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Palmprint Identification Using an Ensemble of Sparse Representations

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ABSTRACT Among various palmprint identification methods proposed in the literature, sparse representation for classification (SRC) is very attractive offering high accuracy. Although SRC has good discriminative ability, its performance strongly depends on the quality of the training data. In particular, SRC suffers from two major problems: lack of training samples per class and large intra-class variations. In fact, palmprint images not only contain identity information but they also have other information, such as illumination and geometrical distortions due to the unconstrained conditions and the movement of the hand. In this case, the sparse representation assumption may not hold well in the original space since samples from different classes may be considered from the same class. This paper aims to enhance palmprint identification performance through SRC by proposing a simple yet efficient method based on an ensemble of sparse representations through an ensemble of discriminative dictionaries satisfying SRC assumption. The ensemble learning has the advantage to reduce the sensitivity due to the limited size of the training data and is performed based on random subspace sampling over 2D-PCA space while keeping the image inherent structure and information. In order to obtain discriminative dictionaries satisfying SRC assumption, a new space is learned by minimizing and maximizing the intra-class and inter-class variations using 2D-LDA. Extensive experiments are conducted on two publicly available palmprint data sets: multispectral and PolyU. Obtained results showed very promising results compared with both state-of-the-art holistic and coding methods. Besides these findings, we provide an empirical analysis of the parameters involved in the proposed technique to guide the neophyte.

INDEX TERMS Biometrics, palmprint, sparse representation, ensemble learning.

I. INTRODUCTION

Over the past few decades, biometrics have become an important tool to enhance security. Nowadays, they are widely used by government agencies and private industries. A large variety of biometric modalities including face, iris, gait, and palmprint have been studied providing different rates of accuracy and robustness [1]. In this work, we consider to enhance palmprint based biometric identification 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 [2]. Various palmprint recognition methods have been proposed, they can be broadly organized in two main categories [3]: holistic and structural. The first one attempts to define the whole palmprint image as a single data set while the second one is based on local information such as lines and texture.

The holistic approaches use full image for recognition. Due to its high dimensionality, many researchers have focused on dimensionality reduction using PCA [4], LDA [5] and ICA [6]. The matrix-based dimensionality reduction methods which have the advantage to preserve the spatial structure have also been used including 2D-PCA [7], 2D-LDA [8] and 2D Locality Preserving Projection (2D-LPP) [9]. The holistic approaches mainly operate at the pixel level leading sometimes to poor performances in the presence of degradation caused by noise, blur, distortion and illumination. To address

TABLE 1. Example of Pre-Processing Transforms for Palmprint Recognition

Transforms	Works
Fourier	[10]
DCT	[11], [12]
Dual-Tree Complex Wavelet	[13]
Haar Wavelet	[14]
Radon	[15]

this problem, several of the shelf transforms summarized in Table 1 have been applied as pre-processing step.

(a) (b) (c)

FIGURE 1. Example of the extracted features from palmprint region of interest in the local approaches. (a) Line-based [17]. (b) Coding-based [32]. (c) Texture-based [29].

The structural or local approaches are based on the extraction of the lines and texture features from the palmprint images (Figure 1). They can be organized as: i) line, ii) coding and iii) texture based.

Line-based approaches:
Palm lines represent the basic features for recognition which can be broadly categorized into three principal lines: heartline, headline and lifeline. Several works have tried to apply various edge detection techniques to extract the palm lines for recognition [16]–[18]. 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 and then different metrics such as Hamming distance are applied for matching. A large variety of coding methods using various number of Gabor filter orientations have been introduced including Palm Code [19], Competitive Code [20], Ordinal Code [21], Fusion Code [22], Binary Orientation Co-occurrence Vector (BOCV) [23], E-BOCV [24], Robust Line Orientation Code (RLOC) [25] and Half Orientation Code (HOC) [26]. The characteristics of each code are summarized in Table 2.

Texture-based approaches:
They seek to extract the palm features using various texture extractors including Local Binary Pattern (LBP) [27], [28], Histogram of Oriented Gradient (HOG) [29] and their variants [30], [31].

TABLE 2. Non Exhaustive Coding-Based Methods

Codes	Remarks	Works
Palm Code	1 Gabor orientation	[19]
Competitive	6 Gabor orientations	[20]
Robust Line Orientation	6 MFRAT directions	[25]
Fusion	4 Elliptical Gabor orientations	[22]
Ordinal	3 2-D Gaussian	[21]
Binary Orientation Co-occurrence	6 Gabor orientations	[23]
E-Binary Orientation Co-occurrence Vector	Masking out the fragile bits	[24]
Half Orientation (HOC)	6 banks of half-Gabor directions	[26]

II. MOTIVATIONS AND CONTRIBUTIONS

From the aforementioned introduction, it can be noticed that not much contributions have been introduced in the holistic approach except some works which tried to apply various conventional subspace learning techniques. On the other hand, it can be seen that the structural approaches and especially coding ones have got a particular interest. Indeed, these methods currently represent the most influential and suitable for one-to-one verification applications. However, it should be also noted that their accuracy strongly depends on the human knowledge for hyper-parameters tuning such as Gabor parameters and the number of directions. Beside of coding methods advantages, they have also some limitations for identification (i.e. one-to-all) due to the need to match each test sample to all the training samples (one by one) [33]. Consequently, inspired by the recent development of sparse coding in the field of machine learning some works based on sparse representations have been introduced for efficient palmprint identification [33]–[35].

SRC [36] has shown its ability to achieve impressive accuracy in several problems including face and object recognition. It considers a query image as a linear combination of all training samples by assuming that the samples of a specific subject lie in a particular linear subspace which is different from the subspaces spanned by the other subjects. Therefore, the query image is expected to be mainly represented by the training samples of a single subject. This may be more efficiently implemented by enforcing sparsity on the linear representation over all training data. In other words, SRC can be seen as a "sparse" collaborative representation method. "Sparse" means that only few training samples are necessary for the representation of the test sample and hence the significant representation coefficients can be used for the classification. SRC represents a good alternative for the conventional classifiers including Linear Regression Classification (LRC) [37] which can be considered as a simple nearest subspace [38]. It directly applies training images as dictionary for the sparse representation. Therefore its performance strongly depends on the quality of the training data. Although SRC has good discriminative ability when the number of training samples of every class is large enough to represent its variations, it may not be proper for classification when the variations of some classes are not well represented by their training samples.

Unfortunately, palmprint images do not only contain identity information but also much other information such as

illumination and distortion due to movement of hand and unconstrained conditions leading to a significant increase of intraclass variability [39]. In this case, the sparse representation assumption may not hold well in the original space due to the large intra-class variations causing a misclassification of a new test sample [38], [40]. Though a growing effort has been devoted in order to develop biometric identification systems that can operate in unconstrained conditions, many problems still remain to be solved, including the design of techniques to handle varying illumination sources and low quality images resulting from such acquisition conditions. The development of techniques effective in such challenging situations requires vigorous research efforts.

A possible solution to alleviate the problem of large intra-class variations for SRC is to find a more effective space where the assumption of separability between subspaces spanned by distinct classes holds better [41]. For this sake, we attempt to learn a discriminative space where samples from different classes are well represented by maximizing the inter-class differences and minimizing the intra-class variability. In other words, our problem is amenable to find a projection matrix based on 2D-LDA [42] which can be seen advantageous compared conventional LDA due to its numerical stability. The sparse representations based on the projected training data in the new space serving as new dictionary are more suitable for classification since this latter one satisfies better the assumption of separability compared to original one.

Despite the impressive results of SRC, its performance also strongly depends on the size of training data. Indeed, limited training samples in some applications including palmprint and face could lead to lower accuracy [38]. To address this problem, we propose to construct an ensemble of sparse representations based on ensemble learning which has the advantage to reduce the sensitivity due to the limited size of training data [43]. Indeed, instead of building a single global sparse representation, we build an ensemble of sparse representations based on an ensemble of discriminative dictionaries through a random sampling method. Existing methods attempt to construct the ensemble by randomly sampling features from the whole image [44], [45] which may destroy inherent local spatial relationship among pixels within the image. In the present work, we propose to use 2D-PCA [46] which has the advantage to keep the image structure in order to build an initial space and then randomly sample subspaces from it to create the ensemble. Furthermore, the dimensionality of the feature space is usually much larger than the number of the training samples per class, this is known as the Under Sample Problem (USP). 2D-LDA often fails when faced the USP and one solution is to reduce the dimensionality of the feature space using 2D-PCA [47]. The final classification decision is obtained by aggregating all sparse representations.

To summarize, palmprint identification based SRC suffers from large intra-class variations and low size of training samples per class. To address this problem, we propose a simple yet efficient method by computing an ensemble of sparse representations through an ensemble of discriminative dictionaries. Unlike in the case of existing methods, the dictionaries are generated by random sampling procedure over 2D-PCA which has the advantage to keep inherent images information. To satisfy SRC assumption and ensure the discrimination of dictionaries, projected training data in each subspace from different classes are further separated by minimizing and maximizing the intra and inter class variation through 2D-LDA. To the best of our knowledge no such method has previously been proposed for palmprint identification.

The effectiveness and the efficiency of the proposed method have been corroborated by extensive experiments conducted on two publicly palmparint dataset: multispectral [48] and PolyU [19]. Experimental results showed very promising results when compared to both holistic [4], [5], [7], [8], [36], [37] and structural methods [19]–[26].

The remainder of this paper is organized as follows. Section III introduces the theoretical description of the proposed method. Section IV reports the experimental results and discussions. Finally, Section V concludes the paper.

III. PROPOSED APPROACH

A. INTRODUCTION

Let us consider $\{(\mathbf{x}_i, y_i)\}_{i=1}^{n}$ where $\mathbf{x}_i \in \mathbb{R}^M$ is an image of M pixels arranged in column vector and $y_i \in \{1, \cdots, C\}$ its label. We consider a class based dictionary $\mathbf{D}_c \in \mathbb{R}^{M \times n_c}$ the n_c training samples associated to each class c. The global dictionary $\mathbf{D} = [\mathbf{D}_1 \cdots \mathbf{D}_C] \in \mathbb{R}^{M \times n}$ represents the concatenation of the class based dictionaries $\{\mathbf{D}_c\}_{c=1}^{C}$. The sparse representation of a test sample $\mathbf{x}'$ over the global dictionary $\mathbf{D}$ noted $\mathbf{a}^T = [\mathbf{a}_1^T \cdots \mathbf{a}_c^T \cdots \mathbf{a}_C^T]$ is given by:

$$\min_{\mathbf{a}} \frac{1}{2} \left\| \mathbf{x}' - \mathbf{D}\mathbf{a} \right\|_2^2 + \lambda \left\| \mathbf{a} \right\|_1 \tag{1}$$

where $\|.\|_1$ denotes the ℓ_1-norm corresponding to the absolute sum of the vector $\mathbf{a}$, λ is a parameter controlling the compromise between the reconstruction error and sample-wise sparsity and $\mathbf{a}$ represents the sparse representation over the global dictionary $\mathbf{D}$. The problem (1) can be efficiently solved using many algorithms [49], [50].

With the assumption that subspaces of distinct classes are independent to each other, the formulation (1) achieves a discriminative representation where significant nonzero coefficients are only associated to the correct subject [51], [52]. Thus the resulting sparse representation in (1) named in the literature Sparse Representation for Classification (SRC) [36] is suitable for classification. The latter is performed by computing residual reconstruction error of the test sample $\mathbf{x}'$ using the training samples of each class c serving as a dictionary $\mathbf{D}_c$ and their corresponding sparse coefficients $\mathbf{a}_c$ as follows:

$$e_c = \left\| \mathbf{x}' - \mathbf{D}_c \mathbf{a}_c \right\|_2^2 \quad c = 1, \cdots, C \tag{2}$$

The class label of the given test sample is assigned to class c minimizing the reconstruction error using $\mathbf{D}_c$ and $\mathbf{a}_c$.

Despite of the impressive results of SRC, a number of works put in doubt its effectiveness for

classification [53], [54]. Indeed, SRC suffers from two major problems: lack of training samples per class and large intra-class variations. Starting by the first one, it has been shown that SRC performs better in large scale problems where training set contains a large and sufficient number of samples per class. The limited training data in real applications is mainly due to the cost of data collection or computation cost. To alleviate this problem, we propose a simple but efficient ensemble learning method in order to build an ensemble of L dictionaries $\{\mathbf{D}\ell\}_{\ell=1}^{L}$ through random subspace sampling on 2D-PCA space which has the advantage to be computationally efficient while keeping fundamental image information.

The second problem is caused by the large intra-class variations of the training samples of different classes (class based dictionaries) $\{\mathbf{D}_c\}_{c=1}^{C}$. In this case, SRC is known to have some stability problems [53]. Typically, given a test sample highly correlated to two training samples originating from two distinct classes, SRC will randomly select one of the two which may lead to unreliable result. To alleviate this problem, existing state-of-the-art methods tried to include training data labels during sparse optimization [55]–[57]. One possible alternative to include class labels is to project the training data in new space where class based dictionaries $\{\mathbf{D}_c\}_{c=1}^{C}$ are well separated [41]. To this end, an easy and effective solution is to find a new space where intra-class and inter-class variations are minimized and maximized respectively through 2D-LDA.

B. ENSEMBLE LEARNING BASED RANDOM SUBSPACE SAMPLING

Randomly sampling features from the whole palmprint image may destroy inherent local spatial relationship among pixels within the image. To tackle this problem, we propose to sample subspaces from the 2D-PCA space.

Given a set of palmprint images $\left\{\mathbf{X}_i \in \mathbb{R}^{n_1\times n_2}\right\}_{i=1}^{n}$, 2D-PCA [46] is used as the first step to reduce the dimensionality of the data. Unlike in 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 $\mathbf{X}_i$ in 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:

$$\begin{cases} \max\limits_{\mathbf{R}\in\mathbb{R}^{n_2\times d}} \ \text{Trace}\left(\mathbf{R}^\top\mathbf{S}\mathbf{R}\right) \\ \text{s.t. } \mathbf{R}^\top\mathbf{R} = \mathbf{I} \end{cases} \tag{3}$$

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 (3) 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:

$$\mathbf{Z}_i = \mathbf{X}_i\mathbf{R}^* \in \mathbb{R}^{n_1\times d} \quad \forall i = 1, \cdots, n \tag{4}$$

To construct our ensemble 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 $\left\{\mathbf{Z}_i^\ell = \mathbf{X}_i\mathbf{R}_\ell\right\}_{i=1}^{n}$.

C. EMBEDDING CLASS LABELS INTO DICTIONARY

In order to obtain discriminative dictionaries satisfying SRC assumption per each subspace ℓ, we propose to include class labels in to the dictionaries. This can be done by boosting more the class-separability [41] of the training data in each subspace ℓ. Indeed we seek 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. Formally, this can be efficiently done through 2D-LDA which seeks to maximize and minimize the between-class and within-class variances leading to the optimization problem [42]:

$$\max_{\mathbf{W}_\ell\in\mathbb{R}^{n_1\times m}} \ \text{Trace}\left(\mathbf{W}_\ell^\top\mathbf{S}_w^\ell\mathbf{W}_\ell\right)^{-1}\left(\mathbf{W}_\ell^\top\mathbf{S}_b^\ell\mathbf{W}_\ell\right) \tag{5}$$

where $\mathbf{S}_b^\ell$ and $\mathbf{S}_w^\ell$ are the between-class and within-class scatter matrices given as by:

$$\mathbf{S}_b = \sum_{c=1}^{C} n_c\left(\bar{\mathbf{Z}}_c - \bar{\mathbf{Z}}\right)\left(\bar{\mathbf{Z}}_c - \bar{\mathbf{Z}}\right)^\top \tag{6}$$

$$\mathbf{S}_w = \sum_{c=1}^{C}\sum_{i=1}^{n}\mathbb{I}_{y_i=c}\left(\mathbf{Z}_i - \bar{\mathbf{Z}}_c\right) \tag{7}$$

n_c is the cardinality of the cth class, $\bar{\mathbf{Z}}_c$ stands for the center of class c, while $\bar{\mathbf{Z}}$ is the global mean. The solution $\mathbf{W}_\ell^*$ of problem (5) corresponds to the m leading eigenvectors of $(\mathbf{S}_w^\ell)^{-1}(\mathbf{S}_b^\ell)$.

In order to obtain more dictionaries robust to the intra-class variation problem, $\left\{\mathbf{Z}_i^\ell\right\}_{i=1}^{n}$ are projected in each subspace ℓ through $\mathbf{W}_\ell^*$ as follows:

$$\mathbf{B}_i^\ell = \mathbf{W}_\ell^{*\top}\mathbf{Z}_i^\ell \quad \forall i = 1, \cdots, n. \tag{8}$$

D. SPARSE REPRESENTATIONS AGGREGATION

Projected training samples in each subspace ℓ, $\{\mathbf{B}_i^\ell\}_{i=1}^{n} \in \mathbb{R}^{m\times N}$ are arranged as column vectors and stacked in a matrix in order to obtain an ensemble of dictionaries $\{\mathbf{D}^\ell \in \mathbb{R}^{s\times n}\}_{\ell=1}^{L}$ where $s = m \times N$. These resulting dictionaries $\{\mathbf{D}^\ell\}_{\ell=1}^{L}$ hold better SRC assumptions and reduce the computational burden since $s < M$. In order to integrate results over multiple subspaces we have used two strategies. In the first one, we assign a label to a testing sample $\mathbf{X}'$ by minimizing reconstruction error over all subspaces:

$$e_c = \sum_{\ell=1}^{L}\left\|\mathbf{x}'_\ell - \mathbf{D}_c^\ell\mathbf{a}_c^\ell\right\|_2^2 \quad \forall c = 1, \cdots, C \tag{9}$$

where $\mathbf{x}'_\ell$ is the vectorized projection of $\mathbf{X}'$ in the subspace ℓ.

In the second strategy, each vectorized test sample $\mathbf{x}'$ is separately classified in each subspace ℓ and the final decision

is taken based on majority voting [58] among all individual decisions. In fact this scheme has helped to generate better accuracy due to a non-linear decision in each subspace.

IV. EXPERIMENTS AND RESULTS

We performed a series of experiments to evaluate the proposed approach on two publicly available palmprint datasets: multi spectral [48] and PolyU [19]. The obtained results are compared with seven state-of-art holistic methods including PCA [4], 2D-PCA [7], LDA [5], 2D-LDA [8], 2D-LPP [9], SRC [36] and LRC [37]. In addition to eight structural coding-based techniques including Palm Code [19], Competitive Code [20], Ordinal Code [21], Fusion Code [22], Binary Orientation Co-occurrence Vector (BOCV) [23], E-BOCV [24], Robust Line Orientation Code (RLOC) [25] and Half Orientation Code (HOC) [26]. For fair comparisons, we have followed the protocols and data splits proposed by *Fei et al.* [26].

A. PALMPRINT DATABASES

The multispectral palmprint dataset[1] contains four independent datasets including Red, Green, Blue and Near Infrared (NIR) spectrums. 12 images per each hand and illumination from 250 subjects were captured. In the following we refer to this dataset by multispectral.

In the left and right palmprint dataset[2], 187 subjects were asked to provide 10 palmprint images per each hand. In the following this dataset is referred to as the PolyU. The content of datasets is summarized in Table 3. Note that the two palms of the same subject are considered as two distinct classes.

TABLE 3. Content of Palmprint Recognition Datasets

PolyU		Multispectral (per spectrum)	
# Classes	# Images	# Classes	# Images
374	3740	500	6000

B. EXPERIMENTAL SETTING

In our experiments we have used the provided palmprint region of interest of fixed size 32×32 (Figure 2) extracted by the algorithm described in [19]. Since we are interested to the identification, the accuracy is measured by the Correct Classification Rate (CCR) corresponding to the ratio of correct classified images to overall images. For sake of comparison, we have used the same number of training samples in the literature following the proposed protocols and data splits. 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.

In the proposed method there are four parameters to tune including N, m, L and λ. The first three represent the dimensionality of subspaces, number of projection directions of the

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

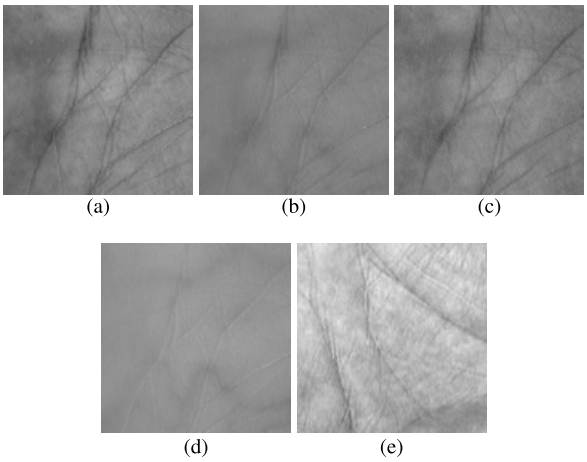


FIGURE 2. Example of palmprint region of interest (ROI). (a)-(d) Different spectrums of multispectral dataset. (e) PolyU dataset.

2D-LDA and the number of subspaces respectively, while λ controls the sparsity. The parameters N, m and λ are optimized using a two-folds cross-validation scheme where 50% of training data is used as validation. The value of N and m are selected from the set $\{2, 4, \cdots, 30\}$ and λ is taken from $\{0.1, 0.2, \cdots, 1\}$. For the selection of L we consider that the number of distinct subspaces of size $N = 30$ out of $n_1 = 32$ are 496. The same number we get for subspaces of size $N = 2$. To remain consistent across subspaces of varying dimensionality and ensure good generalization ability, we select $L = 500$ in all experiments.

C. RESULTS

Tables 4 and 5 compare the accuracy of our algorithm to other state-of-the-art techniques using 2 and 4 training samples respectively. The best two results are highlighted by bold and underline. In Table 4 our algorithm has outperformed all holistic and structural coding-based techniques included in this study. In Table 5, the proposed algorithm obtained better accuracy than all techniques except for the NIR band where Half Orientation Code (HOC) performed better.

While, coding methods depend on human knowledge for hyper-parameters such as Gabor parameters and the number of directions, the proposed algorithm is automated and does not need human expertise to compute discriminative sparse representations for classification. It should be also noticed that in all experiments we obtained better accuracy than conventional SRC method based on single dictionary corresponding to the training data in the original space.

D. IMPACT OF HYPER-PARAMETERS

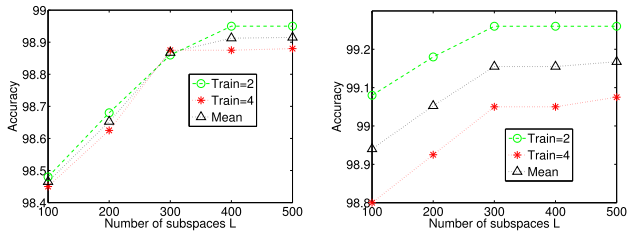
We study the impact of the number of subspaces L on the overall performance accuracy (Figure 3). It can be seen that the accuracy is increasing from $L = 100$ to $L = 300$ due to the involvement of more new discriminative dictionaries. In addition to that, their combination leads to better generalization. However, beyond $L = 300$ the performance becomes

TABLE 4. Palmprint Recognition 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	98.40	**99.23 ± 0.03**
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	**98.62 ± 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	**98.41 ± 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	**98.82 ± 0.08**
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	**99.08 ± 0.03**

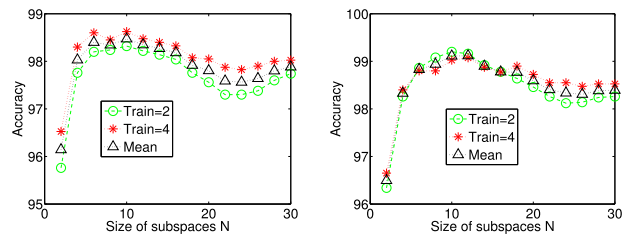
TABLE 5. Palmprint Recognition Accuracy (%) Using 4 Training Samples. Best Two Results Are Highlighted by Bold and Underline

	Methods															
	PCA	2DPCA	LDA	2DLDA	2DLPP	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	99.08	**99.13 ± 0.03**
Green	64.23	64.25	92.45	95.55	52.90	95.60	94.40	98.80	98.17	97.80	93.85	98.05	98.35	97.24	98.68	**99.08 ± 0.06**
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**	98.74 ± 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	99.00 ± 0.08
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	**99.87 ± 0.03**



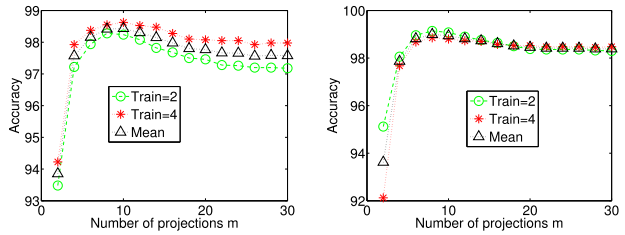
(a) (b)

FIGURE 3. Impact of the number of subspaces L on accuracy for fixed number subspaces dimensionality $N = 10$ and 2D-LDA projections $m = 10$. (a) Blue. (b) Red.



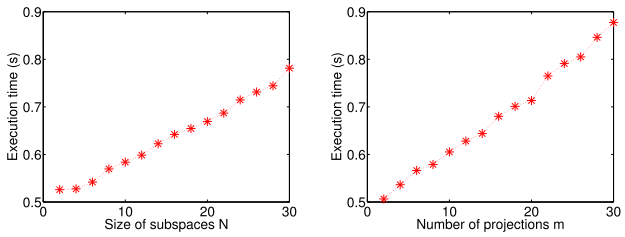
(a) (b)

FIGURE 4. Impact of the dimensionality of subspaces N on accuracy for fixed number of subspaces $L = 500$ and 2D-LDA projections $m = 10$. (a) Blue. (b) Red.



(a) (b)

FIGURE 5. Impact of the number of 2D-LDA projections m on accuracy for fixed number of subspaces $L = 500$ and subspaces dimensionality $N = 10$. (a) Blue. (b) Red.



(a) (b)

FIGURE 6. The execution time variation with increasing (a) dimensionality of the subspace N (with fixed m= 10, $L = 500$) (b) 2D-LDA projection directions m (with fixed $N = 10$, $L = 500$).

saturated since the dictionaries have already captured maximum discriminative information. Therefore adding more subspaces just makes the results more stable.

The variation of performance with the dimensionality of the subspaces is shown in Figures 4 & 5. As N or m is increased the performance improves. In fact smaller dimensional subspaces are not able to satisfy the SRC assumption resulting in poor performances. It should be also noticed that once the dimensionality reaches a peak value then there is no further improvement. In some cases performance may actually degrades which is due to the inclusion of less discriminative dimensions. Indeed, the number of projections m should be large enough to extract important and well separated features from different classes without taking noise into consideration.

E. COMPUTATIONAL COST ANALYSIS

Experiments were performed in Matlab on Dell Precision Tower 5810. The execution time increases linearly with the increasing dimensionality for either N and m as shown in Figure 6. For $N = 10$, for $L = 500$ and $m = 10$ our algorithm takes approximately 0.60 seconds to process one palmprint image. Table 6 compares the execution time of our method to other state-of-the-art terhniqques. It can be seen that the speed of our algorithm is good compared to other techniques, the speed can further be increased by parallel processing.

TABLE 6. Computational Cost of Different Methods in Seconds

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
Proposed	0.60

V. CONCLUSION

In this a paper we considered to tackle the problems of the large intra-class variations and the lack of training samples related to palmprint identification through Sparse Representation for Classification (SRC). This is done by building an ensemble of sparse representations across an ensemble of discriminative dictionaries satisfying SRC assumption. The ensemble learning is performed by a random sampling procedure over 2D-PCA space which has the advantage to keep inherent image information. In order to enforce the SRC assumption, intra-class and inter-class variations of projected training samples from different classes in each subspace serving as dictionary are minimized and maximized respectively. The final decision is taken based on majority voting among all individual decisions. Experimental results on multispectral and PolyU datasets have shown very promising results compared to the state-of-the-art methods.

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