Adaptive Modulation Filtering for Motor Imagery Classification Enhancement

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Introduction: The main objective of a brain computer interface (BCI) is to capture the EEG signals when the subject is performing a mental task, and translate those signals into decisions for interaction with a given equipment [1]. For this, an important step in the EEG signal processing pipeline is to improve the signal-to-noise ratio (SNR) without losing relevant information; this is typically carried on with techniques such as temporal and/or spatial filtering. When a signal is modeled as a product between a low frequency signal and a high frequency signal, the former changes the amplitude of the latter, which is well-known concept of amplitude modulation [2][3]. By analyzing a signal in the modulation domain, it is possible to characterize those amplitude changes overtime, thus revealing second-order periodicities not detectable in the traditional time-frequency representation [3]. In this study, we investigated EEG signals processing in the so-called modulation domain as an enhancement technique to improve classification performance of an EEG-based BCI operating in the motor imagery paradigm. In our experiments, in order to bring EEG signals to the modulation domain, we used first a Fast Fourier Transform (FFT) for spectrotemporal representation and then applied a Continuous Wavelet Transform (CWT) over it. For feature extraction , we used the framework proposed by Fabien Lotte in [4], which combines the CSP algorithm with Tikhonov regularization. Finally, classification was performed with a two-stage approach, using the outputs of two-class Linear Discriminant Analysis (LDA) classifiers as inputs to a Naive Bayes classifier, which made the final four-class decision.

Material and Methods: For this investigation we used Dataset 2a of BCI Competition IV (BCIC IV)[5] where 22-channel EEG was recorded from nine subjects positioned comfortably during two sessions of six runs with a short break between them. While sitting in front of a computer screen, individuals performed four motor imagery tasks: imagination of left-hand (LH), right-hand (RH), foot (FT) and tongue (TG) movements. We used MATLAB to implement the following pipeline: (1) Filtering of modulation spectrograms in the conventional frequency intervals 0.5-5 Hz (region 1) and 50-120 Hz (region 2), both with 0.5-2.5 Hz as the modulation frequency interval; (2) Bandpass filtering with overlapping frequency bands, named as theta + alpha (4-14 Hz), alpha + beta (8-30 Hz) and beta + gamma (15-40 Hz); (3) Feature extraction using CSP combined with Tikhonov regularization; (4) Two-stage classification, first using LDA to build six two-class classifiers: LH x RH, RH x FT, FT x LH, FT x TG, TG x LH, and TG x RH. After, we used the six weighed LDA outputs as inputs to a four-class Naive Bayes classifier, obtaining the final classification.

Results and Conclusions: By applying filtering in the modulation domain for regions 1 and 2 for all subjects, we obtained an overall performance, measured by Cohen's Kappa, of 0.58 and 0.56, respectively. The first result was above the result obtained by the BCIC IV winner (0.57), but the second result was below. However, by applying optimized individual modulation filtering schemes (only region 1, only region 2, or both regions) for each of the nine subjects, we obtained an overall performance of 0.59. While these initial results are encouraging, it is important to mention that the results reported here were based on a small sample (nine subjects). Therefore, future studies should focus on a larger number of subjects, since there are significant differences between users in the synchronization and desynchronization of band energy related to motor imaging tasks [6]. When analyzing the results obtained individually, it is inferred that perhaps this is the reason for one of the subjects having a 26% increase in classification performance when modulation filtering enhancement was used, while in another it was as low as 1%.

References

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