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returned significantly higher performance than the knowledge based method for both decomposition methods. Whilst the IMFs chosen with the brute force method were not consistent between users or decomposition methods, they did focus on the frequency bands known to contain MI information that were identified in the introduction (Figure 1). A single channel analysis of the high-performing brute force method was carried out to further see if embedding temporal data added anything to the EMD process. As CSPs need multiple channels to function the variance of each processed trial was used as the input of the SVM.

As Table 1 shows, there is negligible difference in performance indicating that the added temporal dynamics do not contain any new information. In part, this may be due to the fact that the underlying processes for MI affect all channels, and whilst ERD/ERS and the μ rhythm are expected to be stronger on one side of the brain versus the other, the changes still occur simultaneously for both hemispheres. This implies that the information content for MI is inherent in the lateralisation of the changes - i.e. spatially. In [3] adding temporal dynamics to ICA had a greater impact than with EMD because ICA contains zero temporal information, whilst EMD still uses the data laid out in chronological order. EMD can also only discard background noise if it is unstructured due to its criteria for identifying IMFs.

4 Conclusion

Ultimately the added temporal dynamics did not significantly improve the classification performance. However it might still have some effect on performance if applied to an EEG signal with significant temporally independent features, which is not the case in MI. Another way to enhance the method could be to incorporate both spatial and temporal information by decomposing all channels in their multi-temporal form simultaneously using MEMD.

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