Motor neurorehabilitation through manipulations of the Riemannian manifold

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Introduction and Hypothesis: Neural signals in several brain cortices represent the overt activity of latent variables [1]. Invasive studies in non-human primates and rodents have shown that latent variables describe low-dimensional, embedded curves in the space of all possible neuronal activities known as manifolds. These manifolds appear preserved among species for the same behavior [2] and can be disrupted or changed due to learning and plasticity [3]. In non-invasive brain studies, manifolds are often represented as Electroencephalography (EEG) signals processed in the Riemannian geometry, in the form of covariance matrices [4]. Here, we hypothesize that a similar response to manifold manipulations observed in invasive processing can be elicited in non-invasive settings, with repercussions on behavior. Our study focuses on human motor learning in a rehabilitation context.

Objective: To implement real-time signal processing to identify latent variables, provide subjects with meaningful feedback on these variables, extract and analyze motor behavior manifolds from EEG signals in rehabilitation, and use manifold manipulation to aid sensorimotor recovery.

Materials and Methods: Eight chronic spinal cord subjects with upper and lower limb impairments will undergo motor imagery training in a system combining digital signal processing alongside feedback devices and traditional motor rehabilitation, with a paired control group without feedback, undergoing the same rehabilitation context. The regimen includes twenty training sessions over three months, with full clinical assessments at the start, midpoint, and end, aiming to enhance sensorimotor recovery through targeted feedback and manifold manipulation. We filter EEG signals from 16 channels positioned in the primary and secondary motor cortices in the alpha-beta range (8-35Hz), epoch the data (1-second epoch each 0.0625 second), convert these into covariance matrices, and project them onto a 2D Linear Discriminant Analysis (LDA)-reduced euclidean tangent space. The manifold is produced in the space of covariance matrices, and subjects are asked to reach motor behavior according to their respective regions of representation in the reduced-dimensionality space. The protocol involves initial supervised training of a classification model to label motor imagery trials, followed by sessions where EEG features are translated into visual or tactile feedback of upper and lower limbs' motor imagery. Data alignment via Riemannian Procrustes Analysis (RPA) [5] - to account for data distribution shifts - occurs at the beginning of each session, with model recalibration every two sessions - to account for neural activity changes due to plasticity.

Relevance: This study aims to evidence the effectiveness of exposing the latent variables of motor control to a subject undergoing rehabilitation. This processing makes it possible to interpret and manipulate the same or similar representation of motor control in invasive settings, which has not yet been explored to its full potential in non-invasive settings, as far as we know.

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