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Gender Identification System from Facial Image Using Artificial Neural Network

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Abstract

This paper presents the implementation of gender identification system from a front view facial image using artificial neural network. In this system the facial images from different persons were taken as its input. At first, face images were projected onto a feature space that span the significant variations among face images. The features of the images were extracted using a compression technique that used the artificial neural network for compression. The extracted feature was then given to the input of the multi-layer feed forward neural network. Thus the network was trained and created a knowledge base. Finally, when a facial image was given for identification, the recognition part of the identification system identified the gender with the help of previously stored knowledge base.

Keywords : Gender identification, Facial image, ANN, Back-propagation, Compression network, Feature

1. Introduction

Gender identification is not a simple problem since a new image of a face seen in the recognition phase is usually different from the images previously seen by the system in the learning phase. Although a face has unique features for human identification there are several sources of variations between images of the same face. The image depends on viewing conditions, device characteristics and environment. This includes viewing position (which determines the orientation, location and size of the face in the image), imaging quality (which influences the resolution, blurring and noise in the picture) and the light source (which influences the reflection). In addition to this, the face is a dynamic object and it changes according to expressions, mood, age, hairstyle, beard, glasses, etc.

An automatic Gender Identification System (GIS), which is "flexible" and "efficient", should be able to solve these problems. Early attempts to model gender identification system generally uses a geometric coding in which measurements of the relations between features (as eyes, the nose, the mouth, the chin, etc.) were coded and used for recognition purpose (Kanade, 1973; Brunnelli & Poggio, 1993; Cox, 1996; Chellappa et al., 1995). Three crucial steps were identified: selection of the selective features, machine extraction of those features and decision-making based on the feature measurements. This strategy has showed high recognition speed and smaller memory requirements, but the performance of feature-based systems vastly deteriorates with partial face occlusions and any image degradations. In addition, these features discard important information about the texture and shape of the face.

Recent research on gender identification has found useful to employ a simpler representation of faces that consists of a two dimensional array of pixels. It was concluded that this technique is superior in recognition ratio. The most common gender identification strategies that use this representation is the eigenvector decompositions. This approach is also used in image compression, face detection, etc. Gender identification from Facial image is also becoming an important theme in forensic anthropology because surveillance cameras are used as a silent witness in crime scenes such as convenience stores, banks, etc.

In this paper, a technique was presented for gender identification from facial images using artificial neural networks approaches. The neural networks are able to generalize and recognize incomplete information.

2. Gender Identification System

The GIS consists of data collection, preprocessing, compression, feature extraction and classification is shown in Fig.1. When an unknown test image is given to the system, the input facial image is used for preprocessing and feature extraction. The network is trained using artificial neural network. Then, the acquired knowledge is stored in the reference database as experienced knowledge of the network. However, for known test image, the

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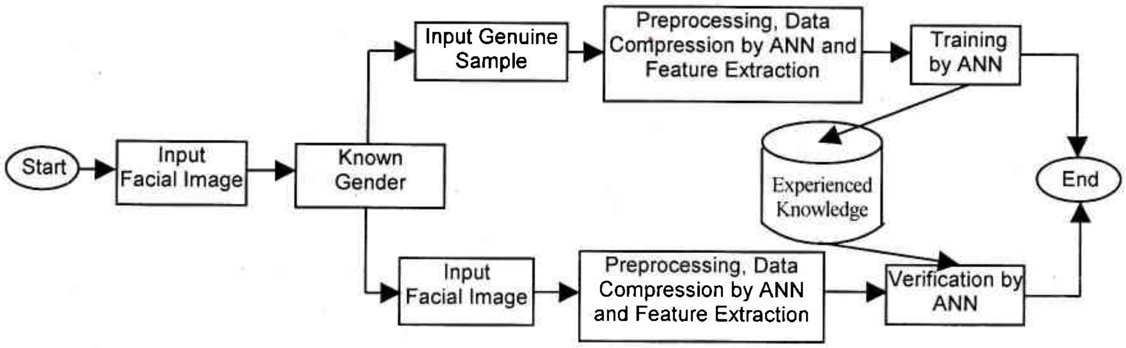

Fig. 1. Gender identification system from facial image using ANN

input facial image is used for identification purpose using the experienced knowledge of the reference database. The identification of the test image is done by locating the image in the database whose weights are the closest to the weights of the test image. By using the observation that the projection of a face image and a no face image are quite different, a method for detecting the presence of a face in a given image is obtained. It is reported that this approach is fairly robust to change in lighting condition but degrades as the scale or the orientation change.

2.1 Data Collection

A simple approach to extracting the information contained in an image of face is somehow to capture the variation in collection of face images, independent of any feature judgement, and use this information to encode and compare individual face images.

In the GIS, the four phases- data acquisition, data preprocessing, data compression, and feature extraction would generate a reference facial image for each individual person. This normally requires a number of facial images of the user to be captured at enrollment or registration time. Sample facial images can be captured in one of two ways. The first of these involves the use of some specialized devices "Graphics Tablet". The second method of capturing facial image is to simplify scan in physical facial image samples and make a computerized copy of the image. For the present study, the facial images were collected from the different persons using the second method. From each person five sample facial images were captured and these faces were scanned through an optical scanner. Fig. 2 shows the five sample faces from the face database.

Fig. 2. Sample facial images

2.2 Preprocessing of Facial Image

The preprocessing is related to remove unwanted images, detecting edges and image scaling. The unwanted images (noise) had been removed using a graphics editor. An algorithm had been developed to detect boundary (Gose et al., 2000) of the facial image. The algorithm preprocesses the facial images by extracting an edge map from the gray level image. The edge detection algorithm was applied to separate the image from the unwanted horizontal and vertical spaces. After detecting the boundary of the image each image was transformed to 30 × 30 pixels image (Fig. 3). If an image is directly input to a neural network, the network would 900 inputs-one for each pixel.

Fig. 3. A Sample scaled image

2.3 Data Compression and Feature Extraction

This phase of study employed extracting features of scaled images. In order to extract features a compression technique had been developed. In this system, the number of inputs were reduced from 900 to 40 with minimal loss of information in the sense that the original image could be adequately reconstructed from the reduced set of 40 inputs.

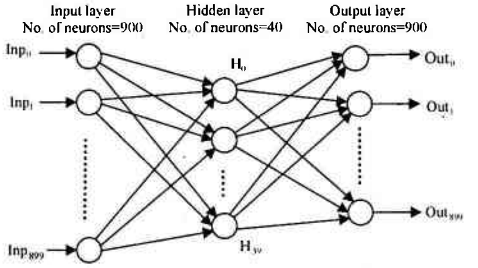

Fig. 4. Auxiliary network architecture used to train the compression network

The compression of facial image was done by using Artificial Neural Network (ANN). The aim of gender processing using the Multi-Layer Perceptrons (MLP) is both to develop a compact representation of faces, which is equivalent to feature extraction, and also classify the input representation of faces according to their typically, sex and identity. A cascade of two MLPs (Golomb et al., 1995) were used for gender classification (Fig. 4 & 5).

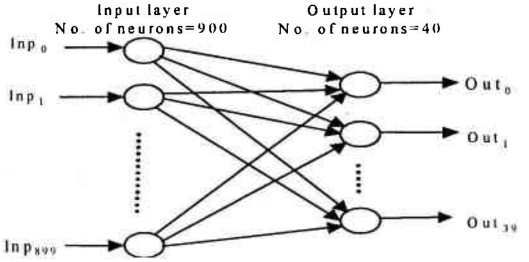

Fig. 5. Data compression network architecture for feature extraction of sample facial image

The auxiliary MLP consists of three neural layers (fig. 4). The values of 30 × 30 (900) pixels image were fed to the auxiliary network. The auxiliary network was trained to reconstruct the faces using a compact representation of the hidden layer. Once the weights in the auxiliary network had reached equilibrium, the weights and threshold values of the auxiliary network were determined and used into the compression network (Fig. 5) which consists of two neural layers. The same values of 30 × 30 (900) pixels image were also fed to the compression network, which used the weights values of between input and hidden layers and threshold values of hidden layer of the auxiliary network and generates 40 features, that is associated a person with its gender.

2.4 Design of Network Architecture for the GIS

The use of neural networks in face recognition has addressed several topics: gender classification, face recognition and classification of facial expressions. The overall computational model of ANN consists of variable interconnections of neurons. The whole experience was stored in the form of interconnections, which were modified during a training stage (James, 1993). The objective of the training stage was to develop an internal representation that would enable to correctly associate similar pattern. Several architectures of ANN were developed to solve the pattern recognition problems (Chelleppa et al., 1995). A variety of systems use MLP as the basic ANN architecture. MLPs contain several fully interconnected layers of nonlinear neurons. The connections between neurons contain weights, whose values contain information about the pattern space of the training patterns. The connection weights were adjusted by the back-propagation rule, which minimized the error of the association.

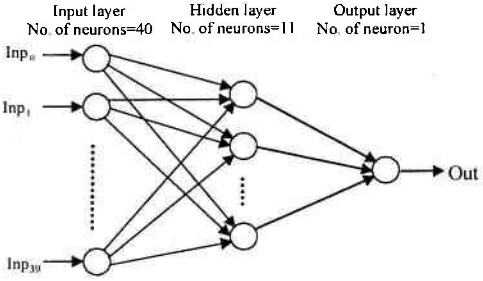

Fig. 6. Classification network architecture of gender identification system

The gender identification system was eventually performed by a three-layer perceptrons, as shown in Fig. 6. The input of the network is 40 (compressed image), one hidden layer with eleven neurons and the output comprised of one unit. The output is a value between 0 and 1 with values greater than or equal to 0.5 indicating a male and values less than 0.5 indicating a female.

To train a network is equivalent to find the proper weights and thresholds values for all connections so that a desired output is produced for corresponding input. The error back-propagation algorithm (Gose et al., 2000; Bose & Liang, 1996) was used for training the MLP network (Jackson & Beate, 1994). Each computational element or a node in a MLP network requires to have a thresholding non-linear sigmoid function, defined as

$$f(s) = 1/(1 + e^{k*s}) \quad (1)$$

Where $s = \sum w_i * x_i$.

The back-propagation algorithm minimizes sum of squared error E_s measured at the output layer as defined below (Gose et al., 2000; Looney, 1997):

$$E_s = \frac{1}{2}\sum_{j=1}^{M}(d_j - y_j)^2 \quad (2)$$

where M is the number of output units, d_j and y_j are the desired and actual outputs at the j-th output unit respectively.

3. The Quality Analysis of The Solution

A face database was used to evaluate the system, which contained a set of faces taken from five different persons including males and females. The database contained variations in facial expression (open/closed eyes, smiling/no smiling), in facial details (glasses/no glasses), in orientation (around 20°), in tilting (around 20°), etc.

The error back-propagation method was used to train the neural network. The neural network was first initialized for processing by removing any run-specific data from the previous iteration. This involved resetting any cached values, including deltas and activation levels, to a random value. The performance (speed up) of the system had improved by using a compression technique in the feature extraction phase which also used artificial neural network, and by reducing the number of iterations in the training of facial images in reducing the number of neurons in the input layer of the network architecture. Thus decreased the time complexity of the system.

The detail of the ANN specified by representing the input in matrix form. During learning time, the error was set less than 0.01 for the network. The number of iterations in which the network reached the specified error-goal were highly dependent on the number of hidden layers to yield a good result. The learning rate of the network was $\eta_1 = \eta_2 = 0.5$ and spread factor was $k1 = k2 = 0.7$. During recognition period, the error tolerance level was fixed at 0.02.

The system was trained using five images of twenty distinct subjects. So, the training set contained 100 gender images. The five remaining images of the twenty subjects were used to test the generalization ability of the system. Another subset of 100 unfamiliar gender images was used to evaluate the ability of the system to reject the unknown genders. Thus, following objects were considered to compute the four ratios:

- **Successful identification ratio (SIR)**: means the percentage of genders, which were successfully identified.
- **Confusion Ratio (CR)**: means the percentage of genders, which were not successfully identified and not rejected.
- **Success of Reject Ratio (SRR):** means the percentage of unfamiliar genders, which were rejected.
- **Failure of Reject Ratio (FRR):** means the percentage of familiar genders, which were rejected.

The rejected genders were those whom the system had classified as unknown. All the gender of the subjects of the training set constitutes the familiar set. The accuracy of gender identification system based on the facial image features using back-propagation neural network technique is presented in Table 1.

It is expected from gender identification system to acquire high accurate recognition rate while the false rejection rate and false inclusion rate should be too low. If false rejection rate and false inclusion rate are high, the security question of the system arises. In Table 1, the accuracy (average successful identification ratio) of the system is 88%, average confusion ratio (ACR) is 1.33%, average success of reject ratio (ASRR) is 8.67% and average failure of reject ratio (AFRR) is 2%. So, from the experimental result, it is seen that the system satisfies all requirements of a gender identification system.

Table 1. Performance of the developed system

Types of Input Facial Images		No. of Samples	SIR	CR	SRR	FRR	Accuracy	ACR	ASRR	AFRR
Familiar Images	Learned Images	100	100%	0%	-	0%	88 %	1.33%	8.67%	2%
	Unlearned Images	100	94%	0%	-	6%				
Unfamiliar Images		100	70%	4%	26%	-				

4. Conclusion

A simple and efficient automatic system had been presented for gender identification from facial image using artificial neural network. Faces represent complex, multidimensional, meaningful visual stimuli and there by, to develop a computational model for gender recognition is difficult. It is very difficult to verify gender quite accurately because of the variations in facial expression. Though it is problematic, if proper feature of the facial image through various preprocessing techniques identified, then the gender may be recognized more accurately. The performance of the system was improved by using a compression technique, which also used artificial neural network, and reducing the number of iterations in the training of facial images in reducing the number of neurons in the input layer of the network architecture. Thus decreases the time complexity of the system. To improve the recognition ability of the network, the size of the input sample image may be increased or more feature like area of black pixel, minimum horizontal projection, ete., may be taken into account for recognition. Since the neural networks were simulated on single processor machine, so the processing speed for recognition and learning was not fast enough for practical use. Parallel architecture can be developed with enough processor speed to allow real time processing on some problem.

This system can be used for the management of agricultural machineries specially to maintain the security of the expensive tools, fruit harvesting and can further be extended to test the deficiency of soil fertility, pesticides etc by using leaf colors.

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