Deep Triplet Network adopting the Kernel and the Range Space Learning for Wi-Fi Handwritten Signature Verification

Young-Woong Kwon, Jooyoung Kim, and Kar-Ann Toh

School of Electrical and Electronic Engineering, Yonsei University, 50 Yonsei-ro, Seodaemun-gu, Seoul 03722, Republic of Korea
{herokwon, harrykim, katoh}@yonsei.ac.kr

Abstract. In this paper, we propose an identity verification system based on the handwritten signature signals captured by the Wi-Fi CSI signals using a triplet network. To refine the triplet inputs for faster loss convergence, the kernel and the range space learning is adopted to mine the distinctive triple inputs from the training set of Wi-Fi signature signals. Subsequently, the triplet network utilizing the ConvNet structure is trained with the mined triplet inputs based on L-2 distance comparison. Our experiments on an in-house Wi-Fi handwritten signature signal dataset show encouraging verification accuracy with faster training loss convergence comparing with the baseline triplet network and the Siamese network.

Keywords: Wi-Fi signature signal · in-air handwritten signature verification · the Kernel and the Range space projection learning · triplet network

1 Introduction

In recent years, several behavioral biometric traits for identity authentication are investigated since they are free from the physical characteristic which user owns [1]. Among the behavioral biometrics, the signature based user authentication [5, 14] is taking considerable interest with the development of the in-air signature recognition systems [5, 8, 11]. With the help of sensors such as a depth camera [11] or mobile sensor [8], the in-air signature recognition systems could have less spatial limitation in the signature acquisition process compare to other contact-based authentication systems.

Recently, the commercial Wi-Fi device is also proposed to be utilized as a in-air signature acquisition sensor due to its easy accessible property [12]. By capturing the Wi-Fi CSI signal to observe the distinctive motions, the Wi-Fi based in-air signature recognition system showed reasonable user verification performance [12]. However, the previous works on Wi-Fi signal based user authentication systems [7, 12] utilized the conventional feature extraction method such as the Principal Components Analysis. Since the conventional feature extraction method is not enough to extract the direction- or pose-invariant features from the acquired in-air data, more recently, some studies attempted to implement the deep learning algorithms in Wi-Fi signal based user authentication systems for the better verification performance [16, 13].

In this paper, we utilize the deep triplet network for identity verification based on Wi-Fi CSI signature signal. To achieve not only the promising verification accuracy but also the fast training loss convergence speed for the commercial use, we adopt the kernel and the range (KAR) space leaning [18–20, 22] to mine the distinctive triplet inputs for training the triplet network. Subsequently, the triplet network utilizing the ConvNet structure as a feature extractor is trained using the mined triplet inputs based on L-2 distance comparison. The main contributions of our work can be summarized as follows:

– Proposal of a system for identity verification based on the Wi-Fi handwritten signature signals using deep triplet network.
– Adopted the KAR space learning to mine the distinctive triplet inputs which boosted the convergence speed of the training loss in triplet network.
– Provision of the experimental study on an in-house Wi-Fi handwritten signature signal dataset collected from 50 subjects.

The paper is organized as follows: the related works including triplet network and KAR space learning will be introduced in Section 2 for immediate reference. Our proposed method will be discussed in Section 3. Section 4 describes our experimental results and analysis. Some concluding remarks will be followed in Section 5.

2 Related Works

2.1 Triplet Network

Metric learning is the training of models to learn a distance function to find similarities between objects. Triplet network a metric learning model which aims to learn useful representations by distance comparisons [6]. It is widely used in person re-identification, which solves the matching problem of individuals and identity between camera images[4, 3, 2, 15, 23]. In above tasks, distinction between classes may be ambiguous as the textures or features of the targets may be similar looking.

Triplet network receives triplet data pairs as input. Triplet is composed of anchor(reference), positive(similar) and negative(dissimilar) data. The training of the triplet network is making feature vectors to be placed in the appropriate separation space, making the positive(similar) data is close to the anchor(reference) and the negative(dissimilar) data is kept away from the anchor.

Since myriad triplet pairs may exist for the training set, training from all possible pairs may time-consuming and unnecessary. Optimizing training becomes necessary as it mines the learning-efficient triplet out of large possible inputs. [3, 4, 23] generates triplet only for small classes, which randomly selected in each iteration. Rescently, in [15] used triplet mining stratege for faster convergence speed. They selects inputs from large mini-batch at each training iteration using the network during training. However, a lot of training data is necessary to make such a large-sized mini-batch. Moreover, in early stages of training, making training data with immature models itself may not help the training.

2.2 kernel and the range space learning

The multilayer feedforward neural networks is generally trained by the gradient descent method and the backpropagation. However, setting the learning parameters such as learning rate or momentum value is important to use the gradient descent method.

Recently, gradient-free learning framework based on series of the kernel and the range (KAR) space manipulation has developed [19, 22]. Since it is trained by linear equations, no learning parameters nor the iteration are needed to train the networks. Using this novel framework, we can train multilayer feedforward neural networks with any numbers and size of layers.

Let the training dataset $\mathbf{X} \in \mathbb{R}^{m\times(n+1)}$ and $\mathbf{G} \in \mathbb{R}^{m\times n}$ is network outputs. Multilayer neural network structure is shown below:

$$\mathbf{G} = \sigma\left(\left[\mathbf{1}, \sigma\left(\ldots\left[\mathbf{1}, \sigma\left(\left[\mathbf{1}, \sigma\left(\mathbf{X}\mathbf{W}_1\right)\right]\mathbf{W}_2\right)\right]\ldots\mathbf{W}_{(i-1)}\right)\right]\mathbf{W}_i\right), \tag{1}$$

where $\mathbf{W}_1 \in \mathbb{R}^{(n+1)\times h_1}$,$\mathbf{W}_2 \in \mathbb{R}^{(h_1+1)\times h_2}$,$\ldots$, $\mathbf{W}_i \in \mathbb{R}^{(h_{(i-1)}+1)\times n}$,$\mathbf{1} = [1, \ldots, 1]^T$ $\in \mathbb{R}^{m\times 1}$ and $\sigma(.)$ is activation function.

Network learning is archived using one-hot encoded target $\mathbf{Y} \in \mathbb{R}^{m\times n}$ instead of network output $\mathbf{G}$. After that, we have the weight matrix $\mathbf{W}_1 \ldots \mathbf{W}_i$ to train. the weight matrix can be separated into weights and bias term as $\mathbf{W}_2 \ldots \mathbf{W}_i = \begin{bmatrix}\mathbf{w}_2^T \\ W_2\end{bmatrix} \ldots \begin{bmatrix}\mathbf{w}_i^T \\ W_i\end{bmatrix}$.

after assign random weights to $\mathbf{W}_1 \ldots \mathbf{W}_i$, we get $\mathbf{W}_1$. it is solved as follows:

$$\begin{aligned}
&\left[\sigma^{-1}\left(\mathbf{Y}\right) - \mathbf{1}\cdot\mathbf{w}_i^T\right] W_i^{\dagger} = \sigma\left(\ldots\left[\mathbf{1}, \sigma\left(\left[\mathbf{1}, \sigma\left(\mathbf{X}\mathbf{W}_1\right)\right]\mathbf{W}_2\right)\right]\ldots\mathbf{W}_{(i-1)}\right) \\
&\Rightarrow \Bigg[\sigma^{-1}\Bigg(\ldots\Bigg[\sigma^{-1}\Bigg(\left[\sigma^{-1}\left(\mathbf{Y}\right) - \mathbf{1}\cdot\mathbf{w}_i^T\right] W_i^{\dagger}\Bigg) - \mathbf{1}\cdot\mathbf{w}_{(i-1)}^T\Bigg] W_{(i-1)}^{\dagger}\cdots\Bigg) \\
&\qquad\qquad - \mathbf{1}\cdot\mathbf{w}_2^T\Bigg] W_2^{\dagger} = \sigma\left(\mathbf{X}\mathbf{W}_1\right) \\
&\Rightarrow \mathbf{X}^{\dagger}\sigma^{-1}\Bigg(\Bigg[\sigma^{-1}\Bigg(\ldots\Bigg[\sigma^{-1}\Bigg(\left[\sigma^{-1}\left(\mathbf{Y}\right) - \mathbf{1}\cdot\mathbf{w}_i^T\right] W_i^{\dagger}\Bigg) - \mathbf{1}\cdot\mathbf{w}_{(i-1)}^T\Bigg] W_{(i-1)}^{\dagger}\cdots\Bigg) \\
&\qquad\qquad - \mathbf{1}\cdot\mathbf{w}_2^T\Bigg] W_2^{\dagger} = \mathbf{W}_1.
\end{aligned} \tag{2}$$

After deriving the $\mathbf{W}_1$, the $\mathbf{W}_2$ also can be optimized as:

$$\Rightarrow \left(\sigma\left(\mathbf{X}\mathbf{W}_1\right)\right)^{\dagger}\left(\dots\left[\sigma^{-1}\left(\left[\sigma^{-1}\left(\mathbf{Y}\right)-\mathbf{1}\cdot\mathbf{w}_i^T\right]W_i^{\dagger}\right)-\mathbf{1}\cdot\mathbf{w}_{(i-1)}^T\right]W_{(i-1)}^{\dagger}\cdots\right) = \mathbf{W}_2. \tag{3}$$

By repeating this process recursively until all weight matrix values are obtained, the $\mathbf{W}_i$ can be obtained as follows:

$$\mathbf{W}_i = \left[\mathbf{1},\sigma\left(\dots\left[\mathbf{1},\sigma\left(\left[\mathbf{1},\sigma\left(\mathbf{X}\mathbf{W}_1\right)\right]\mathbf{W}_2\right)\right]\dots\mathbf{W}_{(i-1)}\right)\right]^{\dagger}\sigma^{-1}\left(\mathbf{Y}\right). \tag{4}$$

3 Proposed System

In this section, we propose an identify verification system based on the Wi-Fi based in-air handwritten signature (will be called Wi-Fi signature signals hereafter) using triplet network. Fig.1 shows an overview of the proposed system utilizing the kernel and the range (KAR) space learning [19, 22] for the triplet mining and the triplet network [15]. Essentially, the KAR space projection learning is trained and utilized to generate the triplet input data by mining the hard positive and the hard negative samples from the each given anchor sample in the training dataset (item (a) in Fig. 1). Subsequently, the ConvNet structure in the triplet network (item (b) in Fig. 1) is trained with the mined triplet data based on the triplet loss function using L-2 distance comparison (item (c) in Fig. 1). The following subsections detail the triplet mining using KAR space learning and the triplet network.

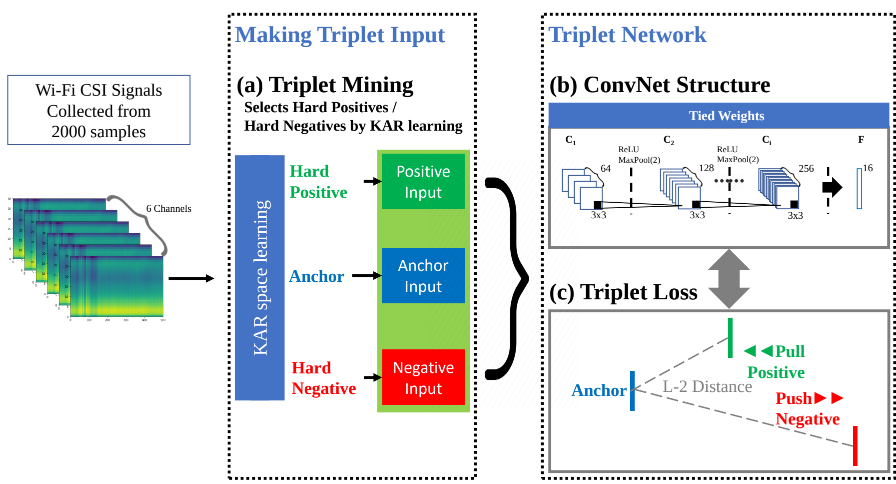

Fig. 1. An overview of the proposed system

3.1 Triplet mining using kernel and the range space learning

According to [15], it is important to select the hard positive sample and the hard negative sample from each given anchor sample for the faster loss convergence when training the triplet network. The hardest positive sample denotes the positive sample whose distance to the anchor sample is the greatest (which is most likely to be misclassified as a negative sample) while the hardest negative sample denotes the negative sample whose distance to the anchor sample is the smallest (which is most likely to be misclassified as a positive sample). However, there is no information about which sample is the hard positive/negative sample before we train the network.

In this work, we propose to adopt the kernel and the range (KAR) space learning (see Section 2.2 for details) as a multilayer feedforward neural network to mine the hard positive/negative sample from the given anchor sample. Since the KAR space learning has no iterative learning process, we can mine the triplet samples without train an another network with backpropagation process just for the input mining.

By training the KAR space network with the training samples, we can calculate the L-2 distance between every training samples by using the output vector from the KAR space network. For every training sample as an anchor sample $\mathbf{x}_{anc}$, positive sample $\mathbf{x}_{pos}$ is selected among the same class with anchor. Where negative sample $\mathbf{x}_{neg}$ is selected among the different class with anchor. For selected sample $\mathbf{x}$, we can choice the hard samples from output of KAR space learning function $f(\mathbf{x}) \in \mathbb{R}^c$. Where c denotes number of classes.

$$f\left(\mathbf{x}\right) = \sigma\left(\left[\mathbf{1}, \sigma\left(\ldots\left[\mathbf{1}, \sigma\left(\left[\mathbf{1}, \sigma\left(\mathbf{x}\cdot\mathbf{W}_1\right)\right]\mathbf{W}_2\right)\right]\ldots\mathbf{W}_{(i-1)}\right)\right]\mathbf{W}_i\right), \tag{5}$$

$\mathbf{W}_1 \in \mathbb{R}^{(n+1)\times h_1}$,$\mathbf{W}_2 \in \mathbb{R}^{(h_1+1)\times h_2}$,$\ldots$, $\mathbf{W}_i \in \mathbb{R}^{(h_{(i-1)}+1)\times n}$,$\mathbf{1} = [1,\ldots,1]^T$ $\in \mathbb{R}^{m\times 1}$ and $\sigma(.)$ is activation function. Here, we randomly select one sample among

$$\left\|f\left(\mathbf{x}_{anc}\right) - f\left(\mathbf{x}_{pos}\right)\right\|_2^2 \geq \mathrm{t}_{pos} \tag{6}$$

as a hard positive sample and one sample among

$$\left\|f\left(\mathbf{x}_{anc}\right) - f\left(\mathbf{x}_{neg}\right)\right\|_2^2 \leq \mathrm{t}_{neg} \tag{7}$$

Since the hardest positive/negative sample can be an outlier which affects the training of the triplet network, we selected hard samples, which has distance above a certain threshold. We empirically set positive threshold to 75 percentile of L-2 distance between anchor to positive samples. Negative threshold is set to 25 percentile of L-2 distance between anchor to negative samples.

3.2 ConvNet Structures

To design the triplet network, we firstly need to select the feature extractor which converts the input triplet data into feature vectors. In this work, we utilize the

ConvNet structure [10] 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 (item (b) in Fig 1) for the 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 layer are applied between each convolutional layers. Following, the features from the last convolutional layer are directly flattened into a vector before the fully-connected layer $\mathbf{F}$. The output vectors from the fully-connected layer are finally transformed using the sigmoid function following with the L-2 normalization.

3.3 Triplet loss

The triplet loss function is proposed in [15] to train the triplet network. For the i_{th} anchor input sample $\mathbf{X}_{anc,i}$, the triplet input is generated by grouping with the hard positive input sample $\mathbf{X}_{pos,i}$ and the hard negative input sample $\mathbf{X}_{neg,i}$ selected based on the KAR space learning. Generated triplet input $\{\mathbf{X}_{anc,i}, \mathbf{X}_{pos,i}, \mathbf{X}_{neg,i}\}$ is then respectively transformed to the anchor, positive and negative feature vectors $\{\mathbf{v}_{anc,i}, \mathbf{v}_{pos,i}, \mathbf{v}_{neg,i}\}$ with the ConvNet structure.

Here, the triplet loss function is calculated by comparing the positive distance (L-2 distance between the anchor vector and the positive vector) and the negative distance (L-2 distance between the anchor vector and the negative vector) as follows:

$$loss = \sum_{i}^{N} max\left(\left[\|\mathbf{v}_{anc,i} - \mathbf{v}_{pos,i}\|_2^2 - \|\mathbf{v}_{anc,i} - \mathbf{v}_{neg,i}\|_2^2 + \alpha\right], 0\right), \tag{8}$$

where N denotes the size of the mini-batch, $\|\bullet\|_2^2$ denotes the L-2 distance and α denotes the preset margin. The ConvNet structure using equation (8) is thus trained to maximize the gap between the positive distance and the negative distance which should be larger than the margin α.

4 Experiments

4.1 Dataset

In order to evaluate the verification performance of proposed system, Wi-Fi CSI signature dataset from [12] was used. Wi-Fi CSI dataset consists of 2000 Wi-Fi CSI signature signals (4 directions $\times$ 50 identities $\times$ 10 samples). Each signal is size of (500 packets $\times$ 30 subcarriers $\times$ 6 antennas). We used only the absolute value among the Wi-Fi CSI signals that come in a complex number. Since the Wi-Fi devices that is used to collect CSI signals has device firmware issues in their phase value in 2.4Ghz frequency mode [24].

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 [12] 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 triplet network.

4.2 Experimental Settings

Performance Evaluation The proposed system is evaluated with others based on verification accuracy. Verification performance is compared with existing linear methods in literature such as Least Square Estimation(LSE), Support Vector Machine(SVM) and Total Error Rate minimization which adopts the Reduced multivariate polynomial Model as basis function(TER-RM2) [17, 21]. Moreover, proposed system is compared by Siamese network [9] and Baseline Triplet network [6], which are also deep learning systems based on the same ConvNet structure as our proposed system. Howeaver, Siamese network receives data pairs as input and trained by contrastive loss between a pair of samples. Baseline Triplet network is similar as our proposed system, but without triplet mining KAR learning process when making input triplet.

Validation performance of the proposed and other systems were evaluated in terms of Equal Error Rates (EER, %) averaged from five runs of two-fold cross-validation tests. We note that in triplet network and Siamese network, We did not use every possible pairs in validation set. Since every possible triplet pairs for validation set is the number of 3 out of 1000 combinations, which is too huge for our experiment. We used randomly sampled negative pairs from validation set until it equals to 9500 positive samples instead.

Network Structure We impose a triplet loss as objective function on our classifier. This objective is combined with standard backpropagation algorithm. The structure of the ConvNet network is specified in Table 1. we train the network starting with a learning rate of 0.00005 via Triplet loss with a mini-batch sized of 32. We optimize the loss by the Adam optimizer with L-2 penalty of 0.0002 except for output layer. Output layer is regularized with L-2 penalty of 0.0001. We initialized all network weights in the convolutional layers from a normal distribution with zero-mean and a standard deviation of 0.01. Biases were also initialized from a normal distribution of standard deviation of 0.01, but with 0.5 mean. Training is conduced with 1500 iterations.

For Table 2, KAR learning trained multilayer feedforward network structure is shown below. We set network layers of 2 and size of the layers are 1024 and 16. Each layer is initialized as uniform distribution over [0, 1). We used arctangent as activation function.

Table 1. The structure of ConvNet

Layer	Activation	Kernel / Stride	Input Size
Conv 1	ReLU	3x3x64 / 1	500x30x6
MaxPool 1		2x2 / 1	500x30x64
Conv 2	ReLU	3x3x128 / 1	250x15x64
MaxPool 2		2x2 / 1	250x15x128
Conv 3	ReLU	3x3x256 / 1	125x8x128
MaxPool 3		2x2 / 1	125x8x256
Fully-Connected	Sigmoid	16	63x4x256
L-2 Norm			1x1x128
Concat			1x1x384

Table 2. The structure of KARnet

Layer	Size	Activation
Input	500x30x6	
Dense 1	1x1x1024	ArcTan
Dense 2	1x1x128	ArcTan
Output	1x1x50	

Parameter Settings For the triplet network, 0.1 of alpha value is used to make triplet loss. For baseline triplet network, we choose random signals for positive and negative input to make triplet input, instead of mining input using KAR learning. For Siamese Networks, we put 2 random signal as input and used binary loss function. For linear methods such as LSE,SVM and TER, we reduced dimension of input signal to 500x30, by averaging through subcarrier axis. Due to limitation of hardware memory. For PCA-LSE, input signal dimension is reduced again to 40 using PCA.

4.3 Results and Discussion

Table 3 shows the best average EER performances obtained by the compared methods. The test EER was averaged from five runs of two-fold cross-validation. Comparing with ConvNet based Siamese and Triplet CNN without KAR learning, proposed methods showed the best EER performance. Due to negative mining process included in making triplet loss. The proposed method showed much better EER than linear methods, such as SVM,LSE and TER-RM2. Since linear methods use reduced input signal.

Loss curves of proposed method are shown in Fig.2. As the proposed method shows steeper training loss curve compared with other deep learning methods, KAR learning not only helps ConvNet to extract better features, but also helps it to boost training speed.

Table 3. Verification Performance

Methology	Best EER (%)	Condition
Proposed	19.35	lr=0.00005, α=0.1
Triplet network without mining	20.34	lr=0.00005, α=0.1
Siamese network	23.53	lr=0.00005
SVM(RBF)	24.31	c=1, γ=0.01/3000
SVM(Linear)	28.23	c=1
LSE(Dimension Reduction by PCA)	30.79	input dimension=40
TER-RM2	35.84	M=1,τ=η=0.5
LSE	48.44	

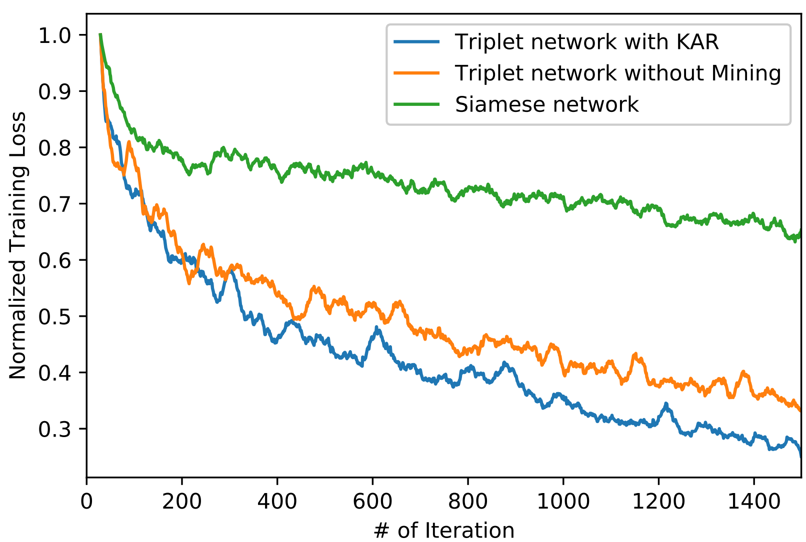

Fig. 2. Training Loss Curve of the Proposed System

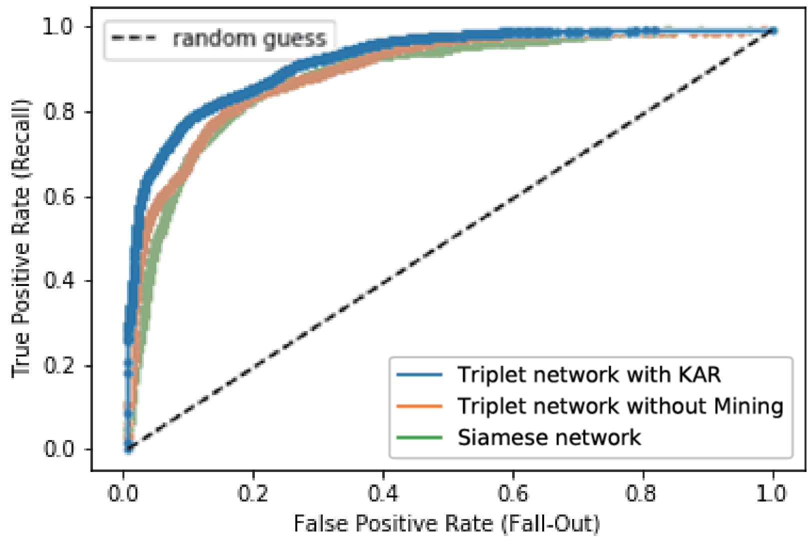

Fig. 3. Receiver Operating Characteristic(ROC) Curve of the Proposed System

5 Conclusion

In this paper, we propose an identity verification system based on the handwritten signature signals captured by the Wi-Fi CSI signal using triplet network. To refine the triplet inputs for the faster loss convergence, the kernel and the range space learning is adopted to mine the distinctive triple inputs from the training Wi-Fi signature signals. Subsequently, the triplet network utilizing the ConvNet structure is trained with the mined triplet inputs based on L-2 distance comparison. Our experiments on an in-house Wi-Fi handwritten signature signal dataset show encouraging verification accuracy with faster training loss convergence compare to the basic triplet network and the Siamese network.

References

1. Bailador, G., Sanchez-Avila, C., Guerra-Casanova, J., de Santos Sierra, A.: Analysis of pattern recognition techniques for in-air signature biometrics. Pattern Recognition **44**(10-11), 2468–2478 (2011)
2. Chen, W., Chen, X., Zhang, J., Huang, K.: Beyond triplet loss: a deep quadruplet network for person re-identification. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. pp. 403–412 (2017)
3. Cheng, D., Gong, Y., Zhou, S., Wang, J., Zheng, N.: Person re-identification by multi-channel parts-based cnn with improved triplet loss function. In: Proceedings of the iEEE conference on computer vision and pattern recognition. pp. 1335–1344 (2016)

4. Ding, S., Lin, L., Wang, G., Chao, H.: Deep feature learning with relative distance comparison for person re-identification. Pattern Recognition **48**(10), 2993–3003 (2015)
5. Galbally, J., Diaz-Cabrera, M., Ferrer, M.A., Gomez-Barrero, M., Morales, A., Fierrez, J.: On-line signature recognition through the combination of real dynamic data and synthetically generated static data. Pattern Recognition **48**(9), 2921–2934 (2015)
6. Hoffer, E., Ailon, N.: Deep metric learning using triplet network. In: International Workshop on Similarity-Based Pattern Recognition. pp. 84–92. Springer (2015)
7. Hong, F., Wang, X., Yang, Y., Zong, Y., Zhang, Y., Guo, Z.: Wfid: Passive device-free human identification using wifi signal. In: Proceedings of the 13th International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services. pp. 47–56. ACM (2016)
8. Jeon, J.H., Oh, B.S., Toh, K.A.: A system for hand gesture based signature recognition. In: 2012 12th International Conference on Control Automation Robotics & Vision (ICARCV). pp. 171–175. IEEE (2012)
9. Koch, G., Zemel, R., Salakhutdinov, R.: Siamese neural networks for one-shot image recognition. In: ICML deep learning workshop. vol. 2 (2015)
10. LeCun, Y., Bottou, L., Bengio, Y., Haffner, P., et al.: Gradient-based learning applied to document recognition. Proceedings of the IEEE **86**(11), 2278–2324 (1998)
11. Malik, J., Elhayek, A., Ahmed, S., Shafait, F., Malik, M., Stricker, D.: 3dairsig: A framework for enabling in-air signatures using a multi-modal depth sensor. Sensors **18**(11), 3872 (2018)
12. Moon, H.C., Jang, S.I., Oh, K., Toh, K.A.: An in-air signature verification system using wi-fi signals. In: Proceedings of the 2017 4th International Conference on Biomedical and Bioinformatics Engineering. pp. 133–138. ACM (2017)
13. Pokkunuru, A., Jakkala, K., Bhuyan, A., Wang, P., Sun, Z.: Neuralwave: Gait-based user identification through commodity wifi and deep learning. In: IECON 2018-44th Annual Conference of the IEEE Industrial Electronics Society. pp. 758–765. IEEE (2018)
14. Sanmorino, A., Yazid, S.: A survey for handwritten signature verification. In: 2012 2nd International Conference on Uncertainty Reasoning and Knowledge Engineering. pp. 54–57. IEEE (2012)
15. Schroff, F., Kalenichenko, D., Philbin, J.: Facenet: A unified embedding for face recognition and clustering. In: Proceedings of the IEEE conference on computer vision and pattern recognition. pp. 815–823 (2015)
16. Shi, C., Liu, J., Liu, H., Chen, Y.: Smart user authentication through actuation of daily activities leveraging wifi-enabled iot. In: Proceedings of the 18th ACM International Symposium on Mobile Ad Hoc Networking and Computing. p. 5. ACM (2017)
17. Toh, K.A.: Fingerprint and speaker verification decisions fusion. In: 12th International Conference on Image Analysis and Processing, 2003. Proceedings. pp. 626–631. IEEE (2003)
18. Toh, K.A.: Kernel and range approach to analytic network learning. International Journal of Networked and Distributed Computing **7**(1), 20–28 (December 2018). https://doi.org/https://doi.org/10.2991/ijndc.1970.1.7.3
19. Toh, K.A.: Learning from the kernel and the range space. In: 2018 IEEE/ACIS 17th International Conference on Computer and Information Science (ICIS). pp. 1–6. IEEE (2018)
20. Toh, K.: Analytic network learning. arXiv preprint arXiv:1811.08227 (November, 2018)

21. Toh, K.A., Eng, H.L.: Between classification-error approximation and weighted least-squares learning. IEEE Transactions on Pattern Analysis and Machine Intelligence **30**(4), 658–669 (2008)
22. Toh, K.A., Lin, Z., Li, Z., Oh, B., Sun, L.: Gradient-free learning based on the kernel and the range space. arXiv preprint arXiv:1810.11581 (2018)
23. Wang, F., Zuo, W., Lin, L., Zhang, D., Zhang, L.: Joint learning of single-image and cross-image representations for person re-identification. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. pp. 1288–1296 (2016)
24. Wang, W., Liu, A.X., Shahzad, M., Ling, K., Lu, S.: Understanding and modeling of wifi signal based human activity recognition. In: Proceedings of the 21st annual international conference on mobile computing and networking. pp. 65–76. ACM (2015)