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Neuroelectrical source imaging of mu rhythm control for BCI applications

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Abstract— **In the last decade, the possibility to noninvasively estimate cortical activity has been highlighted by the application of the techniques known as high resolution EEG. These techniques include a subject's multi-compartment head model (scalp, skull, dura mater, cortex) constructed from individual magnetic resonance images, multi-dipole source model, and regularized linear inverse source estimates of cortical current density. The aim of this paper is to demonstrate that the use of cortical activity estimated from noninvasive EEG recordings of motor imagery is useful in the context of a Brain Computer Interface as compared with others scalp spatial filters usually used on-line.**

Keywords— **Linear inverse source estimate, High resolution EEG, Brain computer interface.**

I. Introduction

A Brain computer interface (BCI) is a communication system able to discriminate different electroencephalography (EEG) patterns in real time [1]. People can learn to control mu or beta rhythm amplitude over their sensorimotor areas using mental imagery of motor actions to control physical or virtual devices ([2],[3). It has been shown that the application of noninvasive BCI technology is able to include real-time multidimensional movement control [4]. Despite these findings it has been proved that due to bad signal-to noise ratio, EEG-based BCI systems display a drop of classification accuracy when more than 2 mental states have to be classified ([3],[5]). An alternative method is represented by direct implants into the brain for computer control, as discussed by Nicolelis (2001). In this case, we have an excellent signal-to-noise ratio and can classify more than 2 mental states with high accuracy but are confronted with all the problems in connection with a highly invasive system. On the other hand, bioelectromagnetic linear inverse problem solutions has the potential to provide a better insight on the cortical activity as showed by several findings ([6], [7]); however, a verification of the usefulness of such estimates in the contest of a brain computer interface has not been performed yet: in fact, as showed in [8] it is possible to apply inverse problem algorithms during on-line BCI training sessions, but it is not clear if these solutions provide a better classification range than using on-line scalp EEG data.

This study represent the first demonstration of usefulness of LI in the context of a BCI as compared with different scalp spatial filters generally used on-line [9].

II. Methods

<u>The experimental setup</u>

Six subjects (males, mean age 30.2 ± 2.9; subjects S1 to S6) participated voluntarily in experiments in which they underwent a series of recording while were trained to gain control on a mu-rhythm brain computer interface (BCI2000 recording software [1]). One of the subjects (S6) presented a traumatic stabilized lesion located at cervical level. During training, the subjects had been asked to perform hands or feet kinesthetic movement imagination to move a cursor upward or downward respectively, towards appearing targets covering half screen. EEG was recorded by using a high resolution cap with 64 channels that were digitized at 200 Hz and stored for off-line analysis (Brainproducts Vision EEG system, bandpass 0.1-50 Hz before digitization), while a subset of them were used to control cursor movement and were re-referenced to the common average reference (CAR). Online feedback was provided through the BCI2000 software system [1] (the cursor moved horizontally across the screen at a fixed rate, while the user controlled vertical movements), CAR was the spatial filter used for training. Training period was made up of 10 weekly sessions. At the end of training each subject gained an accuracy greater than 75%.

<u>The off-line paradigm</u>

Four different scalp spatial filtering methods, e.g. ear referenced (RAW) potentials, common average reference (CAR), Small (SL), Large (LL) Laplacian as considered from McFarland ([9]) and one cortical linear inverse source estimate (LI) were compared, in term of topographical and spectral analysis of R-square (R2) values, according to the attitude of spatially conditioned EEG segments to predict the target at the beginning and at the end of CAR training. User performance can be defined as the level of correlation between user intent and the signal features the BCI employs to recognize that intent [2]. One useful measure of this correlation is R2. Perfect correlation produces an R2 value of 1.00. This measure proved very useful in choosing the best spatial filter method for extracting mu- or beta-rhythm signal features [9]. To better compare the spatial filters considered, the relationship between R2 values measured on EEG data off-line and accuracy gained from users during on line sessions was achieved using about 200 training sessions

The Linear inverse estimation

For all subjects, 182 sequential MR images were acquired and a three-shell realistic head models were generated with the help of the Curry 4.6 software (Compumedics Neuroscan Ltd., El Paso, Texas). The cortical sources were modelled by using a distributed model with realistic cortical shape ([12]; [13]; [14]).
With this approach, the cortical surface is tessellated into triangles so that the relevant geometric features are preserved and a dipolar source is modelled at each vertex of the tessellation (yielding about 5000 source locations). The orientation of each dipole is constrained to be perpendicular to the surface, to model the alignment of the pyramidal neurons with respect to the cortical mantle. The actual strength of these sources was then estimated by using a linear inverse procedure according to a weighted-minimum norm approach ([13]; [15]).
The full procedure for the estimation of current density strength waveforms has been reported in details elsewhere [10]. Such estimation returns a current density estimate for each of the 5000 dipoles constituting the modelled cortical source space and the pseudo-inverse transformation matrix (**G**) able to transform potentials signals in dipoles current densities only by matrix multiplication. **G** matrix, stored off-line can be used on-line as an input filter of BCI2000 recording software. The regulation parameter, λ, is crucial to the performance of inverse method [11]. To optimize LI solutions we considered different values of regulation parameter (from 0,01 to 100) and selected the one that maximize R2.

The statistical analysis

The off-line obtained results were subjected to separate Analysis of Variance (ANOVA). The main factor of the ANOVAs was the FILTERING factor (with five levels: CAR, RAW, SL, LL, LI). Linear inverse solution was employed with the regularization factor that maximize R2 (λ=1).Separate ANOVAs were performed on the off-line results of the first and the last session of training. The post-hoc analysis with the Scheffe's test at the p = 0.05 statistical significance level was then performed.

The on-line paradigm

All subjects were trained on a vertical task (hands or feet movement imagination to move a cursor upward or downward respectively) after an initial screening. To prove the on-line applicability of LI, we realized an horizontal (left or right hand kinesthetic movement imagination) screening of all subjects and selected the two more promising. Given that one of the more promising subject was the best vertical performer (S6), we used a horizontal task for the first subject (S1) and a two-dimensional for the second one (Fig.1). In both cases the pseudo-inverse transformation **G** matrix stored off-line in the previous step was used as an input spatial filter for BCI2000 software system [1].

Fig.1. Left and right panels are representative of 1-dimensional and 2-dimensional tasks used on-line to test the applicability of linear inverse procedure. In the left panel red cursor move upward at a fixed rate while the user control horizontal movements (towards green targets). In the right panel the cursor is controlled completely by the user.

III. Results

Off-line results

All the spatial filters (CAR, RAW, SL, LL, LI) was compared using the maximum values of R2 taking into account the best usable feature (frequency/channel) for all subjects employed in this study at the beginning and at the end of training. All the best features are related to channels/dipoles above sensorimotor areas as showed in Fig.2. According to the experimental design, the R2 variable was measured and subjected to the ANOVA including the FILTERING factor. Results revealed a strong influence of such factors ($F(4, 20)=20.717$, $p=.000001$). Fig. 3A shows the average plots of the influence of the levels of the main factors FILTERING on the R2. In particular, Fig. 3A shows that the average value of the R2 for the linear inverse (LI) filtering procedure is statistically higher than all the other methods. In fact, post hoc tests performed with Scheffe's procedure, revealed a significant differences in R2 values between the LI method and all the others (see TAB. 1) at least for $p<0.01$. The ANOVA was also performed on the R2 values obtained in the experimental subject for the different values of the regularization parameter. The main factor was the LAMBDA with 9 levels (0.01; 0.1, 1, 2, 4, 8, 12, 50, 100). The ANOVA return a significant effect of the main factor LAMBDA with F = 2,738 and p = 0.016. Post hoc tests performed with the Scheffe's procedure reveals no statistical significant differences between the different values of the Lambda factors. This means that all the chosen lambda return levels of the R2 statistically identical.
The results obtained for the last session were similar. In particular the ANOVA performed on the FILTERING factors return a significance influence of the filtering method on the R2 values (F = 70,1; $p < 0.000001$). Also in this case the linear inverse (LI) procedure performed with a regularization value of lambda equal to 1 return the higher value of R2 between all the other method (Fig. 3B). The Scheffe's test support in the statistical sense this visual impression. In particular, there is a statistical significant higher value of R2 when compared with all the other

methods, with a value of p not less than $p < 0{,}000001$ (TAB.2)

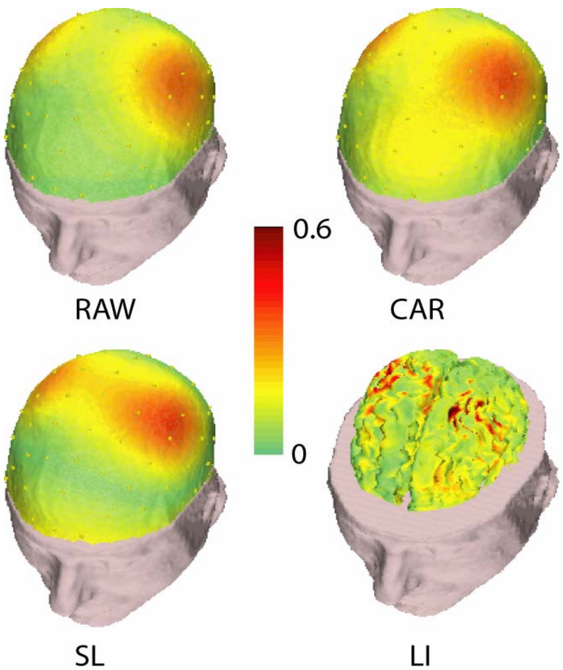

Fig.2. Comparison of topographical distributions of R-square values for a representative subject at the end of training. All maps refer to the EEG frequency that shows the R-square peak for the spatial filters considered.

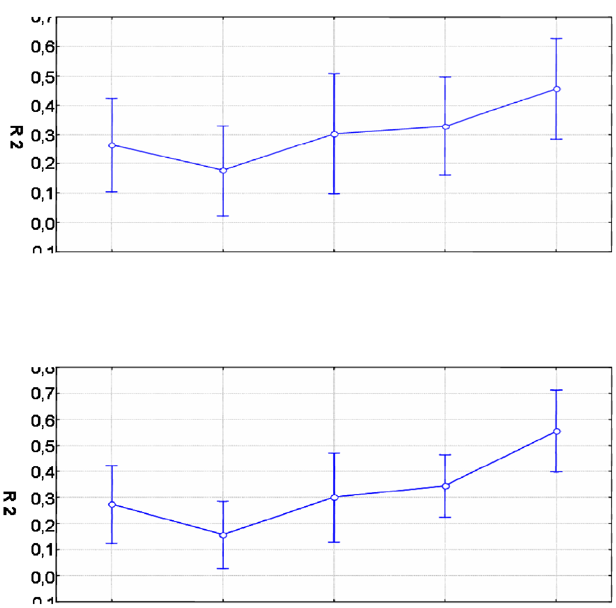

Fig.3. A shows the average value and standard deviation of the R-square for all the six subject and spatial filters considered at the beginning of training. Linear inverse (LI) filtering procedure is statistically higher than all the other methods. In fact, post hoc tests performed with Scheffe's procedure, revealed a significant differences in R2 values between the LI method and all the others (see TAB. 1) at least for $p<0{,}01$.

B) The results obtained at the end of training was similar. Also in this case the linear inverse (LI) procedure performed with a regularization value of lambda equal to 1 return the higher value of R2 between all the other method. The Scheffe's test support in the statistical sense this visual impression (see TAB. 2)

For the last session data, the ANOVA performed on the comparison of the R2 values for the regularization issues returned the same information obtained for the first session. In particular, it was observed a significant influence of the factor LAMBDA ($F = 9{,}33$; $p < 0.001$). However, the Scheffe's test performed at $p<0.05$ returned no significant differences between such regularization values.

	FILTERING	CAR	RAW	SLAP	LLAP	LI 1
1	CAR		0.152	0.823	0.404	$2.1\ 10^{-4}$
2	RAW	0.152		0.016	0.003	$1.0\ 10^{-6}$
3	SLAP	0.823	0.016		0.950	$2.7\ 10^{-3}$
4	LLAP	0.403	0.003	0.950		0.014
5	LI 1	$2.1\ 10^{-4}$	$1.0\ 10^{-6}$	$2.7\ 10^{-3}$	0.014	

TAB.1. Post hoc tests performed on data at the beginning of training with the Scheffe's procedure reveals statistical significant differences between linear inverse (LI) and all the other different spatial filters considered.

	FILTERING	CAR	RAW	SLAP	LLAP	LI 1
1	CAR		0.003	0.870	0.121	$1.0\ 10^{-7}$
2	RAW	0.003		$3.4\ 10^{-4}$	$1.0\ 10^{-5}$	$1.0\ 10^{-7}$
3	SLAP	0.870	$3.4\ 10^{-4}$		0.545	$1.0\ 10^{-7}$
4	LLAP	0.121	$1.0\ 10^{-5}$	0.545		$2.0\ 10^{-6}$
5	LI 1	$1.0\ 10^{-7}$	$1.0\ 10^{-7}$	$1.0\ 10^{-7}$	$2.0\ 10^{-6}$	

TAB.2. Post hoc tests performed on data at the end of training with the Scheffe's procedure reveals statistical significant differences between linear inverse (LI) and all the other different spatial filters considered

On line results

TAB. 3 shows the on-line classification range obtained from the users in four sessions. In average, correct classifications exceed 80% with a peak of 96% considering the 1-dimensional task and 89% considering the 2-dimensional one.

1-D	**LI-1 on-line**	Corr. Class.	Uncorr. Class.
	sess. 1	85%	15%
	sess. 2	96%	4%
	sess. 3	89%	11%
	sess. 4	74%	26%
	ST.DEV	**9.20%**	**9.20%**
	MEAN	**86.00%**	**14.00%**
2-D	**LI-1 on-line**	Corr. Class.	Uncorr. Class.
	sess. 1	78.38%	21.62%
	sess. 2	80.56%	19.44%
	sess. 3	89.19%	10.81%
	sess. 4	72.22%	27.78%
	ST.DEV	**7.02%**	**9.01%**
	MEAN	**80.09%**	**19.91%**

TAB.3. classification range using linear inverse (LI) as spatial filter for BCI2000 recording software [1]. In average, correct classifications exceed 80% with a peak of 96% considering the 1-dimensional task and 89% considering the 2-dimensional task. These results demonstrate the on-line applicability of LI procedure.

IV. DISCUSSION

The aim of this study was to compare linear inverse solutions (LI) with other scalp spatial filters usually used online [9] during BCI sessions of mu rhythm control, to understand whether the use of cortical activity estimated from non-invasive EEG recording could be useful to improve performances. Furthermore, one of the objectives was to demonstrate the on-line applicability of such method using a standard recording software (BCI2000 [1]).

The data reported here suggest that LI improves performances independently from the regularization parameter used for inversion. LI could transform a medium performer ($0.13 \leq R2 \leq 0.27$) in a good performer ($0.25 \leq R2$) (Fig. 4A) with a result as noticeable as R2 increases (quadratic relationship between R2 and performances Fig.4B).

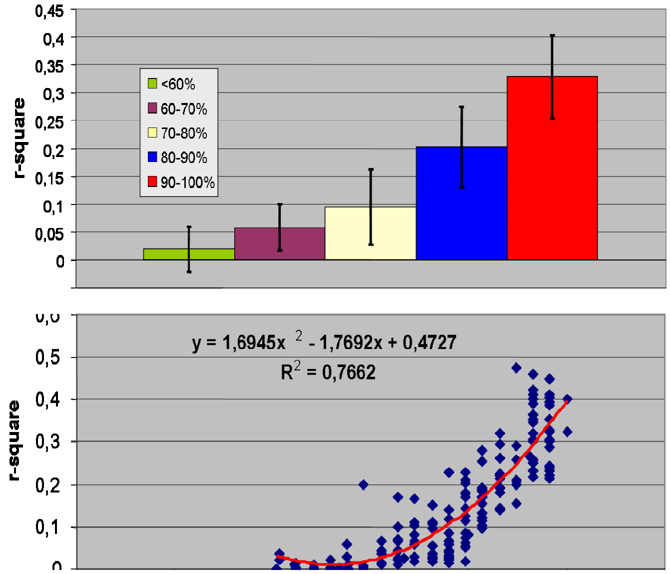

Fig.4. We used about 200 training sessions to recognize: A) average and standard deviation of R2 to identify five classification intervals (<60%; 60-70%; 70-80%; 80-90%; 90-100%) B) relationship between R2 and performances (quadratic).

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