Palmprint Recognition in Eigen-space

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***Abstract*—This paper proposes a novel technique for palmprint recognition in context to biometric identification of a person. Palmprints are images of the inner portion of a person's palm and consist of a complex pattern of randomly oriented curves and lines. This random pattern can provide a unique identifier of a person if a mathematical model can be built to represent and compare it. In this paper the palmprint images are mapped to Eigen-space and a robust code signature is generated from different camera snapshots of the same palm to incorporate tonal and lighting variations. To enable real-time identification, the signature is represented by a low dimensional feature vector to reduce computational overheads. It is observed to produce high recognition accuracies which highlight reliability of the feature.**

Keywords- Eigen vector, palmprint recognition, biometrics, computer vision.

I. Introduction

Biometrics refers to automatic recognition of individuals based on their physiological and behavioral characteristics like iris recognition, facial recognition, fingerprint verification, hand geometry, palmprint recognition, retinal scanning, signature verification, voice verification etc. Among the above mentioned techniques palmprint recognition has a number of advantages : palmprints contain more information than fingerprints and hence are expected to produce more reliable results, palmprint capture devices are cheaper than iris scanning and retinal scanning devices and hence image acquisition processes are easier, they can be combined with other related techniques like hand geometry and fingerprint recognition techniques to improve recognition accuracies, both shape and texture recognition techniques can be applied to model palmprint lines and curves.

The basic steps that are involved in palmprint recognition system are capturing the image of the palm using devices like the scanner or camera. These images are usually represented as grayscale images because recognition is usually based on the pattern of the lines of the palm and usually employ shape based or texture based techniques for building a data model. The images are usually preprocessed which involve passing the images through filters and tonal correction so that the lines are more distinct and clearly visible. Challenges in palmprint recognition are related to building a reliable data model from a set of irregular lines oriented in a random fashion which makes it possible to identify and authenticate individuals. An additional restriction is that the data model should have low dimensionality and small computational overheads, as authentications are required in real-time.

This paper proposes a technique to model and compare palmprint images involving Eigenvector decomposition. The organization of the paper is as follows : section-II provides a survey of the previous work in the area, section-III describes the proposed methodology including the feature representation and classification schemes, section-IV provides details of the experimentations done and results obtained, section-V describes analysis of the current work vis-à-vis contemporary works, section-VI provides the overall conclusions and identifies future scopes for improvements.

II. Past Approaches

In [1] the authors propose a palm print recognition system by extracting features using Sobel operators and using Hidden Markov Models (HMM) as classifiers. In [2] the authors propose translation invariant Zernike moments as palm features and a modular neural network as classifier for recognition. Generalization of the principal component analysis (PCA) referred to as the Kernel PCA and Independent Component Analysis (ICA) have been reported to produce satisfactory results in palmprint recognition [3, 23]. Multi-scale wavelet decomposition of palmprint images and using mean of each wavelet sub-block has been suggested in [4, 17] as a feature for recognition. Integration of Daubechies wavelet with PCA has also been proposed in [11, 12] as a means for palmprint recognition. A weighted fusion of discrete multi-wavelet transform (DMWT) and local binary pattern (LBP) has been proposed in [28] to overcome the limitation of single feature extraction method. The use of phase components in 2D discrete Fourier transform (DFT) have been explored in [5, 16, 21, 27] for palmprint recognition. The use of discrete cosine transform (DCT) coefficients have been proposed in [19] as an effective means for palmprint recognition. 2D Gabor filters have been suggested in [29, 25] as a means for recognizing palmprint images. Kernel Fisher discriminant analysis have been suggested as more advantageous than normal PCA and LDA when number of training samples are small [6]. 2D PCA and 2D LDA over conventional PCA and LDA have been reported to be better for palmprint recognition in [7, 22]. Fusion of palmprint features with other related features like hand geometry [8, 10, 17], hand contour [24], minute crease lines [26] have been suggested to improve recognition accuracies. Hough Space Transform has been used in [9] for palmprint recognition. Noisy images were handled using fuzzy logic [13] while directional filterbanks for computing directional energies have been used in [14]. Eigenvector decomposition have been suggested in [15] as a means of recognition. Differential feature analysis for palmprint authentication have been suggested in [18]. In [20] authors have proposed fusion of multi-color components in RGB, YIQ and HIS color spaces for improving recognition results. In [30] the authors have explored rank-level combination of multiple biometrics representations and a new nonlinear rank-level fusion approach is proposed. A comparative study of several palmprint recognition techniques can be found in [31].

III. Proposed Methodology

This paper presents a novel technique for palm recognition with higher accuracy in lower dimensional feature space, which reduces the template size and hence computational overheads.

A. Training Phase

The training set for each person or class consists of $(p+q)$ sample images belonging to that person, divided into 2 sets : first set of p images $(I_1, I_2, \dots, I_p)$ and second set of q images $(I_{p+1}, I_{p+2}, \dots, I_{p+q})$. The images are resized to standard dimensions of $n \times n$.

The first p image matrices are converted from 2-D to 1-D column vectors $x_1, \dots, x_p$ and concatenated together to form a $(n^2 \times p)$ matrix where $(n \times n)$ is the dimension of each image. If X is the concatenated matrix for a single person or class, we have

$$X = [x_1, \dots, x_p] = \bigcup_{k=1}^{p} x_p \qquad (1)$$

The row-wise mean is calculated and represented by M $(n^2 \times 1)$. The mean is subtracted from each of the 1-D column matrices to generate normalized matrices. The normalized matrices are again concatenated side by side to form $D(n^2 \times p)$

$$D = \bigcup_{k=1}^{p} \varphi_k \, , where, \varphi_k = x_k - M \qquad (2)$$

A $(p \times p)$ square matrix E is generated by multiplying D with its transpose, and eigenvectors E_C and eigenvalues E_L of E are generated. A vector U $(n^2 \times p)$ is formed by product of D $(n^2 \times p)$ and E_C $(p \times p)$

$$U = D.E_C \qquad (3)$$

Weight vectors w_1 and w_2 , each of dimension $(p \times 1)$, are calculated from the second set of q images

$$\begin{gathered} w_1 = U^T.(x_{p+1} - M) \\ \dots \\ w_q = U^T.(x_{p+q} - M) \end{gathered} \qquad (4)$$

These are averaged to form an average weight W $(p \times 1)$ vector for a class :

$$W = \frac{1}{q}(w_1 + w_2 + \dots + w_q) \qquad (5)$$

Various classes (i.e. persons) 1, 2, 3,… are therefore represented by their feature vectors $W_1, W_2, W_3, \dots$

B. Testing Phase

The testing set for each person or class consists of r sample images belonging to that person. Images corresponding to the testing test, are read and converted to 1-D column matrices $L_1,\ L_2, \ldots, L_r$ each of dimension $(n^2 \times 1)$. They are normalized by subtracting the mean M from them.

$$\begin{gathered} y_1 = L_1 - M \\ \ldots \\ y_r = L_r - M \end{gathered} \qquad (6)$$

Scalar weight factors are calculated by multiplying vector U^T $(1 \times n^2)$ with each of $y_1, y_2, \ldots$ of dimension $(n^2 \times 1)$.

$$\begin{gathered} S_1 = U^T . y_1 \\ \ldots \\ S_r = U^T . y_r \end{gathered} \qquad (7)$$

C. Classification Scheme

The j-th test vector S_j is compared with each of the 10 training vectors $W_1 \ldots W_{10}$ using Euclidean distances. Let the distance values be $D_{j,1} \ldots D_{j,10}$. A test image is classified to the class for which the Euclidean distance is minimum.

$$S_j \rightarrow k \ if \ min\left(D_{j.1}, \ldots, D_{j.10}\right) = D_{j,k} \qquad (8)$$

IV. EXPERIMENTATIONS AND RESULTS

All simulation based experiments reported here are developed using the PolyU Palmprint Database of the Biometric Research Center, Hong Kong Polytechnique University [32]. A total of 200 images corresponding to 10 classes have been used with 20 images per class. For each class 12 images have been used as the training set with p=10 and q=2, and the rest 8 images have been used for testing. Each of the images has been standardized to dimensions of 384 × 284 and stored are in BMP format.

A. Training Phase

A total of 120 images have been used for the training set, arranged into 12 images in 10 classes. Sample images of some of the classes are shown in Fig. 1, each row indicating a separate class and each column indicating a sample for a class.

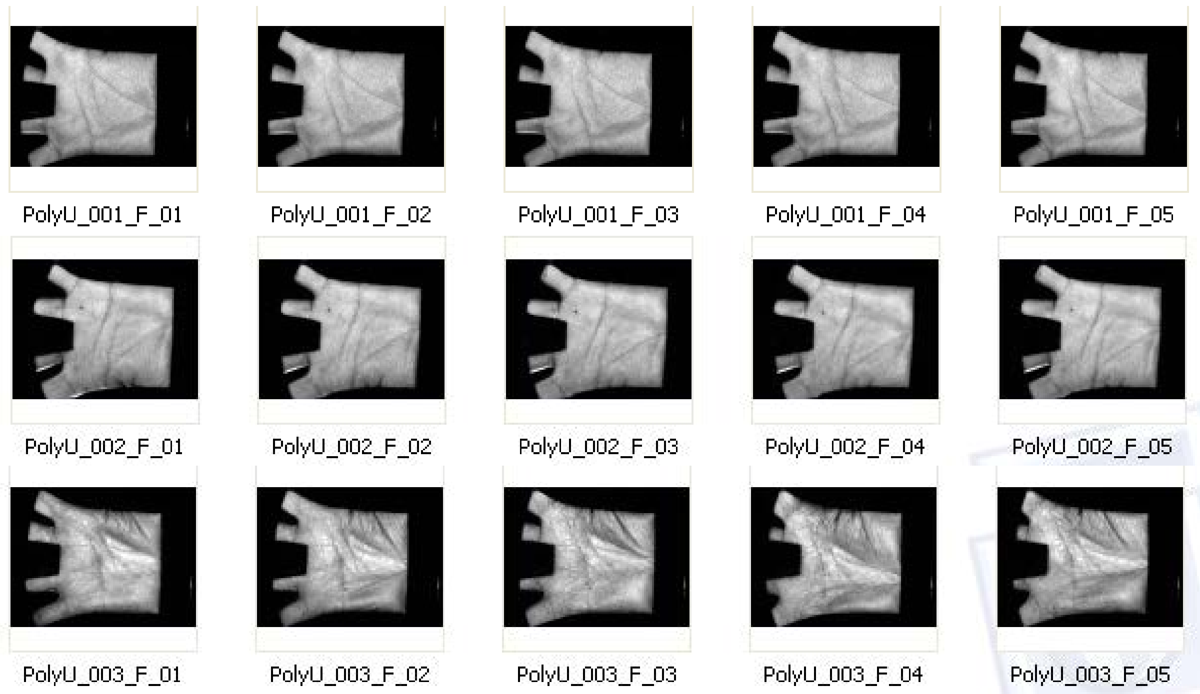

Figure 1. Sample images of the training set

Fig. 2 shows the plot of the 10-element feature vector W corresponding to the 10 classes of the training data set.

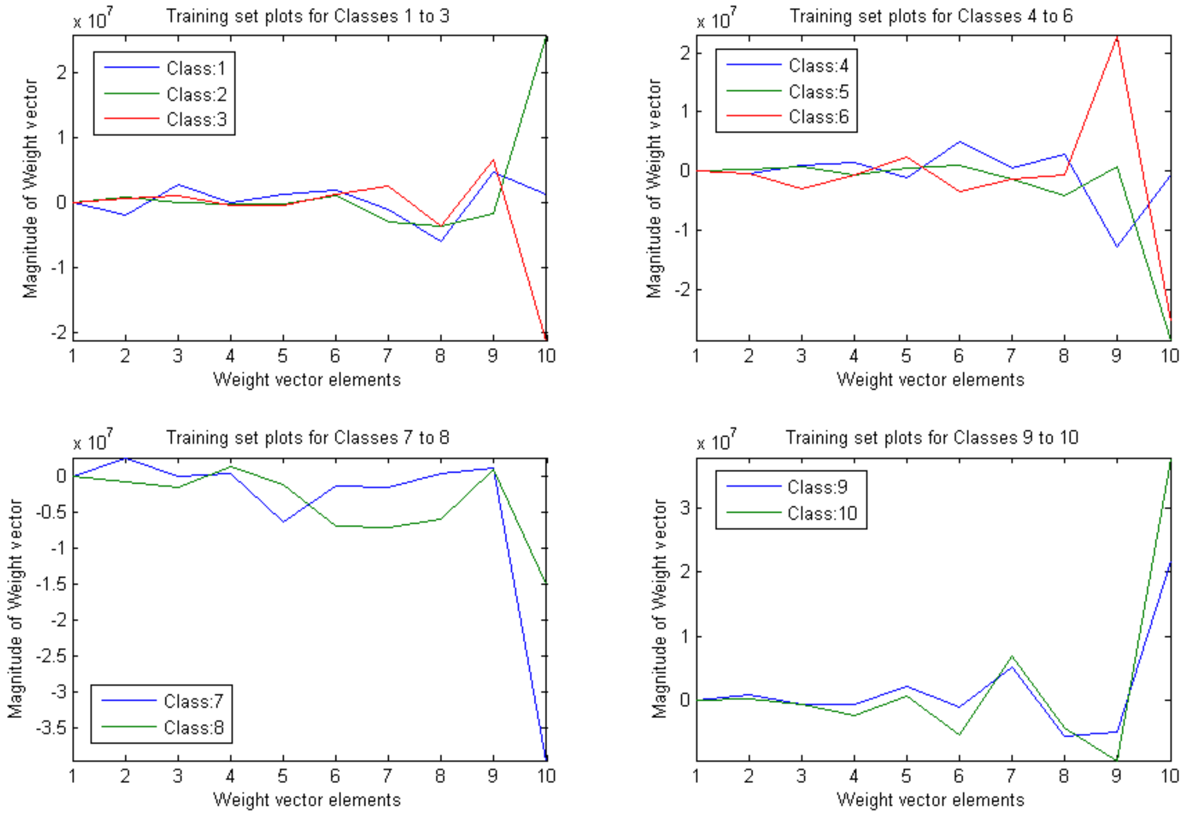

Figure 2. Feature plots for the training set

B. *Testing Phase*

A total of 80 images have been used for the testing set, arranged into 8 images in 10 classes. Sample images of some of the classes are shown in Fig. 3, each row indicating a separate class and each column indicating a sample for a class.

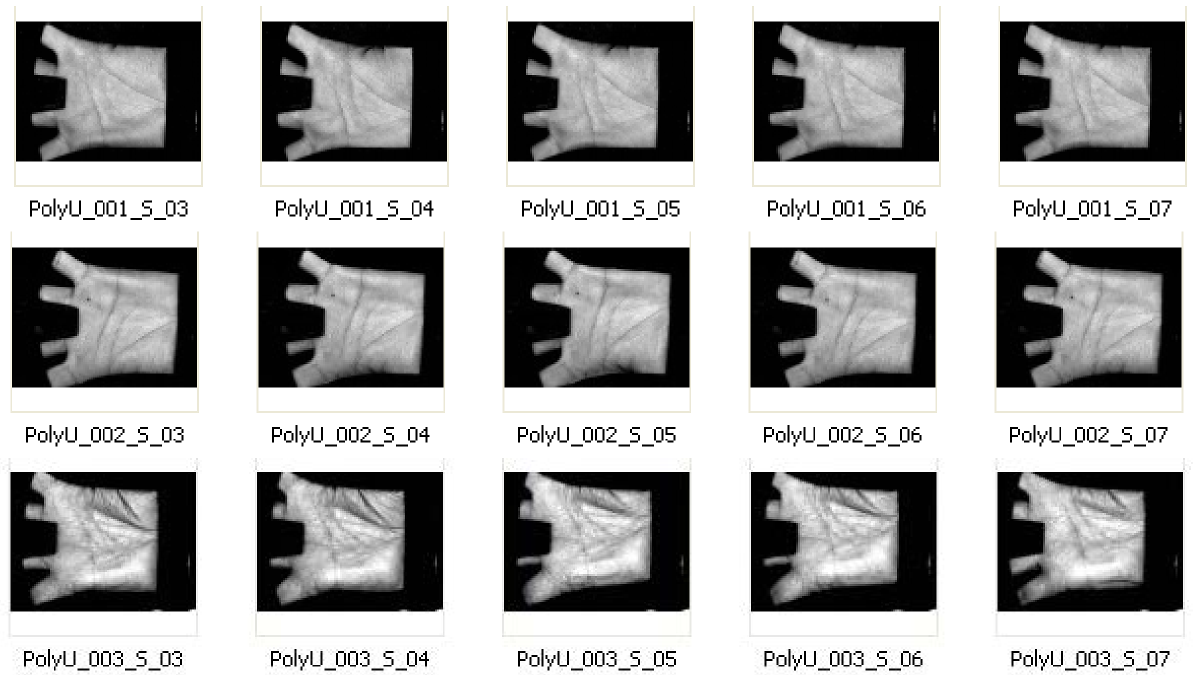

Figure 3. Sample images of the testing set

Fig. 4 shows the plot of the feature values of the first three samples of each of the 10 classes of the testing data set.

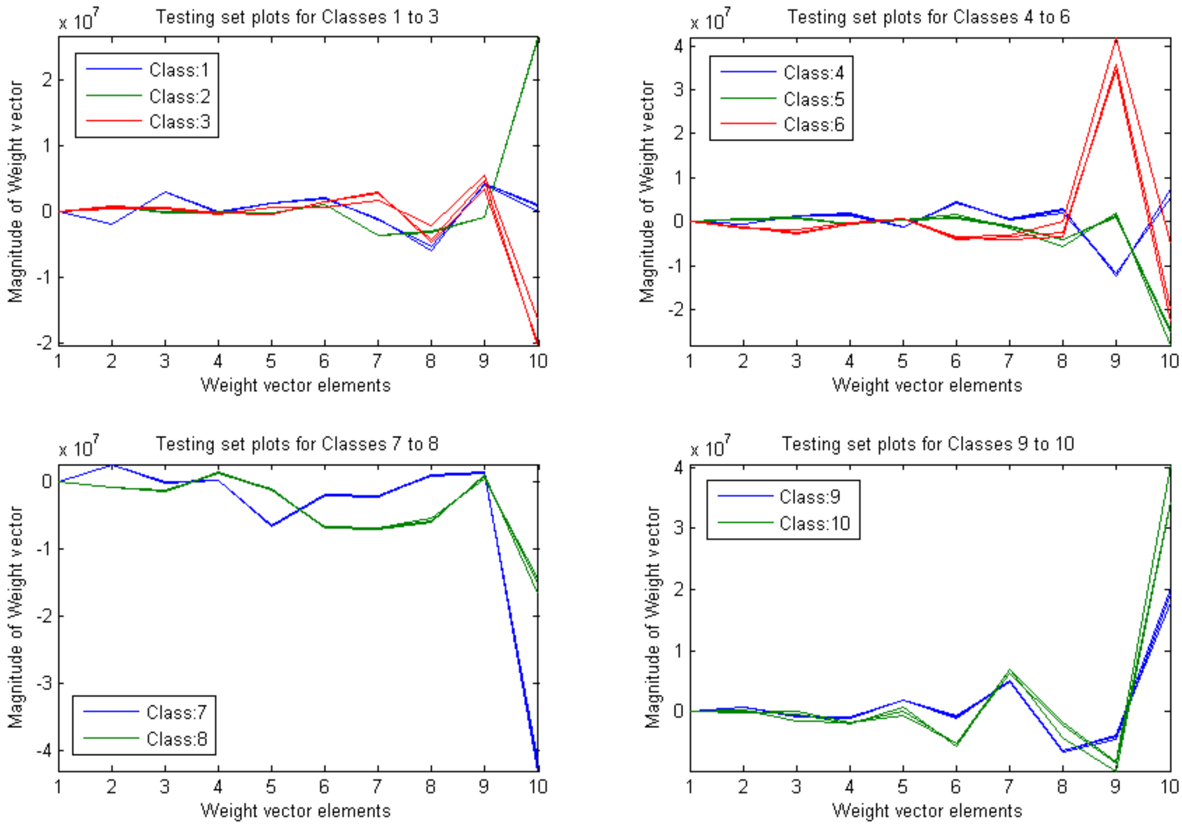

Figure 4. Feature plots for the testing set

C. Computation of Estimated Classes

The test images are compared to each of the training classes using Euclidean difference of their feature values. The minimum difference corresponds to the estimated class of the test sample. Fig. 5 shows the difference plots of the 8 test sample vectors of each class with all the 10 training class vectors. The accuracy results of individual classes and overall accuracy is tabulated in Table 1.

TABLE I. RECOGNITION ACCURACIES

Class	**Percentage Accuracy**
Class-1	100
Class-2	100
Class-3	100
Class-4	87.5
Class-5	100
Class-6	100
Class-7	100
Class-8	100
Class-9	100
Class-10	100
Overall	98.75

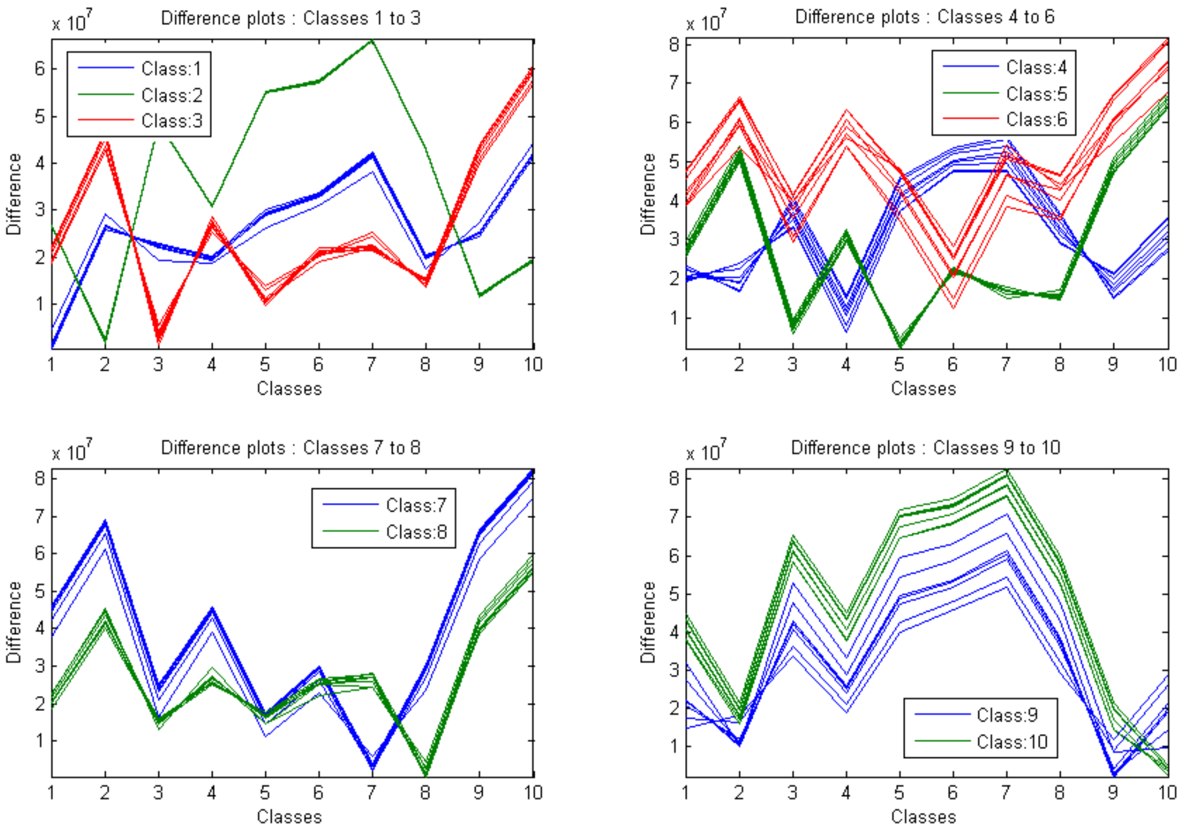

Figure 5. Difference plots for class estimation

V. ANALYSIS

The discrimination the palmprint images of 10 classes is done successfully and with satisfactory accuracy i.e. 98.75%. To put the results in perspective with the state-of-the-art, [1] reports an accuracy of 97% using HMMs and Gaussian mixtures. [2] reports an accuracy of 98% using translation invariant Zernike moments, [3] reports an accuracy of 96% using Kernel PCA analysis, best average accuracy reported in [4] is 95% using Wavelet transform, [6] reports an accuracy of 97% using Kernel Fisher discriminant analysis, around 98% using 2D PCA [7], 100% by fusing hand geometry features with palmprint [10], 98% using fuzzy logic [13], 99% using DCT coefficients [19], 99% using fusion of color components [20]. Hence most of the techniques proposed in extant literature have been reported to have achieved 95% or more recognition accuracy. The most similar paper we can find with respect to the current paper is [15] where eigenvectors in conjunction with PCA have been used to produce an accuracy of 97% however the feature vector is reported to 150 elements in size, in contrast this paper demonstrates comparable accuracies with only a 10 element vector, which substantially reduces computational overheads.

VI. CONCLUSIONS AND FUTURE SCOPES

The proposed approach describes a method for discrimination of palmprint images belonging to different individuals by constructing eigenspaces from 12 training samples per class and constructing a 10-element feature vector. Accuracies obtained from 8 samples per class and over 10 classes, have shown it to be an acceptable and optimized technique providing comparable recognition accuracies and smaller feature representations compared to contemporary works. Salient features of the proposed technique include a low dimensional feature representation of the palmprint texture, low computational overheads and high recognition accuracies of over 98%. This enables recognition and identification possible in real-time applications in a reliable manner. Future work would involve testing on larger number of classes and fusion of other features like color to improve recognition accuracies. This work also does not involve any preprocessing step i.e. the images from the publicly available dataset have been used as it is. In future we would also study the effects of tonal correction on the images and using smaller sub-blocks from the original images for reducing the overheads and size of the database further.

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