BCI Competition IV

Data sets 1 <motor imagery, uncued classifier application>

Group information:

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Description of the algorithm:



Fig1. Step 1 of the Classification Process







Fig.3 Step 3 of the Classification Process

1. Subject-specific frequency bands, temporal windows and channel combinations were selected based on the r^2 values(the proportion of the difference of the means of the power spectral density (PSD) to the standard deviations of the PSD values accounted for by the label information) of the calibration data;

2. Two spatial filters (SF1, SF2 in Fig.1,3) were constructed using Common Spatial Pattern (CSP) algorithm;

3. Support Vector Machines (SVM) were trained on the whole calibration data as the classifiers;

4. Classifying the evaluation data, including 3 steps:

Step 1: A sliding window moves in temporal order on the evaluation data, sample-by-sample, to obtain the features (f1, f2) of the preprocessed evaluation data. The features were classified via the SVM, resulting in two outputs (y1, y2), which were normalized to the interval of [-1 1] and averaged; (Fig. 1)

Step 2: A difference sequence $(\bigtriangleup y)$ of the output of Step 1 was calculated every 50 points, and a threshold was determined to dectect those samples at which the mental states of the subject changed, leading to the temporal intervals of task and non-task; (Fig. 2)

Step 3: Similar to Step 1, those data in the task interval were processed to obtain a value (y). The task was classified as Class 1 if the corresponding y is negative, and Class 2 if it is positive. (Fig. 3)

As an optional requirement, the datasets of subject C and D are considered as artificially generated.

Reference:

Benjamin Blankertz, Guido Dornhege, Matthias Krauledat, Klaus-Robert Müller, and Gabriel Curio. The non-invasive Berlin Brain-Computer Interface: Fast acquisition of effective performance in untrained subjects. *NeuroImage*, 37(2):539-550, 2007
D. Zhang, Y. Wang, X. Gao, B. Hong, and S. Gao. An algorithm for idle-state detection in motor-imagery-based brain-computer interface. *Comput Intell Neurosci*, page 39714, 2007