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IMAGE-BASED HUMAN FACE VERIFICATION MODEL

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ABSTRACT

Face recognition has attracted researches not only because faces represent a challenging class of naturally textured 3-D objects, but also because of many applications of automatic face recognition, such as: physical security, crowd surveillance, face reconstruction, and many more. In this paper, an image-based face recognition model is proposed, that verifies human faces by projecting face images onto a feature space that spans the significant variations among known face images, by computing their significant features: Discrete Cosine Transform (DCT). They do not necessarily correspond to features such as eyes, mouth, etc. These “DCT coefficients” composes the feature vector that represents a human face. An average of 98.5% recognition rate is reached on the Olivetti Research Laboratory (ORL) database of facial images [8].

Keyword: Image Processing, Feature Extraction, Discrete Cosine Transform, Pattern Recognition, Face Recognition

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* EGYPTIAN ARMED FORCES

1. INTRODUCTION

Face recognition is difficult for two major reasons: First, faces form a class of fairly similar objects – all faces consist of the same facial features in roughly the same geometrical configuration. Second, the wide variation in the appearance of a particular face due to imaging conditions such as lighting and pose.

The performance of face recognition systems varies significantly according to the environments where face images are captured and the way user defined parameters are adjusted in different applications[1][2]. Since a face is essentially a 3D object, lighting sources from different directions may dramatically change visual appearances (e.g. due to self shadowing and specular reflections). Face recognition accuracy degrades quickly when the lighting is dim or does not uniformly illuminate the face [3].

One of the techniques for face recognition is to apply Principal Component Analysis (PCA) for the computation of EIGENFACES. These EIGENFACES represent the extracted features for the faces to be recognized. A multi-layer Artificial Neural Network (ANN) trained with back propagation adaptive learning algorithm is used for classification. Although the training of the net is a time consuming process, once the net has been trained, it performs classification very efficiently. Promising results have been achieved, with an average recognition rate of 98%[4]

Alex Pentland et al [5], also experimented eigenfaces to accomplish recognition, verification, and interactive search in a large-scale face database of 2,500 images. Alex varied lighting, size and head orientation for 16 individuals. For the case where every face image is classified as known, they reported that the system achieved approximately 96% correct classification averaged over lighting variation, 85% correct averaged over orientation variation, and 64% correct averaged over size variation. The system achieved an accuracy of 97% over all conditions.

Baback Moghaddam and Alex Pentland [6] genaralized the eigenface approach for detection and recognition of human faces to a view-based and modular eigenspaces. The view-based formulation allows for recognition under varying head orientations and modular description allows for incorporation of important facial features such as eyes, nose and mouth extracted by an automatic feature extraction technique using feature eigentemplates (eigenfeatures). i.e. eigenface plus eigenfeatures. Baback [6] reported recognition rate of 95% using eigenfeatures alone and 98% using modular description for 45 individuals.

Also Baback Moghaddam and Alex Pentland [7] presented a fully automatic system for 2-D model-based image coding of human faces. It operates by locating a face in the input image, normalizing its scale and geometry (maps them to a canonical view), and representing it in terms of a parametric image model obtained with Karhunen-Loève basis requring only 100-BYTES of encoded data. Baback [7] tested the system on more than 2,000 images and achieved a detection accuracy of 97%.

The goal of this paper is to develop and implement a Human Face Verification system Based on Discrete Cosine Transform Coefficients capable of detecting and recognizing faces.

This paper is organized as follows: Section 2 introduces the proposed Face Verification Model (FVM) .The image acquisition and image normalization phases are explained in section 3. Section 4 discusses the feature selection and the extraction phase. Section 5 explains the recognition phase. Experiments and results are discussed in section 6. Finally, Conclusions are drawn in section 7.

2. PROPOSED FACE VERIFICATION MODEL

Face recognition is a pattern recognition task performed specifically on human faces. It can be described as identifying a face either "known" or "unknown", after matching it with stored known individuals. It is also desirable to have a system that has the ability of learning to recognize unknown faces.

Computational models of face recognition must address several difficult problems. This difficulty arises from the fact that faces must be represented in a way that best utilizes the available face information to distinguish a particular face from all other faces. Faces pose is a particularly difficult problem in this respect, where all faces are similar to one another in that they contain the same set of features such as eyes, nose, mouth arranged in roughly the same manner.
The proposed FVM in this paper is depicted in Fig. 1. It is composed of three main phases: (1) input image Normalization that deals with the geometric distortion and illumination; (2) computation of feature vector based on DCT; and (3) classification by applying Euclidean-distance

In this figure, the input image containing the desired face is captured and then normalized. Section 3 will discuss the normalization phase. The normalized image is divided into non-overlapped blocks of 8X8 pixels and then the DCT coefficients are calculated. With these readily extracted features, the identification of object could be realized. The feature extraction phase for computing the feature vector is explained in section 4.

The classification phase means either recognition or verification. Recognition identifies whether a person matches anybody in an existing database of people, while verification verifies that a person matches their previous templates; the Euclidean distance was taken under investigation. Classification technique is discussed in section 5.

A pre-stage is to build a database of a number of subjects with various facial expressions. Since it is a time consuming task, instead a database that is free of charge on the Internet was downloaded and used during the work. The database taken under experimentation was the Olivetti Research Laboratory (ORL) database of 400 images of 40 individuals taken between April 1992 and April 1994 at the Olivetti Research Laboratory in Cambridge, UK [8]. It contains quite a high degree of variability in expression, pose, and facial details. Fig. 2 shows a picture of the 40 individual face under experimentation The face images are in grayscale with a resolution of 92x112 pixels stored in a Portable Gray Map (PGM) file format. Fig. 3 depicts a sample of the ORL database, with 10 different views for the same person.

3. IMAGE ACQUISITION AND NORMALIZATION PHASE

The image acquisition is the module where the face image under consideration is presented to the system. In other words, the user is asked to present a face image to the face recognition model. In this module, the image acquisition module can require a face image from several different environments. The face image can be an image file that is stored on a magnetic disk, it can be captured by a frame grabber or it can be scanned from paper with the help of a scanner.

Two kinds of normalization are performed on the acquired face image, namely geometric distortion and illumination of faces. The first deals with geometric distortions due to varying imaging conditions to compensate for position, scale, and minor orientation variations in faces. In this way, feature vectors are always compared for images characterized by the same conditions. The second kind of normalization deals with the illumination of faces. As variations in pixel intensities between different images of faces could be due to illumination conditions. Normalization in this case is not very easily dealt with, because illumination normalization could result in an artificial tinting of light colored faces and a corresponding lightening of dark colored ones.

4. FEATURE EXTRACTION PHASE

The statistical features deal with the statistical measures such as correlation, variance, means, and error probability of mathematical measurements like moments, Fourier descriptors, entropy minimization, and expansion coefficients. In the present work, the statistical features which used are Discrete Cosine Transform

The importance of facial features for face recognition cannot be overstated. Many face recognition systems need facial features in addition to the holistic face, as suggested by studies in psychology. It is well known that even holistic matching methods, for example, eigenfaces [9] and Fisherfaces [10], need accurate locations of key facial features such as eyes, nose, and mouth to normalize the detected face [11].Three types of feature extraction methods can be distinguished: (1) Generic methods based on edges, lines, and curves; (2) Feature-template-based methods that are used to detect facial features such as eyes;(3) Structural matching methods that take into consideration geometrical constraints on the features.

After performing some pre-processing (if necessary), the normalized face image is presented to the feature extraction module in order to find the key features that are going to be used for classification. In other words, this module is responsible for constructing a feature vector that is well enough to represent the face image.

The image processing phase divides the image into equally sized non-overlapped blocks of 8x8 pixels (Fig. 4). Each block is transformed from the spatial-domain to the frequency-domain using the 2-dimensional Discrete Cosine Transform (2D-DCT). 2D-DCT is utilized because it helps to project each image block into sub-bands of differing importance, where low frequency contents can be captured since they contain most of the face discriminating information [12].

The feature vector representing a face is obtained by computing its DCT, and only a subset of the obtained coefficients is retained. The observation vectors are formed from the 2D-DCT coefficients of each image block then passed to the training phase. The database contains 40 enrolled users with 5 images used for training. All face images poses are divided into blocks, and the 2-D DCT is applied to each block where the highest 5 features are extracted from the 64 features per block, representing the lowest frequency components.

5. FACE CLASSIFICATION PHASE

After choosing a training set and constructing the weight vectors of face library members, now the FVM is ready to perform the recognition process. User initiates the recognition process by choosing a face image. Based on the user request and the acquired image size, pre-processing steps are applied to normalize this acquired image to face library specifications (if necessary). Once the image is normalized, its weight vector is constructed based on DCT coefficients and stored during the training phase.

Classification can be based upon various distance measures like Euclidean distance, cross correlation level, and Mahaaloblis distance. Euclidean distance is adopted hereupon. Other techniques may be calculated [13]. To verify a particular input face, the model compares face feature vector to those of the database faces, using an Euclidean distance nearest-neighbor classifier. If the feature vector of the probe (test face) is ***V*** and that of a database face is ***F***, then the Euclidean distance between both is

$$d = \sqrt{(f_0 - v_0)^2 + (f_1 - v_1)^2 + ... + (f_{M-1} - v_{M-1})^2} \qquad (1)$$

Where

$V = [v_0\ v_1 ... v_{M-1}]^T$, $F = [f_0\ f_1 ... f_{M-1}]^T$, and *M* is the number of DCT coefficients retained as features. A match is obtained by minimizing *d*.

Using the DCT coefficients feature vector selected in section 4, we can compute the distance between the test face ***v*** and the training set ***f*** . The class of the library feature vector producing the smallest Euclidean distance with the input feature vector is assigned to the input face.

6. DISCUSSION AND EXPERIMENTAL RESULTS

This section reports some experiments to test the implemented FVM in different situations. The FVM based on DCT using an Euclidean distance classifier have been tested using a database that contains 40 classes with 10 samples in each class.

To find what will be the effect of changing the training set on the performance of face recognition model. The faces of each class are numbered from 1 to 10; the first 3, 5, and 6 faces of each class were taken as the training set and all the 10 faces as testing set for the conducted experiments. Table 1 depicts the results obtained for the conducted experiments with a variant number of DCT coefficients within each block after sorting them in a descending order. It could be noticed that the recognition rate increases as the number of faces per objects increases and the recognition rate is approximately constant as the number of the highest DCT coefficients within each block for the object increases.In real imaging systems, images are sometimes captured with certain camouflage and distortions like brightness distortion, rotated to a random angle, some changes in a part of the face (glass, beard, mustache, dark bandage ……,).
To simulate the camouflage and rotation distortions, a subset of the face images is subjected to camouflage and rotation effects are selected. Figure 5 illustrates the robustness of the proposed FVM to the camouflage applied on a subset of test face images. It was observed that all the above face images were classified correctly using the proposed FVM. Fig.6 illustrates the robustness of the proposed model to the rotation, skew, and some changes in a part of the face using another subset of the face images. Again, it was observed that all the above face images were classified correctly using the proposed FVM.

7- CONCLUSION

In this paper, an image-based approach is proposed, that verifies human faces by projecting face images onto feature space (DCT) that spans the significant variations among known face images (training faces), by computing significant features “highest coefficients of the DCT in each block”. They do not necessarily correspond to features such as eyes, mouth, etc. These “coefficients” composes the feature vector that represents a human face.

The proposed model was tested using several face images with certain camouflage and distortions like brightness distortion, rotated to a random angle, changes in a part of the face (glass, beard, mustache, dark bandage ……,) , to prove its efficacy. It was observed that all the test face images were classified correctly using the proposed FVM. 98.5% performance efficiency has been achieved on the Olivetti Research Laboratory (ORL) database of facial images using the proposed FVM.

Also, to find what will be the effect of changing the training set on the performance of the proposed face recognition model. The faces of each object are numbered from 1 to 10; the first 3, 5, and 6 faces of each object were taken as the training set and all the 10 faces as testing set for the conducted experiments. It could be noticed that the recognition rate increases as the number of faces per object increases and the recognition rate is approximately constant as the number of the highest DCT coefficients within each block for the object increase.

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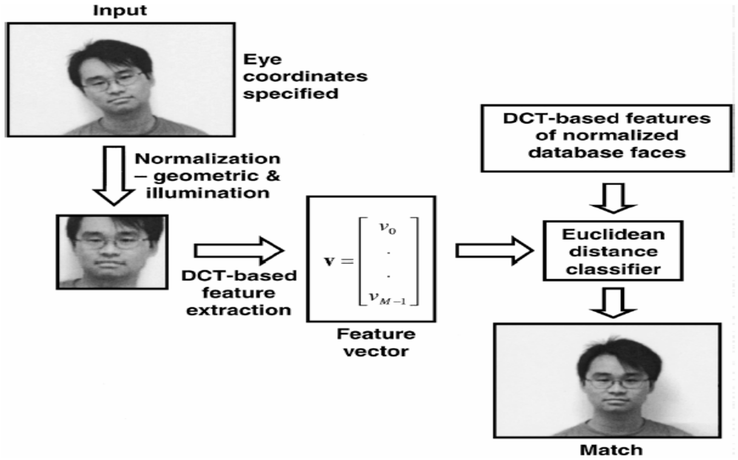


Fig. 1 Face recognition model using the DCT

Fig. 2. A face of the 40 individuals composing ORL Database

Fig. 3. A sample of ORL Database with 10 views

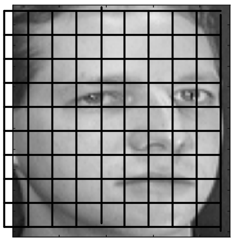
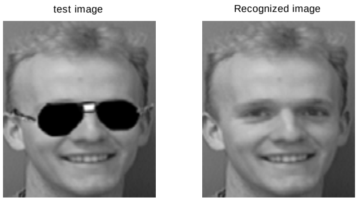


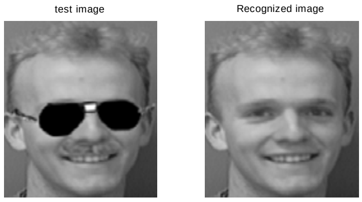
Fig. 4: Segmentation of the image into non-overlapping 8*x*8 blocks

Table 1. The Effect of the number of faces per object in the training set on the FRS performance

Number of DCT Coefficients within each block	Recognition Rate [%] Number of faces for each object as a training set is		
	3	**5**	**6**
1	٩١,٥	٩٧,٥	٩٨,٧٥
2	٩١,٢٥	٩٧,٥	٩٨,٧٥
3	٩١,٢٥	٩٧,٥	٩٨,٧٥
4	٩١،٥	٩٧،٥	٩٨،٧٥
5	٩١,٥	٩٧,٥	٩٨,٧٥
10	٩١,٥	٩٧,٥	٩٨,٧٥

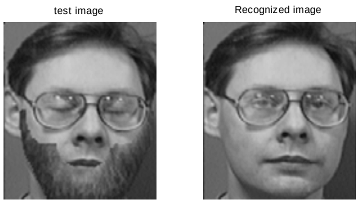


(a)



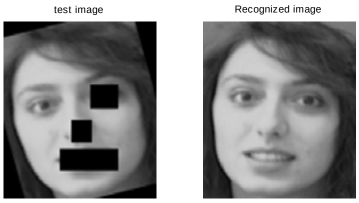
(b)

(c)



(d)

(e)



(f)

Fig. 5. The effect of camouflage on the proposed FVM using selected images and the correct match is found. (a) Face with Glass, (b) Face with glass and mustache, (c) Face with beard, (d) Face with beard and closed eyes, (e) Face with dark bandage on the eyes, and (f) Face with dark bandage on the eye, mouth, and nose.

(a)

(b)

(c)

(d)

(e)

(f)

Fig. 6. The effect of distortions on the proposed model and the correct match is found. (a) Face with dark bandage on the eye and open mouth, (b) Face with dark bandage on the eye and closed mouth, (c) Face with a glass and tongue, (d) Face with closed eyes and closed mouth, (e) rotation with angle, and (f) Laughing face and skew operation is applied.