Automatic extracting event-related potentials within several trials using Infomax ICA algorithm

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This study presents a new method for automatic extracting event-related potentials (ERP) within several trials based on independent component analysis (ICA). After mixed data is decomposed by Infomax ICA, independent component (IC) of ERP is automatically selected according to the standard deviation of fixed temporal pattern of IC, and applied in ERP reconstruction. Visual evoked potential extraction, used to confirm effectiveness of algorithm, can be obtained automatically after 6 trials on experimental data, and result of its Pearson correlation coefficient (PCC) within the average of 205 trials (standard signal) is 0.9106. However, PCC of average result of 6 trials within standard signal is only 0.3066, demonstrating practical applicability of proposed method. This algorithm enhances objectivity of ERP extraction within several trials.

Keywords: Electroencephalograph (EEG), Event-related potential (ERP), Independent component analysis (ICA)

Introduction

Event-related potentials (ERP) are unique evoked potentials (EP) obtained under the positive participation of subjects, and used in psychology, physiology, medical science, neuroscience, artificial intelligence, etc. ERP is very weak (waveforms, 3-21 µV) and can be recognized in actual electroencephalograph (EEG) recordings. From 1970s to 1980s, primary signal treatment employed was the combination of Wiener & Kalman filtering1,2 with AR model of spontaneous EEG. Adaptive-filtering3 was applied in EP extraction later in mid-80s. Neural networks (NN)4 were then widely used in various fields of EEG analysis. Furthermore, principal component analysis (PCA) and singular value decomposition5 presented considerable advantages for feature extraction.

An ERP extraction technique based on independent component analysis (ICA) is extremely applicable to EEG analysis and treatment because each signal is produced by independent sources. In ERP, two cases of ICA technique employed are: i) ICA decomposition of multi-channel EEG data in single trials; and ii) ICA decomposition of single-channel EEG data in multi-trials. Information contained in EEG signals within single trial and multi-channels is highly complicated. Aside from artifacts (eye blinks, eye movement, musculation, skin potential, etc.), ERP shows different processes in each functional area of brain, which makes effective separation difficult of ERP signals via ICA algorithm. Gao et al6 used spatial characteristics of P300 components acquired from ICA decomposition, and extracted P300 from multi-channel EEG data. Wessel et al7 applied ICA to decompose multi-channel EEG data, and then selected ERP component by comparing between spatial-temporal pattern information of each independent component (IC) and information regarding the corresponding ERP geomorphologic map template. Ling et al8 compared performance of 4 ICA decomposition algorithms (AMUSE, SOBI, Infomax, & JADE) in ERP extraction within single trials.

In the same experiment, a stable ERP regarded as independent of spontaneous EEG and artifacts, is shown in single-channel EEG data in multi-trials. Debener et al9 applied Infomax ICA in analyzing EEG data (of each channel), generated by auditory novelty oddball paradigm and discovered distribution characteristics of novel P3 and P3b in EEG/BEAM. Iyer et al10 analyzed simulated EP data and actual auditory N100 EEG recordings, and found that ICA technique, compared with averaging technique and wavelet transform, provides a...
better estimation of real EP incubation and that its extracted auditory N100 signals are smoother and more accurate. Hung et al.\textsuperscript{11} proposed use of ICA technique in extracting SSEP from EEG data to artificially construct a time-domain SSEP template or time-frequency SSEP template. Thus ICA technique demonstrates better decomposition results for single-channel EEG data in multi-trials.

This study presents an ICA-based method for automatic ERP extraction within several trials. After the mixed data are decomposed by Infomax ICA, each IC is endowed a corresponding fixed time pattern (FTP) that reflects changes in IC in every mixed data used in decomposition. Under these changes, required IC for ERP is selected for effective separation of ERP from EEG data.

**Experimental Section**

**Automatic Extraction Technique of ERP within Several Trials**

**Signaling equilibrium (SE)**

ERP wave amplitude (2-10 µV) evoked by a stimulus is smaller than that of spontaneous EEG, causing former to be overpowered. ERP is a weak signal while EEG is a loud type of noise, generating a substantial energy difference that influences accuracy of ERP extraction by ICA technique. Noise levels of superposition averaging or signaling equilibrium (SE) of N trials\textsuperscript{12} is \( (1/\sqrt{N}) \times R \), where R represents noise level of a single trial, and N is number of trials. SE algorithm is the basis for ERP evaluation. Therefore, averaging technique can be applied within several trials to balance signals collected from EEG data. In n trials, data on m trials are chosen for SE to obtain \( C^m_n \) \((m < n)\) mixed data, which can be directly incorporated into ICA decomposition after SE is reached.

**ICA Decomposition**

Matrix is differentially organized by mixed data used for decomposition. In accordance with such organizations, ICA technique is divided into temporal ICA (TICA) and spatial ICA (SICA)\textsuperscript{13,14}. Given the specificity of EEG data decomposed by ICA, SICA has advantages over TICA and hence, for this study, adopted SICA technique, where each row of mixed matrix X for ICA decomposition consists of EEG data of every trial. Infomax ICA algorithm\textsuperscript{15} is employed to decompose X as \( S = WX \) or \( X = W^{-1}S \). Each row in matrix S represents ICs, which are independent of one another, while each row in inverse weight matrix \( W^{-1} \) is FTP of corresponding IC. FTP of IC component reflects changes in each mixed data considered in the decomposition; these changes are used to select required IC.

**Selecting ERP IC**

Fig. 1 shows IC acquired after Infomax ICA decomposition of EEG data with primary treatment in OZ channel, as well as standard deviation of its
corresponding FTP. Suppose that 2 ICs (IC1 & IC2) are acquired after ICA decomposition. For IC1, FTP varies slightly, and standard deviation of IC1 (0.3381) is less than that of IC2, implying that signal represented by IC1 is static. On the basis of similar characteristics of ERP in each trial data, IC1 can be selected as ERP IC, and signals represented by this component can be viewed as ERP. However, For IC2, FTP varies significantly, and standard deviation of IC2 is up to 1.8041, implying that signal from IC2 is variable. Consequently, signal determined by IC2 is viewed as spontaneous EEG signal. Therefore, effectively extracting ICs that correspond to ERP is possible, thereby achieving effective separation of ERP from mixed data. After mixed data are decomposed, IC of ERP is selected by ICA using standard deviation equation as

$$\sigma_i = \sqrt{\frac{1}{n} \sum_{j=1}^{n} (x_{ij} - \bar{x}_i)^2} \quad \ldots(1)$$

where $\sigma_i$, $x_{ij}$, and $\bar{x}_i$ are standard deviations, jth value, and average value of FTP of IC i, respectively; n is dimension of each FTP, or number of trials considered in ICA decomposition.

**Reconstruction**

After ERP ICs is selected, spontaneous EEG IC was set to 0. ERP can be obtained as $X_2 = W^{-1}S_2$, where $S_2$ is matrix of manipulated component, $X_2$ is the result of ERP extracted by proposed algorithm.

**Description of Algorithm**

For extracting ERP from EEG data (Fig. 2), steps involved are as follows: Step 1—Experimental data are treated primarily using built-in software of Neuroscan, which covers functions such as removing electrooculogram (EOG), myoelectricity, power line interference, etc. Then, proposed technique is applied to balance energy of signals in EEG data and obtain mixed data for ICA decomposition; Step 2—Infomax ICA is used to decompose mixed data and acquire ICs; Step 3—IC component that represents ERP is selected according to standard deviation $\sigma$ of each IC FTP; and Step 4—ERP is reconstructed using selected IC components. To demonstrate effectiveness of algorithm, visual evoked potential (VEP) extraction was used.

**ERP Experiment Recording**

**Stimuli and Tasks**

Stimulus source used was an Othello board that changed over a computer screen by turns. A total of 205 stimuli were used and each was displayed for 50 ms at an interval of 500 ms. Sampling frequency was 1000Hz. A healthy male university student, recruited for this study, was asked to sit 70 cm away from display screen and move his eyes across the screen center in a horizontal direction. He was then instructed to watch Othello board as it moved along the screen center during experiment.

**EEG Recording and Primary Data Treatment**

Neuroscan 64 was EEG recording system used, and Ag/AgCl electrodes were placed over the scalp according to international 10/20 system of EEG electrode positions.
Meanwhile, 64-channel EEG data, as well as horizontal and vertical eye movements, were recorded. A bilateral mastoid connection was taken as the reference electrode location. Skin–electrode impedance was <5 kΩ. Built-in Neuroscan software was used for primary treatment of experimental data; thus EOG, myoelectricity, power line interference, etc. were eliminated.

Results and Discussion

Experimental Results
SE results of 205 EEG data trials were considered as standard ERP (overall average result). Pearson correlation coefficient (PCC) \( \rho \) was applied to measure similarity between ERP extracted using proposed algorithm and standard ERP. Larger the \( \rho \), greater the similarity between two ERPs. Pearson product-moment correlation coefficient, used to statistically measure interrelation (linear correlation) between variables \( X \) and \( Y \), whose value ranges within \([-1, +1]\), is extensively used in measuring strength of linear correlation between two variables as

\[
\rho_{XY} = \frac{\text{cov}(X,Y)}{\sigma_X \sigma_Y} = \frac{E(X - \mu_X)(Y - \mu_Y)}{\sigma_X \sigma_Y} \quad \ldots(2)
\]

When overall covariance and standard deviation are replaced with covariance and standard deviation of computational samples, PCC of the sample is

\[
\rho = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2} \sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \quad \ldots(3)
\]

Fig. 3 shows results of automatic extraction of VEP. Under VEP extraction using proposed algorithm (Fig. 3a), 6 original EEG trials were considered and 2 ICs were acquired by ICA decomposition. Average result of 205 trials (Fig. 3c) is regarded as standard VEP. From the perspective of wave pattern, result extracted using proposed algorithm is better and more similar to standard VEP than is the average result for the same trials (Fig. 3b). Furthermore, PCC of the results in Fig. 3a & c is 0.9106, whereas that of the results of Fig. 3b & c is only 0.3066, demonstrating that proposed algorithm can achieve satisfactory results after 6 trials. In addition, wave amplitude of wave pattern extracted by this algorithm is greater than that of the overall average result because the subject was easily fatigued after too many averaging trials and excessively lengthy experiments. These conditions inevitably cause differences in VEP among trials. The more trials conducted for SE, the smaller the wave amplitude of resultant signals.

Effect of Number of Signaling Equilibrium Trials on Results
On the basis of characteristics of random signals for SE, spontaneous EEG will be considerably smaller than VEP in the mixed data if too many trials are conducted in achieving SE. Otherwise, spontaneous EEG will be significantly larger than VEP. Both conditions are disadvantageous to ICA decomposition. After measurements from 205 averaging trials, amplitude of collected EEG data is 11-15µV, whereas that of VEP is 4-6µV, indicating that 2-3 times more spontaneous EEG signals than VEP in collected data. Therefore, only 4-9 trials are required to achieve SE. Numerous experimental results confirm that using original EEG signals from 5 trials yields the best result for SE.
Effect of Number of Mixed Signals for ICA Decomposition on Result

Different numbers of mixed data for ICA decomposition results in varied VEP extraction effects. Theoretically, infinite mixed data generate the best extraction effect in ICA decomposition. However, calculation efforts required for ICA increase and decomposition slow down with increasing number of mixed data for decomposition. In accordance with the number of mixed data decomposed by ICA, variation trend is shown of ICA result and standard signal, in which the number of trials for SE and the number of ICs are considered (Fig. 4). tends to rise with increasing number of mixed data for decomposition. Experiments confirmed that 4 mixed data yield good effect in ICA decomposition.

Effect of Number of ICs Acquired by ICA Decomposition on Result

EEG recordings must contain two components (spontaneous EEG & VEP). VEPs extracted upon separation of components generate the best effect. In accordance with the number of ICs acquired by ICA decomposition, variations are shown in ICA result and standard signal, in which the number of trials for SE and the number of mixed data are considered (Fig. 5). tends to decrease with increasing IC quantity, indicating degeneration of VEP extraction effect. Spontaneous EEG and VEP fundamentally balance each other and show similar strengths in mixed data after SE is achieved. Therefore, mixed data comprise two information source signals that are effectively separated when 2 ICs exist. When more than 2 ICs are present, each IC may contain both a spontaneous EEG component and a VEP component, making complete separation of these components an impossible task.

Conclusions

An Infomax ICA-based algorithm that automatically extracts ERP within several trials is proposed. Its effectiveness was verified by automatic VEP extraction. In ERP experiment, collected EEG data comprise two components (randomly changing spontaneous EEG and stable ERP). After ICA decomposition, characteristics of IC FTP were considered in automatic extracting ICs that correspond to ERP. The ERP were then reconstructed to obtain required ERP. Satisfactory VEPs were automatically extracted after 6 trials on experimental data. PCC of extracted VEP within standard signal reaches 0.9106. However, PCC of average result of 6 trials and standard signal is only 0.3066, demonstrating practical applicability of algorithm and its capability to enhance objectivity of ERP extraction within several trials. When extended to automatic ERP extraction in cognitive neuroscience research and clinical diagnosis, this algorithm can enhance objectivity of extraction and decrease the effect of an excessive number of trials on the extraction result.

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