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FACE RECOGINITION SYSTEM USING FUZZY LOGIC AND SYMBOLIC DATA ANALYSIS

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Abstract:

In face recognition, the goal is to distinguish between a previously identified face and a known or unknown face. Face recognition is a hot study topic in the areas of computer vision, neurology, and psychology, among other subjects. The experts working in this area have suggested major improvements, one of which is the increase in facial recognition that is occurring on a daily basis. Despite the availability of a variety of face recognition methods, the performance obtained by them is not especially impressive, particularly when faced with coarse changes in posture, lighting, and expression, as well as noise and blur impact on the face. Aiming to investigate the development of a set of face recognition algorithms with the capabilities of good perception, low complexity, and small size of feature vectors, the work presented in this article is an attempt to improve upon existing approaches in this field by providing faster performance. A face identification technique known as Symbolic Data Analysis (SDA) is used to extract characteristics from face pictures in both standard and local datasets. It is one of many face recognition techniques available. The performance of the SDA is good. It is an effort to subspace that is given in this article. Face classes were distinguished by using this subspace to make a distinction. A change in the look of the same person may be seen as a result of differences in lighting and facial expression. This kind of scatting is referred to as interpersonal scatting since it occurs inside a class setting. When the identities of the participants vary, this is referred to as between class scattering. This may also be represented by a matrix, and it is referred to as "extra personality." In Symbolic Data Analysis, an effort is made to minimize the distance between face pictures belonging to the same class of images. At the same time, the distance between the images of various classes is increased to its maximum.

Keywords:Fuzzy Logic, Principal Component Analysis. Karhunen-Loeve Transform,Artificial Neural Network, 3 Dimensions, SDA

1. INTRODUCTION

Face recognition is very difficult since it requires distinguishing between facial differences that have a fundamentally similar structure across all appearances. Furthermore, faces are captured from a variety of vantage points and under a variety of lighting situations. Despite the fact that we live in a technologically advanced and computerized society, we still have difficulty distinguishing between people's faces. A person's precise picture cannot be identified due to low quality facial images and blurring effects on the face, even if the individual's data is stored in a computer database or on Facebook. Utilizing sophisticated algorithms, we can recognise faces in online or offline databases from swarms of cameras on consumer devices, whether the faces are in online or offline databases. Thousands of people all around the globe took to the streets to pressure Google into disabling facial-recognition technology on their "Google Glass" smart glasses at the first sign of a possible future in which this occurs. While this is true, for quite a long time now, the innovation has been confronted with different issues such as distinguishing proof (access control), security (smart cards), law and authorization, mixed media administration, and clubs to recognize needed - or undesirable - people caught on surveillance cameras. In addition, the ability to recognize facial expressions has started to appear on the mobile phones of law enforcement officers and even regular consumers. Original perceptron is found to have three layers sensory, associator and response units as shown in figure 1.

Figure 1: Original Perceptron

The sensory and association units have binary activations, while the reaction unit has an activation of +1, 0 or -1, depending on the situation[1-3]. All of the units have their corresponding weighted problems, and the problem is also used to understand the categorization system. Preceptrons are classified into two types: single-layer Preceptrons and multi-layer Preceptrons.

2. Literature survey:

SDAKarl Pearson founded the Society for Developmental Aspects (SDA) in 1901. Currently, it is mostly used as a tool for exploratory information inquiry and for creating prophetic models, both of which are common applications (E.g. face recognition). In the real eigenvector based multivariate studies, SDA is the least complex of the methods to use. Most of the time, its function may be described as revealing the inner structure of the information in a manner that best explains the change (actual components/headings) in the information. If a multivariate dataset (e.g., a set of images) is conceptualized as an arrangement of directions in a high-dimensional information space (1 axis for each variable), SDA can provide the client with a lower-dimensional picture, a "shadow" of the item when viewed from its (in some ways) most useful perspective, called a "shadow image." To begin, SDA is a scientific methodology that employs an orthogonal change to transform an arrangement of estimations of potentially associated M face images into an arrangement of estimations of K uncorrelated variables known as eigenfaces. To do so, SDA employs an orthogonal change to transform an arrangement of estimations of conceivably associated M face images. This means that the number of essential segments (Principal Components) is never precisely or exactly equal to or equal to the number of unique variables, where K M represents the number of unique variables. The number of eigenfaces is never precisely or exactly equal to the number of unique face pictures, which is K M, and this is true all of the time. This shift is characterised in such a way that the first central segment demonstrates the most overwhelming "heading"/"elements" of the dataset, and each succeeding segment demonstrates the most conceivable predominant "course/highlights" of the dataset, with the restriction that each segment be uncorrelated to the previous segments[4]. In order to reduce the number of estimates needed for the discovery of these important segments, the dimensionality of the initial dataset is reduced prior to their computation. The fact that chief segments show the "bearings" of information and that every process part indicates less "headings" and more "clamour" means that just a handful of initial primary segments (say K) are selected, despite whatever is left of the final segments is discarded. Because they define the actual components/bearings that make up the dataset, these K important segments may be used to securely communicate with the complete unique dataset. As a result, each variable in the first dataset can be described in terms of the first K segments of the second dataset. Speaking about an information point in conjunction with these lines (as a combination of K major segments) reduces the number of characteristics (from M to K) that must be remembered in order for it to be remembered. Due to this, the acknowledgement preparation process is more efficient and free of the "error caused by noise." According to the eigenvalue disintegration of an information covariance framework [5], SDA should be feasible.

Symbolic Data Analysis (SDA) is an appearance-based method that is widely used for dimensionality reduction, and it has shown exceptional performance in the recognition of facial expressions. SDA-based methods are often divided into two stages: preparation and acknowledgement [6]. [7, 8] During the preparation step, an Eigen space is constructed from the preparation tests using SDA, and the preparation face pictures are mapped to the Eigen space in order to maintain the order of the preparation face images. When an info face is assigned to the same Eigen space and is sorted by a suitable classifier, the acknowledgment step is considered complete. In order to reduce the measurement of information by using information pressure nuts and bolts, the SDA technique is used, which reveals the optimal low dimensional structure of face instances [7]. When measurements are reduced, data that is not useful is eliminated, and the face structure is clearly disintegrated into orthogonal (uncorrelated) parts known as Eigen appearances. In SDA, every face picture may be seen of as a weighted aggregate, and this is true in practice. As shown in figure 2, a sample facial picture is represented in matrix form according to the image size (as indicated by the pixel values) as shown in figure 3.

$$X = \begin{bmatrix} 253 & \ldots\ldots\ldots\ldots & 255 \\ \vdots & \ldots\ldots\ldots\ldots & \vdots \\ 245 & \ldots\ldots\ldots\ldots & 255 \end{bmatrix}$$

Figure 2: Face image is represented in Matrix Form

3. Theory of SDA

When it comes to SDA, Eigenfaces acknowledgement is named from the German word "eigen," which literally means "own" or "person." Face representation and acknowledgement are both accomplished via the use of SDA, which is a well-known method for determining the order of components [4. This method captures a significant part of the face variation and arranges it into a collection of pictures. It is necessary to construct Eigen space projection in order to use SDA for face recognition in its most basic form. Thereby, it converts the vast 1-D vector of pixels from a 2-D face picture into the smallest possible principal components of the component space. The eigenspace of a face image vector arrangement is calculated by identifying the eigenvectors of the covariance network obtained from an arrangement of facial image vectors. In addition, SDA characterisation is multi-modular, producing a vector of free measurements that may be compared as well as various vectors in a database, and it is also fast. It is dependent on the Eigenvalue and Eigenvector analysis of the covariance grid for SDA to work properly. An example of a covariance network is shown in Figure 1. The corner to corner characteristics represent the fluctuation for each measurement, while the off-askew components represent the covariance across estimate types. Apart from that, long terms in the corners of the room correspond to fascinating measures, while large qualities in the off-slanting room correspond to strong connections (excess). Entirely eigenvectors are diametrically opposed to one another, i.e. they are at right angles to one another. In the case of a lattice, an eigenvector is a vector such that when it is multiplied by the framework, the result is consistently a whole number several of that vector. This whole number quality is the eigenvector's eigenestimate, which is the eigenvector's eigenestimate. Because the foremost segments are orthogonal, the covariance lattice of the foremost segments is slanting. The reduction in dimensionality is achieved by removing all except the most significant core portions, and the resulting reduction in computation time is significant. When compared to their Eigen values, Eigen countenances are positioned in decreasing order of request[8]. The eigenvectors with the highest Eigen quality are the most massive when compared to the eigenvectors with lower Eigen qualities. A test picture is compared to a preparation image by measuring the spacing between the element vectors of their respective element vectors. In order to recognise another picture, it is necessary to anticipate it into the subspace spanned across by the Eigen confronts (referred to as "face space") and then arrange the face by comparing its location in face space with the positions of recognised individuals.

3.1 Face Recognition System Using SDA and Fuzzy Logic

It is used as the standard system for measured example acknowledgment procedure for dimensional decreasing and includes extraction. The principal part investigation, also known as Karhunen-Loeve change, is used as the standard system for dimensional lessening and contains extraction. When a facial picture appears in a two-dimensional measurement with dimensions N x N, it may be thought of as a one-dimensional vector of dimension N2. Example: A facial picture with a size of 200 x 180 pixels from the face95 database is regarded to be a vector with measurements of 36,000 in 36,000 dimensional spaces when it is stored in the face95 database. The fundamental concept of rule segment is the vector acknowledgment, which is a straight blend of unique face images that best records for face image dispersion including the entire image space length N2, depicts a N x N image while characterising subspace face images known as "face space," and depicts a N x N image while characterising subspace face images known as "face space." FIGURE 2 depicts the component diagram of a face recognition framework that makes use of SDA. The main module is responsible for preparing a database. The face is captured with the use of a camera and stored as part of a facial recognition database. In this module, pre-handling of face pictures is critical, and this is shown in the next section: creating a set The original size of the face pictures was

640x480 pixels, but it has been reduced to 100x100 pixels. In this module, the pictures of the faces were converted to a dim scale. It uproots the basis of the facial image and causes it to combust[9]. By using SDA methods, the following module eliminates the component of face pictures, which is then converted into a section or push highlight vector. The classifier is describing an element vector that is used in the preparation of face pictures and the testing of face images. In order to coordinate the information face picture to the subject, it is taken from the preparation set whose element vector is the closest within sufficient edge. Figure 2 depicts the design of a face recognition system that makes use of SDA technology. The creation of the face database has been completed in the first step. The following module is responsible for setting up the set or doing any necessary pre-handling for face pictures. Following that, shading pictures of faces are converted into dark scale images, and finally the size of the face photographs is reduced further. Facial pictures that have been standardised may be obtained by subtracting the mean from the face image[10]. The components that will be considered for extraction and inspection during the element extraction stage are those that provide important information about the face and are arranged in a section or push highlight vector. During the testing step, a test face picture is captured using a camera and stored as part of a face database, which is then used for further testing. All three of the preceding steps, namely pre-preparing, highlight extraction, and highlight vector, are required for the testing stage to be successful. With the use of a classifier, the closest match may be resolved between a known face picture and an obscure face image by comparing the element vector of a testing face to the component vectors of the database. For the purpose of determining the similarity between two facial pictures, the Euclidean separation is used as a classifier [11] [12].

3.2 Algorithm for Face Recognition Using Fuzzy logic with SDA

Query as an input Image of the face

Face recognition as a result of the output

Principal Component Analysis (PCA) is the method used.

Step 1: Choose a face database and convert face pictures from the training set to image vectors.

Step 2: Calculate the mean of the facial image vectors.

Step 3: Make the pictures of the faces as uniform as possible (by subtracting mean from database of face images).

Step 4: Using normalised face pictures, calculate the covariance matrix.

Step 5: Prepare the eigenvectors and eigenvalues of the covariance matrix.

Step 6: Selection of eigenvectors with values less than or equal to the threshold value is performed.

Step 7: Multiply chosen Eigenvectors with normalised facial pictures and create a feature vector.

Step 8: Select the test face picture.

Step 9: Normalize the picture of the test face.

Step 10: By multiplying the normal test face picture with eigenface, which is a feature vector from the training database, we can get the weights of the input test face image (eigenfaces).

Step 11: Using the eigenfaces of the training pictures, normalise the test face image and create a feature vector from the test face image.

Step 12: By comparing each training face picture with each test face image, we reach the last step of the process. The results of this are more similar to the test face pictures.

4. RESULT AND DISCUSSION

Six face databases, with the exception of two (face95 and Yale Face B), were utilised in our method for face identification based on the SDA. Specifically, just two datasets, namely local frontal and local posture variants, are utilised to demonstrate local scope. We utilised degraded face photos from a local database to create our characters' appearances. Using thresholding values (Global thresholding), we attempted to enhance the identification accuracy by separating the foreground and background of the face pictures in a more precise manner. For the standard scope, we have introduced noise into standard database face pictures and attempted to put the above experiment into action as closely as possible. Using standard and local facial pictures, we examined the accuracy of identification. For increased accuracy in recognition, it is essential that the threshold value be precisely established. The recognition rate will drop if it is adjusted to a lower or higher value, therefore it must be set extremely precisely to be effective. The results of SDA-based face recognition for several databases, including face95, Local frontal, and Pose variations databases, are given in this section of the document. This table illustrates the performance of SDA. Face95 database [10] is used to evaluate the conventional SDA method. Initially, the face95 database was designed with dimensions of 200x180 pixels and an input space of 36,000 pixels. It is produced by using a digital camera to capture local frontal and posture variations. Images with the jpeg extension are included. Face pictures with and without noise were subjected to the same testing procedure. Face pictures with no noise were evaluated using SDA on the 71, 10 and 5 face images in the database that did not include noise. The SDA is used to test the 152, 20, and 10 with noisy face pictures. In the case of a noise density of 0.02, salt and pepper noise is added to the facial pictures. In the case of a noise level of 0.02, The threshold value has been established, and it may be adjusted to any value that is appropriate for our system. Trial and error is often used to determine the appropriate value. Every database has a distinct threshold value. Typical face95 dataset pictures are shown in Figures 2.3, 2.4, and 2.5, as well as their mean and training set1 (47 eigenfaces) in the following figures: Figure 2.6 depicts the input and output face images. Images of faces, their mean, and training set2 (six eigenfaces) from the local frontal dataset (LFDSet) are shown in Figures 2.7 through 2.9. Figure 2.10 depicts the input and output face images. Imagery of faces, as well as the training set3 (3 eigenfaces) of local posture variations datasets are shown in Figures 2.11 and 2.12. (LPVDSet). Figure 2.13 depicts the input and output face images. Eigenfaces are used as training sets. Using SDA, the success rate for without noise face pictures recognition 52 is 100 percent, and the success rate for with noise face images recognition 52 is 94.73 percent, 70 percent, and 90 percent, respectively,. The SDA's performance is shown in Table 2.1. Using the Yale face database B [11], the conventional SDA method is evaluated. It has been reduced in size to 168x192 pixels, and the input space has been increased to 32,256 pixels from the original dimensions of Yale face database B. eigenfaces are used in the training set4 in total. It is possible to recognise 96.7 percent of the objects while utilising SDA technology. Using SDA of Yale face database B, the following performance results are shown in Table 1.

Table 1: Fuzzy Logic with Symbolic Data Analysis Performance

Database	Image Type	Image Tested	Threshold Value	Success Rate (Percentage)
Face95	Without Noise	71	5.4285e+006	100
	With Noise	152	5.4285e+006	94.73
Local Database	Without Noise	10	2.4198e+007	100
	With Noise	20	5.4285e+006	70
Pose Variation Database	Without Noise	5	3.4307e+007	100
	With Noise	10	5.4285e+006	90

A linear discriminate analysis method for face recognition is utilised in the LDA algorithm, which stands for linear discriminate analysis. Through the use of class information, it determines the most efficient method to represent the face vector space. This technique distinguishes between changes in facial expressions on the same person's face using the same way. This method makes use of face pictures from the Grimace database, which is a common resource. Using this method, we were able to determine the differences between the two distinct groups of faces. It is possible to express this variation in terms of a projection vector. Figure 5 depicts a visual representation of this concept. In this experiment, we assessed the amount of time it took the CPU to analyse the face pictures for classification, and we discovered that it took 1.263 seconds on average. MATLAB is responsible for developing the LDA facial recognition algorithm (R2010a). Testing of the suggested method is carried out on the grimance database [10]. In this experiment, ten distinct classes of face pictures were utilised, each with a different expression. In class one, there are no expressions of face pictures, and in class two, there are some expressions of face images. The LDA classification method has a good success rate for classification. In figure 6, the graph shows the eigenvalue, eigenvector, and projection vector of these two distinct classes of face pictures, with the eigenvalue being the smallest and the projection vector being the largest. The number of eigen vectors is shown on the x-axis,

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while the values of eigen vectors are represented on the y-axis. The input and output face images of the grimance database are shown in Figure 3.

Figure 3: sample of face images of two classes in grimance database

We are developing an algorithm for the use of the RGB colour separation technique for face identification. We have implemented the use of the colour separation technique RGB for the identification of facial pictures, and we have calculated the accuracy of the recognition. This technique is very seldom utilised in the field of facial recognition. When the same algorithm is used to degraded pictures, the recognition accuracy is evaluated to see whether it has dropped. This experiment makes use of three different databases. Face95 is a well-known and widely used database. It is necessary to utilise a local frontal and local posture variations database.

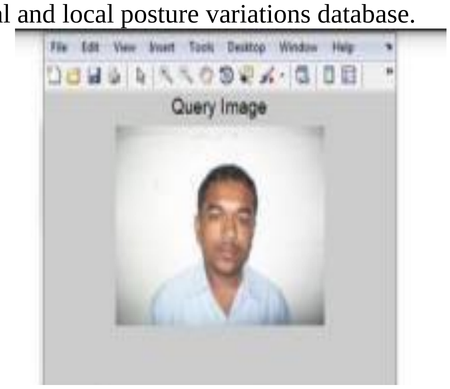

Figure 4: Query Face image

Figure 5: Separating Red, Green and Blue Component of query Face image

Figure 6: Query and output Face image

The same algorithmic processes are performed to face pictures that include noise, and the identification rate that is achieved is compared. The accuracy of local posture variations and local frontal datasets is 80 percent and 90 percent, respectively, according to the results. If we increase the amount of noise in the picture, the accuracy of identification decreases; otherwise, the accuracy of recognition is 100 percent. The method for distinguishing the RGB components of face colour pictures is implemented in MATLAB (R2010a). Standard face95 [10], local frontal, and posture variation databases are used to evaluate the suggested algorithm's performance. A digital camera is used to build a database of local frontal and posture variation data. Face pictures with and without noise were subjected to the same tests. There is no preprocessing involved in the creation of these pictures. The face95 database included ten pictures of faces with no noise, which were examined. Figure 3 shows the face pictures from the standard dataset that are free of noise. Figure 4 depicts the RGB colour components of pictures of people's faces. Image of the query is shown in Figure 5, and image of the question is shown in Figure 6. Image of the query is shown in Figure 6. Figure 4 illustrates the query and output face picture. If the query face picture is not included in the dataset, the face will not be identified, as shown in figure 2. Figure 5 depicts the face pictures of the local pose variations dataset (LPVDSet) that do not include any noise, as well as the RGB colour components of the LPVDSet.

5. CONCLUSION

Feature extraction from face pictures is accomplished using the standard method SDA, and classification of the feature vector of face images and query face images is accomplished using the MLP, which is a classifier. In order to train the network, the MLP NN classifier is utilised. Recognizability preparation and performance calculation are completed by the network. The second experiment, which involves identifying human faces from pictures captured with a digital camera, is a difficult job since these faces are typically motionless and distorted by different sounds and blurring effects, as is the case with most digital camera images. Facial blur affects cause the effectiveness of face recognition systems to deteriorate when there are blur effects on the faces. The face is reconstructed using a new technique for blur effects, which is then used as an input to the TLFF NN. The network is trained with the help of the classifier TLFF NN. After the network has been trained and is ready for recognition, it is possible to calculate its performance.

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