



Temporal Extension Module for Skeleton-based Action Recognition

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Agenda



Overview

Motivation

- ST-GCN
 - Drawback
- Proposed Method
 - Temporal Extension Module (TEM)
- Implementation of TEM
- Ablation Study
- Comparison of State-of-the-art

Overview



Expectation of Action recognition

Applications in human behavior understanding and human social behavior

Mainstream method in action recognition

- Methods using RGB images
- Methods using sequence of skeletons
 - Low-cost computing resources



Motivation



ST-GCN (AAAI 2018)

- The well-known method using graph convolutional network
 - Represents human joints as vertices and their natural connections in human body as edges
 - Draws attention owing of high performance
- Temporal graph
 - Adds edges to same vertex on temporal dimension
 - Extracts feature of trajectory of same joints
- Drawback
 - Cannot extract feature of correlative movement between each joint on the inter-frame
 - Does not add edges to another vertex on temporal graph





Proposed Method



Temporal Extension Module (TEM)

- Extends of temporal graph on inter-frame
 - Adds edges to not only same vertex but also neighboring multiple vertices
 - Sets multiple subsets based on length to center of gravity
 - Adds info of kinematics correlation
- Advantage
 - Extract feature of correlative movement between each joint on inter-frame
 - Good for recognition of action that adjacent joints often move together, such as "throw."
 - Apply to existing model easily





Implementation of TEM



ST-GCN+TEM

*Spacial Graph Convolution and Temporal Graph Convolution

- We attach our module between *S-GC and T-GC.
 - To expand sampling area for temporal dimension gradually
- We do not change the structure of conventional convolutions.
 - Our module can readily apply to many existing methods.



Ablation Study



Methods with TEM outperform without TEM.

■ This showed effectiveness of our module.

TABLE I. COMPARISONS OF THE RECOGNITION ACCURACY THE MODELS WITH TEM AND WITHOUT TEM

Methods	NTU-RGB+D		Kinetics-Skeleton	
	CS (%)	CV (%)	Тор-1 (%)	Тор-5 (%)
ST-GCN	82.6	88.7	32.5	54.9
ST-GCN+TEM	85.2	90.2	34.5	56.7
2s-AGCN	88.6	95.2	36.7	59.8
2s-AGCN+TEM	88.7	95.8	38.6	61.6
MS-AAGCN	90.3	96.1	37.4	60.6
MS-AAGCN+TEM	91.0	96.5	38.0	61.4

Comparison of State-of-the-art



Our model achieves state-of-the-art performance.

TABLE II. COMPARISONS OF THE RECOGNITION ACCURACY WITH MS-AAGCN+TEM AND CURRENT STATE-OF-THE-ART METHODS ON NTU RGB+D DATASET

Mathada	NTU-RGB+D	
Methods	CS (%)	CV (%)
ST-LSTM (Tree Traversal) + Trust Gate [19]	69.2	77.7
TSRJI (Late Fusion) [27]	73.3	80.3
STA-LSTM [16]	73.4	81.2
ESV (Synthesized+Pre-trained) [26]	80.0	87.2
VA-LSTM [20]	79.6	87.6
ST-GCN [7]	81.5	88.3
Si-GCN [34]	84.2	89.1
CNN-based [24]	83.2	89.3
ARRN-LSTM [23]	81.8	89.6
DPRL+GCNN [8]	83.5	89.8
multi-scale network (ResNet152 + 3scale) [25]	85.0	92.3
Complete GR-GCN model [33]	87.5	94,3
2s-AGCN [9]	88.5	95.1
GCN-NAS [11]	89.4	95.7
DGNN [10]	89.9	96.1
MS-AAGCN [12]	90.0	96.2
BAGCN [22]	90.3	96.3
Sym-GNN [13]	90.1	96.4
MS-AAGCN+TEM(Ours)	91.0	96.5

TABLE III. COMPARISONS OF THE RECOGNITION ACCURACY WITH 2S-AGCN+TEM AND CURRENT STATE-OF-THE-ART METHODS ON THE KINETICS-SKELETON

Methods	Kinetics-Skeleton		
Methods	Тор-1 (%)	Тор-5 (%)	
ST-GCN [7]	30.7	52.8	
2s-AGCN [9]	36.1	58.7	
DGNN [10]	36.9	59.6	
GCN-NAS [11]	37.1	60.1	
Sym-GNN [13]	37.2	58.1	
BAGCN [22]	37.3	60.2	
MS-AAGCN [12]	37.8	61.0	
2s-AGCN+TEM (Ours)	38.6	61.6	



Proposed method: Temporal Extension Module (TEM)

- Extend temporal graph on inter-frame
 - Adds edges to not only same joints but also neighboring multiple joints
- Advantage
 - Extract feature of correlative movement between each joint on inter-frame
 - Apply to existing model easily



Experiments on NTU RGB +D and Kinetics-Skeleton dataset

- Showed effectiveness of our module
- Showed that model with our module achieves state-of-the-art performance

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