FASTICA BASED BLIND SOURCE SEPARATION FOR CT IMAGING UNDER NOISE CONDITIONS

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ABSTRACT

A novel blind source separation method, fast independent component analysis (FastICA) is proposed in this paper. The proposed method is extended from the existing FastICA algorithm in one-dimensional signals. The existed FastICA is not suitable for the signals which are under noise. To solve this problem, we combined the image denoising and source separation concepts on medical images under noise conditions. The performance of the proposed method is tested National Electrical Manufacturers Association (NEMA) computer tomography (CT) image database. The results after being investigated the proposed method show that it can separate every independent component effectively under different noise conditions of the images.

KEYWORDS: *Blind source separation, FastICA, CT imaging.*

I. INTRODUCTION

Since the beginning of the last decade, extensive research has been devoted to the problem of blind source separation (BSS). The attractiveness of this particular problem is essentially due to both its applicative and theoretical challenging aspects. This research has given rise to the development of many methods aiming to solve this problem (see [1] and [2] for an overview). An interesting aspect of this emerging field, which is still open to more research, is the fact that the theoretical development evolves in pair with the real-world application specificities and requirements. Extracting components and time courses of interest from fMRI data [3], [4] is a representative illustration of this statement. BSS can be analyzed with two dual approaches: source separation as a source reconstruction problem or source separation as a decomposition problem. In the first approach, one assumes that during an experiment ξ, the collected data $x_{1....T} = \{x_1, ..., x_T\}$ are not a faithful copy of the original process of interest $s_{1....T}$ under study (sources). In other words, the observed data $x_{1....T}$ are some transformation F of the sources $s_{1....T}$ corrupted with a stochastic noise $n_{1....T}$ reflecting either the modeling incertitude or the superposition of real undesirable signals

$$x_{1....T} = F(s_{1....T}) \square\ n_{1....T} \quad (1)$$

where is $\square$ the operator modeling the noise superposition. Given the data $x_{1....T}$ our objective is the recovery of the original sources $s_{1....T}$. The second approach for dealing with the source separation problem is to consider it as decomposition on a basis enjoying some particular statistical properties. For instance, principal component analysis (PCA) relies on the decorrelation between the decomposed components, and independent component analysis (ICA) relies on their statistical independence. The decomposition approach can be considered to be dual to the reconstruction approach (see Fig. 1) as the existence of an original process is not required.

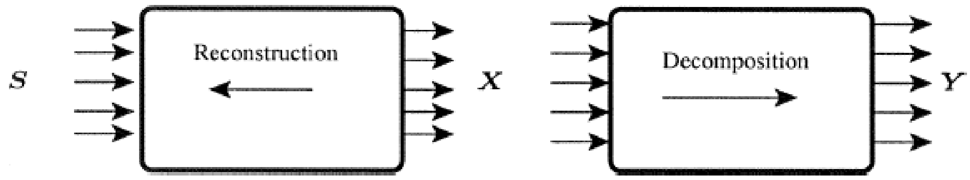

Fig. 1: Duality of reconstruction and decomposition approaches.

Based on independent and identically distributed (i.i.d.) source modeling, many proposed algorithms are designed to linearly demix the observations $x_{1....T}$. The separation principle in these methods is based on the statistical independence of the reconstructed sources (ICA) [5]–[9]. However, ICA is designed to efficiently work in the noiseless case. In addition, with the i.i.d assumption, the separation necessarily relies on high order statistics, and treating the noisy case with the maximum likelihood approach leads to complicated algorithms [10]–[12].

Discarding the i.i.d assumption, source separation can be achieved with second order statistics. For instance, second order correlation diversity in the time domain [13], frequency domain [14], or time frequency domain [15] are successfully used to blindly separate the sources. Non stationary second-order-based methods are also proposed in [16]–[20] (see [21] and the references therein for a synthetic introduction of these concepts). Stationary and non stationary can approximately be seen as dual under Fourier transformation. For instance, based on the circular approximation, it is shown [22] that a finite sample correlated temporal stationary signal has a Fourier transform with non stationary decorrelated samples. We recently proposed a maximum likelihood method to separate noisy mixture of Gaussian stationary sources exploiting this temporal/spectral duality [23], [24]. The Gaussian model of sources allows an efficient implementation of the expectation–maximization (EM) algorithm [25].

In this paper, a fast algorithm of blind source separation based on ICA is introduced on CT images. The results of experiment show that the proposed approach can separate every independent component effectively. Our method is the extension of existing fastICA on signals [26].

This paper is organized as follows. In Section II, the overview of the ICA algorithm is discussed. In Section III, the FastICA is discussed. In Section IV, experimental results and discussions are presented. Finally, Section V concludes the paper.

II. ICA ALGORITHM

2.1. ICA Definition

We can assume the there is an *x(t)* which is N-dimensional signal:

$$x(t)=As(t)+n(t);\ t=1,2,.... \qquad (2)$$

where,*x(t)* is N-dimensional vector ($x_{1....N}$)of the observed signal at the discrete time instant *t*, *A* is an unknown transfer matrix or mixed matrix of signal, *s(t)* is the independence vector of M×N unknown source signal component, *n(t)* is the observed noise vector.

ICA's basic idea is to estimate or separate *s(t)* which is the source signal from *x(t)* which are the mixed observation signals, it is equivalent to estimate matrix *A*. We can assume that there is a *W* matrix, which is the separation inverse matrix of *A*, then *s(t)=Wx(t)*.

The algorithm must follow the below assumptions:

1. The quantities of *x(t)* must be greater than or equal to the quantities of source signal, for the sake of convenience, we can take the same quantity, namely, the mixed matrix *A* is full rank matrix.
2. Each component of *s(t)* is statistical independent.
3. Each vector of source signal is only allowed to have one Gaussian distribution, this is because a number of linear mixed Gaussian signal is still Gaussian distribution, it cannot be separated.
4. It is no noise or only low additive noise. That is, n(t) in Eq. (2) approaches to zero.

III. FAST ICA ALGORITHM

At present, the conventional ICA model estimated algorithm mainly includes information maximization, mutual information minimization and maximum likelihood estimation method. The main problem is the slow convergence rate, large computing quantity. But FastICA is based on a fixed-point iteration scheme which has most of the advantages of neural algorithms, such as parallel, distribution, fast convergence, computing less, and small memory requirements.

❖ Data Pre-processing

If we use a fast fixed-point algorithm for independent component analysis, ICA algorithm is usually required an appropriate pre-treatment for the observation data, this pre-treatment can improve the convergence in the calculation process. In the pre-treatment process, an important step is to whiten the data. The so-called "whiten" refers to a linear transformation of the data, makes sure the sub-vector of new vector unrelated and the new vector's covariance matrix is a identity matrix, then, the new vector is called spatially white, this process is called whiten. We can assume that *x(t)* are zero mean, the pre-whiten treatment for *x(t)* can achieve under the style.

$$P(t)=Qx(t) \tag{3}$$

Where *p(t)* is whiten vector, Q is whiten matrix, which is selected to make sure the sub-vector of whiten vector unrelated and have a unit variance. Therefore, correlation matrix (covariance matrix) of p(t) become a unit matrix, that is, $E\{PP^T\}=I$. Then, Eq. (3) become Eq. (4):

$$P(t)=Qx(t)=QASS(t)=KS(t) \tag{4}$$

Where matrix K=QA is called separation matrix which is a M×M orthogonal mtrix, then

$$E\{PP^T\}=KE|SS^T|K^T=I \tag{5}$$

Therefore,

$$S(t)=K^Tp(t) \tag{6}$$

❖ Determination of Objective Function

Fast fixed-point algorithm (FastICA) is a rapid neural algorithm by seeking a local extremism of observed variable's linear combination of fourth-order cumulant (kurtosis coefficient). Then we can use kurtosis coefficient to get separation matrix.

Kurtosis coefficient is the higher-order statistics of signal, it is a typical function for non-Gaussian description. For a zero-mean random variable y, kurtosis coefficient is defined as:

$$Kurt[y]=E|y^4|-3[E|y^2|]^2 \tag{7}$$

If y is a Gaussian random signal, the kurtosis coefficient is zero. When the random signal is the super-Gaussian distribution, its kurtosis is positive; when the random signal the sub-Gaussian distribution, its kurtosis is negative. For two independent random signal y_1 and y_2, $kurt[y_1+y_2]= kurt[y_1]+ kurt[y_2]$, for a scalar constant β, $kurt[\beta y]=\beta^4 kurt[y]$.

We do pre-whitening treatment for x(t) which is observation signal, then we can get the vector P. Now, we assume that there is a linear combination W^TP, and the norm of W is bounded and $\|W\|=1$, then we can get the greatest or the smallest kurtosis. Definition, $Z=K^TW$. because K is orthogonal matrix, $\|z\|=1$. Because of the character of kurtosis,

$$Kurt(W^TP)=kurt(W^TKS)=kurt(Z^TS)=\sum\nolimits^{n}_{i=1} z^4_i kurt(s_i) \tag{8}$$

Eq. (8) is the objective function what we seek to.

IV. IMAGE DENOISING USING MULTI-SCALE RIDGELET TRANSFORM

4.1. Multi scale Ridgelet Transform

Multiscaleridgelets based on the ridgelet transform combined with a spatial bandpass filtering operation to isolate different scales as shown in [27].

Algorithm:

1. Apply the `a trous algorithm with J scales [28].
2. Apply the radon transform on detail sub-bands of J scales.
3. Calculate ridgelet coefficients by applying 1-D wavelet transform on radon coefficients.
4. Get the multiscaleriglet coefficients for J scales.

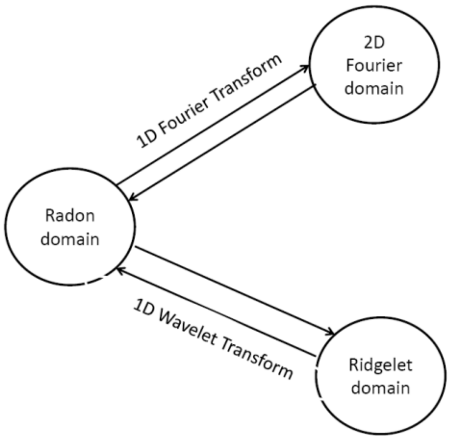

Fig. 2: Relations between transforms.

4.2. Image Denoising

Suppose that one is given noisy data of the form:

$$\overline{I}(x,y) = I(x,y) + \sigma Z(x,y) \tag{9}$$

Where Z(x,y) is unit-variance and zero-mean Gaussian noise. Denoising a way to recover I(x,y) from the noisy image $\overline{I}(x,y)$ as proper as possible. Rayudu et al. [29] have proposed the hard thresholds for Ultrasound image denoising as shown below:

Let y_λ be the noisy ridgelet coefficients (y = MRT*I). They used the following hard-thresholding rule for estimating the unknown ridgelet coefficients:

$$\begin{aligned} \hat{y}_\lambda &= y_\lambda; \quad && if\ |y_\lambda|/\sigma \geq k\,\tilde{\sigma}_\lambda \\ \hat{y}_\lambda &= 0\ ; && else \end{aligned} \tag{10}$$

In their experiments, they have chosen a scale dependent value for *k*; *k* = 4 for the first scale (j = 1) while k = 3 for the others (j > 1).

Algorithm:

1. Apply multi scale ridgelet transform to the noisy image and get the scaling coefficients and multi scale ridgelet coefficients.
2. Chose the threshold by Eq. (10) and apply thresholding to the multi scale ridgelet coefficients (leave the scaling coefficients alone).
3. Reconstruct the scaling coefficients and the multi scale ridgelet coefficients thresholded and get the denoised image.

4.3. Proposed Algorithm

The algorithm of the proposed blind source separation under different noise conditions is given below.

Algorithm:

1. Load the two images for source mixing.
2. Apply the Gaussian noise of zero mean and 0.05 standard deviation.
3. Apply the noise removal algorithm using multi-scale ridgelet transform.
4. Apply the source separation algorithm using FastICA algorithm.

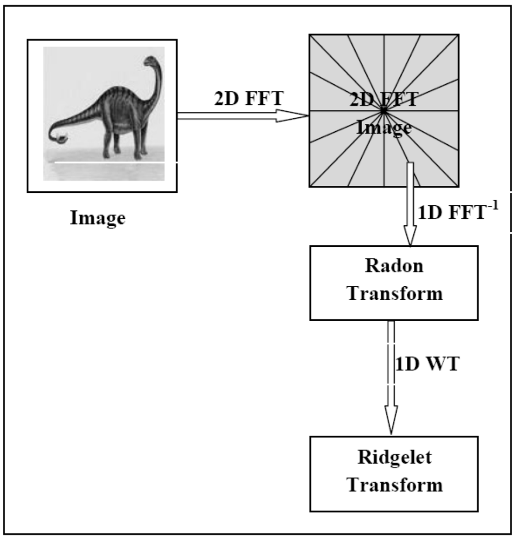

Fig. 3: Flowchart of Discrete ridgelet transform

V. EXPERIMENTAL RESULTS AND DISCUSSIONS

In order to evaluate the proposed method we tested on CT images [30]. The digital imaging and communications in medicine (DICOM) standard was created by the National Electrical Manufacturers Association (NEMA) [30] to aid the distribution and viewing of medical images, such as computer tomography (CT) scans, MRIs, and ultrasound. For this experiment, we have collected 7 CT scans of different parts of human body and results are presented as follows.

Figs. 4 to 8 illustrate the results of proposed algorithm. From Figs. 4 to 8, it is clear that the proposed approach can separate every independent component effectively.

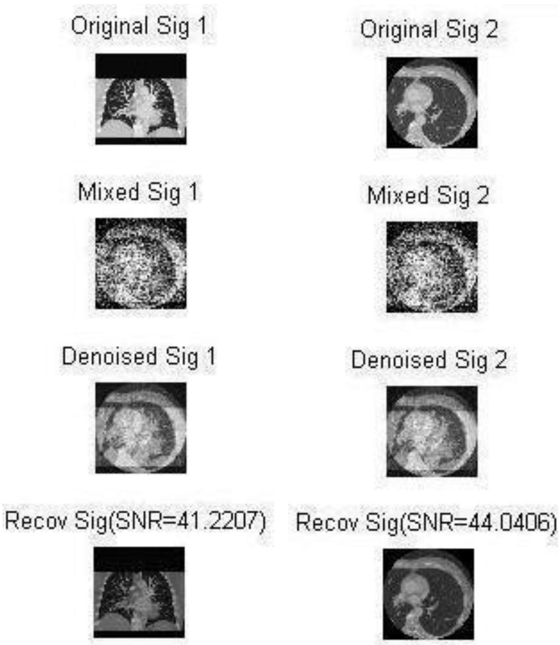

Fig. 4: Results of proposed method on CT images

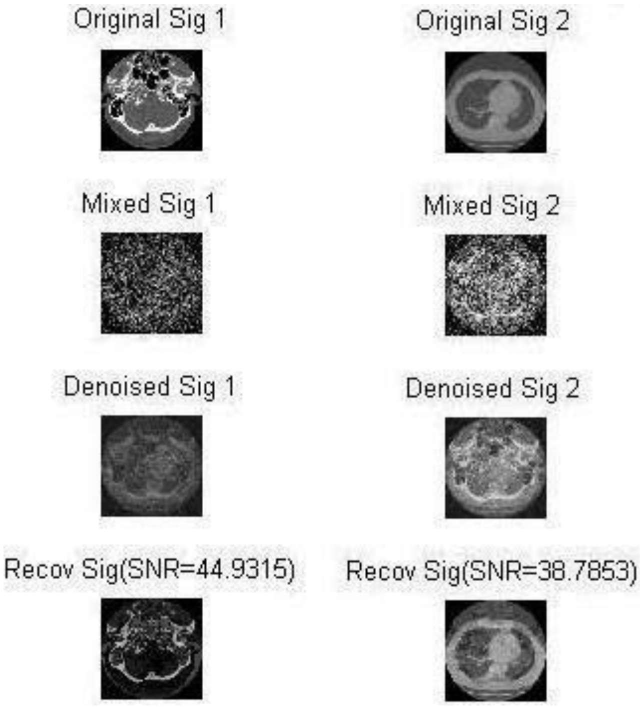

Fig. 5: Results of proposed method on CT images

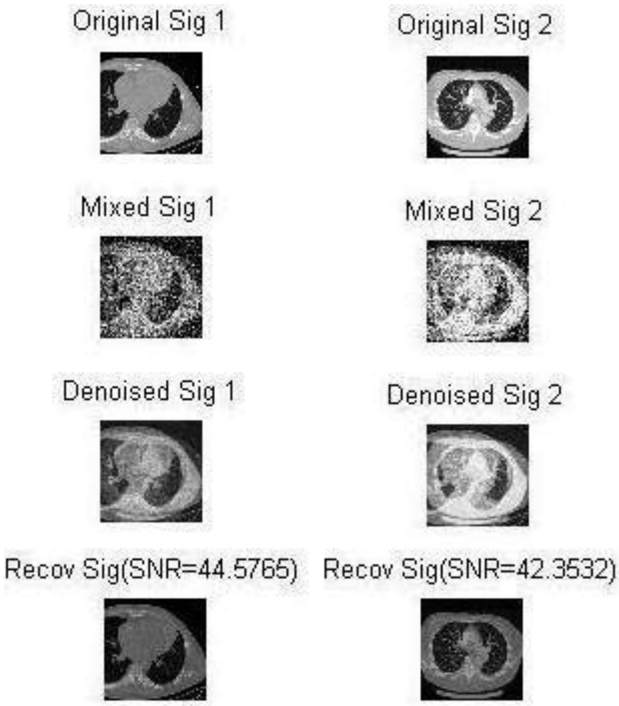

Fig. 6: Results of proposed method on CT images

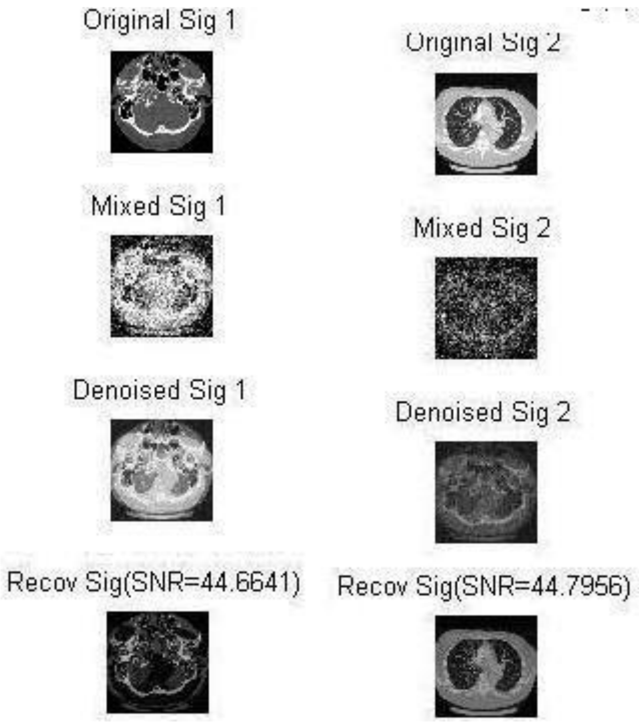

Fig. 7: Results of proposed method on CT images

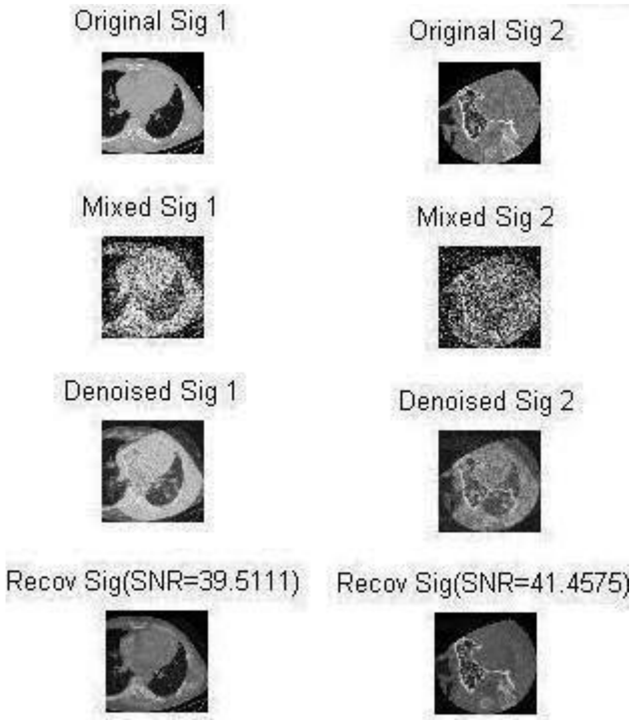

Fig. 8: Results of proposed method on CT images

VI. CONCLUSIONS

A novel combined FastICA and denoising algorithm is proposed in this paper for CT image blind source separation under different noise conditions. Proposed method is extended from the existing FastICA on signals. The performance of the proposed method is tested on NEMA CT image database. The results of experiment show that the proposed approach can separate every independent component effectively.

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