TRANSFER LEARNING OF WI-FI HANDWRITTEN SIGNATURE SIGNALS FOR IDENTITY VERIFICATION BASED ON THE KERNEL AND THE RANGE SPACE PROJECTION

Junsik Jung, Jooyoung Kim and Kar-Ann Toh

Yonsei University, School of Electrical and Electronic Engineering, Seoul, Republic of Korea

INTRODUCTION

- We propose a system for user identity verification based on the handwritten signature captured by the Wi-Fi CSI wave packets at different positions using transfer learning.
- We firstly pretrain the Convolutional Neural Network using the Wi-Fi signature signals collected from one position.
- Subsequently, the pretrained feature extractor is transferred to recognize the Wi-Fi signature signals from another position.
- For computational efficiency, we use the recently proposed learning method named the kernel and the range (KAR) space projection learning algorithm during retraining stage.

PROPOSED SYSTEM

- **Data Preprocessing**
  - Linear interpolation, low-pass filtering, re-sampling, shift-plus subtraction are utilized to standardize the collected raw signals.
- **Pretraining**
  - In the pretraining stage, we update the parameters of pretraining model using gradient descent algorithm.
- **Transfer Learning**
  - To avoid the iterative learning process and reduce the computational cost, we adopt the KAR space projection learning to retrain the classifier.

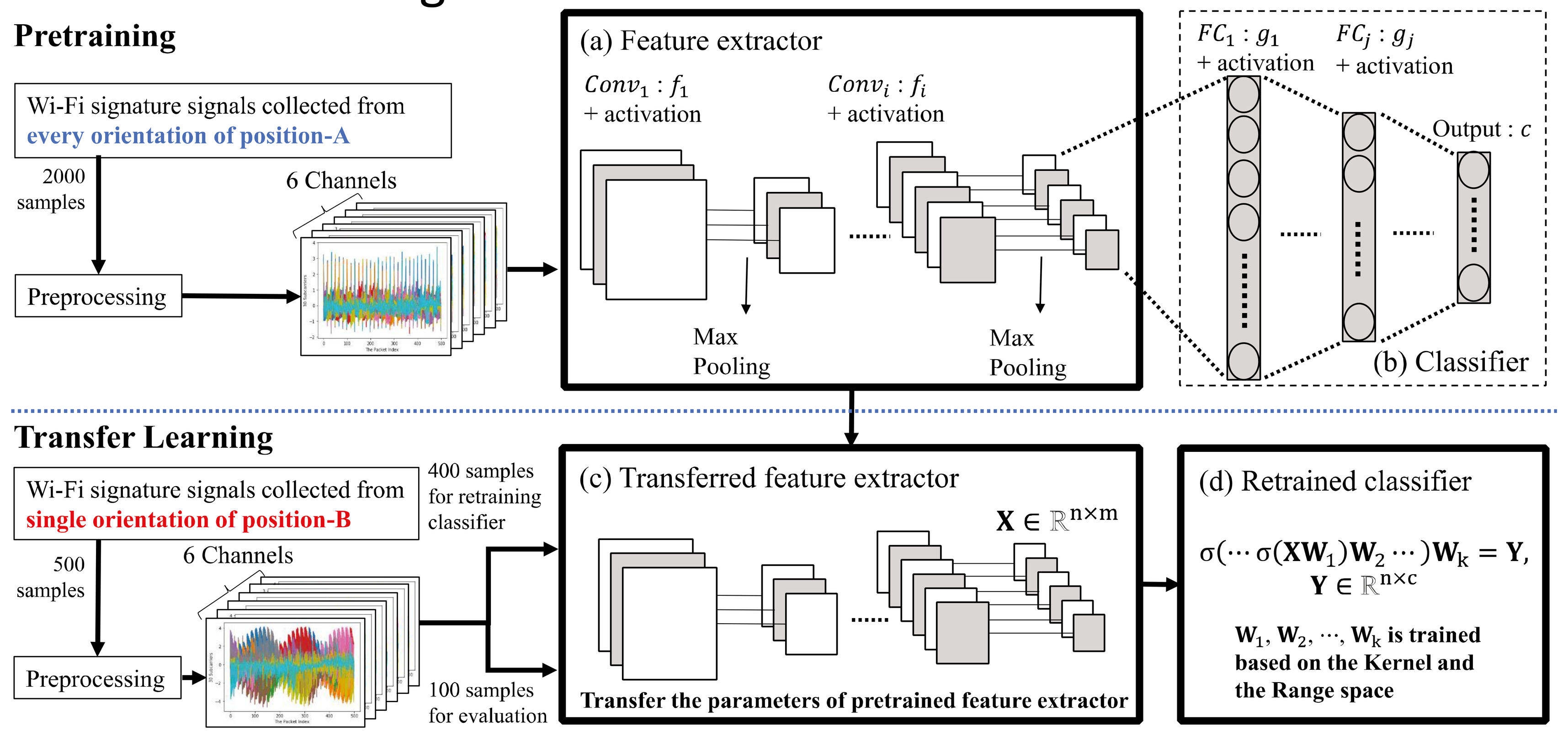

Fig.1 An overview of our proposed system

NETWORK STRUCTURE

Feature Extractor	Conv1	MaxPool	Conv2	MaxPool	Conv3	MaxPool
Attr.	$(3,16)_{/1,1}$, ReLU	$2_{/2,0}$	$(3,32)_{/1,1}$, ReLU	$2_{/2,0}$	$(3,64)_{/1,1}$, ReLU	$2_{/2,0}$
Classifier	**FC1**		**FC2**		**Output**	
Attr.	1024, ReLU		512, ReLU		100, Softmax	

Table. 1 The structure of the pretraining model.
$(\mathrm{m},\mathrm{n})_{/a,b}$ denotes convolution layer with n filters of size $m \times m$, where the stride and padding are a and b respectively.
$\mathrm{p}_{/r,s}$ denotes the max-pooling layers with window of $\mathrm{p} \times p$, where the stride and padding are r and s respectively.

KAR SPACE PROJECTION LEARNING

- The forward propagation of the multilayer network can be written as:

$$\sigma(\cdots\sigma(\boldsymbol{X}\boldsymbol{W}_1)\boldsymbol{W}_2\cdots)\boldsymbol{W}_j = \boldsymbol{Y}$$

- By randomly initializing $\boldsymbol{W}_2, \cdots, \boldsymbol{W}_j$ the weight $\boldsymbol{W}_1$ can be solved as follows:

$$\sigma(\cdots\sigma(\boldsymbol{X}\boldsymbol{W}_1)\boldsymbol{W}_2\cdots) = \boldsymbol{Y}\boldsymbol{W}_j^{\dagger}$$
$$\Rightarrow \sigma(\boldsymbol{X}\boldsymbol{W}_1) = (\cdots\sigma^{-1}(\boldsymbol{Y}\boldsymbol{W}_j^{\dagger})\cdots)\boldsymbol{W}_2^{\dagger}$$
$$\Rightarrow \boldsymbol{W}_1 = \boldsymbol{X}^{\dagger}\sigma^{-1}(\cdots\sigma^{-1}(\boldsymbol{Y}\boldsymbol{W}_j^{\dagger})\cdots)\boldsymbol{W}_2^{\dagger}$$

- After $\boldsymbol{W}_1$ is optimized, it can be back-substituted into forward propagation to solve for $\boldsymbol{W}_2$ as follows:

$$\sigma(\boldsymbol{X}\boldsymbol{W}_1)\boldsymbol{W}_2 = (\cdots\sigma^{-1}(\boldsymbol{Y}\boldsymbol{W}_j^{\dagger})\cdots)$$
$$\Rightarrow \boldsymbol{W}_2 = (\sigma(\boldsymbol{X}\boldsymbol{W}_1))^{\dagger}\,(\cdots\sigma^{-1}(\boldsymbol{Y}\boldsymbol{W}_j^{\dagger})\cdots)$$

- This optimization process is iterated until the weights of the j^{th} layer is solved as follows:

$$\boldsymbol{W}_j = (\sigma(\cdots\sigma(\boldsymbol{X}\boldsymbol{W}_1)\boldsymbol{W}_2\cdots)\boldsymbol{W}_{j-1})^{\dagger}\,\boldsymbol{Y}$$

RESULTS

- **Fig. 2** shows the averaged classification accuracy at different position.
  - ➢ Among the proposed system with different learning algorithms, the KAR space projection transfer learning shows better recognition performance compared to the gradient descent algorithm (GD) based transfer learning in both positions.
- **Table. 2** summarizes the training computing times of the two learning algorithms in our proposed system.
  - ➢ Under both CPU and GPU settings, the KAR space projection transfer learning shows much lower training time than the GD based transfer learning.

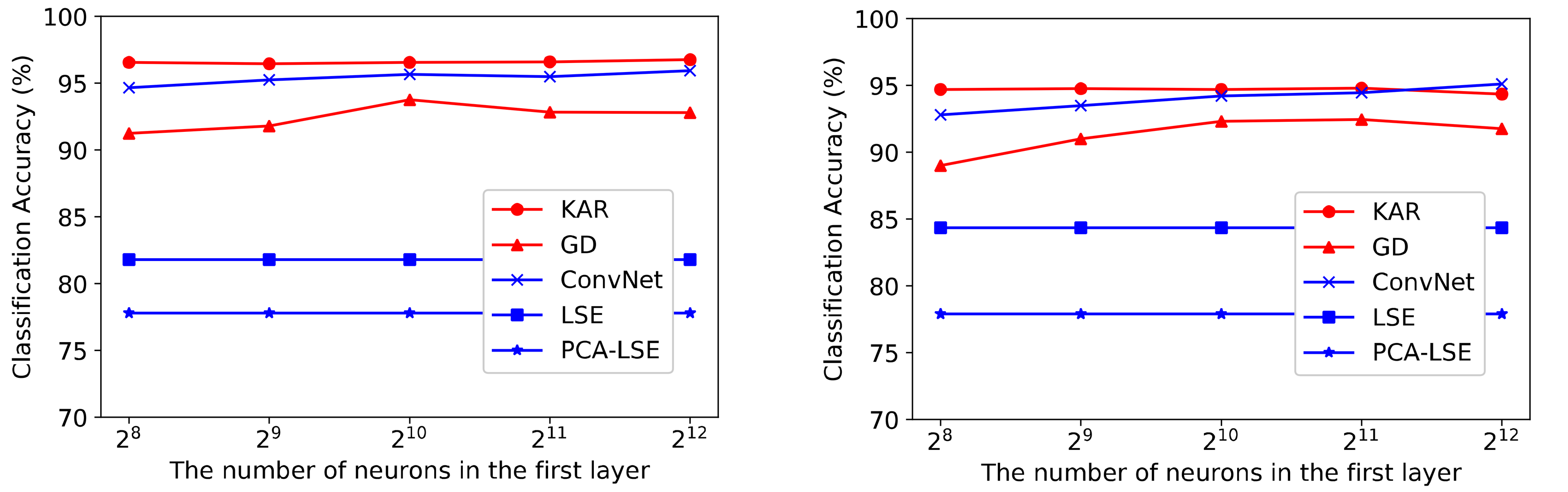

Fig.2 Averaged classification accuracy from all the four orientations with respect to the number of neurons in the first hidden layer.

Setting	GD	KAR
CPU time (s)	1365	4.41
GPU time (s)	30.08	0.7

Table. 2 The total elapsed computing time on CPU / GPU (sec) averaged from five-fold cross-validation

CONCLUSION

- Our experimental results on the in-house Wi-Fi handwritten signature signal dataset show that utilization of the KAR space projection learning can effectively reduce the amount of computational costs and perform better on classifying the signals from new position.