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The advantages of the surface Laplacian in brain–computer interface research

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ABSTRACT

Brain–computer interface (BCI) systems frequently use signal processing methods, such as spatial filtering, to enhance performance. The surface Laplacian can reduce spatial noise and aid in identification of sources. In BCI research, these two functions of the surface Laplacian correspond to prediction accuracy and signal orthogonality. In the present study, an off-line analysis of data from a sensorimotor rhythm-based BCI task dissociated these functions of the surface Laplacian by comparing nearest-neighbor and next-nearest neighbor Laplacian algorithms. The nearest-neighbor Laplacian produced signals that were more orthogonal while the next-nearest Laplacian produced signals that resulted in better accuracy. Both prediction and signal identification are important for BCI research. Better prediction of user's intent produces increased speed and accuracy of communication and control. Signal identification is important for ruling out the possibility of control by artifacts. Identifying the nature of the control signal is relevant both to understanding exactly what is being studied and in terms of usability for individuals with limited motor control.

1. Introduction

Scalp-recorded EEG activity can be the basis for non-muscular communication and control systems, commonly called brain–computer interfaces (BCIs) (Birbaumer et al., 1999; Farwell and Donchin, 1988; Pfurtscheller et al., 1993; Wolpaw et al., 1991). EEG-based communication systems measure specific features of EEG activity and use the results as control signals. In some systems, these features are time-domain potentials evoked by stereotyped stimuli (e.g., Farwell and Donchin, 1988). Other systems use EEG components in the frequency domain that are spontaneous in the sense that they are not dependent on specific sensory events (e.g., McFarland et al., 2010; Wolpaw and McFarland, 1994, 2004).

One popular approach to BCI research uses sensorimotor rhythms (SMR) in mu (8–13 Hz) and/or beta (18–27 Hz) frequency bands over sensorimotor cortex as control signals. SMRs are focused over central scalp regions and are reactive to movement and movement imagery (Pfurtscheller and McFarland, 2012). Learned voluntary control of the SMR was shown to be possible by Kuhlman (1978) and later used as a BCI control signal by Wolpaw et al. (1991). Subsequently SMR-based BCI devices were evaluated as possible methods for communication (e.g., Muller and Blankertz, 2006) and control (e.g., Leeb et al., 2007). More recently, there has been interest in using SMR-based methods for rehabilitation following impairment of motor function by stroke (e.g., Ramos-Murguialday et al., 2013).

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SMR rhythms are not always apparent in "monopolar" surface recordings, in part due to volume conduction of activity from cortical regions associated with other functions. For example, visual alpha rhythms from posterior regions may be volume conducted to the central electrodes where SMRs are typically recorded (Andrew and Pfurtscheller, 1997). In addition, there are distinct effects associated with movements of specific body parts, such as the hands or feet. Movement or imagery involving the hand often produces desynchronization over areas associated with that hand and simultaneous synchronization over foot areas (Pfurtscheller et al., 1997). Thus, there may be several SMRs associated with movement or imagery of different body parts. Signal processing methods to separate the multiplicity of signals present at any single electrode can enhance SMR detection.

With the Wadsworth sensorimotor rhythm-based BCI system, participants learn over a series of training sessions to use SMR amplitudes to move a cursor on a video screen in one or more dimensions (Wolpaw and McFarland, 1994, 2004; McFarland et al., 2010). We use the surface Laplacian as a spatial filter to improve the signal-to-noise ratio of the signal and aid identification of the source(s) (McFarland et al., 1997b). Other BCI researchers also use the surface Laplacian. In a review of signal processing methods used by 96 BCI studies, Bashashati et al. (2007) report that for spatial filtering, 32% used the surface Laplacian, 22% used principal component or independent component analysis, 14% used common spatial patterns, and 11% used common average reference. BCI studies generally compute the surface Laplacian with the finite difference approximation of the second derivative (Hjorth, 1975).

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The surface Laplacian can serve at least two functions in BCI research; it serves as a spatial filter that provides a means of reducing spatial noise (McFarland et al., 1997b), and it helps constrain potential sources of the signal (Tenke and Kayser, 2012). The surface Laplacian has spatial band-bass characteristics that depend upon factors such as the spacing of the electrodes and any spatial smoothing of the particular implementation of the Laplacian being considered. Signals such as sensorimotor rhythms are often focused (i.e., they have a relatively high spatial frequency) relative to artifacts such as eyeblinks and EKG. In addition, since the surface Laplacian emphasizes local sources, it will minimize signals volume conducted from distant sources. The role of the surface Laplacian as a spatial filter can be evaluated by whether it enhances prediction of the BCI user's intent. The surface Laplacian also improves spatial resolution (Law et al., 1993) and thus can aid source identification. The role of the surface Laplacian in source constraint can be evaluated in part by the extent to which it produces signals that are uncorrelated. Both the effects of the surface Laplacian as a spatial filter and in constraining sources are potentially influenced by the spacing of the electrodes that are used in computing the surface Laplacian.

McFarland et al. (1997b) showed that BCI target prediction based on the SMR was better with the use of next-nearest neighbor electrodes as compared to nearest neighbor electrodes using a 64 channel montage (Sharbrough et al., 1991). This effect is probably due to the fact that the Laplacian computed with next-nearest neighbors has lower spatial frequency band-pass characteristics than that computed with nearest-neighbor electrodes (McFarland et al., 1997b). Tenke and Kayser (2012) have discussed the role of electrode spacing on the performance of the Laplacian for constraining sources. For this issue the effects of spacing are complex, depending upon the nature of the source. While most BCI studies emphasize prediction, source identification is also important to the extent that it is necessary to eliminate the possibility that BCI control is due to artifacts (McFarland et al., 2005).

The present study evaluated the impact of electrode spacing on the role of the surface Laplacian in prediction and source constraint. Prediction of target location and the correlation between adjacent electrodes were evaluated by an offline analysis of data collected while BCI participants were learning a cursor movement task based on sensorimotor rhythms. The aim of this analysis is to show that the spatial filtering and source constraining roles of the surface Laplacian are affected differently by electrode distance.

2. Methods

2.1. Participants

The participants were 14 adult volunteers (7 males and 7 females, aged 27–56) who worked at the Empire State plaza in Albany, NY and responded to announcements for paid volunteers. Twelve of the 14 were right-handed. All gave informed consent for the study, which had been reviewed and approved by the New York State Department of Health Institutional Review Board.

2.2. BCI protocol

After an initial evaluation defined the frequencies and scalp locations of each person's spontaneous sensorimotor rhythm activity, he or she learned EEG-based cursor control over 10 sessions (2–3 sessions/week). The standard online protocol, described in previous publications (McFarland et al., 2005), is summarized here. All aspects of data collection and experimental design were controlled by the BCI2000 general purpose software platform (Schalk et al., 2004).

2.3. Initial session

All participants first participated in an initial session involving movement and movement imagery of the right and left hands to identify the SMR features to be used for on-line control (see McFarland et al., 2000). The user sat in a reclining chair facing a 51-cm video screen 3 m away, and was asked to remain motionless during performance. Scalp electrodes recorded 64 channels of EEG (Sharbrough et al., 1991), each referenced to an electrode on the right ear (a relatively quiet site, distant to the left central scalp, as the majority of subjects used C3 or CP3) with an amplification of 20,000, bandpass of 0.1–60 Hz and 160 Hz sampling rate. Data collection lasted 17 min, and was divided into six 2-min runs separated by 1-min breaks. Each run consisted of fifteen 4-s trials separated by 4-s intertrial intervals. During the trials, a vertical bar was present on the left or right edge of the screen. During the intertrial interval the screen was blank. Three movement runs were interspersed with three imagery runs. During the trials of movement runs, the subject repeatedly opened and closed the hand ipsilateral to the target. During the trials of the imagery runs, the subject imagined doing so. During the intertrial intervals, the subject did neither and simply tried to relax.

2.4. Standard online protocol

A daily session had eight 3-min runs separated by 1-min breaks, and each run had 20–30 trials. Each trial consisted of a 1-s period from target appearance to the beginning of cursor movement, a 2-s period of cursor movement, a 1.5-s post-movement reward period that provided feedback, and a 1-s inter-trial interval. Each participant had 2–3 sessions/week at a rate of one every 2–3 days.

To control vertical cursor movement, one EEG channel over left sensorimotor cortex (i.e., electrode locations C3 or CP3) and/or one channel over right sensorimotor cortex (i.e., C4 or CP4) were derived from the digitized data according to a Laplacian transform (McFarland et al., 1997b). These channels were chosen based on analysis of the data from the initial session that selected the maximum bivariate r^2 value when comparing imagery and rest conditions across both frequency and electrode location. Every 50 ms, the most recent 400-ms segment from each channel was analyzed by a 16th-order autoregressive model using the Berg algorithm (i.e., an efficient least-squares algorithm for estimating autoregressive coefficients, see Marple, 1987) to determine the amplitude (i.e., square root of power) in a 3-Hz-wide mu or beta frequency band, and the amplitudes of the one or two channels were used in a linear equation that specified a cursor movement as described above. Thus, cursor movement occurred 20 times per second. Complete EEG and cursor movement data were stored for later offline analyses.

2.5. Offline analysis

The basic performance of the participants across these early training sessions was evaluated in terms of spectra and topographies of the bivariate correlation (r^2) between target position (i.e., a dummy variable, coded -1 and $+1$) and EEG features. This was done with the signal processing parameters used for on-line training. All subsequent analyses were limited to central locations in the mu and beta bands on the side of the scalp with the peak location of r^2. Following the recommendations of Jensen (1971), I am using r^2 to express variance predicted by a model (as opposed to r for the relationship between two variables). Use of Pearson's r tends to produce a skewed distribution that may be normalized by Fishers-Z transformation, but squaring r also reduces skew. The frequencies evaluated were 3 Hz wide bins centered at 9,12,15,18, 21 or 24 Hz. For two participants, the peak r^2 was at C1, for four participants the peak was at C3, for five participants this was at CP3, and for three participants this was at C4 (after Sharbrough et al., 1991). Three different spatial filtering conditions were evaluated at the peak frequency and location of these correlations. These were the nearest neighbor Laplacian, the next-nearest neighbor Laplacian (electrodes either anterior–posterior or medial-lateral to the central electrode), and no transformation (i.e., raw data, the surface potentials referenced to the right ear). These spatial filtering conditions were next evaluated with a multiple correlation at the peak frequency and including 17 channels over the central area of the peak side. In addition, the multiple correlation between the signal at the peak location and frequency and central channels at the same frequency and side was computed separately for each of these three spatial filtering conditions. These 17 central channels were FC5, FC3, FC1, T7, C5, C3, C1, Cz, TP7, CP5, CP3, CP1, CPz, P5, P3, P1 and PO3 for the left side and the corresponding channels on the right for participants having a peak r^2 at C4.

The local Hjorth algorithm (Hjorth, 1975) was used to estimate the second derivative of the scalp voltage based on a finite-difference method. This was done according to:

$$V^{lap}{}_{i} = V^{ear}{}_{i} - \Sigma g_{ij} V^{ear}{}_{ij} \tag{1}$$

where $V^{ear}{}_{i}$ is the voltage recorded at the ith electrode with an ear reference, $V^{ear}{}_{ij}$ is the jth neighbor of $V^{ear}{}_{i}$ *(i.e., j* = 1 to 4) and:

$$g_{ij} = 1/d_{ij}/\Sigma 1/d_{ij} \tag{2}$$

where d_{ij} is the distance between electrodes i and j in relative units. The value of d_{ij} thus varied depending upon whether the nearest neighbor or next-nearest neighbor Laplacian was computed. It should also be noted that the value of d_{ij} (and hence, the spatial band-pass) also depends upon the density of the electrodes in the montage (e.g., the next-nearest neighbor distance for C3 in the Sharbrough et al. (1991) montage is the same as the nearest-neighbor distance for C3 in the standard 10–20 montage).

The resulting data were analyzed with two-factor ANOVAs with repeated measures on both factors. The p values reported are the result of the Greenhouse–Geisser correction where appropriate (i.e., there were more than two levels of a given factor).

3. Results

An overall summary of the BCI user's control of their EEG is shown in Fig. 1. The figure shows the average spectrum of the channel for which participants had maximum control (i.e., largest values of the correlation between target location and EEG feature) as well as the average topography of the frequency associated with maximum control. For comparison, these same data are presented for a single individual. As can be seen in Fig. 1, the BCI user's control was localized over central scalp areas in the mu and beta frequency bands. Comparison with the single individual illustrates that group data are generally not as sharply focused as that for individuals, owing to individual differences in the spatial location and frequency of peak activities. The spatial and frequency specificity of the data shown in Fig. 1 helps to rule out cursor control based on artifacts, which generally have different spatial and spectral characteristics than sensorimotor rhythms (McFarland et al., 1997a).

Group average correlations between target location and the EEG feature at the peak location and frequency in the mu and beta bands for the three spatial filtering conditions are shown in Fig. 2A. Analysis of variance indicated that the effect of spatial filter type (i.e., raw data, next-nearest-neighbor and nearest neighbor Laplacians) was significant ($df = 2/25$, $F = 20.734$, $p < 0.001$, $epsilon = 0.632$) while the effect of frequency band and the interaction between spatial filter type and frequency band were not significant. Post hoc analysis (Newman–Keuls test) indicated that all of the spatial filter types were significantly different ($p < 0.05$ in each case). The next-nearest Laplacian produced the best prediction of target location, while the nearest neighbor Laplacian was better than the raw (untransformed) data. These results are consistent with the findings of McFarland et al. (1997b).

Group average multiple correlations between target location and the EEG features at the peak frequency for all channels in the analysis are shown in Fig. 2B. Analysis of variance indicated that both the main effects of spatial filter type ($df = 2/25$, $F = 20.734$, $p < 0.001$, $epsilon = 0.632$). Post-hoc tests indicated that all of the spatial filter types were significantly different ($p < 0.05$ in each case). The next-nearest Laplacian produced the best prediction of target location, while the nearest neighbor Laplacian was better than the raw data. The difference between the frequency bands within each spatial filter type was not significantly different. However the largest frequency band difference was in the raw data.

Group average multiple correlations between the EEG feature at the peak frequency and location and all of the other channels at the peak frequency as a function of spatial filter type and frequency band are shown in Fig. 3. This metric represents the commonality between the signal at the peak location with its neighbors. Analysis of variance indicated that the main effect of spatial filter type ($df = 2/25$, $F = 56.853$, $p < 0.001$, $epsilon = 0.949$) and the interaction between spatial filter type and frequency band ($df = 2/25$, $F = 3.625$, $p < 0.050$, $epsilon = 0.847$) were both significant. Post-hoc tests indicated that all of the spatial filter types were significantly different ($p < 0.05$ in each case). The nearest Laplacian was least correlated with the other channels in the analysis, while the next-nearest-nearest neighbor Laplacian was less correlated than the raw data. However the effects of frequency bands within each spatial filter type were not significantly different.

4. Discussion

The present study illustrates the two functions of the surface Laplacian; as a spatial filter and as a means of constraining source localization. As a spatial filter, the surface Laplacian can reduce spatial noise and enhance prediction. As a means of constraining source localization, the surface Laplacian produces signals that are less correlated with adjacent channels. The next-nearest neighbor Laplacian was best for prediction while the nearest neighbor Laplacian was best for reducing the correlation between adjacent electrodes. The fact that these two functions can be dissociated indicates that these two roles of the surface Laplacian are somewhat independent.

The utility of signal processing algorithms in BCI research has generally been evaluated in terms of the accuracy with which they predict target identity (Bashashati et al., 2007). Both the nearest-neighbor and the next-nearest neighbor surface Laplacians resulted in improved prediction of target membership. This is likely due in part to the fact that these spatial filters reduce noise from low spatial frequency artifacts such as eyeblinks and EKG (McFarland et al., 1997b). Whether surface Laplacians are effective in attenuating EMG artifacts is uncertain. Goncharova et al. (2003) report that surface Laplacians are not effective in reducing EMG contamination while Fitzgibbon et al. (2011) report that they are. One possibility is that the proximity of the EMG source to the electrodes used to compute the Laplacian may be important. That is, it may be the case that the Laplacian can attenuate distant EMG sources that are volume conduced. In contrast, the Laplacian might actually enhance local EMG sources.

Surface Laplacians also reduce the impact of signals in the same frequency range as sensorimotor rhythms that are volume conducted from remote areas. For example, visual alpha rhythms from posterior regions may be volume conducted to central electrodes where SMRs are typically recorded (Andrew and Pfurtscheller, 1997). Thus, surface Laplacian transformations serve as spatial filters that reduce both neural and non-neural noise.

The next-nearest neighbor surface Laplacian produced somewhat better prediction performance than the nearest neighbor Laplacian. This was true for both the best single channel as well as a composite prediction using all 17 central channels included in the present analysis. This result is consistent with results reported by McFarland et al. (1997b) who interpreted the superiority of the next-nearest neighbor

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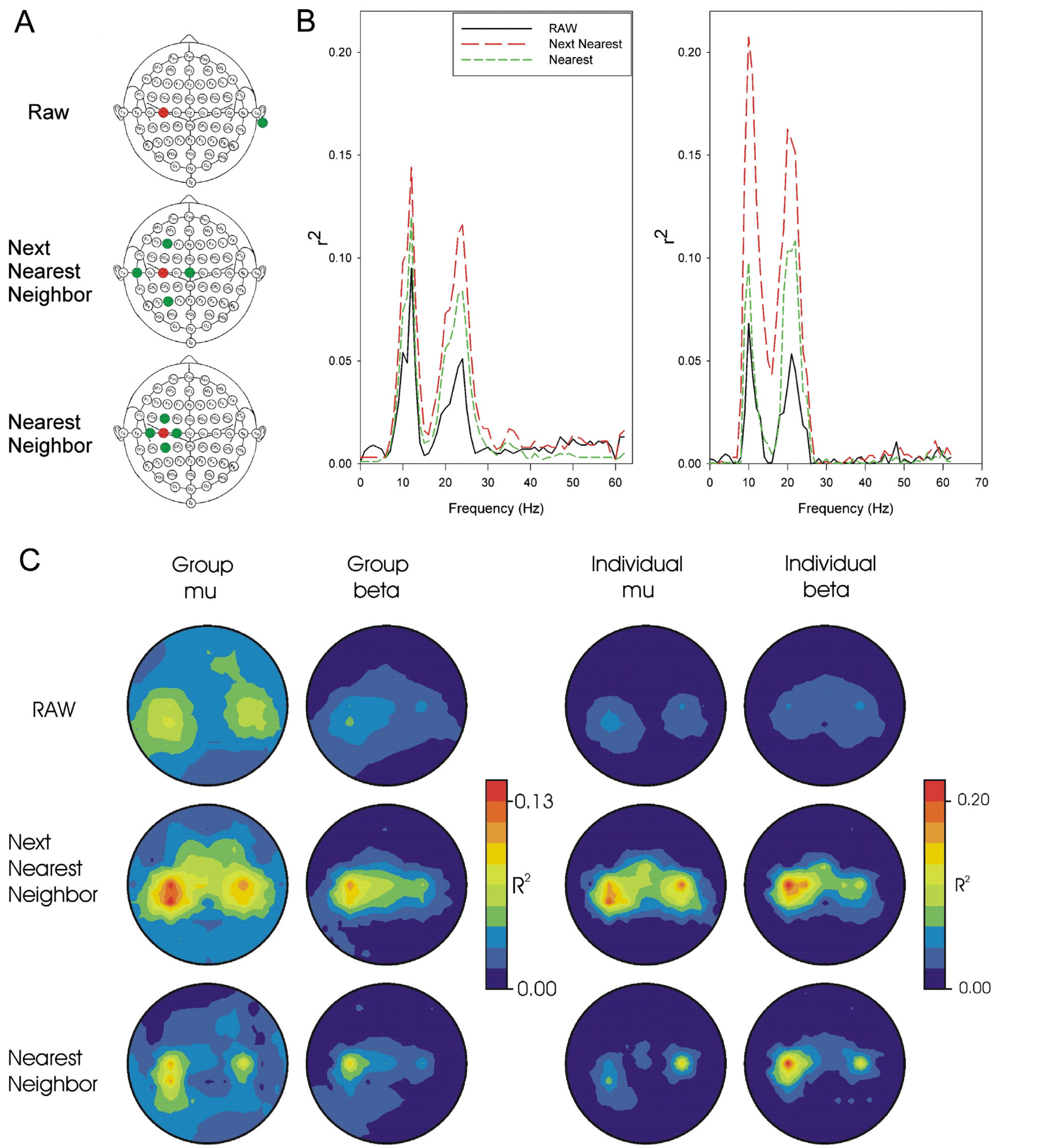

Fig. 1. Characterizing the EEG in BCI performance. A. Electrodes used for raw (top), next-nearest neighbor (middle) and nearest neighbor (bottom) transformations for the signal derived from channel C3. Red represents the electrode of interest and green represents the neighbors used to compute the transformation. B. Correlation (r^2) of spectral features derived by each of the three methods with BCI target location. The left panel shows data from the average of all subjects at the channel with maximum control and the right panel shows data from an individual BCI user. C. Topographies of the correlation (r^2) between spectral features and target location for the three methods. Values for mu represent the maximum between 9 and 13 Hz and those for beta represent the maximum between 18 and 24 Hz. The left panel shows data averaged from all participants at their best frequency. The right panel shows the same individual as in B at 10 and 20 Hz.

algorithm as being due to how closely the band-pass characteristics of the Laplacian matched the spatial extent of the potentials of interest. Consistent with this interpretation, Tenke et al. (1993) showed that simulated signals are attenuated when the spacing of electrodes is smaller than the extent of the source. McFarland et al. (1997b) simulated characteristics of several spatial filters and showed that, with the 64 channel montage used here, the next-nearest neighbor Laplacian has lower spatial band-pass characteristics than the nearest-neighbor Laplacian. The relative prediction performance of these spatial filters would be expected to depend upon the size and distance of the source. It should also be noted that the band-pass characteristics of the surface Laplacian can be modified by other means. For example, Perrin et al. (1989) varied the flexibility of spherical splines and Lu et al. (2013) adaptively varied the radius of a Gaussian kernel-based Laplacian. These

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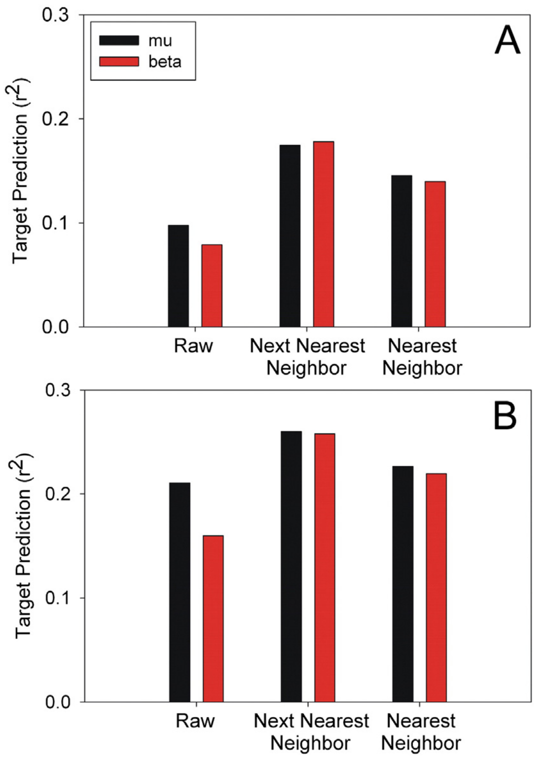

Fig. 2. Target prediction (r^2) with each of the three spatial filters for mu and beta bands. The top panel shows prediction for the best channel for each BCI user. The bottom panel shows prediction using all channels in a multiple regression. Note that the next nearest neighbor transformation produced the best prediction for both bands in both analyses.

methods provide alternative means to adjust the spatial band-pass of the surface Laplacian.

In contrast to the superior prediction performance of the next-nearest neighbor Laplacian, the nearest-neighbor Laplacian had superior spatial resolution, as illustrated in Fig. 3. Here spatial resolution was indexed by the multiple correlation of the best feature with all other features derived from the central channels included in the present analysis. The extent to which a given algorithm reduces the effects of volume conduction should be reflected in the extent to which the resulting signal is uncorrelated with adjacent signals. Thus, the multiple correlation should be inversely related to spatial resolution. The finding that the nearest-neighbor Laplacian produced better spatial resolution is consistent with the simulations of Tenke et al. (1993) who showed that more closely spaced electrodes resulted in less spatial smearing.

As discussed earlier, BCI researchers have used other spatial filters to enhance prediction (Bashashati et al., 2007). Some of these are data-driven, such as independent components analysis (Naeem et al., 2006) or common spatial patterns (Koles et al., 1990; Ramoser et al., 2000). Naeem et al. (2006) describe a rather involved labor-intensive process of selecting independent components for use by a classifier. Despite this effort, subsequent classification of a four-target sensorimotor rhythm task was not significantly different than that with a surface Laplacian transform. Common spatial patterns (CSP) often outperform fixed filters when compared in offline analysis with large amounts of training data (e.g., Sannelli et al., 2011). CSP optimizes a series of spatial filters by simultaneous diagonalization of the covariance matrices of two classes to be discriminated. Resulting principal components are then used as features in a classifier. Since the number of estimated parameters of CSP filters increases with the square of the number of channels, CSP is very sensitive to noise and prone to overfitting with a limited number of training trials (Lotte and Guan, 2011). The surface Laplacian has the advantage of being usable early in training prior to collection of many observations. In addition, some EEG signals used for real-time BCI applications are not stationary (i.e., they have changing statistics over time) and benefit from on-line, real-time adaptation (McFarland et al., 2011). Efficient adaptation may require the use of short time windows that do not favor complex data-driven spatial filters that require estimation of a large number of parameters. Recently Lu et al. (2013) described an adaptive Laplacian algorithm that only requires estimation of a single parameter to optimize the spatial band pass.

In addition to the problem of prediction, BCI systems need to be concerned with identification of the sources of the signals that are modulated by participants. Source identification is important since there is the possibility that BCI control could be the result of various artifacts (McFarland et al., 2005). Generally BCI research has emphasized prediction over identification and many papers do not deal with the issue of artifacts (Fatourechi et al., 2007). However the source identification problem is also important given the potential for artifacts to masquerade as EEG (e.g., EMG or eyeblinks). There are at least two reasons for BCI researchers to be concerned with artifacts. The first reason is scientific. If a potential BCI user is actually controlling something other than EEG then the interpretation of the results will be in error. Furthermore, knowledge of the signal provides insight into how best to record and process the signal. For example, if one wants to use EMG as a control signal then using high density scalp recordings and spectral analysis is very inefficient. The second reason for concern about the nature of the signals used by BCI participants relates to potential practical applications. Much of BCI research has involved the use of healthy participants. However, individuals who could actually benefit from this technology would have very limited motor control and hence would probably have difficulty generating the same kinds of artifacts that healthy volunteers do.

Laplacian transforms provide a well understood method that helps constrain potential sources (Tenke and Kayser, 2012). In contrast, with data driven methods such as CSP (Ramoser et al., 2000) or independent components analysis (Naeem et al., 2006), each realization produces a unique solution. As a consequence, the properties of the derived spatial filters are novel and may have unknown spatial filter characteristics. Consider, for example, that investigators often use several of the principal components derived from CSP as features for a classifier (e.g., Ramoser et al., 2000). Each of these principal components is defined by weights for each of the channels that were used for the derivation and a separate analysis is done for each subject. Thus, there is a considerable challenge in determining what is being used to perform this task for any given subject. Often BCI papers do not report sufficient information to inform the reader about this issue.

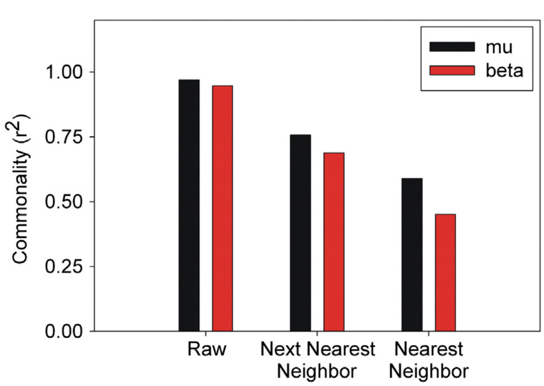

Fig. 3. Commonality (prediction of the channel with the greatest control by all other channels) between the best channel for mu and beta bands and the other channels in the analysis. Note that the nearest neighbor transformation produced the lowest correlations for both bands.

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5. Conclusion

The surface Laplacian is a theoretically based spatial filter that reduces spatial noise and aids in source identification. These two functions are differentially influenced by Laplacian filter design characteristics (e.g., electrode spacing). The Laplacian is particularly useful in BCI research when large amounts of training data are not available or when signals are not stationary.

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