Comparing the Performance of Contralesional and Ipsilesional brain-computer interface in stroke survivors

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A number of clinical trials have recently investigated the effectiveness of using brain computer interfaces (BCI) for upper-limb stroke rehabilitation (Ang et al., 2015b; Foong et al., 2019; Wu et al., 2020). In many BCI clinical trials, electroencephalogram (EEG) produced by the ipsilesional motor cortex have been used to operate the BCI (Bundy et al., 2017). However, the ability to control a BCI using ipsilesional cortical activity has been reported to be reduced in some stroke patients (Buch et al., 2012). This may be one of the main reasons that around 30% of stroke patients encounter BCI deficiency and cannot participate in BCI-based stroke rehabilitation (Shu et al., 2018). Interestingly, several studies have found that when performing motor imagery stroke patients with severe motor impairment have stronger brain activity in the contralesional hemisphere than patients less affected by motor impairment (Kaiser et al., 2012; Antelis et al., 2016). Similarly, a recent study found that for stroke patients encountering BCI deficiency, the contralesional hemisphere has significantly higher brain activity than the ipsilesional hemisphere (Shu et al., 2018). Therefore, we hypothesize that brain signals from the contralesional hemisphere may help some stroke patients to obtain better BCI performance (especially for patients encountering BCI deficiency). The goal of this study is to investigate the EEG brain signals of 136 stroke patients in order to find answers to the following questions.

1. Can stroke patients use the brain activity generated by the contralesional hemisphere to control the BCI?
2. Is there a significant difference in stroke patients' ability to control BCI using brain activity generated by the contralesional hemisphere versus the ipsilesional hemisphere?

Method: We analyzed the EEG datasets of four clinical trials involving 136 stroke patients, 17 of which were in subacute phase (Ang et al., 2015a; Ang et al., 2015b; Ang et al., 2014; Foong et al., 2019). The stroke patients who participated in these clinical trials were instructed to imagine movement of their impaired hand. The BCI session in these clinical trials was divided into four runs. Each run randomly presented with 20 trials of MI tasks and 20 trials of idle state. Following each run, the participant was given a 2 minute break. Each trial lasted approximately 12 seconds, and each run usually took 8 minutes. There were 160 trials in total.

In our present study, the EEG signal was first filtered using a band pass filter (8 to 30Hz). We selected this frequency band because it contains mu (8-12 Hz) and beta (13-30 Hz) frequency bands, which are related to the motor imagery (McFarland et al., 2000). After that band power features (BP) were extracted from nine electrodes covering either the ipsilesional or the contralesional hemisphere (FC3, FCz, T7, C3, Cz, CP3, CPz, P3, Pz; and FCz, FC4, Cz, C4, T8, CPz, CP4, Pz, P4 respectively). BP were calculated according to the method proposed by (Pfurtscheller, 2001). In each trial, we extracted the EEG data during the rest state

(1.5 seconds before the cue), and 4 seconds during the performed motor imagery task. After that the extracted EEG data was squared, averaged over samples and logarithmised.

Because we only employed 9 channels from the contralesional or ipsilesional hemisphere, the total number of BP features extracted by each BCI model is 9. Next, we employed mutual information-based Best individual Feature (MIBIF) selection in order to reduce the dimensionality of input features to our classifier by using only the most discriminative 4 features (Ang and Quek, 2006). Finally, the Naıve Bayesian Parzen Window (NBPW) classifier was used to model and classify the selected feature (Ang et al., 2008). The average 10-fold cross validation outcomes were statistically compared between the two types of BCI (i.e. ipsilesional and contralesional) using the Wilcoxon signed rank test. Since our accuracy comes from 4 different datasets, we used this non-parametric test (Woolson, 2007). The significance level was set to p= 0.05 for all analyses. Figure 1 shows all the steps that have been followed in conducting the current study.

Results: The results of the two types of BCI accuracy (ipsilesional and contralesional) of 136 stroke patients are shown in figure 2, The results show that the stroke patients were able to operate the BCI using EEG signals from either contralesional or ipsilesional hemisphere (mean=72.52, SD=±9.06; and mean=71.99, SD=±9.65 respectively). Furthermore, there was no significant difference between the two groups of BCI accuracy (p=0.641).

Conclusion: The present results suggest that stroke patients are able to operate a BCI using either ipsilesional or contralesional hemisphere without a significant change in performance. This research also found that contralesional BCI can be a feasible alternative for those who are unable to use ipsilesional BCI. Finally, the functional effects of contralesional and ipsilesional BCI are beyond the scope of this study. Thus, further BCI clinical trials are needed to examine the effects of contralesional versus ipsilesional BCI on motor function following a stroke.

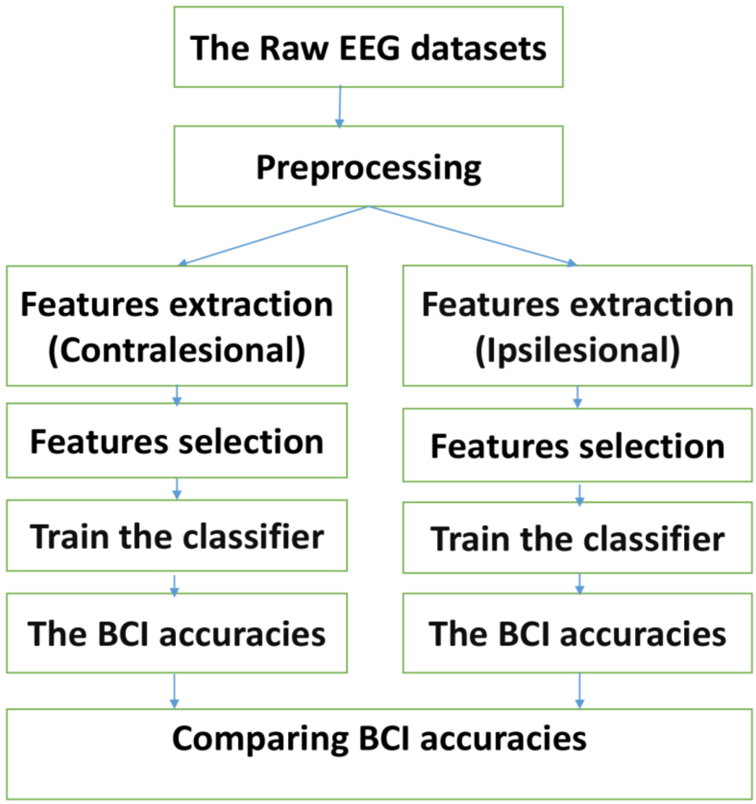

Figure 1 Flowchart with the steps of the current study.

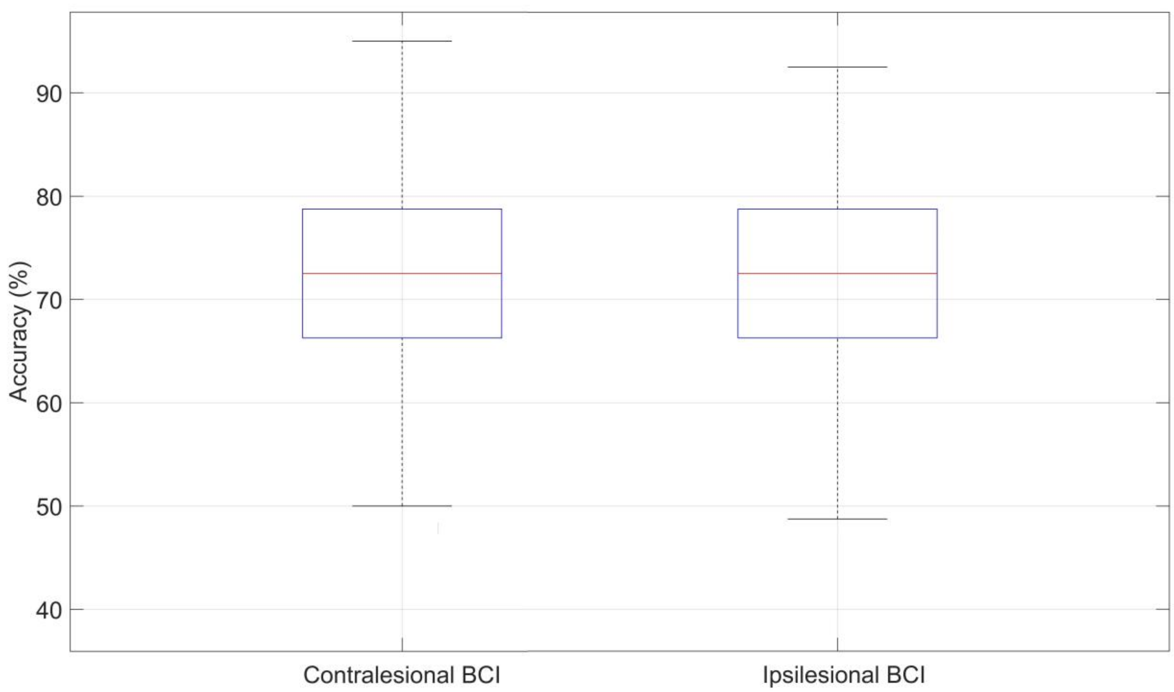

Figure 2. The offline BCI accuracy of 136 stroke patients during motor imagery (MI) using either contralesional or ipsilesional hemisphere. The x axis represents the contralesional and ipsilesional BCI, and the y axis represents the BCI accuracy.

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