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Analysis of Fast- ICA Algorithm for Separation of Mixed Images

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***Abstract*-- Independent component analysis (ICA) is a newly developed method in which the aim is to find a linear representation of nongaussian statistics so that the components are statistically independent, or as independent as possible. Such techniques are actively being used in study of both statistical image processing and unsupervised neural learning application. This paper represents the Fast Independent component analysis algorithm for separation of mixed images. To solve the blind signal separation problems Independent component analysis approach used statistical independence of the source signals. This paper focuses on the theory and methods of ICA in contrast to classical transformations along with the applications of this method to blind source separation .For an illustration of the algorithm, visualized the immixing process with a set of images has been done. To express the results of our analysis simulations have been presented.**

Index Terms – Independent Component Analysis ,Blind Source Separation , Peak signal to Noise ratio.

I. INTRODUCTION AND RELATED WORKS

Blind Source separation (BSS), which consists of recovering original signals from their mixtures when the mixing process is unknown, had remained a widely studied problem in signal processing for the last two decades [1]. Independent component analysis (ICA), a statistical method for signal separation [2], [3], was also a well-known issue in the community.

Independent component analysis for separating complex-valued signals had found utility in many applications such as wireless communications [4] and radar [5], and data analysis in magnetic resonance imaging [6] and electroencephalograph [7]. One approach estimated the unmixing matrix by minimizing the mutual information between the separated sources [8]. Others exploit the non-Gaussianity of the source signals and perform separation by maximizing this non-Gaussianity [3]. One of Wavelet based ICA algorithms used the idea of applying a preprocessing in the transformed domain but separation was performed in the time domain [9]. M.H. Sadeghi et al. [10] proposed an algorithm that separated real image from mixed image and extracted reflected image by applying ICA. This algorithm is very fast and can remove reflect from mixed image. Unfortunately, this algorithm in monotonous area causes texture, but can reduce its effect by performing Fourier transform. The BSS method gave us several sources that enabled us to determine various classes of land use. I. R. Farah and M. B. Ahmed [11] showed that the use of simultaneous BSS method and fusion techniques can really improve the results.

The most important problem in the ICA was to adaptively estimate the source densities. Fast ICA one of the most popular algorithms for ICA, used a properly chooses a nonlinear function to approximate the negentropy. However, it was not sourced adaptive because the nonlinear function was fixed during the separation process.

The Fast-ICA algorithm belongs to the family of fix-point algorithms for ICA, which was based on the iteration to search for the maximum of the non-Gaussianity of variables. In this paper, we shall first review the fundamental theory and basic model of ICA in section II, and then shall elaborate upon the math principle of the fast fixed-point algorithm for ICA. We shall apply the algorithm in blind separation of randomly mixed images in section III, and finally some conclusions shall be drawn in section IV.

II. PRINCIPLES OF ICA ESTIMATION

ICA was a method of performing blind signal separation that aims to recover unknown sources from a set of the observed values, in which they were mixed in an unknown manner. In the basic ICA model [3], the observed mixture signals x(t) can be expressed as

$$x(t) = As(t) \qquad (1)$$

Where A is an unknown mixing matrix, and s(t) represents the latent source signals which was supposed to be statistically mutually independent. The ICA model described an additive noise vector v (t) , and gave a more realistic and general ICA model in the noising case:

$$x(t) = As(t) + v(t) \qquad (2)$$

The independent components s(t) couldn't be directly observed and the mixing coefficients A and the noise v(t) was also assumed to be unknown. If noise is negligible, only the random variables x(t) was observed and both the components s(t) and the coefficients A must be estimated using x(t) .Then, the ICA solution was obtained in an unsupervised way that finded a de-mixing matrix W. The de mixing matrix W was used to transform the observed mixture signals x (t) to gave the independent signals. That was:

$$s(t) = Wx(t) \qquad (3)$$

The signals s (t) were the close estimation of the latent source signals s (t) . If $W = A^{-1}$, then the recovered signals sˆ (t) were exactly the original sources s(t) . The components of sˆ (t), called independent components, were required to be as mutually independent as possible. Some main functions in ICA were described below.

A. Nongaussian was independent

Innately talking, the central concept inassessing the ICA model is its non-gaussian nature. As a matter of the fact, without the non-gaussian nature in the ICA modeling, the estimation would not be possible at all. This can be considered the main reason for the relatively late resurrection of ICA research: In most of the classical statistical theory, random variables were assumed to be having a Gaussian distribution, there by impeding any methods related to ICA.

B. Measures of nongaussianity

For using nongaussianity in ICA estimation, let us have (say y), a quantitative measure of nongaussianity of a random variable. To make the things simplified, let us assume that y was centered (zero-mean) and had variance equal to one. Actually, to make this simplification possible, one of the functions of preprocessing in ICA algorithms is to be covered in Section III.

C. Kurtosis [3]

The classical measure of nongaussianity was kurtosis or the fourth-order cumulant. The kurtosis of x was classically defined by

$$Kurt(y) = E\{x^4\} - 3(E\{x^2\})^2 \qquad (4)$$

Actually, since we assumed that y was of unit variance, the right-hand side simplifies to $E\{x^4\} - 3$, showing kurtosis was basically a normalized version of the fourth moment $E\{x^4\}$. For a Gaussian y, the fourth moment equals $(E\{x^2\})^2$. Thus, kurtosis was equal to zero for a Gaussian random variable. For most of the non-Gaussian random variables, kurtosis was non-zero.

Kurtosis could be both positive and negative. Random variables that had a negative kurtosis were called subgaussian, and those with positive kurtosis were called supergaussian. Typically nongaussianity was measured by the absolute value of kurtosis. The square of kurtosis could also be used. These were zero for a gaussian variable, and greater than zero for most nongaussian random variables. There were nongaussian random variables that had zero kurtosis, but they could be considered as very rare. Kurtosis, or rather its absolute value, had been widely used as a measure of nongaussianity in ICA and related fields. The main reason was its simplicity, both computational and theoretical.

D. Negentropy [3]

A second very important measure of nongaussianity was given by negentropy. Negentropy was based on the information theoretic quantity of (differential) entropy. To obtain a measure of nongaussianity that was zero for a gaussian variable and always nonnegative, one often used a slightly modified version of the definition of differential entropy, called negentropy. Negentropy J was defined as follows

$$J(y) = H(y_{gauss}) - H(y) \qquad (5)$$

Where entropy *H* was defined for a discrete random variable *Y* as H(y) and y_{gauss} was a Gaussian random variable of the same covariance matrix as y. Due to the above-mentioned properties, negentropy was always non-negative, and it was zero if and only if y had a Gaussian distribution. Negentropy had the additional interesting property that it was invariant for invertible linear transformations. The advantage of using negentropy, or, equivalently, differential entropy, as a measure of nongaussianity was that it was well justified by statistical theory.

E. Minimization of Mutual Information

Another approach for ICA estimation, inspired by information theory, was minimization of mutual information.

III. PREPROCESSING FOR ICA

Before applying an ICA algorithm, it was quite necessary and useful to work on some preprocessing on the available data. In this section, we discussed some preprocessing techniques that made the problem of ICA estimation simpler and better conditioned.

A. Centering

This was the most elementary and essential preprocessing, which was used to center the "x", i.e. subtract its mean vector m. E{x} there by making x a zero-mean variable. It simply implied that the input signal was zero-mean as well as; it can be seen by taking expectations on both sides of vector–matrix notation.

B. Whitening

It is additional useful preprocessing technique in ICA which is used to first whiten the detected variables. It signifies that before the application of the ICA algorithm (and after centering), we altered the detected vector x linearly so that we could obtain a new vector x which is white in its characteristic nature, i.e. its components in the image patch are uncorrelated and their variances should also be equal to unity.

C. Further preprocessing

The accomplishment of ICA for a given data set may be governed crucially by performing some application-dependent preprocessing steps. For example, if the data consists of time-signals, some band-pass filtering may be very valuable. Note that if we filter linearly the observed signals xi(t) to obtain new signals, say $x^*_i(t)$, the ICA model still holds for $x^*_i(t)$, with the same mixing matrix. This can be seen as follows. The basic denoted form is by X, the matrix which contains the observations as its latent vectors x(1), ...,x(T) as its columns, and similarly for S. Then the ICA model can be expressed as:

$$X=AS \qquad (6)$$

Now, time filtering of X corresponds to multiplying X from the right by a matrix, let us call it M. This gives

$$X^*=XM=ASM=AS^* \qquad (7)$$

which shows that the ICA model remains still valid.

D. FAST-ICA algorithm *[12]*

Thus we obtain the FAST-ICA algorithm as follows:
(1) Center the data to make its mean zero;
(2) Whiten the data to get $\hat{x}(t)$;
(3) Make i=1;
(4) Choose an initial orthogonal matrix for W and make k=1;
(5) Make $w_i(k) = E[\hat{x}_i (w_i(k-1)^T\hat{x}_i)^3]-3w_i(k-1)$
(6) Make $w_i(k) = \frac{w_{i(k)}}{||w_i(k)||}$
(7) If not converged, make k=k+1 and go back to step (5)
(8) Make i=i+1.
(9) When i<number of original signals, go back to step (4).

In this study, the process is iterated until the weight $|w_i(k)^T w_i(k-1)|$ equal or close to 1, the iteration finish.

IV. RESULT AND ANALYSIS

This section reports on the application of ICA to a synthetic dataset in order to assess the performance of the method on a dataset with known underlying sources. To illustrate the concepts introduced in this paper, we simulate the system with three independent images of different kurtosis values has been generated. These sources were normalized to have a unit variance and were mixed according to image. In simulation result three image taken randomly and mixing process in MATLAB has been done. Separated images are recovered using Fast fixed point ICA algorithm. The separated signals are recovered using Fast fixed point

ICA algorithm. We select two 256×256 images that are cameraman, bank and lena to examine the results, the simulation is as follows: Fig.1 is the source images. Fig.2 is the mixed images Fig.3 is the separated images.

Thus algorithm performance analysis has been described in figure 1~3 and comparison result related to PSNR described in Table 1. To compute the peak-signal-to-noise ratio (PSNR), between the original images X and the mixed or separated image Y, following method is used

$$PSNR=10log\left(\frac{(M*N)^2}{MSE}\right) \qquad (9)$$

Where

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{i=1}^{N}(Y(i,j)-X(i,j))^2 \qquad (10)$$

This algorithm performance analysis has been described in figure 1~3 and comparison result related to PSNR described in figure 6.

Figure .1 Input source images.

Figure.2 The mixed images.

Figure.3 Separated images

Table.1 Experiment Result

Images	Original Image PSNR	Mixed Image PSNR	Separated image using ICA Algorithm PSNR
Bank Image	27.6976	1.1153	27.8493
Cameraman Image	25.9391	12.5550	27.0148
Lena Image	28.2490	16.0757	27.1767

V. CONCLUSION

This paper proposes a study and analysis of Fast-ICA algorithm for images. We have looked at a more general framework for the selection of the nonlinearity in deflation mode fast- ICA. The effect of non-convexity of the nonlinearity on the source separation capabilities of the resulting ICA algorithm were then illustrated through simulations The simulation results showed that the algorithm can blindly separate the mixed images with good accuracy. In practice, we need to process many contaminated images, as they contain much unknown noise, problem like this make it necessary for us to extend the basic framework of ICA during the process of future research.

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