Acquisition of Optimal Connection Patterns for Skeleton-based Action Recognition with Graph Convolutional Networks

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Keywords: Graph Convolutional Networks, Multitask Learning, Skeleton-based Action Recognition.

Abstract: Action recognition from skeletons is gaining attention since skeleton data can be easily obtained from depth sensors and highly accurate pose estimation methods such as OpenPose. A method using graph convolutional networks (GCN) has been proposed for action recognition using skeletons as input. Among the action recognition methods using GCN, spatial temporal GCN (ST-GCN) achieves a higher accuracy by capturing skeletal data as spatial and temporal graphs. However, because ST-GCN defines human skeleton patterns in advance and applies convolution processing, it is not possible to capture features that take into account the joint relationships specific to each action. The purpose of this work is to recognize actions considering the connection patterns specific to action classes. The optimal connection pattern is obtained by acquiring features of each action class by introducing multitask learning and selecting edges on the basis of the value of the weight matrix indicating the importance of the edges. Experimental results show that the proposed method has a higher classification accuracy than the conventional method. Moreover, we visualize the obtained connection patterns by the proposed method and show that our method can obtain specific connection patterns for each action class.

1 INTRODUCTION

Human action recognition has been actively studied due to its importance in video surveillance systems and sports analysis. Conventional human action recognition methods use appearance, optical flows, and skeletons as inputs (Tran et al., 2015) (Simonyan and Zisserman, 2014) (Limin et al., 2016) (Wu, 2012). The use of skeletons is attracting attention because their skeletal data can be captured using depth sensors and high-precision pose estimation methods such as OpenPose (Zhe et al., 2017) and they can be easily adapted to changes in the environment and viewpoint. As skeletal data contains the coordinates of each joint for each frame, many action recognition methods based on skeletons do not consider the relationships between joints (Vemulapalli et al., 2014) (Hongsong and Liang, 2017) (Liu et al., 2017). To consider such a relationships, actions can potentially be determined by expressing skeletons in a graph composed of nodes and edges connecting them. When skeletons are represented as a graph, nodes correspond to joint coordinates and edges correspond to the relationship between joints. Therefore, it is possible to consider the relationship between joints and recognize complex actions. A method using graph convolutional networks (GCN) has been proposed for action recognition with graph skeletons as input (Sijie et al., 2018) (Li et al., 2018). A GCN is a convolutional neural network that takes graph structures as input, enabling it to extract features considering the relationship of connected nodes. GCN are also used in fields such as image classification, document classification, and compound classification (Joan et al., 2014) (Defferrard et al., 2016) (Gilmer et al., 2017).

The spatial temporal GCN (ST-GCN) is an action recognition method that achieved a high recognition accuracy by introducing a spatial graph that considers the relationship between joints and a temporal graph that considers temporal movement. However, only a human skeleton pattern is defined in advance as the connection pattern of the graph used in the spatial graph. Therefore, since the convolution is performed only with the human skeletal pattern, it is difficult to consider the relationship between distant joints. In the case of performing action recognition, the relationship between distant joints is important for many motions, such as the relationship between arms and legs when throwing. In addition, the relationship between important joints may be different for each action.

In this work, we propose an action recognition method that considers the optimal connection pattern for each action. By constructing a connection pattern for each action, the optimal feature between

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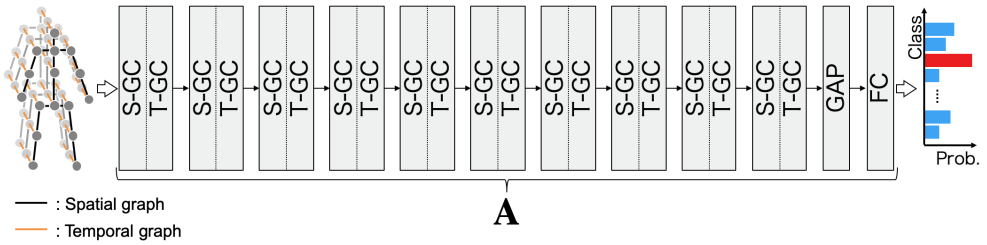


Figure 1: ST-GCN network architecture.

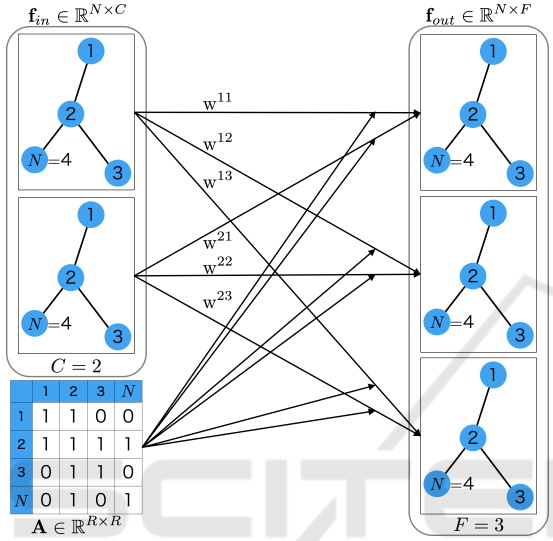


Figure 2: Graph convolution processing.

joints is extracted for each action. Also, instead of using a pre-defined optimal connection pattern, it is possible to construct one automatically during learning. In the proposed method, we introduce multitask learning framework and classify each action class as binary classification problem. This enables the proposed method to define different connection patterns for each task (i.e., each action class) and the optimal pattern is obtained by updating the connection patterns during learning. To update the connection pattern, we focus on the weight matrix indicating edge importance and select the more important edge on the basis of weight value. We propose an action recognition method that obtains the optimal connection pattern for each action by repeatedly updating the pattern during learning.

2 RELATED WORKS

ST-GCN is an action recognition method that represents skeletons as graphs. This method achieves a higher recognition accuracy than that of conventional methods as skeletons are represented as spatial and temporal graphs. A spatial graph considers the relationship between joints by connecting joints in the same frame, and a temporal graph considers the temporal movement of joints by connecting the same joints between frames. The ST-GCN network architecture is shown in Figure 1. Spatial graph convolution (S-GC) and temporal graph convolution (T-GC) are used for the convolution processing of the spatial and temporal graphs, respectively, followed by global average pooling (Min et al., 2014).

ST-GCN recognizes action using a GCN to obtain a feature map by convolution processing, similar to a general convolutional neural network. However, the general convolution process cannot be applied to graphs because each node has a different number of adjacent nodes. Therefore, the convolution processing of graphs in ST-GCN has been achieved in the literature (Kipf and Welling, 2017). An outline of the graph convolution process is shown in Figure 2. For a spatial graph with N nodes, we condider a graph convolution process with C dimensional node feature $\mathbf{f}_{in} \in \mathbb{R}^{N \times C}$. The output $\mathbf{f}_{out} \in \mathbb{R}^{N \times F}$ of the number of feature maps F is obtained by Equation (1) using the adjacency matrix $\hat{\mathbf{A}} \in \mathbb{R}^{N \times N}$ and the weight matrix $\mathbf{W} \in \mathbb{R}^{C \times F}$.

$$\mathbf{f}_{out} = \Lambda^{-\frac{1}{2}} \hat{\mathbf{A}} \Lambda^{-\frac{1}{2}} \mathbf{f}_{in} \mathbf{W}, \tag{1}$$

where $\hat{\mathbf{A}}$ is obtained by Equation (2) using the adjacency matrix $\mathbf{A} \in \mathbb{R}^{N \times N}$ and the unit matrix $\mathbf{I} \in \mathbb{R}^{N \times N}$ indicating the loop of the graph.

$$\hat{\mathbf{A}} = \mathbf{A} + \mathbf{I} \tag{2}$$

The adjacency matrix $\mathbf{A}$ is a matrix indicating the connection relation of nodes. Each element A_{ij} of the adjacency matrix $\mathbf{A}$ indicates the connection relationship between the nodes i and j, and is obtained by Equation (3).

$$\mathrm{A}_{ij} = \begin{cases} 1 & (\text{node } i, j \text{ is connected}), \\ 0 & (\text{node } i, j \text{ is not connected}). \end{cases} \tag{3}$$

Λ in Equation (1) is a diagonal matrix whose diagonal component is the eigenvalue of the graph Laplacian,

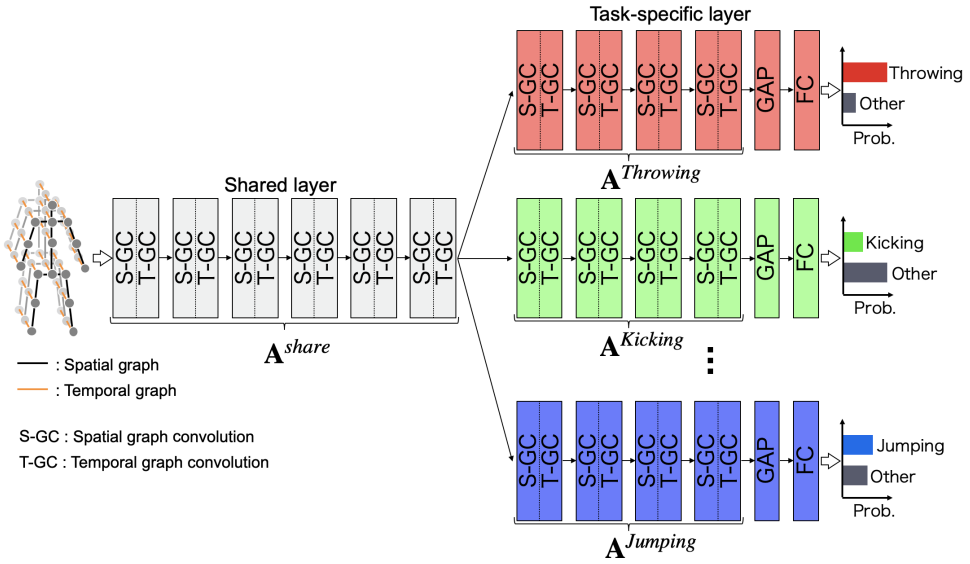


Figure 3: Network architecture of the proposed method.

and its diagonal component is $\Lambda_{ii} = \sum_j (A_{ij} + I_{ij})$. The output feature map can be expressed as a (C, V, T) dimensional tensor with C dimensions, N nodes, and T frames. Therefore, the convolution processing of the temporal graph can be implemented by that of the arbitrary kernel size $1 \times \Gamma$. In ST-GCN, a learning weight matrix $\mathbf{M} \in \mathbb{R}^{N \times N}$ is proposed to consider the importance of edges in action recognition. The learning weight matrix $\mathbf{M}$ is added to the graph convolution process as show in Equation (4).

$$\mathbf{f}_{out} = \Lambda^{-\frac{1}{2}}(\hat{\mathbf{A}} \circ \mathbf{M})\Lambda^{-\frac{1}{2}}\mathbf{f}_{in}\mathbf{W}, \quad (4)$$

where $\circ$ is the element-wise product. By taking the element product of the adjacency matrix $\hat{\mathbf{A}}$ and the learning weight matrix $\mathbf{M}$, a weight can be given to each edge. Updating $\mathbf{M}$ increases the weight of edges connected to important nodes. The classification accuracy of ST-GCN has been reported to have improved by adding the learning weight matrix $\mathbf{M}$ to the graph convolution process.

3 PROPOSED METHOD

The convolution processing of the spatial graph in ST-GCN is performed only with the connection pattern of a human skeleton. Since convolution processing is performed only between adjacent joints, the relationship between distant joints such as right and left hands, and hands and feet is not considered. Also, the relationship of important joints in action recognition may differ depending on the action. For example, in the throwing action, both the right leg and arm are important because the right leg is the axis leg and the object is thrown with the right arm. Moreover, since the whole body moves in the jumping action, the relationship between the whole body is important for action recognition. In this work, we propose an action recognition method that automatically obtains the optimal connection pattern for each action class. The network of the proposed method is shown in Figure 3. The details of the proposed method are described below.

3.1 Extraction of Action Features by Multitask Learning

We introduce multitask learning to extract features specific to each action class. Multitask learning is a method in which multiple tasks can be learned on one neural network. Our proposed method performs two-class classification between specific classes and other classes in each task of multitask learning. The shared part of the network extracts common features from all action classes, and each task extracts specific features from each action class. Also, to obtain the connection pattern of each action class, an independent adjacency matrix is used in the shared layer and a specific task layer of the network.

3.2 Obtaining the Optimal Connection Pattern by Updating the Adjacency Matrix

The adjacency matrix is updated during learning to obtain connection patterns specific to each action

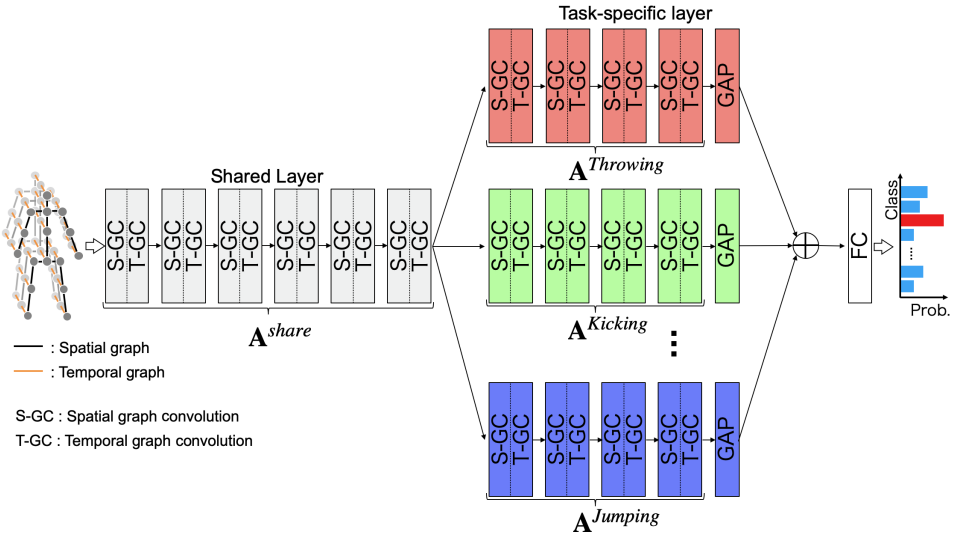


Figure 4: Network architecture with additional multi-class classfication layer.

class. We focus on the learning weight matrix $\mathbf{M}$ proposed in ST-GCN. $\mathbf{M}$ gives weights to each edge by Equation (4), and updating $\mathbf{M}$ increases the weight of edges connected to important nodes. Therefore, the optimal connection pattern can be obtained by selecting important edges on the value of $\mathbf{M}$. The initial values of the adjacency matrix are all 1, that is, all nodes are connected. The adjacency matrix is updated by leaving only K edges with large weights from the value of the learning weight matrix $\mathbf{M}$. Edge weights without connections are not considered. As such, the reduced edge does not connect the nodes again. Also, to maintain the loop in the graph, the diagonal component of the adjacency matrix is always 1 regardless of the weight value. The updated adjacency matrix is then converted into a symmetric matrix to form an undirected graph. That is, $\hat{\mathrm{A}}_{ji} = 1$ when $\hat{\mathrm{A}}_{ij} = 1$.

Let $\mathbf{A}^{share}$ be the adjacency matrix of the shared part and $\mathbf{A}^t$ be that of task t. The learning weight matrix $\mathbf{M}$ exists in each S-GC layer. Therefore, the adjacency matrix $\mathbf{A}^t$ of each task is updated with the value $\mathbf{M}^t$ obtained by adding all the learning weight matrices of task t. The algorithm for updating the adjacency matrix is shown in Algorithm 1. After updating, graph convolution processing is performed using the obtained adjacency matrix. The number of edges is gradually reduced by repeatedly updating the adjacency matrix during learning. As a result, only an edge with a large weight remains, so an optimum connection pattern for action recognition can be obtained.

Algorithm 1: Adjacency matrix update algorithm.

Input: $\mathbf{A}^t$ of size $N \times N$: Adjacency matrix of task t
$\mathbf{M}^t$ of size $N \times N$: Learning weight matrix of task t
K: Number of edges to leave
Output: $\hat{\mathbf{A}}^t$ of size $N \times N$: Updated adjacency matrix of task t

$\hat{\mathbf{A}}^t \leftarrow N \times N$ identity matrix
$s = 0$
while $s <$ K **do**
  $(i, j) \leftarrow \mathrm{argmax}\mathbf{M}^t$
  $\mathrm{M}^t_{ij} \leftarrow 0$
  $\mathrm{M}^t_{ji} \leftarrow 0$
  if $i \neq j$ **then**
    if $\mathrm{A}^t_{ij} \neq 0$ **then**
      $\hat{\mathrm{A}}^t_{ij} \leftarrow 1$
      $\hat{\mathrm{A}}^t_{ji} \leftarrow 1$
      $s \leftarrow s + 1$
    end if
  end if
end while

3.3 Multi-class Classification Layer

In the proposed method shown in Figure 3, each task is classified into two classes. Therefore, when one data is input, the classification result is output for each task. For this reason, there is a possibility that the input data is classified into multiple classes. Our proposed method solves this problem by introducing a multi-class classification layer. Figure 4 shows the network structure when performing multi-class classification. The feature map obtained by GAP for

each task is the input to the additional fully connected layer. To train the additional fully connected layer, we fix the network weights trained by only the additional fully connected layer and the S-GC and T-GC layers.

4 EXPERIMENTS

To show that the reduction of edges leads to the improvement of accuracy, an evaluation experiment was performed in which the number of edges was changed. The optimal number of edges was determined from the experimental results. To verify the effectiveness of the proposed method, a second evaluation experiment based on identification accuracy was performed. By visualizing the acquired adjacency matrix, we confirmed that connection patterns specific to each action class could be acquired. The details of the dataset, learning conditions, experimental results, and visualization of the adjacency matrix are described below.

4.1 Dataset

NTU-RGB+D dataset, a dataset for action recognition with skeletons, is was used for the experiments (Shahroudy et al., 2016). The dataset has a total of 60 different action classes, including daily actions such as walking and sitting, and sports actions such as throwing and kicking. Data was taken from three viewpoints simultaneously, the front and 45 degrees to the left and right. A skeleton comprises 3D coordinates (X, Y, Z) based on information from a Kinect v2 depth sensor and have 25 joints. In this work, we experimented with three action classes (throwing, kicking, jumping). The number of input frames T was 80.

The NTU-RGB+D dataset recommends two evaluation methods: cross-subject and cross-view. Cross-subject is a method that separates 40 subjects into a learning data group and an evaluation data group. Predetermined data for 20 subjects are used for learning. The evaluation is based on data from subjects who were not used for learning. The number of samples for learning and evaluation is 2,010 and 830, respectively. Cross-view is a method that separates the data of the three viewpoints taken by learning and evaluation. The learning uses data taken from the 45 degree direction, and the evaluation uses that from the front. The number of samples for learning and evaluation is 1,900 and 950, respectively.

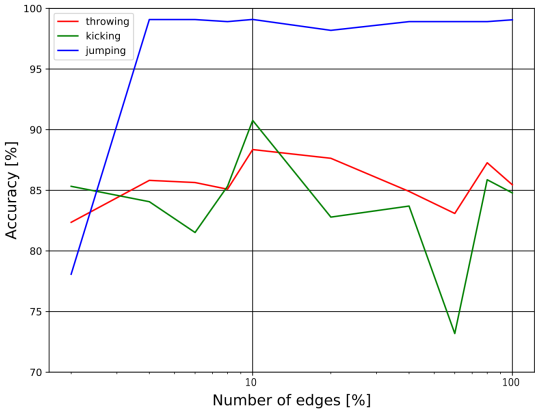


Figure 5: Accuracy per number of connected edges.

4.2 Network Architecture

The network of the proposed method consists of a convolutional block of spatial and temporal graphs. A block first has a spatial GCN, followed by a batch normalization layer, a ReLU layer, a temporal GCN, a dropout layer, a batch normalization layer and a ReLU layer. The kernel size Γ for temporal GCN is set to 9, and the drop rate for the dropout layer is set to 0.5. The shared part has six blocks. The first four blocks have 64 channels and the remaining blocks have 128 channels for output. The task-specific part consists of four blocks. There are 128 output channels for the first block and 256 channels for the following three blocks. The output of the task-specific part is input into the GAP layer and softmax classifier for classification.

During training, we set the batch size as 16. We use the SGD algorithm. The initial learning rate is 0.1 and decays by 0.1 every 20 epochs. In fine tuning, the learning rate is set to 0.0001 and the model is train for 20 epoch.

4.3 Experimenting using a Different Number of Edges

To show that edge reduction affects recognition accuracy, we experimented by changing the number of reduced edges. Experiments were performed using two classes, a specific class and one from other classes. For the other-class one, data randomly selected from action classes other than throwing, kicking, and jumping were used. The model used was a network of ten layers with convolution processing for the spatial and temporal graphs. We set the number of learnings to 100 epochs. The adjacency matrix was updated at 40, 50, 60 and 70 epochs, and the edges were gradually reduced. The recognition accuracy was evaluated by

Table 1: Accuracy of each action class in cross-subject [%].

	Throwing	Kicking	Jumping
ST-GCN	86.91	90.94	99.63
Ind. Network	88.36	90.76	99.09
M.T. Network	**96.86**	**96.98**	**99.74**

Table 2: Accuracy of each action class in cross-view [%].

	Throwing	Kicking	Jumping
ST-GCN	93.72	94.02	98.64
Ind. Network	93.23	93.98	99.01
M.T. Network	**97.57**	**96.43**	**99.26**

calculating the difference in the number of edges at 70 epochs. If all edges are connected, the number of edges is 600, excluding loops.

The experimental results are shown in Figure 5. The results of the throwing, kicking, and jumping classes showed the highest recognition accuracy with 10% edges. The recognition accuracy at 10% is 88.36% for throwing, 90.76% for kicking, and 99.09% for jumping. From the results, it can be seen that a higher accuracy can be obtained by connecting only joints that strongly affect action than learning with all edges connected. This indicates that reducing the number of edges affects recognition accuracy.

4.4 Accuracy Comparison Experiment

4.4.1 Learning Conditions

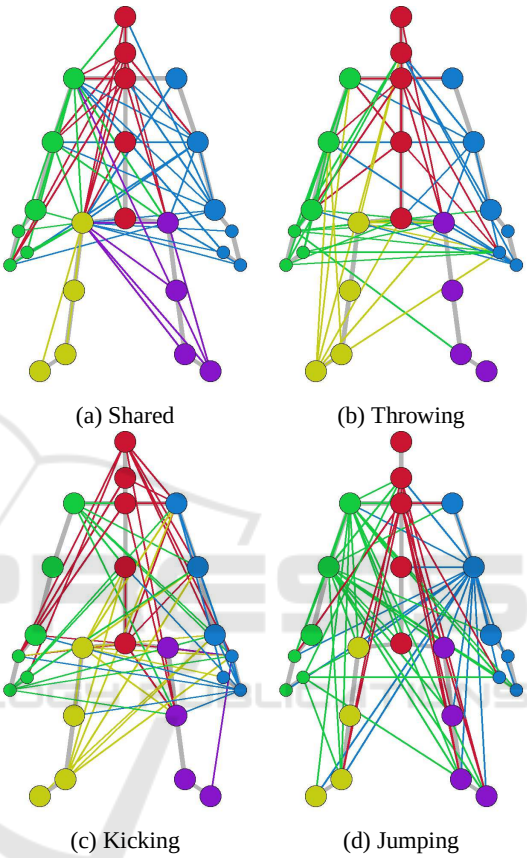
For this experiment,the number of learning was set to 100 epochs, and the adjacency matrix was updated at 40, 50, 60, and 70 epochs. Each update of the adjacency matrix reduces the number of edges by 20% of the total number of edges in the initial state. That is, the number of edges after the update at 70 epochs is 60. The adjacency matrix was not updated in the shared part. The initial value of the learning weight matrix $\mathbf{M}$ was set to $\mathrm{M}_{ij} = 1/N$ using the number of nodes N of the graph.

4.4.2 Experimental Results

Tables 1 and 2 show the classification accuracies of each action class of the proposed method and ST-GCN on the basis of cross-subject and cross-view, respectively. There are two proposed methods, an independent network (Ind. Network) that learns each class by two-class classification, and a multitask network (M.T. Network) that learns three classes with a multitask structure. When comparing M.T. Network with ST-GCN, cross-subject improved accuracy by an average of 5.4 points and cross-view by an average of 2.4 points. Also, the accuracy of the throwing class is particularly improved. The relationship between the arm and the leg is important for the throwing action, and the relationship between the distant joints is more important than that of other action. Therefore, the recognition accuracy can be improved by considering the features between distant joints, not captured by ST-GCN, by the proposed method.

Table 3: Tree-class classification accuracy [%].

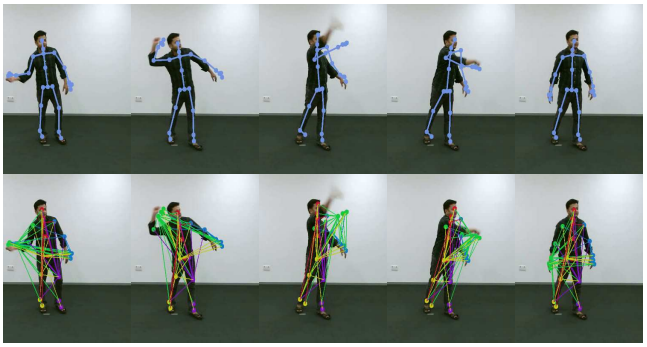
	Cross-subject	Cross-view
ST-GCN	92.38	94.68
M.T. Network w/o class. layer	95.49	95.57
M.T. Network w/ class. layer	**96.61**	**97.05**



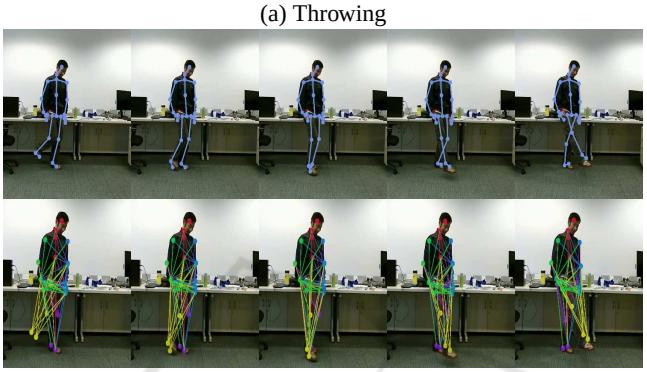
(a) Shared (b) Throwing (c) Kicking (d) Jumping

Figure 6: Visualization of the adjacency matrix at 70 epochs.

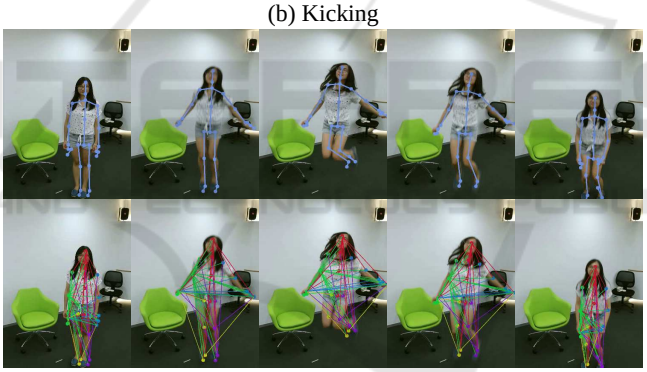
Table 3 shows the results of classification accuracy when three classes are classified. The M.T. Network w/o class. layer is a model that does not include a multi-class classification layer. Classification accuracy is based on the inference result of the class with the highest class probability obtained from each task. The M.T. Network w/ class. layer model includes a multi-class classification layer used to obtain the classification accuracy. The results show that the M.T. Network w/ class. layer model improved classifica-



(a) Throwing



(b) Kicking



(c) Jumping

Figure 7: Visualization examples of connection patterns. Top: ST-GCN. Bottom: Proposed method.

tion accuracy by 4.23 points in cross-subject and 2.37 points in cross-view. This shows the effectiveness of the proposed method.

4.4.3 Visualization of Adjacency Matrix

Figure 6 shows the adjacency matrixes of the shared part and the throwing, kicking, and jumping action classes at 70 epochs. Since the adjacency matrix of the shared part is not updated, all nodes are connected after learning, but only the top 60 with the largest edge weights are drawn. Out of the two-way edges connecting the nodes, the edges are drawn in the same color as the node to which the edge with the higher weight is connected. The resultant drawing is the connection pattern when learning with cross-subject. The pattern of the shared part (Figure 6(a)) shows that the whole body is considered because the edges are connected to the whole body. In the throwing class pattern (Figure 6(b)), many of the subjects performed the throwing action with their right hand, so the edges are concentrated on the right arm and the right leg, which is the pivot foot. Similarly, in the the kicking class pattern (Figure 6(c)), the edge concentrates on the right leg because many subjects kicked with their right leg. In addition, the edges are concentrated on the head when kicking. This is because many subjects face the throwing point of the throw instead of the object, but kicking is done by facing the object. In

the jump class pattern (Figure 6(d)), the whole body moves, so the edges are concentrated at the center of the body and also concentrated on the right arm.

Figure 7 shows an example of rendering the acquired connection pattern on the dataset videos. Figure 7(a) shows that in the throwing class, the right arm greatly moves and the edges are concentrated on the right arm. Similarly, in the kicking class (Figure 7(b)), the right leg greatly moves and the edges are concentrated on the right leg. Also, when throwing, the participant is looking at the target, and when kicking, the participant is looking at the kicking object. In the jump class (Figure 7(c)), the arm greatly moves with the movement of the whole body, so the edges are concentrated on the center of the body and the right arm. From these results, it can be seen that the edges are concentrated on nodes with large movements for each operation class, and connection patterns specific to operation classes were successfully acquired.

5 CONCLUSIONS

In this work, we proposed an action recognition method considering connection patterns that are specific to action classes. In the proposed method, features unique to each action class were acquired by introducing multitask learning, and the optimal connection for each action class was obtained by updating the adjacency matrix on the basis of the learning weight matrix indicating the importance of edges during learning. Evaluation experiments demonstrated that the proposed method improved classification accuracy in all action classes evaluated compared to ST-GCN. Moreover, by visualizing the connection pattern, we confirmed that patterns specific to each action class were generated. Future work includes learning methods that can obtain the optimal number of edges for each action class.

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