

Survey of Face Recognition using ICA

Payal Dangi,
RKDF School of Engg, Indore
Payaldangi123@gmail.com

Shabbir Ahmad,
RKDF School of Engg, Indore
ahmadbhopal@gmail.com

Abstract:- Nowadays, face recognition is used in number of applications as a means of authentication and verification. But the task of face recognition is not easy for a computer system. There are various ways that can be used for face recognition. This paper reviews the problem of face recognition using edge information as independent component. Here, the edge information is obtained by using LoG(Laplacian of Gaussian) and Canny edge detection methods. On the obtained information, Principle Component Analysis (PCA) is applied for preprocessing. Then, the images are trained using Independent Component Analysis (ICA). Then the images are tested.

Keywords: Laplacian of Gaussian(LoG), Canny edge detection, Principle Component Analysis (PCA), Independent Component Analysis(ICA).

I. Introduction:

Nowadays, face detection is widely used in number of applications as a mean of security. Face detect is the task that human performs every day. For human this task is very effortless and easy. Very powerful and low cost desktop and embedded computing systems are widely available. This availability has created interest in automatic processing of images and videos. There are number of applications that use face recognition such as biometric authentication, surveillance, human computer interaction, multimedia management. All these applications have opened an area of research.

Face recognition is one of the most popular and successful applications of digital image analysis and pattern matching. It is having wide range of applications. Face recognition has major application in the area of Law enforcement, forensic, access control, entertainment. A reliable face recognition system can help in providing security in public places from the dangerous terrorist attacks. The current access control systems make use of passwords and cards. But the ATM card may be forged or misplaced. Similarly the pin or password can be hacked. In addition to keep secure password secure, it is must to remember the password is necessary. The passwords that are easy to remember are less secure and the complicated and long passwords cannot be remembered. These are some issues with password authentication.

So, in ATM system can use face recognition to capture the digital image of the person and verify the person identity. But for accurate real time recognition, the current system is not reliable. The performance of the current face recognition system degrades with the lighting conditions, scaling, occlusion or pose variations.[10]

II. Literature Survey

Most current face recognition technique is appearance-based recognition. Kirby and Sirovich had applied the principal component analysis (PCA) to face images, and showed that PCA is an optimal compression scheme that minimizes the meansquared error between the original images and their reconstructions for any given level of compression [4,5].

Then, Turk and Pentland promoted the use of PCA for facerecognition [6]. They computed set of subspace basis vectors called eigenfaces, for databases of images using PCA. After that, they mapped the images into database in the compressed form. The test images were matched to the images stored in that database by mapping or projecting them onto the basis vectors and finding closely compressed image in the eigenfaces.

Then research started to find the other subspaces for improving the performance. One of them is Fisher's linear discriminant analysis (LDA) [7]. The LDA finds N-1 basis vectors for N-classification problem. This vector maximizes the interclass distances while minimizing the intraclass distances. At one point, PCA and LDA are different, i.e. LDA is a supervised learning technique that relies on class labels, whereas PCA is an unsupervised technique. One characteristic of both PCA and LDA is that they produce spatially global feature vectors.

There is also a lot of interest in techniques that create spatially localized feature vectors, in the hopes that they might be less susceptible to occlusion and would implement recognition by parts. The most common method for generating spatially localized features is to apply independent component analysis (ICA) to produce basis vectors that are statistically independent. The feature vectors that uniformly distribute data samples, can also be created using ICA[8,9].

Gabor jets represent a substantially different class of subspace projection techniques. Unlike PCA, LDA, or ICA, the Gabor basis vectors are specified a-priori (although their spatial positions might be trained). In this technique the compression of images is dependent on the size of image and it is far less as compared to other techniques and they may even expand in extreme cases rather than contract the data.

The subspaces defined by Gabor jets may be good for face recognition and recognizing facial expressions. Finally there are some techniques that are mixture of linear subspaces.

III. Edge Detection

The purpose of edge detection is to significantly reduce the amount of data in an image, while preserving the structural properties to be used for processing of images.

Laplacian of Guassian:

Consider the Guassian function,

$$h(r) = e^{-\frac{r^2}{2\sigma^2}}$$

where, $r^2 = x^2 + y^2$ and σ is standard deviation. It is smoothing function. If it is convolved with image, it will blur it. The degree of blurring is determined by the value of σ .

The Laplacian function is

$$\square \square h(r) = \left[\frac{r^2 - \sigma^2}{\sigma^4} \right] e^{-\frac{r^2}{2\sigma^2}}$$

The second derivate is a simple linear operation, both convolving an image with $\square \square h(r)$ and convolving image with the smoothing function first and the computing the Laplacian of result are same. This is the reason, why this detector is known as Laplacian of Guassian.[2]

Canny Edge Detection:

Canny edge detector works optimally for step edges. It works in following five steps:

Smoothing: In this step noise is removed by blurring the image.

1. Finding gradients: Here those edges are marked that has large magnitude of gradients of images. The gradient can be obtained by using derivatives of Guassian filter with specified standard deviation, σ , to reduce noise. The local gradient,

$$g(x,y) = [G^2x + G^2y]^{\frac{1}{2}}$$

and edge direction, $\alpha(x,y) = \tan^{-1}(Gy/Gx)$, computed at each point

2. Non maxima suppression: Only local maxima are marked and non maxima are suppressed.
3. Double thresholding: Two thresholds are used for determining the potential edges. This step detects weak and strong edges. Only those weak edges are considered for output, that are connected with strong edges and remaining are rejected.

IV. Principal Component Analysis(PCA):

It is a popular unsupervised statistical method to find useful image representations. Consider a set of N basis images each of which has N pixels. A standard basis set consists of a single active pixel with intensity 1, where each basis image has a different active pixel. Any given image with N pixels can be decomposed as a linear combination of the standard basis images. In fact, the pixel values of an image can then be seen as the coordinates of that image with respect to standard basis. The goal of PCA is to find a better set of basis images so that in this new basis, the image coordinates are uncorrelated.

The PCA basis vectors are computed from a set of training images I. As a first step, the average image in I is computed and subtracted from the training images, creating a set of data samples,

$$i_1, i_2, \dots, i_n \in I - \bar{I}$$

Then all these data samples are stored in a matrix X, with one column per sample

$$X = \begin{bmatrix} \vdots & & \vdots \\ i_1 & \dots & i_n \\ \vdots & & \vdots \end{bmatrix}$$

Then the sample covariance matrix is given by XX^T . The principal components of covariance matrix are calculated as follows,

$$R^T(XX^T)R = A$$

Where, A is the diagonal matrix of eigen values and R is the matrix of orthonormal eigenvectors.

Basically the N eigenvectors associated with the largest eigenvalues are used to define the subspace. Three related arguments are used for matching the images in subspaces.[2]

- a. Compression, it is more efficient to compare images with reduced dimensions.
- b. Data samples are drawn from normal distribution. The axes of small variance are considered as noise and its removal improves the accuracy of matching images.
- c. It is common preprocessing step. Here, a mean value is subtracted from each image and images are scaled to form a unit vectors.

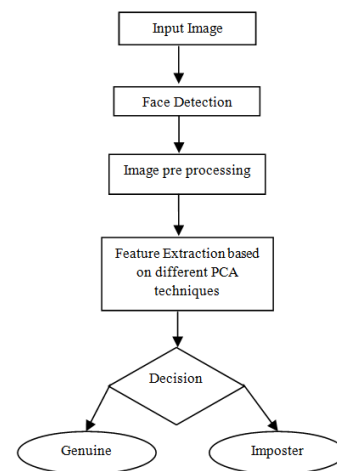


Figure 1: Face recognition using PCA

V. Independent Component Analysis (ICA):

Independent Component Analysis (ICA) is a statistical and computational technique for revealing hidden factors that underlie sets of random variables, measurements or signals. PCA generates compressed data with minimum mean-squared error because it decorrelates the input data using second-order. But the Independent Component Analysis reduces the second order and higher order dependencies in the input samples. It is closely related with the Blind Source Separation (BSS) problem, where the aim is to decompose the observed signal into a linear combination of unknown independent signals. Let s be the vector of unknown source signals and x be the vector of observed mixtures. If A is the unknown mixing matrix, then the mixing model is written as

$$x=As$$

Two assumptions are made here,

- a. Source signals are independent of each other
- b. The mixing matrix A is invertible.

Using these assumptions, ICA finds mixing matrix A or separating matrix W, such that,

$$u=Wx=Was$$

is an estimation of the independent source signals [3].

ICA can be considered as a generalization of PCA. Since, PCA decorrelates the training data sample so that the sample covariance of the training data is zero. Whiteness is a constraint that requires both decorrelation and unit variance. The whitening transform can be determined as $D^{-1/2}R^T$, where D is the diagonal matrix of the eigenvalues and R is the matrix of orthogonal eigenvectors of the sample covariance matrix. Application of whitening to observed mixtures, results in the source signal only up to an orthogonal transformation. ICA goes a step ahead and hence transforms the whitened data into a set of statistically independent signals [22]. Signals are statistically independent when

$$f_u(u) = \prod_i f_{u_i}(u_i)$$

where, f_u is the probability density function of u. It might be possible that there is no matrix W, that can fully satisfy the independence condition, and there is no closed form expression to find W. Instead, various algorithms are available that iteratively approximate W so as to indirectly maximize independence.

Since it is difficult to maximize the independence condition, all the ICA algorithms work on optimization. Each of them tries to optimize a smoothing function and obtain the global optima when the output vectors u are independent.

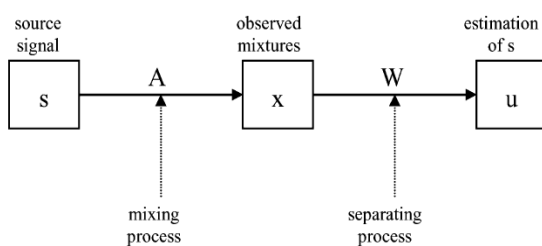


Figure 2: Blind source separation model

To obtain several independent components, it is required to apply ICA algorithm several times with weight vectors w_1, \dots, w_n . Then that the outputs w_1x, \dots, w_nx are decorrelated after each iteration, in order to prevent different vectors converging to the same maxima.

A way to achieve decorrelation is to estimate independent components one by one. Once the p independent components or p vectors $w_1 \dots w_p$ are estimated, the one-unit fixed-point algorithm is run on w_{p+1} . After every iteration, a projection $w_{p+1}^T w_j w_j$ is subtracted from w_{p+1} . Then renormalization of w_{p+1} is performed.

$$W_{p+1} = W_{p+1} - \sum_{j=1}^p W_{p+1}^T W_j W_j$$

$$W_{p+1} = W_{p+1} / \sqrt{W_{p+1}^T W_{p+1}}$$

The ICA algorithm requires little bit of more time as compared to other methods. The training time required will be few seconds. [2]

VI. Conclusion

In this paper, we have discussed the importance of face recognition and the challenges arising in this area. This paper reviews the basic researches carried out in the field of face recognition. This further discussed the edge detection using Laplacian of Gaussian and Canny edge detection methods. It reviews the principal component analysis and independent component analysis algorithms used for face recognition. This finally concludes that Independent Component Analysis (ICA) is better than Principal Component Analysis (PCA) in some cases, but requires at least few seconds as its training time.

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