An Improved Independent Component Analysis Algorithm and Its Application in Preprocessing of Bearing Sounds

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Abstract. Independent Component Analysis (ICA) is known as an efficient technique to separate individual signals from various sources without knowing their prior characteristics. Firstly, the basic principle of ICA is reviewed in Sec 2, and then an improved ICA algorithm based on coordinate rotation (CR-ICA) is proposed. Secondly, two advantages of the CR-ICA algorithm are discussed; the one is that the separation can be carried out without iteration, and the other is that less computation is needed to achieve the same effect. Finally, the experiment in recognition of mixed sound and practical application in preprocessing of bearing sounds proved that the CR-ICA algorithm is better than traditional ICA algorithm in separation precision and computation speed. Moreover, the advantages of the method and the potential for further applications are discussed in the conclusion.

1 Introduction

The data collecting method of multi-measurement points and multi-sensors has been adopted widely in the mechanical equipment online monitoring and fault diagnosis system. The signals collected were sometimes mixed up by the signals coming from different sources. Separating some special signals from these mixed signals may help figure out the essentials of machine faults and enhance the quality of diagnosis information. Blind Source Separation (BSS) is introduced for the signals of unknown of source signal and mixture type. Independent Component Analysis (ICA) is a new technique of statistical signal processing accompanying with the development of BSS problems. ICA deals with the mixed signals derived from the linear and nonlinear combination of independent statistic signals with each other and aims at separating each independent component from the mixed signals.

In 1994, Comon expatiated on the concept of ICA systemically and constructed a cost function directly based on high order statistic variables [1]. Bell and Sejnowski explained the BSS problem from the information theory point of view, and presented the maximum entropy ICA algorithm (Infomax-ICA) [2], i.e. the maximum difference entropy of outputs of neural networks predict the mutual information maximum between inputs and outputs in neural networks. Based on it, they presented stochastic

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gradient declined algorithm to complete maximum difference entropy simultaneously. Hereafter, many people including T.W.Lee etc. expanded the work of Bell and Sejnowski, and developed an improved expanding ICA algorithm.[3] The algorithm was useful for the signals displayed in super-gaussian and sub-gaussian condition. However, these ideas and algorithms were lack of computability or consistency essentially. I.e. the computation carried out with iteration and needed long computation time. In addition, the mixed signal seldom satisfied ideal symmetry distribution in practice, and they present skewness distribution generally [4].

This paper is a first attempt to apply the ICA in engineering diagnosis area. Case studies in this paper reveal its advantages. The potential application is also discussed.

2 Basic ICA Principle and Improved Algorithm

2.1 Basic ICA Principle

ICA was originally developed to deal with the problems that are closely related to the cocktail-party problem [5,6]. Since the recent progress in ICA, it has become clear that this method will find widespread applications as well.

$$X = WS \tag{1}$$

where X is the observed vector, W is the mixed factor matrix, S is the source vector. Obviously, if we can get the inverse matrix of W, indicated by W^T, we may easily obtain the source signal matrix S from the observed signal matrix X, the former S will be written as:

$$S = W^T X \tag{2}$$

ICA can be used to estimate the source signals from the mixtures based on the information of their independence. As we know, independence of two random variables means that the joint probability distribution function (PDF) is equal to the product of individuals as Equation 4.

$$p(x_1, x_2) = p_1(x_1) p_2(x_2) \tag{3}$$

Basically speaking, ICA is an optimization problem; its objective is to optimize the coefficient matrix W so as to obtain the components S, the components of which are statistically as independent to each other as possible. Based on traditional ICA algorithms, this paper presents a new improved ICA algorithm, and applies it in engineering diagnostics area.

2.2 An Improved ICA Algorithm Based on Coordinate Rotation (CR-ICA)

2.2.1 Preprocessing for CR-ICA

In the preceding section, we discussed the principle of the ICA algorithm. Practical detail algorithms based on these principles will be discussed in the next section. However, before applying an ICA algorithm on the data, it is usually very useful to do some preprocessing. In this section, we discuss some preprocessing techniques that make the problem of ICA estimation simpler and better conditioned.

a Centering

The most basic and necessary preprocessing is to center *X,* i.e. subtract its mean vector *M*=*E*{*X*} so as to make *X* a zero-mean variable. This implies that *S* is zero-mean as well, as can be seen by taking expectations on both sides of Equation (1). This preprocessing is made solely to simplify the ICA algorithms.

b Whitening

Another useful preprocessing method is to whiten the observed variables. This means that before the application of the ICA algorithm (and after centering), we transform the observed vector *X linearly* so that we obtain a new vector $\tilde{X}$ which is white, i.e. its components are uncorrelated and their variances equal unity.

With the original signal whitened, the correlation between the mix signals can be eliminated, and the independent component extraction algorithm can be simplified and its performance will be improved. Sometimes only whitening process may recover the waveform of source signals. In the rest of this paper, we assume that the data has been preprocessed by centering and whitening.

2.2.2 Algorithm Flow of CR-ICA

After mixed signals *X* are preprocessed, *X* becomes a unit covariance vector $\tilde{X}$, and the components of $\tilde{X}$ is perpendicular with each other. Then a new improved Independent Component Analysis Algorithm is proposed to process this vector $\tilde{X}$. The algorithm is based on the coordinate rotation theory and can be used to search the optimum rotational angle with the help of the optimum algorithm. The detail steps of the algorithm are shown as follows:

Step 1: Select rotation matrix R. By rotating transforms, matrix S will be obtained.

$$R = \begin{bmatrix} \cos\alpha & -\sin\alpha \\ \sin\alpha & \cos\alpha \end{bmatrix} \quad S = R * \tilde{X} \tag{4}$$

In order to obtain the optimum rotation angle, object function *Q* is built.

$$Q = \sum_i (\cos\alpha \cdot x_i - \sin\alpha \cdot y_i)^3 \tag{5}$$

where x_i, y_i are two column elements of matrix $\tilde{X}_{2\times n}$ which is equal to $\tilde{X}$ and n is column number of matrix $\tilde{X}$.

Step 2: Obtain object function *Q*'s derivative Q'

$$Q' = 3 * \sum_i [(\cos\alpha \cdot x_i - \sin\alpha \cdot y_i)^2 * (\sin\alpha \cdot x_i + \cos\alpha \cdot y_i)] \tag{6}$$

Step 3: In order to obtain extremum of Q', Q' is taken to zero. According to Equation (10)

$$[\sin\alpha(\cos\alpha)^2\sum_i x_i^3 - 2*\cos\alpha(\sin\alpha)^2\sum_i y_i x_i^2 + (\sin\alpha)^3 \cdot \\ \sum_i x_i y_i^2 + (\cos\alpha)^3\sum_i y_i x_i^2 - 2\sin\alpha\cdot(\cos\alpha)^2\sum_i y_i^2 x_i + \cos\alpha\cdot(\sin\alpha)^2\sum_i y_i^3] = 0 \tag{7}$$

Step 4: Suppose $a = \sum_i x_i^3, b = \sum_i y_i x_i^2, c = \sum_i x_i y_i^2, d = \sum_i y_i^3$, then formula (12) can be simplified as follow:

$$c \cdot tg^3\alpha + (d - 2b)tg^2\alpha + (a - 2c)tg\alpha + b = 0 \tag{8}$$

Step 5: Obtain the root value of Equation (12) using $tg\alpha$ as unknown.

Step 6: Search an optimum angle from all angles obtained by step 5 to make object function obtain the minimum.

Step 7: Use Equation (4) to do rotation transformation, then the independent component can be obtained.

3 Experiments

In practical recongnition of signals, sound recongnition is one classical type [8]. Mixed sounds are made up of human voice and alarming whistel sound. The sounds are collected by two recorders and it is no doubtful that each sound collected by single sound recorder will receive another sound's information. Fig.1(a) and (b).show the

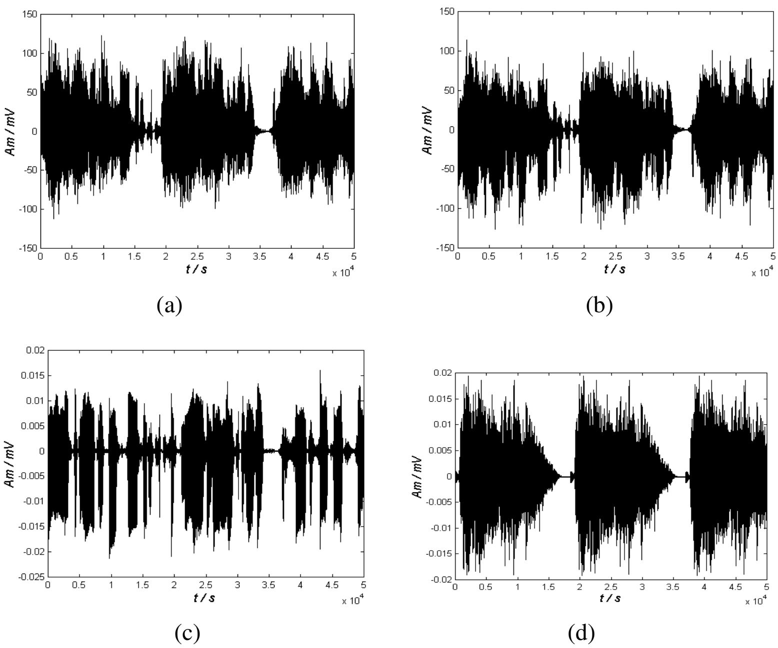

Fig. 1. (a) (b) display the original mixed sound, and separated results are showed in Fig1.(c)(d)

Table 1. The performance of two algorithms in recognition of mixed sounds

Algorithm	SNR/dB		Computation Time/S
	y_1	y_2	
CR-ICA	103.81	102.87	0.806
FastICA	110.39	107.43	1.560

mixed sounds. By whitening the mixed sounds and then applying the improved ICA algorithm, the independent signals can be obtained and shown in Fig.1(c) and (d). Table 1 displays the SNR results by using two algorithms. It is obviously that the proposed CR-ICA algorithm is better than traditional FastICA algorithm in separation precision and computation speed under the same conditions.

4 Applications

The condition monitoring and fault diagnosis of rolling bearing have been investigated for a long time. Many efficient methods have been proposed, such as resonance demodulation and ferrography. Herein, we recognize the bearing faults by sampling bearing sound. In experiment, two Sound level Meters were mounted to pick up the machine sound. One aimed at the motor sound, the other aimed at the bearing sound. It is sure that each collected sound contains other part sound information. We use the CR-ICA method to preprocess the mixed sound. The original signals collected are shown in Fig.2(a,b). The preprocessing results are shown in Fig.2(c,d).

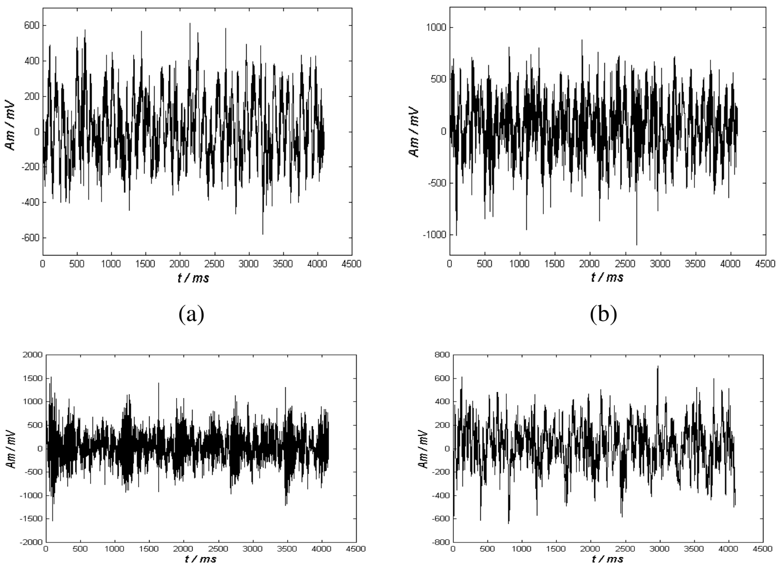

Fig. 2. The observed signals are shown in Fig. (a,b) and the preprocessing results are shown in Fig. (c,d)

As shown in Fig.2(c,d), the separated source like white noise is due to the motor, while the impulsive signal with periodic impacts was originated from the spall in the inner race of the tested bearing.

5 Conclusions

This paper proposes an improved ICA algorithm (CR-ICA), and applies it to tackle the following problems in experiments and engineering diagnosis: recognition of mixed sound and preprocessing of bearing sound. The case studies show that the CR-ICA method performs better than the traditional ICA algorithms.

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