ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 4, Issue 9, September 2015

Human Identification by Classifying the Features of the Sclera Region of the Eye

Therese Yamuna Mahesh[1], Dr. K. L. Shunmuganathan[2]

Research Scholar, Department of Computer Science and Engineering, Bharath University, Chennai, India[1]

Professor and Head of Department, R.M.K College of Engineering, India[2]

Abstract: Sclera based recognition is identification of a person using the features of sclera region of the eye. This method allows the use of existing imaging systems to acquire the image of the sclera region and identify people. Assuming that the entire sclera region was enrolled for matching, off-angle eyes reveal more of the sclera vein pattern for matching. This method does not require frontal gaze images a necessary condition. Thus, even an individual who was actively attempting to avoid detection or recognition by looking away from the matching system would be unable to avoid presenting a valid biometric pattern for identification.

Keywords: Sclera segmentation; Vein pattern enhancement; Feature extraction; classification, multilayer perceptron.

I. INTRODUCTION

The sclera is the white and opaque outer protective covering of the eye. The sclera completely consists of four layers of tissue – the episclera, stroma, lamina fusca, and endothelium. The conjunctiva is a clear mucous membrane, made up of epithelial tissue, and consists of cells and underlying basement membrane that covers the sclera and lines the inside of the eyelids. In general, the conjunctival vascular is hard to see with the naked eye at a distance.

Figure 2, [2] shows an image of an eye under visible wavelength illumination with identification of the sclera vein patterns. For children, the blood vessels in sclera area could be blue in color, but for adults, the blood vessels as seen on the sclera are red in color. The structure of the blood vessels as seen on the sclera are well suited to be used as a biometric - they are visible without undue difficulty and they are anecdotally stable over time and unique for each person. Therefore, the vein patterns in the sclera could be used for positive human identification.

In previous works, identification of users using the sclera region has been referred to as 'conjuctival vasculature recognition' [3]. However, as the conjunctiva is the top-most transparent layer of the sclera and images of the sclera region capture more than just this top-most layer, it is more accurate to refer to the system as performing 'sclera recognition'.[2].

II. STEPS INVOLVED IN THE IDENTIFICATION PROCESS

The Block Diagram of the various steps involved in the sclera region based human identification process is shown in Figure (1) below.

The various blocks are explained respectively under the respective headings.

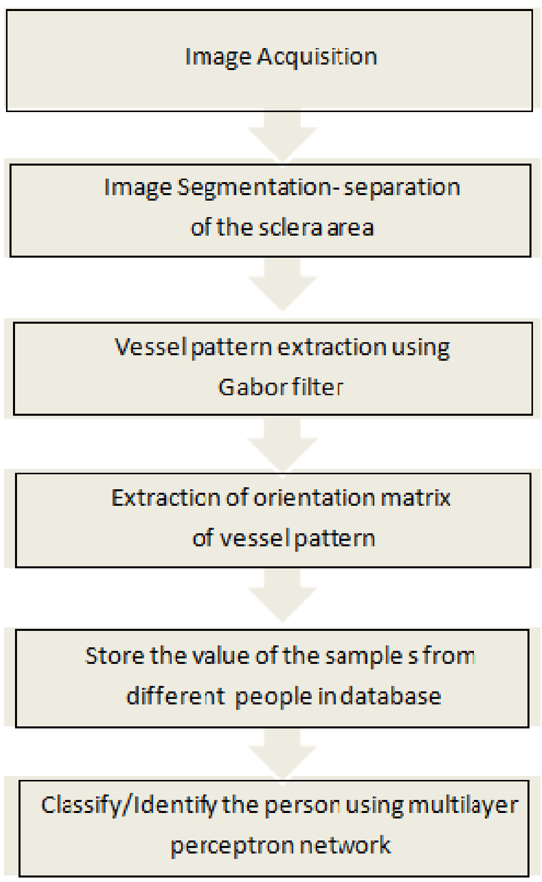

Figure: 1 Block diagram showing the steps in the Human Identification process

III.SCLERA REGION SEGMENTATION

The sclera region of the eye is as shown below:

A. Estimation of Glare area

The image acquisition i.e. the picture of the eye can be taken by any professional cameras like Canon D30, EOS-

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 4, Issue 9, September 2015

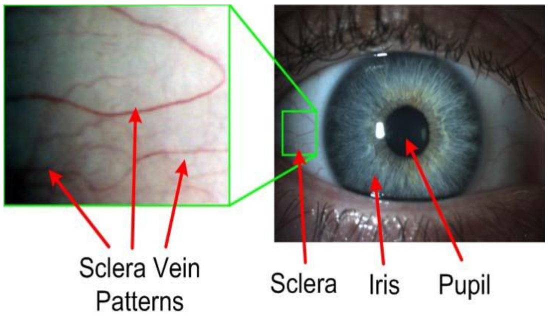

Figure2: Image of an eye under visible wavelength illumination

1D, Nikon D1 series etc. After acquiring the image the glare area that occurs in the center of the iris is identified by using a sobel filter. The glare area is usually a small bright area of the iris image. Glare inside the pupil or nearby the pupil area can be modeled as a bright object on a much darker background with sharp edges. However, in some situations, there could be multiple areas with very bright illumination and unwanted glare areas (glares that are not inside the iris or pupil). For example, there are glares on the surface of the cornea which create challenges for glare detection. A Sobel filter is first applied to highlight desired glare areas. For the glares in the sclera or skin areas, the local background is often brighter than the pupil or iris. Using the Sobel filter, it will not stand out as much as glare in the desired area. Note that the glare detection method is applied in grayscale images. If the original image is a color image, a grayscale transformation is applied.

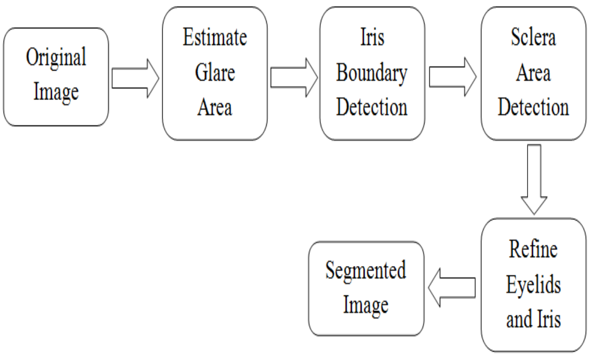

Figure 3: Segmentation steps

B. Iris Boundary Detection

To improve the segmentation speed, the pupil and iris regions are modelled as circular boundaries and typical circular iris segmentation methods were used. Here, the pupil and iris regions are segmented using a greedy angular search, which is performed on the edge-detected image and can accurately detect the pupil boundaries regardless of gaze direction and eyelid/eyelash occlusion. The algorithm searches along the radial direction at a predefined set of angles to estimate the pupil boundaries and then iteratively maps the highest edge value along the angular direction for $\frac{\pi}{2}$ radians for each of these starting angles [4].

Starting at the estimated centre of the pupil, the algorithm searches along a radial direction for the highest edge value within some radial length range,

$$(u, v) = \arg\left\{(x, y) \,\middle|\, \max S(x, y), \text{with } \arctan\left(\frac{y - y_o}{x - x_o}\right) = \theta \right\} \quad (1)$$

Where S(x, y) is the edge detected image, (x_o, y_o) is the estimated pupil center, and θ is the angular search direction. Then, using this detected point as the start of the search, the algorithm iteratively searches for the highest edge value along the angular direction, constraining the possible outcomes to the next pixel in the defined angular direction and its two nearest neighbors along the radial dimension,

$$(u, v) = \arg\left\{(x, y) \middle| \max S(x, y), \begin{pmatrix} x = x_o + r\cos\theta \\ y = y_o + r\sin\theta \\ r' - 1 \le r \le r' + 1 \end{pmatrix}\right. \quad (2)$$

where r' is the previous iteration's radius. The search continues for radians $\frac{\pi}{2}$ and combines the aggregate results for all initialization orientations. The final result will be an image with each pixel's value equal to the number of individual radial searches that include that particular pixel.

C. Estimation of the sclera area

In the estimation of the sclera area, our sclera detection approach uses either color or grayscale images. In grayscale images, the "skin" tone approach for color images would not work. We propose an Otsu's method based sclera segmentation method. Otsu's method is a Linear Discriminant Analysis-based thresholding method. It assumes that there are two classes in an image, foreground (object) and background, which can be separated into two classes by intensity. Otsu's method automatically searches for the optimum threshold that can minimize the interclass variance while maximizing the between-class distance [6]

The process of sclera area detection has the following steps: the region of interest (ROI) selection step, the Otsu's method-based thresholding step and the sclera area detection step. The left and right ROIs are selected based on the iris center and boundaries. The height of the ROI is the diameter of the iris, and the length of the ROI is the distance between the limbic boundary and the margin of the image. Otsu's method is applied to the ROIs to obtain potential sclera areas. The correct left sclera area should be located in the right and center sides, and the correct right sclera area should be located in the left and center. This way, we eliminate non sclera areas. The same approach is applied to detect the right sclera area.

D. Iris and eyelid detection and refinement

The top and bottom boundaries of the sclera region are used as initial estimates of the sclera boundaries, and a polynomial is fit to each boundary. Using the top and bottom portions of the estimated sclera region as guidelines, the upper eyelid, lower eyelid, and iris boundaries are then refined using the Fourier active contour method. Note that some areas are not perfectly

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 4, Issue 9, September 2015

segmented. In reality, perfect segmentation of all images is impossible. Therefore, the feature extraction and matching steps of the system need to be tolerant of segmentation error. [1]

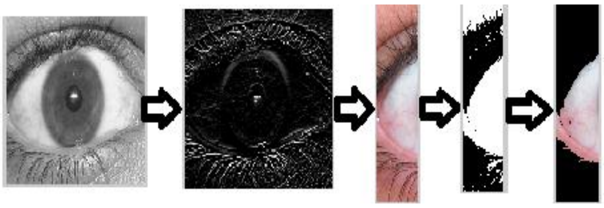

Figure: 4 Results of Sclera Segmentation

IV. VESSEL PATTERN ENHANCEMENT

The segmented sclera area is highly reflective. As a result, the sclera vascular patterns are often blurry and/or have very low contrast. To mitigate the illumination effect to achieve an illumination-invariant process, it is important to enhance the vascular patterns. Daugman [4] shows that the family of Gabor filters is good approximations of the vision processes of the primary visual cortex. Because the vascular patterns could have multiple orientations, in this paper, a bank of directional Gabor filters is used for vascular pattern enhancement. [2]

$$G(x,y,v,s) = e^{-\pi\left(\frac{(x-x_o)^2+(y-y_o)^2}{s^2}\right)} e^{-2\pi i(\cos v(x-x_o)+\sin v(y-y_o))} \quad (3)$$

where (x_o, y_o) is the center frequency of the filter, s is the variance of the Gaussian, and v is the angle of the sinusoidal modulation. For this paper, only the even filter was used for feature extraction of the vessels, since the even filter is symmetric and its response was determined to identify the locations of vessels adequately. The image is first filtered with Gabor filters with different orientations and scales

$$I_F(x,y,v,s) = I(x,y) * G(x,y,v,s) \quad (4)$$

where I(x, y) is the original intensity image, G(x, y, v, s) is the Gabor filter, and I_F (x, y, v , s) is the Gabor-filtered image at orientation v and scale s. Both v and s are determined by the desired features to be extracted in the database being used. All the filtered images are fused together to generate the vessel boosted image F(x, y)

$$F(x,y) = \sqrt{\sum_v \sum_s [I_F(x,y,v,s)]^2} \quad (5)$$

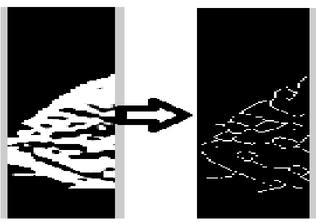

Figure: 5 Vessel pattern after thresholding

In Figure 4, the vessel structure in the sclera region is very difficult to see; however, after Gabor enhancement and before thresholding, the vessel structure is clearly visible. An adaptive threshold, based on the distribution of filtered pixel values, is used to determine a threshold to binarize the Gabor filtered image

$$B(x,y) = \begin{cases} 1, & F(x,y) > th_b \\ 0, & \text{else} \end{cases} \quad (6)$$

And

$$th_b = \arg\left\langle t \middle| \min \left| \sum_{x=1}^{t} Pedge(x) - T_B \right| \right\rangle \quad (7)$$

where B(x, y) is the binary vessel mask image, F(x, y) is the vessel-boosted image, and Pedge(x) is the normalized histogram of the nonzero elements of F(x, y). In practice, the zero elements of the filtered image are a significant portion of the image, and in general, the vascular patterns have higher magnitude than the background. Therefore, T_B is selected to be 1/3. Figure.5 shows a representative result after thresholding.

V. VESSEL PATTERN FEATURE EXTRACTION

Depending on the physiological status of a person (for example, fatigue or non fatigue), the vascular patterns could have different thicknesses at different times, because of the dilation and constriction of the vessels. Therefore, vessel thickness is not a stable pattern for recognition. In addition, some very thin vascular patterns may not be visible at all times. In this paper, binary morphological operations are used to thin the detected vessel structure down to a single-pixel wide skeleton and to remove the branch points. This leaves a set of single-pixel wide lines that represents the vessel structure.

In our project we use angular partitioning method and find out the orientation of the major clearly visible capillaries for feature extraction. The orientation of the capillaries is defined in terms of nine bins covering 180 degrees, each bin defining 20 degrees. The coefficient of the orientation matrix depends on the direction of the visible blood vessels as seen in the sclera region. These coefficients are unique for a given pattern of extracted capillaries. [6]

Due to the movement of the eyes, there will be slight changes in the vessel pattern, however the orientation of the prominent vessels remain more or less similar. So at least five images of the same person with the iris at slightly different positions is taken and stored in the database for matching purposes. However frontal gaze is always preferred for good classification.

VI. SCLERA PATTERN CLASSIFICATION

When acquiring the eye images, the eyelids can have different shapes, the iris location can vary, the pupil size can be different, and the eye may be tilted with respect to the camera. The camera-to-object distance and camera zoom can also vary. All of these could affect the size, location, and patterns of the acquired sclera region in the image. It is important to take these variances into account in sclera matching. Therefore, the first step is to perform sclera ROI registration to achieve global translation, orientation, and scaling invariance’s. In addition, due to

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 4, Issue 9, September 2015

the complex deformation that can occur in the vessel patterns, it is desirable to have a registration scheme that is robust and exhaustive but does not unduly introduce false accepts. Most importantly, the sclera vascular patterns deform nonlinearly with the movement of the eye and eyelids and the contraction/dilation of the pupil. As a result, the segments of the vascular patterns could move individually, and this must be accounted for in the classification scheme.
Considering all the above, best results were obtained when the images were classified using multilayer perceptron Neural Network.

VII. EXPERIMENTAL RESULTS USING THE UBIRIS DATABASE

The UBIRIS database is a publicly available database with iris images acquired in color, in comparison with most iris databases which are acquired using NIR illumination. The database consists of 1877 images (1214 in Session1 and 663 in Session2), composed of 241 users in two distinct sessions. In Session 1, they tried to minimize noise factors, particularly those relative to reflections, luminosity, and contrast, having installed the framework inside a dark room. However, in Session 2, they changed the capture location to introduce a natural luminosity factor. This enabled the appearance of heterogeneous images with respect to reflections, contrast, luminosity, and focus problems. Images collected at this stage tend to simulate the ones captured by a vision system without or with minimal active collaboration from the subjects. In other words, a significant number of the images in Session 2 have very poor quality. In both sessions, the images are generally cropped such that the eye is predominately centered and the eye region is well cropped in the images base as shown in figure 6.

Figure: 6 Picture of Eye

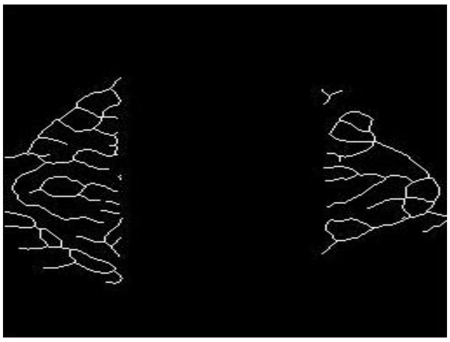

Figure: 7 Extracted Vessel Pattern of the Sclera Region

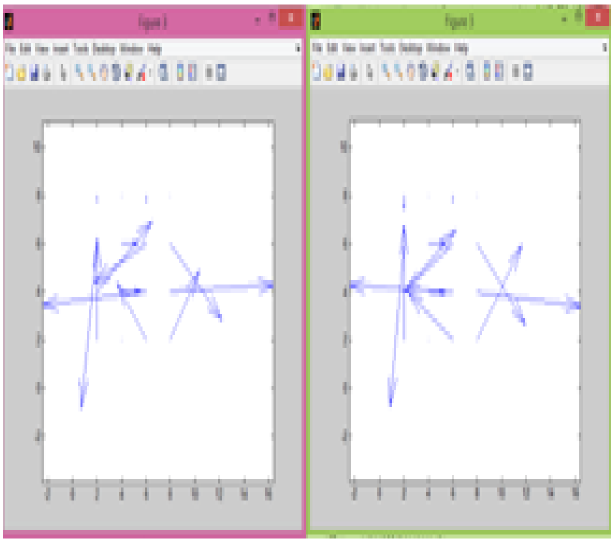

Figure: 8 Orientation of the Vessel Patterns of the Extracted Images for two different angular gaze of same person

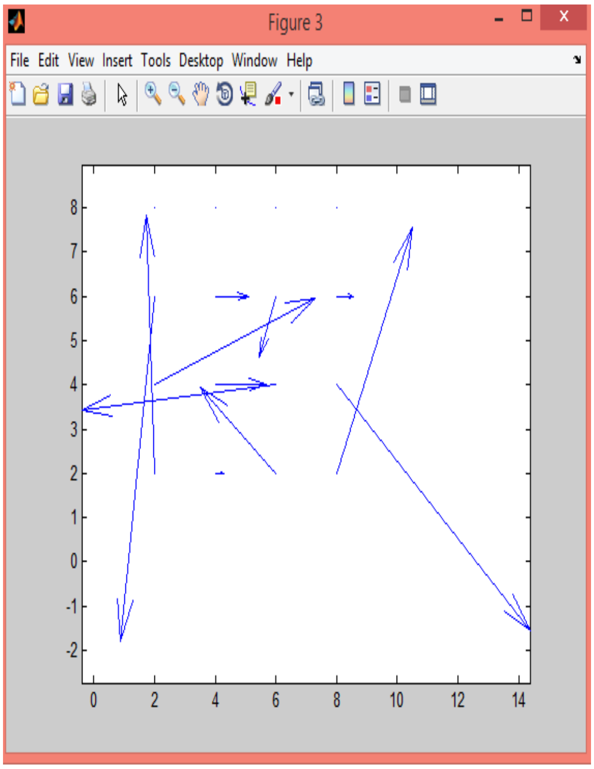

Figure: 9 Orientation of the Vessel Patterns of the Extracted Images of different person

VIII. CLASSIFICATION RESULTS USING MULTILAYER PERCEPTRON CLASSIFIER

The classification using multilayer perceptrons [7], were simulated using WEKA 3.6 software by taking the pictures of the eye of three persons, three sample from each person. Sixty attributes were given from the orientation matrix. The network was trained using two samples from each person and the third sample was used as test data, the results of simulation of the training set is given below:

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

IJARCCE

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 4, Issue 9, September 2015

Simulation Result of Training data

```
Class person1
    Input
    Node 0
Class person2
    Input
    Node 1
Class person3
    Input
    Node 2


Time taken to build model: 0.36 seconds

=== Evaluation on training set ===
=== Summary ===

Correctly Classified Instances          6               100      %
Incorrectly Classified Instances        0                 0      %
Kappa statistic                         1
Mean absolute error                     0.0169
Root mean squared error                 0.0181
Relative absolute error                 3.7915 %
Root relative squared error             3.8301 %
Total Number of Instances               6

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall  F-Measure   ROC Area  Class
                 1         0         1          1         1          1        person1
                 1         0         1          1         1          1        person2
                 1         0         1          1         1          1        person3
Weighted Avg.    1         0         1          1         1          1
```

Figure: 10 Simulation results of the training set

The results of simulation of the test data is as shown below:

Simulation Result of Test data

```
=== Evaluation on test set ===
=== Summary ===

Correctly Classified Instances          1               100      %
Incorrectly Classified Instances        0                 0      %
Kappa statistic                         1
Mean absolute error                     0.0453
Root mean squared error                 0.052
Relative absolute error                10.193  %
Root relative squared error            11.033  %
Total Number of Instances               1

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall  F-Measure   ROC Area  Class
                 0         0         0          0         0          ?        person1
                 1         0         1          1         1          ?        person2
                 0         0         0          0         0          ?        person3
Weighted Avg.    1         0         1          1         1          0

=== Confusion Matrix ===

 a b c   <-- classified as
 0 0 0 | a = person1
 0 1 0 | b = person2
 0 0 0 | c = person3
```

Figure: 11 Simulation results of the test data

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 4, Issue 9, September 2015

IX. CONCLUSION

In this paper, we have proposed a new method of feature extraction of the vessel pattern as seen on the sclera region of the eye. Our research results show that sclera recognition is very promising for positive human ID. In this paper, we focused on frontal looking sclera image processing and recognition. Similar to iris recognition, where off-angle iris image segmentation and recognition is still a challenging research topic, off-angle sclera image segmentation and recognition above a certain degree will be an interesting and challenging research topic. In addition, sclera recognition can be combined with other biometrics, such as iris recognition or face recognition (such as 2-D face recognition) to perform multimodal biometrics. Moreover, the effect of aging and diseased condition of the eye is a challenge in sclera based recognition. Currently, the proposed segmentation and feature extraction system is implemented in Mat lab. The processing speed for large databases can be dramatically reduced by parallel computing approaches.

X. ACKNOWLEDGMENT

The authors would like to thank the University of Beira Interior for providing the UBIRIS database and the Department of Electronics and Communication Engineering at Amal Jyothi College of Engineering for data collection and support.

REFERENCES

[1] Sreelekshmi K.J., Therese Yamuna Mahesh, K.L. Shunmuganathan "Human Identification Based on the Pattern of Blood Vessels as viewed on the sclera using HOG and Interpolation Technique "International Journal of Advanced Research in Computer Science and Management Studies, Volume 2, Issue 9, September 2014

[2] Zhi Zhou, Student Member, IEEE, Eliza Yingzi Du, Senior Member, A NEW SCLERA ITENTIFICATION METHOD IEEE, IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS—PART A: SYSTEMS AND HUMANS, VOL. 42, NO. 3, MAY 2012

[3] N. Luke Thomas, "A new approach for Human Identification using the eye" a Thesis submitted to the Faculty of Purdue University, in partial fulfilment of the requirements for the degree of Master of Science in Electrical and Computer Engineering, May 2010.

[4] J. Daugman, "New Methods in Iris Recognition," IEEE Transactions on Systems, Man, and Cybernetics, Part B, vol. 37, pp. 1167-1175, 2007

[5] Derakhshani, and A. Ross, 2006, "A new biometric modality based on conjunctival vasculature" Appeared in Proc. of Artificial Neural Networks in Engineering (ANNIE), (St. Louis, USA), November 2006

[6] Navneet Dalal and Bill Triggs, "Histograms of Oriented Gradients for Human Detection," Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2005.

[7] R.O. Duda, P.E. Hart and D.G. Stork, 'Pattern Classification' (2nd ed), John Wiley & Sons, 2000, 348:349.

BIOGRAPHY

Ms. Therese Yamuna Mahesh, M. Tech works as Assistant Professor at Amal Jyothi College of Engineering, Kottayam, Kerala, India. She is also a research scholar at Bharath University, Chennai. She has more 15 years of teaching experience and her areas of interest include Image processing, Pattern recognition and Computer networks.

Dr. K. L. Shunmuganathan, B.E, M.E., M.S., Ph.D., works as the Professor and Head of the CSE Department of RMK Engineering College, Chennai, Tamil Nadu, India. He has more than 20 years of teaching experience, and his areas of specialization are artificial intelligence, computer networks and DBMS.