Data Retrieval System Based on Facial Features

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Abstract- *Face is a complex multidimensional structure and needs a good computing technique for recognition. An ideal face contains various facial feature e.g. eyes, nose, mouth, eyebrow. In this project face recognition is done by Local Binary Pattern Histogram (LBPH). Local Binary Pattern Histogram (LBPH) is a robust method used as feature extraction techniques for face recognition. LBPH is one of the easiest face recognition algorithms. The basic form of the LBHP is to minimize the dimensionality of the data set that consist of a large number of the correlated variables, while maintain as possible of the variation present in the set of data.*

It can represent local features in the images. Face will be categorized as known or unknown face after matching with the present database. If the user is new to the face recognition system then his/her template will be stored in the database and also all his documents will be stored in another database. If the user is a registered user then we can retrieve his/her documents using face recognition.

Keywords- Local Binary Pattern Histogram (LBPH)., Face Recognition, Correlated Variable.

I. INTRODUCTION

Face detection has been regarded as the most complex and challenging problem in the field of computer vision, due to the large intra-class variations caused by the changes in facial appearance, lighting, and expression. Such variations result in the face distribution to be highly nonlinear and complex in any space which is linear to the original image space. Moreover, in the applications of real life surveillance and biometric, the camera limitations and pose variations make the distribution of human faces in feature space more dispersed and complicated than that of frontal faces. It further complicates the problem of robust face detection.

Face detection techniques have been researched for years and much progress has been proposed in literature. Most of the face detection methods focus on detecting frontal faces with good lighting conditions. According to Yang's survey, these methods can be categorized into four types: knowledge-based, feature invariant, template matching and appearance-based.

- Knowledge-based methods use human-coded rules to model facial features, such as two symmetric eyes, a nose in the middle and a mouth underneath the nose.
- Feature invariant methods try to find facial features which are invariant to pose, lighting condition or rotation. Skin colors, edges and shapes fall into this category.
- Template matching methods calculate the correlation between a test image and pre-selected facial templates.

1.1.1 Mean

Mean is most basic of all statistical measure. Means are often used in geometry and analysis; a wide range of means have been developed for these purposes. In contest of image processing filtering using mean is classified as spatial filtering and used for noise reduction.This filter is known to retain image detail better than the arithmetic mean filter. Moreover, for some distributions the mean is finite and for some the mean is infinite.

1.1.1.1 Arithmetic Mean

The arithmetic mean filter, also known as averaging filter, operates on an sliding 'm×n' window by calculating the average of all pixel values within the window and replacing the center pixel value in the destination image with the result. Its mathematical formulation is given as follows:

$$f(x,y) = \frac{1}{mn} \sum_{(r,c)\in W} g(r,c)$$

Where 'g' is the noisy image, f(x,y) is the restored image, and 'r' and 'c' are the row and column coordinates respectively, within a window 'W' of size 'm×n' where the operation takes place.

The arithmetic mean filter causes a certain amount of blurring (proportional to the window size) to the image, thereby reducing the effects of noise. It can be used to reduce noise of different types, but works best for Gaussian, uniform, or Erlang noise .

1.1.1.2 GeometricMean

The geometric mean filter is a variation of the arithmetic mean filter and is primarily used on images with Gaussian noise. This filter is known to retain image detail better than the arithmetic mean filter. Its mathematical formulation is as follows:

$$f(x,y)=\left[\prod_{(r,c)\in W} g(r,c)\right]^{1/mn}$$

1.1.1.3 Harmonic Mean

The harmonic mean filter is yet another variation of the arithmetic mean filter and is useful for images with Gaussian or salt noise. Black pixels (pepper noise) are not filtered. The filter's mathematical formulation is as follows:

$$f(x,y)=\frac{mn}{\sum_{(r,c)\in W}\left(\frac{1}{g(r,c)}\right)}$$

1.1.1.4 Contra Harmonic Mean

The contra-harmonic mean filter is another variation of the arithmetic mean filter and is primarily used for filtering salt or pepper noise (but not both). Images with salt noise can be filtered using negative values of R, whereas those with pepper noise can be filtered using positive values of R.

The filter's mathematical formulation is

$$f(x,y)=\frac{\sum_{(r,c)\in W}\left(g(r,c)\right)^{R+1}}{\sum_{(r,c)\in W}\left(g(r,c)\right)^{R}}$$

Where R is the order of filter.

1.1.2 Standard Deviation (σ)

It is a most widely used measure of variability or diversity used in statistics. In terms of image processing it shows how much variation or "dispersion" exists from the average (mean or expected value). A low standard deviation indicates that the data points tend to be very close to the mean, whereas high standard deviation indicates that the data points are spread out over a large range of values. Mathematically standard deviation is given by

$$\tilde{f}(x,y)=\sqrt{\frac{1}{mn-1}\sum_{(r,c)\in W}\left(g(r,c)-\frac{1}{mn-1}\sum_{(r,c)\in W} g(r,c)\right)^2}$$

A standard deviation filter calculates the standard deviation and assigns this value to the center pixel in the output map. As it has capability in measuring the variability, it can be used in edge sharpening, as intensity level get changes at the edge of image by large value. Standard deviation filters can be useful for radar images. The interpretation of radar images is often difficult: you cannot rely on spectral values because of back scatter (return of the pulse sent by the radar). This often causes a lot of 'noise'. By using a standard deviation filter, you may be able to recognize some patterns.

In most image processing problems, features are extracted from the images before processing. Working with rough images is not efficient in face authentication, several images of a single person may be dramatically different, because of changes in viewpoint, and illumination, or simply because the person's face looks different from day to day. One of the methods often used to extract features in face authentication is PCA (Principal Component Analysis) which was revolving regards to theoretical research in face recognition. The PCA method used the first clean vectors of the covariance matrix of the training data.

In this, we show how the method proposed improves the success rate compared to an equivalent system using PCA. The method is simple the face image is collected by a camera. The subject can arise in front of this one and according to the technique used; the system extracts the characteristics from the face to make the comparison with the characteristics of the claimed person which are preserved in a data base.

Choosing the best threshold is an important part of the problem: a too small threshold will lead to a high False Rejection Rate (FRR), while a too high one will lead to a high False Acceptance Rate (FAR). FRR and FAR are defined as the proportion of feature vectors extracted from images in a validation set being wrongly classified, respectively wrongly authentified and wrongly rejected. One way of setting the threshold is to choose the one leading to equal FRR and FAR. If the a priori probabilities of having false acceptances (impostors) and false rejections are equal. We use the global threshold leading to FRR = FAR

III. EXISTING METHOD

3.1 INTRODUCTION

One of the simplest and most effective PCA approaches used in face recognition systems is the so-called eigenface approach. This approach transforms faces into a small set of essential characteristics, eigenfaces, which are the main components of the initial set of learning images (training set). Recognition is done by projecting a new image in the eigenface subspace, after which the person is classified by comparing its position in eigenface space with the position of known individuals.

PCA is a useful statistical technique that has found application in fields such as face recognition and image compression and is a common technique for finding patterns in data of high dimension.It covers standard deviation, covariance, eigenvectors and eigenvalues. This background knowledge is meant to make the PCA section very straight forward but can be skipped if the concepts are already familiar.

The advantage of this approach over other face recognition systems is in its simplicity, speed and insensitivity to small or gradual changes on the face. The problem is limited to files that can be used to recognize the face. Namely, the images must be vertical frontal views of human faces. The whole recognition process involves two steps:

A. Initialization process
B. Recognition process

The principal component analysis (PCA) is a linear mathematical method to data analysis, the rules is to seek the directions of axes which maximizes the variance of the data and minimizes the variation squared compared to the axes.
In the case of face recognition, we regard the set of the faces images of training as a set of a random vectors (matrix of faces vectors), where each vector face is consisted the sequence of the lines or the columns of a face image. The PCA is applied to this matrix of the faces vectors. It primarily consists in carrying out a reduction of dimensionality by coding the faces in a new base formed by the first clean vectors (Eigen Faces) coming from the calculation of the PCA.

An important property of PCA is its optimal signal reconstruction in the sense of minimum mean square error when only a subset of principal components is used to represent the original signal. Following this property, an immediate application of PCA is dimensionality reduction.

3.2 APPLICATION TO COMPUTER VISION

3.2.1 Representation

When using these sorts of matrix techniques in computer vision we must consider representation of images. A square, by image can be expressed as an dimensional vector where the rows of pixels in the image are placed one after the other to form a one dimensional image.

E.g. the first elements will be the first row of the image, the next elements are the next row, and so on. The values in the vector are the intensity values of the image, possibly a single grayscale value.

3.2.2 PCA to Find Patterns

Say we have 20 images. Each image is pixels high by pixels wide. For each image we can create an image vector as described in the representation section. We can then put all the images together in one big image-matrix like this which gives us a starting point for our PCA analysis. Once we have performed PCA, we have our original data in terms of the eigenvectors we found from the covariance matrix. Why is this useful? Say we want to do facial recognition, and so our original images were of people's faces.

3.3 PCA FOR IMAGECOMPRESSION

Using PCA for image compression also known as the Hostelling, or Karhunen and Leove (KL), transform. If we have 20 images, each with pixels, we can form vectors, each with 20 dimensions. Each vector consists of all the intensity values from the same pixel from each picture. This is different from the previous example because before we had a vector for image, and each item in that vector was a different pixel, whereas now we have a vector for each pixel, and each item in the vector is from a different image.

Now we perform the PCA on this set of data. We will get 20 eigenvectors because each vector is 20-dimensional. To compress the data, we can then choose to transform the data only using, say 15 of the eigenvectors. This gives us a final data set with only 15 dimensions, which has saved us of the space. This compression technique is said to be lossy because the decompressed image is not exactly the same as the original, generally worse.

3.4 GENERALIZATIONS

3.4.1 Nonlinear Generalizations

Most of the modern methods for nonlinear dimensionality reduction find their theoretical and algorithmic roots in PCA or K-means. Principal curves and manifoldsgive the natural geometric framework for PCA generalization and extend the geometric interpretation of PCA by explicitly constructing an embedded manifold for data approximation, and by encoding using standard geometric projection onto the manifold.

See also the elastic map algorithm and principal geodesic analysis. Another popular generalization is kernel PCA, which corresponds to PCA performed in a reproducing kernel Hilbert space associated with a positive definite kernel. These generalizations are very simple but also non-linear.

3.4.2 Multi Linear Generalizations

In multi linear subspace learning, PCA is generalized to Multi linear PCA (MPCA) that extracts features directly from tensor representations. MPCA is solved by performing PCA in each mode of the tensor iteratively. MPCA has been applied to face recognition, gait recognition, etc. MPCA is further extended to uncorrelated MPCA, non-negative MPCA and robust MPCA.

3.4.3 Higher Order

N-way principal component analysis may be performed with models such as Tucker decomposition, PARAFAC, multiple factor analysis, co-inertia analysis, STATIS, and DISTATIS.

3.4.4 Robustness-Weighted PCA

While PCA finds the mathematically optimal method (as in minimizing the squared error), it is sensitive to outliers in the data that produce large errors PCA tries to avoid. It therefore is common practice to remove outliers before computing PCA. However, in some contexts, outliers can be difficult to identify. For example, in data mining algorithms like correlation clustering, the assignment of points to clusters and outliers is not known beforehand. A recently proposed generalization of PCAbased on a weighted PCA increases robustness by assigning different weights to data objects based on their estimated relevancy.

3.4.5 Sparse PCA

A particular disadvantage of PCA is that the principal components are usually linear combinations of all input variables. Sparse PCA overcomes this disadvantage by finding linear combinations that contain just a few input variables.

3.5 SIMILAR TECHNIQUES

3.5.1 Independent Component Analysis

Independent component analysis (ICA) is directed to similar problems as principal component analysis but finds additively separable components rather than successive approximations.A recently proposed generalization of PCAbased on a weighted PCA increases robustness. The independent analysis was taken to measure the distance between the main parts of the face. This is because the independent parts are taken the key role for measuring the distance in PCA.

3.5.2 Network Component Analysis

Given a matrix, it tries to decompose it into two matrices such that. A key difference from techniques such as PCA and ICA is that some of the entries of are constrained to be 0. Here is termed the regulatory layer. While in general such decomposition can have multiple solutions, they prove that if the following conditions are satisfied

1. A has full column rank
2. Each column of A must have at least L-1zeroes where L is the number of columns of A (or alternatively the number of rows of P). The justification for this criterion is that if a node is removed from the regulatory layer along with all the output nodes connected to it, the result must still be characterized by a connectivity matrix with full column rank.
3. P must have full row rank.

Then the decomposition is unique up to multiplication by a scalar.

IV. PROPOSING METHOD

4.1 PROPOSED METHODOLOGY

When a large collection of numbers is assembled, we are usually interested not in the individual numbers, but rather in certain descriptive quantities such as the average or the median. In general, the same is true for the image of face. So we shall discuss two such descriptive quantities the mean and Standard Deviation. The proposed approach has followed the fusion of feature extraction by ordered mean values with feature extraction using partial transform coefficients.

Algorithm is based on color histogram. Statistical measurements Mean and standard deviation are computed in histogram. Before applying histogram, Laplacian filter is applied for noise removal. The block diagram of algorithm is show in Figure 4.1

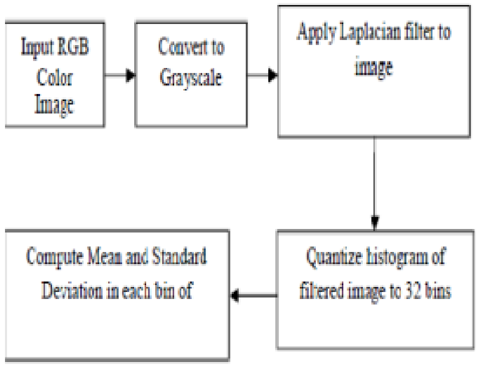

Fig.4.1 Block diagram for Feature extraction of algorithm

Method consists of the following

Steps

1. The input RGB image is acquired and converted into grayscale image.
2. Apply Laplacian filter to grayscale image. The Laplacian filter uses a mask w of 3*3 with -4 at the center. Let f is a histogram equalized image and g is the filtered image. During filtering some information are lost and to restore lost information,Laplacian image is subtracting from original image histogram equalized image such that g1=f-g, to get g1 enhanced image. The filtration process is shown in Figure 4.2.

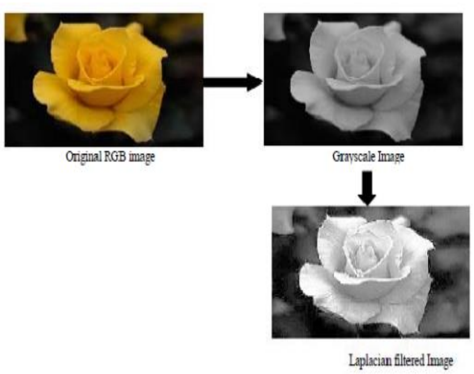

Fig.4.2: Filtration process of algorithm

The principal of this system is the extraction of a feature vector of an individual, in order to compare it with a vector Yi which contain the feature of this same individual extracted starting from his images which are stored in a data base.Also we can use the standard deviation for detecting the components of human face like eyes, mouth and nose which are located at the maxima of the standard deviation and the figure 4 explain this idea clearly.

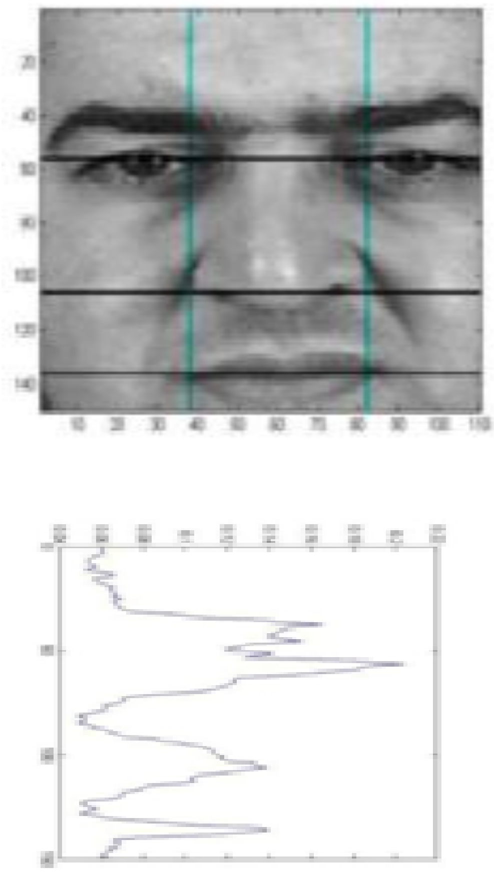

Fig.4.6: Image of face and its Vertical Standard deviation

Detection of eyes, mouth and nose of a human face by the standard deviation of each row and columns of the image. We observe that this method is very interesting and easy and faster for searching the position of different parts of the face image.

V. RESULTS

5.1 EXPERIMENTAL RESULTS

5.1.1 Database XM2VTS

Our experiments were carried out on frontal face images of the data base XM2VTS. The principal choice of this data base is its big size, with 295 people and 2360 images in total and its popularity, since it became a standard in the audio and visual biometric community of multimodal checking of identity. For each person eight catches were carried out in four sessions distributed for five months.

The protocol of Lausanne shares the data base in three sets:

The set of training (training): it contains information concerning the known people of the system (only clients)

The set of evaluation (validation): allows fixing the parameters of the face authentication system.

The set of tests: allows to test the system by presenting images of people to him being completely unknown to him.
For the class of impostors, 95 impostors are divided in two sets: 25 for the set of evaluation and 75 for the set of tests. The sizes of the various sets are included in table.

Table 5.1: Photos distribution in various sets

Set	Clients	Imposters
Training	600 (3 by subject)	0
Evaluation	600 (3 by subject)	200 (8by subject)
Test	400 (2 by subject)	400 (8by subject)

The next figure represents some examples of faces in the data base XM2VTS, the people are of the two sexes and various ages.

Fig. 5.1: Represents some examples of faces images in the data base XM2VTS.

5.1.2 Pretreatment

By looking at the images we clearly note the appearance of characteristics not desired on the level of the neck, like the collars of shirt, the sports shirts, etc. In addition, the hair is also a characteristic changing during the time (change of cut, colour, baldness...). The background appears on the images, it is used for nothing, and inflates the size of the data unnecessarily.

Finally, the ears cause also a problem. Indeed, if the person presents herself slightly differently in front of the camera (rotation), we can see only one ear. This is why we decided to cut the image vertically and horizontally and to keep only one window of size 150x110 cantered on the face.

The background appears on the images; it is used for nothing and inflates the size of the data unnecessarily. Finally, the ears cause also a problem. Indeed, if the person presents herself slightly differently in front of the camera (rotation), we can see only one ear.In the year 2000 a competition on the Xm2vts database along with the Lausanne protocol was carried out.

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Fig. 5.2: The image before (a) and after (b) Cutting

Afterwards, we apply a photo normalization. That wants quite simply to say that for each image, we withdraw from each pixel the average value of those on the image, and that we divide those by their standard deviation. Finally, we make standardization. The photo normalization acts on an image whereas standardization acts on a group of images (for each component, one withdraws the average of this component for all the images and one divides by the standard deviation).For each person eight catches were carried out in four sessions distributed for five months. The background appears on the images; it is used for nothing and inflates the size of the data unnecessarily.

This method effectively reduces the time require for the face detection process and gets higher speed and accuracy than previous algorithms. The method based on OpenCV comes true under the open source vision library. In order to overcome the limitations which can only be achieved the method in the C/C++ environment, we use the native method interface provided by SUN Company and transplant it to the Java platform. We can apply this method to the Android etc. or the embedded operating system using Java as the developing language after improved. The proposed method improves the speed and maintains a higher availability at the same time. We conduct experiments on the PC, the results of the detection rate reaching to 94.28%.

5.2 ADVANTAGES

1. Increase in Accuracy.
2. Training the data base requires less time
3. Output occurs with in milli seconds.
4. Data can be retrieve along with image.

5.3 APPLICATIONS

1. This is used in digital libraries, crime prevention.
2. This can be widely used in colleges and military data base.
3. This can be used in Medicine and Historical research.

VI. CONCLUSION

In this, new technique for image feature extraction and representation was developed. The MS method has many advantages over conventional PCA. In the first place, since MS method based in mean and standard deviation of the image, it is simpler and faster than PCA which involves calculating the eigenvectors of a big covariance matrix. Second, it is better to use for authentication systems of face in terms of success rate. Third, MS method didn't need memory than PCA which need a memory for the matrix of projection. But the difficulty caused by illumination variation, facial expression and aging are still exists for the MS method like PCA.

VII. FUTURE SCOPE

In further works, we propose the use of colour to improve the performance of this system. For wider assistance, we can connect web link server to the program to search through internet. The future work will focus on multi person naming task and thereby increasing efficiency and accuracy of result.In the future, 2D & 3D Face Recognition and large-scale applications such as e-commerce, digital driver licenses, or even national ID is the challenging task in face recognition & the topic is open to further research.

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