Reliable outlier detection by spectral clustering on Riemannian manifold of EEG covariance matrix

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Introduction: Automatically identifying and rejecting artifact-contaminated trials is a key problem to design robust BCIs. Here, we propose a novel outlier detection method based on Riemannian Geometry (RG), a promising approach for BCI classification [1]. With RG, EEG signals are represented and processed as Sample Covariance Matrix (SCM), which is also known to reduce EEG artifacts influence. State-of-the-art outlier detection methods in RG include *Riemannian Potato* (RP) [2] and *Median-Based Trimming* (MBT) [3]. However, both suffer from the need of a threshold to determine outliers, and both always reject some samples as outliers, even when there is none. Thus, we propose *Riemannian Spectral Clustering* (RiSC), to detect outliers by clustering SCMs into non-outliers and outliers by similarity, without thresholds.

Material, Methods and Results: First, RiSC computes the graph of SCMs similarities using the Riemannian distance between SCMs. Then, the graph nodes are clustered using spectral clustering [4], and all clusters except the most numerous one are rejected as outliers. We compared the classification accuracy of a *Minimum Distance to Mean* classifier [1] without outlier rejection (baseline) and after rejecting outliers from each class training data using RP, MBT and RiSC. We used EEG signals from 78 subjects from [5, 6], who performed right or left-hand motor imagery. The first two runs were used for training and the remaining runs for testing. Results showed no significant differences between methods (repeated measure ANOVA, $p = 0.093$). Mean classification accuracy (%) was 59.5±10.2, 59.8±10.1, 59.4±9.99 and 59.5±10.1 for the baseline, RiSC, RP and MBT respectively. RiSC did not detect any outlier for most (68 out of 78) subjects. However, when it removed outliers, this increased accuracy for all but one subject (mean gain: 2.39 ± 2.24 %). On the other hand, RP and MBT detected outliers in all subjects, but this decreased accuracy for 46 and 34 out of 78 subjects respectively.

Discussion: RiSC did not detect outlier for most subjects, which may suggest EEG contamination was already reduced using SCM. Thus, RiSC might be useful on more contaminated data. Contrary to RP and MBT, RiSC did not inadvertently reduce accuracy by rejecting clean data as outliers.

Significance: Describing EEG as SCMs and detecting their outliers by spectral clustering seem to be a robust method that usually does not lead to inadvertent decrease in classification accuracy.

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