SequentialPointNet: A strong parallelized point cloud sequence classification network for 3D action recognition

Xing Li, Qian Huang, Zhijian Wang, Zhenjie Hou, and Tianjin Yang

Abstract—Point cloud sequences of 3D human actions exhibit unordered intra-frame spatial information and ordered inter-frame temporal information. In order to capture the spatio-temporal structures of the point cloud sequences, cross-frame spatio-temporal local neighborhoods around the centroids are usually constructed. However, the computationally expensive construction procedure of spatio-temporal local neighborhoods severely limits the parallelism of models. Moreover, it is unreasonable to treat spatial and temporal information equally in spatio-temporal local learning, because human actions are complicated along the spatial dimensions and simple along the temporal dimension. In this paper, to avoid spatio-temporal local encoding, we propose a strong parallelized point cloud sequence network referred to as SequentialPointNet for 3D action recognition. SequentialPointNet is composed of two serial modules, i.e., an intra-frame appearance encoding module and an inter-frame motion encoding module. For modeling the strong spatial structures of human actions, each point cloud frame is processed in parallel in the intra-frame appearance encoding module and the feature vector of each frame is output to form a feature vector sequence that characterizes static appearance changes along the temporal dimension. For modeling the weak temporal changes of human actions, in the inter-frame motion encoding module, the temporal position encoding and the hierarchical pyramid pooling strategy are implemented on the feature vector sequence. In addition, in order to better explore spatio-temporal content, multiple level features of human movements are aggregated before performing the end-to-end 3D action recognition. Extensive experiments conducted on three public datasets show that SequentialPointNet outperforms state-of-the-art approaches. SequentialPointNet’s code is available at https://github.com/XingLi1012/SequentialPointNet.git.

Index Terms—3D Action recognition, Point cloud sequence, Parallelized network.

I. INTRODUCTION

With the release of low-cost depth cameras, 3D human action recognition has attracted more and more attention from researchers. 3D human action recognition can be divided into three categories based on different data types: 1) skeleton sequence-based 3D human action recognition [1]–[5], 2) depth sequence-based 3D human action recognition [6]–[11], 3) point cloud sequence-based 3D human action recognition [12]–[14]. Compared with skeleton sequence-based approaches, data of point cloud sequence-based methods are more convenient to be collected without additional pose estimation algorithms. Compared with depth sequence-based approaches, point cloud sequence-based methods yield lower computation costs. For these reasons, we focus on point cloud sequence-based 3D human action recognition in this work.

Due to the complex data structures, capturing the spatio-temporal textures from point cloud sequences is extremely challenging. An intuitive way is to convert point cloud sequences to 3D point clouds and employ static point cloud methods, e.g., PointNet++ [15], to process 3D point clouds. However, using static 3D point clouds to represent the entire point cloud sequence loses a lot of spatio-temporal information, which reduces the recognition performance. Therefore, point cloud sequence methods are necessary, which directly consumes the point cloud sequence for 3D human action classification. In order to model the dynamics of point cloud sequences, cross-frame spatio-temporal local neighborhoods around the centroids are usually constructed [16]–[18]. Then, point convolution [16] or PointNet [17], [18] are used to encode the spatio-temporal local structures. However, constructing cross-frame spatio-temporal local neighborhoods can be time-consuming and is not conducive to parallel computing. Moreover, the spatial structures and temporal changes of the point cloud sequence have different importance for recognizing human actions. Compared with the scales of spatial displacements, temporal changes are simple when performing actions and do not require complicated temporal inference.

In this paper, we propose a simple but effective strong parallelized point cloud sequence network called SequentialPointNet, which avoids spatio-temporal local encoding. As point cloud sequences are spatially irregular and complex but ordered and simple in the temporal dimension, the spatial and temporal information is decoupled to model point cloud sequences. Specifically, SequentialPointNet is composed of two serial modules, i.e., an intra-frame appearance encoding module and an inter-frame motion encoding module. The spatial structures and temporal changes are modeled independently in these two serial modules. In the intra-frame appearance encoding module, in order to capture irregular complex spatial structures, the shared PointNet++ is applied to abstract each point cloud frame into a feature vector summarizing the static appearance. A feature vector sequence composed of the feature vectors from all point cloud frames is taken as the input of the inter-frame motion encoding.
module. In the inter-frame motion encoding module, we do not perform strict temporal inference on the feature vector sequence. Inspired by Transformer [19], position encoding is employed to inject temporal information into the feature vector sequence, which makes the symmetry function, i.e., maximum pooling operation performed on feature vector sequences capable of capturing temporal changes. In addition, in order to better capture spatio-temporal information, a multi-level feature learning architecture is designed to concatenate different level features of human actions before performing 3D action recognition. In our SequentialPointNet, different point cloud frames share the same network architectures and network weights before the final classification network layer. Therefore, SequentialPointNet is a strong parallelized point cloud sequence network.

Our main contributions are summarized as follows:

- To the best of our knowledge, we are the first to point out the human action property of strong spatial structures and weak temporal changes and design our point cloud network based on this property.
- We propose a strong parallelized point cloud sequence classification network, dubbed SequentialPointNet, to recognize 3D human actions. To the best of our knowledge, our SequentialPointNet is the first deep neural network to model point cloud sequences without constructing cross-frame spatio-temporal local neighborhoods.
- To the best of our knowledge, SequentialPointNet is the first point cloud sequence network to inject order information using the temporal position encoding.
- Our SequentialPointNet achieves the cross-view accuracy of 97.6% on the NTU RGB+D 60 dataset, the cross-setup accuracy of 95.4% on the NTU RGB+D 120 dataset, and the cross-subject accuracy of 91.94% on the MSR Action3D dataset, which outperforms the state-of-the-art methods.

II. RELATED WORK

A. Static Point Cloud Modeling

With the popularity of low-cost 3D sensors, deep learning on static point clouds has attracted much attention from researchers due to extensive applications ranging from object classification [20]–[24], part segmentation [25]–[29], to scene semantic parsing [30], [31]. Static point clouds modeling can be divided into volumetric-based methods [32]–[37] and point-based methods [38]–[41]. Volumetric-based methods usually voxelize a point cloud into 3D grids, and then a 3D Convolutional Neural Network (CNN) is applied on the volumetric representation for classification. Point-based methods are directly performed on raw point clouds. PointNet [42] is a pioneering effort that directly processes point sets. The key idea of PointNet is to abstract each point using a set of Multi-layer Perceptrons (MLPs) and then assemble all individual point features by a symmetry function, i.e., a max pooling operation. By its design, PointNet lacks the ability to capture local structures. Therefore, in [15], a hierarchical network PointNet++ is proposed to encode fine geometric structures from the neighborhood of each point. PointNet++ is made of several set abstraction levels. A set abstraction level is composed of three layers: sampling layer, grouping layer, and PointNet-based learning layer. By stacking several set abstraction levels, PointNet++ progressively abstracts larger and larger local regions along the hierarchy.

B. Time Sequence Modeling

Sequential data widely exist in various research fields, such as text, audio, and video. The point cloud sequence is also a kind of sequential data. Time sequence models have been studied by the natural language processing community for decades. The emergence of Recurrent Neural Networks (RNN) [43]–[46] pushes the boundaries of time series models. Due to the capability of extracting high-dimensional features to learn complex patterns, RNN performs time-series point prediction. LSTM [47] captures the contextual representations of words with a short memory and has additional “forget” gates to thereby overcoming both the vanishing and exploding gradient problem. GRU [48] comprises of reset gate and update gate, and handles the information flow like LSTM sans a memory unit. TextCNN [49] obtains feature representation through 1-dim convolution. It has a strong ability to extract shallow features of the text. Transformer [19], a fully-connected attention model, models the dependency between words in the sequence. Since the model includes no recurrence and no convolution, Transformer secures the relative or absolute position within the sequence by injecting positional encoding.

C. Point Cloud Sequence-based 3D Human Action Recognition

Point cloud sequence-based 3D human action recognition is a fairly new and challenging task. To capture spatio-temporal information from point cloud sequences, one solution is to convert point cloud sequences to 3D point clouds and employ static point cloud methods, e.g., PointNet++, to process 3D point clouds. 3DV-PointNet++ [50] is the first work to recognize human actions from point cloud sequences. In 3DV-PointNet++, 3D dynamic voxel (3DV) is proposed as a novel 3D motion representation. A set of points is extracted from 3DV and input into PointNet++ for 3D action recognition in the end-to-end learning way. However, since the point cloud sequence is converted into a static 3D point cloud set, 3DV loses a lot of spatio-temporal information and increases additional computational costs.

To overcome this problem, researchers have focused mainly on investigating point cloud sequence networks that directly consume point cloud sequences for human action recognition. MeteorNet [16] is the first work on deep learning for modeling point cloud sequences. In MeteorNet, two ways are proposed to construct spatio-temporal local neighborhoods for each point in the point cloud sequence. The abstracted feature of each point is learned by aggregating the information from these neighborhoods. Fan et al. [17] propose a Point spatio-temporal (PST) convolution to encode the spatio-temporal local structures of point cloud sequences. PST convolution first disentangles space and time in point cloud sequences. Furthermore, PST convolutions are incorporated into a deep network namely PSTNet to model point cloud sequences in...
Fig. 1. The overall flowchart of the proposed SequentialPointNet

a hierarchical manner. To avoid point tracking, Point 4D Transformer (P4Transformer) network [18] is proposed to model point cloud videos. Specifically, P4Transformer consists of (i) a point 4D convolution to embed the spatio-temporal local structures presented in a point cloud video and (ii) a Transformer to encode the appearance and motion information by performing self-attention on the embedded local features. However, in these point cloud sequence networks, cross-frame spatio-temporal local neighborhoods are usually constructed during modeling point cloud sequences, and the construction of spatio-temporal local neighborhoods is quite time-consuming and limits the parallel ability of networks.

Our SequentialPointNet does not construct spatio-temporal local neighborhoods to model dynamic point clouds. According to the human action property of strong spatial structures and weak temporal changes, in SequentialPointNet, spatial structures and temporal changes are independently encoded in two serial modules. In this fashion, each point cloud frame is processed in a completely parallel manner.

III. METHODOLOGY

In this section, we introduce the proposed SequentialPointNet in detail. SequentialPointNet can be regarded as an extension of PointNet++ from static point clouds to point cloud sequences. SequentialPointNet inherits the excellent parallel computing capability of PointNet++. The overall flowchart of SequentialPointNet is described in Fig. 1. As shown in the figure, SequentialPointNet consists of an intra-frame appearance encoding module and an inter-frame motion encoding module. These two modules are executed serially. In addition, the multi-level feature learning architecture is designed to collect the action features learned at each stage of the network and finally send them to the fully connected neural network for action classification. In section 3.1, we first introduce the intra-frame appearance encoding module. In the intra-frame appearance encoding module, the point cloud set of each frame is input and the static appearance feature vector of the corresponding frame is output. In section 3.2, we then introduce the inter-frame motion encoding module. In this module, a feature vector sequence composed of static appearance feature vectors from all frames is taken as input, which is modeled simply and efficiently to characterize the dynamic information. In section 3.3, the multi-level feature learning architecture is introduced.

A. Intra-frame appearance encoding module

When several silhouettes in human action are observed, even without knowing their order, we can perform effective action recognition according to the static appearances. Based on this fact, we propose a hypothesis that human action has the property of strong spatial structures and weak temporal changes. This property means that the spatial structures of the point cloud sequence are more important than the temporal changes for recognizing human actions, which motivates us to decouple spatial and temporal dimensions. In this work, we encode spatial and temporal contents serially. In order to capture the fine-grained spatial texture of human action, an intra-frame appearance encoding module is developed.

In the intra-frame appearance encoding module, each point cloud frame is abstracted into a feature vector by static point cloud processing technology to summarize human static appearance. In our work, the set abstract operation from PointNet++ is improved and recursively used. The intra-frame appearance encoding module is shown in Fig. 2. The set abstraction operation in our work is made of three key layers: sampling layer, grouping layer, and improved PointNet layer. Specifically, let $S = \{S_t\}_{t=1}^T$ denotes a point cloud sequence of $T$ frames, and $S_t = \{x_{t1}, x_{t2}, ..., x_{tn}\}$ denotes the unordered
In the grouping layer, a point set of size \( n_{m-1} \times (d + c_{m-1}) \) and the coordinates of a set of centroids of size \( n_m \times d \) are taken as input. The output is \( n_m \) groups of point sets of size \( n_m \times k_m \times (d + c_{m-1}) \), where each group corresponds to a local region and \( k_m \) is the number of local points in the neighborhood of centroid points. Ball query finds all points that are within a radius to the query point, in which an upper limit of \( k_m \) is set.

The improved PointNet layer in the set abstraction operation is made of an inter-feature attention mechanism, a set of MLPs, and a max pooling operation. The input of this layer is \( n_m \) local regions of points with data size \( n_m \times k_m \times (d + c_{m-1}) \). First, the coordinates of points in a local region are translated into a local frame relative to the centroid point. Second, the distance between each local point and the corresponding centroid is used as a 1-dim additional point feature to alleviate the influence of rotational motion on action recognition. Then, an inter-feature attention mechanism is used to optimize the fusion effect of different features. The inter-feature attention mechanism is realized by Convolutional Block Attention Module (CBAM) in [51]. It is worth mentioning that the inter-feature attention mechanism is not used in the first set abstraction operation due to only the 1-dim point feature. In the following, a set of MLPs are applied to abstract the features of each local point. Then, the representation of a local region is generated by incorporating the abstracted features of all local points using a max pooling operation. Finally, the coordinates of a centroid point and its local region representation are concatenated as abstracted features of this centroid point. The improved PointNet layer is formalized as follows:

\[
    r^i_j = \max_{i=1,\ldots,k_m} \{ \text{MLP} \left( \left[ \left( t^i_{j,i} - o^i_j \right) \odot c^i_{j,i} \oplus p^i_{j,i} \right] \odot A \right) \} \oplus o^i_j
\]

where \( t^i_{j,i} \) is the coordinates of \( i \)-th point in the \( j \)-th local region from the \( t \)-th point cloud frame. \( o^i_j \) and \( p^i_{j,i} \) are the coordinates of the centroid point and the point features corresponding to \( t^i_{j,i} \), respectively. \( c^i_{j,i} \) is the Euclidean distance between \( t^i_{j,i} \) and \( o^i_j \). \( A \) is the attention mechanism with \((3+1+c_{m-1})\)-dim scores corresponding to the coordinates and features of each point. Attention scores in \( A \) are shared among all local points from all point cloud frames. \( \odot \) and \( \oplus \) are the concatenation operation and dot product operation, respectively. \( r^i_j \) is the abstracted features of the \( j \)-th centroid point from the \( t \)-th point cloud frame.

The set abstract operation is performed twice in our SequentialPointNet. Finally, in order to characterize the spatial appearance information of the entire point cloud frame, a set of MLPs and a max pooling operation are used as follows:

\[
    f_t = \max_{j=1,\ldots,n_2} \{ \text{MLP} \left( r^i_j \right) \}
\]

where \( f_t \) is the feature vector of the \( t \)-th point cloud frame. So the feature vector sequence is represented as \( F = \{ f_t \}_{t=1}^T \).

**B. Inter-frame motion encoding module**

Spatio-temporal human actions are a kind of data with strong spatial structures and weak temporal changes. To encode temporal information of human actions, we propose the inter-frame motion coding module as shown in Fig. 3. The inter-frame motion coding module is made of three key layers: temporal position embedding layer, shared MLP layer, and hierarchical pyramid max pooling layer. The temporal position embedding layer injects temporal position information to make
use of the order of the feature vector sequence. The shared MLP layer performs a set of MLPs on each individual feature vector to abstract the spatio-temporal information of each point cloud frame. The hierarchical pyramid max pooling layer is employed to extract the sequential spatial information on multiple temporal scales.

**Temporal position embedding layer.** Given the input feature vector sequence $F = \{f_t\}_{t=1}^T$, we inject order information by adding position encoding. We use the same sine and cosine functions of different frequencies used in Transformer [19] as the temporal position encoding:

$$PE_{t,2h} = \sin \left( \frac{t}{10000^{2h/d_{\text{out}}}} \right)$$

$$PE_{t,2h+1} = \cos \left( \frac{t}{10000^{2h/d_{\text{out}}}} \right)$$

where $d_{\text{out}}$ denotes the dimensions of feature vectors. $t$ is the temporal position and $h$ is the dimension position. The feature vector is updated by adding the position encoding as follows:

$$\hat{f}_{t,h} = f_{t,h} + PE_{t,h}$$

where $\hat{f}_{t}$ is the new feature vector after temporal position embedding. After that, we generate a new feature vector sequence $\hat{F} = \{\hat{f}_t\}_{t=1}^T$.

**Shared MLP layer.** After the temporal position embedding layer, the order information is simply embedded into the spatial information sequence. In order to further abstract the spatio-temporal information, a set of MLPs is applied to each feature vector:

$$\tilde{f}_t = \text{MLP} \left( \hat{f}_t \right)$$

where $\tilde{f}_t$ denotes the updated feature vector using MLP operation. After that, we generate an updated feature vector sequence $\tilde{F} = \{\tilde{f}_t\}_{t=1}^T$.

**Hierarchical pyramid max pooling layer.** In this layer, the max pooling operation is used to aggregate the multiple feature vectors. In order to capture the subactions within the point cloud sequence, encoding more discriminative movement information, the hierarchical pyramid max pooling strategy is proposed and illustrated in Fig. 4, which divides the vector sequence $F$ into multiple temporal partitions of the equal number of point cloud frames and then performs the max pooling operation in each partition to generate the corresponding descriptors. In this work, we employ a 2-layer pyramid with three partitions. Finally, the descriptors from all temporal partitions are simply concatenated to form the sequence-level feature $E$ of human actions.

### C. Multi-level feature learning architecture

SequentialPointNet takes point cloud sequences as the input and is able to progressively capture action features at increasingly larger scales along a multi-level hierarchy. In order to obtain sufficient human movement information, multi-level feature learning architecture is designed to integrate different levels of human action features from each stage of the network. To this end, besides the sequence-level features generated by the hierarchical pyramid max pooling layer, additional partition-level features $P$ and frame-level features $R$ are also extracted as follows:

$$P = \text{MAX}_{t=1,\ldots,T} \left\{ \text{MAX}_{j=1,\ldots,n_2} \{r_{t,j}\} \right\}$$

$$R = \text{MAX}_{t=1,\ldots,T} \{f_t\}$$

where $r_{t,j}$ is the abstracted features generated from the second set abstract operation in the intra-frame appearance encoding module.

Finally, $E$, $P$, and $R$ are simply connected and sent to a set of MLPs for human action recognition.
IV. EXPERIMENTS

In this section, we firstly introduce the datasets and experimental implementation details. Then, we compare our SequentialPointNet with the existing state-of-the-art methods. Again, we conduct detailed ablation studies to further demonstrate the contributions of different components in our SequentialPointNet. Finally, we compare the running time of our SequentialPointNet with 3DV-PointNet++.

A. Datasets

We evaluate the proposed method on two large-scale public datasets (i.e., NTU RGB+D 60 [52] and NTU RGB+D 120 [53]) and a small-scale public dataset (i.e., MSR Action3D dataset [54]).

The NTU RGB+D 60 dataset is composed of 56880 depth video sequences for 60 actions and is one of the largest human action datasets. Both cross-subject and cross-view evaluation criteria are adopted for training and testing.

The NTU RGB+D 120 dataset is the largest dataset for 3D action recognition, which is an extension of the NTU RGB-D 60 dataset. The NTU RGB+D 120 dataset is composed of 114480 depth video sequences for 120 actions. Both cross-subject and cross-set evaluation criteria are adopted for training and testing.

The MSR Action3D dataset contains 557 depth video samples of 20 actions from 10 subjects. Each action is performed 2 or 3 times by each subject. We adopt the same cross-subject settings in [54], where all the 20 actions were employed. Half of the subjects are used for training and the rest for testing.

B. Implementation details

Each depth frame is converted to the point cloud set using the public code provided by 3DV-PointNet++. We sample 512 points from the point cloud set as a point cloud frame. Specifically, we first randomly sample 2048 points from the point cloud set. Then, 512 points are chosen from the 2048 points using the FPS algorithm. In the intra-frame appearance encoding module, the set abstraction operation is performed twice on each point cloud frame to model spatial structures. In the first set abstraction operation, 128 centroids are chosen to determine point groups. The group radius is set to 0.06. The point number in each point group is set to 48. In the second set abstraction operation, 32 centroids are chosen to determine point groups. The group radius is set to 0.1. The point number in each point group is set to 16. The same data augmentation strategies in 3DV-PointNet++ are adopted on training data, including random rotation around Y and X axis, jittering, and random points dropout. We apply Adam as the optimizer. The batch size is set to 32. The learning rate begins with 0.001 and decays with a rate of 0.5 every 10 epochs. Training will end when reaching 90 epochs.

Details on the network architecture. We provide the details of SequentialPointNet as follows. In the intra-frame appearance encoding module, three sets of MLPs are used (i.e., two sets of MLPs are used in two set abstraction operations and another set of MLPs are used to further abstract the features generated by the second set abstraction operation). Each set of MLPs includes three MLPs. The out channels of the first set of MLPs are set as 64, 64, and 128, respectively. The out channels of the second set of MLPs are set as 128, 256, and 256, respectively. The out channels of the third set of MLPs are set as 256, 512, and 1024, respectively. In the inter-frame motion encoding module, only one MLP is used in the shared MLP layer, where the output channel of this MLP is set as 1024. The output channels of the final a set of MLPs used as the classifier are set as 256 and the number of action categories.

C. Comparison with the state-of-the-art methods

In this section, in order to verify the performance of our SequentialPointNet, comparison experiments with other state-of-the-art approaches are implemented on NTU RGB+D 60 dataset, NTU RGB+D 120 dataset, and MSR Action3D dataset.

1) NTU RGB+D 60 dataset: We first compare our SequentialPointNet with the state-of-the-art methods on the NTU RGB+D 60 dataset. The NTU RGB+D 60 dataset is a large-scale indoor human action dataset. As indicated in Table I, SequentialPointNet achieves 90.3% and 97.6% on the cross-subject and cross-view test settings, respectively. Although there is a small gap between our method and skeleton sequence-based DDGCN on the cross-subject test setting, SequentialPointNet surpasses DDGCN by 0.5% on the cross-view test setting. It is worth mentioning that SequentialPointNet shows strong performance on par or even better than other point sequence-based approaches. Our SequentialPointNet achieves state-of-the-art performance among all methods on the cross-view test setting and results in similar recognition accuracy as PSTNet on the cross-subject test setting.

| Method/Year | Input | Cross-subject | Cross-view |
|-------------|-------|---------------|------------|
| Wang et al. (2018) [55] | depth | 87.1 | 84.2 |
| MVDI (2019) [56] | depth | 84.6 | 87.3 |
| 3DFCNN (2020) [57] | depth | 78.1 | 80.4 |
| Stateful ConvLSTM (2020) [58] | depth | 80.4 | 79.9 |
| ST-GCN (2018) [59] | skeleton | 81.5 | 88.3 |
| AS-GCN (2019) [60] | skeleton | 86.8 | 94.2 |
| 2x-AGCN (2019) [61] | skeleton | 88.5 | 95.1 |
| DGNN (2019) [62] | skeleton | 89.9 | 96.1 |
| DDGCN (2020) [63] | skeleton | 91.1 | 97.1 |
| 3s-CrossCLR (2021) [64] | skeleton | 86.2 | 92.5 |
| Sym-GNN (2021) [65] | skeleton | 90.1 | 96.4 |
| 3DV-PointNet++ (2020) [50] | point | 88.8 | 96.3 |
| P4Transformer (2021) [18] | point | 90.2 | 96.4 |
| PSTNet (2021) [17] | point | 90.5 | 96.5 |
| SequentialPointNet (ours) | point | 90.3 | 97.6 |

2) NTU RGB+D 120 dataset: We then compare our SequentialPointNet with the state-of-the-art methods on the NTU RGB+D 120 dataset. The NTU RGB+D 120 dataset is the...
largest dataset for 3D action recognition. Compared with NTU RGB+D 60 dataset, it is more challenging to perform 3D human motion recognition on the NTU RGB+D 120 dataset. As indicated in Table II, SequentialPointNet achieves 83.5% and 95.4% on the cross-subject and cross-setup test settings, respectively. Note that, on the NTU RGB+D 120 dataset, SequentialPointNet gains a strong lead on the cross-setup test setting among all 3D human action recognition methods and achieves state-of-the-art performance.

3) MSR Action3D dataset: In order to comprehensively evaluate our method, comparative experiments are also carried out on the small-scale MSR Action3D dataset. In order to alleviate the overfitting problem on the small-scale dataset, the batch size is set as 16. Other parameter settings remain the same as those on the two large-scale datasets. Table III illustrates the recognition accuracy of different methods when using different numbers of point cloud frames. It’s interesting to see that, as the number of point cloud frames increases, the recognition accuracy of our method increases faster than MeteorNet, P4Transformer, and PSTNet. When using 24 point cloud frames as inputs, our model achieved state-of-the-art performance on the MSR Action3D dataset.

D. Ablation study

In this section, comprehensive ablation studies are performed on NTU RGB+D 60 dataset to validate the contributions of different components in our SequentialPointNet.

1) Verification of the human action property of strong spatial structures and weak temporal changes: Our input is a point cloud sequence captured from human action. It has an important property: strong spatial structures and weak temporal changes. This property means that the spatial structures of the point cloud sequence are more important than the temporal changes for recognizing 3D human actions. This property is the essential basis for designing our SequentialPointNet. We conduct the experiments to demonstrate the strong spatial structures and weak temporal changes of human actions, and the results are reported in Table IV. In this ablation study, since additional spatial information is provided, all of the models do not adopt the multi-level feature learning architecture. Specifically, in order to prove the strong spatial structures of human actions, in SequentialPointNet (w/o tpe, 1lhp, w/o mlfl), we perform the inter-frame motion encoding module with 1-layer hierarchical pyramid max pooling operation and without the temporal position embedding layer. Therefore, the sequence-level features generated by SequentialPointNet (w/o tpe, 1lhp, w/o mlfl) are the union of the spatial appearance contours from all the point cloud frames, which have no temporal information and cannot reflect the execution order of human actions. In order to prove the weak temporal changes of human actions, several powerful time sequence models are used instead of the inter-frame motion encoding module to encode temporal information. In SequentialPointNet (lstm, w/o mlfl), LSTM is employed. In SequentialPointNet (gru, w/o mlfl), GRU is employed. In SequentialPointNet (textcnn, w/o mlfl), TextCNN is used. In addition, SequentialPointNet (ifme, w/o mlfl) containing the complete inter-frame motion encoding module is used as a reference.

We can see from the table that SequentialPointNet (w/o tpe, 1lhp, w/o mlfl) has a recognition accuracy of 94.3%, which supports our intuition that human actions yield strong spatial structures. Even without the aid of temporal information, only spatial information is able to achieve high-precision recognition of human actions. Additionally, this table shows that results of SequentialPointNet (lstm, w/o mlfl), SequentialPointNet (gru, w/o mlfl), and SequentialPointNet (textcnn, w/o mlfl) are close to each other, which verifies the effectiveness of the inter-frame motion encoding module.

Table III: Action recognition accuracy (%) on MSR-Action3D

| Method/Year            | Input | # Frames | Accuracy |
|------------------------|-------|----------|----------|
| Kläser et al.(2008) [69]| depth | 18       | 81.43    |
| Vieira et al.(2012) [70]| depth | 20       | 78.20    |
| Actionlet (2012) [71]  | skeleton | all      | 88.21    |
| 4s Shift-GCN(2020) [67] | skeleton | 4        | 81.14    |
| 3s-CrosSCLR(2021) [64] | skeleton | 8        | 86.53    |
| 3DV-PointNet++(2020) [50] | point | 12       | 91.20    |
| P4Transformer(2021) [18] | point | 16       | 91.20    |
| PSTNet(2021) [17]      | point | 20       | 91.20    |
| SequentialPointNet(ours)| point | 24       | 91.20    |

Table IV: Ablation study results for SequentialPointNet

| Component | Cross-subject | Cross-setup |
|-----------|---------------|-------------|
| LSTM      | 94.3%         | 94.3%       |
| GRU       | 93.6%         | 93.6%       |
| TextCNN   | 94.3%         | 94.3%       |
| Ifme      | 94.2%         | 94.2%       |
tialPointNet (gru, w/o mlfl), and SequentialPointNet (textcnn, w/o mlfl) are much worse when compared with the result of SequentialPointNet (ifme, w/o mlfl). It demonstrates the weak temporal changes of human actions. For the feature vector sequence generated by the intra-frame appearance encoding module, powerful time sequence models are not applicable to encode weak temporal information of human actions.

### 2) Different temporal information embedding manners:
To demonstrate the effectiveness of the temporal position embedding layer in the inter-frame motion encoding module, we also report the results of SequentialPointNet (4D, w/o tpe), which injects the order information by appending the 1D temporal dimension to raw 3D points in each point cloud frame. Results are tabulated in Table V. From the table, we observe that SequentialPointNet with the temporal position embedding layer outperforms SequentialPointNet (4D, w/o tpe). Therefore, the temporal information embedding manner used in SequentialPointNet provides more superior performance. From the experimental results, we can draw a conclusion that premature embedding of temporal information may affect the encoding of spatial information and reduce the accuracy of human action recognition.

### 3) Effectiveness of Multi-level feature learning architecture:
SequentialPointNet progressively abstracts human actions at increasingly larger scales along a multi-level hierarchy. To obtain sufficient human movement information, multi-level feature learning architecture is designed to integrate different levels of human action features from each stage of the network. In order to verify the effectiveness of multi-level feature learning architecture, we report the results of SequentialPointNet (w/o mlfl) that classify human actions without the improved PointNet layer. From Table VII, we observe that the recognition accuracy of SequentialPointNet with the improved PointNet layer increases by 0.5%.

### 5) Results of our SequentialPointNet when setting different numbers of pyramid layers in the hierarchical pyramid max pooling layer:
To investigate the choice of the number of the pyramid layers in the hierarchical pyramid max pooling layer, we compare the performance of our SequentialPointNet with the different numbers of pyramid layers. The results are presented in Fig. 5. Particularly, the 2-layer pyramid is the optimal choice for SequentialPointNet.

### 6) Results of our SequentialPointNet when using different numbers of point cloud frames in the training process:
We also investigate the performance variation of our method when using different numbers of point cloud frames in the training process. As shown in Fig. 6, better performance is gained when the number of point cloud frames increases. When the number of frames is greater than 20, the recognition accuracy tends
to stabilize. Therefore, in order to achieve a better trade-off between data generation speed and recognition accuracy, the number of the point cloud frames is set to 20.

E. Running time analysis

In Table VIII, the overall running time of our SequentialPointNet is compared with 3DV-PointNet++, which includes CPU-based data generation time and GPU-based network forward inference time. Experiments are conducted on the machine with one Intel(R) Xeon(R) W-3175X CPU and one Nvidia RTX 3090 GPU on NTU RGB+D 60. From the results in Table VIII, it is obvious that our SequentialPointNet is much faster than 3DV-PointNet++ for 3D action recognition. Specifically, compared with 3DV-PointNet++, the data generation speed and the network forward inference speed of our SequentialPointNet are increased by approximately 2 times and 4 times, respectively.

| Method                  | CPU  | GPU | Overall |
|-------------------------|------|-----|---------|
| 3DV-PointNet++          | 4842 | 19  | 4861    |
| SequentialPointNet      | 2426 | 5   | 2431    |

V. Conclusion

In this paper, we have proposed a simple but effective strong parallelized point cloud sequence network called SequentialPointNet. Specifically, SequentialPointNet is composed of two serial modules, i.e., an intra-frame appearance encoding module and an inter-frame motion encoding module. The spatial structures and temporal changes are modeled independently in these two serial modules. In the intra-frame appearance encoding module, in order to capture strong spatial structures, the shared PointNet++ is applied to abstract each point cloud frame into a feature vector summarizing the static appearance. For modeling the weak temporal changes of human actions, in the inter-frame motion encoding module, temporal position encoding and hierarchical pyramid pooling strategy are implemented on the feature vector sequence. In addition, in order to better capture spatio-temporal information, a multi-level feature learning architecture is designed to aggregate different levels of human action features before performing 3D action recognition. In our SequentialPointNet, different point cloud frames share the same network architectures and weights. Extensive experiments conducted on three public datasets show that SequentialPointNet outperforms state-of-the-art approaches.

REFERENCES

[1] W. Zhu, C. Lan, J. Xing, W. Zeng, Y. Li, L. Shen, and X. Xie, “Co-occurrence feature learning for skeleton based action recognition using regularized deep lstm networks,” Proceedings of the AAAI conference on artificial intelligence, 2016.
[2] J. Liu, A. Shahrourdy, D. Xu, A. C. Kot, and G. Wang, “Skeleton-based action recognition using spatio-temporal lstm network with trust gates,” IEEE transactions on pattern analysis and machine intelligence, vol. 40, no. 12, 2018.
[3] S. Zhang, X. Liu, and J. Xiao, “On geometric features for skeleton-based action recognition using multi-layer lstm networks,” 2017 IEEE Winter Conference on Applications of Computer Vision, 2017.
[4] C. Li, Q. Zhong, D. Xie, and S. Pu, “Co-occurrence feature learning from skeleton data for action recognition and detection with hierarchical aggregation,” arXiv preprint arXiv:1804.06055, 2018.
[5] Y. Li, R. Xia, X. Liu, and Q. Huang, “Learning shape-motion representations from geometric algebra spatio-temporal model for skeleton-based action recognition,” 2019 IEEE International Conference on Multimedia and Expo, 2019.
[6] P. Wang, W. Li, Z. Gao, J. Zhang, C. Tang, and P. O. Ogbonna, “Action recognition from depth maps using deep convolutional neural networks,” IEEE Transactions on Human-Machine Systems, 2015.
[7] P. Wang, S. Wang, Z. Gao, Y. Hou, and W. Li, “Structured images for rgb-d action recognition,” Proceedings of the IEEE International Conference on Computer Vision Workshops, 2017.
[8] M. Harville and D. Li, “Fast, integrated person tracking and activity recognition with plan-view templates from a single stereo camera,” Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2004.
[9] M.-C. Roh, H.-K. Shin, and S.-W. Lee, “View-independent human action recognition with volume motion template on single stereo camera,” Pattern Recognition Letters, 2010.
[10] X. Yang, C. Zhang, and Y. Tian, “Recognizing actions using depth motion maps-based histograms of oriented gradients,” Proceedings of the 20th ACM international conference on Multimedia, 2012.
[11] H. Rahmani and A. Mian, “3d action recognition from novel viewpoints,” Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2016.
[12] Y. Min, Y. Zhang, X. Chai, and X. Chen, “An efficient pointlstm for point clouds based gesture recognition,” Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2020.
[13] G. Wang, H. Liu, M. Chen, Y. Yang, Z. Liu, and H. Wang, “Anchor-based spatial-temporal attention convolutional networks for dynamic 3d point cloud sequences,” arXiv preprint arXiv:2012.10860, 2020.
[14] H. Wang, L. Yang, X. Rong, J. Feng, and Y. Tian, “Self-supervised 4d spatio-temporal feature learning via order prediction of sequential point cloud clips,” Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, 2021.
[15] C. R. Qi, L. Yi, H. Su, and L. J. Guibas, “Pointnet++: Deep hierarchical feature learning on point sets in a metric space,” Advances in Neural Information Processing Systems, 2017.
[16] X. Liu, M. Yan, and J. Bohg, “MeteorNet: Deep Learning on Dynamic 3D Point Cloud Sequences,” Proceedings of the IEEE International Conference on Computer Vision, 2019.
[17] H. Fan, X. Yu, Y. Ding, Y. Yang, and M. Kankanhalli, “Pstnet: Point spatio-temporal convolution on point cloud sequences,” International Conference on Learning Representations, 2021.
[18] H. Fan, Y. Yang, and M. Kankanhalli, “Point 4d transformer networks for spatio-temporal modeling in point cloud videos,” Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2021.
[19] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, and I. Polosukhin, “Attention is all you need” In Advances in neural information processing systems, 2017.
[20] H. Su, S. Maji, E. Kalogerakis, and E. Learned-Miller, “Multi-view convolutional neural networks for 3D shape recognition,” Proceedings of the IEEE international conference on computer vision, 2015.

[21] T. Yu, J. Meng, and J. Yuan, “Multi-view harmonized bilinear network for 3D object recognition,” Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2018. Z. Yang and L. Wang, “Learning to compose for 3D object recognition,” Proceedings of the IEEE international conference on computer vision, 2019.

[22] C. R. Qi, H. Su, M. Nießner, A. Dai, M. Yan, and L. J. Guibas, “Volumetric and multi-view CNNs for object classification on 3D data,” Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2016.

[23] Y. Feng, Z. Zhang, X. Zhao, R. Ji, and Y. Gao, “GVCNN: Group-view convolutional neural networks for 3D shape recognition,” Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2018.

[24] C. Ma, Y. Guo, J. Yang, and W. An, “Learning multi-view representation with LSTMs for 3D shape recognition and retrieval,” IEEE Transactions on Multimedia, 2018.

[25] Z. Wang and F. Lu, “VoxSegNet: Volumetric CNNs for semantic part segmentation of 3D shapes,” IEEE transactions on visualization and computer graphics, 2019.

[26] E. Kalogerakis, M. Averkiou, S. Maji, and S. Chaudhuri, “3D shape segmentation with projective convolutional networks,” Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2017.

[27] L. Yi, H. Su, X. Guo, and L. J. Guibas, “SyncSpecCNN: Synchronized spectral CNN for 3D shape segmentation,” Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2017.

[28] P. Wang, Y. Gao, R. Shui, F. Yu, Y. Zhang, S. Chen, and Z. Sun, “3D shape segmentation via shape fully convolutional networks,” Computers & Graphics, 2018.

[29] C. Zhu, K. Xu, S. Chaudhuri, L. Yi, L. Guibas, and H. Zhang, “CoSegNet: Deep co-segmentation of 3D shapes with group consistency loss,” arXiv preprint arXiv:1903.10297, 2019.

[30] J. Arandjelovic, O. Sener, A. R. Zamir, H. Jiang, I. Brilakis, M. Fischer, and S. Savarese, “3D semantic parsing of large-scale indoor spaces,” Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2016.

[31] F. Liu, S. Li, L. Zhang, C. Zhou, R. Ye, Y. Wang, and J. Lu, “3DCNN-DQN-RNN: A deep reinforcement learning framework for semantic parsing of large-scale 3D point clouds,” Proceedings of the IEEE International Conference on Computer Vision, 2017.

[32] Z. Wu, S. Song, A. Khosla, F. Yu, L. Zhang, X. Tang, and J. Xiao, “3D shapeNets: A deep representation for volumetric shapes,” Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2015.

[33] C. Maturana and S. Scherer, “VoxNet: A 3D convolutional neural network for real-time object recognition,” 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems, 2015.

[34] G. Rigler, A. Osman Ulusoy, and A. Geiger, “OctNet: Learning deep 3D representations at high resolutions,” Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2017.

[35] P.-S. Wang, Y. Liu, Y.-X. Guo, C.-Y. Sun, and X. Tong, “Octree-based convolutional neural networks for 3D shape analysis,” ACM Transactions On Graphics, 2017.

[36] T. Le and Y. Duan, “PointGrid: A deep network for 3D shape understanding,” Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2018.

[37] Y. Ben-Shabat, M. Lindenbaum, and A. Fischer, “3D point cloud classification and segmentation using 3D modified fisheye vector representation for convolutional neural networks,” arXiv preprint arXiv:1711.08241, 2017.

[38] M. Joseph-Rivilin, A. Zvirin, and R. Kimmel, “Mo-Net: Flavor the moments in learning to classify shapes,” Proceedings of the IEEE international conference on computer vision, 2018.

[39] J. Yang, Q. Zhang, B. Ni, L. Li, J. Liu, M. Zhou, and Q. Tian, “Modeling point clouds with self-attention and gumbel subset sampling,” Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2019.

[40] H. Zhao, L. Jiang, C.-W. Fu, and J. Jia, “PointWeb: Enhancing local neighborhood features for point cloud processing,” Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2019.

[41] Y. Duan, Y. Zheng, J. Lu, J. Zhou, and Q. Tian, “Structural relational reasoning of point clouds,” Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2019.
[64] L. Li, M. Wang, B. Ni, H. Wang, J. Yang, and W. Zhang, “3d human action representation learning via cross-view consistency pursuit,” Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2021.

[65] M. Li, S. Chen, X. Chen, Y. Zhang, Y. Wang, and Q. Tian, “Symbiotic graph neural networks for 3d skeleton-based human action recognition and motion prediction,” IEEE Transactions on Pattern Analysis and Machine Intelligence, 2021.

[66] Z. Liu, H. Zhang, Z. Chen, Z. Wang, and W. Ouyang, “Disentangling and unifying graph convolutions for skeleton-based action recognition,” Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020.

[67] K. Cheng, Y. Zhang, X. He, W. Chen, J. Cheng, and H. Lu, “Skeleton-based action recognition with shift graph convolutional network,” Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020.

[68] P. Zhang, C. Lan, W. Zeng, J. Xing, J. Xue, and N. Zheng, “Semantics-guided neural networks for efficient skeleton-based human action recognition,” Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020.

[69] A. Klüser, M. Marszałek, and C. Schmid, “A spatio-temporal descriptor based on 3d-gradients,” BMVC 2008-19th British Machine Vision Conference British Machine Vision Association, 2008.

[70] W. A. Vieira, E. R. Nascimento, G. L. Oliveira, Z. Liu, and M. F. Campos, “Stop: Space-time occupancy patterns for 3d action recognition from depth map sequences,” Iberoamerican congress on pattern recognition, Springer, Berlin, Heidelberg, 2012.

[71] J. Wang, Z. Liu, Y. Wu, and J. Yuan, “Mining actionlet ensemble for action recognition with depth cameras,” Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2012.

Xing Li received the B.Sc. and M.Sc. degrees in software engineering from Changzhou University, China, in 2016 and 2019, respectively. He is currently pursuing the Ph.D. degree with the Department of Computer Science and Technology, Hohai University, Nanjing, China. His current research interests include machine learning, computer vision and deep learning, especially human action recognition.

Qian Huang received the B. Sc. degree in computer science from Nanjing University, China, in 2003, and the Ph.D. degree in computer science from the Institute of Computing Technology, Chinese Academy of Sciences, in 2010. Since Dec. 2012, he is with Hohai University, Nanjing, China, where he serves as the dean of Computer Science and Technology Department. His research interests include media computing, data mining, and intelligent education.

Zhijian Wang received the Ph.D. degree from Nanjing University, Nanjing, China. He is currently a Professor with Hohai University, Nanjing, China. His current research interests include machine learning, computer vision and deep learning.

Zhenjie Hou received the Ph.D. degree in mechanical engineering from Inner Mongolia Agricultural University, in 2005. From 1998 to 2010, he was a Professor with the Computer Science Department, Inner Mongolia Agricultural University. In August 2010, he joined Changzhou University. His research interests include signal and image processing, pattern recognition, and computer vision.

Tianjin Yang received the B.Sc. and M.Sc. degrees in Computer Science and Technology from Changzhou University, China, in 2018 and 2021, respectively. He is currently pursuing the Ph.D. degree with the Department of Artificial Intelligence, Hohai University, Nanjing, China. His current research interests include machine learning, computer vision.