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<Paper>

Automatic component selection for noise reduction in magnetocardiograph based on independent component analysis

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Magnetocardiogram (MCG) measurement systems require noise reduction, because MCG signals are extremely small compared to environmental magnetic noise. We investigate the efficacy of a novel noise-reduction method, based on an independent component analysis (ICA). The proposed noise reduction method requires a component selection process to distinguish signal from noise. A major challenge in applying ICA-based noise reduction method is the selection of suitable parameters, which in practice is often performed manually with rather subjective parameter choices. To address this issue, we proposed a component selection method that can be performed quantitatively and automatically. The proposed method is based on the peak values of the autocorrelation function and helps distinguish the independent components of the MCG signals from the noise using an appropriate threshold. By using the proposed method, we obtain output signal-to-noise ratios (SNRs) of 33.98 dB, 19.17 dB, and 13.56 dB, corresponding to input SNRs for the simulated data at respectively 0 dB, -10 dB, and -20 dB, after noise reduction. The results show that the proposed method exhibits remarkable promise in extracting a noise-mitigated MCG signal for a wide range of SNRs.

Key words: magnetocardiogram, principal component analysis, independent component analysis, autocorrelation function, component selection

1. Introduction

In recent years, magnetocardiogram (MCG) has become increasingly relevant for clinical research, due to its potential to detect early stages of heart disease. However, it is difficult to assess heart activity precisely without some form of noise reduction, because MCG measurements are extremely small compared to environmental magnetic noise.

A possible solution that can suppress the noise is the use of a digital signal processing (DSP) method. The finite impulse response (FIR) filter is a well-known method in reducing noise via DSP. However, FIR filters have various issues such as distorted waveforms, generation of phase differences, and reduced signal peaks.

Hence, a noise reduction method using an independent component analysis (ICA) is considered. This method has the ability to distinguish between independent components, whether those are MCG signals or noise. Component selection is important for accuracy of noise reduction. There are two steps involved in selecting the independent components that represent MCG signals in an inverse process:

1. Distinguish between independent components separated using the ICA, whether those are MCG signals or noise.
2. Select the independent components that are determined to be MCG signal components.

In many cases, these processes have been performed by individual subjective judgment from a waveform of independent components. Hence, the results of this process differ from person to person. The process cannot be performed automatically and quantitatively, because there are no appropriate parameters that can distinguish the independent components between MCG signals and noise using measurement data. In addition, the component selection process has not been discussed in detail up until now[1)-6)].

Therefore, we propose a new component selection method that can be used to reduce noise automatically and quantitatively by using measurement data. We have considered the proposed method can distinguish between the independent components of MCG signals and noise. We compare the proposed method with other component selection methods such as subjective judgment from the waveforms of independent components and the highest noise reduction accuracy.

2. Noise reduction method using the ICA

2.1 Noise reduction procedure

First, we explain the process of the noise reduction method using the ICA as follows[7)-8)]:

1. Apply principal component analysis (PCA) to measurement data for whitening.
2. Perform dimensional contraction to the whitening data (principal components) for eliminating unnecessary information and amount of calculation.
3. Apply the ICA to the whitening data for separating independent components as source signals (MCG signals, noise, or both).
4. Distinguish the independent components between MCG signals and noise, and select the independent components that represent MCG signals.

5. Apply an inverse process to reconstruct measurement data using the selected independent components. This process uses inverse matrices calculated from each separating matrix produced during the ICA and PCA processes.

After completing these processes, a noise-reduced MCG signal is obtained. Accuracy of the noise reduction depends largely on the selected components. Therefore, the focus should be on the component selection step so that the process can be performed automatically and quantitatively.

2.2 Independent component analysis (ICA)

The ICA is a method designed to separate measurement data into independent components, which represent the source signals. ICA is performed based on statistical independence, and the difference between various ICA algorithms lies in the method of obtaining statistical independence. Independent components are statistically independent from each other. The measurement data model can be expressed in the ICA algorithm as

$$\boldsymbol{X} = \boldsymbol{AS} \cdots (1)$$

where matrix $\mathbf{X}$ is the measurement data, matrix $\mathbf{A}$ is the mixing matrix, and matrix $\mathbf{S}$ contains the source signals. Using this model, we treated the noise as one of the source signals. In this flow, $\mathbf{X}$ is replaced with a matrix that represents whitening and dimensional contraction through PCA. The separating data model can be expressed as

$$\hat{\mathbf{S}} = \mathbf{WX} \cdots (2)$$

where matrix $\hat{\mathbf{S}}$ represents the independent components that are statistically independent from each other, and matrix $\mathbf{W}$ is the separating matrix. Matrix $\mathbf{W}$ is optimized so that $\hat{\mathbf{S}}$ is statistically independent of each other.

2.3 Proposed component selection method

We propose a new component selection method that can perform automatic, quantitative selection. In our previous study[1)], we proposed a component selection method that takes the synchronization of correlation function peaks of independent components and an ECG signal. However, in this study, the proposed method does not require the ECG signal. Instead, the proposed method utilizes the autocorrelation function of the independent components after completing the ICA and the average of the peak values, as follows.

1. Calculate the autocorrelation function of the independent components separated by ICA. The equation of the autocorrelation function is:

$$\mathrm{R}_{(\mathrm{t})} = \frac{1}{\mathrm{N}} \sum_{\mathrm{i}=0}^{\mathrm{N}} \frac{(\hat{\mathrm{s}}_\mathrm{i} - \bar{\hat{\mathrm{s}}}) \times (\hat{\mathrm{s}}_{\mathrm{i+t}} - \bar{\hat{\mathrm{s}}})}{\sqrt{(\hat{\mathrm{s}}_\mathrm{i} - \bar{\hat{\mathrm{s}}})^2} \times \sqrt{(\hat{\mathrm{s}}_{\mathrm{i+t}} - \bar{\hat{\mathrm{s}}})^2}} \cdots (3)$$

$$(0 \leq \mathrm{t} \leq \mathrm{T} - 1)$$

where $\hat{\mathbf{s}}_\mathrm{i}$ are the rows of matrix $\hat{\mathrm{s}}$, which contains independent component data, $\bar{\hat{\mathrm{s}}}$ is the average of $\hat{\mathrm{s}}_\mathrm{i}$, N is the sampling number (500 points = 1 s), T is the measurement time, and t is the shifted time.

2. Detect peaks of the autocorrelation function. We maintain peaks that have the same timing as other independent components because independent components containing the MCG signals have the same timing. We eliminate peaks if the peak interval is below 0.5 s (2 Hz) because the peak interval of MCG signals is approximately 0.5–2 Hz.
3. Calculate the averages of the chosen peaks (AP) of the independent components.

After performing these processes, we set the threshold AP values and distinguish between the independent components representing MCG signals and those corresponding to noise using the threshold.

3. Simulation method

The simulation method had two objectives. First, to assess the difference in the AP values between the MCG signals and the noise components. The second was to compare the component selection performed by the proposed method with the highest accuracy of noise reduction (HANR) method and the method of subjective judgment from waveforms. We explain the method used to determine the HANR method in section 3.2.

3.1 Simulation data

The MCG data was measured using a 64-channel (8×8) SQUID magnetometer in a magnetically shielded room (MSR). To reduce the noise, the MCG data were averaged 150 times. The averaged data represent the ideal data. Fig. 1 shows the ideal data of the 51 channel (highest amplitude position). The noise data were also measured using the same SQUID magnetometer with applying environmental magnetic noise via a coil in the MSR. Fig. 2 shows the applied noise data that was measured outside the MSR using a fluxgate. The simulation data were mixed with the ideal data and the noise data with signal-to-noise ratios (SNRs) of 0 dB, -10 dB, and -20 dB. The sampling frequency of the simulation data was 500 Hz, and the simulation data were 10 s (5000 data points). The equation of the SNR is

$$\mathrm{SNR} = 20 \log_{10} \frac{\mathrm{A_s}}{\mathrm{A_n}} \ [\mathrm{dB}]$$

where $\mathrm{A_s}$ is the peak amplitude of the QRS-complex, which is the highest amplitude sensor position for the ideal data, $\mathrm{A_n}$ is the zero-to-peak amplitude of the noise data. The utilized data are shown in the following figures (Figs. 1 and 2).

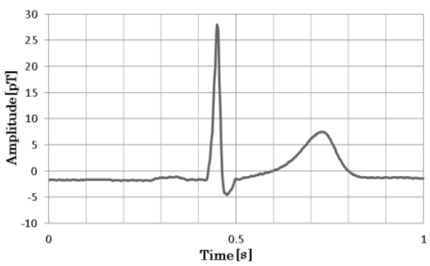

Fig. 1 Ideal data of highest amplitude position

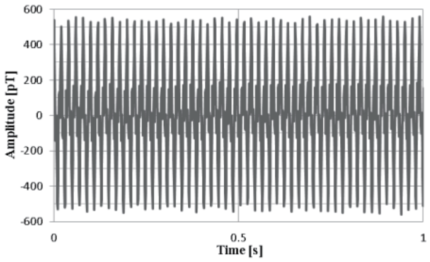

Fig. 2 Noise data that was measured outside the MSR

3.2 Simulation process

The simulation was performed using the same process as the noise reduction method using the ICA, which is explained in section 2. The specific simulation process is as follows:

1. Apply the PCA to the simulation data (64 channels × 5000 points) for whitening.
2. Perform dimensional contraction on the whitening data. We selected eight components from higher contribution ratios. The eight components had 99.9% or more information amount at all simulation data.
3. Apply the ICA to the whitening data (eight components selected in step 2) to separate the independent components.
4. Distinguish the independent components, which represent the noise, from the independent components, which represent the MCG signals, using the proposed automated method; thereafter, select the independent components that represent MCG signals.
5. Apply an inverse process to reconstruct the measurement data using the selected independent components.

To evaluate the proposed method, we calculated the correlation coefficient between the ideal data and the reconstructed data. The reconstructed data are the results of the noise reduction using the proposed method, the selection pattern with the HANR method, and the experimental judgment from waveforms. The HANR method was determined from among all selection patterns in all the simulations. The selection pattern of the HANR method was the one that had the highest correlation coefficient between the ideal data and the reconstructed data.

4. Simulation results

4.1 Peak timing

Fig. 3 shows an example of the independent components (left side) and the autocorrelation functions (right side). The figures in Fig. 3 show three characteristic components from eight independent components. The figure at the top is characteristic of the QRS-complex; the figure at the center is characteristic of a T-wave; the figure at the bottom is one of the noise components. There are differences between the stationary signals and the random signals at peak values and peak timings. In case of the stationary signals, peaks are clearly defined because the autocorrelation function gives high values only when they correspond to peak timings. However, in case of the random signals, peaks are not clearly defined because the autocorrelation function exhibits high values randomly.

Fig. 4 shows the peaks of the autocorrelation function. These figures are same as the ones on the right side of Fig. 3. The upper two signals have the same peak timings, while the lower signal exhibits random peak timings. Hence, we can determine the peak timings that represent the MCG signals.

4.2 AP values

Figs. 5-7 show the AP values of the independent components of the simulation data with SNRs of 0 dB, -10 dB, and -20 dB, respectively. The gray bars indicate the noise components, and the black bars indicate the MCG signal components that were chosen by the selection pattern of the HANR method. In Figs. 5-7, the AP values of the MCG signal components are higher than those of the noise components. The lower AP values of the MCG signal components, the lower SNRs.

Fig. 8 shows the AP values of all the independent components (8 × 3 = 24 components) of the simulation data at all SNRs tested. The 24 independent components have been arranged in descending order of the AP value. All AP values of the MCG signal components were higher than those of the noise components when the noise and MCG signal components were distinguished by the selection pattern of the HANR method. The boundary between the MCG signal and the noise components is at the AP value of 0.6; the MCG signal components had the AP values > 0.6 while noise components had the AP values < 0.6.

4.3 Comparison with waveforms

Figs. 9-11 show the waveforms of the independent components of the simulation data at SNRs of 0 dB, -10 dB, and -20 dB, respectively.

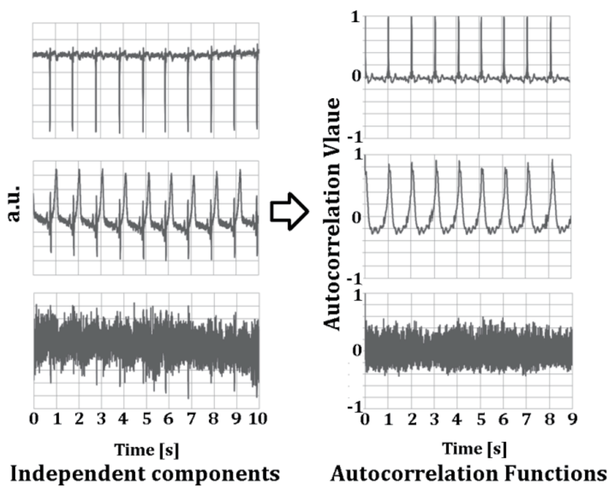

Fig. 3 Example of autocorrelation transformation

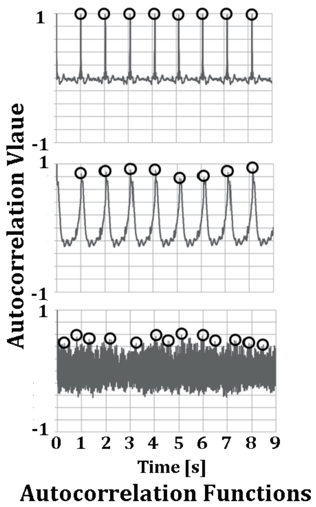

Fig. 4 Peaks of autocorrelation functions

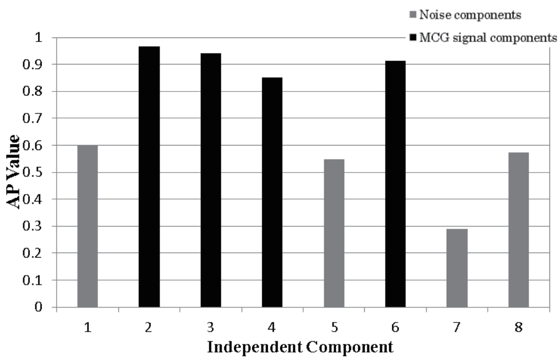

Fig. 5 AP value of simulation data at 0 dB

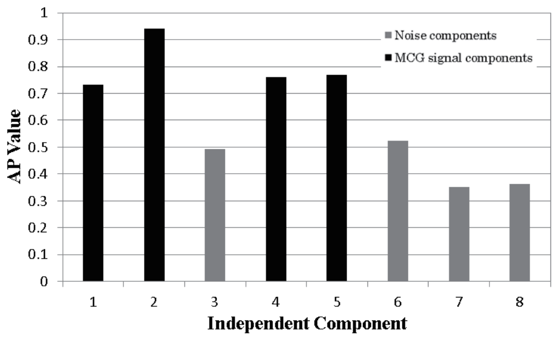

Fig. 6 AP value of simulation data at -10 dB

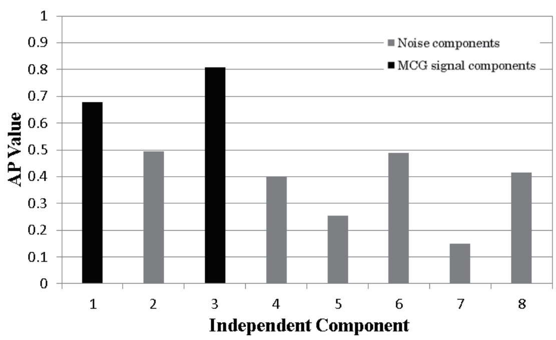

Fig. 7 AP value of simulation data at -20 dB

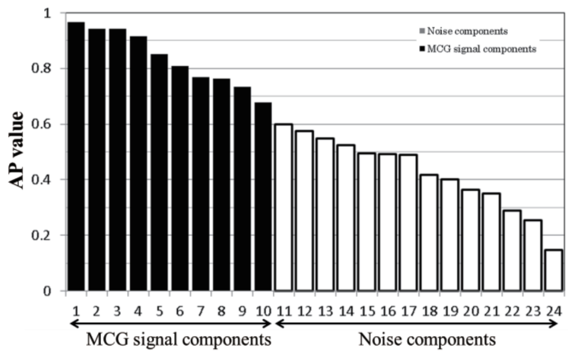

Fig. 8 AP value of all simulation data

In Fig. 9 (0 dB), performing a subjective judgment from the waveforms would lead to the selection of Nos. 2, 3, 4, and 6 as the MCG signals. This selection pattern is identical to the selection pattern of the HANR method. It is also identical to the result using high or low AP values, shown in Fig. 5.

Similarly, the subjective judgment method would select Nos. 1, 2, 4, and 5 in Fig. 10 (-10 dB) and Nos. 1 and 3 in Fig. 11 (-20 dB) as the MCG signals. Moreover, these selection patterns are the same as those determined by the HANR method and the results using high or low AP values, as shown in Figs. 6 and 7.

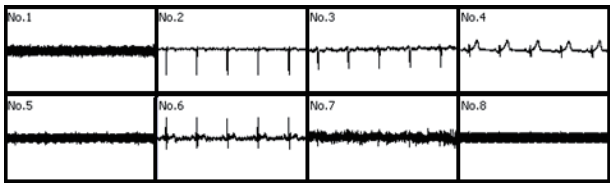

Fig. 9 Waveform of independent components (0 dB)

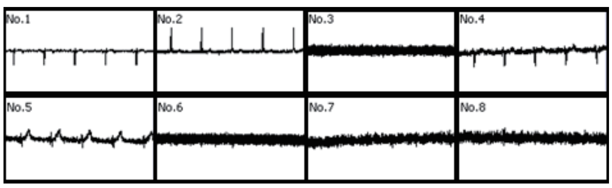

Fig. 10 Waveform of independent components (-10 dB)

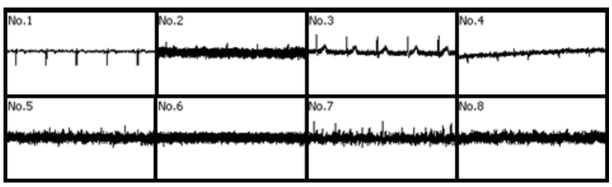

Fig. 11 Waveform of independent components (-20 dB)

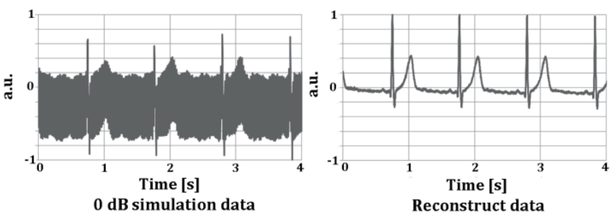

Fig. 12 Result of the noise reduction (0 dB)

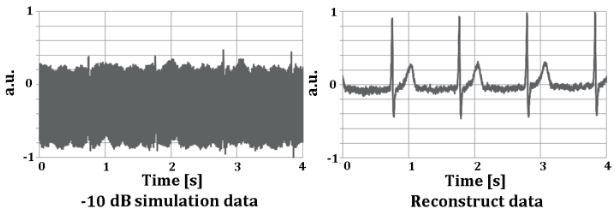

Fig. 13 Result of the noise reduction (-10 dB)

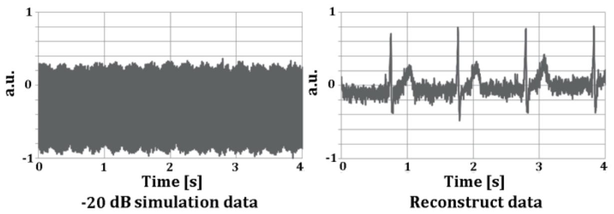

Fig. 14 Result of the noise reduction (-20 dB)

4.4 Waveform of noise reduction

Figs. 12-14 show examples of the waveforms before and after noise reduction for the simulated data at SNRs of 0 dB, -10 dB, and -20 dB, respectively. The SNRs of the reconstructed data were 33.98 dB, 19.17 dB, and 13.56 dB for the simulated data at SNRs of 0 dB, -10 dB, and -20 dB, respectively. The SNRs were calculated from the R-wave peak values (signal) and the baseline amplitudes (noise).

5. Discussion

First, we discuss some relevant conditions for successfully applying the HANR method. In many cases, this method can distinguish the MCG signals from the noise components. This method rejects components that have periods (interval of autocorrelation peaks) of 0.5 s (2 Hz) or less, because the MCG signals have a period of 0.5 s or more. However, this method cannot distinguish, when noise with a period of 0.5 s or more is applied.

Second, we discuss the threshold of the HANR method. The threshold is dependent on the SNR. Hence, as it is possible to approximate the SNR from the amplitude of the environmental magnetic noise and the general MCGs, we will determine the threshold value on which it is based. If the SNR is in the range 0~-20 dB, we can perform this method utilizing the threshold (0.6). Based on the threshold (0.6), Fig. 15 shows the SNRs of the reconstructed data for which the threshold ranged from 0.4 to 0.9. The method was able to maintain the accuracy of noise reduction when the threshold ranged from 0.6 to 0.66.

Third, we discuss the processing time. In this time, these processes were performed by two programs to check the AP values or other selection patterns. The total processing time was approximately 30 s when the method was performed utilizing the two programs. The total time was not considerably long as compared to the measurement time (a few minutes).

Finally, we discuss the application of this method for heart disease. In case of arrhythmia, MCGs can be measured utilizing the proposed method because independent components that are representing MCG signals have same peak timings. However, MCGs cannot be acquired using the proposed method, if we cannot get those synchronization.

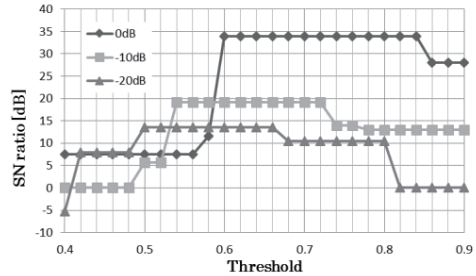

Fig. 15 SNRs with respect to varying threshold

6. Summary

We proposed a new method of component selection using ICA to perform the selection automatically and quantitatively. The ability of this proposed method to distinguish independent components is on par with that of the HANR method and the subjective judgment of waveforms of independent components.

The boundary between the noise and the MCG signal components was at the AP value of 0.6, which was determined using the HANR method. The noise components had AP values of 0.6 or less, while the MCG signal components had AP values of 0.6 or greater.

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