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Iris Recognition using a Scalar based Template in Eigen-space

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***Abstract*—This paper proposes a novel technique for iris recognition in the context of biometric identification of a person. The iris is a portion of the inner eye of an individual and contains an abstract and randomly generated texture pattern arising from orientation of complex tissues within this region. 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 iris images are mapped to Eigen-space and a robust iris code signature is generated from different camera snapshots of the same eye to incorporate tonal and lighting variations. To enable real-time identification the signature is represented as a low dimensional feature for reducing computational overheads. It is observed to produce high recognition accuracies which highlight the reliability of the feature. Moreover the technique is seen to be robust which can work satisfactorily with noisy and partially occluded images.**

***Index Terms*—Iris recognition, texture pattern matching, Eigen space, biometrics, scalar based template, computer vision**

I. INTRODUCTION

BIOMETRICS refers to automatic recognition of individuals based on their physiological and behavioral characteristics like iris scanning, facial recognition, fingerprint verification, hand geometry, retinal scanning, signature verification, voice verification etc. Among the above mentioned techniques, iris recognition provides one of the most reliable and accepted methods for personal identification. The iris is a highly protected portion of the inner eye, which is used for identification of a person. This is possible because firstly, iris patterns possess a high degree of randomness which is never the same for any two individuals, even identical twins, and makes them ideal for personal identification, and secondly, the patterns remain stable throughout a person's lifetime and it being a portion of the inner eye is difficult to tamper with, unlike fingerprints which are relatively easier to change.

The basic steps involved in iris recognition systems involve capturing the image of the eye at a close range using a camera. The image needs to be well illuminated so that the texture patterns of the iris portion are clearly discernable. After that an image processing system is used to create a mathematical model of the iris texture so that it can be compared with other iris images to identify specific individuals. Challenges in an iris recognition system involve building a reliable mathematical model of an abstract texture pattern to reliably identify persons for authentication and identification purposes. The task becomes more difficult as frequently a complete iris image is not obtained but is occluded by portions of the eyelid and eyelashes. Moreover different lighting conditions can change the appearance of the texture patterns by accentuating and attenuating various grey tones. Also the authentication system should work in real-time so that extraction, representation and comparison of texture images should not consume large computational resources.

This paper proposes a novel technique to represent iris patterns for biometric identification of individuals. 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

The possibility of using iris patterns as a basis for personal identification was first proposed in 1885 by French scientist Bertillon [1]. John Daugman [2] played a pioneering role in designing and patenting the first complete commercially available iris recognition system in 1994. Eye images were captured in real-time and integro-differential operators were used to detect the iris region faithfully. The iris portion of the image is normalized to a polar form by a mapping function and is subsequently binary coded using quadrature 2D Gabor wavelets into four levels. In [3] Daugman extended the segmentation and feature extraction process to allow for a compact 256-byte iris code or template for convenience in storage and comparison. In [4] Daugman presents results of 9.1 million comparisons among eye images from trials in Britain, USA, Japan and Korea. New advances in iris recognition are reported in [5] which includes more disciplined methods for detecting and modeling iris inner and outer boundaries with active contours, a Fourier based methods for solving problems related to off-axis gaze, and a statistical interference method for detecting and excluding eyelashes. In [6] the authors demonstrate that only half of the iris is sufficient for detecting individuals instead of the whole extension. Iris detection in Eigen space has been proposed in [7] where eigenvectors are extracted from iris images and weight vectors calculated from the eigenvectors, are used for class discrimination. Discrete Cosine Transform (DCT) coefficients of overlapped angular patches from normalized iris images, have been used in [8] to generate iris codes with various weight parameters to optimize performance. In [9] authors have proposed a new technique involving 2D LDA with embedded 2D PCA, for dimensionality reduction of iris image features. Handling of noisy iris images by 2D Gabor filters have been discussed in [10]. In [11] the authors have used elastic graph matching with 2D Gabor wavelets to extract iris features. 2D Gabor filters have also been used in [12] to analyze local feature structure of iris texture information based on relative distance of key points. The keypoints represent points which can represent local texture most effectively. A survey of major iris recognition techniques can be found in [13].

III. PROPOSED METHODOLOGY

This paper presents a novel technique for iris 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 : a first set of p images $(I_1, I_2, \dots, I_p)$ for calculation of eigenvectors, and second set of q images $(I_{p+1}, I_{p+2}, \dots, I_{p+q})$ for calculating weight features from eigenvectors. The images are resized to standard dimensions of $(n \times n)$. The first p images are read and a set of 2-D covariance matrices $A_1, A_2, \dots, A_p$ are calculated from them each having dimensions of $n \times n$, where the (i,j)-th element of a covariance matrix $C_{i,j}$ for data matrix $X = \begin{bmatrix} x_{1,1} & \dots & x_{1,n} \\ \dots & \dots & \dots \\ x_{n,1} & \dots & x_{n,n} \end{bmatrix}$ is defined in (1) where, $\mu_i = \frac{1}{n}(x_{1,i} + x_{2,i} + \dots + x_{n,i})$.

$$C_{i,j} = C_{j,i} = \frac{1}{n-1} \sum_{k=1}^{n} (x_{k,i} - \mu_i)(x_{k,j} - \mu_j) \qquad (1)$$

The 2-D covariance matrices of dimensions $n \times n$ are converted to 1-D column matrices $B_1, B_2, \dots, B_p$ of dimension $n^2 \times 1$ and the p matrices are concatenated side by side to form B of dimensions $n^2 \times p$

$$B = [B_1 \quad \dots \quad B_p] = \begin{bmatrix} B_{1,1} & \dots & B_{p,1} \\ \dots & \dots & \dots \\ B_{1,n^2} & \dots & B_{p,n^2} \end{bmatrix} \qquad (2)$$

The row-wise mean $M(n^2 \times 1)$ is calculated from :

$$M = \begin{bmatrix} M_1 \\ \dots \\ M_{n^2} \end{bmatrix} = \begin{bmatrix} \frac{1}{p}\sum_{k=1}^{p}(B_{k,1}) \\ \dots \\ \frac{1}{p}\sum_{k=1}^{p}(B_{k,n^2}) \end{bmatrix} \qquad (3)$$

The mean is subtracted from each of the 1-D column matrices $B_1, B_2, \dots, B_p$ to generate normalized matrices, which are concatenated side by side to form $D(n^2 \times p)$.

$$D = [D_1 \quad \dots \quad D_p] = [B_1 - M, \quad \dots, \quad B_p - M] \qquad (4)$$

A $(p \times p)$ square matrix E is generated by multiplying D with its transpose

$$E = D^T.D \qquad (5)$$

Eigenvectors E_C and eigenvalues E_L of E are generated such that : $E.E_C = E_L.E_C$. In this case both E_C and E_L are $(p \times p)$ matrices. Let v_m $(p \times 1)$ be the maximum eigenvector corresponding to maximum eigenvalue γ_m. A vector U $(n^2 \times 1)$ is formed by product of $D(n^2 \times p)$ and v_m $(p \times 1)$:

$$U = D.v_m \qquad (6)$$

Images corresponding to the second set q of the same class, are now read and converted to 1-D column matrices J_{p+1}, $J_{p+2}, \dots, J_{p+q}$ each of dimension $(n^2 \times 1)$. They are normalized by subtracting the mean M from them :

$$(K_{p+1} = J_{p+1} - M), \dots, (K_{p+q} = J_{p+q} - M) \qquad (7)$$

A series of scalar weight factors are calculated by multiplying vector U^T $(1 \times n^2)$ with each of $K_{p+1}, \dots, K_{p+q}$

$$\begin{aligned} w_1 &= U^T.K_{p+1} \\ &\dots \\ w_q &= U^T.K_{p+q} \end{aligned} \qquad (8)$$

The final feature representation W of the class is the scalar average of the weight factors calculated above i.e.

$$W = \frac{1}{q}(w_1 + w_2 + \dots + w_q) \qquad (9)$$

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

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.

$$y_1 = L_1 - M \\ \ldots \\ y_r = L_r - M \tag{10}$$

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

$$S_1 = U^T . y_1 \\ \ldots \\ S_r = U^T . y_r \tag{11}$$

C. Classification Scheme

The classification is done by calculating absolute scalar difference between each test feature and training feature of each class and finding the minimum difference. A test sample is considered member of the class for which the difference is found to be minimum. As an example, the mean difference between the feature vector of j-th test image S_j with all training images of each class is computed as :

$$D_1 = S_j - W_1; D_2 = S_j - W_2; D_3 = S_j - W_3 \ldots \tag{12}$$

The test image is then classified as belonging to that class with which its difference is the least i.e.

$$S_j \rightarrow k \ if \ min(D_{j.1}, \ldots, D_{j.10}) = D_{j,k} \tag{13}$$

IV. EXPERIMENTATIONS AND RESULTS

All simulation based experiments reported here are developed using the CASIA Iris Image Database [14]. 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 177 × 177 and stored in JPG format.

A. Preprocessing

The preprocessing step involves a manual segmentation process for extraction of the iris textured portion from an eye image. An image processor has been used to demarcate and retain the relevant iris portion while discarding the other irrelevant portions of the eye. The extracted iris portion has been subsequently subjected to tonal correction using histogram equalization. Fig. 1 illustrates the basic steps : the first image at top-left shows the original eye image, the second image to the right shows the iris portion selected, the third image bottom-left shows the segmentation of the iris portion and the bottom-right image shows the iris portion after tonal correction so as to bring out clearly the texture marks contained within it.

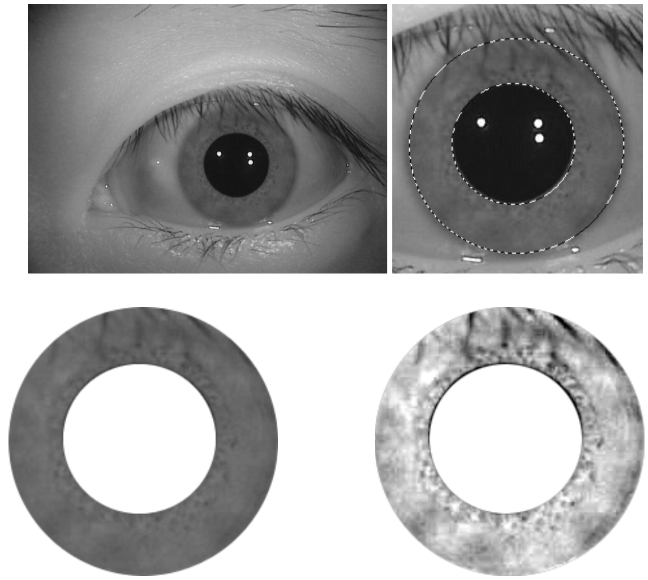

Figure 1. Extraction and tonal correction of the iris portion from an eye image (a) original eye image (b) iris portion selected (c) iris portion extracted (d) iris portion after tonal correction

In some cases part of the iris was found to be occluded by a portion of the eyelid and eyelashes. In such cases only a fragmented portion of the iris texture was extracted and subsequently used for feature generation. Fig. 2 shows such a case.

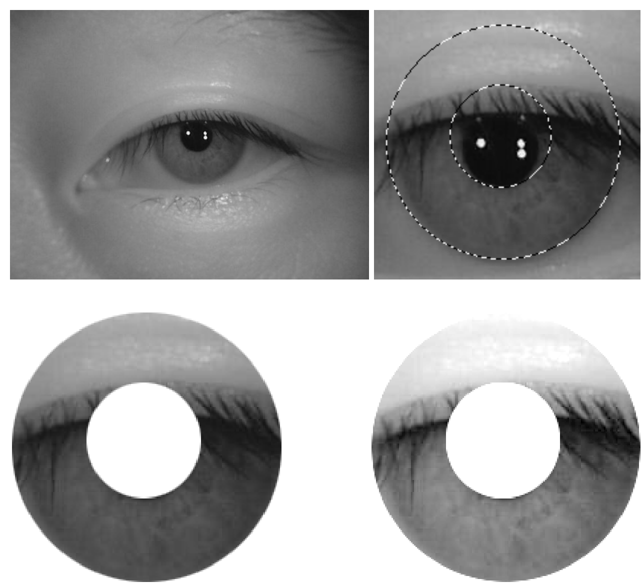

Figure 2. Extraction and tonal correction of a fragmented iris portion partially occluded by the upper eyelids

B. Training Phase

A total of 120 images have been used for the training set. Images have been preprocessed as described above to isolate the iris portion and arranged into 10 classes. Sample images of some of the classes are shown in Fig. 3. The first number indicates the class or person, ‘L’ denotes “left” eye image, and the last two digits indicate the sample number.

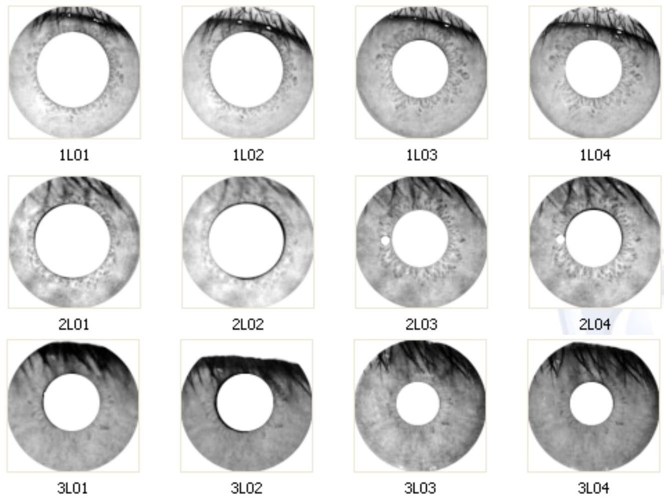

Figure 3. Sample Training set images

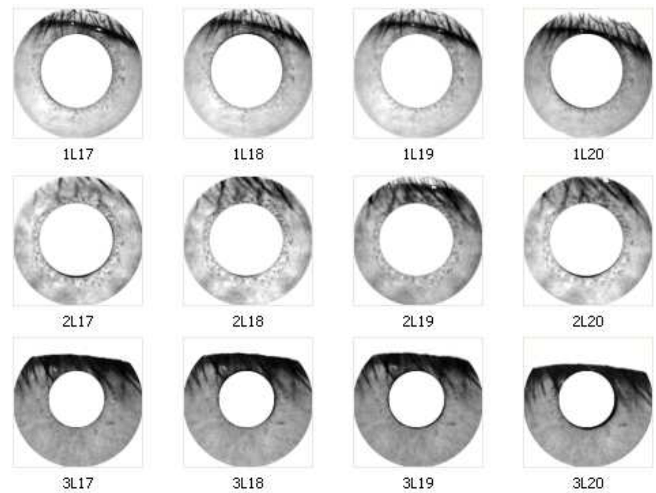

Figure 5. Sample Testing set images

Fig. 4 shows the plot of the feature value W corresponding to the samples of the 10 classes of the training data set. An appreciable amount of discrimination for all the classes could be identified which highlights the suitability of the feature selected.

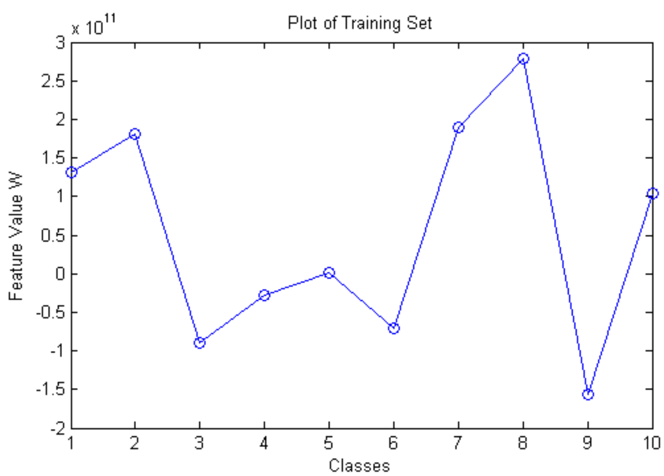

Figure 4. Feature plots of the Training set

C. Testing Phase

A total of 80 images have been used for the testing set. Images have been preprocessed as described above to isolate the iris portion and arranged into 10 classes. Sample images of some of the classes are shown in Fig. 5.

Fig. 6 shows the plot of the feature value S corresponding to the samples of the 10 classes of the testing data set.

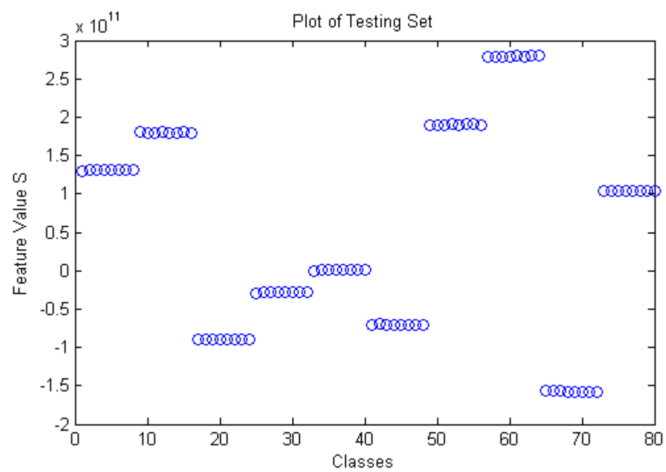

Figure 6. Feature plots of the Testing set

D. Computation of Estimated Classes

The test images are compared to each of the training classes using a scalar difference of their feature values. Fig. 7 shows the difference plots of the samples of each class with all the 10 training classes. The minimum difference corresponds to the estimated class of the test sample. The recognition accuracy is 100% i.e., all 8 samples of each of the 10 classes have been correctly identified.

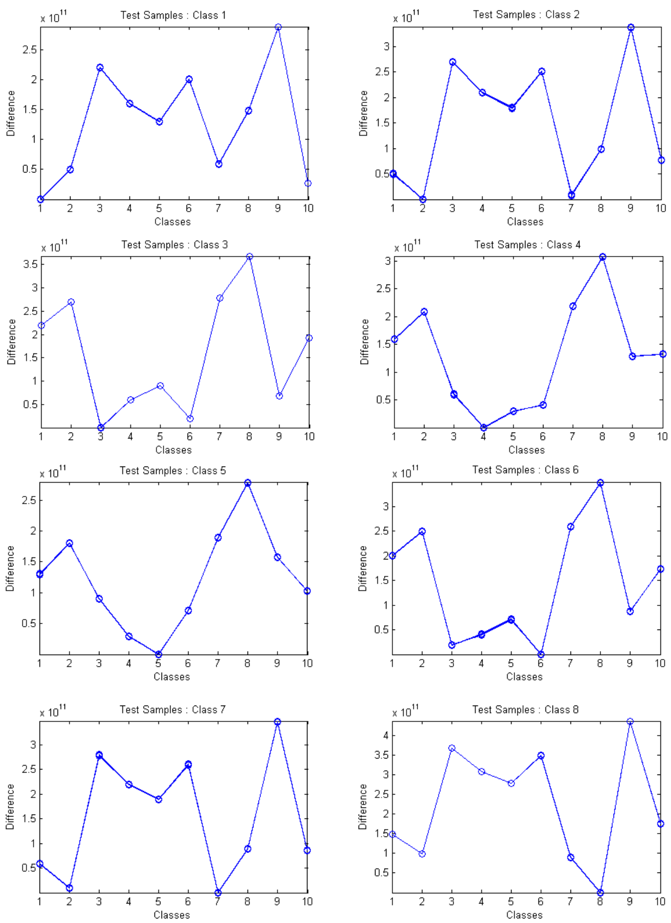

Figure 7. Class estimation plots

V. ANALYSIS

The recognition accuracy for discrimination the iris image of the each class is done successfully and with satisfactory accuracy. To put the results in perspective with the state-of-the-art, we analyzed the most similar work we could find i.e. [7] with regards to recognition accuracy tested on the same dataset. In [7] out of 15 iris images of each person, 10 are used for training set, 2 for calculating the weight vector and the remaining 3 for testing. The first 10 image matrices are converted from 2-D to 1-D column vectors $x_1, \dots, x_{10}$ and concatenated together to form a $(n^2 \times 10)$ 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

$$X = [x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}] = \bigcup_{k=1}^{10} x_k \qquad (14)$$

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 $D(n^2 \times 10)$

$$D = \bigcup_{k=1}^{10} \varphi_k\, , where, \varphi_k = x_k - M \qquad (15)$$

A (10×10) 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 $(n^2 \times 10)$ is formed by product of D $(n^2 \times 10)$ and E_C (10×10)

$$U = D.E_C \qquad (16)$$

Weight vectors w_1 and w_2 , each of dimension (10×1), are calculated from the second set of 2 images and these are averaged to form an average weight W (10×1) vector for a class :

$$\begin{gathered} w_1 = U^T.(x_{11} - M) \\ w_2 = U^T.(x_{12} - M) \\ W = (w_1 + w_2)/2 \end{gathered} \qquad (17)$$

Testing is done using the remaining 3 images for each class by calculating their individual weight vectors:

$$\begin{gathered} w_3 = U^T.(x_{13} - M) \\ w_4 = U^T.(x_{14} - M) \\ w_5 = U^T.(x_{15} - M) \end{gathered} \qquad (18)$$

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

$$w_j \rightarrow k \; if \; min\left(D_{j.1}, \dots, D_{j.10}\right) = D_{j,k} \qquad (19)$$

The above scheme when applied to the current dataset produces training weight vectors for the 10 classes as shown below in Fig. 8.

The Fig. 9 depicts the difference of the test samples of the first four classes with the training set of all classes.

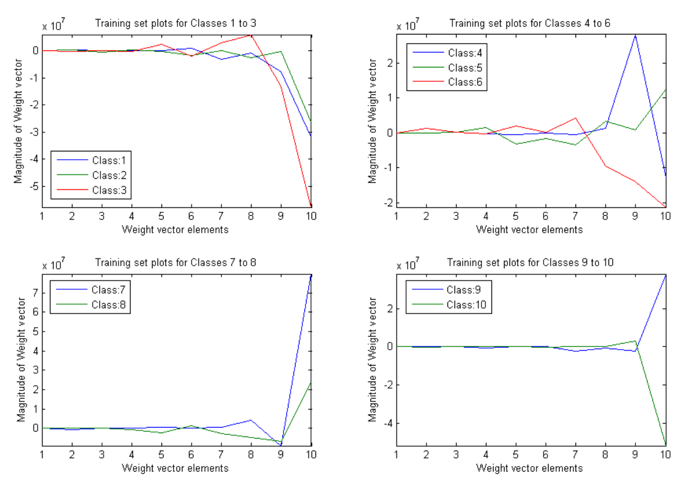

Figure 8. Feature vector plots for previous work in [7]

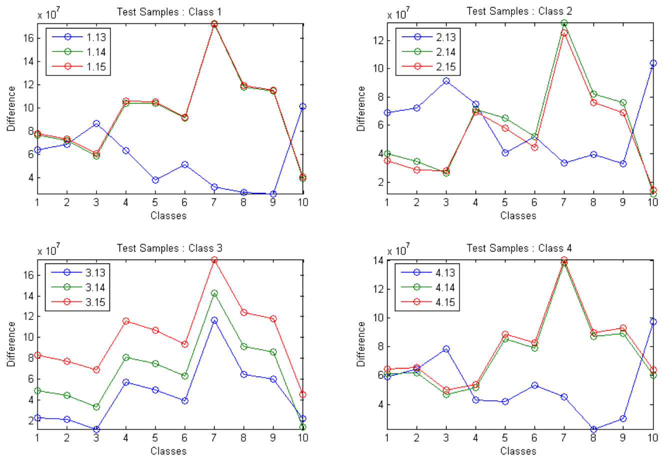

Figure 9. Difference plots for previous work in [7]

The accuracy of the previous algorithm in [7] on the current dataset is observed to be 40% when 3 test samples per class are considered and 38.75% when 8 test samples per class are considered. In both cases a 10-element feature vector is used and comparisons are done using Euclidean distance. In contrast, the current work achieves an accuracy of 100% with 8 samples per class, using scalar feature values, compared using simple scalar differences. A comparison chart is shown in Table 1.

TABLE I
COMPARISON CHART

	Feature representation	**Comparison**	**Accuracy (3 test samples)**	**Accuracy (8 test samples)**
Previous Work [7]	10-element vector	Euclidean distance	40%	38.75%
Current Work	1-element scalar	Scalar difference	100%	100%

VI. CONCLUSIONS AND FUTURE SCOPES

The proposed approach has been proved to be an accurate and optimized technique providing better recognition accuracies and smaller feature representations than contemporary works in extant literature. Salient features of the proposed technique include a low dimensional feature representation of the iris texture, low computational overheads involving only scalar arithmetic and high recognition accuracies. This enables recognition and identification possible in real-time applications. Another important characteristic of this work is the robustness of the method which provides satisfactory results even in presence of eyelids and eyelashes which partially occludes the iris portion. In this work a manual preprocessing step was used to isolate and segment the iris portion from the rest of the eye. Future work would involve an automated segmentation technique involving an edge detector for detecting the iris area from eye images.

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