Human Face Detection and Segmentation using Eigenvalues of Covariance Matrix, Hough Transform and Raster Scan Algorithms

J. Prakash, and K. Rajesh

Abstract—In this paper we propose a novel method for human face segmentation using the elliptical structure of the human head. It makes use of the information present in the edge map of the image. In this approach we use the fact that the eigenvalues of covariance matrix represent the elliptical structure. The large and small eigenvalues of covariance matrix are associated with major and minor axial lengths of an ellipse. The other elliptical parameters are used to identify the centre and orientation of the face. Since an Elliptical Hough Transform requires 5D Hough Space, the Circular Hough Transform (CHT) is used to evaluate the elliptical parameters. Sparse matrix technique is used to perform CHT, as it squeeze zero elements, and have only a small number of non-zero elements, thereby having an advantage of less storage space and computational time. Neighborhood suppression scheme is used to identify the valid Hough peaks. The accurate position of the circumference pixels for occluded and distorted ellipses is identified using Bresenham's Raster Scan Algorithm which uses the geometrical symmetry properties. This method does not require the evaluation of tangents for curvature contours, which are very sensitive to noise. The method has been evaluated on several images with different face orientations.

Keywords—Circular Hough Transform, Covariance matrix, Eigenvalues, Elliptical Hough Transform, Face segmentation, Raster Scan Algorithm.

I. INTRODUCTION

FACE detection and segmentation has always been an area of active research having a wide range of applications such as personal identity verification, surveillance, lip tracking, facial expression extraction and gender classification. The most significant problem in face detection and identification is to segment the human face from its background scene. Generally there are three phases for human face segmentation and detection namely, faces representation, face segmentation and face identification.

A variety of approaches have been suggested for segmenting the human face from images [1] [2]. Kanade [3] used projection analysis on a binary image obtained by a Laplacian operator to gray scale images. Brunelli et al. [4]

uses the projection analysis by performing vertical and horizontal edge detection. They also discussed the segmentation of human face using the geometrical features. Geometric feature based segmentation and matching involves decomposing the face image into pertinent features like eyes, nose, mouth, chin and their spatial relationship to one another using Gabor wavelet decompositions [5]. In template matching approach [6], the construction of an artificial template is used to match with the prominent features of the face. V. Govindaraju et al. [7] attempted to locate the face in an image using a mode template constructed from a hair curve and face side curves. They used a cost function approach to group together prospective left and right face side curves having an appropriate displacement and angular orientation.

Another approach different from template matching is used by Turk et al. [8] [9]. In their approach, faces are projected on to a feature space called the face space defined by eigenfaces and are determined by the set of eigenvectors. Sirohey [10] used an ellipse to represent the head region in edge map. Ismail et al. [11] used the geometric symmetry features to segment the head region. Sangho [12] used a partial ellipse to fit the head counter. Thus, it is observed to have the face region distinguished from the background clutter.

On the other hand, to segment the face region from cluttered images Hough [13] based techniques are also used. The Elliptical Hough Transform [14] deals with finding elliptical objects from edge images. Geometrical symmetry properties are also used along with HT to identify the elliptical objects [15] [16]. But HT based methods takes large memory for Hough space and leads to more computational complexity. Some interesting properties of statistical parameters such as small and large eigenvalues of covariance matrix is used to identify the corners and linear features [17] [18] [19]. The same properties are also used to detect circular and elliptical objects [20].

From the above discussion, it is evident that many of the face segmentation and recognition system works well in a controlled environment, but when moved over to an uncontrolled environment they begin to falter. In face space defined by eigenfaces method, for a new face in the training set, the whole procedure has to be repeated. In our proposed method, we use a hybrid scheme to detect and segment elliptical structure of human face, which uses small and large eigenvalues to find minor and major axial lengths, CHT to

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detect the centre location and Bresenham's Raster Scan Algorithm [21] to obtain the boundary points.

II. PROPOSED METHODOLOGY

Step-1 For the given gray scale image, find out the edge image using suitable edge detection operators.

Step-2 Obtain the large and small eigenvalues for the covariance matrix of the edge image.

Step-3 Obtain the ratio of large eigenvalues to small eigenvalues for different angles.

Step-4 Find out the major and minor axial lengths from the eigenvalues.

Step-5 Perform CHT using sparse matrices technique to find the centre of the ellipse.

Step-6 Calculate the boundary points of the ellipse using Bresenham's Raster Scan Algorithm.

Step-7 Segment the elliptical structure of the face using some post processing operations.

III. COVARIANCE MATRIX AND THEIR EIGENVALUES

In this section, we derive the major and minor axial lengths of the ellipse using the statistical and geometric properties associated with eigenvalues of the covariance matrix on a digital boundary connected over a region of support.

Let the sequence of n digital points describe the boundary of an object p, such that $p = \{p_i = (x_i, y_i), i = 1,2,3,......n\}$, where p_{i+1} is a neighbor of p_i (modulo n), and (x_i, y_i) are the Cartesian coordinates of p_i in the image. Let $s_k(p_i)$ as a small curve of p, which is defined by the region of support between points p_{i-k} and p_{i+k} for some integer k, i.e.,
$s_k(p_i) = \{p_j, j = i-k, i-k+1, ... i+k-1, i+k\}$.

The covariance matrix c of a curve segment $s_k(p_i)$ is given by

$$c = \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix}, \text{ where}$$

$$c_{11} = \left[\frac{1}{2k+1} \sum_{j=i-k}^{i+k} x_j^2 \right] - c_x^2 \tag{1}$$

$$c_{12} = c_{21} = \left[\frac{1}{2k+1} \sum_{j=i-k}^{i+k} x_j \cdot y_j \right] - c_x \cdot c_y \tag{2}$$

$$c_{22} = \left[\frac{1}{2k+1} \sum_{j=i-k}^{i+k} y_j^2 \right] - c_y^2 \tag{3}$$

c_x and c_y are the geometrical centre of the segment $s_k(p_i)$, i.e.,

$$c_x = \left[\frac{1}{2k+1} \sum_{j=i-k}^{i+k} x_j \right] \tag{4}$$

$$c_y = \left[\frac{1}{2k+1} \sum_{j=i-k}^{i+k} y_j \right] \tag{5}$$

The covariance matrix is $2x2$ symmetric and positive semi definite. There are two Eigenvalues λ_l and λ_s for the matrix c, given by

$$\lambda_l = \frac{1}{2} \left[c_{11} + c_{22} + \sqrt{(c_{11} - c_{22})^2 + 4c_{12}^2} \right] \tag{6}$$

$$\lambda_s = \frac{1}{2} \left[c_{11} + c_{22} - \sqrt{(c_{11} - c_{22})^2 + 4c_{12}^2} \right] \tag{7}$$

The eigenvalues of the matrix c can be used to extract the shape information about a curve. It can be shown that when the shape s is a straight line segment, the smaller eigenvalues λ_s for the line segment in the continuous domain will be zero, regardless the length and orientation of the line segment [17] [18]. The two eigenvalues will be equal if the shape s is a full circle. If the shape s is an ellipse, then $\lambda_l > \lambda_s$ and $\sqrt{\lambda_l}$, $\sqrt{\lambda_s}$ are associated with the semimajor and semiminor axial lengths of the ellipse [20]. Therefore the large eigenvalues λ_l and small eigenvalues λ_s of the covariance matrix c can be used to measure the length of the major axis and minor axis of an ellipse respectively.

Fig. 1 shows an ellipse with major axis length of 60 pixels and minor axis length of 40 pixels with different orientations. Table I summarizes the calculated eigenvalues λ_l and λ_s for different region of support (w) and orientations (θ) for the ellipses shown in Fig. 1. From Table I we note that the eigenvalues λ_l and λ_s are associated with major and minor axial lengths of an ellipse and their ratio $r = (\lambda_l / \lambda_s)$ is constant. The actual ratio is 1.5 and the calculated ratio is 1.47. It should to note that the size of the region of support will affect the eigenvalues of a given boundary. In our method we consider the region of support w as 5X5 and 7X7. The region of support for the computation of the covariance matrix can also be selected adaptively.
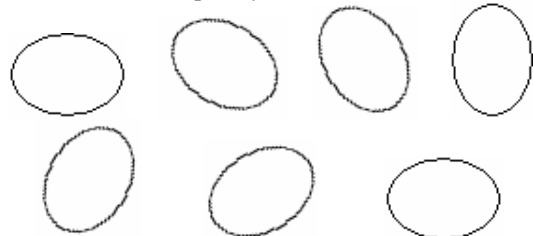

Fig. 1 Ellipse with different orientations

TABLE I

THE EIGENVALUES λ_l AND λ_s FOR DIFFERENT ORIENTATIONS AND REGION OF SUPPORT

θ	Region of support					
	W=5X5			W=7X7		
	λ_l	λ_s	r	λ_l	λ_s	r
0^0	1.0921	0.7432	1.4694	1.0897	0.7398	1.4729
30^0	1.0919	0.7429	1.4697	1.0893	0.7396	1.4728
60^0	1.0917	0.7426	1.4701	1.0890	0.7393	1.4730
90^0	1.0914	0.7422	1.4704	1.0887	0.7391	1.4730
120^0	1.0916	0.7425	1.4701	1.0889	0.7392	1.4730
150^0	1.0919	0.7428	1.4699	1.0894	0.7395	1.4732
180^0	1.0922	0.7433	1.4693	1.0898	0.7399	1.4729

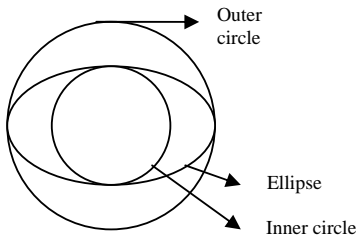## IV. CIRCULAR HOUGH TRANSFORM

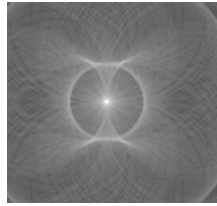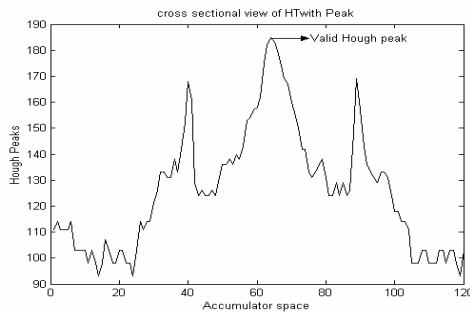Fig. 2(a) Circles formed from ellipse

Fig. 2(b) CHT

Fig. 2(c) Valid Hough peak

Finding the centre is an important step in ellipse detection. In this section, after finding the major and minor axial lengths the centre location of the ellipse can be identified using CHT. In our approach, before performing CHT we removed all the small eigenvalues λ_s whose values are zero or approximately zero using suitable threshold value. The large eigenvalues λ_l

and small eigenvalues λ_s whose values are same are removed because they represent circular feature. Finally, we have only the eigenvalues which represent the major and minor axes of an ellipse. Hence the storage requirement and computational time to perform CHT can be reduced considerably and also 5D accumulator arrays for the ellipse can be reduced to 3D arrays as a circle. Perform CHT using the duality between centers of circles formed by major and minor axes which are shown in Fig. 2(a). The CHT using sparse matrix technique is shown in Fig. 2(b). To find the valid Hough peaks, we used the neighborhood suppression scheme [22]. The cross sectional view of Hough transform with peak identified is as shown in Fig. 2(c). From Fig. 2(c), we observed that the Hough peak for major and minor axial circles is same and it represents the centre location of the ellipse.

V. FINDING RELATIONSHIP BETWEEN ELLIPSE PARAMETERS AND EIGENVALUES

This section gives the detail geometry about ellipses in $xy-plane$. It also gives the mathematical relationship between the small and large eigenvalues with various parameters of the ellipse which are used to detect the elliptical structure of the human face.

An ellipse in the standard form can be oriented via a rotation, so that the major and minor axes are not necessarily parallel to the coordinate axes. The standard form is given by

$$1 = \frac{x^2}{a^2} + \frac{y^2}{b^2} = \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} \frac{1}{a^2} & 0 \\ 0 & \frac{1}{b^2} \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \vec{X}^T D \vec{Y} \qquad (8)$$

where $\vec{X} = [\text{x y}]^\text{T}$, $D = diag\left(\frac{1}{a^2}, \frac{1}{b^2}\right)$ and T denotes the transpose operation.

The quadratic equation for an ellipse is $a_{11}x^2 + 2a_{12}xy + a_{22}y^2 + b_1 x + b_2 y + c = 0$. The matrix form can be written as $\vec{Y}^T A \vec{Y} + \vec{B}^T \vec{Y} + c = 0$, where

$$\vec{Y} = \begin{bmatrix} x \\ y \end{bmatrix}, \qquad A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \quad \text{and } \vec{B} = \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} \quad \text{for}$$

$a_{11}a_{12} - a_{12}^2 > 0$.

The general quadratic form can be written in centre orient form as

$$(\vec{Y} - \vec{K})^T A (\vec{Y} - \vec{K}) = \vec{Y}^T A \vec{Y} - 2\vec{K}^T A \vec{Y} + \vec{K}^T A \vec{K} \qquad (9)$$

$$= (\vec{Y}^T A \vec{Y} + \vec{B}^T \vec{Y} + c) - (2A\vec{K} + \vec{B})^T \vec{Y} + (\vec{K}^T A \vec{K} - c) \qquad (10)$$

$$= -(2A\vec{K} + \vec{B})^T \vec{Y} + (\vec{K}^T A \vec{K} - c) \qquad (11)$$

If we set $\vec{K} = -A^{-1}\vec{B}/2$ then $\vec{K}^T A \vec{K} = \vec{B}^T A^{-1}\vec{B}/4$, $(\vec{Y} - \vec{K})^T A(\vec{Y} - \vec{K}) = \vec{B}^T A^{-1}\vec{B}/4 - c$. Dividing the scalar on

the right hand side and setting $M = \dfrac{A}{(\vec{B}^T A^{-1} \vec{B} / 4 - c)}$

produces $(\vec{Y} - \vec{K})^T M (\vec{Y} - \vec{K}) = 1$. Finally M can be factored using eigen decomposition as $M = RDR^T$, where R is a rotation matrix and D is a diagonal matrix whose diagonal entries are positive.

For a 2×2 matrix, the eigenvector $\vec{V}$ of M corresponding to an eigenvalue λ is a non-zero vector such that $M\vec{V} = \lambda \vec{V}$. The eigenvalues are solutions to the quadratic equation $Det(M - \lambda I) = 0$, where I is the identity matrix. Since M is a symmetric matrix, the eigenvalues must be real numbers. For each eigenvalue, a corresponding eigenvector $\vec{V}$ is a non-zero solution to $(M - \lambda I)\vec{V} = \vec{0}$.

Let $M = \lfloor m_{ij} \rfloor$, the quadratic equation is

$$0 = Det(M - \lambda I)$$

$$= Det \begin{bmatrix} m_{11} - \lambda & m_{12} \\ m_{21} & m_{22} - \lambda \end{bmatrix} \tag{12}$$

$$= (m_{11} - \lambda)(m_{22} - \lambda) - m^2{}_{12} \text{, since } m_{12} = m_{21} \tag{13}$$

$$= \lambda^2 - (m_{11} + m_{22})\lambda + (m_{11} m_{22} - m^2{}_{12}). \tag{14}$$

The roots are

$$\lambda = \frac{(m_{11} + m_{22}) \pm \sqrt{(m_{11} + m_{22})^2 - 4(m_{11} m_{22} - m^2{}_{12})}}{2} \tag{15}$$

$$= \frac{(m_{11} + m_{22}) \pm \sqrt{(m_{11} - m_{22})^2 + 4m^2{}_{12}}}{2}$$

The argument of the square root is non-negative, so the roots must be real and are defined as small eigenvalue λ_s and large eigenvalue λ_l.

$$\lambda_s = \frac{(m_{11} + m_{22}) - \sqrt{(m_{11} - m_{22})^2 + 4m^2{}_{12}}}{2} \tag{16}$$

$$\lambda_l = \frac{(m_{11} + m_{22}) + \sqrt{(m_{11} - m_{22})^2 + 4m^2{}_{12}}}{2} \tag{17}$$

In summary, for an ellipse specified as $a_{11}x^2 + 2a_{12}xy + a_{22}y^2 + b_1 x + b_2 y + c = 0$ with $a_{11}a_{22} - a^2{}_{12} > 0$, we obtained the following parameters.

1. Centre of the ellipse is

$$\vec{K} = (k_1, k_2) = \frac{(a_{22}b_1 - a_{12}b_2, a_{11}b_2 - a_{12}b_1)}{2(a^2{}_{12} - a_{11}a_{22})} \tag{18}$$

2. The semiminor axis of the ellipse is $b = \dfrac{1}{\sqrt{\lambda_s}}$ (19)

3. The semimajor axis of the ellipse is $a = \dfrac{1}{\sqrt{\lambda_l}}$ (20)

4. If $m_{11} \geq m_{22}$, the major axis direction of the ellipse is

$$\frac{(\lambda_l - m_{22}, m_{12})}{|(\lambda_l - m_{22}, m_{12})|} \tag{21}$$

If $m_{11} < m_{22}$, the major axis direction to be

$$\frac{(m_{12}, \lambda_l - m_{11})}{|(m_{12}, \lambda_l - m_{11})|} \tag{22}$$

5. The angle formed by the major axis with $x - axis$ is

$$\tan(2\theta) = \frac{2a_{12}}{a_{22} - a_{11}} \tag{23}$$

6. The coordinates of the ellipse can be obtained using Bresenham's Raster Scan Algorithm as $x = \bar{x} \cos\theta - \bar{y} \sin\theta$ and $y = \bar{x} \sin\theta + \bar{y} \cos\theta$, where $(\bar{x}, \bar{y})$ is the axis-aligned coordinate.

VI. EXPERIMENTAL RESULTS

This section presented the result of experiments in which the proposed method was applied to several images. The set of images was downloaded from MIT media lab. To test the proposed approach we used both moderately uniform background and cluttered images. In addition, we considered the noisy images corrupted by impulse and Gaussian noise also. Fig. 3(a) shows a set of real world gray scale face images. Canny edge operators are used to obtain the edge images shown in Fig. 3(b). To calculate the eigenvalues, we use the window size 'w' as 7X7 with threshold (t) as $1.385 \leq t \leq 1.103$ for λ_l and λ_s respectively. The CHT of the eigenvalue image is very complex, because it consists of all linear and nonlinear points. Sparse matrix technique is used to reduce the storage space and computational complexity. Neighborhood suppression scheme is applied to find the valid Hough peaks which represent the centre location of the ellipses. The CHT with valid Hough peaks identified is shown in Fig. 3(c).The identified ellipse from the CHT are shown in Fig. 3(d). To reveal the correctness and accuracy, the detected ellipses are overlapped with edge images and original image as shown in Fig. 3(e) and 3(f) respectively. The detected and segmented faces are as shown in Fig. 3(g).

After the successful segmentation of face region, face identification is performed based on the various features of the face image. The linear features inside the face region represent different parts of the face. The proposed approach can also be used to identify linear segments. Here we used the properties of the small eigenvalues, which are zero of a covariance matrix for a set of edge pixels connected over a region. Fig. 4(a) represents an edge image of the segmented face. The HT of the edge image with valid Hough peaks is as shown in Fig. 4(b). The linear segments identified with threshold value of $\lambda_s = 0.000536$ and the window size of 3X3 is as shown in Fig. 4(c). From this experiment, we conclude that, the characteristics of statistical parameters such as small eigenvalues can be used to detect linear segments.

Fig. 3(a) Original images

Fig. 3(b) Edge images
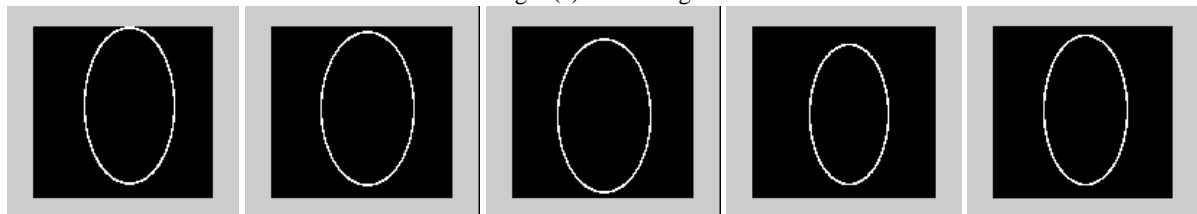

Fig. 3(c) CHT images

Fig. 3(d) Ellipses extracted

Fig. 3(e) Ellipse overlapped with edge images

Fig. 3(f) Ellipse overlapped with original images
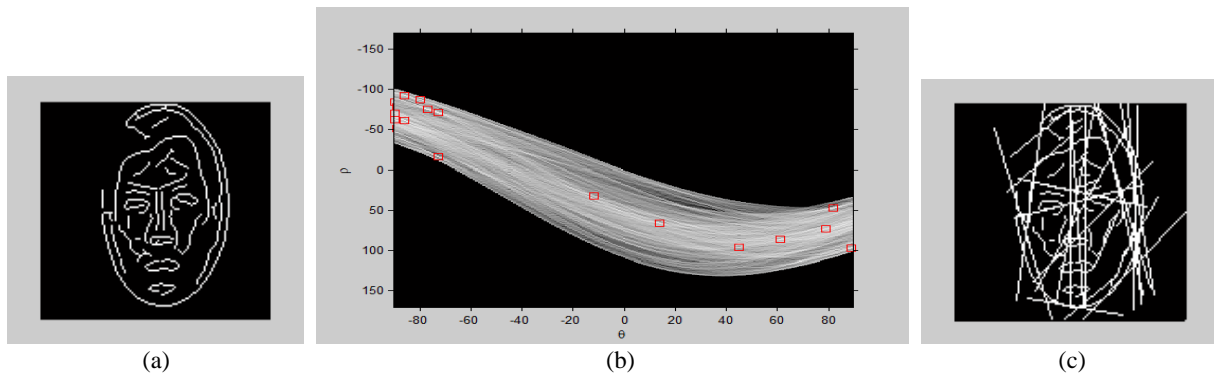

Fig. 3(g) Segmented faces

(a)   (b)   (c)

Fig. 4 Linear features extraction (a) Edge image (b) HT with valid peaks (c) Lines extracted

To test the performance of our approach on images with moderately background clutter, an experiment has been conducted on a set of real world image shown in Fig. 5(a). In this case, if the background is cluttered, then the intensity discontinuities in the background will give rise to feature points that are not part of the face region. But the proposed method locates the feature points of the ellipse by considering the maxima of local curvature in the intensity image. The edge image and the CHT of the edge image are as shown in Fig, 5(b) and 5(c) respectively. The ellipses extracted from the maxima of local curvature by selecting appropriate Hough peak are as shown in Fig 5(d). To test the correctness of the face region, the best fit extracted ellipse is overlapped with edge image and original images are as shown in Fig 5(e) and 5(f) respectively. The segmented face region is as shown in Fig 5(g). From this experiment, we observed that, the proposed approach gives good result for images with cluttered background also.

In order to illustrate the effectiveness of the proposed technique, an experiment is conducted on set images with different orientation and background clutter shown in Fig 6(a). The best fit extracted ellipse using our approach is overlapped with edge image and original images are as shown in Fig 6(b) and 6(c) respectively. From this experiment we conclude that,

the eigenvalue approach gives the correct orientation angle of the major axis. Hence the ellipse extracted based on the long local curvature gives the accurate face region of the image for different angular orientations.

Another evaluation is done to test the resistance of our method against noise. In this evaluation for the original image shown in Fig. 7(a) a Gaussian white noise with variance of 0.01 and 20 % density of salt and pepper noise is added and is as image shown in Fig 7(b). The edge image shown in Fig. 7(c) is a very complex image, since it has noise with cluttered background. The CHT of this edge image is as shown in Fig. 7(d). The best fit ellipse extracted from the proposed approach is as shown in Fig. 7(e). To test the accuracy of the elliptical structure, the extracted ellipse is overlapped with edge image, noisy image and original image shown in Fig. 7(f), 7(g) and 7(h) respectively. The segmented face image of noisy image and original image are as shown in Fig. 7(i) and 7(j) respectively. From this evaluation, we conclude that the proposed method gives accurate elliptical structures in the noise conditions also. This represents the proposed approach is very robust against noise.

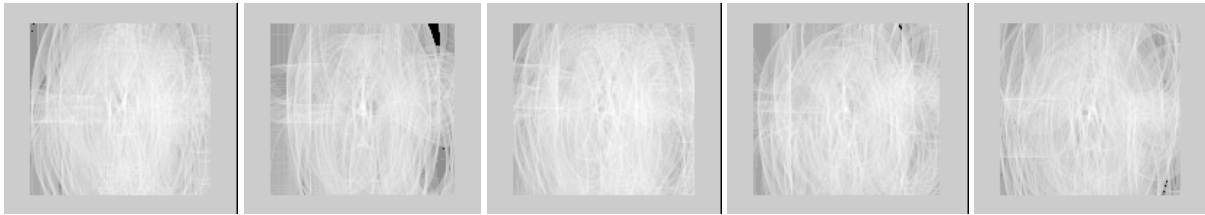Fig. 5(a) Original images

Fig. 5(b) Edge images
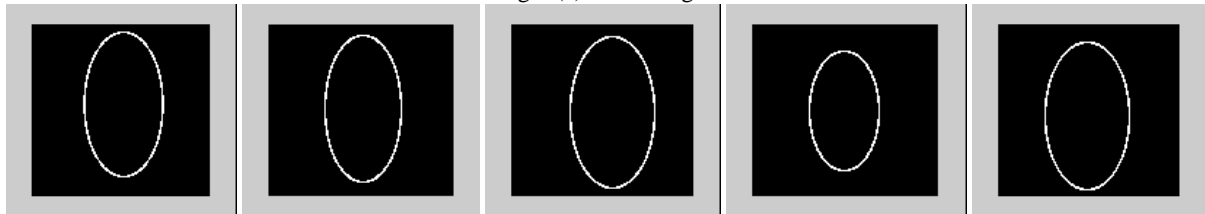
Fig. 5(c) CHT images

Fig. 5(d) Ellipses extracted

Fig. 5(e) Ellipses overlapped with edge images

Fig. 5(f) Ellipses overlapped with original images

Fig. 5(g) Segmented faces

Fig. 6(a) Original image

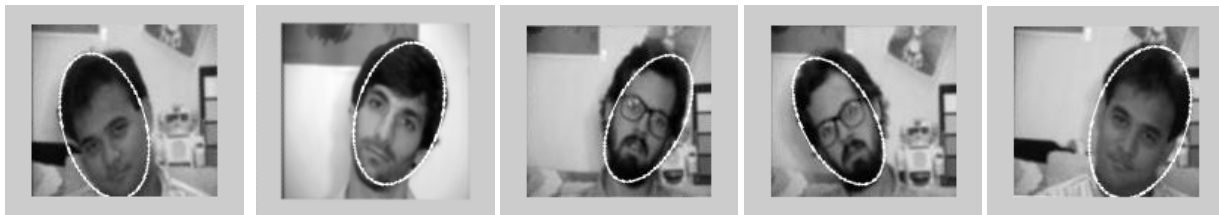Fig. 6(b) Ellipse overlapped with edge image

Fig. 6(c) Ellipse overlapped with original image

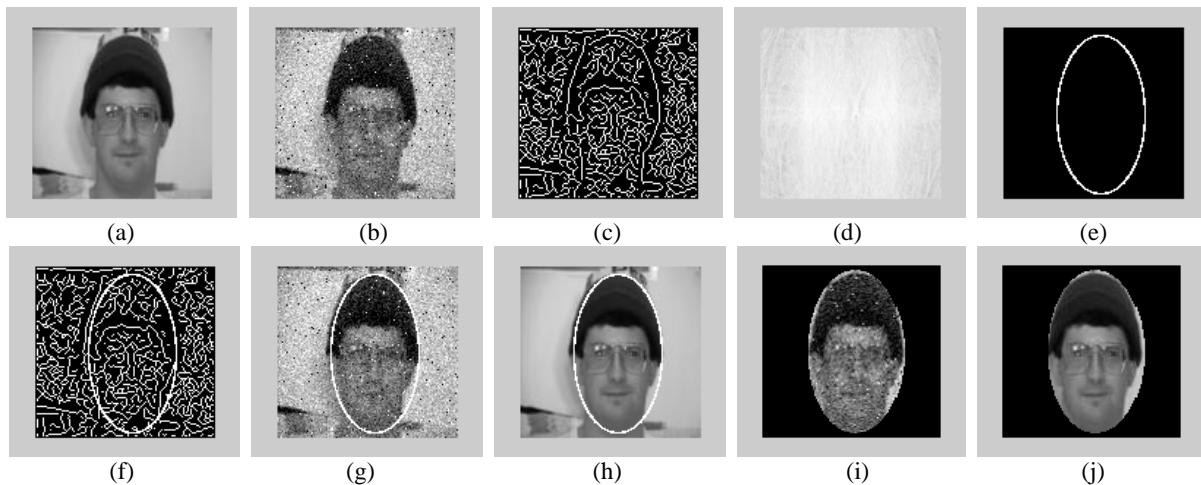| (a) | (b) | (c) | (d) | (e) |

| (f) | (g) | (h) | (i) | (j) |

Fig. 7 Experiment on Noisy image (a) original Image (b) Noisy Image (c) Edge image (d) CHT (e) Ellipse extracted (f) Ellipse overlapped with edge image (g) Ellipse overlapped with noisy image (h) Ellipse overlapped with original image (i) Face identified from noisy image (j) Face identified from original image

To test the robustness of our method against noise an additional experiment is conducted using salt and pepper noise with different densities. In this evaluation the density of salt and pepper noise was increased from 0 to 80 percent and the identification rate was evaluated. Results of this experiment show that the noise with less than 30% density has no effect on the accuracy of the face identification. Further increasing the noise density increases the complexity in CHT. The centre of the ellipse and eigen values corresponding to the semi major and semi minor axis of the ellipse changes. Hence the face identification rate reduces. Fig. 8 draws the identification rate versus noise density. From this it is evident that our proposed method can withstand noise and being efficient to identify the face region up to 60 percent of noise density.
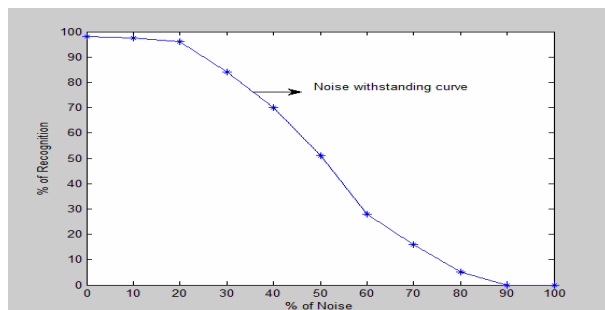

Fig. 8 Noise resistance curve

VII. CONCLUDING REMARKS

In this paper we discussed an efficient and accurate method for human face identification and segmentation in gray scale images. This method utilizes the inherently elliptical nature of the human head and fits an ellipse to the head. The resultant information about the ellipse is then used to mask out unwanted feature points in the recognition phase of the identification system. When compared to other methods, the proposed hybrid method has the advantage of eigenvalues approach, CHT and Raster Scan Algorithm. It does not use the tangent of edge points to extract the ellipses and avoids false alarms. The amount of data required for ellipse detection and parameters estimation using the proposed method is minimal, since it uses only eigenvalues of covariance matrix. When compared to the conventional face space methods, the main strengths of our method are its less computational time, low memory requirements and accuracy of face detection and segmentation. Since, Bresenham's raster scan algorithm is used to identify the positions of the elliptical structure, it works well when the boundary is distorted and disconnected due to noise or occlusions. The proposed method was tested on images with uniform background, cluttered and noisy conditions.

REFERENCES

[1] R. Chellappa, C.L. Wilson, S. Sirohey, "Human and machine recognition of faces: A survey", *Proc. of IEEE,* V83, 1995, pp. 705-740.

[2] A. Samal, P. A. Iyengar *"Automatic recognition and analysis of human faces and facial expressions: A survey", Pattern Recognition*, 25(1), 1992, pp. 65-77.

[3] T. Kanade, "Picture processing system by computer complex and recognition of human faces", *PhD thesis,* Dept. of Information science, Kyota university, Japan, Nov-2003.

[4] R. Brunelli, T. Poggio, "Face recognition through geometrical feature". *Proc. European conference on computer vision,* 1992, pp 792-800.

[5] B.S. Manjunath, R. Chellappa, C. Vonder Malsburg, "A feature based approach to face recognition", *Proc. of IEEE conference, computer vision pattern recognition,* 1992, pp. 373-378.

[6] A.L. Yuille, D.S. Cohen, P.W. Hallinan, "Feature extraction from faces using deformable templates", *Proc. of IEEE conference, computer vision pattern recognition,* 1989, pp. 104-109.

[7] G V. Govindaraju, S.N. Srihari, D.B. Sher, "A computational model for face location", *Proc. international conf. computer vision,* 1990, pp. 718-721.

[8] M.Turk, A.Pentland, "Eigenfaces for recognition*", Journal of Cognitive Neuroscience,* vol.3, No.1, 1991.

[9] M. Turk, A. Pentland*,* "Face recognition using eigenfaces", *Proc. IEEE Conf. on Computer Vision and Pattern Recognition*, 1991, pp. 586-591.

[10] S. A. Sirohey, "Human face segmentation and identification", *Technical Report CAR-TR-695,* Center for Automation Research, University of Maryland, College Park, MD, 1993.

[11] Ismail Haritaoglu, David Harwood, Larry S. Davi, "Multiple people detection and tracking", *ICIAP,* 1999, pp. 280-285.

[12] Sangho Park, "Head segmentation and head orientation for pose estimation of multiple people", *SSIAI,* 2000, pp 192-196.

[13] D. H. Ballard, "Generalizing the Hough transform to detect arbitrary shapes", *Pattern Recogn., 13(2),* 1981, pp. 111–122.

[14] E. R. Davis, "Finding ellipses using the generalized Hough transform", *Pattern Recogn.,* Feb 1989, pp. 87-96.

[15] Wen-Yen Wu, Mao-Jiun J. Wang*,* "Elliptical object detection by using geometric properties", *Pattern Recogn,* Vol. 26, No. 20, April. 1993, pp. 1499-1509.

[16] Chun-Ta Ho, Ling-Hwei Chen, "A Fast ellipse/circle detector using geometric symmetry", *Pattern Recogn.,* Vol. 28, No. 1June 1994, , pp. 117-124.

[17] Du-Ming Tsai, H. T. Hou, H.J. Su, "Boundary based corner detection using Eigen values of covariance matrices", *Pattern. Recogn.* 20, Sept 1998, pp. 31-40.

[18] D. S. Guru B, H. Shekar, P. Nagabhushan, "A simple and robust line detection algorithm based on small Eigen value analysis", *Pattern Recogn.,* 25, Aug 2003, pp. 1-13.

[19] J. Prakash, K. Rajesh, "Extracting geometric primitives: Combined approach of Hough transform, Eigen values and raster scan algorithms", *International Journal of systemics, Cybernetics and Informatics (IJSCI*Jan 2007, *),* pp. 48-55.

[20] J. Prakash, K. Rajesh, *"elliptical features extraction using eigenvalues of covariance matrix, Hough transform and raster scan algorithms", International Journal of computer science and Engineering,* vol 1,No 2. 2007, pp. 97-102.

[21] Donald Hearn, M. Pauline Baker, *"Computer graphics"* (2nd ed), Pearson Education, 2003.

[22] Rafael C. Gonzalez, Richard E. Woods, *"Digital Image processing"* (5th ed), Addison Wesley, 2000.

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