Detection of movement preparation-related slow cortical potentials using Riemannian geometry and template matching

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Introduction: Slow cortical potentials such as the Readiness Potential (RP) or the Contingent Negative Variation (CNV) precede self-paced or cued movements, respectively. Since these neural patterns are related to movement preparation, they can be exploited in several brain-computer interface (BCI) applications, such as robotic exoskeleton control or neurofeedback training. Nevertheless, reliable detection of such patterns is a challenging task. Here we present a novel technique for this purpose that might alleviate some of the shortcomings of previous attempts in the literature.

Material, Methods, and Results: We utilize Riemannian geometry and template matching for pattern detection from electroencephalography (EEG) data, while an adaptive re-centering step is incorporated to reduce non-stationarities between train and test datasets [1]. Each epoch is first concatenated with a previously obtained, subject-specific RP or CNV template. Then, covariance of the composite signal is computed, resulting in a matrix C_i that captures both the covariance structure of the data, as well as how it reflects the target template. Finally, C_i is re-centered so to standardize its distribution and thus reduce non-stationarities. Such covariance matrices then can be utilized in a re-biased Riemannian geometry classification framework [2]. To test our method, we recruited 12 young, healthy volunteers (4 females, age: 26.3±4.8 years) who performed a center-out reaching task on a touchscreen computer. The task was designed to evoke RP and CNV in a sequential manner (self-paced and cued movements, respectively), also incorporating baseline trials for both conditions. EEG was recorded at 512 Hz sampling rate from 9 cortical locations during task performance. Each subject completed 8 runs, resulting in a total of 120 trials for both RP and CNV (and equally for their baselines). Data was evaluated pseudo-online utilizing a leave-one-run-out cross validation scheme. We could detect RPs with a group average accuracy of 62.64±4.75%, while CNVs could be detected at 74.01±7.49%. CNV could be detected well above chance level for all subjects, while RP for all but one.

Discussion: The contrast in performance could be explained by slight differences in the analysis setup; RPs were computed from 2-second, while CNVs from 3-second EEG epochs. Also, due to experimental design, train-test split for RP was 180-60 compared to 210-30 in case of CNV. Notably, the proposed analysis pipeline is comprised only of steps that can be directly adapted to a real online setting. Even though initial performances are modest, they are expected to increase over time once subjects are provided online BCI feedback and learn to modulate their neural patterns [3]. We will also report results of such closed-loop BCI experiment during the conference.

Significance: Our results indicate that slow cortical potentials can be detected with a confidence over chance level utilizing Riemannian geometry and template matching. The adaptive re-centering step facilitates robust and reliable performance over multiple sessions. The proposed method shows promise as a useful tool for future BCI applications aiming on movement preparation and RP and/or CNV detection.

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References

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