

Improving the Triplet Network for Wi-Fi Based Handwritten Signature Verification

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Improving the Triplet Network for Wi-Fi Based Handwritten Signature Verification

A Masters Thesis

Submitted to the School of Electrical and Electronics
Engineering

and the Graduate School of Yonsei University

in partial fulfillment of the
requirements for the degree of

Master of Science in Electrical and Electronic Engineering

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October 2019

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September 2019

ACKNOWLEDGEMENT

October 2019

Young-Woong Kwon

First of all, I would like to thank Professor Kar-Ann Toh for steering the direction of my research. His warm encouragement and careful guidance were very helpful for me. Thank you for my director Kiheon Kim and my manager Jongman Kim for recommending me to study at graduate school at Yonsei university. Thanks for my company, Samsung SDI for supporting me to study at graduate school. I also want to give my special thanks to Jooyoung, Kim. His consideration and positive attitude always motivated me to do better. Thank you to all my lab members for helping to enjoy school life. Last but not least, I couldn't have finished this work without my dear wife, who always trusted and waited for me despite going back to graduate school at a late age.

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Abstract

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Identity verification using Wi-Fi signals is a challenging task since the shape of the signal varies according both the orientation and the position of the user. In this thesis, a system for identity verification is developed based on the hand gesture signature signals sensed by the Wi-Fi Channel State Information (“CSI”). A three-channel ConvNet structure is adopted to learn the discriminative features based on a relatively small size in-air handwritten signature dataset. We propose an input triplet mining based on the kernel and range space learning to improve the convergence speed of the triplet network training. Our experimental results on the Wi-Fi CSI signature dataset shows encouraging accuracy and convergence performances.

Key words : In-air handwritten signature verification, Wi-Fi Channel State Information, Triplet network, and the Kernel and Range space learning

Chapter 1

Introduction

1.1 Background

Handwritten signatures have long been used as an identification tool and various methods for verifying individuals based on them have been developed [1–4]. The use of biometric identity verification is growing with the popularity of mobile devices. Biometric identity verification systems are more secure, convenient, and provide greater accountability than traditional passwords [5–7]. In-air signatures have become possible with the development of specialized sensors, such as depth cameras and magnetic sensors [8–11]. Recently, the in-air signatures can also be acquired using the Wi-fi Channel State Information (“CSI”) signals. Typically the user makes a certain gesture when signing their signature on a piece of paper. With in-air signatures, the user simply makes the same gesture in the air. Their movements are detected by Wi-fi receivers with appropriate software installed. The software detects changes in the Wi-fi signals caused by the hand movements. This technique uses the existing widespread Wi-Fi devices, so it does not require the use of any special input devices. [12, 13] used CSI signals to recognize users’

gestures and [14] used them to specifically identify signatures written in the air. However, due to limitations of the traditional feature extractor, [14] was only able to identify in-air signatures entering from a specific direction. This makes the user difficult to input their signatures. Recent studies have been conducted on the feasibility of using deep learning to characterize the CSI signals. Deep learning-based models are popular because of their automated feature extractors and the fact that they have superior classification capabilities than traditional models. Deep learning has been used to recognize users based on their vital sign [15, 16] and behavior [17, 18]. In this thesis, the deep learning technology is used to create a Wi-Fi CSI system that can recognize a user's identity with multi-direction in-air signatures. The deep learning model tested in this study is a triplet network where our task is to improve the model's convergence speed using the kernel and range space learning technique [19].

1.2 Motivation and Contributions

The main contributions of this thesis

- Proposing a system to verify user identities using Wi-Fi handwritten signature signals using a deep triplet network;
- Using the kernel and range (KAR) space learning to mine distinctive triplet inputs which boost convergence speed and reduce triplet network training loss; and
- Empirically testing the proposed system on a dataset of Wi-Fi handwritten signatures collected from 98 subjects.

1.3 Paper Organization

The rest of this thesis is organized as follows. Section 2 discusses related works about triplet networks and KAR space learning. Section 3 discusses the proposed system. Section 4 describes this thesis’s experimental and analysis results. Section 5 concludes the thesis.

Chapter 2

Related Works

2.1 Deep Metric Learning

Metric learning converts multi-dimensional data to group data in a feature space. It has been used for computer vision tasks such as image classification and content-based image retrieval [20]. In the past, features were extracted and similarity was measured using traditional algorithms like HOG and LBP. Recently, deep learning-based methods have been widely used instead as they have enabled feature extraction and metric learning in a single framework [21]. The deep networks automatically learn image classification features. Our focus in this thesis is the Triplet network.

2.1.1 Triplet Network

Triplet network is a metric learning model which groups triplet data in the feature space [20, 22]. It is widely used to identify a person based on several images in a process known as person re-identification, which is more challenging than biometric identification due to the low quality and high variety of input images [21]. Other factors, such as variation of clothes, poses, and image angles makes it

difficult to identify the target person in question.

The triplet data is composed of anchor, positive, and negative data points. Training of the triplet network involves the creation of feature vectors to be placed in the appropriate feature space in which positive data is close to the anchor and negative data is far from the anchor. It may not be necessary to train an algorithm using a large number of triplets. Training can be optimized by using only the most learning-efficient triplet. [23–25] used triplet networks with used triplets for only a small number of classes, which were used in a random order. Recently, [26] used triplet mining to speed up convergence. They selected inputs from a large set at each training iteration using the network. However, these sets required the availability of a large amount of training data. This type of training requires the use of large amounts of data separated into only a few classes. Empirical data is not suitable for this type of training strategy because there is usually not enough of it and it is divided into too many classes. The kernel and range space manipulation methods were used for training to reduce the number of required triplets.

2.1.2 Siamese Networks

Siamese neural networks consist of twin networks which accept distinct inputs but are joined by an energy function at the top [27]. By using a constrative loss function, Siamese networks determine whether two inputs are in the same class. LeCun et al. introduced Siamese networks as parts of their handwritten signature verification system. Recent studies used Siamese networks to track

pedestrians [28], group objects [29], and [30] capture information from resumes, indicating that they are suitable for image classification tasks.

2.2 the Kernel and the Range space learning

Multi Layer Perceptron (“MLP”) neural networks have been widely used in machine learning. In general, the MLPs are trained using the gradient descent and backpropagation [31]. Learning parameters, such as learning rate and momentum value, have a significant impact on gradient descent performance, they must be set carefully. However, finding the best values through trial and error is time-consuming.

Recently, a gradient-free learning framework for MLP have been developed which rely on KAR space manipulation [19, 32–34]. This learning framework is based on linear algebra and pseudo-inverse functions, so it does not require any iterations.

Given m samples, the training dataset can be denoted by $\mathbf{X} \in \mathbb{R}^{m \times (n+1)}$ and the network output can be denoted by \tilde{Y} . An MLP network composed of $n - 1$ hidden layers $\{h_1, \dots, h_{n-1}\}$ can be represented by the following equation:

$$\tilde{Y} = \sigma \left([\mathbf{1}, \sigma \left(\dots [\mathbf{1}, \sigma \left([\mathbf{1}, \sigma (\mathbf{X}\mathbf{W}_1)] \mathbf{W}_2 \right)] \dots \mathbf{W}_{(n-1)} \right)] \mathbf{W}_n \right) \quad (2.1)$$

where $\mathbf{W}_1 \in \mathbb{R}^{(n+1) \times h_1}$, $\mathbf{W}_2 \in \mathbb{R}^{(h_1+1) \times h_2}$, \dots , $\mathbf{W}_n \in \mathbb{R}^{(h_{(n-1)}+1) \times n}$, $\mathbf{1} = [1, \dots, 1]^T \in \mathbb{R}^{m \times 1}$ and $\sigma(\cdot)$ is activation function. This network can be trained by adopting the one-hot encoded target matrix $Y \in \mathbb{R}^{m \times n}$. The weighted matrices \mathbf{W}_i trained using KAR space manipulation learning can be written as follows [19]:

$$\begin{aligned} \mathbf{W}_i &= [\mathbf{1}, \sigma \left(\dots [\mathbf{1}, \sigma \left([\mathbf{1}, \sigma (\mathbf{X}\mathbf{W}_1)] \mathbf{W}_2 \right)] \dots \mathbf{W}_{(i-1)} \right)]^\dagger \sigma^{-1} (\mathbf{Y}), \\ i &= 1, \dots, n. \end{aligned} \quad (2.2)$$

Chapter 3

The proposed System

3.1 Preprocessing

Wi-Fi signature data must be pre-processed to be used as an input in the proposed system. In this study, only the magnitude of the complex signal was utilized due to device firmware issues with the phase value of the 2.4Ghz Wi-Fi signal [35]. Second, the data must be made to be the same size. All signals have different lengths, so equal length sampling was used to ensure that all data had the same length. Third, outliers must be addressed. Wi-Fi signals are interrupted by other electromagnetic radiation of which burst noise [35] can have significant effects. Thus, only data within one standard deviation of the median were analyzed to minimize the effects of burst noise.

3.2 Proposed Methodology

This thesis proposed an identity verification system based on the Wi-Fi signals produced by in-air handwritten signatures (“Wi-Fi signature”). Triplet networks which utilized ConvNet as the feature extractor were used to learn the direction-

invariant deep representations of in-air signatures [36]. KAR space learning was used to mine triplet inputs to achieve faster loss convergence [19,34]. Figure 3.1

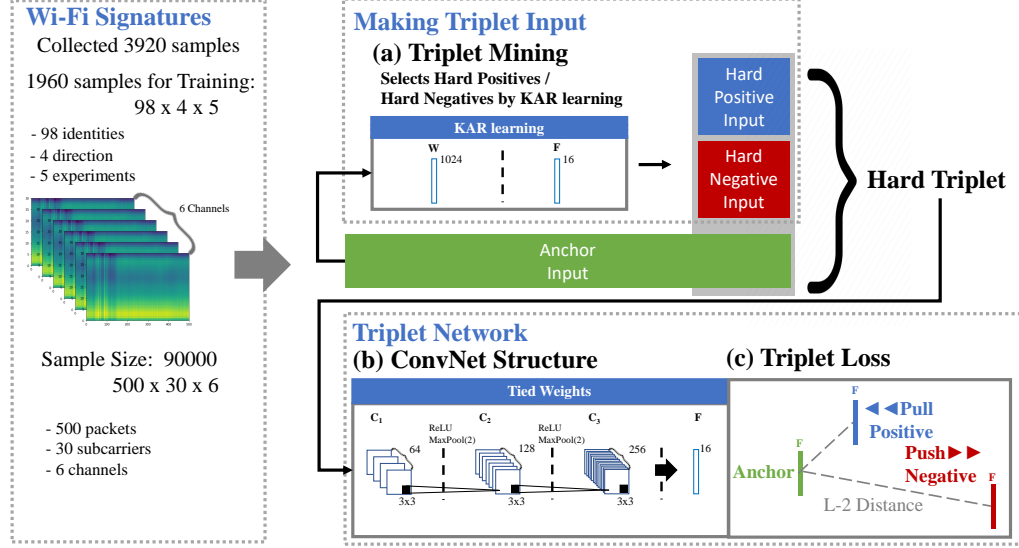


Figure 3.1: An overview of the proposed methodology.

shows an overview of the proposed system. KAR space projection learning is used to mine hard samples from the training dataset to create triplets (Fig. 3.1(a)). The anchor sample is randomly selected from the training dataset. The hard samples are those which are likely to be misclassified by the triplet network for a given anchor sample. After the data is selected, the triplet network (Fig. 3.1(b)) is trained based on the network output vector distance comparison (Fig. 3.1(c)). The following subsections discuss the triplet network architecture, triplet loss, and triplet mining using KAR space learning.

3.2.1 Triplet Loss

Triplet loss [36] trains the ConvNet structure to learn the features that define data position in the feature space. Triplet inputs are composed of a combination of three samples, an anchor sample x_0 , a positive sample x_+ and a negative sample x_- . The anchor sample, the reference for the triplet input, is selected from the training data set. The positive sample has the same identity as the anchor sample while the negative sample has a different identity. $dist\{f(x_0), f(x_+)\}$, the distance between the feature vectors of anchor $f(x_0)$ and positive sample $f(x_+)$ is larger than $dist\{f(x_0), f(x_-)\}$, the distance between feature vectors of the anchor and the negative sample plus a preset margin α to produce discriminative feature vectors. The distance measurement function is:

$$dist\{f(x_0), f(x_-)\} - dist\{f(x_0), f(x_+)\} \geq \alpha \quad (3.1)$$

By using the $L2$ distance as the distance function, triplet loss is defined as:

$$triplet_loss = \sum_i^N \max \left(\left[\|f(x_0) - f(x_+)\|_2^2 - \|f(x_0) - f(x_-)\|_2^2 + \alpha \right], 0 \right), \quad (3.2)$$

Note that if $dist\{f(x_0), f(x_-)\}$ is much larger than $dist\{f(x_0), f(x_+)\} + \alpha$, the output of the loss function is zero, significantly slowing deep network convergence. This condition is likely to occur if triplets are composed by randomly selecting training samples. Thus, triplet inputs must be selected that cause the loss function to produce a non-zero result.

3.2.2 Triplet Mining Based on KAR Space Learning

To train the triplet network faster, a sub-network for mining the hard positive and negative samples from the training dataset was trained. The hard positive sample is likely to be misclassified as a negative sample by the triplet network (Fig. 3.2). The distance between the feature vectors of the anchor and hard positive samples is larger than other positive samples. The hard negative sample is likely to be misclassified as a positive sample because the distance between the feature vectors of the anchor and the hard negative sample is smaller than the difference between the feature vectors of the anchor and other negative samples. Hard triplet inputs are made by combining hard positive and hard negative samples with selected anchor samples. Using hard triplets as triplet network inputs more easily, satisfies 3.1. However, before training the triplet network, it is impossible to identify hard samples. In order to make hard triplets before training the triplet network, a smaller sub-network was trained before training the main triplet network. This smaller sub-network was made of an MLP and was trained using KAR space learning. As KAR space learning has no backpropagation and no iterative learning process, it was trained all at once on the entire training dataset X . The sub-network output was defined as:

$$KAR(\mathbf{X}) = \sigma([\mathbf{1}, \sigma(\dots [\mathbf{1}, \sigma([\mathbf{1}, \sigma(\mathbf{X} \cdot \mathbf{W}_1)] \mathbf{W}_2)] \dots \mathbf{W}_{(n-1)})] \mathbf{W}_n). \quad (3.3)$$

After training the sub-network, the hard samples were mined by measuring the $L2$ distance between every output vector of the sub-network and the output vector of anchor sample. The sub-network output for a given anchor sample x_0 was

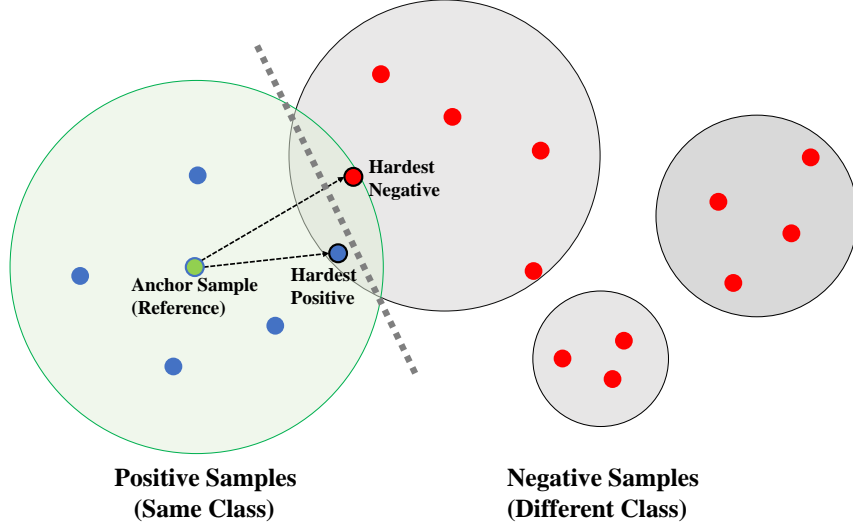


Figure 3.2: Selection of hard samples.

$KAR(x_0)$. To mine hard-positive samples, one sample was selected from among the sub-network outputs for which the distance to the anchor feature vector $KAR(x_0)$ was larger than t_+ . Hard-negative samples were chosen, from among the sub-network outputs for which the anchor feature vector was smaller than t_- . The selected hard-positive and hard-negative samples satisfied the following properties, respectively:

$$\|KAR(\mathbf{x}_0) - KAR(\mathbf{x}_+)\|_2^2 \geq t_+, \quad (3.4)$$

$$\|KAR(\mathbf{x}_0) - KAR(\mathbf{x}_-)\|_2^2 \leq t_-, \quad (3.5)$$

If the hardest sample, outlier data is more likely to be selected than other data, resulting in an increased risk of overfitting [26]. To avoid this problem, the threshold for the hard-positive and the hard-negative samples were empirically

chosen as the 25th and 75th percentiles of the distance between the anchor and sub-network outputs.

3.2.3 ConvNet Structures

The three-dimensional format of the input signature signal is similar to that of image data, so deep ConvNet structures were used as the feature extractor. The ConvNets used in this thesis were made of three layers of ConvNets with triplet loss. Each layer of ConvNet shared their weights. The ConvNets in this

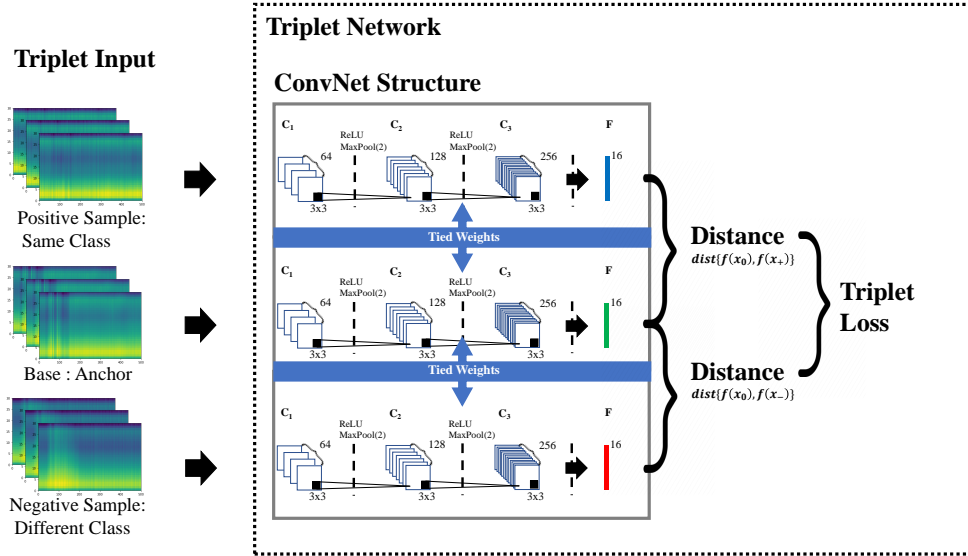


Figure 3.3: ConvNet structure.

study consisted of three filters and a fully-connected output layer (Fig. 3.3). The depth of the ConvNet filters was set at 64,128,256 with stride 1 and ReLU activation functions. The size of the fully-connected layer was 16. The fully-connected output layers were processed through sigmoid activation functions and were normalized according to the $L2$ distance.

Chapter 4

Experiments

4.1 Data set

The Wi-Fi CSI signature dataset [14] at position 1 was used to test the proposed system. These dataset contained 10 signatures made by 98 people in each direction for a total of 980 signatures made in each direction, as shown in 4.1. The size of each sample had a data resolution of 500 x 30 x 6. **Visualization of CSI signature data is shown in Fig. 4.1.**

4.2 Experimental Parameters

To compare the proposed method’s feature extraction performance to that of traditional and deep-learning based methods, feature space was visualized as

Table 4.1: Description of the Dataset.

Direction of signature	# of identities	# of data
1	98	980
2	98	980
3	98	980
4	98	980

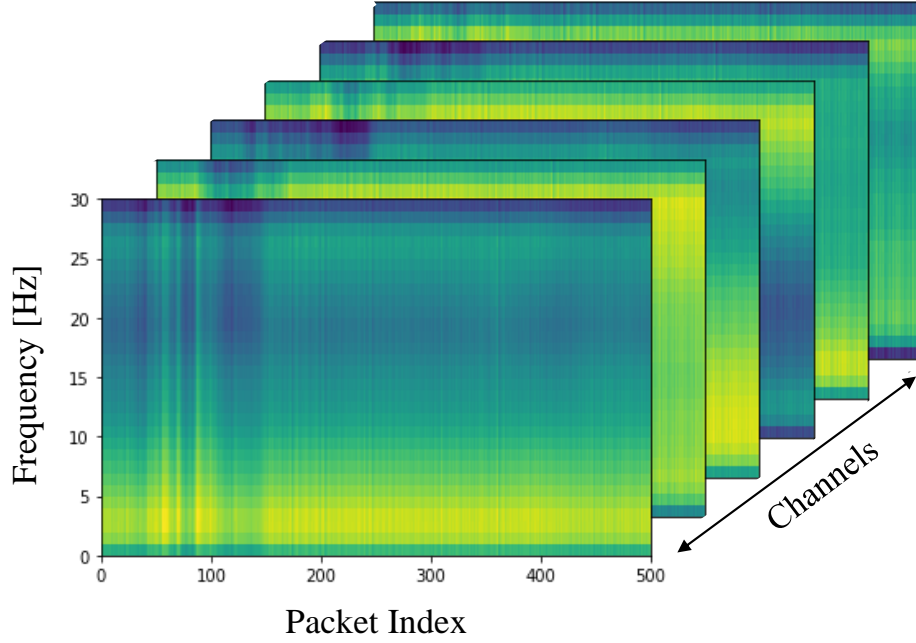


Figure 4.1: Visualization of CSI signal. This data consists of signal strengths for 30 subcarriers per 500 time packet with 6 channels. Each subcarrier corresponds to the frequency, and the intensity value indicates the signal strength.

a 2D Euclidean plane using principal component analysis (“PCA”). The proposed method’s and traditional methods and deep-learning based methods. For handcraft methods’ least square estimations (“LSE”) [37], PCA with LSE [38], support vector machine [39] and the total error minimization with reduced multivariate polynomials [40, 41] were compared. Parameters were selected that performed optimally in each traditional method. For LSE, SVM, and TER, the input signatures were reduced to 500×30 by averaging the subcarrier axis.

For PCA-LSE, the input signature dimension was reduced to 40 following [14]. For SVM with a Gaussian kernel function (“RBF”), the kernel’s parameters c and γ were chosen by a grid search over the range $c \in \{0.01, 1, 10\}$ and $\gamma \in \{0.01/3000, 0.1/3000, 1/3000, 10/3000, 100/3000\}$. For TER, the parameter M was chosen from among $M \in \{1, 2, 3\}$ and $\tau = \eta = 0.5$ following [41]. For comparison with deep-learning based methods, Siamese network [27] and baseline triplet network [36] were used. The proposed method was compared to Siamese networks [27] and baseline triplet networks [36] as deep learning based methods. Verification performance was evaluated in terms of the equal error rate (“EER”). Random five-runs of two-fold cross-validation tests were conducted. Due to hardware memory limitations, the number of negative pairs used was reduced to the number of positive data pairs used for calculating the EER for a total of 18,620 pairs. The structure of the KAR learning MLP sub-networks in the proposed system is shown in 4.2. The three layers’ sizes were set to 1,024, 64 and 16. The size of the third layer was equal to the number of feature vectors of the proposed ConvNet. The weights in the layers were initialized in a normal distribution between 0 and 1 before training. \tan^{-1} was used as an active function following [32]. The same ConvNet structure shown in 4.3 and parameters were used for the proposed and deep learning based methods. The CovNet structure consisted of three 3×3 convolution filters and stride one. A ReLU activation function and 2×2 max-pooling layers were applied between the filters. The depth of each layer was set to $\{64, 128, 256\}$. The output layer with sigmoid activation was regularized according to $L2$ with a penalty of 0.0001. The size of the final

Table 4.2: KAR space learning network structure.

Layer	Size	Activation Function
Input	$500 \times 30 \times 6$	
Fully-connected 1	$1 \times 1 \times 1024$	$\sigma = \tan^{-1}$
Fully-connected 2	$1 \times 1 \times 64$	$\sigma = \tan^{-1}$
Fully-connected 3	$1 \times 1 \times 16$	$\sigma = \tan^{-1}$
Output	$1 \times 1 \times 50$	

Table 4.3: ConvNet model structuer.

Layer	Activation Function	Kernel / Stride	Input Size
Conv 1	ReLU	$(3 \times 3) \times 64 / 1$	$500 \times 30 \times 6$
MaxPool 1		$(2 \times 2) / 1$	$500 \times 30 \times 64$
Conv 2	ReLU	$(3 \times 3) \times 128 / 1$	$250 \times 15 \times 64$
MaxPool 2		$(2 \times 2) / 1$	$250 \times 15 \times 128$
Conv 3	ReLU	$(3 \times 3) \times 256 / 1$	$125 \times 8 \times 128$
MaxPool 3		$(2 \times 2) / 1$	$125 \times 8 \times 256$
Fully-connected	Sigmoid	16	$63 \times 4 \times 256$
L-2 Norm			$1 \times 1 \times 16$
Concat			$1 \times 1 \times 16$

feature vectors was 16. The deep learning network was trained with a learning rate of 0.0005, 3,000 iteration, and a mini-batch size of 32. The Adam optimizer was used to calculate the loss function. The ConvNet structures were initialized before training following [27]. The convolution filters used a normal distribution with a mean of 0 and a standard deviation of 0.0001. The biases used normal distribution with a mean of 0.5 and a standard deviation of 0.01. Triplet loss was calculated with an alpha value of 0.5.

4.3 Experimental Results

4.3.1 Performance

4.4 shows the average EER from the first experiment generated by five-runs of two-fold cross-validation tests under optimal parameter settings. The proposed method had an EER of 19.35%, out-performing both the traditional and deep learning based methods (Table 4.4). Deep learning based methods out-performed the traditional methods because they utilized the entire input signal and had better feature extraction abilities.

Table 4.4: Average EER of five-runs of two-fold cross-validation tests.

Methodology	Best EER (%)	Condition
LSE	48.44	-
PCA-LSE	30.79	Reduced dimension=40
SVM (Linear)	28.23	$c=1$
SVM (RBF)	24.31	$c=1, \gamma=0.01/3000$
TER-RM2	35.84	$M=1, \tau=\eta=0.5$
Siamese network	23.53	$lr=0.00005$
Baseline triplet network	20.34	$lr=0.00005, \alpha=0.1$
Proposed system	16.67	$lr=0.00005, \alpha=0.1$

The proposed method had the widest area under the receiver operating characteristic (“ROC”) curve (Fig. 4.2).

4.3.2 Convergence Speed

Fig. 4.3 shows the convergence of the normalized loss function during training. The proposed method had a faster convergence speed than the deep learning based methods, indicating that KAR learning accelerated the learning speed.

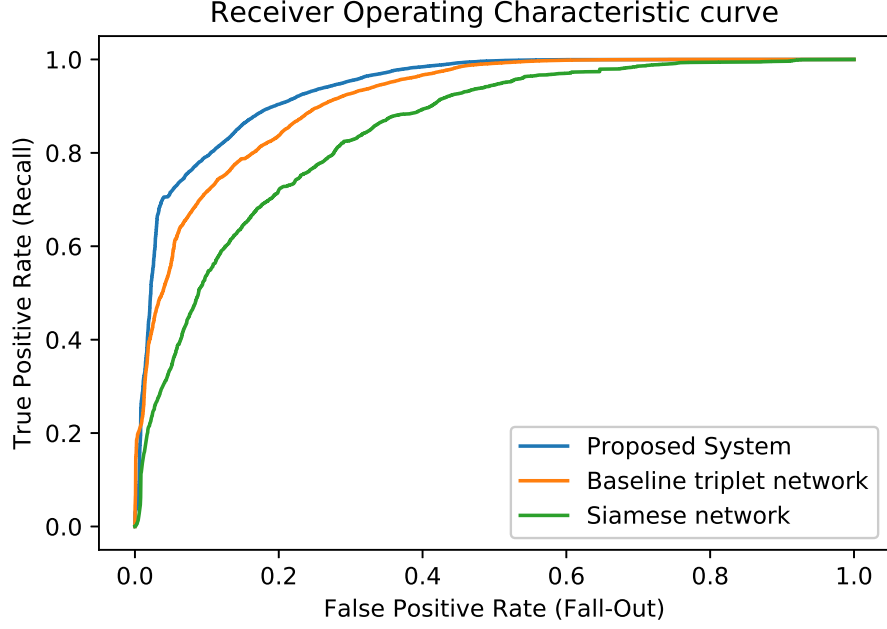


Figure 4.2: Normalized training loss curve.

Feature vector size	16	8	4	2
Siamese network	20.34	22.05	29.39	34.26
Baseline triplet network	18.37	19.52	19.20	24.76
Proposed method	16.67	18.03	18.08	26.64

4.3.3 Feature Vector Size Effect

Fig. 4.4 shows the EERs for different sizes of feature vectors in the feature space. For metric learning systems, feature vector size is generally positively correlated with system performance. The proposed system's performance was negatively correlated with feature vector size.

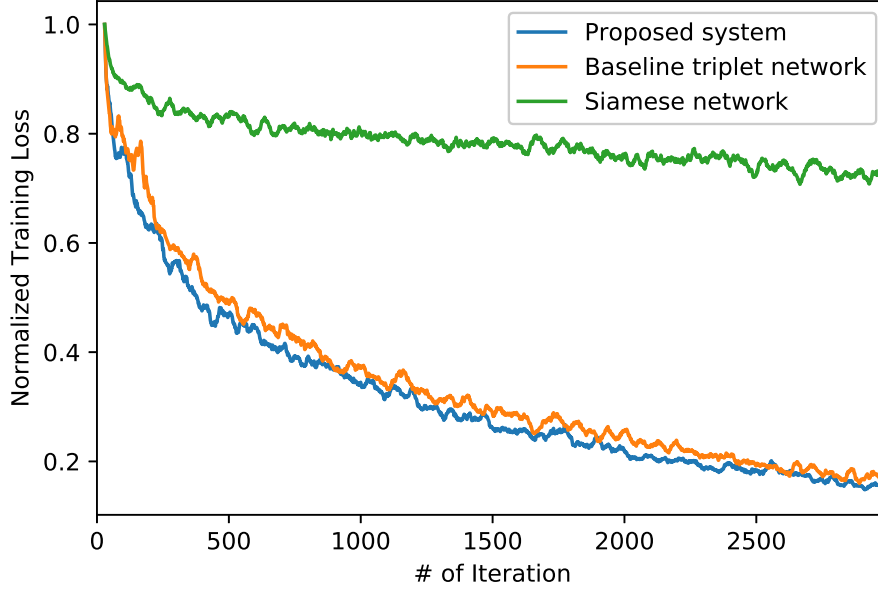


Figure 4.3: normalized training loss trends

4.3.4 Comparison between mining algorithms

In this section, the proposed system is compared to a triplet network that adopted different mining methods. The methods used for mining are the traditional methods given in Table 4.1. We also compared Extreme Learning Machine (“ELM”). ELM is a fast-learning SLFN network which uses an analytic method for calculating the weight of the network [42]. For the traditional methods, the input signals are resized to 500×30 by averaging along the subcarrier axes due to limitation of hardware memory.

Table 4.5 shows the test EER of proposed and compared triplet

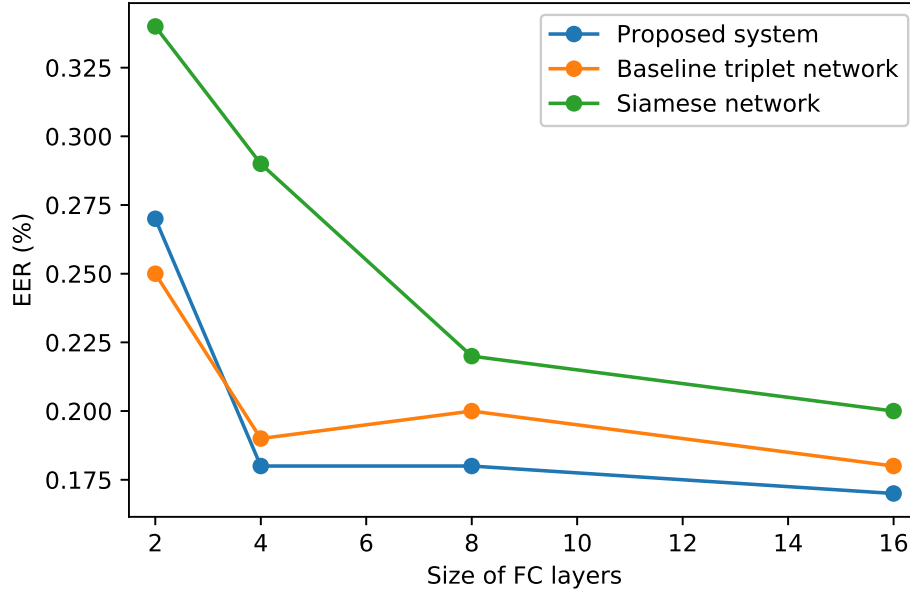


Figure 4.4: Feature Vector Size Effect.

mining methods. TER-RM2 showed the best test EER performance in this case. Proposed system (KAR learning) showed slightly worse performance of 16.67% EER. SVM also showed good performance. From this result, it can be seen that the traditional method can increase the accuracy of the triplet network when applied to the triplet mining.

Table 4.5: Average EER between mining methods.

Methodology	Best EER (%)	Condition
LSE	19.03	-
SVM (Linear)	17.48	$c=1$
SVM (RBF)	17.31	$c=1, \gamma=0.01/3000$
ELM	17.02	layer=[1024,16]
TER-RM2	16.37	$M=1, \tau=\eta=0.5$
Proposed System	16.67	layer=[1024,64,16]

Chapter 5

Conclusion

In this thesis, a system for identity verification was developed based on the hand gesture signature signals sensed by the Wi-Fi Channel State Information (CSI). A three-channel ConvNet structure was adopted to learn the discriminative features based on a relatively small size in-air handwritten signature dataset. We proposed an input triplet mining based on the kernel and range space learning to improve the convergence speed of the triplet network training. Our experimental results on the Wi-Fi CSI signature dataset showed encouraging accuracy and convergence performances.

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개선된 트리플렛 네트워크를 이용한 와이파이 서명 인식 방법

와이파이 신호를 활용해 입력된 수기 서명으로 사용자의 신원을 확인하는 것은 서명이 입력된 방향에 따라 신호의 형태가 변하기 때문에 해석하기 어려운 과제로 인식되어 왔다. 서명 인식에 전통적인 방법을 사용하면 다양한 방향으로 입력된 서명으로부터 신원을 확인하기 어려웠고, 실험 데이터의 크기가 제한되어 딥러닝 모델의 활용 역시 제한되어 왔다. 본 논문에서는 트리플렛 네트워크에 기반하여 와이파이 신호를 이용해 작성된 서명으로부터 신원을 확인하는 새로운 방법을 제안한다. 트리플렛 네트워크의 채택으로 소규모의 실험 데이터셋에서도 차별적인 특징을 학습하며, 커널과 레인지 공간 학습에 기반한 입력 데이터의 추출로 트리플렛 네트워크의 학습 속도를 빠르게 하였다. 와이파이 서명 데이터셋을 이용한 실험을 통해, 제안된 방법이 서명 검증의 정확도와 손실함수의 수렴 속도에서 전통적인 방법과 딥러닝 모델을 능가함을 보여, 다양한 방향으로 입력된 와이파이 신호 기반의 수기 서명을 인식할 수 있음을 검증하였다.

핵심되는 말: 수기 서명 확인, Wi-Fi 채널 상태 정보, 트리플렛 네트워크, 커널과 레인지 공간 학습