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AN ENHANCED EEG-BASED P300 SPELLER USING THE KERNEL ICA

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ABSTRACT
A brain computer interface (BCI) system is to control a computer using bio-signals measured in brain. A P300 speller is one of electroencephalogram (EEG)-based BCI systems. The speller is to display target characters which are what a subject wants to enter. P300 wave, which is the most positive peak 260-410ms in an EEG signal after stimulus onset, is used as a control signal of the speller. The P300 wave has been separated using a blind source separation method in the existing P300 spellers. However, the conventional methods could not separate a source signal with Gaussian distribution from a set of mixed signals. To overcome this problem, we apply a kernel independent component analysis algorithm to P300 speller. The algorithm can successfully extract P300 component from a mixed signal even when it has source signals with nearly Gaussian distribution. In conclusion, the proposed P300 speller has 100% accuracy with less training signals and finds a target character more quickly than the conventional method.

KEY WORDS
Brain-computer interfaces; EEG; P300; ICA.

1. Introduction

Electroencephalography (EEG) is the recording of electrical activity induced by stimulation or thoughts along the scalp. The electrical activity induced by stimulation is called an ERP (event-related potential) which consists of a series of positive and negative voltage curves. For example, N100 component is a negative peak occurred about 100 milliseconds and P300 component is a positive peak appeared about 300 milliseconds after a stimulus is presented. Especially P300 component reflects a higher response by stimulation than other components. Due to this reason, it has been used for various EEG-based brain-computer interfaces (BCIs). A P300 speller is one of such systems [1].

A P300 speller displays a target character by detecting a P300 wave. To detect the wave, a lot of EEG signals are averaged over the whole signals for increasing the signal-to-noise ratio. However, the measured EEG signals are mixed with other bio-signals such as EOG (electrooculography), EMG (eletromyography). Because these unexpected signals could not be approximated by a zero-mean Gaussian random process, it is hard to detect

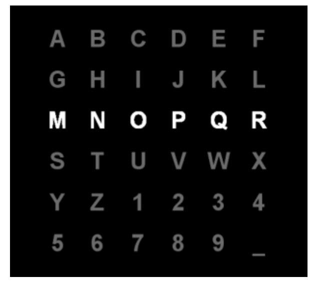


Figure 1. A 6×6 user display in P300 speller.

P300 signals only with the way of simply averaging lots of EEG ensembles. To solve this problem and efficiently acquire P300 signals, blind source separation (BSS) was introduced in a P300 speller [2].

It could be assumed that a measured EEG signal $\mathbf{x}$ is a set of mixed source signals and it is described in a matrix form:

$$\mathbf{x} = \mathbf{A}\mathbf{s} \ , \tag{1}$$

where $\mathbf{s}$ is a matrix of source signals and $\mathbf{A}$ is a mixing matrix. The inverse function of a mixing matrix is an un-mixing matrix which is able to separate independent source signals [3]. BSS is to estimate an un-mixing matrix from only measured EEG signal x for obtaining source signals s. The popular methods of BSS are InfomaxICA (infomax independent component analysis) [4], FastICA [5], JADE (joint approximate diagonalization of eigenmatrices) [6], etc. Xu et al. [2] reported that the P300 speller with the InfomaxICA method results in 100% accuracy. However, it needs EEG training signals for the corresponding 42 target characters to achieve the higher accuracy.

ICA algorithms are known to have difficulties when the source components are nearly Gaussian. However, the kernel ICA algorithm is more robust to near-Gaussianity than the other algorithms [7]. Therefore, we introduce the kernel ICA to improve the performance of a P300 speller. The rest of this paper is organized as follows: In Section 2, a P300 speller is briefly described. Then a kernel ICA is described and an improved P300 speller with a kernel ICA is proposed in Section 3. Through the experimental results, in Section 4, we compare the accuracy and the transfer time of the proposed P300 speller with those of the conventional P300 speller according to the number of training signals. The paper is finally concluded in Section 5.

2. P300 Speller

A P300 speller presents target characters by analyzing P300 wave from EEG signal which is obtained when it provides a visual stimulus for a subject using a display. Farwell and Donchin proposed this speller [1], in which a matrix of 6x6 cells is displayed to represent 36 characters as shown in Fig. 1. For a single target character, each of the 6 rows and 6 columns are intensified and the intensifications are presented in a random sequence. A subject focuses attention on one of the 36 cells of the matrix and then a P300 wave appears in the EEG signal in response to the intensification of a row or column containing the target character. In order to enhance the reliability of the speller, a set of 12 intensifications is repeated 15 times for each character.

P300 waves had been usually detected based on ensemble averaging of much EEG trials. Farwell and Donchin introduced a P300 detection method which is stepwise discriminant analysis (SWDA) [1], and Donchin added discrete wavelet transform (DWT) to the SWDA [8]. In general, the more the EEG trials are averaged, the better the accuracy and reliability will be. However, it expends longer time to detect P300 wave. In a BCI system, both accuracy and transfer time are major considerations. Therefore, a good algorithm for BCI should ensure the high accuracy and reduce the transfer time to enhance performance. In accordance with this reason, Infomax ICA is applied to a P300 speller [2]. However, this method still needs many training EEG signals and long transfer time for the corresponding 42 target characters. Therefore, we attempt to improve the performance of a P300 speller.

3. The P300 speller using a Kernel ICA

3.1 A Kernel ICA

A kernel ICA algorithm is maximizing independence of each source as minimizing correlation with kernel function [7]. There are the two contrast functions, kernel canonical correlation analysis and kernel generalized variance, to minimize the correlation. Kernel based learning algorithms use the following idea: via a non-linear mapping

$$\Phi : \Re^t \to F, \quad \mathbf{x} \to \Phi(\mathbf{x}) \ , \tag{2}$$

the data in the input space $\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_M \in \Re^t$ is mapped to a higher dimensional space F and changed to easy data for analyzing signals. Instead of considering the given learning problem in input space $\Re^t$, one can deal with

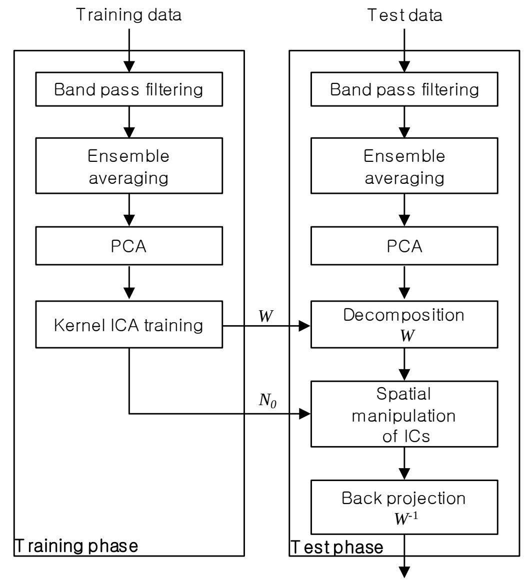


Figure 2. The diagram of the proposed P300 speller.

$\Phi(x_1), \Phi(x_2), \cdots, \Phi(x_M)$ in space F and then we find a linear discriminant function in space F. This linear discriminant function in space F is a non-linear discriminant function in input space $\Re^t$. The idea of the kernel trick is to project the input data into a high dimensional space through a non-linear mapping, and the non-linear relation in the input data can be analyzed in this space F. In implementation, the kernel trick does not need to compute implicit vector in F explicitly. It just needs to calculate the inner product of two vectors in with a kernel function $k(\cdot,\cdot)$:

$$\left\langle \Phi(\mathbf{x}_i), \Phi(\mathbf{x}_j) \right\rangle = k\left(\mathbf{x}_i, \mathbf{x}_j\right) \ , \tag{3}$$

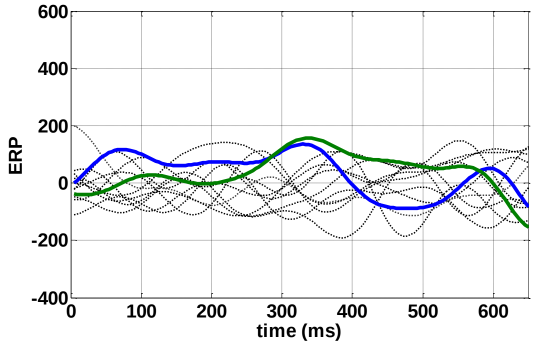
where $\langle \cdot,\cdot \rangle$ denotes an inner product. This is often referred to as the "kernel trick" [7]. There are several kernel functions, and eq. (4) is the Gaussian kernel in general use as following

$$k(\mathbf{x},\mathbf{y}) = \exp\left(-\frac{1}{\delta} \|\mathbf{y}-\mathbf{x}\|^2 \right). \tag{4}$$

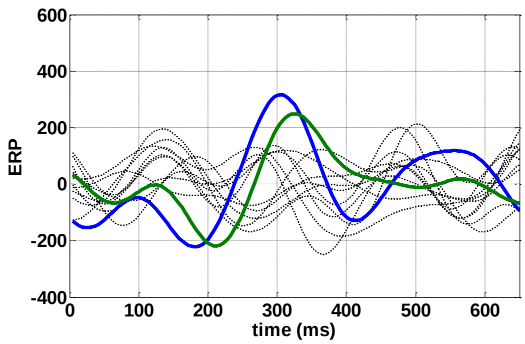
Finally, the un-mixing matrix could be yielded by minimizing a contrast function based on this kernel outputs.

The kernel ICA algorithm presented by Bach is a method for decomposing independent sources based on a kernel function. This algorithm is more robust to near-Gaussianity than the other algorithms [7].

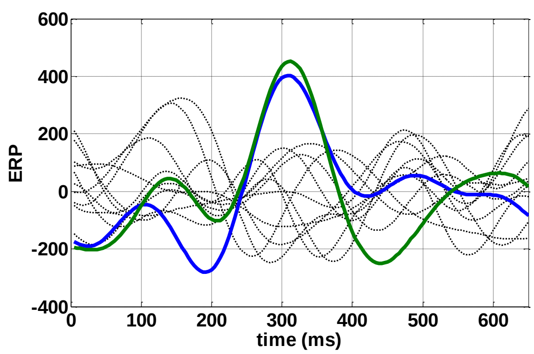
3.2 Algorithm for the P300 Speller



(a) before the spatial manipulation



(b) after the spatial manipulation using infomaxICA



(c) after the spatial manipulation using kernel ICA

Figure 3. A comparison of ERP of the target signals and the other signals.

Fig. 2 is the diagram of the proposed P300 speller. This algorithm consists of two phase, training and test phase. In training phase, the un-mixing matrix is decided by training signals. This matrix is used for decomposing a mixed signal into source components in test phase. More details are as follows.

3.2.1 Training Phase

The training phase is comprised of four stages. (i) Bandpass filtering: The raw training data is passed through a 0.5-8 Hz band-pass filter, because the principal energy of P300 wave is concentrated in the frequency band of 0.5-8 Hz. (ii) Ensemble averaging: A set of 12 intensifications is repeated 15 times for each character. The each data with the same row intensification or column intensification is averaged for each character. (iii) Principal component analysis (PCA): In conventional study, the number of meaningful source components is around 15–35 [9]. Since there are 64 channels of EEG in the original data, PCA was made to reduce the dimension of the data from 64 to 22. The eigenvector matrix $\mathbf{V}\,(64\times 64)$ was sorted according to descending order of eigenvalues. The PCA matrix $\mathbf{V}^*\,(22\times 64)$ is the first 22 rows of $\mathbf{V}$. (iv) Kernel ICA training: The input data of kernel ICA is reduced training data. After the un-mixing matrix $\mathbf{W}$ is fixed by the reduced training data, independent source components IC_n $(n=1,\cdots,22)$ are calculated by multiplying the reduced training data by the un-mixing matrix $\mathbf{W}$. There is the IC for P300 wave, and then the ordinal number N_0 of the IC is selected.

Table 1
A comparison of the P300 speller accuracy using the InfomaxICA and the kernel ICA according to the number of training data

The number of characters	InfomaxICA	Kernel ICA
19	64.5%	100%
39	93.5%	100%

Table 2
A comparison of the P300 speller transfer time using the InfomaxICA and the kernel ICA

	InfomaxICA	Kernel ICA
Average of the number of repeat counts	4.97	3.41

3.2.2 Test Phase

The pre-processing is the same with training phase from band-pass filtering to PCA. After PCA, the reduced test data is multiplied by the un-mixing matrix $\mathbf{W}$ obtained in training phase. Then the data is decomposed into independent source components ICs. After the decomposition, the spatial manipulation of ICs is performed, which wipe off the other ICs by setting them to 0 without changing the selected IC_{N_0}. Finally, the manipulated ICs are applied back projection $\mathbf{W}^{-1}$.

3.2.3 P300 Wave and Character Detection

We found a P300 wave from back projected test data. The window is 250-400 ms, because P300 wave exhibit a peak anywhere between 250-400ms. The character is determined by searching the row and column with the highest peak of a P300 wave at every character.

4. Experimental Results

The EEG data used in this paper is the dataset IIb of BCI Competition II [10]. This dataset represent a complete record of P300 evoked potentials recorded with BCI20001 using a paradigm described by Donchin et al., 2000. In these experiments, a user focused on one out of 36 different characters. The number of EEG channel was 64, and the sampling frequency was 240 Hz. The signal was collected from one subject in three sessions. Each session consisted of the measured signals for 5-10 words. Session 10 and 11 were used for training a P300 speller, and Session 12 was used for testing that.

In this paper, kernel canonical correlation analysis algorithm is used for making a contrast function, and Gaussian kernel function was used for kernel trick in kernel ICA. Fig. 3 shows 12 ERP signals for 6 rows and 6 columns at one character, and Fig. 3(a) is before spatial manipulation, Fig. 3(b) is after that using InfomaxICA, and Fig. 3(c) is after that using kernel ICA. The solid lines plot the target signals for the row and the column of a target character, and the dot lines plot the other signals. It shows that even if the P300 wave did not appear on the averaged signals, we could find the target signals by using the InfomaxICA and the kernel ICA. And compared to the P300 wave of Fig. 3(b), the P300 wave of Fig. 3(c) has more differential over the other waves. It means that the reliability of the P300 speller using the kernel ICA is higher than that of the speller using InfomaxICA.

The proposed P300 speller was examined by comparing the performance of P300 spellers with the kernel ICA and the infomaxICA. The training signals were randomly chosen for the different number of training characters which are 19 and 39, respectively. Then, we derived the performance of the proposed P300 speller using 31 test data. Since this procedure was repeated 10 times, the total number of offline test was 310 times. The proposed P300 speller improved the performance in term of two things. First, the proposed P300 speller needed less training data than the conventional one. As shown in Table 1, the proposed P300 speller needed only 19 training characters to achieve 100% accuracy, while the conventional one needed 39 training characters to get 93.5% accuracy. Second, the proposed P300 speller had shorter transfer time than the conventional one with 100% accuracy. Table 2 represents average of the number of repeat counts for each character with 100% accuracy. It means that the P300 speller using the kernel ICA needs shorter transfer time about the time of a set of 12 intensifications than the one using InfomaxICA.

5. Conclusion

The P300 speller using the conventional InfomaxICA algorithm may have 100% accuracy. However, it needs a lot of training data and many repetitions in test phase. To overcome these problems, we proposed the P300 speller using the kernel ICA. Since the kernel ICA can decompose a mixed signal into independent source components even when source components are nearly Gaussian, the proposed P300 speller achieved the 100% accuracy with less training data and shorter transfer time.

Acknowledgement

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