Deep Learning Based Target Activity Recognition Using FMCW Radar

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Abstract. Target activity recognition has many potential applications in the fields of human-computer interaction, smart environment, smart system, *etc.* Recent years, due to the miniaturized design of the frequency modulated continuous wave (FMCW) radar, it has been widely utilized to realize target activity recognition in our daily life. However, the activity recognition accuracy is usually not high due to the surrounding noise and variation of the activity. To realize high accuracy activity recognition, one feasible way is to extract discriminative features from the weak radar signals reflected by the activity. Inspired by the successful application of deep learning in computer vision, in this paper, we try to explore leveraging deep learning to solve the target activity recognition task. Specifically, based on the characteristics of the FMCW signals, we design the Doppler radio images suitable for the deep network to deal with. Then, we develop a deep convolutional network to extract discriminative activity features from the Doppler radio images. Finally, we feed the features into a Softmax classifier to recognize the activity. We carry out extensive experiments on a 77 GHz FMCW radar testbed. The experimental results show the excellent target activity recognition performance.

Keywords: Deep learning · Activity recognition · FMCW

1 Introduction

Target activity recognition has many potential applications in our daily life. Due to the availability of pervasive wireless signals, it becomes popular to sense our world by leveraging wireless signals [1–6]. Therefore, target activity recognition using wireless signals has drawn considerable attention in recent years. Compared with traditional target activity recognition techniques, such as vision or wearable

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devices based techniques, target activity recognition using wireless signals does not need the target equipped with any devices, could work under dark or smoky conditions, does not concern privacy disclosure, *etc.* These advantages make it an ideal technique to realize human-computer interaction, smart environment, smart system, *etc.*

Researchers have conducted valuable exploration on this technique. Kim and Moon [7] leverage the micro-Doppler signatures to recognize the activity of a person. Wang *et al.* [8–10] explore how to recognize activity gesture under cross-scenario conditions. Gao *et al.* [11] extract the coherence histogram features to characterize different activities. Ma *et al.* [12] solve the activity recognition problem under small sample set. Huang and Dai [13] leverage the link quality as metric to realize activity recognition. However, due to the surrounding noise and variation of the activity, the activity recognition accuracy is still not very high.

To realize high accuracy activity recognition, one feasible way is to extract discriminative features from the weak radar signals reflected by the activity. Inspired by the successful application of deep learning in computer vision, in this paper, we try to explore leveraging deep learning to solve the target activity recognition task. The main contributions of this paper can be summarized as follows:

1. We design a deep network based target activity recognition architecture, which could realize high performance activity recognition.
2. We design the Doppler radio images as the input to the deep network, and develop a deep convolutional network to extract discriminative activity features from the radio images.
3. We develop a 77 GHz frequency modulated continuous wave (FMCW) hardware based prototype system, and carry out extensive evaluations to evaluate the proposed deep learning based target activity recognition method.

The rest of the paper is structured as follows. Section 2 presents the architecture of proposed system. Section 3 introduces the detailed implementation of the proposed system, presents the Doppler radio image construction method, and gives the deep network architecture. Section 4 presents the experimental evaluation. Finally, the conclusion is drawn in Sect. 5.

2 System Architecture

The developed deep learning based target activity recognition system is shown in Fig. 1. It mainly consists of three function modules, *i.e.*, Doppler radio image construction module, deep convolutional network module, and softmax classifier module. The Doppler radio image construction module acquires the reflection wireless signals from the target, build the Doppler radio image of the target, so as to provide measurement information for realizing the activity recognition task. The deep convolutional network module tries to extract discriminative activity features from the Doppler radio images by performing a series of convolution, pooling, and ReLU operations. The softmax classifier module recognizes the target activity by projecting the activity features to the class space. We will present the detailed implementation of each module in the next section.

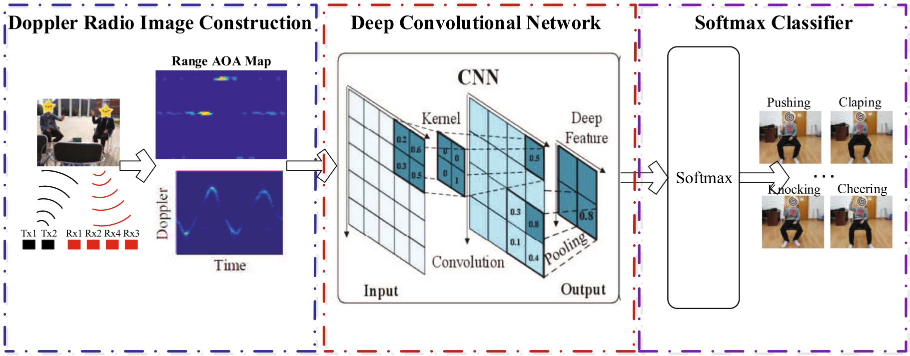

Fig. 1. Architecture of the deep learning based target activity recognition system.

3 System Implementation

3.1 Doppler Radio Image Construction

The FMCW radar transmits a frequency modulated wireless signal to the target, and then receives the reflection signal from the target. When the target locates at different distances with the receiver or performs different activities, the reflection signals will be different. The distance can be identified by the frequency of the reflection signal, and the activities determines the Doppler of the reflection signal. We firstly detect the target in a polar coordinate system by building the Range angle of arrival (AOA) map (RAM). We estimate the range and AOA of the target by performing 2-D Fast Fourier Transform (FFT) Algorithm along the fast time axis and receiver axis, respectively, as follows

$$\mathbf{RAM} = \mathbf{2D} - \mathbf{FFT}\left(\mathbf{S}_{1,1}, \ldots, \mathbf{S}_{i,j}, \ldots, \mathbf{S}_{I,J}\right), \tag{1}$$

where I and J denote the total number of samples on the fast time axis and the number of receivers, respectively. As shown in Fig. 1, we can detect the two targets clearly from the RAM.

With the range and AOA information of the target, we focus on the target by firstly performing beamforming on the expected target. Then, we perform 2-D FFT along the fast time axis and slow time axis to get the range and Doppler information, respectively. As we have know the range of the expected target, we can further filter out the noise by using a narrow range filter. Finally, we integrate the Doppler information within a narrow range and get the expected

Doppler radio image, as shown in Fig. 1. The Doppler radio image characterizes the Doppler information change over time, which depicts the movement of the activity over time. We will leverage it as the measurement information to realize target activity recognition.

3.2 Deep Convolutional Network Based Feature Extraction

Deep Network has been widely utilized to realize many computer vision tasks in recent years. It has a powerful ability to learn latent discriminative features from the data. There are many types of deep networks, such as deep fully connected networks, deep convolutional neural networks, deep recurrent neural networks, generative adversarial networks, *etc.* Different types of deep networks are suitable for different types of tasks. As for the target activity recognition task, deep fully connected networks and deep convolutional neural networks are ideal choice due to their excellent ability of extracting discriminative features. Meanwhile, since of use 2-D Doppler radio images as the measurement, thus, the 2-D deep convolutional neural network is the best choice for the target activity recognition task. Therefore, we leverage it in this paper.

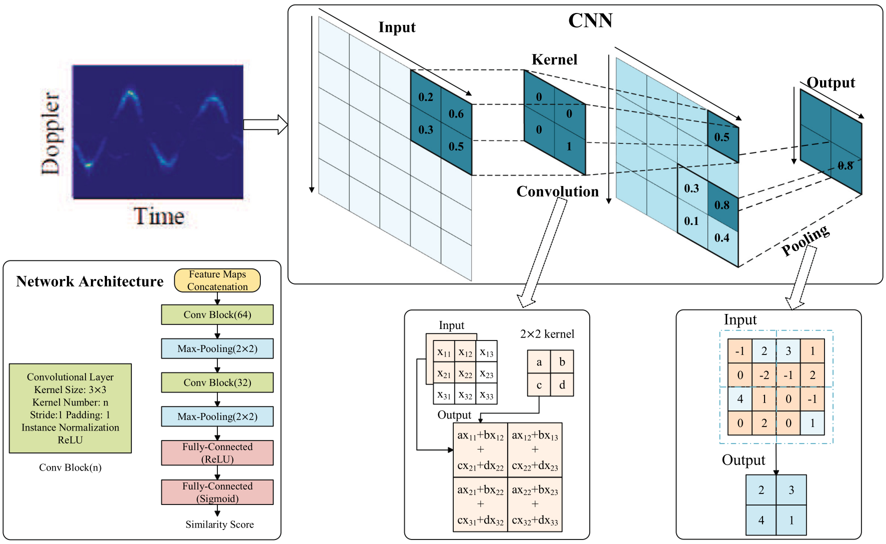

Fig. 2. Working principle implementation of the deep convolutional network.

The working principle and implementation of the developed deep convolutional network is illustrated in Fig. 2. The developed deep convolutional network is made up of a series of convolution operations, ReLU nonlinear operations, and pooling operations. The convolution operation perform convolution on the kernel and input image, and the ReLU operation adds nonlinear information into the network, they jointly capture the informative information of the image. The pooling operation downsampling the radio image. The above three key operations execute in turn for many times in the network. For simplicity, we term a convolution operation and a ReLU operation as a Conv Block. The developed deep convolutional network is made up of two Conv Blocks, two max pooling layers, two fully connected layers, as shown in Fig. 2.

3.3 Softmax Classifier

With the extracted deep features x, we feed it into a softmax classifier to recognize the target activity y as follows

$$h_\theta(x) = \begin{bmatrix} p(y=1|x;\theta) \\ p(y=2|x;\theta) \\ \vdots \\ p(y=C|x;\theta) \end{bmatrix}, \tag{2}$$

where $h_\theta(x)$ is a $C \times 1$ vector which indicates the probabilities that the input radio image belongs to each activity, θ denotes the parameters of the softmax classifier, and C indicates the total number of activity types. With $h_\theta(x)$, we select the class with the largest probability and adopt the activity corresponding to this class as the target activity.

4 Experimental Evaluation

To verify our proposed idea, we develop a target activity recognition system based on a 77 GHz FMCW hardware and conduct extensive evaluations. The system works on the 77–81 GHz band with 1 transmitter and 4 receivers. The layer size of the developed deep network are $64 \times 6 \times 48$, $64 \times 3 \times 24$, $32 \times 3 \times 24$, $32 \times 1 \times 12$, 16×1, respectively. Totally we have 16 kinds of gestures. For each type of gesture, there are 50 samples, we randomly select 25 samples to train the system and leverage the remaining samples as the testing set. The developed hardware system and the experimental scenarios are shown in Fig. 3.

We compare the developed deep learning based activity recognition system with other traditional methods, *i.e.*, the Doppler profile method which uses the proposed Doppler radio image construction scheme to build radio images and evaluates the similarity between different radio images directly to recognize the activity, the raw Doppler method which use the Doppler information without any range and AOA filtering operation. The results are summarized in Table 1. From the results, we can discover that our proposed deep learning based method achieves the best performance, which confirms the effectiveness of the developed deep network. Meanwhile, we also discover that the accuracy of Doppler profile method is better than the traditional raw Doppler method as well, which confirms that the developed Doppler radio image construction method is valid.

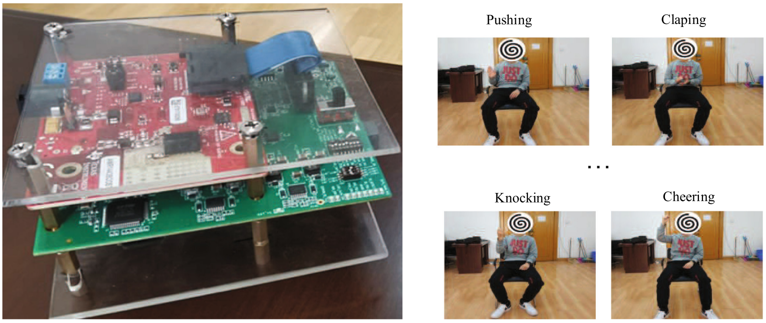

Fig. 3. Developed hardware system and the experimental scenarios.

Table 1. Activity recognition accuracy with different methods.

	Deep Learning	Doppler Profile	Raw Doppler
Accuracy(%)	95.8	91.5	86.5

5 Conclusion

In this paper, we develop a novel deep learning based target activity recognition system using FMCW hardware. We design a scheme to build the informative Doppler radio images, and develop a deep convolutional network to extract discriminative activity features from the Doppler radio images. These strategies guarantee a good activity recognition accuracy. Experiment conducted on a 77 GHz FMCW radar indicates that the developed system could achieve an accuracy of 95.8% when there are 16 types of activities.

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