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Statistical Analysis of Face Recognition Technique

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***Abstract* – This paper presents novel technique for recognizing faces. The proposed method uses Chi square test as a feature extraction technique. Feed forward and Self organizing neural network are used for classification. We evaluate proposed method using FACE94 database and achieved better performance.**

***Keywords* – Biometric, Face Recognition, Chi Square Test, Feed Forward Neural Network, Self Organizing Map Network.**

I. Introduction

The biometrics technologies can be used to identify {identification: who am I?} or to verify {verification or authentication: am I whom I claim to be?} an individual. The biometric identification determines who a person is. It involves measuring individual's characteristics and mapping it with users profile stored in the database. The main purpose of positive identification is to prevent multiple users from claiming a single identity. In positive identification method, the user normally claims an identity by giving a name or an ID number, and then submits a biometric measure. Once submitted, it's matched with the previously submitted measure to verify that the current enrolled user is under the claimed identity. These tasks can be achieved through many non-biometric alternatives in such applications as ID cards, PINs and passwords. Depending on the situation or the environment where it's installed, positive identification biometric method can be made voluntary and those not wishing to use biometrics can verify identity in other ways. It is often used in determining the identity of a suspect from crime scene information. There are two types of identification: positive and negative. Positive identification expects a match between the biometric presented and the template, it is designed to make sure that the person is in the database. While the negative identification is set up to ensure that the person is not in the database, more so, it can take the form of watch list where a match triggers a notice to the appropriate authority for action.

The main function of negative identification in an organization is to prevent claims of multiple identities by a single user. In negative identification, the user who enrolls for biometric authentication claims that he or she have not been previously enrolled and submits a biometric measure, which is compared to all others in the system database. If the user's claim of non-enrolment is verified, that means a match is not found. At the moment there are no reliable non-biometric alternatives in such applications, hence the use of biometrics in negative identification applications must be mandatory in places where it's important. The biometrics verification or authentication method requires less processing power and time. It is often used for accessing places or information, depending on the application domain; a biometric can either be an online or an offline system. To verify an individual's identity a 1:1 check is made between the biometric data and the biometric template obtained during enrolment (see Figure1 for diagrammatic illustration).

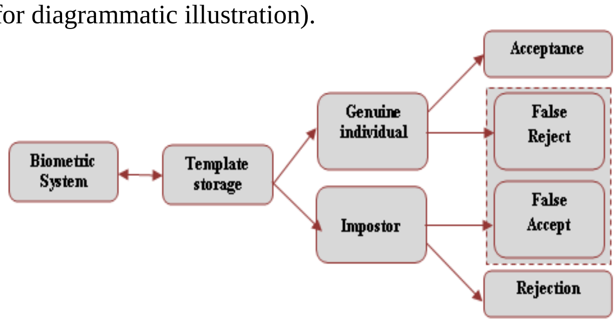

Fig.1. Generic Biometric System Process

For any biometric system to be effective the data should be stored securely and not be vulnerable to theft, abuse or tampering. The data should also be free of errors to prevent false positive and negative results, and the user must be confident that the system is reliable and secure [1].

Face recognition is a nonintrusive method, and facial images are probably the most common biometric characteristic used by humans to make a personal recognition. The applications of facial recognition range from a static, controlled “mug-shot” verification to a dynamic, uncontrolled face identification in a cluttered background (e.g., airport). The most popular approaches to face recognition are based on either: 1) the location and shape of facial attributes such as the eyes, eyebrows, nose, lips and chin, and their spatial relationships, or 2) the overall (global) analysis of the face image that represents a face as a weighted combination of a number of canonical faces. While the verification performance of the face recognition systems that are commercially available is reasonable, they impose a number of restrictions on how the facial images are obtained, sometimes requiring a fixed and simple background or special illumination.

These systems also have difficulty in recognizing a face from images captured from two drastically different views and under different illumination conditions. It is questionable whether the face itself, without any contextual information, is a sufficient basis for recognizing a person from a large number of identities with an extremely high level of confidence. In order for a facial recognition system to work well in practice, it should automatically: 1) detect whether a face is present in the acquired image; 2) locate the face if there is one; and 3) recognize the face from a general viewpoint (i.e., from any pose) [2-3]. Face recognition related research work have been published in part as research papers in [4]&[5].

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The remaining part of this paper is organized as follows. Section2 extends to the pattern matching which also introduces and discusses the Chi square test and FFNN and SOM in detail. In Section3, extensive experiments on FACE94 faces are conducted to evaluate the performance of the proposed method on face recognition. Finally, conclusions are drawn in Section4 with some discussions.

II. Pattern Matching

A. Face Recognition Processing

Face recognition is a visual pattern recognition problem. There, a face as a three dimensional object subject to varying illumination, pose, expression and so on is to be identified based on its two-dimensional image (three dimensional images e.g., obtained from laser may also be used). A face recognition system generally consists of four modules as depicted in Figure 2: detection, alignment, feature extraction, and matching, where localization and normalization (face detection and alignment) are processing steps before face recognition (facial feature extraction and matching) is performed. Face detection segments the face areas from the background. In the case of video, the detected faces may need to be tracked using a face tracking component. Face alignment is aimed at achieving more accurate localization and at normalizing faces thereby whereas face detection provides coarse estimates of the location and scale of each detected face. Facial components, such as eyes, nose, and mouth and facial outline, are located; based on the location points, the input face image is normalized with respect to geometrical properties, such as size and pose, using geometrical transforms or morphing. The face is usually further normalized with respect to photometrical properties such illumination and gray scale. After a face is normalized geometrically and photometrically, feature extraction is performed to provide effective information that is useful for distinguishing between faces of different persons and stable with respect to the geometrical and photometrical variations. For face matching, the extracted feature vector of the input face is matched against those of enrolled faces in the database; it outputs the identity of the face when a match is found with sufficient confidence or indicates an unknown face otherwise.

Face recognition results depend highly on features that are extracted to represent the face pattern and classification methods used to distinguish between faces whereas face localization and normalization are the basis for extracting effective features. These problems may be analyzed from the viewpoint of face subspaces or manifolds, as follows

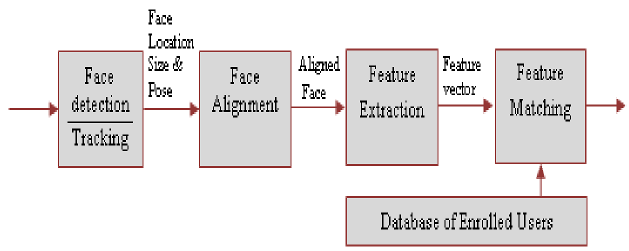

Fig.2. Face Recognition Processing Flow

B. Chi Square Test

Chi-square is a non-parametric test of statistical significance for analysis. Any appropriately performed test of statistical significance lets you know the degree of confidence you can have in accepting or rejecting a hypothesis. Typically, the hypothesis tested with Chi Square is whether or not two different samples (of people, texts, whatever) are different enough in some characteristic or aspect of their behavior that we can generalize from our samples that the population from which our samples are drawn are also different in the behavior or characteristics.

On the basis of hypothesis assumed about the population, we find the expected frequencies Ei (I =1,2,…,n), corresponding to the observed frequencies Oi(i=1,2,…,n) such that $\sum Ei = \sum Oi$. It is known that

$$\chi^2 = \sum_{i=1}^{n} \frac{(Oi-Ei)^2}{Ei} \qquad (1)$$

follows approximately a $\chi 2$ - distribution with degrees of freedom equal to the number of independent frequencies. To test the goodness of fit, we have to determine how far the difference between Oi and Ei can be attributed to fluctuations of sampling and when we can assert that the differences are large enough to conclude that the sample is not a simple sample from the hypothetical population[6][7].

C. Artificial Neural Network

In recent years, there has been an increase in the use of evolutionary approaches in the training of artificial neural networks (ANNs). While evolutionary techniques for neural networks have shown to provide superior performance over conventional training approaches, the simultaneous optimization of network performance and architecture will almost always result in a slow training process due to the added algorithmic complexity [8][9].

1. Feed Forward Network

Feed forward networks may have a single layer of weights where the inputs are directly connected to the output, or multiple layers with intervening sets of hidden units. Neural networks use hidden units to create internal representations of the input patterns [10].

A Feed forward artificial neural network consists of layers of processing units, each layer feeding input to the next layer in a Feed forward manner through a set of connection weights or strengths. The weights are adjusted using the back propagation learning law. The patterns have to be applied for several training cycles to obtain the output error to an acceptable low value.

The back propagation learning involves propagation of the error backwards from the input training pattern, is determined by computing the outputs of units for each hidden layer in the forward pass of the input data. The error in the output is propagated backwards only to determine the weight updates [11]. FFNN is a multilayer Neural Network, which uses back propagation for learning.

As in most ANN applications, the number of nodes in the hidden layer has a direct effect on the quality of the solution. ANNs are first trained with a relatively small value for hidden nodes, which is later increased if the error is not reduced to acceptable levels. Large values for hidden nodes are avoided since they significantly increase computation time [12].

The Back propagation neural network is also called as generalized delta rule. The application of generalized delta rule at any iterative step involves two basic phases. In the first phase, a training vector is presented to the network and is allowed to propagate through the layers to compute output for each node. The output of the nodes in the output layers is then compared against their desired responses to generate error term. The second phase involves a backward pass through a network during which the appropriate error signal is passed to each node and the corresponding weight changes are made. Common practice is to track network error, as well as errors associated with individual patterns. In a successful training session, the network error decreases with the number of iterations and the procedure converges to a stable set of weights that exhibit only small fluctuations with additional training. The approach followed to establish whether a pattern has been classified correctly during training is to determine whether the response of the node in the output layer associated with the pattern class from which the pattern was obtained is high, while all the other nodes have outputs that are low [13].

Backpropogation is one of the supervised learning neural network. Supervised learning is the process of providing the network with a series of sample inputs and comparing the output with the expected responses. The learning continues until the network is able to provide the expected response. The learning is considered complete when the neural network reaches a user defined performance level. This level signifies that the network has achieved the desired accuracy as it produce the required outputs for a given sequence of inputs [14].

2. Self Organizing Map

The self organizing map, developed by Kohonen, groups the input data into cluster which are, commonly used for unsupervised training. In case of unsupervised learning, the target output is not known.

In a self organizing map, the neurons are placed at the nodes of a lattice that is usually one or two dimensional. Higher dimensional maps are also possible but not as common. The neurons become selectively tuned to various input patterns or classes of input patterns in the course of a competitive learning process. The locations of the neurons so tuned (i.e., the wining neurons) become ordered with respect to each other in such a way that a meaningful coordinate system for different input features is created over the lattice. A self organizing map is therefore characterized by the formation of a topographic map of the input patterns in which the spatial locations of the neurons in the lattice are indicative of intrinsic statistical features contained in the input patterns, hence the name "self organizing map"[15] [16].

III. Experimental Results and Discussion

In order to assess the efficiency of proposed methodologies which are discussed above, we have performed experiments over Face94 dataset using FFNN and SOM neural network as a classifier.

A. Face94 Dataset

Face94 dataset consist of 20 female and 113 male face images having 20 distinct subject containing variations in illumination and facial expression. From these dataset we have selected 20 individuals consisting of males as well as females [17].

Fig.3. Some Face Images from FACE94 Database

B. Implementation Steps

The implementation steps for Feature extraction using Chi-Square test as below:

1. Read the image
2. Resize image to 200x180 pixels
3. Divide image into 4x4 block of 50x45 pixels.
4. Compute Chi-Square test
5. Combine the features
6. Classify the faces by FFNN classifier
7. Classify the faces by SOM classifier
8. Analyze the performance of both the classifiers

C. Performance Evaluation

The accuracy of biometric-like identity authentication is due to the genuine and imposter distribution of matching. The overall accuracy can be illustrated by False Reject Rate (FRR) and False Accept Rate (FAR) at all thresholds. When the parameter changes, FAR and FRR may yield the same value, which is called Equal Error Rate (EER). It is a very important indicator to evaluate the accuracy of the biometric system, as well as binding of biometric and user data [18].

A typical biometric verification system commits two types of errors: false match and false non-match. Note that these two types of errors are also often denoted as false acceptance and false rejection; a distinction has to be made between positive and negative recognition; in positive recognition systems (e.g., an access control system) a false match determines the false acceptance of an impostor, whereas a false non-match causes the false rejection of a genuine user. On the other hand, in a negative recognition application (e.g., preventing users from obtaining welfare benefits under false identities), a false match results in

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rejecting a genuine request, whereas a false non-match results in falsely accepting an impostor attempt. The notation “false match/false non-match” is not application dependent and therefore, in principle, is preferable to “false acceptance/false rejection.” However, the use of false acceptance rate (FAR) and false rejection rate (FRR) is more popular and largely used in the commercial environment [19].

Traditional methods of evaluation focus on collective error statistics such as EERs and ROC curves. These statistics are useful for evaluating systems as a whole. Equal-Error Rate (EER) denotes the error rate at the threshold t for which false match rate and false non-match rate are identical: FAR(t) = FRR(t) [20].

FAR and FRR values for all persons with different threshold values. The FRR and FAR for number of participants (N) are calculated as specified in Eq. (2) and in equation Eq. (3) [21]:

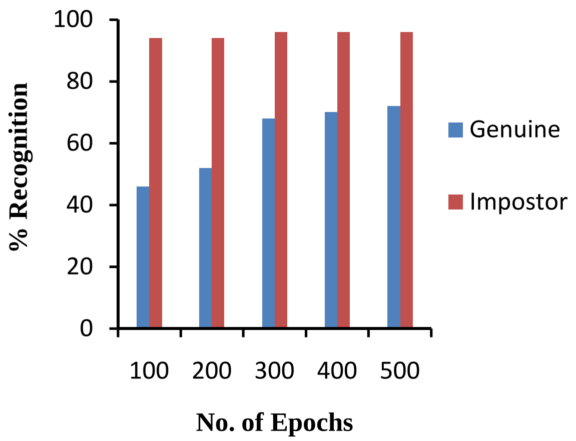
$$FRR = \frac{1}{N}\sum_{n=1}^{N} FRR(n) \quad (2)$$

$$FAR = \frac{1}{N}\sum_{n=1}^{N} FAR(n) \quad (3)$$

The performance of Chi-Square test and FFNN on FACE94 is given in Table1. The performance of Chi-Square test and SOM on FACE94 is given in Table2. The graph of % Recognition Vs Number of epochs is shown for FFNN and SOM is shown in Graph1 and Graph2 respectively.

Table 1: Performance of Chi-Square test and FFNN on FACE94 database

No. of epochs	% Recognition of Genuine faces	FRR	% Recognition of Impostor faces	FAR
100	46	0.54	94	0.06
200	52	0.48	94	0.06
300	68	0.32	96	0.04
400	70	0.30	96	0.04
500	72	0.28	96	0.04

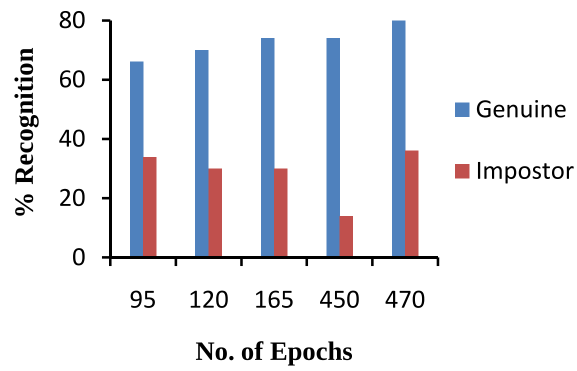


Graph 1: Performance of Chi-square test and FFNN on FACE94 database

When experiment was performed on FACE94, the feedforward neural network is trained with different number of epochs from 100 to 10000. The Self organizing map network is trained with various values of epochs from 5 to 500. While training feedforward neural network, the number of input neuron was 30, number of hidden neuron was 25 and number of output neuron was 10. The transfer function used was ‘tansig’ and training function used was ‘traingda’.

Table 2: Performance of Chi-Square test and SOM on FACE94 database

No. of epochs	% Recognition of Genuine faces	FRR	% Recognition of Impostor faces	FAR
95	66	0.34	34	0.66
120	70	0.30	30	0.7
165	74	0.26	30	0.7
450	74	0.26	14	0.86
470	80	0.20	36	0.64



Graph 2: Performance of Chi-Square test and SOM on FACE94 database

IV. Conclusion

This paper investigates the feasibility and effectiveness of face recognition with Chi square test. Face recognition based on Chi square test is performed by supervised and unsupervised network. Experimental results on Face94 database demonstrate that the proposed methodology outperforms in recognition of genuine faces and impostor faces.

From Table1, it is seen that, % of recognizing genuine faces is 72% and % of impostor face recognition is 96%. From Table2, it is observed that, % of recognizing genuine faces is 80% and % of recognizing impostor faces is 36%
It is also noted that, FAR and FRR are dual of each other. A small FRR usually leads to a larger FAR, while a smaller FAR usually implies a larger FRR.

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