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ELECTRO-ENCEPHALOGRAPHIC FEATURE EXTRACTION FOR P300-SPELLER WAVE DETECTION

BY

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Abstract. P300–Speller systems are extensively studied for their applicability as prosthetic communication devices for persons with amyotrophic lateral sclerosis disease (ALS) or other motor degenerative diseases. This study focuses on the analysis of the visual P300 event-related potential (ERP) for brain-computer interface (BCI) speller applications. Our goal is to extract features for P300 pattern detection in a single trial of the P300-Speller paradigm. The electro-encephalographic (EEG) channel selection was performed using principal component analysis (PCA) and *k*-means clustering. The selection results are discussed. PCA was also used for the validation of ERP’s samples selection. The EEG signal fragments were preprocessed by low-pass filtering, as well as average down-sampling. We found that using a nonlinear PCA based neural network for feature extraction from normalized filtered ERPs, the online classification performance of the P300 speller responses can be significantly improved. We used a radial basis function neural network based classifier for P300 detection, and obtained comparable detection results with those presented in references.

Key words: P300-speller paradigm; PCA; nonlinear PCA; *k*-means clustering; BCI.

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1. Introduction

The P300-Speller paradigm belongs to the class of oddball paradigms, used to generate event-related potential (ERP), detectable in multichannel electro-encephalographic (EEG) recordings, with applications in BCI systems. This paradigm uses a flashed letter/number cluster as visual stimulation in order that a targeted character to be recognized, by means of a detected P300 ERP, and used in brain–computer communication. From its introduction in 1988 by Farwell & Donchin, the most usual approach for P300 pattern detection followed by character classification consists in the offline analysis of the EEG ERPs to repeated visual stimuli flashes, for the enhancement of the eventual P300 pattern occurrence by averaging the related EEG recorded segments (Farwell & Donchin, 1988; Donchin *et al*., 2000; Fira, 2011; Combaz *et al*., 2012). In the recent years a lot of research effort was oriented to the detection in a single trial of the P300 pattern, in order to obtain a faster response (Ramírez-Cortes *et al*., 2010; Hoffmann *et al*., 2005, 2008; Cecotti & Gräser, 2011; Li *et al*., 2011; Panicker *et al*., 2011), for the online applications.

The P300 ERP is a positive peak in an EEG channel recording, representing a cognitive response to a specific stimulus, visual, acoustic or tactile, that occur with a delay of about 300 ms after stimulation, randomly, unexpectedly, phenomenon also known as *oddball paradigm* (Farwell & Donchin, 1988; Ramírez-Cortes *et al*., 2010). Because EEG reflects numerous simultaneously ongoing processes, the response to the recognized visual character stimulus is not easily detectable. Preprocessing is needed, involving averaging multiple responses to repeated stimulations, to enhance P300 waveform. For the online detection of the P300 pattern averaging ERPs is not an option. Features of the P300 pattern have to be rigorously extracted offline, for precise wave detection. An artificial neural network based classification is the best choice for the P300 pattern detection in a single trial, benefiting from the offline feature extraction in a learning phase.

The EEG signal is usually corrupted with noise associated with eye blinks or moves (0…4 Hz), or facial muscles noise or jaw clenching (above 13 Hz) (Boudet *et al*., 2007). A P300 pattern was emphasized through spectral analysis, as being characterized by a 0.1…2 Hz frequency (Polich & Donchin, 1988; Ramírez-Cortes *et al*., 2010; Hoffmann *et al*., 2005; Panicker *et al*., 2011), so a low-pass filtering with cutoff frequency greater or equal to 13 Hz or band-pass filtering between 0.1 and 13 Hz, at least, are adequate approaches.

The contribution of each of the 64 channels of the complete EEG cap was studied and different selections of channels were considered for corroborating their recordings fragments (Hansenne, 2000; Treder & Blankertz, 2010; Ramírez-Cortes *et al*., 2010; Hoffmann *et al*., 2005; Fira, 2011; Combaz *et al*., 2012; Fazel-Rezai & Ramanna, 2005). EEG channels need to be selected for data dimensionality reduction, and also for an eventual P300 waveform enhancement, with the maximization of the quality and amount of information. The most of the research work towards P300 Speller – BCI reports the selection of central, frontal and parietal areas of the scalp as useful signal sources (Treder & Blankertz, 2010; Ramírez-Cortes *et al.*, 2010; Hoffmann *et al.*, 2005, 2008; Fira, 2011). The central area is responsible for providing only the cognitive information, while the frontal area includes attention-driven working memory changes and artifacts associated with eye movements and blinks, which may hide task relevant information. Studies revealed that stimulus contributions for the visual P300 wave formation come from the inferior temporal and superior parietal cortex (Linden, 2005). Investigations like fMRI and EEG recordings suggest that F3, F4, F5, F8, Pz, Cz, P4, P5, PO7 and PO8 may contribute to P300 elicit. The number and position of electrodes employed in the analysis fluctuate in different approaches. The goal is to use a minimum set of channels and still enhance detection performances. Several classification methods were used to emphasize the channels which elicit the most discriminable EEG features evoked by the P300 speller. The election depends on the classifier choice. Anyway, most of the opinions converge in selecting electrodes from the posterior area of the scalp and from the central area in a minimal group of electrodes, of at least 6.

BCI based on P300 ERP have been studied extensively over the last two decades. Other aspects of the environment influence were also considered, such as eye gaze (overt/covert attention) (Treder & Blankertz, 2010; Boudet *et al.*, 2007), target character frequency (Hansenne, 2000), emotion, various pathologies and fatigue. Attention, as well as target-to-target time interval, or the sequence of non-target/target stimulus, and their corresponding time intervals, modulate the ERP (Treder & Blankertz, 2010; Polich, 2007). Age, motivation, the form, colour, duration of the visual stimulus, and the duration of the entire experiment are defining factors for the shape, amplitude and delay of P300 wave.

All of these aspects being taken into account, we analysed the response on each EEG channel to the character matrix flashing stimulation, provided the dataset II of the BCI competition III 2005. Only the first 5 of the 15 trials were used in our investigation. Principal component analysis (PCA) and *k*-means clustering were the methods involved in the selection processes, both for the EEG electrodes and ERP samples. Nonlinear component analysis (NLPCA) was chosen as feature extraction method, providing better classification performance than PCA or simple normalized filtered and average down-sampled signals. Results are presented and discussed. Conclusions close our presentation.

2. Method

2.1. The Dataset Description

Among the requirements of any P300 speller BCI are accuracy and time efficiency for P300 extraction and detection. The signal fragments containing the P300 wave have similar statistical characteristics, such as averages and standard deviations, with fragments that do not contain P300, suggesting that other ERPs in the EEG recordings may overlap the P300 waveform, making it hard to be detected in a single trial.

We used the dataset II from BCI competition III Challenge 2004 (BCI Competition III, 2013) for our research. This dataset consists in records of P300 evoked potentials of two healthy subjects, recorded using BCI200 platform, using the P300 speller paradigm described by Farwell and Donchin (1988). The EEG signal was already band-pass filtered 0.1…60 Hz and digitized at 240 Hz. We supplementary low-pass filtered the data with a cutoff frequency of 13 Hz, to eliminate the eventual muscle noise, and average down-sampled to reduce the number of samples to 40. The results of two filtration procedures were very similar qualitatively, as can be seen in Fig. 1. We used only the training files of the two subjects, *A* and *B*, which we randomly divided in two equal partitions, for training and test. Each original file was a 4-dimensional matrices consisting of 85 character epochs, each representing ERPs of 15 random repetitions of 12 flashed visual stimuli, from 64 EEG channel recordings, two of which were ware target stimuli, resulting in infrequent presentations, so that "oddball paradigm" apply. Each EEG signal was segmented using adjacent information provided together with the signal information, in 240 samples windows corresponding to specific stimulation ERPs, of 1 s time period after stimulation. A P300 pattern may be present in which ever ERP, but those corresponding to target stimuli are expected to have greater amplitude, in a selection of scalp regions.

2.2. Kernel Principal Component Analysis

Principal component analysis (PCA) in EEG was previously applied as a preprocessing step for feature selection before classification, providing classification performance improvement, mostly for naive Bayesian classifiers (Ramírez-Cortes *et al.*, 2010; Hoffmann *et al.*, 2005; Polich, 2007). Vapnik-Chervonenki's theory states that some data mappings to a higher dimensional problem data space may provide a better classification foundation. More characteristics for data means more computation complexity, therefore a selection of the new characteristics may be sufficient to better separate classes in data variance is maximized through this selection. A kernel is defined by

$$k(x,y) = \langle \phi(x), \phi(y) \rangle . \tag{1}$$

PCA provide a data representation in orthonormal coordinate axes, called eigenvectors, with maximal de-correlation between components. The principal axes are obtained by diagonallyzing the covariance matrix of the inputs

$$\mathbf{R} = \frac{1}{n}\mathbf{X}^T \times \mathbf{X}. \tag{2}$$

Here $\mathbf{X}$ is the $m \times n$ matrix of observations, m being the number of observations and n the number of variables. The statistical independent principal components being linear combinations of the original variables

$$\mathbf{p} = \mathbf{A}^T \times \mathbf{x}., \tag{3}$$

the loadings of these variables in each principal component may be used to select an adequate temporal window for the signal for P300 wave detection.

In eq. (3), $\mathbf{p} \in \Re^n$ is the vector of principal components, $\mathbf{x} \in \Re^n$ – an observation and $\mathbf{A}$ is the transformation matrix of eigenvectors, constructed from orthonormal column vectors. The nonlinear extension of PCA described by Scholz *et al*., (2005), was considered for this analysis approach, as the application of linear PCA to the characterization of nonlinear distributed data, as EEG signals are, proved to be inadequate. It implements a simple concept, of auto-association, performing identity mapping, network parameters being performed by calculating the error norm, $\|\mathbf{x} - \hat{\mathbf{x}}\|$. It is based on the assumption that the reconstruction of the original variables through the re-projection of principal components in the input space may be done by means of an auto-associative neural network (AANN) with five layers topology. Such a neural structure proved hard to train, mostly because it is very sensitive to initial conditions and may be affected by premature saturation of the parameters. The middle layer, called *bottleneck*, represents the first principal component. The consequent principal components are extracted with similar structures from the residuals of the approximation, *i.e.* $\|\mathbf{x} - \hat{\mathbf{x}}\|$ would be the input of the network for the second principal component calculation. We obtained better results, from the point of view of the regression performed, by the generalization part of the network, with a six layer neural network, two hidden layers with hyperbolic tangent nonlinearity after the bottleneck, and two processing elements in the bottleneck layer. For one element in bottleneck we added a hidden layer with hyperbolic tangent neurons after the first hidden layer, with Gaussian neurons, of the AANN.

2.3. Channel and Samples Selection

Channel selection was based on k-means clustering as the evaluation method for elementary sets extraction. *Rough sets theory* (RST), proposed by Pawlak in 1982, is concerned with the classification and analysis of imprecise, uncertain or incomplete information, being a non-statistical approach in data analysis. We used RST as conceptualization theory, because our classification problem was complex, we had a lot of data and we were uncertain about which sources of information to use to characterize the P300 pattern for each ERP of a target stimulus. Following RST, we have U as a universe of the 64 EEG channels with ERPs, and as the set of attributes the samples values. We use k-means clustering as a method to identify elementary sets in U, for each target stimulus presentation and each of the first five trials. We are interested that some samples values in time interval 0.25 s…0.6 s to have a positive value. We thus obtain elementary subsets of channels for this selection of samples and restriction of signal amplitude. We choose a selection of channels and decide if they are sufficient for an accurate classification, checking the cardinality of the lower and upper approximations for this selection, for equality. RST may be used to select also the samples, deciding if ignoring certain sample values would change the number of elementary sets. We combined results provided by PCA analysis and *k*-means clustering. The discernibility function, logically combining distinguishing attributes of two elementary sets, may help select the samples segments.

The *k*-means clustering method, which is an unsupervized adaptive classifying algorithm, is based on the idea of grouping together objects from a given dataset, in a predefined number of clusters, by calculating the relative distance from each cluster centroid. An accepted metric choice for electrophysiological signals is the Euclidean distance. Based on its intra-cluster minimization, each object is distributed until the recalculation of the centroids locations no longer varies. The cost function to be minimized is

$$E = \sum_{i=1}^{k} \sum_{j=1}^{m} \left\| x_{ij} - c_i \right\|^2 . \tag{4}$$

In eq. (4), x_{ij} represents the input components while c_i represents the network centroids.

3. Simulation Results

EEG data from the dataset II of the BCI competition III (2013) were preprocessed with an elliptic low-pass filter, for noise reduction, and normalized for signal energy equalization. In order to reduce the data dimensionality, and based on the low frequency of the target waveform, average down-sampling was also performed. We have chosen an elliptic filter type because it provides the desired selectivity at a lower order, with lower computation and implementation complexity. The average down-sampling, that we also applied, showed similar filtering results, providing fewer characteristics. In Fig. 1 one can see an EEG segment filtered with both low-pass elliptic filter of order six and cut-off frequency 13 Hz, and average down-sampling filter decimation, with a window width of six points, resulting in a 40 points representation out of a 240 original signal.

The visual analysis of the signals displayed significant differences regarding the subject (Fig. 2), the EEG channel (Fig. 3) or the trial (Fig. 4). Attention, time interval between two consecutive stimuli, target or not target, fatigue, and taking into account that even if we are speaking of two not target consecutive stimuli, being different they are percept as *unexpected* in an *oddball paradigm* environment, and a P300 type wave may still be elicited (Polich, 2007). So the task of deriving the proper characteristics for the P300 wave elicited when a target stimulus to be discriminatively detected in a single trial, for online signal processing, is a challenging one.

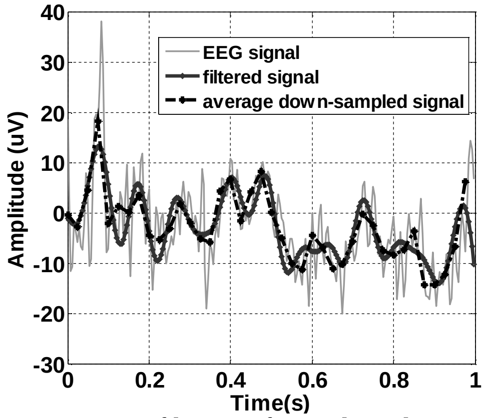


Fig. 1 – Comparative filtering of a single trial EEG response on channel, Cz (electrode 11), to a flashed visual stimulus (column 3 of the character matrix), in a particular trial (3), from epoch 59 of subject *B*, which was supposed to contain a P300 EPR, with a delay of about 0.3 s from the stimulus onset.

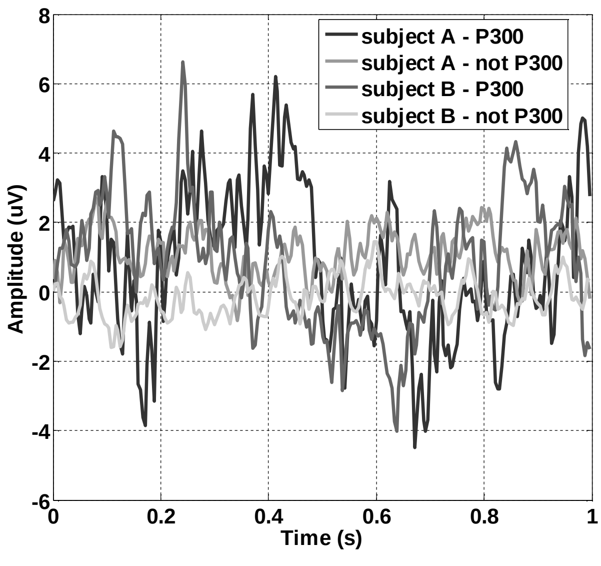


Fig. 2 – Comparative display for one character epoch of averaged ERPs over 15 trials, for both subjects, for both cases, without P300 (also averaged over 10 row/column stimulus) and with P300 wave (supplementary averaged over 2 rows/columns), on channel Cz; one may notice differences in amplitude and location of the P300 waveform.

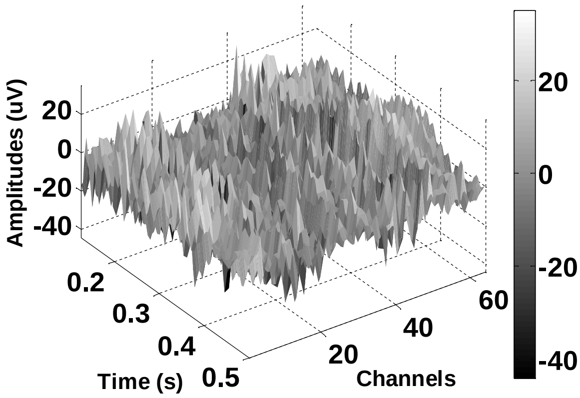


Fig. 3 – Comparative display of averaged down-sampled responses to one flashed target stimulus, over all 64 EEG channels, in trial 4, of subject B. Significant variations in amplitudes and shapes of the registered signals suggest that only a selection of channels will optimize the P300 wave enhancement.

Fig. 6 shows a slight difference in the distribution of distinct class objects, enough for improved classification results.

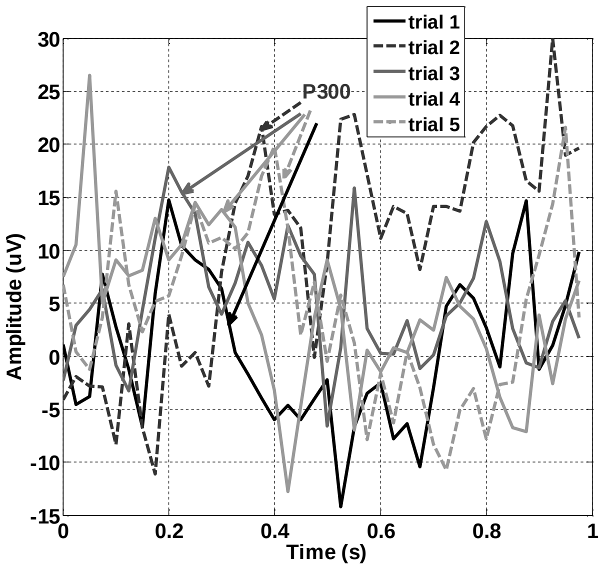


Fig. 4 – Comparative display of averaged down-sampled responses to one flashed target stimulus, in first 5 trials, of subject *A*, epoch 1, channel Pz (electrode 51); variations in amplitudes, shapes and locations of the P300 waveform, for a single target stimulus flashing (first of the two row/column) can be observed.

Each subject dataset was divided into two distinct sets, one for training and one for test, of equal size. Signal matrix were constructed for with-P300 and without-P300 content, resulting in matrix sizes of 37,200 observations over 40 samples, respectively 186,000 observations over 40 samples. PCA was performed on the training with-P300 dataset in order to select channels, and samples for useful signal enhancement and P300 pattern discrimination. PCA coefficients values were used as discrimination criterion. We also performed a *k*-means clustering procedure for channel selection (Fig. 5). A voting procedure over all training epochs of both subjects, 5 trials each, for the selected clusters, was used for channel groups selection. The resulted channels were: FCz, Cz, Pz, PO7, P2, C1, C3, F4.

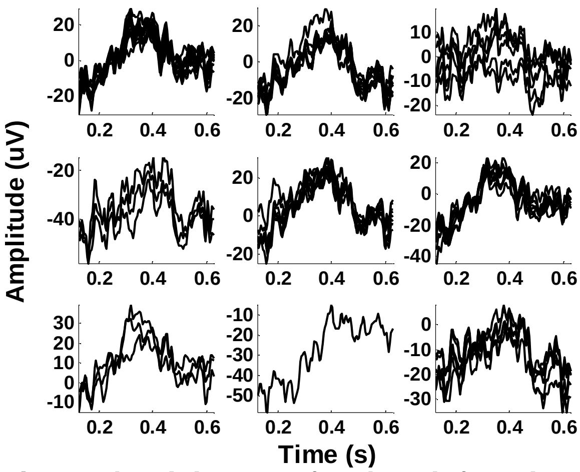
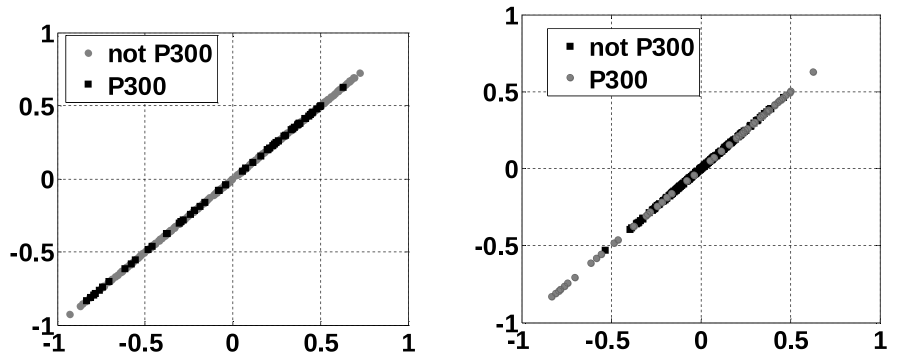


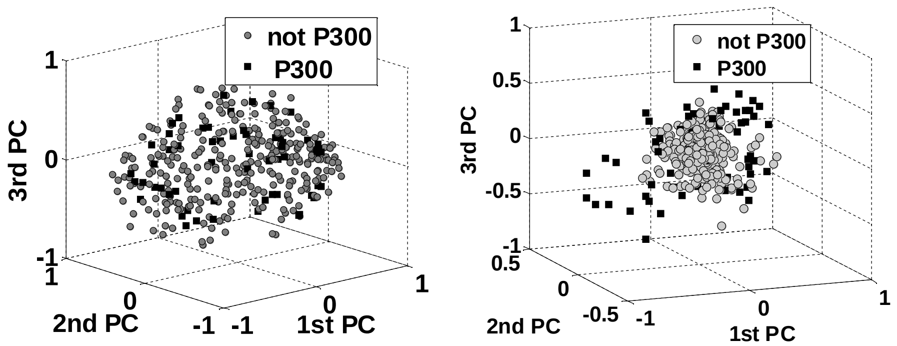
Fig. 5 – *k*-means based clustering of 64 channels for trial 1 of subject B, when P300 pattern should be present; the data tips indicate the average location of the P300 peak.

PCA was also used for features extraction from ERP signals. We searched for characteristics of the P300 pattern in two distinct areas of the registered ERP: one between 0.1 s and 0.25 s after stimulation, where we usually find a negative peak (N100), preceding the P300 wave, and the other between 0.3 s and 0.6 s after stimulus onset, where the proper P300 peak may be found. Fig. 7 *a* displays the distribution of the P300-ERPs and not-P300-ERPs, from a single epoch of subject A, projected on the first three eigenvectors of the analysed signal space. Their dense mixture suggests that a classification problem of the points in the eigenspace is not a trivial one. A nonlinear PCA feature extractor, implemented with a feedforward *bottleneck* neural network with five hidden layers, as the model described by Scholz *et al*., (2005), with Gaussian nonlinearity in the first hidden layer and hyperbolic tangent nonlinearity in second, fourth and fiveth hidden layers, and linear neurons in the bottleneck and output layer, has been chosen as an alternative to the PCA approach (Fig. 7 *b*).



a *b*

Fig. 6 – The first PC of the selected normalized samples of ERPs in 0.1…0.6 s interval (*a*) still need a nonlinear classifier for P300 wave detection; the first nonlinear PC of the same signal samples shows a better distribution of values (*b*).



a *b*

Fig. 7 – The 3-D plots of both first 3 PCs (*a*) and the first 3 nonlinear PCs (*b*) showing an improvement in the distribution of the projections of ERPs in the eigenspace for the latter, for a better and easier classification.

The first half of the network, before the bottleneck, extracts the first nonlinear principal component (PC) of the input data, x. For extracting the following two nonlinear PCs, similar networks are used, with inputs $x - x_1$, respectively $x_1 - x_2$, where x_1 and x_2 are the regression vectors elicited by the second half of the networks providing first PC and second PC. The architecture with 40-30-1-30-50 neurons for each principal component extractor provided an approximation performance of 0.0306 after 27 training iterations for the first PC. The training and validation datasets were randomly selected from the input dataset for training. The detection was carried out by a radial basis functions neural network, on the test datasets, with a rate of successful detection of 93.78%, which is comparable with that reported by Cecotti & Gräser, (2011) and Hoffmann *et al.*, (2008). We have also tried an asymmetrical topology, with 30-2-20-40 neurons in the hidden layers which avoided premature saturation and performed a good generalization. The nonlinearities of the processing elements of the neural layers were as follows: first layer – Gaussian, second and output layers – linear, third and fourth layers – hyperbolic tangent. Three segments of input samples, from time interval 0.1 s…0.6 s were used to provide principal components that combine in a feature vector for classifier.

4. Conclusion

The present paper presents a new approach of researching the EEG ERPs signals, for discriminatory feature extraction from segments of signals where one can seek for a P300 waveform. Combining rough sets theory concepts with *k*-means clustering and PCA resulted in a rigorously selected group of EEG channels and EEG sample values, considered as attributes, that can enhance the characterization of the P300 wave such that it can be discriminated in an ERP signal. This contribution was developed using unmodified standard methods, such as PCA, nonlinear PCA, *k*-means clustering or classification, implemented with radial-basis functions type neural network, in an original manner, to improve the P300 detection performances in a single P300-speller BCI paradigm trial, for online utilization. The nonlinear PCA was used to provide features for the classifier. Its implementation with a generalized feedforward neural network needed to be modified from the classical, five layer symmetrical topology, in order to avoid premature saturation of the parameters during training. The very good classification results encourage us to proceed to testing our approach.

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EXTRAGEREA DE CARACTERISTICI ELECTROENCEFALOGRAFICE PENTRU DETECŢIA UNDEI P300 ÎN APLICAŢII BCI SPELLER

(Rezumat)

Sistemele P300-Speller sunt mult studiate, pentru aplicabilitatea lor ca dispozitive protetice de comunicare pentru persoane cu scleroză laterală amiotrofică (ALS) sau alte boli degenerative motorii. Acest studiu este focalizat pe analiza potenţialelor P300 evocate de evenimente (ERP) vizuale pentru aplicaţii tip *speller* în interfeţe creier–calculator (BCI). Scopul nostru este să extragem caracteristici pentru detecţia formei P300 într-o singură trecere, în cadrul paradigmei P300–Speller. Selecţia canalelor electroencefalografice (EEG) s-a realizat folosind analiza pe componente principale (PCA) şi *k-means clustering.* Rezultatele selecției sunt discutate. S-a folosit PCA şi pentru validarea selecției eşantioanelor din ERP. Fragmentele de semnal EEG au fost preprocesate prin filtrare trece-jos şi au fost subeşantionate prin mediere. S-a constatat că, prin utilizarea unei rețele neurale bazată pe analiza neliniară pe componente principale, pentru extragerea de caracteristici din ERP-uri filtrate şi normalizate, performanțele de clasificare *online* a răspunsurilor spelerului P300 pot fi îmbunătățite semnificativ. Pentru detecția formei P300, s-a folosit un clasificator bazat pe o rețea neurală cu nucleu radial şi s-au obținut rezultate de detecție comparabile cu cele prezentate în bibliografie.