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Analysis of Face Recognition Systems Using Soft Computing Tools: Implemented Using DCT and SOM Classifier

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ABSTRACT

The face recognition becomes one of the challenging areas for the researchers in recent years. This paper provides an up-to-date review of human face recognition using soft computing tools. We first present an overview of face recognition and its applications & a brief note of soft computing tools. Next a literature review of the most recent face recognition techniques, combined techniques of soft computing discussed. And finally paper ended with conclusion.

Keywords: SOM, DCT classifier, Mutation, CrossOver, Static Matching, Eigen faces, epochsetc.

1. INTRODUCTION

Face recognition is one of the most wide area pattern recognition & computer vision due to its numerous practical applications in the area of Biometrics, Information security access control, Law enforcement, smart facial profiles as curves, finding their norm, and then classifying other profiles by their deviations from the norm. This classification cards and surveillance system. A formal method of classifying faces was first proposed in [1]. The author proposed collecting is multi modal, i.e. resulting is a vector of independent measures that could be compared with other vector in a database. In the literatures, face recognition problem can be formulated as static (still) or video images of a scene identify or verify one or more persons in the scene by comparing with faces stored in a database. Face Recognition is a biometric approach that employs automated methods to verify or recognize the identity of a living person based on his /her physiological characteristics. In general, a biometricidentification system makes use of either physiological characteristics (such as a finger print, palm, iris pattern of face) or behavior patterns (such as hand writing, voice, or key-stroke pattern) to identify a person. Face recognition has the benefit of being a passive non intrusive system to verify personal identify in a "natural" and friendly way. In general, biometric devices can be explained with a there step procedure (1) a sensor takes an observation. The type of sensor and its observation depend on the type of biometric devices used. This observation gives us a "Biometric signature of the individual. (2) a computer algorithm "normalizes" the biometric signature so that it is in the same formal as the signatures on the system's database. The normalization of the biometric signature' gives us a "normalized signature" of the individual (3). A matcher compares the normalized signature with the set of normalized signatures on the system's database and compares the individual's normalized signature set. Face recognition starts with the detection of the face patterns in sometimes cluttered scenes, proceeds by normalizing the face images to account for geometrical & illumination changes, possibly using information about the location & appearance of facial landmarks, identifies the faces using appropriate classification algorithms & post processes the results using model-based schemes & logistic feedback [3]. The application of face recognition technique can be categorized into two main parts: law enforcement application and commercial application.

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Face recognition technology is primarily used in law enforcement applications, especially mug short (static matching) and surveillance (real time matching by video image sequences). The commercial application range from static matching of phonographs' on credit cards, ATM cards, passports, driver's license and photo ID to real time matching with still images or video images sequences for access control, Each application presents different constraints in terms of processing. All face recognition algorithms consistent of two major parts; 1) Face detection and normalization and 2) face identification. Algorithms that consist of both parts are referred to as fully automatic algorithms & those that consist of only the second part are called partially automatic algorithms. Partially automatic algorithms partially automatic algorithm are given a facial image & the coordinates of the centre of eyes. Fully automatic algorithms are only given facial images.Face recognitions are also done by using some of soft computing tools there are many soft computing tools in that fuzzy logic, NN, GA, various approaches to face detection & facial features extraction. Many different approaches are reported ranging from the geometrical description of salient facial features of the expansion of digitized images of the face on appropriate basis of images [4]. Different techniques have been introduced recently such as neural networks, genetic algorithms, fuzzy logic, wavelet transform and soon. All these are also called soft computing tools.

1.1. Face recognition using soft computing tools

1.1.1. Genetic algorithm

Genetic algorithms belong to a class of stochastic search method represented by natural population genetics. The GA's have been employed in a wide variety of problems related to pattern recognition, image processing, medical image registration image segmentation, contour recognition and so on. In face recognition using Genetic algorithms, first Genetic search used to detect human face in a complex background. Face detection is achieved by employing template matching between a known face image & the input image.In this approach color image converted to into gray scale image. The normalization is performed by mapping the facial features to some fixed locations in an MXN image. The face image may be of poor contrast because of the limitations of the lighting conditions. So histogram equalization is used to compensate for the lighting conditions & improve the contrast of the images [5].Various sources of noise may exist in the input image. The fine details of the image represent high frequencies which mix up with those of major of noise pewit filter is used to suppress. The Genetic algorithm is a stochastic search method based on the mechanics of natural selection & genetics analogous to natural evolution. The algorithm starts with an initial set of random solutions called population. Each individual in the population, known as chromosome, represents a particular solution of the problem. Each chromosome is assigned a fitness value depending on how good its solution of the problem. Each chromosome is assigned a fitness value depending among how good its solution to the problem is after the fitness allotment, the natural selection is executed and the survival of the fittest chromosome can prepare to breed for the next generation. A new population is then generated by means of genetic operations: cross–over & mutation. This evolution process is iterated until near-optimal solution is obtained or a given number of generations are reached. The fitness of a chromosome is defined as the function of the difference between the intensity value of the input image and that of the template image measured for the expected location of the chromosome. I.e. for each chromosome n, fitness function is defined as;

$$f(n) = 1 - \frac{(x,y)\sum_{\in} w \left| f(x,y) - f_{n,t}(x,y) \right.}{B \ \max Xx \ size \ Xy \ size}$$

Where Bmax is the maximum brightness of the numbers of pixels in the horizontal and vertical directions of the template images, *f* & *fn, t* are the intensity values of the original images and the template image when it is justified for the n –th position of the chromosome respectively. Selection operator is a process in which chromosome are selected in to a matching pool according to their fitness function.Crossover operator randomly chooses a crossover point where two parent chromosomes break and then exchanges the chromosome parts after that point. Produce two off-springs from two parent chromosomes. With the cross over probability exchange parts of the two selected chromosomes & create tow offspring. Mutation, which is rare in nature, represents a change in the gene and aids us in avoiding loss of genetic diversity. Its role is to provide a guarantee that the search algorithm is not trapped on a local optimum.The effectiveness and robustness of the algorithm is justified using different images with various kinds of expressions. When a complex image is subjected in the input, the face detection result highlights the facial part of the image. The system can also cope with the problem of partial occlusions of mouth & wearing sunglasses images of different persons are taken at their own places and at different environments both in shiny & gloomy weather. The algorithm is capable of detecting single face in an image[6]. A total of 150 images, including more than 80 different persons are used to investigate the capacity of the proposed algorithm. Among them only 2 faces are found false. Experimental results demonstrate that the success rate of approximately 99% is achieved. The main reason behind the failure of those images in finding face regions is the occlusion.

1.1.2. Neural Networks

The attractiveness of using neural networks could be due to its non linearity in the network. Hence, the feature extraction step may be more efficient than the linear Karhunen-Loeve methods. One of the first artificial neural networks (ANN) techniques used for face recognition is a single layer adaptive network called WISARD which contains a separate network for each stored individual [7]. The way in constructing a neural network structure is crucial for successful recognition. It is very much dependent on the intended application. For face detection, multilayer perception [8] and convolution neural network [9] have been applied. For face verification [10] is multi-resolution pyramid structure. Reference [9] proposed a hybrid neural network which combines local image sampling, a self-organizing map (SOM) neural network, and a convolution neural network. The SOM provides a quantization of the image samples into a topological space where inputs that are nearby in the original space are also nearby in the output space, thereby providing dimension reduction and invariance to minor changes in the image sample. The convolution network extracts successively larger features in a hierarchical set of layers and provides partial invariance to translation, rotation, scale, and deformation. The authors reported 96.2% correct recognition on ORL database of 400 images of 40 individuals.

The classification time is less than 0.5 second, but the training time is as long as 4 hours. Reference [11] used probabilistic decision-based neural network (DBNN) [12]. The PDBNN can be applied effectively to 1) face detector: which finds the location of a human face in a cluttered image, 2) eye localizer: which determines the positions of both the eyes in order to generate meaningful feature vectors, and 3) face recognizer PDNN does not have fully connected network topology. Instead, it divides the network into K subnets. Each subnet is dedicated to recognize one person in the database. PDNN uses the Gaussian activation function for its neurons, and the output of each “face subnet” is the weighted summation of the neuron outputs. In other words, the face subnet estimates the likelihood density using the popular mixture of Gaussian model. Compared to the AWGN scheme, mixture of Gaussian provides a much more flexible and complex model for approximating the time likelihood densities in the face space. The learning scheme of the PDNN consists of two phases, in the first phase; each subnet is trained by its own face images. In the second phase, called the decision-based learning, the subnet parameters may be trained by some particular samples from other face classes. The decision-based learning scheme does not use all the training samples for the training. Only misclassified patterns are used. if the sample is misclassified to the wrong subnet, the rightful subnet will tune its parameters so that its decision-region can be closer to the misclassified sample. PDBNN-based biometric identification system has the merits of both neural networks and statistical approaches, and its distributed computing principle is relatively easy to implement on parallel computer.

In [12], it was reported that PDBNN face recognizer had the capability of recognizing up to 200 people and could achieve up to 96% correct recognition rate in approximately 1 second. However, when the number of persons increases, the computing expanse will become more demanding. In general neural network approached encounter problems when the number of classes (i.e. individuals) increases. Moreover, they are not suitable for a single model image recognition test because multiple model images per person are necessary in order for training the systems to “optimal “parameter setting.

2.1. Combined Soft computing tools

2.1.1. Based Neural Networks & fuzzy logic

A face recognition system developed by neural networks & fuzz logic technique which gives improved & lower parts of the human face feature is extracted for the face recognition process[14]. Different weight ages are given more weight age than the lower face features by using a fuzzy logic technique. This system has been proven effective in developing a security system with high recognition rate for different human facial expressions.The Neural Network training is performed is offline mode & the trained upper & lower – face neural network are then employed in face recognition mechanism during online recognition mode.In neural N/w training mode, acquisition of a suitable face image is essential to train neural N/W that can characterize the user satisfactorily. There areas of interest on the face are used for neural N/W training upper face, lower face & eye. A frame is divided into upper half & lower half. For eye extraction a frame is used. In neural N/W training head detector & eye detector are done automatically in on-line. Spatial preening has been used to locate eye. Face rotation mapping is done for tilled image in this upper face is a trained upper & lower face neural N/W determines the recognition level associated with the upper face & lower face of a given image respectively the fuzzy system acts as the final decision making stage by utilizing the recognition level information provided by the upper-face & lower face neural networks.In the recognition process, the fuzzy system fuzzifies the recognition leveled from both the upper—face & lower face neural n/w by using the input membership functions. Subsequently, the fuzzified inputs are processed by an inference engine in which the fuzzy system determines the authority of a given image by means of well-defined fuzzy sets and they are given in a form of fuzzy associative. Tests are done for authorized & unauthorized faces. A system recorded 94% success for authorized & 92 %.* success for unauthorized cases failures were due to subjects wearing spectacle.

2.1.2. Eigen faces and Neural Networks

Eigen faces has been applied to extract the basic face of the human images. Unique features of human faces are extracted by using Eigen faces. The features vector can be used to identify an unknown face by using the back propagation of neural network that user Euclidean distance for classification & recognition. The Eigen’s faces including implemented Jacobi’s method for Eigen values and Eigen vectors has been performed. The classification & recognition using back propagation neural N/W showed impressive result to classify face images.With the experiment, it shows that more images, the Eigen faces become more whitening. Means, lesser images make the Eigen faces become darker & indistinct.The Eigen faces used for each training images & unknown images to determine its weight vectors to describe class identify. These features are used for classification & recognition the unknown human face.The back propagation neural network is used for the classification & networks 16 patterns are used 8 inputs per-pattern, 5 hidden neurons, 3 output neurons, 0.9 for momentum, 0.7 for learning rate & the error were set to 0.001 for stopping condition.In the recognition, the identity of human face is less than error (0.001). if entire training pattern used then recognition is very is performance high. If only one image is used than performance is decreases. However, when face images with different pose are added in learning step, the recognition rate increase.

2.1.3. **Genetic Algorithm and Neural Network**

Feature selection & classification technique for face recognition on using genetic algorithms & artificial neural networks.The Genetic algorithm & Artificial neural network based technique is used to identify the significant areas in each facial region & perform fusion & selection of features for face recognition. Genetic algorithm is used to find potential significant features which will generate higher recognition rate. The areas represent the possible selection of the significant features. Each chromosome is multiplied by the input features set to generate the input feature vector to Artificial Neural Networks. The input features vector fed to Artificial Neural Networks for classification. Back propagation algorithm is used to train the network. The testing classification error is used to calculate the fitness of corresponding individual in Genetic Algorithm. In the reproduction, the fittest individual that achieves the best testing classification rate is retained in the next generation. The chromosomes in each generation of genetic Algorithm that achieve the best classification rate are recorded. All the features are ranked according to how many times it has been selected. The areas that contain the features inside top n ranking are the top n significant areas.The Genetic Algorithm and Artificial Neural The best testing classification rate is improved to 94% when compared with other methods the recognition rate is improved by 1.3% compared to KAM, 36% compared to ARENA method, on data set containing 3 images or class for training, It improved the recognition rate further when 4 or more images per class were used.

2. IMPLEMENTATION

Implementation is carried out in MAT lab using DCT features. Features are trained using SOM classifier in a feed forward neural network. Results are listed below.

3. EXPERIMENTAL RESULTS

3.1. Image Database

A face image database was created for the purpose of benchmarking the face recognition system. The image database is divided into two subsets, for separate training and testing purposes. During SOM training, 25 images were used, containing five subjects and each subject having 5 images with different facial expressions. Fig. 7 shows the training and testing image database constructed. The face recognition system presented in this paper was developed, trained, and tested using MATLAB™ 7.2. The computer was a Windows XP machine with a 3.00 GHz Intel Pentium 4 processor and 1 GB of RAM.

3.2. Validation of Technique

The preprocessed grayscale images of size 8 × 8 pixels are reshaped in MATLAB to form a 64 × 1 array with 64 rows and 1 column for each image. This technique is performed on all 5 test images to form the

(a)

(b)

Figure 1: Training and testing image database.
(a) Image database for training.(b) Untrained image for testing

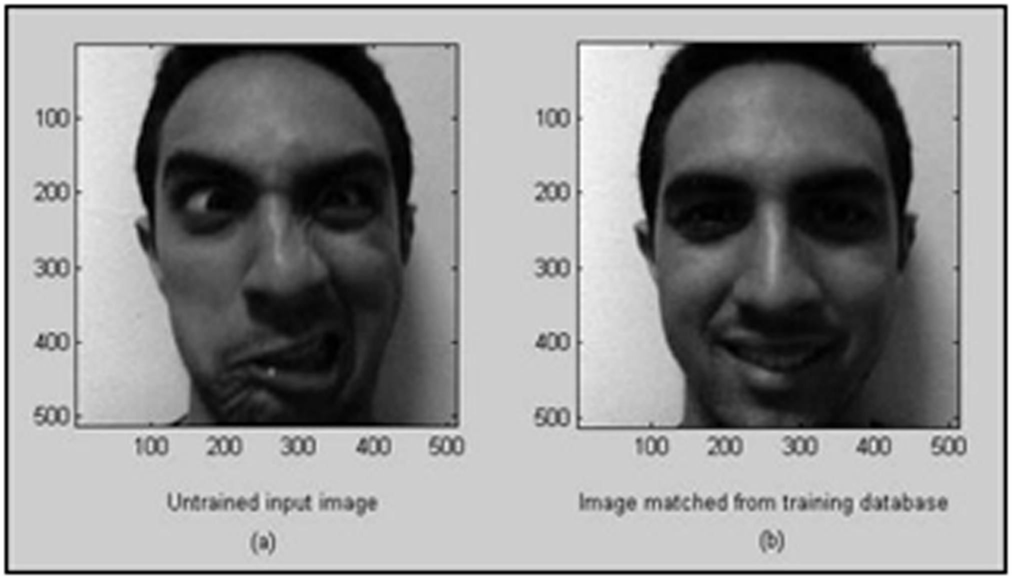

Figure 2: Weight vectors of SOM.
(a) Simulated 3D-SOM.(b) Untrained SOM. (c) Trained SOM

input data for testing the recognition system. Similarly, the image database for training uses 25 images and forms a matrix of 64 × 25 with 64 rows and 25 columns. The input vectors defined for the SOM are distributed over a 2D-input space varying over [0 255], which represents intensity levels of thegrayscale pixels. These are used to train the SOM with dimensions [64 2], where 64 minimum and 64 maximum values of the pixel intensities are represented for each image sample. The resulting SOM created with these parameters is a single-layer feed forward SOM map with 128 weights and a competitive transfer function. The weight function of this network is the negative of the Euclidean distance[3]. This SOM network is used for all subsequent experiments. As many as 5 test images are used with the image database for performing the experiments. Training and testing sets were used without any overlapping. Fig. 8 shows the result of the face recognition system simulated in MATLAB using the image database and test input image shown in Fig. 1. for this simulation displaying its neuron positions is shown in Fig. 2(a). Weights vectors of the untrained image database in Fig. 2(b) and trained image database in Fig. 2(c) in comparison to the simulated 3D-SOM map in Fig. 2(a) are shown below; the result obtained from this simulation identifies that the subject in the input image Fig. 2(a) is “present” in the image database.

The best match image displayed in Fig. 1(b) illustrates that subjects with different facial expressions in the image database can be easily identified.

Euclidean distance for DCT-feature vectors for the untrained image database and SOM trained image database is shown in Fig. 3.The next section presents results for 3 experiments in which different system parameters were altered. In the first two experiments the number of epochs used for vector[2].

3.3. DCT Block Size

The first experiment studies the effect of DCT block size on the rate of recognition of the system with each DCT coefficient being used in the feature vector[2]. Table I shows that the best recognition rate obtained is for the case of 8 × 8 block sizes, and this block size was used in all subsequent experiments.

3.4. Reducing DCT-feature Vector Size

The second experiment is concerned with computational load, which comes from large sized DCT-feature vectors[2]. The aim of this experiment is to determine if a smaller feature vector could be constructed from

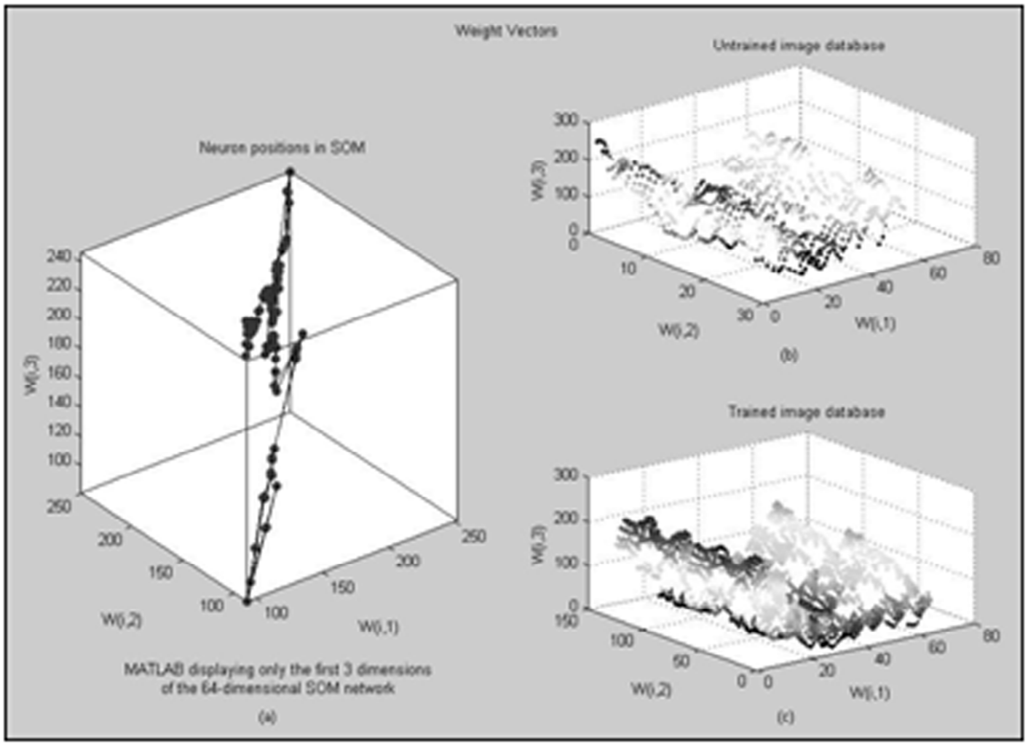

Figure 3(a):

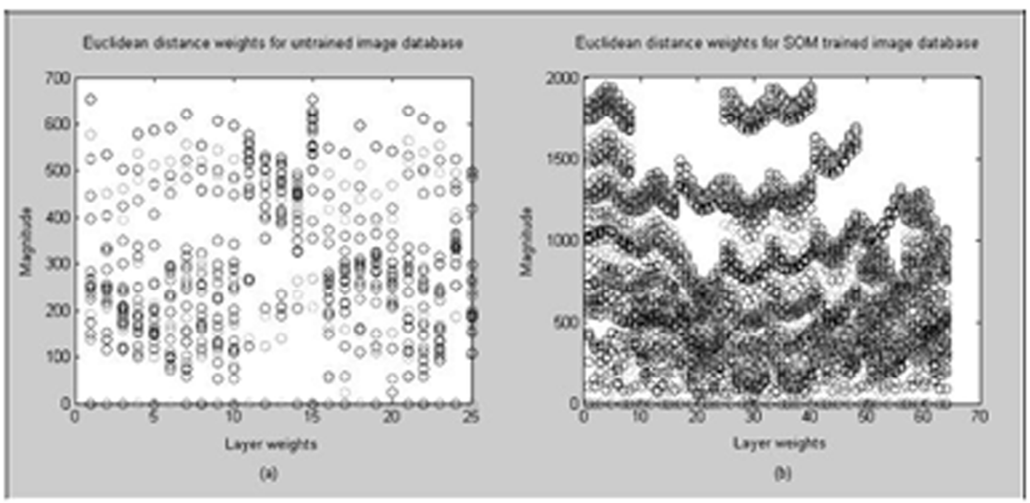

Figure 3(b):

a set of DCT coefficients, without significantly degrading system performance.The current chosen DCT block size of 8×8 pixels uses only 8 out of 64 DCT coefficients for computation. Using statisticalanalysis, by assessing the variance of each of the 64 dimensions of the feature space, it is possible to determine which of the coefficients contribute most to the final decision of the classifier. Variances were computed using[2]:

$$K \operatorname{var}\left(x_j\right) = \sum \left(X_i - \bar{X}\right)^2$$

$$i = 1$$

where variable j is the DCT coefficient index, i is the sample index, and k is equal to the available number of samples.

Table 1
Recognition Rate Vs. Dct Block Sizes

Block Size	*Recognition Rate (%)*
4 × 4	73.31
6 × 6	77.43
8 × 8	78.82
10 × 10	75.82
12 × 12	74.64
16 × 16	73.64

Table 2
The Effect of Reducing Dct-feature Vector Size

DCT coefficients	*Training Time (s)*	*Recognition rate*	*Memory consumption (bytes)*
4	96.81	79.43%	2836740
8	163.05	78.82%	6589430

Table 3
Reducing Processing Time by Optimizing Number Ofepochs for Training

Number of epochs	*Training time (s)*	*Recognition rate*
700	49.97	73.03%
750	57.21	77.91%
800	63.94	78.54%
850	72.53	81.36%
900	85.40	80.51%
1000	96.81	79.43%
1050	108.94	75.98%

Statistical variances of the 64 DCT-feature vectors for the training database and testing images indicated that there are 2 prominent areas where high-variance occurs. This suggests that these particular features perform prominent roles during classification[2]. Hence, we defined a reduced size feature space based on the 2 high-variance DCT coefficients and excluded other coefficients. The results obtained revealed that the new DCT-feature vectors consisted of 4 DCT coefficients only. Table II compares the performance of the system for the full size and reduced-size DCT-feature vectors. In spite of the dramatic reduction from 8 features to only 4, the recognitionrates obtained are essentially the same. In addition to recognition rates, the table also shows the training time and memory usage.This experiment demonstrates that good face recognition performance is possible, even with feature vectors that are dramatically reduced in size relative to the usual case for DCT-based analysis [2].

3.5. Reducing Processing Time based on Epochs

The third experiment is concerned with the processing time of the overall system. Processing time contributes mainlytowards the time required for training the SOM network. Training time depends upon the number of epochs used for training[3]. The aim of this experiment is to reduce training time, while maintaining the previously calculated recognition rate in experiment 2 for the reduced DCT-feature vectors. Table 3 shows that the best recognition rate achieved with the least amount of processing time is for the case of 850 training epochs. Recognition rate results obtained are the average of ten consecutive simulations.

4. CONCLUSION

This paper has presented a novel face recognition technique that uses features using DCT coefficients, along with a SOM-based classifier. The system was evaluated in MATLAB using an image database of 25 face images, containing five subjects and each subject having 5 images with different facial expressions. After training for approximately 850 epochs the system achieved a recognition rate of 81.36% for 10 consecutive trials. A reduced feature space, described for experiment 2 above, dramatically reduces the computational requirements of the method as compared with standard DCT-feature extraction methods. This makes our system well suited for low-cost, real-time hardware implementation. Commercial implementations of this technique do not currently exist. However, it is conceivable that a practical SOM-based face recognition system may be possible in the future.Comparison of face features are carried out using cross over and mutation.

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