



Recurrent Graph Convolutional Networks for Skeleton-based Action Recognition

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• What have we done?



- Propose a recurrent graph convolutional network (R-GCN)
- Learn the graph topologies for different layers,
 different time steps and different kinds of actions
- Evolve the graph topology across the consecutive frames adaptively
- Capture the interactions of different subsets of joints beyond corresponding neighboring joints in the neighboring frames





Existing graph convolutional networks

• ST-GCN



[1] S. Yan, Y. Xiong, D. Lin, and xiaoou Tang, "Spatial temporal graph convolutional networks for skeleton-based action recognition," in AAAI Conference on Artificial Intelligence (AAAI), 2018, pp. 7444–7452.

[2] X. Gao, W. Hu, J. Tang, P. Pan, J. Liu, and Z. Guo, "Generalized graph convolutional networks for skeleton-based action recognition." arXiv preprint arXiv:1811.12013, 2018.





Architecture Overview



- Apply the adaptive graph convolution and the recurrent graph convolution into ST-GCN
- "Graph Convolution BN ReLU Temporal Convolution – BN - ReLU" structure for each block (B1 – B10)
- > A residual connection for each block





Experimental Results

• Ablation Study

Networks	BP on Embedding	Natural Connectivity	Accuracy(%)	Parameter Size	
R-GCN + Dot-Prod		\checkmark	93.8		
			93.5	3.2M	
		\checkmark	94.2		
	\checkmark		93.8		
R-GCN + Gaussian		\checkmark	93.9	3 2M	
	\checkmark	\checkmark	94.1	5.211	
R-GCN + EmbedGaussian		\checkmark	93.9	3.8M	
	\checkmark	\checkmark	94.2		
R-GCN* + Dot-Prod		\checkmark	93.7		
			93.2	2 2M	
		\checkmark	93.9	3.3W	
			93.7		





Experimental Results

• Comparison with the State-of-the-art

Networks	Stream	NTU RGB+D		Kinetics-Skeleton	
		X-Sub(%)	X-View(%)	Top-1(%)	Top-5(%)
2s-AGCN [9]	Joint	-	93.2	35.1	57.1
	Bone	-	93.2	33.3	55.7
	Both	88.5	95.1	36.1	58.7
AGC-LSTM [21]	Joint	87.5	93.5	-	-
	Part	87.5	93.8	-	-
	Both	89.2	95.0	-	-
R-GCN	Joint	86.3	94.2	35.1	57.5
	Bone	87.6	94.1	34.6	57.1
	Both	89.2	95.6	36.9	59.8





Experimental Results

• Comparison with the State-of-the-art

Methods	X-Sub(%)	X-View(%)
Lie Group [3]	50.1	82.8
HBRNN [4]	59.1	64.0
Deep LSTM [5]	60.7	67.3
ST-LSTM [6]	69.2	77.7
STA-LSTM [26]	73.4	81.2
VA-LSTM [27]	79.2	87.8
ARRN-LSTM [28]	80.7	88.8
Ind-RNN [29]	81.8	88.0
Two-Stream 3DCNN [30]	66.8	72.6
TCN [31]	74.3	83.1
Clips+CNN+MTLN [7]	79.6	84.8
Synthesized CNN [32]	80.0	87.2
CNN+Motion+Trans [33]	83.2	89.3
3Scale ResNet152 [34]	85.0	92.3
PA-GCN [16]	80.4	82.7
ST-GCN [8]	81.5	88.3
DPRL+GCNN [35]	83.5	89.8
BPLHM [36]	85.4	91.1
3s RA-GCN [37]	85.9	93.5
AS-GCN [10]	86.8	94.2
PB-GCN [15]	87.5	93.2
2s-ASGCN [13]	88.3	95.4
2s-AGCN [9]	88.5	95.1
AGC-LSTM [21]	89.2	95.0
Two-stream R-GCN	89.2	95.6

Methods	Top-1(%)	Top-5(%)
Feature Enc. [38]	14.9	25.8
Deep LSTM [5]	16.4	35.3
TCN [31]	20.3	40.0
ST-GCN [8]	30.7	52.8
BPLHM [36]	33.4	56.2
2s-ASGCN [13]	34.5	56.9
AS-GCN [10]	34.8	56.5
2s-AGCN [9]	36.1	58.7
Two-stream R-GCN	36.9	59.8





Visualization of the Evolved Graph Topologies







Thanks for listening!





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