A Robust Beamforming Approach for Early Detection of Readiness Potential with Application to Brain-Computer Interface Systems

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Abstract—**Early detection of intention to move, at self-paced voluntary movements from the activities of neural current sources on the motor cortex, can be an effective approach to brain-computer interface (BCI) systems. Achieving high sensitivity and pre-movement negative latency are important issues for increasing the speed of BCI and other rehabilitation and neurofeedback systems used by disabled and stroke patients and helps enhance their movement abilities. Therefore, developing high-performance extractors or beamformers is a necessary task in this regard.**

In this paper, for the sake of improving the beamforming performance in well reconstruction of sources of readiness potential, related to hand movement, one kind of surface spatial filter (spherical spline derivative on electrode space) and the linearly constrained minimum variance (LCMV) beamformer are utilized jointly. Moreover, in order to achieve better results, the real head model of each subject was created, using individual head MRI, and was used in beamformer algorithm. Also, few optimizations were done on reconstructed source signal powers to help our template matching classifier with detection of movement onset for five healthy subjects.

Our classification results show an average true positive rate (TPR) of 77.1% and 73.1%, false positive rate (FPR) of 28.96% and 28.74% and latency of -512.426$\pm$396.7ms and -360.29$\pm$252.16 ms from signals of current sources of motor cortex and sensor space respectively. It can be seen that the proposed method has reliable sensitivity and is faster in prediction of movement onset and more reliable to be used for online BCI in future.

Keywords: Electroencephalography (EEG); Readiness potential (RP); Spatial filter; Beamformer; Brain-computer-interface (BCI)

I. INTRODUCTION

The Bereitschafts potential (BP) or Readiness potential (RP), has been known since 1964, by Kornhuber and Deecke [1]. Activity of this potential starts between 2 to 3s before starting a self-paced voluntary movement till movement onset. RP is divided into two main components. One slow low amplitude wave called BP, starting 2 or 3s till 1s before movement onset and a negative slope wave called NS' component which starts nearly 1s before movement onset, till initiation of movement. Invasive studies show BP component is generated by sources in supplementary, pre-motor and walls of the central sulcus and NS' component is generated in the crown of primary motor cortex with most activities on walls of central sulcus [1]. Therefore, because of existing brain geometry, the BP component is generated by current sources with radial and tangential direction to scalp and NS' component is generated by neural current sources with tangential direction of activation to the scalp. Due to the existing artifacts in raw EEG data, it is more reasonable to follow the second component, NS' or tangential sources, at early stages of generation. Till now, many papers have been published on early detection of movement intention [2]. Niazi et al. [3] could achieve an average sensitivity of 82.5% and average early detection of 187ms before movement onset for healthy subjects. They applied a Laplacian spatial filter on band-pass filtered EEG which was correlated with RP template and applied a likelihood method for movement onset detection. The authors of the paper [4] applied LCMV beamformer on EEG of hand movement in spherical head model and extracted power feature vector of source signals from predefined locations of radial sources as inputs for a logistic regressor classifier. A group in [5] worked on brain MEG signals, which measures magnetic fields of brain sources with lower amount of noise compared with the EEG. Their focus was not on early detection of movement onset. They showed that even if working on raw MEG without time consuming preprocessing, LCMV beamforming has a good effect on signal to noise ratio (SNR) improvement and eye blink suppression in source space. Beamforming is solving an inverse problem and a good approach for directly extracting source activities from predefined parts of the cortex. LCMV beamformer is a good adaptive one with high performance among beamformers and has a simple formulation [6]. Using real impedance head model extracted from anatomical magnetic resonance imaging (MRI) data helps beamformer achieve more accurate source activity reconstruction from regions of interest. In the simple case, the Laplacian surface spatial (LS) filter improves the SNR in sensor space by subtracting activities of adjacent electrodes and studies show good classification results using LS filter [7]. With the assumption of electrode positions on a spherical coordinate, it has been also proved that the LS filtered EEG is proportional to the radial component of the electric field entring the scalp [8]. It is also possible to increase the sensitivity of EEG to tangential electric fields (TEF) crossing the skull and entring the scalp. The TEF is achieved by calculating the derivative of the voltage difference between every electrode pair in two spherical directions perpendicular to the radial directions on each electrode location [8]. The TEFs are generated by activities of current sources that are mostly integrated on the crown of primary motor cortex and walls of central sulcus which are

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978-1-5090-2809-2/17/$31.00 ©2017 IEEE

generators of both components of readiness potential [1]. Therefore, applying beamformers on LS and TEF filtered EEG, instead of EEG, may lead to better source reconstruction.

Studies show beamformers have deficiency in localization and reconstruction of correlated sources (even if moving one hand, correlated RPs generate in both hemispheres). Employing the surface spatial filter (LS or TEF) before beamforming helps better source discrimination due to its physical concepts and formulations [9].

Moreover, appropriate optimization based manipulations are done on estimated source powers to estimate the best source direction, with maximum power, for predefined locations of primary motor cortex. This leads to more accurate reconstructions of RP sources in each single trial before movement onset. Results can be equal to what is recorded in invasive studies by deep electrodes. In other words a robust beamformer can be a good tool to avoid invasive studies in BCI and other applications of source space studies.

II. Methods

The only preprocessing is band-pass filtering EEG and eliminating some parts of data contaminated with the myogenic artefact. We avoided further preprocessing such as online eye blink removal because of using beamforming method which is supposed to have a spatial focus on the region of interest.

A. Experimental Setup

The experiment included a random execution of hand movement. Subjects were asked to be calm and relaxed and randomly close their fist to press a pushbutton in their hand. In order to simulate real life and to avoid any unwanted potentials, subjects were only asked not to have any movement for at least 5s (without counting) after each self-paced movement. Signals were recorded with a 64-channel (10-10 %) EEG system (G. USB amp). EEG of each subject was recorded in two sessions (10 minutes each). To compute LFM and beamformer weights, individual T1-weighted anatomical MRI of the head was acquired by Siemens system at the National Brain Mapping Laboratory (NBML) [14]. Results of onset detection are validated with a 10% threshold of maximum amplitude of EMG as movement onset marker that was equal to signal markers generated by pressing the push button when initiating the movement.

B. Preprocessing

The myogenic artifact was removed by discarding parts of main EEG which after band-pass filtering (between 20 to 40 Hz) crossed a threshold of 35μv. Then, the manipulated EEG was band-pass filtered between 0.1 and 12 Hz to contain motor unit activities and BP signals. The following steps are needed for LFM calculation respectively: MRI segmentation, mesh generation from segmented parts (scalp, skull, brain for three-layer segmentation), electrode alignment to scalp and solving the impedance equation of forward problem. These processes were done using Fieldtrip software package [10].

C. LCMV Beamforming

As a comparison between beamformers showed [6], adaptive minimum variance beamformers such as LCMV have better gain and localization accuracy in comparison with the minimum norm based beamformers. The weight vector is calculated as follows [11]:

$$\mathbf{w(r)} = \underset{\mathbf{w(r)}}{\operatorname{argmin}} \ \mathbf{w(r)}^{T}\mathbf{Rw(r)}, \text{subject to}\ \mathbf{w(r)}^{T}\mathbf{l(r)} = 1, \qquad (1)$$

where $\boldsymbol{w}$(r) is a $N_e \times 1$ vector, $\mathbf{R}$ denotes the EEG covariance matrix and $\mathbf{l(r)} = \mathbf{L(r)}\boldsymbol{\eta}\mathbf{(r)}$, where $\boldsymbol{L}(\mathbf{r})$ is $N_e \times 3$ lead-field matrix (from MRI) and $\boldsymbol{\eta}(\boldsymbol{r})$ is 3×1 momentum vector at position $\boldsymbol{r}$ and N_e denotes the number of electrodes. The solution of equation (1) can be formulated as:

$$\mathbf{w(r)} = \frac{\mathbf{R}^{-1}\,\tilde{\mathbf{l}}\mathbf{(r)}}{[\tilde{\mathbf{l}}\mathbf{(r)}^{T}\mathbf{R}^{-1}\tilde{\mathbf{l}}\mathbf{(r)}]}, \qquad (2)$$

where, $\tilde{\boldsymbol{l}}(\mathbf{r}) = \boldsymbol{l(r)}/\|\boldsymbol{l}(\boldsymbol{r})\|$ is the normalized lead-field vector**.** Consequently, the estimated source magnitude is given by:

$$\hat{\mathbf{s}}(\mathrm{r},\mathrm{t}) = \frac{\tilde{\mathbf{l}}\mathbf{(r)}^{T}\mathbf{R}^{-1}\mathbf{X}_{e}}{[\tilde{\mathbf{l}}\mathbf{(r)}^{T}\mathbf{R}^{-1}\tilde{\mathbf{l}}\mathbf{(r)}]}, \qquad (3)$$

where $\mathbf{X}_e = \sum_{\mathbf{i}} \mathbf{L}(\mathbf{r}).\boldsymbol{\eta}(\mathbf{r}).\mathbf{s_i}(\mathbf{r},\mathrm{t})$ is the EEG signal matrix with N_e rows and each row is the activity of one of N_e electrodes for. Finally, the source power can be estimated as $\frac{\tilde{\mathbf{l}}\mathbf{(r)}^{T}\tilde{\mathbf{l}}\mathbf{(r)}}{[\tilde{\mathbf{l}}\mathbf{(r)}^{T}\mathbf{R}^{-1}\tilde{\mathbf{l}}\mathbf{(r)}]}$.

In absence of source direction, for scalar LCMV beamformer the dominant direction with the most power is calculated by [11]:

$$\boldsymbol{\eta}_{\mathrm{opt}}(\mathbf{r}) = \upsilon_{\min}\{\mathbf{L}(\mathbf{r})^{T}\mathbf{R}^{-1}\mathbf{L}(\mathbf{r}), \mathbf{L}(\mathbf{r})^{T}\mathbf{L}(\mathbf{r})\}, \qquad (4)$$

where ϑ_{min} is the eigenvector corresponding to minimum eigenvalue of the statement in the braces.

D. Spherical Spline Surface Laplacian Spatial Filter and Tangential Electric Fields

We assumed to have a spherical head model (for the sake of simplicity, we calculated radius of head for each subject from the scalp mesh) and followed spherical coordinate considerations, (r, θ, φ), for electrode positioning and surface derivatives (LS and TEF filter) extraction . The θ is the angle from the positive direction of z-axis in cartesian coordinate. The +z direction is from the center of head to vertex. The parmeter φ is a clockwise angle in x-y plane starting from nasion. All is done to compute this kind of spatial filter is defining scalp potential distribution ($\mathbf{v}_{\lambda}(r)$) at electrode positions by a spline interpolation function and applying spherical derivatives at electrode locations [7][8]. We show surface Laplacian of EEG at each time sample by:

$$\mathbf{I}_\lambda = \Delta_{surf}\mathbf{v}_\lambda = \frac{1}{R^2\sin\theta}\frac{\partial}{\partial\theta}\left(\sin\theta\frac{\partial\,\mathbf{v}_\lambda}{\partial\theta}\right) + \frac{1}{R^2\sin\theta^2}\frac{\partial^2\mathbf{v}_\lambda}{\partial\varphi^2}. \quad (5)$$

R is head radius. Calculating derivatives in 2 other spherical coordinates leads tangential electric fields (TEFs) which are

$$E_{\theta,\lambda} = \frac{-1}{\boldsymbol{r}_{\mathrm{scalp}}}\frac{\partial\,\mathbf{v}_\lambda}{\partial\theta}, \; E_{\varphi,\lambda} = \frac{-1}{\boldsymbol{r}_{\mathrm{scalp}}\sin\theta}\frac{\partial\,\mathbf{v}_\lambda}{\partial\varphi}.$$

Fig. 1 shows effect of surface Laplacian in better source separation at a sample of time before movement onset in comparison with raw EEG. Brain mesh is also shown to have a preview of source space.

E. *Applying LCMV on Surface Laplacian Filtered EEG and Lead-field Matrix Correction*

In a simulation study on EEG [9], it was shown that separating sensor space into left and right hemisphere and computing Laplacian weight matrix from electrode cap of each hemisphere is an effective approach to distinctly extract radial correlated sources from each hemisphere. Hence, it can be concluded that the deficiency of LCMV was mitigated for radial sources. Similarly, in this paper, this approach was employed for reconstructing tangential electric fields (TEFs), the main sources of both RP components.

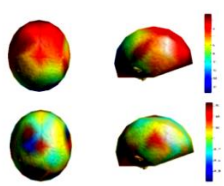

Figure 1: Scalp EEG before (top row) and after (bottom row) LS filter are shown in two views at a time sample before movement onset. Brain mesh is also shown to have a preview of source space.

Recalling the forward problem and due to the linearity of Laplacian and TEF operator, the operator matrix must be applied to the original lead-field. Hence, the corrected lead-field matrix is $\mathbf{L}_{\mathrm{new}}(\mathbf{r}) = \mathbf{ZL}(\mathbf{r})$, where $\mathbf{Z}$ is the spatial filter operator matrix. Fig. 2 shows source extraction by joint TEF-LCMV (on electrodes shown by dots over cortex) for a window of 1.5s before left hand movement on motor cortex.

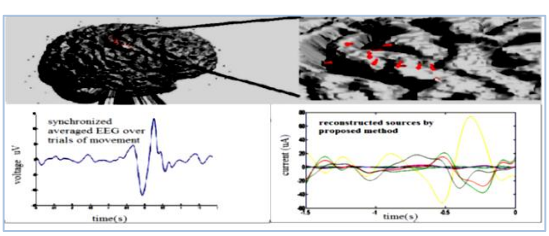

Figure 2: Source activity extraction by TEF-LCMV for a window of 1.5s before left hand movement from predefined locations on the primary motor cortex (right curve). The template of RP computed by synchronized averaging over trials of left hand movement from electrode C4 (left curve). The end of negative slope in template is movement initiation or movement onset.

F. *Results*

A template matching based classifier was designed for movement onset detection and applied on sliding windows of 1.5s with 250ms shift. In order to evaluate the designed classifier a 5-fold cross-validation (by choosing 50% of trials of movement in each fold as train trials to produce the template signal) was applied. Then, the average correlation coefficient of trained template with signals from sources in each time window is calculated and compared with an appropriate predefined threshold to predict movement onset and consequently calculate the true positive rate (TPR), false positive rate (FPR) and the latency of correct predictions. The average correlation coefficient of the template with train trials was selected as a prior threshold for movement detection from average correlation coefficient outputs of test trials. If the classifier detects readiness template during 1.5s before movement onset (detected by marker while pressing push button) this prediction is considered as a true positive (TP) result and movement detections in other time samples are considered as false positives (FPs). The sensitivity or TPR is computed by the number of TPs divided by the number of all movements. FPR is calculated by the number of FPs divided by the total number of detections. Also, the latency is defined as the difference between detected movement onset and real movement onset. Having a large negative latency is desired in a practical BCI system. Fig. 3 shows a period of experiment and movement onset detections besides real onsets. The proposed classifier was also applied on sensor space signals acquired from TEF filtered EEG for comparison with papers working on sensor space. Results over subjects are shown in Table 1. We achieved an average TPR (sensitivity) of 77.1% and 73.1%, FPR of 28.96% and 28.74%, and average latency of -512.426ms and -360.29ms with our proposed method from source space and sensor space calculations respectively.

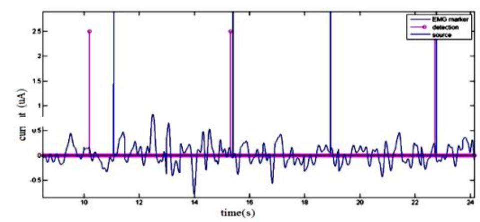

Figure 3: Movement onset detection (pink bar) with respect to real onsets from source space (one dominant source is plotted for each trial).

Table 1: Results of movement detection over 5 healthy subjects from source and sensor space

TEF-LCMV	*Sensitivity(TPR) (%)*		*FPR(%)*		*Negative Latency (s)*	
	Source space	*Sensor space*	*Source space*	*Sensor space*	*Source space*	*Sensor space*
S1	**77.5±5.3**	**73.8±1.8**	**26.1±4.2**	**24.4±8.8**	**0.47±0.33**	**0.33±0.23**
S 2	**76.2±1.4**	**69±2.7**	**29.1±1.9**	**27.7±5.4**	**0.49±0.45**	**0.31±0.26**
S 3	**78.2±5.1**	**71.7±1.6**	**33.3±4.1**	**30.4±3.4**	**0.52±0.38**	**0.25±0.25**
S 4	**73.4±0.9**	**74.4±4.5**	**29.2±5.4**	**33.5±2.9**	**0.52±0.34**	**0.40±0.26**
S 5	**80±2.12**	**76.6±4.7**	**27.1±2.8**	**27.7±4.4**	**0.54±0.46**	**0.49±0.24**
Mean ***STD***	**77.1** **2.46**	**73.1** **2.89**	**28.96** **2.76**	**28.74** **3.41**	**0.51±0.39** **27.4**	**0.36±0.25** **93.5**

III. DISCUSSION AND COMPARISON

We proposed a robust beamforming based method for early detection of voluntary RPs. For comparison, we focused on those papers with healthy subjects and the similar experimental protocol and ignored the difference between subjects in each group. Compared with the works proposed in [3] and [12] our results from sensor space show almost equal level for sensitivity and better negative latency. The proposed method in this paper results a considerable decrease in latency to about 160ms (in sensor space) and 300ms (in source space) in comparison with results achived by Aliakbary et al. (sensitivity of 75% and latency of -206ms) and much better early detections than Niazi et al. (sensitivity of 82.5% and latency of -187ms). The latency results reported by Bai et al. [13] (-620ms) is around 110ms earlier than what was achieved in this paper, while they reported much less sensitivity (about 50%) than ours. In [13] the same experiment protocol as the protocol used in this work was used, but they used a different method for movement detection. Results by using MEG data in beamforming [5] are the same as results by beamforming tangential electric fields of EEG. Since both components of RP are generated by tangential sources, results on Table 1 show the capability of tangential components of EEG in reconstruction and early detection of movement intention. The focus of the work proposed at [5] wasn't on early detection of the readiness potential to be able for comparison. They used beamformer for localization of pre- and post-movement magnetic fields. The only related work [4] applied LCMV beamformer on 128-channel EEG and spherical head models and showed beamforming as a robust method comparing other spatial filtering methods (surface Laplacian spatial filter and common spatial pattern) when working with noisy data in BCI. They achieved average sensitivity of 79.8% by applying LCMV and 76.1% by Laplacian spatial filtered EEG. They computed power feature vectors as input for a logistic regressor classifier for detection. They also refused preprocessing such as eye blink removal because of beamforming. Since, they did not deal with measuring the detection latency and also low detail on detection algorithm, we were not able to compare our latency results.

IV. CONCLUSION

In this work, the focus was on accurate extraction of both components of readiness potential current sources of the motor cortex by a robust beamforming approach for each single trial of before moving. The proposed method is specially robust to correlatedness of two generated RPs at left and right hemispheres. This robustness is more due to applying surface spatial filter to each individual hemisphere prior to applying LCMV beamformer. In order to reduce the computational complexity, our work was focused on extracting and manipulating samples of sources of RP instead of extracting and classifying complex features. The major achievement of paper is estimating both components of readiness potentials by applying beamformer on tangential electric fields of EEG. Results by applying our joint use of two kinds of spatial filters, surface spatial filter and beamformer, shows an acceptable sensitivity and an improvement in latency of detection in comparison with the separate use of each two approaches. Accurate source extraction can be equivalent to what is recorded in invasive studies by deep electrodes on cortex, which is harmful. So, the proposed method can be a good replicate for other applications where it isn't possible to record invasive EEG. The accuracy of source estimation will be increased by applying surface derivatives on real head geometry instead of spherical, which is our future plan. Due to low computational cost, high sensitivity and earlier detection of movement onset, the proposed method can be a proper candidate for online BCI application.

ACKNOWLEDGMENT

This study was part of an MSc thesis supported by Tehran University of Medical Sciences; Grant no.93-04-30-27553.

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