regarding Stairs Using Plantar Pressure Sensors," IEEE Sensors Journal, vol. 17, pp. 2638-2639, 2017.
- [2] X. Qi, G. Zhou, Y. Li, et al, "RadioSense: Exploiting Wireless Communication Patterns for Body Sensor Network Activity Recognition," IEEE Real-Time Systems Symposium, pp. 95-104, 2012.
- [3] Q. Sun, X. Liu and M. Fu, "Classification of hyperspectral image based on principal component analysis and deep learning," IEEE International Conference on Electronics Information and Emergency Communication, pp. 356-359, 2017.
- [4] Y. Wang, R. Pan, D. Yang, et al, "Remaining Useful Life Prediction of Lithium-ion Battery Based on Discrete Wavelet Transform," Energy Procedia, vol. 105, pp. 2053-2058, 2017.