

Face Recognition Using Som Neural Network With Ddct Facial Feature Extraction Techniques

Swati jadon, Mahendra Kumar, Yogesh Rathi

Abstract— This paper deals with 4 different techniques for feature extraction of image. Face detection is a necessary first-step in face recognition systems, with the purpose of localizing and extracting the face region from the background. The Self-Organizing Map (SOM) Neural Network has been used for training of database and simulation of FR system. The developed algorithm for the face recognition system formulates an image-based approach, using Directional discrete cosine transform (DDCT), discrete wavelet transform (DWT), discrete cosine transform (DCT) and Sobel edge detection, simulated in MATLAB. Simulation results are very promising.

Index Terms— Face Recognition (FR); Directional Discrete Cosine Transform (DDCT); Discrete Cosine Transform (DCT); Discrete Wavelet Transform (DWT); Sobel Edge detection (SED); SOM Neural Network.

I. INTRODUCTION

Automatic recognition of people is a challenging problem which has received much attention during the recent years due to its many applications in different fields. Face recognition is one of those challenging problems and up to date, there is no technique that provides a robust solution to all situations and different applications that face recognition may encounter. Face recognition has several characteristics that are advantageous for consumer applications. In addition to, the need for an automatic face recognition system especially at the border control, like airports is becoming very important to strengthen the security. Generally, feature extraction and classification criterion are the two basic operations of any face recognition system. As a result, to improve the recognition performance of such systems one has to enhance these operations. Prior to classification, the features should be extracted from the human face images. Feature extraction in the sense of some linear or nonlinear transforms

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of the face images with subsequent feature selection is commonly used for reducing the dimensionality of these images so that the extracted features are as representative as possible. However, the problem of extracting features from a human face remains a barrier to apply the practical applications, since it is influenced by the lighting condition, illumination changes, various backgrounds and individual variations. In recent years, several methods for feature extraction have been proposed [1-5]. Of these reported techniques, the principle component analysis (PCA) [1] and linear discriminant analysis (LDA) [2] are regarded to be the well known feature extraction methods. PCA linearly projects the image space along the direction of maximal variance into a low-dimensional subspace. These methods are statistical linear projection methods which largely rely on the representation of the training samples. The major drawbacks with these techniques are the performance drop of face recognition whenever face appearances are subject to variations by factors such as illumination, expression, pose, accessories and aging. Moreover, they require intensive computations in determining the basis space for a large number of images and when adding new images to a facial image database. On the other hand, multi-resolution techniques have been used for feature extraction in many face recognition systems [5–8]. Among them, the most popular are the discrete wavelet transform (DWT). 2D DWT has been used in various face recognition systems in order to extract multiple sub-band face images. These sub-band images contain coarse approximations of the face as well as horizontal, vertical and diagonal details of faces at various scales. These wavelet-based methods focus on the sub-bands that contain the most relevant information to better represent the face image.

Further we use the discrete cosine transform (DCT) has been employed in face recognition [9]–[12]. The DCT has several advantages over the PCA. First, the DCT is data independent. Second, the DCT can be implemented using a fast algorithm. The discrete cosine transform (DCT) represents an image as a sum of sinusoids of varying magnitudes and frequencies. The DCT has the property that, for a typical image, most of the visually significant information about the image is concentrated in just a few coefficients of the DCT. For this reason, the DCT is often used in image compression applications. For example, the DCT is at the heart of the

international standard lossy image compression algorithm known as JPEG. The other one technique is Sobel Edge detection is the process of localizing pixel intensity transitions. The edge detection have been used by object recognition, target tracking, segmentation, and etc. Therefore, the edge detection is one of the most important parts of image processing. The remainder of the paper is organized as follows: In Section II, Three proposed face recognition method is briefly explained. The SOM neural network system is described in Section III. Experimental results and conclusions are presented in Sections IV and V, respectively.

II. FACE RECOGNITION METHOD

A block diagram of the proposed face recognition system is shown in fig. 1. In this figure the three key steps of face recognition, namely, face detection, facial feature extraction and face recognition are identified. Detailed descriptions of these steps are addressed in the following sub-sections.

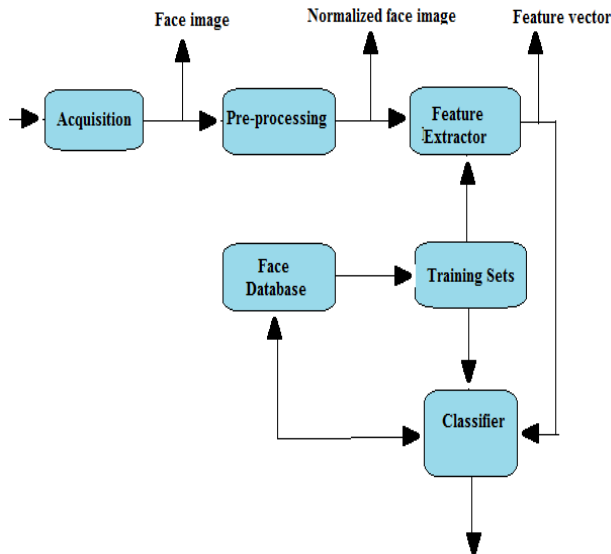


Fig 1: Block diagram of the face recognition system [15]

Pre-processing:

Face detection is the first step in any face recognition system. Many face detection techniques have been proposed in the past decade. They can be classified into geometry-based face detectors and color-based face detectors. Among the geometry-based face detectors, a method examines the triangle-relationship between eye and mouth regions to identify the face region. In addition to, the traditional eye detection methods can be simply and efficiently implemented for frontal face images but can be difficult for complex images. Moreover, skin color has been proven to be an effective image feature for face detection. The automatic face detectors based on skin colors are relatively fast and therefore are beneficial for consumer applications such as real-time face recognition embedded in a smart home environment. In the pre-processing stage of the proposed system, a facial region based on skin color detection is cropped from an input image. The obtained facial region is then resized into an 8×8 pixel

image to make the face recognition system scale invariant. After then, histogram equalization is applied to enhance the image brightness and contrast.

Facial Feature Vector Extraction:

In search result there are so many technique available for facial extraction .We are dealing with feature extraction methods based which is based on the transforms such as the DWT, DCT and Sobel edge detection also commonly represent the face images with a large set of features. The features of every image stored in our data based are extracted and then stored into the feature vector. Once the feature vectors for all existing images are developed the new database consist of all feature vectors is formed and then stored inside our storage device. To retrieve all images that are similar to the target image, we must extract the features of the target image and compare it with all features vectors. Discrete cosine transform (DCT) is a powerful transform to extract proper features for face recognition. After applying DCT to the entire face images, some of the coefficients are selected to construct feature vectors.

III. SELF-ORGANIZING MAP (SOM) NEURAL NETWORK

Network Architecture:

SOMs can be one-dimensional, two-dimensional or multi-dimensional maps. The number of input connections in a SOM network depends on the number of attributes to be used in the classification [14].

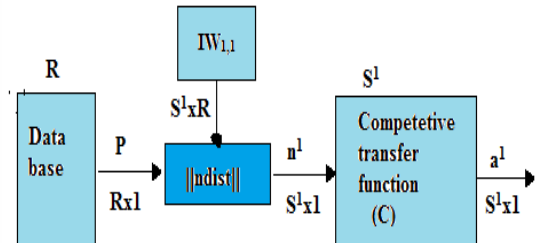


Fig 2: Architecture of a simple SOM Neural Network [15]

The input vector p shown in fig. 2 is the row of pixels of the input compressed image. The $\|dist\|$ box accepts the input vector p and the input weight matrix $IW^{1,1}$, which produces a vector having S^1 elements. The elements are the negative of the distances between the input vector and vectors ${}_jIW^{1,1}$ formed from the rows of the input weight matrix. The $\|dist\|$ box computes the net input n^1 of a competitive layer by finding the Euclidean distance between input vector p and the weight vectors. The competitive transfer function C accepts a net input vector for a layer and returns neuron outputs of 0 for all neurons except for the winner, the neuron associated with the most positive element of net input n^1 . The winner's output is 1. The neuron whose weight vector is closest to the input vector has the least negative net input and, therefore, wins the competition to output a 1. Thus the competitive transfer function C produces a 1 for output element a^1_i corresponding

to i^* , the “winner”. All other output elements in a^1 are 0[16].

$$n^1 = - \left\| W_{11} - p \right\|$$

$$a^1 = \text{compet}(n^1)$$

Thus, when a vector p is presented, the weights of the winning neuron and its close neighbours move toward p . Consequently, after many presentations, neighbouring neurons learn vectors similar to each other[16]. Hence, the SOM network learns to categorize the input vectors it sees.

The SOM network used here contains N nodes ordered in a two-dimensional lattice structure. In these cases, each node has 2 or 4 neighboring nodes, respectively. Typically, a SOM has a life cycle of three phases: the learning phase, the training phase and the testing phase.

Directional Discrete Cosine Transforms (D-DCT): In this method, first, we have computed 2D-DCT of a word image. Let the 2D-DCT coefficient matrix of a word image be D . Then, principal diagonal, upper $N - 2$ and lower $N - 2$ diagonals of D is extracted before and after flipping D , and further computed their standard deviations respectively as discussed in the aforementioned paragraph. Meanwhile, we have also extracted features based on conventional DCT. In this case, its coefficient matrix is divided into four zones and standard deviation of each zone is computed. Thus, a feature vector of four features is formed.

IV. EXPERIMENTAL RESULT

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, 30 images were used, containing six subjects and each subject having 5 images with different facial expressions. Fig 3 shows the training and testing image database constructed.



Fig 3: Image database for training [15]

The face recognition system presented in this paper was developed, trained, and tested using MATLAB™ 7.5. The computer was a **Windows 8** with a 2.40GHz Intel(R) core(TM) i3-3110M processor and 2 GB of RAM.

Validation of Technique:

The pre-processed 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 input data for testing the recognition system. Similarly, the image database for training uses 30 images and forms a matrix of 64×30 with 64 rows and 30 columns. The input vectors defined for the SOM are distributed over a 2D-input space varying over $[0 \ 255]$, which represents intensity levels of the gray scale 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 [13]. 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. 4 shows the result of training and testing simulated in MATLAB using the image database and test input image.

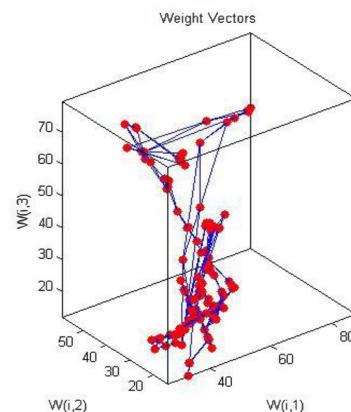
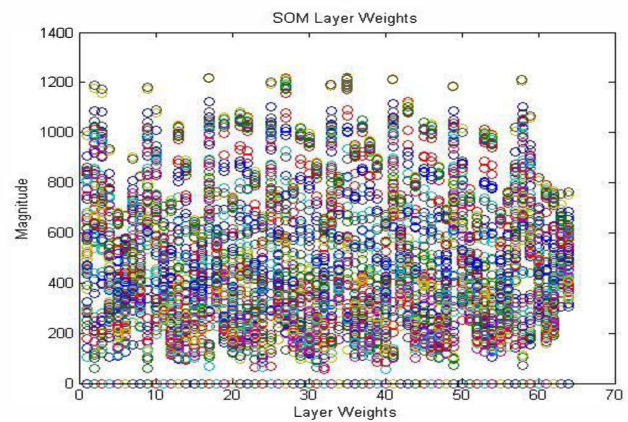


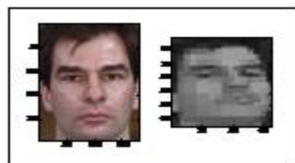
Fig 5: For DDCT: (a) SOM Layer Vector (b) Weight Vector

TABLE 1
FACE RECOGNITION RATE AT EPOCH=1000

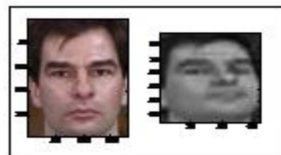
Technique	Test Img 1	Test Img 2	Test Img 3	Test Img 4	Test Img 5	Test Img 6	Recogn- ition- rate
SED	NR	R	R	R	R	R	84.33%
DCT	R	R	R	R	R	R	100%
DWT	R	R	R	R	R	R	100%
DDCT	R	R	R	R	R	R	100%

V. CONCLUSION

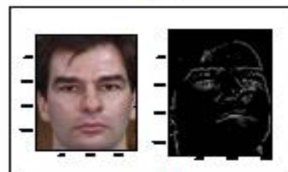
This paper presents a novel face recognition technique that uses features derived from DDCT, DCT, DWT, Sobel coefficients, along with a SOM-based classifier. The system was evaluated in MATLAB using an image database of 30 face images, containing six subjects and each subject having 5 images with different facial expressions. After training for approximately 1000 epochs the system achieved a recognition rate of as shown in table 1 for 5 consecutive trials. A reduced feature space, described for experiment, dramatically reduces the computational requirements of the methods. DDCT feature extraction method gives better results compared to DWT, DCT and SED methods as shown in table 2. This makes our system well suited for high speed, low-cost, real-time hardware implementation.



(a)



(b)



(c)



(d)

Fig 6: Best match image of subject found in training database (a) Face recognition using DWT (b) Face recognition using DCT (c) Face recognition using SOBEL edge detection (d) (c) Face recognition using DDCT.

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TABLE 2
COMPARISON AT EPOCH=1000

Technique	Time	Test Img 1	Test Img 2	Test Img 3	Test Img 4	Test Img 5	Test Img 6	Remarks (Speed)
SED	Training Time	444.9407	444.9407	444.9407	444.9407	444.9407	444.9407	
	Execution Time	583.2211	618.3278	656.7674	690.6356	719.1419	742.9051	High speed
DCT	Training Time	584.3152	584.3152	584.3152	584.3152	584.3152	584.3152	
	Execution Time	632.9374	696.4970	726.4075	751.5318	781.8307	804.9730	Low speed
DWT	Training Time	528.6507	528.6507	528.6507	528.6507	528.6507	528.6507	
	Execution Time	582.0531	638.0103	671.4976	705.3821	731.0787	753.2664	Medi. Speed
DDCT	Training Time	534.2712	534.2712	534.2712	534.2712	534.2712	534.2712	
	Execution Time	581.3175	610.4082	664.9835	702.5441	727.5838	791.8648	High Speed