Face and Gender Recognition Using Principal Component Analysis

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***Abstract*— Face recognition is a biometric analysis tool that has enabled surveillance systems to detect humans and recognize humans without their co-operation. In this paper we evaluate the basics of the Principal Component Analysis (PCA) and verify the results of this algorithm on a training database of images. The same principle is in effect used to recognise the gender of the test image by evaluating the Euclidian distance of the test image from the images in the database. The proposed gender and face recognition technique using PCA is verified for both test images of a man and a woman. It was observed that if the number of images of a particular subject was more in the database, the gender recognition becomes even better. The effect of salt and pepper noise and image cropping was also observed and the results hold true for noise up to 40 percent of the image pixels.**

Keywords- Face Recognition, Gender Recognition, Principal Component Analysis, Eigenfaces, noise, cropping.

I. INTRODUCTION

The human brain has the ability to recognize faces in cluttered scenes with relative ease, the ability to identify distorted images, coarsely quantized images, and faces with occluded details. Emulating this unique ability of humans is what we term as machine recognition of faces.

Face recognition is emerging as an active research area spanning several disciplines such as image processing, pattern recognition, computer vision and neural networks. Face recognition technology has numerous commercial and law enforcement [17] applications that range from static matching of controlled format photographs such as passports, credit cards, photo ID's, driving licenses and mug shots to real time matching of surveillance video images.

Within today's environment of increased importance of security and organization, identification and authentication methods have developed into a key technology. Such requirement for reliable personal identification in computerized access control has resulted in the increased interest in biometrics [7].

Biometric characteristics and traits are divided into behavioural or physical categories. Behavioural biometrics encompasses such behaviours as signature and typing rhythms [15]. Physical biometric systems use the eye [8], finger [9], hand [9], voice [10] and face [9], for identification. Fingerprints are unique to each human being. It has been observed that the iris of the eye, like fingerprints, displays patterns and textures unique to each human and that it remains stable over decades of life. Speech recognition also offers one of the most natural and less obtrusive biometric measures, where a user is identified through his or her spoken words.

While appropriate for bank transactions and entry into secure areas, such technologies have the disadvantage that they are intrusive both physically and socially. They require the user to position their body relative to the sensor, then pause for a second to declare himself or herself.

A face recognition system would allow user to be identified by simply walking past a surveillance camera. Human beings often recognize one another by unique facial characteristics. Facial recognition is becoming the most successful form of human surveillance. There are two predominant approaches to face recognition: geometric (feature based) and photometric (view based). The most widely and commonly used algorithm for face recognition is the Principal Component Analysis (PCA) [1], [16].

The techniques used for face recognition are either geometrically oriented [11] or photometric based [12] in nature. The technique that is most commonly used for face recognition is the Principal Component Analysis approach. This technique classifies images in the form of eigenfaces. The test image is reconstructed using the eigenfaces obtained. Even if the test image is not from the training set, it can to a very large extent guess the closest looking image in the database. Moreover, this technique can also be used for image compression purposes as it effectively de-correlates the image data.

Almost all the modern face recognition algorithms use the Principal Component Analysis approach as the starting point for dimensionality reduction. Principal Component Analysis proves to be the most robust and novel algorithm for face recognition and this can be verified by the fact that almost every other face algorithm such as the Linear Discriminant Analysis and the Gabor filter approach make use of the Principal Component Analysis [16] for dimensionality reduction.

II. Principal Component Analysis [3], [8], [5]

Given a database of images, the task of a face recognition system is to show that the test image belongs to a person in the database. Every image is random in nature because the lighting conditions, arrangement of eyes, facial features, hair, spectacles, moustache as well as orientation is different for different people. However, statistical characterization can still be carried out on this random set. The important aspect to realize is that in every image, there are patterns repeated in the facial domain. There will always be certain features like the set of eyes, nose, mouth and their relative distances which help classify a face. These characteristic features are called the principal components or the eigenfaces.

They can be extracted out of original image data by means of a mathematical tool called Principal Component Analysis (PCA) [6]. By means of PCA one can transform each original image of the training set into a corresponding Eigen face. An important feature of PCA is that one can reconstruct any original image from the training set by combining the eigenfaces [3].

The original face image can be reconstructed from eigenfaces if all the eigenfaces (features) are added in the right proportion. Each Eigen face represents only certain features of the face, which may or may not be present in the original image.

If the feature is present in the original image to a higher degree, the share of the corresponding Eigen face in the "sum" of the eigenfaces should be greater. If, contrary, the particular feature is not (or almost not) present in the original image, then the corresponding Eigen face should contribute a smaller (or not at all) part to the sum of eigenfaces. So, in order to reconstruct the original image from the eigenfaces, one has to build a kind of weighted sum of all eigenfaces. That is, the reconstructed original image is equal to a sum of all eigenfaces, with each Eigen face having a certain weight. This weight specifies, to what degree the specific feature (Eigen face) is present in the original image.

If one uses all the eigenfaces extracted from original images, one can reconstruct the original images from the eigenfaces exactly. But one can also use only a part of the eigenfaces. Then the reconstructed image is an approximation of the original image. However, one can ensure that losses due to omitting some of the eigenfaces can be minimized. This happens by choosing only the most important features (eigenfaces). Omission of eigenfaces is necessary due to scarcity of computational resources.

Thus, to sum up, the jobs which the PCA technique can do are prediction, redundancy removal, feature extraction and data compression.

A. *Mathematical approach of the PCA [5]*

Assume that the facial image is a two-dimensional image. It is first converted into a one-dimensional vector by concatenating the rows and columns. Suppose we have M vectors each of size N (rows * columns) representing a set of sampled images. Let 'p_j' represent the values of the pixels.

$$xi = [\ p1,p2,p3,p4,\ldots,pN\ ]\ ;\ i = 1,2,3,4,\ldots M. \quad (1)$$

The images are then mean centred by subtracting the mean image from each image vector. Let m represent the mean image:

$$m= (1/M)*(\sum xi) \quad (2)$$

Let wi be the mean centred image:

$$w_i = x_i - m \quad (3)$$

The goal is to find the values of ei's which have the largest possible projection onto each of the wi's. The purpose is to find M orthonormal vectors ei for which the quantity

$$\lambda i = (1/M) \sum(ei^T*w_n)2 \quad (4)$$

is normalised with the orthonormality constraint:

$$e_l^T*e_k = \delta_{lk} \quad (5)$$

The values of e_i's and λ_i's are calculated from the Eigen vectors and the Eigen values of the covariance matrix:

$$C = W*W^T \quad (6)$$

W is a matrix formed by the column vectors w_i places side by side. The size of the covariance matrix is enormous (N*N). It is not possible to solve for eigenvectors directly. In mathematics, there are areas where one needs to find the numbers λ and the vectors v that satisfy the equation where A is the square matrix:

$$Av=\lambda v \quad (7)$$

Any λ satisfying the above equation is the Eigen value of A. The vector v is called the eigenvector of A. The Eigen values and eigenvectors are obtained by solving the equation:

$$[A - \lambda I] = 0 \quad (8)$$

For every λ, we calculate the corresponding eigenvectors and then normalise them. The eigenvectors are then sorted in the ascending order. This gives us the final KL Transform matrix. The covariance matrix of the final transformed image will have the Eigen values as their diagonal elements. Moreover, the mean of the final image would be zero.

B. *Practical approach of the PCA[3]*

The first step is to create a database of images of different people. The database considered in this case is the "Face Recognition Database, University of Essex, UK," by Dr. Libor Spacek. The images will exhibit different variations in the positioning of the head, the hair, the light content, the contrast, the skin colour and the expressions of the people.

Figure 1. Training Images Database for Men with varying conditions of the background and facial features

Figure 2. Training Images Database for Women with varying conditions of the background and the facial features

Because the system we design is inherently acting as a means for face and gender recognition, we split the original database into the database of Men and database of Women. To remove the effect of variations to some extent, the images are mean centred i.e. the mean of all images is calculated and the corresponding images in the database are normalized with respect to each other. Normalization is done in the RGB domain. Hence, we obtain three different images for the same database image normalised.

Figure 3. Normalised Training Images Database for Men are also referred to as the zero mean images. Three images represent the normalisation in the R, G and B plane.

These can also be considered the zero-mean images. Figure 3 shows only some of the normalized images for the database of Men. The important step is that normalisation of both the databases is to be done together and not separately to obtain a common mean and standard deviation for all the training images. Each such normalized image is then used to calculate the mean image.

Figure 4. Mean Image for Men and Women created from the respective database images.

The next step involves generation of eigenfaces. The covariance matrix is evaluated from the image matrix by concatenating the rows and columns. This covariance matrix actually evaluated the amount by which neighbouring signals are related to each other. Since, the mean is zero (as the images are mean centred), the correlation is the same as the covariance. Hence, the next step involves solving the covariance matrix.

The solution of this matrix is done using basic linear matrix operations. The solutions obtained are referred to as the Eigen values. For every Eigen value, there is a corresponding eigenvector. These eigenvectors are then normalized. Each such Eigen value generates an Eigen face. The first few eigenfaces are shown in figure 5. The eigenvectors are sorted from high to low according to their corresponding Eigen values. The eigenvector associated with the largest Eigen value is the one that reflects the largest variance in the image.

Figure 5. First few Eigen faces for Men

Each Eigen face contributes to reconstruct the test image. The weight of the input face is the amount of contribution from each Eigen face to the test image. For both Men and Women database, the weights are evaluated. Figure 6 shows the evaluation for the Men's database. At the same time, the test image is given as an input. This test image must have the same number of pixels as the training images.

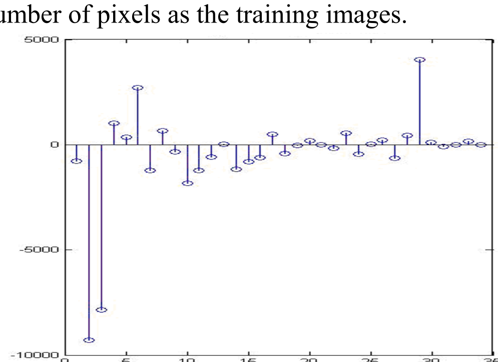

Figure 6. Weight of the Eigen Faces for the Men database

Figure 7 shows the test image considered for analysis.

Figure 7. Test Input Image having same number of pixels as the database images.

The test image is then reconstructed considering the entire training set. The reconstructed image for both the databases is as shown in figure 8.

Figure 8. Reconstructed Image using Men's database

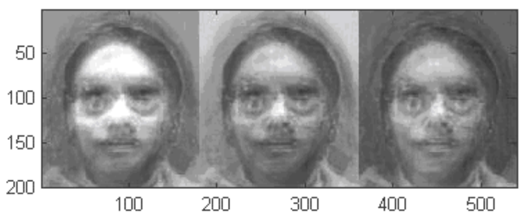

Figure 9. Reconstructed Image using Women's database

In figure 8, the reconstructed image bears a high amount of resemblance with the test image. The Euclidian distance evaluates the difference between the reconstructed image and the training images. The Euclidian distance actually evaluates how far the KL transformed matrix of the test image is from the KL transformed matrix of each of the database images. Thus, in effect, it evaluates how close the reconstructed image from all the database images is. Hence, ideally, the most similar face will have the smallest Euclidean distance. This is verified by the plot shown in the figure for the Men's database.

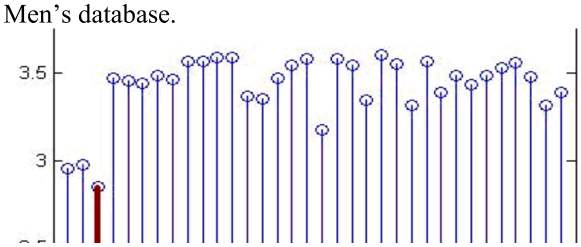

Figure 10. Euclidian Distance of the input image in Men's database obtained by drawing a relation between the Eigen vector values and the reconstructed image

As can be seen in the plot shown in figure 10, the Euclidian distance is the least for the training image number 3 and its value is 2.8496 units. This indicates that the test image corresponds to the image of the person who was numbered as 3 in the database. The same evaluation can be done for the Woman's database. As shown in figure 11. In this case, the minimum Euclidian distance is 3.1277 units. Thus, the Euclidean distance is more when the test image is evaluated using the women's database. The difference in the values of the minimum Euclidian distance in both the databases is 0.27810 units.

Using this, we can conclude that the test image is that of a man. The amount of difference between the values of the minimum Euclidian distances in both the databases is a function of the number of images of the particular subject. For the same test image, if two more images of the subject are introduced into the woman's database, the difference increases. The rate of change of the difference depends on the amount of effect the introduced images have on the mean and the standard deviation of the entire database.

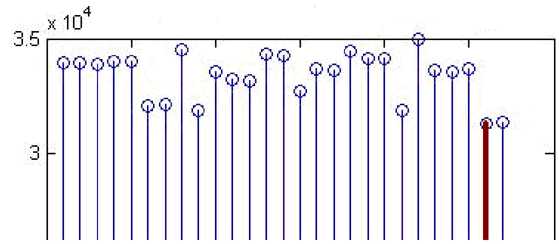

Figure 11. Euclidian Distance of the input image in Women's database obtained by drawing a relation between the Eigen vector values and the reconstructed image.

Noise can get introduced in images due to several reasons and the effect of this noise must also be countered by the algorithm. In the case of our algorithm, the effect of introducing the noise does not affect the final result until about 40 percent of the pixels of the test image are noisy. Even under such conditions, gender recognition still holds true. The gender recognition continues to remain true until the noise percentage is 60.

Moreover, Image cropping techniques are also employed and we have checked our approach for cases where the effect of a moustache is to be neutralised. We have been successful in doing so without significantly changing the results. Figure 12 shows the test image.

Figure 12. Test image having 10 percent 'salt and pepper' noise and in which cropping is done to normalise the effect of a moustache.

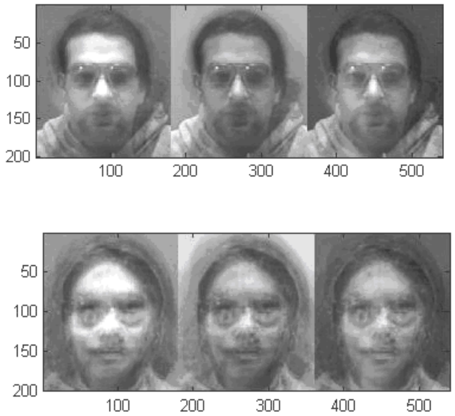

Figure 13. Reconstructed image using men's database and women's database.

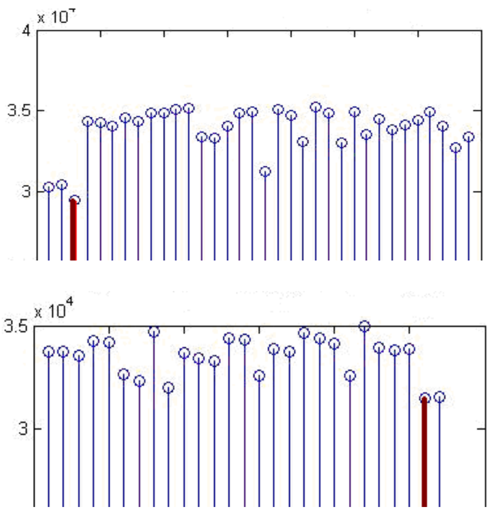

Figure 14. Euclidian Distance of the input image in Men's and Women's database obtained by drawing a relation between the Eigen vector values and the reconstructed image.

In this case, the difference between the two minimum values is less. The minimum Euclidian distances evaluated in this case are 2.9456 units for men's database and 3.1473 units for women's database.

In this case, the minimum Euclidian distance difference between the men's database and the women's database reduces. Its value becomes 0.20162 units. However, the gender and the face are properly recognized and reconstructed. Although detection of face depends on exactness of the minimum values, gender recognition is based only on comparison of the values. Hence, gender recognition would hold true for even large amount of noise being introduced.

There can be two issues that crop up while evaluating the face recognition capability of the PCA approach. The first being evaluating whether the given test image is a face or not. This defect is easily overcome by using the first Eigen face which acts as a filter and can evaluate whether the image is highly correlated with it. Smaller correlations can be directly rejected.

Second issue could be that the test image is not from the database. If the image is from the database, then its reconstruction error will be very small. However, if not from the training set, the reconstruction error would be large. A threshold value can be set to evaluate such faces.

The essence of Principal Component Analysis lies in creating a linear sub-space in which the variance of random data can be minimized by using the correlation properties of the data [6].

III. CONCLUSION

The Principal Component Analysis approach can effectively be used for the purpose of Face Recognition and Gender Recognition. The advantage of using this technique is the simplicity and the high probability of obtaining the correct results.

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