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A clinical evaluation of non-invasive motor imagery-based brain-computer interface in stroke

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Abstract—**This clinical study investigates whether the performance of hemiparetic stroke patients operating a non-invasive Motor Imagery-based Brain-Computer Interface (MI-BCI) is comparable to healthy subjects. The study is performed on 8 healthy subjects and 35 BCI-naïve hemiparetic stroke patients. This study also investigates whether the performance of the stroke patients in operating MI-BCI correlates with the extent of neurological disability. The performance is objectively computed from the 10×10-fold cross-validation accuracy of employing the Filter Bank Common Spatial Pattern (FBCSP) algorithm on their EEG measurements. The neurological disability is subjectively estimated using the Fugl-Meyer Assessment (FMA) of the upper extremity. The results show that the performance of BCI-naïve hemiparetic stroke patients is comparable to healthy subjects, and no correlation is found between the accuracy of their performance and their motor impairment in terms of FMA.**

I. INTRODUCTION

Brain-Computer Interface (BCI) is a communication system that directly translates brain signals into commands for controlling an external device [1], which bypasses the normal motor output neural pathways [2]-[4]. The brain signals can be acquired by scalp-recorded electroencephalogram (EEG) non-invasively from a subject. Studies have shown that distinct mental processes such as Event-Related Desynchronization or Synchronization (ERD/ERS) [5],[6] are detectable from EEG measurements for both real and imagined motor movements in healthy subjects [7]-[9]. Hence, Motor Imagery-based BCI (MI-BCI), which translates the mental imagination of movements into commands, provides a promising communication channel for stroke patients who suffer from motor disabilities.

The challenge in MI-BCI is the huge inter-subject variability with respect to the characteristics of the brain signals [1]. There are two approaches of operating a MI-BCI. In the operant conditioning approach, the subject learns to control a specific EEG feature that is hardwired in the BCI system [10]. In the machine learning approach, the BCI adapts to specific brain signals of the subject [1]. Recently, the latter approach has been shown to be very promising. Specifically, the Common Spatial Pattern (CSP) algorithm [1],[11] is effective in constructing optimal spatial filters that discriminates two classes of EEG measurements in MI-BCI [11]. Although the performance of this spatial filter is dependent on its operational frequency band, the Filter Bank Common Spatial Pattern (FBCSP) algorithm [12] addresses this issue by performing autonomous selection of key temporal-spatial discriminative EEG characteristics for MI-BCI.

At present, there exists only one study which has investigated MI-BCI on a large healthy subject population [13]. Prior studies [1] were performed on BCI-artful healthy subjects who were experienced in operating MI-BCI. To the best of our knowledge, there exists only one study performed on BCI-naïve healthy subjects [14], and a limited number performed on stroke patients operating MI-BCI [11],[15],[16]. Similar studies were performed on stroke patients operating EEG-based but not MI-BCI [17]-[19]. Studies have shown that the performance of MI-BCI varied across subjects [11],[16], but the reasons have not been extensively investigated [16]. In addition, the performance of MI-BCI on BCI-naïve paralyzed patients are hypothesized to be comparable to those of healthy subjects [16], but this has yet to be investigated.

Since stroke patients suffer from neurological damage, the portion of the brain that is responsible for generating ERD/ERS in MI-BCI could be compromised. Hence, the issue remains as to whether stroke patients are capable of operating MI-BCI effectively. Specifically, whether their performance in operating MI-BCI is correlated to the neurological damage present. This paper explicitly addresses this issue by performing a clinical study of non-invasive EEG-based MI-BCI on stroke patients. Hemiparetic stroke patients are recruited for this study because the Fugl-Meyer Assessment (FMA) [20] can quantitatively measure their motor impairment and recovery after post-stroke rehabilitation [21]. Hence, measuring the neurological motor function by FMA provides an indication of the neurological damage. This preliminary study will be extended to include functional Magnetic Resonance Imaging (fMRI) evaluation in the near future. Since ERD/ERS are detectable for both

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imagined and real motor movements in healthy subjects [7], it is more intuitive for BCI-naïve hemiparetic stroke patients to perform actual tapping by the able arm and motor imagery by the paralyzed arm.

The remainder of this paper is organized as follows. Section II provides a brief description of the FBCSP algorithm used in this clinical study. Section III describes the experimental studies and presents the results. Section IV concludes this paper with an analysis of the experimental results.

II. FILTER BANK COMMON SPATIAL PATTERN

The *Filter Bank Common Spatial Pattern* (FBCSP) algorithm shown in Fig. 1 comprises four progressive stages of EEG measurements processing: multiple bandpass filters using zero-phase Chebyshev Type II filters, spatial filtering using the CSP algorithm, feature selection of the CSP features, and classification of the selected CSP features.

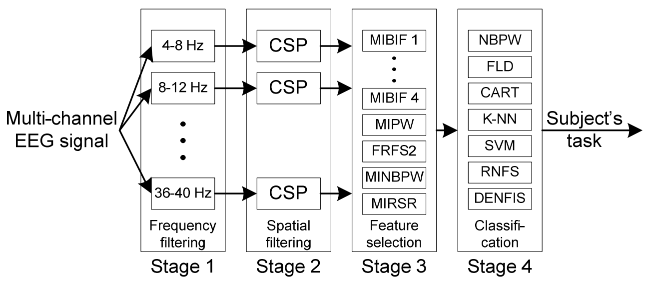

Fig. 1. Architecture of the proposed Filter Bank Common Spatial Pattern (FBCSP) machine learning approach

The first stage employs a filter bank that bandpass filters the EEG measurements into multiple bands. The second stage performs spatial filtering on each of these bands using the CSP algorithm. Thus, each pair of bandpass and spatial filter yields CSP features that are specific to the frequency range of the bandpass filter. The third stage employs a feature selection algorithm to select the discriminative CSP features from the filter bank. The fourth stage employs a classification algorithm to model and classify the selected CSP features. Based on the experimental results of comparing different feature selection and classification algorithms for MI-BCI in [12], the Mutual Information Best Individual Feature (MIBIF) algorithm and the Naïve Bayes Parzen Window (NBPW) are used to select and classify the CSP features respectively in this paper.

The neurophysiological background of MI-BCI is that motor activity, both actual and imagined [22],[23] causes an attenuation or increase of localized neural rhythmic activity called ERD/ERS [5],[6]. The *Common Spatial Pattern* (CSP) algorithm is highly successful in calculating spatial filters for detecting ERD/ERS [1]. The objective of spatial filtering employing the CSP algorithm [24] in MI-BCI is to compute the features whose variances are optimal for discriminating two classes of EEG measurements [24],[25].

The method employed by CSP is based on the simultaneous diagonalization of two covariance matrices [24],[26]. In summary, the spatially filtered signal $\mathbf{Z}$ of a single trial EEG $\mathbf{E}$ is given as

$$\mathbf{Z} = \mathbf{W}\mathbf{E}\,, \tag{1}$$

where $\mathbf{E}$ is an $N\times T$ matrix representing the raw EEG measurement data of a single trial; N is the number of channels; T is the number of measurement samples per channel. $\mathbf{W}$ is the CSP projection matrix. The rows of $\mathbf{W}$ are the stationary spatial filters and the columns of $\mathbf{W}^{-1}$ are the spatial patterns.

The spatial filtered signal $\mathbf{Z}$ given in (1) maximizes the differences in the variance of the two classes of EEG measurements. However, the variances of only a small number m of the spatial filtered signal are generally used as features for classification [24]. The m first and last rows of $\mathbf{Z}$ i.e. $\mathbf{Z}_p$, $p\in\{1..2m\}$ form the feature vector X_p given in (2) as inputs to a classifier.

$$X_p = \log\left(\operatorname{var}\left(\mathbf{Z}_p\right) \Big/ \sum_{i=1}^{2m} \operatorname{var}\left(\mathbf{Z}_i\right) \right). \tag{2}$$

III. EXPERIMENTAL RESULTS

This section describes the experiments performed in this study and presents the results. The experiments comprises: a comparison of the performance of MI-BCI using the FBCSP algorithm with prevailing approaches on a publicly available dataset; a study of MI-BCI on 8 healthy subjects who performed tapping and motor imagery respectively using the FBCSP algorithm; and a study of MI-BCI on 35 hemiparetic stroke patients using the FBCSP algorithm.

A. Publicly available BCI Competition III dataset IVa

The BCI Competition III dataset IVa [27] is collected from 5 subjects (labeled 'aa', 'al', 'av', 'aw', 'ay') who performed right hand and right foot imagination [28]. The data for each subject comprises 280 trials of EEG measurements from 118 electrodes. Two sets of experiments are performed. The first set extracts data from all electrodes 0.5s to 2.5s after the visual cue. The second set extracts data from electrodes and time segments that are manually selected for each subject consistent with the experiment in [29]. FBCSP employed 9 bandpass filters and the NBPW classifier, whereas CSP employed the SVM classifier. CSP configured with a broad bandpass filter of 8-30Hz [24] in the first set, and configured with manually selected frequency for each subject in the second set.

Fig. 2 shows the results of unbiased 10×10-fold cross-validations performed using FBCSP, Iterative Spatio-Spectral Pattern Learning (ISSPL) [29], and CSP. The regularization parameter and stopping iteration of ISSPL performed in [29] are manually selected. However, they are set to default values in this experiment to avoid ad-hoc tuning of the classifiers in order to make a fair comparison. The first set of results show that FBCSP yields a better test accuracy (89.9±0.9%) than ISSPL (81.3±2.0%) and CSP (87.6±0.9%), and the second set shows that FBCSP

(91.9±0.6%) is comparable to CSP (92±0.7%) and better than ISSPL (90.3±1.0%). Hence, the FBCSP algorithm is used in the subsequent experiments.

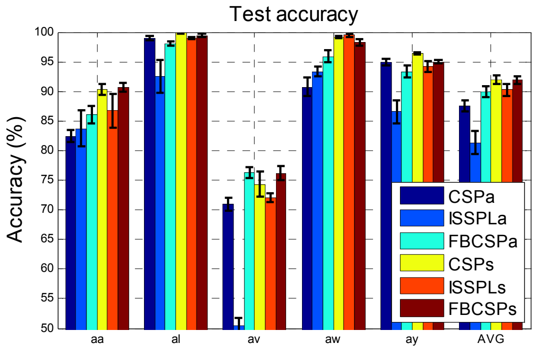

Fig. 2. Experimental results on the test accuracies of 10×10-fold cross-validations performed on BCI Competition III dataset IVa. The 3 dark blue, blue and cyan bars show the test accuracies of 10×10-fold cross-validations performed using CSP, ISSPL and FBCSP on all channels and fixed time segment respectively, and the next yellow, red and brown bars on subject-specific channels and time segments selections. The vertical lines show the standard deviations of the test accuracies.

B. Tapping versus imagery from 8 healthy subjects

This dataset is collected using Neuroscan NuAmps from 8 healthy subjects (labeled 1 to 8). These subjects are BCI-artful who have prior experience in operating MI-BCI. The data is collected with approval from the Ethics Approval Board. The subjects performed left and right hand tapping in one session, and motor imagery in another separate session. The data for each subject comprises 160 trials of EEG measurements from 27 electrodes starting from 0.5s to 2.5s after the visual cue. The data from all trials are used without any removal of artifacts such as Electrooculogram (EOG).

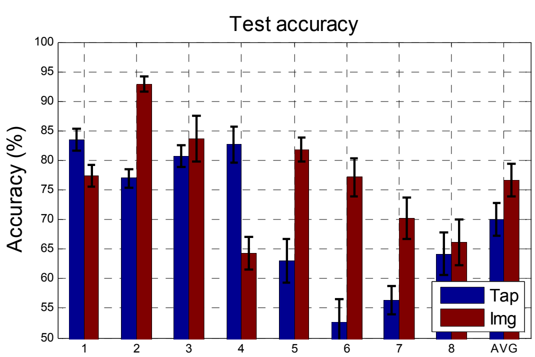

Fig. 3. Experimental results on the EEG data collected from 8 healthy subjects for Brain-Computer Interface. The blue and red vertical bars show the test accuracies of 10×10-fold cross-validations performed using FBCSP on the EEG data of the subjects performing tapping and motor imagery respectively. The vertical lines show the standard deviations of the test accuracies.

Fig. 3 shows the results of unbiased 10×10-fold cross-validations performed using the FBCSP algorithm on the tapping versus motor imagery data. The results show a significant variation in inter-subject performance in operating MI-BCI. This is consistent with the finding in [11],[16]. It is observed that subject 4 performed well for tapping (82.7±3.1%) but poorly for motor imagery (64.34±2.8%); whereas subject 6 performed poorly for tapping (52.8±3.9%) but well for motor imagery (77.1±3.3%). Hence, the results also show a significant intra-subject variation between tapping and motor imagery for some subjects. The results show that the average accuracy of the 8 healthy subjects performing motor imagery (76.7±2.8%) is better than tapping (70.0±2.7%). A paired samples t-test on the accuracy of tapping and motor imagery for the healthy subjects yields a p-value of 0.22. Hence, there is no significant difference between the accuracy of tapping versus motor imagery for healthy subjects, which is consistent with the evidence in the literature that suggests a shared neural substrate between imagined and executed movements [7].

C. Tapping and imagery from 35 hemiparetic patients

This dataset is collected using Neuroscan NuAmps from 35 hemiparetic stroke patients (labeled 1 to 35) who are all BCI-Naïve. The data is collected with approval from the Ethics Approval Board. The extent of neurological deficit is estimated using the Fugl-Meyer Assessment (FMA) of the upper extremity. A further study of their neurological injury is ongoing using fMRI. Since the results in the previous experiment and evidence in the literature suggest a shared neural substrate between imagined and executed movements [7], the patients are instructed to perform tapping on the able arm and motor imagery on the paralyzed arm. The data for each patient comprises 160 trials of EEG measurements from 27 electrodes starting from 0.5s to 2.5s after the visual cue. The data from all trials are used without any removal of artifacts such as Electrooculogram (EOG).

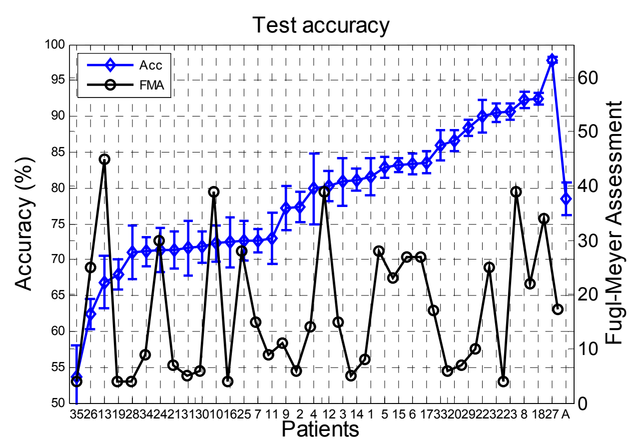

Fig. 4. Experimental results on the EEG data collected from 35 hemiparetic stroke patients for Brain-Computer Interface. The blue line with diamond markers shows the test accuracies of 10×10-fold cross-validations performed using FBCSP on the EEG data of the patients, the blue vertical line shows the standard deviations of the test accuracies, and black line with circle markers shows the Fugl-Meyer Assessment of the patient

Fig. 4 shows the results of unbiased 10×10-fold cross-validations performed using the FBCSP algorithm on the patients' data. The results are sorted in ascending accuracy and a plot of the FMA of each patient is included. The results show that the average accuracy of the 35 hemiparetic stroke patients (78.5±2.3%) is better than the 8 healthy subjects (73.3±2.8%). The Pearson correlation coefficient between the accuracy of each patient and their FMA is 0.19. Hence, this result shows that the performance of the hemiparetic stroke patients is not linearly correlated to their FMA. Since the performance of the hemiparetic stroke patients is better than healthy subjects, this shows that the neurological damage in the hemiparetic stroke patients does not significantly affect their capability of operating MI-BCI.

IV. CONCLUSIONS

This clinical study investigates whether BCI-naïve hemiparetic stroke patients are capable of operating a non-invasive MI-BCI effectively compared to healthy subjects. The study was performed on 8 healthy subjects and 35 hemiparetic stroke patients. The study also revealed that comparable performance is attainable from tapping versus motor imagery by BCI-artful healthy subjects. The study demonstrated that although hemiparetic stroke patients suffered from neurological injury, they were capable of operating MI-BCI as effectively as healthy subjects, and their performance is not correlated with the level of motor impairment as measured by FMA on the upper extremity.

However, the performance of the hemiparetic stroke patients in this preliminary study may originate from the tapping by the able arm instead of motor imagery by the paralyzed arm. Hence, a further study on the spatial patterns of the hemiparetic patients is performed in [30] to verify the neurophysiological plausibility of the computed solution.

REFERENCES

[1] B. Blankertz, G. Dornhege, M. Krauledat, K.-R. Muller, 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, 2007.

[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, no. 6, pp. 767-791, 2002.

[3] N. Birbaumer, "Brain-computer-interface research: Coming of age," *Clin. Neurophysiol.*, vol. 117, no. 3, pp. 479-483, 2006.

[4] J. R. Wolpaw, N. Birbaumer, W. J. Heetderks, D. J. McFarland, P. H. Peckham, G. Schalk, E. Donchin, L. A. Quatrano, C. J. Robinson, and T. M. Vaughan, "Brain-computer interface technology: a review of the first international meeting," *IEEE Trans. Rehabil. Eng.*, vol. 8, no. 2, pp. 164-173, 2000.

[5] G. Pfurtscheller and F. H. Lopes da Silva, "Event-related EEG/MEG synchronization and desynchronization: basic principles," *Clin. Neurophysiol.*, vol. 110, no. 11, pp. 1842-1857, 1999.

[6] G. Pfurtscheller and C. Neuper. "Future prospects of ERD/ERS in the context of brain-computer interface (BCI) developments", in *Progress in Brain Research: Event-Related Dynamics of Brain Oscillations*, C. Neuper and W. Klimeschm, Eds. Elsevier, 2006, vol. 159, pp. 433-437.

[7] M. Stavrinou, L. Moraru, L. Cimponeriu, S. Della Penna, and A. Bezerianos, "Evaluation of Cortical Connectivity During Real and Imagined Rhythmic Finger Tapping," *Brain Topography*, vol. 19, no. 3, pp. 137-145, 2007.

[8] G. Pfurtscheller, C. Neuper, C. Brunner, and F. L. da Silva, "Beta rebound after different types of motor imagery in man," *Neurosci. Letts*, vol. 378, no. 3, pp. 156-159, 2005.

[9] G. Pfurtscheller, C. Brunner, A. Schlogl, and F. H. Lopes da Silva, "Mu rhythm (de)synchronization and EEG single-trial classification of different motor imagery tasks," *NeuroImage*, vol. 31, no. 1, pp. 153-159, 2006.

[10] N. Birbaumer, A. Kubler, N. Ghanayim, T. Hinterberger, J. Perelmouter, J. Kaiser, I. Iversen, B. Kotchoubey, N. Neumann, and H. Flor, "The thought translation device (TTD) for completely paralyzed patients," *IEEE Trans. Rehabil. Eng.*, vol. 8, no. 2, pp. 190-193, 2000.

[11] G. Pfurtscheller and C. Neuper, "Motor imagery and direct brain-computer communication," *Proc. IEEE*, vol. 89, no. 7, pp. 1123-1134, 2001.

[12] K. K. Ang, Z. Y. Chin, H. Zhang, and C. Guan, "Filter Bank Common Spatial Pattern (FBCSP) in Brain-Computer Interface," *Proc. IJCNN'08,* pp.2391-2398, 2008.

[13] C. Guger, G. Edlinger, W. Harkam, I. Niedermayer, and G. Pfurtscheller, "How many people are able to operate an EEG-based brain-computer interface (BCI)?," *IEEE Trans. Neural Syst. Rehabili. Eng.*, vol. 11, no. 2, pp. 145-147, 2003.

[14] B. Blankertz, R. Tomioka, S. Lemm, M. Kawanabe, and K.-R. Muller, "Optimizing Spatial filters for Robust EEG Single-Trial Analysis," *IEEE Sig. Pro. Mag.*, vol. 25, no. 1, pp. 41-56, 2008.

[15] G. R. Muller-Putz , R. Scherer, G. Pfurtscheller, and R. Rupp, "EEG-based neuroprosthesis control: A step towards clinical practice," *Neurosci. Letts*, vol. 382, no. 1-2, pp. 169-174, 2005.

[16] G. Krausz, R. Scherer, G. Korisek, and G. Pfurtscheller, "Critical Decision-Speed and Information Transfer in the "Graz Brain-Computer Interface"," *Appl. Psychophysiol. Biofeedback*, vol. 28, no. 3, pp. 233-240, 2003.

[17] C. Neuper, G. R. Muller, A. Kubler, N. Birbaumer, and G. Pfurtscheller, "Clinical application of an EEG-based brain-computer interface: a case study in a patient with severe motor impairment," *Clin. Neurophysiol.*, vol. 114, no. 3, pp. 399-409, 2003.

[18] T. Hinterberger, A. Kubler, J. Kaiser, N. Neumann, and N. Birbaumer, "A brain-computer interface (BCI) for the locked-in: comparison of different EEG classifications for the thought translation device," *Clin. Neurophysiol.*, vol. 114, no. 3, pp. 416-425, 2003.

[19] A. Kübler, F. Nijboer, J. Mellinger, T. M. Vaughan, H. Pawelzik, G. Schalk, D. McFarland, N. Birbaumer, and J. R. Wolpaw, "Patients with ALS can use sensorimotor rhythms to operate a brain-computer interface," *Neurology*, vol. 64, no. 10, pp. 1775-1777, 2005.

[20] 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," *Scand. J. Rehabil. Med.*, vol. 7, no. 1, pp. 13-31, 1975.

[21] D. J. Gladstone, C. J. Danells, and S. E. Black, "The Fugl-Meyer Assessment of Motor Recovery after Stroke: A Critical Review of Its Measurement Properties," *Neurorehabil. Neural Repair*, vol. 16, no. 3, pp. 232-240, 2002.

[22] G. Pfurtscheller and A. Aranibar, "Evaluation of event-related desynchronization (ERD) preceding and following voluntary self-paced movement," *Electroenceph. Clin. Neurophysiol.*, vol. 46, no. 2, pp. 138-146, 1979.

[23] A. Schnitzler, S. Salenius, R. Salmelin, V. Jousmaki, and R. Hari, "Involvement of Primary Motor Cortex in Motor Imagery: A Neuromagnetic Study," *NeuroImage*, vol. 6, no. 3, pp. 201-208, 1997.

[24] H. Ramoser, J. Muller-Gerking, and G. Pfurtscheller, "Optimal spatial filtering of single trial EEG during imagined hand movement," *IEEE Trans. Rehabil. Eng.*, vol. 8, no. 4, pp. 441-446, 2000.

[25] J. Muller-Gerking , G. Pfurtscheller, and H. Flyvbjerg, "Designing optimal spatial filters for single-trial EEG classification in a movement task," *Clin. Neurophysiol.*, vol. 110, no. 5, pp. 787-798, 1999.

[26] K. Fukunaga. *Introduction to Statistical Pattern Recognition*, 2nd ed. New York:Academic Press, 1990.

[27] B. Blankertz, "BCI Competition III*"*, Fraunhofer FIRST.IDA, http://ida.first.fraunhofer.de/projects/bci/competition_iii, 2005.

[28] G. Dornhege, B. Blankertz, G. Curio, and K.-R. Muller, "Boosting bit rates in noninvasive EEG single-trial classifications by feature combination and multiclass paradigms," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 6, pp. 993-1002, 2004.

[29] W. Wu, X. Gao, B. Hong, and S. Gao, "Classifying Single-Trial EEG During Motor Imagery by Iterative Spatio-Spectral Patterns Learning (ISSPL)," *IEEE Trans. Biomed. Eng.*, vol. 55, no. 6, pp. 1733-1743, 2008.

[30] K. K. Ang, C. Guan, K. S. G. Chua, B. T. Ang, C. W. K. Kuah, C. Wang, K. S. Phua, Z. Y. Chin, and H. Zhang, "A clinical evaluation on the spatial patterns of non-invasive motor imagery-based brain-computer interface in stroke," *Proc. EMBC'08,* in press.