Direction-Free In-Air Signature Verification Using WIFI CSI Signal

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Abstract. The abstract should briefly summarize the contents of the paper in 15–250 words.

Keywords: First keyword · Second keyword · Another keyword.

1 Introduction

1.1 Motivation

i. Pros of In-Air WIFI CSI signature system 1) Cheap: Use commercial device 2) Easy: No additional devices is needed 3) Secure: Hard to forgery ii. Cons of In-Air WIFI CSI signature system 1) Setting direction problem a) Different direction -> Different feature is needed b) Hard to set exactly same direction as authentication before Size of signature can varies

1.2 Contribution

- Overcome cons of WIFI signature system - Robust to signal direction, size

2 Related Works

2.1 ConvNets

Convolutional Neural Networks is a specal case of Multi Layer Perceptron and it has unified feature extractor and classifier in one network. It has been widely applied to visual objects such as image, video or 2D array input. Several factors make ConvNets attractive in image related tasks. Local connectivity captures local correlation property of image. It is applycable by using ConvNet filter.Weight sharing helps to reduce the number of weights in feature maps. Also, CUDA libraries makes the tranining feature maps easier to reduce training time.

2.2 Siamese Networks

In [1], LeCun et al. Introduced Siamese nets as parts of their handwritten signature verification system. A siamese neural network consists of twin networks which accept distinct inputs but are joined by an energy function at the top.[2]

It is important that not only the architecture of the subnetworks is identical, but the weights have to be shared among them as well for the network to be called “siamese”. Usually, siamese networks perform binary classification at the output, classifying if the inputs are of the same class or not

They proposed a feature extractor based on Time Delay Neural Networks[3] and feature matcher based on cosine distance of feature vector.

In a recent related study, pedestrian tracking [4], object cosegmedtation [8] showed that Siamese Networks can be used for image classification tasks and [6] captures semantics from job resumes.

3 Proposed System

In this section, we propose a direction-free identify verification system based on the Wi-Fi based in-air handwritten signature (will be called Wi-Fi signature signals hereafter). An overview of the proposed system utilizing the Siamese network learning is shown in Fig.1. Essentially, the Wi-Fi signature signals are preprocessed to create the input data for our Siamese network. Subsequently, the Siamese network using ConvNet structure is trained to measure the similarity between two inputs. The resultant similarity score is utilized to verify whether the input signals are belong to the same identity regardless of the capturing directions. The following subsections detail the data preprocessing and the Siamese network model.

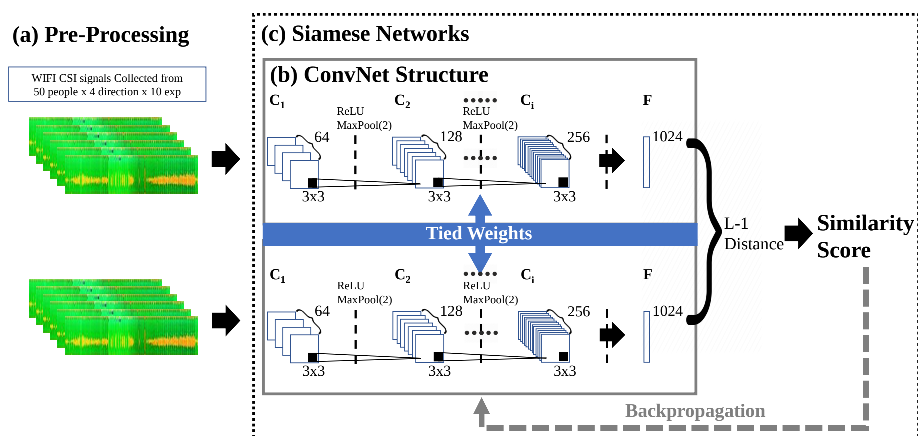

Fig. 1. Structure of Siamese network

3.1 Data Preprocessing

Since every Wi-Fi signature signal has different data size, we firstly adopted the gradient operation with respect to the time instance to measure the short time energy. Data points with the highest short-time energy within the time period are then manually selected as the starting and the ending points of the in-air signature action. Subsequently, the Fast Fourier Transform based re-sampling method [7] is implemented to unify the length of the signals. As a result, three-dimensional Wi-Fi signature signals with unified data size are obtained as the input of the ConvNet structure in the Siamese network.

3.2 Siamese Networks for Identity Verification

To design the Siamese networks, we firstly need to select the feature extracting networks which convert the input data into a vector. In this work, we utilize the ConvNet structure [5] as a feature extractor since the three-dimensional data format of our preprocessed input signal can be regarded as an image data format with multiple channels.

Our ConvNet structure (See Fig 1 (b)) for the Siamese network consists of i convolutional layers $\mathbf{C}_i$ and one fully-connected layer $\mathbf{F}$. The number of convolutional filters to be trained in each layer is empirically chosen as $\{64, 128, ..., 2^{6+i}\}$, with fixed filter size of 3×3 and stride of 1. The Rectified Linear (ReLU) function as an activation function and the max-pooling layers are applied between each convolutional layers. The features from the last convolutional layer are directly flattened into a single vector without activation function and the Max-pooling layer followed by the fully-connected layer. Since the Siamese networks utilize two ConvNet structures which ties the weights each other, noting here that two structures described in Fig 1 (b) are actually the same model.

The Siamese networks employ a learning process based on the similarity between two inputs [2]. In our Siamese networks, we utilize the L_1 distance to calculate the similarity score. Let $\mathbf{m} \in \mathrm{R}^{d\times1}$ and $\mathbf{n} \in \mathrm{R}^{d\times1}$ be two feature vectors extracted from the ConvNet structure. Then the L_1 distance d between the two features can be calculated as follows:

$$d = \sigma\|\mathbf{m} - \mathbf{n}\|_1, \tag{1}$$

where σ is the sigmoidal activation function.

The label y for input $()x_1, x_2)$ becomes 1 when $()x_1, x_2)$ is in the same class and 0 otherwise. When the size of each minibatch is set to M, the label for the i-th batch is $\mathbf{y}_i(x_1^{(i)}, x_2^{(i)})$.

The loss function of our model is given by the following binary cross entropy and passed into standard backpropagation algorithm to calcuate weights.

$$BCE = \mathbf{y}_i(x_1^{(i)}, x_2^{(i)}) \log(\mathbf{d}(x_1^{(i)}, x_2^{(i)})) + (1 - \mathbf{y}_i(x_1^{(i)}, x_2^{(i)})) \log(1 - \mathbf{d}(x_1^{(i)}, x_2^{(i)})) \tag{2}$$

We initialized the weights of each layer to normal distribution with zero-mean and a standard deviation of 0.01. Biases are initialized to mean 0.5 and standard deviation 0.01, as presented in the paper[2].

4 Experiments

5 Conclusion

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