A four command BCI system based on the SSVEP protocol

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Abstract – **This paper discusses the development of a four command BCI system. This system is composed of a wearable electroencephalogram acquisition unit interfaced to a computer by a wireless Bluetooth® (BT) connection. The implemented system relies on the SSVEP protocol applied to a four selection system. In order to achieve the maximum reliability against false positives a five class classifier was used considering the idle state as an independent class. In order to maximize the usability of the system a two channel solution was tested and adopted. The BCI algorithm was based on a supervised multi-class classifier implemented by combining different binary Regularized Linear Discriminant Analysis (RLDA) classifiers. The biofeedback was evaluated by combining the resultant time signed distance with quality index related to the number of coherent identification obtained with the one-vs-all approach.**

I. Introduction

THE purpose of a Brain Computer Interface (BCI) is the establishment of a direct connection between the human brain and a computer in order to provide an alternative and enhanced communication channel capable to restore the interaction with the surrounding environment for people affected by heavily disabling pathologies.

The visual evoked potential (VEP) is an electrical potential generated in the brain and recorded from the occipital region of the scalp after the presentation of a visual stimulus: when the stimulus repetition rate is higher or equal to 6 Hz, the evoked response appears as a periodic activity. This activity increases the power spectral density (PSD) in correspondence to the integer multiples of the stimulus flashing frequency: this particular type of brain response is known as steady-state visual evoked potential.

The development of a four class BCI system, based on the SSVEP protocol, is presented here. Although 2 class SSVEP BCI systems are already diffused an have been widely proposed in the literature [1,8], only few studies have been presented for multi-class interfaces [2]. The innovative aspect of this research is that to provide a portable, wearable and user-oriented BCI system able to discriminate four different control commands. This feature is a big step forward in the efficiency and the usability of such an interface.

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II. Materials and Methods

Considering the Human-machine Interface (HMI) as a control loop, several hardware (HW) and software (SW) components have been designed and integrated in order to realize a multi-class wearable BCI system [4]:

- a wearable device for EEG signal recording. The EEG signal is recorded by means of standard Ag/AgCl electrodes. The communication to the host PC is achieved by a Bluetooth® (BT) connection;
- a stimulation system composed of small sized light sources which can be easily applied to a standard LCD monitor;
- a three states protocol composed of a training, meta-training and validation phase;
- a BCI software composed of a C++ core which can control and communicate to the mathematical engine (MATLAB®, Mathworks Inc., Massachusetts, USA) for the offline analysis of the data acquired and for the single-sweep online classification of the signal.

A. *The input device: Kimera*

A 12 bit signal conversion was performed at 250sps through a miniaturized wireless transmission board, based on ARM® CPU and BT transmission [4]. Two analog front-ends were devoted to the amplification and the filtering of the signal using a simple 3.3V supply voltage [3]. The EEG signal was collected by means of standard Ag/AgCl electrodes applied using standard gels. The signal was acquired from the primary visual cortex by means of two bipolar channels placed on O1 and O2 position each referenced to the contralateral earlobe.

B. *The BCI software: Bellerophonte*

Bellerophonte was characterized by multithreaded modular functions which made it suitable for the implementation of many different protocols using the same HW acquisition system. A GUI module was created in order to provide information, biofeedback and protocol management through a graphic user interface. A specific function was developed in order to reduce the maximum desynchronization between the signal and the GUI generated triggers within four samples. A thread was dedicated to the communication with the mathematical engine and to route the response of the algorithm to the appropriate module. A specific callback function was invoked by the Windows® multimedia timer and controlled the user's stimulation circuitry.

C. Stimulation device

The visual stimulation system consisted of four cubic spotlights with sides of 2 cm, each cube can be attached to the four sides of a standard monitor, allowing the user to ideally associate each light to a simple direction: up, down, left or right. Each light included a high efficiency green (wavelength 500nm) led. In order to avoid direct exposition to the light and to diffuse the light beam in a more efficient way, we used a matt film to close the exposed face of the cube. The device accepted up to 8 LEDs and ensured the possibility to adjust their intensity.

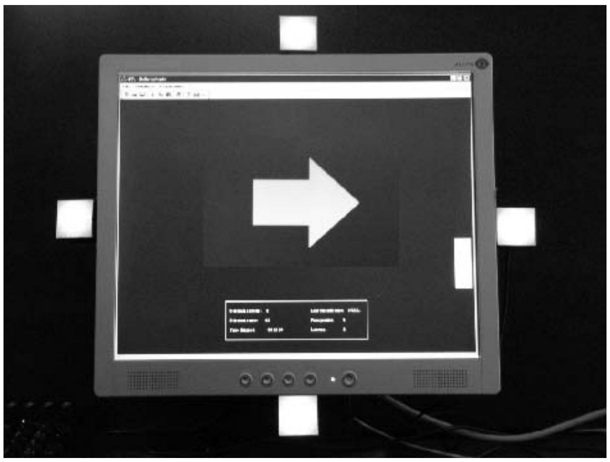

Fig 1. The GUI and the stimulation unit during the meta-training phase

D. The protocol

Our system was based on a supervised translation algorithm and the protocol adopted consisted of three main functioning modes:

- Training mode;
- Meta-training mode;
- Testing mode.

The first mode acted as a data acquisition stage in order to record useful information for the later training of the supervised classifier. The interface guided the user through the training phase inviting him, by means of vocal instructions and a mobile cue at the centre of the screen, to gaze alternatively at the different light sources.

We provided two main alternative structures for the training session: *consistent* and *partitioned*. Each structure scheme and the corresponding partial and total durations are summarized in Fig. 2.

The main advantages of a partitioned training structure consisted in the provision to the classifier of more information regarding the signal, during the onset and offset of each stimulus. Moreover it allowed the training of the classifier on data evoked by the same stimulus, but acquired during different time periods. It is worth noting that this particular training structure also led to less tiring sessions, helping the user to maintain a stable concentration.

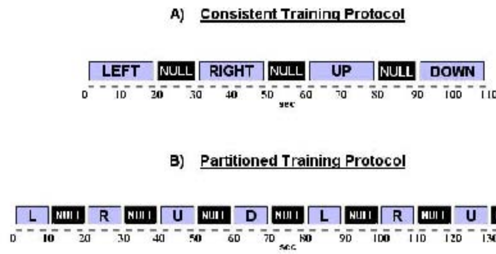

Fig 2. Training session structures. The training session can be consistent or partitioned

Meta-training Mode: in this configuration the system had been trained on the basis of the signal acquired during the previous stage, consequently it was ready for a real-time classification while the user is still guided by the BCI software. The user was asked to focus his attention on a particular light source while the signal was processed and identified continuously by the online translation algorithm. The switching from one stimulus to another occurred only after the system identified a command related to the actual target source. Together with the current estimated command (LEFT, RIGHT, UP, DOWN, NULL), the number of false positives and correct assignment were presented and continuously updated by the GUI.

Four level bars were placed in correspondence to each stimulus (Fig.1) providing a biofeedback that acted as a quality and reliability index of the elicited signal identification.

False positive occurrence caused by the physiological time of reaction in stimulus fixation onset and offset and by the windowed data analysis was avoided introducing a latency between different classifications. In such period all the lights were switched off and the classification was not performed.

During this protocol stage the performances were evaluated on the basis of a system configured using only the training set. It was possible to use the acquired meta-training data-set in order to integrate the training data. As a matter of fact the meta-training data-set is unbalanced and contains more data regarding commands that were difficult to identify.

Testing Mode: the BCI system performs a continuous real-time classification of the signal, translating the estimated intention in a control command. In this configuration both stimuli related biofeedbacks and latency were active.

E. The classification algorithm

At the end of each training session the reliability of the acquired training set was evaluated by means of an offline analysis, aimed at obtaining a preliminary and quick assessment of the performances. For each portion of the dataset related to a particular light stimulation and EEG channel, the system returned a report including:

- an analysis in the frequency domain by means of a Welch's average periodogram method referred to non-stimulus data subset. Window amplitude and overlap values were similar to those used in the latter single-sweep identification;

- a joint Time-Frequency Analysis (JTFA) referred to the baseline correspondent to the non-stimulus data subset and represented by means of a colormap;

- effect-size (ES) values related to the local power spectral densities (Local-PSDs [4]) centered on the first three harmonics of each stimulus frequency, computed using SSVEP data as an experimental group and non-stimulus data as the control group. The ES values obtained were evaluated according to an empirical previously defined quality scale.

At the end of the offline analysis it was possible to specify which harmonics to consider during the training and the classification stages in order to maximize the reliability of the information.

The single-sweep signal processing and identification block included the following main steps:

F. Signal preprocessing

The signal was high-pass filtered at 2Hz in order to avoid baseline fluctuations and to guarantee the typical SSVEP response band (>6 Hz). It was also possible to activate an adaptive filtering (Adaptive Line Enhancer) with coefficients adjusted according to the LMS method. This allowed to highlight the typical SSVEP periodic components hidden in the basal activity and to obtain a better SNR [6];

G. Feature extraction

The PSD of the convolution of the signal acquired from the two channels was calculated on a window of predefined size. The local-PSDs centered on the harmonics of interest of each stimulation frequency were combined point-to-point in order to limit the number of features for each stimulation frequency and to consider the information from multiple harmonics. The bandwidth of the considered local-PSDs was chosen accordingly to the effective frequency resolution and consequently to the minimum gap between the flashing frequencies in use and the analysis window size. This approach avoided confusing simple in-band amplitude variations (such as variations in the alpha band related, for example, to relaxation or attention [7]) with the more localized (in frequency domain) SSVEP. Fig 4 shows the mean values of the features during four different frequency stimulation compared to the idling phase. The different pattern of each class demonstrates the features to be consistent for the specific application.

H. The classifier

It consisted of a regularized linear discriminant analysis (RLDA) based on the modified samples covariance matrix method. The RLDA included a boosting algorithm based on a cyclic minimization of the classification error on the training set and an algorithm for outliers rejection. The multi-class identification problem was solved by means of a combination of binary classifiers using a one-vs-all approach. The reliability in classification (feedback) was evaluated by combining the resultant time signed distance on all the boosting cycles with quality index related to the number of coherent identification obtained with the one-vs-all approach. The system was trained in order to identify five different classes referred to as LEFT, RIGHT, UP; DOWN and NULL for the non-stimulus class.

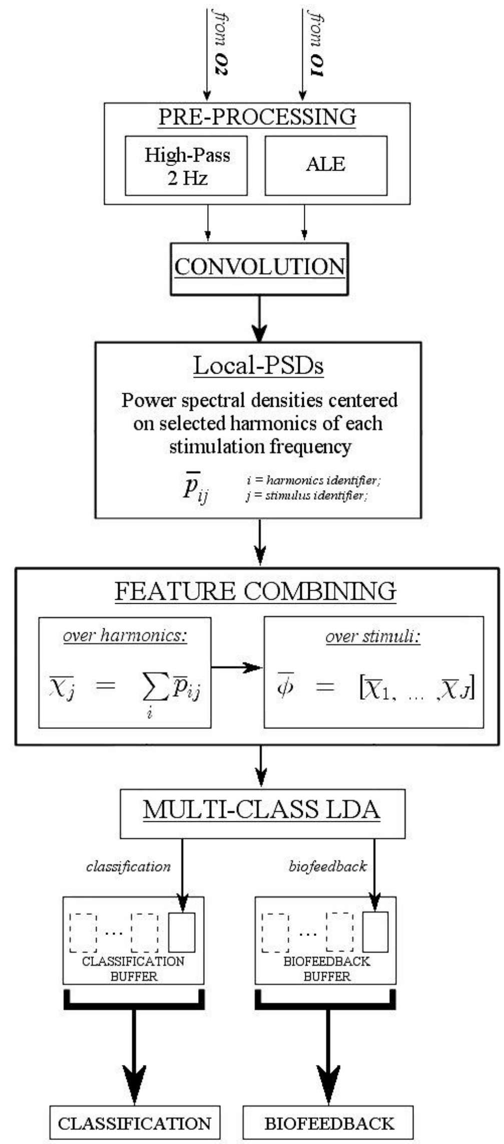

Fig 3. Scheme of the signal proccessing and classification algorithm.

I. Postprocessing on classification outputs:

Two FIFO buffers of predefined length were continuously and respectively updated with the current feedback and classification values. The effective classification and feedback values returned to the user were the results of the time-weighted combinations of the values contained in each buffer. In this way it was possible to analyze a specific portion in the past of the recent classification values in order to enhance the system stability in terms of false positives allowing a smoother perception of the achieved control. In case of uncertainty, the system forced the classification to NULL.

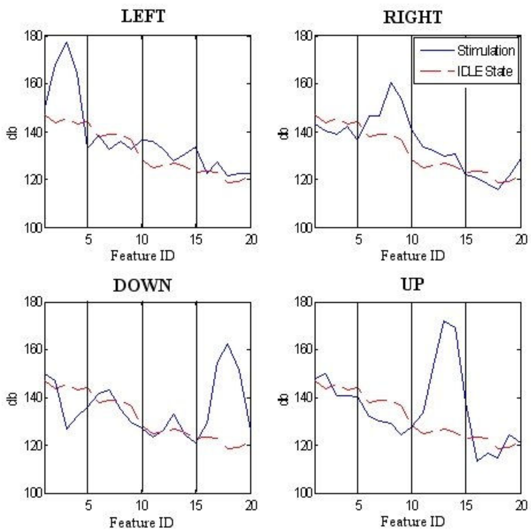

Fig 4. Average values of the features during four different frequency stimulation (6, 7, 8 and 10Hz) referred to the idling state.

III. RESULTS & DISCUSSION

During preliminary tests (5 healthy subjects, 2 females and 3 males), the system showed good robustness against false positives and was able to achieve an accuracy (calculated over the meta-training data-set) between the 80% and 100%. The average speed was of 10-15 commands per minute, depending on the response of the subject to the visual stimulation in terms of number of harmonics and amplitude of the signal. The performance analysis was based on the system control level perceived by the user: the NULL classification was considered as an idling condition so it was not involved in the characterization of the system in terms of accuracy, but it was indirectly considered in terms of speed.
It was also possible to verify the reliability of the stimulation provided by a low end personal computer. Table I shows the frequency confidence interval of each stimulation.

TABLE I
PERFORMANCES OF THE STIMULATION SYSTEM

Nominal stimulation frequency	Mean (Hz)	STD (Hz)
6Hz	5.971	0.042
7Hz	6.996	0.066
8Hz	7.995	0.086
10Hz	9.992	0.151

IV. CONCLUSION & FUTURE WORKS

The aim of this project was to provide a reliable, smart and low cost BCI system. This objective had been achieved by designing a framework for the development, the test and the application of a BCI, based on a wearable EEG acquisition device. Our system was composed of an EEG helmet connected to a control software by a low-power RF connection. The implemented SSVEP protocol lead to an easy to use communication system which required only the application of four electrodes: the four commands based communication provided an increase in communication speed making it possible to control more complex interfaces. The user-friendliness and the low cost of the proposed platform will make it suitable for the development of home BCI applications, and long term application studies.

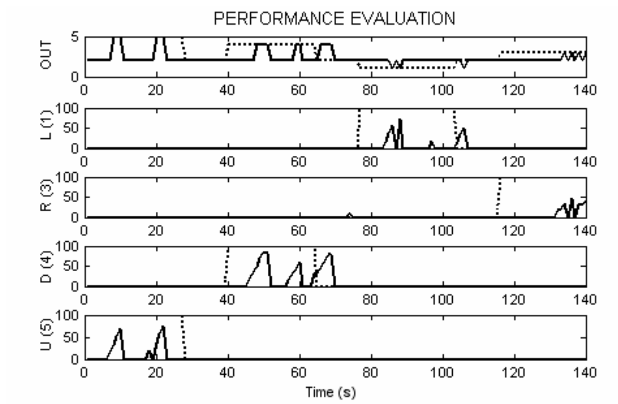

Fig 5. Online testing results during a meta-training phase. In the upper part it shows the real-time traces related to the classification output (solid line) versus the target tasks (dashed line). The returned biofeedback, which indicates the punctual reliability of the instantaneous classification, is shown below. It is possible to notice the switching delay both in the classification and in the biofeedback.

V. REFERENCES

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