Comparison of Vibro-tactile ERPs Classification Methods

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Abstract. Vibro-tactile ERPs were recorded using whole hand stimulation in a classical odd-ball paradigm. Five different classification methods applied to single brain responses were compared off-line to perform a sub-optimal selection of the algorithm for future on-line implementation of a brain-computer interface.
Keywords: ERPs, vibro-tactile, classification, comparison, odd-ball.

1. Introduction

Event-related potentials (ERPs) are currently used to assess clinical/cognitive status of paralyzed and non-responsive patients [Kotchoubey et al., 2003] and to restore basic yes/no communication in severely paralyzed patients [Kübler and Birbaumer, 2008]. Recently, the tactile stimulation has been used with stimulator placements such as waist, fingertips, foot big toe tip and lip [Brouwer and van Erp, 2010; van der Waal et al., 2012; Murguialday et al., 2011] because of compromised vision. Restoring basic yes/no communication, detection of tactile ERPs was usually performed by arbitrarily selecting the classification algorithm. In this pilot study we placed the stimulator for ERPs recording on the palm of one hand (high density of sensory receptors) and we investigated the possibility to make a sub-optimal selection of the classification method to be applied to single-trial non-target and target brain responses (odd-ball paradigm, [Sutton et al., 1965]). At this aim we compared five classifiers for future on-line implementation with feedback: least-squares regression (LS), stepwise regression (SWLDA), logistic regression (LG), genetic algorithm (GA) and support vector machine (SVM) methods were employed.

2. Material and Methods

2.1. Participants

ERPs measurements were carried out on a group of six healthy volunteers (four females and two males, mean age of 33 years, range 27-50 years) and one Amyotrophic Lateral Sclerosis (ALS) patient (33 years old female, ALS-functional rating score 26, [Cedarbaum et al., 1999]). Informed consent was obtained for each participant according with the Declaration of Helsinki.

2.2. Recording Setup and ERP Paradigm

EEG was recorded using 4 Ag/AgCl scalp electrodes (Cz, Pz, P3, P4) according to the International 10–20 System, sampled at 512 Hz (band-pass pre-conditioning filter from 0.1 up to 30 Hz; gUSBAmp, g.tec) by BCI2000 platform [Schalk et al., 2004]. Vibro-tactile stimulation of the hand was provided by the end-effector of a haptic device (Phantom, Sensable). A single stimulus consisted of a sinusoidal force field along the x-axis of the end-effector lasting for 600ms. The force field frequency was set to 20Hz for non-target stimuli and 100Hz for target stimuli, its magnitude was set to 1.5N for both cases. EEG epochs of 1.25s length synchronized with each stimulus (.25s before and 1s after stimulus onset, error smaller than 5ms) were grouped in two classes (non-target and target). Exploiting the classical odd-ball paradigm, a pseudo-random sequence of non-target (probability .7) and target (probability .3) stimuli was presented to each participant with an inter-stimulus interval of 2s. Each participant was asked to grasp the end-effector, close his/her eyes and count target stimuli. Four sequences of 40 stimuli were presented to each participant (i.e. 160 epochs).

2.3. Off-line ERPs Analysis

Off-line classification of brain responses to target and non-target stimuli were performed using the following algorithms: LS, SWLDA and LG methods as implemented in BCI2000; GA as described in Dal Seno et al. (2008); radial-basis function kernel SVM as described in Joachims (1999). To compare the five classification methods, the same set of 32 features was extracted from each single epoch applying the following procedure to every single channel separately: low-pass filtering at 8Hz (order 4, zero-phase), direct current adjustment using pre-epoch interval (.25s) and down-sampling of the post-stimulus interval (1s) with a factor of 16. For each participant a randomly chosen half of the ERPs dataset (i.e. 80 epochs) was used to train the five classifiers, the remaining half to test them. The cross-validation procedure was repeated 50 times for each classifier and for each recorded channel separately. The mean error was estimated by the averaging of the classification errors considering all epochs and repetitions. A two-way ANOVA for repeated measures was performed only on healthy subjects' results considering *channels* and *classifiers* as factors. ALS patient's ERPs classification results were compared to the healthy subjects' results by means of single-case test [Crawford and Garthwaite, 2002]. Averaged ERPs and mean classification errors evaluated at channel Pz are illustrated in Fig.1.

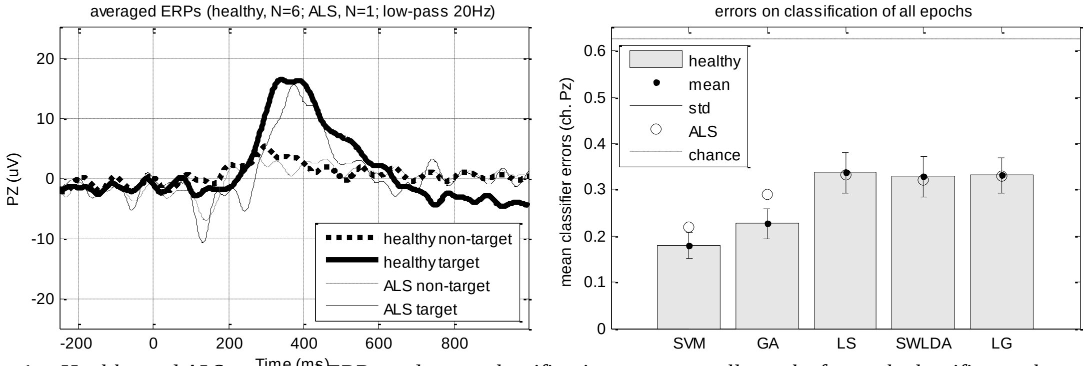

Figure 1. *Healthy and ALS averaged ERPs and mean classification errors on all epochs for each classifier at channel Pz.*

3. Results

ANOVA of mean errors showed a significant main effect of *classifier* ($F(4,100)=73.6;\ p<.001$), but no significant main effect of *channels* ($F(3,100)=.49;\ p=.69$). Contrasts revealed that SVM error estimates were significantly lower than the other four classifiers error estimates (always $p<.001$). Repeated t-test between error estimates of each couple of channels and for each classifier showed non-significant results (Pz was used in later comparisons). Concerning ALS patient ERPs classification results we found no significant differences between error estimates at channel Pz and those of healthy participants (considering each classifier separately).

4. Discussion

The first result indicates that a sub-optimal selection of the classifier is possible. The SVM classification outperformed all others methods. The second evidence indicates that there is no difference concerning the channel selected for feature extraction among the channels used in this experiment since the classification was performed for each channel separately with the same procedure. Hence a single channel could be used to record and classify this type of ERPs. The third evidence is that ALS patient's ERPs can be classified with errors similar to those of healthy subjects.

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