Spatio-Temporal Tuples Transformer for Skeleton-Based Action Recognition

Helei Qiu, Biao Hou*, Bo Ren, Xiaohua Zhang
Xidian University

Abstract: Capturing the dependencies between joints is critical in skeleton-based action recognition task. Transformer shows great potential to model the correlation of important joints. However, the existing Transformer-based methods cannot capture the correlation of different joints between frames, which the correlation is very useful since different body parts (such as the arms and legs in "long jump") between adjacent frames move together. Focus on this problem, A novel spatio-temporal tuples Transformer (STTFormer) method is proposed. The skeleton sequence is divided into several parts, and several consecutive frames contained in each part are encoded. And then a spatio-temporal tuples self-attention module is proposed to capture the relationship of different joints in consecutive frames. In addition, a feature aggregation module is introduced between non-adjacent frames to enhance the ability to distinguish similar actions. Compared with the state-of-the-art methods, our method achieves better performance on two large-scale datasets.

1 Introduction

Recently, skeleton-based action recognition has attracted substantial attention since its compact skeleton data representation makes the models more efficient and robust to complex background, illumination conditions, viewpoint changes and other environmental noise. In addition, the development of cost-effective depth cameras and human pose estimation methods makes it easier to obtain human skeleton information.

The raw skeleton data is usually converted into point sequences, pseudo images or graph, and then input into deep network (such as recurrent neural network (RNN), convolutional neural network (CNN) or graph neural network (GCN)) for feature extraction. However, the RNN-based methods [36,30,29] processes sequences recursively, and the CNN-based methods [19,12,42,11] performs local operations on a fixed size window. Both methods capture only short-range correlations. The GCN-based methods [38,26,20,22,15,7,8] rely on the inherent graph topology of the human body, and cannot effectively use the correlation between unconnected joints (such as hands and feet in “put on shoes”). In general, the above methods cannot effectively model the long-term dependence of sequences and the global correlation of spatio-temporal joints.

The Transformer-based methods does not depend on the human structure, and can model the relationship between all joints compared with the above-mentioned methods. Considering this advantage, Transformer [32] is applied to skeleton-based action recognition tasks [35,23,28]. How to use Transformer to model spatio-temporal correlation is crucial since the spatiotemporal joints of skeleton data are correlated. [35] regards
Fig. 1. Two spatio-temporal self-attention schemes. (a): This scheme only establishes the relationship of intra-frame joints and the same joints between inter-frames. (b): This scheme captures the relationship of all joints in several consecutive frames at the same time.

spatio-temporal skeleton data as a single sequence to capture the related information of all joints. However, this strategy is unreasonable since the spatial and temporal joints have different semantic information. Specifically, the relationship between spatial joints reflects the interaction between various parts of the human body, and the same joints between temporal frames represent the motion trajectory of a certain part of the human body. In addition, this method needs to calculate the self-attention of all joints in the sequence at the same time, which will significantly increase the computational cost. Focus on these problems, [23] introduces self-attention into graph convolution, and uses a spatial and temporal self-attention module to model the correlation of intra-frame and inter-frame joints respectively. Similarly, [28] uses pure self-attention to capture the relationship of the spatio-temporal joints. However, these methods only focus on the same joints between frames (Fig. 1(a)), and the extracted related motion features are too simple. It is observed that different joints in several consecutive frames are related. For example, in the action "long jump", the arms of the previous frame are related to the legs of the next frame since the joints of these parts move together in cases of action movement. Therefore, it is very useful to extract the related features of different joints between adjacent frames.

Based on the above observations, we construct a novel spatio-temporal tuples Transformer (STTFormer) model for skeleton-based action recognition. Specifically, a skeleton sequence is divided into several non-overlapping parts. Each part is called a ”tuple” and contains several consecutive frames. Because different joints in several consecutive frames have correlation, each tuple is flattened into a short sequence, and then a spatio-temporal tuple self-attention (STTA) module is used to extract the related features of joints in each short sequence simply and effectively as shown in Fig. 1(b). This method not only capture the correlation of different joints between consecutive frames, but also hardly increase the computational cost. Because although all joints of several frames need to be modeled at the same time, the size of time dimension is greatly reduced. In addition, we aggregate features on the time dimension composed of several tuples. If a tuple is regarded as a sub-action, the inter-frame feature aggregation (IFFA) can be regarded as the integration of a series of sub-actions. the
IFFA module will help distinguish similar actions. Finally, multi-mode data is also used to further improve performance. The code will be made publicly available at https://github.com/heleiqiu/STTFormer

The main contributions of this work are as follows:

- A spatio-temporal tuple encoding strategy is proposed to explicitly flatten the joints of several consecutive frames, so that our model can capture the related information of different joints between frames.
- A spatio-temporal tuple Transformer is proposed, in which the spatio-temporal tuple attention is used to capture the related features of the joints in each tuple, and the inter-frame feature aggregation module is used to integrate all tuples.
- We conducted extensive experiments on two challenging benchmarks. Ablation experiments verify the effectiveness of each component of our model, and the performance of our method exceeds the existing state-of-the-art methods.

2 Related Work

2.1 Self-Attention Mechanism

Recently, Transformer [32] has become the leading language model in natural language processing. The self-attention is an important component of Transformer, which can learn the relationships between each element of a sequence. Transformer can handle very long sequences and solves the problem that LSTM and RNN networks cannot effectively model long-term sequences. In addition, the multi-headed self-attention mechanism can process sentences in parallel, rather than processing sentences word by word recursively like LSTM and RNN networks.

Due to the advantages of self-attention, which has also been introduced into computer vision tasks such as image classification and recognition [37,6], object detection [3,41] and action recognition [2,23,1]. [37] combined CNN and self-attention to model the local and global dependencies for image classification. [2] used self-attention to learn spatio-temporal features from a sequence of frame-level patches for video action recognition. Based on GCN, [23] used self-attention instead of regular graph convolution in space and time for skeleton-based action recognition. In contrast to [23], we use pure self-attention to model skeleton data, and the correlation of all joints in several consecutive frames is calculated at the same time.

2.2 Skeleton-Based Action Recognition

Skeleton-based action recognition has been widely studied for decades. Previously, skeleton-based motion modeling methods mainly used 3D information of joints to design handcrafted features [33,9]. With the breakthrough of high-performance computing and deep learning technology, deep learning shows excellent ability to extract features. At present, the deep learning methods for skeleton-based action recognition are mainly divided into three categories: (1) The RNN-based methods [36,30,29,31] is based on the natural time properties of the skeleton sequence, and then modeled by Long Short Term Memory (LSTM), Gated Recurrent Unit (GRU), etc.; (2) The CNN-based methods [19,12,42,17] usually convert the skeleton sequence into the pseudo-images using specific transformation rules, and model it with efficient image classification networks. The CNN-based methods usually combined with RNN-based methods to
model the temporal information of skeleton sequence. (3) The GCN-based methods utilize the natural topology and regular sequence of skeleton data in space and time to encode the skeleton into spatio-temporal graph, and use graph convolution network to model it. Unlike the above-mentioned methods that represent skeleton data as images or graph, we directly use self-attention to model the skeletal data.

2.3 Context Aware-based Methods

The context aware-based methods are designed to extract the features of spatio-temporal non-local joints since they are also related (such as clapping and typing request the cooperation of both hands). superimposes an adaptive matrix on the fixed adjacency matrix to learn the non-local relationship between joints. This method alleviates the limitation caused by the fixed graph topology of the existing GCN-based methods. However, the method only connects the same joints between frames, and cannot model the relationship of different joints between frames. proposed a context aware graph convolution model, which uses three different functions of inner product, bi-linear form and trainable relevance score to calculate the correlation between joints, and then embeds it into the graph convolution to enrich the local response of each body joint by using the information of all other joints. focuses on adding connections on adjacent vertices between frames, and extracting additional features based on the extended temporal graph. Similarly, proposed a multi-scale aggregation scheme to separate the importance of nodes in different neighborhoods in order to achieve effective remote modeling. In addition, a unified spatio-temporal graph convolution operator is proposed, which takes the dense cross spatio-temporal edges as skip connections to directly propagate information on the spatio-temporal graph. However, the above method can be regarded as an extension of graph topology and cannot ensure that important joints are connected. In this work, self-attention is utilized to model cross spatio-temporal joints and adaptively capture important joints related to human actions.

3 Method

In this section, the overall architecture of the proposed method first is summarized. In the follow, the spatio-temporal tuples encoding and positional encoding strategy is introduced. Finally, each component of the spatio-temporal tuples Transformer is described in detail.

3.1 Overall Architecture

The overall architecture of our model is shown in Fig. 2. The input is a skeleton sequence with \(V_0\) joints and \(T_0\) frames. We divided the sequence into \(T\) parts, each one containing \(n\) consecutive frames, a total of \(V = n \times V_0\) joints. Then a tuple encoding layer is utilized to encode each tuple data. A total of \(L\) layers are stacked in spatio-temporal tuples Transformer, and each layer is composed of STTA and IFFA, in which STTA module is used to model the relationship between joints in tuples and IFFA is used to integrate all tuples. Finally, the obtained features are input into a global average pooling layer and a full connection layer to obtain classification scores. In the following sections, the details of each module will be introduced.
Fig. 2. Illustration of the overall architecture of the proposed model, which consists of two main modules: the spatio-temporal tuples encoding and spatio-temporal tuples Transformer.

### 3.2 Spatio-Temporal Tuples Encoding

To model the relationship between different joints in several consecutive frames, we propose a strategy to encode these joints. The spatio-temporal tuples encoding procedure is illustrated in Fig. 3.

Firstly, the raw skeleton sequence $X_0 \in \mathbb{R}^{C_0 \times T_0 \times V_0}$ is fed to a feature mapping layer to expand the input channel to a set number $C_1$. The feature mapping layer is implemented by one convolution layers with BatchNorm and Leaky ReLU function. Subsequently, the skeleton sequence is divided into $T$ non-overlapping tuples:

$$X = [x_1, x_2, \cdots, x_T], \quad x_i \in \mathbb{R}^{C_1 \times n \times V_0}$$

(1)

where $n$ denotes the number of frames contained in a tuple. In the follow, each tuple is flattened:

$$X \in \mathbb{R}^{C_1 \times T \times n \times V_0} \rightarrow \mathbb{R}^{C_1 \times T \times V}$$

(2)

where $T = T_0/n$, $V = n \times V_0$. Finally, $X$ is fed to a spatio-temporal tuples encoding layer implemented by one convolution layer with Leaky ReLU function to get the final tuples encoding $X \in \mathbb{R}^{C \times T \times V}$. 

Fig. 3. Illustration of the proposed spatio-temporal tuples encoding module.
3.3 Positional Encoding

The tensor obtained by tuples encoding does not contain the order of joints, and the identity of joints cannot be distinguished, which will reduce the performance of action recognition [28,34], which is also confirmed by the experimental results in Tab 1. Considering this problem, a position encoding module is used to mark each joint, and the sine and cosine functions with different frequencies are utilized as the encoding functions:

\[
PE(p, 2i) = \sin(p/10000^{2i/C_{in}})
\]

\[
PE(p, 2i + 1) = \cos(p/10000^{2i/C_{in}})
\]

(3)

where \(p\) and \(i\) denote the position of joint and the dimension of the position encoding vector, respectively. To model the relationship of all joints in a tuple, it is necessary to distinguish the joints of different consecutive frames, so all joints in a tuple are assigned different IDs.

3.4 Spatio-Temporal Tuples Transformer

As shown in Fig. 4, the spatio-temporal tuple Transformer layer includes two main components: spatio-temporal tuple attention and inter-frame feature aggregation, which will be described in detail below.

Spatio-Temporal Tuples Attention  The essence of self-attention can be described as the mapping from a query to a series of key and value pairs. After spatio-temporal tuples encoding and positional encoding of skeleton sequence, the multi-headed self-attention mechanism can be used to model the relationship between input tokens.

Specifically, when calculating self-attention, not only the impact of all other nodes on the node \(n_i\), but also the impact of the node \(n_i\) on other nodes must be considered. Therefore, the encoded sequence \(X_{in}\) is usually projected into the query \(Q\), key \(K\) and value \(V\). In this work, a convolution layer with \(1 \times 1\) kernel size is used to project the encoded sequence \(X_{in}\):

\[
Q, K, V = \text{Conv}_{2D}(1 \times 1)(X_{in})
\]

(4)

Then, the weights can be obtained by calculating the similarity between the query \(Q\) and the transpose of the key \(K\). Like the standard Transformer, the dot-product is simply used as the similarity function. Subsequently, the Tanh function is utilized to normalize the obtained weights. And then the weights and corresponding value \(V\) are weighted and summed to obtain final attention.

\[
X_{attn} = \text{Tanh} \left( \frac{QK^T}{\sqrt{C}} \right) V
\]

(5)

where \(C\) denotes the number of channels of the key \(K\), which can avoid excessive inner product to increase gradients stability during training. Considering the fixed relationship of human joints, learn from DSTANet [28], a spatial global regularization is utilized to introduce this relationship.
To obtain better performance, the multi-headed self-attention mechanism is usually applied, which allows the model to learn related information in different representation subspaces. Specifically, the self-attention operation is performed on multiple groups of $Q, K, V$ projected by different learnable parameters, and then the multiple groups of attention were concatenated.

$$X_{Attn} = Concat(X_{attn}^1, \cdots, X_{attn}^h)$$ (6)

In the follow, the obtained $X_{Attn}$ is projected into an output space by a convolution operation with $1 \times k_1$ kernel size to obtain the result of multi-headed self-attention.

$$X_{STTA} = Conv_{2D}(1 \times k_1)(X_{Attn})$$ (7)

where $k_1$ corresponding to the flattened dimension of spatio-temporal tuples.

Similar to the transformer, a feed forward layer implemented by 1x1 2D convolution is added to fuse the output.

![Diagram](image)

**Fig. 4.** Illustration of the proposed spatio-temporal tuples Transformer layer, the complete STTFormer is stacked by L such layers.

**Inter-Frame Feature Aggregation** An action can be regarded as composed of several different sub-actions, such as ”long jump” including sub-actions such as ”run-up”, ”take-off” and ”landing”. In our method, each tuple contains a sub-action, which is obtained by modeling several consecutive $n$ frames using STTA. If the correlation of these sub-actions (such as ”run-up”, ”take-off” and ”landing”) is constructed, it will help to action recognition and distinguish similar actions (such as high jump and long jump).
Therefore, the IFFA operation is proposed to aggregate these sub-actions. A convolution operation with $k_2 \times 1$ kernel size is used to realize inter-frame feature aggregation in temporal dimension.

$$X_{IFFA} = Conv_{2D}(k_2 \times 1)(X_{STTA})$$ (8)

Finally, the residual connections in Fig. 4 are also used to stabilize network training. It should be noted that all outputs connected to the rest should be regularized.

4 Experiments

In this section, we conducted extensive comparative experiments to evaluate the performance of our method. Firstly, the datasets are described. Then the experimental setup is introduced. In the follow, we conducted extensive ablation studies on NTU RGB+D [24] skeleton sequence data to evaluate the contribution of each parts of our method. Finally, the proposed method is compared with the state-of-the-art methods on NTU RGB+D and NTU RGB+D 120 [18] skeleton sequence data to prove the advantages of our method, and the corresponding analysis is given.

4.1 Datasets

**NTU RGB+D**. NTU RGB+D dataset is a large-scale benchmark for 3D human action recognition captured simultaneously using three Microsoft Kinect V2 sensors. The dataset was completed by 40 volunteers and contained 56,000 action sequences in 60 action classes, including 40 daily actions, 9 health-related actions and 11 mutual actions. This experiment only uses the skeleton data containing the three-dimensional positions of 25 body joints per frame. The dataset is divided into training set and test set by two different standards. The Cross-Subject (X-Sub) divides the dataset according to the person ID, the training set and the test set contains 20 subsets respectively. The Cross-View (X-View) divides the dataset according to camera ID. The samples collected by cameras 2 and 3 are used for training, and the samples collected by camera 1 are used for testing. It should be noted that the horizontal angles of the three cameras differ by 45° respectively.

**NTU RGB+D 120**. NTU RGB+D 120 dataset extends NTU RGB+D by adding another 60 classes and another 57,600 samples. The dataset was completed by 106 volunteers and has 114,480 samples and 120 classes in total, including 82 daily actions, 12 health-related actions and 26 mutual actions. Like NTU RGB+D, the dataset is also divided by two different standards. For Cross-Subject (X-Sub), the 106 subjects are split into training and testing groups. Each group consists of 53 subjects. For Cross setup (X-Set) takes samples with even collection setup IDs as the training set and samples with odd setup IDs as the test set.

4.2 Experimental Setting

All experiments were performed on 2 GTX 3090 GPUs. All skeleton sequences are padded to 120 frames by replaying the actions. Our model is trained using a Stochastic Gradient Descent (SGD) optimizer with Nesterov momentum 0.9 and weight decay
0.0005, using cross entropy as the loss function. The training epoch is set to 90, the initial learning rate is 0.1, and it is adjusted to one-tenth at 60 and 80 epochs respectively. The batch size is 64. Each tuple contains 6 consecutive frames, that is, \( n = 6 \). The number of spatio-temporal self-attention layers is set to 8, and the output channels are 64, 64, 128, 128, 256, 256, 256, and 256, respectively.

4.3 Ablation Studies

In this section, the effectiveness of the proposed method is investigated on NTU RGB+D Skeleton dataset. For fair comparison, other settings are the same except for the explored object.

Ablation Studies for Position Encoding and IFFA

The effect of the position encoding and the IFFA module are investigated. As shown in Tab. 1, the accuracy of the STTFormer model without position encoding is lower than that of complete model, it shows that position encoding can significantly improve performance. The main reason is that different spatio-temporal joints play different roles in an action, and reasonable use of this sequence information will effectively improve performance.

Table 1. Ablation studies for position encoding and IFFA on the NTU RGB+D Skeleton dataset in joint mode. PE denotes position encoding.

| Method                  | X-Sub (%) | X-View (%) |
|-------------------------|-----------|------------|
| STTFormer without PE    | 89.3      | 91.8       |
| STTFormer without IFFA  | 84.5      | 88.1       |
| STTFormer               | 89.9      | 94.3       |

Tab. 1 also shows the effect of the IFFA module. It can be found that removing the IFFA module will seriously reduce the performance. The main reason is that the module can effectively model the relationship between sub-actions, which is conducive to distinguish similar actions, thereby improving the performance of the model.

Ablation Studies for STTA

In order to verify the effectiveness of our STTA module, a set of comparative experiments are constructed. The number of consecutive frames \( n \) contained in each tuple is set to 1 and 6, respectively. \( n = 1 \) means that only the relationship between intra-frame joints is modeled, The scheme is similar to Fig. 1(a); When \( n = 6 \), it means that the relationship between different joints in 6 consecutive frames is modeled at the same time. To ensure the fairness of the experiment, the kernel size \( k_1, k_2 \) are set to 1 to eliminate the influence of different convolution kernel sizes.

The experimental results are shown in Tab. 2. It is obvious that the proposed STTA can significantly improve the performance of the model. The main benefit is that the proposed STTA module can not only model the relationship between joints in a frame, but also capture the relationship between different joints in several consecutive frames, so as to improve the performance.
Table 2. Effect of spatio-temporal tuple attention evaluated on NTU RGB+D Skeleton dataset in joint mode.

| Method                  | X-Sub (%) | X-View (%) |
|-------------------------|-----------|------------|
| STTFormer \((n = 1; k_1, k_2 = 1)\) | 82.9      | 86.0       |
| STTFormer \((n = 6; k_1, k_2 = 1)\) | 86.2      | 91.3       |

Effect of Parameters \(n\)  The effects of the number of consecutive frames \(n\) on our model is explored, as shown in Fig. 5. It can be found that the accuracy of our model is the best when \(n = 6\), which is consistent with the fact. Because if \(n\) is too small, it cannot effectively extract features from the joints of insufficient consecutive frames; And if \(n\) is too large, the joint relationship between several consecutive frames is too complex, and the correlation between the first and last frames of each part is low.

Effect of Multi-Modes Data  Different patterns of data have different characteristics. Fusing multi-modes data can significantly improve performance. Like most SOTA methods, our model is trained using joint, bone and joint motion modes data respectively, and then average the reasoning outputs of our models to get the final results. The experimental results in Tab. 3 verify our viewpoint.

4.4 Comparison with the State-of-the-Art Methods  The proposed STTFormer method is compared with the state-of-the-art methods on two different datasets: NTU RGB+D, NTU RGB+D 120 Skeleton. Tab. 4 shows the com-
Table 3. Ablation studies for the multi-mode data on the NTU RGB+D Skeleton dataset.

| Method                  | X-Sub (%) | X-View (%) |
|-------------------------|-----------|------------|
| STTFormer (joint)       | 89.9      | 94.3       |
| STTFormer (bone)        | 88.8      | 93.3       |
| STTFormer (joint motion)| 87.0      | 93.6       |
| Fusion                  | 92.3      | 96.5       |

Comparison of recognition accuracy. The comparison methods include CNN-based, RNN-based, GCN-based and Transformer-based methods.

Table 4. Recognition accuracy comparison against state-of-the-art methods on NTU RGB+D and NTU RGB+D 120 Skeleton dataset.

| Methods      | NTU RGB+D  | NTU RGB+D 120 |
|--------------|------------|---------------|
|              | X-Sub (%)  | X-View (%)    | X-Sub (%)  | X-Set (%) |
| MTCNN[10]    | 81.1       | 87.4          | 61.2       | 63.3      |
| IndRNN[16]   | 81.8       | 88.0          | -          | -         |
| HCN[13]      | 86.5       | 91.1          | -          | -         |
| ST-GCN[38]   | 81.5       | 88.3          | -          | -         |
| 2s-AGCN[27]  | 88.5       | 95.1          | 82.9       | 84.9      |
| DGNN[25]     | 89.9       | 96.1          | -          | -         |
| Shift-GCN[5] | 90.7       | 96.5          | 85.9       | 87.6      |
| Dynamic-GCN[39]| 91.5     | 96.0          | 85.9       | 87.6      |
| MS-G3D[20]   | 91.5       | 96.2          | 86.9       | 88.4      |
| MST-GCN[4]   | 91.5       | **96.6**      | 87.5       | 88.8      |
| ST-TR[23]    | 89.9       | 96.1          | 82.7       | 84.7      |
| DSTA-Net[28] | 91.5       | 96.4          | 86.6       | 89.0      |
| STTFormer(Ours)| **92.3** | 96.5          | **88.3**   | **89.2**  |

Compared with the CNN and RNN-based methods [10,16,13], our proposed STTFormer has significant advantages. The main reason for the poor performance of the CNN and RNN-based methods is that they cannot fully utilize the information of skeleton data. In contrast, the GCN based methods can effectively use the topology of skeleton data and has better recognition performance.

Compared with the GCN-based methods [38,27,25,5,39,20,4], our method has certain advantages. The reason is that some actions depend on non-local joint interaction, and the STTFormer can fully utilize the interaction information.

Compared with the Transformer-based methods [23,28], our method also achieves state-of-the-art performance. The main benefit is that the STTFormer makes effective use of the correlation of non-local joints between frames.
5 Conclusion

In this work, we propose a novel spatio-temporal tuples Transformer (STTFormer) method for skeleton-based action recognition. Our method consists of two modules: STTA and IFFA. The STTA module is used to effectively capture the relationship between different joints in continuous frames, and the IFFA module is used to aggregate the characteristics of several sub-action segments. Ablation studies show the effectiveness of the proposed method. On two large-scale datasets NTU RGB+D and NTU RGB+D 120 Skeleton, the proposed STTFormer achieves better performance with the existing state-of-the-art methods.

References

1. Anurag Arnab, Mostafa Dehghani, Georg Heigold, Chen Sun, Mario Lučić, and Cordelia Schmid. Vivit: A video vision transformer. ArXiv, abs/2103.15691, 2021. 3
2. Gedas Bertasius, Heng Wang, and Lorenzo Torresani. Is space-time attention all you need for video understanding? In The Thirty-eighth International Conference on Machine Learning, Jul 2021. 3
3. Nicolas Carion, Francisco Massa, Gabriel Synnaeve, Nicolas Usunier, Alexander Kirillov, and Sergey Zagoruyko. End-to-end object detection with transformers. In European Conference on Computer Vision (ECCV 2020), pages 213–229, Cham, 2020. 3
4. Zhan Chen, Sicheng Li, Bing Yang, Qinghan Li, and Hong Liu. Skeleton-based action recognition with shift graph convolutional network. In Proceedings of the AAAI Conference on Artificial Intelligence, pages 1113–1122, 2021. 11
5. Ke Cheng, Yifan Zhang, Xiangyu He, Weihan Chen, Jian Cheng, and Hangqing Lu. Skeleton-based action recognition with shift graph convolutional network. In 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pages 180–189, 2020. 11
6. Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, Jakob Uszkoreit, and Neil Houlsby. An image is worth 16x16 words: Transformers for image recognition at scale. ArXiv, abs/2010.11929, 2021. 3
7. Haodong Duan, Yue Zhao, Kai Chen, Dian Shao, Dahua Lin, and Bo Dai. Revisiting skeleton-based action recognition. ArXiv, abs/2104.13586, 2021. 1
8. Xiaoke Hao, Jie Li, Yingchun Guo, Tao Jiang, and Ming Yu. Hypergraph neural network for skeleton-based action recognition. IEEE Transactions on Image Processing, 30:2263–2275, 2021. 1
9. Jian-Fang Hu, Wei-Shi Zheng, Jianhuang Lai, and Jianguo Zhang. Jointly learning heterogeneous features for rgb-d activity recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, 39(11):2186–2200, 2017. 3
10. QiuHong Ke, Mohammed Bennamoun, Senjian An, Ferdous Sohel, and Farid Boussaid. Learning clip representations for skeleton-based 3d action recognition. IEEE Transactions on Image Processing, 27(6):2842–2855, 2018. 11
11. Ce Li, Chunyu Xie, Baochang Zhang, Jungong Han, Xiantong Zhen, and Jie Chen. Memory attention networks for skeleton-based action recognition. IEEE Transactions on Neural Networks and Learning Systems, pages 1–15, 2021. 1
12. Chao Li, Qiaoyong Zhong, Di Xie, and Shiliang Pu. Skeleton-based action recognition with convolutional neural networks. In 2017 IEEE International Conference on Multimedia Expo Workshops (ICMEW), pages 597–600, 2017. 1, 3
13. Chao Li, Qiaoyong Zhong, Di Xie, and Shiliang Pu. Co-occurrence feature learning from skeleton data for action recognition and detection with hierarchical aggregation. In Proceedings of the 27th International Joint Conference on Artificial Intelligence, pages 786–792, 2018. 11

14. Jianan Li, Xuemei Xie, Zhifu Zhao, Yuhan Cao, Qingzhe Pan, and Guangming Shi. Temporal graph modeling for skeleton-based action recognition. ArXiv, abs/2012.08804, 2020. 4

15. Maosen Li, Siheng Chen, Xu Chen, Ya Zhang, Yanfeng Wang, and Qi Tian. Symbiotic graph neural networks for 3d skeleton-based human action recognition and motion prediction. IEEE Transactions on Pattern Analysis and Machine Intelligence, pages 1–1, 2021. 1

16. Shuai Li, Wanqing Li, Chris Cook, Ce Zhu, and Yanbo Gao. Independently recurrent neural network (indrnn): Building a longer and deeper rnn. In 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 5457–5466, 2018. 11

17. Yanshan Li, Rongjie Xia, and Xing Liu. Learning shape and motion representations for view invariant skeleton-based action recognition. Pattern Recognition, 103:107293, 2020. 3

18. Jun Liu, Amir Shahroudy, Mauricio Perez, Gang Wang, Ling-Yu Duan, and Alex C. Kot. Ntu rgb+d 120: A large-scale benchmark for 3d human activity understanding. IEEE Transactions on Pattern Analysis and Machine Intelligence, 42(10):2684–2701, 2020. 8

19. Mengyuan Liu, Hong Liu, and Chen Chen. Enhanced skeleton visualization for view invariant human action recognition. Pattern Recognition, 68:346–362, 2017. 1, 3

20. Ziyu Liu, Hongwen Zhang, Zhenghao Chen, Zhiyong Wang, and Wanli Ouyang. Disentangling and unifying graph convolutions for skeleton-based action recognition. In 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pages 140–149, Seattle, WA, USA, Jun 2020. 1, 4, 11

21. Yuya Obinata and Takuma Yamamoto. Temporal extension module for skeleton-based action recognition. In 2020 25th International Conference on Pattern Recognition (ICPR), pages 534–540, 2021. 4

22. Wei Peng, Xiaopeng Hong, and Guoying Zhao. Tripool: Graph triplet pooling for 3d skeleton-based action recognition. Pattern Recognition, 115:107921, 2021. 1

23. Chiara Plizzari, Marco Cannici, and Matteo Matteucci. Skeleton-based action recognition via spatial and temporal transformer networks. Computer Vision and Image Understanding, 208-209:103219, 2021. 1, 2, 3, 11

24. Amir Shahroudy, Jun Liu, Tian-Tsong Ng, and Gang Wang. Ntu rgb+d: A large scale dataset for 3d human activity analysis. In 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 1010–1019, 2016. 8

25. Lei Shi, Yifan Zhang, Jian Cheng, and Hanqing Lu. Skeleton-based action recognition with directed graph neural networks. In 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pages 7904–7913, 2019. 11

26. Lei Shi, Yifan Zhang, Jian Cheng, and Hanqing Lu. Two-stream adaptive graph convolutional networks for skeleton-based action recognition. In 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pages 12018–12027, Long Beach, CA, USA, Jun 2019. 1, 4

27. Lei Shi, Yifan Zhang, Jian Cheng, and Hanqing Lu. Two-stream adaptive graph convolutional networks for skeleton-based action recognition. In 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pages 12018–12027, 2019. 11

28. Lei Shi, YiFan Zhang, Jian Cheng, and Hanqing Lu. Decoupled spatial-temporal attention network for skeleton-based action recognition. In Asian Conference on Computer Vision, 2020. 1, 2, 6, 11

29. Chenyang Si, Wentao Chen, Wei Wang, Liang Wang, and Tieniu Tan. An attention enhanced graph convolutional lstm network for skeleton-based action recognition. In 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pages 1227–1236, 2019. 1, 3
30. Chenyang Si, Ya Jing, Wei Wang, Liang Wang, and Tieniu Tan. Skeleton-based action recognition with spatial reasoning and temporal stack learning. In Computer Vision – ECCV 2018, pages 106–121, Cham, 2018. Springer International Publishing.

31. Chenyang Si, Ya Jing, Wei Wang, Liang Wang, and Tieniu Tan. Skeleton-based action recognition with hierarchical spatial reasoning and temporal stack learning network. Pattern Recognition, 107:107511, 2020.

32. Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. In Proceedings of the 31st International Conference on Neural Information Processing Systems, pages 6000–6010, Red Hook, NY, USA, 2017.

33. Raviteja Vemulapalli, Felipe Arrate, and Rama Chellappa. Human action recognition by representing 3d skeletons as points in a lie group. In 2014 IEEE Conference on Computer Vision and Pattern Recognition, pages 588–595, 2014.

34. Qingtian Wang, Jianlin Peng, Shuze Shi, Tingxi Liu, Jiabin He, and Renliang Weng. Ip-transformer: Intra-inter-part transformer for skeleton-based action recognition, 2021.

35. Xiaolong Wang, Ross Girshick, Abhinav Gupta, and Kaiming He. Non-local neural networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 7794–7803, June 2018.

36. Shenghua Wei, Yonghong Song, and Yuanlin Zhang. Human skeleton tree recurrent neural network with joint relative motion feature for skeleton based action recognition. In 2017 IEEE International Conference on Image Processing (ICIP), pages 91–95, 2017.

37. Haiping Wu, Bin Xiao, Noel C. F. Codella, Mengchen Liu, Xiyang Dai, Lu Yuan, and Lei Zhang. Cvt: Introducing convolutions to vision transformers. ArXiv, abs/2103.15808, 2021.

38. Sijie Yan, Yuanjun Xiong, and Dahua Lin. Spatial temporal graph convolutional networks for skeleton-based action recognition. In In Proceedings of the AAAI conference on artificial intelligence, 2018.

39. Fanfan Ye, Shiliang Pu, Qiaoyong Zhong, Chao Li, Di Xie, and Huiming Tang. Dynamic gcn: Context-enriched topology learning for skeleton-based action recognition. In Proceedings of the 28th ACM International Conference on Multimedia, pages 55–63, New York, NY, USA, 2020.

40. Xikun Zhang, Chang Xu, and Dacheng Tao. Context aware graph convolution for skeleton-based action recognition. In 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pages 14321–14330, 2020.

41. Minghang Zheng, Peng Gao, Xiaogang Wang, Hongsheng Li, and Hao Dong. End-to-end object detection with adaptive clustering transformer. ArXiv, abs/2011.09315, 2020.

42. Aichun Zhu, Qianyu Wu, Ran Cui, Tian Wang, Wenlong Hang, Gang Hua, and Hichem Snoussi. Exploring a rich spatial-temporal dependent relational model for skeleton-based action recognition by bidirectional lstm-cnn. Neurocomputing, 414:90–100, 2020.