Multispectral Palmprint Matching based on Joint Sparse Representation

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***Abstract*—A novel method for multispectral palmprint matching based on the joint sparse representation is proposed. We use joint sparse representation to model the identity assurance system that involves identification as well as verification. The method represents the given palmprint as a linear combination of the multispectral palmprints. The information from different spectrum are fused by means of feature level fusion. The nearest neighbour classification based on class wise reconstruction error is used for classification. Experiments are conducted on PolyU multispectral palmprint database. The results show that the proposed method works better in comparison with the existing techniques.**

I. Introduction

Nowadays, the biometric based systems are gaining popularity to provide a robust and an accurate authentication to many of the routine business transactions. Among the different biometrics, palmprint based human identity assurance has recently received significant attention since it is less intrusive and high user acceptance [6] [7] [17] and finds its application in physical access control, immigration systems and management of medical records etc.

In the literature, we have seen the number of representation schemes to represent the palmprint. Kong et al. [6] broadly classifies these methods into four categories namely: subspace based approaches, geometrical approaches, statistical approaches and other(hybrid) approaches. The representation of feature in any of these approaches is crucial to the success of these approaches. In this context, we have seen many works based on compressive sensing and sparse representation which attracted many researchers [11] [12]. Using compressive sensing technique we can represent a signal by means of linear combination with few signals from appropriate dictionary. This type of representation is sparse since the total number of nonzero coefficients are small compared to the total number of coefficients. Thus sparse representation is the representation of an image as a linear combination of several finite number of elementary images. It is an excellent tool to achieve high performance in the presence of noise and compression [12].

In this paper, we use joint sparse representation to design an identity assurance system that involves identification as well as verification. Here, the whole training samples together form the dictionary. The proposed method represents the probe palmprint as a linear combination of template palmprints from the dictionary which is collected during the training phase. The intensity information from red, green, blue and near-infrared spectrum are fused by means of feature level fusion. The nearest neighbour classification based on class wise reconstruction error is used to identify the probe. In case of verification, if the reconstruction error is less than the threshold it is classified as genuine. The value of the threshold is determined automatically through the experiments.

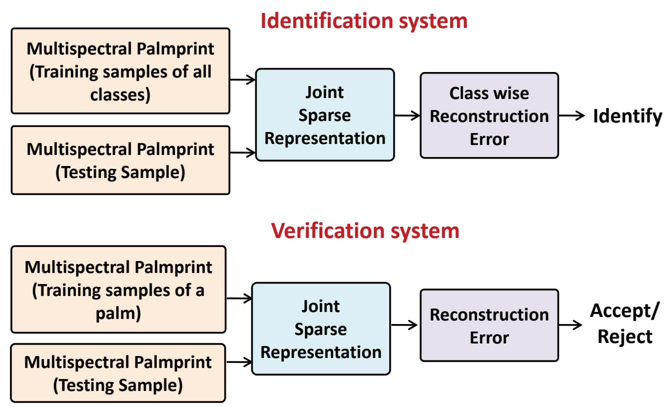


Fig. 1. Identification and verification framework for the proposed method

II. Related Work

The pioneer works on palmprint recognition and verification is carried out by Zhang et al. [16] and continued to be addressed by many researchers to provide an accurate solution. In this context, few prominent methods are discussed in this section. Many researchers used principal component analysis (PCA) to extract the features from the palmprint [3] [8]. It is done either directly on the downscaled image or on the global features extracted from the palmprint. Wu et al. proposed similar methods based on the fisherpalms [13]. Researchers also used features of Gabor filters to represent the palmprint [4] [7] [10]. These features give robust and invariant representation of palmprint. Kisku et al [5] used Gabor features to multispectral palmprint verification. Recently, Badrinath et al. [2] proposed palmprint identification based on the phase-difference information. They extracted the features block wise and performed score level fusion to get good recognition accuracy. Hamming distance is used to speed up the matching process.

On the other hand, sparse representation is extensively used in many pattern recognition problems. In [12], Wright et al. effectively applied sparse representation for face recognition. Nibouche et al. [9] applied sparse representation for palmprint captured in visible light. The analysis is made by varying the size of the sample and its effect on optimization process and sparse representation in their experimental study. In [14], Xu et al. proposed bimodal biometric based palmprint recognition based on sparse representation. In [14], Xu et al. concatenated the features and selected prominent training samples from the whole training set. The test sample is represented and reconstructed only using these samples. Whereas in our work, we represent the probe using all templates. We perform feature level fusion to achieve the joint sparse representation. Although our work is similar to [14] in the sense of having sparse representation, it differ in terms of training, feature extraction and classification.

III. Methodology

The sparse representation of a palmprint represents a probe palmprint as a linear combination of training samples. The joint sparse representation use features from the multispectral images. During the sparse representation, it is more likely that the contribution from training samples belonging to the class of the probe is high. Thus, if we reconstruct the probe palmprint only using the training samples belonging to a class, the reconstruction error is minimal for the class for which it belongs to. The probe is classified into the class of training samples with minimal error.

Let us consider the multispectral images those belong to C different classes and four spectrum namely red, green, blue and near-infrared (NIR). Let X represent all the training samples which forms the dictionary. Let t be the total training samples from each class and d be the dimension of each sample.

We represent

$$X = [X^1, X^2, X^3, X^4] \tag{1}$$

$$X^i = [X^i_1, X^i_2, ..., X^i_C], i = 1, 2, 3, 4 \tag{2}$$

where X^i represent training samples from i^{th} spectrum. It is the dictionary with size $d \times (t * C)$ belonging to C different classes. Here X^i_j represents the data of i^{th} spectrum and j^{th} class with size $d \times t$. X^i_j can be expanded by,

$$X^i_j = [X^i_{j,1}, X^i_{j,2}, ..., X^i_{j,t}] \tag{3}$$

where $X^i_{j,k}$ represents the single atom from the dictionary.

Analogous to the notation of X, we also represent the testing samples Y,

$$Y = [Y^1, Y^2, Y^3, Y^4] \tag{4}$$

$$Y^i = [Y^i_1, Y^i_2, ..., Y^i_m] \tag{5}$$

where each Y^i belongs to the i^{th} spectrum and m is the total test samples. Y^i_j is the j^{th} testing sample belonging to i^{th} spectrum. In case of identification, the aim is to identify the test samples in Y, for which class it belongs to. During verification, the aim is to test whether the sample belongs to the respective class or not.

A. Identification

Let Y be the given test sample.

$$Y = [Y^1, Y^2, Y^3, Y^4] \tag{6}$$

Let us say, Y^i belongs to the k^{th} class, then Y^i can be represented as,

$$Y^i = X^i C^i + E^i \tag{7}$$

where C^i is the sparse matrix corresponding to coefficients and E^i is the matrix corresponding to noise. The coefficient sparse matrix can be computed as ,

$$C = arg\ min_C \sum_{i=1}^{4} ||Y^i - X^i C^i||_2 + \lambda ||C^i||_1 \tag{8}$$

where $||.||_2$ is the l_2 norm and $||.||_1$ is the l_1 norm. λ is the parameter whose value should be positive. The alternating direction method of multipliers [15] based optimization algorithm is used to approximate the coefficient matrix C.

On computation of C, the class label corresponding to the test sample Y is determined using the Eqn. 9. The class label for Y is declared as j if the training samples of class j that reconstruct Y is with least approximation error. i.e.

$$j = arg\ min_j \sum_{i=1}^{4} ||Y^i - X^i \delta^i_j C^i||_2 \tag{9}$$

where δ is a function that selects only the training samples from X belonging to j^{th} class.

B. Verification

Let Y be the given test sample as in Eqn 7. Now it is represented from training samples of a class against which verification has to be conducted. Thus, now X contains samples of same class. Y can be represented as

$$Y^i = X^i C^i + E^i, i = 1, 2, 3, 4 \tag{10}$$

Compute the reconstruction error e as follows

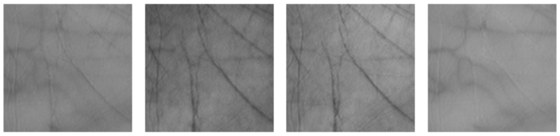
$$e = \sum_{i=1}^{4} ||Y^i - X^i C^i||_2 \tag{11}$$

If e is less than the threshold th, we conclude that Y is *accepted*, otherwise it is *rejected*. The value of th is computed experimentally.

IV. Experiments

A. Dataset

The experiments are conducted using PolyU multispectral palmprint dataset [1]. It consists of 12000 multispectral palmprint images belonging to 500 palms. This includes both left and right palmprints. For each palm, the images are captured in four different spectrum: red, green, blue and near-infrared. The images are captured in two different sessions. The average time interval between the first session (session-1) and the second session (session-2) was about 9 days. In each session six samples per palm are captured. So a sample means, four palmprint images of a palm belonging to four diffrent spectrum. (500 palms $\times$ 6 images $\times$ 4 spectrum $\times$ 2



a) Red b) Green c) Blue d) NIR

Fig. 2. Preprossed palmprint images of Red, Green, Blue and Near-Infrared spectrum

sessions = 12000 images). The size of the original palmprint image was 352 x 288. It is preprocessed and region of interest (ROI) is extracted using the method specified in [16]. Here the original palmprint image is low-pass filtered using a Gaussian filter and binarized. The gaps between the fingers are found and a tangent is drawn. The ROI is extracted keeping tangent as a reference line. The size of ROI is fixed as 128×128. The pre-processed image belongs to four different spectra are shown in Fig. 2.

B. Experimental results

1) Identification: The required number of training samples are selected from each class randomly which belongs to the session-1. The training samples to create dictionary are selected from session-1 and probes are selected from session-2. This method is chosen since it is the realistic scenario. The recognition rate is computed as a average of four executions.

Experiments are conducted to evaluate the performance of the proposed method which uses four multispectral images with respect to the performance of individual spectrum. The observed recognition accuracy are listed in Table I. The joint sparse representation based feature level fusion outperforms the results of basic sparse representation based identification of the individual spectrum. This proves the superiority of joint sparse representation technique over basic sparse representation.

Table I also lists the performance of the methods with varied number of training samples. As expected, the accuracy increases with the more number of training samples.

We also compared the identification accuracy of the proposed method with contemporary techniques such as PCA and LDA. The proposed method gives better results than these techniques. Here the number of training samples per subject is chosen as three for the experimental purpose. Table II summarizes the result.

TABLE I. IDENTIFICATION ACCURACY OF PROPOSED METHOD FOR DIFFERENT NUMBER OF TRAINING SAMPLES IN COMPARISON WITH INDIVIDUAL SPECTRUM

Spectrum	Training samples used		
	3	2	1
Proposed Model (R, G, B and NIR)	98.83	98.80	96.83
Red	97.80	97.60	94.20
Green	98.00	94.66	92.50
Blue	98.30	95.33	93.67
Near-Infrared	97.20	97.17	95.16

TABLE II. COMPARISON OF IDENTIFICATION ACCURACY OF PROPOSED METHOD WITH PCA AND LDA

Method	Identification Rate
Proposed method	98.83
LDA [13]	97.50
PCA [3]	93.40

TABLE III. RESULT OF VERIFICATION USING DIFFERENT CONFIGURATIONS

Config.No.	Samples/Methodology	FAR	GAR
1.	All 12 samples of a palmprint using leave-one-out method	10^{-3}	99.97
		10^{-2}	99.97
2.	Training: 3 from session-1, 3 from session-2 Testing: 3 from session-1, 3 from session-2	10^{-3}	99.00
		10^{-2}	99.75
3.	Training: 6 from session-1 Testing: 6 from session-2	10^{-2}	98.50
4.	Training: 6 from session-2 Testing: 6 from session-1	10^{-2}	96.00

2) Verification: We conducted the experiments to perform verification. The performance of the proposed method is measured using false acceptance rate (FAR) and genuine acceptance rate (GAR).

Experiments are conducted in four different configurations. The results are shown in Table III. The first configuration uses leave-one-out strategy. This method uses one sample under consideration as a test sample and all remaining samples are used as training samples. FAR is found by taking the testing samples from different class and GAR is found by taking the test samples from the same class. We are able to achieve best verification result in this configuration with GAR as 99.97% at FAR = 10^{-3}. The second configuration divides whole samples in to two sets. The both set contains half of the samples form each session. One set of samples is used for training and another is used for testing. Here also proposed model results in GAR as 99% at FAR = 10^{-3}. The third configuration matches with the realistic scenario where training samples chosen from session-1 and testing samples chosen from session-2, which results 98.50% of verification accuracy. The third and fourth configuration accounts for the robustness system for the verification process in real-time situation where training and testing samples are captured in different time intervals .

During the experiments it is observed that the reconstruction error for a TRUE sample is considerably small in comparison with the reconstruction error of the FALSE sample. So we are able to identify a threshold value e which separates the genuine and false samples clearly, which results in good GAR result. The reconstruction error of few genuine and false samples are shown in Fig. 3. The receiver operating characteristic curve for the same is given in Fig. 4.

V. CONCLUSION AND FUTURE WORK

We proposed a palmprint representation technique to perform identification and verification for multispectral images. It represents a palmprint using joint sparse representation. Experiments are conducted by varying configurations to test the effectiveness of the proposed technique. In future, we would like to automate the selection of total number of training samples for each class, which in turn optimize the number of training samples required.

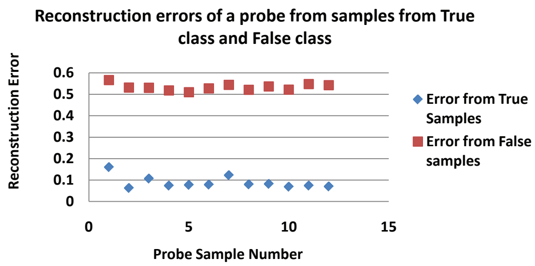


Fig. 3. Reconstruction error of a probe from training samples from same/true class different/false class.

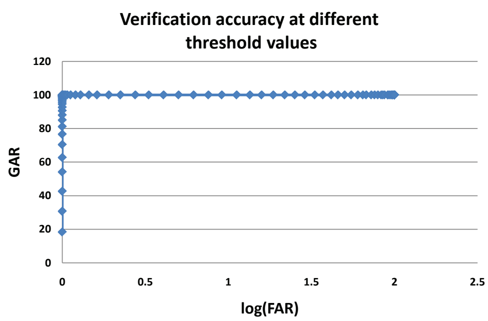


Fig. 4. Receiver operating characteristic curve for verification.

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