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it should function like a random classifier with a mean accuracy of 25 %. In this case the average accuracy for shuffled data is 27 % - indicating that there are some irregularities in the dataset which can be exploited by the ESN. Therefore this is a better benchmark for chance level accuracy, which the reported results still exceed.

4 Discussion

Using the methods described, a classification accuracy of 65 % was achieved for subject 1, and for subject 2 a lower classification accuracy of 36 % (Figure 4). This is higher than, but consistent with, the winning BCI Competition IV entrant who achieved 59.5 % accuracy for subject 1, and 34.3 % for subject 2, with a smaller training dataset and without the benefit of checking their results [3]. The other entrants did not achieve results above chance level.

Manipulating the training dataset showed that brain activity related to the task was localised to the left hemisphere. More training rounds, and a higher electrode density could potentially be used to localise it more precisely. The approximate frequency of the activity was also determined, which shows the potential for using an ESN as a crude way to investigate brain activity with unknown characteristics, or find activity in new frequency bands.

When the ESN was trained with both subjects data combined it achieved an accuracy of 47 %. This is unusual as typically BCIs must be trained for each individual due to variation in brain activity. This may suggest that a single ESN BCI can be trained to work with multiple subjects, or be generalised to work with any subject. However it is impossible to tell without data from more subjects. A result of 47 % is comparable to the accuracy from simply combining the results from both subjects. This means the ESN may simply have been trained to differentiate between subjects and classify them accordingly (this in itself would be interesting).

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