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Face Recognition System using EBGM and ANN

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Abstract—There are many challenges associated with face recognition systems which make them a complex and difficult process. These factors include—pose variations, facial expressions, occlusion, age etc. These factors affect the face recognition systems and deteriorate their accuracy. The face recognition problem can be solved by using some statistical techniques such as PCA, ICA and LDA. Some feature based techniques—Elastic Bunch Graph Matching (EBGM), Artificial Neural Network (ANN), etc. have also been used and implemented to solve the face recognition problem. In this paper an insight is provided into various techniques available for face recognition, and a method is proposed that provides an efficient and feasible solution for real-time face recognition system. The proposed method uses EBGM technique, which in turn uses facial features for the identification of the test images that may be captured from a live video. Experimental results show that by involving ANN, better matching results with EBGM were obtained. Moreover, for face recognition in live videos and under low illumination conditions, the proposed system works more efficiently and gives better matching results when compared with the other techniques.

Keywords— Elastic Bunch Graph Matching (EBGM), fiducial points, Independent Component Analysis (ICA), jets, Linear Discriminant Analysis (LDA and Principal Component Analysis (PCA).

I. INTRODUCTION

Of all the biometric systems known, Face recognition is one of the most potential biometric. It uses the most important human identifier the 'face'. Face recognition technology has a large number of applications which include law enforcement, access control, forensic and commercial applications. The face recognition system is further divided into two parts: verification and identification.

In verification phase, a 1:1 match is made that compares test image with the other images in the dataset and verifies that whether the test image is matched or not matched to the images present in the database. On the other hand, in identification phase, a 1: N match is made that compares the test image to the rest of the gallery images and responds with the images with best match.[1]

A. Face Recognition

It can be described as classifying a face either "known" or "unknown", after comparing it with stored images in the database of some known individuals. Face recognition involves comparing an image with a database of stored faces in order to identify the individual in the test image. Fig. 1 outlines the block diagram of a face recognition system.

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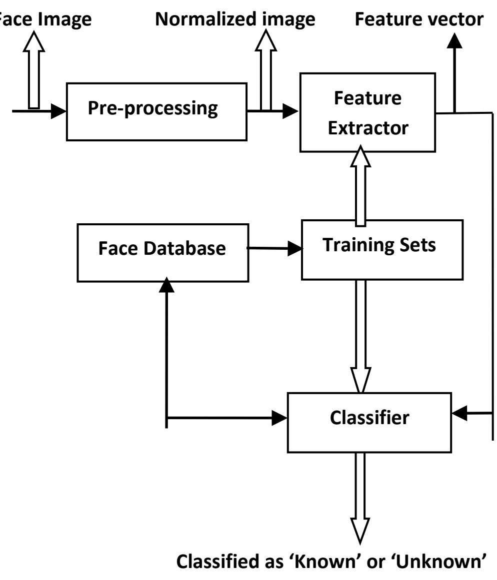

Fig. 1: Outline of a face recognition system.[11]

B. Face Recognition Challenges

Regardless of the large developments in the face recognition technology, it still remains a very challenging task. There are mainly five factors that can significantly affect the performance of these systems, which include illumination, pose changes, time delay, facial expressions and occlusion.

Due to these factors, there are variations in facial appearance and they can be categorized into two types: intrinsic and extrinsic. Intrinsic variations are independent of any external sources and are due to the physical nature of the human face.

Extrinsic variations are caused by the sources that do not depend on the human face and are due to factors such as illumination and viewing geometry.[2]

II. LITERATURE REVIEW

The face recognition systems use two main steps to achieve efficient face recognition: Subspace Projection and Classification. There are many face recognition applications which include identification for law enforcement, authentication for banking and security system access, human-computer interaction, and customizable animation. The existing methods for automated face recognition are mainly based on three steps: Face detection, Facial feature extraction and Classification from the observed facial image.

A few of the face recognition techniques are PCA, ICA, Gabor jets, Linear Discriminant Analysis (LDA or Fisher-faces), and Hybrid methods.

In this review of the literature, we explored various face recognition methods. Among them, the most commonly used are statistical techniques (PCA and ICA), wavelet matching (Gabor wavelet techniques, and an EBGM technique.

With the review of literature, it becomes perceptible that as compared to the other face recognition techniques and algorithms commonly used, the EBGM algorithm is independent of the variation in lighting, face position, and expression. The EBGM algorithm easily assimilates new face template data without modifications to the existing templates but the other techniques and algorithms may need to modify the gallery database information when new data is added to the database which is not desirable in all cases.

Moreover, the facial features used for the identification of the test image are insensitive to lighting variation and only features at key points in the face image are used rather than the entire image.

Because of the above cited advantages, EBGM is used in this proposed work to extract the facial features from the live video to make the face recognition real-time and more reliable.

III. PROPOSED METHOD

A. Design and Implementation

Here a detailed explanation of the design technique, used for the implementation of the proposed work, is outlined.

B. Programming Language

The programming language used to design and implement the face recognition system is MATLAB.

C. Image Processing

Image processing consists of the following six steps:

a) Image Acquisition
b) Image Pre-processing
c) Import Faces Images to MATLAB
d) Feature Extraction
e) Image Data Reshape

a. Image Acquisition

Face images of different individuals were taken under uniform light conditions and light backgrounds with a digital camera for the training database. The face images were then transferred from the digital camera to the computer. Similarly, additional pictures of each individual subject with different profiles were also taken.

b. Image Pre-processing

Images were then pre-processed. Image pre-processing has two phases:

1) Auto adjusting image levels, contrast, brightness and colors
2) Image conversion from RGB color to grayscale

c. Import Face Images to MATLAB

After all face images were preprocessed, then they were imported into MATLAB.

d. Feature Extraction

In this step, the features were extracted from the test image by using the EBGM technique and were stored in the form of arrays.

e. *Image Data Reshape*

At this stage, the features extracted from the face image were in the forms of matrices, corresponding to a particular fiducial point on the human face. These feature matrices were arranged in the form of arrays and were further provided as input weights to the ANN for the particular face image. Hence the image data needed to be reshaped from an 8 x 8 matrix to an array for it to be used both for the input and training database of the BPNN.

The implementation of proposed technique using ANN was successful. The performance of the techniques, which were studied in review of literature, deteriorates to recognize the face images with different lighting conditions and facial poses, but the algorithm used here involves the EBGM technique which gives more accurate results.

The proposed work proved to be highly accurate by recognizing face images under a test of a training database of 20 face images, and input face images with different facial poses and lighting conditions.

IV. ELASTIC BUNCH GRAPH MATCHING

The EBGM technique obtains a bunch of jets from the key points in the face image which is used for the training of the system. By joining bunch of jets, a graph is obtained which is known as a graph node. Later a bunch graph, which is a collection of facial images, is obtained which in turn compared with the probe image provided for the identification. During the process of matching an image to the bunch graph, the jets extracted from the facial features of the test image are compared to all jets in the corresponding bunch attached to the bunch graph and the best matching one is selected.[8]

A bunch graph contains different faces with different features or properties to generate a model graph. The nodes joining the model graph are placed over the probe image and jets are extracted from the fiducial points. The jets so extracted are used for comparing the model graph with the test image. In the final step, a match is obtained between the probe image and the model graph using a similarity function.[15]

A. ALGORITHM

The basic steps followed in EBGM algorithm are: the image is kept to the normalized form using the pre-processing steps, then the landmark locations are localized, after that a face graph for each image is created in the gallery images, and in the final step a distance measure is obtained between the face graph obtained and the given test images.

As studied in the review of literature, the EBGM approach is independent of variation in lighting, pose, and expression. Facial features at the key position in the image are used for identification instead of the whole face image due to the fact that the facial features are insensitive to lighting variation.[8]

As studied, the PCA technique seems to be computationally efficient but it has many disadvantages which are; PCA's performance deteriorates when the lighting, face position, and expression change significantly especially in case of images from a live video.[7]

Regardless of the above discussed advantages and disadvantages of PCA; EBGM is independent of the variation in lighting, face position, and expression.[8] The only major drawback of the EBGM technique is that the process is time consuming. [9]

V. NEURAL NETWORKS

A set of interconnected group of artificial neurons that uses a mathematical or computational model for information processing are called as an ANN. They are also commonly known as Neural Network. Depending upon the external or internal information that flows through the network, the ANN changes its structure that is why the network is also known as 'adaptive system'. The ANN is a type of artificial intelligence that is designed to replicate the way the human brain works. Neural networks are made up of a thickly interconnected set of simple units, where each unit receives a number of external inputs which may be the outputs of other units and they finally output a single real - valued value (output) which may become the input of other connected units.[16]

These networks are designed in a similar fashion as the biological neural network performs functions. The biological neural network functions collectively in units, rather than performing a task single handedly, the task is divided into subtasks and a particular task is assigned to various units. Rather than working in a similar fashion as a digital model work; in which all the computations involves binary bits i.e. zeros and ones, a neural network works by creating interconnections between processing units, which are known as 'neurons'.

Fig. 2 shows a general architecture of ANN with three layers—input, hidden and output. Computations are mainly undertaken in hidden layer.

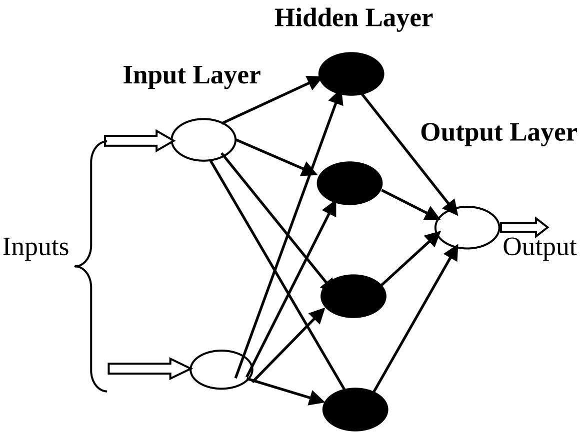

Fig. 2: Neural network architecture.

A. RECURRENT NEURAL NETWORK

There are many learning algorithms being used for neural networks training which are further used for computing and formulating various results.

The ANNs are able to learn by examples that makes them very flexible and powerful tool in computing world. Because of their fast learning through examples and less computational times, they become a choice for real-time applications.

Even though neural networks have a huge potential but the current focus in this proposed work is to integrate recurrent neural network (BPNN) with EBGM algorithm. The reason for choosing BPNN is due to the fact that they are well suited for pattern recognition problems and for developing artificial intelligence systems.[11]

VI. EXPERIMENTS AND RESULTS

The experimental setup consists of a Graphic User Interface (GUI) which shows two windows i.e. the left window and the right window as shown in the Fig. 3. The left window is used for the training of the system and the right window is used for the identification of the test image.

Both the windows can also be used for real-time applications or when the image is to be captured from a webcam. The image captured from the webcam is used as a test image to identify the face image from the training set, which includes 20 face images of different persons with different profiles and expressions.

In order to compare the proposed work, the identification will be performed by both the algorithms— Eigenfaces and EBGM independently. The training and recognition phase is implemented using BPNN. The features extracted have a particular weight and are used as an input to the ANN for training. When a test image is used, the features are extracted corresponding to the particular fiducial points on the face image and these features are arranged in the form of matrices or arrays and are provided as input weights to the trained ANN, which compares the features extracted to the already stored templates for the gallery images and provide a best suitable mach at the output.

Later in the experiments, we realize that the identification results, incase of the EBGM algorithm, are more accurate as compared to the Eigenface algorithm and this was achieved by using ANN.

The setup identifies the test image separately for both the algorithms and shows the result by finding out the particular face from the gallery images, which is a best match to the test image. The setup also shows the time-taken by both Eigen and EBGM algorithms separately.

In the similar fashion, different test images of different persons were taken and were identified through both the algorithms separately and the time-taken by both the algorithms was computed separately and a comparison was made through tables for both the algorithms in terms of the time taken and the image identified by the particular algorithm. The face image identified by both the algorithms was displayed over the GUI with a particular face number being assigned to the different gallery images. The time-taken by each algorithm will be measured in seconds.

The experiments were further divided into three steps and the results obtained for each step were computed and arranged in tabular form for performing comparison. A snapshot for each experiment is also shown.

A. STEP I: *Identification of input image in case of frontal or near-frontal faces.*

Table 1 shows the comparison of Eigenface and EBGM algorithms in terms of time-taken to identify an image for the gallery images and the particular face image identified by both the algorithms independently.

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Table 1: Comparison of Eigenfaces and EBGM techniques for frontal faces.

Input Face	Time-taken for Eigenface	Face identified	Time-taken for EBGM	Face identified
Face 1	0.12457s	Face 1	3.235s	Face 1
Face 2	0.12134s	Face 2	3.488s	Face 2
Face 3	0.11948s	Face 3	3.606s	Face 3
Face 4	0.12467s	Face 4	3.573s	Face 4
Face 5	0.24132s	Face 5	6.940s	Face 5
Face 6	0.12195s	Face 6	3.691s	Face 6

From the analysis of Table 1, it becomes clear that for frontal faces, the time-taken by both the algorithms is not equal but the accuracy is same.

For each test image, the time-taken by EBGM algorithm is more as compared to the Eigenface algorithm and for both the techniques; the face image identified is also same. So, we concluded that for the frontal face images, the Eigenface technique is more suitable as compared to the EBGM technique.

Fig. 3: Snapshot for frontal face image.

B. STEP II: *Identification of input image in case of left pose face images.*

Table 2 shows the results obtained in case of left poses of face images. For left poses, the time-taken by both the techniques is not equal but the accuracy of EBGM is more in comparison to Eigenface.

Table 2: Comparison of Eigenfaces and EBGM techniques for Left poses.

Input Face	Time-taken for Eigenfaces	Face identified	Time-taken for EBGM	Face identified
Face1	0.12412s	Face 14 (incorrect)	4.086s	Face 1
Face2	0.1374s	Face 2	3.356s	Face 2
Face3	0.13205s	Face 18 (incorrect)	3.249s	Face 3
Face4	0.12167s	Face 9 (incorrect)	3.499s	Face 9 (incorrect)
Face14	0.12678s	Face 6 (incorrect)	3.343s	Face 14

As shown in the Fig. 4, for the test image, the face identified by the Eigenface technique is Face 14 but the face image identified in case of EBGM is Face 1. When the results are confirmed from the database images, the face obtained in case of EBGM is correct and the face identified by the Eigenface is incorrect.

Fig. 4: Snapshot for left pose face image.

C. STEP III: *Identification of input image for right pose face images.*

Table 3 shows some cases when the identification of face image by Eigenface algorithm is incorrect but on the other hand, the results for EBGM algorithm are correct. So, we can say that for right poses of face images the accuracy of EBGM algorithm is more.

Table 3: Comparison of Eigenfaces and EBGM techniques for Right poses.

Input Face	Time-taken for Eigenfaces	Face identified	Time-taken for EBGM	Face identified
Face1	0.1182s	Face 1	3.464s	Face 1
Face3	0.12075s	Face 8 (incorrect)	3.848s	Face 3
Face6	0.13487s	Face 2 (incorrect)	3.064s	Face 6
Face9	0.11956s	Face 11 (incorrect)	3.2517s	Face 9
Face12	0.13287s	Face 12	3.6457s	Face 12

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Fig. 5*: Snapshot for right pose face image.*

The Fig 5 shows the face image identified by Eigenface algorithm is Face 8 but that by EBGM is Face 3. When confirmed form the database images, it was found that EBGM technique had given the correct result.

D. Discussion and Analysis of Results

The experimental results verified the accuracy of the EBGM technique using ANN. These experiments confirm that the face recognition system proposed has best possible accuracy for facial images with different facial poses under different lighting conditions, backgrounds and poses.

With the association of the neural networks for comparison and classification of facial features, the accuracy and time requisite for identification of the probe image was further enhanced to obtain a high-speed face recognition system. These results justified the use of neural networks to obtain a high-speed efficient face recognition system.

From the analysis of the results, it can be said that the design and implementation of a real-time face recognition system has been successfully achieved as the primary objective of this proposed work.

VII. CONCLUSIONS AND FUTURE WORK

As discussed in the experimental results, the time-taken to identify a test image, in case of EBGM, is more as compared to the Eigenface algorithm but as far as the matching accuracy is concerned, which is more in case of EBGM framework due to the involvement of ANN. Matching accuracy is the most important aspect as far as the authentication of the face recognition system is concerned.

Moreover, the identification results obtained from EBGM algorithm is accurate, even for illumination and pose variant face images, when compared with Eigenface algorithm and this fact is mainly exploited in the present work. The main limitation of the EBGM algorithm was the long time duration required to compute the 'distance measure' between the face features matrix and the time consumed in the comparison phase by the ANN. But with the availability of more processing power, this limitation may soon be irrelevant. So, the proposed work has a scope for modifications in terms of computational efficiency.

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