Poster: Continuous Human Activity Recognition Based on WiFi Imaging

Li Zhu, Xinyu Zhao, Zhi Wang, and Jizhong Zhao
Xi'an Jiaotong University, China
726400621@qq.com, xyz_0530@stu.xjtu.edu.cn, {zhiwang, zjz}@xjtu.edu.cn

Abstract

Automatic segmentation and action recognition have been a long-standing problem in sensorless sensing. In this paper, we propose WICAR, a **W**i-Fi **I**maing based **C**ontinuous **A**ctivity **R**ecognition system to solve these problems in a different way. The key idea is that: different body parts reflect transmitted signals, the receiver receives the combination of them. We separate the received signals and get the signal intensity in each direction to draft the heat map, which shows the shape of the object. To make the features easier to extract, we detects key points of human bones through the heat map. The imaging sequence contains multiple pictures recording a continuous action at different time, and we can easily separate and recognize the action based on SVM. We implement WICAR using commodity Wi-Fi devices to evaluate its performance under different environments. Experiments show that WICAR achieves an average recognition accuracy of 90%.

1 Introduction

Human activity recognition is an important technique in current applications, such as the human-computer interaction, somatic game, and smart home. Recent solutions fall into three categories: camera-based, sensor-based and wireless-based approaches. Camera-based approaches guarantee high resolution for activity recognition, however, they have fundamental limitations including the line-of-sight detection, good illumination, and potential privacy leakage. Meanwhile, sensor-based approaches usually require targets to carry sensors, which is inconvenient. Different from above solutions, leveraging wireless signals to achieve device-free activity recognition[2][4] becomes promising.

Recent advance in the research of Wi-Fi networks proposes to utilize Channel State Information(CSI) to realize fine-grained fingerprinting for activity recognition. CSI is sensitive to channel variances and position changes, which makes it possible to capture the change as the experimenter performs action. However, CSI fingerprint based device-free activity recognition remains challenges. It is extremely difficult to perform continuous activity segmentation with CSI especially when matching changes to the specific movements. Another challenge is the device incompatibility. Due to the imperfect manufacturing process, different devices exhibit different signal gains. While CSI is sensitive to slight changes, to eliminate random disturbance caused by environmental noises and electromagnetic interferences is necessary to avoid unpredictable errors.

In order to meet the aforementioned challenges, we propose a **W**i-Fi **I**maing based **C**ontinuous **A**ctivity **R**ecognition system in this paper. Our system has several attractive features. First, WICAR proposes a novel approach to perform imaging using Wi-Fi signals and achieves preferable effect. Second, WICAR solves the problem of continuous motion segmentation by Wi-Fi imaging. Third, WICAR detects key points of human bones after imaging to achieve better recognition. Last but not least, WICAR builds a bridge between wireless and optical imaging system. Our extensive experiments show that WICAR achieves high accuracy in action recognition and insensitive to the diversity of individual users.

2 System Design

2.1 WICAR's Imaging Algorithm

WICAR's approach is similar to optical imaging systems where images are typically formed by measuring the incoming signal intensities from each azimuth and elevation angle. It performs imaging using multiple antennas as Wi-Fi receiver which receives a linear combination of the multiple reflections from different directions. In our scenario, we can use the MUSIC algorithm[3] to get the steering matrix to derive the azimuth and elevation angle. We want to observe the influence of the human activity on multiple packets, so we proposed an idea to obtain an imaging picture using only one data packet which includes 30 subcarriers. Through the information carried by these subcarriers, we can get the following measurement matrix:

$$X_{matrix} = \begin{bmatrix} CSI_{0,0,1} & \dots & CSI_{0,0,30} \\ \dots & \dots & \dots \\ CSI_{N-1,M-1,1} & \dots & CSI_{N-1,M-1,30} \end{bmatrix}$$

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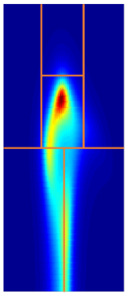
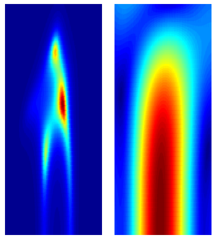


Figure 1. Body segmentation



(a) WICAR (b) Wision

Figure 2. Imaging result

Table 1. Confusion matrix of activity identification

Actual \ Estimated	Left hand raising	Right hand raising	Left leg lifting	Right leg lifting	Squating
Left hand raising	0.85	0.10	0.05	0.0	0.0
Right hand raising	0.15	0.8	0.0	0.05	0.0
Left leg lifting	0.05	0.05	0.9	0.0	0.0
Right leg lifting	0.0	0.05	0.0	0.95	0.0
Squating	0.0	0.0	0.0	0.0	1.0

With the above matrix, the following algorithm can be used to get the final imaging results:

1.Construct sample covariance matrix $R = \frac{1}{p}\sum_{i=1}^{p} XX^H$, where P is the number of subcarriers.

2.Perform eigenvalue decomposition of the matrix R. Order eigenvectors of R according to eigenvalues. Let eigenvectors corresponding to L largest eigenvalues span signal subspace S, and remaining eigenvectors span noise subspace G.

3.Construct spatial spectrum $P_{music}(\Psi,\alpha) = \frac{1}{\vec{\alpha}(\Psi,\alpha)^H GG^H \vec{\alpha}(\Psi,\alpha)}$.

Through the above steps, we can get the spatial spectrum P_{music}, which represents the possibility of the existence of a signal in each direction. P_{music} can be understood as the intensity of the signal in each direction called heat map.

2.2 Continuous Activity Segmentation

WICAR uses the bodys reflection signal to measure the angle of each part. However at some point, our receiving antenna can only receive reflection from only some parts of the body. Because the propagation of the signal conforms to the law of reflection, the reflected signals of various parts of the body are not always received by the receiver. As shown in Fig.1, we determine the center of the image according to the strongest reflection position, and then divide a picture into the following six parts. The upper part of the chest represents the head, the left and right sides of the chest respectively represent the left and right arms, and the lower part of chest are the effect caused by the left and right legs respectively.

2.3 Activity Recognition with Deep Learning

After WICAR obtains image sequences by using Wi-Fi imaging method, we apply the human bone critical point detection technology[1] to the heat map in order to achieve robust recognition result. With this approach, we can further enhance the emphasis of the features to improve the accuracy of recognition in ambiguous situations.

The feature vector is then extracted from the sample(i.e. a sequence), and sent to the trained SVM classifier. The final classification result can be obtained from the SVM. For each row of each picture, we take the following nine features: the mean, the standard deviation, the median absolute deviation, the mean absolute deviation, interquartile range, the root mean square, the entropy, the skewness, and the kurtosis.

3 Preliminary Evaluation

We evaluate the performance of our WICAR system over prototype in an office building. We use 4×4 antenna array as receiver and the distance between every two adjacent antennas is half wavelength. WICAR sends OFDM symbols which contain multiple subcarriers and the central frequency is 2.4G. Due to the movement of the experimenter, different body parts will introduce a reflection signal, and the imaging result are shown in Fig.2. Finally, we use SVM to classify five actions and for each action there are 50 sample data. 80% are used as training sets and 20% test sets. The results of the classification are shown in the confusion matrix.

4 Conclusions

In this paper, we propose WICAR which can easily realize Wi-Fi imaging after solving automatic segmentation and action recognition problem. char leverages Wi-Fi imaging the transmitted signals reflected from different body parts. The evaluations demonstrate that WICAR can reach an average 90% high matching accuracy under a wide variety of environment.

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6 References

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