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File System Security by using image Sequence and Eigen Analysis

Animesh Tripathi[1] Annu Kumar[2] Mukesh Jadhav[3] ,Srishti Mukharya[4], Asst. Prof. S.M. Shedole[5]

[1-5] *Dept of Computer Engg, SIT Lonavala*

***Abstract**: Faces represent complex, multidimensional, meaningful visual stimuli and developing a computational model for face recognition is difficult. This paper describes a system for File Security by using an image sequence and subsequently doing Eigen Analysis over a training dataset of images to minimize the overall error rate and enhance the accuracy level. Motion information is used to find the moving regions, and probable eye region blobs are extracted by thresholding the image. These blobs reduce search space for face verification, which is done by template matching. Eigen analysis of edginess representation of face is used for face recognition. One dimensional processing is used to extract the edginess image of face. The face recognition is carried out by cumulatively summing up the Euclidean distance between the test face images and the stored database, which shows good discrimination for true and false subjects. We can identify at least two broad categories of face recognition systems:1. we want to find a person within a large data-base of faces (e.g. in a police database). These systems typically return a list of the most likely people in the database. Often only one image is available per person. It is usually not necessary for recognition to be done in real-time.*

2. We want to identify particular people in real-time (e.g. in a security monitoring system, location Tracking system, etc.), or we want to allow access to a group of people and deny access to all others (E.g. access to a building, computer etc.) [Multiple images per person are often available for training and real-time recognition is required. The recognizer provides a measure of confidence in its output and classification error approaches zero when rejecting as few as 10% of the examples. We use a database of 400 images of 40 individuals which contains quite a high degree of variability in expression, pose, and facial details.

***Keywords –** Eigen Analysis, Edginess, Euclidean Distance.*

I. INTRODUCTION

Face plays an important role in social communication.Face biometric itself is used in many applications likesecurity, forensic and other commercial applications.Similarly facial expressions are the fastest means of communication, while conveying any type of information. Face detection and recognition are challenging tasks due to variation in illumination, variability in scale, location, orientation (up-right, rotated) and pose (frontal, profile).

In this paper, we introduce a new approach to automatically classify facial features. First, we detect facial features namely: eyes, eyebrows and mouth using vertical and horizontal projections. Next, we segment facial features using active contour since it gives moreclose and natural representation of the detected feature shape. Afterwards, we extract relevant facial features points which define the prominent landmarks surrounding facial components. This is an improvement over the manual annotation method for Facial Characteristic Points (FCPs). Then, we have defined a set of distances so as to measure facial features deformation.

The user should be able to secure the data using Facial Recognition and should be able to access the same data over the network safely and securely. The user should secure data at the server side and access the same secured data from the client side over the wired network.

II. FACE DETECTION

In an image sequence the position of the head is not stationary, as there is always some motion. Therefore the regions having significant motion are extracted by subtracting consecutive frames and thresholding it. Figure 1 shows two consecutive frames from a video sequence. Let It represent the image at time t. The difference image D is given by:-

$$D(i,j) = 1, \quad if\ I_t(i,j) - I_{t-1}(i,j) > \lambda \qquad 0, Otherwise \qquad (1)$$

Where (I, j) are the (row, column) indices of the image, and λ is the threshold, which is set such that D is zero when there is no significant motion. The contour in the difference image D is traced to find an approximate bounding box. The corresponding region in image It is referred as E. Figure 2 shows the threshold difference image D with the bounding box, and the corresponding grey level image E. Since objects other than face can also be in motion, a decision has to be made whether it is a face or not. Correlation between the averaged face template and the test pattern is computed, and the test pattern is accepted as face if the correlation[9,10] exceeds a certain threshold. To localize the face in the image E, the face template has to be passed overthe image with different scales and orientations. To speed up the process, first the

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possible region of the eye pair is extracted. It is known that the eye region is usually darker than other facial parts such as nose and mouth. To extract these dark regions, a threshold γ calculated as:

$$\gamma = \mu_E - \sigma_E \quad (2)$$

Where μ_E is the mean and σ_E is the standard deviation of the image E. Let B be the binary image given by:

$$B(i,j) = 1, \quad if \;\; E(i,j) < \gamma \qquad 0, \quad Otherwise \qquad (3)$$

Where (i, j) are the (row, column) indices of the image E. Figure 3(a) shows the binary image. Morphological operators are used to close small discontinuities in the image B. This results in blobs as shown in Figure 3(b). Along with the possible eye pair region there may be other dark regions which are extracted. The size of the eye region is approximately known, and larger regions than this size are filtered out. Figure 3(c) shows the image after region filtering. The pair of blob gives the orientation of face, which is used to normalize the test pattern to the size of the face tem-plate. Correlation between the face template and test pattern is computed. If the correlation exceeds certain threshold level, it is accepted as face. This eliminates the search for face in all scales and orientations. Figure 3(d) shows the detected face resized to 50x50 pixels after template matching. Figure 4 shows the detected faces for 5 different subjects.

Figure 1: Two consecutive frames from a video

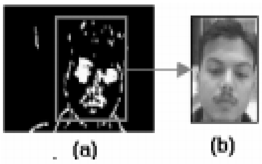

Figure 2: Threshold difference image D and the corresponding grey level image E.

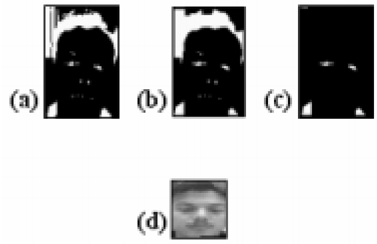

Figure 3: (a) Thresholded image B. (b) Image after Morphological Operations applied to B. (c) Image after region filtering. (d). Detected face resized to 50x50 pixels after template matching.

III EDGINESS IMAGE OF FACE

To extract the edginess image of a face, computationally efficient method of one dimensional (1-D) processing of images proposed in [5] is used. In this method, the image is smoothed using a 1-D Gaussian filter along the horizontal (or vertical) scan lines to reduce noise. A differential operator (first derivative of 1-D Gaussian function) is then used in the orthogonal direction, i.e., along the vertical (or horizontal) scan lines to detect the edges. This method differs from the traditional approaches based on 2-D operators in the sense that smoothing is done along one direction and the differential operator is applied along the orthogonal direction. The traditional 2-D operators smooth the image in all directions, thus resulting in smearing of the edge information. The smoothing filter is a 1-D Gaussian filter[1], and the differential operator

Where σ1 is the standard deviation of the Gaussian function. The first order derivative of 1-D Gaussian is given by:

$$C(y) = \frac{-y}{\sqrt{2\pi\sigma_3}} e^{-\frac{y^2}{2\sigma_2^2}} \qquad (5)$$

Where σ_1 is the standard deviation of the Gaussian function. The smoothing filter and the differential operator are shown in Figure 5. The values of σ_1& σ_2 decide the spatial ex-tent of these 1-D filters. The response of the 1-D Gaussian filter applied along a particular scan line of an image in one direction (say, along the horizontal scan line yr of pixels) can be expressed as:

h(x, yr) = k(x,yr) * g(x) (6)

Where * denotes the 1-D convolution operator, g(x) represents the 1-D Gaussian filter, (K(x, y) r) represents the rth row of the image K, and h(x,y)r is the corresponding filter response. The response is computed for all rows in the image to obtain h(x,y). For the 1-D Gaussian filter output h(x, y), obtained using Equation 6 for all the rows, the differential operator is applied along each column to extract the edges oriented along the horizontal lines of the pixels. The result is given by:

f(xc,y) = h(xc,y) * c(y) (7)

is the first order derivative of the 1-D Gaussian function. The 1-D Gaussian filter is given by:

$$g(x) = \frac{1}{\sqrt{2\pi\sigma_1}} e^{-\frac{x^2}{2\sigma_1^2}} \quad (4)$$

Where C(x, y) is 1-D differential operator, and h (x_c, y) denotes the Cth column in the 1-D Gaussian filtered image h(x, y). The resulting image, obtained by applying Equation 7 for all columns, produces the horizontal components of edginess (strength of an edge)[15,3] in the image. Similarly, the vertical components of edginess are derived by applying the 1-D smoothing operator along all the vertical scan lines of the image and further processing with the 1-D differential operator along the horizontal scan lines of pixels. Finally, the partial edge informationobtained in both the horizontal and vertical directions are added to extract the edginess map of the original image. Figure 6 shows a grey level image, binary edge image and edginess image of a face. It is obvious that the edginess image carries additional part of the information which is missing in the binary edge image. The edginess of a pixel in an image is identical to the magnitude of the gradient of the grey level function, which corresponds to the amount of change across the edge. Hence capturing directly the gradual variation[7,2,4] present in a facial image is better and accurate than constructing the edginess image artificially from the edge image of the face.

Figure 4: Result of Face Detection (Faces resized to 50x50 pixels).

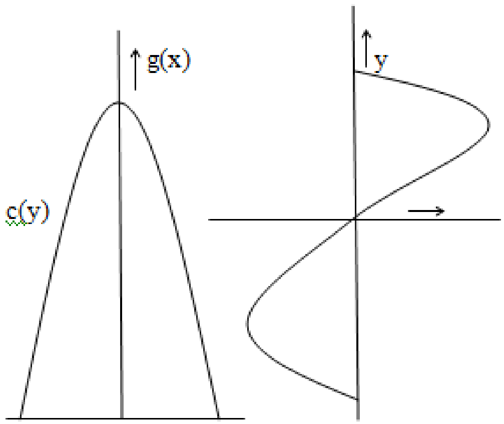

Figure 5: (a) Gaussian Function in the Horizontal Direction (smoothing Filter) and (b) First Order Derivative of Gaussian Function in Vertical Direction (differential Operator).

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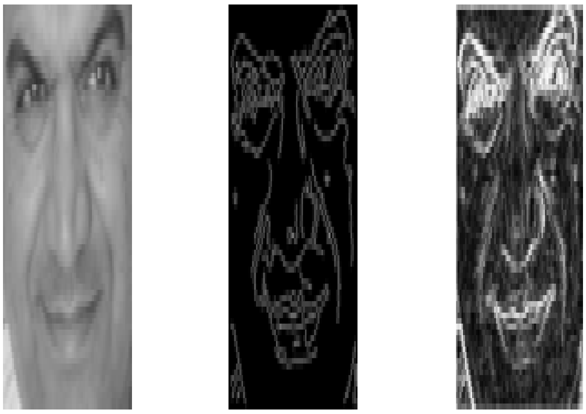

Grey Level image Edge Image Edginess

Figure 6: Different representation of facial image

IV EIGENEDGINESS

Consider a set of P sample images Ipr x c, p=1, 2, P, with resolution r x c. The pixels in the image are Vectorized into a N¬-dimensional vector x_p , p =1, 2,….. , P, where ¬N=r x c. The vectors obtained in this manner from all the P sample images can be denoted as X={X1, X2……. Xp}. For a given set of¬-dimensional vector representation of faces, principal component analysis (PCA) can be used to find the subspace whose basis vectors correspond to the directions of maximum variance in the original space. Let W represent the linear transformation that maps the original¬-dimension space onto an M-dimension feature subspace, where M << N ¬. This yields a set of projection vectors Yp Ɛ RM where Yp = WT x_p p=1,2,…….P. The columns of W are the M eigenvectors[3,6,8,12]ie, corresponding to the first M eigenvalues obtained by solving the Eigen equation, Cei=λiei, where C is the co-variance matrix, λi is the Eigen value associated with Eigen vector ei. The reduced dimension representation of the edginess image of a face is determined using the PCA technique. Eigenvectors of the covariance matrix[11,4] of the edginess images are referred as Eigen Edginess. In an image sequence, number of face images are captured for training. For each of the training face vector Xi, u, the projection vector is given by:

$$Y_{i,u} = W^T X_i, u, \quad 1 \le l \le L,\ 1 \le u \le U \quad (8)$$

Where L is the number of subjects, and U is the number of face images per subject. The identity of the person (φ) from Q test face vectors Xq, q=1, 2, .Q, is calculated as follows:

$Y_q = W^T X_q$(9)

$d_{t,q} = \min ||y_q - y_{t,v}||^2$(10)

$\emptyset = \arg(\min(\sum_{q=1}^{Q} dt, q))$(11)

Where Yq is the Projection Vector of the qth test face vector and dt, q is the minimum Euclidean Distance of the Test Face image from q from the lth subject.

V EXPERIMENTAL RESULTS

The experiment is conducted with 5 subjects. For each subject 30 faces are captured to form the training set. Similarly for the testing data set, 30 faces per subject were collected on a different day. Each face image is resized to 50x50 pixels. The edginess image of the face is calculated as described in Section 3. To reduce the dimension of the vector, the first 20 eigenvectors of the edginess images, are used. The test face pattern is classified by taking the minimum Euclidean distance between the stored pattern and the test pattern in the Eigen edginess space. Face recognition results for a total of 150 test face patterns for 5 subjects (30 faces per subject) is shown in Figure 7. The graph shows the number of faces classified into a particular class for each subject. For test face patterns of subject 1 the graph shows that 23 faces were recognized correctly as subject 1, none were recognized as subject 2, 4 faces were recognized as subject 3, 2 faces were

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recognized as subject 4, and 1 face was recognized as subject 5. The performance is 86% for 150 faces. Figure 8 shows the minimum Euclidean distance[1,13,14] plot for the test face patterns (subject 4) against all subjects. Figure9 shows the cumulative Euclidean distance for the test face patterns of subject 4. The cumulative sum of Euclidean distance for the test face patterns gives better discrimination than from a single test face pattern.

VI CONCLUSION

In this paper we presented a face detection and localization technique in a video. To speed up the process of face detection, motion information is used, and probable eye pair regions are extracted, which guides the template matching for face verification. With this approach, scanning the image for different scales and orientation is avoided. In our method Eigen analysis of edginess representation of face is used for recognition. For each subject, 30 face images are captured from the video, and the face is recognized based on minimum cumulative sum of the Euclidean distances, which gives better performance than the distance from a single face image.

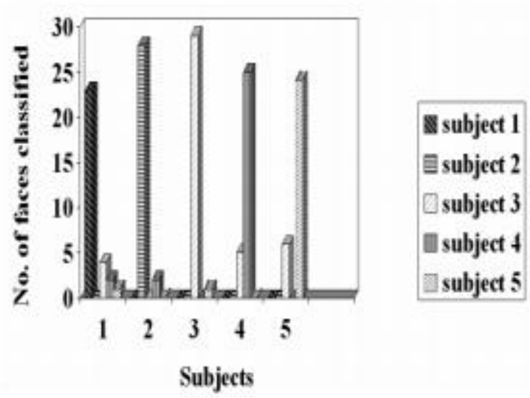

Figure 7: Expected System Performance. The Bar graph shows number of faces classified out of 30 test faces patterns for each subject.

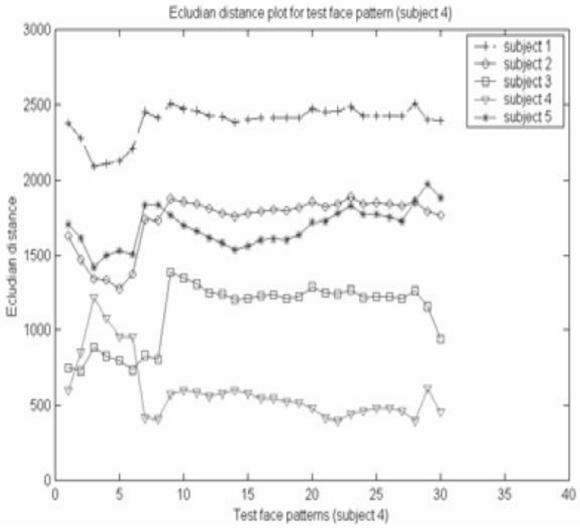

Figure 8: Minimum Euclidean Distance for Test Face patterns against different subjects and varying intensity levels.

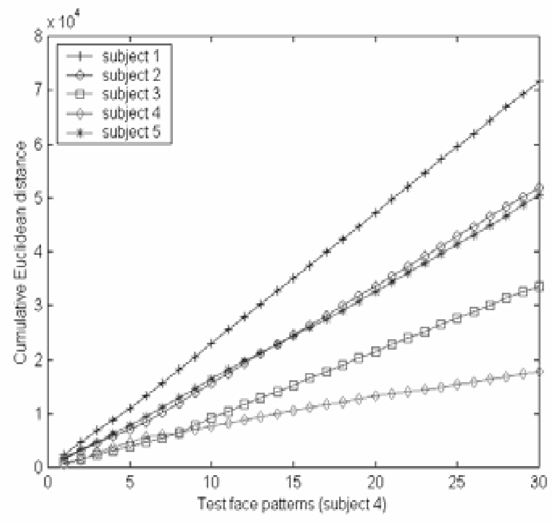

Figure 9: Cumulative Euclidean Distance Plot for Test Faces and Patterns against different subjects and intensity levels.

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