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Survey – A Comparative Analysis of Face Recognition Technique

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Abstract- In this paper we survey some of the most prominent published literature in face recognition system based on 2DPCA technique published in last Ten years. A comparative analysis is done between various approaches using 2DPCA technique in order to recognizing the faces. There is an attempt to estimate the best approach that could be used that satisfies all the indicated parameters in order to develop the computational model for face recognition that will be fast, simple and accurate in different environments. The important of such work cannot be underestimated as for the disabled and the older ones, face recognition may remain the only mechanism to recognize the faces, so that a truly automatic face recognition system is feasible, current feature extraction methods improved and extended with regards to robustness in natural environments as well as independence of manual intervention during initialization and development.

Keywords- Face recognition, PCA, ICA, LDA, 2DPCA, TD2DPCA, B2DPCA, DWT

INTRODUCTION

Face recognition: A very popular research topic in recent years. Early face recognition algorithm used in simple geometric models but now matured into a science of mathematical representation and matching processes. In the past 10-15 years major advancement have propelled face recognition technology into the spot light. The subject face recognition is as old as computer vision, both because of the practical importance of the topic and theoretical interest from cognitive scientists. Face recognition has always remains a major focus of research because of its non-invasive nature. Despite the fact that other method of identification such as finger print and retina scan can be more accurate.

Beginners of automated face recognition are Woody Bledsoe, Helen Chan Wolf and Charles Bissy. During 1960's Bledsoe, Chan Wolf and Bisson developed the first semi-automated system using the computer to recognized human faces. It used featured such as eyes, ears, nose, mouth. These distances and ratio were calculated using these marks to a common reference point and compared reference data. This recognition problem is made difficult by the great variability in head rotation and angel, facial expression, aging, etc. some other attempts at facial recognition by machine have a loud for little or no variability is great. In particular, the correlation is very low between two pictures of the same person with two different head rotation [1].

Goldstein, Harmon and Lesk used a set of 21 specific subjective marker such as hair color, lip thickness, chick, jaw etc. in the early 1970's. During 1988 Kirby and Siovich applied principle component analysis using less than 100 marker to the face recognition problem. Later Kohonen demonstrated that a simple neural net could perform face recognition for aligned and normalized face recognition. He computed a face description by just approximating the Eigen vector of the face image's autocorrelation matrix and these Eigen vector known as Eigen faces and at the end Kohonen's system do not have any practical success, because of the need for precise alignment and normalization [2]. Turk and Pentland in 1991 discovered that while using the Eigen faces technique the residual error could be used to detect faces in images.

FACE RECOGNITION

Face recognition is a subfield in a larger field of pattern recognition research and technology. Statistical techniques used by pattern recognition to detect and extract patterns from data in order to match it with patterns stored in database.

Face recognition is a biometric software computer application used for identifying or verifying a specific individual from a digital image or a video source by comparing the selected face with the image stored in database.

Face recognition is an important method as compared to other biometrics such as fingerprint when probes are uncooperative or in uncontrolled environments. The image used to test the algorithm are called probes. A probes is either a new image of individual in the database or an image not in the database or gallery. The probes are presented to an algorithm, and algorithm returns the best match between the each probe and image in the database. The estimated identity of a probe is the best match.

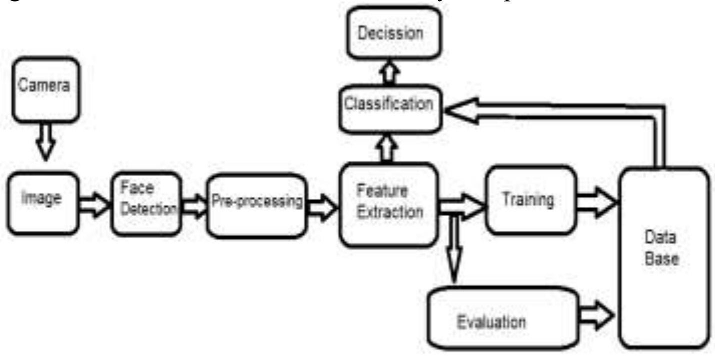

Fig.1. Face recognition system

Face recognition system has three stages: (1) Preprocessing (2) Feature extraction and (3) Classification which is shown in Fig. 1. The first stage includes face detection, normalization and elimination of background and parts of the face which may affect the recognition rate. The second stage in face recognition is categorized in two groups, namely featured based and holistic based [3]. Feature based methods basically rely on facial features like eyes, nose, chin and mouth which are analyzed and try to identify the position and relationship between them[4]. But in the holistic approaches images are analyzed as a whole. As facial features detection is difficult against rotation, scale and illumination variation, holistic approaches are generally implemented features are extracted by using deterministic or statistical transformation for feature vectors [5], [6]. In the holistic approaches proper depending upon database [7]. Among deterministic approaches Discrete Cosine Transform (DCT) [8], [9], Discrete Fourier Transform (DFT) [10], and Discrete Wavelet Transform (DWT) [11] are the most important powerful in face recognition application whereas Principal Component Analysis (PCA) [12] and its variations like Kernel PCA [13], Modular PCA [14] , Diagonal PCA [15], Curvelet based PCA [16] and 2DPCA [17], Linear Discriminate Analysis (LDA) [18],[19] and Independent Component Analysis (ICA) [20],[21] are mostly used for feature extraction and dimension reduction been found that most efforts are given mainly on developing feature extraction methods and employing powerful classifiers reduction as statistical transformations. In the literature it has such as Euclidean distance classifier [22], Neural Networks [23], [24], Hidden Markov Models (HMMs) [25], Support Vector Machine (SVM) [26], Extreme Learning Machine (ELM) [27].

VARIOUS APPROACHES FOR FACE RECOGNITION

Geometric Approach

Face geometry was the first historical way to recognize people. There are lot of geometric features based on the points. These geometric features may be generated by segments, perimeters and areas of some figures formed by the points [28]. Geometric features includes Lip thickness, Nose profile, eyes separation etc. The approach is automatic point location, which may cause problem to bad quality images [28].

Elastic face matching

Elastic graph matching (EGM) is a biologically inspired algorithm for object recognition in the field of computer vision. Visual objects in EGM are represented as labeled graphs, where the nodes represent local textures based on Gabor wavelets and the edges represent distances between the nodes location on an image [29].

Neural Network for access control

Face recognition is a widespread technology used for access control. A multilayer perceptron neural network is considered for access control based on face recognition. The NN architecture if in explored from may be used in real time application [30].

Principal Components Analysis

PCA is a technique pioneered by Kirby and Sirovich in 1988, it is commonly referred to as the use of Eigen face. The size of the probe and gallery image must be of same size and normalized to a line up the eyes and mouth of the subject within the images. PCA technique is used to reduce the dimension of the data by means of data compression basics [31] and reveals the most effective low dimensional structure of the facial patterns. The reduction in the dimension will remove the information that is not useful [32] and it will decomposes the face structure into orthogonal component known as Eigen face and each of the Eigen face are represented as the weighted sum of the Eigen face, which are stored in 1D array. Then the probe image is compared with the gallery image by measuring the distance between their between their respective feature vectors. Basically in PCA technique requires the full frontal face which is to be presented each time otherwise the image will result in poor performance.

Principal Component Analysis also called Karhunen- Loeve transform (KLT), is a classical feature extraction and data representation technique widely used in the area of pattern recognition and computer vision [17]. PCA was invented in 1901 by Karl Pearson, as an analogue of the principal areas theorem in mechanics; it was later independently developed and named by Harold Hotelling in the 1930's. Sirovich and Kirby used PCA to represent pictures of human face recognition in 1991. The problem of dimensionality of the face space was discussed by the Penev and Sirovich when Eigen faces was used for representation. PCA is a statistical procedure that uses an orthogonal transformation to convert a set of observation of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components.

It is technique that effectively and efficiently represent picture of faces into its Eigen faces components. It reduces data dimensionality by performing a covariance analysis between factors [2]. If we consider an object as a point in dimension space then these components are the Eigen vectors of the related covariance matrix of this set of image, these face image are individual known as Eigen faces and these are represented by a linear combination of Eigen faces or we can say best Eigen faces.

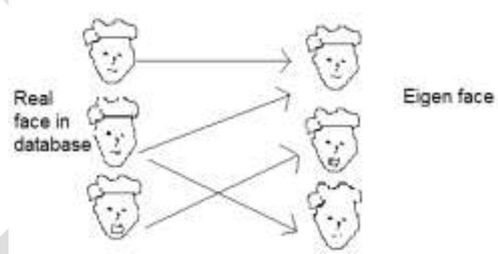

Fig. 2. Faces are linear combination of Eigen faces

Two- Dimensional Principal Component analysis

2DPCA technique is developed for image representation and for image feature extraction. 2DPCA is totally opposite to the PCA, 2DPCA is based on 2D matrices rather than 1D vectors due to be previously transformed into a vector prior to feature extraction. Instead of this image covariance matrix is constructed directly by using the original image matrix and by which size of the image covariance matrix using 2DPCA is much smaller. Basically 2DPCA have lots of advantages like it is easier to evaluate the covariance matrix accurately and also it take less time to determine the corresponding Eigen vector [17].

Independent Component Analysis

ICA derived from a linear representation of non-Gaussian data. The most common method for generating spatially localized features is to apply independent component analysis (ICA) to produce basis vectors that are statistically independent. A number of algorithms for performing ICA have been proposed and has been proved successful for separating randomly mixed auditory signals (the cocktail party problem) and for separating electroencephalogram (EEG) signals and functional magnetic resonance imaging (MRI) signals.

Independent component analysis, or ICA is a statistical technique which in many cases characterizes the data in a natural way. ICA and the related blind source separation (BSS) problem have grown important research and application topics both in unsupervised neural learning and statistical signal processing. Comparisons between PCA and ICA are complex, because differences in tasks, ICA algorithms and distance metrics must be taken into an account. ICA chooses a different subspace than PCA. PCA is only sensitive to the power spectrum of images suggests that it might not be particularly well suited for representing images. However ICA is sensitive to high-order statistics in the data, not just the covariance matrix.

Linear Discriminant Analysis

LDA is a classification method originally developed in 1936 by R.A. Fisher. It is a simple mathematically robust and often produces models whose accuracy is as good as more complex methods. Discriminant analysis is a classical method of classification that has stood the test of time. LDA is based upon the concept of searching for a linear combination of variables (predicators) that best separates two classes (targets). LDA is closely related to analysis of variants (ANOVA) and regression analysis, which also attempt to express one dependent variable as a linear combination of other features of measurements. LDA is an enhancement to PCA and factor analysis constructs a discriminant subspace that minimizes the scatter between images of same class and maximizes the scatter between different class images. LDA does not perform very well due to the testing simples are from persons not in the training set and also when markedly different samples of trained classes are presented, samples are presented from different background. Therefore later on LDA is overcome from these drawbacks [33], [34].

Gabor Wavelets

Gabor acts as a filtering device. It transforms the facial image into small wavelets that helps in easier recognition of the desired feature. Gabor is a very effective tool because the Gabor filtered images stand strong and unaffected to the variations or changes made in illumination and facial expression or poses. Further Gabor wavelet representation has higher degree of correlation with human semantic ratings.

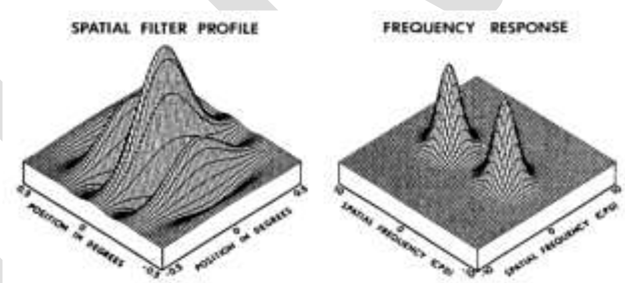

Fig. 3. Gabor filter in space (left) and frequency (right) domain [35]

Gabor wavelets are represented by a 2-D plane waves in the spatial domain. One characteristic of wavelets is that they can be located somewhere between the space and the frequency domain. In the frequency domain as shown in Fig. 3 the Gabor wavelet filters can be represented as Gaussian windows.

Discrete Cosine Transform (DCT)

DCT is basically a technique for image compression. It compresses the image by removing the information which is not of use.

The DCT mechanism transfers an image from the time domain.

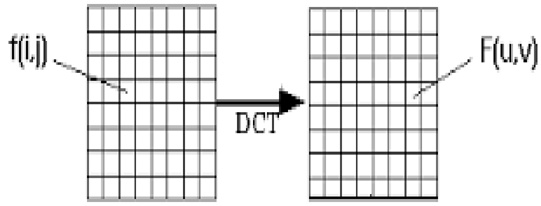

Fig. 4. Discrete Cosine Transform [36]

$$f(u,v) = \frac{\Lambda(u)\Lambda(v)}{4}\sum_{i=0}^{7}\sum_{j=0}^{7} cos\frac{(2i+1).u\pi}{16}.cos\frac{(2j+1).v\pi}{16}.f(i,j)$$

$$\Lambda(\xi) = \begin{cases} 1/\sqrt{2} & for\ \xi = 0 \\ 1 & otherwise \end{cases}$$

Harr Wavelet Transforms

It is another frequently used image filtering method. It is based on the mechanism of filtering the image by separating the frequency bands into two groups-low and high.

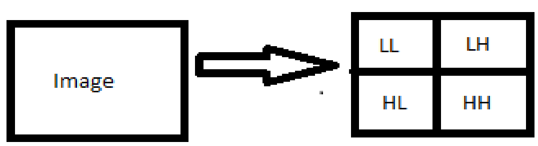

Fig. 5. One filter stage in 2-D DWT

Wavelet functions for 2-D DWT can be obtained by multiplying two wavelet functions or wavelet and scaling function for one-dimensional analysis. Also, in higher dimensions as the two- dimensional case, there can be three wavelet functions that scan details in horizontal Ψ1 (x, y) = Φ(x) Ψ(y), vertical Ψ2(x, y) = Ψ(x).Φ(y), and diagonal directions Ψ3 (x, y) = Ψ(x), Ψ(y). This may be represented as a four channel perfect reconstruction filter bank as shown in Fig. 5. Now each filter is 2-D with the subscript indicating the type of filter (HPF or LPF) for separable x- axis and separable x- axis and y-axis components. The resulting four transform components consist of all possible combination of high and low pass filtering in the two directions.

FILTERED FEATURE CLASSIFICATION

FFC is the next very important and sensitive stage in the face recognition system. It is sensitive in the sense that even the slightest changes in the movement of the face expression, poses, illumination variation and rotation determine that is exactly what is need to be captured and differentiated during this stage. Since facial features detection is difficult against rotation, scale and illumination variation.

To overcome the above problem very recently, some newer approaches have been used. There are two main categories of feature classification approach:

Statistical non-machine learning approach such as Euclidean and linear discrimination analysis.

Machine learning approach such as Feed forward Neural Network, Multilayer Perceptron, Radial Basis Function Network, etc

RESULT AND ANALYSIS

We have studied 12 recent papers that were good in this research area. All researchers have tried to improve the performance of the face recognition system by enhancing feature extraction techniques and classification techniques. Table shows the summary of research work (chronological order starting from 2004 to 2014).

Reference	Feature extraction technique	Database	Classifier	Sample size	Performance	Important mark
Jain Yang, David Zhang, 2004 [17]	2DPCA	ORL, AR, YALE face database	Nearest Neighbor Classifier	ORL database contain 40 individuals each providing 10 different images (92×112) Pixels AR database contains 4000 of 126 people (50×40) pixels, YALE face database contains 165 images (100×80) pixels	ORL=96.0% (using first five images for training), 98.3% (leave-one-out) AR= 96.1% YALE = 84.24% recognition accuracy	2DPCA is better than PCA in terms of recognition accuracy. 2DPCA was not efficient as in terms of storage requirements.
Maataz M. Abdelwahab, Wasfy B. Mikhael, 2006 [36]	TD2DPCA for face recognition in the presence of salt and pepper as well as Gaussian noise	ORL and YALE dataset	Euclidean distances between the feature matrix of testing images and training images	ORL dataset consist of 400 images of 40 different individuals (112×92) pixels, YALE database consist of 165 images of 15 different subjects	ORL= 73.61% (experiment 1), 92.0% (experiment 2) YALE=78.3% recognition accuracy	This technique retains its high accuracy for noisy images. It reduced the storage requirement by 90% and computational speed by a factor of two relative to existing

				(243×320) pixels		techniques of comparable recognition accuracy.
P. Sanguansat, W. Asdornwied, S. Jitapunkul, S. Marukatat, 2006 [37]	B2DPCA+ FSS	YALE database	Nearest Neighbor Classifier	165 images of 15 subjects , 11 images per subject (100×80) pixels	Accuracy = 94.44%	The excellent performance over conventional 2DPCA and B2DPCA under variations in expression and illumination, it shows the improvement recognition accuracy on well-known face database. It require more memory for storing each classes and recognition rate.
Lin Wang, Yongping Li, Chengbo Wang, Hongzhou Zhang, 2007 [38]	Gabor face based 2DPCA and$(2D)^2$ PCA classification with ensemble and multichannel model	ORL and YALE database	Gabor face – based 2DPCA and $(2D)^2$PCA classifier	ORL database consist of 400 frontal faces (112×92) pixels, YALE database consist of 165 images of 15 subjects. In both the dataset each face image is rescaled to 3232 using a bi-cubic interpolation to facilitate	ORL dataset EGFR+$(2D)^2$PCA = 98.0%, YALE database EGFR+$(2D)^2$PCA = 96.67%	This method is based on 2D Gabor Face matrices rather than 1D sampled feature vectors. Therefore there is no loss of information due to down sampling

				the Gabor face representation and reduced the computational complexity		
Yanwei Pang, Dacheng Tao, Yuan Yuan and Xuelong Li, 2008 [39]	Binary 2DPCA	YALE face dataset	Threshold Q determine the approximation precision and the number of selected 1D Haarlike function	YALE database contains face images collected from 15 individual, with 11 images	B-2DPCA outperforms B-PCA, particularly when the number of selected features is small	The important observation is that the performance degenerate little when threshold θ is large. By increasing θ, the number of Haarlike functions reduces in a dictionary. So the time cost of testing procedure can be reduces in a dictionary.
Jun Ying Gan, Si-Bin He, 2009 [40]	Improved 2DPCA	ORL and YALE face dataset	Nearest Neighbor Classifier	ORL database contains 400 images, including 40 distinct people and reach with 10 images (112×92) pixels, YALE face database contains 15 distinct people each with 11 images (243×320) pixels	ORL= 98.33%, YALE = 97.78% Recognition accuracy	Experiment performed on ORL and YALE face database and no. of class and samples is limited. Therefore, the validity of algorithm on a large face database and in a more complex condition need to be studied.
Dongmin Jeong, Minho Lee, Sang-	$(2D)^2$ PCA-ICA	ORL and YALE B face database	Nearest Neighbor Classifier	ORL contains images from 40	ORL = 92.5%, YALE= 91.0%	In future work consider an incremental

Woo Ban, 2009 [41]				individuals, each providing 10 different images (112×92) pixels, YALE B face database contains 200 images of 10 individuals each person has 20 different images (60×50) pixels	Recognition accuracy	scheme to properly deal with a large-scale database, which can incrementally learn high dimensional data without computing the corresponding covariance matrix and without knowing a prior knowledge about the data in advance.
Lin Yang, Yuan Liang, 2011 [42]	Improved Modular 2DPCA	YALE face dataset	Nearest Neighbor Classifier	it contains 15 person 11 images each person total 165 images	Recognition rate = 90.7%	Weight the sub matrix can increase the recognition rate effectively. Increase the weight of these sub images can increase the different among classes, and improve the fault tolerance. But, luck of correlative research stop us to set the weight accurately, this problem can be further research.

Zhao Lihong, Yang Caikun, Pan Feng, Wang Jiahe, 2012 [43]	PCA+ 2DPCA + Gabor	ORL dataset	Nearest Neighbor Classifier	Total 400 people, 40 people, 10 images per people	Recognition rate = 96%	2DPCA with PCA method based on the Gabor wavelet is superior to single 2DPCA or PCA. It recognition rate is higher.
Shimin WANG, Jihua YE, Dequan uan YING, 2013 [44]	2DPCA Principal component uncertainty	ORL database	Euclidean distance	ORL database contains 400 face images contains 40 people, 10 images per person	Recognition rate= 97.80%	From the uncertainty principal we obtained α and β with α increase, β also increase. So, as to enhance or suppress the 2DPCA principal component and the capability of face recognition also increase. But it only can increase to a certain extent, since excessively enhance or suppress, the capability of face recognition decrease.
Swarup Kumar Dandpat, Sukadev Meher, 2013	PCA and 2DPCA	ORL and YALE database	Euclidean distance between two principal component	ORL contains 400 images that having 40 people with each person in	ORL = 92.8% (experiment A) YALE = 92.3% (experiment A)	Further experiment on different database with more subject.

[45]			vectors. In this paper it consider the three Nearest distance for all test.	10 different poses (92×112) pixels, YALE database 165 images in GIF format 15 individual 11 images per person (100×100) pixels.	ORL = 93.8 % (experiment B) YALE = 92.8% (experiment B)	
Aili Wang, Na Jiang and Yuan Feng, 2014 [46]	Wavelet transform and improved 2DPCA	ORL dataset	Nearest Neighbor Classifier	40 volunteers have 10 images individual total 400 faces (112×92) pixels	Recognition rate = 92.0%	In wavelet transform, the higher decomposition layers will lost a lot of information by which reduce the recognition rate.

Table 1. A Summary of some face recognition system based on 2DPCA (2004-2014)

LIMITATION IN PREVIOUS WORK

(1) Recognition accuracy is not achieved up to the mark.

(2) 2DPCA was not efficient as in terms of storage requirements.

(3) Experiment performed on ORL and YALE face database and no. of class and samples is limited. Therefore, the validity of algorithm on a large face database and in a more complex condition need to be studied.

(4) Increase the weight of these sub images can increase the different among classes, and improve the fault tolerance. But, luck of correlative research stop us to set the weight accurately, this problem can be further research.

(5) From the uncertainty principal we obtained α and β with α increase, β also increase. So, as to enhance or suppress the 2DPCA principal component and the capability of face recognition also increase. But it only can increase to a certain extent, since excessively enhance or suppress, the capability of face recognition decrease.

(6) In wavelet transform, the higher decomposition layers will lost a lot of information by which reduce the recognition rate.

(7) Some paper, have shown that their results and performance are database dependent. Further experiment on different database with more subject.

PROPOSED WORK

In light of the deficiencies explored by the detailed comparative analysis in the studied papers, we have chosen in the current work to overcome the following deficiencies:

(1) Remove the difficulty against rotation, scale, and uneven lighting and illumination variations.

(2) Further experiment on different database with more subject.

(3) In future work consider an incremental scheme to properly deal with a large- scale database, which can incrementally learn high dimensional data without computing the corresponding covariance matrix and without knowing a prior knowledge about the data in advance.

(4) Improving the recognition rate.

(5) Develop the computational model for face recognition that will be fast, simple and accurate in different environments.

CONCLUSION

Under the comparative analysis of the various state of the art techniques available for face recognition, we have encountered various pitfalls. This covers the major shortcomings specified under the 'proposed work' as well as others. We also plan to conduct further experiments on different databases with more subjects. The research will be focused to develop the computational model for face recognition that will be fast, simple and accurate in different environment.

Finally, it can be stated that if truly automatic face recognition system are to be feasible, current feature extraction methods have to be improved and extended with regard to robustness in natural environments as well as independence of manual intervention during initialization and deployment.

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