WiMTAR: A Contactless Multi-target Activity Recognition Model

Pengsong Duan[1], Chen Li[1], Chenfei Jiao[1], Wenning Zhang[2,3](✉), and Jinsheng Kong[1]

[1] School of Software, Zhengzhou University, Zhengzhou 450000, Henan, China
[2] Software College, Zhongyuan University of Technology, Zhengzhou 450000, Henan, China
zhangwn@zut.edu.cn
[3] State Key Laboratory of Mathematical Engineering and Advanced Computing, Zhengzhou 450000, Henan, China

Abstract. At present, most Wi-Fi based sensing researches aim at single target scene, due to the difficulties in separation of mixed signals. In this paper, a Wi-Fi based model for multi-target activity recognition is proposed. A diverse dataset of sufficient volume for multi-target activity recognition is first collected in our paper. After blind source separation algorithm (FastICA) processing, the dataset is input to the proposed signal sort algorithm named CC-ICA for efficient and accurate signal sort according to CSI correlation coefficient. Experimental results show that CC-ICA algorithm can effectively solve the problem of random order caused by FastICA. Separated CSI data is input into a neural network consisting of ABiGRU and TCN for training and multi-target recognition evaluation. The experiments demonstrate that accuracy of WiMTAR is improved by 26% after CSI data is processed by CC-ICA for multi-target recognition, and accuracy of WiMTAR is also more than 2.6% higher than that of other single target recognition schemes.

Keywords: Wi-Fi sensing · Multi-target · Blind source separation · Deep learning

1 Introduction

In the era of artificial intelligence, how to sense target behavior more conveniently and efficiently in human-computer interaction has always been the focus of academic and industrial circles. Recently, with the rapid development of Internet of Things technology, human activity sensing technology [1] has been initially applied in behavior analysis [2], smart home [3, 4], medical monitoring [5] and other aspects.

Common sensing technology can be divided into computer vision-based, special sensor-based and wireless signal-based according to different acquisition equipment. Computer vision-based technology is to collect image or video information of human activity and use computer image processing technology to extract human activity information for recognition. Such technology has high accuracy and wide application range.

C. T. Calafate et al. (Eds.): MONAMI 2021, LNICST 418, pp. 167–181, 2022.
https://doi.org/10.1007/978-3-030-94763-7_13

However, it is easy to be affected by light and obstacles, and may cause invasion of user privacy. Special sensors-based technology uses special sensors or wearable devices to collect activity data, and then realizes human activity sensing through relevant analysis, which can be used for human activity recognition such as running and walking. This method achieves high recognition accuracy, but it is difficult to be widely deployed due to the high cost, poor convenience and so on. Wireless signal-based technology utilizes the theory that different human behaviors have different perturbations to wireless signals and achieves contactless perception based on perturbation data analysis, attracting extensive attention in recent years.

The sensing technology based on wireless signal can be divided into two kinds, including special radio frequency (RF) signal based and Wi-Fi signal based. RF signal-based technology needs special customized equipment, which costs a lot in installation and maintenance, is not conducive to large-scale use. In recent years, with the extensive deployment of Wi-Fi devices, Wi-Fi signal based human activity recognition has been widely researched. In 2011, Halperin et al. released the CSI Tool [6], which greatly facilitates the extraction of CSI based on physical layer from commercial off-the-shelf Wi-Fi devices. CSI describes how a signal propagates from a transmitter to a receiver and reflects the combined multipath effects such as scattering, reflection, diffraction, etc. of surrounding objects. CSI contains abundant attenuation and phase shift information, which enables to be applied in finer-grained human activity monitoring and recognition systems, such as sleep monitoring [7–9], fall detection [10, 11], gesture recognition [12, 13], vital sign monitoring [14, 15], activity recognition [16–18], etc.

At present, Wi-Fi sensing technology mainly focuses on single person activity recognition, and there are few researches on multi-person activity recognition. In a multi-person scene, the received signals contain not only the changes caused by the activity of the targets but also the signals reflected from the targets to each other due to multipath effect. Therefore, direct recognition on such mixed signals cannot ensure enough accuracy and generalization ability. In 2018, Wi-Run [19] and WIMU [20] made the first attempt to solve the problem of multi-person activity recognition. Wi-Run used Canonical Polyadic (CP) decomposition to separate signals of multiple persons' activity, and achieved recognition accuracy rate of 88.25%. However, only when the mixed signal was sinusoidal can the Wi-Run effectively decomposed the signal, which limited its application. WIMU used random combination of single gesture to generate a virtual sample of multi-person mixed gestures, and then compared it with the real multi-person mixed sample to identify them. The accuracy rates of 2, 3, 4, 5 and 6 simultaneously executed gestures were 95.0%, 94.6%, 93.6%, 92.6% and 90.9%, respectively. However, due to the different data generated by human gestures in different positions, WIMU needed to collect action samples from all positions in advance, which led to high training cost and limited scalability. Although there have been researches on multi-person activity recognition, effective separation of mixed data and accuracy of multi-person activity recognition still are needed to be improved.

To solve the above problems, this paper uses FastICA, which is one of blind source separation algorithms, and deep learning method to realize Wi-Fi based multi-person activity recognition. The contributions of this paper are as follows:

- This paper proposes a sorting algorithm CC-ICA based on subcarrier relevance mechanism to solve the problem of random signal sequence after being separated by FastICA algorithm. Experimental results demonstrate the effectiveness of CC-ICA.
- This paper proposes a hybrid neural network model, named as Multi-Target Activity Recognition (WiMTAR), which integrates attention mechanism. The model takes the separated data as input, and then features of the data are fully extracted by fusing attention mechanism based Bi-directional Gate Recurrent Unit (ABiGRU) and Temporal Convolutional Network (TCN).

2 Basic Theory

2.1 Problem Definition

Assume that subcarrier frequency is f, then relationship between transmitter signal $T(f, t)$ and receiver signal $R(f, t)$ is formalized as:

$$R(f, t) = H(f, t)T(f, t) \tag{1}$$

where $H(f, t)$ represents Channel Frequency Response (CFR) of the carrier. In Wi-Fi environment, transmission of wireless signals is always hindered by various objects between receiver and transmitter, which cause multipath effect in transmission process of signals. Signals on different paths may have delay, fading and frequency diffusion, leading to signal distortion. As shown in the Fig. 1, when collecting multi-target data in the Wi-Fi environment, the signal in transmission will be reflected due to existence of fixed objects such as walls and furniture. We name the reflected signal and the signal on Line-of-Sight (LoS) path between receiver and transmitter as static signal. The influence of human body movement on the signal in transmission is called dynamic signal. Therefore, CFR obtained during data acquisition is a superposition of static signal and dynamic signal, which can be expressed as:

$$H(f, t) = \sum\nolimits_n a_n e^{-j2\pi f \tau_n} + \sum\nolimits_m a_m \xi(f) e^{-j2\pi f \tau_m(t)} \tag{2}$$

where $\sum_n a_n e^{-j2\pi f \tau_n}$ represents CFR in static signal, and $\sum_m a_m \xi(f) e^{-j2\pi f \tau_m(t)}$ represents dynamic CFR changing with time t.

CSI is the result of sampling CFR, and can be used to approximate influence of environment on channel. We take CSI data as the analysis source and realize multi-person activity detection by feature recognition of data from different activities. CSI matrix contains abundant mixed information of static signals and dynamic signals. CSI information carried by each subcarrier is expressed as:

$$X = [H_{1,k}\ H_{2,k}\ \cdots\ H_{j,k}]^T \tag{3}$$

where $H_{j,k}$ represents CSI data on the k^{th} subcarrier at time j.

To simplify problem definition, a CSI data set with different activity labels is represented as $\boldsymbol{D} = \{(\boldsymbol{X}_i, \boldsymbol{Y}_i)\}_{i=1}^{I}$, where data set $\boldsymbol{D}$ contains I CSI sequences and corresponding labels. Therefore, multi-target recognition problem can be summarized as a mapping model construction problem to predict corresponding activity label $\boldsymbol{Y}$ according to input CSI data matrix $\boldsymbol{X}$.

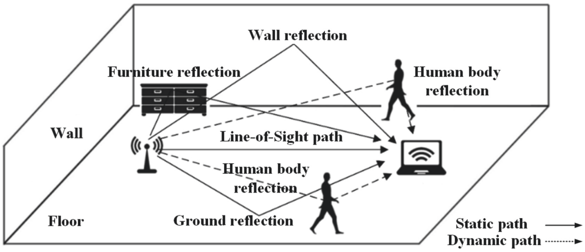


Fig. 1. Collecting multi-target data in the Wi-Fi environment.

2.2 Frequency Energy Graph

When processing single subcarrier sequence data, only activity features reflected by the CSI data within subcarriers can be extracted, while activity features among subcarriers are insufficient. 30 subcarriers of different frequencies obtained during data acquisition have different sensitivities to actions. Therefore, CSI data can be constructed into a two-dimensional matrix to convert original time series form into frequency energy graph (FEG) as follow:

$$\mathbf{X}=\begin{bmatrix} A_{1,1} & A_{1,2} & \cdots A_{1,k} & \cdots & A_{1,K} \\ A_{2,1} & A_{2,2} & \cdots A_{2,k} & \cdots & A_{2,K} \\ \vdots & \vdots & \vdots & & \vdots \\ A_{j,1} & A_{j,2} & \cdots A_{j,k} & \cdots & A_{j,K} \\ \vdots & \vdots & \cdots & & \vdots \\ A_{J,1} & A_{J,2} & \cdots A_{J,k} & \cdots & A_{J,K} \end{bmatrix} \tag{4}$$

where $A_{j,k}$ represents the amplitude of CSI data on the k^{th} subcarrier at time j. We simplify formula (4) as $\boldsymbol{X} = \left[\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_j, \ldots, \boldsymbol{x}_J\right]^{\mathrm{T}} j \in J$, where $\boldsymbol{x}_j$ represents CSI data at time j.

FEG not only visually demonstrates energy attenuation of wireless signals, but also contains more activity information. FEG takes activity duration and the number of subcarriers as horizontal and vertical coordinates. A visual FEG is shown in Fig. 2.

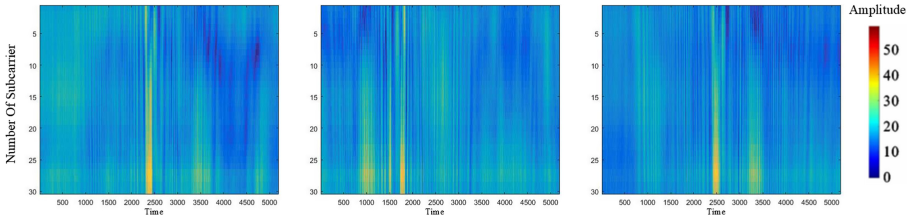


Fig. 2. Frequency energy graph.

2.3 CC-ICA Algorithm

Blind source separation refers to a series of algorithms that separate source signal according to the received mixed signal without information of source signal and transmission channel. Current blind source separation algorithms include JADE [21], FastICA [22], and SOBI [23]. FastICA algorithm is widely used in the fields of sound signal separation, ECG denoising and wireless source signal separation. Among various blind source separation algorithms, FastICA converges faster and has a better application prospect in large-scale data sets.

In order to provide more accurate target activity feature, this paper selects FEG as data reconstruction mechanism. The FEG in this paper is a two-dimensional matrix containing $N_t \times N_c$ pixels, where N_c is the number of subcarriers and N_t is the number of sampling timestamps. Figure 3 is a FEG of two persons running and sitting in the same environment respectively.

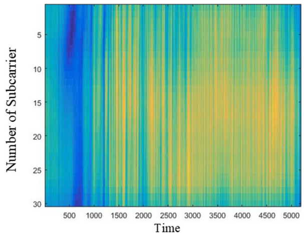
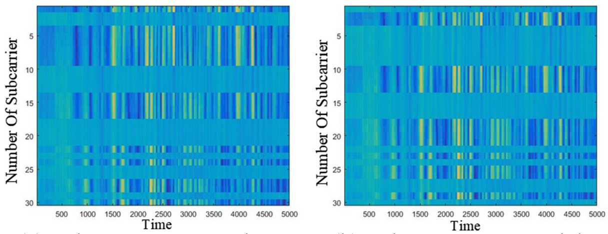


Fig. 3. Frequency energy graph of running and sitting.

Single target feature separation of mixed data is essential for realizing multi-target activity recognition. In this paper, CSI data of each subcarrier is decomposed by FastICA algorithm, and the number of decomposed targets is consistent with the number (i.e. two in this paper) of targets known in advance. Then, the two groups of decomposed subcarriers are reconstructed into two FEGs, as shown in Fig. 4.



(a) Subcomponent graph a (b) Subcomponent graph b

Fig. 4. Separation results of FastICA.

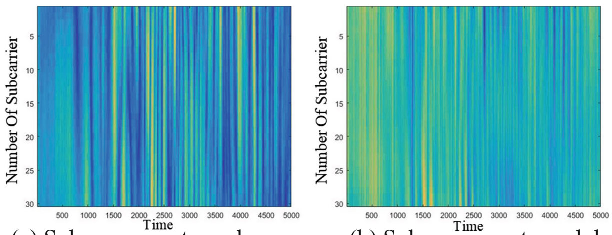
As shown in Fig. 4, result of direct separation is not ideal. Positions of multiple subcarriers in the two images are misjudged. The reason is that result of blind source separation algorithms is fuzzy. For FastICA algorithm, the fuzziness of the separation results is mainly manifested in two aspects which are amplitude and order. The essential reason is that blind source separation algorithm requires the independence of source signals, and amplitude and order of signals do not affect the independence of the components. FastICA carries out blind source separation on each subcarrier in turn, which leads to disorder of subcomponents in the reconstruction process, resulting in poor performance of activity recognition.

In a multiple-input-multiple-output (MIMO) based Wi-Fi system, signals between adjacent subcarriers are highly correlated, which can be used as the basis for reconstruction of FEG. Inspired by this property, we propose a sorting algorithm CC-ICA based on signal correlation coefficient. Concept of correlation coefficient is introduced to measure correlation degree of two subcarriers, and its definition is as follow:

$$\rho_{xy} \overset{def}{\Rightarrow} \frac{c_{xy}}{\sigma_x \sigma_y} = \frac{E\left[x(t)y^H(t)\right]}{\sqrt{E\left[\left|x(t)\right|^2\right]E\left[\left|y(t)\right|^2\right]}} \tag{5}$$

where c_{xy} represents cross covariance of signal $x(t)$ and $y(t)$, σ_x^2 and σ_y^2 represent variance of $x(t)$ and $y(t)$, respectively. According to Caucht-Schwartz inequality, $0 \le \left|\rho_{xy}\right| \le 1$. Correlation coefficient gives similarity degree between signal $x(t)$ and $y(t)$. ρ_{xy} close to 0 indicates a smaller correlation between the two signals, while it close to 1 indicates a greater correlation between the two signals. This paper calculates correlation coefficient between a subcarrier and its previous one to determine whether the subcarrier is adjacent to the previous subcarrier, so the correct order of subcarrier could be determined. After CC-ICA algorithm, blind source separation results of the finally decomposed FEG are shown in the Fig. 5.

Compared with the results of direct separation in Fig. 4, subcarriers processed by CC-ICA return to normal order, indicating effectiveness of CC-ICA in solving sequential fuzziness problem of FastICA. Figure 5 demonstrates that different decomposed subcomponents have better independence and correlation between adjacent subcarriers in the same FEG is high. Experimental results show that CC-ICA algorithm could effectively sort the subcarriers, thus achieving multi-target activity recognition.



(a) Subcomponent graph a (b) Subcomponent graph b

Fig. 5. Result of CC-ICA algorithm.

3 WiMTAR Architecture

This paper establishes a multi-target activity recognition model, WiMTAR, on the sort results of CC-ICA algorithm. Taking an indoor scenario as an example, the overall process of WiMTAR is shown in Fig. 6, including data acquisition module, data processing module and activity recognition module. This section mainly introduces the detailed design of activity recognition module.

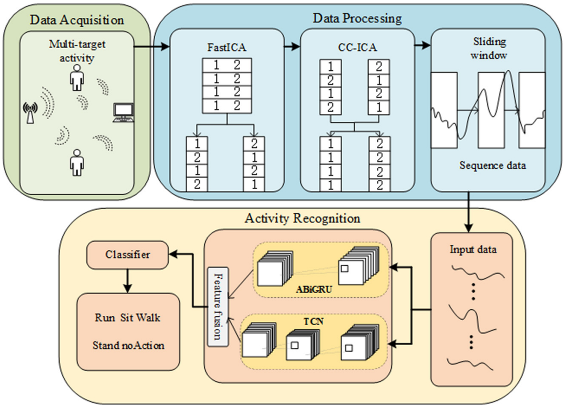


Fig. 6. WiMTAR architecture.

3.1 ABiGRU

ABiGRU adopts Bi-directional Gate Recurrent Unit (BiGRU) and attention mechanism to extract the activity information from FEG, which includes past and future information and focuses attention on crucial information.

BiGRU. Traditional Recurrent Neural Networks (RNN) and its variants such as Long-Short Term Memory (LSTM) [24] can only remember the past information while extracting feature of time series data. For multi-target activity recognition task, activity is a continuous action, thus feature extraction of past and future is very important. Therefore, BiGRU with Gate Recurrent Unit (GRU) [25] as the basic neuron is adopted in WiMTAR to extract the past and future information of activity data to enrich feature information and thus improve model recognition performance.

As shown in Fig. 7, update gate z_t is used to control the extent to which the state information of the previous time t is carried into the state of the current time t in GRU. The larger value of update gate is, the more state information is brought in at time $t-1$. Reset gate controls how much state information is written to candidate set for the current time t at time $t-1$. r_t represents reset gate, the smaller value of r_t is, the less the state information at time $t-1$ is written.

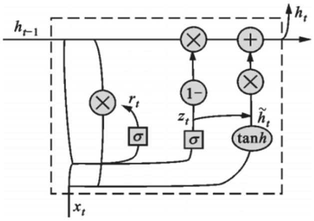


Fig. 7. Structure of GRU.

Attention Mechanism. WiMTAR utilizes attention mechanism for multi-target activity recognition, which makes the model pay more attention to the important feature information of activity. The core of attention mechanism is the weight of parameters. Importance of each parameter is learned, and then the weight is assigned to each parameter according to its importance. Assume that the input is $b_t = [b_1, b_2, \cdots, b_n]$, $(0 < t \leq T)$, n is sequence length. Attention mechanism first extracts feature vectors from the input as follow:

$$C_t = f(b_t) \tag{6}$$

where $f(\cdot)$ could be RNN or fully connected neural network. Then, weight vector of each feature in C_t is calculated as:

$$w_t = \frac{\exp(C_{ti})}{\sum_{i=1}^{n} \exp(C_{ti})} \tag{7}$$

Finally, the input data b_t is multiplied by its weight vector w_t, and summed to get the final output as:

$$o = \sum b_t \bullet w_t \tag{8}$$

3.2 TCN

TCN has been proved to be effective in [26] for extracting feature of time series data. Multi-target activity data is also a kind of time series data, so this paper adds TCN to WiMTAR. In TCN, let $X_t \in R^{F_0}$, $(0 < t \leq T)$ be input feature vector with the length of F_0 at time t. In this paper, time T is fixed and set as 800, which is consistent with the length of sliding window. The true label of each time series is given by $p_i \in \{1, \cdots, c\}$, where c is the number of categories. Assume that the network contains L convolutional layers, with each convolution layer using a set of one-dimensional convolution kernels to extract the variation feature of activity data in the time dimension. Each convolution kernel is parameterized by weight tensor $W^l \in R^{F_l \times d \times F_{t-1}}$ and bias $b^l \in R^{F_l}$, in which L is layer index and D is convolution kernel size. Output of the l^{th} convolutional layer $E_{i,j}^l \in R^{F_l}$ is function of input matrix $E_{i,j}^{l-1} \in R^{F_{l-1} \times T}$ from previous layer. The function is as:

$$E_{i,j}^l = f_{relu}\left(b_i^l + \sum_{r=1}^{d} W_{i,\tau}^l, E_{i,t+d-\tau}^{l-1}\right), \tag{9}$$

where $\langle \bullet \rangle$ represents correlation function and $f_{relu}(\bullet)$ represents activation function Rectified Linear Unit (ReLU).

TCN conducts a layered approach to extract multi-target activity data features on a time scale. In this paper, TCN can fully mine the relationship among multi-target data features, so as to improve model performance.

3.3 Activity Recognition Network

Figure 8 shows overview of activity recognition network. Data processed by CC-ICA algorithm pass through TCN network and ABiGRU network respectively for activity feature extraction. Then the activity features extracted from the two networks are fused and finally input to SoftMax classifier for classification. Because the datasets in this paper are about two-target activities, the model designed is more suitable to two-target activity recognition.

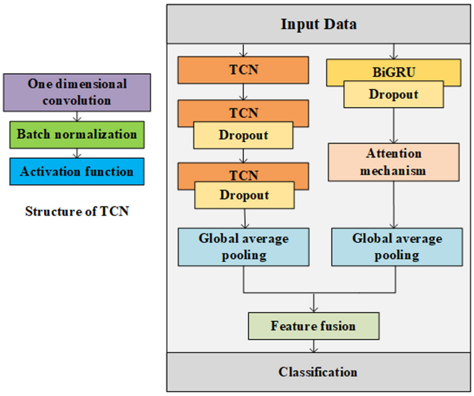


Fig. 8. Activity recognition network.

TCN network is composed of three TCN blocks, each of which contains a one-dimensional convolutional layer, a normalized layer and an activation layer. We abandon Dropout layer in the first TCN block, thus low-level features can be retained to the maximum extent to prevent feature loss. Whereas the Dropout layer in other two TCN blocks is retained to avoid overfitting. In order to fix data distribution after one-dimensional convolution, model uses batch normalization to process the data, which is then entered into the activation layer for nonlinear transformation, and then into the Dropout layer. Finally, we add a global average pooling layer to prevent overfitting and reduce the number of network parameters.

ABiGRU network consists of two parts. GRU neuron based BiGRU is used to extract the past and future features of activity data. Then the features are input into Dropout layer. We introduce attention mechanism to assign weights for each feature, so as to distinguish the importance of different features to the current activity. Global average pooling is used to adjust data dimensions to facilitate feature fusion in the next step. To realize attention mechanism, we first utilize fully connected layer for features extraction, and then calculate the weight vector by SoftMax function. Finally, the input data is multiplied by its weight vector and summed to get the output result.

4 Experimental Results and Analysis

4.1 Experimental Setup

In the field of Wi-Fi multi-target activity recognition, there is currently no available open dataset for use. Therefore, self-collected data sets are needed for model validation. In order to construct a typical activity dataset and avoid the influence of environmental factors such as indoor layout. At present, only an empty indoor room, as shown in Fig. 9, is chosen as data acquisition scenario in this paper. When the model has high accuracy, data in multiple scenario will be collected to enhance the robustness of the model. Detailed experimental parameters are shown in Table 1.

Fig. 9. Data acquisition scenario.

To ensure objectivity and universality of data set, 10 volunteers are distributed between the ages of 18 and 30 and divided into 5 different groups. During data acquisition, activity data of two volunteers are collected each time. The two volunteers walk back and forth along the direction perpendicular to LoS path at the same time, and they are guaranteed to cross LoS path only once. In the process of data acquisition, in order to effectively capture multi-person activities, two experimenters are required to repeat different activities simultaneously, and 5 s of data fragments are collected each time as a data sequence. In this dataset, five daily activities (no action, walk, sit down, stand up and run) are collected from five groups of volunteers, as well as all possible combinations of two of these activities. The actual activities of each target are recorded as labels during collection. After processing, there are 2500 valid data in this dataset. In order to promote faster development of Wi-Fi sensing research, this paper will publish the dataset late.

4.2 Experimental Results

In order to fully evaluate the performance of WiMTAR, this paper conducts comparative experiments in various aspects.

Table 1. Detailed configuration of experimental equipment and parameters.

Index	Name	Parameter
1	Transmitter	TP_LINK AC1750 wireless router
2	Receiver	Intel 5300 NIC
3	Number of transmitting antenna	1
4	Number of receiving antenna	3
5	Number of subcarriers	30
6	Work frequency	5 GHz
7	Sampling frequency	1 kHz
8	Sampling duration	5000 ms
9	Sliding window size	800 ms
10	Sliding step length	200 ms

Validation of CC-ICA Algorithm. To verify the effectiveness of CC-ICA algorithm, performance of WiMTAR model before and after using CC-ICA will be compared in this paper. On the one hand, the multi-target data are pre-processed by CC-ICA algorithm. Then, input into activity recognition module of WiMTAR for training and recognition. On the other hand, a control group is experimentally set up, and it is trained by using the same model structure, but the training data are not processed by CC-ICA algorithm, and multi-person labels as a whole are coded as a single category in one-hot form. For classification results of the two groups, the four evaluation indicators introduced above are used to evaluate respectively, and the results are shown in Fig. 10.

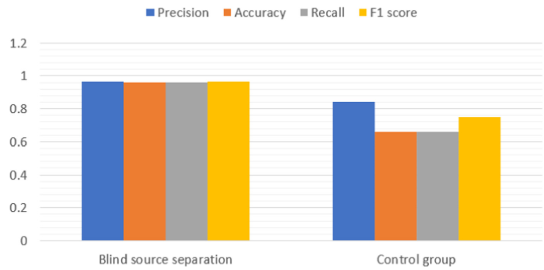
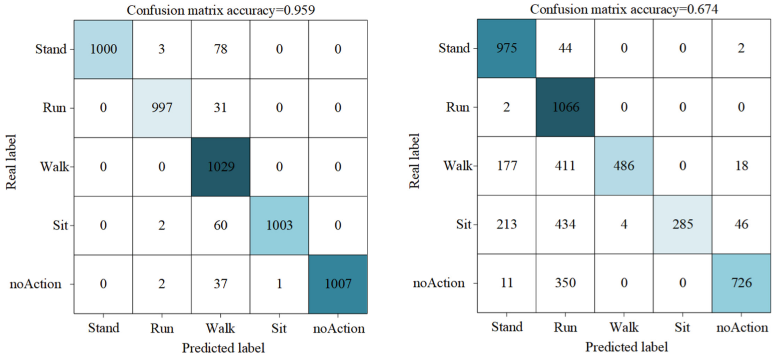


Fig. 10. Performance comparison of blind source separation.

It can be seen that after using CC-ICA algorithm, performance of WiMTAR in the four evaluations metrics has been significantly improved. The reason is that when mixed signals of multi-target activities are recognized as a whole, there are too many combinations of activity labels (10 combinations for 5 activities), and mixed information contains not only environmental noise but also interference factors among the targets, leading to poor recognition performance. Confusion matrix of recognition results in both cases is shown in Fig. 11.



(a) Subcomponent graph a (b) Subcomponent graph b

Fig. 11. Confusion matrix contrast.

As can be seen from Fig. 11, after CC-ICA algorithm, although the signals corresponding to each target activity have been separated, a small number of recognition errors exist due to mutual interference existing among the targets that is still difficult to completely eliminate. For direct recognition, because the overall recognition introduces more interference factors, identification error items also increase significantly. Since sitting action is larger in magnitude than other actions, it greatly affects recognition of other activities without feature separation, leading to a decrease in performance. CC-ICA algorithm, however, sorts the features after separation, which better solves problem of multi-target activity recognition.

Comparison of Different Models. Experiment will firstly use CC-ICA algorithm to separate and sort the collected data, transform multi-target activity recognition problem into multiple single-target activity recognition problems, and then carry out comparative experiments with existing similar models. Since the input of WiMTAR model is time-series data, GRU and ABLSTM models, which are usually excellent at processing time-series data, are selected for comparison in this paper. In addition, since convolutional neural networks are used in WiMTAR, classical neural network FCN [27] is also selected for comparison. GRU is a model with timing signal as input which is composed of three GRU layers in this paper. FCN is a model suitable for computer vision field, and the one used in our experiment contains three CNN layers. ABLSTM is a relatively new network structure for Wi-Fi based activity recognition in existing studies. ABLSTM used in comparison experiments in this paper has the same network structure as that in the published papers. Results of comparison experiments are shown in Fig. 12.

As can be seen from Fig. 12, the accuracy of WiMTAR, ABLSTM, GRU and FCN reaches 95.9%, 93.3%, 92.3% and 92.2%, respectively. Classification accuracy of WiMTAR is at least 2.6% higher than the other three models, indicating structural superiority and stronger feature extraction capability of WiMTAR. In addition, since the four models are all tested on the basis of the separated dataset in this chapter, it can be seen that CC-ICA has a wide validity in the multi-target recognition tasks. The technical route of

Fig. 12. Accuracy of different models.

independent feature extraction is not only applicable to WiMTAR, but also achieve high performance combining with other models.

5 Conclusion

This paper mainly proposes a multi-target activity recognition model based on Wi-Fi sensing. The proposed model contains three modules including data acquisition, data processing and activity recognition. In this paper, CC-ICA algorithm proposed is used for sort data after blind source separation to obtain independent single target data. Activity recognition module takes the sorted activity data as input, and after being trained by the specially designed neural network model (i.e. mainly composed of ABiGRU and TCN), multi-target activity recognition can be realized. Experimental results show that WiMTAR performs better in multi-target activity recognition scenarios.

In the future, WiMTAR will be further improved in the following three aspects: (1) Try to use the phase information from CSI information. (2) Increase the number of simultaneous targets in the experimental scenario (two people in this paper). (3) Improve generalization ability of the model in different environments.

References

1. Lu, Y.: Research review of human behavior sensing technology based on wi-fi signals. Chin. J. Comput. **42**(02), (2019)
2. Gu, Y., Zhang, X., Liu, Z., Ren, F.J.: BeSense: leveraging Wi-Fi channel data and computational intelligence for behavior analysis. IEEE Comput. Intell. Mag. **14**(4), 31–41 (2019)
3. Gu, Y., et al.: WiONE: One-shot learning for environment-robust device-free user authentication via commodity Wi-Fi in man-machine system. IEEE Trans. Comput. Soc. Syst. **8**(3), 630–642 (2021)
4. Li, Q.Y., et al.: AFDCGAN: amplitude-feature deep convolutional GAN for fingerprint construction in indoor localization system. IEEE Transactions on Emerging Topics in Computational Intelligence, vol. 5, no. 3, pp. 468–480 (2021)
5. Gu, Y., et al.: EmoSense: computational intelligence driven emotion sensing via wireless channel data. IEEE Trans. Emerg. Topicsin Comput. Intell. **4**(3), 216–226 (2020)

6. Halperin, D., Hu, W., Sheth, A., et al.: Tool release: gathering 802.11n traces with channel state information. ACM SIGCOMM Comput. Commun. Rev. **41**(1), 53 (2011)
7. Liu, X., Cao, J., Tang, S., Wen, J.: Wi-Sleep: contactless sleep monitoring via wi-fi signals. In: Proceedings of the IEEE 35th IEEE Real-Time Systems Symposium. Rome, pp. 346–355 (2014)
8. Lin, N., et al.: Contactless body movement recognition during sleeping via Wi-Fi signal. IEEE Internet Things J. **7**(3), 2028–2037 (2020)
9. Gu, Y., Wang, Y.T., Liu, Z., Liu, J., Li, J.: SleepGuardian: an RF-based healthcare system guarding your sleep from afar. IEEE Netw. **34**(2), 164–171 (2020)
10. Han, C., Wu, K., Wang, Y., et al.: WiFall: device-free fall detection by wireless networks. In: IEEE INFOCOM (2014)
11. Maheshwari, S., Tiwari, A.K.: Ubiquitous fall detection through wireless channel state information. In: International Conference on Computing and Network Communications (CoCoNet). IEEE (2015)
12. He, W., Wu, K., Zou, Y., et al.: WiG: Wi-Fi-based gesture recognition system. In: 2015 24th International Conference on Computer Communication and Networks (ICCCN). IEEE (2015)
13. Li, H., Yang, W., Wang, J., et al.: WiFinger: talk to your smart devices with finger-grained gesture. In: Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing. ACM (2016)
14. Abdelnasser, H., Harras, K.A., Youssef, M.: UbiBreathe: a Ubiquitous non-Invasive WiFi-based breathing estimator (2015)
15. Nguyen, P., Zhang, X., Halbower, A.: Continuous and fine-grained breathing volume monitoring from afar using wireless signals. In: IEEE INFOCOM 2016 - IEEE Conference on Computer Communications. IEEE (2016)
16. Gao, Q., Wang, J., Ma, X.: CSI-based device-free wireless localization and activity recognition using radio image features. IEEE Trans. Veh. Technol. 66, 10346–10356 (2017)
17. Chen, Z., Zhang, L., Jiang, C.: WiFi CSI based passive human activity recognition using attention based BLSTM. IEEE Trans. Mobile Comput. 18, 2714–2724 (2018)
18. Duan, P., Li, H., Zhang, B.: APFNet: amplitude-phase fusion network for CSI-based action recognition. Mobile Netw. Appl. **26,** 2024–2034 (2021)
19. Zhang, L., Liu, M., Lu, L., Gong, L.: Wi-run: Multi-runner step estimation using commodity wi-fi. In: 2018 15th Annual IEEE International Conference on Sensing, Communication, and Networking (SECON), pp.1–9. IEEE (2018)
20. Venkatnarayan, R.H., Page, G., Shahzad, M.: Multi-user gesture recognition using wifi. In: Proceedings of the 16th Annual International Conference on Mobile Systems, Applications, and Services, pp. 401–413. ACM (2018)
21. Guo, K., Chen, L., Chen, H.: Research on blind separation of random noise from seismic data based on JADE algorithm. Earth Sci. Front. **18**(3), 302–309 (2011)
22. Mahajan, A., Birajdar, G.: Blind source separation using modified contrast function in fast ICA algorithm. Int. J. Comput. Appl. **6**(4), 14–17 (2010)
23. Wang, Y.: Research on blind signal processing method in mechanical noise monitoring. Kunming University of Science and Technology (2010)
24. Hochreiter, S., Schmidhuber, J.: Long short-term memory. Neural Comput. **9**(8), 1735–1780 (1997)
25. Schuster, M., Paliwal, K.K.: Bidirectional recurrent neural networks. IEEE Trans. Signal Process. **45**(11), 2673–2681 (1997)

26. Wang, Z., Yan, W., Oates, T.: Time series classification from scratch with deep neural networks: a strong baseline. In: Proceedings of the International Joint Conference Neural Network (IJCNN), pp. 1578–1585 (2017)
27. Long, J., Shelhamer, E., Darrell, T.: Fully convolutional networks for semantic segmentation. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 3431–3440 (2015)