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Cortical Imaging of Sensorimotor Rhythms for BCI Applications

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Abstract—**Rhythmic electroencephalographic (EEG) activities associated with movement imaginations are widely used in developing noninvasive Brain-Computer Interface (BCI) towards replacing or restoring the lost motor function in the paralytics. And it is of great importance to develop imaging techniques to enhance the spatial resolution and specificity of the EEG modality. In our work, we developed an innovative approach of imaging the distributed rhythmic brain activity in the spectral domain. In the present study, we evaluated the proposed technique in experimental data of offline and online imaginations in naive and well-trained BCI subjects. Our results identified the cortical origins of sensorimotor rhythms. We also applied the source imaging approach to classifying mental states for BCI applications and demonstrated its feasibility and superior performance.**

I. Introduction

THE study of Brain-Computer Interface (BCI) is of great promise in rehabilitating paralytic patients by providing them with a non-muscular channel of communication and control [1]. BCI based on electroencephalographic (EEG) signals has the advantage of no surgical risk, signal stability and low cost. Particularly, rhythmic EEG signals used in movement imagination-based BCI has been demonstrated to provide a two-dimensional control that is within the range reported for invasive BCI studies in monkeys [2].

Several EEG studies have shown that the planning, execution and imagination of movement lead to a decrease of rhythmic EEG activity in the mu (8-12 Hz) and beta (13-28 Hz) frequency bands, i.e. the sensorimotor rhythms [3]. Such characteristic decreases are used as control signals in BCI by classifying people's mental states relating to the planning/imagination of different types of limb movements. However, EEG signals suffer from the low signal-to-noise ratio and also degraded temporal and spatial specificity due to the volume conduction effect, which limits our understanding of the sensorimotor rhythms and further advancement of EEG-based BCIs.

Using recently developed EEG/MEG source imaging techniques, the movement-related rhythmic activities have been investigated with enhanced spatial resolution. Sources of mu rhythm during offline motor imagery were previously studied using dipole localization method [4, 5] or distributed source imaging [4, 6, 7]. Different from the above studies in which source estimates are obtained from every sample point in the temporal domain, we have developed a new computationally efficient approach to estimate the sources in the frequency domain (Minimum Norm Estimate in Frequency Domain, MNEFD) [8]. Using this method, the cortical distribution of source power in a specific frequency band can be directly estimated from single trial EEG data.

In the present study, we evaluated the Minimum Norm Estimate in the Frequency Domain (MNEFD) method in EEG experimental data from both naive and well-trained subjects performing movement imaginations in offline and online BCI settings respectively. We imaged the cortical modulations of sensorimotor rhythms associated with imagined movements of left and right hand. Also we investigated the feasibility of classifying imagination types based on the estimated cortical sources.

II. Methods

A. Experimental Setup and Data Acquisition

One naive subject participated in the offline imagination experiments and two well-trained subjects participated in the online BCI experiments. All subjects were healthy and gave written consent to the research protocols approved by the Institutional Review Board of the University of Minnesota. EEG activity was recorded from 64 electrode locations distributed over the entire scalp. The signals were acquired with a BrainAmp amplifier (BrainProducts, Germany) at the sampling frequency of 1000 Hz.

In the offline imagination experiment, the subject was instructed to imagine or execute the movement of left or right hand according to the texts shown on the computer screen. The task and rest conditions appeared in an interleaved block manner, which each lasted for 20 s. Within a task block, there were six trials during which subjects performed the instructed task for 2 s (imagination or movement execution) interleaved with inter-trial intervals of varying durations from 1 s to 2 s. The same tasks were performed within a block and the sequence of block types was randomized and balanced across runs. Eight runs of offline imagination were collected for the subject, resulting in 96 trials for each task condition.

In the online BCI experiment, subjects imagined left/right

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hand to move a cursor to hit the left/right target on the computer screen. Using the general-purpose system BCI2000 [9], the horizontal cursor movement was controlled by a linear equation of a weighted combination of the amplitude in mu band from EEG channels over the left and right hemisphere. A trial started when a target appeared at one of two locations on the periphery of the screen at 0 s, with a fixation cross at the center till inter-trial interval. One second later, the cursor appeared in the middle of the screen and began to move horizontally with its movement controlled by the user's EEG activity until it hit a target within 6 s. The experiment consisted of eight 5-min runs separated by 2-min breaks, and each run had 30 - 40 trials.

The individual anatomical MRI data set consisted of 176 contiguous sagittal slices with 1 mm slice thickness (matrix size: 256 * 256, FOV: 256mm * 256mm). The images were acquired using a Turboflash sequence (TR/TE=20 ms/5 ms) on a 3T MRI system (Siemens Trio, Siemens, Erlangen, Germany). The physical landmarks (nasion and left, right preauricular points) and electrode positions were digitized using a Polhemus Fastrak digitizer (Polhemus, Colchester, VT) and 3DSpace software from the SCAN software package.

B. *Minimum Norm Estimate in the Frequency Domain*

The EEG source activities were computed using the MNEFD method [8], which provides a capability to imaging rhythmic modulation associated with motor imagery tasks from single trial data.

Using a cortically constrained distributed source model [10, 11, 8], the relationship between source amplitudes and scalp potentials can be expressed by $\Phi(t) = AS(t)+N(t)$, where Φ is a matrix of the measured EEG. S is the unknown matrix of amplitudes of the dipoles along the time. A is the transfer matrix. Data are corrupted by an additive noise N. The cortical surface reconstructed from individual subject's MRIs will be used to restrict the source locations and orientations. Although the measured data Φ do not give the source strengths S unambiguously as the number of discretized sources is larger than the number of sensors, a minimum-norm estimate (MNE) in the sense of L_2-norm can be obtained by applying a linear inverse operator to the measured signals $\hat{S} = W\Phi$, where W can be obtained by $W=RA^T(ARA^T+\lambda^2C)^{-1}$, and λ is regularization parameter [12, 8]. As no prior knowledge of source activity is assumed, R is an identity matrix here. The data with 15% lowest global field power will be selected for noise estimation. The noise covariance matrix C is constructed as a diagonal matrix with diagonal elements proportional to the average noise power over all channels. In order to compensate the tendency of the minimum-norm solution to favor superficial sources, depth-weighting method will also be used. Using the Fourier transform, both single-trial $S(t)$ and $\Phi(t)$ can be transformed to $S'(f)$ and $\Phi'(f)$ respectively in the frequency domain [13]. Thus, we will have the following linear equation $\Phi'(f) = AS'(f) + N'(f)$ which will hold with both the real $\Phi_{Re}'(f)$ and imaginary part $\Phi_{Im}'(f)$. Then $\Phi_{Re}'(f)$ and $\Phi_{Im}'(f)$ of the Fourier transformed signal will be applied to the MNE method resulting in the current distributions $S_{Re}'(f)$ and $S_{Im}'(f)$. The real and imaginary parts will be subjected to source estimation in L2-norm and then summed up to obtain the single-trial source power.

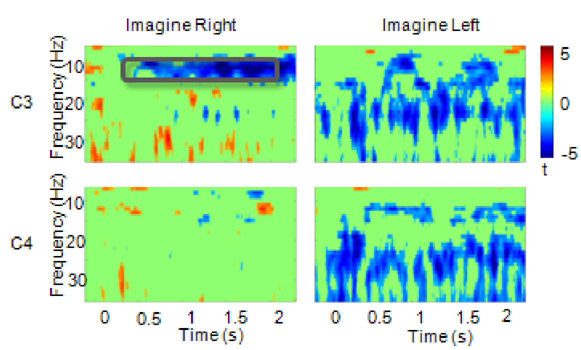

Fig. 1. Time-frequency representations of power change during imagination in relative the baseline from C3 and C4 channels in the naïve subject. Only t statistic thresholded by $p < 0.05$ was plotted. The black rectangle indicated the selected time and frequency window for source analysis.

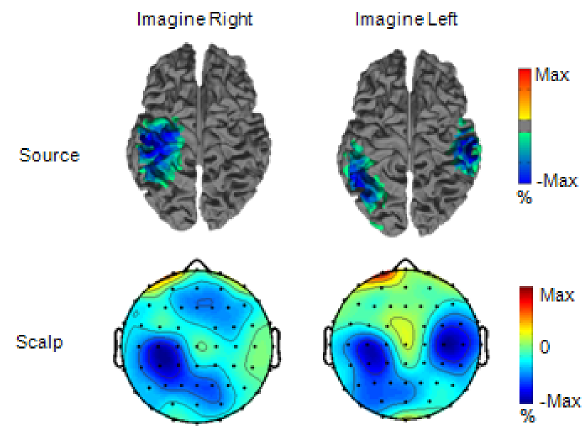

Fig. 2. The source (upper row) and scalp (lower row) distributions of percentage change during imagination of left hand (right column) and right hand (left column) in the naïve subject. The source distribution was thresholded using two-sample t test between imagination and baseline conditions ($p < 0.05$, corrected).

C. *Data Analysis*

After standard preprocessing, EEG data were segmented into epochs starting from 1 s before the trial till 1 s after the disappearance of imagination cue in the offline setting or 1 s after cursor hitting the target in the online BCI. Time-frequency representations (TFR) of these single-trial EEG data were computed individually using a Morlet wavelet-based technique over the 6 - 30 Hz frequency range, with center frequencies at 1 Hz intervals. The TFR changes during offline imaginations from the naive subject (subject #1) were plotted in t statistic, by contrasting the TFR during the task period to the TFR of 100 ms before the trial onset.

The single-trial source power during the imagination and baseline periods were computed separately. Based on the source estimates, the negative (ERD) or positive (ERS) spectral change is characterized by comparing the

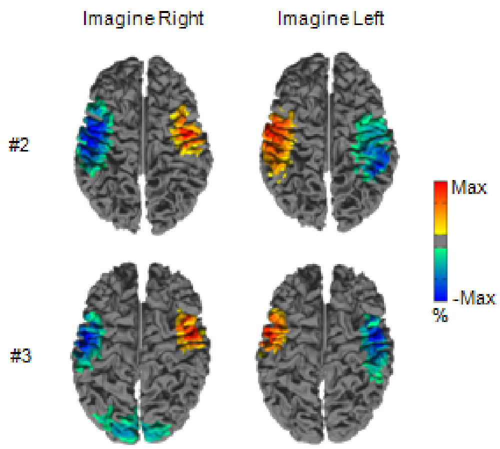

Fig. 3. Cortical distributions of percentage change in mu rhythm during imagination of right hand (left column) and left hand (right column) in the two well-trained subjects. Each map was thresholded using two-sample *t* test between imagination and baseline conditions ($p < 0.05$, corrected)

distributions of mu powers for each imagery type with the pooled rest distributions. The relative change was defined as the difference of power between task and baseline conditions and normalized by the baseline power. The percentage maps were thresholded according to the *p* value of the two-sample *t* test with Bonferroni correction.

Fisher Linear Discriminant (LDA) analysis was applied to the source-estimated and scalp-derived signals during offline imagination in the naive subject. EEG power in the mu frequency band was extracted from the regions (channels or dipoles) characteristic to the imagination of left/right hand and averaged respectively. Thus features of two dimensions were classified into imagination of left hand or right hand using the LDA. The sequence of trials were randomized and 80% of them were used for training the classifier while the rest for testing. The randomization and classification procedures were repeated for 100 times.

III. Results

Fig. 1 plotted the TFR changes of C3 and C4 channels during offline imaginations from the naive subject (subject #1) in *t* statistic ($p<0.05$). A decrease in the mu frequency band was shown accompanying the imagination dominantly on the contralateral electrode. Compared with the right hand imagination, imagined movement of left hand generated a stronger decrease at the ipsilateral side. Fig. 2 illustrated the percentage change in mu frequency band from source estimates and scalp recordings associated with imaginations of left hand and right hand from subject #1. The modulation of mu rhythms was shown to mainly originate from the sensorimotor cortex.

The average accuracy of target hits out of all the trials from the two subjects was 90.48± 4.85% and the average hitting time was 2.62 ± 1.07 s. The cortical changes of mu rhythms during online BCI experiment were depicted in Fig. 3 from the two well-trained subject (subjects #2 and #3). It was consistently shown in the two subjects that decrease of mu rhythms were found at the contralateral side of sensorimotor cortex while there was some increased activity at the ipsilateral side. The dominant contralateral decrease in mu rhythm was in line with the pattern of the offline imagination setting where no online feedback was provided.

The distributed features from source and scalp power were plotted in Fig. 4. The average classification accuracy for source- and scalp-based features was 75.7 ± 5.73% and 62.2 ± 7.20% respectively.

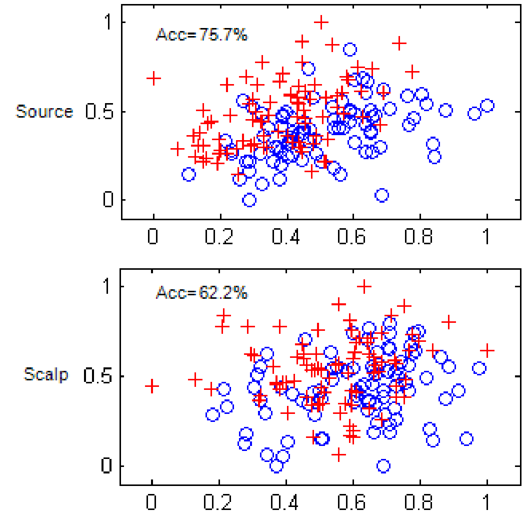

Fig. 4. Distribution of source- (upper) and scalp-based (lower) features used for classification. The average accuracy by LDA classifier was 75.7 ± 5.73% and 62.2 ± 7.20% respectively. The symbols 'o' and '+' represent the features corresponding to imaginations of left hand and right hand, respectively.

IV. Discussion

In the present study, we evaluated the MNEFD method in experimental data of movement imaginations in offline and online settings. EEG activities associated with movements and imaginations have been studied using advanced imaging techniques with high spatial resolution. Although rhythmic activities from scalp recordings are widely exploited for BCI control [1, 2], it is still unclear how the cortical rhythmic activities are distributed in the brain and how they correlate with the imaginations during the online and offline processes. Our results demonstrated that the distributed EEG rhythms originated from the sensorimotor cortex and indicate their dominant role in underlying the cursor control. Our results were consistent with previous studies on offline imagination in identifying the primary motor cortices as the source of sensorimotor rhythms [3, 4, 5, 6]. Furthermore, we extended previous studies by imaging the cortical activity during online control.

Tremendous effort has been made to improve the spatial resolution of EEG. Previous studies on imaging the movement-/imagination-related activities have been focusing on reconstructing the spatio-temporal source activity [4, 5, 7]. In the present MNEFD approach, Fourier transformation converts EEG signals in the temporal domain into concrete representation in the frequency domain; this enables one to directly image the source activities in the targeted frequency band, avoiding laboriously searching each time-sample over the whole segment of oscillatory signals.

By deconvolving the sensorimotor rhythms from scalp measurements, the source imaging technique promises to provide a new signal channel with enhanced spatial resolution and specificity. In the pilot study, we demonstrated the feasibility of applying the MNEFD approach in classifying mental states of movement imaginations. We also demonstrated the source-derived signal has a superior performance over the scalp-derived activity in the naive subject.

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