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A comparison of classification techniques for a gaze-independent P300-based brain–computer interface

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Abstract

This off-line study aims to assess the performance of five classifiers commonly used in the brain–computer interface (BCI) community, when applied to a gaze-independent P300-based BCI. In particular, we compared the results of four linear classifiers and one nonlinear: Fisher's linear discriminant analysis (LDA), stepwise linear discriminant analysis (SWLDA), Bayesian linear discriminant analysis (BLDA), linear support vector machine (LSVM) and Gaussian supported vector machine (GSVM). Moreover, different values for the decimation of the training dataset were tested. The results were evaluated both in terms of accuracy and written symbol rate with the data of 19 healthy subjects. No significant differences among the considered classifiers were found. The optimal decimation factor spanned a range from 3 to 24 (12 to 94 ms long bins). Nevertheless, performance on individually optimized classification parameters is not significantly different from a classification with general parameters (i.e. using an LDA classifier, about 48 ms long bins).

(Some figures may appear in colour only in the online journal)

1. Introduction

Brain–computer interface (BCI) systems aim to restore communication and interaction with the external world in people suffering from severe motor impairment. Non-invasive BCIs rely on the detection of voluntary or involuntary modulations of the electroencephalographic (EEG) signal which are translated in a control signal for an external device. Different EEG features can be used to control a BCI such as sensorimotor rhythms (SMRs), steady state visual evoked potentials (SSVEPs) and event-related potentials (ERPs). One of the most commonly used ERPs to control a BCI system is the P300 potential. The latter has a positive deflection (about 10–20 μV) which occurs about 250–500 ms after the subject recognizes a stimulus that he identifies as a target (rare stimulus) between a train of non-target stimuli (frequent stimuli—Fabiani *et al* 1987). One of the most widely applied paradigms for the P300-based BCI is the P300 Speller (Farwell and Donchin 1988), which consists of a matrix containing alphanumeric characters. Stimuli are provided by the intensification of rows and columns in the matrix, and the intensification of the row and the column containing the character the subject wants to select, elicits a P300 potential. However, recent studies (Brunner *et al* 2010) demonstrated that this approach is not suitable when the user is not able to control the movements of his eyes. In fact, using this interface in cover attention status (de Haan *et al* 2008) one finds that the performance significantly decreases. These experimental results led to a growing interest for new and more effective visual stimulation paradigms requiring no eye gaze. A first example of this method was the Hex-O-Spell, developed by Treder and Blankertz (2010), and subsequently improved by introducing a color code for the different stimuli (Treder *et al* 2011). Acqualagna *et al* (2010) proposed a new

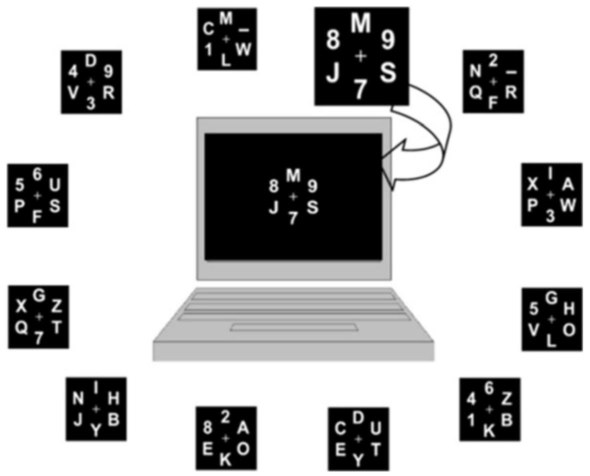

Figure 1. GeoSpell. Each group contains six alphanumeric items that are presented in a random sequence in the center of a screen.

stimulation paradigm based on the central rapid serial visual presentation (RSVP) of the stimuli, in which every single character is presented in the middle of the screen. Liu *et al* (2010) developed an interface relying on the presentation of character groups organized on the vertex of a geometrical figure. A similar approach was implemented and validated by Aloise *et al* (2012) with their GeoSpell (Geometric Speller—figure 1) interface. Both Treder and Blankertz (2010) and Aloise *et al* (2012) demonstrated in their works that the visual evoked potentials (VEPs) do not contribute to the classification process. In fact, while with the P300 Speller (used in 'overt attention' status), the spatial distribution of the characters elicits stronger VEPs for the target stimuli which the subject is gazing at with respect to the non-target. In a 'covert attention' visual task, the VEPs elicited were the same for target and non-target stimuli.

In order to extract control parameters for the independent eye gazing visual P300-based BCI, the same classification techniques already used for classical P300 Speller were implemented. However, the state-of-the-art gaze-independent BCIs still did not reach the accuracy level of the P300 Speller used in overt attention status, or they experienced a decrease of speed; in fact more repetitions of the stimuli are needed, with respect to the classical P300 Speller in overt attention conditions, to correctly recognize the desired character. Several factors could explain this deterioration of performance, such as: the reduced ability to discriminate target stimuli within non-targets; the absence of significant differences between the VEPs elicited by rare and frequent stimuli; and the higher difficulty of the task, since subjects are required not to move their eyes and focus on the stimulation (Brunner *et al* 2010).

In this work, different classification techniques were tested also evaluating different preprocessing modalities of the EEG signal (decimation). In fact, some classifiers work better when smaller training datasets are available and thus high decimation can improve classification. Particularly we provided a comparison of the results obtained with four linear classifiers and one nonlinear: Fisher linear discriminant analysis (LDA), stepwise linear discriminant analysis (SWLDA), Bayesian linear discriminant analysis (BLDA), linear supported vector machine (LSVM) and Gaussian supported vector machine (GSVM). Except for BLDA, these methods were first evaluated for the Farwell and Donchin's P300 Speller by Krusienski *et al* (2006) on healthy subjects and recently validated on persons with motor disabilities (Manyakov *et al* 2011) where the BLDA was introduced. Both demonstrated that linear classifiers generally perform better than the nonlinear one; the best performance for healthy subjects was obtained with the SWLDA and LDA.

The aim of the current work is provide a comparison of the different classification techniques for gaze-independent BCIs based on visual stimulation. This study involved 19 healthy subjects and intends to provide guidelines for EEG classification in covert attention visual tasks. Taking into account the lower and less stable potentials elicited by the considered gaze independent visual paradigm, there are no reasons to exclude different results with respect to the previous work on this topic. Also, it will be investigated whether a specific optimization of the classification parameters for every single subject could lead to higher performance with respect to their generalization on the basis of overall performance.

2. Materials and methods

2.1. Study design and participants

Nineteen healthy subjects (mean age = 26.32 ± 4.55) were involved in this study. Each of them had previous experience with P300-based BCIs and had already used the GeoSpell interface. All subjects had normal or corrected to normal vision.

The GeoSpell interface allows for controlling in covert attention status, since the 36 characters of the P300 Speller are organized on vertices of 12 hexagons following the same logic as a 6 × 6 matrix. Each hexagon or group consists of six characters and each character belongs to exactly two groups where it occupies the same spatial position (Aloise *et al* 2012). A fixation point was placed on its center to help the subject avoid eye movements. Since in covert attention status changes in spatial attention should occur with the eyes remaining fixed (Wright and Ward 2008, Posner *et al* 1982) we determined the angular distance between the fixation cross and each character in the group: the subject sat 1 m away from a 17″ LCD monitor; the distance between the cross and the letters was 2.64 cm, yielding a 0.9° angle. The visual angle subtended by the subject's eyes did not exceed 1°, which allowed us to observe high VEP responses (Sutter 1992). While assembling the set of characters, care was taken that the number of white pixels in each layout was comparable (mean = 3274.33 pixels; SD = 2.93%). This is expected to minimize the differences between the VEPs elicited by each group, thus preventing any influence on the system's accuracy. As expected, the early components of the ERPs, which are mainly modulated by the physical characteristics of the stimulus, will not contribute to the classification; they will be solely based on the modulation of later components, such as P300, which is cognitively induced by the subject (Aloise *et al* 2012).

Stimulation consisted of the pseudorandom intensification of groups on the screen; each group was intensified for 125 ms and the interval between the end of one stimulus and the onset of the subsequent (inter stimulus interval—ISI) was also set to 125 ms. We use the term ‘stimulation sequence’ to refer to a single intensification of all the 12 character groups. A trial consisted of a time interval in which the target stimulus remained the same; in this study we fixed eight stimulation sequences for trial, which means 16 presentations of the target character per trial. Classification of the attended character can be performed at the end of each sequence. As in the P300 Speller, the selection of a character is given by the intersection of the two most likely selected groups.

Scalp EEG potentials were acquired from 8 Ag/AgCl electrodes covering the left, right, and central scalp locations (Fz, Cz, Pz, Oz, P3, P4, PO7, PO8) according to the 10–10 standard. Each electrode was referenced to the linked earlobes, and grounded to the right mastoid. EEG was acquired by a g.USBamp amplifier (g.Tec, Austria), and digitized at 256 Hz. Data were high-pass and low-pass filtered with cut-off frequencies of 0.1 and 60 Hz, respectively, using an eighth-order Butterworth hardware filter. The electrodes’ impedance did not exceed 10 kΩ. Visual stimulation and acquisition were operated by the BCI2000 software (Schalk *et al* 2004), using a stimulus presentation modified for the purpose of this study.

During the recording sessions, eye movements were monitored by an eye tracker system with 0.5° spatial resolution. The system was composed of an infrared-light camera (iSlim 320, Genius corp., Taipei, Taiwan) managed by the open source software ‘ITU GazeTracker’ (San Agustin *et al* 2010). Eye gaze coordinates (in pixels) were sent via UDP protocol to the BCI2000 software, which stored them keeping the temporal correspondence with the EEG data and stimulation markers. This allowed us to quantify ocular movements and to correlate them with the stimuli during the offline analysis. The eye tracker system was mounted on a chinrest, on which the subject placed his/her head during the recording session to avoid head movements.

2.2.1. Experimental protocol. Each subject performed a single recording session consisting of six runs with EEG acquisition. Each run consisted of six trials, a total of 36 trials for the whole session. By the term ‘trial’ we refer to an ensemble of epochs in which the target was the same; in particular in a trial each group was randomly presented eight times, with a total of 96 epochs. Since each character belongs to two groups, we collected 16 target epochs and 80 no-target epochs for each trial. Every character on the interface was presented as a target once in the recording session. During the 2 s before the beginning of each trial, the system cued the target character to the subject visualizing it in its position. Subjects were required to gaze at the fixation cross in the middle of the interface and to focus their attention on the target character, mentally counting its occurrences. The eye tracker system was calibrated at the beginning of the recording session and between the third and the fourth run, allowing to the subject to move his head from the chinrest and relax for a few minutes.

2.2.2. Classification methods.

Preprocessing. Data was first divided into segments of 800 ms, starting in correspondence of the onset of each stimulus. The segments were then decimated exploring different decimation values (3, 4, 8, 12, 16, 20 and 24). Decimation was carried out by segmenting the data into blocks of length equal to the selected decimation factor. The mean of these blocks was calculated and used as the feature. The resulting data arrays were then concatenated by channel for each stimulus, creating a single vector for the stimulus used to train the classifiers.

Linear discriminant analysis (LDA). Fisher’s LDA looks for the hyperplane separating the different classes. It assumes normal distributions of the data, with an equal covariance matrix for the classes. For a two-class problem, separating the hyperplane is obtained by seeking the projection that maximizes the distance between the two classes’ means and minimizes the interclass variance (Fukunaga 1990). The great advantage of this technique is the low computational effort required; furthermore it is simple to use and provides good results (Lotte *et al* 2007).

Stepwise linear discriminant analysis (SWLDA). The SWLDA is an extension of the LDA which performs a reduction of the features’ space by selecting the most significant ones. Particularly, the SWLDA consists of combination of forward and backward stepwise analysis where the input features are weighted using ordinary least-squares regression to predict the target class label. The method starts by creating an initial model of the discriminant function with the most statistically significant features for predicting the target labels (p-value <0.1). Then at each new step a new term is added to the model and a backward stepwise analysis is performed to remove the least statistically significant feature (p-value > 0.15). This process goes on until the predefined number of significant features is reached or until there are no features satisfying the entry/removal condition (Krusienski *et al* 2006). In this work the number of features of the final discriminant function was set to 60.

Bayesian linear discriminant analysis (BLDA). The BLDA is an extension of Fisher’s LDA. In fact, BLDA implements a regularization which prevents problems of over-fitting due to high dimensional and possibly noisy datasets. The BLDA allows us to automatically and quickly estimate the degree of regularization from the training data without time consuming cross-validation. In this work we used the algorithm described by Hoffmann *et al* (2008) and which was successfully used in the work of Manyakov *et al* (2011).

Linear and nonlinear support vector machines (SVMs). The SVM uses a hyperplane to distinguish between classes. The selected hyper plane is the one that maximizes the margins, and then the distance between the nearest training points, increasing the generalization capabilities of the classifier. In this work we tested both linear SVM (LSVM) using a least-squares method to find the separating hyperplane and Gaussian

SVM (GSVM). The latter consists of mapping the features' space in a higher-dimensional space using a Gaussian kernel function and to define the separating hyperplane we used a sequential minimal optimization algorithm where the classifier is a one-norm soft margin SVM. Furthermore, training data were shifted to zero mean and scaled to unit variance and then we defined the two hyper-parameters: the regularization parameter C that enables accommodation to outliers and allows errors on the training set and σ that denotes the width of the Gaussian function used (Lotte *et al* 2007). Also for the LSVM there is the need for an optimization of the regularization parameter C. In order to choose the best performing values for each subject, a leave one word out (LOWO, Liu *et al* 2010) cross-validation was performed on the data acquired during experimental sessions, testing different combinations of these parameters both for the LSVM and GSVM. In particular, for each subject we performed a six rounds of cross-validation using all the possible combinations of five runs for training and the remaining one for testing. In order to find the optimal value for parameter C, we explored a range from 2^{-5} to 2^{15} increasing the exponent value with each step of 2, both for the LSVM and GSVM. When the same level of accuracy was reached with different values of C we used the lowest, since it guarantees a higher reliability of the classifier. Regarding parameter σ, defined as $\sigma = \sqrt{\frac{1}{2^{\gamma}}}$, we considered for γ a range from –10 to 3 a step of 1.

2.2.3. Performance evaluation. In order to assess the performance for each classification method and decimation value, we performed a LOWO (Liu *et al* 2010) cross validation, using at each round five runs as a training set and the remaining one as a testing dataset, for a total of six rounds. Accuracy was estimated for each stimulation sequence by averaging the results of the cross validation rounds for each subject and for each decimation values. The written symbol rate (WSR—Furdea *et al* 2009) was also estimated. In fact the maximum WSR value for each subject provides an objective evaluation of the system performance by combining the accuracy level with the time needed to reach it, in terms of the number of stimulation sequences. The WSR index is based on the symbol rate (SR—McFarland and Wolpaw 2003), which in turn depends on the bits (B) per trial. Referring to the formula described in Pierce (1980) the number of B transmitted per trial is defined as:

$$B = \log_2 N + P \log_2 P + (1 - P)\log_2\left(\frac{1 - P}{N - 1}\right) \qquad (1)$$

where N is the number of possible targets and P is the probability that the target is accurately classified. Then from equation (1) the symbol rate is determined as:

$$\mathrm{SR} = \frac{B}{\log_2 N}.$$

If T is the trial duration in minutes, the WSR can be determined as follows:

$$\mathrm{WSR} = \begin{cases} \dfrac{2\mathrm{SR} - 1}{T} & \mathrm{SR} > 0.5 \\ 0 & \mathrm{SR} \leqslant 0.5. \end{cases}$$

Table 1. Classifier and decimation factors which achieved the best performance for each subject. Values were chosen according to the highest WSR value achieved by each subject.

Subject	Classifier	Decimation	Subject	Classifier	Decimation
Subj1	SWLDA	12	Subj 11	SVM	12
Subj2	SWLDA	8	Subj 12	SWLDA	8
Subj3	gSVM	8	Subj 13	LDA	12
Subj4	SVM	20	Subj 14	LDA	20
Subj5	LDA	12	Subj 15	LDA	16
Subj6	gSVM	12	Subj 16	SWLDA	16
Subj7	SVM	12	Subj 17	SVM	20
Subj8	SWLDA	3	Subj 18	SWLDA	24
Subj9	SVM	4	Subj 19	LDA	8
Subj10	LDA	20			

3. Results

The eye tracker data from the BCI session were analyzed in order to quantify eye movement and highlight correlations with the target stimuli. On average we detected less than the 2% percent eye movements, which were probably due to involuntary movements since they did not correlate with the presentation of the target stimuli. Figure 2 shows a grand average of ERP waveforms for target and non-target stimuli; it is possible to see that the main difference between the target and non-target is in the P300 component while the VEPs components are overlaid.

Figure 3 shows the results of LOWO cross validation. Graphics are organized with decimation factors on the rows and classifiers on the columns.

Figure 4 illustrates the WSR values for each subject and the stimulation sequence for every combination of classifier and decimation factor. All the classifiers exhibited comparable WSR values.

We selected the best decimation factor for each classifier, and we performed two two-way repeated measures ANOVA (confidential interval = 0.95), using the *subject* and *classifier* as factors and *accuracy/WSR per stimulation sequences* as dependent variables. The tests showed that both WSR and accuracy values related to all the classifiers, did not exhibit statistically significant differences (WSR (subject × classifier): $F = 0.38$, $p = 0.99$; accuracy (subject × classifier): $F = 0.51$, $p = 0.99$). All the classifiers achieved higher performances, both in terms of accuracy and WSR with a decimation factor of 12.

Considering these results, the next step was to evaluate whether performance could be improved considering, for each subject, which combination of the classifier with the decimation value provides the best performance. The performances obtained with the subject specific best parameters (SSBPs) were then compared with the performances obtained considering the general best parameters (GBPs): LDA with a decimation of 12. The SSBPs are displayed in table 1. Figure 5 provides a summary of the performances obtained with both GBPs and SSBPs.

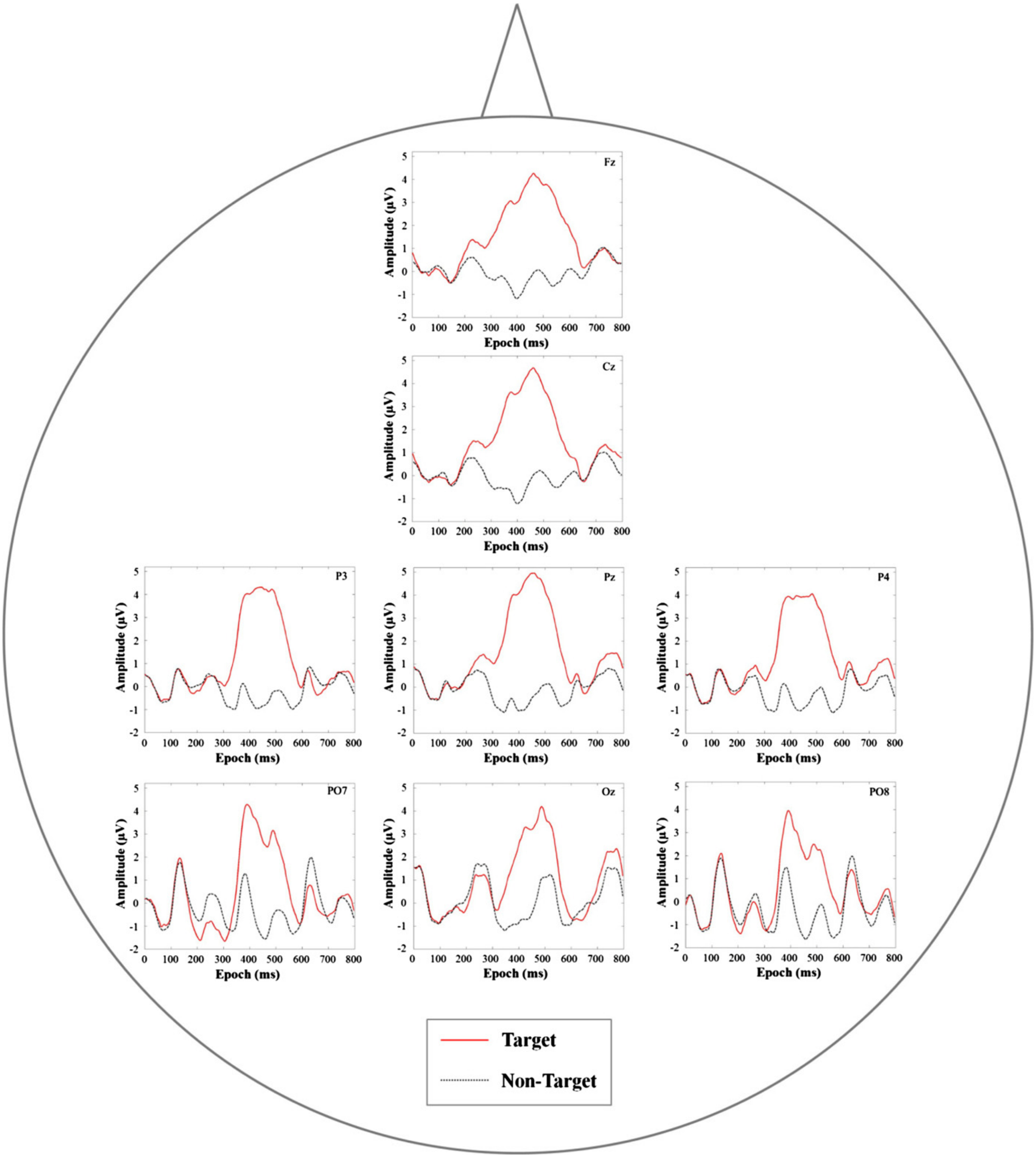

Figure 2. Grand average of ERP waveforms for target and non-target stimuli.

We performed eight Whitney–Mann–Wilcoxon tests in order to compare the accuracy values using the interface with both GBPs and SSBPs for each stimulation sequence. In order to counteract the problem of multiple comparisons, we applied the Bonferroni correction ($\alpha = 0.05/\mathrm{nr}$, where nr = 8 stimulation sequences) to the tests. Test results showed no statistically significant differences for all of the stimulation sequences for the two conditions (see table 2).

Table 2. Whitney–Mann–Wilcoxon test ($\alpha = 0.05/\mathrm{nr}$, where nr = 8 stimulation sequences—Bonferroni correction) related to the accuracy values using the interface with both GBPs and SSBPs at each stimulation sequence.

$\alpha = .05/8$	Seq 1	Seq 2	Seq 3	Seq 4	Seq 5	Seq 6	Seq 7	Seq 8
p	0.98	0.52	0.80	0.75	0.68	0.45	0.96	0.40
z	0.03	0.64	0.25	0.32	0.41	0.75	−0.04	0.85

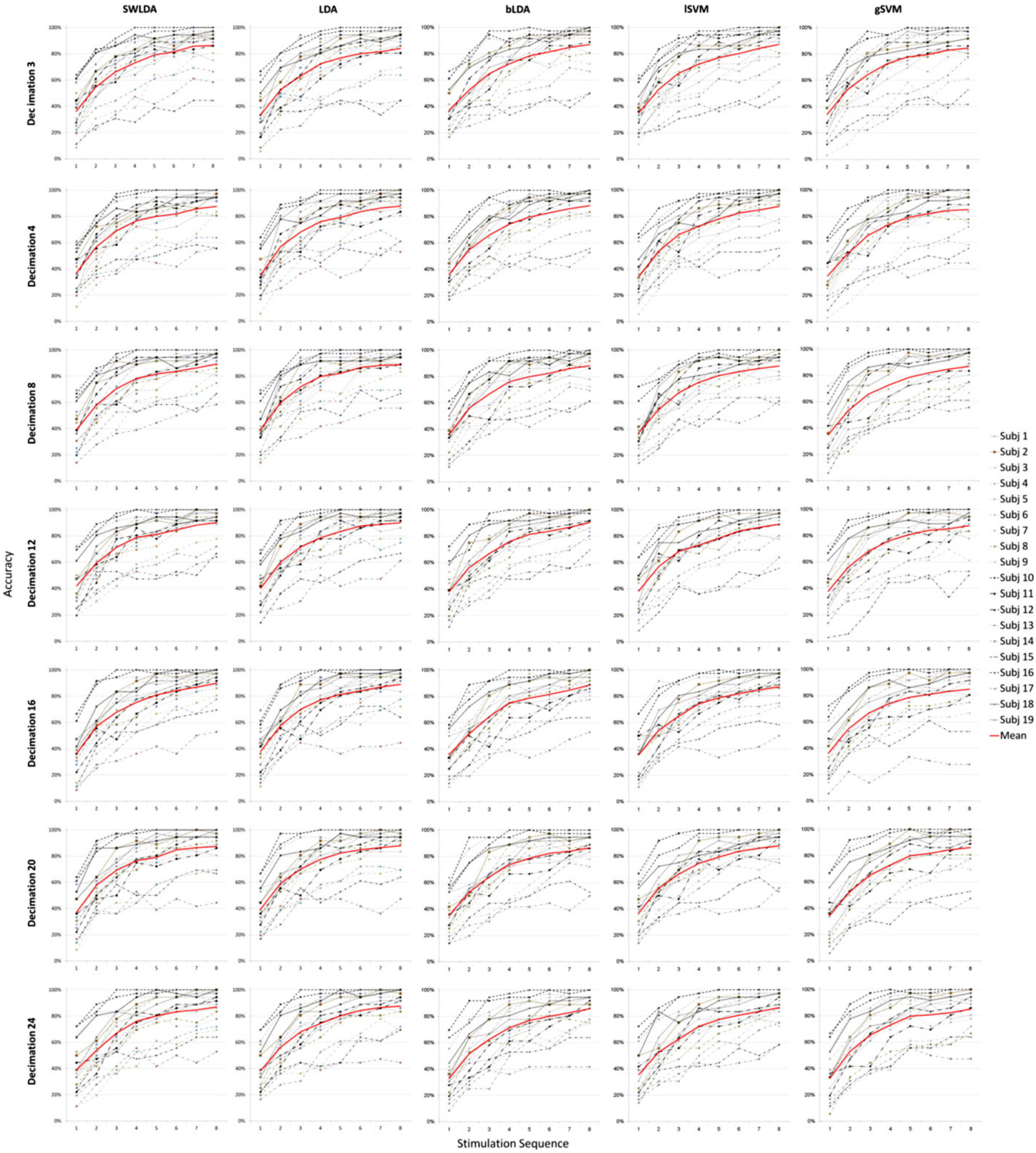

Figure 3. Accuracy values as a function of the stimulation sequence for each subject. Performance is provided for each combination of classifier and decimation factor. Rows corresponds to different decimation values while columns correspond to different classifiers.

4. Discussion

In this work we compared the performance of different classifiers for a gaze-independent BCI based on visual stimuli. The four linear classifiers (SWLDA, LDA, BLDA, LSVM) and the nonlinear one (GSVM) did not exhibit significant differences in performance, contrary to Krusienski *et al*'s (2006) findings. Maybe the lower performance for the GSVM that they reported was due to the data variance, which affected the performance of the classifier. Also we detected an increase in performance with higher decimation factors. Overall, there were no significant differences between the classifiers tested

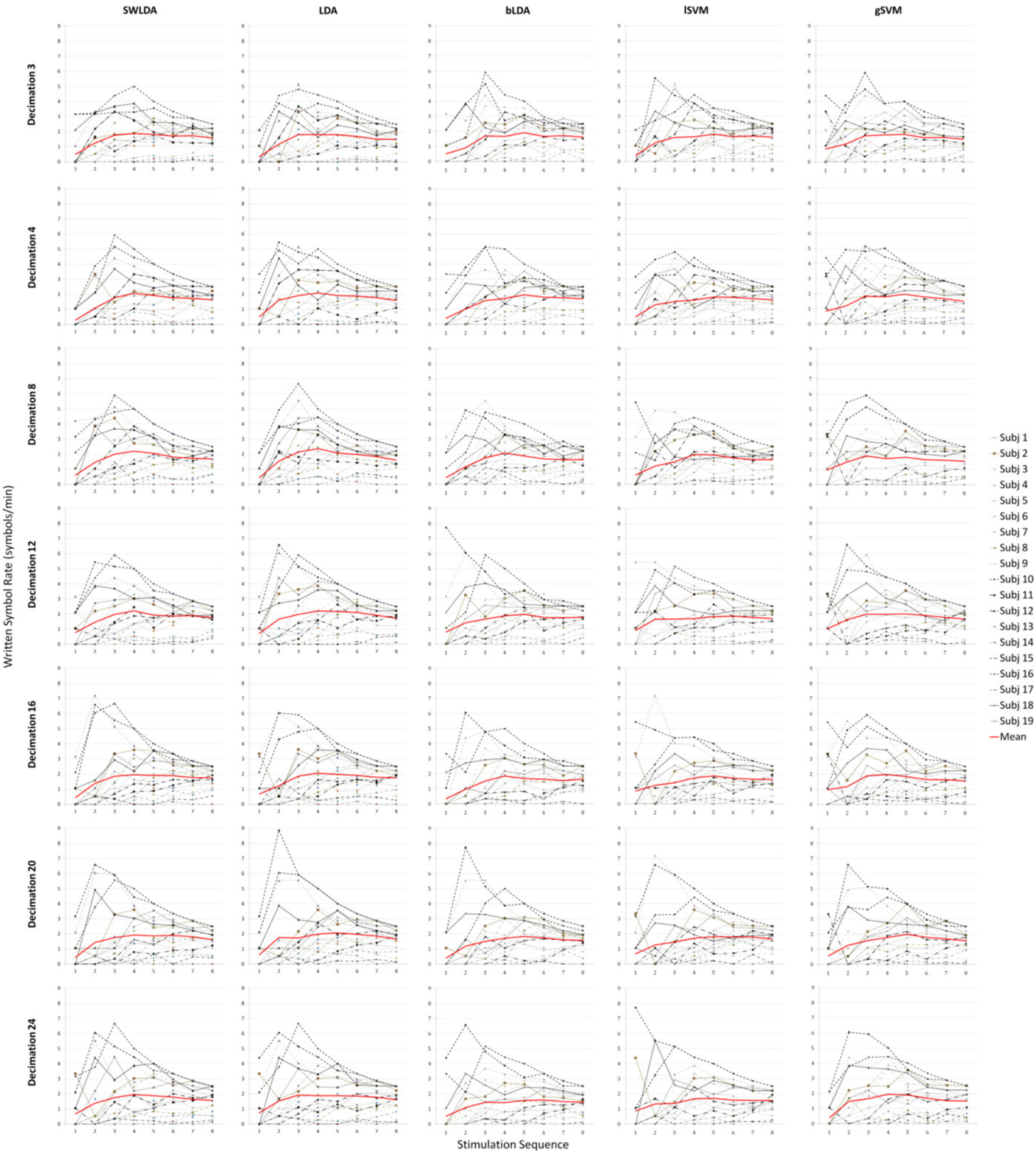

Figure 4. WSR values as a function of the stimulation sequence for each subject. WSR values are provided for each combination of classifier and decimation factor. Rows corresponds to different decimation values while columns correspond to different classifiers.

here, so the reasons to choose one classifier over another are due to their intrinsic features. The LDA is very easy to use; in fact it fits a multivariate normal density in each class, with a pooled estimate of covariance. Also it does not require any parameterization, resulting in rapid training and an implementation with a good level of accuracy. In fact it was successfully used to extract control features for gaze independent BCIs in Treder and Blankertz (2010), Treder *et al* (2011) and in Acqualagna *et al* (2010).

The SWLDA is an efficient classifier since it performs an automatic reduction of the features' space by selecting the most significant features. Furthermore, with respect to the LDA, the

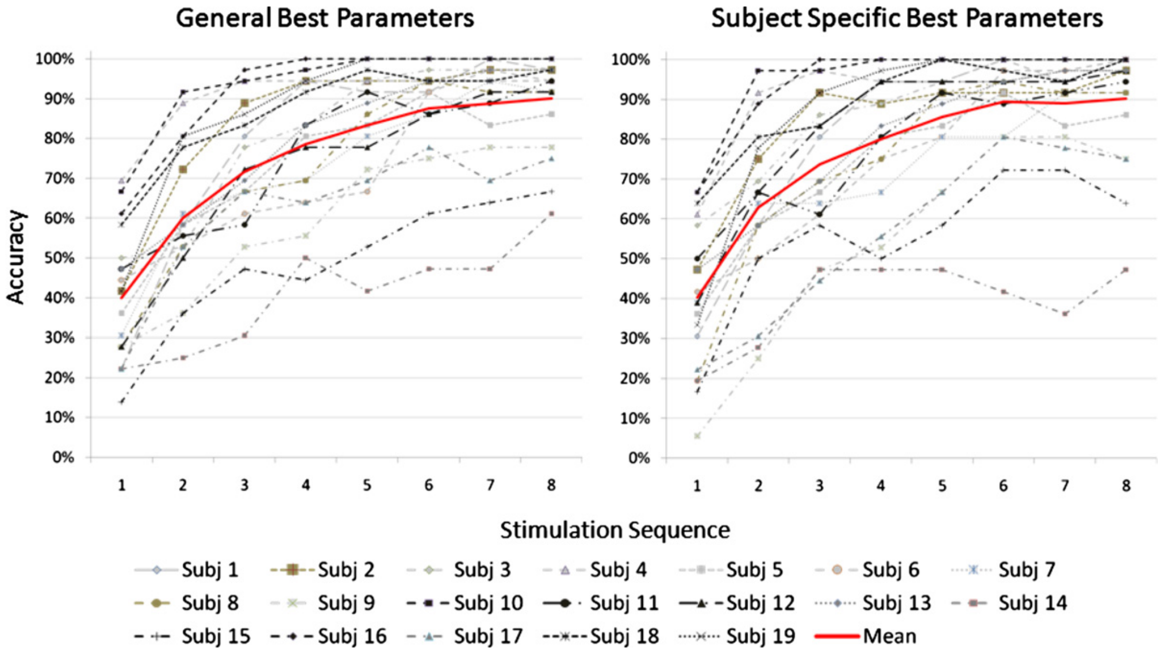

Figure 5. Accuracy as a function of the stimulation sequence for each subject. On the left, performance obtained with the GBPs and on the right, performance obtained with the SSBPs.

results obtained by SWLDA do not deteriorate with large input feature spaces if there is an insufficient number of training observations. It is widely used to extract control features for P300-based BCIs, also for visual paradigms requiring no eye gaze (Aloise *et al* 2012, Liu *et al* 2010). The BLDA is a simple and fast method which prevents data overfitting. Finally, despite the theoretical properties and advantages of SVMs there was no evidence for a better performance using the LSVM and the GSVM with respect to LDA, BLDA, and SWLDA that could justify the higher computational load and time needed for its optimization.

A subjective variation of the best performing parameters was observed among subjects. In this regard, we investigated whether tuning the system with the SSBPs could improve general performance. The results showed that there were no significant differences between the performances obtained with the SSBPs and those achieved using the GBPs for all the subjects. However, looking at single subject performances, the SSBPs allow for higher performances, mainly in terms of WSR. For instance, subject 10 reached 97.2% accuracy with SSBPs after two stimulation sequences, while he needs four stimulation sequences to reach the same level of accuracy with GBPs; also subject 3 never reached 100% accuracy with GBPs but this happened after six stimulation sequences with SSBPs. In the light of these results, despite the optimization of the combination of the classifier and decimation factors and that it is a time consuming procedure, it should still be considered for an independent and long-term usage in the BCI system as an assistive technology where it is extremely important to maximize the system performance and reliability.

5. Conclusion

This work provides a comparison of the different classification techniques for gaze independent P300-based BCIs. Four linear classifiers (LDA, BLDA, SWLDA and LSVM) and one nonlinear classifier (GSVM) were tested with different decimation values. Our results on the classification of data acquired in a covert attention paradigm extend those obtained by Krusienski *et al* (2006) for Farwell and Donchin's P300 Speller used in overt attention: the linear classifiers did not exhibit higher performance with respect to the nonlinear classifier, and no statistically significant differences between the considered classifier's performance were detected. Furthermore, we demonstrated that a generalization across subjects of the best combinations of classifiers and decimation factors does not affect performance.

We conclude that classification of the gaze-independent P300-based BCI is optimized by the same parameters (classifier and decimation) as a gaze-dependent P300-based BCI.

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