Impact of Locally Linear Regression and Fisher Linear Discriminant Analysis in Pose Invariant Face Recognition

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Summary
Face Recognition is an increasingly popular identification technique which faces challenging problems in real life applications because of the variation in the input face images. Various face recognition algorithms, along with their extensions, have been proposed during the past three decades. In recent years, the focus is on the research on pose-invariant face recognition system and many prominent approaches have been proposed. But, there are several issues in face recognition across pose variation which still remains open ended. This paper provides a research on the impact of Locally Linear Regression (LLR) and Fisher Linear Discriminant Analysis (FLDA) in pose invariant Face recognition where LLR is predicting the frontal image of non-frontal face image, FLDA does recognition of faces with Principal Component Analysis (PCA) used for dimensionality reduction of the face image before the recognition. Image-based face recognition in varying pose is one of the most challenging task in face recognition. The existing techniques in 2D pose Invariant face recognition are comprehensively reviewed and discussed. Validation of this approach is done with Yale Face Database B. Experimental results show the effectiveness of this approach in performance.

Keywords:
Face Recognition; Pose variation; Locally Linear Regression(LLR); Fisher Linear Discriminant Analysis(FLDA); Principal Component Analysis(PCA).

1. Introduction

Face recognition is a popular biometric technique adopted mainly for security in identifying or verifying a person automatically, which has become one of the successful applications of digital image analysis. In recent years, face recognition has gained the attention of the research groups as well as the commercial communities. Many commercial applications of face recognition are also available such as criminal identification, security system, image and film processing. The main advantage of face recognition is the non-intrusiveness of recognition where, the system helps to identify even an uncooperative face in uncontrolled condition without the knowledge of the person. But all the face recognition algorithms face a performance drop each time the face appearances are changed due to the factors such as occlusion, illumination, expression, pose, accessories or aging. However, the face recognition system must consider the pose, illumination or expression variation into account in a practical situation. Two of the most challenging problems among these are the change of facial image under pose and illumination conditions among which the pose is an unavoidable problem that appear in real life applications, since people may not always be in the frontal position to camera. The possible answer to this query is the pose-invariant face recognition which allows the pose of the input face image to vary in angles when considered for face recognition. It is difficult for the computer to do the face identification when the poses differs between the probe and gallery images. Moreover, there exist great difficulty in obtaining the training face images under various poses[5]. The more number of multi-poses samples the training set have, the slow the performance of the recognize system. The difficulty in pose-invariant recognition is the face samples of multi-poses which can't be achieved easily. Many algorithms were proposed in face recognition with pose variation. A common solution in handling the pose variations in face recognition is the view-based method. In this method, face images of the individuals to be recognized are acquired from different view angles. The major limitation of this approach is the requirement to acquire and store a large number of views for each face[3]. This technique is impractical in situations where only one or a few views of the face to be recognized are available. The eigenface approach works reasonably well when the input space is restricted to frontal face images. A variety of different methods have been proposed to deal with the problem of changes in viewing angle. Various algorithms have been developed for face recognition from fixed viewpoints, however very little efforts have been given to solve with the problem of combined variation of pose and illumination, expression, etc. Some drawbacks such as computational complexity, cost and huge memory requirements are present in it.

This paper focus on obtaining the virtual frontal view of non-frontal face image using the Locally Linear Regression technique(LLR). The identification of face is accomplished by using the Fisher Linear Discriminant Analysis(FLDA)and Principal Component Analysis(PCA) is used for dimensionality reduction. The organization of

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the paper is as follows: Literature review is presented in Section 2. Description about the techniques used in pose invariant face recognition is presented in section 3. Methodology of the approaches is presented in Section 4. Experimental results and the comparative analysis is given in section 5 and finally the conclusion and future works are summed up in Section 6.

2. Literature Review

Several approaches had been proposed to reduce the problem of the effect of pose in face recognition. In this section, a brief review of some important contributions from the existing literature is presented.

The eigenface approach provides satisfactory results when the input space is purely stored with frontal face images. So, the appearance based method like Eigenfaces [1] need a number of training images for each subject to cope with the pose variability. Beymer and Poggio[2] extended the earlier attempt by having a single image of a subject and making use of face class information to create the virtual views using 2D images of rotating prototype. The combined set of one real view and multiple virtual views used to provide the sample views for the pose invariant recognition system that are used in a view based recognizer

Pentland et. al [3] deals with the problem of multiple head poses by building separate eigenspaces for nine different views. During the recognition, they first determine the subspace which is most representative for the test image and then find the closest match between this image and a model in the chosen subspace. Graham and Allinson [4]. built a common eigenspace from faces of all views and observed that a face which continuously changes pose between the two profile views forms a convex curve in the subspace. Using a radial basis function network they were able to exploit this fact and recognize the faces in previously unseen views.

Congcong Li et al [7] proposed image synthesis and recognition to improve the performance of face recognition. In image synthesis, a series of pose-variant images are produced based on images with front, left and right profile poses, and are added in the gallery to overcome the pose inconsistence between probes and images in the database. In recognition, a multi-level fusion method based on Gabor-combined features and gray-intensity features (GCGIF) is presented. Fusion is introduced in both the face representation level and the confidence level.

Xiujuan Chai et al. [6] have discussed that one of the impediments in face recognition has been the significant degradation face recognition systems due to the variation of facial outlook caused by viewpoint (pose). From any given non frontal view, creating frontal view to acquire a virtual gallery/probe face has been one of the possible solutions. Following this idea, they have proposed a simple, but competent, innovative locally linear regression (LLR) method to create the virtual frontal view from a given non frontal face image. Initially they have substantiated their fundamental assumption that a near linear mapping exists between a non frontal face image and its frontal counterpart. They have presented a globally linear regression by representing the evaluation of the linear mapping as a prediction problem. LLR has been further proposed to enhance the accuracy of prediction under coarse alignment. In LLR, several overlapped local patches are obtained by carrying out dense sampling in the non frontal face image. Then they have predicted its virtual frontal patch by employing the linear regression technique to the small patch. The virtual frontal view has been created by combining all these patches. The unique advantages of the proposed method over Eigen light-field method has been proved by the obtained experimental results on the CMU PIE database.

In the work by Zhang et al. [11] frontal and side-view face images are used to generate virtual views of a subject. Once shape and texture of a subject’s face are estimated, virtual images in different poses are generated. For recognition, holistic methods are used. In another method, the pose parameters are assigned with typical values of frontal faces and so a virtual frontal mesh is obtained. With facial symmetry, we overcome problems due to self-occlusion and synthesize a virtual frontal face by sampling texture from the original image onto the new mesh, using Thin Plate Splines-based warping. Once the virtual face is obtained, then the Gabor responses are extracted and used for comparison.

In 3D, one of the most successful methods is the 3D morphable model proposed by Blanz and Vetter[8], where each face can be represented as a linear combination of 3D face examplars. Many approaches use the 3D Morphable Model for recognition. The main limitation of this method is the high computational complexity needed to recover image parameters. The virtual view concept has been extended to include full 3D face model for synthesizing virtual views for invariant face recognition. Jiang et al. [10] presented that a 3D model in which a human face is generated from a sample view and it is used to synthesize the appearance of the face under different poses, expressions, and lighting conditions. It is difficult to have correspondence reliably in the features between the sample view and the stored view of images in practice.

Blanz et al.[9] use the 3D Morphable Model to synthesize the frontal faces from non-frontal views, which are then fed into the recognition system. Many researchers have tried to generate frontal faces from non frontal views using LLR. But, the high computational complexity of 3D methods in comparison with 2D algorithms makes them unsuitable for real-time applications.

Hossein Sahoolizadeh *et al*. [22] have proposed a PCA (Principal Component Analysis), LDA (Linear Discriminant Analysis) and neural networks based face recognition method. The four steps that have been involved in the method are: i) Preprocessing, ii) PCA based dimension reduction, iii) LDA based feature extraction and iv) Neural network based classification. When the obtainable samples are few, a combination of PCA together with LDA has been utilized for enhancing the capability of LDA. The number misclassification due to not-linearly separable classes has been reduced by using the Neural Classifier. Yale face database has been used to inspect the proposed method. The decreased number of misclassification compared to earlier methods in the experimental results has proved the effectiveness of the proposed method for face recognition.

3. Techniques in Pose Invariant Face Recognition

Face recognition approaches are sensitive to pose variations [12], and so, a number of approaches have been proposed to handle the pose variations. Various 2D techniques [2, 6, 13] 1) pose-tolerant feature extraction [3, 23], 2) real view-based matching [16], and 3) 2D pose transformation[2, 24] were used to handle the appearance variations of human faces brought by changing poses. Pose-tolerant feature extraction approach tends to find face classifiers or preprocessing of linear or non-linear mapping in the image space that can tolerate pose variations. Real view-based matching stores a large number of real views to cover all the possible poses for face recognizer. If there exist only a single or limited number of real views per person stored in the database, real view-based matching is not possible. 2D pose transformation changes the known face images to the unknown poses to synthesize virtual views to help the face recognizer in recognition across pose. The virtual view synthesis can be undertaken in 2D space as pose transformation or in 3D space as 3D face reconstruction and projection. 2D pose transformation was performed on a model database containing image under different poses without virtual view synthesis in [7]. But the LLR[6] predict the frontal view from the non-frontal face image.

4. Methodology

Recognizing the face image under a variety of poses is the main intention of my research work. The category of the image is obtained as an input from the user. After receiving the input from the user, the proposed system, if the image category is a non frontal image, then the pose invariant process is carried out first and the virtual frontal view image is obtained. Locally Linear Regression (LLR) method is applied to perform the pose invariant process. After creating the virtual frontal view face image, FLDA method is used in recognizing the image.

4.1 Locally Linear Regression Method

The basic idea of Linear Object Class(LOC), is that, we try to predict the frontal view of a given non-frontal face image using regression method based on the prototypes in a training set with corresponding image pairs of some specific poses. In the proposed Local Linear Regression (LLR) method, we partition the whole non-frontal face image into multiple local patches and apply linear regression to each patch for the prediction of its frontal patch. The pose invariant face recognition can be effectively achieved by means of the virtual frontal face images, once the non-frontal face images are transformed into the virtual frontal view, as an alternative of all the non frontal face images in the database. In other words, the possibility of considering the proposed method as a preprocessing technique independent of the subsequent feature extraction and classifier design is implied by such strategy. Therefore, it is possible to combine LLR with any face recognition tools. Because Fisher faces method is one of the most successful face recognition methods, it is used in this paper for validating the efficiency of the proposed method.

4.2 Fisher Linear Discriminant Analysis

The image can be identified using FLDA method, once the virtual frontal view for the non frontal image is created. Discriminant analysis can be used only for classification (i.e., with a categorical target variable), not for regression. In FLDA, by maximizing the fisher separation criterion, the input face image is transformed to a subspace where the between class scatter is maximized and the within class scatter is minimized. Because the within-class scatter matrix may be singular, one has to deal with it carefully when designing a FLDA classifier. PCA is first performed to decrease the dimensionality to less than $N-C$ for preventing the singularity problem, where N and C are the number of train examples, and the number of classes respectively. Then the features transformed by PCA are given as input to the final FLDA for classification.

4.3 Principal Component Analysis (PCA)

PCA involves a mathematical procedure that transforms a number of correlated variables into a number of uncorrelated variables called *principal components*. PCA is a linear method for unsupervised dimensionality reduction. tends to find a t-dimensional subspace whose basis vectors correspond to the maximum variance direction in the original image space for an s-dimensional vector representation of each face in a training set of M images. This new subspace is normally lower dimensional.

5. Experimental Results

In this section, we have investigated the performance of LLR and FLDA approach. This proposed approach is implemented in Matlab (7.10) and face recognition was performed using the large set of Yale Database B under various poses. The results show that our approach has an encouraging performance. Accuracy in face recognition is to computed with the false acceptance rate (FAR) which is percentage of incorrect acceptances and false rejection rate (FRR) which is the percentage of incorrect rejections. The genuine acceptance rate is computed using these factors and it determines the overall accuracy measurement of the approach. The latest experimental results shows that the approach of LLR with FLDA improves the accurate recognition rate in face recognition. The sample output obtained from the pose Invariant process is shown in Fig.1.

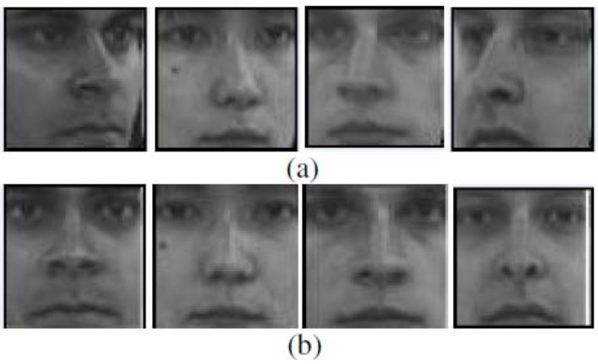

Fig..1: Sample output obtained from the Posed invariant process a) non frontal face images b) virtual frontal view of the corresponding Non frontal face images using LLR.

The table 1 clearly shows the efficiency of LLR and FLDA in terms of the recognition rate.

Table 1: Recognition rate on Pose Invariant condition

Database	*FRR (%)*	*FAR (%)*	*Accuracy (%)*
Yale Database B	6.82	8.25	93.4

6. Conclusion

In this paper, the impact of locally linear regression (LLR) method in pose invariant face recognition system is discussed. Since variation of pose in input face image is the major problem in face recognition, plenty of techniques were developed for effective recognition under these circumstances. The technique such as LLR with FLDA in Yale Database B shows good recognition rate. With these results, I conclude that the combination of LLR with any other approaches could be experimented in order to improve the pose invariant recognition accuracy. However, it is identified that the efficiency of the face recognition system could be increased by the fusion of the existing approaches in a system so that, the combinational results will outperforms the existing methods in face recognition. Therefore, in future work, the fusion of two pose invariant face recognition approaches could be experimented for recognition efficiency in order to determine the most effective approach in face recognition across pose variations.

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