Memory Group Sampling Based Online Action Recognition Using Kinetic Skeleton Features*

Guoliang Liu, Qinghui Zhang, Yichao Cao, Junwei Li, Hao Wu and Guohui Tian

Abstract—Online action recognition is an important task for human centered intelligent services, which is still difficult to achieve due to the varieties and uncertainties of spatial and temporal scales of human actions. In this paper, we propose two core ideas to handle the online action recognition problem. First, we combine the spatial and temporal skeleton features to depict the actions, which include not only the geometrical features, but also multi-scale motion features, such that both the spatial and temporal information of the action are covered. Second, we propose a memory group sampling method to combine the previous action frames and current action frames, which is based on the truth that the neighbouring frames are largely redundant, and the sampling mechanism ensures that the long-term contextual information is also considered. Finally, an improved 1D CNN network is employed for training and testing using the features from sampled frames. The comparison results to the state of the art methods using the public datasets show that the proposed method is fast and efficient, and has competitive performance.

I. INTRODUCTION

Online action recognition has important application value in elderly care, medical rehabilitation, security surveillance, and human–robot interaction and collaboration. There are many sensors can be used to capture human actions, e.g., RGB camera, RGBD camera, IMU, 3D laser scanner. The RGB camera is the most common sensor to analyze human actions [1][2], since it is similar to the human biology vision that can capture natural and substantial informations. In addition, its price is more acceptable than IMU and laser scanners. However, the 2D image is projected from 3D world, such that the human action recognition can be affected by the view point. In contrast, the recent popular RGBD camera can directly output the depth information of the environment, which can be used for 3D human skeleton pose detection [3][4] that is invariant to the view direction, e.g., Microsoft Kinect, Intel realsense, Asus Xtion. In addition, the RGBD camera has low cost price, real time 3D reconstruction capability and easy-to-use features, which drive its popularity in the field of human pose estimation and action recognition.

The skeleton of the human is one of the most common way to model human pose using RGBD sensors, which includes a number of spatial connected bone joints. Each joint has a 2D coordinate in the RGB image or depth image, such that the skeleton is just a vector with very limited length, which can save computational cost to analyze the human pose and action. Currently, most of the human action recognition methods using skeleton data are offline processing, which use a recorded video clip with a fixed length as input [5], or predict the start frame and end frame of the action in the sequential images [6][7]. On the other hand, the online action recognition is still an ongoing problem which is difficult to be solved, since only previous frames of current time are available and the start point of the action is unknown [8][9]. Furthermore, the real time requirement of the online action recognition is the other challenge issue due to the expensive computational cost of the recent deep learning algorithms.

In this paper, we focus on online action recognition using 3D skeleton sequences derived from RGBD sensors. The novelty of our idea are as follows:

(1) We first introduces a group of kinetic skeleton features that can capture both of the spatial and temporal features of the human action, which includes joint collection distance feature, multi-scale motion feature and geometrical features.

(2) We propose to use a memory group sampling mechanism to handle the uncertainty of the temporal scale of the actions, such that long-term contextual information can be considered for action recognition.

(3) We then use a fast, small and efficient neural network to combine these kinetic skeleton features, which can return a competitive performance for online action recognition.

The rest parts of the paper are structured as follows. We first discuss related works in the field of action recognition using skeleton data in Section[II] and then introduce our kinetic skeleton features, memory group sampling and neural network for action recognition in Section[III]. The demonstrated experiments on the public datasets can be found in Section[IV]. Finally, the paper is concluded in Section[V].

II. RELATED WORK

In this section, we review the related works of action recognition using skeleton data, which includes offline algorithms and online algorithms.

A. Offline Action Recognition

For offline action recognition, the skeleton sequence data for processing is often segmented for each action in advance, such that we can easily label these data and train the learning methods. In addition, it is convenient to use segmented data
In addition, the sliding window method can lose long-term context information, such that it has very low accuracy for such situations. Zolfaghari et al. [16] proposed a sampling mechanism for online high-quality action recognition using RGB video stream, which exploits that neighboring frames are largely redundant. In this paper, we use a similar idea for online human action recognition by sampling the kinetic skeleton sequences to balance the data which is far away from the present and the data which is relatively close. We also show that the proposed sampling method can be better than the sliding window for long term actions recognition.

III. METHODS

In this section, we introduce our ideas to extract advanced features from original skeleton sequences for handling the problems causing by the view changes, and discuss the idea of memory group sampling to extract the frames from previous frames for handling the problem of unknown starting point of the actions. Finally, a convolution neural network (CNN) is used for action recognition. The overall flowchart of the propose method can be seen in Fig 1.

A. Advanced Kinetic Skeleton Feature Representation

To fully describe the action of human, we use not only the advanced spatial geometrical information of the human joints, but also the temporal motion features.

Joint collection distances (JCD) feature is first proposed in [17], which is a location viewpoint invariant feature. If each human skeleton has N joints with corresponding Cartesian coordinates $g^k_i = (x, y, z)$ for the $k_{th}$ frame and the $i_{th}$ joint, the joint collection distances can be calculated as follows:

$$ F^k = \begin{bmatrix} \|g^k_2 g^k_1\| & \cdots & \|g^k_N g^k_{N-1}\| \\ \|g^k_N g^k_1\| & \cdots & \|g^k_{N-1} g^k_{N-2}\| \end{bmatrix} $$ (1)

where $\|g^k_i g^k_j\|$ represents the Euclidean distance between joint $g^k_i$ and joint $g^k_j$. Since $F^k$ is a symmetry matrix, we only use the lower triangular matrix as JCD features.

In addition to the JCD features, we also explore the feature information from joint orientation, joint-line distance, line-line angle, joint-plane distance, line-plane angle, plane-plane angle from original skeleton joints according the work.
TABLE I
GEOMETRIC FEATURE CALCULATION METHODS AND FEATURE DESCRIPTION

| Feature                      | Symbol | Calculation Methods                                                                 | Description                          |
|------------------------------|--------|--------------------------------------------------------------------------------------|--------------------------------------|
| Joint Orientation            | \(g_{g,o}\) | \(gg.o(g_1,g_2) = \text{unit}(g_1,g_2)\)                                           | Direction from joint \(g_1\) to \(g_2\) |
| Joint Line Distance          | \(g_{x,l}\) | \(gx.l(g,x_{g_1,g_2}) = 2S_{g_1,g_2} / \|g_1,g_2\|\)                          | Distance from joint \(g_1\) to line \(x_{g_1,g_2}\) |
| Line Line Angle              | \(x_{x,o}\) | \(xx.o(x_{g_1,g_2},x_{g_3,g_4}) = \arccos(gg.o(g_1,g_2) g_3,g_4) / \|g_1,g_2\|\) | Angle between lines \(x_{g_1,g_2}\) and \(x_{g_3,g_4}\) |
| Joint Plane Distance         | \(g_{P,l}\) | \(g_{P,l}(g,P_{g_1,g_2}) = (g - g_1) \odot gg.o(g_1,g_2) / \|gg.o(g_1,g_2)\|\) | Distance from joint \(g_1\) to plane \(P_{g_1,g_2}\) |
| Line Plane Angle             | \(x_{P,o}\) | \(x_{P,o}(x_{g_1,g_2},P_{g_3,g_4}) = \arccos(gg.o(g_1,g_2) g_3,g_4) / \|gg.o(g_1,g_2)\|\) | Angle between line \(x_{g_1,g_2}\) and normal vector of plane \(P_{g_3,g_4}\) |
| Plane Plane Angle            | \(P_{P,o}\) | \(PP.o(P_{g_1,g_2},P_{g_3,g_4}) = \arccos(gg.o(g_1,g_2) g_3,g_4) / \|gg.o(g_1,g_2)\|\) | Angle between normal vector of plane \(P_{g_1,g_2}\) and normal vector of plane \(P_{g_3,g_4}\) |

![Fig. 2. Six advanced geometric features used in this paper.](image)

presented in [13]. To reduce the information redundancy, we select these lines and planes according to the following rules:
• Lines: \(x_{g_1,g_2}\) is a line connected by joint \(g_1\) and \(g_2\), which satisfies one of the following constraints. 1. \(g_1\) and \(g_2\) are directly adjacent in the human structure. 2. One of \(g_1\) and \(g_2\) is the end joint (like head joint, left or right hand joint, left or right foot joint), and the other is the joint separated by a joint in the human structure. 3. \(g_1\) and \(g_2\) are both end joints.
• Planes: \(P_{g_1,g_2,g_3}\) is a plane determined by a triangle formed by \(g_1, g_2\) and \(g_3\). Only five planes that corresponding to body, two arms and two legs are considered.

According to these selected lines and planes, six types of geometric features are chosen as shown in the table. Here, we remove these repetitive features caused by symmetry of the human body. The examples of geometric features are shown in Fig.2.

The geometrical features only depict the spatial relations of the human skeleton joints, whereas the temporal information is missed which is important for human action recognition using a video sequence. Therefore, we further employ the global motion features by differential the spatial position \(G^g\) of human skeleton joints between two \(k\)th frame and \(k+s\) frame where \(s\) is the temporal scale. Here we use two scales for capture the fast motion \(Y_{fast}^k\) and slow motion \(Y_{slow}^k\), i.e., \(s = 1, 2\). The motion features are calculated as

\[
Y_{slow}^k = G^{k+1} - G^k, k \in \{1, 2, \cdots, K - 1\}
\]

\[
Y_{fast}^k = G^{k+2} - G^k, k \in \{1, 2, \cdots, K - 2\}
\]

B. Memory Group Sampling Mechanism
For online action recognition, the unknown start and end action time is a challenge problem compared to the offline action recognition which uses segmented action sequences. The sliding window method is the popular method for tradition online action recognition [15], which has fixed window size and can lose long-term context information. We here propose a memory group sampling mechanism to balance the information that near and far from current frame.

A fixed number of frames are chosen as the input of the action classifier. The sampling function is defined as:

\[
I^T = \bigcup_{t=1}^{T} \{0.5^T Q^0 \}
\]

\[
T = \left\lfloor \frac{j}{N} \right\rfloor - 1
\]

where \(I^T\) is the image frames obtained in the T-th sampling, \(Q^t\) is a queue which stores \(N\) consecutive frames of data before the sampling step \(t\) in the data stream, \(j\) is the number of frames currently received, 0.5 means 50% sampling of the data, \(N\) is the number of sampling frames required for action classifier input.

At the beginning of the video sequence (T=0), we use all \(N\) frames of data received in the current data stream:

\[
I^0 = \{0.5^T Q^0 \} = Q^0
\]
The architecture of the 1D CNN is shown in Fig. 3. This 1D CNN [17] to train the action classifier by using all features. To store these sampled frames, we use a memory group which will be replaced by the working group shown in Algorithm 1.

To train the neural network, we use a computer with a GeForce GTX 1080 Ti, trained classifier $C$, sampling frame number $N$.

For the third sampling $(T=2)$, the sampling equation is shown as:

$$I^2 = \{0.5^2Q^0\} \cup \{0.5^2Q^1\} \cup \{0.5^1Q^2\}$$

where $I^2$ consists of three parts, including 25% of $Q^0$, 25% of $Q^1$, and 50% of $Q^2$. It shows that the latest frames have more probability to be chosen than the older frames, whereas the long-term contextual information is also considered. The specific steps of the memory group sampling algorithm are shown in Algorithm 1.

C. 1D CNN for Online Action Recognition

After obtaining geometrical feature and motion feature representations of the original data, we concatenate all features to a vector, and use a 1D convolution neural network (CNN) to train the action classifier by using all features. The architecture of the 1D CNN is shown in Fig. 3. This 1D CNN classifier is very fast and efficient, which is suitable for online action recognition.

### Algorithm 1 Online Action Recognition Based on Memory Group Sampling Mechanism

**Require**: Live human skeleton stream $L$, trained classifier $C$, sampling frame number $N$.

1. Initialize the empty queue $Q$ to save the sampled $N$ frames.
2. Initialize the memory group $M$.
3. Initialize output average recognition probability $p_a$.
4. **while** New frame available from $L$ do
   5. Add frame $f$ to queue $Q$.
   6. if $i \% N$ then
      7. $I = \text{sample } 50\% \text{ } Q$ and sample $50\% \text{ } M$.
      8. Empty queue $Q$.
      9. Feed $I$ to the classifier $C$ to get recognition probability $p$.
   10. $M = I$.
   11. $p_a = \text{average } p_a$ and $p$.
   12. Output action recognition probability $p_a$.
5. **end if**

IV. EXPERIMENTS

To demonstrate the performance of the proposed method, we use two public skeleton-based datasets: JHMDB dataset [24] and UT-Kinect dataset [25]. The JHMDB dataset contains 928 sample data with 2D skeleton data inferred from RGB data. The UT-Kinect dataset contains 200 sequences of 10 action classes with the 3D skeleton data from depth camera. Every action is recorded twice for each subject.

To train the neural network, we use a computer with a
Nvidia TITAN X GPU. The Adam [26] optimizer is used for learning. We set the initial learning rate to 0.001. When the loss function value of the validation set does not decrease after more than 5 epochs of training, the learning rate is reduced at a rate of 0.5 until it is reduced to 0.00001. A total of 400 epochs were trained.

To show the advance performance of the proposed spatial and temporal kinetic skeleton features, we compare our method to the state of the art action recognition methods in the offline manner using JHMDB and UT-Kinect datasets respectively, which is shown in Table. [I] and Table. [III]

Our algorithm achieves higher classification accuracy than ChainedNet, EHPi, PoTion and DDNet on JHMDB dataset. Compared to our method, ChainedNet [18] uses a 3D CNN classifier and directly inputs the original joint sequences, which achieves 56.8% recognition rate. Similarly, EHPi [19] encodes original joint coordinates as the color information over a fixed period of time, such that the motion of joints can be seen from color changes, then this color image is fed into a CNN for classification, which achieves 65.5% recognition rate. PoTion [20] extracts joint heatmaps for each frame and colorize them using a color that depends on the relative time in the video clip. For each joint, they aggregate them across all frames, which constitutes colored images that are further stacked together as an action representation for classification, which achieves 67.9% recognition rate. DDNet [17] employs 1D CNN network for action classification using the JCD feature and global motion feature, which achieve less accuracy result 77.2% since our method explores more advanced geometrical features from original skeleton data as shown in Fig. [2]

For UT-Kinect dataset, we use half of the samples for training and the other half for testing. Our methods achieve the competitive performance compared to the state of the art methods. Skeleton Joint Features based method proposed by [21] computes the frame difference and pairwise distance of skeleton joints positions to characterize the spatial information of the joints in 3D space, which achieves 87.9% recognition accuracy. Elastic Functional Coding based method proposed by [22] employs the TSRVF space that provides an elastic metric between two trajectories on a manifold to learn the latent variable space of human actions, and propose mfPCA for compact and robust representation of features, which achieves 94.9% recognition accuracy. GeoFeat [13] uses advanced geometric features to model human action sequences, and uses a three-layer LSTM network to classify actions, which achieves 95.9% recognition accuracy. GFT [23] leverages skeletal temporal graph structures to represent body joints, and the graph transform GFT is utilized to extract representations of human motion data, which achieves 96% recognition accuracy. Compared to these methods, we use advanced geometric features and multi-scale motion features to capture spatial and temporal information of human action, and employ a 1D CNN for action classification, which achieves 96.9% recognition accuracy.

To show the effectiveness of the memory group sampling for online action recognition using skeleton sequences, we compare the proposed method to the sliding window method. We first define online action recognition rate as the ratio of the number of positive samples to the total number of samples. The size of the input samples for the online action classifiers is 16, so the sliding window has a fixed size as shown in [15]. The results are shown in Table. [IV] which shows that memory group sampling achieves higher mean accuracy. For short action sequence, the sliding window method has similar performance with ours, such as the action pick up, carry, throw, push, pull, wave. However, the sliding window can not handle the long action sequences well, such as walk, sit down, stand up and clap hands due to its fixed window size. The confusion matrices of human action recognition using sliding window and memory group sampling are shown in Fig. [4] and Fig. [5] respectively.

V. CONCLUSIONS

In order to solve the problem of online human action recognition, we propose a memory group sampling based 1D CNN action classifier using both of the spatial and temporal kinetic skeleton features. The memory group sampling is superior to the traditional sliding window method, since it can capture long term context information while the
nearby frames have higher sampling density. In addition, we combine the JCD feature, advanced geometrical feature and global motion feature to represent the human action information, such that the spatial and temporal information are considered. Furthermore, a simple and effective 1D CNN is used for online classification of concatenated multiple skeleton features. Finally, we demonstrate our method on JHDMB and UT-Kinect datasets, and compare to the state of the art methods, which shows that the proposed method can achieve competitive performance.

REFERENCES

[1] J. Donahue, L. Anne Hendricks, S. Guadarrama, M. Rohrbach, S. Venugopalan, K. Saenko, and T. Darrell, “Long-term recurrent convolutional networks for visual recognition and description,” in Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 2625–2634, 2015.

[2] Y. Zhang, X. Liu, M.-C. Chang, W. Ge, and T. Chen, “Spatio-temporal phrases for activity recognition,” in European Conference on Computer Vision, pp. 707–721. Springer, 2012.

[3] 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,” in Thirtieth AAAI Conference on Artificial Intelligence, 2016.

[4] Y. Du, W. Wang, and L. Wang, “Hierarchical recurrent neural network for skeleton based action recognition,” in Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 1110–1118, 2015.

[5] Y. Kong, Z. Tao, and Y. Fu, “Deep sequential context networks for action prediction,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 1473–1481, 2017.

[6] J. Gao, Z. Yang, K. Chen, C. Sun, and R. Nevatia, “Turn tap: Temporal unit regression network for temporal action proposals,” in Proceedings of the IEEE international conference on computer vision, pp. 3628–3636, 2017.

[7] C. Lea, M. D. Flynn, R. Vidal, A. Reiter, and G. D. Hager, “Temporal convolutional networks for action segmentation and detection,” in proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 156–165, 2017.

[8] Y. Li, C. Lan, J. Xing, W. Zeng, C. Yuan, and J. Liu, “Online human action detection using joint classification-regression recurrent neural networks,” in European Conference on Computer Vision, pp. 203–220, Springer, 2016.

[9] S. Baek, K. I. Kim, and T.-K. Kim, “Real-time online action detection forests using spatio-temporal contexts,” in 2017 IEEE Winter Conference on Applications of Computer Vision (WACV), pp. 158–167, IEEE, 2017.

[10] H. Wang and L. Wang, “Modeling temporal dynamics and spatial configurations of actions using two-stream recurrent neural networks,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 499–508, 2017.

[11] J. Liu, A. Shahroury, D. Xu, and G. Wang, “Spatio-temporal lstm with trust gates for 3d human action recognition,” in European conference on computer vision, pp. 816–833, Springer, 2016.

[12] P. Wang, Z. Li, Y. Hou, and W. Li, “Action recognition based on joint trajectory maps using convolutional neural networks,” in Proceedings of the 24th ACM international conference on Multimedia, pp. 102–106, 2016.

[13] S. Zhang, X. Liu, and J. Xiao, “On geometric features for skeleton-based action recognition using multilayer lstm networks,” in 2017 IEEE Winter Conference on Applications of Computer Vision (WACV), pp. 148–157, IEEE, 2017.

[14] R. De Geest, E. Gavves, A. Ghodrati, Z. Li, C. Snoek, and T. Tuytelaars, “Online action detection,” in European Conference on Computer Vision, pp. 269–284, Springer, 2016.

[15] M. Zanfir, M. Leordeanu, and C. Sminchisescu, “The moving pose: An efficient 3d kinematics descriptor for low-latency action recognition and detection,” in Proceedings of the IEEE international conference on computer vision, pp. 2752–2759, 2013.

[16] M. Zolfaghari, K. Singh, and T. Brox, “Eco: Efficient convolutional network for online video understanding,” in Computer Vision – ECCV 2018 (V. Ferrari, M. Hebert, C. Sminchisescu, and Y. Weiss, eds.), (Cham), pp. 713–730. Springer International Publishing, 2018.

[17] F. Yang, Y. Wu, S. Sakit, and S. Nakamur, “Make skeleton-based action recognition model smaller, faster and better,” in Proceedings of the ACM Multimedia Asia, pp. 1–6, 2019.

[18] M. Zolfaghari, G. L. Oliveira, N. Sedaghat, and T. Brox, “Chained multi-stream networks exploiting pose, motion, and appearance for action classification and detection,” in 2017 IEEE International Conference on Computer Vision (ICCV), pp. 2923–2932, 2017.

[19] D. Ludl, T. Guilde, and C. Curio, “Simple yet efficient real-time pose-based action recognition,” in 2019 IEEE Intelligent Transportation Systems Conference (ITSC), pp. 581–588, 2019.

[20] V. Choutas, P. Weinzaepfel, J. Revaud, and C. Schmid, “Potion: Pose motion representation for action recognition,” in 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 7024–7033, 2018.

[21] Y. Zhu, W. Chen, and G. Guo, “Fusing spatiotemporal features and joints for 3d action recognition,” in 2013 IEEE Conference on Computer Vision and Pattern Recognition Workshops, pp. 486–491, 2013.

[22] R. Anirudh, P. Turaga, J. Su, and A. Srivastava, “Elastic functional coding of human actions: From vector-fields to latent variables,” in 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 3147–3155, 2015.

[23] J. Kao, A. Ortega, D. Tian, H. Mansour, and A. Vetro, “Graph based skeleton modeling for human activity analysis,” in 2019 IEEE International Conference on Image Processing (ICIP), pp. 2025–2029, 2019.

[24] H. Jhuang, J. Gall, S. Zuffi, C. Schmid, and M. J. Black, “Towards understanding action recognition,” in Proceedings of the IEEE international conference on computer vision, pp. 3192–3199, 2013.

[25] L. Xia, C.-C. Chen, and J. K. Aggarwal, “View invariant human action recognition using histograms of 3d joints,” in 2015 IEEE Conference on Computer Vision and Pattern Recognition Workshops, pp. 20–27, IEEE, 2012.

[26] D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” arXiv preprint arXiv:1412.6980, 2014.

Fig. 5. The confusion matrix of memory group sampling based recognition on UT-Kinect dataset.