AN ENSEMBLE LEARNING METHOD BASED ON RANDOM SUBSPACE SAMPLING FOR PALMPRINT IDENTIFICATION

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ABSTRACT

Palmprint recognition is an important and widely used biometric modality with high reliability, stability and user acceptability. In this paper we propose a simple and effective ensemble learning method for palmprint identification based on Random Subspace Sampling (RSS). To achieve it, we rely on 2D-PCA to build the random subspaces. As 2D-PCA is an unsurpevised technique, features are extracted in each subspace using 2D-LDA. A simple 1-Nearest Neighbor classifier is associated to each subspace, the final decision rule being obtained by majority voting rule. The experimental results on multispectral and PolyU palmprint datasets show very encouraging performances compared to state-of-the-art techniques.

***Index Terms*—** Biometrics, palmprint, ensemble learning, random subspace sampling

1. INTRODUCTION

Over the past few decades, biometrics have become an important tool to enhance security. A large variety of biometric modalities including face, gait, iris, and palmprint have been studied providing different rates of accuracy and robustness [1, 2]. In this work, we consider to enhance human identification based palmprint due to its high reliability, stability, and user acceptability. A palmprint is defined as the inner surface of a hand containing a large variety of discriminative features [3]. Various palmprint recognition methods have been proposed, they can be broadly organized in two main categories: holistic and structural. The fist one attempts to define the whole palmprint image as a single data set while the second one is based on local information including lines and texture.

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1.1. Holistic Techniques

The holistic or global methods attempt to process palmprint image as a whole. They can be divided into two main subcategories: i) subspace-based and ii) representation-based.

Subspace-based approaches

These techniques seek to find a transformation mapping the original data residing in a high-dimensional space into a lower one using statistical learning techniques such as, PCA, 2D-PCA, ICA, LDA, 2D-LDA and 2D-LPP [4].

Representation-based approaches

In this setting, the query image is considered as a linear combination of all training samples. It is common that the palmprint of a specific subject lies in a linear subspace. With this assumption, the query image is expected to be well represented by the training samples of the same subject, which may lead to a sparse representation over all training data. Sparse Representation-Based Classification (SRC) method [5, 6] and Linear Recognition Classification (LRC) [7] are two representative techniques.

1.2. Structural Methods

The structural or local approaches rely on the extraction of the lines and texture features from the palmprint image. The structural methods can be organized in three sub-categories: i) line, ii) coding and iii) texture based described below.

Line-based approaches

Palmprint lines represent the basic features for recognition. Several works have tried to apply various edge detection techniques to extract the palm lines for recognition [8]. Unfortunately, the performance of these algorithms strongly depends upon the accuracy of the underlying line detectors.

Coding-based approaches

They encode the responses of a bank of filters into bitwise codes. A large variety of coding methods using various number of Gabor filter orientations have been introduced including Palm Code [9] Competitive Code [10] Ordinal Code [11] Fusion Code [12], Robust Line Orientation Code (RLOC) [13], Binary Orientation Co-occurrence Vector (BOCV) [14], E-BOCV [15] and Half Orientation Code (HOC) [16].

Texture feature extraction

In this approach, the palm features are generated using texture feature extractors including LBP, HOG and their variants [17].

2. MOTIVATIONS AND CONTRIBUTIONS

From the afore introduced overview of palmprint techniques, feature extraction and learning appears to be a key tool for successful recognition system. The exploited features in the literature can be roughly divided into features designed by relying on predefined human knowledge (coding-based), features issued from global or local elaborated transforms and automatically learned (representation-based). Coding methods currently represent the most influential and suitable for one-to-one verification applications. Unfortunately, they have also some limitations for identification (i.e. one-to-all) due to their high computation cost [18]. In the present paper, we introduce a novel holistic subspace learning method for palmprint identification directly applied to image pixels. The contributions are listed below:

- The conventional subspace representation learning methods in palmprint identification mainly rely on a single projection subspace and an embedded classifier, hence their performances are sensitive to the selected dimensionality of the subspace. Indeed, a small subspace might loose discriminative information while a large one could lead to overfitting [19]. In addition to that, palmprint recognition suffers from the limited training samples per class. To tackle these problems we explore an ensemble learning approach based on Random Subspace Sampling (RSS) which has the advantage to provide more generalization ability and reduce the sensitivity due to the limited size of training data.

- Sampling features from the whole palmprint image in order to construct the ensemble may destroy inherent local spatial relationship among pixels within the image [20]. The introduced RSS constructs multiple subspaces by a random procedure on 2D-PCA space while keeping image spatial structure.

- As 2D-PCA is unsupervised feature extraction, discriminative features are extracted in each subspace using 2D-LDA.

3. PROPOSED METHODOLOGY

We intend to build an ensemble of representations across varying discriminative subspaces. To this end, we use 2D-PCA [21] to build an initial space (a space spanned by the eigenvectors associated to leading eigenvalues of the covariance matrix) from which subspaces are randomly sampled. Under this 2D-PCA model, each palmprint image is projected into a new matrix in each subspace. However, as 2D-PCA acts in an unsupervised manner, resulting images in each subspace are further transformed through 2D-LDA [22] to ensure class separability and more discrimination ability. Nearest Neighbor classification (NN) rule, which has shown good ability to deal with such discrimination problems, is applied to each subspace. The final classification decision is obtained by majority voting among the individual NN classifiers.

3.1. 2D Principal Component Analysis (2D-PCA)

Given a set of palmprint images $\{\mathbf{X}_i \in \mathbb{R}^{n_1 \times n_2}\}_{i=1}^{n}$, 2D-PCA [21] is used as the first step to reduce the dimensionality of the data. Contrary to conventional one-dimensional PCA, 2D-PCA preserves the matrix structure of $\mathbf{X}_i$. Formally, 2D-PCA aims at finding a transformation matrix $\mathbf{R} \in \mathbb{R}^{n_2 \times d}$ which projects each image $\mathbf{X}_i$ on to a matrix $\mathbf{Z}_i = \mathbf{X}_i \mathbf{R} \in \mathbb{R}^{n_1 \times d}$ of reduced dimension ($d \leq n_2$). It solves the following optimization problem

$$\max_{\mathbf{R} \in \mathbb{R}^{n_2 \times d}} \ \text{Trace}\left(\mathbf{R}^\top \mathbf{S} \mathbf{R}\right) \quad \text{s.t.} \quad \mathbf{R}^\top \mathbf{R} = \mathbf{I} \qquad (1)$$

where $\mathbf{S} = 1/n \sum_{i=1}^{n} \left(\mathbf{X}_i - \bar{\mathbf{X}}\right)^\top \left(\mathbf{X}_i - \bar{\mathbf{X}}\right)$ is the covariance matrix and $\bar{\mathbf{X}}$ is the mean of training images. The solution $\mathbf{R}^*$ of (1) corresponds to the d-dominant eigenvectors of $\mathbf{S}$. Any image can be projected in the subspace spanned by the columns of $\mathbf{R}^*$ as

$$\mathbf{Z}_i = \mathbf{X}_i \mathbf{R}^* \in \mathbb{R}^{n_1 \times d} \qquad \forall\, i = 1, \cdots, n \qquad (2)$$

3.2. Random Subspace Sampling (RSS)

Random sampling from original image is time-consuming and often breakdowns inherent local spatial relationship among pixels [20]. To tackle this problem, we sample subspaces from the 2D-PCA space obtained in the last step. We consider L subspaces, each spanned by $N \ll d$ randomly selected eigenvectors from $\mathbf{R}^*$. Hence, starting from the solution of 2D-PCA, we generate L projection matrices $\left\{\mathbf{R}_\ell \in \mathbb{R}^{n_1 \times N}\right\}_{\ell=1}^{L}$ where $\mathbf{R}_\ell$ is a set of N randomly sampled columns from $\mathbf{R}^*$. For each matrix $\mathbf{R}_\ell$, we proceed as follows: the whole training data is projected in to the subspace spanned by the corresponding eigenvectors giving $\left\{\mathbf{Z}_i^\ell = \mathbf{X}_i \mathbf{R}_\ell\right\}_{i=1}^n$.

3.3. 2D Linear Discriminant Analysis (2D-LDA)

To obtain more class-separability in each subspace ℓ, 2D-LDA is applied to the features $\left\{\mathbf{Z}_i^\ell\right\}_{i=1}^n$. It seeks to determine a projection matrix $\mathbf{W}_\ell \in \mathbb{R}^{n_1 \times m}$, for fixed $m \leq n_1$ in order to maximize class separability. 2D-LDA seeks to maximize and minimize the between-class and within-class variances leading to the optimization problem [22]

$$\max_{\mathbf{W}_\ell \in \mathbb{R}^{n_1 \times m}} \operatorname{Trace}\left(\mathbf{W}_\ell^\top \mathbf{S}_w^\ell \mathbf{W}_\ell\right)^{-1}\left(\mathbf{W}_\ell^\top \mathbf{S}_b^\ell \mathbf{W}_\ell\right) \quad (3)$$

where $\mathbf{S}_b^\ell$ and $\mathbf{S}_w^\ell$ are the between-class and within-class scatter matrices. The solution $\mathbf{W}_\ell^*$ of problem (3) corresponds to the m leading eigenvectors of $(\mathbf{S}_w^\ell)^{-1}(\mathbf{S}_b^\ell)$.

To sum up, starting from the raw palmprint images $\mathbf{X}_i$, the application of 2D-PCA followed by 2D-LDA brings to the representation $\mathbf{B}_i^\ell \in \mathbb{R}^{m \times N}$ on which relies the classification system given by

$$\mathbf{B}_i^\ell = \mathbf{W}_\ell^{*\top} \mathbf{Z}_i^\ell \;\; \forall\, i = 1, \cdots, n \;\; \& \;\; \forall\, \ell = 1, \cdots, L \quad (4)$$

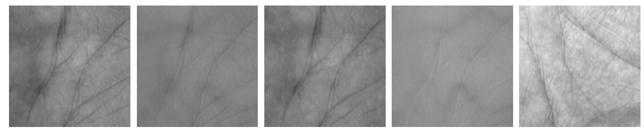
4. EXPERIMENTS AND RESULTS

We performed a series of experiments to evaluate the proposed approach on two publicly available palmprint datasets: multi spectral [23] and PolyU [9]. The obtained results are compared with seven state-of-art holistic methods including PCA, 2D-PCA, LDA, 2D-LDA, 2D-LPP [4], SRC [5] and LRC [7]. In addition to eight structural coding-based techniques including Palm [9], Competitive [10], Ordinal [11], Fusion [12], BOCV [14], E-BOCV [15], RLOC [13] and HOC [16]. For fair comparisons, we have followed the protocols and data splits proposed by Fei *et al.* [16].

The multispectral dataset [1] contains four spectral bands including red, green, blue and NIR. Twelve palmprint images were captured for each hand from 250 subjects. The PolyU dataset [2] contains 187 subjects, where ten palmprint images were captured per hand. Note that for both datasets, two hands of the same subject are considered as two distinct classes.

4.1. Experimental Setting

In our experiments we have used the provided 32×32 palmprint region of interest as is shown in Figure 1. The accuracy is measured by the Correct Classification Rate (CCR) corresponding to the ratio of correct classified images to overall images. We perform our experiments with 2 and 4 training samples and the remaining ones as test. Each experiment is repeated 10 times to average out the effect of random subspace sampling and we report the mean accuracy and standard deviation.



(a) Blue (b) Red (c) Green (d) NIR (e) PolyU

Fig. 1. Example of palmprint region of interest (ROI). (a)-(d) multispectral dataset. (e) PolyU dataset.

The proposed method involves three tuning parameters: the dimension of the random subspace N, the number of projection directions of the 2D-LDA m and the number of subspaces L. The parameters N and m can be easily optimized using a cross-validation scheme due to their limited range (either n_1 or n_2). Hence they are selected among the set $\{2, 4, \cdots, 30\}$. The choice of L appears demanding as we do not have beforehand any hint about its convenient range. However inspiring from [24] we set $L = 500$, a sufficiently high value in order to draw diverse random subspaces and ensure good generalization ability. This empirical choice was further confirmed by the impact of hyper-parameters analysis conducted in Section 4.3.

4.2. Results

Tables 1 and 2 compare the accuracy of our method to other state-of-the-art techniques using 2 and 4 training samples respectively. The best two results are highlighted by bold and underline. It can be seen that the proposed method has outperformed all holistic and structural coding-based techniques included in this study. It can be also noticed that the proposed method outperforms single subspace learning techniques. Indeed, our ensemble learning strategy significantly improves over these conventional techniques based on a single subspace and classifier such as PCA/2D-PCA and LDA/2D-LDA. Finally, it can be observed that the coding methods perform good and frequently outperform the conventional holistic approaches.

4.3. Impact of Hyper-Parameters Analysis

In the conducted analysis, we fix two parameters and we check the accuracy's sensitivity to the third one by changing its value within a range. In the following we consider $L \in [100, 500]$, $N \in [2, 30]$ and $m \in [2, 30]$ (see Figure 2).

In order to build performing ensemble classifier, we seek to learn a large number of classifiers on different and discrimi-

[1] www4.comp.polyu.edu.hk/~biometrics/MultispectralPalmprint/MSP.htm

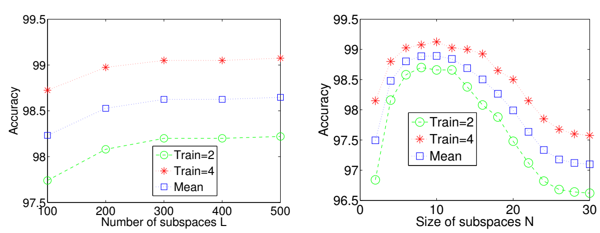
[2] www4.comp.polyu.edu.hk/~biometrics/index.htm

Table 1. Palmprint identification accuracy (%) using 2 training samples. Best two results are highlighted by bold and underline.

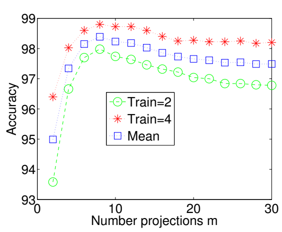
Methods	PCA	2D-PCA	LDA	2D-LDA	2D-LPP	LRC	SRC	Comp	Ordi	Fusn	Palm	BOCV	EBOCV	RLOC	HOC	Proposed
Red	85.72	85.72	91.54	96.52	86.94	95.54	95.78	98.18	97.80	97.62	96.12	97.76	97.72	96.26	<u>98.40</u>	**98.94 ± 0.06**
Green	56.88	56.92	88.24	91.70	41.58	93.02	94.26	97.86	97.02	96.64	91.58	97.12	97.52	95.60	<u>98.16</u>	**98.20 ± 0.04**
Blue	92.44	92.68	93.72	96.38	91.96	95.50	95.94	97.76	97.08	96.82	93.50	97.42	97.98	96.53	<u>98.06</u>	**98.30 ± 0.02**
NIR	88.48	88.70	97.60	96.38	92.02	95.46	93.98	<u>98.54</u>	97.96	97.28	95.88	96.56	96.30	96.50	<u>98.54</u>	**98.71 ± 0.10**
PolyU	96.46	96.52	94.79	98.00	95.12	96.79	95.52	97.00	96.79	94.89	86.48	94.64	95.76	94.66	<u>98.01</u>	**99.18 ± 0.02**

Table 2. Palmprint identification accuracy (%) using 4 training samples. Best two results are highlighted by bold and underline.

Methods	PCA	2D-PCA	LDA	2D-LDA	2D-LPP	LRC	SRC	Comp	Ordi	Fusn	Palm	BOCV	EBOCV	RLOC	HOC	Proposed
Red	91.05	91.05	95.63	97.48	93.97	97.38	95.68	98.95	98.82	98.27	97.85	98.52	98.55	98.11	<u>99.08</u>	**99.22 ± 0.04**
Green	64.23	64.25	92.45	95.55	52.90	95.60	94.40	<u>98.80</u>	98.17	97.80	93.85	98.05	98.35	97.24	98.68	**98.91 ± 0.10**
Blue	94.33	94.53	97.45	97.63	95.17	96.93	96.18	<u>98.70</u>	98.20	97.85	95.92	98.07	98.70	97.87	<u>98.75</u>	**99.10 ± 0.04**
NIR	90.55	91.38	98.73	97.53	94.65	97.80	93.95	<u>99.15</u>	99.00	98.47	97.67	98.05	98.00	97.99	99.10	**99.37 ± 0.06**
PolyU	98.66	98.71	99.05	99.07	98.71	99.02	97.01	98.27	97.86	96.47	88.60	96.10	96.76	96.28	<u>99.08</u>	**99.96 ± 0.01**



(a) N=8, $m = 10$ (b) $L = 500$, $m = 10$



(c) $L = 500$, $N = 8$

Fig. 2. Impact of the hyper-parameters of the proposed method on accuracy. (a) number of subspaces L, (b) dimensionality of subspaces N and (c) projection directions m.

native subspaces. We remark that a medium size of subspaces gives the best accuracy. The intuition behind this finding is that we are able to sample a larger number of nonidentical subspaces (i.e. classifiers). It can be also seen that taking a large number of subspaces in consideration increases the accuracy and makes it more stable. However, beyond $L = 300$ the performance becomes saturated since the maximum discriminative information is captured. Finally, it can be observed that with $m = 10$ we are able to extract discriminative features which help to build performing classifiers. Larger values of m do not have a significant influence on the accuracy, which even slightly decreases. This is particularly noticeable with a training set of solely 2 images. In fact, a larger feature set more likely contains noisy or less informative features.

4.4. Computation Time

Experiments were performed in Matlab R2012a on MacBook Pro, Intel Core i5 (2.5 GHz) and 8 GB RAM. For $L = 500$, $N = 8$ and $m = 10$ our algorithm takes approximately 0.06 seconds to classify one test palmprint image, which shows the speed of the algorithm is quite good for real time applications.

5. CONCLUSION

In this paper, we have proposed a simple but effective palmprint identification method. L subspaces are randomly generated from the eigenvectors of 2D-PCA. The resulting L projections are refined through 2D-LDA. Then, on each subspace, subject is identified with a 1-Nearest Neighbor (1-NN) classifier. Eventually, the L decisions are aggregated with majority voting. Extensive experiments on two public palmprint recognition datasets have been conducted to analyze impact of hyper-parameters and to compare the proposed approach to conventional palmprint recognition methods. The experimental results showed very promising performances compared to state-of-the-art techniques.

6. REFERENCES

[1] Imad Rida, Xudong Jiang, and Gian Luca Marcialis, "Human body part selection by group lasso of motion for model-free gait recognition," *IEEE Signal Processing Lett.*, vol. 23, no. 1, pp. 154–158, 2016.

[2] Imad Rida, Somaya Almaadeed, and Ahmed Bouridane, "Gait recognition based on modified phase-only correlation," *Signal, Image and Video Processing*, vol. 10, no. 3, pp. 463–470, 2016.

[3] Lunke Fei, Shaohua Teng, Jigang Wu, and Imad Rida, "Enhanced minutiae extraction for high-resolution palmprint recognition," *International Journal of Image and Graphics*, vol. 17, no. 04, pp. 1750020, 2017.

[4] Meng Wang and Qiuqi Ruan, "Palmprint recognition based on two-dimensional methods," in *IEEE 8th International Conference on Signal Processing*. IEEE, 2006, vol. 4.

[5] John Wright, Allen Y Yang, Arvind Ganesh, S Shankar Sastry, and Yi Ma, "Robust face recognition via sparse representation," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 31, no. 2, pp. 210–227, 2009.

[6] Somaya Al Maadeed, Xudong Jiang, Imad Rida, and Ahmed Bouridane, "Palmprint identification using sparse and dense hybrid representation," *Multimedia Tools and Applications*, 2018.

[7] Imran Naseem, Roberto Togneri, and Mohammed Bennamoun, "Linear regression for face recognition," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 32, no. 11, pp. 2106–2112, 2010.

[8] Lunke Fei, Yong Xu, Bob Zhang, Xiaozhao Fang, and Jie Wen, "Low-rank representation integrated with principal line distance for contactless palmprint recognition," *Neurocomputing*, vol. 218, pp. 264–275, 2016.

[9] David Zhang, Wai-Kin Kong, Jane You, and Michael Wong, "Online palmprint identification," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 25, no. 9, pp. 1041–1050, 2003.

[10] AW-K Kong and David Zhang, "Competitive coding scheme for palmprint verification," in *ICPR 2004*. IEEE, 2004, vol. 1, pp. 520–523.

[11] Zhenan Sun, Tieniu Tan, Yunhong Wang, and Stan Z Li, "Ordinal palmprint represention for personal identification [represention read representation]," in *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2005, vol. 1, pp. 279–284.

[12] Adams Kong, David Zhang, and Mohamed Kamel, "Palmprint identification using feature-level fusion," *Pattern Recognit.*, vol. 39, no. 3, pp. 478–487, 2006.

[13] Wei Jia, De-Shuang Huang, and David Zhang, "Palmprint verification based on robust line orientation code," *Pattern Recognit.*, vol. 41, no. 5, pp. 1504–1513, 2008.

[14] Zhenhua Guo, David Zhang, Lei Zhang, and Wangmeng Zuo, "Palmprint verification using binary orientation co-occurrence vector," *Pattern Recognit. Lett.*, vol. 30, no. 13, pp. 1219–1227, 2009.

[15] Lin Zhang, Hongyu Li, and Junyu Niu, "Fragile bits in palmprint recognition," *IEEE Signal Processing Lett.*, vol. 19, no. 10, pp. 663–666, 2012.

[16] Lunke Fei, Yong Xu, and David Zhang, "Half-orientation extraction of palmprint features," *Pattern Recognit. Lett.*, vol. 69, pp. 35–41, 2016.

[17] Xiumei Guo, Weidong Zhou, and Yanli Zhang, "Collaborative representation with hm-lbp features for palmprint recognition," *Machine Vision and Applications*, pp. 1–9, 2017.

[18] Lin Zhang, Ying Shen, Hongyu Li, and Jianwei Lu, "3d palmprint identification using block-wise features and collaborative representation," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 37, no. 8, pp. 1730–1736, 2015.

[19] Nam Nguyen, Wanquan Liu, and Svetha Venkatesh, "Random subspace two-dimensional pca for face recognition," in *Pacific-Rim Conference on Multimedia*. Springer, 2007, pp. 655–664.

[20] Yulian Zhu, Jun Liu, and Songcan Chen, "Semi-random subspace method for face recognition," *Image and Vision Computing*, vol. 27, no. 9, pp. 1358–1370, 2009.

[21] Jian Yang, David Zhang, Alejandro F Frangi, and Jing-yu Yang, "Two-dimensional pca: a new approach to appearance-based face representation and recognition," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 26, no. 1, pp. 131–137, 2004.

[22] Jieping Ye, Ravi Janardan, and Qi Li, "Two-dimensional linear discriminant analysis," in *Advances in neural information processing systems*, 2005, pp. 1569–1576.

[23] David Zhang, Zhenhua Guo, Guangming Lu, Lei Zhang, and Wangmeng Zuo, "An online system of multispectral palmprint verification," *IEEE Trans. Instrum. Meas.*, vol. 59, no. 2, pp. 480–490, 2010.

[24] Yu Guan, Chang-Tsun Li, and Fabio Roli, "On reducing the effect of covariate factors in gait recognition: a classifier ensemble method," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 37, no. 7, pp. 1521–1528, 2015.