One-stage Action Detection Transformer

Lijun Li, Li’an Zhuo, Bang Zhang
Alibaba Group
{shenfei.llj, lianzhuo.zla, zhangbang.zb}@alibaba-inc.com

Abstract

In this work, we introduce our solution to the EPIC-KITCHENS-100 2022 Action Detection challenge. One-stage Action Detection Transformer (OADT) is proposed to model the temporal connection of video segments. With the help of OADT, both the category and time boundary can be recognized simultaneously. After ensembling multiple OADT models trained from different features, our model can reach 21.28% action mAP and ranks the 1st on the test-set of the Action detection challenge.

1. Introduction

With the explosion of video contents, video understanding has gained lots of interest from computer vision researchers [10,11,13,14,20]. In this field, action related tasks form the basis of video understanding. Compared with traditional action recognition [12,18,21], action detection not only recognizes action classes, but also detects the temporal boundaries simultaneously. Although only solve one another task, it is much difficult to distinguish the boundary since the action interval is ambiguous. In order to solve the action detection task, most traditional works firstly generate action proposals sorted by confidence score, then use another separate module to classify the proposals. With the great success of transformer in vision, a few works start to insert transformer into the action detection pipeline [22,23]. We follow similar pipeline and propose a one-stage network OADT for action detection.

2. Our Approach

The overall structure is showed in Fig. 1. The network is composed of three parts: video encoder, transformer neck and detection heads. In the following, we will describe each part in details.

2.1. Video Encoders.

Limited by the device memory, the raw video cannot be directly fed to the network. Therefore, the clip-level features are extracted from the untrimmed video using the video encoders. The video encoders are adapted from action recognition without the classification head. In this work, five superior action recognition methods are implemented.

Omnivore [8]. Omnivore is based on the swin-transformer, which leverages the flexibility of transformer-based architectures and is trained jointly on classification tasks from different modalities. For action recognition, the videos are converted into spatio-temporal tubes, and then these tubes are projected into embeddings using the linear layer.

MVit [6]. Multiscale Vision Transformers create a multiscale pyramid of features on the vision transformer, which hierarchically expands the feature complexity while reducing visual resolution.

Motionformer [17]. Motionformer introduces the trajectory attention that aggregates information along implicitly determined motion paths on the video transformer.

Slowfast [7]. SlowFast proposes a two-pathway architecture for video recognition. A slow pathway with a low frame rate is designed to capture spatial semantics. In contrast, a fast pathway, operating at high temporal resolution, is responsible for dealing with rapid motion.

TimeSformer [2]. TimeSformer is a transformer-based approach built exclusively on self-attention over space and time, where temporal attention and spatial attention are separately applied within each block.

2.2. Transformer Neck

The transformer neck is composed of a sequence of transformer [19] layers. It takes in the clip embeddings obtained by the video encoder and performs self-attention. As is shown in the right of Fig. 1, the basic transformer layer includes the layer norm (LN) operations [1], multi-head self-attention (MHSA), residual connections [9], multi-layer...
Figure 1. Overview of our proposed OADT. It is composed of three parts: video encoder which extracts clip-level features from untrimmed videos, transformer neck that takes in the clip embeddings and performs self-attention and detection heads which classify the clips and regress the time boundary.

perceptron (MLP) and the downsampling operation. Furthermore, a feature pyramid with different temporal resolutions is created to capture the various temporal range of actions.

2.3. Detection Heads

Different from the two-stage approaches that generate the segment proposals firstly, the detection heads solve the action classification and segment regression in a synchronous manner. The detection heads predict $N$ results directly, where $N$ is the predefined maximum of the proposals. For the regression head, the segments including the begin and end time are predicted by the several full-connection layers. For the classification head, verb and noun are also predicted by the full-connection layers separately for corresponding proposals, and then both are combined into action classification using the simple operations, i.e., addition or multiplication. The focal losses [15] are employed on optimizing verb, noun and action classification, and the 1D IOU losses are used for segment regression.

3. Experiments

Epic-KITCHENS-100 [5] is a large-scale egocentric action dataset. The dataset is very challenging because it contains various kinds of verb and noun classes from fine-grained action videos which capture all daily activities in the kitchen.

3.1. Experimental Details

In this challenge, we employ the video classification methods and pretrain them on Kinetics600 [4] dataset firstly. Then they are finetuned on EPIC-KITCHENS-100 dataset for action recognition. After finetuning, clip-level features are generated with sliding windows. For each sliding window, the time interval is 32 frames and the temporal stride is 16 frames. In the training stage of action detection, the model is trained for 27 epochs and the input resolution is $456 \times 256$. AdamW [16] optimizer is used with weight decay of 0.0005. The batch size is 2 and the learning rate is set to 0.0001 with the cosine scheduler. We generate the action labels by combining verb and noun predictions. The corresponding time intervals are obtained from the regression head. In inference, Soft-NMS [3] is used for post-processing to suppress redundant action segments.

Evaluation metrics. Mean Average Precision (mAP) is used to evaluate verbs, nouns and actions at different temporal IOU thresholds as well as average mAP. In EPIC-KITCHENS-100 dataset, temporal IOU thresholds range from 0.1 to 0.5 with a step of 0.1. We follow the official split of training, validation and test. For test submission, our model is first trained on the training&validation set and then test on the test set.

Ensemble models. In order to further boost our performance, we apply the five action recognition methods mentioned in Section 2.1 as video encoder separately and train each OADT model. To make full use of different models, we ensemble OADT model trained from different features as our final model.
| Team                | Label | Test mAP(%) @0.1 | @0.2 | @0.3 | @0.4 | @0.5 | Avg |
|---------------------|-------|------------------|------|------|------|------|-----|
| richard61           | Verb  | 22.78            | 21.68| 20.14| 18.34| 15.54| 19.69|
|                     | Noun  | 19.33            | 17.98| 16.55| 14.69| 12.28| 16.17|
|                     | Action| 14.33            | 13.63| 12.80| 11.53| 9.93 | 12.44|
| Bristol-MaVi        | Verb  | 18.99            | 17.87| 16.41| 14.43| 11.36| 15.81|
|                     | Noun  | 15.03            | 13.76| 12.40| 10.53| 8.75 | 13.72|
|                     | Action| 14.71            | 13.98| 12.86| 11.56| 9.85 | 12.59|
| CTC-AI              | Verb  | 22.62            | 21.73| 20.68| 17.74| 15.16| 19.58|
|                     | Noun  | 20.65            | 19.58| 18.34| 16.18| 12.88| 17.52|
|                     | Action| 16.68            | 16.11| 15.15| 13.59| 11.66| 14.64|
| Alibaba-MMAI-Research| Verb | 25.33            | 23.99| 21.91| 19.61| 17.08| 21.38|
|                     | Noun  | 18.99            | 17.87| 16.41| 14.43| 11.36| 15.81|
|                     | Action| 14.71            | 13.98| 12.86| 11.56| 9.85 | 12.59|
| 4Paradigm-UWMadison-NJU | Verb | 22.62            | 21.73| 20.68| 17.74| 15.16| 19.58|
|                     | Noun  | 20.65            | 19.58| 18.34| 16.18| 12.88| 17.52|
|                     | Action| 16.68            | 16.11| 15.15| 13.59| 11.66| 14.64|
| Ours                | Verb  | 30.67            | 29.40| 26.81| 24.34| 20.51| 26.35|
|                     | Noun  | 30.96            | 29.36| 26.78| 23.27| 18.80| 25.83|
|                     | Action| 24.57            | 23.50| 21.94| 19.65| 16.74| 21.28|

Table 1. Final results on EPIC-KITCHENS-100 test set.

Table 2. Detection results on EPIC-KITCHENS-100 validation set.

Results. Tab. 2 shows our results on validation set. From the table, we can see that OADT using Omnivore as the video encoder performs best. While Motionformer and MVit perform slightly worse and are roughly 2% lower. In the end, we ensemble all the five models and can reach 24.02% which is about 1.5% higher than the single best model in action mAP. In Tab. 1, we compare our result to existing state-of-the-art results on the test set. Our solution can get 21.28% mAP which is 5% higher than the winning solution of last year. We outperform prior work especially on verb class by a large margin of +3%.

4. Conclusion

We present our OADT model used in the EPIC-KITCHENS-100 2022 Action Detection challenge. Our model is a one-stage transformer-based architecture composed of the video encoder, transformer block and multiple heads for classification and regression. After ensembling five models, our model can reach the state-of-the-art result of 21.28% average mAP on the EPIC-KITCHENS-100 test set.

Acknowledgement. We would like to thank the whole EPIC-KITCHENS team for hosting such a great challenge.

References

[1] Jimmy Lei Ba, Jamie Ryan Kiros, and Geoffrey E Hinton. Layer normalization. arXiv preprint arXiv:1607.06450, 2016.
[2] Gedas Bertasius, Heng Wang, and Lorenzo Torresani. Is space-time attention all you need for video understanding? In Proceedings of the International Conference on Machine Learning, 2021.
[3] Navaneeth Bodla, Bharat Singh, Rama Chellappa, and Larry S Davis. Soft-nms--improving object detection with one line of code. In Proceedings of the IEEE International Conference on Computer Vision, pages 5561–5569, 2017.
[4] Joao Carreira, Eric Noland, Andras Banki-Horvath, Chloe Hillier, and Andrew Zisserman. A short note about kinetics-600. arXiv preprint arXiv:1808.01340, 2018.
[5] Dima Damen, Hazel Doughty, Giovanni Maria Farinella, Antonino Furnari, Evangelos Kazakos, Jian Ma, Davide Moltisanti, Jonathan Munro, Toby Perrett, Will Price, et al. Rescaling egocentric vision: Collection, pipeline and challenges for epic-kitchens-100. International Journal of Computer Vision, 130(1):33–55, 2022.
[6] Haoqi Fan, Bo Xiong, Karttikeya Mangalam, Yanghao Li, Zhicheng Yan, Jitendra Malik, and Christoph Feichtenhofer. Multiscale vision transformers. In Proceedings of the IEEE International Conference on Computer Vision, pages 6824–6835, 2021.
[7] Christoph Feichtenhofer, Haoqi Fan, Jitendra Malik, and Kaiming He. Slowfast networks for video recognition. In Proceedings of the IEEE International Conference on Computer Vision, pages 6202–6211, 2019. 1, 3

[8] Rohit Girdhar, Mannat Singh, Nikhila Ravi, Laurens van der Maaten, Armand Joulin, and Ishan Misra. Omnivore: A Single Model for Many Visual Modalities. In Proceedings of the IEEE conference on Computer Vision and Pattern Recognition, 2022. 1, 3

[9] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 770–778, 2016. 1

[10] Shuviwang Ji, Wei Xu, Ming Yang, and Kai Yu. 3d convolutional neural networks for human action recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, 35(1):221–231, 2012. 1

[11] Andrej Karpathy, George Toderici, Sanketh Shetty, Thomas Leung, Rahul Sukthankar, and Li Fei-Fei. Large-scale video classification with convolutional neural networks. In Proceedings of the IEEE conference on Computer Vision and Pattern Recognition, pages 1725–1732, 2014. 1

[12] Lijun Li and Shuling Dai. Action recognition with deep network features and dimension reduction. KSII Trans. Internet Inf. Syst., 13(2):832–854, 2019. 1

[13] Lijun Li and Boqing Gong. End-to-end video captioning with multitask reinforcement learning. In IEEE Winter Conference on Applications of Computer Vision, pages 339–348, 2019. 1

[14] Yandong Li, Lijun Li, Liqiang Wang, Tong Zhang, and Boqing Gong. NATTACK: learning the distributions of adversarial examples for an improved black-box attack on deep neural networks. In Proceedings of the 36th International Conference on Machine Learning, pages 3866–3876, 2019. 1

[15] Tsung-Yi Lin, Priya Goyal, Ross Girshick, Kaiming He, and Piotr Dollár. Focal loss for dense object detection. In Proceedings of the IEEE international conference on computer vision, pages 2980–2988, 2017. 2

[16] Ilya Loshchilov and Frank Hutter. Decoupled weight decay regularization. arXiv preprint arXiv:1711.05101, 2017. 2

[17] Mandela Patrick, Dylan Campbell, Yuki Asano, Ishan Misra, Florian Metze, Christoph Feichtenhofer, Andrea Vedaldi, and João F Henriques. Keeping your eye on the ball: Trajectory attention in video transformers. Advances in Neural Information Processing Systems, 34, 2021. 1, 3

[18] Karen Simonyan and Andrew Zisserman. Two-stream convolutional networks for action recognition in videos. Advances in Neural Information Processing Systems, 27, 2014. 1

[19] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. Advances in Neural Information Processing Systems, 30, 2017. 1

[20] Limin Wang, Yuanjun Xiong, Zhe Wang, Yu Qiao, Dahua Lin, Xiaoou Tang, and Luc Van Gool. Temporal segment networks for action recognition in videos. IEEE Transactions on Pattern Analysis and Machine Intelligence, 41(11):2740–2755, 2018. 1

[21] Chao-Yuan Wu, Christoph Feichtenhofer, Haoqi Fan, Kaiming He, Philipp Krahenbuhl, and Ross Girshick. Long-term feature banks for detailed video understanding. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 284–293, 2019. 1

[22] Mingze Xu, Yuanjun Xiong, Hao Chen, Xinyu Li, Wei Xia, Zhuowen Tu, and Stefano Soatto. Long short-term transformer for online action detection. Advances in Neural Information Processing Systems, 34, 2021. 1

[23] Chen-Lin Zhang, Jianxin Wu, and Yin Li. Actionformer: Localizing moments of actions with transformers. CoRR, abs/2202.07925, 2022. 1