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A Survey of Different Independent Component Analyses Algorithms used for Pattern Recognition

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ABSTRACT- Data security attacks remain a top concern, and the research on reliable recognition of human-machine interaction i.e face recognition is the topmost priority. A central problem in neural network research, as well as in statistics and signal processing, is finding a suitable representation of the data, using a suitable transformation This paper reviews the problem of face recognition using a survey of different algorithms as an independent component. Here, the edge information is obtained by using the Independent Gabour feature method (IGF), it derives the Gabour feature vector based upon a set of down-sampled Gabour wavelet representations of images by incorporating different orientation and scale local features.

KEYWORDS- Independent Component Analysis, Independent Gabour Feature Method, Face recognition, Neural Network.

I. INTRODUCTION

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

In this paper, we shall focus on the problem of representing continuous-valued multidimensional variables. Let us denote by x an m-dimensional random variable; the problem is then to find a function f so that the n-dimensional transform

s = (s1; s2; :::; sn)T denoted by s = f (x) (1)

has some desirable properties. (Note that we shall use in this paper the same notation for the random variables and their realizations: the context should make the distinction clear.) In most cases, the representation is sought as a linear transform of the observed variables, i.e.,

S = Wx (2)

where W is a matrix to be determined. Using linear transformations makes the problem computationally and conceptually simpler, and facilitates the interpretation of the results. Thus we treat only linear transformations here Most of the methods described here can be extended for the non-linear case. Such extensions are, however, outside the scope of this research

Recently, a particular method for finding a linear transformation, called Independent Component Analysis[1] (has gained widespread attention. As the name implies, the basic goal is to find a transformation in which the components Si are statistically as independent from

each other as possible. ICA can be applied in Ex. Blind source separation in which the observed value of x correspond to a realisation of an m-dimensional discrete time – signal x(t) , t=1, 2, 3,………… Then the component Si (t) is called source signals, which are usually original uncorrupted signals or noise sources. The use of ICA for feature extraction is motivated by results in neurosciences that suggest the similar principle of redundancy reduction explains some aspects of the early processing of sensory data of the brain.

II. LITERATURE SURVEY

The most current face recognition technique is appearance-based recognition. Kirby and Sirovich applied the principal component analysis (PCA) to face images and showed that PCA is an optimal compression scheme that minimizes the mean squared error between the original images and their reconstructions for any given level of compression [8,9].

The Independent Component Analysis (ICA) was introduced in 1986 [5]. However, in that paper, there is no theoretical explanation was presented and the proposed algorithm was not applicable in several cases in the year early 1990 partial theoretical structure was laid down [6]. Thus, the ICA technique remained mostly unknown till mid-1990, when the name ICA appeared and was introduced as a new concept [7] where it is suggested that signals of the sources are independent.

Several algorithms have been proposed since then for calculating different ICA techniques, which differ among themselves in the handling of statistical independence, estimation of the separation matrix, and use of statistics of higher order. ICA's linear mixture model attempts to separate source signals according to certain assumptions:

The source vectors are statistically independent.

The mixing matrix (A, as defined in the next section) should be a square and full rank.

The source matrix (S, as defined in the next section) does not have any external noise.

The data are centered (zero mean).
The signals from the source should be a non-Gaussian probability density function (pdf) with one source expected, which may be Gaussian.

Independent Component Analysis (ICA) has been employed for nearly 30 years for unmixing of complex signals. Independent components analysis (ICA) is a probabilistic method, whose goal is to extract underlying component signals that are maximally independent and non- Gaussian, from mixed observed signals. The mixing coefficients are also unknown. The latent variables are non-Gaussian and mutually independent and they are called the independent components of the observed data. By ICA, these independent components, also called sources or factors, can be found. Thus, ICA can be seen as an extension of Principal Component Analysis and Factor Analysis. However, ICA is a much richer technique capable of finding the sources when these classical methods fail. The measurements are often given as a set of parallel signals or time series.
ICA technique deals with two independent clauses, i.e. Single method of optimization used for different contrast functions or a different method of optimization used for single contrast functions.
The widespread and interdisciplinary applications of ICA in the context of image processing, text mining, data mining, audio signal processing, biomedical signal processing, and time series applications motivate us to present ICA theory and its most used methods in one paper. The goal of this review is to explain ICA and to present some of the widely used algorithms for ICA computation as well as some more contrast functions in addition to Aapo Hyvarinen's much earlier survey in 1999 [1].
The remainder of the survey is organized in the following way. We give an introduction to ICA in section 1. Section 2 addresses Literature Survey. Section 3 gives different ICA algorithms. Section 4 gives applications of ICA in the real world. Finally, section 5 of the survey is the conclusion and references.

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 images

A. Gabor Feature for face recognition

The Gabor feature vector is given the Gabor wavelet representation of an image is the convolution of the image with a family of Gabor kernel.

B. Gabor feature Analysis

Principal component Analysis is the method of choice when the primary goal is to project the similarity judgment for face recognition into a low dimensional space. An important property of PCA is its optimal signal reconstruction in the sense of minimum mean square error (MSE) when only a subset of principal components is used to represent the original signal. The formula for dimensionality reduction is given below:

$$\gamma\rho = Pt * X\rho$$

Where P = (P1, P2, Pn) consist of then eigenvectors corresponding to the leading eigenvalues of the covariance matrix.

IV. PRINCIPAL COMPONENT ANALYSIS

Several principles have been developed in statistics, Neural Computing, and signal processing to find suitable linear representations of a random variable, Principal Component Analysis is one of them. This is a popular unsupervised statistical method to find useful image representations. It is a statistical process that converts the observations of correlated features into a set of linearly uncorrelated features with the help of orthogonal transformation. These new transformed features are called the Principal Components. . 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

$$i1, i2, i3,in \in I - I^{-}$$

Then all these data samples are stored in matrix X with one column per sample then the sample covariance matrix is given by XXT. Then the principal component of the covariance matrix is calculated as:

$$RT\ (XXT)\ R = \lambda$$

Where λ is the diagonal matrix of the eigenvalue

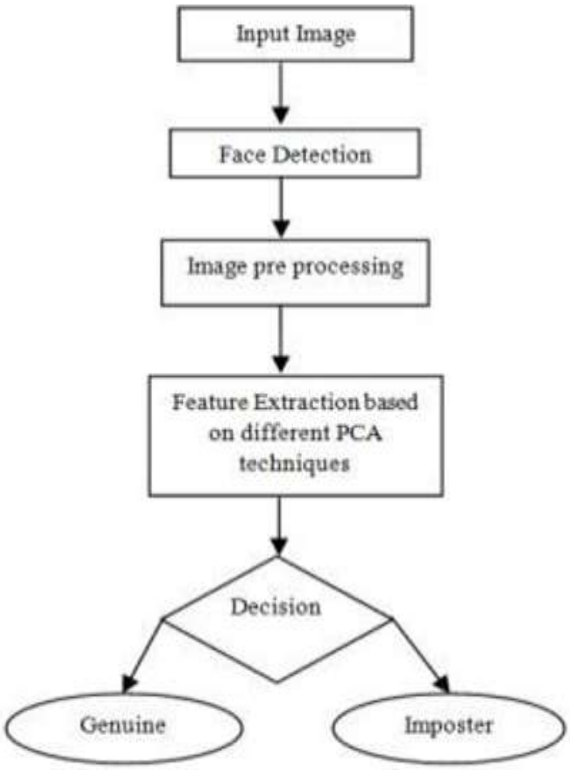

Figure 1: face recognition using Principal Component Analysis

V. INDEPENDENT COMPONENT ANALYSIS

Independent Component Analysis (ICA) [1,2,3,4] is a statistical tool for the transformation of an observed multidimensional random vector into statistically independent components. This approach is used to separate the mixed signals. PCA functions only in second-order statistics and provides optimal data for the Gaussian distribution sets. ICA is a PCA extension designed to optimize non-Gaussianity or minimize the Gaussianity of the datasets. ICA attempts to find independent components by assuming their statistical property of higher order.

Independent Component Analysis(ICA) is a method of data transformation that finds independent sources of activity in recorded mixtures of sources. This is a computational technique for revealing hidden factors that underlie sets of measurements or signals. ICA assumes a statistical model whereby the observed multivariate data, typically given as a large database of samples, are assumed to be linear or nonlinear mixtures of some unknown latent variables. In mathematical terms, we need to find a suitable, proper multivariate description of random vectors this, ICA can be seen as an extension of Principal Component Analysis and Factor Analysis. However, ICA is a much richer technique capable of finding the sources when these classical methods fail.

ICA can be used to perform face recognition where face images are considered as a combination of not known independent sources of unknown mixing matrix where ICA finds separating matrix to obtain statistical basis images, These basis images are shown in the figure. 2.

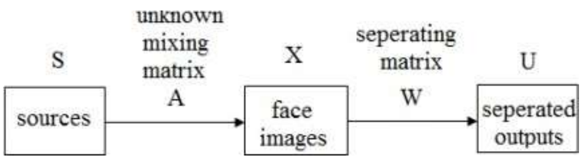

Figure 2: ICA implementation for face recognition

Let S be unknown independent Sources and X be observed mixtures then in the matrix notation it can be derived as

$$X=AS$$

Where A is unknown mixing matrix now, for this model our goal is to find both A and S Where A is square matrix and computed easily once it is computed then W can be found And independent sources can be found as

$$S = WX$$

Goal of ICA is to determine separating matrix W. Now, to obtain W various iterative algo is used and W can be computed easily.

VI. APPLICATIONS OF ICA IN THE REAL WORLD

ICA for analysing financial time series.
It can be used as a separation of mixture signals into different sources

- Feature Extraction
- Telecommunication
- Biomedical signal analysis

VII. CONCLUSION

In this paper, the importance of face recognition and the challenges arising in this area have been discussed. The paper reviews the basic research carried out in the field of face recognition. Then further discussed edge detection using Gabor feature vector methods. It reviews the Principal Component Analysis and Independent Component Analysis algorithms used for face recognition. The paper finally concludes that Independent Component Analysis (ICA) is better than Principal Component Analysis (PCA) in most cases, but requires a few seconds as its training time.

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