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# MULTIPLE COMPONENTS DETECTION IN VISUAL ERPs SINGLE TRIAL

BY

**CARMEN GRIGORAŞ[1,2], CAMELIA LAZĂR[2] and VICTOR GRIGORAŞ[3,*]**

[1]"Gr. T. Popa" University of Medicine and Pharmacy of Iasi,
Faculty of Medical Bioengineering,
[2]Institute of Computer Science of the Romanian Academy - Iasi Branch,
[3]Technical University "Gheorghe Asachi" of Iaşi,
Department of Electronics,Telecommunications and Information Technology

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**Abstract.** The usual approach for components extraction from event-related potentials (ERPs) is based on averaging techniques over multiple trials, for each experimental condition and each subject, in order to reduce the noise in analysed signals. In this paper we present the results of some ERP components extraction from single trial data of the BCI Competition dataset II, speller paradigm. The P100, N100, P200, N200 and P300 components of the ERPs were extracted by means of independent component analysis (ICA), and rough sets theory method applied for independent components and EEG channels selections, which have significant contribution to the targeted ERP component detection. Constrained ICA with reference signals (ICA_R) algorithm was also used, and the ERP processing approaches performances were discussed.

**Key words:** BCI speller paradigm; ERP components extraction; ICA; ICA_R; rough set theory.

## 1. Introduction

A great variety of methods were developed in the recent years for event-related potential (ERP) extraction from a background EEG, and P300 waveform

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[*]Corresponding author: *e-mail*: grigoras@etti.tuiasi.ro

detection since the first BCI Competition was released, in 2000. As described by Polich (Polich, *et al*., 1995), the P300 waveform is an endogenous component of an ERP, corresponding to cognitive activity, elicited as a positive significant peak, at about 300ms after a rare, task-relevant, stimulus onset. Its applications are diverse. One of them is brain-computer interface (BCI), used for non-contact control of certain devices developed to be controlled by relevant detected components from online EEG recordings. Other applications refer to communication by means of neural prosthesis, or are related to diagnosis of certain brain diseases, such as Parkinson, Altzheimer, or schizophrenia diseases, to pursue their evolution, or to control their treatment. Mostly for those medical purposes, other ERP components than P300, such as P100, N100, P200, and N200, displayed interesting diagnosis properties. Their names refer to the fact that they have positive, or respectively negative peaks, and that they occur after about 100ms, respectively 200ms after a stimulus onset. Their peak amplitudes and latency after stimulus onset, as representative features, were extensively studied, by means of noise removal and enhancing through averaging over a various number of ERPs obtained through repetitive similar experiments, named trials, based on different paradigms (Polich *et al*., 1995, 2007; Delorme *et al*., 2007; Pritchard *et al*., 1991; Stewart *et al*., 2014).

Neural oscillations recorded on the scalp through EEG are associated with a mixture of sensory, cognitive or motor processes, all flooded with noise. Due to the fact that the amplitudes of these oscillations reflect the level of spatial neural synchronization corresponding to certain states on neural activities (Making *et al*., 1999), independent component analysis (ICA) is an appropriate approach for feature extraction in order to detect the above mentioned EEG waveforms from ERPs. This method is generally used for artifacts removal from EEG recordings. Its use for feature extraction, through blind source separation paradigm, was mostly based on the averaging of repeated trials, and optionally, several subjects (Making *et al*., 1999; Rieder *et al*., 2011). It proved advantageous, as well, in investigating the interaction between neural regions that activate or deactivate during cognitive tasks, and may allow discovering signal components which may not be identified otherwise. Spatial aspects reflected in the scalp distribution of the projections of these independent components (ICs) and the linear combination of a selection of them emphasized the possibility to enhance the detection rate of a particular waveform (Xu *et al*., 2004). The proper selection of ICs represents a key problem, when dealing with both detection accuracy and real time response. Constraining this selection by incorporating a priori information into ICA, to derive the specific to task IC (Grigoraş *et al*., 2013; Rieder *et al*., 2011), represent the most recent approach, materialized in constrained ICA with reference signal. Finding the most adequate method for feature extraction and selection, as well as for the most advantageous electrodes locations selection, for a discrimination task, represent challenges for real-time ERP components detection improvement. Single trial P300 waveform detection is also the most recent challenge for BCI application, for its enhanced speed response, useful for communication purposes (Stewart *et al.*, 2014).

In this paper we present a method for the detection of multiple components of an ERP elicited through P300-Speller BCI paradigm described in (Donchin *et al.*, 2000; Farwell *et al.*, 1988), namely P100, N100, P200, N200 and P300. Our simulation results were obtained by testing our method on BCI Competition Dataset III (2005). A rough set theory (RST) based method was used for the channels selection, using features extracted from ICs of the segmented dataset, also selected using this technique. ICA with reference signal, the ICA-R algorithm, was also used as an alternative to ICA and RST, in the preprocessing step, for feature extraction and the detection results were discussed.

## 2. Method

Mostly from the point of view of the physio pathological behavior of the brain, as response to various stimuli, ERPs characterization in different stimulation paradigms, through latency and amplitude of some specific elicited waveforms, was comprehensively resumed by Polich (Polich, 2007), whose research is considered to be state of art for this topic. His studies manipulated stimulus information to assess how electric brain patterns varied with the stimulation conditions. The data collected throughout BCI Competition P300-Speller Paradigm (BCI Competition III Dataset II) reflect a complex problem, because all the stimuli in the paradigm may be interpreted by one subject as targets and distractors that occur infrequently. In this situation the distractors will elicit a P3a type waveform, with, eventually, higher amplitude than a P3b waveform, which is elicited by a target stimulus, as in the argument presented in (Polich, 2007). Also all the visual stimuli are familiar to subjects, eliciting a P400 component as well. The analysis of the other ERP components, eliciting prior to P300, is important, being linked to the causality of P300 generation, in organizing the process of neural inhibition, to delimit the foreign events from the target ones, which modulate the focus of selective attention and promote the memory operations of the targets. For a short period of time, in a P300 oddball speller paradigm, targets and distractor stimuli may be memorized throughout the entire experiment, from trial to trial, justifying the variability of the components waveforms, peaks and latencies with respect to stimulus onset, making their detection in a single trial difficult. Some observations about the targeted ERP components for this study, which were taken into account throughout their detection process, as a priori information for the task, are resumed in the following. They were used to validate channel and samples selections, as well as independent component (ICs) selection from their scalp projections.

The P1 (P100) component is the first significant positive peak in the averaged ERP, with a latency of 70,…,100 ms after stimulus onset. The P1 component is detected whenever a visual stimulus is presented to the subject, with maximum amplitude distribution on the scalp in lateral-occipital areas, originating probably in the posterior-parietal area, as reported in (Polich *et al.*, 1995; Polich, 2007; Makeing *et al.*, 1999).

The N1 (N100) component, with average latencies after stimulus onset of 150,…,200 ms, on averaged ERPs over multiple trials, and negative polarity, is considered to have its amplitude correlated with the stimulus discrimination process.

The P2 (P200) component, with an average post-stimulation latency of 150,…,275 ms as reported in (Polich, 2007), has reported maximal amplitudes distributions on the scalp, on averaged trials ERPs, in the central and anterior areas, with supposed sources in the inferior-occipital and parietal-occipital areas. This waveform elicitation seems to be linked to every visual stimulation, target or non-target, the short term memory and recognition (Pritchard *et al.*, 1991; Polich, 2007).

The N2 (N200) component, with an average latency reported to stimulus onset of 180,…,325 ms (Polich, 2007; Pritchard *et al.*, 1991), and negative polarization, is achieved in an oddball visual paradigm and also before a motor type response (Riedel *et al.*, 2011; Delorme *et al.*, 2007), suggesting its link with a cognitive process, of identification and discrimination of a stimulus. Medical evidence reported in the previously mentioned citations suggests that N2 may originate from the parietal-occipital inferior area, temporal-occipital junction, the inferior temporal lobe, or even the frontal cortex.

The P3 (P300) component, with its subcomponents P3a (linked to the novelty of the stimulus) and P3b (linked to rare random events), with maximum amplitudes in central and frontal areas on the scalp, as reported in (Polich, 2007), with an average latency post-stimulation of 300ms, and a possible encounter of the maximum in the range 250,…,500 ms. In (Polich, 2007) it is stipulated that P3a and P3b maximal amplitudes may be encountered in the central area for P3a, which may be elicited by a distracter, and occipital and parietal areas for P3b, elicited by targets, with supposed origins in the frontal and temporal - parietal activations. It is also emphasized that P3a may occur earlier than P3b, and may have higher amplitude.

### 2.1. The Dataset

Throughout our study we used the training sets for both subjects, A and B, figuring 85 character epochs, including 15 trials of 12 responses to flashing visual stimuli in a random order, to extract ERP components features for our detection purposes. The EEG recordings from 64 electrodes, with sample frequency of 240 Hz, were segmented in 1s long temporal windows ERPs post visual stimulation, with a square matrix of 6 rows and 6 columns of characters, randomly flashing with a frequency of 5.7 Hz, as described in (Donchin *et al.*, 2000; Farwell *et al.*, 1988). Although the dataset consists of two sets of EEG signals, one for training and the other for test, in order to accomplish our goal we have restricted our investigation only to the training set, split in two subsets, one for trial (30 epochs) and the other for test (the remaining 55 epochs), and only the first trial of each epoch. The 7543 samples on each channel (EEG cap electrode) resulted into 15300 segments of 240 post-stimulus samples, grouped in character-epochs (CE), 2 segments × 15 trials × 64 channels for target stimuli and 10 segments × 15 trials × 64 channels for non-target stimuli. From these, only 2,880 samples per channel and per CE, for each of the two subjects, were used in our research. Our goal was to study the detection potential of only one trial of visual stimulation. The signals, already band-pass filtered in the range 0.1,…,60 Hz, were supplementary low-pass filtered with a 6 order elliptic filter with cut-off frequency of 13 Hz, in order to eliminate some noise associated with blinking or muscle movements, as described in (Grigoraş *et al.*, 2013).

### 2.2. ICA and ICA_R for ERP Components Extraction

The independent component analysis (ICA) is a well-documented method which was intensively applied to EEG analysis, even particularly applied to P300 detection, and still presents research interest regarding its capability of P300 detection in a single trial (Stewart *et al.*, 2014).

Let $\mathbf{x}$ be the observations vector, with $n$ the signal length and $N_x$ the number of channels:

$$\mathbf{x} = \left(x_1, ..., x_{N_x}\right) \in \mathbb{R}^{N_x \times n}. \tag{1}$$

The concept of ICA is to find a linear decomposition of the observed signal in statistically independent components, by maximizing the non-Gaussianity of the components, using kurtosis and neg-entropy (4) to evaluate it (Stewart *et al.*, 2014):

$$\begin{cases} \mathbf{As} = \mathbf{x}, \quad \mathbf{x} = \mathbf{Ws}, \quad \mathbf{A} = pinv(\mathbf{W}), \\ \mathbf{s} = [s_1, ..., s_{N_s}] \in \Re^{N_s \times n}, N_s \le N_x. \end{cases} \tag{2}$$

Centering and whitening the observed signals and an eventual PCA preprocessing for dimensional reduction is applied, as shown in eqs. (2) and (3). The $\mathbf{w}_k^T$ vectors are obtained through adaptive computation, where $k$ is the IC order:

$$\mathbf{x}_c = \mathbf{x} - E\{\mathbf{x}\}, \tag{3}$$

$$white = \mathbf{E} \times \mathbf{D} \times \mathbf{E} \cdot \mathbf{x}_c, \quad y_i = \mathbf{w}_i^T \cdot white \tag{4}$$

Function $E\{.\}$ in eq. (3) is the first order statistics of the values in brackets, while $\mathbf{E}$ in eq. (4) is the orthogonal matrix of eigenvectors, and $\mathbf{D}$ is the diagonal matrix of eigenvalues.

$$\max_{\mathbf{w}} \rho \cdot \left[ E\{G(y)\} - E\{G(v)\} \right]^2, \quad G(y) = \log(\cosh(y)) \quad (5)$$

$$E\left\{\mathbf{y}^2\right\} - 1 = 0 \,. \quad (6)$$

Variable $v$ is Gaussian with 0 mean and unit variance, while constant $\rho > 0$. In the case of the ICA-R algorithm, restriction eq. (6) changes to:

$$E\left\{(\mathbf{y} - \mathbf{r})^2\right\} - \xi \le 0, \quad (7)$$

where: **r** is the reference vector, and $\xi > 0$ (Lu et al. 2005). The Lagrange multipliers method will find the weights to ensure the minimum of $G$ in (4).

Several implementations are available in MATLAB for the methods mentioned above. The proper choice of parameters and input signals, according with a priori knowledge about the paradigm and the ERP properties, are critical.

### 2.3. Rough Sets Theory Based Selection Method

Rough sets theory (RST) was introduced in (Powlack, 1982) to deal with the uncertainty mainly due to inconsistency in data and to ease their classification. Recorded electrophysiological signals are noisy, and their values lack the capacity to uncover the biological processes that produced them. In order to decide which process produced the observed system behavior, reflected in the recorded signals, one has to recognize some patterns correctly. ERP involve indiscernible patterns with respect to their relation with a specific mental event. RST, as an approximate reasoning method, is able to approximate dependencies between attributes of data and to evaluate their significance for a certain classification task (Revett *et al*., 2006).

The rough set method was used for finding reducts from the ICA patterns, selecting a minimum set of independent components to combine, when ICA algorithm was used, and also for the channel selection in the detection process. The final pattern is formed from the reduced ICA patterns, from the selected channels.

The main steps of the RST method are:

1. create a decision table $DT = (U, C, D)$, with $U$ = the universe of discourse, $C$ = a finite set of conditions (attributes), and $D$ = a finite set of decisions (categories);

2. define an evaluation function for the significance of attributes with respect to their discriminatory properties for U, used to tile a reduced set of attributes, $A \subseteq C$, such as $snf(U,A,D)>0$;

3. define an evaluation function for validation of the efficacy of the reduced set of attributes over the decision task: $eff(A,D)=eff(C,D)$.

The goal is to reduce the number of attributes, which may be EEG channels with certain characteristics, in order to map similar objects in a decision class; similar attributes, which lead to indecision, must be eliminated. Each class is approximated by an upper bound (UB) and a lower bound (LB) which includes objects in *DT*, by means of attributes reduction. The resulted collection of attributes is called reduct. The difficulty with RST reasoning consists in the selection of data for the *DT* construction and results validation. Preprocessed data are included in *DT*. The result of applying RST reasoning are reducts which may be expressed in decision rules, or may be used in other decision environments.

## 3. Simulation Results

EEG signals, corresponding to each flashed visual stimulus in the character matrix, for each subject, were preprocessed through ICA and ICA-R. The training subset was used in the calibration phase. The data were previously bandpass filtered as mentioned before. For ICA-R we used some of the functions from the MATLAB toolbox EEGIFT software package (Eichele *et al*., 2011) and for ICA, AMUSE function from ICALAB (Cichocki *et al*., 2003; Cichocki *et al*., 2005) was used. RST served for both reducing the number of samples in the segment, and also for channel selection.

The ICs obtained from the original ERPs were projected back on the scalp. Fig. 1 reflects such a blind source separation (BSS) for the ERP elicited by the first target stimulus, to subject A, epoch 1. Reducts were obtained using

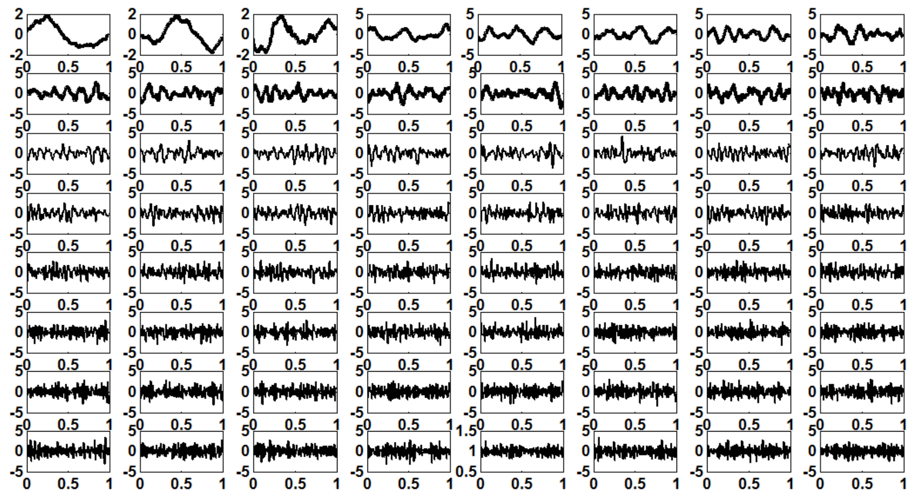


Fig. 1 – Independent components (ICs) for 1st target stimulus ERP in epoch 1, subject A.

as attributes location and maximum amplitudes of these projections on each of the 64 channels, in the specific temporal window corresponding to each target

ERP component. Linear combinations of the selected sources emphasize the components of interest in ERP segments, as can be seen in Fig. 2.

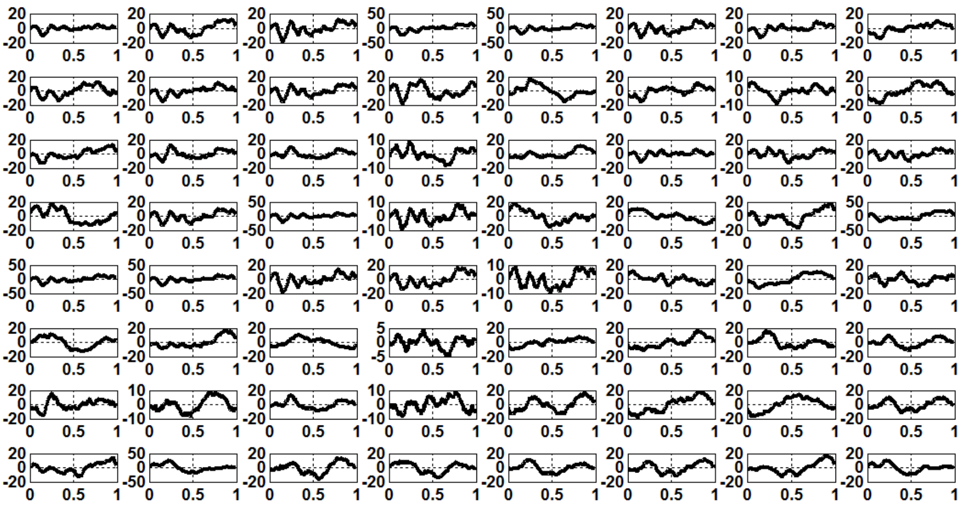


Fig. 2 – Linear recombination of first 8 ICs projections on the 64 EEG channels for the ERP corresponding to 1st target stimulus presented to subject A, 1st epoch.

Some topographical projections on the simplified scalp topography, as presented in Figs. 3 and 4, may suggest the location of the IC with the maximum impact on the studied ERP component, in target ERPs and non-target ones.

For the ICA preprocessing the selection of the IC's to be combined on the back projection on each EEG channel involved IC's amplitude on typical location of maximum amplitude of the component, and correlation coefficients between the averaged components obtained in the training phase, and the reconstructed ERPs through back projection of selected ICs in the signal space. An example of such a recombination is presented in Fig. 5.

Fig. 6 *a* represents averaged ERPs for the first trial, for the training dataset of subject A. In the consecutive Figs. 6 *b* and 6 *c*, one can see the sliding of peak locations for both target and not-target stimuli responses, and each stimulus, for target or not-target visual event, and also their amplitude variation, which explain the difficulties encountered in detecting each component, in what concerns the choice of discriminative characteristics, or reference signals for ICA-R. The temporal windows were: for P1 0.85s – 0.15s, for N1 0.12s – 0.17s, for P2 0.16s – 0.25s, for N2 0.2s – 0.28s and for P3 0.25s – 0.4s. We included only two averaged not-stimulus ERPs in trial 1, instead of ten, in order not to load the figure excessively. In Fig. 7 the ICA-R, for P300 component, averaged over the trial dataset. It was used as correlation pattern.

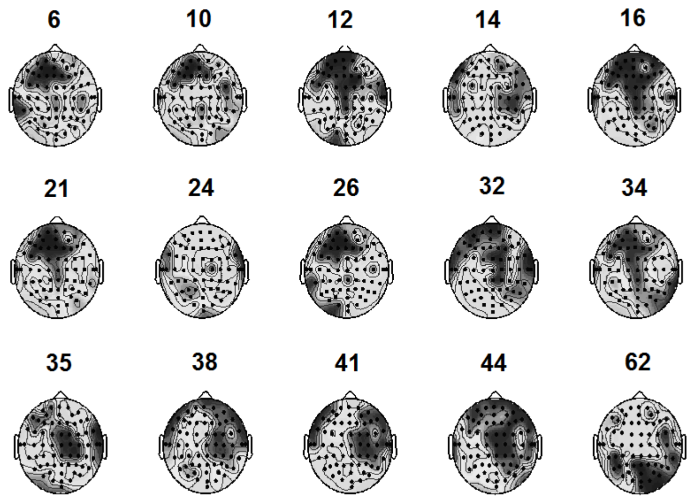
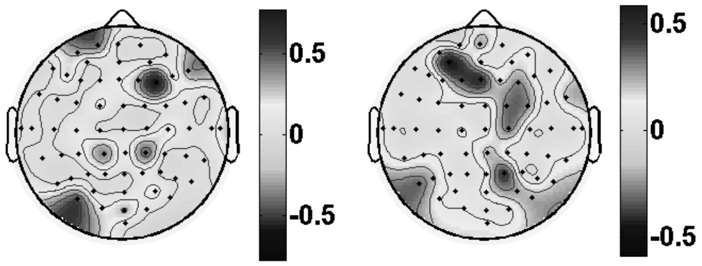



Fig. 3 –ICs projections on scalp with maximum statistical correlation index with averaged target ERP, for 2$^{nd}$ target stimulus, epoch 23, subject B.




*a* *b*

Fig. 4 – Distribution over scalp topography of the correlations between IC3's projections and the corresponding N1 amplitude from the averaged target ERPs (*a*), respectively P1 maximum values (*b*), both on 2$^{nd}$ target ERP, subject A, 10$^{th}$ epoch.

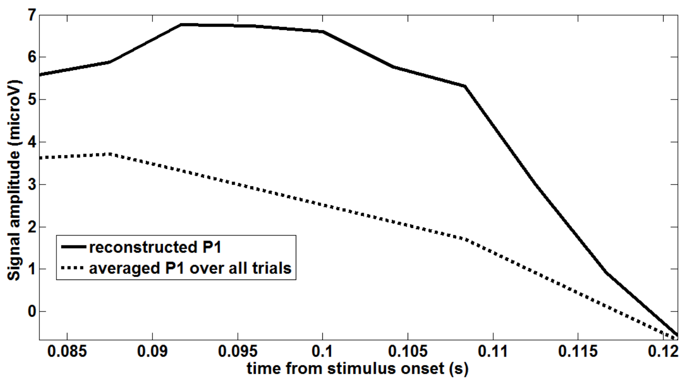
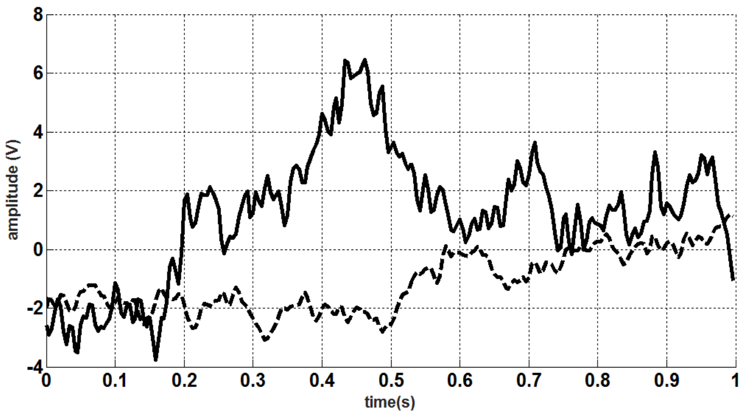
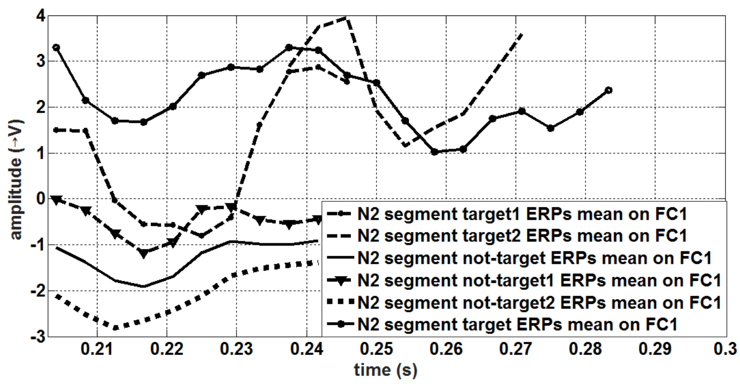


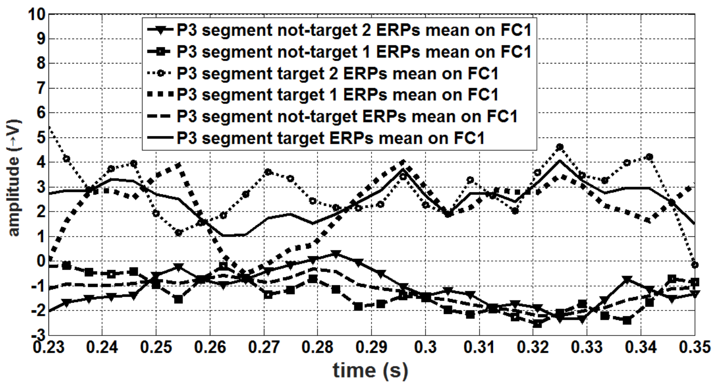

Fig. 5 – Reconstruction of P1 from ICs 4, 11,18, 24, 28 and 45.




*a*




*b*




*c*

Fig. 6 – Average of ERPs over trial 1for training dataset of subject A (*a*); averaged segments of 20 samples of ERPs for N2 component detection (*b*), and respectively for P3 component detection (*c*).

For ICA-R pre-processing the DTs for RST reasoning included through attributes, channel projection maximum amplitude in the reference window and the spectral power of this projection on the channel. A selected channel must be discriminative for the most of the segments for the specified ERP component.

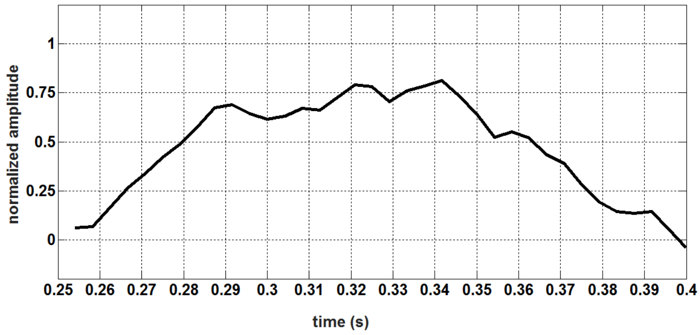



Fig. 7 – Averaged ICA-R for P3, windowed with reference signal, for subject A, on the training dataset.

## 4. Discussion

The first trial, as single trial, is not the best choice for a good detection of ERP components, especially for P300. ICA preprocessed ERPs provided a better choice of attributes for the DT of the RST method, much more controllability, and consequently, a better insight of the components detection criteria. A reduced size of the ERPs considered as inputs, from 240 samples to 42 samples, was provided. In fact, the presence or non presence of P3 in an individual ERP is disputable as long as we only have information about the target and not-target stimuli, and the ERP recordings, from the datasets provided through BCI competition. A P400 component is present in all the ERPs, probably because of the familiarity with the visual stimuli, as stated in (Carver *et al.*, 2006), and maybe other complex characteristics of the stimulation paradigm (Dien *et al.*, 2010), not studied enough. We considered the temporal window for the P300 peak between 0.25 s and 0.4 s for the construction of the reference signal, based on our observations on averaged data, and in order to delimit from an eventual P400 component.

## 5. Conclusions

This paper presents a new approach for the research concerning single trial visual ERPs analysis for significant components detection. Only the first trial from the available data in BCI Competition III, speller paradigm dataset was investigated, with data presented as 1s segments after stimulus onset. Multiple components, such as P1, P2, P3, N1 and N2 were studied for detection possibility, through ICA and constrained ICA with reference signal (ICA-R) preprocessing, and RST reasoning reduction of attributes. Further work will include a multivariate analysis of our results.

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## DETECŢIA UNOR MULTIPLE COMPONENTE ALE POTENŢIALELOR EVOCATE DE EVENIMENTE (ERP) VIZUALE ÎNTR-O SINGURĂ ÎNCERCARE

(Rezumat)

Abordarea uzuală pentru extragerea componentelor din potenţialele evocate de evenimente (ERPs) se bazează pe tehnici de mediere pe mai multe încercări, pentru fiecare condiţie de stimulare şi fiecare subiect, pentru eliminarea zgomotului din semnalul analizat. În această lucrare se prezintă rezultatele de extracţie a mai multor componente ERP din datele corespunzătoare unei singure încercări, obţinute din setul de date BCI Competition dataset II, paradigma speller. Componentele P100, N100, P200, N200 şi P300 ale ERP-urilor considerate au fost extrase prin preprocesare cu analiză pe componente independente (ICA), şi aplicarea metodei bazate pe teoria seturilor brute pentru selecţia componentelor independente şi a canalelor EEG, ce au dovedit contribuţii semnificative la extragerea componentelor ERP ţintă. S-a folosit de asemena un algoritm ICA restricţionat cu semnale de referinţă (ICA_R), şi s-au discutat rezultatele abordărilor prelucrării semnalelor ERP.