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Automation of Inter-Networked Banking and Teller Machine Operations

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Abstract— In this article about biometric systems the general idea is to use of facial recognition to reinforce security on one of the oldest and most secure piece of technology that is still in use to date thus an Automatic Teller Machine. The main use for any biometric system is to authenticate an input by Identifying and verifying it in an existing database. Security in ATM's has changed little since their introduction in the late 70's. This puts them in a very vulnerable state as technology has brought in a new breed of thieves who use the advancement of technology to their advantage. With this in mind it is high time something should be done about the security of this technology beside there cannot be too much security when it comes to people's money.

Keywords— Biometrics, Facial Recognition, GSM Standards, Biometric Standards, Automatic Teller Machine Technology, Biometric Predecessors.

1. INTRODUCTION

Face detection and recognition are challenging tasks due to variation in illumination, variability in scale, location, orientation (up-right, rotated) and pose (frontal, profile). Facial expression, occlusion and lighting conditions also change the overall appearance of face. Face detection and recognition has many real world applications, like human/ computer interface, surveillance, authentication and video indexing. Face detection using artificial neural networks was done by Rowley [7]. It is robust but computationally expensive as the whole image has to be scanned at different scales and orientations. Feature-based (eyes, nose, and mouth) face detection is done by Yow *et al.*[15]. Statistical model of mutual distance between facial features are used to locate face in the image [4]. Markov Random Fields have been used to model the spatial distribution of the grey level intensities of face images [1]. Some of the eye location technique use infrared lighting to detect eye pupil [2]. Eye location using genetic algorithm has been proposed byWechsler [3]. Skinpaper, motion information is used to reduce the search space for face detection. It is known that eye regions are usually darker than other facial parts, therefore probable eye pair regions are extracted by thresholding the image. The eyes pair region gives the scale and orientation of face, and reduces the search space for face detection across different scales and orientations. Correlation between averaged face template and the test pattern is used to verify whether it is a face or not.
Recognition of human face is also challenging in human computer interaction [6, 10, 11, 14]. The proposed system for face recognition is based on Eigen analysis of edginess representation of face, which is invariant to illumination to certain extent [8, 9]. The paper is organized as follows: Section 2 describes the face detection process. The method of obtaining edginess image and eigenedginess of a faces are discussed in Sections 3 and 4, respectively. Experimental results are presented in Section 5. color is used extensively to segment the image, and localize the search for face [13, 12]. The detection of face using skin color fails when the source of lighting is not natural

2. FACE RECOGNITION TECHNIQUES

The method for acquiring face images depends upon the underlying application. For instance, surveillance applications may best be served by capturing face images by means of a video camera while image database investigations may require static intensity images taken by a standard camera.
Some other applications, such as access to top security domains, may even necessitate the forgoing of the nonintrusive quality of face recognition by requiring the user to stand in front of a 3D scanner or an infra-red sensor.
Therefore, depending on the face data acquisition methodology, face recognition techniques can be broadly divided into three categories: methods that operate on intensity images, those that deal with video sequences, and those that require other sensory data such as 3D information or infra-red imagery. The following discussion sheds some light on the methods in each category and attempts to give an idea of some of the benefits and drawbacks of the schemes mentioned therein in general.

2.1EIGENEDGINESS

Edginess is a strong feature extraction method and has proved to be better than other edge representations [2]. The reason behind this is that edginess is based on one dimensional processing of images. The traditional 2D operators smooth the image in all directions resulting in the smearing of edge information. To extract the edginess map, the image is smoothed using a 1D Gaussian filter along the horizontal (or vertical) direction to reduce noise. The smoothing filter is a 1D Gaussian filter is given by

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

Where σ_1 is the standard deviation of the Gaussian function. The response of the 1 D Gaussian filters applied along a particular scan line of an image in one direction. A differential operator (first derivative of 1-D Gaussian function) is then applied in the orthogonal direction, i.e., along the vertical (or horizontal) scan lines to detect the edges. The first order derivative of 1D Gaussian is given by

$$c(y) = \frac{-y}{\sqrt{2\pi}\sigma_2^{\,3}} e^{\frac{-y^2}{2\sigma_2^2}} \quad \text{----------} \ (2)$$

The resulting image obtained by applying equation 1 produces the horizontal components of edginess (strength of an edge) in the image. Similarly, the vertical components of edginess are derived by applying the above filters on original images in orthogonal directions of those used in obtaining the horizontal components of edginess. Finally the total magnitude of partial edge information obtained in both the horizontal and vertical edge components gives the edginess map of the original image. Figure 1a and 1b show a plot of Gaussian mask and its derivative. Figure 2a-2f shows the various steps in creating an edginess image from a gray scale image. The edginess of a pixel in an image is identical to the magnitude of the gradient of gray level function,[12,13] which corresponds to the amount of change across the edge. The edginess images of an example face are shown in Figure 2f.

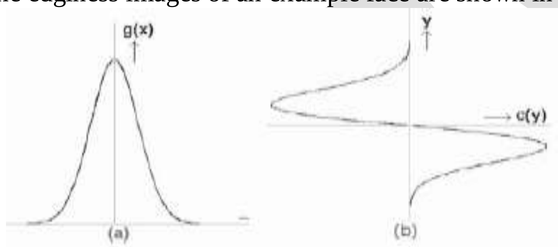


Fig 1. 1(a) Gaussian Function (smoothing filter), 1(b) First derivative of Gaussian (differential operator).

It is visually clear the edginess image carries more information than the edge map of an image. The intuitive reason for this is that the edginess gives a very low output when it operates on completely smooth regions with no useful information.

However, unlike the edge detection process, the edginess maintains an output in the regions having even low amount of texture. Again, the 1-d and orthogonal processing of the Gaussian and its derivative is less affected by the tradeoff between smoothing out the noise and smoothing the image features. Thus as seen from the face images, the smooth regions of the face that carry no discriminate information, and may cause class overlap in the classification, are removed. However, the regions with even a small amount of discriminate texture are visible in the output. This is the intuitive motivation behind this research, where we need to know whether this information at the output of the edginess filter is really made mainly of the discriminate information of the face.

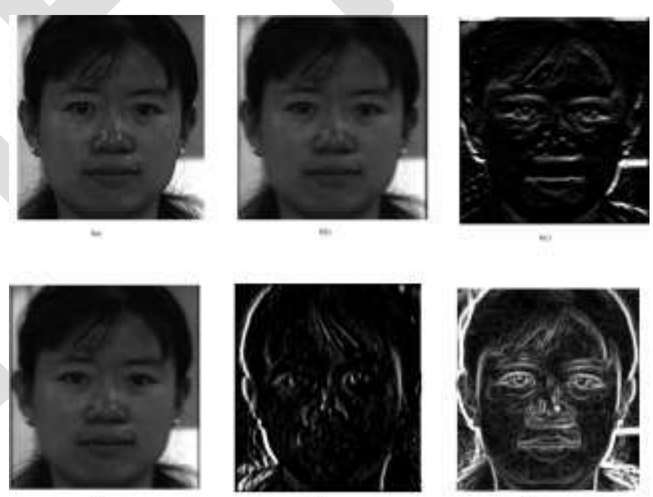


Fig 2. 2(a) Gray Scale Image, 2(b) Image after smoothing in horizontal direction, 2(c) Image after applying the differential operator to 2(b)in vertical direction, 2(d) Image after smoothing in vertical direction, 2(e) Image after applying the differential operator to 2(d) in vertical direction, 2(f) Edginess Image.

2.1.1 EXPERIMENTAL RESULTS

In order to establish the performance of Edginess-SVM in comparison with Euclidian distance based NN classification, we carried out the experiments on a set of CMU PIE database. All the images considered had a frontal pose and nearly the same expression with wide changes in illumination conditions. We have considered 24 images for one individual and these have been randomly distributed for the training and testing sets. The training and testing sets are so chosen that there is no overlap between them. Different experiments have been performed considering varying number of images for training and the recognition rates have been recorded for both Euclidian distance based NN classification scheme and SVM based classification scheme. The testing set consists of 12 images chosen randomly. Figure 3 shows the comparison of recognition rates between the Eigenedginess-SVM method and Eigenedginess-NN method, [13, 14].

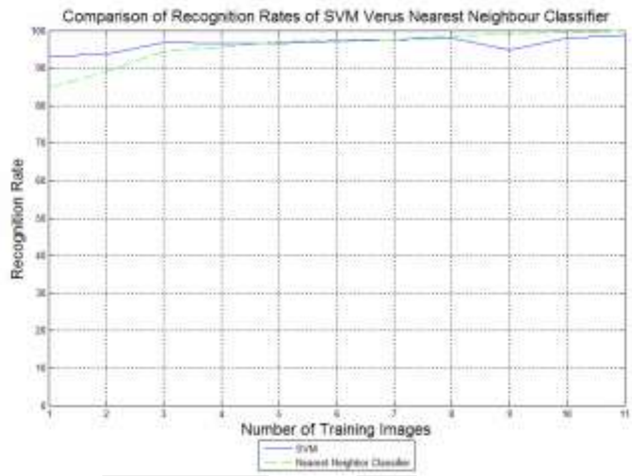


Fig 3. The graph shows a comparison of recognition rate between SVM and NN classifier for different number of training images

As observed from the graph in Figure 3, the performance of both NN and SVM is nearly same except for the cases when the number of training images is less. However, in [4] the authors have shown that classification by SVM's is more efficient than that by nearest neighbor scheme for face recognition problem with PCA as the feature extraction technique. The reason for this is that nearest neighbor based scheme is very sensitive to noisy inputs and can easily get confused with the neighboring classes in the eigen space. The latter is due to the fact that it does not perform classification based on discriminatory function like in SVM's but on the data points itself. This leads us to conclude that possibly edginess is a strong feature extraction method and the classification is not affected much by the classifier used at the back end,[13]

2.2 FACE RECOGNITION FROM INTENSITY IMAGES-

Face recognition methods for intensity images fall into two main categories: feature-based and holistic, an overview of some of the well-known methods in these categories is given below.

2.2.1 FEATURED-BASED

Feature-based approaches first process the input image to identify and extract (and measure) distinctive facial features such as the eyes, mouth, nose, etc., as well as other fiducial marks, and then compute the geometric relationships among those facial points, thus reducing the input facial image to a vector of geometric features. Standard statistical pattern recognition techniques are then employed to match faces using these measurements Early work carried out on automated face recognition was mostly based on these techniques. One of the earliest such attempts was by Kanade [19], who employed simple image processing methods to extract a vector of 16 facial parameters - which were ratios of distances, areas and angles (to compensate for the varying size of the pictures) - and used a simple Euclidean distance measure for matching to achieve a peak performance of 75% on a database of 20 different people using 2 images per person (one for reference and one for testing).

Another well-known feature-based approach is the elastic bunch graph matching method proposed by Wiskott et al. [22] . This technique is based on Dynamic Link Structures [17]. A graph for an individual face is generated as follows: a set of fiducial points on the face are chosen. Each fiducial point is a node of a full connected graph, and is labeled with the Gabor filters' responses applied to a window around the fiducial point. Each arch is labeled with the distance between the correspondent fiducial points. A representative set of such graphs is combined into a stack-like structure, called a *face bunch graph*. Once the system has a face bunch graph, graphs for new face images can then be generated automatically by Elastic Bunch Graph Matching. Recognition of a new face image is performed by comparing its image graph to those of all the known face images and picking the one with the highest similarity value. Using this architecture, the recognition rate can reach 98% for the first rank and 99% for the first 10 ranks using a gallery of 250 individuals. The system has been enhanced to allow it to deal with different poses (Fig. 3) [11] but the recognition performance on faces of the same orientation remains the same. Though this method was among the best performing ones in the most recent FERET evaluation [12, 13], it does suffer from the serious drawback of requiring the graph placement for the first 70 faces to be done manually before the elastic graph matching becomes adequately dependable [14]. Campadelli and Lanzarotti [15] have recently experimented with this technique, where they have eliminated the need to do the graph placement manually by using parametric models, based on the deformable templates proposed in [10], to automatically locate fiducial points. They claim to have obtained the same performances as the elastic bunch graph employed in [19]. Other recent variations of this approach

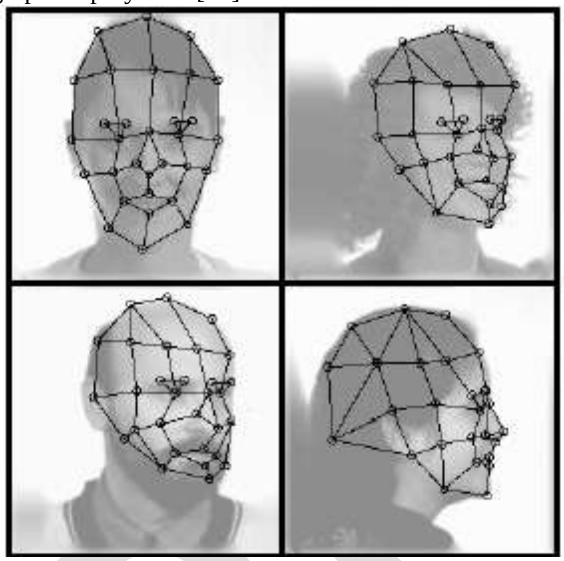


Fig. 3. Grids for face recognition [21]. (©1999 IEEE)

Replace the Gabor features by a graph matching strategy [16] and HOGs (Histograms of Oriented Gradients [17]. Considerable effort has also been devoted to recognizing faces from their profiles [08-12] since, in this case, feature extraction becomes a somewhat simpler one-dimensional problem [17, 11]. Kaufman and Breeding [10] reported a recognition rate of 90% using face profiles; however, they used a database of only 10 individuals. Harmon et al. [18] obtained recognition accuracies of 96% on a database of 112 individuals, using a 17-dimensional feature vector to describe face profiles and utilizing a Euclidean distance measure for matching. More recently, Liposcak and Loncaric [01] reported a 90% accuracy rate on a database of 30 individuals, using subspace filtering to derive a 21- dimensional feature vector to describe the face profiles and employing a Euclidean distance measure to match them (Fig. 4).

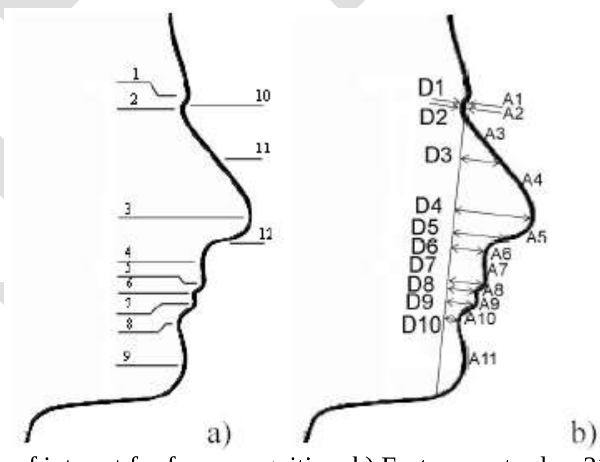


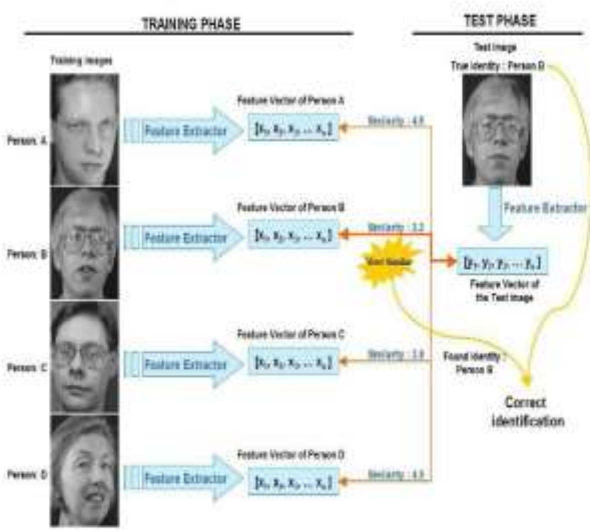
Fig. 4. a) The twelve fiducial points of interest for face recognition; b) Feature vector has 21 components; ten distances D1-D10 (normalized with / (D4+D5)) and eleven profile arcs A1-A11 (normalized with /(A5+A6)) [21]. (Courtesy of Z. Liposcak and S. Loncaric)

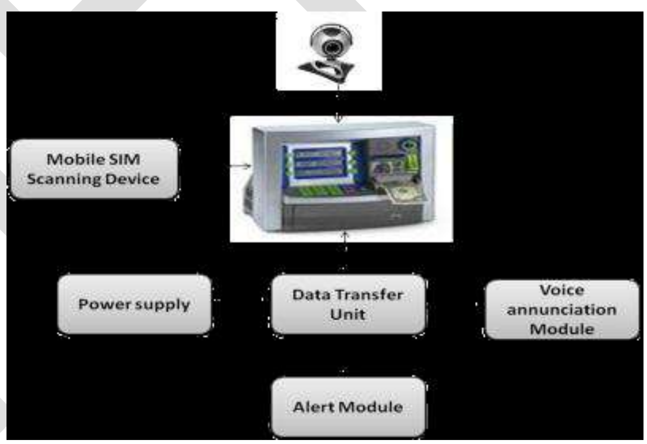
2.3 PCA ALGORITHM

Automatic face recognition systems try to find the identity of a given face image according to their memory. The memory of a face recognizer is generally simulated by a training set. In this project, our training set consists of the features extracted from known face images of different persons. Thus, the task of the face recognizer is to find the most similar feature vector among the training set to the feature vector of a given test image. Here, the identity of a person where an image of that person (test image) is give to the system is recognized. PCA is itself a feature extraction algorithm.

In the training phase, the feature vectors for each image are extracted in the training set. Let ΩA be a training image of person A which has a pixel resolution of M × N (M rows, N columns). In order to extract PCA features of ΩA, the image is converted into a pixel vector ΦA by concatenating each of the M rows into a single vector. The length (or, dimensionality) of the vector ΦA will be M ×N. Use the PCA algorithms a dimensionality reduction technique which transforms the vector ΦA to a vector ΩA which has a dimensionality d where d «M ×N. For each training image Ωi, you should calculate and store these feature vectors ωi

In the recognition phase (or, testing phase), you will be given a test image Ωj of a known person. Let αj be the identity (name) of this person. As in the training phase, you should compute the feature vector of this person using PCA and obtain ωj. In order to identify Ωj, you should compute the similarities between ωj and all of the feature vectors ωi's in the training set. The similarity between feature vectors can be computed using Euclidean distance. The identity of the most similar ωi will be the output of our face recognizer. If i = j, it means that we have correctly identified the person j, otherwise if i ≠ j, it means that we have misclassified the person j. Schematic diagram of the face recognition system that will be implemented is shown in Figure 2.





Mobile scanning device scans SIM number through GSM Modem Collected data is given to the Automated teller machines (ATMs) for further processing. At the same time, web camera captures the images and compares using digital signal processing with the image stored in the data base. Each processing information produces by voice annunciation module.

Power supply unit consists of a step down transformer along with rectifier unit to convert 230 V AC into required 7 V DC. 7 V DC supply is given to the micro controller for its action. It may be difficult for blind people to use existing ATM so we can add voice annunciates to indicate each and every process to the blind people. It enables a visually and/or hearing impaired individual to conveniently and easily carry out financial transactions or banking functions. Each processing information produces by voice annunciation module

If images and PIN number are same then further processing is continued, otherwise it gives alarm through Alert module. Data trasfer unit consist of a micro controller of no AT89352 which transfers the data between alert module, voice annunciation module & ATM machine. Automated teller machines (ATMs) are well known devices typically used by individuals to carry out a variety of personal and business financial transactions and/or banking functions ATMs have become very popular with the general public for their availability and general user friendliness.

ATMs are now found in many locations having a regular or high volume of consumer traffic. For example, ATMs are typically found in restaurants, supermarkets, Convenience stores, malls, schools, gas stations, hotels, work locations, banking centers, airports, entertainment establishments, transportation facilities and a myriad of other locations. ATMs are typically available to consumers on a continuous basis such that consumers have the ability to carry out their ATM financial transactions and/or banking functions at any time of the day and on any day of the week. Existing ATMs are convenient and easy to use for most consumers. Existing ATMs typically provide instructions on an ATM display screen that are read by a user to provide for interactive operation of the ATM. Having read the display screen instructions, a user is able to use and operate the ATM via data and information entered on a keypad.

CONCLUSION

This paper presents a system creates the new generation ATM machine which can be operator without the ATM card. By using this system ATM machine can be operator by using our SIM in the mobile phone. When we insert our SIM in the reader unit of the ATM machine it transfers the mobile to the server. In server we can collect the related information of the mobile number (i.e) the users account details, their photo etc. the camera presented near the ATM machine will capture the users image and compare it with the user image in the server. Only when the image matches it asks the pin number and further processing starts. Otherwise the process is terminated. So by using this system need of ATM card is completely eliminated we can operate the ATM machine by using our SIM itself. By using this system malfunctions can be avoided. Our transaction will be much secured. One more application can also be added in this system for helping the blind people. In the existing system all the transactions are done through keyboard only. It may be difficult for blind people so we can also add voice enunciator to indicate each and every process to the blind people. It that enables a visually and/or hearing impaired individual to conveniently and easily carry out financial transactions or banking functions.

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