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Modeling EEG-based Motor Imagery with Session to Session Online Adaptation

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Abstract—Subject-specific calibration plays an important role in electroencephalography (EEG)-based Brain-Computer Interface (BCI) for Motor Imagery (MI) detection. A calibration session is often introduced to build a subject specific model, which then can be deployed into BCI system for MI detection in the following rehabilitation sessions. The model is termed as a fixed calibration model. Progressive adaptive models can also be built by using data not only from calibration session, but also from available rehabilitation sessions. It was reported that the progressive adaptive model yielded significant improved MI detection compared to the fixed model in a retrospective clinical study. In this work, we deploy the progressive adaptation model in a BCI-based stroke rehabilitation system and bring it online. We dub this system nBETTER (Neurostyle Brain Exercise Therapy Towards Enhanced Recovery). A clinical trial using the nBETTER system was conducted to evaluate the performance of 11 stroke patients who underwent a calibration session followed by 18 rehabilitation sessions over 6 weeks. We conduct retrospective analysis to compare the performance of various modeling strategies: the fixed calibration model, the online progressive adaptation model and a light-weight adaptation model, where the second one is generated online by nBETTER system and the other two models are obtained retrospectively. The mean accuracy of the three models across 11 subjects are 68.17%, 74.04% and 74.53% respectively. Statistical test conducted on the three groups using ANOVA yields a p-value of 9.83-e06. The test result shows that the two adaptation models both have significant different mean from fixed mode. Hence our study confirmed the effectiveness of using the progressive adaptive model for EEG-based BCI to detect MI in an online setting.

I. INTRODUCTION

The principle behind Brain-Computer Interface (BCI)-based post-stroke rehabilitation is to detect a subject's motor intention using Motor Imagery (MI) for robotic control, thereby creating a closed loop neurofeedback to boost neural function recovery. Electroencephalography (EEG)-based MI detection is challenging as EEG signal has a rather low spatial resolution [1] and is prone to be contaminated by eye and muscle movements. Various methodologies have been developed to advance EEG decoding for MI detection. The modeling process can be categorized into general model and subject-specific model. The first general model was proposed by Wolpaw et al., who demonstrated that subjects could be trained to use the mu rhythm (8-12 Hz) extracted from EEG for one-dimension

control [2]. In a subsequent study [3], subjects were trained to manipulate mu (8-12 Hz) and beta (18-26 Hz) rhythms over the left or right sensorimotor cortex for control with a Sensorimotor Rhythm (SMR)-based BCI. Another recent study also shows that subjects can use SMR-based BCI to detect MI for three-dimensional control of a quadcopter in physical space [4].

The ability to perform motor imagery varies across people, and this capability would have a major effect on the effectiveness of motor imagery training [5]. Subject-specific model tackles the issue by identifying subject-specific EEG features and signal patterns. Thus, it is more effective in MI model training. In an earlier study [6], we conducted retrospective analysis to compare subject-specific models trained with only one calibration session (termed fixed model), or trained progressively using data acquired in calibration session and the following rehabilitation sessions (termed adaptive model). It was reported that the progressive adaptive model yielded significantly improved MI detection compared to the fixed model.

Motivated by the conclusions drawn in [6], we implemented the online mode of session-to-session transfer adaptation approach and deployed it into a BCI rehabilitation system called nBETTER (Neurostyle Brain Exercise Therapy Towards Enhanced Recovery). In this paper, we will present extensive results on the online adaptation model feedback accuracies of detecting MI from stroke patients and compare it to the fixed model accuracy resulted from retrospective analysis.

II. METHOD

A. Subject-Specific Model

Machine learning (ML) techniques were employed in BCI to tackle the issue of high variability in EEG for single-trial data [7]. One of the key ML techniques developed for BCI is Common Spatial Pattern (CSP) [8], designed to increase the signal-to-noise ratio [9] of the inherently low spatial resolution of standard EEG [1].

CSP built models using subject data recorded from a single calibration sessions. This sets it apart from general, manually tuned models which require subjects to undergo several sessions to learn to control a specific EEG rhythm. One calibration session is sufficient, where the subject is instructed

to perform MI tasks such as left and right hand MI. The CSP algorithm is then applied to the EEG data collected to compute a CSP filter. However, the performance of CSP algorithm still relies on several manually selected parameters, such as the temporal frequency band-pass filtering of the EEG signals and the time segment of the EEG extracted relative to the instruction cue to the subject [9]. To address this issue, Ang et al. proposed the Filter Bank Common Spatial Pattern (FBCSP) algorithm [10] which selected parameters based on mutual information between the spatial-temporal patterns from the EEG.

Fig. 1. EEG-based MI modeling processing using FBCSP (Filter band common spatial pattern) algorithm

As illustrated by figure 1, the FBCSP algorithm first employs a filter bank that decomposes the EEG into multiple frequency bands using a number of band-pass filters, for example, 4-8 Hz, 8-12 Hz, ..., 36-40 Hz. Next, CSP spatial filtering is performed for each pair of band-pass whereby each spatial filter extracts CSP features that are specific to that band-pass frequency range. Subsequently, feature selection is performed based on the mutual information computed between each feature and the corresponding MI tasks. Finally, a classification algorithm is used to build the MI detection model.

B. Session-to-Session Online Adaptation Model

In [6], we proposed an adaptive strategy to improve the performance of the calibration model. Figure 2 shows the difference between the improved adaptive model from the subject-specific calibration model.

Left side of figure 2 shows the training method for fixed model, the parameters are computed from subject's EEG data recorded from a single calibration session. Right side of figure 2 shows the progressive model, which is first crafted using EEG data recorded from calibration session, then progressively updated with subsequent feedback sessions. To address the session-to-session non-stationarity in the EEG [10], one approach is to compute the adaptation subject-specific model using EEG data collected from the calibration session and subsequently update the model using EEG data collected from the following sessions [11]. The adaptation can be performed using either a supervised or unsupervised manner [12], [13]. In this study, adaptation algorithm is performed at the features filtering level.

Fig. 2. Online adaptation strategy calibrates the model using information from all previous sessions. Left: subject-specific calibration. Right: improved online adaptation calibration

Let D_j denote the EEG data used to compute the subject-specific model to detect MI for the j^{th} online feedback session. The fixed calibration model employing the machine learning algorithm, $D_j = \hat{D}$, where $\hat{D}$ denotes the EEG data from the offline calibration session.

In the j^{th} feedback session ($j > 1$), the EEG data collected from the previous $(j-1)^{th}$ sessions are readily available. The adaptation strategy fully utilize such data, the training data for j^{th} session is:

$$D_j = \begin{cases} \hat{D}, & \text{if } j = 1 \\ \bigcup_{k=0}^{j-1} D_k, & \text{if } j > 1, \text{ where } D_0 = \hat{D} \end{cases} \quad (1)$$

where D_k denotes the EEG data from the k^{th} online feedback session, and $\bigcup$ denotes the union operator.

III. CLINICAL TRIAL AND RESULT ANALYSIS

A. nBETTER system for Clinical Trial

The nBETTER system is a portable, internet-connected device that detects the imagined movement of a patient stroke-affected limb. It is an EEG-based MI BCI that provides visually engaging feedback for exercising the brain towards better recovery after stroke. The system consists of a computer connected to an EEG cap through an EEG amplifier. Using nBETTER, we conducted a single arm multi-site clinical trial on an EEG-based MI-BCI. The objective of the trial is to investigate the efficacy of using nBETTER together with standard occupational therapy for upper-limb rehabilitation of subacute and chronic hemiparetic stroke survivors. Ethics approval for the clinical trial was obtained from the Institutions Domain Specific Review Board, National Healthcare Group, Singapore. Out of 13 stroke patients recruited, 11 patients completed the intervention and our analysis will be based on these 11 subjects' EEG data.

A screen session was conducted to decide whether a subject is clinically suitable, eligible for the BCI task. Recruited subjects then completed a MI-BCI calibration session, followed by 6 weeks of thrice-weekly, total 18 rehabilitation sessions supervised by an occupational therapist and bioengineer. In all sessions of MI trials, subjects were instructed to perform upper-arm kinesthetic MI of their affected side, e.g., to *imagine to move* the stroke-affected arm and hand forward to repeatedly reach for an imaginary target in front of them. If the Idle task was to be performed, the subjects were instructed to relax, keep still and stare straight at the computer screen. The MI brain signals were detected using the FBCSP algorithm [10]. Detailed protocol design and trial description will be reported in a separate publication.

Fig. 3. Calibration and rehabilitation sessions conducted in BCI-MI clinical trial, based on results generated from 18*40 MI trials

Each subject undergoes one screening session and another calibration session in week 0, followed by 18 rehabilitation sessions of nBETTER training coupled with standard arm therapy over 6 weeks (3 sessions per week). Each of the sessions comprised 40 trials. Figure 3 illustrates the data of sessions and trials used in this study.

B. EEG data acquisition

EEG data from 24 channels were collected using the Neurostyle acquisition hardware with unipolar Ag/AgCl electrodes channels, digitally sampled at 256Hz with a resolution of 24 bits for voltage ranges of 300mV.

C. Settings for model comparison

The online adaptation model has been deployed into the nBETTER system during the clinical trial. Hence, the 11 subjects' EEG data acquired from the trial already contains MI labels and the detection accuracies of the online adaptation model. We further conducted retrospective analysis to build the offline calibration model, and a light-weight adaptation model. Overall, we compare three models in this work:

- *Setting A. Retrospective offline calibration model*

In this strategy, the subject model is calibrated using a single calibration session whereby the subject were instructed to learn motor imagery. The model accuracy

is obtained through retrospective calculation using the EEG data with MI labels obtained through the trial using Matlab (R2015b)

- *Setting B. The online adaptation model using all previous sessions*

This strategy revised the model session-to-session progressively. Each new session is trained using a recalibrated model that make use of all available data acquired prior to the current session. The accuracy of this model is recorded in the nBETTER system after each session, implemented in C++.

- *Setting C. Retrospective light-weight adaptation model using last 4 sessions data*

This strategy calibrates the subjective model using only the last 4 sessions prior to the current session. Again, the model accuracy is obtained through retrospective manner, performed using Matlab.

D. Result and analysis

Figure 4 presents the comparison of the three modeling strategies. The vertical bars are the boxplot which represent the accuracy distribution of each subject, based on results generated from $18 \times 40 = 720$ MI trials. For clarity, the subjects are sorted based on the mean accuracy of setting A, the retrospective offline calibration model. The online adaptation models (setting B and C) outperform the offline calibration model for 9 out of 11 subjects.

Fig. 4. Comparison of performance of three MI detection models for each subject

We further compare the averaged session-to-session MI detection performance of the three settings. In Figure 5, the upper sub-figure shows the boxplot of session-wide accuracy, using 11 subjects' 40 trial data acquired in each rehab session. In the first session, as all models are build using data from calibration session only, there is no different in performance. Please note that the result of setting A and C varied slightly from the online result when calculated retrospectively. This is

probably due to a difference in calculation accuracy between Matlab and C++. From session 2 onward, the online adaptation models begin to show their advantages. The lower sub-figure plots the relative improvement of online adaptation models compare to offline calibration model. Clearly, an incremental trend of improvement along the session become obvious when more data is available for adaptive training.

Fig. 5. Comparison of performance of three MI detection models along the rehabilitation sessions. Top: The vertical bar of each session shows the distribution of 11 subjects' 40 trial data. Bottom: The relative accuracy gains are calculated based on average values per session.

E. Accuracy and Statistic Test

The mean accuracy across 11 subjects, 18 sessions of 40 rehabilitation trials for settings of three approaches: A) fixed calibration model, B) online adaptation model with all previous sessions; and C) light-weight adaptation model with up to last 4 sessions data are 68.17%, 74.04% and 74.53% respectively.

We conduct an ANOVA test on the three settings and obtained a p-value of 9.83-e06. The ANOVA test shows that setting B and C have significantly different mean from setting A. However, no significant difference is found between setting B and C.

Our results confirmed the effectiveness of using the progressive adaptive model for EEG-based BCI to detect MI in an online setting.

IV. DISCUSSION AND CONCLUSION

In this study, we conducted comprehensive analysis to validate the possibility of using a data driven model to improve the EEG-based MI detection in a BCI-based stroke rehabilitation systems. We believe that this data driven approach will become more popular as computational power become faster and cheaper.

We have implemented the online adaptation models into nBETTER. We then compare the MI detection performance of three modeling approaches, fixed calibration model, adaptation with all previous data and a light-weight adaptation model. Our results show that both adaptation calibration model significantly improve the performance of EEG-based MI detection. Interestingly, the light-weight model even performs slightly better than the full model, though not by much. Hence, when there are computational constraints in the system, we may replace the full adaptation with a light-weight adaptation model.

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