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Palmprint gender classification by convolutional neural network

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Abstract: Palmprint gender classification can revolutionise the performance of authentication systems, reduce searching space and speed up matching rate. However, to the best of their knowledge, there is no literature addressing this issue. The authors design a new convolutional neural network (CNN) structure, fine-tuning Visual Geometry Group Network, up to 19 layers to achieve a 20-layer network, for palmprint gender classification. Experimental results show that the proposed structure could achieve good performance for gender classification. They also investigate palmprint images with 15 different kinds of spectra. They empirically find that a palmprint image acquired by the Blue spectrum could achieve 89.2% correct classification and could be considered as a suitable spectrum for gender classification. The neural network is able to classify a 224 × 224 × 3-pixel palmprint image in <23 ms, verifying that the proposed CNN is an effective real-time solution.

1 Introduction

Gender classification is still an important problem that exists in biometric recognition. It plays a key role in many potential applications, such as passive demographic data collection, biometric authentication and intelligent human–computer interfaces. It can also be applied in different areas such as security systems and the forensic sciences.

These days, gender classification based on human characteristics such as face [1–3] finger [4–6] and iris [7, 8] are becoming more and more popular. For example, a number of techniques [9–12] have been proposed in recent years to classify gender using facial images and have achieved state-of-the-art results. Bansal *et al.* [13] used support vector machine (SVM) for iris-image-based gender classification, which achieved an 83.06% accuracy rate. Costa-Abreu *et al.* [14] combined multiple features including: geometric, texture and their combination for iris gender classification with a 90% accuracy rate. Shinde *et al.* [15] employed wavelet transformations and singular value decomposition methods to classify gender using fingerprint images.

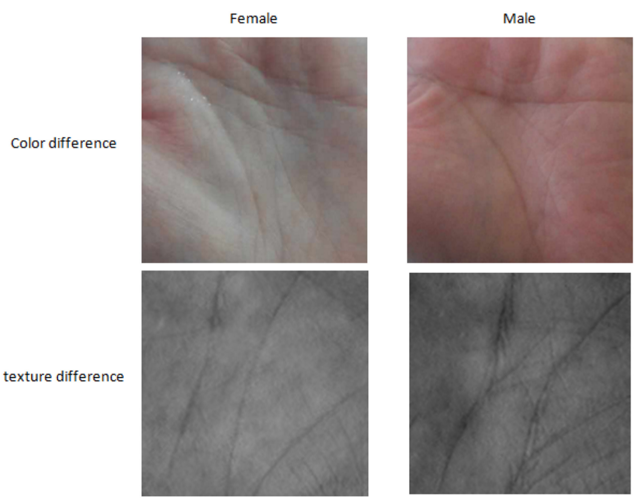

Fig. 1 *Palmprint image samples of a female and a male*

Although many achievements have been obtained in face, iris and fingerprint-based gender classification, there is no literature addressing gender classification by palmprint images. As shown in Fig. 1, there are many differences between the male and female palm, such as palm colour and texture. According to the study of Zhong *et al.* [16], there is a definite colour difference between healthy men and women. For example, a male's palm usually shows a reddish colour and dark partial state. Furthermore, the grip strength of a man is generally greater than that of a women's, so his palmprint line will be deeper and will contain different texture features. Overall, it is feasible to classify gender by palmprint imaging.

A common method of gender classification is to first extract features, and then use feature vectors to train a classifier, which requires a combination of several methods, such as, Fisher linear discriminant analysis [17], principal component analysis (PCA) [18], Adaboost algorithm [19] and SVM [20]. Some new feature extraction algorithms have been proposed recently. For example, to use generative prior knowledge, Gu *et al.* [21] proposed structural minimax probability machine to capture the structural information of the data from binary classification and demonstrated its effectiveness. To avoid the exceptions in ν-support vector classification (ν-SvcPath), Gu *et al.* [22] presented a new equivalent dual formulation for ν-SVC and, a robust ν-SvcPath, based on lower upper decomposition with partial pivoting. However, recently, convolutional neural network (CNN) has achieved great performance in image classification [23, 24] after the pioneering work by Krizhevsky *et al.* [25]. Some studies [26, 27] used CNN for face gender classification and achieved promising results. Thus, it motivates us to apply CNN for palmprint gender classification.

The main contributions of this paper could be summarised as follows:

(1) A proposal of an effective and real-time method for palmprint gender classification.
(2) A scheme of two-step training strategy for network fine-tuning, which could obtain better result and is easy to train.
(3) An empirical study using different spectra for palmprint gender classification resulting in the Blue as a suitable spectrum.

This paper is organised as follows: Section 2 discusses some prior works on gender classification. Section 3 describes the

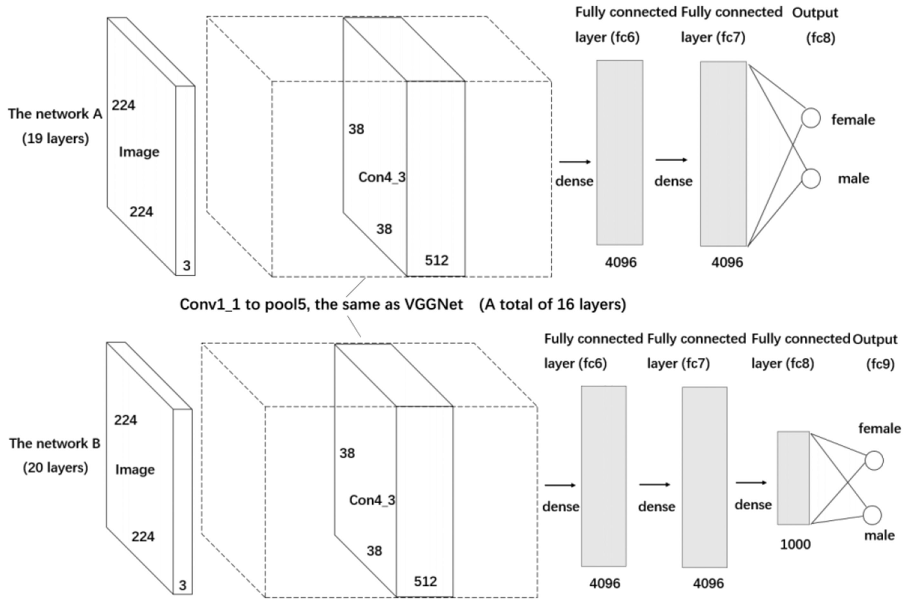

Fig. 2 *Network configuration*

architecture of two networks and introduces how to fine-tune the Visual Geometry Group Network (VGGNet) to fit the task of palmprint gender classification. Section 4 presents experimental results, and finally Section 5 concludes our work and discusses possible future works.

2 Related works

Although gender classification can play a significant role in biometric recognition, there still exists much exploration into recognition problems. Based on our understanding, most of the existing works can be divided into two categories. The first one extracts features and trains the classifier separately, while the second one combines feature extraction and classification in an end-to-end neural network (NN). In this section, we will discuss the related works briefly.

In the first category, there are many approaches for gender classification. Hassanpour *et al.* [28] applied PCA and the fuzzy clustering technique for facial gender classification, which achieved 91.89, 95.4 and 90.9% accuracy rates for the FG-Net, Stanford and FERET databases, respectively. Garg and Trivedi [10] combined Viola&Jones face detection [29], topographic independent component analysis feature extraction, and the SVM classifier for face gender classification. Badawi *et al.* [30] extracted different kinds of fingerprint features, such as ridge count, ridge thickness to valley thickness ratio and white line count. Then they applied three kinds of classifiers, fuzzy C-means, linear discriminant analysis (LDA) and NN classifiers, and obtained accuracy rates of 80.39, 86.5, and 88.5%, respectively. Gornale *et al.* [31] used discrete wavelet transform (DWT) to extract statistical features from a fingerprint with 91 and 89% classification rates obtained by using SVM with polynomial and RBF Kernels, respectively. For iris gender classification, texture features and statistical wavelet features are widely used. Bansal *et al.* [13] proposed a classification model based on SVM. Tapia *et al.* [32] explored uniform local binary patterns, and acquired over 91% correct gender prediction using the texture features of the iris.

In the second category, Tivive and Bouzerdoum [26] employed a novel shunting inhibitory CNN to classify gender, which had achieved 97.2% accuracy on the FERET face database. Using a CNN, Lagree and Bowyer [7] reported very high classification accuracies of 98.75 and 99.38% on the SUMS and AT&T databases, respectively. Zhang *et al.* [27] presented a method for gender classification by facial imaging based on CNN. Their experimental results showed that their approach could achieve better results on FERET and CAS-PEAL-R1 datasets. Rajan *et al.* [33] trained an NN to extract features from both iris and fingerprint images and finally achieved a joint feature vector to classify gender. Ceyhan *et al.* [34] proposed an artificial NN model to classify gender by a fingerprint image. Generally speaking, the above-mentioned CNN-based and NN-based approaches demonstrate potential in achieving a superior performance for gender classification.

3 Architecture of the proposed method

The VGGNet achieves state-of-the-art image classification performance, which also took the second place in the ILSVRC-2014 (ImageNet Large Scale Visual Recognition Challenge) classification challenge [35]. There are five configurations of VGGNet, which denoted as VGGNet-A, B, C, D, E. Here, we choose VGGNet-E, which could get the best result in our experiments. We fine-tune the VGGNet-E (up to 19 layers) to classify the gender of palmprint images for the following two reasons. First, it is a good model that has been trained by a large-scale dataset, whereas there are limited palmprint images to train a net directly. Second, VGGNet has a deep network that can extract many abstract or high-level palmprint features. Thus, it is conducive to find out the difference between different gender palmprint images.

In this section, we reveal how to fine-tune the VGGNet model and get a new network. In the following, we will refer to the nets by their names (A, B). We pre-train network A which is a basic network of network B. Network B could achieve better results for palmprint gender classification. All configurations following the generic design are presented in Fig. 2.

We followed these steps to get to network B. Firstly, we began with training network A, which was similar to VGGNet (19 layers) but differed under the fully connected layer FC6. The last two fully connected layers were named as FC7 and FC8, initialised by Gaussian random numbers and the layers before FC7 were initialised with VGGNet. In FC7, all the biases were initialised with 1, the value of standard deviation of the Gaussian distribution was set to 0.005. The activation function *f* was rectified linear units (Relu):

$$x^{\ell} = f(u^{\ell}), \quad \text{with } u^{\ell} = W^{\ell} x^{\ell - 1} + b^{\ell} \tag{1}$$

$$\mathrm{Relu}(u^{\ell}) = \max\,(u^{\ell}, 0) \tag{2}$$

where ℓ denotes the current layer, W^{ℓ} is the weight of λ layer, $x^{\ell-1}$ represents the output of $\ell - 1$ layer (input of current layer), b^{ℓ} is the bias. u^{ℓ} is the input of Relu. In FC8, the biases were initialised with 0, the value of standard deviation of the Gaussian distribution was 0.01. The above-mentioned values for biases and standard

Table 1 Some important parameters for the proposed network

Momentum (m)	Initial learning rate (α)	Step size	Batch size
0.9	0.001	1000	40

Table 2 Detail information of the palmprint datasets

Dataset	Number of images	Number of male's hand	Number of female's hand	Number of palmprint images for each hand	Number of Spectra
PolyU multispectral palmprint [39]	12,000	412	88	24	15
CASIA palmprint image database [40]	11,004	476	148	1∼16	1

deviations were chosen empirically. There were three fully connected layers in the configuration of network A, the first two had 4096 neurons, and the third one performed two-class classification and thus contained two neurons (one for each class). The final layer was the soft-max transform layer. During training, the layers before the fully connected layer FC7 were initialised with VGGNet, and then fine-tuned layers until FC6 by back propagation [36]. Back propagation is followed by (3)–(5). (More details could be found in [37].)

$$E^N = \frac{1}{2}\sum_{n=1}^{N}\sum_{k=1}^{c}(t_k^n - y_k^n)^2 \tag{3}$$

$$\frac{\partial E}{\partial b} = \frac{\partial E}{\partial u}\frac{\partial u}{\partial b} = \delta \tag{4}$$

$$\delta^{\ell} = \left(W^{\ell+1}\right)^{\mathrm{T}}\delta^{\ell+1} \circ f'\left(u^{\ell}\right) \tag{5}$$

For a multi-class problem with N training samples and c classes, the training error E is given by (3). Here t_k^n is the kth dimension of the nth pattern's corresponding target (label), similarly, y_k^n is the value of the kth unit in the output layer. δ can be thought as the 'sensitivities' of each unit with respect to bias b and in the case $\partial u/\partial b = 1$. Where '$\circ$' denotes element-wise multiplication. The 'errors' which we propagate backwards through the network can be thought of as 'sensitivities'. According to the training error computed by (3), we can compute the sensitivities by (4). Since the sensitivity and the derivative of the error with respect to a unit's input is equivalent, sensitivities could be back-propagated from higher layers to lower layers using (5).

The training was carried out using mini-batch gradient descent [38] (based on back propagation) with momentum. A mini-batch gradient descent with learning rate α and momentum m updates the weight W as

$$W = m \times W - \alpha\frac{\partial E}{\partial W} \tag{6}$$

The batch size was set to 256, m was 0.9, and initial α was set to 0.001 and was divided by 10 for every 1000 iterations (step size). These parameters were chosen empirically. Within 3000 iterations, we found that the verification accuracy was improving, and the training loss was declining. However, after 3000 iterations, training loss stopped declining and further training could not improve the model. Thus, we trained the network for 3000 iterations. Finally, network A model was obtained.

Then, we modified the configuration of network A to get network B. The latter contained one more fully connected layer (FC8), so it had 20 layers in total. Since there are limited palmprint images, it is hard to train a good deep net directly. Instead training a 20-layer network directly, we use a two-step training strategy. First, network A was trained by the training set. Then, network A was applied to initialise network B, and the above-mentioned training rule was utilised for network B. The original VGGNet is a 1000-class classifier, so in its last two fully connected layers the number of neurons changed from 4096 to 1000. However, in our network A, the neurons changed from 4096 to 2. Such a sudden change may influence performance, thus in an effort to transition smoothly the number of neurons in the additional layer (FC8) was set to 1000. Similar as in network A, the weight parameters of FC8 and FC9 in network B were initialised by Gaussian random numbers, while the other layers were initialised by network A. We also fine-tuned layers until FC6 by back propagation. Network B was trained for 2000 iterations. After 2000 iterations, the verification accuracy remained almost the same and the training loss did not drop. Some important parameters for training are presented in Table 1.

4 Experimental results

4.1 Dataset

PolyU multispectral palmprint database. It contains 15 kinds of palmprint images, which were taken from 15 different spectra using an equipment developed by the PolyU Biometric Research Center [39]. The spectra include Blue, Blue_Infrared, Green, Green_Blue, Green_Blue_Infrared, Green_Infrared, Infrared, Red, Red_Blue, Red_Blue_Infrared, Red_Green, Red_Green_Blue, *Red_Green_Blue_Infrared, Red_Green_Infrared and Red_Infrared*. There are 206 males and 44 females, each hand has 12 images under each spectrum, so each person has 24 images by each spectrum. Totally, this database includes 250 people and 90,000 images. To expand our data set, we mirrored every palmprint image, so that each spectrum contained 500 hands and there were 24 images for each hand.

CASIA palmprint image d. It contains 5502 palmprint images captured from 312 subjects (74 females and 238 males). For each subject, the palmprint images from both left and right palms were collected. All palmprint images are 8-bit grey-level JPEG files [40]. We also mirrored every palmprint image. Table 2 shows detail information of these two databases.

4.2 Data preprocessing

After region of interest extraction [39], a fixed-size 128 × 128 greyscale image was cropped for each palmprint image. Since the input of VGGNet is a fixed-size 224 × 224 RGB image, we converted the grey image to colour by duplicating the grey channel first. Then we expanded the image by linear interpolation. Finally, the image is 224 × 224 × 3-pixel, as shown in Fig. 3. We empirically found that duplicating grey channel and getting a 'fake' colour image could get better results than using a greyscale image directly. It is probably because VGGNet is trained by a large scale of colour images and more suitable for RGB input.

4.3 Model comparison

There are several models which achieve state-of-the-art performance on image classification tasks, such as VGGNet, GoogLeNet [24] (Google Network), and AlexNet [25] (Alex Krizhevsky Network). In this section, we will compare these three popular models on the task of palmprint gender classification. Here, we utilised these models as a feature extractor and used SVM for classification. This is mainly because SVM is a binary classifier that can optimally separate two classes. It exhibits many

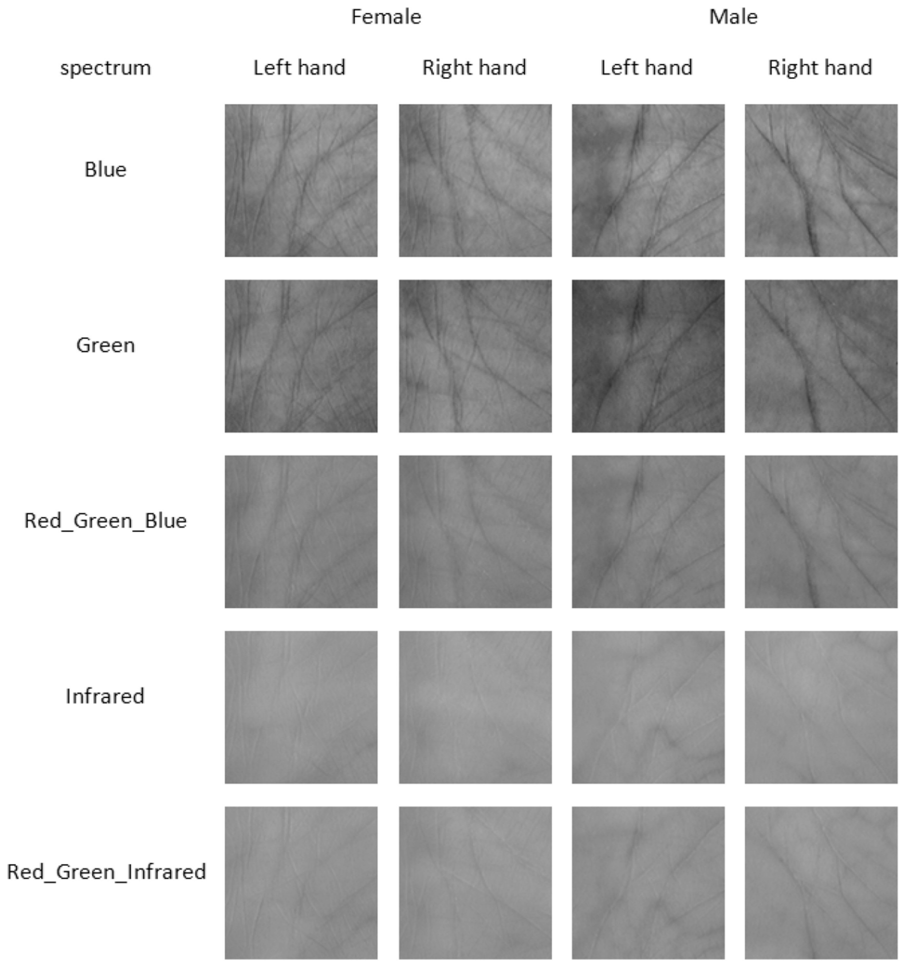

Fig. 3 *Palmprint image samples of PolyU database*

Table 3 Experimental results for SVM

Method	Kernel function	Average accuracy, %	Standard deviation, %	Average accuracy of female, %	Average accuracy of male, %
VGGNet + SVM	linear	60.22	10.68	26.09	93.30
	polynomial	50.43	2.31	0.00	100.00
	radial basis	48.78	1.96	85.85	11.11
AlexNet + SVM	linear	71.19	6.38	65.64	76.06
	polynomial	49.99	2.21	59.52	40.00
	radial basis	48.90	1.89	87.26	10.00
GoogLeNet + SVM	linear	57.12	8.24	16.56	96.11
	polynomial	48.59	7.44	46.12	49.92
	radial basis	47.84	2.29	74.70	20.00

advantages in solving the small sample size problem, and it has been successfully applied in gender classification [13, 31, 41]. We obtained a 4096-dimensional feature vector in the FC7 layer of VGGNet and AlexNet, which was a fully connected layer but output a global feature of one image. As for GoogLeNet, a 1024-dimensional feature in the last average pool layer was acquired. First, these features were used to train SVM directly. Then, we applied PCA [18] and LDA [42] to reduce dimension, and trained SVM again. In order to find out the best model for palmprint gender classification, 10-fold cross validation was carried out on the CASIA palmprint image database. The training set contained 4032 images (126 hands from female and male, respectively), and we selected 448 images (14 hands from female and male, respectively) as a test set. Different kernel functions were tested and their results are reported in Tables 3 and 4. The average accuracy was obtained by the following equations:

$$X_i = \frac{C}{N} \times 100\% \quad (7)$$

$$\bar{X} = \frac{\sum_{i=1}^{n} X_i}{n} \quad (8)$$

$$S = \sqrt{\frac{\sum_{i=1}^{n} (X_i - \bar{X})^2}{n(n-1)}} \quad (9)$$

where X_i denotes the ith correct classification rate, C is the number of correct trails, N is the number of testing samples. $\bar{X}$ is the average of X_i, because we carry out 10-fold cross validation, so $n = 10$. S denotes the standard deviation.

The results in Table 4 indicate that using PCA and LDA for dimension reduction performs better for CASIA database. The features extracted from the deep nets are redundant for binary classification. It can be found that VGGNet outperforms the other two models. It achieves the highest accuracy of 75.17% and a standard deviation of 6.93%. Although AlexNet could achieve 74.37% accuracy and 6.85% standard deviation which are close to

Table 4 Experimental results for PCA + LDA + SVM

Method	Kernel function	Average accuracy, %	Standard deviation, %	Average accuracy of female, %	Average accuracy of male, %
VGGNet + PCA + LDA + SVM	linear	70.59	5.85	50.51	89.89
	polynomial	75.17	6.93	72.67	76.95
	radial basis	74.55	7.09	69.40	78.97
AlexNet + PCA + LDA + SVM	linear	69.63	8.72	48.51	90.08
	polynomial	73.82	6.72	69.85	77.16
	radial basis	74.37	6.85	68.52	79.59
GoogLeNet + PCA + LDA + SVM	linear	60.08	5.89	23.28	96.18
	polynomial	68.87	12.34	48.8	88.17
	radial basis	67.37	10.99	51.58	82.39

Table 5 Experimental results for blue spectrum

Method	Kernel function	Average accuracy, %	Standard deviation, %
VGGNet + SVM	linear	88.7	1.7
	polynomial	85.7	2.7
	radial basis	87.8	2.7
VGGNet + PCA + LDA + SVM	linear	82.4	4.8
	polynomial	78.0	11.3
	radial basis	82.5	4.8
fine-tune VGGNet (network A)		86.9	2.2
fine-tune VGGNet (network B)		92.1	2.7

VGGNet, its average accuracy between female (68.52%) and male (79.59%) is much different, unlike VGGNet which can get similar performance for female (72.67%) and male (76.95%). This is mainly because VGGNet is a deep net with small filters, which help to extract many abstract or high level palmprint features. As can be seen in Fig. 3, the palmar friction ridges and the palmar flexion creases are long and thin, small filters can extract richer feature information while larger filters may ignore details. Meanwhile, a deep net contributes a lot for in-depth features extraction which are beneficial to palmprint gender classification. Although VGGNet has more parameters and more layers than AlexNet, it can converge quickly without many iteration [35]. Thus, in the following, we apply VGGNet as a basic tool for palmprint gender classification.

4.4 Single spectrum experimental results

In order to test the performance of the proposed method, 10-fold cross validation was carried out for the Blue spectrum of the PolyU multispectral palmprint database. Owing to the limited sample of palmprint images, in order to make full use the training set, here, we combine all training images of 15 spectra as a whole training set to train VGGNet. Each spectrum has 88 hands for training (44 hands from female and male, respectively, totally 2112 images, and half of them are original images), 32 hands for validation (16 hands from female and male, respectively, totally 768 images, and half of them are original images), and 56 hands for testing (28 hands from female and male, respectively, including 672 original and 672 mirrored images). There is no imbalance between male and female in these three datasets.

From Table 5, we can find that the performance of the first three kernel functions is similar and using linear kernel could achieve an 88.7% accuracy rate. If the training set is composed of only one spectrum, accuracy will drop nearly 15%. However, their average prediction accuracy is still higher than the network A (86.9%), which is achieved by fine-tuning VGGNet. Unlike CASIA, feature reduction by PCA and LDA could not improve performance. This is probably because with enough training data, VGGNet is not overfitting and the extracted features could represent the image well, thus linear feature reduction brings a negative effect.

From Table 5, we can find that the accuracy of the network A is 86.9%. However, after we change the network A to attain network B, it achieves the highest accuracy. Meanwhile, the standard deviation of network B is as low as 2.7%. The experimental results show that fine-tuning VGGNet for palmprint gender classification performs superiorly with a 92.1% accuracy rate. It validates the effectiveness of the proposed two-step training strategy. However, many parameters were set empirically, we believe performance could be further improved by tuning parameters.

We also follow the two-step training strategy to train a model using the CASIA palmprint image database, the results are shown in Table 6. The training validation and test set contained 3584 images (112 hands from female and male, respectively), 448 images (14 hands from female and male, respectively), respectively, 448 images (14 hands from female and male, respectively), respectively. Similarly, 10-fold cross validation was carried out. As can be seen in Table 6, the proposed method could achieve 80.09% recognition accuracy with 8.73% standard deviation. Compared with the result on PolyU multispectral palmprint database, it does not achieve the same high accuracy. This is probably because the CASIA palmprint image database contains some noise, and the number of palmprint images is too small for training a deep net.

4.5 Multi-spectrum experimental results

In Section 4.4, we have showed the optimal performance of network B by fine-tuning the VGGNet. In order to investigate the best spectrum for gender classification, a 10-fold cross validation was implemented again. We followed the steps that were introduced in Section 4.4 to get a classification model for all spectra by all training sets and tested every spectrum by its individual test set. In order to verify the robustness of the model, the test set was added with 324 male hands, so that it involves 28 female hands (including 336 original images and 336 mirrored images) and 352 male hands (including 4224 original images and 4224 mirrored images) for each spectrum. A 10-fold cross validation was carried out and the results are outlined below in Table 7.

The recognition rate of the different genders was shown for better analysis. Palmprint gender classification is not only related to the texture characteristics of a male and female palm but also associated with different spectral imaging effects. Taking the Red spectrum as an example, it penetrates the skin up to a certain depth. Thus, it not only captures most of the palm line information but also captures some palm vein structures, which play an important role in classifying those palmprints with similar palm lines. Since the female's palm skin is thinner than the male's, their vein imaging

Table 6 Experimental results in CASIA palmprint image database

Method	Kernel function	Average accuracy, %	Standard deviation, %	Average accuracy of female, %	Average accuracy of male, %
VGGNet + PCA + LDA + SVM	linear	70.59	5.85	50.51	89.89
	polynomial	75.17	6.93	72.67	76.95
	radial basis	74.55	7.09	69.40	78.97
VGGNet + SVM	linear	60.22	10.68	26.09	93.30
	polynomial	50.43	2.31	0.00	100.00
	radial basis	48.78	1.96	85.85	11.11
Fine-tune VGGNet (network B)		80.09	8.73	82.64	77.6

Table 7 Gender classification by different spectra using the proposed network B

Light source	Average accuracy, %	Standard deviation, %	Average accuracy of female, %	Average accuracy of male, %
Blue	89.2	0.7	87.2	89.3
Blue_Infrared	84.4	1.8	91.8	83.8
Green	89.2	1.9	77.5	90.1
Green_Blue	88.4	1.2	86.6	88.6
Green_Blue_Infrared	80.1	2.6	95.3	78.9
Green_Infrared	79.7	3.1	92.8	78.6
Infrared	76.2	3.7	92.1	74.9
Red	79.3	2.8	92.0	78.3
Red_Blue	78.8	2.2	97.6	77.3
Red_Blue_Infrared	82.8	2.2	94.6	81.9
Red_Green	79.5	2.8	94.8	78.3
Red_Green_Blue	79.3	2.4	96.8	77.9
Red_Green_Blue_Infrared	84.7	2.2	94.0	84.0
Red_Green_Infrared	83.2	2.5	94.3	82.3
Red_Infrared	83.2	2.2	92.1	82.4

effect is better than that of a male palm, which is good for gender classification of female palmprints. Thus, the female average rate (92.0%) is higher than the male (78.3%). As for the Red_Blue and Red_Green spectrum, both of them have similar performance in average accuracy but behave poorly in classifying male palmprints. This is mainly because Blue and Green are correlated [43] while Red shows superiority in female palmprint classification. Under the spectrum of Red_Green_Infrared, the average prediction accuracy reached 83.2%. However, the standard deviation (2.5%) is a little large, so that the performance of this model is not stable. We may get a poor performance by using such spectrum for palmprint gender classification.

A comprehensive comparison of these statistical values finds that Blue spectrum in palmprint gender classification is the best one, reaching a rate of 89.2%. What is more, the male and female classification performance is nearly the same, and the standard deviation is small (0.7%). As a different spectrum could enhance different features of palms while Blue collects much palm line information [44], so it could enhance most of the useful features for gender classification and achieve a good accuracy.

4.6 Comparison with other biometrics

In the past, many approaches have been proposed for gender classification. Table 8 shows some state-of-the-art performance for gender classification by different biometric traits. Our work has achieved good performance among them. Compared with iris [47, 48] or fingerprint [49–51], palmprint images have a large area containing rich information and can be easily collected. Furthermore, texture features are much more stable. The acquisition equipment is simple and the cost is much lower than iris recognition acquisition devices. Moreover, scientific studies have shown that biological characteristics of the hands are the least infringed when they are collected. These demonstrate that palmprints have an advantage over other biometrics. Our experiments demonstrate the potential of achieving a broad application in gender classification by palmprint imaging. Nowadays, biometrics systems are facing spoofing. For example, some artificial fingerprints can trick the fingerprint authentication system and access information using real users' identification. Therefore, a fingerprint liveness detection algorithm needs to be designed to prevent illegal users from accessing private information. For example, Yuan *et al.* [52] presented a software-based liveness detection approach using multi-scale local phase quantity and PCA to detect the liveness of users achieving high recognition accuracy. Since liveness detection is a binary classification task. We may apply the proposed network for palmprint liveness detection in the future.

4.7 Computation cost

We use a workstation with Windows Server 2012 R2 for our experiments. Its hardware includes Intel(R) Core(TM) Xeon(R) 2.00 GHz CPU, 128 GB memory, and GeForce GTX TITAN Z (3 GB memory). Computation cost for different methods is illustrated in Table 9. It shows that the proposed method could be used for real-time applications.

5 Conclusion

In this paper, an effective and feasible method for gender classification by palmprint images is proposed. Our work demonstrates that using a two-stage method to fine-tune the VGGNet could achieve sound performance. By analysing different spectra, palmprint imaging by Blue spectrum is shown to be the most suitable one for gender classification. In the future, we will study how to apply the proposed work for palmprint identification system, which aims at reducing searching space, and speeding up matching rate.

6 Acknowledgments

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Table 8 State-of-the-art gender classification performance by different biometric traits

Biometrics	Method	Accuracy	Dataset
fingerprint	DWT + SVM(polynomial) [31]	89%	300 males and 300 females fingerprints collected by the authors
	DWT + SVM(RBF) [31]	91%	
	DWT + SVD + KNN [45]	88.28%	An un-published database of 3570 fingerprints, 1980 for male and 1590 for female.
iris	LBP [32]	91%	UND iris database: it contains 750 females and 750 males, with 3000 images totally
	Iriscode [46]	89%	Gender-From-Iris dataset for training: it contains 1200 distinct persons and 2400 images A self-collected dataset UND_V for validation, contains 972 persons
face	CNN [3]	98.75 and 99.38% on the SUMS and AT&T databases	SUMS database: consists of 200 females and 200 male images AT&T database: contains 10 images of 40 subjects (36 males and 4 females)
	PCA [28]	91.89, 95.4 and 90.9% accuracies for the FG-Net, Stanford and FERET databases	In FERET facial database, they used 200 images for testing The Stanford database consists of 200 males and 200 female images The face and gesture net database contains 400 females and 400 male images
palmprint	Fine-tune the VGGNet (the proposed network B)	89.2% under Blue spectrum	PolyU Multispectral Palmprint database: it contains 500 hands, a total of 6000 images under each spectrum. There are 15 different kinds of spectra. We flipped the data set so that there were 672 female images and 8448 male images for testing under every spectrum

Table 9 Execution time

Methods	Average test time, ms
fine-tune VGGNet (network A)	21.9
fine-tune VGGNet (network B)	22.5
VGGNet + PCA + LDA + SVM	5.8
VGGNet + SVM	16.1

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