Communications

Linear Classification of Low-Resolution EEG Patterns Produced by Imagined Hand Movements

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***Abstract*—Electroencephalograph (EEG)-based brain–computer interfaces (BCI's) require on-line detection of mental states from spontaneous EEG signals. In this framework, surface Laplacian (SL) transformation of EEG signals has proved to improve the recognition scores of imagined motor activity. The results we obtained in the first year of an European project named adaptive brain interfaces (ABI) suggest that: 1) the detection of mental imagined activity can be obtained by using the signal space projection (SSP) method as a classifier and 2) a particular type of electrodes can be used in such a BCI device, reconciling the benefits of SL waveforms and the need for the use of few electrodes. Recognition of mental activity was attempted on both raw and SL-transformed EEG data from five healthy people performing two mental tasks, namely imagined right and left hand movements.**

***Index Terms*—Brain–computer interface(BCI), movement imagination, signal space projection (SSP), surface Laplacian (SL), surface Laplacian electrodes.**

I. Introduction

In the framework of the design of an electroencephalograph (EEG)-based brain–computer interface (BCI), Wolpaw and McFarland's results [1] indicate that EEG patterns are better detected with a surface Laplacian (SL) transformation of signals than with raw potentials. SL-transformed EEG data has been largely used in BCI research, although the accurate computation of SL—i.e., spline methods—requires the use of many EEG electrodes (typically, 40–64), which are available in the so-called high resolution EEG systems [2], [3]. The necessity for a high number of electrodes, however, is in contradiction with the requirements of portability and ease of use that BCI devices must exhibit to allow their operation by laypersons. In this respect, a practical BCI should record scalp potentials with less than ten electrodes, either conventional (low-resolution EEG, with approximate SL estimation) or advanced sensors that directly perform spatial deblurring by hardware [4].

Currently, in the framework of a joint European project, we are developing an Adaptive Brain Interface (ABI) that uses a portable battery-driven system with up to eight electrodes for the detection of several EEG patterns [5]. Two of the directions we have investigated in the first year of this ABI project concern:

i) the use of simple linear classifiers that exploit the reproducibility of EEG patterns related to the imagination of movements;
ii) the effect of SL transformation of EEG data on classification performance.

Other directions, such as the application of local neural networks to cognitive tasks, are addressed in [5]. Here we only report results obtained with a linear classifier based on the *Signal Space Projection (SSP)* algorithm [6] applied to EEG data from a group of five healthy people performing two motor-related mental tasks, namely imagined right and left hand movements. We compare two elemental SSP classifiers, one working with features obtained from SL-transformed data and the second from raw potentials. In addition, we investigate the performance of the SSP classifiers with respect to different frequency bands (either the combined α–β bands or a broad band from 8 to 30 Hz).

II. Methods

A. Signal Space Projection (SSP)

In the SSP method, a n-dimensional space is defined so that a "measure" vector $M(t)$, whose components are features extracted from incoming data, is represented in that space by a point. Given m vectors of n-dimensional "patterns" ($S_1, S_2, \ldots, S_m$), the m components of the "activation" vector:

$$\hat{A}(t) = \mathbf{S}^+ M(t)$$

weight the presence of each pattern in $M(t)$. $\mathbf{S}^+$ is the pseudoinverse of the projection matrix **S** whose columns are the patterns $(S_1, S_2, \cdots, S_m)$.

B. Data Collection and Preprocessing

Five healthy subjects (three males and two females) participated voluntarily in experiments where they performed several mental tasks, including imagination of the movement of the right middle finger (RI) and the left middle finger (LI). The whole scalp was covered with 26 EEG electrodes placed onto standard locations according to the extension of the 10–20 international system. Sampling frequency was 400 Hz, and signal was bandpass filtered between 0.1–100 Hz before digitization. In addition, we recorded ocular and muscular activity to detect possible eye and hand movements.

At the beginning of a recording session, subjects remained in a resting state—relax with eyes opened—for 60 s. The EEG activity of this period is used as a baseline for subsequent analysis of the mental tasks. Then, subjects started performing a given mental task immediately after the operator instructed them to do so, and they maintained that task for more than 10 s. Every subject executed four times each mental task during the recording session, with a resting period of 10 s between each. After removal of 1-s segments contaminated with either ocular artifacts or execution of actual movements, it remains about 40 seconds of EEG signals for every mental task for every subject.

The analytical SL transformation of EEG potentials is computed with a spherical spline of order 2 [3] using raw signals from all 26 channels.

We compute spectrograms (time varying spectra) of either raw or SL-transformed EEG data by estimating the Power Spectral Density (PSD) of 2-s long epochs, each starting 1 s after the previous one. We

Manuscript received August 9, 1999; revised February 28, 2000. This work was supported by the European ESPRIT programme, LTR Project 28193.

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Publisher Item Identifier S 1063-6528(00)04242-7.

TABLE I
DETECTION SCORES FOR RIGHT (RI) AND LEFT (LI) MOVEMENT IMAGINATION TASKS USING THE NINE CHANNELS SET-UP, BOTH FOR SL-TRANSFORMED AND RAW POTENTIALS

Band	Subject	RI(%)		LI(%)	
		SL	raw	SL	raw
α, β bands (6 bins)	Cl01	90	87	64	62
	Mj01	63	61	81	74
	Ra01	87	87	42	42
	Rb01	87	90	80	73
	Ta01	95	84	73	65
	Mean±SD	84±12	82±12	68±16	63±13
8÷30 Hz (23 bins)	Cl01	95	90	59	54
	Mj01	76	68	94	79
	Ra01	94	87	94	77
	Rb01	95	92	83	63
	Ta01	100	84	81	73
	Mean±SD	92±9	84±14	82±14	69±10

use the Welch periodogram algorithm [7] to estimate the PSD. Epochs are divided into segments of 1 s, with a Hann window of the same length applied to each segment, and 50% overlapping between the segments. This gives a frequency resolution of 1 Hz. Finally, the power components are referred to the corresponding values of the estimated PSD of the baseline and transformed in decibels—i.e., we take the logarithm of the division. The resulting values are the features in the present implementation of the SSP method.

C. Estimation of the Patterns

As our objectives are to investigate the SSP method along two different dimensions, each having two possibilities, four different sets of patterns are computed. The first dimension is the use of either raw potentials or SL-transformed EEG data for the computation of the PSD over the nine fronto–centro–parietal channels, namely F3, Fz, F4, C3, Cz, C4, P3, Pz, and P4. The second dimension concerns the frequency bands. The selected power components belong to either a narrowband around α and β peaks (three components per peak) or to a broad one (from 8–30 Hz). The α and β peaks are specific for each subject according to the individual spectral estimate profile. The α and β peaks range between 9–11 Hz and 17–20 Hz across subjects, respectively. In the case of a narrow band, the patterns have 54 features (six power components times nine channels), whereas they have 207 features (23×9) in the case of a broad band.

The pattern describing one of the mental tasks, S_R or S_L, is the mean of the selected components of the PSD computed during the 40 s the subject was imagining the corresponding single movement (right or left). It is worth noting that, for every possible combination, individual patterns S_R and S_L are obtained for every subject. This is a key point of our approach that seeks to develop individual interfaces since not two people are the same either physiologically or psychologically.

The measure vector $M(t)$ has the same kind of features as the patterns, namely the selected components of the current PSD that is computed every second.

D. Classification

The $i^{\rm th}$ mental task is recognized when the maximum of activity of the waveforms $A(t)$ is located on its corresponding component, $A_i(t)$. Dealing with two mental tasks only, the SSP classifier detects an imagined right movement if the activity related to the S–R pattern is greater than that associated to S_L (and vice versa for the imagined left movement). This is probably the most elemental SSP-based classifier one can design. Indeed, the patterns are a simple mean and classification is based on a linear projection. However, despite its simplicity, the results achieved are quite promising.

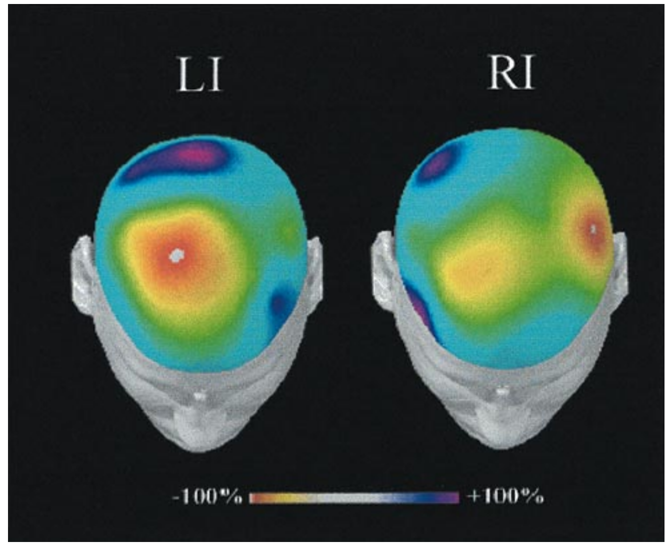

Fig. 1. Representation of patterns in the α band, estimated from spectral SL-transformed data using a 26 channels setup, for the subject RA01.

III. RESULTS

Table I reports the recognition rates of imagined right (RI) and left (LI) movements using the nine fronto-centro-parietal electrodes. Results are shown for each of the five subjects investigated, together with the mean and standard deviation for the four possible SSP classifiers.

The SL-based SSP classifiers achieve the best results for almost all the subjects in both frequency bands. In particular, for the RI mental task the best mean scores are 92 and 84% for SL-transformed and raw potentials, respectively. For the LI mental task the best mean scores are 82 and 69% for SL-transformed and raw potentials, respectively.

Concerning the influence of the frequency band in the performance of the SSP classifiers, in most cases the use of the broad frequency band outperforms the combined α–β bands.

IV. DISCUSSION

This study has shown that nine electrodes, placed over fronto–centro–parietal areas, are sufficient to detect two mental states related to imagined movements with the SSP technique. This is a promising result that opens the possibility to deploy BCI outside laboratory settings. In addition, the study has also demonstrated that the use of SL-transformed data improves the recognition rates of such mental states with respect to raw EEG potentials. Since an accurate SL estimate from raw potentials needs many electrodes, it may be argued that there is a contradiction with the previous requirement of using as few electrodes as possible. Physical SL electrodes resolve this tradeoff [8]. Such SL electrodes are evaluated elsewhere [4]. Briefly, there exists a strong correlation between signals gathered by SL electrodes and software SL computed on Somatosensory Evoked Potentials (SEP).

Our results indicate that recognition is easier if the patterns are obtained from a broad frequency band rather than from only the combined α–β bands. These results are in agreement with Pfurtscheller and coworkers' recent observation in which the optimal band selection for the detection of motor-related mental tasks is the band from 8 to 30 Hz [9].

Fig. 1 illustrates one of the patterns computed by means of the SSP method. In order to facilitate visual interpretation, the pattern has been derived from all 26 electrodes. Also, for the sake of simplicity, only the features related to the α peak are visualized. The figure shows the distributions of the features in the subject RA01 for the imagined right and left movements when using SL-transformed potentials.

The simplicity of the classifier we have utilized suggests that it is still possible to increase the recognition rates if SSP is combined with more powerful classifiers. In particular, SSP can be used either as a preprocessor for an artificial neural network, or to classify data using patterns obtained through Self Organizing Maps. This is subject to ongoing research.

Results obtained in this first year of the ABI project also indicate that SL electrodes return waveforms correlated with the numerically computed surface Laplacian. A new design of these electrodes, which is easier to place and less noisy, is under study. In the context of a Brain Computer Interface a few SL electrodes can improve the quality of the acquired signals.

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A Virtual Reality Testbed for Brain–Computer Interface Research

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***Abstract*—Virtual reality promises to extend the realm of possible brain–computer interface (BCI) prototypes. Most of the work using electroencephalograph (EEG) signals in VR has focussed on brain–body actuated control, where biological signals from the body as well as the brain are used. We show that when subjects are allowed to move and act normally in an immersive virtual environment, cognitive evoked potential signals can still be obtained and used reliably. A single trial accuracy average of 85% for recognizing the differences between evoked potentials at red and yellow stop lights will be presented and future directions discussed.**

***Index Terms*—Brain–computer interface (BCI), P3, virtual reality (VR).**

I. INTRODUCTION

Recent brain–computer interface (BCI) work has shown the feasibility of online averaging and biofeedback methods in order to choose characters or move a cursor on a computer screen with up to 95% accuracy [1]–[4]. Previous research in virtual reality (VR) has looked at brain–body actuated control [5] or steady state visual evoked potentials [6]. VR promises to extend the realm of possible BCI prototypes through allowing individuals to interact directly with an environment rather than a computer monitor while still maintaining the environmental control necessary in research. The safety of VR also makes it an excellent candidate for BCI research on real-time tasks and VR can serve as a motivational tool for people because it is often perceived as an interesting environment.

BCI's are most often used for augmentative communication by individuals with locked-in syndrome. The P3-evoked potential (EP) is a positive waveform occurring approximately 300–450 ms after an infrequent task-relevant stimulus [7], [8]. It has been shown that even when the P3 evoked potential (EP) component disappears after a brain stem injury, it can be regained [9]. Thus, this particular EP is a widely available signal that does not heavily depend on the problems of a particular patient.

II. MATERIALS AND METHODS

A. The System

The VR environment is rendered on a SGI Onyx. For immersion, subjects wear a binocular head-mounted display (HMD) containing a camera-based eye tracker. While collecting EEG data, eye tracking data is also collected and overlaid onto a videotape of the virtual scene. This dual data collection enables a comparison of what an individual is looking at with what the BCI is doing and can be used to find BCI recognition errors that could not be found by looking at the EEG data alone.

The heart of this system is the NeuroScan commercial package on a Pentium PC. A dynamic linked library (DLL) provided by NeuroScan enables locally written software to have access to all unprocessed data

Manuscript received August 2, 1999; revised January 25, 2000. This work was supported by the NIH/PHS under Grant 1-P41-RR09283, by the National Physical Science Consortium Fellowship, and by a stipend support from NASA Goddard Space Flight Center.

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Publisher Item Identifier S 1063-6528(00)04110-0.