BRAIN COMPUTER INTERFACE
Feedback Effect Analysis by Comparison of Discrimination Capability of On-line and Off-line Experimental Procedures based on LDA

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Abstract: This paper analyses the user's feedback influence in the mental task discrimination capability through the comparison of results obtained from Off-line and On-line Brain Computer Interface experimental procedures. Experiments performed under these two paradigms were carried out by five male volunteers. In order to develop a wearable BCI device only two electrodes in C3 and C4 zones have been used for electroencephalographic signal acquisition. These procedures apply seven different types of preprocessing windows and Linear Discrimination Analysis technique to reduce the dimension of the feature space before the quantification of the discrimination capability between the proposed mental activities.The discrimination capability is quantified through statistical analysis, based on bilateral contrast test, between the population of the LDA transformed feature vectors.

1 INTRODUCTION

The objective of Brain Computer Interface technology is the direct communication of user's mind with external devices, it uses the encephalographic signal as primary source of commands for the external devices (Wolpaw et al. 2000), (Birbaumer, N. et al., 2000), (Wolpaw, 2007). A variety of methods for monitoring brain activity might serve in BCI technology: electroencephalography (EEG), magnetoencephalography (MEG), positron emission tomography (PET), functional magnetic resonance imaging (fMRI), and optical imaging. At present, only EEG meets the requirements of short time constant, affordable cost, and it is relatively simple to implement.

In order to control an external device using thoughts, it is necessary to associate some mental patterns to device commands, so an algorithm that detects, acquires, filters and classifies the human electroencephalographic signal is required (Wolpaw et al., 2002), (Vidal, 1973), (Kostov and Polak, 2000), (Pfurtscheller et al. 2000b). Usually all BCI systems are compounded of the following blocks:

- *Signal Acquisition*. In this block the signal is acquired by the recording electrodes, amplified, and digitalised. BCI devices can be categorised by the different approaches they use for the signal acquisition: non-invasive recordings with standard scalp electrodes, and invasive recording with epidural, subdural, or intracortical electrodes.
- *Signal Processing: Feature Extraction.* The digitalised signals are subjected to feature extraction procedures, such as spatial filtering, voltage amplitude measurements, spectral analysis, or single-neuron separation (Lopes da Silva, 1999).
- *Signal Processing: The Translation Algorithm.* It translates the signal features into device commands-orders that carry out the user's intent.
- *The Output Device.* Generally the output device is a computer screen and the output is the selection of targets, letters, or icons presented on it. Initial studies are exploring BCI control of a neuroprothesis that provides hand closure to people with cervical spinal cord injuries(Pfurtscheller et al., 2000a).
- *The Operating Protocol.* It is the protocol that guides the operation of the BCI device.

BCI devices fall into two classes: dependent and independent (Chiappa, 2006). A dependent BCI does not use the brain's normal output pathways to carry the message, but activity in these path-ways is needed to generate the brain activity that does carry it. An

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independent BCI does not depend in any way on the brain's normal output pathways.

This paper focus on the user's feedback influence in the discrimination capability of three different mental activities, it analyses the applicability of LDA to BCI and how the windowing effect affects the discrimination capability of the brain proposed activities.

Section 2 describes the Off-line and On-line experimental procedures applied to evaluate the user's feedback influence (Martinez and Barrientos, 2007); because the main changes in brain activity are associated to changes in the power amplitude of frequency bands, spectrograms based on FFT are used to obtain initial feature vectors. To minimise the leakage effect seven types of preprocessing windows has been considered: rectangular, triangular, Blackman's, Hamming's, Hanning's, Kaiser's and Tukey's (Proakis and Manolakis, 1997), (Allen and Rabiner, 1977). The evidence of statistical difference in the feature populations associated to different brain activities has been previously shown (Martinez and Barrientos, 2006). In the experiments considered for this report a low number of scalp-electrodes has been used to capture the electroencephalographic signal, in order to facilitate the use of this technology it is important to make it easy to use, as the fewer of electrodes used, the higher the comfort, (Wolpaw, 2007).

Section 3 describes the LDA technique used to combine these initial features in order to reduce the dimensionality of the input space (Ripley, 2000).

Section 4 explains the bilateral contrast test used to determine the discrimination power between the proposed cerebral activities and the effect of the preprocessing windows, the results of each contrast is both qualitative and quantitative, qualitative in order to accept or reject the null hypothesis of equality in the population of features, quantitative in order to compare the discrimination power through significance contrast level $\alpha = 1 - p = 2.5\%$.

Sections 5 and 6 present and analyse the results.

Section 7 is devoted to conclusions.

2 EXPERIMENTAL PROCEDURES

Off-line and On-line tests were carried out on five healthy male subjects, one of them has been trained before, but the other four were novice in the use of the system. The Off-line tests have been carried out before On-line tests in order to have data to allow the training procedure of a simple classifier. The subjects were sat down in front of the acquisition system monitor, at 50 cm from the screen, their hands were in

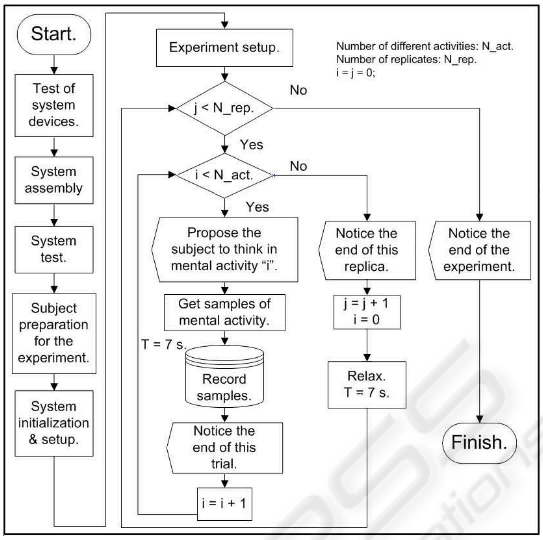

Figure 1: Diagram of the Off-line experiment realization.

a visible position, the supervisor of the experiments controlled the correct development of them (Neuper, 2001), (Penny et al., 2000).

2.1 Procedure for Off-line Experiments

The experimental Off-line process is shown on fig.1.

Test of system devices. Checks the correct level of battery, and the correct state of the electrodes.

System assembly. Device connections: superficial electrodes (Grass Au-Cu), battery, bio-amplifier (g.BSamp by g.tec), acquisition signal card (PCI-MIO-16/E-4 by National Instrument), computer.

System test. Verifies the correct operation of the whole system.

Subject preparation for the experiment. Application of electrodes on subject's head. It is verified that electrode impedance was lower than 4 KOhms.

System initialisation and Experiment setup. Verification of data register. The supervisor sets-up the number of replications, $N_{rep} = 10$, and the quantity of different mental activities, $N_{act} = 3$. The duration of each mental activity, a trial, is $t = 7s$, the acquisition frequency is $f_s = 384Hz$. The system randomly suggests the mental activity to think about.

2.2 Procedure for On-line Experiments

In these tests, a cursor in the centre of the screen and a square goal are shown to the subject, the square goal appears half the trials on the left of the screen and the other half on the right. The subject shall try to move the cursor towards the goal thinking in the cerebral ac-

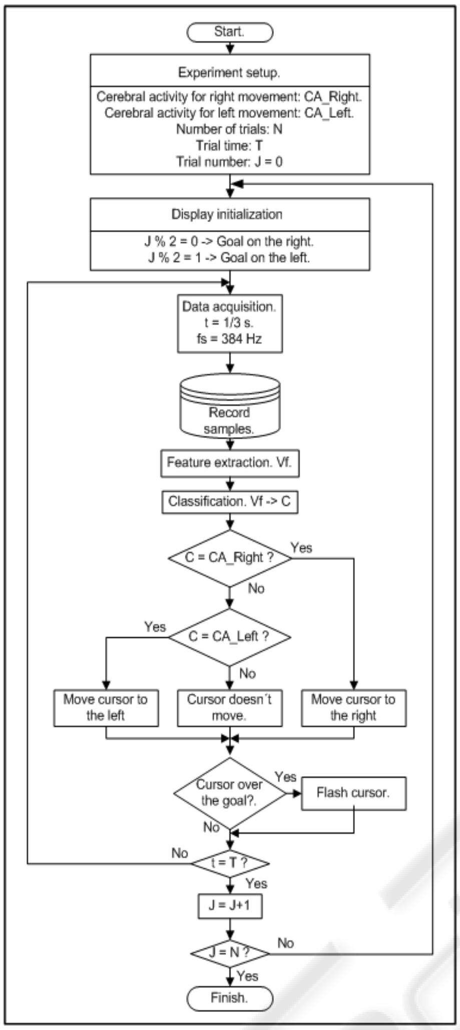

Figure 2: Diagram of the On-line experiment realization.

tivities proposed in the Off-line experiments.The experimental On-line process is shown on fig.2.

Experiment set-up. In this phase it is determined which cerebral activities are used to move the cursor to the left and to the right, the number of trials and the time for each trial.

Display initialisation. It initialises the display, for even trials the goal is on the right, for odds on the left.

Data acquisition. In this phase 128 samples per channel are acquired at $fs = 384Hz$.

Record samples. The previous samples are recorded for a posterior analysis.

Feature extraction. A vector of features is extracted from the acquired samples.

Classification. The vector of features is classified as belonging to one of the previous cerebral activities, and the associated movement is performed.

Figure 3: Electrode placement.

2.3 Position of the Electrodes and Description of Cerebral Activities

For both types of experimental procedures, the electrodes were placed in the central zone of the skull, next to C3 and C4, two pair of electrodes were placed in front of and behind of Rolandic sulcus, this zone is one with the highest discriminant power, it takes signal from motor and sensory areas of the brain (Penny et al., 2000),(Pfurtscheller et al. 2000b). Reference electrode was placed on the right mastoid, two more electrode are placed near to the corner of the eyes to register blinking.

The supervisor of the experiment asks the subject to figure out the following mental activities, these activities will be the tasks to differentiate among them.

Activity A. Mathematical task. Recursive subtraction of a prime number from a big quantity.

Activity B. Motor imagery. The subject imagines moving their limbs or hands, but without the materialisation of the movement.

Activity C. Relax. The subject is relaxed.

2.4 Feature Selection

For Off-line experiments the registered signal is chopped in packages of samples, similar to the bundles of samples obtained from the acquisition card in the On-line cases. Each package has 128 samples, acquired at $f_s = 384Hz$. A vector of six features is extracted from each package, see table 1, this vector is made up as the mean of the amplitudes of the frequency bands (Proakis and Manolakis, 1997), (Neuper, 2001).

Because the frequency of normal human brain is under 40-50Hz, only frequencies between 6 and 38Hz have been considered.

Table 1: Feature vector.

Index	Denomination.	Frequency (Hz).
1	θ.	6 - 8
2	α_1.	9 - 11
3	$\alpha 2$.	12 - 14
4	β_1.	15 - 20
5	β_2.	21 - 29
6	β_3.	30 - 38

3 LINEAR DISCRIMINANT ANALYSIS PROCEDURE

3.1 Introduction

Supposed C classes of observations, Linear Discriminant Analysis is a preprocess technique that finds the transformation matrix W which separates in an optimal way two or more classes. It is used in machine learning as linear classifier or as a technique to reduce the feature space dimension before the classification process. LDA considers maximising the following objective:

$$J(W) = \frac{W^T S_B W}{W^T S_W W} \tag{1}$$

where S_B is the between classes scatter matrix and S_w is the within classes scatter matrix, the definitions of the both matrices are:

$$S_B = \sum_c N_c(\mu_c - \bar{x})(\mu_c - \bar{x})^T \tag{2}$$

$$S_W = \sum_c \sum_{i \in c} (x_i - \mu_c)(x_i - \mu_c)^T \tag{3}$$

$$\mu_c = \frac{1}{N_c} \sum_{i \in c} x_i \tag{4}$$

$$\bar{x} = \frac{1}{N} \sum_i x_i = \frac{1}{N} \sum_c N_c \mu_c \tag{5}$$

and N_c is the number of samples in class c.

Because J is invariant to rescaling of the vectors $W \to \alpha W$, hence it is possible to choose W such that the denominator is $W^T S_W W = 1$. So the problem of maximising J can be transformed to the following constrained optimisation problem,

$$min_W \quad -\frac{1}{2} W^T S_B W \tag{6}$$

$$s.t. \quad W^T S_W W = 1 \tag{7}$$

corresponding to the Lagrangian,

$$L_P = -\frac{1}{2} W^T S_B W + \frac{1}{2} \lambda (W^T S_W W - 1) \tag{8}$$

With solution (the halves are added for convenience):

$$S_B W = \lambda S_W W \Rightarrow S_W^{-1} S_B W = \lambda W \tag{9}$$

This is a generalised eigen-problem, and using the fact that S_B is symmetric positive definite and can hence be written as $S_B^{\frac{1}{2}} S_B^{\frac{1}{2}}$, where $S_B^{\frac{1}{2}}$ is constructed from its eigenvalue decomposition as $S_B = U \Lambda U^T \to S_B^{\frac{1}{2}} = U \Lambda^{\frac{1}{2}} U^T$. Defining $V = S_B^{\frac{1}{2}} W$ it is get

$$S_B^{\frac{1}{2}} S_W^{-1} S_B^{\frac{1}{2}} V = \lambda V \tag{10}$$

this is a regular eigenvalue problem for a symmetric positive definite matrix, with solutions λ_k as eigenvalues and V_k as eigen-vectors, which leads to solution:

$$W = S_B^{-\frac{1}{2}} V \tag{11}$$

Plugging the solution back into the objective $J(W)$, it is found that the desired solution which maximise the objective is the one with largest eigenvalues.

3.2 Operational Procedure

1. Samples from each mental tasks are obtained.
   X_a Mathematical Activity.
   X_b Movement imagination.
   X_c Relax.
2. Population statistical definitions: $(i = a, b, c)$.
   $$\bar{\mu_i} = E[x_i] \quad S_i = E[(x_i - \bar{\mu_i})(x_i - \bar{\mu_i})^T] \tag{12}$$
3. Calculation of the scattering matrices (eq.2 & 3).
4. Application of LDA optimising criterion (eq.10).
5. Calculation of the transformation matrix, W (eq.11), formed by the eigen-vectors, V_k, which eigen-values are bigger than $1 * 10^{-4}$ ordered form high to low magnitudes.
6. Transformation of the data sets: $(i = a, b, c)$.
   $$X_i \Rightarrow \quad X_i' = W^T * X_i \tag{13}$$

4 STATISTICAL ANALYSIS PROCEDURE

Bilateral contrasts between two population are used to determine if there is statistical evidence of difference between the population of features obtained from each mental activity. Each component of the vector is considered to determine its significance and separability power. Bilateral contrast makes use of population variance, if the equality of both population variances is rejected it is necessary to apply a correction factor in the degrees of freedom. These contrasts were done for each type of filtering window.

- *Bilateral contrast of two independent normal and homocedastic populations.*

  Null hypothesis H_o vs. alternative hypothesis H_1.
  n_1 : sample size of the first population.
  n_2 : sample size of the second population.
  $\hat{S_1}$: variance estimation of the first population.
  $\hat{S_2}$: variance estimation of the second population.
  T = Student distribution.
  $$H_o : \mu_1 - \mu_2 = \Delta \;\; vs. \;\; H_1 : \mu_1 - \mu_2 \neq \Delta \tag{14}$$

  The variances of the both population are equal but unknown.

$$T_{Exp} = \frac{(\bar{X_1} - \bar{X_2}) - (\mu_1 - \mu_2)}{\sqrt{\hat{S}(\frac{1}{n_1} + \frac{1}{n_2})}} \quad (15)$$

In which $\hat{S}$ is the pseudo-variance of $\hat{S_1}$ and $\hat{S_2}$

$$\hat{S} = \frac{(n_1 - 1) * \hat{S_1} + (n_2 - 1) * \hat{S_2}}{n_1 + n_2 - 2} \quad (16)$$

The zone of H_o acceptance is:

$$T_{Teo} = t_{(n_1+n_2-2, 1-\frac{\alpha}{2})} \quad (17)$$

If $|T_{Exp}| \leq T_{Teo}$ then H_o is accepted, on the contrary H_1 is accepted and H_o is rejected.

5 RESULTS

In figures 4 to 9 are represented the results of the bilateral contrast test for the transformed coordinate X_1 considering the Off-line and On-line experiments. The figures show for each channel (C3'-C3" and C4'-C4"), and for each type of preprocessing window, the results p of the associated probability of the bilateral contrast tests between the mental tasks. In order to represent the dispersion of the results the mode value and bars from 15th to 85th percentile have been used.

6 DISCUSSION

The comparisons between the discrimination capabilities of On-line and Off-line experiments are shown in the figures 4 to 9. From the bilateral contrast test carried out with a significant level of $\alpha = 2.5\%$, $\alpha = 1 - p$, it is obtained that in almost all cases the null hypothesis H_o, which maintains the equality in the populations of the features associated to the mental tasks, shall be rejected for both types of experiments; in the comparison of mathematical task versus motor imagery, p values are lower for the On-line case in both channels and with all types of preprocessing windows than the ones obtained for the Off-line case; the dispersion of the results is similar in both experiments. It is also shown that for X_1, channel C4'-C4" performs better than C3'-C3". The best results are obtained for X_1 with Tukey's and Kaiser's windows.

The highest contrast power is obtained in the comparison of *Motor imagery* vs. *Relax*, it is followed by *Mathematical task* vs. *Relax*, and the lowest is for *Mathematical task* vs. *Motor imagery*.

In all cases only two eigen-values have got significant magnitudes, so only two eigen-vectors have been considered in the transformation matrix. This causes that LDA technique had projected the original six dimensional feature space over a bidimensional space, weighting the power amplitude of the frequency bands and maintaining the intrinsic characteristics of each cerebral activity.

7 CONCLUSIONS

In this paper has been estudied the user's feedback influence in BCI technology by analyzing the discrimination capability obtained under the Off-line and On-line experiments carried out with five male volunteers, the results indicate that it is possible to differentiate between the proposed mental tasks under the On-line paradigm, but also that the discrimation capability is a bit lower ($< 0.3\%$) than the one obtained under the BCI Off-line case, (Pineda et al., 2003).

Because the experiments have been carried out only with five volunteers these preliminary conclussions have to be corroborated with more tests.

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APPENDIX

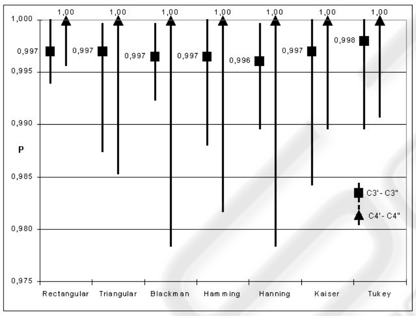

Figure 4: Off-line. Math task vs. Motor imagery. Coordinate X1.

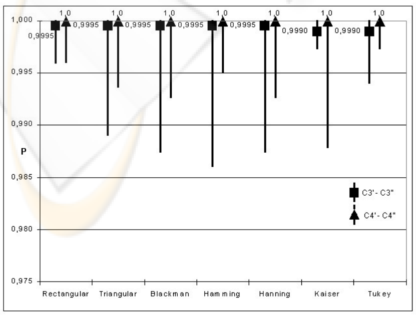

Figure 5: Off-line. Math task vs. Relax. Coordinate X1.

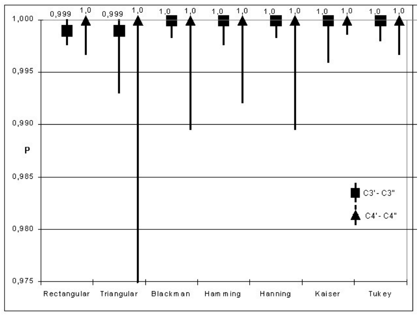

Figure 6: Off-line. Motor imagery vs. Relax. Coordinate X1.

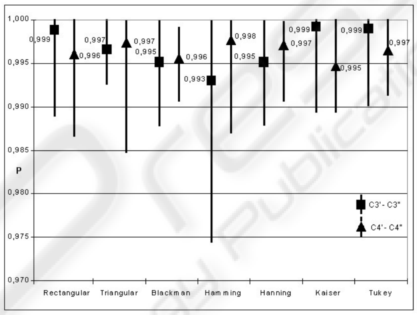

Figure 7: On-line. Math task vs. Motor imagery. Coordinate X1.

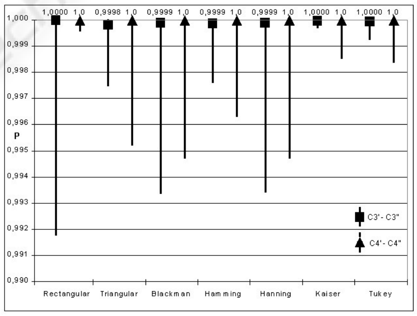

Figure 8: On-line. Math task vs. Relax. Coordinate X1.

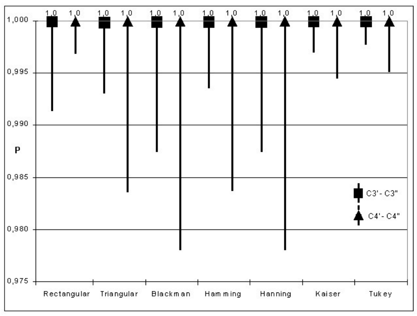

Figure 9: On-line. Motor imagery vs. Relax. Coordinate X1.