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Palmprint recognition with an efficient data driven ensemble classifier

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ABSTRACT

Palmprint recognition is an important and widely used modality in biometric systems. It has a high reliability, stability and user acceptability. This paper proposes a new and effective ensemble classifier for palmprint recognition based on Random Subspace Method (RSM). The method relies on 2DPCA to build nearly incoherent random subspaces. As 2DPCA is an unsupervised technique, features are extracted in each subspace using 2DLDA. A simple 1-Nearest Neighbor classifier is associated to each subspace, the final decision rule being obtained by a majority voting rule. Extensive experiments on three public palmprint datasets have been conducted to compare the proposed approach to existing methods. The experimental results demonstrate that our method improves on the state-of-the-art. It turns out that for this kind of data, the use of weak classifiers learned over nearly incoherent features is very efficient. Besides these findings, we provide an empirical analysis of the parameters involved in the random subspace technique to guide the user in the choice of the appropriate hyper-parameters.

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1. Introduction

Over the past two decades, biometric security is increasingly becoming an important tool to enhance security and brings greater convenience. Nowadays, biometric systems are widely used by government agencies and private industries. A large variety of biometric modalities including face, iris, gait, fingerprint and palmprint, have been studied providing different rates of robustness, accuracy and user acceptability (Rida et al., 2016). Among these modalities, palmprint-based recognition has gained a growing interest because of its reliability, stability and high user tolerance.

Palmprint refers to the inner surface of hand. This contains an abundant variety of salient features, such as principal lines, wrinkle, ridges, minutiae and textural features (Fei et al., 2017). Most palmprint identification systems leverage on the extraction of these discriminative features to attain valuable recognition/matching performances. For instance the principal lines are detected using classical edge detectors or dedicated Radon transforms which project the palmprint image intensity along lines oriented at specific angles (Huang et al., 2008). Other systems consider the orientations of the lines as the most distinctive

feature and design a bank of Gabor filters with predefined orientations. From the convolution of the filters with the palmprint image, the dominant orientations at each pixel are identified as bitwise code (Zhang et al., 2003; Kong and Zhang, 2004; Fei et al., 2016a; Xu et al., 2016).

Contrary to these highly elaborated methods for feature extraction, subspace-based approaches (Sang et al., 2009; Yang et al., 2007; Raghavendra and Busch, 2014) learn the useful representations of the palmprint images by applying statistical methods such as Principal Component Analysis (PCA), Discriminant Analysis or sparse coding either to the raw palmprint images or to the coefficients issued from Fourier/wavelet transforms of the images. These methods, called subspace-based approaches, have the merit to learn automatically and in task driven way the discriminative features without making use of any prior knowledge of the palmprint structure. However their simplicity comes with some limitations: their recognition performances appear rather lower compared to orientation coding-based techniques which produce state-of-the-art results (Jia et al., 2017).

Though a growing effort has been devoted in order to develop robust and high accuracy palmprint recognition systems that can operate in various conditions, many problems still remain to be solved, including the design of techniques able to handle various illumination sources and low quality images result-

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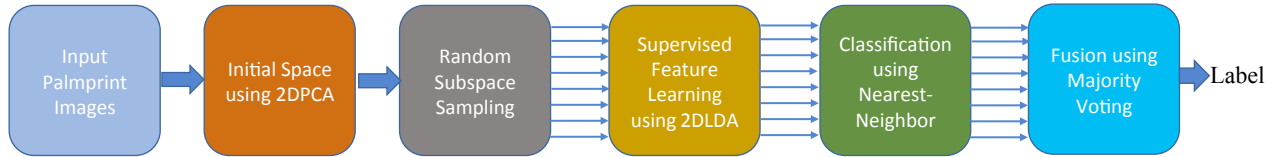


Fig. 1. The flowchart of our proposed method. Each small arrow represents a subspace over which a classifier is learned.

ing from uncontrolled acquisition conditions (Lu et al., 2017; Yang et al., 2017; Ni et al., 2015; Zhang et al., 2010b; Pan and Ruan, 2008). In these adversarial situations, the performances of subspace-based approaches may be severely impacted. To overcome these limitations, we investigate an effective ensemble learning technique for robust palmprint recognition.

In this paper, we introduce a novel subspace learning method directly applied to image pixels for palmprint recognition. Conventional subspace methods mainly seek to determine a relevant low-dimensional subspace in a high-dimensional input space in order to learn a suitable representation. Hence their performances are sensitive to the selected dimensionality. A small-dimensional subspace might lose discriminative information while a large dimensionality could lead to overfitting (Nguyen et al., 2007). To tackle this problem we explore an ensemble learning approach based on Random Subspace Method (RSM) (Ho, 1998; Guan et al., 2015; Li et al., 2015; Guan and Li, 2013). The RSM builds multiple subspaces by using a random procedure. A simple classifier is associated to each subspace. The final decision rule is achieved by aggregating the outcomes of the learned classifiers. Indeed, the RSM builds many weak classifiers which may not provide individually good recognition performances but their combination may achieve high recognition accuracy. The main contributions brought by the paper are as follows:

- We propose a new and effective palmprint recognition method based on RSM. This ensemble learning technique proves more efficiency than individual classifiers (Kuncheva, 2004; Rokach, 2010) and was recently applied with success to gait recognition (Guan et al., 2015).
- To achieve a simple method, we rely on 2DPCA to build random subspaces. 2DPCA is a linear dimensionality reduction technique for dealing with 2D images as it works on matrices rather than vectors. Contrary to conventional one-dimensional PCA, it has the advantage to preserve the spatial structure of the palmprint images and requires less computational cost (Yang et al., 2004). The subspaces are randomly selected such as they are nearly incoherent (Zhang and Li, 2010). The incoherence indicates the degree of dissimilarity between subspaces and is desirable in order to promote different subspaces, hence diverse classifiers.
- As 2DPCA is unsupervised, discriminative features are extracted in each subspace using 2D Linear Discriminant Analysis (2DLDA). A Nearest Neighbor (NN) with Euclidean distance is implemented for each subspace. Finally,

the non-linear decision function is obtained and consists in a majority voting of the individual classifiers.

The flowchart of the proposed method is depicted in Figure 1. Its effectiveness and efficiency are assessed by extensive experiments on three public palmprint datasets in order to: (i) compare RSM to conventional palmprint recognition methods and, (ii) analyze the influence of hyper-parameters involved in RSM (as the number of subspaces or their dimensionality) on recognition accuracy.

The paper is organized as follows. Section 2 summarizes related work. Section 3 describes the proposed random subspace method. Section 4 reports the experimental results and discussions. Finally, Section 5 concludes the paper.

2. Related work

We provide a brief overview of palmprint recognition methods. Existing methods in the literature essentially differ by the type of discrimination features they use and can be broadly organized in two main categories (Li and Kim, 2017), holistic and structural methods, presented hereafter.

2.1. Holistic techniques

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

Subspace-based approaches

These techniques aim to find a transformation mapping the original data residing in a high-dimensional space onto a lower one using statistical learning techniques. Among them, the most representative unsupervised ones are Principle Component Analysis (PCA) (Lu et al., 2003) and its 2D variant (Sang et al., 2009) used in order to preserve spatial structure information of palmprint images. In addition to PCA, Independent Component Analysis (ICA) has been also used (Connie et al., 2005). While PCA seeks to find uncorrelated features, the ICA attempts to find statistically independent ones. Supervised projection methods including Linear Discriminant Analysis (LDA) (Wu et al., 2003) and 2DLDA (Wang and Ruan, 2006) have been also explored. Another interesting approach Locality Preserving Projection (LPP) which seeks to preserve the neighborhood structure of the data (He and Niyogi, 2004) and its 2D (Hu et al., 2007) and non-linear kernel (Feng et al., 2006) variants.

Table 1. Example of pre-processing transforms for palmprint recognition.

Transforms	Works
Fourier	(Hennings-Yeomans et al., 2007)
Haar Wavelet	(Tamrakar and Khanna, 2016)
2D Discrete Cosine	(Leng et al., 2017)

The holistic approaches mainly act at the pixel level and are subject to poor performances in the presence of degradations caused by noise and blur (Laadjel et al., 2015). To address this problem, several transformation shown in Table 1 have been applied as pre-processing step. The resulting features are then combined with the aforementioned subspace learning techniques.

Representation-based approaches

In this group of techniques, 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 (Zhang et al., 2015; Xu et al., 2015). 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 (Wright et al., 2009; Raghavendra and Busch, 2014) and Linear Recognition Classification (LRC) (Cui et al., 2015) are two representative techniques.

2.2. 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 two sub-categories: i) line-based, ii) coding-based and iii) texture-based described below.

Coding-based approaches

They represent the most influential and state-of-the-art palmprint recognition techniques. They encode the responses of a bank of filters into bitwise codes. PalmCode introduced by (Zhang et al., 2003) represents the basis of other coding-based methods. It essentially encodes the response of one Gabor filter with an orientation equals to $\pi/4$. Motivated by the success of PalmCode, a large variety of coding methods have been proposed and are summarized in Table 2.

Table 2. Non exhaustive coding-based methods for palmprint recognition.

Codes	Remarks	Works
PalmCode	1 Gabor orientation	(Zhang et al., 2003)
Competitive	6 Gabor orientations	(Kong and Zhang, 2004)
Ordinal	3 2-D Gaussian	(Sun et al., 2005)
Fusion	4 Elliptical Gabor orientations	(Kong et al., 2006)
Robust Line Orientation	6 MFRAT directions	(Jia et al., 2008)
Binary Orientation	6 Gabor orientations	(Guo et al., 2009)
E-Binary Orientation	Masking out the fragile bits	Zhang et al. (2012)
Half Orientation	6 banks of half-Gabor directions	(Fei et al., 2016b)
Double Orientation	2 maximum of 6 Gabor responses	(Fei et al., 2016a)

Texture feature extraction

In this approach, the palm features are generated using texture feature extractors including Local Binary Pattern (LBP), Histogram of Oriented Gradient (HOG) and their variants. Table 3 shows some of the state-of-the-art feature extractors for palmprint recognition.

Table 3. Example of texture extractors for palmprint recognition.

Texture extractors	Works
Local Binary Pattern (LBP)	(Michael et al., 2008)
Block-based Histogram of Oriented Gradient	(Hong et al., 2015)
Weighted Histogram of Oriented Gradient	(Hong et al., 2016)
Hierarchical multi-scale LBP histogram	(Guo et al., 2017)

Table 4 summarizes the different techniques as well as their strengths and limitations.

3. Random Subspace Method for Palmprint Recognition

3.1. Problem formulation

Let $\mathcal{D} = \{(\mathbf{P}_i, y_i)\}_{i=1}^n$ be a set of n samples where $\mathbf{P}_i \in \mathbb{R}^{N_1 \times N_2}$ is a palmprint image and $y_i \in \mathcal{Y}$ the associated label. \mathcal{Y} is a discrete set of cardinality $|\mathcal{Y}| = C$ representing the identities to whom palmprints to be recognized belong to. The pursued objective is to find a decision function $f(\mathbf{P})$ able to assign to a given image \mathbf{P} its correct label y . An interesting strategy for providing an efficient model f is ensemble learning which combines the strengths of diverse weak classifiers and proves effective in different application fields (Fernández-Delgado et al., 2014; Guan et al., 2015).

One popular ensemble method is the Random Subspace Method (RSM) (Ho, 1998; Guan et al., 2015; Li et al., 2015; Guan and Li, 2013). The idea behind RSM is to use different subsets of features, randomly selected from an initial set, to learn the individual classifiers. Effectiveness of such an approach relies on one side in building a set of relevant and diverse simple classifiers and on the other side in aggregating the results of these classifiers. In the present work, we focus in the first issue. Specifically we intend to extract, from the raw images \mathbf{P}_i , discriminative features well suited to palmprint classification. The images \mathbf{P}_i are customary high-dimensional and only a few training samples are available for a given subject, leading to numerical issues (Ye et al., 2005) when linear subspace learning techniques (see section 2.1) are applied. Inspiring from (Guan et al., 2015), we adopt 2DPCA (Yang et al., 2004) to build an initial feature space (a space spanned by the eigenvectors associated to leading eigenvalues of the covariance matrix of the data) from which the subspaces are randomly sampled. Under this 2DPCA model, each palmprint image is projected onto a new matrix in each subspace. However, as 2DPCA acts in an unsupervised manner, resulting images in each subspace are further projected onto new features using a 2DLDA method (Ye et al., 2005) to ensure class separability. Finally a 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 (Kittler et al., 1998) among the individual NN classifiers. In the following, after a brief description of 2DPCA and 2DLDA, we develop our random subspace methodology.

Table 4. Summary of the most representative techniques for palmprint recognition.

Approach	Summarize	Advantages & Limitations
Subspace	Find subspace with intrinsic features	(+) Good description ability (+) Low computational cost (-) Sensitivity to the size of subspace
Representation	Learn discriminative features	(+) Ability to learn data-driven representations (+) Good discrimination ability (-) Classes should be well represented by training data
Coding	Extract direction features	(+) High discrimination ability (+) Stable characteristics (-) High computational cost
Texture	Extract texture features	(+) Captured from low resolution images (+) Stable characteristic (-) Sensitive to noise

3.2. 2D Principal Component Analysis

Given the set of palmprint images $\{\mathbf{P}_i \in \mathbb{R}^{N_1 \times N_2}\}_{i=1}^n$ 2DPCA, used as a first step of our RSM, seeks to reduce the dimensionality of the data. Contrary to conventional one-dimensional PCA, 2DPCA preserves the matrix structure of \mathbf{P} instead of working on its vectorized representation (which can be potentially of high dimension when N_1 and N_2 take high values leading to tedious eigenvalue decomposition problem). Formally, 2DPCA aims at finding a transformation matrix $\mathbf{R} \in \mathbb{R}^{N_2 \times d}$ to project each image \mathbf{P}_i onto a matrix $\mathbf{Z}_i = (\mathbf{P}_i - \bar{\mathbf{P}})\mathbf{R} \in \mathbb{R}^{N_1 \times d}$ of reduced dimension i.e. $d \leq N_2$. $\bar{\mathbf{P}} = \frac{1}{n} \sum_{i=1}^n \mathbf{P}_i$ is the mean of the training images. The original image can be reconstructed back as $\hat{\mathbf{P}}_i = \mathbf{Z}_i \mathbf{R}^\top$. Mathematically, 2DPCA minimizes the reconstruction error by addressing the following optimization problem

$$\min_{\mathbf{R} \in \mathbb{R}^{N_2 \times d}} \frac{1}{n} \sum_{i=1}^n \|\mathbf{P}_i - \hat{\mathbf{P}}_i\|_F^2 \quad \text{s.t.} \quad \mathbf{R}^\top \mathbf{R} = \mathbf{I}$$

where $\|\cdot\|_F$ represents the Frobenius norm and \mathbf{I} the identity matrix. The equality constraint $\mathbf{R}^\top \mathbf{R} = \mathbf{I}$ ensures columns' orthogonality of \mathbf{R} . Using the property $\text{Trace}(\mathbf{A}\mathbf{A}^\top) = \|\mathbf{A}\|_F^2$ and after some algebra the previous problem becomes

$$\max_{\mathbf{R} \in \mathbb{R}^{N_2 \times d}} \text{Trace}(\mathbf{R}^\top \mathbf{S} \mathbf{R}) \quad \text{s.t.} \quad \mathbf{R}^\top \mathbf{R} = \mathbf{I} \quad (1)$$

where $\mathbf{S} = \frac{1}{n} \sum_{i=1}^n (\mathbf{P}_i - \bar{\mathbf{P}})^\top (\mathbf{P}_i - \bar{\mathbf{P}})$ is the covariance matrix.

Solution \mathbf{R}^* of problem 1 can be shown to correspond to the d -dominant eigenvectors of \mathbf{S} (Yang et al., 2004). Any training image can therefore be projected onto the space spanned by the columns of \mathbf{R}^* giving

$$\mathbf{Z}_i = (\mathbf{P}_i - \bar{\mathbf{P}})\mathbf{R}^* \in \mathbb{R}^{N_1 \times d} \quad \forall i = 1, \dots, n \quad (2)$$

3.3. 2D Linear Discriminant Analysis

To extract discriminative representation of the data, 2DLDA is applied to the features \mathbf{Z}_i . It intends to determine a projection matrix $\mathbf{W} \in \mathbb{R}^{N_1 \times m}$, for fixed $m \leq N_1$, in order to maximize

class separability. 2DLDA seeks to maximize the between-class variance relatively to within-class variance leading to the optimization problem (Ye et al., 2005)

$$\max_{\mathbf{W} \in \mathbb{R}^{N_1 \times m}} \text{Trace}(\mathbf{W}^\top \mathbf{S}_w \mathbf{W})^{-1} (\mathbf{W}^\top \mathbf{S}_b \mathbf{W}) \quad (3)$$

under column orthogonality of \mathbf{W} . The matrix $\mathbf{S}_b = \sum_{k=1}^C n_k (\bar{\mathbf{Z}}_k - \bar{\mathbf{Z}})(\bar{\mathbf{Z}}_k - \bar{\mathbf{Z}})^\top$ is the between-class covariance matrix whereas $\mathbf{S}_w = \sum_{k=1}^C \sum_{i=1}^{n_k} \mathbb{1}_{y_i=k} (\mathbf{Z}_i - \bar{\mathbf{Z}}_k)(\mathbf{Z}_i - \bar{\mathbf{Z}}_k)^\top$ represents the within-class covariance matrix. In these expressions n_k is the cardinality of the k^{th} class while $\bar{\mathbf{Z}}_k$ stands for the mean matrix of class k and is calculated based on the projected samples \mathbf{Z}_i issued from 2DPCA. $\bar{\mathbf{Z}}$ is the global mean of the training samples. Solution \mathbf{W}^* of problem 3 corresponds to the m leading eigenvectors of $\mathbf{S}_w^{-1} \mathbf{S}_b$. To sum up, starting from the raw palmprint images \mathbf{P}_i , the application of 2DPCA followed by 2DLDA brings to the representation

$$\mathbf{X}_i = \mathbf{W}^{*\top} \mathbf{Z}_i = \mathbf{W}^{*\top} (\mathbf{P}_i - \bar{\mathbf{P}})\mathbf{R}^* \in \mathbb{R}^{m \times d} \quad \forall i = 1, \dots, n \quad (4)$$

The classification stage of our proposed approach relies on these learned features.

3.4. Random Subspace construction

RSM is a very simple and popular ensemble learning method. We may randomly sample the features related to each subspace directly from the raw palmprint images. However this is not practical as the sampling procedure may loose local spatial relationships among the pixels within the image (Zhu et al., 2009).

In order to preserve these spatial information and build nearly incoherent subspaces, we adopt 2DPCA to generate the random subspaces. Indeed, following (Guan et al., 2015) we consider L subspaces, each spanned by $N \ll d$ randomly selected eigenvectors from \mathbf{R}^* . Hence, starting from the solution of 2DPCA problem, we generate L projection matrices $\{\mathbf{R}_\ell \in \mathbb{R}^{N_2 \times N}\}_{\ell=1}^L$ where $\mathbf{R}_\ell = \mathbf{R}^*(:, \mathcal{I}_\ell)$ with \mathcal{I}_ℓ a set of N indexes sampled in the range $[1, d]$. During the procedure we promote the sampling of subspaces ℓ_1 and ℓ_2 such that the term $\varphi_{\ell_1, \ell_2} = \|\mathbf{R}_{\ell_1}^\top \mathbf{R}_{\ell_2}\|_F^2$ is

enough small, leading to nearly incoherent subspaces (Ramirez et al., 2010). Indeed, because of the orthogonality of the eigenvectors, the term φ_{ℓ_1, ℓ_2} provides a measure of the mutual coherence of subspaces ℓ_1 and ℓ_2 .

After sampling each matrix \mathbf{R}_ℓ , we proceed as follows: the whole training images are projected onto the subspace spanned by the corresponding eigenvectors giving $\mathcal{D}_\ell = \{\mathbf{Z}_i^\ell = (\mathbf{P}_i - \bar{\mathbf{P}})\mathbf{R}_\ell\}_{i=1}^n$. These new data \mathbf{Z}_i^ℓ are further used to learn 2DLDA matrix \mathbf{W}_ℓ by solving problem 3 in order to extract discriminative features. Finally, we attain the representation of the data in the ℓ^{th} random subspace as $\{(\mathbf{X}_i^\ell = \mathbf{W}_\ell^* \mathbf{Z}_i^\ell, y_i)\}_{i=1}^n$. It shall be noticed that our random subspace generation procedure transforms each initial palmprint image $\mathbf{P}_i \in \mathbb{R}^{N_1 \times N_2}$ into representations $\mathbf{X}_i^\ell \in \mathbb{R}^{m \times N}$ (with $m \leq N_1$ and $N \leq d \leq N_2$) for all $\ell = 1, \dots, L$ corresponding to a given subspace. The representations \mathbf{X}_i^ℓ differ by the selected eigenvectors (of number N) in \mathbf{R}^* and the related LDA projection matrix \mathbf{W}_ℓ . It should be noticed that in addition to getting more discrimination ability, 2DLDA also performs dimensionality reduction of the data along rows while 2DPCA has already reduced dimensionality along columns. The processing flow is summarized in algorithm 1.

Algorithm 1 Random Subspace Method (RSM)

Input:

- Training set: $\{(\mathbf{P}_i, y_i) \in \mathbb{R}^{N_1 \times N_2} \times \mathcal{Y}\}_{i=1}^n$
- Hyper-parameters: N , size of random subspaces; L number of subspaces and m , number of 2DLDA projection directions.

Output:

- $\{\mathbf{R}_\ell\}_{\ell=1}^L$ random subspace matrices and related LDA projection matrices $\{\mathbf{W}_\ell\}_{\ell=1}^L$

Solve problem 1 for 2DPCA projection matrix $\mathbf{R}^* \in \mathbb{R}^{N_2 \times d}$;
for $\ell = 1$ to L **do**

Generate a subspace spanned by $\mathbf{R}_\ell \in \mathbb{R}^{N_2 \times N}$ by randomly selecting N ($N \ll d$) eigenvectors from \mathbf{R}^* ;

Determine unsupervised representation of the data and form $\mathcal{D}_\ell = \{\mathbf{Z}_i^\ell = (\mathbf{P}_i - \bar{\mathbf{P}})\mathbf{R}_\ell\}_{i=1}^n$ using equation 2;

Calculate accordingly the 2DLDA projection matrix $\mathbf{W}_\ell \in \mathbb{R}^{N_1 \times m}$.

end for

Once the parameters of the subspaces are learned, we associate for simplicity sake a simple 1-Nearest Neighbor classification function to each subspace. The decision rule is the majority vote over the outcomes of these weak classifiers.

4. Experiments

In this section, we perform several experiments to evaluate the effectiveness of the proposed approach on three popular palmprint datasets: left and right palmprint database (Zhang et al., 2003), multi spectral palmprint database (Zhang et al.,

2010a) and 2D palmprint database (Li et al., 2010). The observed performances (recognition rate) are compared to those of the state-of-the-art holistic and structural approaches. In addition, the influence of hyper-parameters involved in RSM on the performances and the computation cost of our proposed RSM are investigated.

4.1. Palmprint datasets

The left and right database was provided by the Hong Kong Polytechnic University (PolyU)¹. 187 subjects have been asked to provide 10 palmprint images per each hand. In the following this dataset is referred to as PolyU.

The multispectral dataset contains four independent spectral palmprint databases, including Red, Green, Blue and Near Infrared (NIR) spectrums databases². 12 palmprint images have been recorded per each hand and illumination from 250 volunteers. This dataset will be termed in the sequel as the multispectral dataset.

In the 2D database, 20 palmprint images have been collected per each hand from 200 subjects³. The characteristics of the employed datasets are summarized in Table 5. Note that the two palms of the same subject are considered as two distinct classes.

Table 5. Content of palmprint recognition datasets.

PolyU		Multispectral (per each spectrum)		2D	
# Classes	# Images	# Classes	# Images	# Classes	# Images
374	3740	500	6000	400	8000

In our experiments we have used the provided palmprint region of interest of 32×32 (see Figure 2).

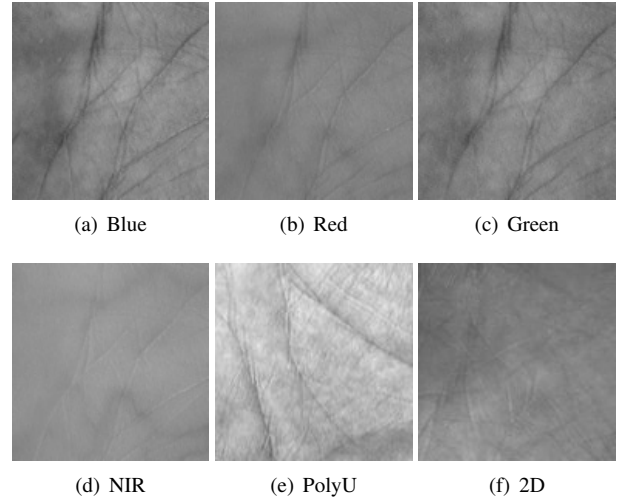


Fig. 2. Example of palmprint region of Interest in different databases.

¹<http://www4.comp.polyu.edu.hk/~biometrics/index.htm>

²<http://www4.comp.polyu.edu.hk/~biometrics/MultispectralPalmprint/MSP.htm>

³<http://www4.comp.polyu.edu.hk/~biometrics/index.htm>

4.2. Choosing the hyper-parameters of our RSM

The proposed method involves three tuning parameters: the dimension of the random subspace N , the number of projection directions of the 2DLDA 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_2 or N_1 , the dimensions of the images). Hence they are selected among the set $\{2, 4, \dots, 30\}$. The choice of L appears more demanding as we do not know beforehand its convenient range. However following (Guan et al., 2015) we set $L = 500$, a sufficiently high value in order to draw diverse and nearly incoherent random subspaces in order to ensure a good generalization ability. This empirical choice was further confirmed by the study exposed in section 4.5.

4.3. Experimental protocol

We have compared our proposed method to subspace learning techniques including PCA, 2DPCA, LDA, 2DLDA and 2DLPP as well as representation-based techniques including Sparse Representation-based Classification (SRC) (Wright et al., 2009) and Linear Regression Classification (LRC) (Cui et al., 2015). In addition to the previous approaches, our method is also compared to coding-based techniques which have shown good efficiency and ability to tackle palmprint recognition problem including Palm code (Zhang et al., 2003), Competitive Code (Kong and Zhang, 2004), Ordinal Code (Sun et al., 2005), Fusion Code (Kong et al., 2006), Robust Orientation Line Code (RLOC) (Jia et al., 2008), Binary Orientation Co-occurrence Vector (BOCV) (Guo et al., 2009), E-BOCV Zhang et al. (2012), Half Orientation Code (HOC) (Fei et al., 2016b) and Double Orientation Code (DOC) (Fei et al., 2016a).

For comparison sake, we have performed the same experiments using the same data splits and protocols in (Fei et al., 2016a). Several experiments have been conducted using various number of training samples. The first "train" images from each class were employed as training samples while the remaining ones serve as test set. We respectively use 2, 4, 6 training images per class.

Because of the small number of samples per class in the training set, we adopt 2-fold cross-validation strategy on the training set to select the optimal hyper-parameters of RSM. Due to the random nature of proposed RSM method, the results of different runs may vary to some extent. For this reason we repeat all the experiments 10 times and we report the mean accuracy with the standard deviation.

4.4. Performance evaluation and discussion

The accuracy is measured by the Correct Classification Rate (CCR) corresponding to the ratio of well classified images to overall samples. Tables 6 to 8 compare proposed RSM to other palmprint recognition techniques in terms of accuracy, using 2, 4 and 6 training samples respectively. The best two results are highlighted by bold and underline. It can be seen that RSM outperforms single subspace learning techniques in all palmprint datasets. Indeed, we can notice that our ensemble learning strategy significantly improves over these conventional techniques based on a single subspace and classifier such as PCA/2DPCA

and LDA/2DLDA in all experimental settings. The same remarks hold for the representation based techniques (SRC and LRC). When compared to coding-based methods, the proposed method shows very promising results. Specifically, RSM improves over these state-of-the-art approaches in the most challenging setup where only a few training images are available as shown in Table 6. On the other setups RSM performs slightly better or match-up with the coding-based techniques on many datasets.

A worth mentioning fact is the consistency of our proposed technique which outperforms the state-of-the-art methods over different datasets acquired under various illumination conditions. This is illustrated by the mean accuracy of all compared methods as shown in tables 6 to 8, demonstrating the ability of RSM to be robust to varying environmental conditions. The intuition behind this robustness is the fact that RSM aggregates several weak and diverse classifiers, hence reducing the sensitivity to noise that may result from adversarial acquisition conditions. A similar effect has been pointed out by (Carbonneau et al., 2016) in the context of multi-instance learning ensembles. Moreover, it is known that random subspace approaches generally provide accurate and robust classification results when training data are scarce (Kuncheva, 2004). Nonetheless, one may question the potential vulnerability of RSM to spoofing attacks. Although we do not directly address this issue, it is well known that spoofing palmprint, especially at different wave lengths, is more difficult than spoofing other biometrics as fingerprints, faces and iris (Marcel et al., 2014).

Finally we shall state that coding methods remain very attractive but they heavily rely on priori knowledge to choose Gabor filter parameters and the number of orientations. Moreover their computation cost is high at testing stage (Zhang et al., 2015). This is confirmed by Table 9 which compares the execution time of our method to coding-based techniques. On the other side, our method proposes a fully integrated pipeline and does not require any expertise on the structure or morphology of human palm hand to extract discriminative features. It should be noticed that RSM also involves hyper-parameters which can be selected using a cross-validation strategy. We provide hereafter an analysis to guide the user in the choice of these hyper-parameters.

4.5. Analyzing the influence of RSM hyper-parameters on accuracy

Here we are interested in the impact of the number of subspaces L , the size of subspaces N and the number of 2DLDA projection directions m on the accuracy. It has been shown that aggregating a large number of accurate and diverse individual classifiers leads to performing ensembles (Kuncheva, 2004). The feature subspaces on which these individual classifiers are learned represent the key indicator in order to build classifiers with some desired characteristics. (Kuncheva et al., 2010) introduced three notions *diversity*, *coverage* and *usability* that may be helpful in order to interpret the results:

- Diversity: in an ensemble classifier, two classifiers are considered non-identical or different if they are learned on two incoherent or different subspaces.

Table 6. Palmprint recognition accuracy (%) using 2 training samples. Best two results are highlighted by bold and underline. The first column represents the datasets and the remaining ones report the accuracy of proposed RSM and the competitors. The last row depicts the mean accuracy over the first five datasets. The details of compared methods are provided in the text.

	Subspace-based					Representation-based					Coding-based					RSM	
	PCA	2D-PCA	LDA	2D-LDA	2D-LPP	LRC	SRC	Comp	Ordi	Fusn	Palm	BOCV	EBOCV	RLOC	HOC		DOC
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	98.40	98.70	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	98.16	98.16	98.21 ± 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	98.06	98.18	98.30 ± 0.02
NIR	88.48	88.70	97.60	96.38	92.02	95.46	93.98	98.54	97.96	97.28	95.88	96.56	96.30	96.50	98.54	98.94	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	98.01	98.43	99.18 ± 0.02
2D	53.81	53.92	77.72	75.42	70.90	91.21	90.22	-	-	-	-	-	-	-	-	-	92.25 ± 0.21
Mean	84.00	84.11	93.18	95.80	81.52	95.26	95.10	97.87	97.33	96.65	92.71	96.70	97.06	95.91	98.23	98.48	98.67

Table 7. Palmprint recognition accuracy (%) using 4 training samples. Best two results are highlighted by bold and underline.

	Subspace-based					Representation-based					Coding-based					RSM	
	PCA	2DPCA	LDA	2DLDA	2DLPP	LRC	SRC	Comp	Ordi	Fusn	Palm	BOCV	EBOCV	RLOC	HOC		DOC
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	99.08	99.17	99.22 ± 0.04
Green	64.23	64.25	92.45	95.55	52.90	95.60	94.40	98.78	98.17	97.80	93.85	98.05	98.35	97.24	98.68	98.85	98.90 ± 0.11
Blue	94.33	94.53	97.45	97.63	95.17	96.93	96.18	98.70	98.20	97.85	95.92	98.07	98.70	97.87	98.75	98.82	99.10 ± 0.04
NIR	90.55	91.38	98.73	97.53	94.65	97.80	93.95	99.15	99.00	98.47	97.67	98.05	98.00	97.99	99.10	99.35	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	99.08	99.23	99.96 ± 0.01
2D	60.14	60.17	86.23	75.81	76.28	94.25	91.08	-	-	-	-	-	-	-	-	-	94.50 ± 0.14
Mean	87.76	87.98	96.66	97.45	87.08	97.35	95.44	98.77	98.41	97.77	94.78	97.76	98.07	97.50	98.94	99.08	99.31

Table 8. Palmprint recognition accuracy (%) using 6 training samples. Best two results are highlighted by bold and underline.

	Subspace-based					Representation-based					Coding-based					RSM	
	PCA	2DPCA	LDA	2DLDA	2DLPP	LRC	SRC	Comp	Ordi	Fusn	Palm	BOCV	EBOCV	RLOC	HOC		DOC
Red	91.60	91.67	96.83	97.60	95.27	98.00	95.13	99.20	98.93	98.53	97.93	98.37	98.50	98.35	99.07	99.23	99.23 ± 0.03
Green	62.10	62.40	94.80	94.60	49.07	96.27	93.60	98.93	98.37	97.87	94.03	98.20	98.43	97.78	98.97	99.10	98.95 ± 0.07
Blue	94.10	94.37	95.00	97.50	95.07	97.10	95.30	98.93	98.43	97.97	96.57	98.17	98.77	98.68	98.97	99.10	99.02 ± 0.02
NIR	90.60	90.60	95.60	97.93	94.37	98.10	93.33	99.13	98.90	98.47	97.57	98.20	98.10	98.13	99.14	99.40	99.54 ± 0.04
PolyU	99.33	99.33	99.60	99.67	99.33	99.47	97.86	99.92	99.87	99.92	99.80	99.92	99.87	99.80	98.99	99.23	99.94 ± 0.01
2D	59.77	59.75	87.00	74.45	74.58	94.30	90.41	-	-	-	-	-	-	-	-	-	94.64 ± 0.16
Mean	87.55	87.67	96.37	97.46	86.62	97.79	95.04	99.22	98.90	98.55	97.18	98.57	98.73	98.55	99.03	99.21	99.34

422 • Coverage: represents the ability to learn a large number of 439
423 non-identical classifiers. 440

424 • Usability: when a classifier is learned on only spurious 441
425 features its performance may be totally random. A classi- 442
426 fier is considered usable when it is learned on subspaces 443
427 containing discriminative features. 444

428 In order to build a performing ensemble classifier, these 445
429 criteria should be fulfilled as far as possible, i.e. learning a 446
430 large number of classifiers on incoherent and discriminative 447
431 subspaces. Figures 3 to 5 respectively depict the evolution of 448
432 the accuracy according to the size of subspaces N , the number 449
433 of subspaces (classifiers) L and the number of 2DLDA projec- 450
434 tion directions m . Note that in the conducted analysis, we fix 451
435 two parameters and we check the accuracy's sensitivity to the 452
436 third one on the test set by changing its value within a range 453
437 ($L \in [20, 500]$, $N \in [2, 30]$ and $m \in [2, 30]$). For clarity sake 454
438 we solely show the obtained graphs over Multispectral dataset. 455

We shall mention that the observed variations and drawn conclusions extend to PolyU and 2D datasets.

In Figure 3 we fix the number of subspaces and 2DLDA projections to $L = 500$ and $m = 10$ respectively and we range the size of subspaces N . We remark that a medium size of subspaces gives the best accuracy. This finding is due to the ability to sample a larger number of nearly incoherent subspaces (i.e. classifiers) which satisfy the diversity assumption.

To generate the graphs of Figure 4, we fix the size of subspaces and 2DLDA projections to $N = 8$ and $m = 10$ and we range the number of subspaces L . It can be seen that taking a large number of subspaces in consideration increases the accuracy and makes it more stable. Indeed, taking a large value for the number of subspaces supports meeting the coverage criteria. However it can be seen that beyond $L = 300$ the accuracy reaches a plateau since the maximum discriminative information is captured.

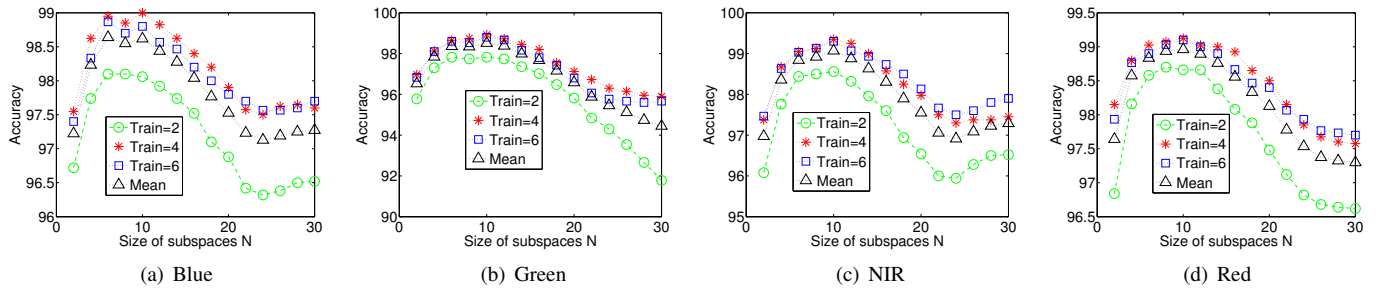


Fig. 3. Impact of the size of subspaces N .

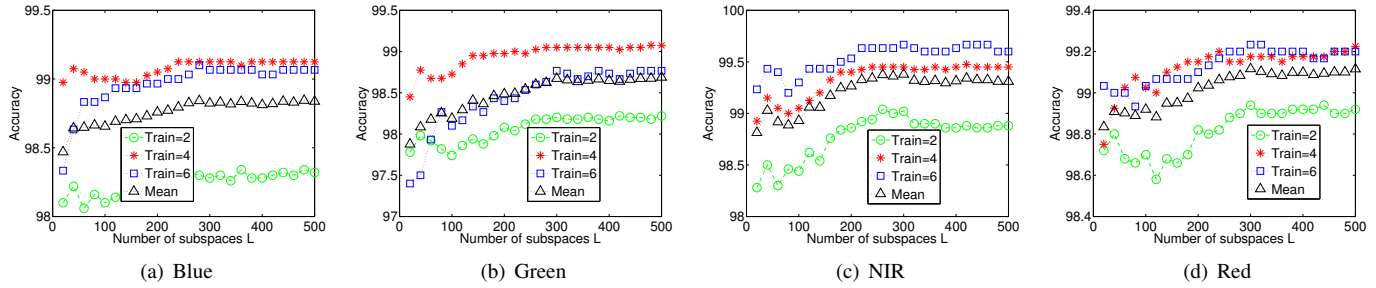


Fig. 4. Impact of the number of subspaces L .

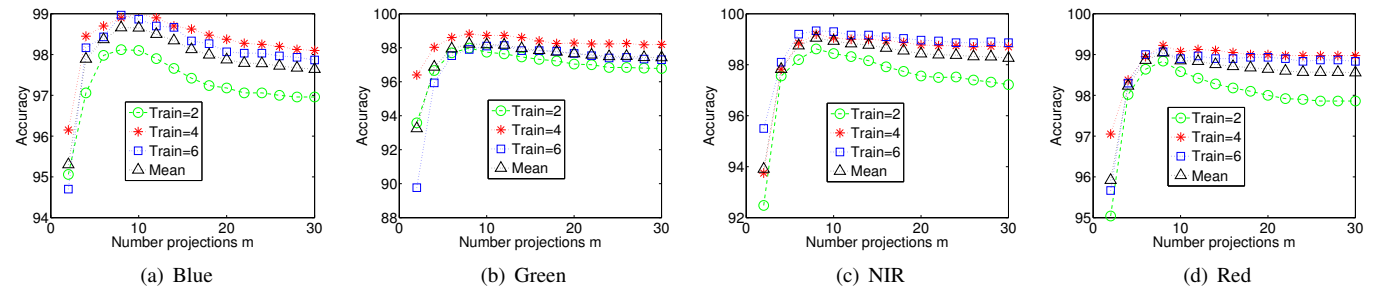


Fig. 5. Evolution of the recognition accuracy with varying values of m .

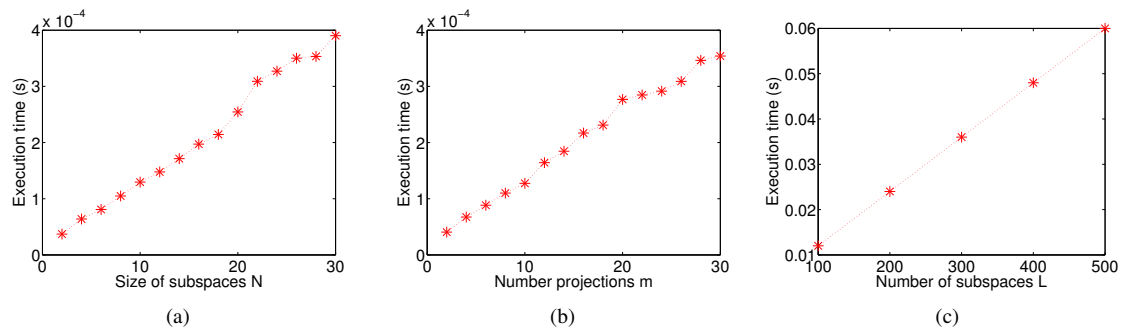


Fig. 6. The execution time variation with increasing (a) dimensionality of the subspace N ($m = 10, L = 1$) (b) 2DLDA projection directions m ($N = 8, L = 1$) (c) number of subspaces L ($N = 8, m = 10$).

456 Finally, in Figure 5, we fix $N = 8$ and $L = 500$ and we vary
 457 m . It can be seen that with $m = 10$ we are able to extract suffi-
 458 ciently discriminative features which help to build usable clas-
 459 sifiers. Larger values of m do not have a significant influence
 460 on the accuracy, which even slightly decreases. This is particu-

larly noticeable with a training set of solely 2 images. In fact, a
 larger feature set more likely contains noisy or less informative
 features. Indeed, the number of projections m should be large
 enough to extract important features without taking noise into
 consideration.

4.6. Computational Cost Analysis

Experiments were performed in Matlab R2012a on MacBook Pro, Intel Core i5 (3.2 GHz) and 8 GB RAM. The execution time to classify a new test palmprint image increases linearly with the increasing dimensionality for either N , m and L as shown in Figure 6.

For $N = 8$, $L = 500$ and $m = 10$ our algorithm takes approximately 0.06 seconds to classify one test palmprint image, which shows that the speed of proposed method is quite good for real time applications. The speed can further be increased by parallel processing. Table 9 compares the execution time of our method to other state-of-the-art coding-based techniques. It can be seen that the speed of our algorithm compares very favorably.

Table 9. Computational cost (at test time) in seconds of the most perform- ing methods tested in our experiments.

Methods	Execution Time (s)
Competitive Code	0.08
Palm Code	0.20
Fusion Code	0.20
Ordinal Code	0.90
RLOC	3.70
BOCV	0.90
E-BOCV	2.10
HOC	0.15
DOC	3.50
RSM	0.06

5. Conclusion

In this paper we have proposed a new and effective palmprint recognition method based on Random Subspace Method (RSM). L nearly incoherent subspaces are randomly generated from the eigenvectors of a 2DPCA. The resulting L projections are refined through 2DLDA. Then, on each subspace, subject is identified with a 1-Nearest Neighbor (1-NN) classifier. Eventually, the L decisions are aggregated with Majority Voting (MV).

Extensive experiments on three public palmprint datasets, with different illumination conditions, have been conducted to compare proposed approach to conventional palmprint recognition methods. The experimental results establish that our random subspace strategy improves on the state-of-the-art techniques, such as coding-based methods over all the environmental conditions under investigation. We provide an analysis to give insights on the tuning of hyper-parameters involved in RSM. It appears that, on the studied palmprint datasets, the combination of several weak classifiers (a simple 1-NN classification method) learned over nearly incoherent or different subspaces leads to consistent performances over various acquisition conditions. Hence we believe that RSM can partially contribute to the development of robust biometric recognition systems. Finally the paper demonstrates that the computation burden of RSM at testing stage is very competitive as its computation time is lower than the one of current influential methods for palmprint recognition.

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