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IRIS RECOGNITION USING SUPERVISED REGULARIZED MULTIDIMENSIONAL SCALING

Sohana Jahan[1], Sonia Akter[2] and Farhana Ahmed Simi[3]

[1,2,3] Department of Mathematics University of Dhaka, Bangladesh

Corresponding author: Sohana Jahan, Email; sjahan.mat@du.ac.bd

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ABSTRACT. *Iris Recognition is regarded as the most reliable and accurate biometric identification system available. In Iris Recognition, a person is identified by the iris region of the eye using image processing, pattern matching and the concept of neural networks. A typical Iris Recognition system involves three steps, Iris pre-processing, Iris feature extraction and Iris Classification. Most of the researchers use Daugman's integro-differential operator and Daugman's rubber sheet model for pre-processing. A number of feature extraction methods can be used to achieve a reasonable recognition rate. In our work we have used Supervised Regularized Multidimensional Scaling proposed recently for feature extraction that is used directly on iris image regarded as high dimensional vector. The method uses radial basis function to select some images as centres and then projects higher dimensional vectors into a lower dimensional space using an Iterative majorization algorithm. The projection is done in such a way that data of same class projects together and also it selects the most effective features that leads to better recognition rate. This approach excludes the pre-processing that saves computation time. We have compared our approach with Principal Component Analysis and implemented on a benchmarking data MMU iris data. K-Nearest Neighbor classifier is used for the classification. Numerical experiments show that Supervised Regularized Multidimensional Scaling successfully achieves better recognition and outperforms some other approaches such as Principal Component Analysis with and without pre-processing of iris images.*

KEYWORDS. Multi-Dimensional Scaling, Radial Basis Function, Iterative Majorization, Iris recognition, Biometrics, k-NN.

INTRODUCTION

Iris recognition is one of the top research topics nowadays due to its high reliability and capability of human identification applications. Among all of the different biometric modalities such as fingerprint, palm print, hand geometry, typing pattern, hand-written etc. Iris patterns are believed to achieve high accuracy in identifying a person. Moreover, irises are barely change compare to other biometric traits unless there are accidents or surgery. Also, it is impossible to find two persons who have the same iris features even for the twins (Chirchi *et al*., 2013).

A general iris recognition problem can be stated as follows:

Suppose a set of iris images is given and a system is trained up with these existing iris images. The problem is to match a new iris image with the existing ones up to a threshold.

Motivation

A typical Iris recognition system involves three steps, Iris pre-processing (segmentation and normalization), Iris feature extraction and Iris classification. Depending on the length and quality of dataset, the pre-processing step may take a long time and also sometimes loss important features that may lead to low classification rate. So, in our work we propose to implement Supervised Regularized Multidimensional Scaling (SRMDS) proposed recently (Jahan *et al*., 2016, Jahan, 2018) that do not require the pre-processing step and therefore can be used on raw iris data to extract most of the important features which leads to better recognition rate as well as less computation time.

Any Biometric system (Sallehuddin *et al.*, 2016) works by first capturing a sample of the feature, such as taking a digital colour image for face recognition or a digital image of the eye for iris recognition. In an iris recognition system, a sample of an eye is first transformed into a biometric template. The biometric template will provide a normalized, efficient and highly discriminating representation of the feature, which can then be objectively compared with other templates to determine identity. Applications such as passenger control in airports, access control in restricted areas, border control, database access and financial services are examples where the iris patterns have been applied.

Iris is a thin circular diaphragm, which lies between the cornea and the lens of the human eye as shown in Figure 1. The iris is perforated close to its center by a circular aperture known as the pupil. The average diameter of the iris is 12 mm, and the pupil size can vary from 10% to 80% of the iris diameter (Daugman, 2002).

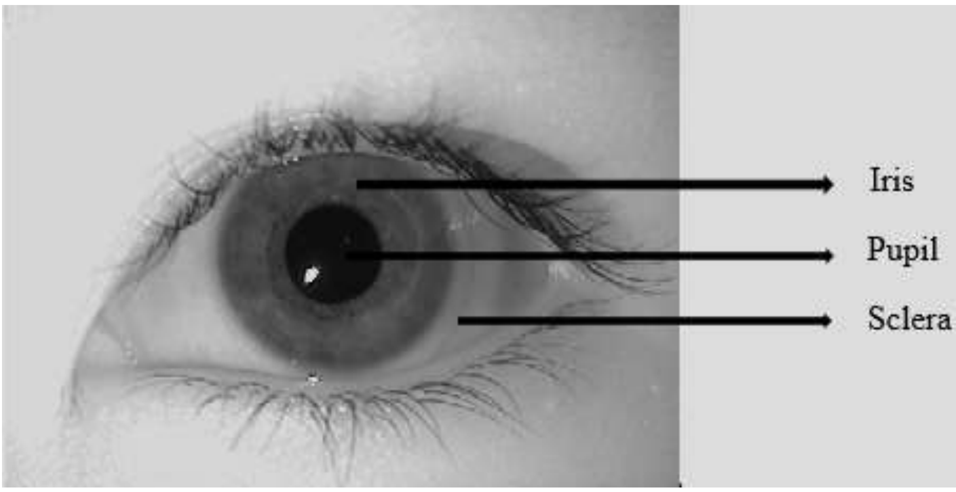

Figure 1. A front view of the Human Iris

The iris is an externally visible, yet protected organ whose unique epigenetic pattern remains stable throughout adult life. These characteristics make it very attractive for use as a biometric for identifying individuals. The first concept of iris recognition was proposed in 1987 by Flom and Safir. They proposed highly controlled and non-functional conditions to change the illumination so that size of the pupil in all images remains same for suitable Iris segmentation. This theoretical work on Iris recognition system has considered as a basis for all practical approaches of Iris recognition system (Bodade *et al.*, 2014, Sallehuddin *et al.*, 2016, Sanderson, *et al.*, 2000, Sheela *et al.*, 2010, Wildes, 1997). Another pioneering work in the early history of iris biometrics is that of Daugman (Daugman, 2002). Daugman's 1994 patent and early publications became standard reference model. Integro-differential operations are used to detect the center and diameter of the iris. Feature extraction algorithm uses the 2D Gabor wavelets to generate the iris codes which are then matched using Hamming distance. Researchers also use Discrete Wavelet Transform (DWT) (Raja *et al.*, 2011), Discrete Cosine transform (Abdo *et al.*, 2020) to extract features from the iris. Many of these methods ignore the upper and lower portion of the iris which is covered by the eyelids and eyelashes. Some researchers used Histogram Equalization (HE) to enhance the image and get high contrast (Raja *et al.*, 2011, Abdo *et al.*, 2020). Radial basis function neural network also being used nowadays in iris recognition system (Dua *et al.*, 2019).

A typical iris recognition system includes four main stages (Sheela *et al.*, 2010).

- The first stage is image acquisition that is done with capturing the series of images.
- The second stage is image pre-processing that consists of two steps, one is segmentation and another is normalization.
  – Segmentation includes iris and pupil boundary detection and additionally detect eyelids and eyelashes.
  – Normalization means converting the iris region into a form of a rectangle.
- The third stage is feature extraction which means extracting features from the normalized iris image and encodes these features to a design that is suitable for recognition.
- The last stage in iris recognition system is classification which actually compares the features created by imaging the iris with stored features in the database. Basic structure of an iris recognition system is given in Figure 2.

For experimental purpose the existing iris images are divided into two subsets, training and testing. At first, the training set is used to complete the pre- processing and extract the main feature to train up the system. Using the key information from the training set, main feature from the testing dataset can be extracted. Then matching stage is done to complete the verification. These steps are shown in Figure 2.

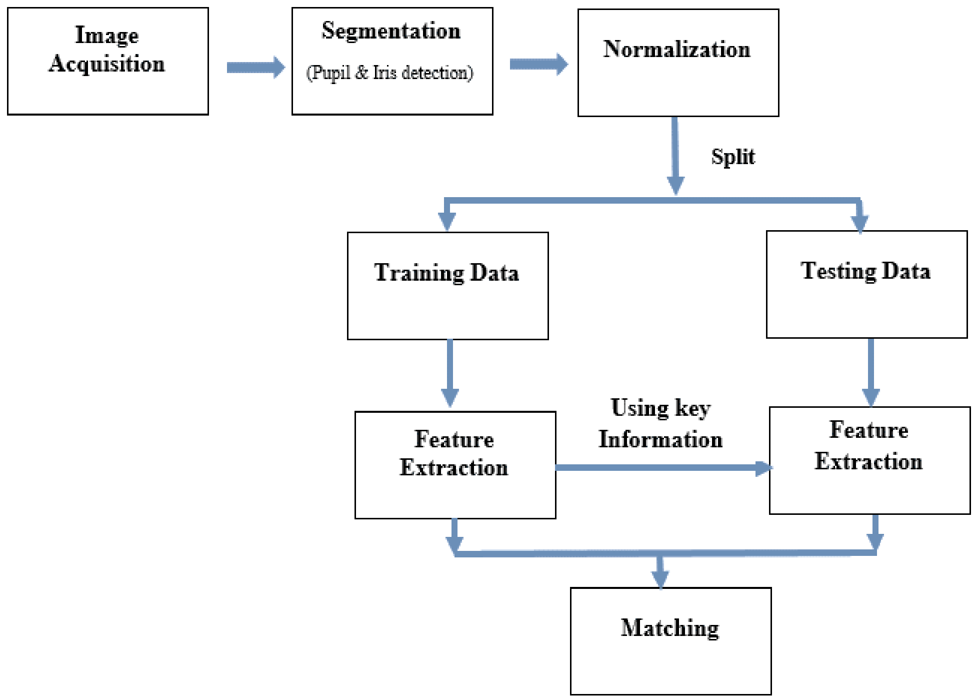

Figure 2. Basic structure of iris-based verification system

Our main contributions in this paper are summarized as follows:

- We have proposed to use a dimension reduction method Supervised Regularized Multidimensional Scaling (SRMDS) proposed (Jahan *et al*., 2016, Jahan, 2021) recently for iris feature extraction.

- SRMDS does not need to go through the pre-processing stages to extract the main features, therefore reduces computation time and also shows significant improvements, when implemented on MMU Iris data set, compared to other methods such as PCA.

The remaining parts of this paper are organized as follows: Since most of the iris recognition system includes iris pre-processing, we will first discuss the usual stages of iris pre-processing and feature extraction in the next section. The following section consists of a brief discussion of SRMDS. Then we will apply SRMDS and Principal Component Analysis (PCA) on a well-known iris dataset Multimedia University Malaysia (MMU) iris database. Finally, we will conclude our findings.

MATERIAL AND METHODS

Iris Pre-Processing

Achieving high performance of iris recognition system requires overcoming some of the major difficulties, such as choosing the appropriate database and unifying dimensions of the images, recruiting sufficient number of images in each experiment. The acquired image that contains irrelevant parts (e.g. eyelid, eyelash, pupil, etc.) should be removed. For the purpose of analysis, the original image needs to be pre-processed. Image pre-processing consists of:

- segmentation and
- normalization.

Segmentation

The first stage of iris recognition is to isolate the actual iris region which can be done by localizing the boundary of pupil and iris area. The major aim of segmentation is removing non-useful regions such as the parts outside the iris (eyelids, eyelashes and skin) (Gupta *et al.* 2013). The success of the segmentation process depends on the quality of the eye image. The segmentation stage is crucial for an iris recognition system, since poorly represented data leads to poor recognition rates. The segmentation process determines the iris and pupil boundaries and then converts this part to a suitable template in normalization stage.

Here for segmentation, we have used Daugman's Integro-Differential Operator given by

$$max_{(r,x_0,y_0)}|G\sigma(r) * \frac{\partial}{\partial x}\oint_{r,x_0,y_0} \frac{I(x,y)}{2\pi r}ds|$$

where,
$I(x,y)$ is the density of the pixel at the co-ordinates (x,y) in the iris image.
r refers to the radius of different circular regions with the co-ordinates center at $(x0,y0)$.
σ is the standard perversion of the Gaussian distribution.
$G\sigma$ refers to a Gaussian filter of scale sigma(σ).
$(x0,y0)$ is considered as the center of co-ordinates of the iris.
s is the contour of the circle given by $(r,x0,y0)$.
The operator searches for the circular path as shown in Figure 3 where there is maximum change in pixel values, by varying the radius and center x and y position of the circular contour. The operator is applied iteratively with the amount of smoothing progressively reduced in order to attain precise localisation. Eyelids are localised in a similar manner, with the path of contour integration changed from circular to an arc.

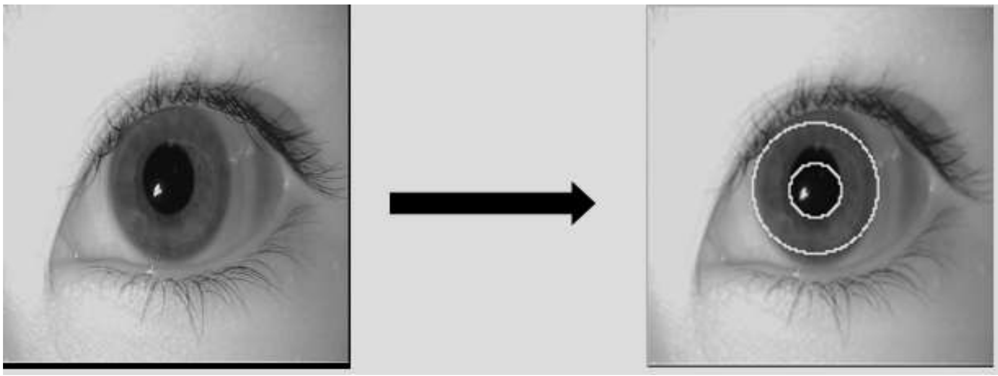

Figure 3. Iris segmentation using Daugman's Integro-Differential operator

Normalization

Once the iris region is successfully segmented from an eye image, the next stage is normalization (Chitte *et al*., 2012) which transforms the iris region into a rectangular region so that all the images have fixed dimensions in order to allow extraction of the features. The dimensional inconsistencies between eye images are mainly due to the stretching of the iris caused by pupil dilation from varying levels of illumination. Other sources of inconsistency include, varying imaging distance, rotation of the camera, head tilt, and rotation of the eye within the eye socket. Normalization is done using Daugman's Rubber Sheet Model discussed briefly as follows:

Daugman's Rubber Sheet Model

The homogenous rubber sheet model devised by Daugman (Daugman, 2002) remaps each point within the iris region to a pair of polar coordinates (r, θ) where r is on the interval $[0, 1]$ and θ lies in $[0, 2\pi]$. The Cartesian to polar transform can be represented as:

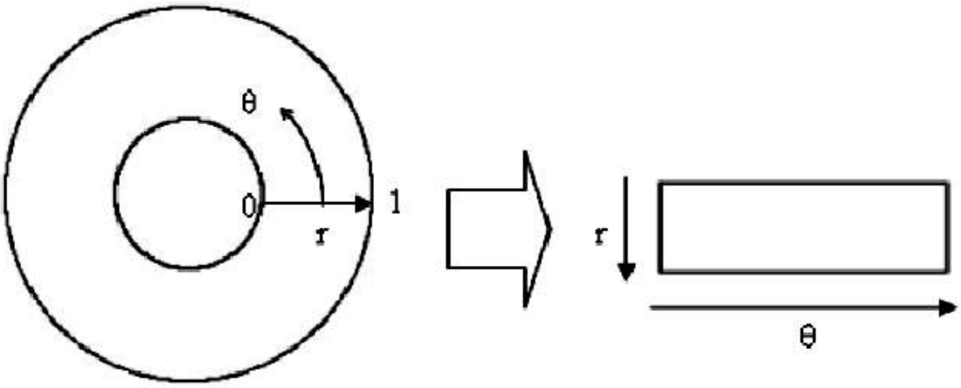

Figure 4. Daugman's Rubber Sheet Model

$$I(x(r,\theta), y(r,\theta)) \rightarrow I(r,\theta)$$

where,

$$x(r,\theta) = (1 - p) \times xp(\theta) + p \times xi(\theta)$$
$$y(r,\theta) = (1 - p) \times yp(\theta) + p \times yi(\theta)$$

$I(x, y)$, refers to iris image.
(x, y), are the actual co-ordinates.
(r, θ), are the corresponding polar co-ordinates.
(xp, yp) and (xi, yi), are the co-ordinates of pupil and iris boundaries respectively along the θ direction.

Even though the homogeneous rubber sheet model accounts for pupil dilation, imaging distance and non-concentric pupil displacement, it does not compensate for rotational inconsistencies. Therefore, it produces a normalized pattern with fixed and persistent dimensions. Applying the rubber sheet model on iris segmented of MMU database yields the iris as shown in Figure 5 that is converted from circular shape to rectangular shape, thus the iris has become ready to feature extraction stage.

Figure 5. Normalized Iris of MMU database

Feature Extraction of Normalized Iris images

After normalization, the next step is feature extraction stage. For getting accurate recognition of individuals, the most preferential information present in an iris pattern must be extracted. Feature extraction refers to the process of encoding the discriminatory information obtained from the segmented and normalized iris, called a feature vector (Jillela *et al*., 2015). To extract these main features, we have used Principal Component Analysis (PCA) on the normalized iris images. For the classification task we have used K-nearest neighbour rule.

Regularized Multidimensional Scaling

Regularized Multidimensional scaling is recently proposed (Jahan *et al*., 2016, Jahan, 2018) for dimension reduction which extracts important features from data. It is a modification of a nonlinear variants of classical Multi- Dimensional Scaling (MDS) involving Radial Basis Functions (RBF) proposed by A.R Webb (Webb, 1995, Webb, 1996 (a), Webb, 1996 (b)) in the context of MDS.

The idea is to represent N data points $\{x_i\}_{i=1}^{N} \epsilon R^n$ in a lower-dimensional space Rm $(m \ll n)$ in such a way that the metric distance $dij = \| x_i - x_j \|$ between x_i and x_j in the original space matches the dissimilarity q_{ij} in the lower dimensional space as closely as possible.

In (Webb,1996),Webb used the radial basis function $\varphi_i(x) = exp\{-\| x - c_i \|^2/h^2\}$ $i = 1,\ldots,l$ to map the data to another space called feature space R^l, where h is the bandwidth and ci is the center of φi. Secondly, the data is represented in Rm, using the function f:

$$f(x) = W^T \Phi(x), \quad \forall x \in R^n \tag{1}$$

where, $W \epsilon R^{l\times m}$The method seeks the best matrix W that minimizes the raw STRESS (i.e., loss function):

$$\sigma^2(W) = \sum_{i,j=1}^{N} \alpha_{ij}(q_{ij}(W) - d_{ij})^2 \tag{2}$$

where, for $i,j = 1,\ldots,N, \alpha_{ij} > 0$ are known weights and

$$q_{ij}(W) = \| f(x_i) - f(x_j) \| = \| W^T (\Phi(x_i) - \Phi(x_j)) \| \tag{3}$$

In Jahan *et al*. (2016), the authors have extended the idea of Webb (Webb,1996) to select the centers of the Radial Basis function efficiently and introduced RMDS, where the regularized term, (2, 1)-norm $\| W \|_{2,1}^2$ is introduced. The method minimizes the objective function

$$P(W) = \sum_{i,j=1}^{N} \alpha_{ij}(q_{ij}(W) - d_{ij})^2 + \gamma \| W \|_{2,1}^2 \tag{4}$$

Supervised Regularized Multidimensional Scaling (SRMDS)

The modification of RMDS (Jahan *et al*., 2016) is SRMDS (Jahan, 2021) that includes a structure preserving term J_{SP} and a class separability term J_{SE}. In this approach the transformation matrix W is determined by minimizing the function

$$J = (1-\lambda)J_{SE} + J_{SP}$$

Here $J_{SE} = \sum_{i,j=1}^{N} \delta(i,j)\alpha_{ij}q_{ij}{}^2$ and JSP is the structure preserving term given in (4). The parameter $(0 \le \lambda \le 1)$ controls the relative effects of the structure preserving term to the class separability criterion.

Here

$$\delta(i,j)\ \delta(i,j) = \{1\ if\ \ i{\sim}j\ (x_i\ and\ x_j\ belongs\ to\ same\ class\ )\ 0\ \ otherwise$$

and

$$\alpha_{ij} = \frac{\frac{1}{d_{ij}(X)}}{\sum_{i,j=1}^{n} (\frac{1}{d_{ij}(X)})} \tag{5}$$

The class separability term in SRMDS enhances the discriminant ability of the data and the loss function pulls the features of the same class to their centers. Jahan (2021) showed that after some manipulation, the objective function of SRMDS can be written as

$$J = (1-\lambda)(\sum_{i,j=1}^{n} \delta(i,j)\alpha_{ij}\, q_{ij}{}^2) + \lambda\sigma^2(W) + \gamma \| W \|_{2,1}^2 \tag{6}$$

Majorizing the stress term $\sigma^2(W)$ and making some simplification, equation (6) reduces to

$$Q_m(W,V,D) = \sigma_m^2(W,V) + \lambda_\gamma(WW^T, D^\dagger) \tag{7}$$

For details explanation, the readers are suggested to see Jahan's works (Jahan *et al*., 2016, Jahan, 2021). The key issue in employing Radial basis functions in RMDS and SRMDS is to decide their centers. This includes the number and the location of the centers. To identify the appropriate centres SRMDS continuously normalizes the transition matrix which optimize the original loss function. The (2, 1)-norm $\| W \|_{2,1}^2$ favours a small number of nonzero rows in the matrix W, which ensures the selection of the most effective features (Argyriou *et al.* 2007, Argyriou *et al.* 2008). A two-stage iterative block majorization algorithm (Jahan *et al*., 2016, Jahan, 2021) is used to obtain the transformation matrix W that minimizes the stress. The algorithm is as follows

Two - stage Iterative Block Majorization Algorithm

First stage:

Initialization: Initially and are chosen. The successive value of   and are iteratively calculated as follows:

S1: Set and update by

S2. Update by

Apply this stage to get most important centers.

Second stage:

Apply Webbs (Webb,1996) algorithm to minimize the stress.

Applying these two stages, we get the vectors in a lower dimensional space which represents the most effective features. When we apply the above algorithm to iris data it first selects the centers that are actually some iris images. This selected iris images help to project other irises in lower dimensional space so that the error minimizes and leads to a good recognition rate. The best part of this approach is that it does not need to go through the steps segmentation and normalization, hence reducing computation time.

Research Methodology:

We have applied SRMDS for feature extraction of iris images. After feature extraction, K-Nearest Neighbor classifier is used for matching the testing image set with the training set. SRMDS do not require pre-processing. Experimental evaluations show that its performance is satisfactory without pre-processing. For comparison, we have implemented PCA. We have applied PCA on two sets of data, one with pre-processing and another without pre-processing. During pre-processing, Daugman's integro-differential operator was used for segmentation and Daugman's rubber sheet model was used for normalization. Initially 80% of the data were selected randomly as training data and 20% of the data were selected as testing data. We have applied 1- nearest neighbor rule for matching. The classification error rate is calculated as the ratio of number of mis- classified points (images) to the total number of test samples. All the calculations are carried out using MATLAB.

IMPLEMENTATION

In our research we have used MMUIRIS database to demonstrate the performance of our approach over others.

MMUIRIS Database Description

Multimedia University Malaysia (MMU) database (MMU1 and MMU2 Iris Image Databases, 2008, Woodard *et al.*,2009) contains 450 grey scale eye images that were taken from 45 people, each person has 10 images, 5 images from left eye and 5 images from right eye. This database was built within the Multimedia University Malaysia. These images were captured by a LG Iris Access 2200 camera. Size of the images are 320 × 280 pixels.

Table:1 presents the most important information about the database. To apply the traditional methods, during segmentation, Daugman's integro-differential operator could not determine the iris and pupil boundary for each of the eye images. About 300 images were successfully segmented. So, we implemented our approaches on these 300 images of 30 persons.

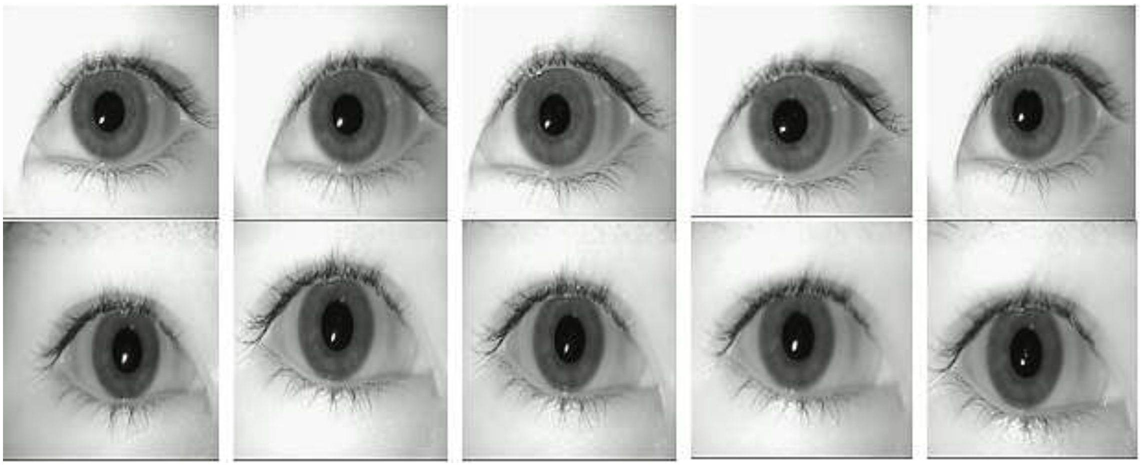

Figure 6. Examples from MMU Database

Table 1. MMU Database

Database	MMU
Number of Persons	45
Number of images of each person	10 (5 of each eye)
Number of total images	450
Format	BMP
Size	320 × 280 pixels
Camera	LG 2200

Segmentation of Iris

Some samples of segmented images with a boundary of pupil and iris area are given in Figure 7.

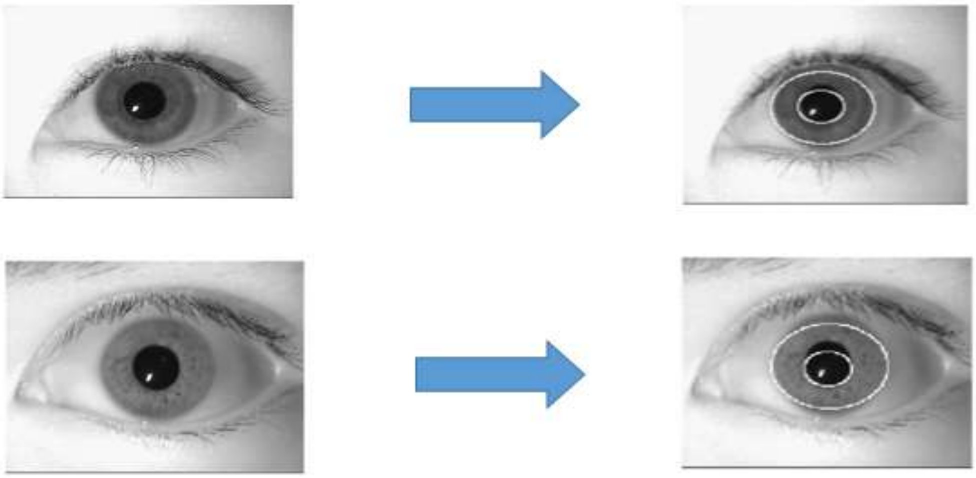

Figure 7. Some Segmented Iris

After determining the center and radius of pupil and iris area of each of these 300 images, we have applied Daugman's rubber sheet model to unfold the perforated iris area as shown in Figure 8. We have applied PCA (Chowhan *et al.*, 2009, Moravec *et al.* 2009, Chitte *et al*., 2012, Alam *et al*., 2020, El-Tarhouni *et al*., 2021,) on these 2 sets of images i) without pre-processing the images, ii) with pre-processing the images. Then we have checked the performance of PCA in recognising testing iris images. We reshape each of the normalized iris images into 160×160 matrix.

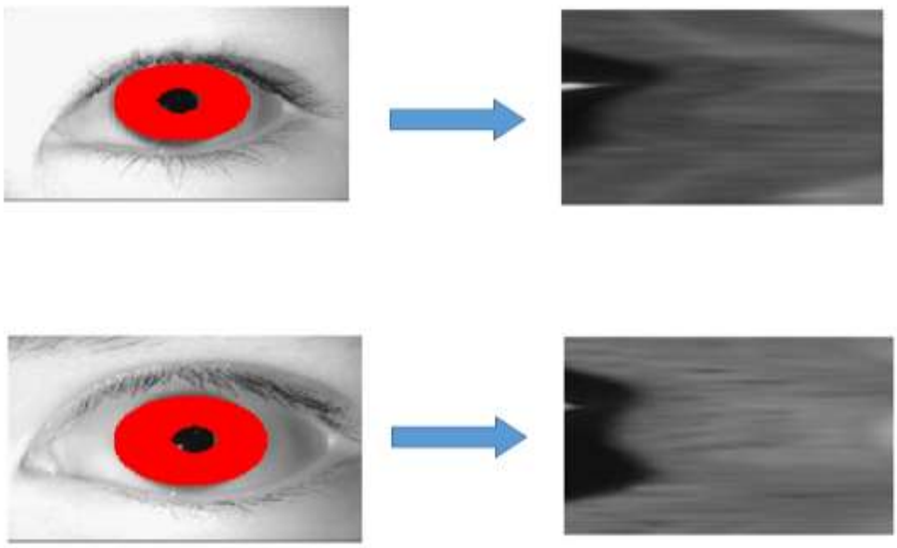

Figure 8. Normalized iris images

Thus, each of the iris images represents a matrix which describes the pixel information of that image. First of all, each of these matrices are converted into column vectors. Suppose we have a 3×3 matrix of the form

$$image = [x_{11}\ x_{12}\ x_{13}\ x_{21}\ x_{22}\ x_{23}\ x_{31}\ x_{32}\ x_{33}\ ]$$

This matrix can be converted to a column vector as follows $X = [\ x_{11}\ x_{21}\ x_{31}\ \ x_{12}\ x_{22}\ x_{32}\ x_{13}\ x_{23}\ x_{33}\ \ ]$

Thus, we have n = 300 images and therefore n column vectors each of size $M\ =\ l\ \times\ l$ (in our case $l = 160$). We create a matrix Z of size $M \times n$ such that $Z = [X_1\ \ X_2 \ldots X_n]$. Define the average image by ψ : where $\psi = \frac{1}{n}\sum_{i=1}^{n} \quad X_i$. Subtracting the mean of these column vectors to eliminate the common part from these images we have, $\varphi_i\ = Xi\ - \psi\ (i = 1,2,3, \ldots, n)$. Therefore, we get the matrix φ on which we will apply PCA.

Implementation of PCA

Training phase of PCA

Consider the matrix φ:

$$\varphi = [\varphi_1 \ldots\ \ \varphi_2 \ldots\ \ \varphi_3 \ldots\ \ \ldots \ldots\ \ \varphi_n \ldots]$$

The covariance matrix of the dataset is thus defined by: $C = \varphi^T \varphi$. The next step is to determine the eigenvectors u_k of the covariance matrix C. Eigenvectors u_k are actually images and are called eigeniris. Among those eigenirises, the ones with higher eigenvalues are the most useful in the recognition process. Therefore, those eigenirises are used for constructing the eye space for image projections, which are used in iris identifying, classifying or recognizing.

Testing Phase of (PCA)

At testing phase, first we transform the testing image X_t into eigenirises: $\omega_k = {u_k}^T(X_t - \psi)$ where, ω_k is the k^{th} coordinate of the Ω in the new 'eye space'. $\Omega^T = [\omega_1\ \ \ \omega_2\ \ \ .\ \ .\ \ .\ \ \omega_n]$
This vector Ω is used in finding the class of this input image.

Implementation of SRMDS

Using the training data (images) first we determine the transformation matrix W that minimizes the stress given by equation 4. To do this, initially 80% data were selected for training which means for each person we have selected 8 images for training and 2 images for testing. Thus, the training set contains $30\ \times\ 8\ =\ 240$ images and testing set contains $30\ \times\ 2\ =\ 60$ images. So, there is no overlap. Among these 240 images, 40% were initially selected as centers of the radial basis functions. We have extracted best 100 features that means we reduced the dimension from $160\ \times\ 160$ to 100 which leads to reduction of huge computational time. The value of the parameter h = 10 and λ = 0.1 are chosen for better performance. After getting the transformation matrix 'W', we use this to testing data to reduce the dimension.

NUMERICAL RESULTS

We have applied $1 - NN$ classifier (Jiawei, Theodoridis *et al*., Jahan, 2018) for matching. The recognition rate is calculated as the ratio of number of successful recognition and the total number of test samples. In the same manner, the error rate is calculated as the ratio of number of failures in recognition to the total number of test samples. At first, we have selected random 80% training images and took the average of 50 runs. The recognition rate using PCA after image pre-processing (segmentation and normalization) is 76% whereas using SRMDS, this rate is 82%. It should be noted that if we use PCA on the raw image data that means if we do not pre-process the image using segmentation or normalization then the recognition rate is poor whereas the use of PCA after segmentation gives a higher recognition rate. Further, we have constructed random subsets with p $(= 2, 3, 4, 5, 6, 7, 8)$ per individual were taken with labels to form the training set and the rest of the images were considered to form the testing set. Figure 9 represents the recognition rate in identifying the test iris images with different training samples (TRp, where p represents the number of training image per individual), which is also reported in Table 2. We can observe that if we increase the number of training images per individual, we get a better recognition rate for both methods. But increasing the number of training images increases the recognition rate more for SRMDS than PCA. From Table 2 it can be observed that an increase in the number of training images results in an increase in the recognition rate for each of these approaches. This is

Table 2: Recognition rate of PCA and SRMDS

	TR_p	PCA-P	SRMDS	PCA-WP
Recognition rate(mean)	TR_2	.4121	.4213	.391
	TR_3	.5145	.5321	.4152
	TR_4	.5672	.5765	.4321
	TR_5	.6444	.6721	.4441
	TR_6	.6812	.7281	.4801
	TR_7	.7221	. 7841	.5634
	TR_8	.7613	.8234	.6023

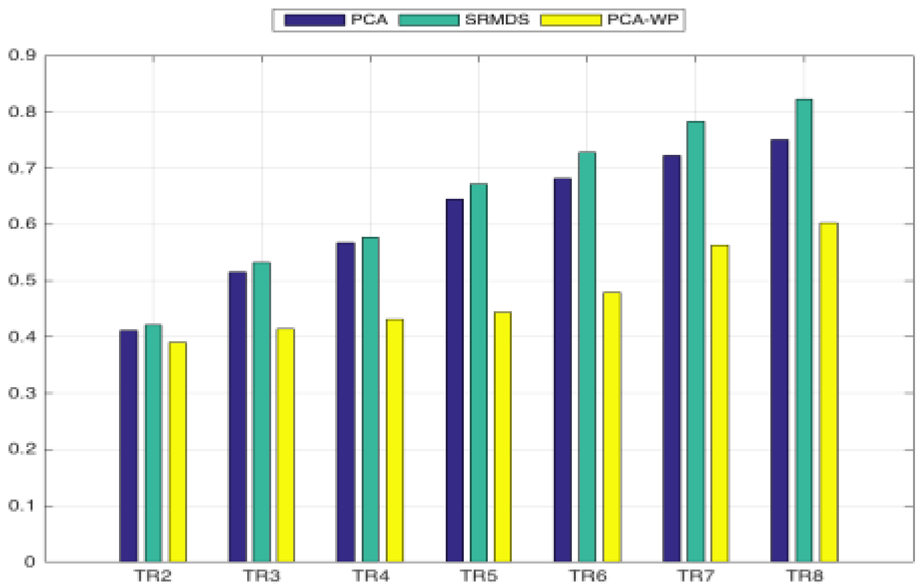

Figure 9. Iris image recognition rate using PCA with pre- processing (PCA-P), PCA without pre-processing (PCA-WP) and SRMDS for different training sample.

mainly due to the fact that iris images when taken in different positions are slightly out of phase. Therefore, multiple iris images of the same individual in the database increase the identification rate.

SRMDS first selects some images as centers. Then depending on these centers it projects other images in a reduced dimensional space in such a way that images of same class cluster together in the reduced dimensional space. The class separability term used in the objective function enhances the discriminant ability of the data and the loss function pulls the features of the same class to their centers. This approach helps to identify the class of the test images better than other methods.

Figure 9 represents that SRMDS outperforms PCA in whatever the number of training images. As we increase the number of training samples, the error rate for SRMDS decreases more than PCA which can be seen in Figure 10. A great advantage of using SRMDS is that it does not require pre-processing step and therefore takes $30 - 40\%$ less computation time than PCA for different number of training images. It can be seen from Figure 11 that though SRMDS takes more time than PCA when applied on images without pre-processing, it reduces the error rate as shown in Figure 10.

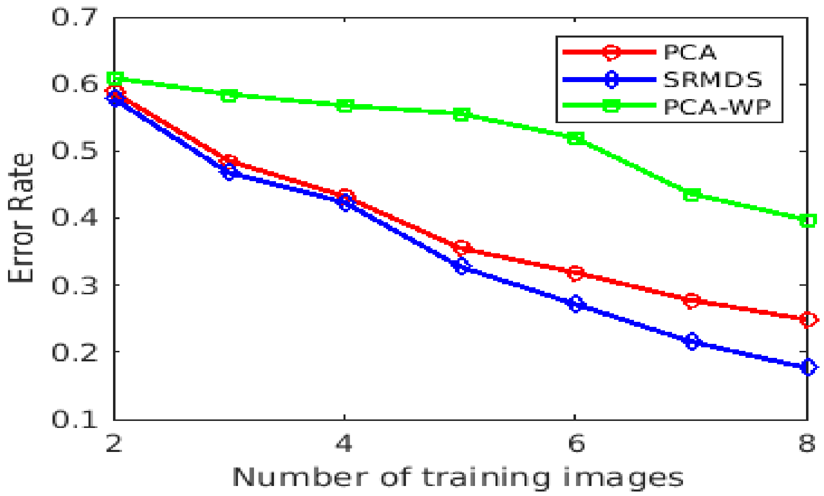

Figure 10. Error rate for different number of training images in three approaches

As SRMDS can be applied on raw image dataset, so we have applied this algorithm on total 450 images of MMUiris database. With 80% images for training, we have achieved 77% images that are correctly identified.

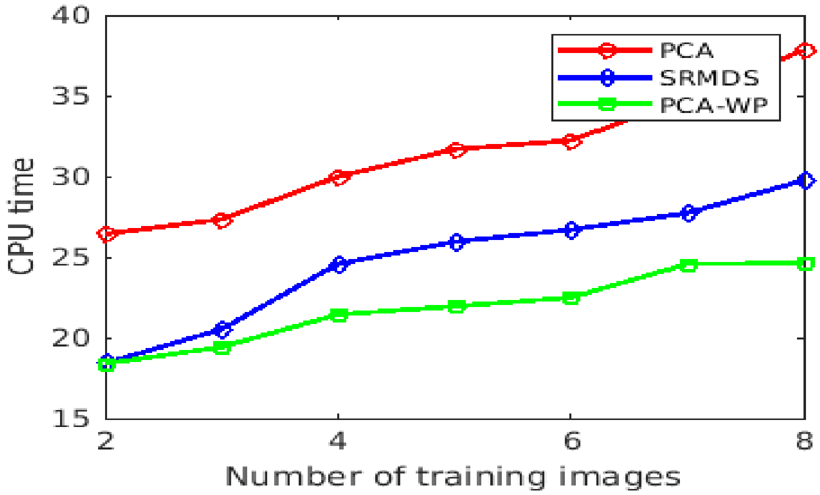

Figure 11. CPU time for different number of training images in three approaches

CONCLUSION

In a biometric system, a person is identified automatically by processing the individual's unique features. Iris Recognition is regarded as the most reliable and accurate biometric identification system available. In this paper, iris recognition system has been investigated. We have applied two feature extraction approaches PCA and SRMDS on benchmarking data MMUIris database of greyscale eye images and compare their performance. We have applied PCA on two sets of MMU iris data, one with pre-processing step and another without pre- processing. For the pre-processing step, firstly, we have used Daugman's integro-differential operator for segmentation, which localizes the pupil and iris region from an eye image. Next, the segmented iris region was normalized to eliminate dimensional inconsistencies between iris regions. This was achieved by implementing a version of Daugman's rubber sheet model, where the iris image is modelled as a flexible rubber sheet, which is unwrapped into a rectangular block with constant polar dimensions. Finally, the feature is extracted using PCA. On the other hand, we have applied SRMDS on the raw data which contains the pixel information of the eye images. SRMDS first selects some images as centers. The class separability term used in the objective function enhances the discriminant ability of the data and the loss function pulls the features of the same class to their centers. The method projects other images in a reduced dimensional space in such a way that images of the same class cluster together in the reduced dimensional space. We have implemented $1-NN$ classifier for matching purposes. It should be noted that, many factors impact the recognition rate of testing images such as camera resolution, image quality, training choice of images etc. Numerical results show that an increase in the number of training images improves the recognition rate for both the methods but SRMDS outperforms PCA (when PCA is applied on images with pre-processing or without pre-processing). Also, another advantage of using SRMDS over other methods is that it does not require pre-processing steps that lead to less computation time.

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