Channel-Wise Dense Connection Graph Convolutional Network For Skeleton-Based Action Recognition

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Outlines

- Motivations & Challenges
- Proposed Method
- Experiments and Results
- Conclusions

Motivations & Challenges

- Motivations

  - Build an skeleton-based action recognition system
  - Construct global information for action and select more related features
  - Generate and utilize features to adapt for difference on action movements
  - Extracted temporal feature representation

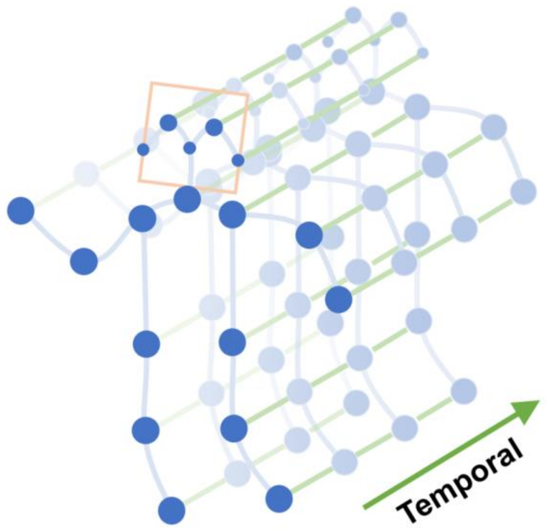
- Challenges

  - The importance of different channels varies in actions
  - Some human actions only involve a small part of bodies
  - Confusion on reversing actions

Proposed Method

◆ Data-preprocessing

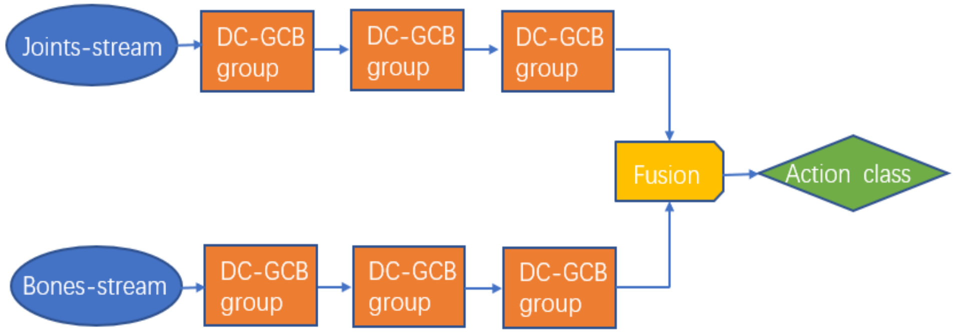
- Skeleton graph *G = (V,E)*
- Joints as vertices (V) and the connection between joints as edges (E)
- Vertice's joint coordinate $v_i = (x_i, y_i)$
- Bone information, extracted from neighboring vertices, $b_{ij} = (x_i - x_j, y_i - y_j)$
- Motion information of joints and bones, extracted from consecutive frames of data, $m_i = (x_i^{t+1} - x_i^t, y_i^{t+1} - y_i^t)$
- Concatenate the information of joints and their motion in the frame dimension. The same procedure was conducted with the bones.



Skeleton graph

◆ Model Structure

- Two-stream fashion, each stream consists of 12 graph convolution blocks in each stream with late fusion
- A graph convolution block (GCB) , consists of a spatial GCN, a temporal GCN and a channel-wise attention module (CAM), followed by a residual connection
- A DC-GCB group, consists of 4 GCBs with Dense connection implemented, followed by a transition layer



Framework of the proposed 2s-CDGCN

Proposed Method

◆ Graph convolution block (GCB)

- Spatial graph convolution and temporal convolution, followed by a channel-wise attention module
- Channel-wise attention module

$$z_c = F_{sq}(u_c) = \frac{1}{F \times V} \sum_{i=1}^{F} \sum_{j=1}^{V} u_c(i,j), u_c \in \mathbf{R}^{F \times V}$$

For input features maps $U \in R^{C \times F \times V}$, C denotes input feature channels, F denotes the number of input frames, and V denotes the number of input vertices

- An overall feature descriptor $z \in R^{C}$ to indicate the statistics distribution of input feature channels
- To analyze the interdependence between channels

$$\mathbf{s} = \mathbf{F}_{ex}(\mathbf{z}, \mathbf{W}) = \sigma(g(\mathbf{z}, \mathbf{W})) = \sigma(\mathbf{W}_2 \delta(\mathbf{W}_1 \mathbf{z}))$$

- Two fully-connected layers, $W_1 \in R^{\frac{C}{r} \times C}$ and $W_2 \in R^{C \times \frac{C}{r}}$

- A channel-wise multiplication between s and U is made to represent a global information based on feature channels

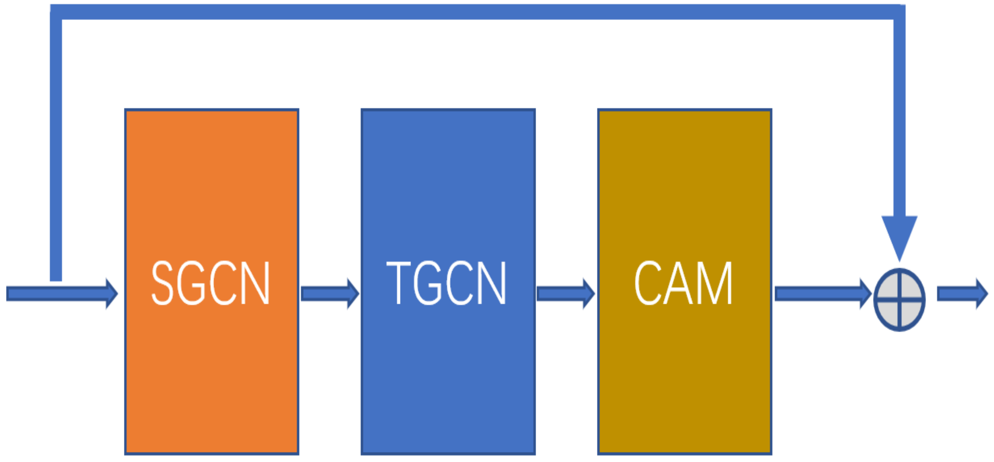


Illustration of Graph convolution block (GCB)

Proposed Method

◆ DC-GCB Group

- Concatenation of all the preceding graph convolution block's output features maps

$$\mathbf{x}_b = F_b\left(\left[\mathbf{x}_0, \mathbf{x}_1, \ldots, \mathbf{x}_{b-1}\right]\right)$$

- x_b is the output features map for b-th graph convolution block, F_b denotes the graph convolution operations in the b-th block
- With fewer parameters added and less computation, a larger and sufficient features map is generated for graph convolution blocks

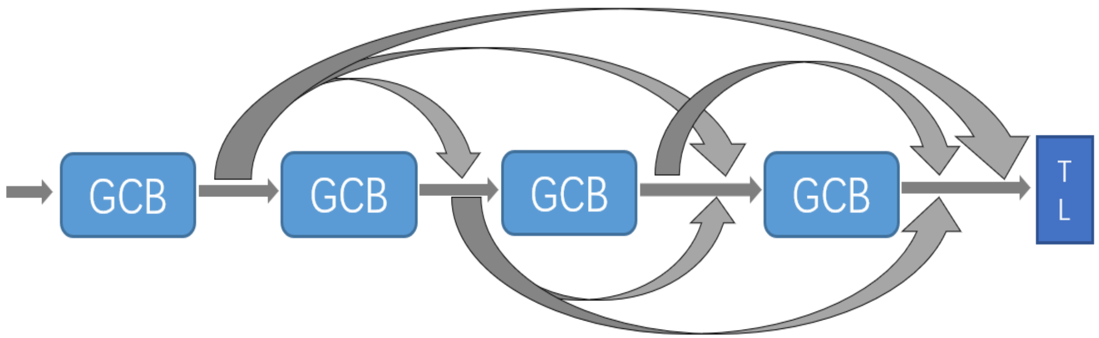


Illustration of DC-GCB group, grey curve arrows denote the dense connections

Experiments and Results

◆ Datasets

- NTU-RGB+D
  - ➢ 60 different action classes including daily and health-related actions
  - ➢ 25 body joints collected by Microsoft Kinect v2
  - ➢ 40 distinct subjects recorded from 3 different horizontal angles
  - ➢ Cross-subject evaluation and cross-view evaluation
- Kinetics
  - ➢ 400 action classes with at least 400 video clips
  - ➢ 18 body joints obtained by OpenPose toolbox

◆ Ablation Study

- ■ Comparison with the State-of-the-Art methods
- ➢ Methods include hand-crafted methods, CNN-based methods, RNN-based methods and GCN-based methods
- ➢ Outperforms hand-crafted methods, CNN and RNN methods with a large margin
- ➢ A competitive result comparing with the state-of-the-art GCN-based methods

Methods	Top-1(%)	Top-5(%)
Feature [49]	14.9	25.8
Deep LSTM [20]	16.4	35.3
TCN [43]	20.3	40.0
ST-GCN [3]	30.7	52.8
AS-GCN [1]	34.8	56.5
2s-AGCN [4]	36.1	58.7
DGNN [48]	36.9	59.6
GCN-NAS [14]	37.1	60.1
2s-CDGCN	37.0	59.8

Comparison on Kinetics dataset

Methods	Cross-Subject(%)	Cross-View(%)
Lie Group [42]	50.1	52.8
Deep LSTM [20]	60.7	67.3
STA-LSTM [11]	73.4	81.2
TCN [43]	74.3	83.1
C-CNN + MTLN [44]	79.6	84.8
VA-LSTM [45]	79.4	87.6
ST-GCN [3]	81.5	88.3
SR-TSL [46]	84.8	92.4
HCN [5]	86.5	91.1
3scale ResNet152 [47]	85.0	92.3
RA-GCN [15]	85.9	93.5
DenseIndRNN [10]	86.7	93.7
PB-GCN [13]	87.5	93.2
AS-GCN [1]	86.8	94.2
AGC-LSTM [9]	89.2	95.0
2s-AGCN [4]	88.5	95.1
GCN-NAS [14]	89.4	95.7
DGNN [48]	89.9	96.1
2s-CDGCN	90.0	96.1

Comparison on NTU-RGB+D dataset

Experiments and Results

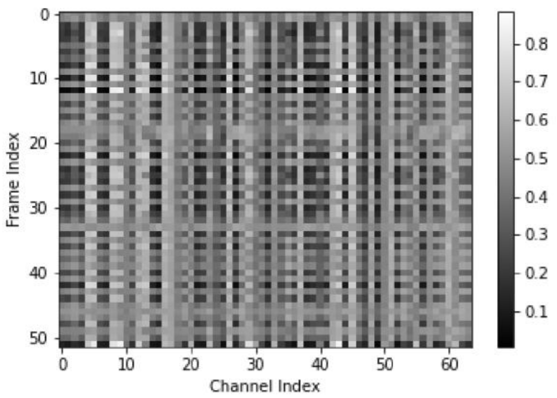
◆ Ablation Study

- ■ Channel-wise Attention Module
- ➢ Choose dataset NTU-RGB+D to test the Top-1 accuracy
- ➢ Valid effect on improving the performance of the model
- ➢ The module learns the non-linear relations between channels and the scale is not one-hot encoding
- ➢ Emphasize multiple channels with more importance

- ■ Dense Connection
- ➢ Performance improvement shows that the network takes the advantage of Dense Connection
- ➢ Produces a larger and sufficient features map to achieve better results
- ■ CAM, compared with DC, achieves higher accuracy improvements on cross-view benchmark, and vice versa, which can be explained by the relationship between modification modules and NTU-RGB+D setup

Methods	Cross Subject (%)	Cross View (%)
2s-AGCN [4]	88.5	95.1
2s-CDGCN without DC	89.3	95.9
2s-CDGCN without CAM	89.5	95.5
2s-CDGCN	90.0	96.1

Ablation study experiments to validate modules



Example of activations in CAM

Conclusions

- ✓ Extract the motion features from skeleton data and concatenating them with original spatial features
- ✓ Introduce a channel-wise attention module to emphasize channels with important features
- ✓ Use dense connection to ensure reuse of skeleton features and to generate a larger and sufficient features map
- ✓ Our model shows competitive performance with the state-of-the-art model on two large datasets, NTU-RGB+D and Kinetics
- ✓ Extensive evaluations were conducted to prove the effectiveness of our model.