Novelty Assessment Report

Paper: Riemannian High-Order Pooling for Brain Foundation Models

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Abstract

Electroencephalography (EEG) is a noninvasive technique for measuring brain electrical activity that supports a wide range of brain-computer interaction applications. Motivated by the breakthroughs of Large Language Models (LLMs), recent efforts have begun to explore Large EEG foundation Models trained on broad unlabeled corpora. However, most advances focus on improving the backbone while neglecting the classification head. Existing models often rely on a single class token, underutilizing the spatiotemporal structure and second-order statistics that are crucial for EEG decoding. We propose Riemannian High Order Pooling (RHOP), a plug-and-play module that injects principled Riemannian statistics into the classifier. RHOP maps each token to a quotient Gaussian jointly encoding mean and second-order information, yielding scale-invariant descriptors. Tokens are then aggregated by estimating a Riemannian Gaussian on the SPD manifold, where the Fréchet mean and covariance are embedded into an SPD descriptor. The resulting normalized vector is fused with the class token for prediction. RHOP is backbone-agnostic and integrates with modern EEG foundation models, e.g., BIOT and LaBraM. Across diverse EEG benchmarks, it improves accuracy, robustness, and efficiency under full fine-tuning, linear probing, and from-scratch training settings.

Core Task Landscape

This paper addresses: **EEG Foundation Model Classification via Riemannian Geometric Pooling**

A total of **36 papers** were analyzed and organized into a taxonomy with **24 categories**.

Taxonomy Overview

The research landscape has been organized into the following main categories:

- **Riemannian Geometry-Based Spatial Filtering and Feature Extraction**
- **Deep Riemannian Network Architectures for EEG Decoding**
- **Riemannian Classifier Frameworks and Ensemble Methods**
- **Preprocessing, Transfer Learning, and Domain Adaptation**
- **Hybrid Riemannian-Euclidean and Spatio-Temporal Learning**
- **Application-Specific Riemannian EEG Methods**
- **Optimization, Robustness, and Computational Tools**
- **Foundation Models with Riemannian High-Order Pooling**

Complete Taxonomy Tree

- EEG Foundation Model Classification via Riemannian Geometric Pooling Survey Taxonomy
- Riemannian Geometry-Based Spatial Filtering and Feature Extraction
  - Spatial Filtering via Riemannian Distance Maximization (2 papers)
  - [1] Enhancing motor imagery EEG classification with a Riemannian geometry-based spatial filtering (RSF) method (Lincong Pan, 2025) View paper
  - [14] Riemannian geometry-based spatial filtering (RSF) method for motor imagery EEG classification (Lincong Pan, 2024) View paper
  - Discriminative SPD Feature Learning on Manifolds (1 papers)
  - [13] A discriminative SPD feature learning approach on Riemannian manifolds for EEG classification (Byung Hyung Kim, 2023) View paper
  - Dimensionality Reduction and Embedding on SPD Manifolds (3 papers)
  - [21] Dimension selection for EEG classification in the SPD Riemannian space based on PSO (Zirui Zhang, 2023) View paper
  - [25] Riemannian Embedding Banks for Common Spatial Patterns with EEG-based SPD Neural Networks (Hyung, 2021) View paper
  - [36] DGPDR: discriminative geometric perception dimensionality reduction of SPD matrices on Riemannian manifold for EEG classification. (Ming Meng, n.d.) View paper
- Deep Riemannian Network Architectures for EEG Decoding
  - Convolutional and Attention-Based Riemannian Networks (3 papers)
  - [4] Multi-scale convolutional attention and Riemannian geometry network for EEG-based motor imagery classification (Ben Zhou, 2024) View paper
  - [20] Convolutional neural network and riemannian geometry hybrid approach for motor imagery classification (Wenchao Liu, 2022) View paper
  - [26] A Multiscale Convolutional Fusion Riemannian Manifold Learning Method for EEG Decoding (Chuan Deng, 2025) View paper
  - Transformer and Second-Order Pooling Networks (1 papers)
  - [8] A transformer-based network with second-order pooling for motor imagery EEG classification (Jing Jin, 2025) View paper
  - Pure Deep Riemannian Networks and SPDNet Variants (4 papers)
  - [9] Deep Riemannian Networks for end-to-end EEG decoding (Daniel Wilson, 2025) View paper
  - [11] Deep Riemannian Networks for EEG Decoding (Wilson Daniel, 2022) View paper

  - [18] Harneshing the potential of EEG in neuromarketing with deep learning and Riemannian geometry (Kostas Georgiadis, 2023) View paper
  - [27] Prediction of fatigue-related driver performance from EEG data by deep Riemannian model (Mehdi Hajinoroozi, 2017) View paper
  - Dual-Branch and Multiscale Riemannian Architectures (1 papers)
  - [32] A Dual-Branch Riemannian Learning Network for EEG Speech Imagery Decoding (Liying Zhang, 2024) View paper
  - Lightweight and Efficient Riemannian Architectures (2 papers)
  - [3] GREEN: A lightweight architecture using learnable wavelets and Riemannian geometry for biomarker exploration with EEG signals (Joseph Paillard, 2025) View paper
  - [33] Sub-100 Î¼W Multispectral Riemannian Classification for EEG-Based Brain-Machine Interfaces. (Xiaying Wang, 2022) View paper
- Riemannian Classifier Frameworks and Ensemble Methods
  - Minimum Distance to Riemannian Mean Classifiers (2 papers)
  - [19] Riemannian geometry applied to BCI classification (Alexandre Barachant, 2010) View paper
  - [23] Riemannian Classification of EEG Signals with Missing Values (Hippert-Ferrer, 2022) View paper
  - Ensemble Learning with Riemannian Geometry (2 papers)
  - [7] Optimizing EEG Signal Classification for Motor Imagery BCIs: FilterBank CSP with Riemannian Manifolds and Ensemble Learning Models (M. Moein Esfahani, 2023) View paper
  - [17] Riemannian geometric and ensemble learning for decoding cross-session motor imagery electroencephalography signals (Kun Wang, 2023) View paper
  - Decision Tree and Multiclass Riemannian Frameworks (2 papers)
  - [2] Multiclass Classification Framework of Motor Imagery EEG by Riemannian Geometry Networks (Yuxuan shi, 2024) View paper
  - [35] Motor Imagery EEG Classification Based on Decision Tree Framework and Riemannian Geometry. (Shan Guan, 2019) View paper
- Preprocessing, Transfer Learning, and Domain Adaptation
  - Transfer Learning and Cross-Subject Adaptation (1 papers)
  - [10] Transfer learning algorithm of P300-EEG signal based on XDAWN spatial filter and Riemannian geometry classifier (Feng Li, 2020) View paper
  - Artifact Rejection and Preprocessing with Riemannian Geometry (1 papers)
  - [12] Riemannian manifold-based epileptic seizure detection using transfer learning and artifact rejection techniques (Kazi Mahmudul Hassan, 2024) View paper
  - Self-Supervised and Reconstruction-Based Riemannian Learning (1 papers)
  - [24] EEG-ReMinD: Enhancing Neurodegenerative EEG Decoding through Self-Supervised State Reconstruction-Primed Riemannian Dynamics (Wang Zi-rui, 2025) View paper
- Hybrid Riemannian-Euclidean and Spatio-Temporal Learning
  - Tangent Space Projection and Hybrid Spatio-Temporal Learning (1 papers)
  - [16] Spatio-temporal EEG representation learning on riemannian manifold and euclidean space (Guangyi Zhang, 2023) View paper
  - Multivariate Decomposition with Riemannian Classification (1 papers)
  - [6] A multi-class EEG-based BCI classification using multivariate empirical mode decomposition based filtering and Riemannian geometry (Pramod Gaur, 2018) View paper
- Application-Specific Riemannian EEG Methods
  - Neuromarketing and Consumer Behavior EEG Analysis (2 papers)
  - [22] RNeuMark: A Riemannian EEG Analysis Framework for Neuromarketing (Kostas Georgiadis, 2022) View paper
  - [28] An efficient Deep Riemannian Learning methodology for EEG-based Neuromarketing research (Georgios, 2024) View paper
  - Clinical and Physiological State Detection (1 papers)
  - [30] Riemannian geometry applied to detection of respiratory states from EEG signals: the basis for a brainâ□□ventilator interface (Fallani F. De Vico, 2016) View paper
  - Emotion Recognition and Affective Computing (1 papers)
  - [15] The Efficacy and Utility of Lower-Dimensional Riemannian Geometry for EEG-Based Emotion Classification (Zubaidah Al-Mashhadani, 2023) View paper
  - Olfactory and Specialized Sensory EEG Classification (1 papers)
  - [34] A novel channel selection scheme for olfactory EEG signal classification on Riemannian manifolds. (Xiao-Nei Zhang, 2022) View paper
- Optimization, Robustness, and Computational Tools
  - Time Window and Hyperparameter Optimization (1 papers)
  - [31] Time Window Optimization for Riemannian Geometry-based Motor Imagery EEG Classification (Fanbo Zhuo, 2024) View paper
  - Outlier Detection and Distribution Modeling on Manifolds (1 papers)
  - [29] Modeling Complex EEG Data Distribution on the Riemannian Manifold Toward Outlier Detection and Multimodal Classification. (Maria Sayu Yamamoto, 2024) View paper
  - Computational Frameworks and Quantum Integration (1 papers)
  - [5] pyRiemann-qiskit: A Sandbox for Quantum Classification Experiments with Riemannian Geometry (Anton Andreev, 2023) View paper
- Foundation Models with Riemannian High-Order Pooling ★ (1 papers)
  - [0] Riemannian High-Order Pooling for Brain Foundation Models (Anon et al., 2026) View paper

Narrative

Core task: Improving EEG foundation model classification through Riemannian geometric pooling. The field of EEG decoding has increasingly embraced Riemannian geometry to exploit the symmetric positive-definite structure of covariance matrices, yielding a rich taxonomy of approaches. At the broadest level, the landscape divides into several complementary directions: spatial filtering and feature extraction methods that leverage manifold-aware transformations (e.g., RSF Spatial Filtering[1]), deep network architectures that embed Riemannian layers for end-to-end learning (e.g., Riemannian Geometry Networks[2], Deep Riemannian Networks[9]), classifier frameworks and ensemble strategies that combine multiple Riemannian pipelines (e.g., FilterBank CSP Ensemble[7]), preprocessing and domain adaptation techniques to handle cross-session or cross-subject variability (e.g., XDAWN Transfer Learning[10], Seizure Detection Transfer[12]), hybrid models that fuse Riemannian and Euclidean representations (e.g., CNN Riemannian Hybrid[20]), application-specific solutions targeting motor imagery, emotion recognition, or neuromarketing (e.g., Deep Riemannian Neuromarketing[28]), optimization and computational tools for efficient manifold operations (e.g., pyRiemann-qiskit[5]), and emerging foundation models that integrate high-order pooling strategies to capture richer geometric structure.

Recent work has explored how to scale Riemannian methods beyond hand-crafted pipelines, with deep architectures (Deep Riemannian EEG[11], Discriminative SPD Learning[13]) learning task-specific manifold embeddings and hybrid approaches (Multiscale Convolutional Fusion[26]) blending spatial and temporal cues. A key tension lies between interpretability—classical spatial filters remain transparent—and representational power, where deep networks can discover complex patterns at the cost of opacity. Riemannian High-Order Pooling[0] sits within the foundation model branch, aiming to enhance large-scale pretrained EEG classifiers by incorporating geometric pooling that respects the manifold structure of covariance features. This contrasts with earlier deep Riemannian works like Deep Riemannian Networks[9], which focus on building manifold-aware layers from scratch, and with transformer-based methods such as Transformer Second-Order Pooling[8], which also leverage second-order statistics but may not fully exploit Riemannian metrics. By integrating high-order pooling into foundation models, Riemannian High-Order Pooling[0] bridges the gap between classical geometry-driven pipelines and modern large-scale pretraining paradigms.

Related Works in Same Category

No sibling papers and no sibling subtopics were found under the same parent taxonomy node; the paper appears structurally isolated in the taxonomy.

Contributions Analysis

Overall novelty summary. The paper proposes Riemannian High-Order Pooling (RHOP), a plug-and-play module that enhances EEG foundation model classifiers by injecting Riemannian geometric statistics into the classification head. It occupies a unique leaf in the taxonomy—'Foundation Models with Riemannian High-Order Pooling'—with no sibling papers, indicating this is a newly emerging research direction. The taxonomy contains 36 papers across multiple established branches (spatial filtering, deep networks, classifiers, preprocessing), yet the foundation model integration of Riemannian pooling appears to be an unexplored niche within this broader landscape.

The taxonomy reveals several neighboring directions: deep Riemannian networks that build manifold-aware layers from scratch (e.g., SPDNet variants), transformer architectures with second-order pooling that capture high-order dependencies, and hybrid models fusing Riemannian and Euclidean representations. RHOP diverges by targeting pretrained foundation models (BIOT, LaBraM) rather than training end-to-end architectures, positioning itself at the intersection of large-scale pretraining and geometric manifold learning. The absence of papers in its leaf suggests this integration strategy—retrofitting foundation models with Riemannian pooling—has not been systematically explored in prior work.

Among 20 candidates examined across three contributions, none were flagged as clearly refuting the proposed methods. The Quotient Gaussian embedding examined 1 candidate with no refutations, the RHOP module examined 10 candidates with no refutations, and the empirical validation framework examined 9 candidates with no refutations. This limited search scope—top-K semantic matches plus citation expansion—suggests that within the examined literature, no direct prior work implements quotient Gaussian embeddings or Riemannian pooling specifically for foundation model classification heads, though the analysis does not claim exhaustive coverage of all possible related work.

Based on the 20-candidate search, the work appears to occupy a sparse intersection between foundation models and Riemannian geometry. The taxonomy structure confirms that while Riemannian EEG methods are well-established, their integration into large-scale pretrained models is nascent. The analysis covers top semantic matches and citations but does not guarantee discovery of all relevant preprints, concurrent work, or domain-specific applications that may overlap with the proposed approach.

This paper presents **3 main contributions**, each analyzed against relevant prior work:

Contribution 1: Quotient Gaussian Embedding for Scale-Invariant EEG Representations

Description: The authors introduce a quotient Gaussian embedding that normalizes per-token covariances to correlation form, removing temporal scale discrepancies while preserving dependency structure. This embedding jointly encodes mean and second-order statistics, providing scale-invariant descriptors for EEG features.

This contribution was assessed against **1 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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1. Time series classification with feature covariance matrices

URL: View paper

Brief Assessment

Feature Covariance Matrices[56] focuses on time series classification using covariance matrices as features, while the original paper introduces quotient Gaussian embeddings that normalize per-token covariances to correlation form for EEG foundation models. The candidate does not demonstrate prior work on quotient Gaussian distributions or scale-invariant embeddings via correlation normalization.

Contribution 2: Riemannian High-Order Pooling Module

Description: The authors propose RHOP, a plug-and-play geometry-aware pooling head that aggregates token information by estimating a Riemannian Gaussian on the SPD manifold. This module preserves spatiotemporal structure and captures high-order dependencies through an SPD descriptor, addressing limitations of conventional global pooling methods.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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1. Automatic multi-gait recognition using pedestrian's spatiotemporal features

URL: View paper

Brief Assessment

Multi-gait Recognition[47] focuses on pedestrian gait recognition using spatiotemporal features with 3D convolutions and mentions Riemannian manifolds only briefly in relation to inner products. It does not propose a geometry-aware pooling module for aggregating token information via SPD manifolds or Riemannian Gaussians as RHOP does.

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2. A domain adaptation method based on domain selection and dual-space feature extractor

URL: View paper

Brief Assessment

Domain Adaptation Selection[53] focuses on cross-subject motor imagery classification using domain adaptation with Riemannian manifold embedding for feature extraction, not on developing a geometry-aware pooling head for aggregating spatiotemporal tokens in foundation models.

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3. A compact and recursive Riemannian motion descriptor for untrimmed activity recognition

URL: View paper

Brief Assessment

Recursive Motion Descriptor[55] focuses on activity recognition in untrimmed videos using covariance matrices computed from motion trajectories, not on pooling token representations from foundation models for EEG classification.

4. Intrusion detection using spatial-temporal features based on Riemannian manifold

URL: View paper

Brief Assessment

Intrusion Detection Manifold[49] focuses on network intrusion detection using covariance matrices for spatial-temporal feature extraction in network traffic data, not on EEG foundation models or token-level pooling architectures for brain signals.

5. Understanding Matrix Function Normalizations in Covariance Pooling through the Lens of Riemannian Geometry

URL: View paper

Brief Assessment

Matrix Function Normalizations[46] focuses on understanding matrix logarithm and power normalizations in global covariance pooling from a Riemannian geometry perspective, not on designing pooling modules for spatiotemporal feature aggregation or EEG foundation models.

6. Manifold Integrated Gradients: Riemannian Geometry for Feature Attribution

URL: View paper

Brief Assessment

Manifold Integrated Gradients[48] focuses on feature attribution methods for explainability in deep learning models, not on pooling mechanisms for spatiotemporal feature aggregation in EEG foundation models. The candidate addresses a fundamentally different problem domain (model interpretability via gradient-based explanations) compared to the original's contribution (geometry-aware pooling for EEG classification).

7. Generalized rank pooling for activity recognition

URL: View paper

Brief Assessment

Generalized Rank Pooling[51] focuses on activity recognition in videos using subspace representations on the Grassmann manifold to preserve temporal order of video frames. The original paper addresses EEG foundation models using SPD manifold geometry for spatiotemporal token aggregation. These are fundamentally different application domains (video vs. EEG) and different manifold structures (Grassmann vs. SPD), making direct novelty comparison infeasible.

8. Riemannian spatio-temporal features of locomotion for individual recognition

URL: View paper

Brief Assessment

Locomotion Individual Recognition[54] focuses on individual recognition from skeletal sequences using Riemannian geometry for locomotion analysis, not on pooling modules for neural network architectures or EEG foundation models.

9. PointDMIG: a dynamic motion-informed graph neural network for 3D action recognition

URL: View paper

Brief Assessment

PointDMIG[50] focuses on dynamic point cloud sequences for 3D action recognition using graph neural networks with motion encoding, not Riemannian geometry-based pooling methods for spatiotemporal feature aggregation on SPD manifolds as described in the original contribution.

10. SymNet: A simple symmetric positive definite manifold deep learning method for image set classification

URL: View paper

Brief Assessment

SymNet[52] focuses on SPD manifold learning for image set classification using covariance matrices, not on token-level spatiotemporal pooling for EEG foundation models. The candidate addresses static image sets rather than temporal EEG signals with foundation model architectures.

Contribution 3: Comprehensive Empirical Validation Framework

Description: The authors provide extensive experimental validation demonstrating that RHOP improves accuracy, robustness, and efficiency across diverse EEG benchmarks. The validation covers multiple training settings including full fine-tuning, linear probing, and training from scratch with modern foundation models.

This contribution was assessed against **9 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Zero-Shot Neural Priors for Generalizable Cross-Subject and Cross-Task EEG Decoding

URL: View paper

Brief Assessment

Zero-Shot Neural Priors[40] focuses on zero-shot cross-subject EEG decoding for behavioral prediction using transformers, not on validating pooling heads across multiple training regimes (full fine-tuning, linear probing, training from scratch) as done in the original paper's RHOP framework.

2. Reducing Inter-Subject Variability for Robust Sleep Eeg Classification Via Single-Subject-Based Training

URL: View paper

Brief Assessment

Single-Subject Training[45] focuses on reducing inter-subject variability in sleep EEG classification through single-subject-based training, not on comprehensive validation frameworks comparing fine-tuning versus linear probing across diverse EEG benchmarks with foundation models.

3. Learning topology-agnostic EEG representations with geometry-aware modeling

URL: View paper

Brief Assessment

Topology-Agnostic Representations[38] focuses on cross-dataset EEG pre-training with different montages and validates on emotion recognition tasks, not on the diverse benchmarks (abnormal detection, epileptic events, motor imagery, event-related potentials) or training regimes (full fine-tuning, linear probing, from-scratch) examined in the original paper.

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4. Beatrix: Out-of-Distribution Generalization of Large EEG Model via Invariant Contrastive Fine-Tuning

URL: View paper

Brief Assessment

Beatrix[43] focuses on out-of-distribution generalization for EEG models using contrastive fine-tuning, not on comparing full fine-tuning versus linear probing training regimes as a primary contribution. While both papers evaluate EEG models, their core contributions differ fundamentally.

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5. Evaluating the structure of cognitive tasks with transfer learning

URL: View paper

Brief Assessment

Cognitive Task Transfer[39] focuses on transfer learning between different cognitive tasks in EEG decoding, not on validating foundation models across training regimes (full fine-tuning, linear probing, from-scratch). The candidate evaluates task transferability rather than comprehensive validation of a single model architecture.

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6. Eeg-dino: Learning eeg foundation models via hierarchical self-distillation

URL: View paper

Brief Assessment

EEG-DINO[37] focuses on self-supervised learning methods for EEG foundation models and mentions linear probing versus fine-tuning comparisons, but does not provide the same comprehensive validation framework across diverse benchmarks with RHOP's specific focus on pooling head architectures and Riemannian geometry.

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7. Uni-NTFM: A Unified Foundation Model for EEG Signal Representation Learning

URL: View paper

Brief Assessment

Uni-NTFM[41] evaluates on different EEG tasks (emotion recognition, motor imagery, sleep staging) than RHOP's focus on abnormal detection, event classification, and motor imagery. The validation approaches differ in scope and task selection, making direct comparison of validation frameworks difficult.

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8. EEG-Clip: Finetune Clip Model for EEG Classification

URL: View paper

Brief Assessment

EEG-Clip[42] focuses on adapting CLIP for multi-label EEG diagnosis with linear probing, not on comprehensive validation across diverse benchmarks with multiple training regimes (full fine-tuning, linear probing, training from scratch) as in the original paper.

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9. BrainAlign: Leveraging EEG Foundation Models for Symmetric, Interpretable Alignment with Visual Representations

URL: View paper

Brief Assessment

BrainAlign[44] focuses on EEG-to-image alignment using foundation models for visual object classification, not on validating training regimes (full fine-tuning, linear probing, training from scratch) across diverse EEG benchmarks as RHOP does.

Appendix: Text Similarity Detection

No high-similarity text segments were detected across any compared papers.

References

- [0] Riemannian High-Order Pooling for Brain Foundation Models View paper
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