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Noise Enhanced Array Signal Detection in P300 Speller Paradigm using ICA-Based Subspace Projections

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***Abstract*—This paper explores how noise can improve prediction accuracy of the Event-Related Potential (ERP) based on P300 signals. We propose an array of ICA-Based P300 processing systems with additive white Gaussian noise. The array system attains maximum accuracy when noise intensity is not zero and thus the system shows the stochastic resonance effect. The prediction accuracy increases as the number of stages of the array increases. Experimental results show that increasing the array size with the proper amount of noise can improve the accuracy of the original P300 signal detection using ICA-based subspace projection technique.**

I. Introduction

The well-known problem of brain-computer interface (BCI) based on P300 signals is the inaccuracy of detection and the requirement of a large number of stimulus repetitions [1-7]. The detection performance depends on the number of repetitions, the number of electrodes, and the signal varies over time and persons. The P300 signal is the event-related potential. This signal is a small change in the brain activity and corresponds to a positive deflection at latency about 300 ms [2, 3]. The response usually occurs 300 ms after stimulus when a subject pays attention to the desired character [2]. The purpose of a P300 speller system is to detect the presence of P300 in the EEG.

Researchers have continuously developed algorithms to improve P300 detection performance [1-7]. The key processes in P300 detection are feature extraction and classification. Kaper *et al.* propose support vector machines (SVM) for classification [5]. The algorithm finds the correct prediction using only five repetitions and requires only 10 electrodes on strong signal positions. Xu *et al*. introduce an algorithm based on independent component analysis (ICA) for P300 detection [6]. They show that the algorithm achieved an accuracy of 100% in P300 detection within five repetitions. Bostanov proposes the continuous wavelet transform (CWT) and Student's t-statistic [7]. The method is suitable for classification of single-trial ERPs. This algorithm achieves an accuracy of 100% in P300 detection within six repetitions.

Stochastic resonance (SR) is a phenomenon when noise at certain levels of intensities can enhance weak input signals [8-11]. The SR effect can also occur in array systems [12-15]. Coupling together more than one SR elements can improve output performance. Patel and Kosko propose that noise can improve statistical signal detection for the array-based nonlinear correlators in Neyman-Pearson (NP) and maximum-likelihood (ML) signal detection [13]. They show that the noise benefit rate improves in the small-quantizer noise limit as the number of array quantizers increases. Das *et al.* examine the effects of suprathreshold stochastic resonance in a parallel array of identical nonlinear threshold-based devices [14]. They show that the phenomenon can enhance the transmission of signals of any distribution and amplitude. Lei *et al.* present array-enhanced logical stochastic resonance [15]. They show that increasing the number of arrays can extend the range of optimal parameter domain in which the reliable logic output can be obtained.

We propose an array of P300 processing systems with additive white Gaussian noise. We use the ICA-based subspace projection techniques [6] as a building block in the array with additive white Gaussian noise. We test our systems on the BCI competition II dataset IIb (P300 speller paradigm) [16, 17]. Experimental results show that noise can improve the P300 detection performance. This implies that we have noise benefits or the "stochastic resonance" effect. The results also show that increasing the number of stages can enhance the prediction accuracy.

II. P300 Speller Paradigm Detection and Array Enhanced Stochastic Resonance

This section describes the idea of ICA-based subspace projection technique to analyze the P300 signals [6, 18-21]. Then we describe the concept of stochastic resonance with array processing.

A. ICA-based subspace projection

We preprocess the data signal x with a 0.5-8 Hz bandpass filter to obtain x'. Then we process x' using principle component analysis (PCA) algorithm to reduce the dimension of the EEG data from 64 channels to 22 channels. The reduced-dimension data $z = Vx'$ is the input data for independent component analysis [6].

Independent component analysis (ICA) attempts to recover the independent sources from multichannel observations [6]. Let $s = [s_1, s_2, \dots, s_n]$ be n independent unknown sources. We can only observe the signals $z = [z_1, z_2, \dots, z_m]$ as a linear combination of s:

$$z = As \tag{1}$$

where A is the unknown mixing matrix. The goal is to recover s or approximate it with u using a linear operation

$$u = Wz \tag{2}$$

where W is the desired demixing matrix. We apply ICA algorithm to the data z to obtain the demixing matrix W.

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There are several ICA techniques to separate the original source signals s from the observed signals such as FastICA, Infomax ICA and Extended Infomax ICA [19-21]. The FastICA algorithm is appropriate for extracting artifacts from EEG data [21]. We use the FastICA algorithm to find the demixing matrix W. We also apply the principal component analysis (PCA) to reduce the dimensions of the signals obtained from sensors.

Steps of FastICA [19]:

1) Initialize weight vector w_0 (random)
2) Let $w_{i+1}^{+} = E\left(zg\left(w_i^T z\right)\right) - E\left(g'\left(w_i^T z\right)\right)w_i$

   where $g(w_i^T z) = \tanh(w_i^T z)$ for $i = 0,1,2,\ldots$
3) Let $w_{i+1} = \dfrac{w_{i+1}^{+}}{\left\| w_{i+1}^{+} \right\|}$.
4) Go back to step 2 if not converged ($|w_{i+1} \cdot w_i| \not\approx 1$)

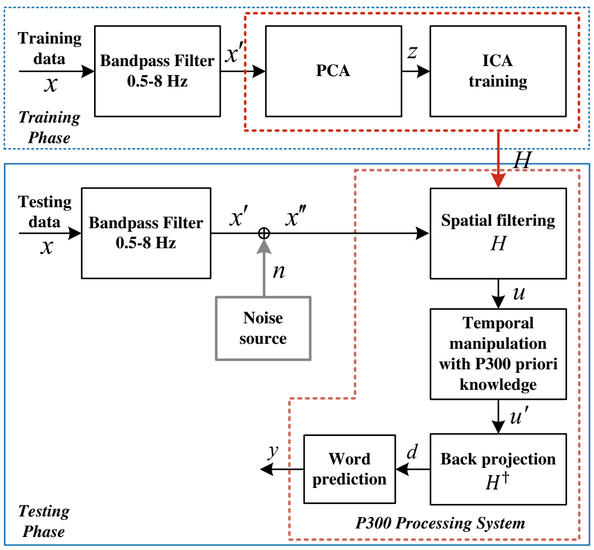

Figure 1. P300 processing system using ICA-based subspace projection.

Figure 1 shows the ICA-based P300 speller prediction system that consists of training and testing phases [6, 9-11, 22, 23]. The training phase finds the spatial filtering H from PCA and ICA of the data. The testing phase uses H to obtain the enhanced signal and processes that signal for character prediction.

Training phase: We preprocess the EEG data x with a 0.5-8 Hz bandpass filter to obtain x'. Then we average the data x' from the same stimulus of all repetitions at the time window of 0-650 ms after stimulus. Then the PCA algorithm reduces the dimension of the EEG data from 64 channels to 22 channels: $z = Vx'$ where z is the reduced-dimension data. Then we apply FastICA to the projected data z to obtain W. The spatial filtering H is the product of the matrix V from PCA and the matrix W from FastICA [6]: $H = WV$.

Testing phase: We classify testing data using the spatial filtering H from training phase and the temporal manipulation of these independent components with P300 priori knowledge [6]. The temporal manipulation considers the independent components in time domain during the latency range of P300. We keep the independent components u' that have peak amplitudes between 250-367 ms after stimulus. Then we find the back projection of u':

$$d = H^{\dagger} u' \tag{3}$$

where d is the enhanced signals, $H^{\dagger}$ is pseudo-inverse of the spatial filtering H, and u' is the result of u after temporal manipulation of independent components. Thus our algorithm is a part of the algorithm that proposes in [6].

The word prediction block considers which character is most likely from the peak and area of the corresponding row and column of the enhanced signal d in the 275-370 ms window. It also considers peak and area of the average of signals from the corresponding row and column of a character in the 275-370 ms window. Thus each character has four features. Note that there are 6 rows and 6 columns in the P300 speller paradigm (36 characters in the alphabet set). Then the block gives as output a character that has highest count of the highest peaks and areas [6].

B. Stochastic Resonance in Array System

We consider the collective noise benefits that occur in a system of parallel elements or blocks. Noise benefits or stochastic resonance in parallel array can improve the accuracy of signal detection [12-15].

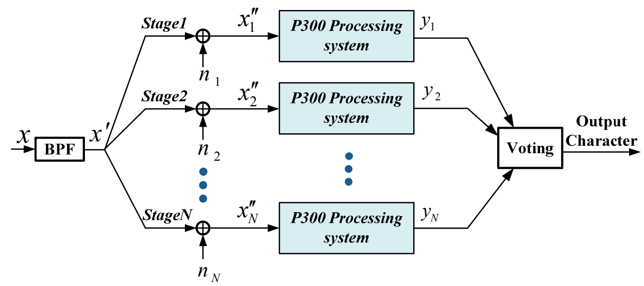

Figure 2. Noise-added array processing. The P300 Processing system can use ICA-based subspace projection technique as shown in Figure 1 or other techniques. The system uses independent white Gaussian noise n_i with equal variance σ_n

Figure 2 shows the schematic diagram of our SR-array processing. The system uses N stages of P300 processing systems. Each stage processes the same filtered signal x' of the raw EEG data x obtained from sensors. Then each system adds independent white Gaussian noise n_i to the signal x' to obtain the noise-added signal x_i'':

$$x_i'' = x' + n_i \tag{4}$$

where n_i is zero-mean noise with variance σ_n^2 at stage i. The output y_i is one of the 36 characters {A,…,Z,1,…,9,_}. Then the voting block picks as its output the character that obtains the highest counts from N stages. In case of ties we randomly pick the output character from the ties. Then we calculate the prediction accuracy P_A as a ratio of the number of correct prediction and the total number of test characters in the experiment:

$$P_A = \frac{D}{M} \times 100 \tag{5}$$

where D is the number of correct characters and M is the number of target characters.

The SR effect occurs when the performance of the system is maximized at nonzero noise intensity. The noise source can be artificial noise that design engineers would add to maximize the performance. An array of P300 systems with a suitable level of noise intensity can improve the prediction accuracy.

III. Experimental Results

A. EEG Data

We use the EEG dataset IIb from the BCI competition 2003 database [16, 17] to test our system. The dataset contains signals collected from one subject with 64 electrodes and sampled at 240 Hz. The set of test data consists of 73 characters. The P300 response of each character is collected from 12 random flashing rows/columns which were repeated 15 times (15 repetitions) in order to reinforce the P300 response. We test our systems using 1 to 15 repetitions of the signals.

B. Experiment Setup and Results

We use an original ICA-based P300 prediction system as a building block for an array system as shown in Figure 2. Then we add white Gaussian noise to the EEG signal. The noise in each block is independent of the others. The noise intensity varies from 1 μV to 130 μV. The number of stages N also varies: $N = 1$, 5, 15 and 20. We test the system based on 1 to 15 signal repetitions but show only a few cases.

Table I shows the prediction accuracy of the array systems based on various numbers of signal repetitions and array sizes. The results show the maximum prediction accuracy in each case with respective optimal noise intensity (μV). The prediction accuracy with noise is higher than without noise in all cases except when the system uses signal with 15 repetitions and the array has only one stage $N = 1$ (the original P300 speller). But the accuracy increases as the number of stages of the array increases.

Figure 3 shows that the prediction accuracy tends to increase as noise intensity increases from zero. The prediction accuracy attains a maximum at nonzero noise intensity and it decreases when the noise intensity is too large. Figure 4 shows that prediction accuracy increases from 23.29% to 95.89% as the number of signal repetitions grows from 1 to 15 for a system with single stage (N=1) and without noise (original P300 speller system).

TABLE I. Accuracy of P300 Speller Prediction

Number of Repetitions	Accuracy without noise (%)	Maximum accuracy (%) (Optimal noise intensity, σ_{opt} (μV)) Number of Stages N: 1	5	15	20
1	23.29	25.07 (22)	26.44 (80)	26.30 (94)	**26.71** (112)
3	45.21	48.63 (18)	50.68 (70)	52.33 (86)	**52.88** (66)
5	63.01	65.21 (22)	69.04 (66)	70.68 (88)	**72.47** (98)
7	75.34	78.22 (10)	77.81 (16)	79.45 (88)	**80.41** (96)
9	83.56	86.03 (16)	85.89 (16)	85.62 (54)	**86.44** (40)
11	89.04	91.37 (10)	92.74 (16)	92.74 (52)	**92.74** (32)
13	90.41	92.05 (12)	93.84 (30)	94.52 (62)	**95.34** (74)
15	**95.89**	95.89 (0)	95.34 (16)	96.58 (44)	**97.12** (56)

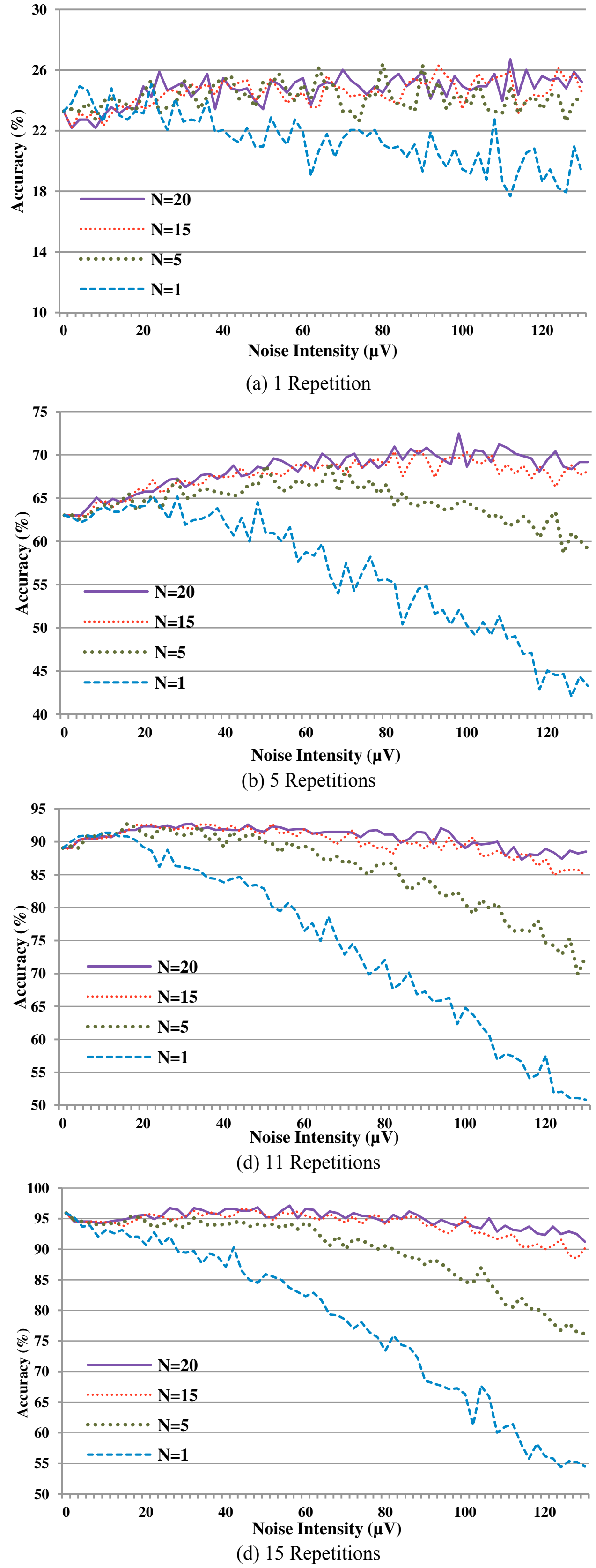

Figure 3. Noise improves prediction accuracy of P300 speller. The plots show prediction accuracy improvement for 1, 5, 11, and 15 signal repetitions with number of stages $N = 1$, 5, 15 and 20. The system attains maximum accuracy when noise intensity is nonzero in most cases. The prediction accuracy also increases as the number of stages N increases.

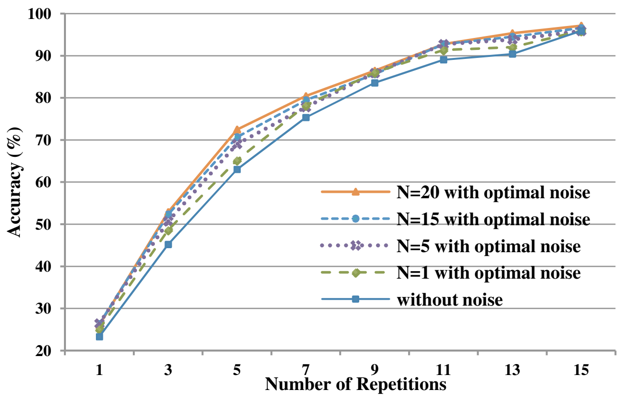

Figure 4. Summary of P300 prediction accuracies. Noise can improve the prediction accuracy in array systems. The results also show that accuracy tends to increase as the number of stages increases. The noise benefit is more pronounced when the system uses only a few stimulus repetitions.

The results also show that prediction accuracy tends to increase as the number of stages N in the array increases from N=1 to N=20. We obtain maximum prediction accuracy at 97.12% with optimal noise (σ_{opt} = 56 µV) for N=20 and 15 signal repetitions. Note that our regular P300 processing system does not achieve 100% prediction accuracy for this data set because we do not use the spatial manipulation of the independent components as in [6]. But this imperfection allows us to examine the effect of noised-added array systems.

The regular P300 speller system processes 15 repetitions of signals. The accuracy of this system (regular ICA-based P300 detection with N=1) decreases as we add more noise. But the results show that the prediction accuracy increases as we add more stages and use a suitable level of noise intensity as shown in Figure 3(d). Figure 4 shows a summary of noise benefits that prediction accuracy tends to increase as the number of stages increases. The noise benefits are more pronounced when the systems use only a few number of stimulus repetitions.

IV. CONCLUSION

This paper explores the use of array of ICA-Based P300 detection systems with additive white Gaussian noise. Experimental results show that we can improve P300 signal detection accuracy by adding independent noise into the brainwave signals obtained from sensors. The system shows the stochastic resonance effect when we consider the speller prediction accuracy. The prediction accuracy also tends to increase as array size increases. The optimal noise intensity also depends on the number of stages and the number of signal repetitions and remains an open research problem. The results also suggest that future research work on EEG signal classification should consider the role of noise and the use of array systems to improve the prediction accuracy.

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