Signal Integrity Evaluation for Fetal Magnetocardiography

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Abstract—The fixed-point independent component analysis (FastICA) algorithm was widely used for extraction of the fetal magnetocardiography (fMCG) signals. Although effective, it may cause signal distortions if not properly designed. In this paper, we developed a simple yet effective method to evaluate the FastICA algorithm from the experimental and synthetic data. The method was based on the detection of simulating the FastICA algorithm from the experimental and synthetic paper, we developed a simple yet effective method to evaluate the performances of the FastICA algorithm quantitatively. The evaluation results turned out to be very effective for parameters optimization of the algorithm and integrity evaluation of the fMCG signal.

I. INTRODUCTION

Fetal magnetocardiography (fMCG) is a noninvasive technique to monitor the magnetic field generated by the electrical activity of fetal heart [1]. These fields are extremely weak and can be recorded outside the maternal abdomen by using superconducting quantum interference devices (SQUIDs) with extremely high sensitivity. Usually, fMCG measurements are implemented within a magnetic shielded room (MSR) in order to suppress the strong environmental magnetic fields. Although effective, the data still contain a mixture of magnetic signals from the maternal and fetal cardiac activities, as well as the environmental magnetic noise. Therefore, adequate processing has to be applied to extract the desired fMCG signal.

Over the last few years, independent component analysis (ICA) algorithms have attracted great interests in biomedical signal processing [2]-[4]. ICA is a statistical method for transforming an observed multidimensional vector into independent components. Based on the multichannel fMCG recordings, many ICA algorithms have been proposed and demonstrated to be very effective for the retrieval of high-quality fMCG signals [5]-[7]. Moreover, Mantini and Hild have compared the performances of six ICA algorithms for the fetal cardiac signal extraction from synthetic and real fMCG data [8]-[9]. By comparing the accuracy (signal to noise ratio, SNR), detection rate of P-QRS-T waves, and convergence speed, FastICA was validated to be best. However, no detail information about the signal integrity was given. At present, most ICA algorithms applied to fMCG extraction direct to the processing of the real fMCG data and automated classification of independent components, while the evaluation of the signal distortions are ignored to some extent [10]. To confirm the effectiveness of the ICA processing, it is necessary to quantitatively evaluate the integrity of the retrieved fMCG signals before putting it into practice.

Previously, we have developed a quantitative evaluation method for MCG signal and demonstrated its effectiveness [11]. In this study, the popular used FastICA algorithm for fMCG signal extraction was evaluated with data of digital synthesis and experiments. The sources of the MCG and fMCG signals were constructed by using two individual electrocardiography (ECG) signals with adjustable frequency and amplitude. Three key performance indexes (KPIs) were employed for parameter optimization of the FastICA algorithm and integrity evaluation of the retrieved fMCG signal.

II. METHODS

A. ICA Algorithm

Consider an n-dimensional vector $\mathbf{s}$ of source signals whose components are mutually independent and an observed m-dimensional vector $\mathbf{x}$, ICA algorithm assumes a linear transformation given by

$$\mathbf{x} = \mathbf{A}\mathbf{s},$$

where, $\mathbf{x} = [x_1, x_2, ..., x_m]^T$, $\mathbf{s} = [s_1, s_2, ..., s_n]^T$, and $\mathbf{A}$ is a constant m×n matrix to be estimated. As the maternal and fetal hearts are physically separate sources, the mutual independence of sources overlapped in fMCG data is satisfied. Based on the assumptions, the problem is to determine a constant weight matrix $\mathbf{W}$ by using only the observed vector $\mathbf{x}$, so that

$$\mathbf{s} = \mathbf{W}\mathbf{x}.$$
As one of the ICA algorithms, the fixed-point algorithm (FastICA) is popular used for fMCG extraction because of its fast convergence and small estimation errors [13]. In the FastICA algorithm, minimization of the mutual information is roughly equivalent to find directions in which the negentropy is maximized. Given a random vector \( y = [y_1, y_2, \ldots, y_n] \) with probability density \( P(y) \), the negentropy \( J \) is defined by

\[
J(y) = H(y_{\text{gauss}}) - H(y),
\]

where \( y_{\text{gauss}} \) is a Gaussian random vector of the same covariance matrix as \( y \), and \( H \) is the differential entropy. The definition of differential entropy \( H \) is given by

\[
H(y) = -\int P(y) \log P(y) \, dy.
\]

By maximizing the negentropy \( J \), the independent component can be estimated one by one. In practice, the FastICA algorithm can be modified to add a step size parameter \( \mu \) in case of the uncertain convergence.

B. Simulation and Experiments

The FastICA algorithm was evaluated by using experimental and synthetic data as shown in fig. 1. The experiments were established by using a low-Tc SQUID system, which had a configuration of four signal channels and three references. The maternal and fetal cardiac sources were simplified to a big coil and a small coil locating at a vertical distance of 55 mm and 90 mm to the bottom of the dewar, respectively. In addition, the fetal coil was placed under the bottom of the dewar with a horizontal distance of 200 mm to the maternal coil. The simulated MCG and fMCG signal were generated by using two known electrocardiography (ECG) signal (ECG and fECG) with adjustable amplitude and frequency to drive the two coils, respectively. The simulated signals as well as the environmental noises were recorded by the SQUID system and sent for processing and evaluation. All the measurements were performed in a MSR.

In the synthetic data, four sources were chosen, which consists of the two ECG signal and two noises separated from the experimental data. The synthetic data \( x \) are obtained by mixing the four sources with a constant matrix \( A \). As the four sources derive from the experimental data, the evaluation results between the synthesis and experiments can be comparable.

C. Data Processing and Evaluation

In the processing procedure, high-frequency and power line frequency noises of the experimental recordings were firstly removed by a combination of digital low-pass (120 Hz) and notch FIR filters (48.5-51.5 Hz). Then the outputs of the signal channels were compensated by subtract the outputs of the reference magnetometers based on a smoothing least-square algorithm. Through the preliminary processing, the SNR of the fMCG data was improved. Afterwards, the sources were separated from the four-channel fMCG data by using the FastICA algorithm. In order to accelerate the convergence of the algorithm, a step size \( \mu \) was employed. Relative to the experimental data, the synthetic data were directly sent for the FastICA processing.

For the fMCG source derives from the fECG signal, the retrieved fMCG signal can be evaluated by comparing with the corresponding fECG signal. Three key performance indexes (KPIs) were given as follows:

1) Correlation Coefficient \( \rho_t \) in Time Domain: The coefficient \( \rho_t \) reflects the whole similarity between the retrieved fMCG signal and the driving fECG signal. The better the fMCG signal is extracted, the closer the coefficient approaches to unity.

2) Relative Heights: The relative heights are defined by the ratios of the peak of Q-wave, P-wave and T-wave to R-wave. Relative to the whole statistic information from correlation coefficients, the relative heights give the local characteristics of the fMCG signal.

3) Correlation Coefficient \( \rho_f \) in Frequency Domain: The coefficient \( \rho_f \) gives the statistical energy distribution in the frequency lines, which is complementary to the coefficient \( \rho_t \) in time domain.

Based on the above KPIs, the performances of the FastICA algorithm under different step sizes \( \mu \) and SNRs of the fMCG signal have been evaluated.
III. RESULTS AND DISCUSSIONS

The typical experimental fMCG recordings $x$ after preliminary processing were shown in fig. 2(a). The desired fMCG signal was overlapped by MCG signal and environmental noises, showing a low SNR. It is difficult to obtain the diagnostic information directly. Fig. 2(b) gave the corresponding synthetic fMCG data, which have the same characteristics as the experimental data. By using the FastICA algorithm, the source of the fMCG signal was separated.

![Fig. 2. Four-channel fMCG recordings x: (a) Experimental data; (b) Synthetic data.](image)

Fig. 2. Four-channel fMCG recordings $x$: (a) Experimental data; (b) Synthetic data.

Fig. 3(a) plots the correlation coefficients $\rho_t$ and $\rho_f$ under different step sizes $\mu$ as a function of the SNRs of the fMCG signal. The change trends were similar between time and frequency domain. During the FastICA processing, $\mu$ was set to be 1 and 1e-7. Obviously, for a larger $\mu$, it is difficult for the FastICA algorithm to converge to a steady solution, showing smaller coefficients $\rho_t$ and $\rho_f$. However, when $\mu$ was lowered to be 1e-7, the efficiency of the FastICA algorithm improves greatly. In addition, the coefficients $\rho_t$ and $\rho_f$ were proportional to the SNRs of the fMCG signal. Because averaging was very effective to suppress the noises, the coefficients $\rho_t$ and $\rho_f$ approached to unity with little distortions, even under a large $\mu$. Fig. 3(b) gives the relative heights under different $\mu$ with SNRs of the fMCG signal. The results were coincident with the correlation coefficients. When $\mu$ was set to be 1e-7, the ratios of the peaks of Q-wave, S-wave, and T-wave to the peak of R-wave were almost same as the theoretic values as the SNRs of the fMCG signal increase.

![Fig. 3. KPIs from the experimental data: (a) Correlation coefficients in time and frequency domain; (b) Relative heights.](image)

By comparison, fig. 4 shows the same KPIs under different SNRs of the fMCG signal. The results had some differences from that obtained by experiments. At the step size of 1e-7, the correlation coefficients and relative heights seemed to be uncorrelated to the SNR values. Even when the fMCG signal was totally hidden in the noises (SNR=1), the fMCG signal still can be successfully separated with little distortion. The reasons may be due to the differences of the sources. Because the sources of the experimental recordings were previous unknown, the number of the sources may be larger than 4. In this case, the effectiveness of the FastICA algorithm dropped. In addition, the noise sources may have weak dependences, deteriorating the separated performances of the algorithm.
IV. CONCLUSIONS

In summary, we have developed a simple method for integrity evaluation of the fMCG signal from experimental and synthetic data. By using two known ECG signals to simulate fMCG and MCG signals, three key performance indexes were introduced, which are correlation in time domain, relative heights, and correlation in frequency domain.

With the optimized step size, the FastICA algorithm was evaluated to be very effective for separation of the fMCG signal from the mixed recordings. The correlation coefficients approach to unity in both time and frequency domains, and the relative heights stabilize at the theoretical values. However, the experimental KPIs are influenced by the SNRs of the fMCG signal, while the synthetic results are not. The reason may be due to the source differences, which will be studied in the future.

REFERENCES