International Journal of Advanced Research in Computer Engineering & Technology (IJARCET)
Volume 3 Issue 12, December 2014

A Survey on Face Recognition in Present Scenario

Parul Jain, Nilay Jain and Rohit Raja

***Abstract*— Face recognition has been a quick growing, challenging and fascinating field in real time applications. In the field of biometrics an oversized variety of face recognition algorithms are developed in last decades. In this paper a trial is formed to review a large variety of methods used for face recognition. This includes PCA, LDA, ICA, Batch_ccipca, Ind_ccipca, LibSVM and ISVM. This review investigates include all these face recognition methods with parameters that challenges face recognition like illumination, pose variation, facial expressions.**

***Index Terms*—Face Recognition, PCA, LDA, ICA, SVM.**

I. Introduction

The study of biometry is changing into vital in recent years. Many security applications area unit developed supported biometric personal identification like computerised access management. With personal identification, identity of a private are often determined, preventing unauthorized access of vital knowledge. Most of the biometry signals area unit used for this type of application face recognition, speech, iris, fingerprint, signatures, and area unit instances. Using these signals, face recognition would be addressed here as a result of its wide usage within the field of security application and transmission search engines.

In the large database face recognition provides a convenient way to identify and recognize a person. Using face recognition, we will identify or verify an individual by simply taking a photograph of that person. User now not has to scan his fingerprint or iris for private identification however simply ought to change front of a camera. The system will check its information to identify or verify the person from his image.

Face recognition is a crucial a part of the capability of human perception system and could be a routine task for humans, whereas building an analogous computational model of face recognition. The computational model not only contribute to theoretical insights however additionally to several sensible applications like automatic crowd surveillance, access management, design of human computer interface (HCI), criminal identification and content based image database management and so on.

The earliest work on face recognition are often derived back a minimum of to the 1950s in psychology [1] and to the 1960s within the engineering literature [2]. A number of the earliest studies include work on facial features emotions [3]. However, analysis on automatic machine recognition of faces started within the 1970s [4-5]. In 1995s, a review paper [6-7] gave an intensive survey of face recognition technology. At that time, video-based face recognition was still in a very nascent stage. During the past decades, face recognition has received inflated attention and has advanced technically. In several business systems for still face recognition are now available.

Recently, vital analysis efforts are focused on video-based face modeling/tracking, recognition and system integration. New databases have been created and evaluations of recognition techniques exploitation these databases are carried out. Now, the face recognition has become one among the most active applications of image analysis, pattern recognition and understanding.

II. Face recognition algorithms

A. Principal Component Analysis (PCA)

PCA is one of the oldest and most popular face recognition algorithms [8], which is based on Principle Component Analysis (PCA). The work of PCA is to reduce the dimensionality of each face image by exploiting similarities between all face images. In this way, PCA extract a set of images (eigenfaces) that combine linearly to describe all face images. Given M face images arranged as column vectors $\Gamma_1\Gamma_2,\dots,\Gamma_M$ the average face $\Psi = \frac{1}{M}\sum_{N=1}^{M}\Gamma n$ is subtracted from each image $\Phi_i = \Gamma_i - \Psi$. Joining the face images into a single matrix $A = [\Phi_1\ \Phi_2 \dots \Phi_M]$. PCA finds a set of orthonormal vectors that best represents the data. These vectors are the eigenvectors u_k of the covariance matrix $C = AA^T$. In Eigenspace terminology, each face image is projected by the top M' significant eigenvectors u_k to obtain weights $w_k = u_k^T(\Gamma_i - \Psi)$ that best linearly weight the eigenfaces into a representation of the original image. Knowing the weights of the training images and a new test face image, a nearest neighbour approach determines the identity of the face. Eigenfaces has the

Manuscript received Dec, 2014.
***Parul Jain**, Department of Computer Science and Engineering, SSGI, SSTC, Bhilai., Durg, India, 7587488017*
***Nilay Jain**, Department of Computer Science and Engineering, Ramtek Nagpur, raipur, India, 9425505168*
***Rohit Raja**, Department of Computer Science and Engineering, SSGI, SSTC, Bhilai., Durg, India, 9827164467*

advantage of being simple and fast at the cost of low accuracy when expression, illumination and pose vary significantly.

B. Incremental PCA (IPCA)

In face recognition scenario is an incremental training process where users continuously changing photos, we chose to also explore Covariance-Free Incremental Principle Component Analysis (CCIPCA) [9]. In CCIPCA incrementally estimates of the eigenvectors of the covariance matrix which is calculated from all images. IPCA requires far less memory and is often faster with a slight degradation in accuracy.

A shortcoming of the training process for PCA is that the entire training dataset images must be available beforehand in order to start the training process. This defect is elegantly handled by Incremental PCA (IPCA) methods which allow adding new images and updating the PCA representation accordingly; thus offering the great benefit of dispensing with the recently added images after model update.

The incremental methods proposed in [10-15] are tailored for temporally weighted learning allowing newer images to have a larger influence on the estimation of the current subspace than the older ones. Ref [16] studied incremental learning for online face recognition and proposed new approach to face recognition in which not only a classifier but also a feature space of input variables is learned incrementally to adapt to incoming training samples; as suggested, a benefit of this type of incremental learning is that the search for useful features and the learning of an optimal decision boundary are carried out in an online fashion. Incremental PCA algorithms that compute the principal components without computing the covariance matrix are presented in [17-20].

Individual IPCA

As IPCA incrementally updates the eigenfaces, the weights for previously trained images become invalid because the eigenspace in which they reside has been changed. After that, the previously trained face images must be kept and reprojected into the updated eigenspace. Liu et al. in [21] describes a fully incremental method that does not require trained face images for updates. Instead of creating a single eigenspace to represent all faces of individual person, a smaller set of 5-10 eigenfaces is created for processing. Recognition is not done by nearest neighbor, but by projecting the unknown face into each user's eigenspace and finding the one that best represents the face. Training times are very fast and fully incremental, but accuracy is poorer and recognition is slower.

C. The Candid Covariance-free IPCA Algorithm: CCIPCA

The candid covariance-free IPCA (CCIPCA) was introduced to compute the principal components of a sequence of samples incrementally without estimating the covariance matrix (thus covariance-free) [18]. The algorithm keeps the scale of observations and computes the mean of observations incrementally. Because this method is appropriate for real-time applications, and thus it does not allow iterations. For high dimensional image vectors it converges very fast. The CCIPCA algorithm generates "observations" in a complementary space for the computation of the higher order principal components.

D. Independent Component Analysis (ICA)

Independent Component Analysis (ICA) seeks a set of vectors that reduces the dimensionality of input images [22].However, ICA does not require the ortho normalization of vectors, which allows higher-order dependencies in image pixels to be exploited. As the mean (first-order statistic) is removed from the images in PCA, ICA removes the first and second-order statistics by "sphering" the data. Each image (with the mean subtracted) is stored as a row vector in X, which is multiplied by the whitening matrix$W_z = 2cov\ (X) - 1/2$. ICA finds statistically independent images, represented by the rows in matrix U, that are mixed together with matrix W such that $U = WX$. In comparison to PCA, the rows of U are analogous to eigenfaces and the columns of $W^{-1}$are the weights of each image. ICA can account for more variations in the input images, but suffers from slower performance.

E. Linear Discriminant Analysis (LDA)

The major limitation of PCA and ICA is that the distances between weights from faces of the same subject are greater than face weights from different people. To overcome this, a method called Fisherfaces [23], based on Linear Discriminant Analysis (LDA), attempts to find vectors that not only describe the data, but also best discriminate between classes of data. Given c classes (people) with the mean of class j denoted by μj and the i^{th} image in class j denoted by x_i^j a "within-class" scatter matrix S_w and a "between-class" scatter matrix S_b is calculated.

$$S_b = \sum_{j=1}^{c} (\mu_j - \mu)(\mu_j - \mu)^T$$

$$S_w = \sum_{j=1}^{c} \sum_{i=1}^{Nj} (x_i^j - \mu_j)\ (x_i^j - \mu_j)^T$$

To maximize the between class measure and simultaneously minimizing the within-class measure LDA produces a set of projection vector by using scatter matrices. Literature shows that LDA is often superior to PCA for well distributed classes in small datasets [23], Since LDA requires significantly more computation than PCA for large datasets.

F. Support Vector Machine (SVM)

For face recognition Support Vector Machines (SVM) is one of the most useful techniques in classification problems. However, when the feature vectors defining samples have missing entries the SVM cannot be applied. A classification algorithm that has successfully been used in this framework is the all-known Support Vector Machines (SVM) [24], which can be applied to the original appearance space or a subspace of it obtained after applying a feature extraction method [25-27]. The advantage of SVM classifier over traditional neural network is that SVMs can achieve better generalization performance.

Recently, Support Vector Machines (SVMs) have received much attention for their applicability in solving pattern recognition problems. SVMs were first proposed as a binary classifier. A hyperplane that maximizes the margin, or distance, between the hyperplane and the closest points and then SVM compute the support vectors through determining points. As described in [28], the problem begins with a set of N points $x_1 \in \mathbb{R}^n,\ i = 1, 2, \dots, N$. Each point is labeled as one of two classes $y_i \in \{-1,1\}$. The best, or optimal separating hyperplane (OHS), is defined as $f(x) = \sum_{i=1}^{l} \alpha_i y_i x_i \cdot x + b$ where the sign of $f(x)$ determines the class of the data, for the non-separable case and solving for the coefficients α_i and b refer to [25]. Compared to one-vs-all the initial test, one-vs-one recognition strategy as performance is better. The one-vs-one technique uses binary tree classification to expand to a multi-class scenario, where at each level two classes are compared and the top class is selected with:

$$d(x) = \frac{\sum_{i=1}^{l} \alpha_i y_i x_i \cdot x + b}{\|\alpha_i y_i x_i . x\|}$$

where the sign of d is the class.

III. Conclusion

In this paper, we have addressed the problems needed to overcome for face recognition such as light intensity variable, facial expression etc. And we have discussed certain requirements for a reliable and efficient face recognition system like accuracy, efficiency. We have reviewed different face recognition algorithm (PCA, LDA, ICA, Batch_ccipca, Ind_ccipca, LibSVM and ISVM). Our future works is made a comparison of these algorithms and have discussed the advantages and drawbacks of each of them.

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Parul Jain has completed her B.E. in Computer Science & Engineering Branch in 2012 with 1st Division from Shri Shankacharya College of Enginnering & Technology, Bhilai (chhatisgarh swami vivekanada technical university,durg). She is pursuing her M.E. in Computer Technology and Application from Shankaracharya Group of Institution, Bhilai.

Nilay Jain has completed his B.TECH. in Computer Science & Engineering Branch in 2012 with 1[sst] division from Kavikulguru Institute Of Technology & Sciences(RTMNU).He is currently working at Tech Mehendra,Pune as a software enggineer

Rohit Raja is working as a Professor in Shankaracharya Group of Institutions, Bhilai(C.G.). He has received his M.E. degree in Computer Technology and Application in 2009 from SSGI, Bhilai (C.G) and B.E. degree in Computer Science & Engineering in 2004 from R.I.T (R.S.U) Raipur (C.G.). Presently he is pursuing his Ph.D. from C.V Raman University, Bilaspur. He has published more than 15 Papers in various reputed Journals, National & International Conferences.

