Lower-Limb Motor Imagery-Based Brain-Computer Interface to Control Treadmill Velocities

Aura Ximena Gonzalez-Cely[1,2], Surjo R. Soekadar[2], Denis Delisle-Rodriguez[3], and Teodiano Bastos-Filho[1]
Universidade Federal do Espirito Santo[1], Charité Universitätsmedizin Berlin[2], Instituto Santos Dumont[3]

INTRODUCCION

Brain-Computer Interfaces (BCIs) commanding treadmills have demonstrated their potential for promoting the activation in the sensorimotor cortex, improving gait in post-stroke patients [1]. EEG power-based analyses, such as Power Spectral Density (PSD) and Event-Related Synchronization/Desynchronization (ERD/ERS) have been used to translate brain responses into brain-signal related feedback during rehabilitation [2].

[1] E. Bobrova, V. Reshetnikova, A. Frolov, and Y. P. Gerasimenko, "Use of imaginary lower limb movements to control brain–computer interface systems," Neuroscience and Behavioral Physiology, vol. 50,pp. 585–592, 2020
[2] V. Quiles, L. Ferrero, E. Ianez, M. Ortiz, ´A. Gil-Agudo, and J. M. Azorın, "Brain-machine interface based on transfer-learning for detecting the appearance of obstacles during exoskeleton-assisted walking," Frontiers in Neuroscience, vol. 17, p. 1154480, 2023.

PROPOSED BRAIN-COMPUTER INTERFACE

This protocol consists of three stages: (1) Condition 1, where participants alternate between active walking and Motor Imagery (MI) while treadmill velocity is adjusted via Kinesthetic Neurofeedback (KNF); (2) BCI Calibration, during which EEG data is used to obtain both classification and KNF models; (3) Condition 2, where the BCI system classifies MI and rest states, controlling the treadmill speed based on brain activity.

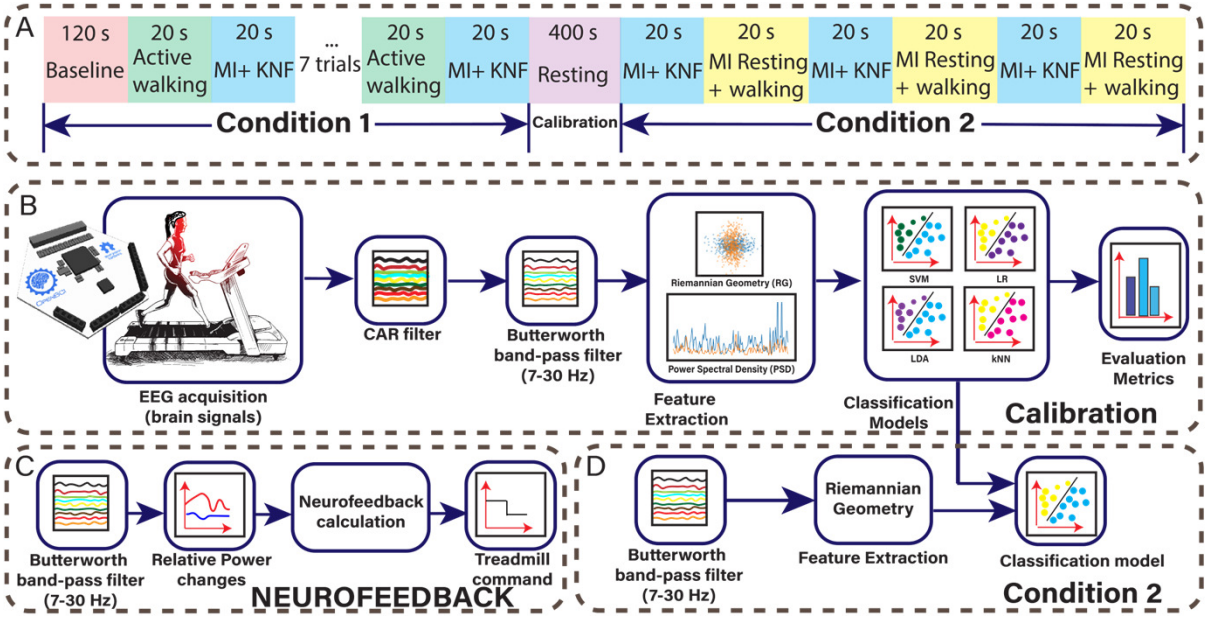


Fig. 1: MI-based BCI methodology. (A) Protocol implemented in Condition 1, system calibration and Condition 2 of the MI-based BCI; (B) System calibration since EEG data acquisition for model generation; (C) Neurofeedback stage calculating relative power changes to control the treadmill; (D) Condition 2 based on classification model and KNF parameters generated in the system calibration

CORTICAL ACTIVATION

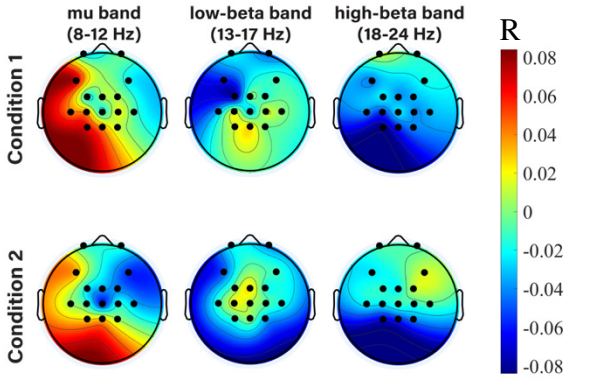
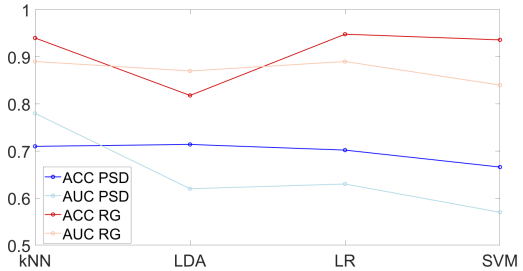


Fig. 2: Top maps showing higher R-values in the mu band on the lateral and parietal areas, and lower R-values in the low- and high-beta bands. In Condition 2, compared to Condition 1, lower R-values were found around Cz in the mu band.

PSEUDO-ONLINE ANALYSIS

Logistic Regression (LR) and Support Vector Machine (SVM) achieved the highest Accuracy (ACC), with 0.95 and 0.94, respectively, while implementing Riemannian Geometry (RG) features, instead of Power Spectral Density (PSD). Linear Discriminant Analysis (LDA) achieved a mean ACC of 0.72.



CONCLUSION

In this study, LR and SVM achieved the highest ACC (0.95 and 0.94), whereas LDA achieved an ACC of 0.72 while recognizing MI and resting classes. Despite these positive findings, the study was limited by only a single-participant sample and preliminary classifier configurations.

e-mail: aura.cely@edu.ufes.br