

Adaptive Embedding for Long-Range High-Order Dependencies via Time-Varying Transformer on fMRI

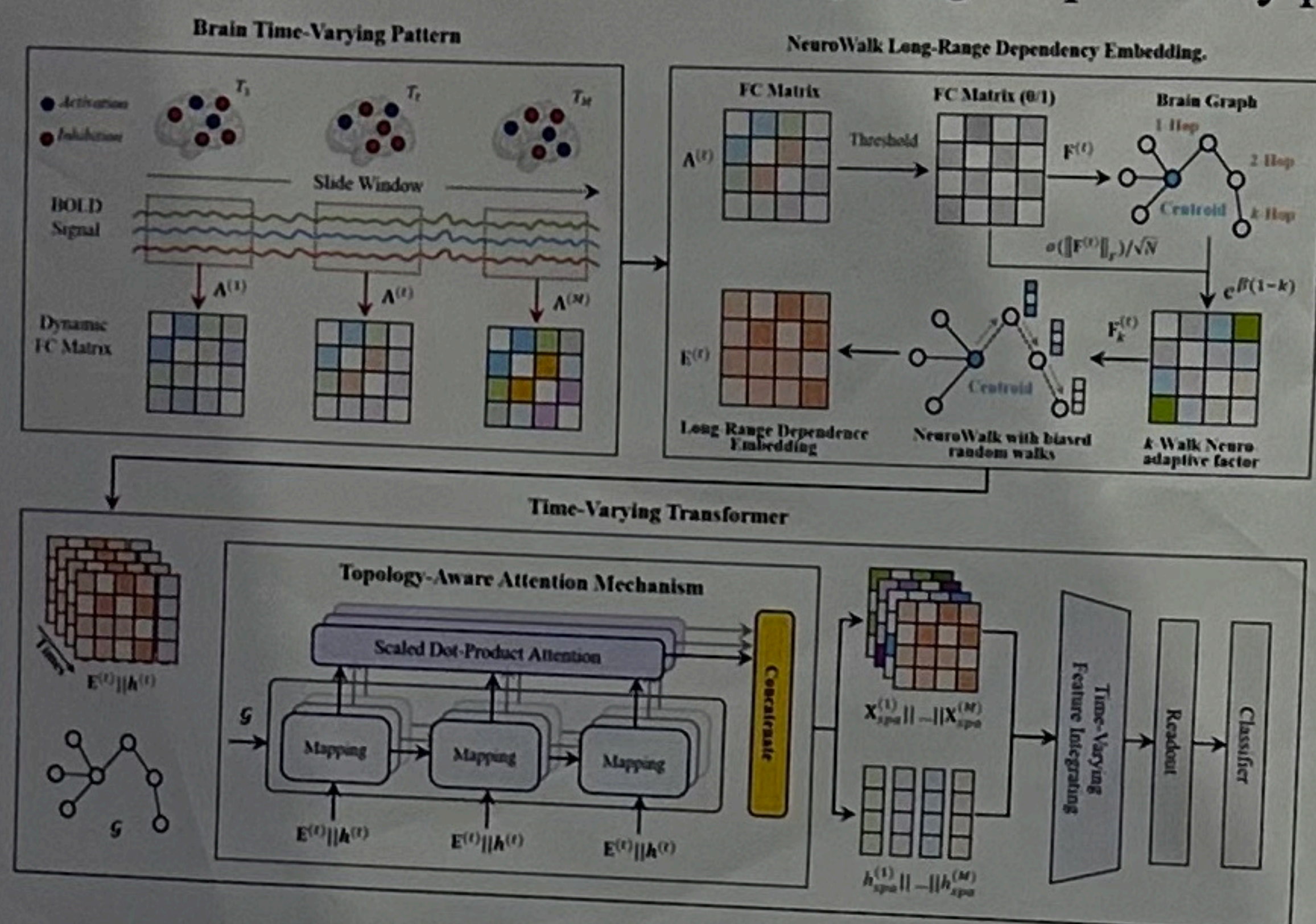
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Introduction

- Existing methods for modeling dynamic brain networks typically analyze pairwise relationships through sliding window or time-frequency coherence, failing to capture long-range high-order information flow beyond immediate neighbors.
- Recent studies introduce random-walk kernels to model long range dependencies, the designed static kernels exhibit two critical shortcomings: 1) inability to adapt to the time-varying nature of functional connectivity and 2) failure to encode neurophysiological multi-scale long-range dependency patterns corresponding to different steps.



Method

We propose **LHDFormer**, a physiologically grounded framework that combines **neuroadaptive long-range dependency embedding** with **temporal dynamic integration**. Specifically, we develop a biased random walk sampling strategy with a time-varying NeuroWalk kernel that enables dynamically regulating the process of multi-step information propagation to generate long-range high-order dependency embeddings. Subsequently, local spatial dependencies within the brain and global dynamic connectivity patterns are integrated via a time-varying transformer based on the long-range embeddings.

Adaptive Embedding for Long-Range High-Order Dependencies

- k -Walk Neuroadaptive Factors:** $F_k^{(t)} = e^{\beta(1-k)} \cdot \sigma(\|F^{(t)}\|_F / \sqrt{N})$,
- Time-varying NeuroWalk Kernel:** $R^{(t,k)} = (F_k^{(t)} \odot A^{(t)})(D^{(t)})^{-1}$
- NeuroWalk Long-Range Dependency Embedding:** $e_i^{(t)} = [I, R^{(t,1)}, \prod_{k=1}^2 R^{(t,k)}, \dots, \prod_{k=1}^{K-1} R^{(t,k)}]_{i,i}$.

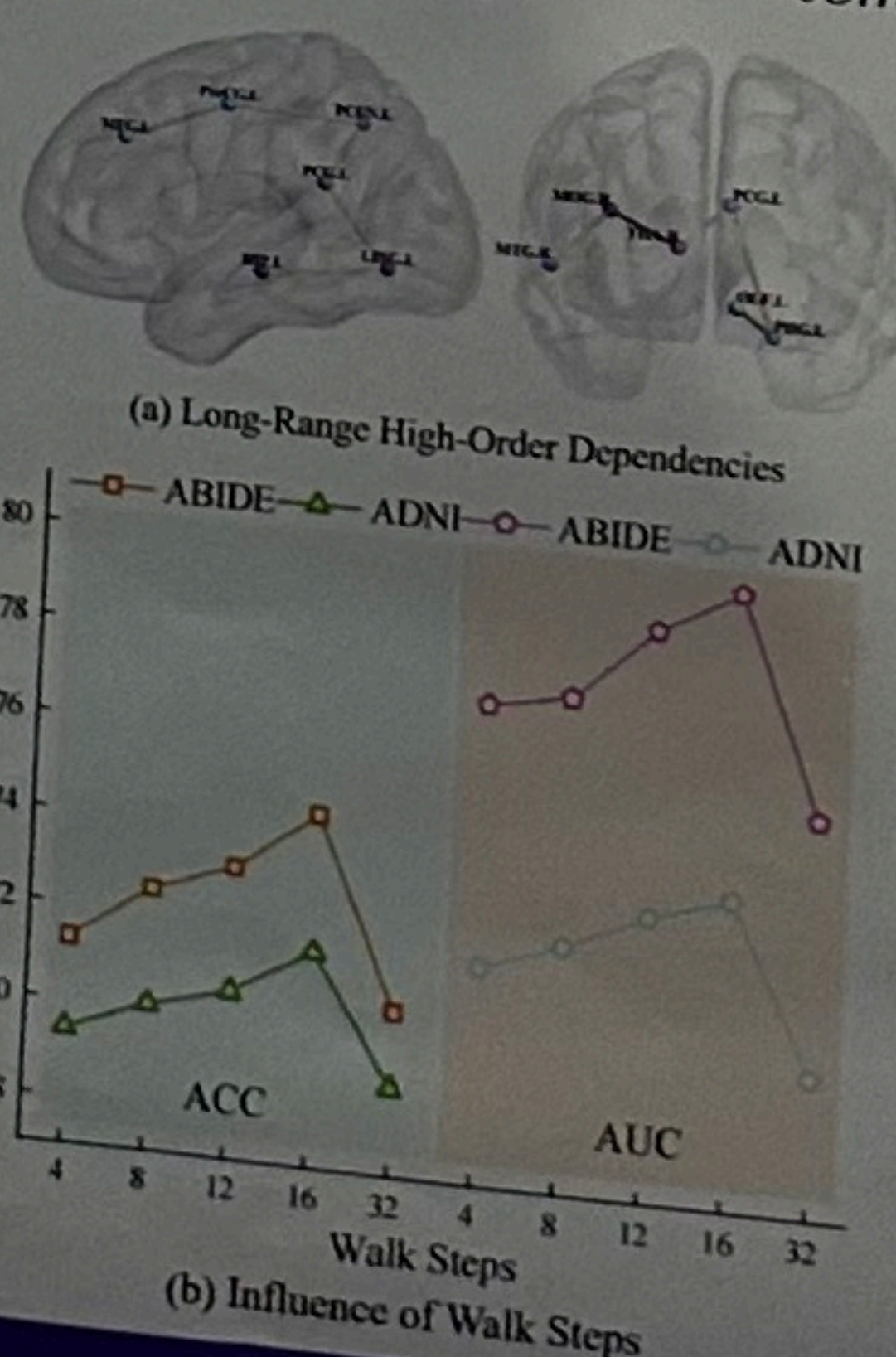
Time-Varying Transformer

- Local Spatial-Domain Feature Encoding:** $(X^{(t)}, h^{(t)}) \rightarrow (X_{spa}^{(t)}, h_{spa}^{(t)})$.
 $Q_i^{(t)}, K_i^{(t)}, V_i^{(t)} = \text{ReLU}((D^{(t)})^{-1/2} A^{(t)} (D^{(t)})^{-1/2} X^{(t)}) (W_Q, W_K, W_V), X_{spa}^{(t)} = W_o(\|_{i=1}^D X_i^{(t)}), X_i^{(t)} = \text{softmax}(\frac{Q_i^{(t)} (K_i^{(t)})^\top}{\sqrt{d}}) V_i^{(t)}$.
- Global Time-Varying Feature Integrating:** $(\|_{t=1}^M X_{spa}^{(t)}, \|_{t=1}^M h_{spa}^{(t)}) \rightarrow X_{tem}$.

Result

Table 1. Experimental Results of the Comparison Methods.

Dataset	Method	ACC(%)	SEN(%)	SPE(%)	AUC
ABIDE	STGCN [15]	65.52±2.46	62.96±7.51	67.74±5.00	0.6628±0.0243
	BrainIB [16]	69.21±8.64	65.32±5.70	72.94±5.32	0.6902±0.0327
	RGTNET [17]	69.75±1.41	70.30±4.71	68.87±3.84	0.7051±0.0117
	MSSTAN [7]	71.40±1.49	70.35±1.80	72.55±1.83	0.7678±0.0076
	ALTER [9]	71.23±2.86	71.27±3.84	71.22±2.02	0.7547±0.0207
	LHDFormer	74.29±1.17	73.48±1.10	75.09±2.04	0.7978±0.0103
ADNI	STGCN [15]	62.82±4.46	65.23±5.49	60.36±4.65	0.6254±0.0582
	BrainIB [16]	64.68±2.94	66.36±9.01	63.62±8.14	0.6583±0.0390
	RGTNET [17]	65.75±3.23	66.32±4.28	64.54±3.15	0.6826±0.0449
	MSSTAN [7]	67.88±2.84	69.38±3.83	66.40±2.73	0.7130±0.0457
	ALTER [9]	68.50±1.17	69.32±2.28	67.33±2.58	0.7200±0.0181
	LHDFormer	71.42±1.70	72.52±2.02	70.27±1.10	0.7347±0.0209

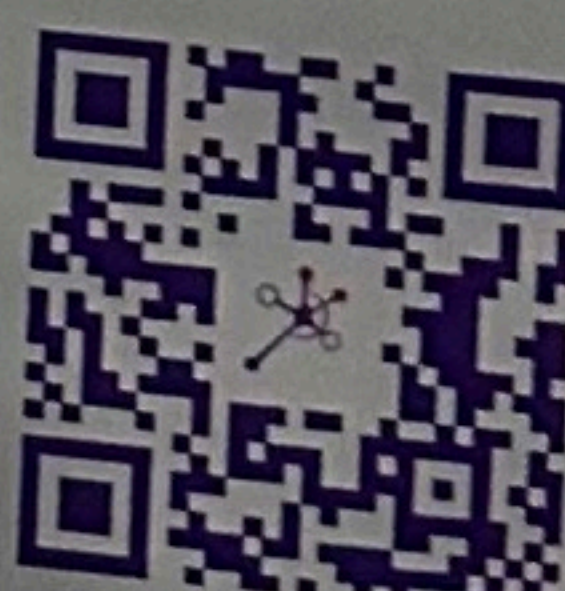


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THU-iMoonLab

Code: iMoonLab / LHDFormer



DeepHypergraph