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Removal method of correlation artifact based on reference magnetic signal

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Summary:

An OPMs-based hardware system has been constructed for the synchronous recording of magnetoencephalography (MEG) signals and reference magnetic signals of physiological artifacts such as eye blinks and cardiac magnetic fields. The randomized dependence coefficient (RDC) is used to evaluate the correlation between independent components and reference signals. Removing physiological artifacts according to the threshold of correlation can significantly improve the signal-to-noise ratio of MEG signals. In the calculation of RDC, the input features are standardized by Copula transform, and then high-dimensional features are constructed by random projection and activation function. Finally, the correlation is obtained by regularized canonical correlation analysis (RCCA).

Keywords: Optically pumped magnetometer, Magnetoencephalography, Physiological artifacts, Random correlation coefficient, Copula transform, Sensors, Independent component analysis.

Title

Removal method of correlation artifact based on reference magnetic signal.

Headlines

The paper outlines the existing physiological artifact removal methods, the OPM-MEG hardware system, data collection and preprocessing, correlation computation, and artifact removal evaluation metrics, highlighting the significance of reference-magnetic-signal-based correlation methods in advancing the field of automatic artifact removal.

Background and Motivation

The high spatiotemporal resolution of OPM makes it a valuable tool for brain functional imaging, as it can accurately capture neural activity in the brain. However, common physiological artifacts, such as eye blinks and cardiac signals, overlap with conventional neural source signals in the alpha, theta, and delta frequency bands (1 Hz–20 Hz), leading to signal contamination. This poses challenges for observing neural activity and studying brain-related disorders. Traditional approaches rely on expert visual inspection or EEG-based references, which are time-consuming or imprecise. Therefore, there is a need to develop a cost-effective, automated system for artifact recognition and removal based on reference magnetic signals.

Description of reference magnetic signal artifact recognition system

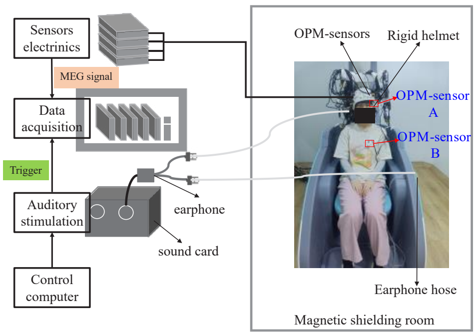

Fig. 1. Synchronous acquisition system of MEG and reference signal

The current approach primarily focuses on removing physiological artifacts using reference electrical signals [1], whereas this study enables artifact recognition and removal based on reference magnetic signals. A 34-channel OPMs hardware system was constructed for synchronous signal acquisition, in which two OPM sensors were placed near the eyes and chest to capture reference magnetic signals for eye-blink and cardiac artifacts, while the remaining 32 OPMs formed the OPM-MEG system to record neural activity in the brain. The sensor data from the OPM-MEG system were then decomposed using independent component analysis (ICA) to extract independent components. The randomized dependence coefficient (RDC) method [2] was

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used to compute the correlation between each independent component and the reference signals. Artifacts were identified and removed based on correlation ranking and a defined threshold. Additionally, a beep-based auditory paradigm was used during data collection to stimulate the participants' brains.

Correlation calculation

The correlation between reference magnetic signals and artifact components was calculated using the randomized dependence coefficient (RDC) method, where the inputs are independent components of MEG and reference magnetic signals of physiological artifacts. The correlation score was obtained by optimizing Equation (4) using the regularized canonical correlation analysis (RCCA) method [3].

$$\mathrm{RDC}(X,Y)=\max_{\mathbf{a},\mathbf{b}}\frac{\mathrm{cov}(\mathbf{a}^{\mathrm{T}}\phi(X),\mathbf{b}^{\mathrm{T}}\phi(Y))}{\sqrt{\mathrm{var}(\mathbf{a}^{\mathrm{T}}\phi(X))\,\mathrm{var}(\mathbf{b}^{\mathrm{T}}\phi(Y))}}$$

Finally, components with the highest correlation ranking and a threshold greater than 0.3 were recognized as artifacts. Based on the recognized artifact component indices, the corresponding artifacts in the OPM-MEG signals were removed using the ICA component removal method.

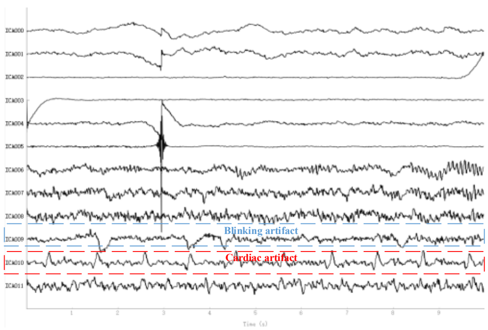

Fig. 2. Independent component analysis decomposition

Result

The correlation analysis results demonstrate that the Randomized Dependence Coefficient (RDC) can effectively evaluate the correlation between independent components and reference signals. After artifact removal based on correlation computation, the signal-to-noise ratio (SNR) of the OPM-MEG signals was calculated before and after artifact removal using the SNR evaluation method described in reference [4]. The results show that the proposed artifact identification method based on reference magnetic signal correlation significantly improves the quality of OPM-MEG signals. The RDC method effectively captures the nonlinear correlation between reference magnetic signals and artifact components, offering valuable insights into its potential applications in brain magnetic signal processing.

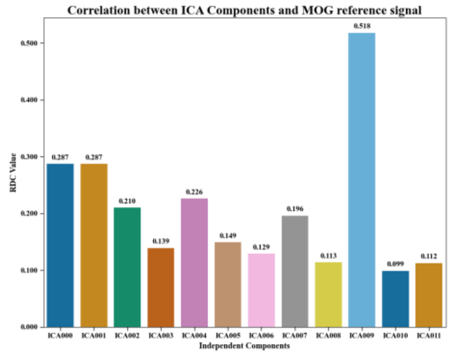

Fig. 3. Correlation result of blink artifacts

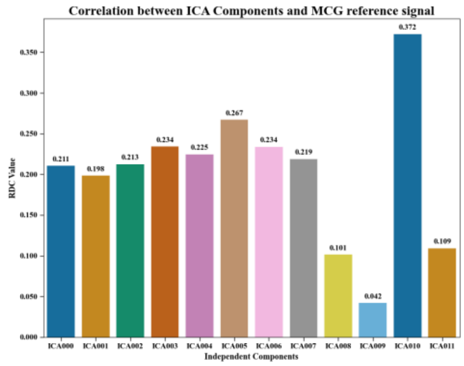

Fig. 4. Correlation result of cardiac artifacts

Tab. 1: Comparison of signal-to-noise ration

Participants	Before artifact removal	After artifacts removal
1	-0.72	8.24
2	3.18	11.31
3	1.86	9.17
4	1.94	9.15

References

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