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ORIGINAL ARTICLE

Dimensional contraction by principal component analysis as preprocessing for independent component analysis at MCG

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Abstract We propose a noise reduction method for magnetocardiograms (MCGs) based on independent component analysis (ICA). ICA is useful to separate the noise and signal components, but ICA-based automatic noise reduction faces two main difficulties: the dimensional contraction process applied after the principal component analysis (PCA) used for preprocessing, and the component selection applied after ICA. The results of noise reduction vary among people, because these two processes typically depend on personal qualitative evaluations of the obtained components. Therefore, automatic quantitative ICA-based noise reduction is highly desirable. We will focus on the first difficulty, by improving the index used in the dimensional contraction process. The index used for component ordering after PCA affects the accuracy of separation obtained with ICA. The contribution ratio is often used as an index. However, its efficacy is highly dependent on the signal-to-noise ratio (SNR) it unsuitable for automation. We propose a kurtosis-based index, whose efficacy does not depend on SNR. We compare the two decision indexes through simulation. First, we evaluate their preservation rate of the MCG information after dimensional contraction. In addition, we evaluate their effect on the accuracy of the ICA-based noise reduction method. The obtained results show that the kurtosis-based index does preserve the MCG signal information through dimensional contraction, and has a more consistent behavior when the number of components increases. The proposed index performs better than the traditional index, especially in low SNRs. As such, it paves the way for the desired noise reduction process automation.

Keywords Magnetocardiogram · Principal component analysis · Independent component analysis · Dimensional contraction · Kurtosis · Contribution ratio

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1 Introduction

Magnetocardiograms (MCGs) have become increasingly relevant in clinical research, because of their potential to detect the early stages of heart disease. However, MCG signals are extremely small compared with the environmental electromagnetic noise, and it is therefore difficult to assess heart activity precisely, without some form of noise reduction. One solution is to use digital signal processing (DSP) techniques. The use of finite impulse response filters is a well-known method of reducing noise via DSP. Low-pass filtering with a 40 Hz cutoff frequency is generally sufficient for noise reduction. However, the low-pass filtering approach suffers from various issues, such as distorted waveforms, generation of phase differences, and reduced signal peaks. We therefore consider here a noise reduction method based on independent component analysis (ICA) [1].

To perform automatic noise reduction using ICA, two problems must be solved. The first one lies in the dimension contraction applied after principal component analysis (PCA), a commonly used preprocessing step for ICA. The purpose of this dimensional contraction is to reduce the computational complexity of the subsequent steps to process and the information amount of expect MCGs, but it

must be performed without a significant loss of the relevant original information. When the signal-to-noise ratio (SNR) differs from the assumed value, it becomes difficult to determine the boundary on which to base this dimensionality reduction. The second problem lies in component selection after applying ICA. In many cases, this process is based on a human subjective evaluation of the obtained independent components. The results of such a human-based process will differ from person to person. This is because there are no pre-determined parameters to help distinguish which independent components are due to the MCG signal, and which are due to additive noise.

In this study, we will be focused on the first problem (dimension contraction after PCA), not only because it is difficult to decide the index to be used for dimensional contraction as discussed above but also because this process has a very considerable impact on the ICA separation accuracy [2, 3].

In particular, we propose a new dimensional contraction index (based on kurtosis) to prioritize the MCG signal components after PCA. For comparison, we simulate the performance of both the proposed kurtosis-based index and the traditionally used index, based on the contribution ratio. These simulations confirm the impact of the index prioritization in the accuracy of the subsequent noise reduction procedure.

2 Noise reduction method using the ICA

2.1 Noise reduction procedure

The ICA-based approach to noise reduction can be summarized as follows [4].

1. Apply PCA to measurement data for whitening.
2. Perform dimensional contraction on the whitened data (the principal components) to eliminate unnecessary information and thus reduce the subsequent computational complexity.
3. Apply ICA to the whitened data to separate the independent components of the different source signals (MCG and noise or both of them).
4. Distinguish the independent components between the MCG signal and the noise, and select the independent components that represent the MCG signal.
5. Apply an inverse process to reconstruct the measurement data, but using only the selected independent components. This process uses inverse matrices calculated from each separating matrices produced during the PCA and the ICA processes.

At the end of this procedure, a noise-reduced MCG signal is obtained. The accuracy of the noise reduction is greatly dependent on the dimensional contraction and component selection processes. We will be focused on the dimensional contraction process, and consider the best way to perform it without knowing the SNR of the measurement data.

2.2 Independent component analysis

ICA is a method designed to separate the measurement data into independent components that represent the different source signals. The approach is based on the statistical independence between the different components; the difference between the various ICA algorithms lies in the method used to obtain statistical independence. The obtained components are statistically independent from each other. The measurement data model in the ICA algorithm is:

$$\mathbf{X} = \mathbf{AS}, \tag{1}$$

where $\mathbf{X}$ is the measurement data matrix, $\mathbf{A}$ is the mixing matrix, and matrix $\mathbf{S}$ contains the different source signals. To use this method for noise reduction, noise is treated as one of the source signals. In noise reduction case, $\mathbf{X}$ is replaced with a matrix that represents the whitening data obtained from the preceding PCA process. The separating data model is:

$$\hat{\mathbf{S}} = \mathbf{WX}, \tag{2}$$

where $\mathbf{W}$ is the separating matrix, and $\hat{\mathbf{S}}$ is constituted by the independent components. The statistical independence of the components in $\hat{\mathbf{S}}$ is optimized by $\mathbf{W}$.

2.3 Dimensional contraction index

In this study, two indexes for dimensional contraction are compared through simulation. One is the contribution ratio, the traditionally used index; the other one is the proposed kurtosis-based index.

2.3.1 Contribution ratio

The contribution ratio is calculated by dividing the eigenvalues of each principal component by the sum of the eigenvalues of all the principal components, as follows:

$$\mathrm{CR}_i = \lambda_i \Big/ \sum_{i=1}^{\mathrm{N}} \lambda_i \tag{3}$$

where N is the number of sensors, i (1, 2,…, N) identifies the principal component, λ_i is the eigenvalue of the ith principal component, and CR_i is the contribution ratio of the ith principal component. The eigenvalues are calculated when applying PCA. This index is a measure of the fraction of the measurement data information contained in the respective principal component.

Generally, the threshold established for this index determines the degree of dimensional contraction. If the index value of a principal component is below the threshold, that component is considered to contain unnecessary information and discarded. This index cannot directly evaluate whether a component contains from the MCG or the noise. For example, when the measurement data has low SNR, almost all the information in the measurement data is noise information. It means that the MCG-contained principal components will be below the threshold, and will be lost. Therefore, it is necessary to improve the index and threshold decision scheme.

2.3.2 Kurtosis

Kurtosis is one of the parameters characterizing probability distributions [5]. This index represents the sharpness of a distribution (for example, the kurtosis of the Gaussian distribution is zero). The excess kurtosis (relative to the Gaussian distribution) is also often used as a measure. Kurtosis will therefore be calculated here with the following equation.

$$K_i = \frac{m(m+1)}{(m-1)(m-2)(m-3)} \sum_{i=1}^{m} \left(\frac{x_i - \bar{x}}{s} \right) - 3 \frac{(m-1)}{(m-2)(m-3)} \quad (4)$$

where i identifies the principal component, K_i is the excess kurtosis of the ith principal component, x_i is the data of the ith principal component, $\bar{x}$ is the average of x_i, s is standard deviation of x_i, and m is the number of data points.

Kurtosis, as calculated by (4), will exhibit a low value when probability distribution of the data has dull peak by having high randomness, or high variance; on the other hand, it will exhibit a high value when probability distribution of the data has a sharp peak. Therefore, given that the MCG signal components have sharp peaks (for example, the QRS-complex) and the noise components have randomness or high variance in nature (for example, power line noise), we may expect the MCG-contained principal components to have high values and the noise-contained components to have low values in this metric. The actually probability distributions of MCG signal and noise are shown in Figs. 1 and 2 on Sect. 3.1.

3 Simulation method

Simulations were carried out in this study with two main objectives. The first was to assess the priority given to the MCG signal components with each index. The second one was to assess the impact to noise reduction accuracy obtained with each index.

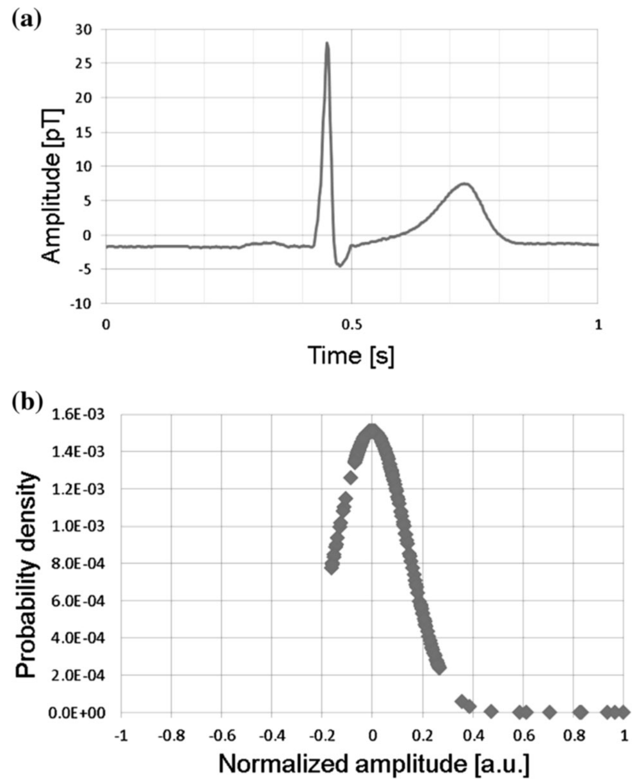

Fig. 1 Ideal data at the highest amplitude sensor position. **a** Waveform of ideal data. **b** Probability distribution of ideal data

The use of human subjects in this study was approved by the Ethics Committee of Iwate Medical University (approval number H22–147).

3.1 Simulation data

The MCG data was measured with a 64-channel (8 × 8) SQUID magnetometer in a magnetically shielded room (MSR). To reduce noise, the data were averaged 150 times. The averaged data represent here the ideal data. Figure 1 shows waveform and probability distribution of the ideal data at channel 51 (the highest amplitude position). Noise data were also measured with the same SQUID magnetometer while applying environmental magnetic noise with a coil in the MSR. Figure 2 shows waveform and probability distribution of the applied noise data (), as measured outside the MSR with a fluxgate. For the simulations, the ideal data and noise data were mixed with SNRs of 0, −10, and −20 dB. The sampling frequency of the simulation data was 500 Hz, and 10-s sequences (5000 data points) were used. The SNR was calculated as follows:

$$SNR = 20 \log_{10} \frac{A_s}{A_n} [dB], \quad (5)$$

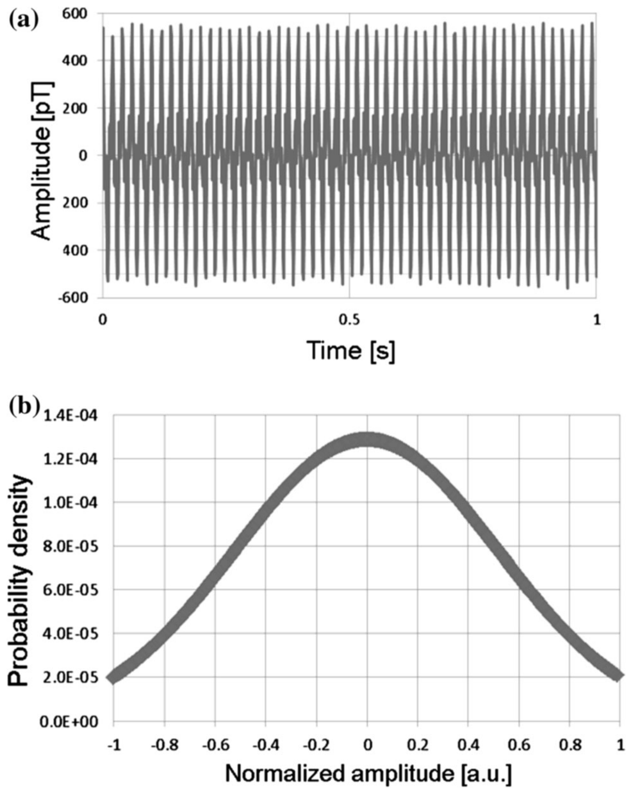

Fig. 2 Noise data measured outside the MSR. **a** Waveform of noise data. **b** Probability distribution of noise data

where A_s is the peak amplitude of the QRS-complex (the highest amplitude sensor position of ideal data), and A_n is the zero-to-peak amplitude of the noise data. Waveforms of the used data are shown in Figs. 1 and 2.

3.2 Simulation procedure

The first simulation (Sim-1) was designed to assess the priority given to the MCG signal components by the two indexes (therefore, the preservation rate after dimensional contraction). The second simulation (Sim-2) was designed to assess the impact to noise reduction accuracy obtained with each index.

3.2.1 Sim-1 procedure

As mentioned, this simulation was designed to assess the preservation rate of the MCG signal components with each index. The simulation proceeded as follows [1]:

1. Apply PCA to the simulation data (64 channels $\times$ 5000 points) for whitening.
2. Sort the principal components according to the ordering provided by each index (contribution ratio and kurtosis).
3. Select the principal components with higher values for each index. The selected number of principal components increases at each repetition. This step simulates the dimensional contraction of the noise reduction procedure.
4. Apply the inverse process to the whitening data using only the principal components selected in Step 3, thus obtaining the reconstructed simulation data.
5. Calculate the correlation coefficient between the reconstructed simulation data and the ideal data, to assess the preservation rate of the MCG components with each index.

The selected number of principal components is varied from 1 to 64, and steps 3 to 5 are repeated with each case. In particular, when the number of selected components reaches 64, all the principal components are being selected, with no exclusion. If the used index can give priority to the MCG signal components over the noise components, the correlation coefficient will exhibit high values, even for a small number of selected components.

3.2.2 Sim-2 procedure

As mentioned, this simulation was designed to assess the impact to noise reduction accuracy obtained with each index. This simulation uses the ICA-based noise reduction procedure discussed in Sect. 2:

1. Apply PCA to the simulation data (64 channels $\times$ 5000 points), for whitening.
2. Sort the principal components according to the ordering provided by each index (contribution ratio and kurtosis).
3. Perform the dimensional contraction of the whitening data. For each index, the principal components with higher value are selected. The selected number of principal components increases at each repetition.
4. Apply ICA to the whitening data (the principal components selected in Step 3), to obtain independent components.
5. Check the correlation coefficients of all the possible selection patterns, to determine the selection with highest noise reduction accuracy.
6. Apply an inverse process to the independent components selected in Step 5.
7. Calculate the correlation coefficient between the reconstructed simulation data and the ideal data, to assess the noise reduction accuracy with each index.

The selected number of principal components is varied from 1 to 8, and steps 3 to 7 are repeated with each case. If there is positive impact to the noise reduction accuracy, the noise reduction accuracy with the increase in the number of

selected components is increased, and the behavior of that is smooth and consistent.

4 Simulation results

4.1 Sim-1 results

Figure 3 shows the normalized 64 principal components, ordered by contribution ratio. Figure 4 shows the same normalized 64 principal components, but this time ordered by kurtosis. The data shown in Figs. 3 and 4 were obtained after applying PCA to the simulation data at an SNR of 0 dB. The difference between Figs. 3 and 4 is only the order of the components. Number shown in side of waveforms in Figs. 3 and 4 are the component number of left and right end components. As shown in Fig. 3, the first principal component in the contribution ratio ordering is a noise component; in the kurtosis case, however, the first component is an MCG signal component, as shown in Fig. 4. A similar tend can be found by comparing the next few components in Figs. 3 and 4. This means that using kurtosis as an index gives priority to the MCG signal components.

Figure 5 shows the final results of Sim-1: the preservation rate of the MCG signal components. There is a big difference in the achieved correlation coefficients, because in the contribution ratio case the first component is a noise component (shown Fig. 3). From the results of this simulation, we conclude that kurtosis provides a higher preservation rate of the MCG signal components than the contribution ratio. This will naturally have a profound impact in the noise reduction accuracy, as will be shown in next results.

4.2 Sim-2 results

Figures 6 and 7 show the results obtained with Sim-2 (the noise reduction accuracy for SNRs of −10 and −20 dB, respectively. For an SNR of −10 dB (Fig. 6), the correlation coefficients are similar for both indexes. However, for a −20 dB SNR (Fig. 7), the kurtosis-based index exhibits much smoother and consistent results than the contribution ratio index in the behavior with the increase in the number of selected components. In the contribution ratio case, it is even difficult to define a threshold for component selection, because the behaviors in the correlation coefficient (the noise reduction accuracy) are random and large.

5 Discussion

First, we discuss about the priority given to the MCG signal components by each the indexes. As shown in Figs. 3 and 4, the kurtosis-based index prioritized the MCG signal components, but the contribution ratio index done not. This is because the noise-contained information increases when the measurements are performed in low SNR. Given that the contribution ratio is a measure of the amount of information contained in each component, it tends to give priority to the noise components when the data is measured in low SNR. In contrast, the kurtosis does not depend on the information contents of the components, but only on the data randomness and variance. In the high SNR cases, the difference in performance between both indexes is not considerable, because the noise-contained information is small. To summarize in low SNRs, the kurtosis-based index performs better than the contribution ratio index; in high SNRs, there is not a difference in the both indexes.

Second, we discuss about the preservation rate by each the indexes. As shown in Fig. 5, kurtosis-based index have high preservation rate compare with contribution ratio index. However, when we select the 63th component, the preservation rate is decreased sharply. This is because the 63th component is the high amplitude noise component enough to change waveforms. In addition, the first component of contribution rate order is high amplitude noise

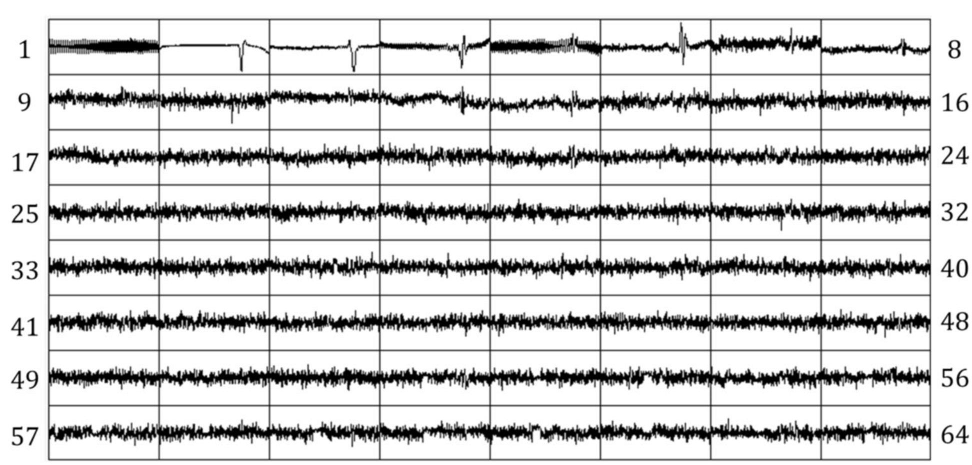

Fig. 3 Principal components in contribution ratio order

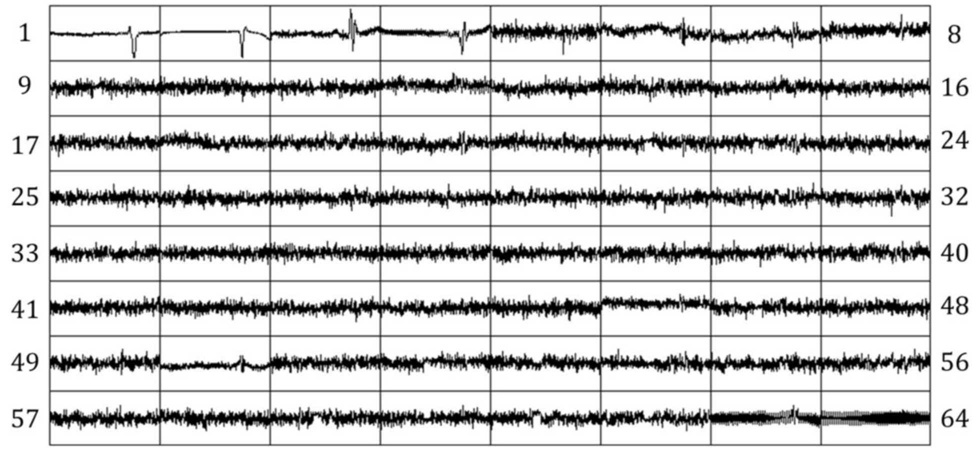

Fig. 4 Principal components in kurtosis order

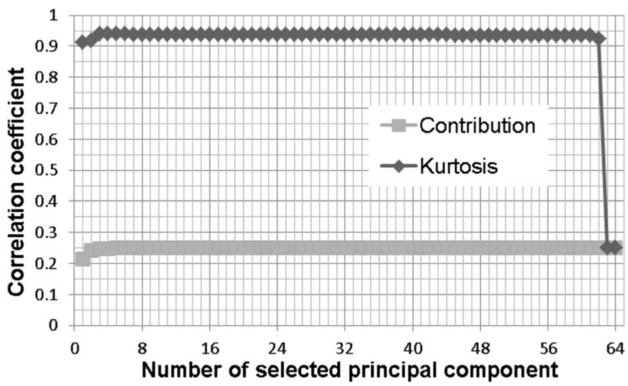

Fig. 5 Preservation rate of the MCG signal components

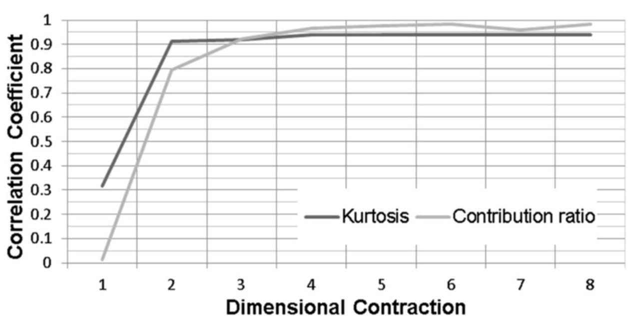

Fig. 6 Noise reduction accuracy at an SNR of −10 dB

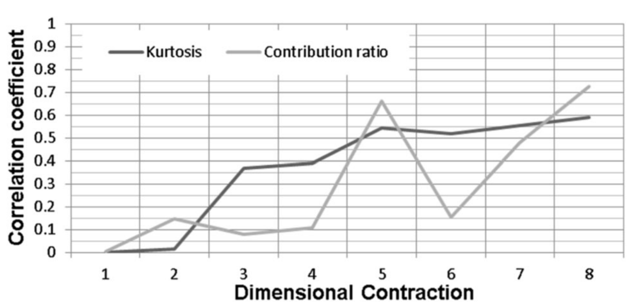

Fig. 7 Noise reduction accuracy at an SNR of −20 dB

component; on the other hand, the first component of kurtosis order is MCG signal component. Therefore, selected components information is occupied by noise components in the case of contribution ratio; however, selected components information is occupied by MCG signal components. This is the reason why there is so big difference between each index order on the preservation rate. Amplitude of principal components by each index order is shown in Fig. 8.

Finally, we discuss about the impact of the noise reduction accuracy. From Figs. 6 and 7, we find that the kurtosis-based index exhibits much smoother and consistent results in the lower SNR case. The performance is not difference between both indexes at an SNR of −10 dB, because in this case MCG signal components are not so lose in both cases at dimensional contraction. However, at an SNR of −20 dB, the kurtosis-based index is noticeably more consistent than the contribution ratio index, because the preservation rate of noise components in the contribution ratio case is high when compared with the preservation rate of the MCG signal components. Therefore, in the contribution ratio case, MCG signal components are lose compare with in the kurtosis case.

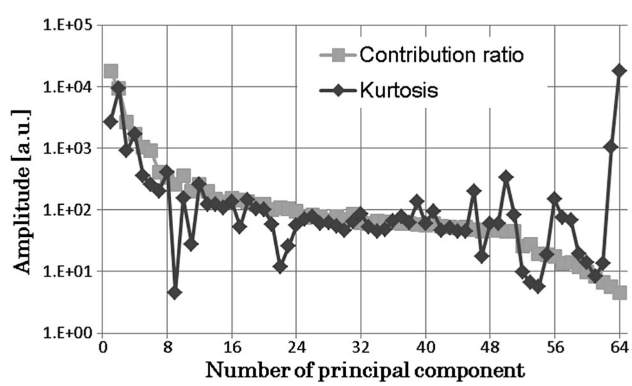

Fig. 8 Amplitude of components at an SNR of 0 dB

6 Summary

In this paper, we evaluated the impact of the criterion used for dimensionality contraction after PCA on the performance of the ICA-based noise reduction method, for the particular noise reduction case on MCG measurements. The evaluation was done through simulation, in two different steps. First, we assessed the preservation rate of the MCG signal components after the threshold operation involved in the dimensional contraction step. This was done by ordering the principal components obtained from PCA using both the conventional and proposed indexes. The impact of the index choice on the overall accuracy of the ICA-based noise reduction method was then evaluated.

The kurtosis-based index was found to prioritize the MCG signal components, and thus provide a higher preservation rate of the MCG signal components after dimensional contraction than the contribution ratio index. It was also found that the kurtosis-based index exhibits a much smoother and consistent increase in accuracy than the contribution ratio index when the number of selected components increases. In fact, in the case of the contribution ratio index, it was even difficult to decide on the threshold to use, because the changes in the accuracy of the noise rejection process in low SNR was found to be almost random.

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