REAL TIME FACE AUTHENTICATION SYSTEM USING AUTOASSOCIATIVE NEURAL NETWORK MODELS

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ABSTRACT

This paper proposes a novel method for video-based real time face authentication. The proposed method uses motion information to detect the face region, and the face region is processed in YC_rC_b color space to determine the location of the eyes. The system extracts only the gray level features relative to the location of the eyes. Autoassociative Neural Network (AANN) model is used to capture the distribution of the extracted gray level features. Experimental results show that the proposed system gives an equal error rate of less than 1% in real time for 25 subjects. The performance of the proposed method is invariant to size and tilt of the face, and is also insensitive to variations in natural lighting conditions.

1. INTRODUCTION

Automatic recognition of human faces is one of the challenging problems in pattern recognition. A comprehensive survey of still and video-based face recognition techniques can be found in [1]. Various methods have been proposed in the literature such as eigenface [2], elastic graph matching [3], neural network [4],[5], line edge map [6] and support vector machines [7]. The method proposed in this paper satisfies the following requirements for a face authentication technique;

1. Invariant to size and tilt of the face
2. Invariant to variations in natural lighting conditions
3. Able to authenticate a subject within a reasonable time
4. New subject can be added to the system without using the features of other subjects.

Most of the methods described in the literature are not able to satisfy at least one of the above requirement. The proposed real time face authentication system consists of three modules, namely face detection, feature extraction and face authentication. The face detection and feature extraction techniques are described in Section 2 and 3, respectively. Section 4 describes the AANN model for face authentication. The experimental results are discussed in Section 5.

2. FACE DETECTION

Detecting faces automatically from the intensity or color image is an essential task for many applications like face recognition or authentication, face tracking and video indexing [8]. Recent methods for face detection use neural networks [9], skin color segmentation [5],[10] and motion information [11] for tracking faces in the video. We used a simple method to detect the face region using only the motion information in order to implement the system in real time. In our method, the face region is determined from the upper head contour points which are extracted from the thresholded interframe difference image. The RGB image is converted to gray level image (I), and the interframe difference image (D) is obtained by

$$\begin{aligned} D(i,j,k) &= I(i,j,k) - I(i,j,k-1) \\ & \quad 0 \le i < w, 0 \le j < h, k \ge 1 \end{aligned} \tag{1}$$

where k is the frame number in the video, w and h are the width and height of the image, respectively.

The thresholded difference image T is obtained by

$$T(i,j,k) = \begin{cases} 1, & if\ D(i,j,k) > \lambda \\ & or\ T(i,j-1,k) = 1 \\ 0, & otherwise \end{cases} \tag{2}$$

where λ is the threshold, which is the smallest integer such that $T(i,j,k) = 0$, for all i and j, whenever there is no moving region in the camera view.

The thresholded difference image is scanned from top to bottom to find out the approximate top pixel (c_x, c_y) of the moving region. The RGB image in the region below the pixel (c_x, c_y) is converted to YC_rC_b space, and then checked for skin pixels as given in [12]. If there are no skin pixels, then the scanning process is continued until it finds the pixel (c_x, c_y) or reaches the bottom of the image. The upper portion of the head contour points are extracted by scanning the thresholded difference image from the pixel (c_x, c_y). The width of the face (w_1) is estimated from the head contour points, and this process is repeated for every two consecutive frames in order to track the face in the video. Fig.1(a) shows the thresholded difference image as given by the Eq.(2). Fig.1(b) shows the extracted head contour points and the face region.

(a) Difference image (b) Contour and face region

Fig. 1. Face detection.

3. FEATURE EXTRACTION

Feature extraction is a key step in any pattern recognition task. This paper proposes a new method for extracting features from the face, which are relative to the location of the eyes, and hence the features are invariant to size and tilt of the face. A similar method is proposed in [10] for locating the eyes.

The face region is converted to YC_rC_b space, and the skin pixels are identified as given in [12]. The face region is thresholded to obtain the thresholded face image (R), given by

$$R(i,j,k) = \begin{cases} 255, & if\ \ Y(i,j,k) < \lambda_1 \text{ and } \\ & \quad C_r(i,j,k) < \lambda_2 \text{ and } \\ & \quad C_b(i,j,k) > \lambda_3 \\ I(i,j,k), & otherwise \end{cases} \tag{3}$$

where λ_1, λ_2 and λ_3 are the average Y, C_r and C_b values of the detected skin pixels in the face region, respectively. Morphological closing operation is applied to the thresholded face image, and the centroid of all the blobs are estimated.

The eyebrow(E) pixels are estimated using

$$E(i,j,k) = \begin{cases} 1, & if\ \ Y(i,j,k) \geq \lambda_1 \text{ and } \\ & \quad Y(i,j+1,k) \geq \lambda_1 \text{ and } \\ & \quad Y(i,j+2,k) < \lambda_1 \\ 0, & otherwise \end{cases} \tag{4}$$

The centroid of the blobs which are nearer to the center of the eyebrow pixels are taken as the location of the eyes. Fig.2(a) shows the thresholded face image, and Fig.2(b) shows the location of the eyes and other facial regions. The distance from the center of the eyes to the pixel (c_x, c_y) is used for estimating the position of top 8 facial regions in Fig.2(b), and the position of other 65 facial regions are estimated relative to the location of the eyes. The distance between the eyes is used to estimate the size of the region. The region can be of size 2x2, 3x3 or 4x4 pixels. The average gray value in each region is used as an element in the 73 dimensional feature vector $x_1, x_2, ..., x_{73}$.

(a) Thresholded face (b) Facial regions

Fig. 2. Feature extraction.

4. AUTOASSOCIATIVE NEURAL NETWORK MODEL FOR FACE AUTHENTICATION

Autoassociative neural network models are feedforward neural networks performing an identity mapping of the input space, and are used to capture the distribution of the input data [13]. The five layer Autoassociative neural network model as shown in Fig.3 is used to capture the distribution of the feature vectors for each subject.

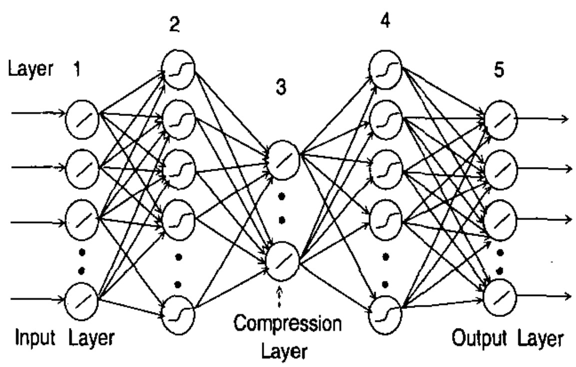

Fig. 3. AANN model used for face authentication.

The second and fourth layers of the network have more units than the input layer. The third layer has fewer units than the first or fifth. The activation functions at the second, third and fourth layer are nonlinear. The structure of the AANN model used in our study is 73L 90N 30N 90N 73L, where L denotes a linear unit, and N denotes a nonlinear unit. The integer value indicates the number of units used in that layer. The nonlinear units use $tanh(s)$ as the the activation function, where s is the activation value of the unit. The standard backpropagation learning algorithm is used to adjust the weights of the network to minimize the mean square error for each feature vector.

The 73 dimensional feature vector $x_1, x_2, ..., x_{73}$, is normalized as follows:

$$y_i = \frac{2(x_i - x_{min})}{(x_{max} - x_{min})} - 1 \quad (5)$$

where x_{max} and x_{min} are the maximum and minimum values in the feature vector. The normalized feature vector $y_1, y_2, ..., y_{73}$, is used as input to the AANN model. Feature vectors are extracted from 400 face images for each subject for training the AANN model. The feature vectors from face images are extracted in two sessions (day time and night time), in order to handle the lighting effects in uncontrolled environment. In each session, 200 face images of each subject with variation in size, tilt of the face, and also variation in yaw and pose to certain extent, are used to form the training set. In this system there is no need to store the face images in the database. The AANN model is trained using the standard backpropagation learning algorithm for 1000 epochs. One such model is created for each subject. A new subject can be easily added to the system without using the features of other subjects. The training of a subject with 200 feature vectors for 1000 epochs requires approximately 7 minutes on a Pentium machine at 500 MHz.

For testing the identity claim of a subject, the 73 dimensional feature vector is extracted from the face image of the subject, and the vector is given as input to the corresponding model. The output of the model is compared with the input to compute the square error. The error (ε) is transformed into a confidence value (c) by using the equation $c = exp(-\varepsilon)$. The confidence value is used to decide the identity claim of the subject.

5. EXPERIMENTAL RESULTS

Performance of the proposed real-time face authentication system is evaluated for 25 subjects using a camera with a resolution of 160x120. Since humans rarely sit perfectly for a long time, motion information is used to estimate the face region as described in Section 2. The estimated face region is not changed until there is a significant motion of the head in the video. The method tracks only a single face and is not sensitive to size of the face and lighting conditions. The location of the eyes and other facial regions are identified as described in Section 3, and the feature vector is extracted from the face image only when the following heuristics are satisfied:

1. The distance between the eyes lies between $0.5 * w_1$ and $0.25 * w_1$, where w_1 is the width of the face.
2. All the 73 facial regions are inside the face or head region.

Fig.4 shows sample face images used to extract the feature vector. The results show that the feature extraction technique is invariant to size and tilt of the face.

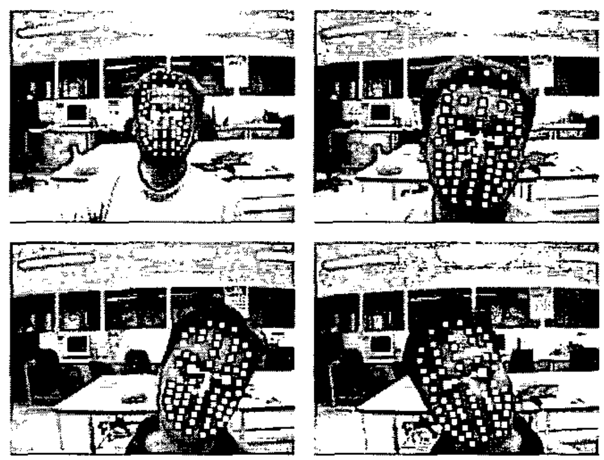

Fig. 4. Sample face images.

The AANN models are trained as described in Section 4 for 25 subjects. For testing the identity claim, we collected feature vectors from 10 face images of the subject with variation in size and tilt of the face one month after collecting the training data, and the average confidence value is estimated. The average confidence value is used to accept or reject the identity claim. In our experiment the identity claim of a subject is accepted if the average confidence value is greater than the threshold 0.9, and in general the threshold can be determined from the experimental studies. Fig.5 shows the average confidence values for 10 test subjects of the experiment against 10 corresponding models. High confidence value along the diagonal indicate that the system accepts the correct identity claim and low values in the off-diagonal indicate that the system rejects all the incorrect claims. The confidence values can be used to estimate the resemblance of a subject with other subjects.

The performance of the authentication system is invariant to the size and tilt of the face, and is also insensitive to variations in natural lighting conditions. The system tests the identity claim of a subject in real time, and it gives an equal error rate of less than 1%. The face detection and feature vector extraction techniques are computationally inexpensive, and testing 10 feature vector of a subject in the corresponding model requires less than 30 msec on a Pentium machine at 500 MHz.

Test subjects	Models: m1	m2	m3	m4	m5	m6	m7	m8	m9	m10
t1	0.95	0.09	0.11	0.69	0.03	0.76	0.84	0.04	0.33	0.02
t2	0.07	0.97	0.75	0.01	0.59	0.48	0.23	0.81	0.46	0.85
t3	0.06	0.74	0.93	0.00	0.76	0.35	0.14	0.68	0.70	0.82
t4	0.69	0.02	0.03	0.91	0.02	0.56	0.74	0.02	0.06	0.00
t5	0.27	0.64	0.68	0.01	0.93	0.70	0.47	0.61	0.49	0.55
t6	0.76	0.13	0.14	0.47	0.34	0.91	0.79	0.15	0.30	0.04
t7	0.69	0.16	0.05	0.54	0.11	0.68	0.92	0.13	0.29	0.03
t8	0.05	0.70	0.36	0.01	0.63	0.52	0.37	0.96	0.24	0.60
t9	0.53	0.36	0.72	0.19	0.73	0.69	0.68	0.57	0.94	0.60
t10	0.01	0.83	0.78	0.00	0.68	0.42	0.11	0.76	0.45	0.92

Fig. 5. Confidence values for 10 test subjects.

6. CONCLUSION

In this paper, we have proposed a method for real time face authentication using autoassociative neural network models. The proposed method extracts features relative to the location of the eyes, and hence it is invariant to size and tilt of the face. Experimental results show that the system gives an equal error rate of less than 1% in real time for 25 subjects under natural lighting conditions. In this system, a new subject can be easily added without using the features of other subjects. Better discrimination in the confidence values can be achieved by adding additional facial features like appearance of the face and color information. Audio features, if available, may be used to further improve the robustness of the face authentication system [14].

7. REFERENCES

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