Magnetocardiogram Topography with Automatic Artifact Correction using Principal Component Analysis and Artificial Neural Network

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Abstract

Magnetocardiogram (MCG) topography is a useful diagnostic technique that employs multi-channel magnetocardiograms. Measurement of artifact-free MCG signals is essenctial to obtain MCG topography or map for a diagnosis of human heart. Principal component analysis (PCA) combined with an artificial neural network (ANN) is proposed to remove a pulse-type artifact in the MCG signals. The algorithm is composed of a PCA module which decomposes the obtained signal into its principal components, followed by an ANN module for the classification of the components automatically. In the experiments with volunteer subjects, 97% of the decisions that were made by the ANN were identical to those by the human experts. Using the proposed technique, the MCG topography was successfully obtained without the artifact.

Key words : MCG topography, magnetocardiography, principal component analysis, artificial neural network

I. INTRODUCTION

A biomagnetic field is a weak magnetic field generated by currents related to organ functions. Magnetocardiogram (MCG) is a biomagnetic field that is produced by cardiac electrical activity. The MCG signal can be measured with the use of a superconducting quantum interference device (SQUID) [1-2]. A two-dimensional map, MCG topography, can be obtained from multi-channel MCG sensors [3].

In the 61-channel MCG system installed at Samsung Medical Center, a pulse-type artifact is often observed in some channels related to the operation of other machines near the MCG system. From experiments, the artifact occurs randomly for a duration of 50-100 milliseconds with a finite bandwidth. The authors find it difficult to remove the artifact using conventional filtering techniques or time-domain analysis schemes. Principal component analysis (PCA) has been known as an effective technique in removing a correlated noise. It yielded positive results when it was used to improve the signal-to-noise ratio in the evoked neuromagnetic field by eliminating the correlated spontaneous field [4]. To remove the artifact, the PCA approach was employed to decompose the measured field into its component fields [5-6]. Then, the componsents were classified as belonging to the artifact class or to the signal class. Automatic classification was carried out by an artificial neural network (ANN) module [7]. After classification, the signal was restored through the reconstruction of the components that belong to the signal class.

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II. METHODS

In applying the principal component analysis, a covariance matrix was first calculated, then eigen values and eigen vectors were obtained. The principal component score (PCS) for the k-th component (PCS_k) indicated in Eq.(1) was used as a screening parameter to determine the amount of the component's energy relative to that of the entire signal.

$$PCS_k = \frac{\lambda_k}{\sum_{j=1}^{p} \lambda_j} \tag{1}$$

In this paper, a two-stage algorithm based on PCA and an ANN is proposed. For PCA, a rectangular time window synchronized with the cardiac cycle was used. The dominant components were then chosen based on the PCS. Since the energy of the artifact was relatively high, only those components with PCS larger than 0.1 were examined with the ANN. The overall procedure is shown in Fig. 1.

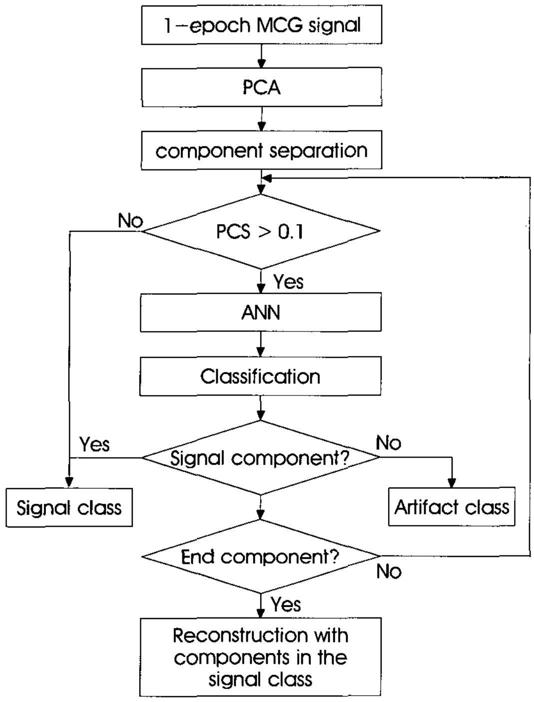

Fig. 1. Proposed artifact rejection algorithm.

The partial results of the simulation that was conducted to eliminate sinusoidal noise artifact with the use of the proposed PCA algorithm are shown in Fig. 2 and Fig. 3. For noise, 60Hz and 1 Hz sinusoidal noises were used for high and low frequency artifacts, respectively. As seen in these figures, high frequency and low frequency artifacts were successfully removed by the proposed PCA algorithm.

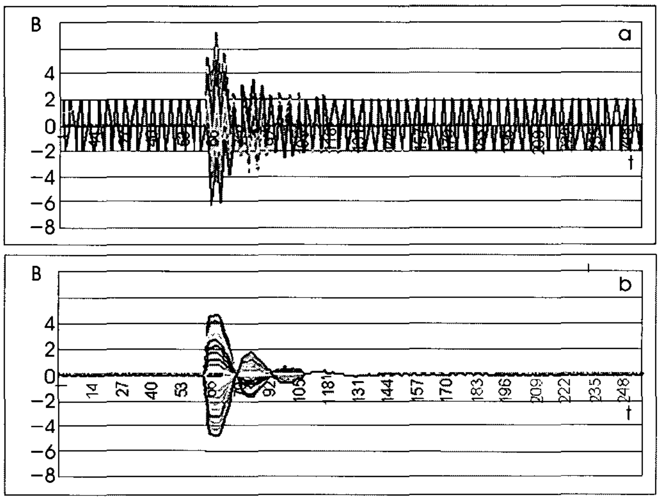

Fig. 2. Removal of a high frequency artifact using the proposed PCA algorithm. (a) Original simulated data with the artifact (60Hz noise). (b) Data after the removal of the artifact using the proposed algorithm. Horizontal axis denotes sampling time with a sampling interval of 4ms, and vertical axis represents a simulated magntic field with an arbitrary unit.

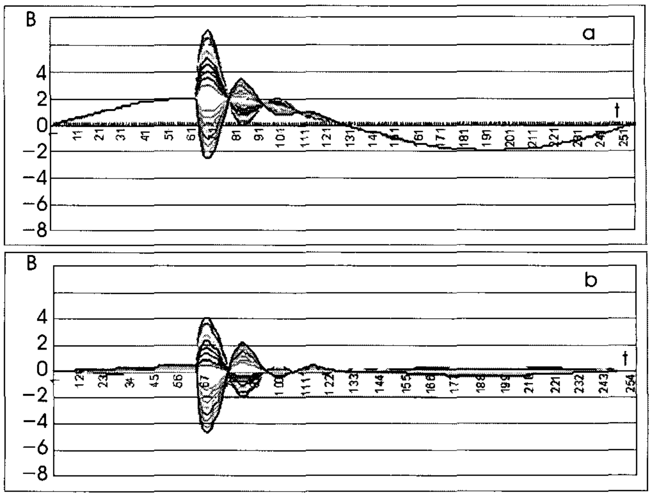

Fig. 3. Removal of a low frequency artifact using the proposed PCA algorithm. (a) Original simulated data with the artifact (1Hz noise). (b) Restored data after the removal of the artifact using the proposed algorithm.

The ANN module that was used for the automatic classification of the components into signal and artifact classes is shown in Fig. 4. The ANN module has one input layer with seven input nodes, one hidden layer with seven hidden nodes, and one output node. A sigmoid function was applied to the nodes in the hidden and output layers.

Seven parameters that had been calculated from each component were used as inputs to the artificial neural network. These were maximum value, minimum value, peak-to-peak value, variance, mean, skewness, and kurtosis of the magnetic field in each component during one epoch [5,7]. The output node had a continuous value within the range of [0,1].

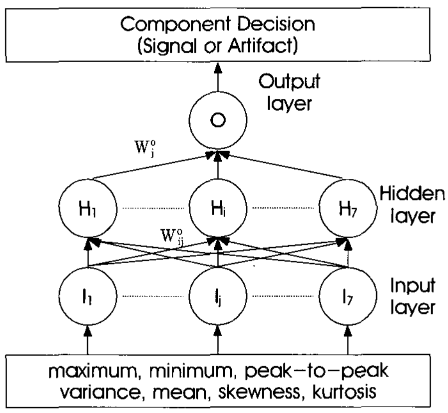

Fig. 4. The artificial neural network that was used for the classification of the components.

For a training set, 0 and 1 were assigned to the artifact and signal components, respectively, by the human experts. During the training, if the decision made by the artificial neural network was different from the desired (pre-assigned) value, the error was fed back to the weight matrices in such a way that a proper output can be obtained by the modified weight matrices, with the use of the error back propagation algorithm. Upon the completition of the training, the output value would be close to 1 for a component that belongs to the signal class, while it would be close to 0 for a component that belongs to the artifact class. A threshold-based decision rule is applied to the output. When all the components have been classified, a restored MCG signal is obtained by summing up the components that belong to the signal class.

Ⅲ. RESULTS

Experiments were carried out with five volunteers to test the algorithm. For each volunteer, 100 epochs of MCG signals were acquired. The dominant components whose PCS> 0.1, are shown in Fig. 5 as an example of an acquired MCG signal, where the component in the lower-left corner is an artifact. Although the classification of the components may not be a difficult task, it is important to implement it automatically using an ANN in a practical application. Supervised learning, where the error back propagation algorithm is employed, was used to train the neural network. A total of 500 epochs from five volunteers were decomposed into their principal components through principal component analysis. Half of the components were used to train the neural network, and the other half were used to test it, so that a generalization could be arrived at. The neural network was trained fast: 95% of the components were correctly classified within 100 iterations. Upon completion of the training, 97% were identical to those made by the human experts.

Figure 6 shows the superposed 61-channel MCG signals that were obtained with a pulse-type artifact (a), and the signal that was restored using the proposed method (b). The positive and negative amplitudes of the MCG signals are due to the different field directions, i.e., the positive polarities are the fields directed outward from the body, and the negative polarities are the fields directed inward into the body. As can be seen in Fig. 6(b), the pulse-type noise was completely removed when the proposed method was applied. Unlike the conventional artifact removal methods which were mainly based on the entire waveform of the signal [8], the proposed technique is a component-by-component technique, which is more effective since it adapts to the various characteristics of the artifact. Instead of rejecting an entire distorted signal, the proposed algorithm restores the signal by rejecting distorted components only, which is important when signal averaging is limited, as in single-event experiments. Figure 7 shows an MCG topography (isofield contour map)

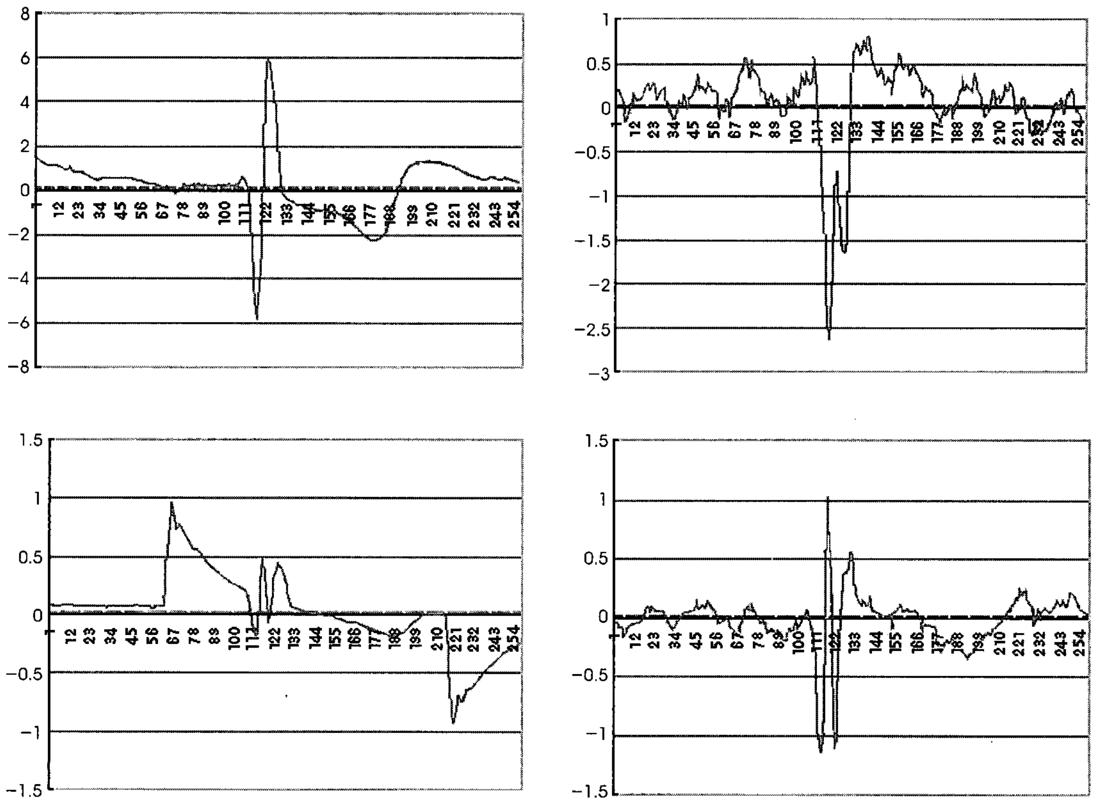

Fig. 5. Dominant components of the measured MCG signal, whose PCS > 0.1. The one on the lower left is an artifact.

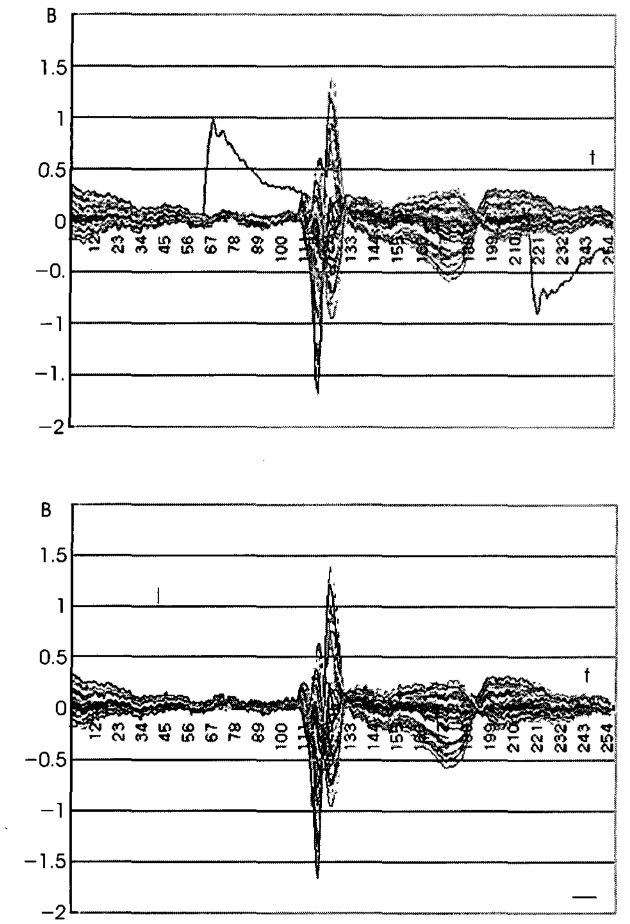

Fig. 6. Measured MCG signal with artifacts (a), and the restored signal by using the proposed method (b). Horizontal axis denotes sampling time with a sampling interval of 4ms, and vertical axis represents measured biomagnetic field with an arbitrary unit.

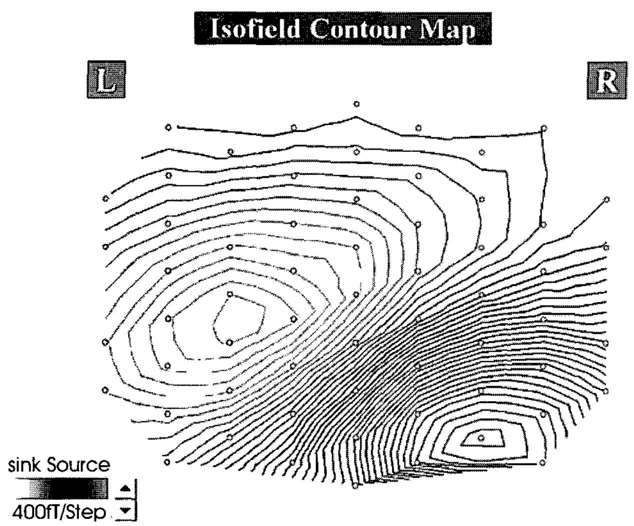

Fig. 7. MCG topography measured at R-peak for an isofield contour map from the measured 61-channel MCG data after the removal of the artifact.

obtained at R-peak from the 61-channel MCG signal after the artifact was removed using the proposed algorithm. The locations of the SQUID sensors are indicated by the small white circles. The field directions are represented by different grey scales (the inner most closed loops at the upper left and lower right corners are the locations showing the highest magnetic field in opposite directions). As seen in Fig. 7, an artifact-free topography can be obtained with the use of the proposed algorithm.

Ⅳ. CONCLUSION

A two-dimensional topography from 61-channel magnetocardiograms (MCG) is used to diagnose the human heart. To obtain the MCG topography, the artifact-free MCG signals had to be measured. A two-stage algorithm based on the principal component analysis (PCA) and an artificial neural network(ANN) is proposed to eliminate a pulse-type artifact when measuring the MCG signal. The PCA module decomposes the obtained signal into its principal components. The ANN module then classifies the components into signal and artifact classes automatically. Considering the characteristics of artifacts, only those components with PCS larger than 0.1 are considered for the classification. Seven parameters calculated from each component (maximum value, minimum value, peak-to-peak value, variance, mean, skewness, and kurtosis) are used as inputs to the ANN. In the experiments that were conducted with five volunteer subjects, 97% of the decisions that were made by the ANN were identical to those made by the human experts. Unlike the artifact removal methods previous used, which are based mainly on the entire waveform of the signal, the proposed technique is based on the components, which may make it more effective for the classification of complex artifacts with various characteristics. Instead of rejecting an entire distorted signal, the proposed algorithm restores the signal by removing only the artifact components, which is desirable when signal averaging is limited, as in single-event experiments. Using the proposed technique, the MCG topography was successfully obtained without artifact.

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