 DOI: 10.3217/978-3-85125-467-9-170

Comparison of Hierarchical and Non-Hierarchical Classification for Motor Imagery Based BCI Systems

C. Lindig-León[1,3*], N. Gayraud[2], L. Bougrain[3,1], M. Clerc[2]

[1]Inria, Villers-lès-Nancy, F-54600, France; [2]Inria, BP93, 06902 Sophia Antipolis, France

[3]Université de Lorraine/LORIA, UMR 7503, Vandœuvre-lès-Nancy, F-54506, France

*E-mail: cecilia.lindig-leon@inria.fr

Introduction: Motor imagery (MI) based BCI systems record and analyze the brain activity to determine users' intentions while imagining moving some parts of their body [1]. In order to build systems that are able to detect several commands, multiclass schemes need to be applied. Hierarchical methods allow solving multiclass problems by using a tree of binary classifiers, whose root discriminates between two groups, each one containing a half of the classes. Each succeeding node includes again only one half of the classes from the selected group, and the process is recursively repeated until each node contains a single class, from which the final decision can be inferred. In this study we compare a series of multiclass approaches to assert the benefits of hierarchical classification. The compared methods are based on two effective techniques for MI-discrimination, namely, Common Spatial Patterns (CSP) and Riemannian geometry, for which the hierarchical and non-hierarchical approaches have been considered. We include the CSP by Joint Diagonalization method (CSPbyJAD) [2], which corresponds with a non-hierarchical approach; and its hierarchical counterpart, namely, Binary CSP [3]. In addition, the non-hierarchical Minimum Distance to Riemannian Mean method (MDRM) [4] is also evaluated, together with its analogous hierarchical approach; a contribution of the present work called Hierarchical MDRM algorithm (HMDRM). All these methods have been applied on dataset 2a of the BCI competition IV to facilitate their comparison.

Material, Methods and Results: Dataset 2a contains 22 EEG recordings from two different sessions of 9 healthy subjects performing four MIs (left hand, right hand, feet, and tongue). Signals were filtered using a Butterworth filter within the frequency range [8-30 Hz]. For each trial, a 2s-window starting 0.5 s after the task cue was considered for classification. Data from session 1 were used to train all the compared methods, which were subsequently evaluated with data from session 2. For the implementation of the HMDRM algorithm, the features of each trial correspond to the coefficients of its estimated covariance matrix, and every choice to select the next node of the decision tree is based on the MDRM algorithm. The performances achieved with all methods are shown in Table 1. For comparison purposes, we also include the winner of the competition, named Filter Bank Common Spatial Patterns (FBCSP) [5].

Table 1

Kappa value achieved with all methods using the dataset 2a of the BCI competition IV.

Method	S1	S2	S3	S4	S5	S6	S7	S8	S9	AVG
BCSP	*0.77*	*0.56*	*0.77*	*0.57*	*0.49*	*0.47*	*0.83*	*0.69*	*0.68*	***0.65***
HMDRM	*0.74*	*0.37*	*0.75*	*0.56*	*0.40*	*0.36*	*0.64*	*0.58*	*0.70*	***0.57***
FBCSP	*0.68*	*0.42*	*0.75*	*0.48*	*0.40*	*0.27*	*0.77*	*0.75*	*0.76*	***0.57***
MDRM	*0.75*	*0.37*	*0.66*	*0.53*	*0.29*	*0.27*	*0.56*	*0.58*	*0.68*	***0.52***
CSP by JAD	*0.65*	*0.40*	*0.77*	*0.50*	*0.44*	*0.19*	*0.25*	*0.72*	*0.50*	***0.49***

Discussion: The highest accuracies were reached by the BCSP and HMDRM methods, confirming the effectiveness of hierarchical algorithms. The BCSP algorithm achieves an accuracy that is improved by 8% compared to the winner of the competition, and by 16% compared to the CSPbyJAD method. The HMDRM approach also improves the accuracy with respect to the non-hierarchical MDRM algorithm by approximately 5%, and reaches the same results as the winner of the competition.

Significance: The present work shows that it is advantageous to split the original multiclass task into groups and hierarchically perform the corresponding binary classification, presumably due to an overtraining reduction. Moreover, it contributes with the implementation of a hierarchical method based on Riemannian geometry.

Acknowledgements: This research is partially funded by Inria project-lab BCI-LIFT.

References

[1] Wolpaw, J. R., and Wolpaw, E. W. *BCI: Principles and Practice. Oxford University Press, 2012.*

[2] Grosse-Wentrup, M., and Buss, M. Multi-class common spatial patterns and information theoretic feature extraction, *IEEE Transactions on Biomedical Engineering*, vol. 8, no. 55, 2008.

[3] Fang, Y., Chen, M., Zheng, X., and Harrison, R. F. Extending CSP to detect motor imagery in a four-class BCI. *Journal of Information and Computational Science*, 9(1), Pp. 143-151, 2012.

[4] Barachant A, Bonnet S, Congedo M, Jutten C. Multi-Class Brain Computer Interface Classification by Riemannian Geometry. *IEEE Transactions on Biomedical Engineering* 59(4), 2012, 920-928.

[5] Ang, K. K., Chin, Z. Y., Wang, C., Guan, C., and Zhang, H. Filter bank common spatial pattern algorithm on BCI competition IV datasets 2a and 2b. *Frontiers in Neurosciences,* vol. 6, p. 39, 2012.