Journal Tri.Math.Soci 16(2014-15)11-23

A STUDY ON INDEPENDENT COMPONENT ANALYSIS BASED FACE RECOGNITION

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Abstract As society is becoming more and more electronically connected, the importance of the capability to automatically establish an identity of individuals using face has increased. Huge availability of powerful and low-cost configured systems has created an extreme interest in automatic processing of digital images in a number of areas, including pattern recognition field, computer vision and biometric communities. It can be applied in security measure at criminal face recognition, passport verification, visa processing, and verification of electoral identification. In many unsupervised statistical methods help to identify broad face recognition technique. In those methods, a set of face database images is to be found and represent faces as a linear combination of those images. Independent Component Analysis (ICA) is a well-liked example of such methods. ICA can be used in different kinds of application area such as feature extraction, bio-medical signal processing, audio signal separation, telecommunication etc. Here ICA could be used to estimate the independent characteristics of human faces. In human faces, there is a correlation or dependency between different faces. Applying ICA on those correlation faces to extract independent face is a challenging task.

This paper represents a theoretical study of face recognition system for human face identification and verification using ICA with feed-forward neural network (FFNN) is presented. This scheme to enhance the performance of ICA based features extraction by the utilization of FFNN classification technique. The scheme consists of two phases. First phase is the offline training process where the extracted features using ICA in the database is classified by FFNN classification. The second phase is an online testing where the obtain query test image is compare with the database images. As a result, it says query face images are authorized or unauthenticated person based on the similarity measure.

Keywords: *Face Recognition, Survey, Independent Component Analysis (ICA), Feed Forward*

1. Introduction

Face recognition has been a challenging and quite attractive key biometric technology with a huge range of potential applications related to identity fraud, passport verification, and visa processing for a very long time. Different research groups are proposed various algorithms in the world and comparing different report gives contradictory results. Over last ten years or so, face recognition is a famous or interesting area of research in computer vision and most successful applications of image analysis and understanding. It is becoming crucial in advance technology such as the internet and mobile devices, digital cameras and increased demands on security. Faces can vary considerably in their orientation, facial expression, scale, and lighting, therefore, face recognition is considered a difficult problem to solve.

In general, based on face representation face recognition techniques are divided into two groups they are *feature-based* methods which use extracting local geometric facial features (mouth, eyes, brows, cheeks etc.), from an image of the subject's face and geometric relationships between them. However, facial features are not always easy to extract and discard textual information like the "smoothness" of faces or hair style that might contain strong identity information. This observation has led to *holistic-based* methods which use features extracted from the whole image (i.e., global features) [1]. Another important approach is *template-based* methods over the last decade. These models consider faces as the points in high-dimensional spaces and reduce the dimension to find a more meaningful description.

The central issue is how to determine and define face appearance in a high-dimensional image space to a low-dimensional subspace. The most noticeable method in this category is Independent Component Analysis (ICA). ICA technique is a relatively new invention which has been mainly used to Blind Signal Separation (BSS), though it has been successfully applied to the face recognition problem too [2]. It was the first time introduced in early 1980's by J. Herault, C. Jutten, B. Ans [3, 4, 5] in the context of a neural network modeling. The motivation to use ICA is to deal with problems that are closely related to the cocktail party problem or blind source separation problem [28]. Question is about what is cocktail party problem? Imagine that you are in a room where two people are speaking simultaneously [28]. You have two microphones, which you hold in different locations [28]. The microphones give you two recorded signals. Each of these recorded signals is a weighted sum of the speech signals emitted by the two speakers [28]. It is not identified exactly how humans are able to separate the different sound sources. ICA can do it if there are at least two microphones in the room. This whole description depicts in Figure 1.

Before face recognition process by ICA initially performs the pre-processing procedure in the training dataset images using the centering and whitening methods. Then the extracted features from the ICA are used in the classification process by feedforward neural network (FFNN). In classification, the classifier classifies the online query testing images based on the similarity measure.

The paper is organized as follows. In section 2 survey of ICA, section 3 applications of ICA, section 4 the theoretical framework, section 5 Independent Component Analysis (ICA), and section 6 Feed Forward Neural Network (FFNN), section 7-conclusion and future work. Finally, there is an acknowledgement in section 8.

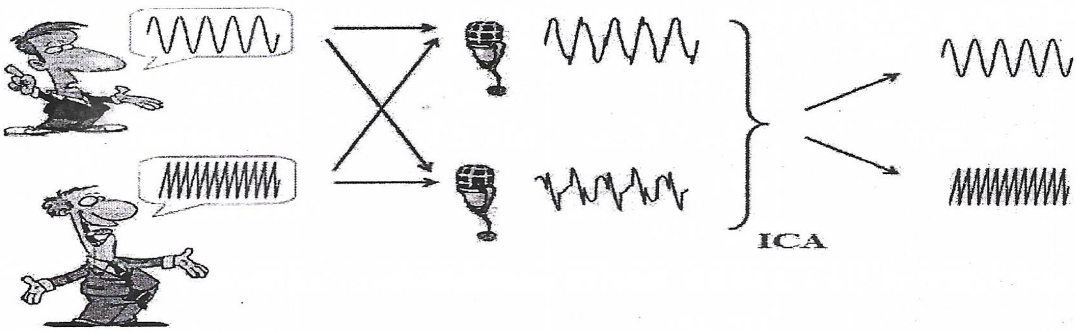


Figure 1 The Cocktail Party Problem

2. A survey of ICA

In [17], Mark D. Plumbley et al. propose to exploit the quasi-periodicity of the heart signals to transform the signal from one moving sensor, into a set of measurements, as if from a virtual array of sensors. Then use ICA to perform source separation. They showed that this technique can be applied to heart sounds and to electrocardiograms (ECG) [17].

In [18], J. Karhunen et al. consider an extension of ICA and BSS techniques to several related data sets. The goal is to separate mutually dependent and independent components or source which the assumed data model holds, and provides interesting and meaningful results for real world functional magnetic resonance imaging (fMRI) data [18].

PUBLISHER, YEAR	AUTHORS	METHOD USED	DATABASE
IEEE, 2011	Mark D. Plumbley et al. [17], 2011	FastIICA	Heart Sounds and EletroCardioGrams (ECG)
IEEE, 2012	J. Karhunen et al. [18], 2012	FastICA, EGLD-ICA, Pearson-ICA	functional Magnetic Resonance Imaging (fMRI) data
ELSEVIER, 2010	Jesse M. Engreitz et al. [19], 2010	Iterated FastICA	Gene Expression Omnibus (GEO)
IEEE, 2013	Mitianoudis N. et al. [20], 2013	Several methods including ICA	Audio, Video, Medical Imaging, Remote Sensor Imaging
EUSIPCO, 2014	Jutten C. et al. [25], 2014	Blind Source Separation (BSS)	iEEG recordings of four GAERS
IEEE, 2010	Kishor S. Kinage and S.G. Bhirud [26], 2010	PCA, ICA	ORL database
IEEE, 2007	Mark D. Plumbley [27], 2007	Not Mention	Musical Audio

Table 1 A survey work

In [19] Jesse M. Engreitz et al., modeling cellular gene expression where extracting biologically relevant gene expression features from microarray data. They used the Gene Expression Omnibus (GEO) database.

In [20], Mitianoudis N. et al. presents a virtual laboratory (VLab) known as MASTERS (Multimedia System in Telecommunications, mEdical and Remote Sensing application). The MASTERS VLab uses GUIs to implement several interaction exercises, giving students practical experience of important theoretical aspects of multimedia processing [20]. Here ICA was introduced for medical image de-noising.

In [25], Jutten C. et al. wonder if the temporal brain sources are similar during a given seizure or if they change. The proposed method is applied on intracranial EEG recordings of Genetic Absence Epilepsy Rat from Strasbourg (GAERS) [25].

In [26], Kishor S. Kinage and S.G. Bhirud a multi-resolution analysis on ICA for face recognition is examined. They extracted image features of facial images from various wavelet transforms (Haar, symlet, Biothogonal, Reverse Biothogonal) by decomposing face images in subbands 1 to 8 [26]. These features analyzed by ICA and Euclidean distance measure [26]. A series of experiments based on ORL database were then performed to evaluate the performance [26].

In [27], Mark D. Plumbley et al. present a simple and efficient method for beat tracking of musical audio. With the aim of replicating the human ability of tapping in the time to music, they formulate an approach using a two state model [27]. The first state performs tempo induction and tracks tempo changes, while the second maintains contextual continuity within a single tempo hypothesis [27].

3. Applications of ICA

The success of ICA in Blind Source Separation (BSS) has resulted in a number of applications practically. These include,

3.1 Audio signal processing

Audio source separation is the problem of automated separation of audio sources present in a room, using a set of differently placed microphones, capturing the auditory scene [21]. ICA most practically used in audio signal processing for noise removal purpose without using any filters or Fourier transforms.

3.2 Feature Extraction

ICA is effectively useful for lip reading and face recognition. The main purpose of face recognition is to train a system which can recognize and classify similar faces on different trained face database images. The test images are showing the face images under different pose or different lighting conditions.

3.3 Telecommunications

One of the emerging applications with respect to ICA is telecommunication. In telecommunication field ICA use in Code Division Multiple Access (CDMA). This problem is semi-blind, in the sense that certain additional prior information is available on the CDMA data model [22].

ICA also useful on natural image de-noising, text document analysis, biomedical signal processing, finding hidden factors in financial data etc..

4. A Theoretical Framework

Figure 2 shows a block of theoretical framework of a face recognition using Independent Component Analysis (ICA). First step of this framework is pre-processing all database images in order to make simpler and diminish the complexity of the problem for the actual ICA algorithms. Some pre-processing techniques in those algorithms are *centering* and *whitening*. Then extracting features from pre-processed data using ICA algorithms. The extracted features using ICA then classified by feedforward neural network (FFNN) classifier. This whole process of training database images will do in offline mode. The testing will do in online mode where the obtain query test images is compared with the classified images and is classified as authorized or unauthorized person based on the similarity measure.

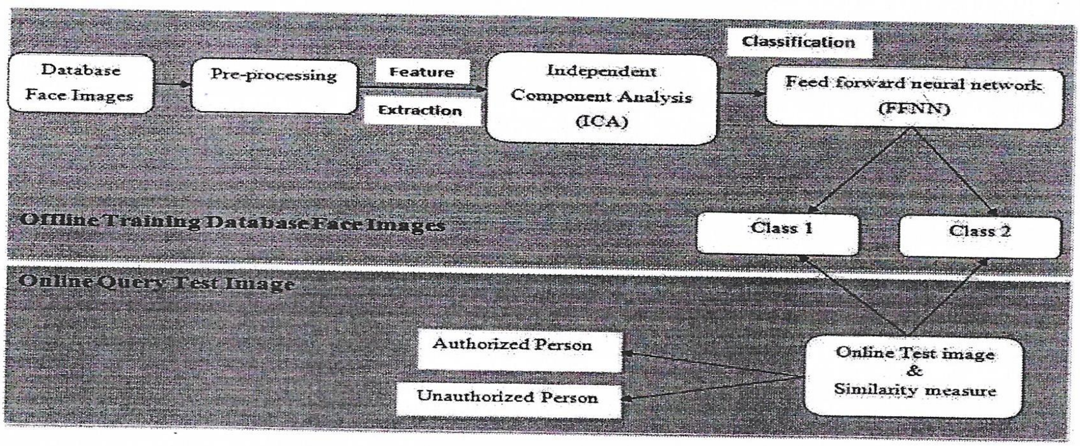


Figure 2 Theoretical Framework for Face Recognition Using ICA

5. Independent Component Analysis (ICA)

ICA is a technique for extracting statistically independent variables from a mixture of them [6]. To rigorous definition of ICA using vector matrix notation, the mixing model is written as

$$x = As \tag{1}$$

The statistical model in equation (1) is called ICA model. Assume that mixture vector x as well as independent component vector s is random vectors. Without loss of generality, it can assume that both the mixture vector and the independent component vector have zero mean. Since the independent components cannot be directly observed, so they are called latent variables. The mixing matrix A is considered to be unknown and square pattern. Also assume that the independent component vector s must have a non-Gaussian distribution. Non-gaussianity is an essential and important principle in ICA estimation. According to central limit theorem, the distribution of the sum of independent components with arbitrary distribution tends toward a Gaussian distribution than the distribution under of the original independent components under certain conditions [7]. So the extracting of independent components from their mixtures can be accomplished by making their linear transformation as non-Gaussian as possible.

All observe is the random vector x and task is to estimate both A and s using it. After estimating the mixing matrix A, compute its inverse is measured as W, and obtain the independent component simply by:

$$s = Wx \tag{2}$$

The block diagram in Figure 3 illustrates above the discussion of ICA model.

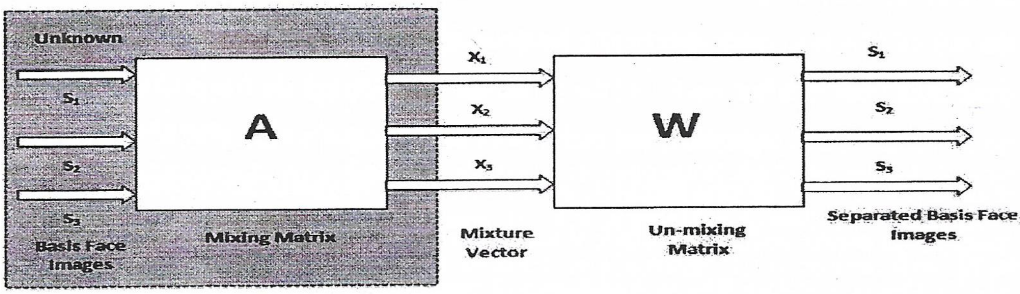


Figure 3 Independent Component Analysis

Irrespective of which algorithm is used to compute ICA for feature extraction, there are two architectures to apply ICA to face recognition.

5.1 Architecture 1: Statistically Independent Basis Images

In architecture 1, the input face images in X are to be a linear mixture of statistically independent basis images S and an unknown mixing matrix A. Through ICA algorithm the weight matrix W will evaluated, which is used to recover a set of independent basis images in the rows of U in Figure 4 (a). In this architecture 1, the face images are considered as random variables and the pixel values provide observations for the variables. Figure 4 (b) on Architecture 1 represent to find a set of images , the images in X are considered to be a linear combination of statistically independent basis images , S, where A is an unknown matrix [23]. The basis images were estimated as the learned ICA output U [23].

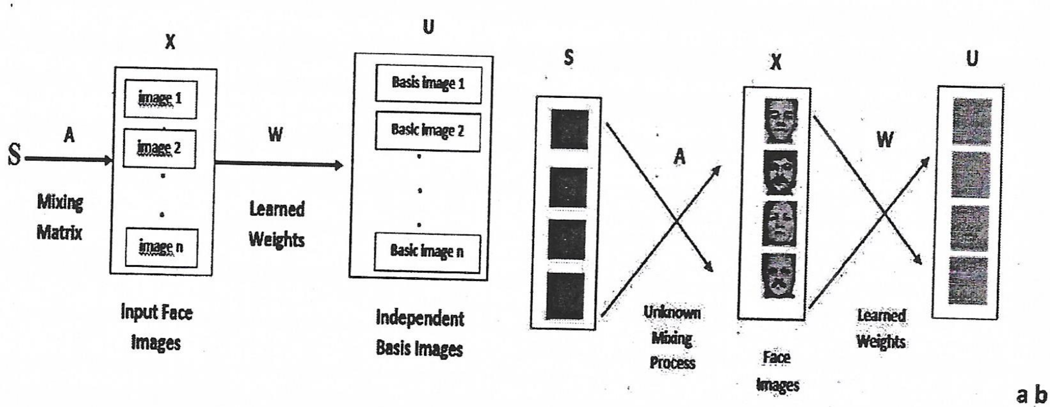
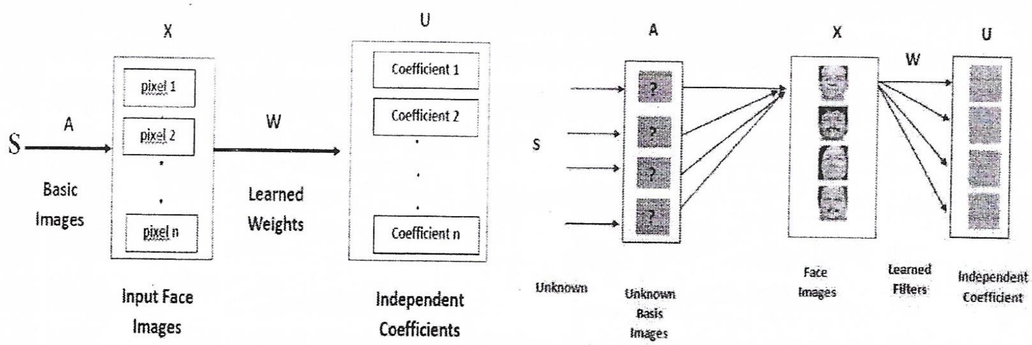


Figure 4 Architecture 1: Statistically Independent Basis Images [23, 24]

5.2 Architecture 2: Statistically Independent Coefficients

In architecture 2, the pixels as random variables and the images as outcomes. In architecture 2, the task of ICA is to catch statistically independent coefficients for input data. Here the input is transposed from architecture 1, i.e., the pixels are variables and the images are observation. The pixels do the source separation, and each row of the evaluated weight matrix W is an image. The inverse matrix of W, mixing matrix A, contains the basis images in its columns. The statistically independent source coefficients are S; it comprises the input images are recovered in the columns of U in Figure 5. Figure 5(b) on Architecture 2 assume each image in the dataset was considered to be a linear combination of underlying basis images in the matrix A [23]. The basis images were each associated with a set of independent "causes", given by a vector of coefficient in S [23].



a b

Figure 5 Architecture 2: Statistically independent coefficients [23, 24]

The Figure 6 (a) shows six-basis images produced in architecture 1. They are spatially localized, unlike those provided by ICA architecture 2 in Figure 6 (b). The six-basis images are shown in Figure 6 (b) show more global properties than the basis images produced in architecture 1.

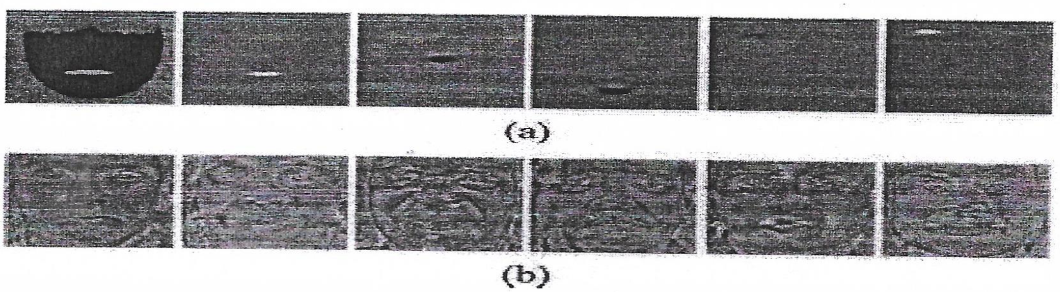


Figure 6 Basis images corresponding to ICA Architecture 1 and ICA Architecture 2. (a) Basis images corresponding to ICA Architecture 1. (b) Basis images corresponding to ICA Architecture 2 [8].

5.3 Pre-Processing

These two architectures have a different approach to estimation the independent component analysis (ICA) model. Practically when using the ICA algorithms to real data; some practical considerations arise which is necessary to be taken into account. To overcome these practical considerations, some preprocessing techniques are done on algorithms that are *centering* and *whitening*. Preprocessing may be useful and even necessary before the applying the ICA algorithms in practice. These preprocessing steps are simplified and reduce the complexity of the

5.3.1 Centering

A simple preprocessing step is commonly performed is to "center" the mixture vector x by subtracting its mean vector m i.e. the centered mixture vector, x_c. This step simplifies ICA algorithms by making a zero mean mixture vector x_c.

5.3.2 Whitening

Another step which is very helpful in practice is to whitening the centered mixture vector x_c. Whitening involves linearly transforming the centered mixture vector such that its components are uncorrelated and have unit variance [9]. Let x_w denote the whitened mixture vector. In other words, the covariance matrix of x_w equals the identity matrix. Whitening ensures that all dimensions are treated a priori equally before the algorithm is run.

There are several well-known algorithms for ICA available in the literature. However, the following three algorithms are widely used in numerous signal processing, feature extraction and many other applications. These include *FastICA, JADE,* and *Infomax*. Every algorithm used a different approach to solve the equation. Since this paper representing a theoretical study, do not describe these algorithms.

6. Feed Forward Neural Network (FFNN)

A feed-forward neural network (FFNN) is an artificial neural network where connections between the units do not form a directed cycle [29]. There are two types of feed-forward neural network; these are single-layer perceptron and multi-layer perceptron (MLP). Here focus is only on multi-layer perceptron which is a classification algorithm biologically inspired networks consists of at least three layers: an input layer, a hidden layer(s) and the output layer. Every processing unit in present layer is connected with all the processing units in the previous layer. These links are not all equal; each connection may have different strength or *weight*. The weights on these links encode the knowledge of the system. Processing units in neural networks are called *nodes*.

In Figure 7 shows the architectural graph of a multi-layer perceptron. The network shown is fully connected, i.e., a neuron in any layer of the network is connected to all the neuron in the previous layer. In this classification problem, the desired response corresponds to the classes of images. For this specific problem, the number of output neurons equals the number of classes of images.

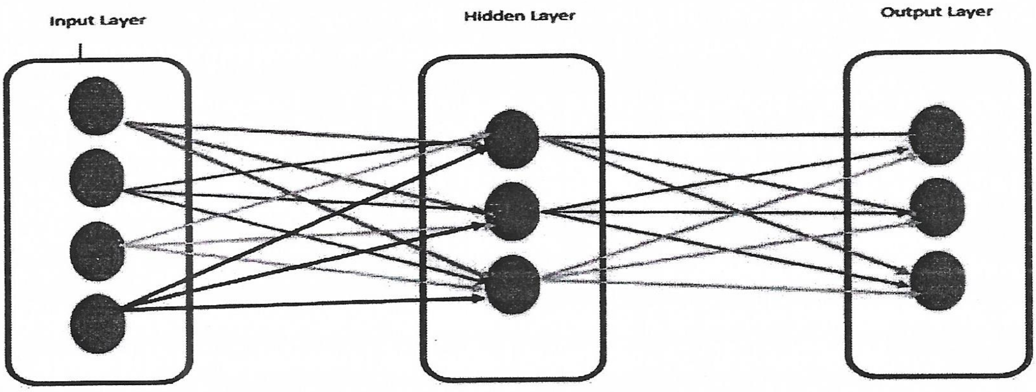


Figure 7 Multi-layer Perceptron (MLP) of one hidden layer

In many cases, multi-layer perceptron networks are not directly trained with pixel values of the face images because, it is time consuming and expensive. So, it is not directly trained with pixel values of face images. Multi-layer perceptron network performed better when extracted features from face images, and it is considered as input of the neural networks.

7. Conclusion and Future Work

The paper presenting an ICA of face images has been studied theoretically and used for face recognition. In this theoretical study, the scheme combined both offline and online mode. In offline mode, the face database images are trained using ICA and FFNN. The paper describes a procedure for using ICA feature extractor in the circumstance of face recognition. And in online mode, the query test images are compared with classified images and taking decision based on similarity measure.

This paper is representing only the theoretical study of ICA and FFNN for face recognition. Furthermore, we draw a mathematical study of ICA algorithms and collection of face database images may be different expressions, orientations and change in illumination.

8. Acknowledgement

The work presented here is being conducted in the Biometrics Laboratory of Department of Computer Science and Engineering of Tripura University (A central university), Tripura, Suryamaninagar-799022. The research work was supported by the Grant No. 12(2)/2011-ESD,

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