

Structure-Preserving Graph Kernel For Brain Network Classification

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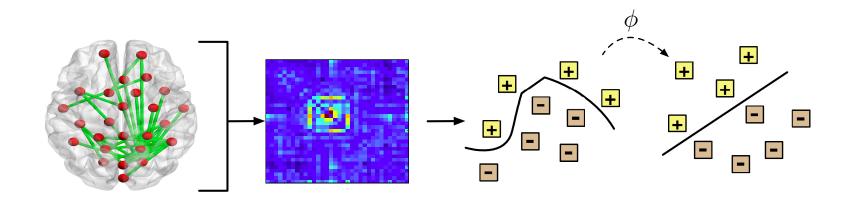
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The Proposed Framework



Brain network

Graph modeling

Graph-based kernel learning





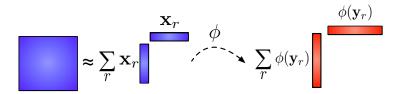


Key Optimization Problem

Graph approximation:

$$\min_{\mathbf{a}_r} \|\mathbf{X} - \sum_{r=1}^R \mathbf{a}_r \otimes \mathbf{a}_r\|_F^2 + \lambda \sum_{r=1}^R \|\mathbf{a}_r\|_1,$$

Graph mapping:



$$\phi: \sum_{r=1}^R \mathbf{x}_r \otimes \mathbf{x}_r \to \sum_{r=1}^R \phi(\mathbf{x}_r) \otimes \phi(\mathbf{x}_r).$$







Structure-preserving Symmetric Graph Kernel (SSGK)

 Apply the kernel function on our sparse recovery matrix, we can derive the SSGK model:

$$\kappa(\mathbf{X}, \mathbf{Y}) = \kappa(\sum_{r=1}^{R} \mathbf{x}_r \otimes \mathbf{x}_r, \sum_{r=1}^{R} \mathbf{y}_r \otimes \mathbf{y}_r)$$

$$= \left\langle \sum_{r=1}^{R} \phi(\mathbf{x}_r) \otimes \phi(\mathbf{x}_r), \sum_{r=1}^{R} \phi(\mathbf{y}_r) \otimes \phi(\mathbf{y}_r) \right\rangle$$

$$= \sum_{p=1}^{R} \sum_{q=1}^{R} \kappa(\mathbf{x}_p, \mathbf{y}_q) \kappa(\mathbf{x}_p, \mathbf{y}_q).$$







Visualization & Experimental Results

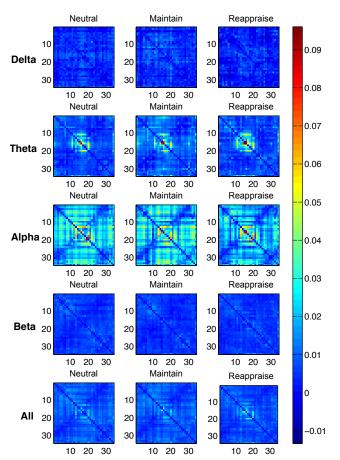


Table 1. The classification accuracy in percentage (%) by competing methods and the proposed method for five tasks. The best results for each task are highlighted in boldfont.

			0 0			
	l .	Frequency Band				
Category	Method	Delta	Theta	Alpha	Beta	All
Traditional	Edge	42.42	54.55	51.52	51.52	45.45
	CC	54.55	54.55	42.42	51.52	42.42
	CPL	48.48	42.42	45.45	48.48	39.39
	gSpan	39.39	51.52	39.39	54.55	48.48
	DuSK-2D	51.52	63.64	51.51	51.52	54.55
	DuSK-3D	57.58	57.58	57.58	54.55	48.48
	DuSK-4D	54.55	54.55	51.52	54.55	57.58
Deep Learning	CNN-2D	51.11	43.71	43.07	42.54	41.48
	CNN-3D	46.67	45.93	41.48	57.04	44.44
	GCN	41.31	48.08	41.01	40.61	37.37
Ours	SSGK _{w/o sparse}	57.58	66.67	63.64	54.55	57.58
	SSGK	63.64	69.70	72.73	60.61	57.58

