Improving Accuracy of Event-Related Potentials Classification by Channel Selection Using Independent Component Analysis and Least Square Methods

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ABSTRACT

This paper proposes a method for achieving a high performance of N200 and P300 classification by applying independent component analysis to select the channels, which deliver brain signals with large N200 and P300 potentials and small artifacts. In this study, the authors find out the relationship between the highest accuracy and the weights of the independent components and use this relationship to predict the optimal channels of each individual subject. They compare five channel selection methods: the ICA-based method and the curve-fitting-based method proposed in this paper, the amplitude-based method, the experiential optimal 8 channel combination and all 30 channel combination methods. The comparative studies show that the ICA-based method achieves an average accuracy of 99.3% across four subjects, which is superior to the other four methods.

KEYWORDS

Artifacts, Channel Selection, Classification Accuracy, ICA, Individual Difference

1. INTRODUCTION

A mind-controlled system constructs a bridge between human brain and external devices for communication and control (Wolpaw, 2000; Lebedev, 2006; Ortiz-Rosario, 2013). This technology extracts some specific features of user’s brain activity that related to their intention and afterwards transfers those features to control commands (Wang et al., 2013). Event-related potential (ERP) (Wei and Luo, 2010) includes two kinds of potentials that have been used for a mind-controlled humanoid robot: N200 potential is a negative deflection that occurs at post-stimulus 180–325ms (Li et al., 2014a) and P300 potential is a large positive deflection that occurs at post-stimulus 200–800ms (Li et al., 2014b). N200 and P300 have been applied into many areas, such as the control of a robotic arm (Palankar, 2008), an internet browser (Mugler, 2008), a humanoid robot (Li et al., 2013a), and a wheelchair (Puanhvuan and Wongsawat, 2012).

Achieving high classification accuracy is one of the key issues in N200-based and P300-based control systems. The high classification accuracy is closely related to the channel combination for...
effective feature extraction (Shahriari and Erfanian, 2011). Therefore, it is important to determine
the channels with obvious ERP features for classification. Several research groups have investigated
the channels where N200 and P300 potentials occur frequently, e.g., the channels often selected for
exploring P300 distribution are Fz, Cz, Pz, Oz, P3, P4, P7 and P8 (Hoffmann et al., 2008) because
the P300 potential mainly appears from these channels; the channels selected for examining N200
distribution are usually P3 and/or P7 because the amplitudes of the N200 potential in these channels
are large (Hong, 2009). However, there exist individual differences in inducing brain signals, e.g.,
latency, amplitude and scalp distribution. To choose the channels for ERP feature extraction correctly
by considering individuals would be able to significantly improve the classification accuracy. The
average classification accuracy across all the subjects may be low if every subject adopts the same
channel combination for classification because they may produce their highest amplitudes in different
channels. Decreasing the impact of individual differences on processing brain signals is a wise way to
improve the classification accuracy. Some research groups have taken the individual differences into
consideration when extracting brain signal features. The work (Hong, 2009) selected the channels with
the largest N200 amplitude for classification. The work (Zhang, 2010) proposed an algorithm based
on Discrete Particle Swarm Optimization (DPSO) to select the optimal channel combination of P300.

The signal to noise ratio (SNR) of P300 is quite low (Luck, 2005; Espinosa, 2013) because the
amplitude of P300 potential is usually low to about 10uV and the signal noise is relatively high.
Artifacts are one kind of noise that can interfere with neurological phenomena, including muscle
artifacts, ocular artifacts (Mozaffar and Petr, 2002) and so on. They are interferences of potentials caused
by body movements. The artifacts are usually very large and tightly mixed with the potential produced
by brain activities, so the artifacts distort the N200 and P300 potentials and decrease the classification
accuracy. We hypothesis that the signals from the selected channels appearing large N200 and P300
potentials and small or no artifacts would be able to greatly improve the classification accuracy due
to their clear N200 and P300 potentials’ features.

In this study, we used Independent Component Analysis (ICA) algorithm to determine the
optimal channel combination, i.e., we used several independent components to compose the detected
multiple brain signals and immediately to process them for the channel selection. The superposition
of independent components is regarded as a linear instantaneous mixture which makes ICA suitable
in brain signal processing (Jung et al., 2001). ICA is able to provide the scalp distribution of each
independent source signal to show a strength level which is used to compare the performance of an
independent source signal from each channel. Because a channel’s classification accuracy is roughly
consistent with its strength levels of N200, P300 and artifacts’ source signals, it is possible to achieve
the high classification accuracy according to their distributions. We applied ICA to obtain the N200,
P300 and artifacts’ source signal distributions for each individual subject and further to determine
the channels with significant N200 and P300 and small artifacts. The ICA-based method achieved
the average accuracy of 99.3% across four subjects.

The paper is organized as follows: Section 2 presents the experiment paradigm and the procedure.
Section 3 describes the method for ERP feature extraction and reviews some existing methods for
channel selection, and proposes the method of selecting channels based on ICA. Section 4 compares
the classification accuracy of the ICA-based method with the existing methods and further derives
a curve-fitting method from the ICA-based method. Section 5 discusses the advantages of the ICA-
based method and draws some conclusions.

2. EXPERIMENT

The experiment design was based on the classical ‘oddball’ paradigm. Figure 1 shows the visual
stimulus interface, which displays six robot images as visual stimuli constructing a 2*3 matrix with
contexts on screen. The visual stimuli are located in each element position of the matrix to represent
six robot walking behaviors accordingly: walking forward, walking backward, shifting right, shifting
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