

# EEG-Based Strategies to Detect Motor Imagery for Control and Rehabilitation

Kai Keng Ang, *Senior Member, IEEE*, and Cuntai Guan, *Senior Member, IEEE*

**Abstract**—Advances in brain–computer interface (BCI) technology have facilitated the detection of Motor Imagery (MI) from electroencephalography (EEG). First, we present three strategies of using BCI to detect MI from EEG: operant conditioning that employed a fixed model, machine learning that employed a subject-specific model computed from calibration, and adaptive strategy that continuously compute the subject-specific model. Second, we review prevailing works that employed the operant conditioning and machine learning strategies. Third, we present our past work on six stroke patients who underwent a BCI rehabilitation clinical trial with averaged accuracies of 79.8% during calibration and 69.5% across 18 online feedback sessions. Finally, we perform an offline study in this paper on our work employing the adaptive strategy. The results yielded significant improvements of 12% ( $p < 0.001$ ) and 9% ( $p < 0.001$ ) using all the data and using limited preceding data respectively in the feedback accuracies. The results showed an increase in the amount of training data yielded improvements. Nevertheless, results of using limited preceding data showed a larger part of the improvement was due to the adaptive strategy and changing subject-specific models did not deteriorate the accuracies. Hence the adaptive strategy is effective in addressing the non-stationarity between calibration and feedback sessions.

**Index Terms**—Adaptive, brain–computer interface (BCI), electroencephalography (EEG), machine learning, motor imagery (MI), operant conditioning, stroke rehabilitation.

## I. INTRODUCTION

MOTOR imagery (MI), the mental process of imagining movements without physical movement [1], is useful to healthy people for learning new motor skills in sports [2] and also useful to paralyzed people for motor recovery in rehabilitation [3]. The rationale of performing MI arises from activation of brain regions in the sensorimotor network similar to that of physical movement [4]. Hence patients who have difficulty in performing physical movement during rehabilitation can perform MI to activate the partially damaged motor networks towards motor recovery [5]. However, the integration of MI in rehabilitation yielded mitigated results because while

motor execution is observable, MI cannot be observed for compliance. Hence MI is practiced in rehabilitation using a wide variety of methods, such as the use of audiotapes or one-to-one guidance by a therapist [6].

Recent advances in brain signals processing and computing capabilities have enabled the use of brain signals for communication [7], control [8] and rehabilitation [9], [10] without using their neuromuscular system. This technology called brain–computer interface (BCI) thus provides an alternative means for paralyzed people who have suffered nervous system injury [10], [11]. Brain signals can be measured non-invasively from electrical potentials on the scalp [electroencephalography (EEG)], magnetic fields changes [magnetoencephalography (MEG)], or metabolic processes related to brain function [positron emission tomography (PET), functional magnetic resonance imaging (fMRI), and functional near infrared imaging (fNIR)]. Brain signals can also be measured semi-invasively from electrical potentials on the brain surface underneath the skull [electrocorticography (ECoG)], or invasively within the brain using microelectrode recordings [12]. At present, EEG is the most practical choice for BCI as it is non-invasive, safe, relatively inexpensive, can capture fast changes in brain activity, and can function in most environments.

It was discovered that neurophysiological phenomena called event-related desynchronization or synchronization (ERD/ERS) are detectable from EEG when MI is performed [13]. ERD or ERS is also highly frequency band-specific [14], but it was demonstrated that they can be observed from mu (9–13 Hz) or beta rhythms (22–29 Hz) extracted from EEG over the primary sensorimotor area for some subjects [15]. Thus a BCI that extracts and processes frequency band-specific EEG can be used to detect the performance of MI [16]. However, EEG measures the electrical potential between the signal electrode and a reference electrode. As such, EEG may be contaminated by eyes and muscles movements. In addition, standard EEG has a low spatial resolution (5–9 cm) [17] that can only measure the electrical potential from a population of neurons over a large brain area. Hence processing EEG for detecting MI is challenging because EEG only allows the detection of relatively gross brain signal changes.

In the development of EEG-based BCI for control, Wolpaw, et al. [18] were the first to demonstrate that subjects could be trained to use the mu rhythm (8–12 Hz) extracted from EEG for one-dimension control of a cursor on the computer screen. This was known as operant conditioning [19]

Manuscript received January 29, 2016; revised August 7, 2016 and December 2, 2016; accepted December 18, 2016. Date of publication December 30, 2016; date of current version April 11, 2017. This work was supported by the Science and Engineering Research Council of A\*STAR (Agency for Science, Technology and Research).

The authors are with the Institute for Infocomm Research, Agency for Science, Technology and Research (A\*STAR) 138632, Singapore and also with the School of Computer Science and Engineering, Nanyang Technological University 639798, Singapore (e-mail: kkang@i2r.a-star.edu.sg; ctguan@ntu.edu.sg).

Digital Object Identifier 10.1109/TNSRE.2016.2646763

based on studies that trained subjects to suppress or enhance certain frequency band for therapeutic purposes [20]. Subsequently, EEG-based BCI in which subjects were trained to suppress or enhance mu (8–12 Hz) and beta (18–26 Hz) rhythms over the left or right sensorimotor cortex for control was known as sensorimotor rhythm (SMR)-based BCI [21]. Weighted combinations of mu and beta rhythms facilitated the extension to a two-dimension control of a cursor on the screen [22], [23], and subsequently to detect MI for three-dimension control of a cursor on the screen [24] or a virtual helicopter [25], [26]. Recently, it was demonstrated that subjects can use SMR-based BCI to detect MI for three-dimensional control of a quadcopter in physical space [27].

On the other hand, EEG data can be first collected from subjects performing MI tasks such as left hand, right hand and foot during calibration. In this way, subject-specific rhythms can be selected and mapped to control actions. It was demonstrated that a tetraplegic patient was able to perform MI of the right hand and foot to regulate beta rhythms at 17 Hz after four months of intensive training to control a wheelchair with accuracies between 90% and 100% [28]. The selection of subject-specific EEG features for controlling a wheelchair with high accuracy was also demonstrated in [29], [30].

There were numerous works that reported the use of operant conditioning or SMR-based BCI for control (the reader is referred to [8] for a recent review). However, there were relatively fewer studies that reported the use of EEG-based BCI for rehabilitation [31], [32]. Prasad, et al. [33] extracted SMR (10–15 Hz) from EEG of five stroke patients to provide a computer game-based feedback. Their results showed positive improvement in at least one of the outcome measures in all the patients who used BCI with feedback. Ramos-Murguialday, et al. [34] extracted mu (8–13 Hz) rhythm from EEG over ipsilesional sensorimotor cortex of patients to control an arm orthoses feedback. A randomized control trial (RCT) was performed on 16 patients who used BCI with orthoses feedback compared to 14 other patients who used BCI with random orthoses feedback. Their results on the former group had an averaged 3.4 Fugl-Meyer motor assessment (FMMA) [35] improvement compared to 0.4 in the latter group. Rayegani, et al. [36] also extracted theta (4–8 Hz), sensorimotor rhythms (12–18 Hz) and beta (13–30 Hz) bands from EEG to provide neurofeedback. An RCT was performed on 10 patients who received occupational therapy (OT) with neurofeedback compared to 10 patients who received OT with additional biofeedback and 10 patients who received only OT. However, the results showed that all three groups had similar motor improvements. In addition, Ono, et al. [37] extracted subject-specific frequency bands of alpha and beta rhythms from EEG over bilateral parietal regions to provide feedback. The subject-specific frequency bands were manually identified from EEG data collected from the subjects. They studied six patients who received BCI with simple visual feedback of animated open and grasp picture of the hand versus six patients who received BCI with somatosensory feedback. The results showed that three out of six patients in the latter group had motor improvements, but none in the former group improved. They also reported that there was no

significant difference in the BCI performance between both groups without detailed analysis on the BCI performance. Recently, Pichiorri, et al. [38] extracted sensorimotor rhythms from EEG to detect MI of the stroke-affected hand with visual feedback. An RCT was performed on 14 patients who received BCI with visual feedback versus 14 who received MI training without BCI support. The results showed that the former had a significantly higher probability of achieving FMMA increase than the latter. Mrachacz-Kersting, et al. [39] extracted movement-related cortical potential from EEG during repetitions of foot dorsiflexion [40] to trigger an associative electrical stimulation of the target muscle. A study was performed on 13 patients who used the associative BCI compared to nine other patients who used non-associative BCI that activated the stimulation randomly. The results showed significant clinical improvements in the associative BCI group. Last but not least, there were also other studies on patients that used BCI with other physiological signals, known as hybrid BCI (the reader is referred to [41] for a recent review).

In this paper, we present three EEG-based strategies of using BCI to detect MI for control and rehabilitation. We then review prevailing works and present our past work that employed these strategies with focus on the EEG processing steps and the session-to-session transfer accuracies in detecting MI, while strategies on how to use BCI to provide feedback for neurorehabilitation such as in combination with robotics and their clinical efficacies were covered in a separate review [42]. In this aspect, we present extensive results on the session-to-session transfer online feedback accuracies of detecting MI from stroke patients employing one of the strategies for rehabilitation. These results on the detection accuracies were not previously presented since the focus in the report of the RCT was on the clinical efficacy instead [43]. Finally, we present a retrospective offline study in this paper on the EEG data collected from these stroke patients employing another strategy. We then compare the offline results with the former online results to analyze if it addresses an issue inherent in the strategy we employed in the RCT. Finally, we discuss the advantages and disadvantages of each of the three EEG-based strategies.

## II. EEG-BASED STRATEGIES TO DETECT MI

This section presents the three main EEG-based strategies of using BCI to detect MI for control and rehabilitation:

### A. Operant Conditioning

Fig. 1 shows the operant conditioning strategy of using EEG-based BCI to detect MI for control and rehabilitation, which has a history that dated back to 1980s [20]. SMR-based BCI employed the operant conditioning strategy by extracting sensorimotor rhythms to detect MI for control [21]. Employing this strategy has recently enabled three-dimensional control of a quadcopter in physical space [27], and is also employed in the recent EEG-based clinical studies [34], [36], [37] for stroke rehabilitation.

The key characteristic in this strategy is the use of a fixed model, which comprises the parameters on the EEG features to extract, the features to select, and how to translate the selected

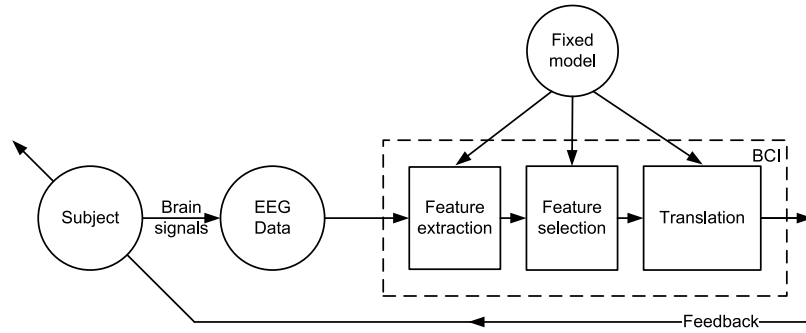


Fig. 1. **Operant conditioning strategy** of using a fixed model for detecting MI from EEG to trigger a feedback for control and rehabilitation.

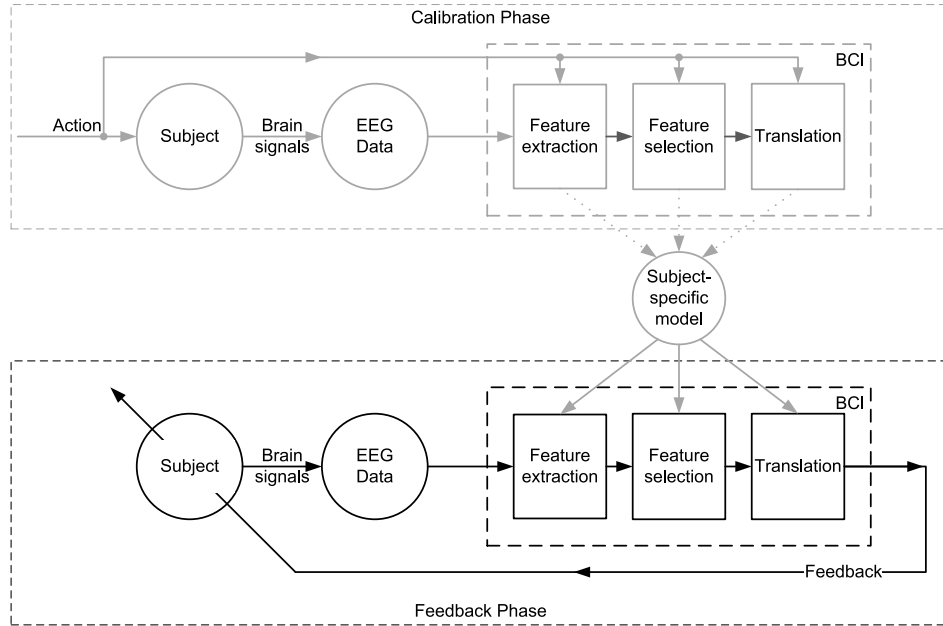


Fig. 2. **Machine learning strategy** of using a subject-specific model computed from the EEG recorded during calibration for control and rehabilitation. The modules illustrated in gray shows the difference from the operant conditioning strategy.

features to provide feedback to the BCI user. As such, the subjects have to learn to control a specific EEG feature, such as the mu (8–12 Hz) and beta (18–26 Hz) rhythms for two-dimension control of a cursor in [22], or the mu (8–13 Hz) rhythm to control an arm orthoses in [34]. These fixed EEG features are then selected for a specific purpose, such as the mu rhythm to control horizontal cursor movement and beta rhythm to control vertical cursor movement in [22].

### B. Machine Learning

Fig. 2 shows the machine learning strategy of using EEG-based BCI to detect MI for control and rehabilitation. The use of machine learning was introduced in BCI to address the issue of subject training for the operant conditioning strategy [44], and to address the high variability in EEG for single-trial data [45]. This strategy was facilitated largely by the common spatial pattern (CSP) algorithm [46], which helps to increase the signal-to-noise ratio [47] of the inherently low spatial resolution of standard EEG [17].

The key characteristic in this strategy is the way the subject-specific model is tuned. In contrast to the fixed subject-specific model that is often manually tuned in Fig. 1, the parameters

of the subject-specific model are computed from EEG data of the subject recorded from a calibration session. As such, this strategy does not require the subjects to undergo several sessions of learning to control a specific EEG rhythm. During the calibration session, the subjects are instructed to perform two or more 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. Höhne, et al. [48] employed this strategy whereby optimized spatial filters using the CSP algorithm and a shrinkage-regularized linear discriminant analysis classifier were computed on EEG data collected from a screening session to evaluate MI control by severely motor-impaired patients. They found that by employing this approach and a flexible BCI setup, three out of four patients were able to establish significant MI control within six sessions.

However, the CSP algorithm requires several 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 [47]. Although these parameters can be selected manually or heuristically [49], the performance of CSP can be enhanced by subject-specific parameters [50]. To address this issue, we have

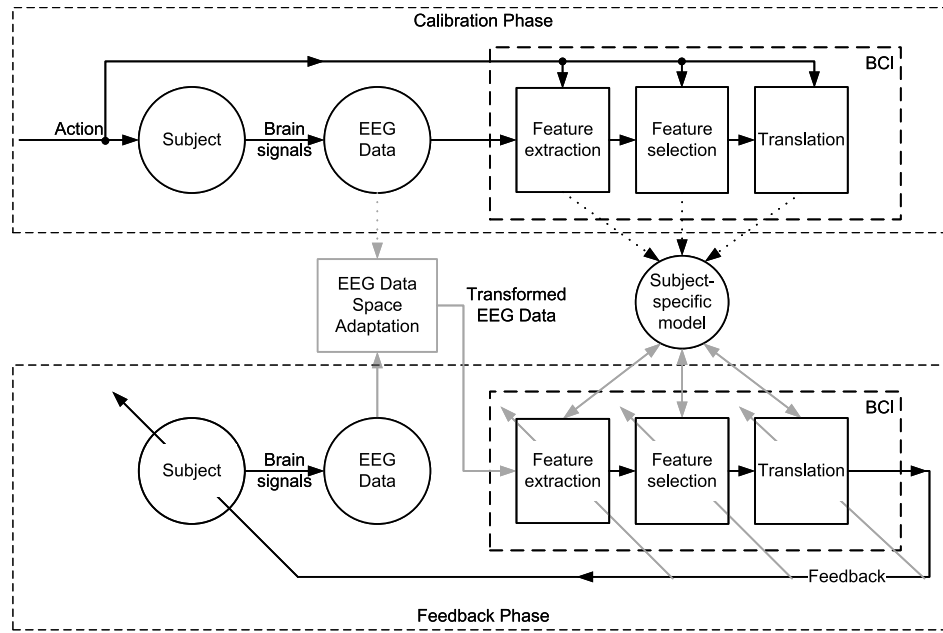


Fig. 3. Adaptive strategy of continuously computing the subject-specific model from the EEG data recorded during calibration as well as the feedback sessions to perform MI detection for control and rehabilitation. The lines illustrated in gray show the differences from the machine learning strategy.

developed the filter bank common spatial pattern (FBCSP) algorithm [51] to select these parameters based on the mutual information between the spatial-temporal patterns from the EEG.

The FBCSP algorithm first employs a filter bank that decomposes the EEG into multiple frequency pass bands using a total of nine band-pass filters, namely, 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 the band-pass frequency range. Subsequently, feature selection is then performed based on the mutual information computed between each feature and the corresponding MI tasks. Finally, a classification algorithm is used to model the selected CSP features.

### C. Adaptive

Fig. 3 shows an adaptive strategy of using EEG-based BCI to detect MI for control and rehabilitation. The key characteristic in this strategy is the use of a subject-specific model that is similar to the machine learning strategy. However, in contrast to the machine learning strategy in Fig. 2, the parameters of the subject-specific model are computed from EEG data of the subject recorded from a calibration session as well as EEG data recorded from subsequent feedback sessions. The purpose in the adaptation of the subject-specific model is to address the session-to-session non-stationarity in the EEG [52]–[55]. Adaptive BCI may not be benefit all BCI applications since study had shown that the performance of SMR-based BCI was enhanced but not P300-based BCI [56]. There are several approaches to adapt the subject-specific model. One approach is to compute the subject-specific model using EEG data collected from the calibration session and subsequently adapt the model using EEG data

collected from the feedback sessions [52]–[55]. The adaptation can be performed using supervised learning on labeled data, or using unsupervised learning on unlabeled data [57], [58]. Adaptation can be performed on the features extracted using spatial filters [59], the features selected such as the frequency band-pass filters, or the parameters of the classifier [57], [60], [61] that translates the features to provide the feedback. Furthermore, since the subject also learns to produce better discriminable brain activity from the feedback sessions, the co-adaptation approach provides feedback as early as possible so that the subject and the subject-specific model are continuously adapted [62], [63]. In online BCI applications where the data are usually unlabeled, adaptive classifiers using semi-supervised learning had been shown to yield improved accuracy for multi-class motor imagery of left hand, right hand foot and tongue from the BCI Competition IV dataset 2a [64]. Another approach is to transform the EEG in the feedback sessions so that the difference between the feedback and calibration sessions is minimized [65]. Although the adaptive strategy showed promises in improving the accuracy in the feedback session, there is still scanty evidence of using this strategy in BCI rehabilitation.

### III. RANDOMIZED CONTROL TRIAL

We had conducted an RCT that employed the machine learning strategy of using BCI to detect MI and deliver feedback using a haptic knob (HK) robot [66], [67] for stroke rehabilitation. The RCT was conducted over 2.5 years from 1 January 2011 to 30 June 2013.

In the RCT, EEG measurements from 27 channels were collected using the NuAmps EEG acquisition hardware (<http://www.neuroscan.com>) sampled at 250 Hz. The EEG data from all channels were bandpass filtered (0.05–40 Hz) by the acquisition hardware.

有监督/无监督学习  
可以对利用空间滤波器提取的特征进行自适应，比如使用频率带通滤波器，或者将这些特征转化，为分类器的参数提供反馈。

RCT：将研究对象随机分组，对不同组实施不同的干预，以对照效果的不同

自适应策略的参数由校准 session 和反馈 session 共同决定

自适应BCI不适合全部BCI应用，在SMR效果好，在P300等不完全适用



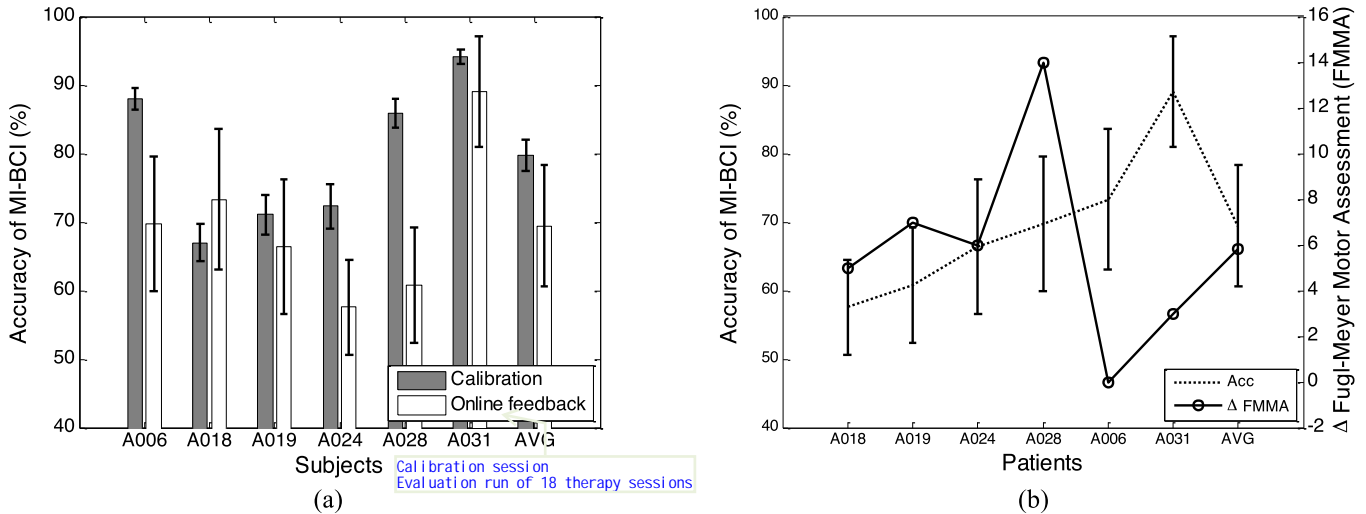


Fig. 4. Accuracies of detecting MI employing machine learning strategy on EEG-based BCI for stroke rehabilitation. (a) Plots the 1010-fold cross-validation accuracies of the calibration session and the averaged accuracies across 18 session-to-session transfer of calibration to online feedback sessions for each patient. The vertical bar plots the standard deviations across each run of the 10-fold cross-validations for calibration, and across the 18 online feedback sessions. (b) Plots sorted averaged accuracies across 18 online feedback sessions for each patient and their change in Fugl-Meyer Motor Assessment (FMMA) at the end of the therapy session. The vertical bar plots the standard deviations across the six patients for each online feedback session.

For the RCT, we sought to investigate the clinical benefits of using an EEG-based MI-BCI coupled with a haptic knob (HK) for stroke rehabilitation. In this article, we investigate the online session-to-session performance of employing the machine learning strategy and the adaptive strategy in using the FBCSP algorithm to detect MI from EEG of stroke patients.

In the RCT, stroke patients were first screened for their ability to operate EEG-based MI-BCI [68]. Patients with  $10 \times 10$ -fold cross-validation accuracy  $> 57.5\%$  assessed using the Filter Bank Common Spatial Pattern algorithm [51] were then recruited for the RCT. The chance level performance was computed using the inverse of binomial cumulative distribution ( $p = 0.05$ ). Patients who passed the screening were then recruited to receive one of the three interventions, namely BCI-HK, HK, and standard arm therapy (SAT).

Patients recruited to receive the BCI-HK intervention underwent a calibration session whereby they were instructed to perform MI of the stroke-impaired hand while strapped to the HK and idle condition. The calibration session consisted of two runs of 80 trials each for a total of 160 trials of which there were 80 trials each for the MI class and the idle class. The EEG data collected from the calibration session were used to compute a subject-specific model using the FBCSP algorithm [51] to detect MI in the subsequent 18 therapy sessions performed over six weeks.

Each therapy session comprised of one evaluation run of 40 trials with feedback, and four rehab runs of 30 trials with feedback for a total of 120 trials for rehab. The evaluation run comprised 20 trials each for MI and idle class. However, the rehab runs comprised 120 trials for the MI class and none for the idle class. An inter-run break of 3–5 min was provided after each run. In the evaluation run, the patients were instructed to perform MI of the stroke-impaired hand and idle condition similar to the calibration session. In the rehab

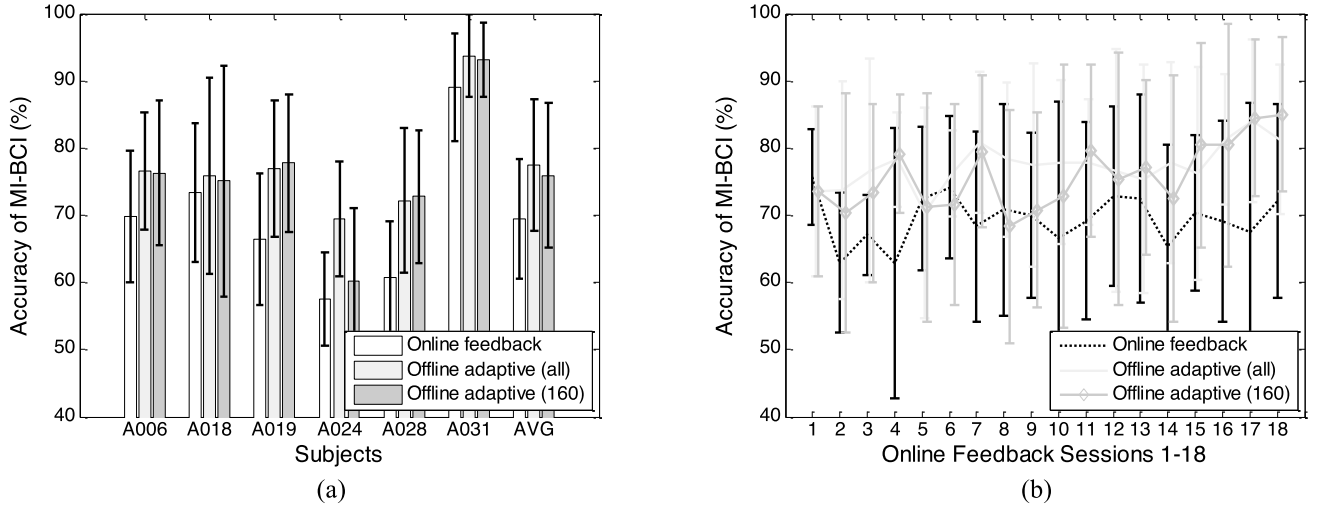
runs, the patients were only instructed to perform MI of the stroke-impaired hand. In both the evaluation and rehab runs, if MI was successfully detected by the FBCSP algorithm using the subject-specific calibration model, then the HK robot-assisted hand physical practice would be initiated.

#### IV. RESULTS FROM CLINICAL TRIAL

The RCT screened a total of 34 chronic stroke patients out of which 29 patients passed BCI screening. Subsequently, 22 patients who passed BCI screening were recruited for randomization to 1 of the 3 interventions, and the remaining seven who passed BCI screening declined further participation. Out of the 22 patients, seven patients were randomized to the BCI-HK, but 1 dropped out in the fifth week of intervention. There were four men and two women with mean age 54.0 years and mean stroke duration of 285.7 days. Among the six patients, there were two with infarction and four with hemorrhage, and five had subcortical stroke and 1 had cortical stroke. The clinical efficacy results from these six patients showed an average FMMA improvement of 7.2 at the end of the intervention at week six relative from the baseline FMMA before the intervention, thus showing statistically and clinically significant motor improvements [43].

##### A. Machine Learning

Fig. 4 presents the results on the performance of employing the machine learning strategy using the FBCSP algorithm to detect MI from EEG of six stroke patients who completed the BCI-HK intervention. These results were previously not presented in our recent review [42] as well as the report of the RCT [43] because the focus was on the clinical efficacy instead. Fig. 4(a) plots the  $10 \times 10$ -fold cross-validation accuracies on the 160 trials of EEG collected from the calibration session and the averaged session-to-session transfer from



**Fig. 5.** Accuracies of detecting MI employing different strategies on EEG-based BCI for stroke rehabilitation. (a) Plots averaged session-to-session transfer from calibration to online feedback employing machine learning, the offline feedback accuracies employing adaptive strategy using all available data and using only preceding 160 trials data across 18 feedback sessions for each patient. The vertical bar plots the standard deviations across 18 feedback sessions. (b) Plots the averaged session-to-session transfer from calibration to online feedback accuracies employing the machine learning, the offline feedback accuracies employing the adaptive strategy using all the available data using only preceding 160 trials data of each feedback sessions across the six patients. The vertical bar plots the standard deviations across the six patients for each feedback session.

calibration to online feedback accuracies of using the subject-specific to detect MI across 18 feedback sessions. The analysis for each online feedback session comprised of 40 trials from the evaluation run of each therapy session. In the rehab runs of the therapy session, the patients were only instructed to perform MI and not the idle condition. As such, EEG data from the rehab runs were not analyzed since accuracies in detecting MI cannot be computed with only one class of data. Fig. 4(b) plots the sorted averaged accuracies across 18 online feedback sessions in increasing order for each patient and their change in FMMA at the end of the therapy session.

The results in Fig. 4(a) showed an averaged calibration accuracy of 79.8% across the six patients and an averaged session-to-session transfer accuracy of 69.5% across the six patients over 18 online feedback sessions. The results showed an averaged drop of 10.3% accuracy in the session-to-session transfer from calibration to online feedback sessions. The results in Fig. 4(b) showed that the averaged accuracies of the online feedback sessions were not correlated with the change in FMMA at the end of the therapy sessions ( $r = -0.29$ ,  $p = 0.58$ ).

### B. Adaptive

In this subsection, we performed a retrospective offline study on the EEG data collected from the calibration and 18 online feedback sessions of the six stroke patients using the adaptive strategy.

Let  $\mathbf{V}_i$  denote the EEG data used to compute the subject-specific model to detect MI for the  $i$ th online feedback session. In the previous Section IV-A, for the online feedback sessions employing the machine learning strategy

$$\mathbf{V}_i = \tilde{\mathbf{V}} \quad (1)$$

where  $\tilde{\mathbf{V}}$  denotes the EEG data from the offline calibration session.

Since there are many approaches of employing the adaptive strategy, we performed adaptation by retraining using the following approach:

In the  $i$ th feedback session given that  $i > 1$ , the EEG data collected from the previous  $(i - 1)$ th were readily available. Hence for this retrospective offline study, for the offline feedback sessions employing the adaptive strategy

$$\mathbf{V}_i = \begin{cases} \tilde{\mathbf{V}} & \text{if } i = 1 \\ \tilde{\mathbf{V}} \cup \bigcup_{j=1}^{i-1} \mathbf{X}_j & \text{if } i > 1, \end{cases} \quad (2)$$

where  $\mathbf{X}_j$  denotes the EEG data from the  $j$ th online feedback session, and  $\cup$  denotes the union operator.

The calibration session comprised of 160 trials, and each therapy session comprised of one evaluation run of 40 trials and four rehab runs of 120 trials. Since the rehab runs only comprised of trials for the MI class, these 120 trials could not be used for adaptation. Using the above approach,  $160 + 40 = 200$  trials of data were available for training the FBCSP algorithm in the second feedback session. In the last eighteenth feedback session,  $160 + 40 \times 17 = 840$  trials of data were available for training. Since using an increased amount of data may yield improved performance, the performance of employing the adaptive strategy was also evaluated using limited preceding 160 trials of data available from offline calibration session and previous feedback sessions. For example, in the fifth feedback session, only 160 trials from the first to fourth feedback and none from the calibration session were used to train the FBCSP algorithm. This way of employing the adaptive strategy using limited preceding data will also help to reveal if a changing subject-specific model will deteriorate the subject's performance.

Fig. 5 presents the offline results on the performance of employing the adaptive strategy using the FBCSP algorithm

法1. 校准 session + 当前 session 全部数据进行训练

法2. 当前 session 前共 160 trials 数据进行训练

based on (2) to detect MI from EEG of six stroke patients. Fig. 5(a) plots the averaged session-to-session transfer accuracies of using the subject-specific calibration model to detect MI across 18 online feedback sessions, the averaged offline session-to-session transfer accuracies using the subject-specific model computed using all the data, and using limited preceding 160 trials of data from the calibration and previous feedback sessions to detect MI across the 18 feedback sessions for each patient. Fig. 5(b) plots the averaged online accuracies employing machine learning, the averaged offline accuracies employing adaptive strategy using all the data and using limited preceding 160 trials of data of each feedback sessions across the six patients.

The results in Fig. 5(a) showed an averaged session-to-session transfer offline accuracy of **77.5%** and **75.9%** from employing the adaptive strategy across the six patients using all the data and using limited preceding data respectively compared to the averaged session-to-session transfer online accuracy of **69.5%** from employing the machine learning strategy. The results showed that all the six subjects improved using all data or limited preceding data. The results from most of the six subjects employing the adaptive strategy using all the data were comparable to using limited preceding data except for subject A024. Nevertheless, paired t-tests performed on the results showed an averaged significant improvements of **12%** ( $p < 0.001$ ) and **9%** ( $p < 0.001$ ) from employing the adaptive strategy using all the data and using limited preceding data respectively compared to the online feedback session employing the machine learning strategy across the six patients. The results in Fig. 5(b) also showed that most of the sessions in the averaged session-to-session transfer accuracies employing the adaptive strategy using limited preceding data across the six patients improved except for sessions 1 and 5. In addition, the results also showed that the standard deviations across the six patients were reduced by employing the adaptive strategy compared to employing the machine learning strategy in the later sessions.

## V. DISCUSSION

We had performed BCI screening employing the machine learning strategy shown in Fig. 2 on 34 stroke patients in the RCT we conducted. A total of 29 patients passed BCI screening, which showed a majority 85% of the stroke patients could use EEG-based BCI for stroke rehabilitation. This is close to our initial finding in [68] and falls within the estimated range of 70%–85% commonly found in BCI laboratory, of which is based on the finding that BCI fails to work for an estimated 15%–30% proportion of participants [69]. We collected EEG data from one calibration session and 18 feedback sessions from six patients. While the results showed a drop of 8.3% in accuracy from calibration to session-to-session transfer online feedback sessions, the patients had clinically significant averaged FMMA score improvement of 7.2 end-intervention at week 6 after 18 therapy sessions [43]. This showed that the machine learning strategy was effective in detecting MI for stroke rehabilitation. Hence a key advantage of employing the machine learning strategy is that a subject-specific model can be computed from EEG data collected from a calibration

session, and subjects can use the BCI immediately in the next therapy session. In contrast, the operant conditioning strategy shown in Fig. 1 requires subjects to undergo several sessions of learning to control a specific EEG rhythm. This may not appeal to patients in rehabilitation since they have to invest more time in the learning sessions prior to the therapy sessions.

The results showed an averaged online session-to-session feedback accuracy of 69.5% across all patients employing the machine learning strategy. Only patient A031 had very high calibration and feedback accuracies. This averaged accuracy was slightly lower than the recommended accuracy of 70% for BCI in control [70]. Nevertheless, the clinically significant improvements in FMMA despite the low accuracy may be due to a higher level of engagement by the patient to perform MI of the stroke-impaired upper limb for rehabilitation. In addition, the results showed that the improvements in the FMMA from the patients were not correlated to the session-to-session online feedback accuracies. Therefore, a high accuracy in detecting MI may not be a crucial factor in rehabilitation since the BCI is used to provide feedback and not for control that requires high degree of accuracy [71]. Hence a key advantage of employing the operant conditioning strategy is that subjects are able to learn to control a specific EEG rhythm to achieve high level of accuracy needed for control. In contrast, it is not possible to achieve high accuracies for all subjects employing the machine learning strategy on EEG data collected from one single calibration session. This is perhaps a reason why most of the works employed the operant conditioning strategy for control purpose [21], [22], [25]–[27].

Nevertheless, the results showed despite having relatively lower calibration accuracy than other patients, the feedback accuracy of patient A018 was higher than the calibration accuracy. This showed that some subjects employing the machine learning strategy could also learn to improve their accuracies similar to subjects employing the operant conditioning strategy. The results also showed that despite having good calibration accuracies, a relatively large drop in accuracies were observed in the online feedback sessions of patients A006, A024, and A028. This large drop in accuracies between the calibration and feedback sessions was mainly due a difference between the calibration session and the feedback sessions. This difference is known as non-stationarity in the EEG data [72], which can be caused by changes in the subject's brain due to fatigue, change of task involvement, changes in placement or impedance of the EEG electrodes, and artifacts such as swallowing or blinking, among other reasons [52]. Since the machine learning strategy intrinsically assumed stationarity between the calibration and feedback sessions, the results clearly showed that the inherent session-to-session non-stationarity in EEG can result in deteriorated performance.

Adaptive BCI is known to be better than non-adaptive BCI [52], and results had shown improved accuracy employing adaptive classifier using semi-supervised learning on multi-class BCI Competition IV dataset 2a [64]. However, in detecting MI for stroke rehabilitation, the therapy session for rehab comprised trials for the MI class and none for the idle class. Since this impeded the use of semi-supervised learning, we

performed an evaluation run comprised 20 trials each for MI and idle class in each therapy session where labeled data were available.

Finally, we performed a retrospective offline study of employing the adaptive strategy in Fig. 3 on the calibration and 18 online feedback sessions we collected from the RCT. Since labeled data were available in the evaluation runs from the 18 online feedback sessions, we evaluated the adaptive strategy using adaptation by retraining given in (2). The results of employing the adaptive strategy on limited preceding 160 trials of data yielded improved session-to-session transfer feedback accuracies in all the subjects with an averaged accuracy of 75.88%. Thus the results yielded a significant improvement of 9% compared to the averaged session-to-session online feedback accuracies employing the machine learning strategy. The improved accuracies brought the session-to-session feedback accuracy closer to the averaged calibration accuracy of 79.8%. In addition, the results from all but one of the subjects employing the adaptive strategy using limited preceding data were comparable to using all the data. Comparing the results of using all data versus using limited preceding data, an increase in the amount of training data yielded further improvement of 3%. This showed that a larger part of the improvement of 9% were due to the adaptive strategy. In addition, the results of using limited preceding data involved a changing subject-specific model that did not deteriorate the accuracies compared to the machine learning strategy.

Hence, the results clearly showed evidence that employing the adaptive strategy can address the non-stationarity between the calibration and feedback sessions. Since a very simple approach of computing the subject-specific model by adaptation by retraining using the EEG data from previous feedback session and the calibration session was used here, extreme care has to be taken to interpret the results of more complex adaptive methods proposed in the literature to address this non-stationarity. In addition, the results that showed an increase in offline classification accuracy employing the adaptive strategy may not necessary translate to an increase in online classification accuracy. This is because a changing subject-specific model strategy may be disturbing to the subjects as they have to constantly change their strategy in performing motor imagery. Thus without online experimental results, we cannot conclude that the adaptive strategy is better online. Furthermore, the results showed that the classification accuracy was not correlated to the rehabilitation outcome. As such, improving the online classification accuracy may not even be necessary at all. However, the absence of significant correlation between the classification accuracy and rehabilitation outcome may be due to the small sample size of six subjects. Thus we also cannot conclude that there is no correlation at all.

## VI. CONCLUSION

In this paper, we presented three EEG-based strategies of using BCI to detect MI for control and rehabilitation: operant conditioning, machine learning and adaptive. We reviewed works in the literature and found that most employed the

operant conditioning for control and some applied it for rehabilitation. This strategy requires the subjects to undergo several sessions of learning to control a specific EEG rhythm. In contrast, the machine learning strategy only requires the subjects to undergo one calibration session to compute a subject-specific model for subsequent session-to-session transfer to online feedback sessions. Thus, the latter facilitates rapid BCI deployment in detecting MI for rehabilitation. However, as the calibration session initially performed to compute the subject-specific model may differ from the subsequent online feedback sessions performed some days later, there is non-stationarity in the session-to-session transfer from the calibration to online feedback sessions. In this aspect, the adaptive strategy is recently proposed to address this session-to-session non-stationarity inherent in the machine learning strategy. Although there are several approaches proposed, there are scanty results reported on the use of the adaptive strategy on patients for rehabilitation in the literature.

We presented results on the session-to-session online feedback accuracies of detecting MI from a RCT we conducted that employed the machine learning strategy for stroke rehabilitation. Although the use of the machine learning strategy only required one calibration session, the results showed an averaged drop of 8.3% in the averaged accuracy from calibration to online feedback sessions due to the inherent session-to-session non-stationarity between the calibration session and feedback sessions. Although no significant correlation between online feedback accuracies and motor improvements were found, the drop in accuracy is undesirable as it may affect the subjects' use of BCI in rehabilitation. We then presented results of a retrospective offline study on the session-to-session feedback accuracy of detecting MI from the RCT we conducted by employing the adaptive strategy based on adaptation by retraining. The results showed a significant improvement of 12% in the averaged accuracy by employing the adaptive strategy using all the data from previous sessions compared to the machine learning strategy. We also presented results of using only limited preceding 160 trials from the previous session. The results showed that an increase in the amount of training data yielded improvement, but a larger part of the improvement of 9% were due to the adaptive strategy using only limited preceding data. This involved a changing subject-specific model that did not deteriorate the accuracies compared to the machine learning strategy. Hence the adaptive strategy holds promise to improve the accuracy of detecting MI using machine learning approach by addressing the drop in accuracy due to non-stationarity between calibration and feedback sessions. Thus more research effort should be directed towards its deployment for control and rehabilitation. However, care should be taken to interpret the results of proposed adaptive approach as comparison with a baseline such as the simple approach used in this study should be performed in order to clearly show the effectiveness of the proposed approach.

## ACKNOWLEDGMENTS

The authors acknowledge the following clinicians and therapists for conducting the Randomized Control Trial:

自适应策略离线分类精度的提高不一定能转化为在线分类精度的提高



K. S. G. Chua, C. W. K. Kuah, and G. J. Ephraim Joseph. They also acknowledge the following scientists and engineers who are involved in developing the EEG-based BCI system for neuro-rehabilitation after stroke: H. Zhang, L. Zhou, K. S. Phua, C. Wang, Z. Y. Chin, and K. Y. Tang.

## REFERENCES

- [1] M. Jeannerod, "Mental imagery in the motor context," *Neuropsychologia*, vol. 33, no. 11, pp. 1419–1432, Nov. 1995.
- [2] S. M. Murphy, "Imagery interventions in sport," *Med. Sci. Sports Exerc.*, vol. 26, no. 4, pp. 486–494, 1994.
- [3] N. Sharma, V. M. Pomeroy, and J.-C. Baron, "Motor imagery: A backdoor to the motor system after stroke?" *Stroke*, vol. 37, no. 7, pp. 1941–1952, Jul. 2006.
- [4] S. Kraeutner, A. Gionfriddo, T. Bardouille, and S. Boe, "Motor imagery-based brain activity parallels that of motor execution: Evidence from magnetic source imaging of cortical oscillations," *Brain Res.*, vol. 1588, pp. 81–91, Nov. 2014.
- [5] S. H. Johnson, "Imagining the impossible: Intact motor representations in hemiplegics," *Neuroreport*, vol. 11, no. 4, pp. 729–732, Mar. 2000.
- [6] F. Malouin, P. L. Jackson, and C. L. Richards, "Towards the integration of mental practice in rehabilitation programs. A critical review," *Front. Human Neurosci.*, vol. 7, p. 576, Sep. 2013.
- [7] S. Gao, Y. Wang, X. Gao, and B. Hong, "Visual and auditory brain-computer interfaces," *IEEE Trans. Biomed. Eng.*, vol. 61, no. 5, pp. 1436–1447, May 2014.
- [8] H. Yuan and B. He, "Brain-computer interfaces using sensorimotor rhythms: Current state and future perspectives," *IEEE Trans. Biomed. Eng.*, vol. 61, no. 5, pp. 1425–1435, May 2014.
- [9] J. J. Daly and J. E. Huggins, "Brain-computer interface: Current and emerging rehabilitation applications," *Arch. Phys. Med. Rehabil.*, vol. 96, no. 3, pp. S1–S7, Mar. 2015.
- [10] J. J. Daly and J. R. Wolpaw, "Brain-computer interfaces in neurological rehabilitation," *Lancet Neurol.*, vol. 7, no. 11, pp. 1032–1043, Nov. 2008.
- [11] A. Burns, H. Adeli, and J. A. Buford, "Brain-computer interface after nervous system injury," *Neuroscientist*, vol. 20, no. 6, pp. 639–651, Dec. 2014.
- [12] G. Schalk, "Sensor modalities for brain-computer interfacing," in *Proc. 13th Int. Human, Comput. Interact.*, vol. 5611, 2009, pp. 616–622.
- [13] 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. 642–651, 1997.
- [14] G. Pfurtscheller and F. H. L. da Silva, "Event-related EEG/MEG synchronization and desynchronization: Basic principles," *Clin. Neurophysiol.*, vol. 110, no. 11, pp. 1842–1857, 1999.
- [15] G. Pfurtscheller and C. Neuper, "Motor imagery activates primary sensorimotor area in humans," *Neurosci. Lett.*, vol. 239, nos. 2–3, pp. 65–68, 1997.
- [16] G. Pfurtscheller and C. Neuper, "Motor imagery and direct brain-computer communication," *Proc. IEEE*, vol. 89, no. 7, pp. 1123–1134, Jul. 2001.
- [17] C. Babiloni, V. Pizzella, C. D. Gratta, A. Ferretti, and G. L. Romani, "Fundamentals of electroencephalography, magnetoencephalography, and functional magnetic resonance imaging," *Int. Rev. Neurobiol.*, vol. 86, pp. 67–80, Jul. 2009.
- [18] J. R. Wolpaw, D. J. McFarland, G. W. Neat, and C. A. Forneris, "An EEG-based brain-computer interface for cursor control," *Electroencephalogr. Clin. Neurophysiol.*, vol. 78, no. 3, pp. 252–259, Mar. 1991.
- [19] J. Wolpaw and E. W. Wolpaw, *Brain-Computer Interfaces: Principles and Practice*. New York, NY, USA: Oxford Univ. Press, 2012.
- [20] J. F. Lubar, H. S. Shabsin, and S. E. Natelson, "EEG operant conditioning in intractable epileptics," *Arch. Neurol.*, vol. 38, no. 11, pp. 700–704, 1981.
- [21] D. J. McFarland and J. R. Wolpaw, "Sensorimotor rhythm-based brain-computer interface (BCI): Feature selection by regression improves performance," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 13, no. 3, pp. 372–379, Sep. 2005.
- [22] J. R. Wolpaw and D. J. McFarland, "Control of a two-dimensional movement signal by a noninvasive brain-computer interface in humans," *Proc. Nat. Acad. Sci. USA*, vol. 101, no. 51, pp. 17849–17854, Dec. 2004.
- [23] Y. Li *et al.*, "An EEG-based BCI system for 2-D cursor control by combining Mu/Beta rhythm and P300 potential," *IEEE Trans. Biomed. Eng.*, vol. 57, no. 10, pp. 2495–2505, Oct. 2010.
- [24] D. J. McFarland, W. A. Sarnacki, and J. R. Wolpaw, "Electroencephalographic (EEG) control of three-dimensional movement," *J. Neural Eng.*, vol. 7, no. 3, p. 036007, 2010.
- [25] A. S. Royer, A. J. Doud, M. L. Rose, and B. He, "EEG control of a virtual helicopter in 3-dimensional space using intelligent control strategies," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, no. 6, pp. 581–589, Dec. 2010.
- [26] A. J. Doud, J. P. Lucas, M. T. Pisansky, and B. He, "Continuous three-dimensional control of a virtual helicopter using a motor imagery based brain-computer interface," *PLoS ONE*, vol. 6, no. 10, p. e26322, 2011.
- [27] K. LaFleur, K. Cassady, A. Doud, K. Shades, E. Rogin, and B. He, "Quadcopter control in three-dimensional space using a noninvasive motor imagery-based brain-computer interface," *J. Neural Eng.*, vol. 10, no. 4, p. 046003, 2013.
- [28] R. Leeb, D. Friedman, G. R. Müller-Putz, R. Scherer, M. Slater, and G. Pfurtscheller, "Self-paced (asynchronous) BCI control of a wheelchair in virtual environments: A case study with a tetraplegic," *Comput. Intell. Neurosci.*, vol. 2007, Apr. 2007, Art. no. 7.
- [29] T. Carlson and J. D. R. Millan, "Brain-controlled wheelchairs: A robotic architecture," *IEEE Robot. Autom. Mag.*, vol. 20, no. 1, pp. 65–73, Mar. 2013.
- [30] F. Galán *et al.*, "A brain-actuated wheelchair: Asynchronous and non-invasive brain-computer interfaces for continuous control of robots," *Clin. Neurophysiol.*, vol. 119, no. 9, pp. 2159–2169, Sep. 2008.
- [31] K. K. Ang and C. Guan, "Brain-computer interface in stroke rehabilitation," *J. Comput. Sci. Eng.*, vol. 7, no. 2, pp. 139–146, Jun. 2013.
- [32] A. Venkatakrishnan, G. Francisco, and J. L. Contreras-Vidal, "Applications of brain-machine interface systems in stroke recovery and rehabilitation," *Current Phys. Med. Rehabil. Rep.*, vol. 2, no. 2, pp. 93–105, Jun. 2014.
- [33] G. Prasad, P. Herman, D. Coyle, S. McDonough, and J. Crosbie, "Applying a brain-computer interface to support motor imagery practice in people with stroke for upper limb recovery: A feasibility study," *J. Neuroeng. Rehabil.*, vol. 7, no. 1, p. 60, Dec. 2010.
- [34] A. Ramos-Murguialday *et al.*, "Brain-machine interface in chronic stroke rehabilitation: A controlled study," *Ann. Neurol.*, vol. 74, no. 1, pp. 100–108, Jul. 2013.
- [35] A. R. Fugl-Meyer, L. Jääskö, I. Leyman, S. Olsson, and S. Steglind, "The post-stroke hemiplegic patient. 1. A method for evaluation of physical performance," *Scandin. J. Rehabil. Med.*, vol. 7, no. 1, pp. 13–31, 1975.
- [36] S. Rayegani *et al.*, "Effect of neurofeedback and electromyographic-biofeedback therapy on improving hand function in stroke patients," *Topics Stroke Rehabil.*, vol. 21, no. 2, pp. 137–151, Mar. 2014.
- [37] T. Ono *et al.*, "Brain-computer interface with somatosensory feedback improves functional recovery from severe hemiplegia due to chronic stroke," *Front. Neuroeng.*, vol. 7, p. 19, Jul. 2014.
- [38] F. Pichiorri *et al.*, "Brain-computer interface boosts motor imagery practice during stroke recovery," *Ann. Neurol.*, vol. 77, no. 5, pp. 851–865, May 2015.
- [39] N. Mrachacz-Kersting *et al.*, "Efficient neuroplasticity induction in chronic stroke patients by an associative brain-computer interface," *J. Neurophysiol.*, vol. 115, no. 3, pp. 1410–1421, Mar. 2016.
- [40] N. Mrachacz-Kersting, N. Jiang, K. Dremstrup, and D. Farina, "A novel brain-computer interface for chronic stroke patients," in *Brain-Computer Interface Research*, J. L. Pons, D. Torricelli, and M. Pajaro, Eds. Berlin, Germany: Springer-Verlag, 2013, pp. 837–841.
- [41] G. Müller-Putz *et al.*, "Towards noninvasive hybrid brain-computer interfaces: Framework, practice, clinical application, and beyond," *Proc. IEEE*, vol. 103, no. 6, pp. 926–943, Jun. 2015.
- [42] K. K. Ang and C. Guan, "Brain-computer interface for neurorehabilitation of upper limb after stroke," *Proc. IEEE*, vol. 103, no. 6, pp. 944–953, Jun. 2015.
- [43] K. K. Ang *et al.*, "Brain-computer Interface-based robotic end effector system for wrist and hand rehabilitation: Results of a three-armed randomized controlled trial for chronic stroke," *Front. Neuroeng.*, vol. 7, p. 30, Jul. 2014.
- [44] B. Blankertz *et al.*, "The Berlin brain-computer interface: EEG-based communication without subject training," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 14, no. 2, pp. 147–152, Jun. 2006.

- [45] K.-R. Müller, M. Tangermann, G. Dornhege, M. Krauledat, G. Curio, and B. Blankertz, "Machine learning for real-time single-trial EEG-analysis: From brain-computer interfacing to mental state monitoring," *J. Neurosci. Methods*, vol. 167, no. 1, pp. 82–90, Jan. 2008.
- [46] H. Ramoser, J. Müller-Gerking, and G. Pfurtscheller, "Optimal spatial filtering of single trial EEG during imagined hand movement," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 8, no. 4, pp. 441–446, Dec. 2000.
- [47] B. Blankertz, R. Tomioka, S. Lemm, M. Kawanabe, and K. R. Müller, "Optimizing spatial filters for robust EEG single-trial analysis," *IEEE Signal Process. Mag.*, vol. 25, no. 1, pp. 41–56, Jan. 2008.
- [48] J. Höhne, E. Holz, P. Staiger-Sälzer, K.-R. Müller, A. Kübler, and M. Tangermann, "Motor imagery for severely motor-impaired patients: Evidence for brain-computer interfacing as superior control solution," *PLoS ONE*, vol. 9, no. 8, p. e104854, 2014.
- [49] G. Dornhege, B. Blankertz, M. Krauledat, F. Losch, G. Curio, and K. R. Müller, "Combined optimization of spatial and temporal filters for improving brain-computer interfacing," *IEEE Trans. Biomed. Eng.*, vol. 53, no. 11, pp. 2274–2281, Nov. 2006.
- [50] B. Blankertz, G. Dornhege, M. Krauledat, K.-R. Müller, and G. Curio, "The non-invasive Berlin brain-computer interface: Fast acquisition of effective performance in untrained subjects," *NeuroImage*, vol. 37, no. 2, pp. 539–550, Aug. 2007.
- [51] K. K. Ang, Z. Y. Chin, C. Wang, C. Guan, and H. Zhang, "Filter bank common spatial pattern algorithm on BCI competition IV datasets 2a and 2b," *Front. Neurosci.*, vol. 6, no. 1, p. 39, 2012.
- [52] P. Shenoy, M. Krauledat, B. Blankertz, R. P. N. Rao, and K.-R. Müller, "Towards adaptive classification for BCI," *J. Neural Eng.*, vol. 3, no. 1, p. R13, 2006.
- [53] M. Krauledat, G. Dornhege, B. Blankertz, and K.-R. Müller, "Robustifying EEG data analysis by removing outliers," *Chaos Complex. Lett.*, vol. 2, no. 3, pp. 259–274, 2007.
- [54] L. Yan, H. Kambara, Y. Koike, and M. Sugiyama, "Application of covariate shift adaptation techniques in brain-computer interfaces," *IEEE Trans. Biomed. Eng.*, vol. 57, no. 6, pp. 1318–1324, Jun. 2010.
- [55] S. R. Liyanage, C. Guan, H. Zhang, K. K. Ang, J. Xu, and T. H. Lee, "Dynamically weighted ensemble classification for non-stationary EEG processing," *J. Neural Eng.*, vol. 10, no. 3, p. 036007, Jun. 2013.
- [56] D. J. McFarland, W. A. Sarnacki, and J. R. Wolpaw, "Should the parameters of a BCI translation algorithm be continually adapted?" *J. Neurosci. Methods*, vol. 199, no. 1, pp. 103–107, Jul. 2011.
- [57] C. Vidaurre, M. Kawanabe, P. von Büna, B. Blankertz, and K. R. Müller, "Toward unsupervised adaptation of LDA for brain-computer interfaces," *IEEE Trans. Biomed. Eng.*, vol. 58, no. 3, pp. 587–597, Mar. 2011.
- [58] J. Q. Gan, "Self-adapting BCI based on unsupervised learning," in *Proc. 3rd Int. Workshop Brain-Comput. Interface*, 2006, pp. 50–51.
- [59] C. Sannelli, C. Vidaurre, K.-R. Müller, and B. Blankertz, "Ensembles of adaptive spatial filters increase BCI performance: An online evaluation," *J. Neural Eng.*, vol. 13, no. 4, p. 046003, May 2016.
- [60] J. Blumberg, J. Rickert, S. Waldert, A. Schulze-Bonhage, A. Aertsen, and C. Mehring, "Adaptive classification for brain computer interfaces," in *Proc. Conf. IEEE Eng. Med. Biol. Soc.*, Aug. 2007, pp. 2536–2539.
- [61] A. Buttfield, P. W. Ferrez, and J. R. Millan, "Towards a robust BCI: Error potentials and online learning," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 14, no. 2, pp. 164–168, Jun. 2006.
- [62] C. Vidaurre, C. Sannelli, K.-R. Müller, and B. Blankertz, "Co-adaptive calibration to improve BCI efficiency," *J. Neural Eng.*, vol. 8, no. 2, p. 025009, 2011.
- [63] J. Faller, R. Scherer, U. Costa, E. Opisso, J. Medina, and G. R. Müller-Putz, "A co-adaptive brain-computer interface for end users with severe motor impairment," *PLoS ONE*, vol. 9, no. 7, p. e101168, 2014.
- [64] L. F. Nicolas-Alonso, R. Corralejo, J. Gomez-Pilar, D. Álvarez, and R. Hornero, "Adaptive semi-supervised classification to reduce intersession non-stationarity in multiclass motor imagery-based brain-computer interfaces," *Neurocomputing*, vol. 159, pp. 186–196, Jul. 2015.
- [65] M. Arvaneh, C. Guan, K. K. Ang, and C. Quek, "EEG data space adaptation to reduce intersession nonstationarity in brain-computer interface," *Neural Comput.*, vol. 25, no. 8, pp. 2146–2171, Aug. 2013.
- [66] O. Lambercy, L. Dovat, R. Gassert, E. Burdet, C. L. Teo, and T. Milner, "A haptic knob for rehabilitation of hand function," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 15, no. 3, pp. 356–366, Sep. 2007.
- [67] O. Lambercy *et al.*, "Effects of a robot-assisted training of grasp and pronation/supination in chronic stroke: A pilot study," *J. Neuroeng. Rehabil.*, vol. 8, no. 1, p. 63, Nov. 2011.
- [68] K. K. Ang *et al.*, "A large clinical study on the ability of stroke patients to use EEG-based motor imagery brain-computer interface," *Clin. Neurosci.*, vol. 42, no. 4, pp. 253–258, Oct. 2011.
- [69] B. Blankertz *et al.*, "Neurophysiological predictor of SMR-based BCI performance," *NeuroImage*, vol. 51, no. 4, pp. 1303–1309, Jul. 2010.
- [70] C. Vidaurre and B. Blankertz, "Towards a cure for BCI illiteracy," *Brain Topogr.*, vol. 23, no. 2, pp. 194–198, Jun. 2010.
- [71] B. M. Young *et al.*, "Case report: Post-stroke interventional BCI rehabilitation in an individual with preexisting sensorineural disability," *Front. Neuroeng.*, vol. 7, p. 18, Jun. 2014.
- [72] D. Gribkov and V. Gribkova, "Learning dynamics from nonstationary time series: Analysis of electroencephalograms," *Phys. Rev. E, Stat. Phys. Plasmas Fluids Relat. Interdiscip. Top.*, vol. 61, no. 6, pp. 6538–6545, 2000.



**Kai Keng Ang** (M'05–SM'15) received the B.A.Sc degree (First Hons.), M.Phil. and Ph.D. degree in computer engineering from Nanyang Technological University, Singapore, in 1997, 1999, and 2008, respectively.

From 1999 to 2003, he was a Senior Software Engineer with Delphi Automotive Systems Singapore Pte Ltd working on embedded software for automotive engine controllers. He is currently the Deputy Department Head of Neural and Biomedical Technology, Brain-Computer Interface Lab Head and a Senior Scientist at the Institute for Infocomm Research, Agency for Science, Technology and Research, Singapore. He is also an Adjunct Assistant Professor in the School of Computer Science and Engineering, Nanyang Technology University, Singapore. His research interests include brain-computer interface, computational intelligence, machine learning, pattern recognition and signal processing.

Dr. Ang was the recipient of the g.tec Annual BCI Research Award 2010 and IES Prestigious Engineering Achievement Award 2009.



**Cuntai Guan** (M'92–SM'03) received the Ph.D. degree in electrical and electronic engineering from Southeast University, in 1993.

He is a Professor in the School of Computer Science and Engineering, Nanyang Technological University (NTU), Singapore. He is concurrently also the co-Director of Rehabilitation Research Institute of Singapore (RRIS), and Principal Scientist at Institute for Infocomm Research (I2R), Agency for Science, Technology and Research (A\*STAR), Singapore. His research interests are in the fields of brain-computer interfaces (BCI), brain-machine interfaces (BMI), neural engineering, machine learning, data analytics, and neuro-technologies.

Dr Guan is on the editorial board of IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, *IEEE Access*, *Frontiers in Neuroscience*, and *Brain Computer Interfaces*.