

Towards Reliable Out-of-Lab pBCIs: Riemannian Geometry Framework for Mitigating Covariate Shift in Real-World Passive Brain-Computer Interfaces

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ABSTRACT: Passive brain-computer interfaces (pBCIs) are promising tools for real-world, out-of-lab monitoring of cognitive states (e.g. mental workload). However, their reliability (e.g. classification accuracy) is often compromised by covariate shift caused by changes in headset positioning among different sessions. This study introduces a Riemannian-based correction method designed to mitigate the negative effect of the shift. We evaluated the framework by training a random forest classifier on a source domain to classify two mental workload levels and then tested on a target domain (representing a channels shift) both before and after applying the transformation. The validation involved three levels of analysis: (i) classification performance via area under curve (AUC) analysis, (ii) statistical assessment of manifold alignment through Riemannian distance, and (iii) correlation between geometric correction and AUC recovery. The application of the correction significantly improved workload classification, significantly overcoming AUC scores compared to the uncorrected target data. Statistical analysis revealed a significant reduction in Riemannian distance between the source and target manifolds after correction ($p = 2.36e^{-5}$). Furthermore, correlation analysis showed a strong positive relationship between geometric alignment and performance gain (Pearson correlation $R = 0.628$).

INTRODUCTION

The increasing need of interaction between humans and machines in modern industrial environments, often termed Industry 5.0, necessitates robust and seamless interfaces for monitoring operator state and optimizing performance [1]. Passive brain-computer interfaces (pBCIs) offer a promising, non-invasive solution by continuously assessing cognitive and emotional parameters in real-time [2]. Among the most relevant mental states in real-world applications, particularly in safety-critical environments, is mental workload. Elevated workload levels are strongly associated with performance decrements and increased error rates [3], [4]. While EEG signals have demonstrated effectiveness in workload assessment, particularly through analysis of theta and alpha band activity

in frontal and parietal regions [5], translating pBCI systems from controlled laboratory settings to real-world operational environments presents significant challenges. Unlike the highly controlled conditions of the lab settings, real-world deployment introduces substantial variability in EEG signal characteristics. Factors such as electrode impedance and, most notably, inconsistent sensor positioning on the scalp (i.e. because of changing in headset placement) can significantly impact signal amplitude and spectral features [6]. Maintaining the standardized 10-20 EEG placement protocol is often impractical when users prioritize convenience and rapid deployment, leading to a phenomenon known as covariate shift, where changes in data distribution degrade model performance over time [7]. Although extensively investigated in the broader field of artificial intelligence, covariate shift remains a relatively underexplored problem within the pBCI domain. Numerous studies have demonstrated how the non-stationarity of EEG signals can lead to variations in the distribution of data collected in different recording sessions [8], [9]. Some solutions proposed in the literature require the labeling of new data before starting the classification process [10], [11]. Deep adversarial frameworks offer optimal within- and cross-subject correction accuracy, often reducing calibration to just a few target trials. However, their disadvantages include high computational and implementation complexity and low interpretability, since these models learn complex latent representations that make it difficult to understand which signal features drive the predictions, for example which EEG channels or frequency bands influence the decision. [12], [13], [14]. To overcome these limitations, Riemannian geometry has emerged as a robust framework for BCI. Riemannian geometry methods have been successfully applied to compensate for transfer learning and cross-subject in active BCI [15], [16], [17]. These approaches typically operate on the manifold of symmetric positive definite (SPD) covariance matrices to find invariant representations. This study addresses the challenge of covariate shift resulting from variations in EEG headset positioning among different recording sessions, a common occurrence when users take off and put on again the device. Building upon previous work focused on

detecting such shift [18], we now propose a method for its correction.

Our approach leverages a normalization function applied to EEG features associate to workload, utilizing pre-recorded “eyes open” (EO) data as a stable reference point to recalibrate the data distribution across sessions. This normalization strategy aims to minimize the impact of inconsistent headset placement without requiring labeled data or extensive model retraining, a significant advantage over existing adaptation techniques.

MATERIALS AND METHODS

This study investigates the challenge of covariate shift in electroencephalography (EEG) data arising from inconsistencies in headset positioning across recording sessions, a common issue in ecological passive BCI applications. This study extends a previous research [19], using the same dataset consisting of EEG recordings from 18 right-handed male participants (mean age 25 ± 3 years), recruited from the National University of Singapore (NUS) student and staff population. Participants were selected for their proficiency in video games, general good health, and lack of psychological or pharmaceutical conditions. The experiments were conducted following the principles outlined in the 1975 Declaration of Helsinki, as revised in 2022 [20]. Experiments were approved by the Ethical Committee of the Sapienza University of Rome. The experimental design included six recording sessions distributed over three days, two sessions per day (morning and afternoon), to systematically assess performance changes under controlled conditions. During each session, participants engaged in four runs of the Multi-Attribute Task Battery (MATB) [21], a benchmark task designed to modulate cognitive workload through varying task complexity. Specifically, participants completed two “easy” runs, maintaining a cursor center position with a joystick, and two “hard” runs, simultaneously managing the same cursor control task alongside additional sub-tasks intended to simulate a flight emergency scenario. Each run lasted 2.5 minutes and was preceded by a one-minute eyes-open (i.e. EO) baseline recording to establish resting-state EEG activity. To mitigate potential confounding factors, stimulus parameters were randomized across sessions and participants received comprehensive training to ensure consistent performance and minimize learning effects. This yielded a comprehensive dataset of twelve pairs of “easy-hard” condition recordings, representing the variation in workload across the three experimental days. EEG data was acquired using a Waveguard ANT Neuro amplifier with a sampling rate of 256 Hz from 64 Ag/AgCl electrodes positioned according to the standardized 10-10 international system [22], referenced to the right mastoid electrode and grounded to AFz. To mimic the channels configuration of more practical, low-channel-count wearable EEG systems (e.g. Mindtooth system [23]), data analysis focused on a subset of eight electrodes: five frontals (FPz, AF3, AF4, AF7, AF8) and three parietals (Pz, P3, P4). This selection allowed us to investigate the impact of positional

shift on positions relevant for workload evaluation. To simulate covariate shift stemming from variations in headset placement, we constructed a control dataset and a test dataset, introducing deliberate shifts in electrode selection. Due to the use of pre-recorded high-density EEG dataset, which precluded physical reposition of the headset, we simulated the shift by selecting an adjacent row of electrodes. Specifically, the channels configurations were as follows:

- Control (Source): FPz, AF3, AF4, AF7, AF8, P3, P4, PZ
- Test (Target): FZ, F3, F4, F7, F8, PO3, PO4, POz

Prior to subsequent analysis, the EEG signal underwent a pre-processing pipeline employing a fifth-order Butterworth band-pass filter (2–30 Hz) to remove frequency components not relevant for workload evaluation. Eye blink artifacts were detected and corrected using the o-Clean method [24]. Data segmentation into 1-second epochs was followed by a conservative artifact rejection threshold of $\pm 80 \mu V$, chosen to minimize data loss while ensuring signal quality. From these cleaned EEG data, we computed across frequency band only, the global field power (GFP) [25], for the theta and alpha frequency bands. GFP serves as a robust estimator of cortical synchronization, providing a time-domain representation of overall EEG activity within the specified frequency ranges. Individual alpha frequency (IAF) was determined from the baseline eyes-open recordings to ensure consistent band definition across participants [26]. To evaluate the mental states, we utilized a random forest classifier implemented in Python’s scikit-learn library [27], an ensemble learning technique that combines multiple decision trees to enhance predictive accuracy and minimize overfitting. The goal of this classifier was to distinguish between the “easy” and “hard” conditions based on the extracted GFP features. To comprehensively assess the impact of task difficulty, we focused our classification efforts on one mental state: workload. For the classification of workload, we leveraged the sensitivity of frontal and parietal cortical regions to cognitive demands [28], [29]. Specifically, features were extracted from the theta band activity recorded from the five frontal electrodes (FPz, AF3, AF4, AF7, AF8) and the alpha band activity from the three parietal electrodes (Pz, P3, P4). This selection was based on a substantial body of existing literature demonstrating a strong correlation between increased theta power in frontal regions and heightened cognitive effort [30], and alpha band modulation in parietal areas reflecting allocation of attentional resources.

To mitigate the covariate shift effect induced by headset repositioning, we employed a Riemannian geometry-based correction function. Unlike standard Riemannian applications that use the covariance matrix directly as the input for the classifier [31], [32], our approach applies a Riemannian transformation to the raw EEG time series. This function operates on the covariance matrices of the EEG signals, computed using all eight selected channels to maximize the information content and accurately capture the underlying neural dynamics. The transformation

function is defined as:

$$T_{mapping} = C_{Source}^{\frac{1}{2}} C_{Target}^{-\frac{1}{2}}$$

Where C_{Target} and C_{Source} represent the Riemannian mean of the covariance matrices for the target and source eyes-open sessions, respectively.

The underlying principle of the proposed approach is that, although the absolute amplitude of EEG signals may vary due to headset repositioning, the relative relationships between signals recorded from electrodes located in a consistent anatomical configuration are expected to remain relatively stable. To exploit this property, we adopt a Riemannian geometry-based framework operating on the covariance matrices of the EEG signals.

Specifically, covariance matrices are computed from 1-second EEG epochs and represented as points on the Riemannian manifold of symmetric positive definite matrices. This representation allows us to measure the distance between the covariance structure of the current session and that of a reference session recorded under a standardized condition. In this study, the reference is derived from an eyes-open resting-state recording. The core of our method consists of a whitening and re-coloring transformation. We first estimate the geometric mean of the covariance matrices from the EO baseline of both the source and target configurations. Then, a transformation matrix is derived to “whiten” the data and “re-color” it according to the source configuration’s statistics. Crucially, this transformation is applied directly to the EEG data of the task session. This ensures that the signal is realigned in the original sensor space before feature extraction and GFP calculation, allowing for a real-time implementation. The choice of eyes-open sessions is motivated by both methodological and practical considerations. First, these recordings do not require task execution or expert annotation, making them naturally unsupervised. This enables a simple recalibration procedure that can be autonomously performed by the user after headset repositioning. In practice, once the headset is removed and worn again, the user only needs to record a short eyes-open resting-state segment (e.g., approximately 30 seconds). The covariance matrices computed from this segment are then used to estimate the transformation matrix required to realign the current session with the reference distribution. To simulate a realistic scenario in which no relationship exists between source and target, the first 50% of the EEG recordings from the eyes-open session in the Source channel configuration was used to compute the covariance matrices C_{Source} , while the remaining 50% of the EEG recordings, acquired in the Target configuration, was used to compute the covariance matrices C_{Target} . To evaluate the effectiveness of the proposed Riemannian-based correction for covariate shift, we conducted three complementary analyses: (i) classification performance evaluation, (ii) Riemannian covariance alignment analysis, and (iii) the correlation between the two metrics.

Classification Performance

A random forest classifier was trained using, each time,

two paired sessions from the source configuration. The features used for training and testing were the GFP values for each configuration. For the testing phase, a separate session was selected to serve as the benchmark in three distinct scenarios:

- Source_test: Unshifted source GFP data.
- Target: GFP data affected by the covariate shift
- Debiased: The target GFP data after applying the Riemannian correction on EEG signal.

By using a session-wise data split, we ensured that the training and test sets were completely independent. Specifically, for each training phase, two recording sessions were used for training while a separate session was reserved exclusively for testing. Because no data from the test session was included during training, this procedure prevented any potential data leakage. This process was repeated across the three sessions in a cross-validation scheme, and the final performance was computed as the average AUC obtained from the three individual test sessions. To evaluate classification performance, we used the area under curve (AUC) score as the primary metric. Additionally, AUC was computed at different decimation time points (i.e. by averaging the model’s predicted values (0 or 1) over various time intervals, from 1 to 60.

At each decimation step, the number of correct assessments is determined by comparing the predicted values with the actual values, both obtained by applying a moving average with a window size of t and a unit step.

For each decimation value, considering all 18 subjects, we performed a one-side Wilcoxon signed-rank test to evaluate whether the AUC distribution after data transformation (Debiased) was statistically different compared to the AUC distribution obtained when using the untransformed test condition (target).

Riemannian covariance alignment

To quantify the alignment between source and target domains, we employed the Riemannian distance as a metric of similarity between covariance matrices. This analysis included all sessions across all subjects. We calculated the distance between source and target covariance matrices, before (Pre-Correction) and after (Post-Correction/Debiased) the transformation. The objective was to statistically determine whether the correction significantly reduced the distance between the two distributions, effectively aligning the target domain with the source manifold. To this end, a two-sided Wilcoxon signed-rank test was used to compare the pre- and post-correction distances. While the sample size ($n=144$) might support parametric approaches, the observed non-normal distribution of the differences made the Wilcoxon test a more robust and appropriate choice.

Correlation between Geometric Alignment and Classifier Gain

Finally, we investigated the relationship between the geometric correction and the resulting improvement in classification accuracy. For each subject, we calculated two metrics:

- $\Delta AUC = AUC_{Debiased} - AUC_{Target}$

$$\Delta D = D_{Target} - D_{Debiased}$$

Where D_{Target} and $D_{Debiased}$ are the Riemann Distance between the covariance matrices of the target pre and post transformation.

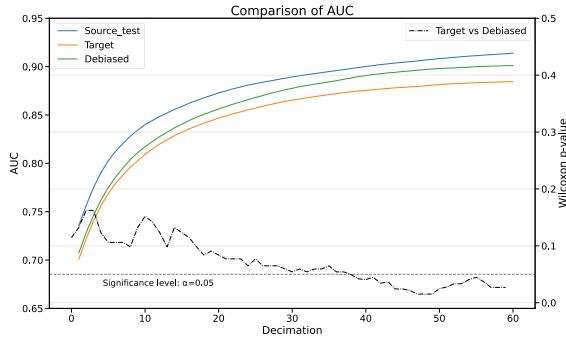


Fig. 1: Comparison of the AUC on the three test configuration: source, target and debiased.

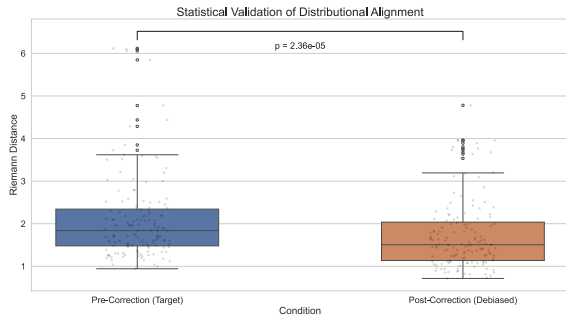


Fig 2: Distribution of Riemann distance between covariance matrix, for each session, of source and target configuration before and after the correction.

RESULTS

The effectiveness of the proposed debiasing transformation was evaluated by comparing the classification performance (AUC) across three conditions: source_test (i.e., test session of Source configuration), target (shifted positioning), and debiased (shifted positioning with Riemannian correction). As illustrated in Fig. 1, the target condition (orange line) exhibited a consistent performance drop compared to the source_test (blue line), confirming that electrode displacement induces a significant covariate shift that degrades the Random Forest classifier's reliability. However, the application of the Riemannian-based normalization (green line) successfully recovered a substantial portion of the lost performance. Notably, the Debiased AUC trend closely follows the source_test trajectory, consistently outperforming the uncorrected target data across all decimation levels. To statistically validate this improvement, a sliding Wilcoxon signed-rank test was performed between the target and debiased distributions (black dashed line). The geometric impact of the Riemannian alignment is summarized in

Fig. 2. The boxplot illustrates the distribution of Riemannian distances between the Source reference mean and the target covariance matrices, both before and after the correction.

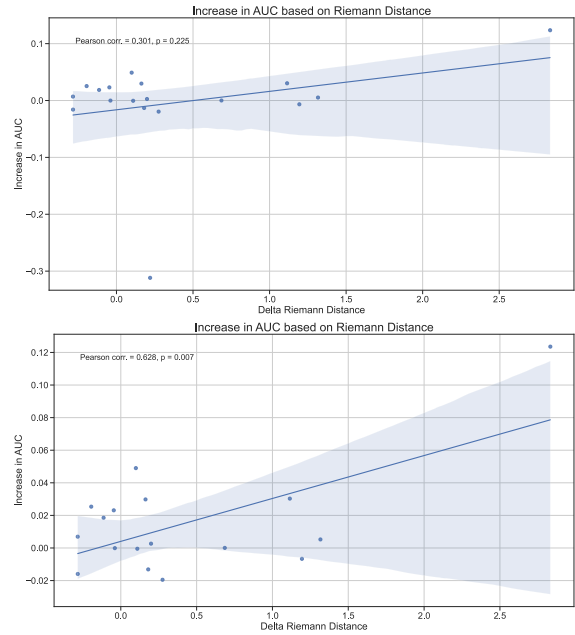


Fig 3: Relationship between Δ Riemann Distance and Δ AUC.

Fig. 3 shows the relationship between the reduction in distance (ΔD) and the improvement in AUC. These results are computed using the entire dataset (top) and after removing a single outlier (bottom). Most data points are located in the upper-right quadrant, and the regression line shows a positive trend. This indicates that subjects who experienced a larger reduction in Riemannian distance also tended to show a higher increase in classification performance. As summarized in Fig. 3, the initial correlation, including all subjects was weak and not statistically significant (Pearson = 0.301, $p = 0.224$). However, by excluding one outlier the correlation became significantly stronger. In the bottom plot of Fig. 3, the Pearson coefficient increases to 0.628 with a significant p-value of 0.007.

DISCUSSION

The results of this study demonstrate that Riemannian geometry could represent an effective way to handle covariate shift in passive BCI systems. The classification results show that shifting channels between tests creates a domain gap that lowers the AUC of the random forest model. However, by applying the debiasing transformation, we were able to move the Target data closer to the original Source distribution, resulting in a significant increase in AUC. Fig.1 reveals that the performance gain becomes statistically significant ($p < 0.05$) after less than 40 seconds, where the p-value drops below the threshold (indicated by the horizontal dashed line). These results

demonstrate that the proposed method effectively realigns the feature distributions on the manifold, mitigating the impact of inconsistent headset placement without the need for additional labelled training data. The statistical analysis of the Riemannian distances provides a clear explanation for this improvement. The significant decrease in distance post-correction ($p = 2.36e^{-5}$) proves that the algorithm successfully aligns the covariance matrices of the two domains. Essentially, the geometric noise caused by the channel shift is reduced, making the data more consistent for the classification model. The most interesting finding is the positive correlation between the Δ metrics. The fact that a larger reduction in Riemannian distance leads to a higher AUC gain suggests that this geometric distance is a reliable predictor of model performance. If we are able to minimize the distance between the two configurations (i.e. source and target) on the Riemannian manifold, we can directly improve the reliability of the BCI. The fact that the p-value dropped from 0.224 to a significant 0.007 proves that the observed trend is not a matter of chance. While the majority of subjects followed a clear linear trend, one subject deviated from this pattern, suggesting that additional factors may occasionally affect the correction. This study has some limitations, mainly due to the relatively small sample size and the use of a laboratory dataset, recorded under optimal conditions. Furthermore, the covariate shift was artificially created and not due to actual incorrect repositioning of the headset by the user. These design choices were intentional, aiming to avoid additional complexities and possible biases associated with EEG signals. However, this work serves as a preliminary step toward addressing covariate shift.

CONCLUSION

This study suggests that Riemannian-based alignment may represent a promising preprocessing strategy for improving the classification AUC of passive BCI applications. However, it should be noted that the analyses presented in this work were conducted in controlled laboratory conditions. Within this context, our findings indicate that the covariate shift induced by changes in electrode positioning can be partially mitigated using Riemannian geometry. This is particularly relevant for passive BCI systems, such as cognitive workload monitoring, where the absence of explicit user commands makes real-time calibration challenging. Unlike active BCI tasks, there adaptation often relies on supervised task-related data, our approach demonstrates that covariate shift can be addressed as a global deformation of signal space. Despite the limited sample size, the results provide statistical evidence supporting the hypothesis of this work. In particular, we observed a significant reduction in the Riemannian distance between configurations, which was associated with an improvement in workload decoding performance. The significant correlation between Δ Riemann Distance and Δ AUC further suggests that reducing the distance between source and target manifolds may contribute to improving cross-session stability. Most of the

18 participants showed improvements in classification performance after geometric correction. This highlights the effectiveness of using a neutral baseline, such as an “eyes-open” state, to define a transformation function that can be applied directly to the EEG time series in real-time. However, the presence of a case in which AUC decreased despite the geometric alignment suggests that additional factors may influence the effectiveness of the proposed approach. In some instances (i.e., 1 participant out of 18), the signal-to-noise ratio in the target configuration may be sufficiently degraded that covariance alignment alone cannot fully recover the lost information. Overall, the results indicate that the proposed method may represent a useful step toward improving the robustness of passive BCI systems under electrode displacement, offering a practical alternative to complex model retraining. Future work will focus on extending the analysis to larger datasets, developing a structured implementation of the proposed framework, and evaluating its performance on real-world datasets collected in operational environments.

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