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

YoungWoong KWON[1], JooYoung KIM[1], and Kar-Ann TOH[1]

[1] Yonsei University
[2] lncs@springer.com
http://www.springer.com/gp/computer-science/lncs
[3] ABC Institute, Rupert-Karls-University Heidelberg, Heidelberg, Germany
{abc,lncs}@uni-heidelberg.de

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 WIFI CSI

- An In-Air Signature Verification System Using Wi-Fi Signals

CSI captures signal strength and phase information for OFDM subcarriers and between each pair of transmit-receive antennas. It runs on a commodity 802.11n NIC, and records Channel State Information (CSI) based on the 802.11 standard. The CSI contains information about the channel between sender and receiver at the level of individual data subcarriers, for each pair of transmit and receive antennas.

In a frequency domain, the CSI of sub-carrier **c** between transmitter(Tx) and receiver(Rx) can be modeled as $R_c = \mathbf{H}_c T_c + N$ where the R_c and T_c denote the received and the transmitted signal vector of dimension r and t, respectively. The N is the additive channel noise and $\mathbf{H}_c$ is the $r \times t$ channel matrix. The CSI of sub-carrier c can be modeled as follows:

$$h_c = | h_c | e^{\angle \theta}, \tag{1}$$

where $| h_c |$ and θ represent the amplitude and the phase of the sub-carrier, respectively.

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] They proposed a feature extractor based on Time Delay Neural Networks[3] and feature matcher based on cosine distance of feature vector. Apart from this work based on ConvNet as feature extractor and L1 distance as feature matcher. In this paper, we propose a for signature verification system that is applicable for WIFI CSI signal, which is more complex and larger than handwritten images. Based on Convnets as feature extractor, we are able to make feature vector from CSI signal reflecting local connectivity between signals at a near frequency range and closer measurement time. The proposed method achieved better performance because it is applicable to all points of CSI signals. This is due to the weight sharing the property of the Convnet filter.

3 Proposed System

3.1 System Overview

In this section, we introduce a system for recognition of Wi-Fi based in-air signature which utilizes the Siamese network learning for validation. An overview of the proposed system is shown in Fig.1.

This system receives two Wi-Fi CSI signals as input. The main purpose of the system is to verify if two input signals are of the same signature.

Our system must have the ability to distinguish signatures by reading Wi-Fi CSI signals. The verification model learns to identify input pairs according to the probability that they belong to the same class or different classes.[2]

Since signals may differ in the direction in which they are entered, our system must be capable of extracting non-direction-related characteristics from two signals.

Even if a signal belongs to the same class, the shape of the input is very different if the signal is oriented differently. To classify regardless of the direction of the signal, we focused on the model shall be capable of extracting features unrelated to the direction.

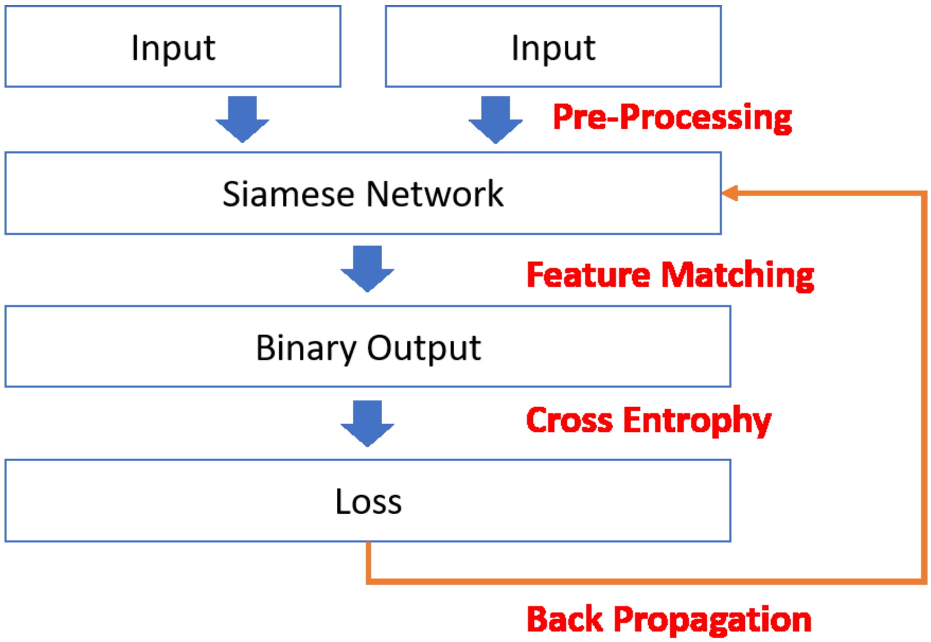

Fig. 1. Overview of the proposed system

3.2 Data Preprocessing

In order to be used as an input to a siamese network, the signal must be preprocessed.

First, the signal has to be converted to non-complex form. Since the Wi-Fi signature signals in CSI packets in 2.4Ghz has firmware issues in their phase [6]. we used only absolute value.

Second, all inputs must be arranged of the same size. Since all signals have different length, the gradient operation with respect to the time instance is adapted to measure the short time energy. Data points with the highest short-time energy within the time period are regarded as the starting and the ending points of the in-air signature. And they are re-sampled uniformly based on Fast Fourier Transform (FFT) to normalize the length of the data. [5]

3.3 Siamese Network For Verification

Siamese neural networks employ a unique structure to naturally rank similarity between inputs. It can discriminate between the class-identity of image pairs. [2]

Two preprocessed signals enter the Siamese network and the network extracts non-directional characteristics from two signals and calculates how similar the two extracted characteristics are. The model outputs the probability that the two signals are of the same class. This network consists of feature extraction and feature matching part.

Feature Extraction To perform the feature extraction, we first need to have convolutional neural networks to serve as the feature extractor Based on the ConvNet structure.[4]

When two processed signals come as the input, they are put to 2 symmetric ConvNet. Some of the features CNN extracted are related to the shape of the signature, but CNN's features are not just those that help to classify signatures. some may be heavily influenced by the direction in which the signature was entered. Structure of the network is shown in Fig.2. We aim to classify the

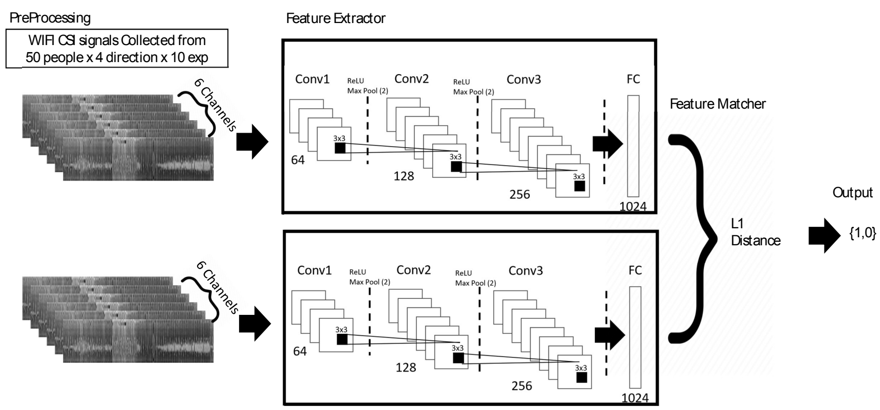

Fig. 2. Structure of Siamese network

signature in a direction that is not related to the direction in which it was entered. This type of property interferes with the classification of signatures. To focus on characteristics conducive to classification, The two CNN networks are arranged side by side symmetrically. It was also designed to have the same weight on the symmetrical CNN network.

This feature extractor is composed of two sister network, which are identical ConvNets with the exact same weights

Purpose of ConvNet in our model is to extract a feature vector from the CSI signal.

this ConvNets are consists of a number of consecutive convolution layers with active functions, and a pooling layer in the end. the Convolution Layer has n convolution filters in it.

Their weights are tied to extract the same characteristics from signals in different directions. By sharing their feature map, this ConvNet is trained to learn characteristics regardless of the direction.

Through a convolution filter, each CSI signal is transformed into a feature vector. this entire process is jointly optimized by backpropagation.

Feature Matching Let $\mathbf{m} \in \mathrm{R}^{d\times 1}$ and $\mathbf{n} \in \mathrm{R}^{d\times 1}$ be feature vectors extracted from two samples. The L-1 distance between the two features can be calculated as follows: Where $\mathbf{p}$ denotes the L-1 distance. In the Siamese networks, this L-1 distance is utilized to match between two feature vectors.

$$\mathbf{p} = \sigma(\sum_j \alpha_j \mid \mathbf{m}^{(j)}_{1,L-1} - \mathbf{n}^{(j)}_{1,L-1} \mid) \tag{2}$$

where is the sigmoidal activation function. This final layer induces a metric on the learned feature space of the (L − 1)th hidden layer and scores the similarity between the two feature vectors. The j are additional parameters that are learned by the model during training, weighting the importance of the component-wise distance. This defines a final Lth fully-connected layer for the network which joins the two Siamese twins.

The output of the CNN is feature vectors extracted from two samples. The Euclidean distance between the two features can be calculated. In the proposed system, this Euclidean distance is utilized to match between two feature vectors.

4 Experiments

Loss and Backpropagation We impose a regularized cross-entropy objective on our binary classifier. This objective is combined with standard backpropagation algorithm, where the gradient is additive across the twin networks due to the tied weights. We initialized all network weights in the convolutional layers from a normal distribution with zero-mean and a standard deviation of 10−2. Biases were also initialized from a normal distribution, but with mean 0.5 and standard deviation 10−2.

5 Conclusion

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