

Adaptive Classification of EEG Signals for Bimanual Motor Imagery using Riemannian Geometry

A.E. Cortés-Téllez¹, J.R. López-Gutiérrez¹, A.A. Torres-García¹

¹Instituto Nacional de Astrofísica, Óptica y Electrónica, Puebla, México

E-mail: ahiram.cortest@inaoep.mx

ABSTRACT: Brain-computer interfaces (BCIs) experience severe performance degradation when transitioning from unilateral to bimanual decoding due to simultaneous bihemispheric interference. To address this, we developed the Adaptive Topological BCI (AT-BCI) architecture. By embedding temporal dynamics into Hankel matrices and applying Riemannian geometry to align neural distributions, the model enables zero-shot transfer without target-domain calibration. Treating the covariance shift as a purely geometric discrepancy isolates mixed signals and prevents the expansion of peripheral noise. We evaluated AT-BCI on the PhysioNet dataset, projecting unilateral motor imagery onto bimanual tasks. After applying a strict amplitude filter to exclude electromyographic artifacts and physiological desynchronization, evaluation on a validated cohort of 10 subjects yielded a mean F1-score of 0.7468 and a Cohen's Kappa of 0.4901. These results demonstrate that restricting spatial topology and enforcing geodesic alignment stabilizes bimanual control, advancing the clinical viability of neuroprosthetic interfaces without the burden of daily recalibration.

INTRODUCTION

Motor-imagery-based brain-computer interfaces (BCIs) traditionally rely on unimanual tasks to decode user intent [1, 2]. Standard classification models achieve high accuracy in controlled single-limb paradigms, but practical daily activities inherently demand bimanual coordination. Transitioning a BCI from a unimanual calibration phase to a bimanual execution environment introduces severe non-stationarities in the electroencephalographic (EEG) signals. This transition abruptly degrades classifier performance [3], presenting a major bottleneck for functional neurorehabilitation. The root of this degradation lies in the neurophysiology of simultaneous movement. The execution of a bimanual motor task induces a complex, bilateral activation across the sensorimotor network. This dual activation generates an interhemispheric masking effect, which disrupts the localized event-related desynchronization (ERD) patterns typically observed during isolated unimanual tasks [4, 5]. Con-

sequently, classical spatial filters, such as Common Spatial Patterns (CSP) [6], are compromised because the bilateral interference violates the underlying assumption of spatial separability between classes.

Mathematically, this discrepancy between the unimanual training domain and the bimanual testing domain constitutes a severe domain shift [7]. To restore decoding reliability without burdening the user with exhaustive bimanual retraining sessions, adaptive transfer learning techniques are required [8]. Building upon the augmented covariance matrix (ACM) framework introduced by Carrara et al. [9], which demonstrated that embedding delayed EEG signals into higher-dimensional spaces captures non-stationary spatial patterns, we propose to resolve this displacement. While generic recentring techniques attempt to align data distributions [10], they typically process broad frequency bands and fail to account for the temporal dynamics of interhemispheric communication, leading to sub-optimal adaptations. To overcome these limitations, we propose the Adaptive Topological BCI (AT-BCI) architecture. We hypothesize that by restricting the spatial topology strictly to the sensorimotor cortex, embedding temporal dynamics through an analytically derived delay, and resolving the domain shift via geometric alignment, we can neutralize bimanual interference [8, 11].

The main contributions of this work are:

- We introduce a pipeline that treats bimanual covariance shifts as an unsupervised geometric alignment problem on a Riemannian manifold, bypassing the need for target-domain calibration.
- We incorporate temporal embeddings derived analytically from the central frequency of the signal to capture the dynamic nature of bilateral motor intentions, avoiding exhaustive heuristic searches and preventing temporal overfitting.
- We provide an *in silico* evaluation across a validated cohort of 10 subjects from the PhysioNet dataset [12, 13], utilizing strict amplitude filters to discard severe electromyographic artifacts. The results indicate that AT-BCI miti-

gates performance drops during zero-shot transfer tasks.

The remainder of this paper is structured as follows: Section II details the dataset audit, the topological restriction, and the proposed unsupervised domain alignment. Section III presents the population classification results and visualizes the spatial projections. Section IV examines the physical implications of the findings, and Section V concludes the paper.

MATERIALS AND METHODS

The complete processing pipeline of the proposed Adaptive Topological BCI (AT-BCI) architecture is illustrated in Fig. 1. The framework is logically structured into four sequential phases: spatial and artifact restriction, temporal embedding, geometric domain alignment, and isolated parametric optimization.

Data Management and Artifact Filtering: Empirical evaluation relied on electroencephalography records from the public PhysioNet dataset [12, 13]. Zero-shot transfer depends mathematically on computing an accurate Riemannian mean from the unimanual calibration session. The geodesic distance metric exhibits high sensitivity to spatial outliers. Consequently, high-amplitude artifacts shift the centroid of the reference matrix, irreversibly corrupting the subsequent domain alignment.

To neutralize this operational vulnerability, the algorithm integrates a cleaning protocol based on peak-to-peak amplitude. Before estimating covariances, the system systematically purges epochs exceeding a $100\mu\text{V}$ threshold. Applying this filter excluded records with massive electromyographic contamination or biological desynchronization deficiency, consolidating a valid cohort of 10 subjects. Concurrently, the spatial topology was reduced to 15 channels concentrated across the sensorimotor strip (FC3, FC1, FCz, FC2, FC4, C3, C1, Cz, C2, C4, CP3, CP1, CPz, CP2, CP4). This dimensional reduction ensures that the Riemannian alignment operates on features of strictly cortical origin, preventing the model from expanding parasitic noise from prefrontal and occipital zones during temporal processing.

Spatiotemporal Embedding via Augmented Covariance: To structure the temporal dynamics of the signal, the architecture employs the augmented covariance matrix (ACM) framework proposed by Carrara and Papadopoulou [9]. The procedure concatenates the original data with time-delayed versions of itself, forcing the cross-covariance to encode temporal dependencies across different brain regions.

Prior implementations of this model located the optimal delay using grid search methods. Analysis of the logs indicated that this practice induces data leakage and causes sample overfitting. Evaluating the mathematical relationship between the time domain

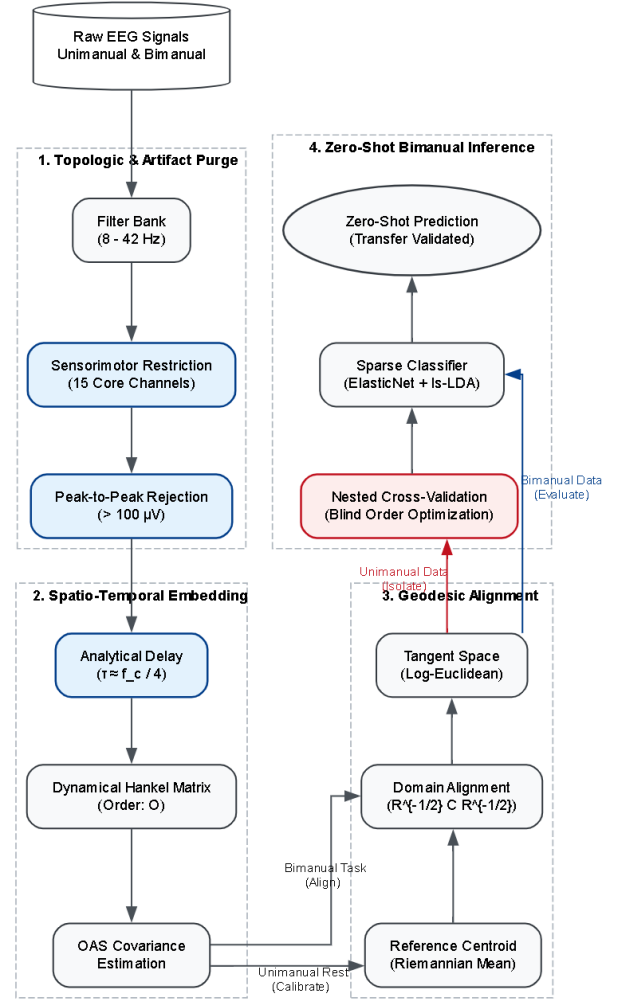


Figure 1: Flowchart of the AT-BCI architecture. The framework integrates a strict $100\mu\text{V}$ amplitude threshold and a 15-channel spatial restriction to prevent noise expansion. Temporal embedding relies on an analytically derived delay ($\tau \approx f_c/4$), while a nested cross-validation loop isolates the unimanual calibration from the bimanual zero-shot inference, eliminating data leakage.

and frequency coherence shows that capturing cross-dependencies requires an independent delay for each spectral band under evaluation. Therefore, the system abandons empirical exploration to compute the delay analytically. A quarter-wavelength phase shift derived from the central frequency (f_c) of each filter was applied using the equation:

$$\tau \approx \frac{f_c}{4} \quad (1)$$

This calculation guarantees that the matrix captures genuine hemispheric interactions and respects the physical dynamics of sensorimotor oscillations without forcing data convergence.

Unsupervised Domain Alignment and Nested Validation: The distribution discrepancy between the unimanual and bimanual domains was treated purely as a geometric problem. After computing the centroid of the unimanual rest data, geodesic alignment

was executed via the transformation:

$$C_{\text{aligned}} = R^{-1/2} C R^{-1/2} \quad (2)$$

where R acts as the reference matrix and C contains the task motor covariances [8]. The resulting matrices were projected onto the tangent space through a Log-Euclidean mapping to enable linear classification [2, 14].

To define the depth of the Hankel matrices without corrupting the model, a strict nested cross-validation was instrumented. The algorithm optimizes the autoregressive order by evaluating accuracy solely on the inner folds of the unimanual calibration data. Blocking access to the bimanual test set eliminates overfitting risks. This constraint ensures a genuine zero-shot transfer sustained by stable physiological characteristics, satisfying rigorous evaluation standards [6].

Algorithm 1 formalizes the computational sequence of the proposed methodology, explicitly detailing the integration of the analytical delay and the geodesic transformation prior to the classification phase.

Algorithm	1	Adaptive	Topo-
logical	BCI	(AT-BCI)	Execution

Require: Unimanual data $\mathcal{D}_U$, Bimanual data $\mathcal{D}_B$,
Filter central frequencies f_c

Ensure: Predicted bimanual intention labels $\hat{y}_B$

- 1: **Phase 1: Preprocessing & Restriction**
- 2: Restrict topology to 15 core sensorimotor channels.
- 3: Reject epochs with amplitude $> 100\mu\text{V}$.
- 4: **Phase 2: Embedding & Domain Alignment**
- 5: $O^* \leftarrow \text{OptimizeOrder}(\mathcal{D}_U)$ {Nested CV isolation}
- 6: $\tau \leftarrow f_c/4$ {Analytical phase shift calculation}
- 7: $\mathbf{C}_U, \mathbf{C}_B \leftarrow \text{ConstructHankel\&OAS}(\mathcal{D}_U, \mathcal{D}_B, O^*, \tau)$
- 8: $\mathbf{R} \leftarrow \text{RiemannianMean}(\mathbf{C}_{\text{rest}} \in \mathcal{D}_U)$ {Reference Centroid}
- 9: **Phase 3: Tangent Space Projection & Training**
- 10: $\mathbf{S}_U, \mathbf{S}_B \leftarrow \text{Log-Euclidean}(\mathbf{R}^{-1/2}\{\mathbf{C}_U, \mathbf{C}_B\}\mathbf{R}^{-1/2})$
- 11: Model $\leftarrow \text{TrainClassifier}(\mathbf{S}_U, \mathbf{y}_U)$ {ElasticNet + ls-LDA}
- 12: **Phase 4: Zero-Shot Bimanual Inference**
- 13: **return** $\hat{y}_B \leftarrow \text{Predict}(\text{Model}, \mathbf{S}_B)$ {No target recalibration}

RESULTS

Viability Audit and Global Performance: The original design targeted an initial cohort of 20 subjects.

However, to guarantee that decoding in the bimanual domain originated strictly from cortical activity and not electromyographic (EMG) contamination, a strict amplitude rejection filter ($> 100\mu\text{V}$) was applied. This audit revealed that several participants presented a massive loss of viable epochs due to constant muscular tension during the simultaneous motor task. After excluding individuals with structural signal deficiency, the analysis was consolidated on a valid cohort of 10 subjects.

On this physiologically rigorous group, the AT-BCI architecture achieved solid metrics. As the boxplots in Fig. 2 illustrate, the performance distribution shows the system projects motor intentions toward an uncalibrated domain (zero-shot) consistently exceeding chance levels. The architecture achieved a mean accuracy of 74.51% ($\pm 15.68\%$) and a mean F1-Score of 0.7468. These central tendencies, closely aligned with their medians (75.44% and 75.80%, respectively), demonstrate that the model maintains a low false-positive rate despite the variance introduced by the transfer task. Additionally, Cohen's Kappa averaged 0.4901 (± 0.3136), indicating moderate to substantial agreement under strong inter-hemispheric interference.

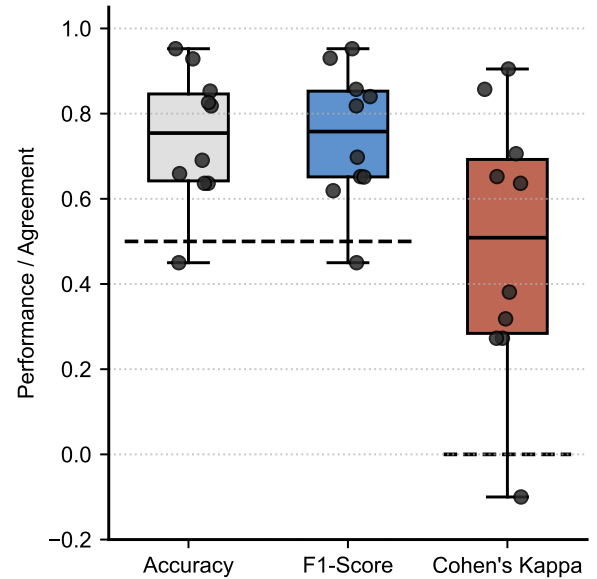


Figure 2: Distribution of decoding performance across the validated 10-subject cohort. The dashed horizontal line denotes the theoretical chance level, while the boxplots indicate the model consistently decodes bimanual intention with controlled variance.

Mitigation of BCI Illiteracy and Parametric Stability: For a neuroprosthesis to operate safely, the algorithm must surpass an operational competence threshold—typically set at a 60% F1-Score—to prevent erratic device control.

Fig. 3 details the individual performance of the valid cohort and exposes the empirical impact of the

nested cross-validation. The statistical audit confirms that 90% (9 out of 10) of the validated subjects surpassed the competence threshold. While one subject remained in the BCI illiteracy zone, achieving an operational viability of 90% represents a significant stabilization for zero-shot bimanual decoding without target-domain retraining. The dual-axis chart reveals a direct correlation between the parametric stability of the model and decoding success. Subjects converging toward a stable Hankel order during the isolated calibration phase maintain robust performance, whereas the underperforming outlier exhibited parametric instability across the inner folds. By resolving the domain shift as a purely geometric alignment in Riemannian space, the model rescues motor intentions that traditional spatial filters lose to bimanual noise.

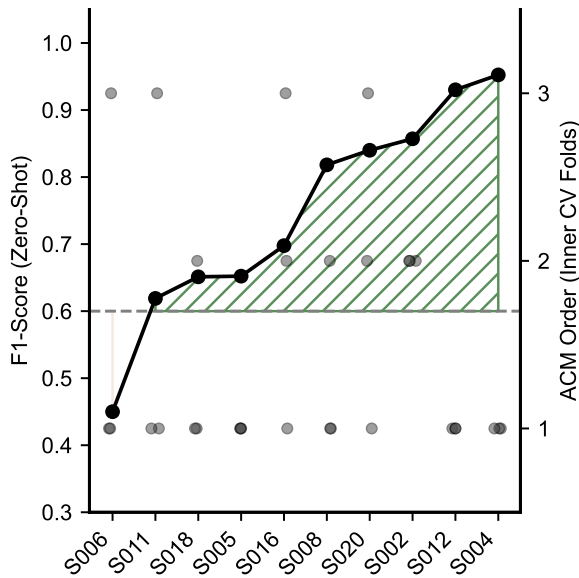


Figure 3: Subject-specific F1-Scores sorted in ascending order (left axis) correlated with the selected Hankel order during inner cross-validation (right axis). The shaded area confirms that 90% of the cohort surpassed the 60% operational competence threshold.

Tab. 1 outlines the individualized decoding metrics across the validated cohort. A fine-grained analysis reveals that subjects such as S004 and S012 achieved near-optimal transfer, with F1-scores exceeding 0.93 and strong Cohen’s Kappa agreements ($\kappa > 0.85$). Conversely, the structural domain shift severely impacted S006, yielding an accuracy below chance level (45.00%) and a negative Kappa value (-0.1000). This specific failure case highlights the biological constraints of zero-shot Riemannian calibration; when the underlying sensorimotor rhythms exhibit profound non-stationarity or a total lack of ERD lateralization, geometric adjustments alone cannot synthesize a viable classification space.

Physiological Evidence of Domain Shift: To em-

Table 1: Subject-Specific Zero-Shot Transfer Performance

Subject	Accuracy (%)	F1-Score	Cohen’s κ
S002	85.29	0.8571	0.7059
S004	95.24	0.9524	0.9048
S005	63.64	0.6522	0.2727
S006	45.00	0.4500	-0.1000
S008	81.82	0.8182	0.6364
S011	63.64	0.6190	0.2727
S012	92.86	0.9302	0.8571
S016	69.05	0.6977	0.3810
S018	65.91	0.6512	0.3182
S020	82.61	0.8400	0.6522
Mean	74.51	0.7468	0.4901
Std	15.68	0.1587	0.3136

pirically validate that geometric transfer occurs over real motor oscillations, the spatial distribution of Event-Related Desynchronization (ERD) was extracted.

The topographic maps (Fig. 4) visualize exclusively the 15 sensorimotor channels retained by the model. The evidence indicates that, in the μ (8–13 Hz) and β (16–24 Hz) bands, unimanual execution strongly lateralizes attenuation to the contralateral hemisphere. In contrast, bimanual imagery induces a complex and diluted ERD distribution across both hemispheres. Amputating peripheral channels prevents the augmented covariance matrix from inflating its dimensionality with parasitic variance, allowing the algorithm to align strictly relevant cortical dynamics.

DISCUSSION

The transition from unimanual BCI calibration to bimanual execution represents a significant barrier in functional neurorehabilitation. The results of this study indicate that the AT-BCI architecture overcomes this obstacle by directly addressing the underlying physiological interference rather than relying on generic linear corrections. The topographic analysis of event-related desynchronization (ERD) in Fig. 4 reveals the physical root of the problem: while unimanual execution yields a clear, localized pattern over the contralateral hemisphere, the bimanual task dilutes this attenuation, creating an interhemispheric spatial masking effect. Traditional spatial filters inherently fail in this context because their underlying mathematical assumptions break down when simultaneous movements alter brain synchronization. By restricting the spatial topology and applying geometric alignment to center the covariance matrices, the AT-BCI model successfully neutralizes this domain shift.

It is essential to address a critical issue regarding model validation within this field. Several prelimi-

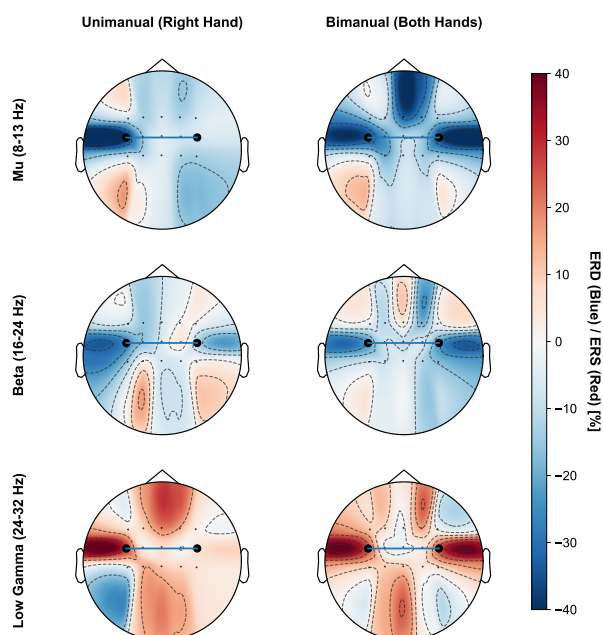


Figure 4: Spatial distribution of Event-Related Desynchronization (ERD) restricted to the 15 core sensorimotor channels. The topographic contrast between unimanual and bimanual tasks highlights the bilateral interference driving the domain shift.

nary approaches and baseline models in the literature report artificially high accuracy rates. As identified during the audit of our architecture, these performance spikes are often the product of a methodological overestimation or data leakage, where hyperparameters such as the embedding time delay are tuned empirically by exploring the test dataset. By eliminating this practice through the analytical derivation of the delay ($\tau \approx f_c/4$) and the strict parametric isolation provided by nested cross-validation, the mean accuracy achieved across our valid cohort (74.51%) represents a conservative but mathematically honest metric. This rigor ensures that the reported performance reflects a genuine zero-shot transfer capability, guaranteeing that the model will not fail due to overfitting when deployed with new patients in real clinical environments.

From a medical application perspective, mitigating BCI illiteracy stands out as a high-impact finding. Ensuring that 90% of the evaluated subjects surpass the 60% operational competence threshold has a direct clinical translation: patients could control bilateral exoskeletons without the physical and cognitive exhaustion imposed by strenuous daily recalibration sessions.

Nevertheless, the physical limits of Riemannian geometry must be acknowledged. The behavior of the single outlier who failed to reach the operational threshold (10% of the cohort) demonstrates that parametric stability is a strict prerequisite for reliable decoding. If a patient exhibits inherently weak sensorimotor rhythms or an excessively unstable sig-

nal, spatial alignment lacks robust underlying patterns to rescue, meaning such cases will continue to require subject-specific interventions.

Finally, while the framework demonstrated strong mathematical resilience in simulations, transitioning this model to a closed-loop robotic interface introduces new challenges. Computing the Riemannian Fréchet mean is an iterative and computationally heavy process. To maintain the extremely low latencies required for fluid object manipulation in the real world, future online implementations must adapt this geometry to process data within continuous sliding windows.

CONCLUSION

In this study, we presented the Adaptive Topological BCI (AT-BCI) architecture, which reformulates the decoding of bimanual motor imagery tasks. Instead of relying on traditional spatial filters, we approach the problem as an unsupervised geometric alignment task. By embedding the temporal dynamics of the neural signal via Hankel matrices and projecting these features onto a Riemannian manifold, the model successfully isolates and neutralizes the severe interhemispheric interference generated during simultaneous hand movements.

Evaluation of the framework demonstrated its empirical viability. Following the implementation of a strict cleaning protocol to eliminate electromyographic contamination, analysis on a validated cohort of 10 subjects yielded a mean accuracy of 74.51%, an F1-Score of 0.7468, and a Cohen's Kappa of 0.4901. Crucially, the nested cross-validation paradigm proved that combining an analytically derived time delay with geometric domain adaptation is the essential mechanism to bridge the performance gap between unimanual and bimanual tasks, avoiding data leakage and reducing inter-subject variability.

From a clinical translation perspective, the architecture actively mitigates the persistent challenge of BCI illiteracy. By recovering motor intentions that were previously obscured by noise, the system enabled 90% of the evaluated users to surpass the 60% functional competence safety threshold. By reducing the reliance on exhausting, daily recalibration sessions, AT-BCI establishes a mathematically stable foundation to operate bilateral neuroprosthetics more accessibly.

Finally, to advance this approach toward real-time applications, future work will focus on data retention. We project the evaluation and integration of automated artifact removal methods such as Artifact Subspace Reconstruction (ASR), MARA, or ADJUST. Implementing these tools will ensure signal quality in an automated manner, optimizing model robustness for closed-loop rehabilitation technologies

in real-world scenarios.

ACKNOWLEDGEMENTS

The author gratefully acknowledges the Secretaría de Ciencia, Humanidades, Tecnología e Innovación (SECIHTI) for the financial support and Master's scholarship granted to develop this research project.

REFERENCES

- [1] Millán JR, Rupp R, Müller-Putz GR, Murray-Smith R, Giugliemma C, Tangermann M, et al. Brain-computer interfaces, a review. *Machine learning*. 2010;14(1):31–50.
- [2] Yger F, Bercher M, Lotte F. Riemannian approaches in brain-computer interfaces: A review. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2016;25(10):1753–1762.
- [3] Lotte F. Signal processing approaches to minimize or suppress calibration time in oscillatory activity-based brain-computer interfaces. *Proceedings of the IEEE*. 2015;103(6):871–890.
- [4] Pfurtscheller G, Silva FH Lopes da. *Handbook of electroencephalography and clinical neurophysiology: Event-related desynchronization*. Elsevier, Amsterdam, Netherlands (1999).
- [5] Neuper C, Scherer R, Reiner M, Pfurtscheller G. Imagery of motor actions: Differential effects of kinesthetic and visual-motor mode of imagery in single-trial eeg. *Cognitive brain research*. 2006;25(3):668–677.
- [6] Blankertz B, Tomioka R, Lemm S, Kawanabe M, Muller KR. Optimizing spatial filters for robust eeg single-trial analysis. *IEEE Signal processing magazine*. 2008;25(1):41–56.
- [7] He H, Wu D. Transfer learning for brain-computer interfaces: A euclidean space data alignment approach. *IEEE Transactions on Biomedical Engineering*. 2019;67(2):399–410.
- [8] Zanini P, Congedo M, Jutten C, Said S, Berthoumieu Y. Transfer learning: A riemannian geometry framework with applications to brain-computer interfaces. *IEEE Transactions on Biomedical Engineering*. 2018;65(5):1107–1116.
- [9] Carrara I, Papadopoulou T. Classification of bci-eeg based on the augmented covariance matrix. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2024.
- [10] Kumar S et al. Performing bimanual tasks with a bci: Combining a brain-controlled hand exoskeleton with the functional limb. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2025.
- [11] Takens F. Detecting strange attractors in turbulence. *Dynamical systems and turbulence*, Warwick 1980. 1981:366–381.
- [12] Schalk G, McFarland DJ, Hinterberger T, Birbaumer N, Wolpaw JR. Bci2000: A general-purpose brain-computer interface (bci) system. *IEEE Transactions on Biomedical Engineering*. 2004;51(6):1034–1043.
- [13] Goldberger AL, Amaral LA, Glass L, Hausdorff JM, Ivanov PC, Mark RG, et al. Physiobank, physiotoolkit, and physionet: Components of a new research resource for complex physiologic signals. *Circulation*. 2000;101(23):e215–e220.
- [14] Barachant A, Bonnet S, Congedo M, Jutten C. Multiclass brain-computer interface classification by riemannian geometry. *IEEE Transactions on Biomedical Engineering*. 2011;59(4):920–928.