Calibration Time Reduction through Source Imaging in Brain Computer Interface (BCI)

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Abstract. Brain Computer Interface (BCI) is mainly divided into two phases; calibration phase for training and feedback phase. A calibration phase is usually time-consuming, thereby, being likely to raise subjects' fatigue at the early stage. For more convenient and applicable BCI system it should be investigated to reduce such preparation (calibration) time before feedback phase. Beamformer is a source imaging technique widely used in MEG/EEG source localization problem. It passes only signals produced at the designated source point and filters out other signals such as noise. We conjecture information in source space may be consistent over well trained and good subjects. This idea facilitates to reuse existing datasets from the same or different subjects. Using IVa data in BCI competition III, we constructed a classifier from other 4 subject's training data and performance was evaluated in source domain. In this work, we observed the proposed approach worked well, resulting in relatively good accuracies (73.21%, 74.21%) for two subjects.

Keywords: Brain Computer Interface, Source imaging, Transfer learning, Zero training.

1 Introduction

Brain computer interface (BCI) has been paid attention as one of interesting applications in bio-signal processing society [1, 2, and 3]. BCI system, in general, consists of two phases. One is a calibration phase and the other is a feedback phase. In the calibration phase, some amount of training data are collected, thus it is more likely to have users tired and distracted before the feedback phase (on-line phase). Matthias Krauledat [4] proposed one approach to reduce this phase called as "zero-training". Another approach was reported using the application of source imaging for zero-training [5]. Source imaging likely yields some features unseen in the sensor space and voxel points at the source space could be chosen at user's discretion [6]. This means that for different sessions or subjects, the same voxel points in the co-registered source space can be chosen. In other words, for different sensor configurations (as it is varying over sessions or subjects), it is possible to project sensor data onto the fixed voxel points at the source space after co-registration of each subject into a typical head coordinated space. This point gives an advantage in that collected data for any sessions or any subjects under the same experimental paradigm

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could be used independently as additional trials for any calibration phase, which may possibly reduce calibration phase. This procedure is described in Fig. 1. For example, if some datasets (for different session or subject) are available under the same experiment, then these are projected onto the same source space through source imaging technique. We expect that variability between sessions or subjects at the source space would be diminished significantly because source imaging is likely to reduce some noise and yield more discriminative information. If it would be true, existing datasets would be used to do feature extraction and classification without collecting additional data. Thus, it is likely to reduce the calibration time and further to have zero-training achievable.

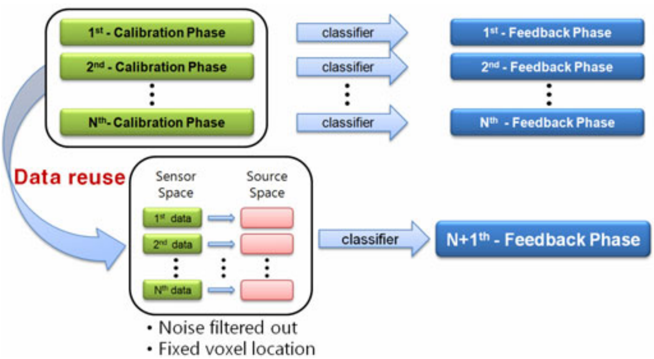

Fig. 1. Proposed zero training procedure

2 Datasets

To see plausibility of our proposed idea, we used dataset IVa in BCI competition III [9]. The description of the datasets is as follows. Five subjects conducted motor imagery experiment ('right' or 'foot'), and datasets were collected using 118 EEG channels. Different numbers of train or test trials were given for subjects (see Table 1). The thrill for this competition was to classify test trials using given train datasets for each subject. Due to the absence of sensor location, we used standard sensor locations for every subject that were obtained from the competition organizer. For more significant temporal and spectral information, we applied frequency filtering with 10Hz to 30Hz since the range certainly includes μ as well as β rhythm. The target signal was extracted from 0.4 sec to 2.4 sec after cue for imagery instruction.

Table 1. Different number of trials for subjects

Subjects	aa	al	av	aw	ay
Trials (Train / Test)	168 / 112	224 / 56	84 / 196	56 / 224	28 / 252

3 Methods

We propose to construct a classifier using source space features over subjects. For this purpose, we introduced three shell Ary 1 head model [7] and beamforming method for source imaging [8].

3.1 Source Imaging by Beamforming

Multi-layer Ary 1 model consists of three concentric spherical layers representing brain, skull and scalp from inner to outer. We considered an outmost layer of radius 100 mm for scalp and other layers were generated according to the radius and relative conductivity ratio of each layer, as tabulated in Figure 2. 1000 voxels were put on the inner-most layer representing brain cortex. To solve the multi-shell model we used Zhang's method [7] and minimum-variance beamforming method [8] was applied for source imaging.

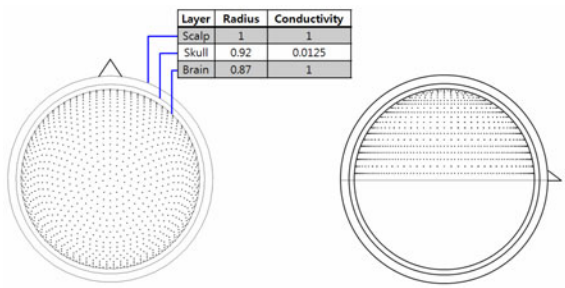

Fig. 2. Head model and 1000 voxels generated on the inner-most sphere

A minimum-variance beamformer is one of the representative adaptive spatial filters [8]. When $\mathbf{m}(t)$ is the spatiotemporal sensor measurement, source activity reconstruction is conducted through the following spatial filtering technique.

$$\hat{Q}(\mathbf{r},t) = \mathbf{w}^T(\mathbf{r})\mathbf{m}(t), \quad \mathbf{w}(\mathbf{r}) = \frac{\mathbf{R}^{-1}\mathbf{l}(\mathbf{r})}{\mathbf{l}^T(\mathbf{r})\mathbf{R}^{-1}\mathbf{l}(\mathbf{r})}, \tag{1}$$

where $\hat{Q}(\mathbf{r},t)$ is the estimated magnitude of the source activity at location $\mathbf{r}$. Here $\mathbf{l}(\mathbf{r})$ and $\mathbf{R}$ denote lead-field vectors representing the meaning of a sensitivity matrix and a covariance matrix of the spatiotemporal signal $\mathbf{m}$(t); $\mathbf{R}=\langle\mathbf{m}(t)\mathbf{m}^T(t)\rangle_t$ and $\langle\bullet\rangle_t$ indicates the time average over a certain given time window.

3.2 Performance Assessment

We have training datasets and testing datasets for each subject, so the performance was assessed only on testing datasets while training datasets were involved to construct a classifier. For comparison, we estimated classification accuracies for two ways; one way is a conventional sensor level approach that a classifier is generated with subject's original sensor training data only and then testing dataset is tested by this classifier. The other way is our proposed approach that sensor data is projected into source space by source imaging method and then a classifier is constructed by source features in the source space from other subjects' data. In this assessment, Linear Discriminant Analysis (LDA) was applied to classify. For channel selection (to choose more discriminative channels among sensors or voxels), channels were sorted in the descending order of significance of student t-test. Finally, accuracies were calculated over the number of channels (in sensor or in voxel) to see the performance behavior as the number channels increases.

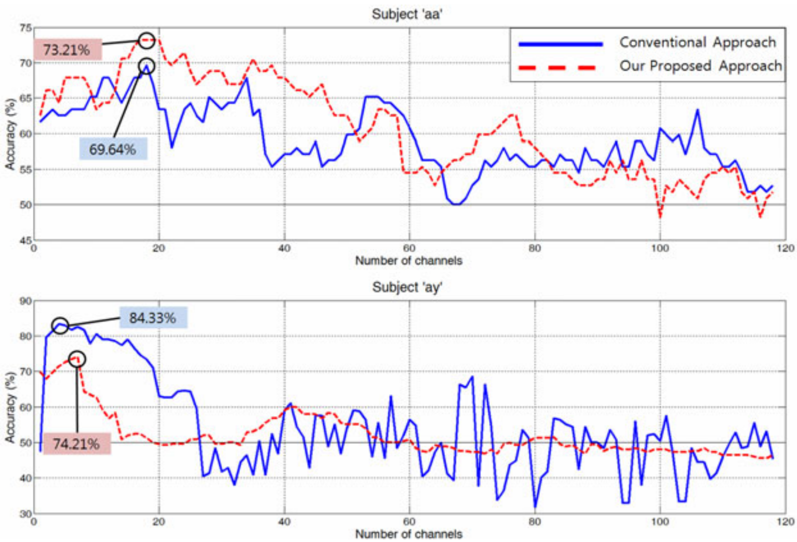

Fig. 3. Classification accuracy behavior between conventional approach using the subject's training data and our proposed approach using source features of other subjects' data

4 Results

As a result, we observed the meaningful performance of our proposed approach for two subjects who are subject 'aa' and subject 'ay' (see Fig. 3). For both subjects, the proposed approach shows good accuracies which are highly above chance level (50%). For subject 'aa', our proposed approach performed even better than conventional approach using the subject's own training data only. We did not observe this behavior for other three subjects ('al','av' and 'aw', not shown here). One interesting observation is that the subject 'ay' shows reasonably comparable performance even though the number of training trials was only 28, which is considerably small compared to the number of testing trials; it is inferred that these 28 trials well represented the entire feature spaces.

5 Conclusion

One critical issue in BCI is to reduce the time-consuming calibration phase. This calibration phase is more likely to make users tired and distracted before the feedback phase, making it hard to collect consistent brain activity, and therefore degrading BCI performance. To overcome this, we proposed a zero-training approach using source imaging. From the investigation using well known dataset IVa in BCI competition III, we observed two subjects showed comparable performance and in one subject of them, our proposed approach performed better than conventional approach using subject's own training data only. Our findings show some possibility that the proposed approach may reduce the calibration time by using other subject's dataset. However, for better understanding, more thorough investigation is necessary, which is under study.

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