

Palmprint Recognition with Deep Convolutional Features

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Abstract. Palmprint recognition has become popular and significant in many fields because of its high efficiency and accuracy in personal identification. In this paper, we present a scheme for palmprint features extraction based on deep convolutional neural network (CNN). The CNN, which naturally integrates low/mid/high-level feature, performs excellently in processing images, video and speech. We extract the palmprint features using the CNN-F architecture, and exactly evaluate the convolutional features from different layers in the network for both identification and verification tasks. The experimental results on public PolyU palmprint database illuminate that palmprint features from the CNN-F respectively achieve the optimal identification rate of 100% and verification accuracy of EER = 0.25%, which demonstrate the effectiveness and reliability of the proposed palmprint CNN features.

Keywords: Deep convolutional neural network · Palmprint recognition
Feature extraction

1 Introduction

As a kind of biometric identification technology, palmprint recognition has become a research focus in the field of artificial intelligence, pattern recognition and image processing in recent years. Existing palmprint recognition methods can be divided into several categories including structure-based methods, texture-based methods, subspace-based methods, statistics-based methods. The structure-based methods are to extract the relevant point features and line features [1, 2]. However, the recognition accuracy of the structure-based methods is relatively low, and the features need more storage space. Texture-based methods are to extract rich texture information from palmprint, for instance, PalmCode [3], Competitive Code [4], RLOC [5], BOCV [6] and double half-orientation based method [7]. These methods have stronger classification ability as well as good recognition accuracy. However, they may be affected by the translation and rotation of palmprint image because of the coding of palmprint features. The subspace-based methods means that the palmprint images are regarded as high dimensional vectors or matrices. They are transformed into low dimensional vectors or matrices by mapping or transformation, and make representations and matching for the palmprint in the low dimensional space [8–10]. The subspace methods possess high recognition accuracy and fast recognition speed. The statistics-based methods, Fourier Transform [11] and

Wavelet Transform [12, 13], employ the center of gravity, mean value and variance of the palmprint image as the features. The features that the statistics-based methods extract are relatively small. All of the above methods indicate a superiority performance in palmprint recognition. Palmprint features extraction is the most basic and important part of palmprint recognition, which is the key to the recognition performance.

Recently, deep neural networks, whose fundamental ingredient is the training of a nonlinear feature extractor at each layer [14, 15], have demonstrated the excellent performance in image representation. A variety of depth convolutional neural networks, such as AlexNet [16], VggNet [17] and ResNet [18], achieve outstanding performance on processing images. Learning from a large-scale ImageNet database [19], they can extract genetic feature representations that generalize well and could be transplanted onto other image applications [20, 21]. Since we do not have enough palmprint images to train deep convolutional neural network from scratch, we employ the pre-trained deep convolutional neural network, CNN-F [22], as a feature extractor for the palmprint image in this paper. The goal is to introduce the pre-trained CNN-F for palmprint features extraction, and extensively evaluate the CNN features for palmprint verification and identification tasks.

The rest of paper is organized as follows. In Sect. 2, we briefly introduce the architecture of CNN-F and palmprint convolutional features. Experimental results for verification and identification tasks are given in Sect. 3, followed by the conclusion in Sect. 4.

2 Palmprint Recognition Based on CNN-F

2.1 Architecture of the CNN-F

The CNN-F (“F” for “fast”) network [17] is made by Chatfield et al. [22] and inspired by the success of the CNN of Krizhevsky et al. [16]. It examined in Reference [22]. This network is meant to be architecturally similar to the original AlexNet [16]. The CNN-F configuration is given in Table 1. It has recently achieved state-of-the-art performance on image classification on ImageNet database, and includes 8 learned layers. The first five learned layers are said to be convolutional layers, the last three learned layers on the top of architecture are called Fully Connected (FC). The first convolutional layer (“layer 1”) filters the $224 \times 224 \times 3$ size input image with 64 kernels of size $11 \times 11 \times 3$ with a stride of 4 pixels (this is the distance between the receptive field centers of neighboring neurons in a kernel map). The second convolutional layer (“layer 5”), which takes as input the output of the previous layer, filters it with 256 kernels of size $5 \times 5 \times 256$. Different from [17] and similar to [16], the first two convolutional layers include the Local Response Normalization (LRN) [16] operator. As well, the next three convolutional layers (“layer 9”, “layer 11” and “layer 13”) each has 256 kernels of size $3 \times 3 \times 256$. The first two FC layers (“layer 16” and “layer 17”) are regularized using dropout [16], and output 4096 dimensional convolutional features. The output of the last FC layer (“layer 20”) are 1000 dimensions. Please consult [22] for further details.

Table 1. The CNN-F configuration (For each convolution layer, the number of convolution filters, receptive field size, the convolution stride and spatial padding are indicated.)

Layer	0	1	2	3	4	5	6	7	8	9	10
Type	input	conv	relu	lrn	mpool	conv	relu	lrn	mpool	conv	relu
Name	-	conv1	relu1	norm1	pool1	conv2	relu2	norm2	pool2	conv3	relu4
Filt dim	-	3	-	-	-	64	-	-	-	256	-
Num filt	-	64	-	-	-	256	-	-	-	256	-
Stride	-	4	1	1	2	1	1	1	2	1	1
Pad	-	1	0	0	1	1	0	0	1	1	0
Layer	11	12	13	14	15	16	17	18	19	20	21
Type	conv	relu	conv	relu	mpool	conv	relu	conv	relu	conv	softmax
Name	conv4	relu4	conv5	relu5	pool5	fc6	relu6	fc7	relu7	fc8	prob
Filt dim	256	-	256	-	-	256	-	4096	-	4096	-
Num filt	256	-	256	-	-	4096	-	4096	-	1000	-
Stride	1	1	1	1	2	1	1	1	1	1	1
Pad	1	0	1	0	1	1	0	1	0	1	0

2.2 Palmprint Convolutional Features

The CNN-F is suitable to images of 224×224 pixels size, which must be colorful. Our image size is 128×128 and gray. So we have made a little pre-processing, which palmprint images are first resized to 224×224 and transferred to be colorful. Each layer has a plurality of feature maps, one of which is extracted by a convolution filter. For example, the input image is convoluted with 64 kernels of size $11 \times 11 \times 3$ to obtain 64 feature maps, which is the extracted convolution feature of the first convolutional layer. The feature maps, as input data, are then processed by the next layers to obtain other different feature maps according to the number of convolution filters and the filter size. Similar processing is done in other layers. Finally, we can capture the features of each layer and extract features of different layers from the network. We measure the recognition rate of the palmprint images according to the features. Then, we use cosine distance to calculate the difference of the inter-class and intra-class palmprint images, according to the cosine distance calculate the value of False Acceptance Rate (FAR), False Reject Rate (FRR), Equal Error Rate (EER) and recognition rate.

3 Experiments and Analysis

The experiments extract the palmprint images features using various layers of the network, and evaluate them on the PolyU palmprint database [23] for both recognition and verification tasks. All of our experiments are carried out on a PC machine with 3.30 GHz CPU, 4G memory and Matlab R2015b.

3.1 The PolyU Palmprint Database

The palmprint database of Hong Kong Polytechnic University (PolyU) is the most authoritative palmprint database in the world. It contains 7752 images of 386 different palms captured from two sessions with the size of each original image being 384×284 . The experiments use the first session of the database, including 3855 images from 386 palms. The image size of the region of interest (ROI) segmented is 128×128 pixels. The partial palmprint images after segmentation are given in Fig. 1.

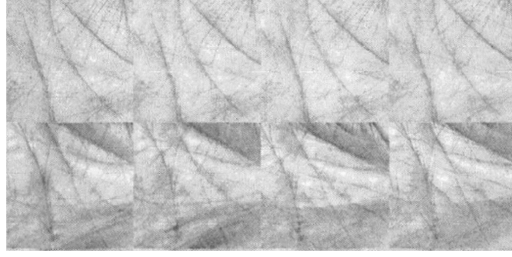


Fig. 1. Typical ROI images in PolyU palmprint database

3.2 The Verification Results

Figure 2 is the receiver operating characteristic (ROC) curve to evaluate the accuracy. Each point on the curve corresponds to the FAR and FRR under a safe threshold. A low value of EER indicates that our algorithm has a high recognition rate. We extract the convolutional features of the layers respectively, and use them to calculate the cosine distance of inter-class and intra-class palmprint images. Among the layers, the best performance is achieved by the features in 13th layer. In the curve, it is illuminated that the proposed method achieves the optimal verification accuracy of $EER = 0.25\%$.

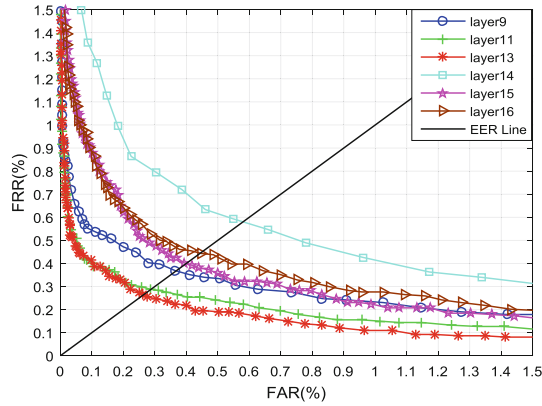


Fig. 2. The comparative ROC curves obtained by using various layers

Figure 3 is the matching degree distribution curve of true matching and false matching. The experiment adopts one to one matching strategy. A total of 91675 feature matching have been performed, in which the times of true matching (feature matching from the same palm) are 17370, the times of false matching (feature matching from different palms) are 78305. On the matching degree distribution curve, the distributions of true matching scores and false matching scores are similar to the Gauss distribution. The center of true matching scores is near 0.91 while the center of false matching scores is near 0.59. As show in Fig. 3, our method can effectively distinguish different palmprint images, which the two centers have a certain distance, and the intersection of the two curves is not much.

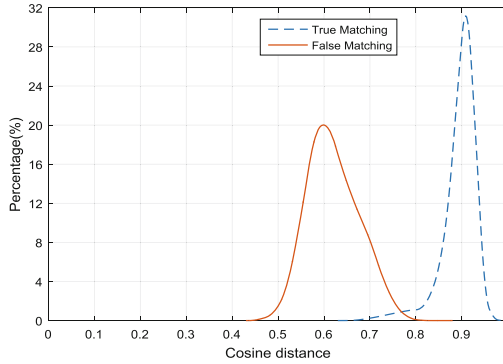


Fig. 3. Matching curves of intra-class and inter-class

Table 2 shows the proposed CNN-based method comparison of EERs with other methods, including WBFF [12], OWE [13], BDCT [24], 2D-DOCT [25], LLDP [26], WHOG-LSP and FVO-HOG-LSP [27].

Table 2. Comparison of EERs with other methods

Methods	EER(%)	Methods	EER(%)
WBFF	1.95	LLDP	0.37
OWE	1.37	WHOG-LSP	0.36
BDCT	1.07	FVO-HOG-LSP	0.55
2D-DOST	0.93	Proposed	0.25

3.3 The Identification Results

The CNN-F trained on the large-scale ImageNet database can extract genetic feature representations. It could be transplanted onto other image recognition tasks and achieve impressive performance [20, 21]. Here, due to the large difference of palmprint images with ImageNet database, we explore the performance of convolutional features of different layers from CNN-F. As shown in Fig. 4, our method with 1, 3 and 5 training images of each palm with different convolution layers of CNN-F achieves remarkable

performance. Among the layers, the best performance is achieved by the features in 8th–16th layers, which achieves 100% recognition rate on gallery set with 3 and 5 images per palm. Only using a single image per palm as gallery set, our method obtains a high identification accuracy of 99.62%. Then, the comparative recognition rate results with other state-of-the-art methods are shown in Table 3.

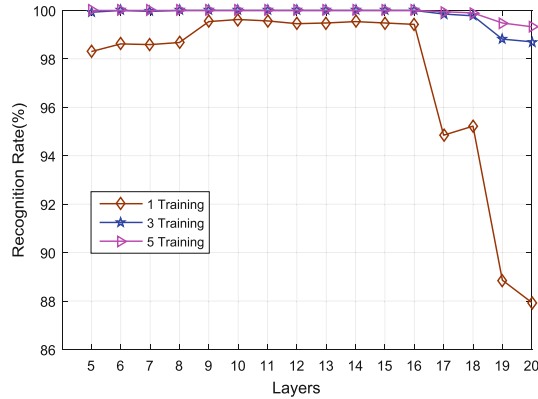


Fig. 4. The recognition rate results obtained by using palmprint features of different layers

Table 3. Recognition rates of different methods on PolyU database

Methods	Total samples	Different palms	Train samples	Recognition rate(%)
RLOC [5]	7752	386	1	98.37
Contourlet transform [28]	7752	386	3	88.91
2D-DOST [25]	900	150	3	97.29
BDCT [24]	2000	100	4	98.93
KPCA+GWR [29]	3860	386	4	99.69
OWE [13]	2000	100	5	98.90
2DGaborwavelets +PCNN [30]	3860	386	5	97.37
Proposed	3855	386	3	100

4 Conclusion

In this paper, we introduce deep convolutional features for palmprint recognition. The top layers of CNN-F describe the global features of palmprint images, but they include too much tuned for palmprint classification task. Meanwhile, the intermediate layers describe the local features of palmprint images, and they can serve as good descriptors for the new features of input images. Hence, extracted features from intermediate layers of CNN-F achieve better recognition performance than other layers. Moreover, even

without any training operation, the palmprint convolutional features of middle layers outperform most of the other baselines. In future, we mainly have two tasks. Firstly, we will give more pre-processing to the palmprint images on the PolyU database. Secondly, we should use data augmentation approach to obtain more training palmprint images, and then train a network with the palmprint images database to improve the recognition performance.

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