Cross-Subject Neural Alignment via Soft Graph Matching and Dynamic Latent Space Projection for Brain-Computer Interfaces

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Abstract

Individual variability in neural activation patterns presents a major challenge for non-invasive and invasive Brain-Computer Interfaces (BCIs). Direct cross-subject alignment often fails because identical sensory stimuli or cognitive tasks can evoke distinct neural representations across individuals. In this work, we propose a mathematical framework that leverages topological invariance to align neural responses into a universal latent space Z. By relaxing Quadratic Assignment Problems (QAP) to doubly stochastic soft graph matching, incorporating dynamic time-series confidence metrics, and optimizing a joint contrastive-topological loss function, our framework enables universal neural decoding without sacrificing individual relational brain structures.

1 Introduction

Brain-Computer Interfaces (BCIs) aim to decode neural activity into actionable signals or semantic representations. However, cross-subject decoding suffers from high inter-subject variability, where a neural interaction in subject X does not directly map to the same raw signal in subject Y:

$$R_{ik,jl} \neq (i \xrightarrow{x} k) = (j \xrightarrow{y} l) \tag{1}$$

Despite these differences in raw feature spaces, the relational topology across brain states remains invariant. We present a unified framework that projects heterogeneous neural signals into a shared, universal latent space Z.

2 Mathematical Formulation

2.1 Stage A: Soft Graph Matching (Relational Topology)

To overcome the NP-hard nature of discrete node assignment matrices ($M_{ij} \in \{0, 1\}$), we apply a continuous relaxation over the space of doubly stochastic matrices $\mathcal{DS}$:

$$\max_{M \in \mathcal{DS}} \left[\sum_{i,j} M_{ij} S_{ij} + \lambda \sum_{i,k,j,l} M_{ij} M_{kl} R_{ik,jl} \right] \tag{2}$$

where S_{ij} denotes node-level feature similarity, $R_{ik,jl}$ measures edge/relational structure preservation, and subject to $\sum_j M_{ij} = 1$ and $\sum_i M_{ij} = 1$.

2.2 Stage B: Dynamic Temporal Adjustment

Time-series alignment yields a feature vector $k_{xy} = (V_c, A_c, W_c)$ representing similarity (V_c), peak alignment (A_c), and signal confidence (W_c). We dynamically adjust the topological regularization weight λ_{dynamic}:

$$\lambda_{\text{dynamic}} = f(W_c) \cdot \text{Sim}(V_c, A_c) \tag{3}$$

2.3 Stage C: Universal Projection & Total Loss Function

Raw neural signals X and Y are projected into the universal latent space Z using subject-specific transformation mappings W_x and W_y:

$$Z_x = \sigma_X(W_x \cdot X), \quad Z_y = \sigma_Y(W_y \cdot Y) \tag{4}$$

The model optimizes the overall loss function $\mathcal{L}_{\text{Total}}$, balancing angular directional alignment in Z-space with graph structure preservation:

$$\mathcal{L}_{\text{Total}} = \sum_{k=1}^{K} \left(1 - \frac{Z_x^{(k)} \cdot Z_y^{(k)}}{\|Z_x^{(k)}\| \|Z_y^{(k)}\|} \right) - \gamma \left[\sum_{i,j} M_{ij} S_{ij} + \lambda_{\text{dynamic}} \sum_{i,k,j,l} M_{ij} M_{kl} R_{ik,jl} \right] \tag{5}$$

3 Conclusion

This unified objective function guarantees that while raw subject coordinates differ, their mappings converge to identical directional coordinates in Z-space without destroying intra-subject topological logic.