PSEUDO-FISHERFACE METHOD FOR SINGLE IMAGE PER PERSON FACE RECOGNITION

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ABSTRACT

The problem of recognizing a face from a single sample available in a stored dataset is addressed. A new method of tackling this problem by using the Fisherface method on a generic dataset is explored. The recognition scheme is also extended to multiscale transform domains like wavelet, curvelet and contourlet. The proposed method in the transform domain shows better recognition errors than the SPCA algorithm and Eigenface Selection method, both of which are specially tailored for recognizing faces from single samples.

Index Terms— Face Recognition, Fisherface, Curvelet, Contourlet

1. INTRODUCTION

Face Recognition is one of the few biometric technologies that is non-intrusive. It has a variety of potential applications in information security, law enforcement and surveillance, smart cards, access control etc. For this reason, Face Recognition has received significantly increased attention from both the academic and industrial communities during the last couple of decades. The aim is to identify or verify one or more persons from still images or video images of a scene using a stored database of faces.

Most face recognition methods that exist today, depend on a stored set of multiple facial images of each individual (called training set) before a new image (test image) of that individual can be identified. These techniques fail when a single sample is available in the stored dataset. However in many real world applications like mug-shot database matching, identity authentication, access control, information security, and surveillance, only one image of each person is available. To address this problem, new methods have been developed in recent years.

In this paper we propose a new method that uses a generic face dataset for recognizing faces when only a single prior sample of the individual is available. In the following section we will discuss briefly some of the related work that has been done so far. In section 3 we will describe our proposed recognition method. In section 4 we will discuss the results. In section 5, the conclusions are summarized.

2. REVIEW OF LITERATURE

In [1] the single image per person face recognition methods have been broadly classified into two groups: Holistic methods and Local methods.

Holistic methods address the face recognition problem in two ways. The first tries to obtain as much information as possible from the single face image in the database, either in the high dimensional face space or more commonly, in the dimensionality-reduced eigenspace. Examples of the latter are $(PC)^2A$ [2], Enhanced $(PC)^2A$ [3], Singular Value Perturbation [4] and 2DPCA [5]; all use extensions of the Principal Component Analysis (PCA) method to recognize faces from single images.

The second approach enlarges the available dataset by artificially constructing novel views for each of the prior available images. In [6-8] the database of single training images are extended by synthesizing new facial images, and then by applying standard face recognition techniques on the enlarged dataset. Also $E(PC)^2A$ and the Singular Value Perturbation methods, mentioned above, can be used to generate new training images for enlarging the dataset.

Local methods are subdivided into local feature based methods and local appearance based methods. Early local feature based methods used distinguishing facial features like width of the head, distance between eyes etc. for recognizing faces. In later feature based techniques, topological graphs were constructed based on face images and the face recognition was formulated as a graph matching problem.

Local appearance based methods define local regions on the face images; the regions may be rectangular elliptical or strips. PCA, LDA or texture measures are used on these local regions for feature extraction. The information from different regions is finally combined for recognition.

In a recent work [9], Wang et al departed from the traditional methods of recognizing face images from single samples. They used a generic face dataset that contained multiple facial samples for each person. This is not impossible to collect as standard face databases having multiple samples of each person are easily available. Their method was based on finding the principal components of the generic face dataset in such a way, that not only the intersubject variation but also the intrasubject variation is maximized. The selection procedure was developed on the generic dataset. When addressing the problem at hand, that of recognizing faces when only a single sample is available, the selection procedure previously developed, was applied to each image available in the stored dataset. The test samples were also subjected to the same selection procedure. Finally the test sample was classified by finding its nearest neighbour in the training set. Their method was named Eigenface Selection.

3. RECOGNITION PROCEDURE

Our work was motivated by [9] and is based on the assumption that a feature selection procedure, which can find good discriminating features for a given set of faces, will find good features for any other new face as well. Their work was based on an eigenface approach. Since standard eigenface techniques depend on the principal component analysis, which tends to find a subspace whose basis vectors correspond to the maximum variance direction in the original image space, it does not take into account the inter subject discrimination among the classes. For this reason, the original eigenface method was modified in [9] by selecting eigenfaces in such a way that the variation among classes is also maximized. Our approach involves a less complicated method for maximizing the intersubject variation. We use the Fisherface technique which is based on linear discriminant analysis and is known to find those vectors in the subspace provides best inter and intra subject discrimination.

We will employ the Fisherface technique to obtain the best discriminating features within classes. But Fisherface techniques require multiple samples in each class which we do not have. For our problem we have only a single prior sample (facial image) for each class (person). As in [9] we bypass this problem by collecting a generic face dataset that is different from the face images that we already have as our training set. This face dataset will have multiple face samples of each person. We then apply Linear Discriminant Analysis (LDA) to this generic face dataset to arrive at a fisher subspace which contains vectors that best discriminates the faces within the given dataset. The transformation matrix that maps the original image space to the Fisher subspace may be regarded as the feature selection procedure that best finds the distinguishing features in a given face dataset. As per our assumption, this transformation matrix can be used for selecting good discriminating features from other faces as well.

For the next step we use the same transformation matrix (obtained by applying LDA on the generic dataset) to find the discriminating features for each image our training set: the set where we have only a single facial image for each person. This will not be a problem since it only requires a matrix multiplication of each facial image with the transformation matrix to arrive at a dimensionality-reduced subspace that corresponds to that image. We do the same for each face image corresponding to each person so that all the images are mapped to the same subspace. This subspace is not a strictly Fisher subspace since it was not obtained by applying LDA on the prior available training images, thus we can call it a pseudo-Fisher subspace in the future.

While testing, the test image is mapped to the pseudo-Fisher subspace in the manner described in the previous paragraph; that of by multiplying the test image by the transformation matrix. Now a simple distance based classifier such as the K-Nearest Neighbour classifier can be used to find the class nearest to the test sample in the pseudo-fisher subspace. A pictorial description of the entire scheme is provided in figure 1.

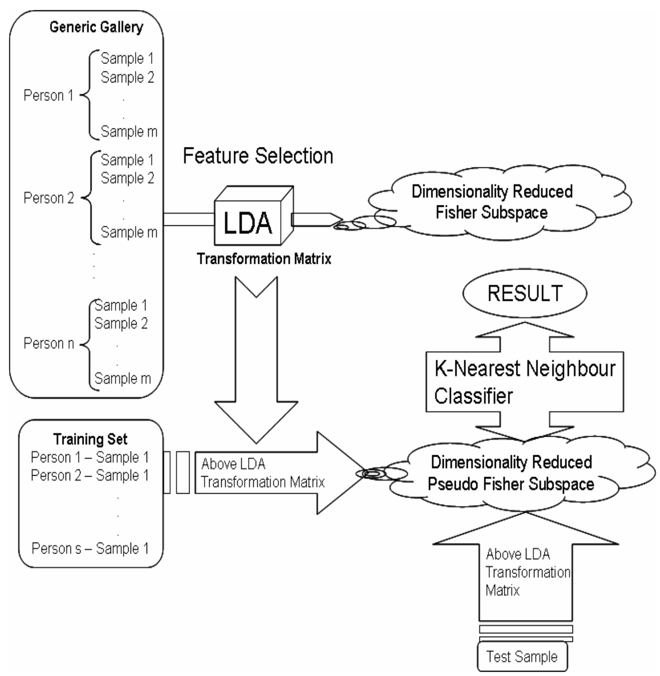

Fig. 1. Recognition Scheme

The procedure we described above is entirely in the spatial domain. We would like to extend this method to the transform domain. The motivation behind this extension follows from some recent work [10, 11], where it was shown that better face recognition results can be obtained in wavelet domain compared to the spatial domain. Also the use of curvelet [12] and contourlet [13] showed promising results in face recognition. We believe that by using transform coefficients instead of the pixel values of the images, better recognition accuracy can be achieved. The proposed scheme will remain the same as in figure 1. But instead of the original images, we will present the transform (wavelet, curvelet or contourlet) coefficients of the corresponding images as inputs to the LDA scheme.

We have also carried out the experiments by PCA replacing LDA as the feature selection scheme. The LDA based method showed much better recognition results compared to the PCA. Thus, we will not show the results of the PCA method in this. We will compare our results with the SPCA [4] and Eigenface Selection [9].

For the mathematical formalisation of the curvelet and contourlet transforms, the interested reader can refer to the works of Candes and Donoho [14] and Do and Vetterli [15]. The curvelet transform was implemented by the Curvelab 2.0 [16] toolbox and contourlet transform by the Contourlet [17] toolbox. The reader can also find a good work in the comparative study of different multivariate methods in spatial domain face recognition in the work of Delac et al [18]. For understanding our simple classification method which is a K-Nearest Neighbour classifier, the reader is referred to [19].

4. RESULTS

We tested our method on two types of face database - database of frontal faces and database having images with some head movement. We chose the Faces94 database [20] as the database for frontal images and the AtnT database of faces [21] as the one which contains faces with head tilts. A few sample images from both the databases are shown in Figures 2 and 3.

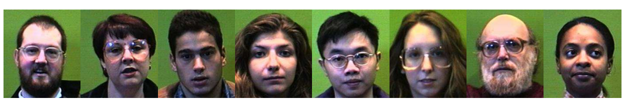

Fig. 2. Images from Faces94 Database (Frontal)

Fig. 3. Images from AtnT Database of Faces (With Head Tilt)

Faces94 had images of 152 people each photographed 20 times and the AtnT database had images of 40 people with 10 samples of each face. Since our recognition scheme demands a generic face database, it is imperative that we choose the generic database keeping in mind the purpose it will be used for, i.e. we try to choose a generic database of frontal faces if we know that the actual problem is of recognizing frontal faces. We choose a generic database of head tilted images if we know beforehand that we will be required to identify faces and having variations in head position. So we divided the databases each into two halves. For the Faces94, 76 randomly selected people along with 20 samples each served as the generic database. For the AtnT database, 20 people along with their 10 samples formed the generic database.

The condition of the problem is that, the training and the testing images should be separate from those of the gallery images. So, the training and the testing sets were constituted from the images of the remaining 76 people for the Faces94 and the remaining 20 people for the AtnT database.

For the test set, we randomly chose five images from remaining set of Faces94 and five from the remaining set of AtnT.

In previous work [4] related to recognizing faces from single prior samples, multiple training sets were created from the available databases. Following [4] we also create multiple training sets. Five training sets were created for the AtnT database by randomly choosing one sample for each of the 20 people in each training set. Similarly for the Faces94, eight training sets were created by randomly choosing a single image for each of the 76 people in each training set. The following diagram explains the entire division of the datasets into different sets.

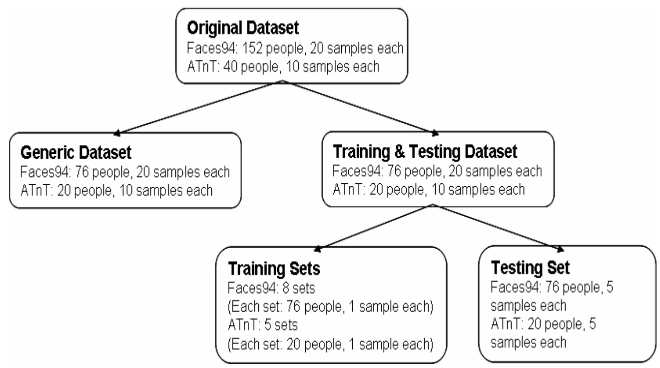

Fig. 4. Division into different sets

As a preprocessing step we only converted the colour images in the Faces94 database to grayscale and normalized all the images to 128X128. The results for the two databases are shown in the following graphs. These results are actually the average results obtained using multiple training sets. The following graphs compare the proposed method vis-à-vis the SPCA [4] and Eigenface Selection [9].

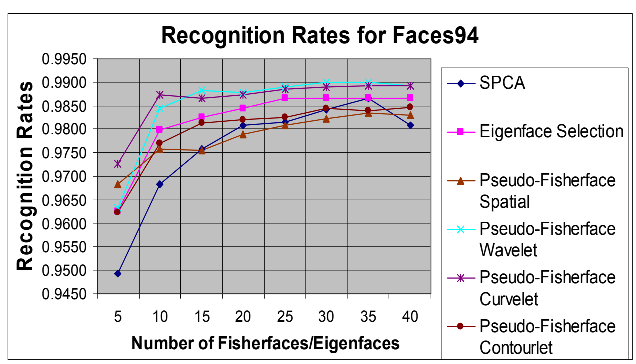

Fig. 5. Recognition Rates for Faces94

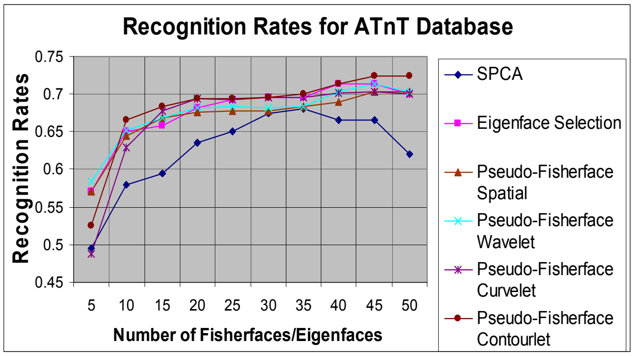

Fig. 6. Recognition Rates for ATnT

Our proposed Pseudo-Fisherface method show better results compared to both SPCA and Eigenface Selection. The best results on the frontal faces database i.e. the Faces94 was obtained by the proposed Pseudo-Fisherface method in the Wavelet domain. The recognition accuracy achieved was 99.01%. For the database having head tilts i.e. the AtnT database, the best recognition result of 72.4% was obtained by the proposed Pseudo-Fisherface method in the Contourlet domain.

5. CONCLUSION

Our proposed pseudo-Fisherface method achieved around 0.33% better recognition accuracy for the frontal faces (where the recognition accuracy is around 99%), and was marginally better by 1% for the database having head tilts (the recognition accuracy being around 72%), when compared with the Eigenface Selection method. The recognition rate from SPCA was way below both the proposed method as well as the Eigenface Selection. However our proposed Fisherfaces have the advantage of being more computationally efficient i.e. it is faster than Eigenface Selection and SPCA. Firstly, unlike SPCA and Eigenface Selection our proposed method does not need to calculate Fisherfaces whenever new images are added to the existing database. Secondly, it does not artificially synthesize new samples from the exiting ones to enlarge the training samples, as is the case with SPCA.

In view of future work we will study how variations in the generic dataset such as changes in the number of samples for each person, or changes in the number of persons, affect the recognition accuracy.

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