Pose Refinement Graph Convolutional Network for Skeleton-based Action Recognition

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Abstract—With the advances in capturing 2D or 3D skeleton data, skeleton-based action recognition has received an increasing interest over the last years. As skeleton data is commonly represented by graphs, graph convolutional networks have been proposed for this task. While current graph convolutional networks accurately recognize actions, they are too expensive for robotics applications where limited computational resources are available. In this paper, we therefore propose a highly efficient graph convolutional network that addresses the limitations of previous works. This is achieved by a parallel structure that gradually fuses motion and spatial information and by reducing the temporal resolution as early as possible. Furthermore, we explicitly address the issue that human poses can contain errors. To this end, the network first refines the poses before they are further processed to recognize the action. We therefore call the network Pose Refinement Graph Convolutional Network. Compared to other graph convolutional networks, our network requires 86%-93% less parameters and reduces the floating point operations by 89%-96% while achieving a comparable accuracy. It therefore provides a much better trade-off between accuracy, memory footprint and processing time, which makes it suitable for robotics applications.

I. INTRODUCTION

Action recognition has received an increasing interest in recent years due to its broad range of applications such as video surveillance, gesture recognition and human-robot interaction. Despite the success of deep learning models in recognizing activities from video data [1], [2], these approaches are computationally expensive and cannot be used on mobile systems with limited computational resources. To alleviate this problem, many researchers addressed the action recognition task with skeleton data [3], [4]. In contrast to video data, skeleton-based action recognition models require much less resources and several approaches based on convolutional neural networks and recurrent neural networks have been proposed [5]–[7].

Despite the success of the previous approaches, their performance was limited as they did not consider the intrinsic differences between video data and skeleton data. While video frames have a grid structure where standard 2D or 3D convolutional neural networks can be applied, skeleton data is represented by graphs. The spatial-temporal graph convolutional network (ST-GCN) [8] therefore models skeleton sequences as spatial-temporal graphs and uses graph convolutions. Inspired by this work, further improvements have been proposed to increase the accuracy [9], [10]. While the variants of graph convolutional networks achieve very good results in terms of accuracy, the improvements come at a high increase of memory consumption and computational cost. Indeed, [10] has more than twice the number of parameters than ST-GCN and increases the GFLOPS by a factor of around 2.5. This prevents the application of these networks within the robotics domain.

In this work, we therefore propose a graph convolutional network that achieves a higher action recognition accuracy compared to ST-GCN, but that is much more efficient. Instead of increasing the size of the model, we present a new architecture that requires 7 times less parameters than ST-GCN and reduces the GFLOPS by a factor of 9. This is achieved by treating the temporal and spatial relations in a different way. To this end, we combine temporal and graph convolutions. While the graph convolutions focus on the spatial relations, the temporal convolutions aggregate the temporal information. Whereas in a sequential model the temporal and graph convolutions follow each other, we propose to separate them in a parallel structure and gradually fuse them as part of the gradual fusion module (GFM) as illustrated in Fig. 1. In contrast to a spatial-temporal graph, the temporal dimension gets early reduced within the network and not only at the end, which results in a very efficient and compact network.

As a second contribution, we address the problem that the estimated 2D or 3D human poses can be inaccurate. Although many approaches for human pose estimation from RGB or depth sensors exist and some of them can be deployed on robotics platforms, pose estimation errors occur due to the limited view or occlusions. Previous works on skeleton-based action recognition did not address this issue explicitly, assuming that the networks deal with pose estimation errors implicitly. In this work, we propose to add a module that refines the human poses by taking the spatial and temporal information into account. The so-called pose refinement module (PRM) estimates offsets for each joint and refines the poses by the offsets. As shown in Fig. 1, the pose refinement module first refines the poses and the gradual fusion module with an additional temporal aggregation estimates then the action class probabilities. However, the entire network is trained only with an action classification loss such that no additional supervision is required. We therefore call the approach pose refinement graph convolutional network (PR-GCN).

Our contribution is thus two folded:

• We propose the pose refinement graph convolutional network (PR-GCN), which is a compact model for skeleton-based action recognition that gradually fuses position and motion information and provides a better trade-off between effectiveness and efficiency compared
We introduce the pose refinement module that reduces the impact of pose estimation errors and further improves the accuracy at a very small increase of computational cost.

We evaluate the proposed approach on two very challenging action recognition datasets, namely Kinetics [11] with estimated 2D human poses [8] and NTU RGB+D [12] with estimated 3D human poses. Compared to other variants of graph convolutional networks, our method achieves a competitive accuracy but at a small fraction of the required computational resources. Compared to the state-of-the-art approach [10], the number of parameters are reduced by factor 14 and the computational cost by factor 22, which makes it suitable for robotics applications.

II. RELATED WORK

A. Skeleton-based action recognition

Skeleton-based action recognition is an important research area that has received an increasing attention recently. Earlier approaches represent the human body with hand-crafted features [3], [4], [13], [14]. However, these hand-crafted features are designed for specific applications and do not generalize to new scenarios. In contrast to the hand-crafted features, data-driven methods directly learn the features from data. These approaches can be divided into two categories: approaches based on convolutional neural networks (CNN) and approaches based on recurrent neural networks (RNN). As CNNs are applied on images with a regular grid-structure, CNN-based methods represent the skeleton data as pseudo-images based on manually designed transformation rules [5], [15], [16]. On the contrary, RNN-based methods are usually proposed for sequential data. Hence, RNN-based methods model the skeleton data as a sequence of vectors, each of them representing the coordinates of the body joints [6], [7], [12], [17]–[19]. Despite the success of both RNN and CNN based methods, their performance is limited as the representations adopted to model the skeletons do not explicitly capture the dependencies between the body joints. Skeleton data is naturally embedded in the form of graphs rather than vectors or 2D images. Recently, some approaches [8]–[10] therefore model the skeleton data as spatio-temporal graph structures and use graph convolutions instead of 2D convolutions.

B. Graph convolutional neural networks

There are many works that focus on graph convolutional networks (GCN). In these works, GCNs are usually constructed in the spatial or spectral domain [20]–[27]. In the spatial domain, the graph is constructed and normalized based on manually designed rules [23], [26], [28]–[30] and the convolution operation is directly applied on the graph vertices and their neighbors. Whereas spectral methods perform the graph convolutions in the frequency domain with the help of the graph Fourier transform [20]. The spectral methods do not require any extra effort to extract locally connected regions from graphs at each convolutional step [20], [22], [25], [27]. Our method follows the spatial approaches.

III. POSE REFINEMENT GRAPH CONVOLUTIONAL NETWORK

The proposed pose refinement graph convolutional network (PR-GCN) is a very compact and efficient network for skeleton-based action recognition. It combines graph convolutional and temporal convolutional layers, which we will describe first. We will then describe the network architecture that is illustrated in Fig. 1 including the novel pose refinement and gradual fusion modules.

A. Graph Construction

Similar to ST-GCN [8], each skeleton sequence is modeled as a spatial-temporal graph \( G(V, E) \) as shown in Fig. 2 (left). The vertices \( V \) denote body joints represented by their 2D or 3D joint coordinates. The edges \( E \) comprise spatial and temporal edges. Spatial edges \( E_s \) represent connections between vertices at each frame whereas temporal edges \( E_t \) connect the same body joint between two adjacent frames.

B. Basic Operations

PR-GCN includes graph convolution and temporal convolution layers.
1) Graph Convolution Layer: We first briefly describe the graph convolutions [8]. The graph convolutions operate on a pre-defined graph structure. In the spatial dimension, the graph convolution for each vertex \( v \) is formulated as:

\[
f_{\text{out}}(v_i) = \sum_{v_j \in B_i} \frac{1}{Z_{ij}} f_{in}(v_j) \cdot w(l_i(v_j)),
\]

where \( f(v) \) denotes the feature for vertex \( v \) and \( w \) is a weight function. \( v_i \) is the target vertex and \( B_i \) is the set of neighbor vertices including \( v_i \). In our implementation, \( B_i \) contains all 1-distance neighbors as it is illustrated in Fig. 2 (right). Since the number of vertices in \( B_i \) varies based on the selection of \( v_i \), [8] introduced a mapping function \( l_i \) that maps neighbor vertices into a set of predefined groups: the vertex itself \( (G_{i1}) \), the vertices that are close to the center of gravity \( (G_{i2}) \) and vertices that are far from the center of gravity \( (G_{i3}) \) as shown in Fig. 2 (right). This means that the weighting function \( w \) generates three different weights, one for each group. \( Z_{ij} \) is the cardinality of \( G_{ik} \) that contains \( v_j \). It is used to balance the contribution of each group.

The input skeleton sequence is organized as a tensor of size \((C, T, N)\), where \( C \) is the number of channels, \( T \) is the sequence length and \( N \) denotes the number of vertices. Hence, (1) is transformed into:

\[
f_{\text{out}} = \sum_{k=1}^{K_v} W_k(f_{in}A_k) \odot M_k,
\]

where \( K_v \) is the kernel size of the spatial dimension which equals 3 as defined above. \( A_k = \hat{A}_k^{1/2} \hat{A}_k \hat{A}_k^{1/2} \) where \( \hat{A}_k \) indicates the connection of vertices. An element \( \hat{A}_k^{ij} \) is nonzero only if vertex \( v_j \in B_i \), \( \hat{A}_k^{ii} = \sum_j \hat{A}_k^{ij} + \alpha \) is the normalized diagonal matrix and \( \alpha \) is set as 0.001 to avoid division by zero. \( W_k \) is a weight vector of a \( 1 \times 1 \) convolution operation and corresponds to \( w \) in (1). An attention map \( M_k \), which indicates the importance of each vertex, is applied on each vertex by an element-wise product \( \odot \). The graph convolution layer with additional batch normalization layers and a skip connection is shown in Fig. 3 (left).

2) Temporal Convolution Layer: For each vertex, there are only two connected vertices along the temporal dimension. The temporal convolution is a \( K_t \times 1 \) convolution where \( K_t = 3 \) is the kernel size in the temporal dimension. We also use batch normalization and residual connections for the temporal convolution layers as shown in Fig. 3 (right).

C. Architecture

The architecture of the proposed network is illustrated in Fig. 1. The input skeleton sequences are first passed through a pose refinement module to reduce the impact of errors in the skeleton data. Then the refined skeleton sequences are fed into the gradual fusion module which fuses position and motion information gradually. Finally, the temporal aggregation module generates the final prediction. In the following, we describe each module in detail.

D. Pose Refinement Module

Due to partial visibility of the human body and inaccurate predictions from human pose estimation algorithms, the input skeleton data can contain errors, which influences the action recognition accuracy. To reduce this influence, we refine each joint position by the pose refinement module as shown in Fig. 4. For pose refinement, we estimate offsets for each joint position by the pose refinement module as shown in Fig. 3 (right).
As shown in Fig. 4, the offset is estimated by a combination of $1 \times 1$ convolution layers, graph convolution layers and one temporal convolution layer. While the graph convolutional layers exploit the spatial relations of the joints to refine the poses, the temporal convolutional layer exploits temporal consistency. In case of 2D skeleton data, we use the $x$ and $y$ coordinates as well as the joint estimation confidence as input, which we obtain from the human pose estimation approach. The estimated 2D offset $(\Delta x, \Delta y)$ is then added to the 2D coordinates for each joint.

**E. Gradual Fusion Module**

Previous works like [10] iterate between spatial and temporal graph convolutions. This is, however, not only very inefficient but we also show in Sec. IV that this can even slightly decrease the accuracy when motion and spatial information are sequentially processed. Furthermore, the temporal edges do not model the full motion of the joints. Instead, we model the motion by temporal differences:

$$M_{i,t} = P_{i,t} - P_{i,t-1} \tag{3}$$

where $M_{i,t}$ is the motion of joint $i$ at time $t$, $P_{i,t}$ and $P_{i,t-1}$ are the positions of joint $i$ at time $t$ and $t - 1$, respectively. As shown in Fig. 5, the motion flow takes $M$ as input and the position flow $P$. In order to include the spatial relations between the joints as additional information for the motion flow, we include one graph convolution layer to the motion flow. In order to capture long-term dependencies, we furthermore reduce the temporal resolution within the gradual fusion module by using stride 2 and 3 for the first and second temporal convolutional layer, respectively. The position flow is in parallel to the motion flow, but we gradually fuse the two flows as shown in Fig. 5. It is worth noting that the dimensions of the spatial features and the temporal features do not match due to the reduction of the temporal resolution in the motion flow. We therefore perform max-pooling over the spatial features along the temporal dimension such that the dimensions match at each fusion step. This is shown in Fig. 6.

**F. Temporal Aggregation Module**

Finally, we aggregate the features to obtain the final class probabilities for each action class as shown in Fig. 7. The fused features from the gradual fusion module are first fed into an average pooling layer across the temporal dimension. The features are then recalibrated according to the similarity among different channels. To this end, we scale each feature channel $f_{in}$ by a scalar value:

$$f_{out} = f_{in} \cdot \sigma(\text{Conv}(\text{ReLU}(\text{Conv}(\text{Avg}(f_{in}))))).$$

While the average pooling layer (Avg) squeezes the input features $f_{in}$ to a vector, the $1 \times 1$ convolutions (Conv) learn the weight for each channel, which are then mapped by the sigmoid function to values between zero and one. After the features are recalibrated, a graph convolution layer is applied to aggregate spatial information for the last time. Finally, the features are processed by an average pooling layer, a convolution layer and a softmax function for predicting the probabilities of the action classes.

**IV. Experiment**

**A. Datasets & Evaluation Metrics**

We evaluate our approach on the two challenging large-scale human action datasets Kinetics [11] and NTU RGB+D [12].
## Ablation Study on the Impact of the Pose Refinement Module (PRM) and the Temporal Aggregation Module (TAM) on the Kinetics Dataset.

Compared to other graph convolutional networks, the proposed PR-GCN requires only a fraction of parameters and GFLOPS. Inference time denotes the time in seconds to classify all 20,000 video clips of the validation set.

| Methods          | PRM | TAM | Top-1 (%) | Top-5 (%) | Params (M) | GFLOPS | Infer. time (s) |
|------------------|-----|-----|-----------|-----------|------------|--------|-----------------|
| ST-GCN [8]       | ✓   | ✓   | 30.7      | 52.8      | 3.5        | 15.6   | 160.5           |
| AS-GCN [9]       | ✓   | ✓   | 34.8      | 56.5      | 5.0        | 27.0   | -               |
| 2s-AGCN [10]     | ✓   | ✓   | 36.1      | 58.7      | 7.1        | 38.5   | -               |

| PR-GCN           | ✓   | ✓   | ✓         | ✓         | ✓         | ✓      | ✓               |
|                  | 29.3| 51.8| 0.3       | 1.3       | 42.6      | 54.0   |                 |

| Position        | Motion | Sequential | Parallel | Top-1 (%) | Top-5 (%) |
|-----------------|--------|------------|----------|-----------|-----------|
| Cross-subject   | ✓      | ✓          | ✓        | 32.9      | 32.2      |
| Cross-view      | ✓      | ✓          | ✓        | 32.7      | 33.6      |
|                 | ✓      | ✓          | ✓        | 55.1      | 55.0      |

| Kinetics [11] contains video clips with 400 classes retrieved from YouTube videos. We follow the evaluation setting from [8] that uses OpenPose [31] to extract 2D skeletons in every frame of the video clips. The structure of the 2D skeleton is shown in Fig. 2. The extracted skeleton data is split into a training set (240,000 clips) and a validation set (20,000 clips). As in [8], we report the top-1 and top-5 accuracy on the validation set.

| NTU RGB+D [12] contains 56,880 video clips with 60 actions that are performed by 40 persons, which are between 10 and 35 years old. The video clips have been recorded with multiple cameras and the 3D human poses are estimated by the Kinect v2 SDK. There are two evaluation protocols for this dataset [12]:
| • Cross-subject (X-Sub): The videos are split into a training set (40,320 videos) and test set (16,560) according to different actors.
| • Cross-view (X-View): The videos are split according to different cameras. The training set contains 37,920 videos recorded by cameras 2 and 3, whereas the test set includes 18,960 videos recorded by camera 1.

We report top-1 accuracy for both protocols.

| B. Implementation |

All experiments are conducted using the PyTorch deep learning framework. Our model is trained with stochastic gradient descent with a learning rate of 0.01 and momentum of 0.9. The learning rate is decayed by 0.1 every 10 epochs apart from the first 10 epochs. The size of the input data of Kinetics is 300 frames. We apply data augmentation during training as [8], where 300 frames are randomly chosen from the input skeleton sequences and slightly disturbed with randomly chosen rotations and translations.

### C. Ablation Study

We first examine the effectiveness of the pose refinement module (PRM) and the temporal aggregation module (TAM) in Tab. I. If PRM is not included, the entire module is removed, i.e., we do not refine the poses for action recognition. If TAM is not included, we use only the last average pooling layer, convolution layer and the softmax function of Fig. 7.

First, we evaluate our model without both modules. We can see from the table that our model achieves a slightly worse accuracy than ST-GCN [8], but it has more than 11 times less parameters and it is nearly 4 times faster. It requires a little bit more than 2ms to process a single video clip. More important than the inference runtime is the reduction of GFLOPS since this measurement is hardware independent. Compared to ST-GCN, the GFLOPS are reduced by factor 12. One can also see that AS-GCN [9] and 2s-AGCN [10] increased the accuracy of ST-GCN by massively increasing the number of parameters and GFLOPS.

By adding the pose refinement module (PRM) and the temporal aggregation module (TAM) in Tab. I, the accuracy increases while the number of parameters or runtime increases only slightly. By adding both PRM and TAM, we can see that both modules complement each other and achieve the best accuracy with an improvement of 4.3% on the top-1 accuracy and top-5 accuracy. It is interesting to note that the pose refinement module only marginally increases the number of parameters but it slightly increases the runtime. Whereas the temporal aggregation module increases the parameters but only marginally the runtime. This is due to the fact that we have at the beginning of the network very few channels but the full temporal resolution and it is the other way around at the end of the network. Depending on the available memory or computational resources, one of the modules can be deactivated if necessary. While our approach outperforms ST-GCN [8] in terms of accuracy, memory footprint and runtime, it achieves nearly the same accuracy as [9] but with only 10% of the parameters and around 6% of the GFLOPS. Only the state-of-the-art method [10] achieves a higher accuracy, but at the cost of more than doubling the memory footprint and runtime of ST-GCN.
In a second ablation study we explore the impact of the gradual fusion module. The results are shown in Tab. II. To prove the effectiveness of our design, we tested two settings: a sequential architecture where we stack temporal convolutional layers and graph convolutional layers in a single flow and the parallel architecture shown in Fig. 5. For the sequential and parallel architecture, we also consider two cases. In case of using only position information we use only the joint positions \( P \) as input and in case of position and motion information, we use both \( P \) and the motion of joints \( M \).

In the first two columns of Tab. II we evaluate the impact of using the additional motion information \( M \) for a sequential architecture. In this case, we concatenate \( P \) and \( M \). The results show that the accuracy even slightly decreases if motion is added to a sequential architecture. When we compare the columns 1 and 3, we see that there is no substantial difference between a sequential and parallel architecture if only \( P \) is used. In the parallel case, we use \( P \) as input for both branches. Only if we use \( P \) and \( M \) for the parallel architecture as shown in Fig. 5 we observe an increase in accuracy as reported in the last column. This shows on the one hand that the additional motion information improves the accuracy and on the other hand that the proposed fusion module is essential for fusing the position and motion information.

D. Comparison with State-of-the-Art

We finally compare our method with current state-of-the-art methods for skeleton-based action recognition on the Kinetics and NTU RGB+D datasets. The results are shown in Tab. III and Tab. IV. The tables include methods with handcrafted features [4], RNN-based methods [12], CNN-based methods [15] and GCN-based methods [8]–[10]. As shown in the tables, our method achieves an accuracy that is better or close to state-of-the-art methods. This shows that the proposed approach works very well for 2D human poses as well as 3D human poses. The approaches that achieve a higher accuracy use adaptive graph convolutions [9] or adopt auxiliary strategies to further improve the accuracy like an ensemble of networks [10]. This, however, makes these approaches demanding in terms of computational resources and difficult to deploy on robot platforms. As shown in Tab. II our network requires only 10% of the parameters and around 6% of the GFLOPS compared to [9] and only 7% of the parameters and around 4% of the GFLOPS compared to [10]. Compared to our baseline [8], our model achieves a much higher accuracy with only 14% of the parameters, runs 3 times faster and the GFLOPS are reduced by 89%. Our model achieves therefore a better trade-off between efficiency and accuracy compared to the state-of-the-art and is suitable for robotics applications with limited computational resources.

V. CONCLUSIONS

In this paper, we proposed a highly efficient model called Pose Refinement Graph Convolutional Network for 2D or 3D skeleton-based action recognition. It refines the human poses and gradually fuses motion and spatial information. Compared to previous graph convolutional networks, the proposed approach is very efficient in terms of memory footprint and runtime. It reduces the number of parameters by 86%-93% and the computational operations by 89%-96% while achieving a comparable accuracy. It therefore provides a much better trade-off between efficiency and accuracy and is thus suitable for robotics applications.

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| Methods             | Top-1 (%) | Top-5 (%) |
|---------------------|-----------|-----------|
| Feature Enc [4]     | 14.9      | 25.8      |
| Deep LSTM [12]      | 16.4      | 35.3      |
| TCN [15]            | 20.3      | 40.0      |
| ST-GCN [8]          | 30.7      | 52.8      |
| Conv [32]           | 30.8      | 52.6      |
| Conv-48x48 [32]     | 30.9      | 53.0      |
| AS-GCN [9]          | 34.8      | 56.5      |
| 2s-AGCN [10]        | 36.1      | 58.7      |
| Ours                | 33.7      | 55.8      |

TABLE III

Comparison with state-of-the-art methods on the Kinetics dataset.

| Methods             | X-Sub (%) | X-View (%) |
|---------------------|-----------|------------|
| Lie Group [3]       | 50.1      | 82.8       |
| HBRNN [33]          | 59.1      | 64.0       |
| Deep LSTM [12]      | 60.7      | 67.3       |
| ST-LSTM [17]        | 69.2      | 77.7       |
| STA-LSTM [34]       | 73.4      | 81.2       |
| VA-LSTM [6]         | 79.2      | 87.7       |
| ARR-LSTM [18]       | 80.7      | 88.8       |
| TCN [15]            | 74.3      | 83.1       |
| Chips+CNN+MTLN [5]  | 79.6      | 84.8       |
| Synthesized CNN [35]| 80.0      | 87.2       |
| RGB+Skeleton [36]   | 84.2      | 89.3       |
| FO-GASTM [37]       | 82.8      | 90.1       |
| Bayesian GC-LSTM [38]| 81.8     | 89.0       |
| ST-GCN [8]          | 81.5      | 88.3       |
| AS-GCN [9]          | 86.8      | 94.2       |
| 2s-AGCN [10]        | 88.5      | 95.1       |
| Ours                | 85.2      | 91.7       |

TABLE IV

Comparison with state-of-the-art methods on the NTU RGB+D dataset.
