High-efficient MRS noise cancellation using independent component analysis

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SUMMARY

This paper addresses feature extraction of the higher-order statistics, which can effectively characterize the transients, using independent component analysis (ICA) for the SMRS signal, and then proposes a novel automatic technique for detecting the harmonic and random noise in MRS signals with the low signal-to-noise ratio by ICA feature extraction. The basic principle of the ICA-based transient detection method is that the independent components (ICs) coefficients of the transients and the noise can be effectively distinguished by their different properties. Specifically, the proposed method for processing the MRS signal mainly includes three steps: denoising the harmonic noise by creating the channel structure; cancelling the random noise by ICs coefficients using the shrinkage function; and reconstruct the MRS signals through the ICA basis functions. Experimental results through the simulated signal analysis and field MRS signal analysis show that the ICA-based method is very effective for acquiring high quality MRS signal when only 3 stacks were needed.

Key words: independent component analysis; denoising; SMRS; harmonic noise; random noise

INTRODUCTION

Since the late 1980s magnetic resonance sounding (MRS) has steadily evolved towards being a competitive technique for non-invasive investigations of groundwater resources. In particular, the method allows for a direct determination of the water content of the subsurface. The main obstacle currently limiting a more widespread use of the method is the very low signal-to-noise ratio of MRS signals.

There are three main noise sources for MRS signals:1) spike noises; 2) Harmonic noise; 3) random noise component. For both of the signal channel and multi-channel MRS instruments, the entire data processing working flow are similar, *i.e.*, Despiking first, and then performed the harmonics noise cancelling. The random noise can be suppressed by standard averaging of multiple recordings, normally larger than 20 times. Finally, the parameters of the MRS signals can be extracted by envelop detection.

The first generations of the MRS instruments were single channel instruments. With single channel instruments, both magnetic resonance excitation and signal recording is done with a single loop and various forms of filtering can be used to suppress noise, in particular power line harmonics. However, with a notch filter the MRS signal may be distorted and with the figure-8 loop setup the penetration is decreased. Considering the above drawbacks, the multichannel MRS instruments with multiple loops have been constructed. The primary loop is still used for magnetic resonance excitation and signal recording. In addition, a number of reference loops, physically displaced from the primary loop, measure only noise. Depending on the correlation coefficients, parts of the noise recorded by the reference loops will be correlated with the noise in the primary coil. With the sophisticated noise cancelling techniques to the spike noise and harmonic noise separately, the multi-channel instrument was considered to improve the SNMR method efficiently. Whereas, as mentioned above the efficiency of the multichannel instrument relay mostly on the coefficients between the signal channel to noise channel, correct prediction of the noise sources is the most important part.

In this work we presented here, we report our progress on optimizing the noise cancelling in single-channel SNMR instrument. Our motivation is that the single-channel instrument , *e.g.* NUMIS^{plus} and JLMRS-I instrument, still are undergoing used in SNMR surveys to the time-efficient measurement. We introduce the ICA algorithms to SNMR algorithms for the first time aiming to cancel both the harmonic noise as well as the random noise. Our ICA algorithms were compared to the two most often used methods of noise cancelling, *i.e.*, the notch filter and the average stacks. The results indicate that with the ICA algorithms, only 3 measurements are needed to get the acceptable signal to noise ratio. Therefore, the high-efficient SNMR measurement can be expected.

ICA Method

ICA is a method for finding underlying structure in multivariate data. The main purpose of ICA is to find a linear representation of data so that the components are statistically independent or as independent as possible without the prior information of the data.

To extract independent feature vectors from a one-dimensional measured vibration signal, ICA algorithm is applied to a number of segments, which are randomly generated from the signal ***s***. Assume through training an ICA network, signal segment x is then represented as a linear combination ***A*** as follows:

$$\mathbf{x} = \mathbf{A}\,\mathbf{s} + N \qquad (1)$$

in which N represents noise, ***A*** is a scalar square matrix and represents the basis functions generating the observed segments of the vibration signal in the real world whereas W= $\boldsymbol{A}^{-1}$ refers to the basis filters that transform the segments into source coefficients as follows:

$$\mathbf{y} = \mathbf{W}\,\mathbf{x} \qquad (2)$$

To extract basis features one has to train the mixing matrix ***A*** or the demixing matrix ***W***. The objective of ICA is to infer both the unknown sources ***s*** and the unknown basis functions ***A*** from the signal segments. A large amount of algorithms have been developed for performing ICA.

During the traditional studies, ICA can be used in many ways. One of the best methods is the fixed-point-FastICA algorithm, where the negentropy is used as the criterion to estimate ***s***. Entropy is a measure of the average uncertainty in a random variable and the differential entropy H of random variable $\boldsymbol{\xi}$ with density:

$$H(\xi) = -\int p(\xi)\log p(\xi)d\xi$$

A Gaussian variable has the maximum entropy among all random variables with equal variance. In order to obtain a measure of non-Gaussianity that is zero for a Gaussian variable, the negentropy $\boldsymbol{J}$ is defined as:

$$J[x] = H(x_{guass}) - H(x)$$

where x_{gauss} is a Gaussian random variable with the same variance as x. Negentropy is zero for Gaussian variable and always non-negative. To estimate negentropy efficiently, a simpler approximation of negentropy as follows is used:

$$J(x) \approx [E\{G(x)\} - E\{G(v)\}]^2 \quad (3)$$

where x is assumed to be of zero mean and unit variance, and G is any non-quadratic function. Using a fixed-point iteration scheme to find directions, in which the negentropy is maximised, the demixing matrix W can be achieved as following:

$$w_j^{'} = E\{xg(w_j^{\mathrm{T}}x)\} - E\{g^{'}(w_j^{\mathrm{T}}x)\}w_j \quad (4)$$

where w_{j} is the vector that makes up the row vector of matrix W; $w_{\mathrm{j}}^{\mathrm{T}}$ is the transpose of w_{j} ; $E(\cdot)$ is the mathematical expectation. When convergence is satisfied, we stop the iteration and search for the next row vector w_{j} of matrix w. This is how the matrix W is obtained.

G ($\cdot$) is the first order derivative of G, g'($\cdot$) is the second order derivative of G. The flow chart of the ICA algorithm was shown in Fig.1.

Simulations of removing harmonic noise by using ICA algorithms

There are four original sources s_1, s_2, s_3 and s_4 which represent MRS signal, power-line harmonic of 2200Hz, 2300Hz and 2350Hz, respectively. The observed data is a mix of the four original sources according to certain proportion and it can be modelled by :

$$x_1 = a_{11}s_1 + a_{12}s_2 + a_{13}s_3 + a_{14}s_4$$

where $s_1 = E_0\,\mathrm{e}^{(-t/T_2^*)}\cos(2\pi f_L t + \Phi)$ is MRS signal with Larmor frequency $f_L = 2326\mathrm{Hz}$ initial amplitude $E_0 = 200\mathrm{nV}$, relaxation time constant $T_2^* = 100\mathrm{ms}$, initial phase $\Phi = -\pi/3\mathrm{rad}$. s_2 to s_4 are power-line harmonics, we assume $a_{11} = 1$, $a_{12} = 0.2$, $a_{13} = 0.5$, $a_{14} = 0.3$. The signal length is 16000 and the sampling frequency is 66700Hz . Fig.2a shows the time domain of the observed data.

According to Fig.2, we synthesize sine wave and cosine wave at frequency of 2200Hz, 2300Hz and 2350Hz. The expressions of cosine wave and sine wave are $\cos(2\pi f_i t)$ and $\sin(2\pi f_i t)$, respectively, where $i = 1,\cdots,3$ and f_1=2200Hz, f_2=2300Hz, f_3=2350Hz. Then, the FastICA algorithm is performed to decomposition and the results are called ICs. The main component of one IC is MRS signal, remained six ICs consist of power-line harmonic. Fig.2b shows the time domain of ICs. Fig.2c shows the frequency spectrum of ICs. Reserving the IC with MRS signal, removing the ICs with power-line harmonic, the amplitude of the IC with MRS signal is recovered using data reconstruction. Fig.2d shows the time domain of reconstruction data after ICA. Comparing Fig.2a with Fig.2d, the result indicates that ICA algorithm ensures effective power-line harmonic suppression.

As is known to all, the notch filter is another valid method to power-line harmonic cancelling. In order to certify the consequence of power-line harmonic cancelling using ICA algorithm , we utilize notch filter to suppress power-line harmonic in the same experiment environment. Fig.3b shows spectra of observed data before and after using notch filter, where the MRS signal suffers from attenuation and there are residual power-line harmonic. Fig.3a shows spectra of observed data before and after using FastICA algorithm, where the power-line harmonics distribute in 2200Hz, 2300Hz and 2350Hz have been thoroughly removed and the MRS

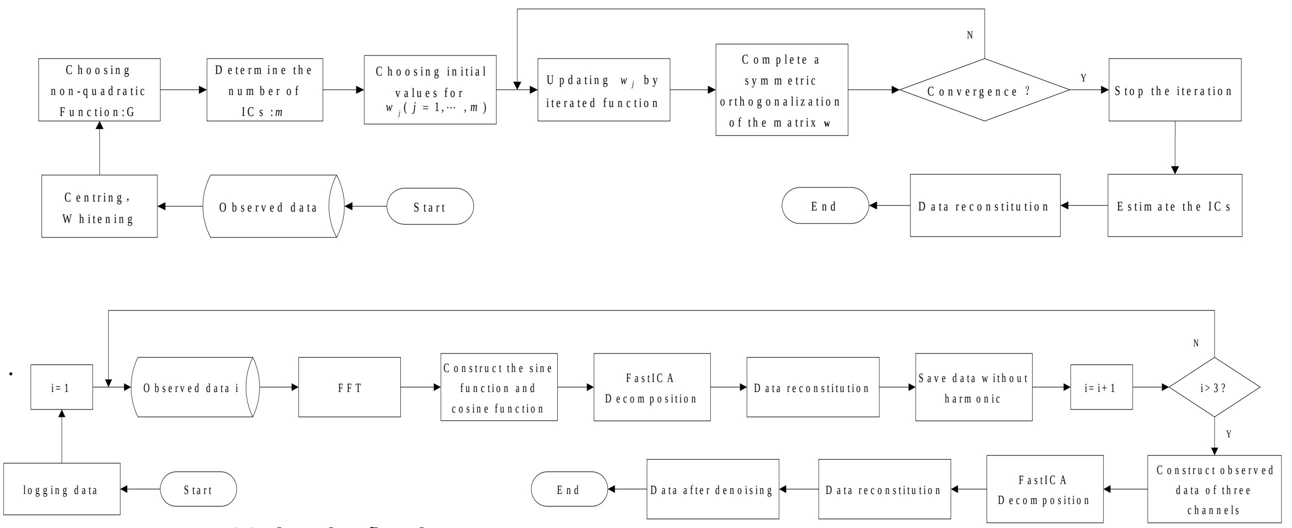

Fig.1 ICA algorithm flowchart

signal is reserved without being destroyed. It can be concluded that ICA algorithm is effective compared with notch filter.

(a)

(b)

(c)

(d)

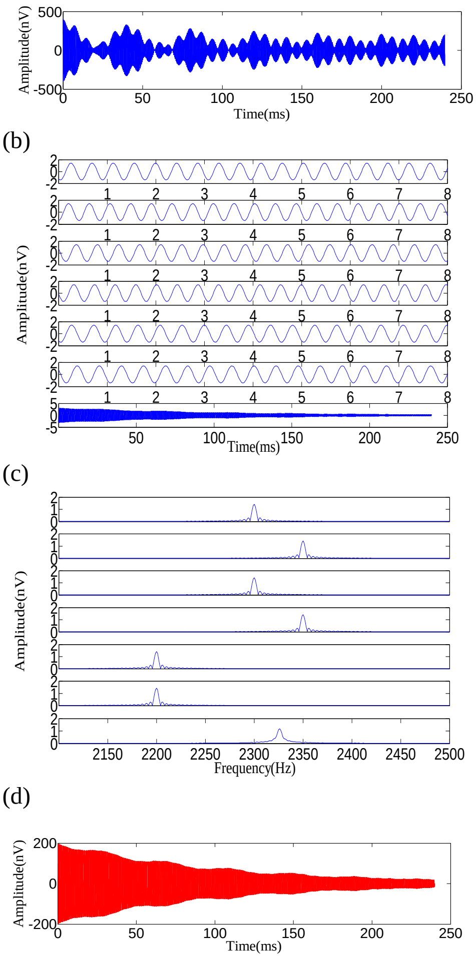

Fig.2 Power-line harmonic cancelling based on FastICA. (a) Time domain of the observed data. (b) Time domain of ICs. (c) Frequency spectrum of ICs. (d) Time domain of reconstruction data after ICA.

(a)

(b)

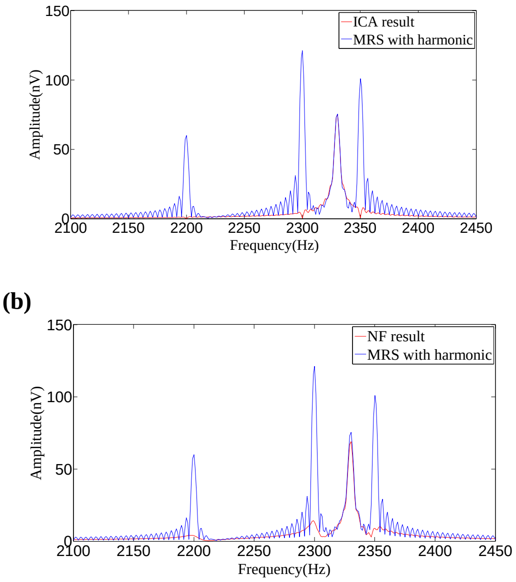

Fig.3 Spectra of observed data before and after using FastICA algorithm (a) and notch filter (b) Larmor frequency of MRS detection is different related to the intensity of geomagnetic field.

Simulations of removing random noise by using ICA algorithms

In this part, there are three original sources s_1, s_2 and s_3 which represent MRS signal, 2300Hz power-line harmonic, white Gaussian noise, respectively. The MRS signal is contaminated by 2300Hz power-line harmonic and white Gaussian noise. In order to close to the actual, assuming the three sources occur simultaneously， constructing two channels of the observed data just as the MRS instrument receiver measuring twice, the results are as follow：

$$x_1(t) = a_{11}s_1(t) + a_{12}s_2(t) + a_{13}s_3(t)$$

$$x_2(t) = a_{21}s_1(t) + a_{22}s_2(t) + a_{23}s_3(t)$$

Where $s_1 = E_0 e^{(-t/T_2^*)}\cos(2\pi f_L t + \Phi)$ is MRS signal with Larmor frequency $f_L = 2326\text{Hz}$ initial amplitude $E_0 = 200\text{nV}$， relaxation time constant $T_2^* = 0.1\text{s}$ and initial phase $\Phi = -\frac{\pi}{3}\text{rad}$； $s_2 = A\cos(2\pi f_H t + \alpha)$ is power-line harmonic with $A = 200\text{nV}$，$f_H = 2300\text{Hz}$，$\alpha = -\frac{\pi}{4}\text{rad}$；s3 is white Gaussian noise and the signal to noise ratio(SNR) is 15dB.The signal length is 16000 and the sampling frequency is 66700Hz. Fig.4a shows time domain of original sources. $a_{ij}(i = 1,2,\ j = 1,2,3)$ are the elements of mixed matrix $\mathbf{A}$ and they are different correlation with ambient noise such as the power-line harmonic in different frequency, phase and amplitude, the random noise with different probability density function. In the simulation, a_{ij} are randomly selected constants， assuming the mixing matrix is as follows：

$$\mathbf{A} = \begin{bmatrix} 1 & 0.8 & 1.9 \\ 1 & 0.4 & 1.7 \end{bmatrix}$$

$x_i(t)(i = 1,2)$ are observed data made of three sources s1,s2 and s3. Three observed data are needed in random noise cancelling. However, in simulation, there will remain two components (MRS signal and random noise) after power-line harmonic suppression. In general, ICA assumes that the number of observed data is no less than that of ICs. Many simulation tests demonstrate that the MRS signal decomposed will been decomposed twice when the number of observed data is more than the number of ICs. Therefore it’s better to make the number of observed data equal to that of ICs in simulation.

Fig.4b shows the reference channels’ construction under one of observed data, the three channels are observed data, cosine wave and sine wave which own the same frequency with power-line harmonic in observed data and same length with observed data, respectively. We can see the MRS signal is almost lost affected by power-line harmonic and white Gaussian noise. On the purpose of making cosine wave and sine wave obvious, we cut out 8ms in time domain and extend it. It is the same with Fig.4c, Fig.4e shows the reference channels’ construction of the other observed data. After that, use FastICA algorithm to power-line harmonic cancelling. Fig.4d is the result, obviously the envelope of sine wave is removed.

Fig.4e shows the decomposition result, we can see the ICs resolved are exactly MRS signal and random noise. Only the amplitude of them seriously decrease compare with original sources. Fig.4f shows the time domain of reconstruction data and one of observed data. In Fig.4f the red curve presents reconstruction data after ICA, the blue curve presents one of observed data. Obviously, the MRS signal recovers effectively from observed data almost without any signal loss. The amplitude of MRS signal is the same as original sources with the use of data reconstruction. It can be concluded that using FastICA algorithm to suppressing random noise is successful.

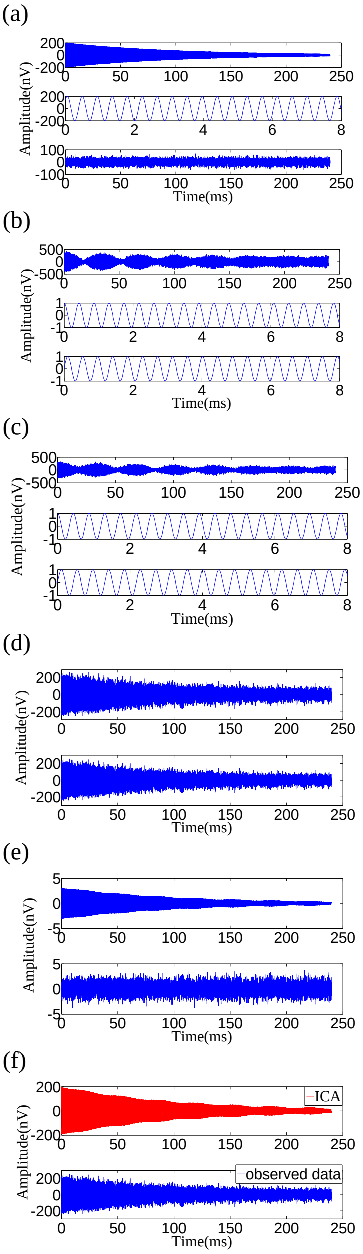

Fig.4 Random noise cancelling based on FastICA. (a) Time domain of the original sources. (b) Reference channels' construction under one of observed data. (c) Reference channels' construction under the other observed data. (d) Observed data in the next ICA processing. (e) decomposition result. (f) Time domain of reconstruction data and one of observed data.

Field Examples

Using the field experiment data acquired using JL-MRS array system, we substantially proved that ICA algorithms is effectively and high efficient compared with notch filter as well as stacks. Noted in Fig.5(a), three measured data were recorded during one pulse moment. By using ICA to remove the harmonic noise, the spectrum were shown in red lines in Fig.5b. Finally, we compared the random noise cancellation with the stacks method. After reconstruction data using ICA, the random noise was effectively removed (Fig.5c).

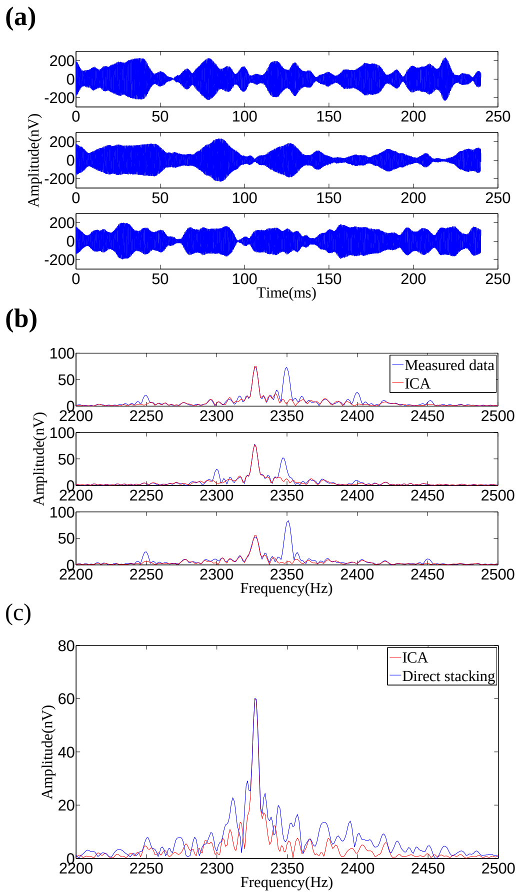

Fig.5 Field data noise cancelling based on FastICA. (a) time domain of measured data in three channels. (b) frequency spectrum of measured data and reconstruction data after ICA. (c) Frequency spectrum of reconstruction data after ICA and the result on the basis of stacking 24 times using the measured data in the same pulse of current.

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