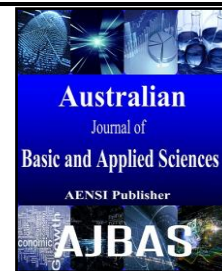




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Face Recognition Techniques using PCA and LDA

¹Dr Ravi Subban and ²Savitha Soundararajan¹Department of Computer Science, School of Engineering and Technology, Pondicherry University, Pondicherry, India - 605014²Department of Computer Science, Acharya College of Arts and Science, Pondicherry, India - 605014

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ABSTRACT

This paper is a survey on face recognition techniques using principle component analysis and linear discriminant analysis, analysing the different variations, advantages, disadvantages and accuracy of the methods used. The recognizing the human face is simple for a human being even seeing a person after several years. But doing the same task by a computer not simple because the computer will have problems in the recognizing the human face if there is a change in the facial image like, lighting conditions, complex background, pose and occlusion. Still recognizing faces in images is an emerging trend of research in image processing streams.

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INTRODUCTION

Face is the index of human mind. Recognizing faces in images is an emerging trend of research in image processing streams. Face recognition is a rapidly evolving technology, which has widened the hands from biometric science like face recognitions, fingerprint recognition, iris scan, and speech recognition and used in forensics such as criminal identification, secured access, and prison security. It is a complex multidimensional structure and needs a good computing technique for recognition. Computers are easily confused while using automatic system for face recognition in presence of illumination, variation in poses and change in angles of faces.

2 Holistic Approach or Appearance Based Method: 2.1 Principal Component Analysis (PCA):

Matthew A. Turk *et al.* (1991) had considered face recognition as a two-dimensional recognition problem and proposed a novel face recognition method using eigen faces. The main idea of this method is to consider the head and then compare it with the face of a known person. The method recognizes face in an unsupervised manner. The method was a success for its simplicity and speed in recognizing faces. However, this method cannot find solution for object recognition problem. Baback Moghaddam and A. Pentland (1994) proposed a view-based eigenspace approach for face recognition. The method attempts to automatically establish the head orientation and scale. The target object is viewed in terms of 2D as-

pects. The method captures the head pose automatically without lowering the recognition accuracy. The method is robust to localized variations in object appearance. An expansion encoding approach to image classification is presented by Peter McGuire *et al.* (2001). A localized principal component is applied locally rather than on the entire image. The "eigenpaxels" are statistically determined using a database. Neural network is used for classification. Eigenpaxal uses two types of key elements namely, expansion encoding and subsampling. Tested using a database has proven the performance to other comparable methods. Added on the method is robust to noise variations. The major drawback of the algorithm is that it is not efficient for general problems. The classification stage may be further improved by utilizing a Bayesian approach. The algorithm can also be extended to include color and stereo images as well as motion cues.

Jian Yang *et al.* (2004) proposed a new technique for image feature extraction and representation - two-dimensional principal component analysis (2DPCA). 2DPCA has many advantages over conventional PCA (Eigen faces). In the first place, since 2DPCA is based on the image matrix, it is simpler and more straightforward to use for image feature extraction. Second, 2DPCA is better than PCA in terms of recognition accuracy. Third, 2DPCA is efficient than PCA in terms of computation. However, 2DPCA-based image representation was not as efficient as PCA in terms of storage requirements, since it requires more coefficients for image representation

than PCA. Finally, there are still some aspects of 2DPCA that deserve further study. When a small number of the principal components of PCA are used to represent an image, the mean square error (MSE) between the approximation and the original pattern is minimal. Yu-sheng Lin *et al* (2008) have proposed a novel method called two dimension locally principal component analysis (2DLPCA) for face recognition, which is based directly image matrix rather than 1D image vectors. 2DPCA preserves the global geometric structure of image data when given image data are lineally distributed. But, when the image data are distributed in nonlinear way, 2DPCA may fail to discover the intrinsic structure of image data due to its intrinsic linearity. Experimental results on ORL face database show the effectiveness of the proposed method.

J. Shi *et al.* (2006) have used PCA model in the complex number domain because complex PCA keeps the relationship of x and y coordinates. Using complex principal component analysis a refined Procrustes distance as the similarity measure for the landmark-based face model have been proposed. The refined Procrustes distance incorporates the statistical correlation of landmarks. The highlighting feature of the method shows that a human face can be effectively modeled by well-defined biologically meaningful landmarks and their geometrical features. The method finds difficulty in focusing on developing robust approaches to automate feature extraction and combine landmark geometry and local feature appearance for better face recognition performance.

A.A. Mohammed *et al.* (2011) have proposed a new human face recognition algorithm based on bidirectional two dimensional principal component analysis (B2DPCA) and extreme learning machine (ELM). The proposed method is based on Curvelet image decomposition of human faces and a subband that exhibits a maximum standard deviation in dimensionally reduction using an improved dimensionality reduction technique.

Images from each database are converted into gray level image with reduction in image size. Each database is randomly divided into training and testing set so few images of each subject are used as prototypes and remaining images are used during testing phase. Curvelet transform is used to generate initial feature vectors. Curvelet decomposition of all images within each database is computed at three scales and eight angular orientations generating 25 distinct sub bands. The standard deviation of every subband is calculated and a subband that exhibits highest standard deviation is selected as an initial feature vector. Discriminative feature sets are generated using B2DPCA to ascertain classification accuracy. The other contributions of the proposed work include major improvements in classification rate, reduction in training time and minimal dependence on the number of prototypes. Xi Chen *et al.* (2011) have introduced multi-directional Orthogonal Gradient Phase Face

(OGPF), which provides a more efficient and stable face representation for single sample face. An illumination insensitive orthogonal gradient phase face is obtained by using two vertical directional gradient values of the original image. A technique called Multi-directional orthogonal gradient phasefaces can be employed to extend samples for single sample face recognition. Multi-directional OGPF plus PCA and LDA algorithm enhances the discriminating power of original orthogonal gradient phase face and reduces the length of template. Experimental results on several databases have proven the efficiency of the proposed algorithm.

Müge Çarıkç *et al.* (2011) used an Eigen faces method for face recognition considering Principal Component Analysis (PCA) as the basis. The method formulates Eigen face for the given face image, and the Euclidian distances between this Eigen face and the previously stored Eigen faces are calculated. The Eigen face with the smallest Euclidian distance is the one the person resembles the most. The method is implemented using the Matlab program highlighting eye-glasses, beard, and mustache. The success rate for the large database was identified to be 94.74%.

Many face recognition techniques have gained popularity but the all the methods doesn't focus on all variations of facial recognition. Usama, Ijaz, Bajwahave (2012) proposed a single classifier that performs better against all facial image variations. Two different approaches like weighted sum and re-ranking were applied and tested for their suitability with different facial tasks. The various advantages of this method are: simple approach like re-ranking gives better results when compared to a weighted scoring, increasing the number of constituent baseclassifiers might worsen the results of the unified classifier and the unified classifier has clearly outperformed on average performance over all the databases like FERET, YALE and ORL for facial variations. The method focuses on identifying the influence of base classifier's error distribution and identifying the relationship between dimensionality reductions methods are the key areas to proceed with. Ying Wen *et al.* (2012) has proposed a new face recognition method based on difference vectors plus KPCA(Kernel CA) approach. Difference vector is got by finding the difference between the original image and the common vector of the class. The optimal feature vectors are obtained by KPCA procedure for the difference vectors.

The recognition result is derived from finding the minimum distance between the test difference feature vectors and the training difference feature vectors. Experiments conducted on various database shows that the method has an encouraging recognition rate. Tomasz Marciniak *et al.* (2013) had analyzed real-time system for face detection and recognition from low-resolution images. The main idea is to combine with biometric face images. Both the extraction and identification of face is checked for cor-

rectness under scientific database. This program uses an algorithm based on PCA (principal component analysis). Face recognition is based on the distance from the nearest class, according to the numbering assigned at the beginning to individual photograph. The method is widely used in CCTV image analysis where the images can be recognized from a large distance. The main advantage of this approach is that it works correctly even when the training data is less. In continuous processing the image is acquired from a webcam (e.g. D-Link DSC-930L) or a standard USB camera and recognizes face belonging to the person, which is in front of the camera. In case of problems automatic conversion from YUV to RGB color space was used. The next step is noise reduction, face detection in an image and also the background removing - in order to reduce the processing area and the calculation time. Images entering the base must be the same size. In batch processing mode images are loaded from the database and results are saved in.xls format.

2.2 Linear Discriminant Analysis(LDA):

Appearance-based methods have wide spreaduse in object recognition systems. Aleix M. Martinez *et al.* (2001) have made a comparative study on Principal Components Analysis (PCA) and Linear Discriminant Analysis (LDA). After several experimental analyses it is proved that PCA outperform LDA when the number of samples per class is small or when the training data nonuniformly sample the underlying distribution. Several experiments show the superiority of Principal Components Analysis (PCA) over Linear Discriminant Analysis (LDA). Principal Components Analysis (PCA) is less sensitive to different training data sets. For higher-dimensional spaces Linear Discriminant Analysis (LDA) outperforms Principal Components Analysis (PCA). A new Face Recognition (FR) method has been proposed by Jewie Lu *et al.* (2003). The proposed method combines kernel-based methodologies with discriminant analysis techniques. The kernel function is utilized to map the original face patterns to a high-dimensional feature space, where the highly non-convex and complex distribution of face patterns is linearized and simplified, so that linear discriminant techniques can be used for feature extraction. The small sample size problem caused by high dimensionality of mapped patterns is addressed by an improved D-LDA technique which exactly finds the optimal discriminant subspace of the feature space without any loss of significant discriminant information. Experimental results indicate that the performance of the Kernel D-Discriminant Analysis (KDDA) algorithm is superior to Kernel Principal Component Analysis (KPCA) or GDA approaches. The algorithm is a general pattern recognition method for nonlinearly feature extraction from high-dimensional input patterns without suffering from the SSS problem. The algorithm provides excellent performance in applica-

tions where classification tasks are routinely performed, such as content-based image indexing and retrieval, video and audio classification. To overcome the Eigen faces, YD-LDA and JD-LDA problem, a new Linear Discriminant Analysis (LDA) method called Regularized Linear Discriminant Analysis (R-LDA) for Face Recognition tasks is proposed. The method is based on regularized Fisher's discriminant criterion, which is robust against the SSS (Small-Sample-Size) (Lu, J., 2002) problem. The purpose of regularization is to reduce the high variance related to the eigenvalue estimates of the within-class scatter matrix at the expense of potentially increased bias. Experimental results show that the method outperforms the Linear Discriminant Analysis (LDA). A new optimization criterion based on posterior error rate was proposed (Dai, D., P.C. Yuen, 2007). A new method called Regularized Discriminant Analysis (RDA) using robust cross-validation (RCV) was implemented to solve the optimal problem. It tries to solve the Small Sample Size (SSS) problem. A drawback of the proposed algorithm is that the computation load of the proposed method is higher than that of the Fisher Face method in the training stage. Therefore, the future direction is to reduce the number of regularized parameters so that the computation load can be reduced. Another approach to Small Sample Size (SSS) (Cevikalp, H., 2005) is called the Discriminative Common Vector method based on a variation of Fisher's Linear Discriminant Analysis. Two different algorithms are given to extract the discriminative common vectors representing each person in the training set of the face database. One algorithm uses the within-class scatter matrix of the samples in the training set while the other uses the subspace methods and the Gram-Schmidt orthogonalization procedure to obtain the discriminative common vectors. The findings are used for classification of new faces. The proposed method yields an optimal solution. The test results show that the Discriminative Common Vector method is superior to other methods in terms of accuracy, efficiency, and stability.

An elastic local reconstruction (ELR) (Xie, X., K.M. Lam, 2008) method is proposed based for comparing image blocks, which can handle a range of single frontal-view image for each face subject. The method is in need of only a single face image under frontallighting and with neutral expression for training. To compare two near-frontal face images, each face is considered as a combination of a sequence of local image blocks. Each of the image blocks of one image can be reconstructed according to the corresponding local image block of the other face image. The algorithm is not only beneficial in terms of robustness to various image variations, but is also computationally simple because there is no need to build the face manifold. The approach is evaluated for performance with different databases, under varied conditions, like lightings, expressions, with/without glasses and occlusions. Consistent ex-

perimental results show that the algorithm can improve the recognition rates under all the different conditions. However, the method cannot handle more facial variations. A novel approach, called K-mode optimization, is presented by Shuicheng Yan *et al.* (Yan, S., 2007) to iteratively learn the subspaces by unfolding the tensor along different tensor directions. The algorithm is named as multilinear discriminant analysis (MDA), which has the following characteristics: i) multiple interrelated subspaces can collaborate to discriminate different classes, ii) for classification problems involving higher order tensors, the MDA algorithm can avoid dimensionality dilemma and alleviate the small sample size problem and iii) the computational cost in the learning stage is reduced to a large extent owing to the reduced data dimensions in-mode optimization. Extensive experiments on different databases by encoding face images as second-or third-order tensors to demonstrate that the proposed MDA algorithm based on higher order tensors has the potential to outperform the traditional vector-based subspace learning algorithms for small sample sizes. Haitao Zhao *et al.* (2008) have presented Incremental Linear Discriminant Algorithm (ILDA) called GSVD-ILDA. With the dynamically added images, the GSVD-ILDA can effectively obtain the projection matrix with low computational cost and low memory requirement. Experiments using the publicly available databases have been performed to evaluate the performance of the GSVD-ILDA algorithm. Two recent ILDA-based face recognition strategies, namely, the IDR/QR and the algorithm of Pang *et al.*, are used for comparison. The experimental results show that the GSVD-ILDA gives better recognition performance than that of the other two methods. They have also performed extensive experiments to evaluate and compare the proposed GSVD-ILDA algorithm with its original batch-mode LDA/GSVD algorithm. Experimental results show that the proposed GSVD-ILDA algorithm gives the same performance as the LDA/GSVD with smaller complexity. It is important to point out that the proposed GSVD-ILDA algorithm is generic. The proposed algorithm can be applied to other pattern recognition and machine learning applications. The proposed incremental algorithm will give the same result as its batch-mode method when k is equal to the rank of the matrix $(X - m_eT)$. It is worth further investigating the error to be introduced when k is smaller than the rank of the matrix $(X - m_eT)$. Second, this paper mainly works on how to develop an ILDA algorithm, and a simple minimum distance classifier is used.

The complete linear discriminant analysis (CLDA) algorithm is an effective tool for face recognition but it may not be suitable for incremental learning problem. Gui-Fu Lu *et al.* (2012) have proposed a new implementation of CLDA, which is similar to the original implementation of CLDA but which is more efficient than the original one. The

main advantage of this method is the frequent updation of discriminant vector rather than recomputing which reduces computational cost. The results on face databases have shown good recognition accuracy over the original implementation of complete linear discriminant analysis (CLDA). The method may further be implemented in complete kernel LDA algorithm. Traditional LDA-based methods suffer a fundamental limitation originating from the parametric nature of scatter matrices, which are based on the Gaussian distribution assumption. The performance of these methods degrades when the actual distribution is non-Gaussian. To address this problem, Zhi-feng Li *et al.* (2009) have proposed a novel method, called nonparametric discriminant analysis (NDA) and multi classifier integration. Two multiclass NDA-based algorithms (NSA and NFA) were introduced to exploit the discriminant information in both the principal space and the null space of the intraclass scatter matrix. The NFA is more effective in the utilization of the classification boundary information as compared to the NSA. To boost up the recognition performance Gabor representation for face images are employed. Experiments have proven the method to be a success with good recognition accuracy. Hong Huangn *et al.* (2012) have proposed a novel method, called complete local Fisher discriminant analysis (CLFDA), for face recognition. The method has been aimed at extracting faces from both regular and irregular fashion. In order to achieve best performance Laplacian score technique is used to rank the regular and irregular features. Experiments performed on AT&T, YaleB and CMU PIE face databases demonstrates that the proposed method increases the recognition accuracy. It suffers from both computational and time complexity.

3 Discussion:

The face recognition using eigen faces is simple and fast, but it is successful for only full frontal view in a constrained environment. It is effective for pose estimation and robust detection for large space database with the accuracy of 99.35%. Face recognition using eigenpaxels is robust to various types of image noises producing error rates of 2.9% for ORL database. Two dimensional PCA is simple, accurate and computationally efficient, but needs more coefficients for image representation. Two dimension locally principal component analysis (2DLPCA) is accurate, but not efficient for non-linear distribution of images producing 96% accuracy. Complex PCA eigenvalue weighted cosine (EWC) distance shows good performance in identifying variations in face expressions like pose, position and aging. But it has difficulty in combining landmark geometry and local feature appearance for better face recognition getting 99.63% accuracy rate. Bidirectional two dimensional principal component analysis (B2DPCA) has the improved recognition at a substantially faster rate, reduction in training time and minimal dependence on

the number of prototypes. Multi-directional Orthogonal Gradient Phase Face (OGPF) is effective for single sample face recognition under illumination, expression, decorations, etc. Kernel-PCA(KPCA) and Generalized Discriminant Analysis (GDA) deals with the nonlinearity of the face patterns and solves Small Sample Size (SSS) problem. But it is useful with only a very small set of features. Regularized Linear Discriminant Analysis (R-LDA) eliminates Small-Sample-Size(SSS) problem and exhaustive search consumes time. Incremental CLDA(complete linear discriminant analysis) updates discriminant vector reduces computational cost. Complete local Fisher discriminant analysis(CLFDA) increased recognition accuracy and use of matrices eigen decomposition leads to computation expensive in both time and memory. Nonparametric discriminant analysis (NDA) used to easily address the non-Gaussian aspects of sample distributions.

4 Conclusion:

Face recognition is a challenging problem in the field of image processing and computer vision. Because of lots of application in different fields the face recognition has received great attention. In this paper, different face recognition algorithms are studied with their advantages and disadvantages. This can be used by anyone as per requirement and application. We have an idea of improving the efficiency of the discussed algorithms and improve the performance.

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