Subject-to-Subject Adaptation to Reduce Calibration Time in Motor Imagery-based Brain-Computer Interface

Mahnaz Arvaneh[1], Ian Robertson[1] and Tomas E. Ward [2]

***Abstract*— In order to enhance the usability of a motor imagery-based brain-computer interface (BCI), it is highly desirable to reduce the calibration time. Due to inter-subject variability, typically a new subject has to undergo a 20-30 minutes calibration session to collect sufficient data for training a BCI model based on his/her brain patterns. This paper proposes a new subject-to-subject adaptation algorithm to reliably reduce the calibration time of a new subject to only 3-4 minutes. To reduce the calibration time, unlike several past studies, the proposed algorithm does not require a large pool of historic sessions. In the proposed algorithm, using only a few trials from the new subject, first, the new subject's data is adapted to each available historic session separately. This is done by a linear transformation minimizing the distribution difference between the two groups of EEG data. Thereafter, among the available historic sessions, the one matched the most to the new subject's adapted data is selected as the calibration session. Consequently, the previously trained model based on the selected historic session is entirely used for the classification of the new subject's data after adaptation. The proposed algorithm is evaluated on a publicly available dataset with 9 subjects. For each subject, the calibration session is selected only from the calibration sessions of the eight other subjects. The experimental results showed that our proposed algorithm not only reduced the calibration time by 85%, but also performed on average only 1.7% less accurate than the subject-dependent calibration results.**

I. INTRODUCTION

Brain-computer interface (BCI) provides a direct communication pathway between a human brain and an external device [1]. Using appropriate sensors and data processing algorithms, BCI maps patterns of brain activities associated with a volitional thought onto signals for communication and control [2], [3]. Such technology holds great promise as a basis for assisting people with severe communication and motor disabilities.

In majority of current BCI systems, the brain signals are measured by electroencephalogram (EEG), due to its low cost and high time resolution [4]. Since, the EEG patterns considerably vary between subjects, a new subject typically requires to undergo a 20-30 minutes calibration session to collect sufficient labeled data for training a BCI model based on his/her EEG patterns. This time-consuming preparation step is especially inconvenient and fatiguing for patients, leaving reduced time for actual therapeutic interaction. Therefore, it is highly desirable to substantially reduce the calibration time using existing data from other subjects, while the system is still accurate enough.

One of the first attempts to reduce the calibration time was based on concatenating and clustering the historic spatial filters of the same user [5]. The previous findings in [5] were further confirmed in an online study published in [6]. In another study, it was shown that the calibration model obtained by concatenating a large number of historic sessions from the same patient can be reliably used in BCI-based stroke rehabilitation [7]. Although the methods proposed in [5], [6], [7] yielded promising results, they are not applicable for a new BCI user with no previous data available. To overcome this limitation, Fazli et al. proposed a method to omit the calibration phase for new BCI users by an ensemble of historic sessions [8]. However, the requirement of using a large number of historic data from other subjects may still limit the practicality of this method.

There are also some approaches to reduce the calibration time using co-adaptive learning [9] or semi-supervised learning [10]. In these approaches, the BCI model is built first using very few signals from the new subject, and then it is adapted online using unsupervised or co-adaptive learning algorithms. These approaches have initially limited performances, becoming good only after a significant adaptation time.

This paper aims at reducing the calibration time for new BCI users while only a limited number of historic sessions from other subjects are available. The new proposed algorithm consists of two steps. In the first step, using a few labeled trials from the new subject, the new subject's data is adapted to each available historic session separately. This is done by the EEG data space adaptation (EEG-DSA) algorithm [11], linearly transforming the new subject's data such that the distribution difference between the new data and the considered historic session is minimized. Thereafter, in the second step, the proposed decision making algorithm decides which session among a few existing historic sessions is the most suitable one to be used as the calibration session. Consequently, the previously trained model based on the selected historic session is entirely used for the classification of the new subject's upcoming data after adaptation.

The proposed algorithm is evaluated using a publicly available dataset with 9 subjects. For each subject the calibration session is selected from one of the 8 sessions from the other subjects. In this study only 20 trials from the new subject are used for EEG data space adaptation, and

*This work was supported by Science Foundation Ireland (SFI), under Grant No. 12/RC/2289.

[1] M. Arvaneh and I. Robertson are with Trinity College Institute of Neuroscience and School of Psychology, Trinity College Dublin, Dublin, Ireland, (emails:arvanehm,iroberts@tcd.ie)

[2] T. E. Ward is with Dept. of Electronic Engineering, National University of Ireland, Maynooth, Co. Kildare, Ireland. (email: tomas.ward@eeng.nuim.ie).

978-1-4244-7929-0/14/$26.00 ©2014 IEEE

subsequently finding the best calibration session among the available historic sessions. Thus, the calibration time can be reduced from 20-30 minutes to 3-4 minutes.

II. Method

The new proposed algorithm consists of two steps. The first step adapts the new subject's data to each available historic session individually. The second step selects the historic session that is matched the most to its corresponding adapted new data. Consequently, the trained model based on the selected historic session is used to classify the upcoming data from the new subject after adaptation. These steps are described in detail in the next subsections.

A. Subject-to-Subject Adaptation

In this work, the set of the band-pass filtered EEG trials from the k^{th} existing historic session is denoted as $\bar{D}_k = \{(\bar{\mathbf{x}}_{k,i}, \bar{\mathbf{y}}_{k,i})\}_{i=1}^{\bar{N}}$, where $\bar{\mathbf{x}}_{k,i} \in \bar{\mathbf{X}}_k \subset \mathbb{R}^{n\times s}$ denotes the i^{th} single-trial EEG of k^{th} historic session, and $\bar{\mathbf{y}}_{k,i} \in \bar{\mathbf{Y}}_k \subset \mathbb{R}$ is the class label of the $\bar{\mathbf{x}}_{k,i}$. n and s denote the number of channels and samples respectively. In a same line, the available labeled EEG trials from the new subject are denoted as $D = \{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^{N}$, where $\mathbf{x}_i \in \mathbf{X} \subset \mathbb{R}^{n\times s}$, and $\mathbf{y}_i \in \mathbf{Y} \subset \mathbb{R}$. In this study, we assume only 20 labeled trials (i.e. 10 trials per class) from the new subject are available.

The dissimilarities between the k^{th} historic session and the new subject's data yield different joint distributions. However, changing the representation of $\mathbf{X}$, while the representation of $\mathbf{Y}$ is fixed, can change the joint distribution of the new subject's data. Thus, if a transformation function can be computed to transform the new subject's data, such that the joint distributions of the new subject's data and the k^{th} historic session become similar, the optimal model that classifies the k^{th} historic data will be still proper for classifying the new subject's data. For this purpose, a linear transformation function is proposed as

$$\mathbf{h}_k = \mathbf{V}_k^{\mathrm{T}}\mathbf{X}, \tag{1}$$

where $\mathbf{V}_k \in \mathbb{R}^{n\times n}$ denotes the EEG-DSA transformation matrix. The transformation matrix $\mathbf{V}_k$ should be computed such that the distribution difference between the new subject's data and the k^{th} historic data is reduced.

We assume that the differences between the new and the historic data can be observed in the first two moments of the single-trial EEG (i.e. mean and covariance) [12]. Following this assumption, to simplify the problem, we only compare the average distributions of the new subject's data and the k^{th} historic data to compute $\mathbf{V}_k$. We use the Kullback-Leibler (KL) divergence between Gaussians to measure the differences between the average distributions of two EEG groups. Since the single-trial EEG is band-pass filtered, it has zero mean value. Thus, the KL divergence between two groups of band-pass filtered EEG data can be calculated as

$$\mathrm{KL}[N_0||N_1] = \frac{1}{2}[\mathrm{tr}(\overline{\boldsymbol{\Sigma}}^{-1}\boldsymbol{\Sigma}) - \ln(\frac{\det(\boldsymbol{\Sigma})}{\det(\overline{\boldsymbol{\Sigma}})}) - d], \tag{2}$$

where $\overline{\boldsymbol{\Sigma}}$ and $\boldsymbol{\Sigma}$ denote the average covariance matrices of the two groups of the EEG trials; $\det$ and d denote the determinant function and the dimensionality of the data respectively.

Let $N(0, \overline{\boldsymbol{\Sigma}}_{k,j})$ be the average distribution of the EEG trials belonging to the class j from the k^{th} historic data. The average distribution of the transformed EEG trials belonging to the class j from the new subject is estimated as $N(0, \mathbf{V}_k^{\mathrm{T}}\boldsymbol{\Sigma}_j\mathbf{V}_k)$, where $\mathbf{V}_k$ denotes the EEG-DSA transformation matrix, and $\boldsymbol{\Sigma}_j$ is estimated using D. When the class probabilities are balanced, using the KL divergence the optimal $\mathbf{V}_k$ can be computed as the solution of the minimization problem

$$\begin{aligned}\mathrm{L}(\mathbf{V}_k) &= \min_{\mathbf{V}_k}\sum_{j=1}^{2}\mathrm{KL}[N(0,\mathbf{V}_k^{\mathrm{T}}\boldsymbol{\Sigma}_j\mathbf{V}_k)||N(0,\overline{\boldsymbol{\Sigma}}_{k,j})] = \\ &\min_{\mathbf{V}_k}\sum_{j=1}^{2}\frac{1}{2}[\mathrm{tr}(\overline{\boldsymbol{\Sigma}}_{k,j}^{-1}\mathbf{V}_k^{\mathrm{T}}\boldsymbol{\Sigma}_j\mathbf{V}_k) - \ln(\frac{\det(\mathbf{V}_k^{\mathrm{T}}\Sigma_j\mathbf{V}_k)}{\det(\overline{\boldsymbol{\Sigma}}_{k,j})}) - d].\end{aligned} \tag{3}$$

To minimize (3), it is sufficient to calculate the first order derivative of the loss function $\mathrm{L}(\mathbf{V}_k)$ with respect to $\mathbf{V}_k$, and set it to zero;

$$\frac{d\mathrm{L}}{d\mathbf{V}_k} = \frac{1}{2}\sum_{j=1}^{2}\frac{d}{d\mathbf{V}_k}[\mathrm{tr}(\overline{\boldsymbol{\Sigma}}_{k,j}^{-1}\mathbf{V}_k^{\mathrm{T}}\boldsymbol{\Sigma}_j\mathbf{V}_k) - \ln(\det(\mathbf{V}_k^{\mathrm{T}}\boldsymbol{\Sigma}_j\mathbf{V}_k))]. \tag{4}$$

Setting (4) to zero results in (see [11] for details)

$$\mathbf{V}_k^* = \sqrt{2}((\overline{\boldsymbol{\Sigma}}_{k,1}{}^{-1}\boldsymbol{\Sigma}_1 + \overline{\boldsymbol{\Sigma}}_{k,2}{}^{-1}\boldsymbol{\Sigma}_2)^{\dagger})^{0.5}, \tag{5}$$

where $\dagger$ denotes the pseudo inverse of the matrix that always exists [13]. $\mathbf{V}_k^*$ is the optimal linear transformation matrix that transforms the EEG data of the new subject, such that the distribution difference between the new data and the k^{th} historic data is minimized.

B. Selecting the Best Calibration Model

As described in the previous subsection, the dissimilarities between the new subject's data and each available historic session is reduced using a separate EEG-DSA transformation matrix. Nevertheless, the distribution dissimilarities between the historic sessions and their corresponding transformed (adapted) new data are still different. The transformed new data may be more similar to some of the historic sessions compared to the other ones. Thus, the second step of the proposed algorithm is selecting the best historic session among the available sessions as the calibration session for the new subject's data.

Fig. 1 illustrates how the proposed algorithm selects the best historic session. The available new subject's trials are first adapted using the EEG-DSA transformation matrices, and then classified using the models obtained by the corresponding historic sessions. The historic session that yields the highest classification accuracy is selected as the calibration session (i.e. the best historic session) for the data to be collecting from the new subject. If more than one session yield the highest classification accuracy, the one with the smallest KL divergence with the transformed new subject's data is selected as the calibration session. It is shown in (6))

$$k^{*} := \arg\min_{k\in\phi} \sum_{j=1}^{2} \mathrm{KL}[N(0, \mathbf{V}_k^{\mathrm{T}} \mathbf{\Sigma}_j \mathbf{V}_k) || N(0, \overline{\mathbf{\Sigma}}_{k,j})], \quad (6)$$

where ϕ denotes the set of historic sessions that yielded the highest accuracy in classifying the new subject's data after adaptation.

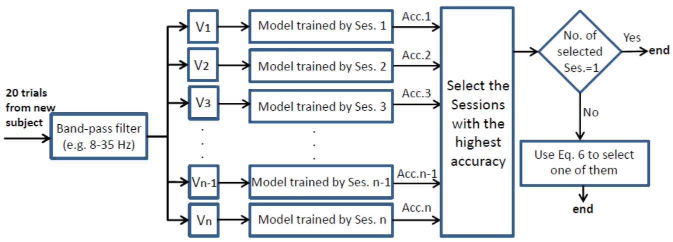

Fig. 1. The second step of the proposed algorithm: selecting the best historic session. Ses. indicates Historic Session, and n denotes the number of available historic sessions.

III. Experiments

In this study, EEG data from BCI competition IV, Dataset IIa [14] were used. This data set contains EEG signals recorded from 9 subjects (named A1, A2, ..., A9) using 22 electrodes per subject. During each experiment, the subject was given visual cues that indicated four motor imageries should be performed: left hand, right hand, feet and tongue. Only the EEG signals corresponding to the right and left motor imagery tasks were applied in the present study. A training and a testing set recorded in different days were available for each subject, and both sets contain 72 trials for each class. In this study, each training set was used as a possible calibration session for the other 8 subjects.

For each subject, signals from 0.5 to 2.5 seconds after the cue were applied in this work (as done by the winner of BCI competition IV, data set IIa). EEG signals were classically filtered into 8 to 35 Hz frequency band using an elliptic filter. In fact, this frequency band contains all the main frequencies involved with the motor imagery. Thereafter log of variances of the three first and the three last rows of the filtered signals, obtained by common spatial patterns (CSP) were used as the inputs of the LDA classifier.

IV. Results and Discussion

In this study, only the first 20 trials of each test session were used for adaptation and finding the best subject independent calibration sessions. Subsequently, all the classification results presented in this section were obtained using the reminder of the test sessions.

A. Calibration Sessions Selected by Subject-to-Subject Adaptation

Table I compares the performance of the proposed algorithm against different calibration methods. The first row presents the classification results obtained by the subject-dependent calibration sessions recorded previously. This method is abbreviated as SD-Cal. The second row presents the classification results when only the 20 trials recorded at the beginning of the test session were used for calibration. Since the 20 trials were recorded from the same subject in the same session as the test trials, they were not affected by subject-to-subject and session-to-session variations. However, since the number of trials is too few, they may not lead to a proper model for classification of upcoming test trials. Indeed, the results in the second row confirm this issue. Compared to SD-Cal, calibration models obtained by the 20 trials slightly improved the classification results of the subjects A1, A3 and A9. This would be due to eliminating the possible strong session-to-session non-stationarity in these subjects. However, on average the SD-Cal method yielded 5.5% higher classification accuracy (not statistically significant $p = 0.14$). Particularly, the decrease in the performance of the subjects A4 and A6 were substantial (i.e. 29% and 11.3% respectively).

TABLE I

Performance Comparison of Different Calibration Methods. The Proposed Algorithm Was Abbreviated as SI-Cal/Adapt.

Data Set IIa, BCI Competition IV										
Subject	**A1**	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**	**Mean**
SD-Cal	82.2	54	91.1	75	69.3	63.7	80.6	96.8	84.7	77.5
20-Test-Trial-Cal	83.0	50	93.5	46	63.7	52.4	75	96	88.7	72
All-Others-Cal	65.3	54	95.9	61.3	60.5	54.8	70.1	95.2	65.3	69.2
SI-Cal/NoAdapt	79.8	51.6	81.4	75	54.8	58.9	77.4	76.6	60.5	68.4
SI-Cal/Adapt	82.2	53.2	96.8	75	64.5	63.7	73.4	95.2	78.2	75.8

[1] *SD: subject-dependent, Cal: calibration, SI: subject-independent, Adapt: adaptation.*

In this study, three different subject-independent calibration models were evaluated. The results of these three models are presented in the third, fourth and fifth rows of Table I. In the third row, the calibration models were built by concatenating all the available training sessions from the other eight subjects. The results show that the calibration models obtained by this method performed significantly worse than SD-Cal by an average of 8.3% ($p = 0.014$). In the fourth row, for each subject one of the available training sessions from the other eight subjects was selected as the subject-independent calibration session. To select the subject-independent calibration session, the second step of the proposed algorithm was applied. Thus, for each subject, the first 20 trials of the test session were used to evaluated the available calibration sessions from the other subjects. This method was abbreviated as SI-Cal/NoAdapt since no adaptation was applied. The results on the fourth row of Table I indicates that the SI-Cal/NoAdapt method performed worse than all the methods discussed so far. Precisely, the SD-Cal method significantly outperformed the SI-Cal/NoAdapt method by an average of 9.1% ($p = 0.014$).

Finally, the last row of the table presents the classification results obtained by the proposed algorithm abbreviated as SI-Cal/Adap. The results show that the proposed algorithm outperformed the calibration models obtained by the first 20 trials of the test session, concatenating the trials from the

TABLE II

ADAPTATION USING SESSIONS FROM THE SAME SUBJECT AND OTHERS

Data Set IIa, BCI Competition IV										
Subject	**A1**	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**	**Mean**
SD-Cal/Adapt	93.5	53.2	96.8	76.6	76.2	62.9	77.4	96	87.1	79.3
SI&SD-Cal/Adapt	93.5	53.2	96.8	76.6	76.2	63.7	77.4	97.2	87.1	79.4

[2] *SD: subject-dependent, Cal: calibration, SI: subject-independent, Adapt: adaptation.*

other subjects, and the SI-Cal/NoAdap method by an average of 3.8%, 6.6% and 7.4% respectively (p =0.33, 0.017, and 0.028 respectively). Importantly, the classification accuracies obtained by the proposed SI-Cal/Adap algorithm were only 1.7% less accurate than the results of the SD-Cal method ($p = 0.23$). The results suggest that using the proposed SI-Cal/Adap algorithm, the BCI session can be accurately and reliably started for a new subject just by collecting 3-4 minutes data.

B. Session-to-Session Adaptation for the Same Subject

In the previous subsection, we assumed that for each new subject no previous sessions are available. Subsequently, we looked for the best calibration session among the available sessions from other subjects. In this subsection, we assume that a session recorded on another day is available for each subject. However, due to session-to-session variations the model trained based on the previous session may not be optimal. Indeed, the distribution difference between the test and train sessions of the same subjects can be also reduced using the EEG-DSA transformation matrix computed by the first 20 trials of the new session. This algorithm is abbreviated as SD-Cal/Adap, and its classification results are presented in the first row of Table II. Comparing the first rows of Table I and Table II shows that using the EEG-DSA algorithm to adapt the new data to the subject-dependent calibration session recorded on another day improved the results by an average of 1.8% (although not statistically significant $p = 0.25$) .

Now, the question arises of whether or not the results can be further improved if the calibration session is selected from a set of historic sessions including sessions from the same and other subjects. To answer this question, for each subject we changed the set of historic sessions from 8 to 9 by including the session from the same subject. This method is abbreviated as SI&SD-Cal/Adapt, and its corresponding results are presented in the second row of the Table II. The results show that for 8 of the 9 subjects the selected calibration session was that which was recorded from the same subject. Subject A6 was the only exception. The historic session from the first subject, A1, was selected in this case yielding 0.8% higher classification results.

Considering the computation time and based on the very small improvement in the classification accuracy, the SI&SD-Cal/Adapt is not especially attractive. Overall, our results suggest to apply the SD-Cal/Adap algorithm (i.e. session-to-session adaptation) when a session recorded on another day from the same subject is available. In case where no historic session from the subject is available, the proposed SI-Cal/Adapt could be reliably used to start the BCI application with feedback as early as possible.

V. CONCLUSIONS

This paper proposed a new algorithm to substantially reduce the calibration time for a new subject in motor-imagery based-BCI applications. Using the EEG data space adaptation algorithm, the new subject's data is adapted to each available historic session separately. Thereafter, the historic session matched the most to the adapted new data is chosen to be used as the calibration session for the new subject. Unlike several past studies, the proposed algorithm does no require a large pool of data from other subjects. Importantly, it can be easily applied in online applications, as computing the EEG-DSA transformation matrix and adapting the new data to that can be done in less than a second. Furthermore, the adapted new data are evaluated by a model previously trained using the selected calibration session. The experimental results showed that the proposed algorithm performed only 1.7% less accurate than the subject-dependent calibration method, while the calibration time was substantially reduced to 3-4 minutes.

REFERENCES

[1] N. Birbaumer, "Brain-computer-interface research: Coming of age," *Clin. Neurophysiol.*, vol. 117, pp. 479- 483, 2006.

[2] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain-computer interfaces for communication and control," *Clin. Neurophysiol.*, vol. 113, pp. 767-91, 2002.

[3] E. A. Curran and M. J. Stokes, "Learning to control brain activity: A review of the production and control of EEG components for driving brain-computer interface (BCI) systems," *Brain Cogn.*, vol. 51, pp. 326-36, 2003.

[4] G. Pfurtscheller, C. Neuper, D. Flotzinger, and M. Pregenzer, "EEG-based discrimination between imagination of right and left hand movement," *Electroencephalogr. Clin. Neurophysiol.*, vol. 103, no. 6, pp. 642-51, 1997.

[5] M. Krauledat, M. Schroder, B. Blankertz, and K. Muller, Reducing calibration time for brain-computer interfaces: A clustering approach, *Advances Neural Information Processing Syst.*, vol. 19, pp. 753, 2007.

[6] M. Krauledat, M. Tangermann, B. Blankertz, K. Muller, "Towards zero training for brain-computer interfacing," *PLoS ONE*, vol. 3, no. 8, pp. 1-12, 2008.

[7] M. Arvaneh, C. Guan, k. Ang, and C. Quek, "Omitting the intrasession calibration in EEG-based brain computer interface used for stroke rehabilitation." *Proceedings of the 34th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, San Diego, 2012, pp. 4124-7.

[8] S. Fazli, F. Popescu, M. Danoczy, B. Blankertz, K. Muller, C., Grozea, "Subject independent mental state classification in single trials", *Neural Networks*, vol. 22, pp. 1305-12, 2009.

[9] C. Vidaurre, C. Sannelli, K.-R. Müller, and B. Blankertz, "Machine-learning-based coadaptive calibration for brain-computer interfaces," *Neural Comp.*, vol. 23, no. 3, pp. 791-816, 2011.

[10] Y. Li, C. Guan, H. Li, and Z. Chin, "A self-training semisupervised SVM algorithm and its application in an EEG-based brain computer interface speller system," *Pattern Recognition Letters*, vol. 29, no. 9, pp. 1285-94, 2008.

[11] M. Arvaneh, C. Guan, K. K. Ang, and C. Quek, "EEG data space adaptation to reduce intersession nonstationarity in brain-computer interface," *Neural Computation*, vol. 25, no. 8, pp. 2146-71, 2013.

[12] P. von Bunau, F. C. Meinecke, F. Kiraly, and K.-R. Müller, "Estimating the stationary subspace from superimposed signals," *Physical Review Letters*, vol. 103, p. 214101, 2009.

[13] K. B. Petersen and M. S. Pedersen, "The matrix cookbook," [Online]. Available: http://www2.imm.dtu.dk/pubdb/p.php?3274, 2006. version: 20070905.

[14] M. Naeem, C. Brunner, R. Leeb, B. Graimann, and G. Pfurtscheller, "Seperability of four-class motor imagery data using independent components analysis," *J. Neural Eng.*, vol. 3, pp. 208-16, 2006.