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4 Discussion and Conclusion

By using CSP features instead of DFT features, the average peak, mean and median performance during the feedback period was significantly improved from 82% to 89.7%, from 66.8% to 79.3% and from 67.7% to 80.4%, respectively when combined with a RF classifier and from 82% to 87.3%, from 66.8% to 77.2% and from 67.7% to 77.8%, respectively when combined with an sLDA classifier. It is not surprising that an optimized spatial filtering outperforms the DFT features. CSP features have a higher signal-to-noise ratio and are therefore easier to classify. For example, the peak classification accuracy of one participant was improved by $\sim$ 22% (Table 1, P9). However, our results show that a RF classifier can make better use of CSP features than an sLDA classifier, at least for the present data. This is remarkable, as the RF classifier relies on a complex, non-linear model and the trials-to-features ratio is low (100/90 = 1.11). The effect of using a RF classifier instead of a sLDA classifier is small (peak $\sim$ 2%, mean $\sim$ 2%, median $\sim$ 3%), but statistically significant for mean and median performance and consistent over the participants. For 8 of the 10 participants the combination of a RF classifier with CSP features is the best performing method. For participant P7 the combination of sLDA with CSP features performed slightly better, but not in median performance. For participant P10, both methods failed, since the achieved performance is around 70% only. The enhancement of the sustained (i.e. mean and median) performance is of particular importance, as the Graz-BCI paradigm calls for these. Concluding, the present work on performance, in combination with previous work on RF classifiers as powerful tools for data analysis [7], underlines the potential of the RF classifier in the field of BCIs. Further, we argue that the widespread view that linear methods are ideal for BCIs should be reconsidered.

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