A Stronger Baseline for Ego-Centric Action Detection

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Abstract

This technical report analyzes an egocentric video action detection method we used in the 2021 EPIC-KITCHENS-100 competition hosted in CVPR2021 Workshop. The goal of our task is to locate the start time and the end time of the action in the long untrimmed video, and predict action category. We adopt sliding window strategy to generate proposals, which can better adapt to short-duration actions. In addition, we show that classification and proposals are conflict in the same network. The separation of the two tasks boost the detection performance with high efficiency. By simply employing these strategy, we achieved 16.10% performance on the test set of EPIC-KITCHENS-100 Action Detection challenge using a single model, surpassing the baseline method by 11.7% in terms of average mAP.

1. Introduction

Temporal action detection is a challenging task, especially for the EPIC-KITCHENS-100 dataset [9], where (a) most actions spans a short period, compared to the duration of the original untrimmed videos and (b) consistently altering action categories under the same background environment requires the network to have the ability to look for fine-grained features and discriminate complicated spatio-temporal interactions. To alleviate these issues, we propose the following strategies: (a) We use sliding windows to restrict the length of the input untrimmed videos for each video clip that is to be evaluated. This ensures that enough features are assigned to the short action segment candidates, which will be otherwise overwhelmed by the features from other segments in a long video that is simply normalized. The possibility is also increased that the length of the potential action segments can be matched to the pre-defined temporal anchors. (b) For more accurate verb and noun classifications, pre-trained backbones are employed for the classification of each video clip in the long videos. Additionally, we noticed an optimization conflict for proposal evaluation and classification, where the performances of both tasks drop drastically when a joint head is used to perform both tasks. Hence, we propose to use separate heads for evaluating the proposals as well as performing the classifications.

2. Our Approach

The overall architecture of our approach is visualized in Figure 1. The general process can be divided into four steps, respectively, (i) the pre-training of the classification models, (ii) feature extraction process, (iii) proposal generation process as well as the (iv) detection result generation process. We will discuss all the four stages one by one in the following sections.

2.1. Pre-train of Classification Models

Transfer learning is an important measure to improve the generalization ability of the model. Supervised training [24, 26, 8, 29, 25, 11] as well as unsupervised ones [15, 13, 21] are two mainstream pre-training strategy. Although the latter strategy can leverage a larger set of data, leading to a more generalized representation, supervised pre-training utilizes training data more efficiently and effectively. There-
Figure 1: The overall framework of our approach. In feature extraction process, the input videos are divided into N clips, which are fed to the pre-trained backbone to extract features as well as verb and noun predictions. In the proposal generation stage, the sliding windows are uniformly distributed along temporal dimension, and clip-level features covered by each sliding window are fed to the Boundary Matching Network to generate proposals. In detection generation stage, the classification results for each proposal are sampled from classification scores yielded by the pre-trained backbone. Finally, the verb and noun predictions are fused with proposals to generate detection result with action predictions.

Therefore, we adopt the former strategy. Recently, Transformer-Based methods have shown great potential in image recognition [10, 33] and video understanding [1, 3]. We employ ViViT [1] and CSN [25] as our backbone for comparison and first pre-train it on Kinetics700 [7] dataset, mostly following the training recipes in DeepViT [33]. And then the pre-trained backbone is fine-tuned on EPIC-KITCHENS-100 dataset with verb head and noun head. In the fine-tuning stage, the FPS of the videos are normalized to 60, we sample 32 frames with sampling rate of 2 for each clip. The training details of the backbone models can be referred to our Action Recognition report [14].

2.2. Feature Extractor

Limited by the GPU memory, the raw frames cannot be directly fed to the backbone. Because of the limited GPU memory, it is impossible to put the whole video to the computing device. Therefore, multiple high-dimensional feature vectors are extracted from the untrimmed video using the pre-trained backbones, which will be further used in the later stage to generate action proposals. For the feature extraction process, we mostly follow the common setting in the temporal action detection community [18, 19, 17, 30, 12, 5, 2, 31, 23, 27, 16, 28]. Specifically, given the number of frames $l$ in a video, we split the video according to a fixed stride $\delta$ between consecutive video clips. Hence, the whole video is split into $N$ clips, where $N = l/\delta$. In our experiments, the value of $\delta$ is set to 16. It is worth noting that, besides the feature vectors, the verb and noun predictions are saved at the same time for each clip when extracting its features.

2.3. Generation of Proposals

In our observations, different from mainstream action detection datasets [6, 32], 98.15% of the duration of the ground truth action segments are less than 20s. However, the average duration of the videos is up to 512.43s, which results in an extremely low percentage that the action segment candidate accounts for in the entire video. Therefore, we propose to generate action proposals within sliding windows. For each sliding window, we include features for 200 video clips. Because the interval between two consecutive video clips are 16 frames, which can be converted to 0.2667s in a 60-fps video, each sliding window contains contextual information lasting around 53.33s. The time interval between each sliding window is half of the size of one sliding window, which is 26.67 seconds. To ensure that at least one sliding window will cover the whole action segment candidate, we limit the maximum length of the potential action segment to be 26.67 seconds.

With sliding windows, Boundary Matching Network (BMN) [18] is employed to generate accurate proposals. Given the clip-level features $x \in \mathbb{R}^{N \times C}$, BMN extracts candidate-level features for each potential action seg-
Table 1: Action detection results on EPIC-KITCHENS-100 dataset. Features are extracted by the backbone in the feature backbone column. BMN in the classification column indicates that two classification heads are added upon the BMN feature to perform verb and noun predictions, while CSN and ViViT in the classification column indicates that we directly sample the prediction results temporally to obtain the final classification. The predictions results of CSN and ViViT are saved during the feature extraction process.

| Feature Backbone | Classification | mAP(Val) for Action @0.1 | mAP(Val) for Action @0.2 | mAP(Val) for Action @0.3 | mAP(Val) for Action @0.4 | mAP(Val) for Action @0.5 | mAP(Test) for Action @0.1 | mAP(Test) for Action @0.2 | mAP(Test) for Action @0.3 | mAP(Test) for Action @0.4 | mAP(Test) for Action @0.5 | Avg |
|------------------|-----------------|---------------------------|--------------------------|-------------------------|-------------------------|-------------------------|---------------------------|--------------------------|--------------------------|-------------------------|-------------------------|------------------|
| ViViT [1]        | BMN [18]        | 6.84                      | 6.01                     | 5.28                    | 4.42                    | 3.26                    | 5.16                      | 5.86                     | 5.33                     | 4.67                    | 4.03                    | 3.03  | 4.59       |
| CSN [25]         | BMN [18]        | 7.30                      | 7.01                     | 6.56                    | 6.05                    | 5.08                    | 6.40                      | 13.08                    | 11.97                    | 10.84                   | 9.56                    | 8.00  | 10.69      |
| ViViT [1]        | CSN [25]        | 13.90                     | 13.23                    | 11.98                   | 10.48                   | 8.80                    | 11.68                     | 18.76                    | 17.73                    | 16.26                   | 14.91                   | 12.87 | 16.11      |
| ViViT [1]        | ViViT [1]       | 21.14                     | 20.10                    | 19.02                   | 17.32                   | 15.11                   | 18.53                     | 18.76                    | 17.73                    | 16.26                   | 14.91                   | 12.87 | 16.11      |

(a) Action detection results for Action.

| Feature Backbone | Classification | mAP(Val) for Verb @0.1 | mAP(Val) for Verb @0.2 | mAP(Val) for Verb @0.3 | mAP(Val) for Verb @0.4 | mAP(Val) for Verb @0.5 | mAP(Test) for Verb @0.1 | mAP(Test) for Verb @0.2 | mAP(Test) for Verb @0.3 | mAP(Test) for Verb @0.4 | mAP(Test) for Verb @0.5 | Avg |
|------------------|-----------------|-------------------------|-------------------------|------------------------|------------------------|------------------------|-------------------------|-------------------------|------------------------|------------------------|------------------------|------------------|
| ViViT [1]        | BMN [18]        | 11.32                   | 10.07                   | 8.64                   | 6.73                   | 5.00                   | 8.35                     | 10.07                   | 9.41                   | 8.29                   | 6.63                   | 4.80  | 7.84       |
| CSN [25]         | BMN [18]        | 12.89                   | 12.39                   | 11.55                  | 10.42                  | 8.09                   | 11.06                    | 17.58                   | 15.91                  | 14.21                  | 12.23                  | 9.73  | 13.93      |
| ViViT [1]        | CSN [25]        | 16.57                   | 15.56                   | 14.10                  | 12.12                  | 10.21                  | 13.71                    | 22.77                   | 22.01                  | 19.63                  | 17.81                  | 14.65 | 19.37      |
| ViViT [1]        | ViViT [1]       | 22.92                   | 21.86                   | 20.89                  | 18.33                  | 15.66                  | 19.93                    | 26.44                   | 24.55                  | 22.30                  | 19.82                  | 16.25 | 21.87      |

(b) Action detection results for Verb.

| Feature Backbone | Classification | mAP(Val) for Noun @0.1 | mAP(Val) for Noun @0.2 | mAP(Val) for Noun @0.3 | mAP(Val) for Noun @0.4 | mAP(Val) for Noun @0.5 | mAP(Test) for Noun @0.1 | mAP(Test) for Noun @0.2 | mAP(Test) for Noun @0.3 | mAP(Test) for Noun @0.4 | mAP(Test) for Noun @0.5 | Avg |
|------------------|-----------------|-------------------------|-------------------------|------------------------|------------------------|------------------------|-------------------------|-------------------------|------------------------|------------------------|------------------------|------------------|
| ViViT [1]        | BMN [18]        | 9.70                    | 8.35                    | 7.21                   | 5.77                   | 4.08                   | 7.02                     | 9.76                    | 8.67                    | 7.43                   | 6.02                   | 4.19  | 7.22       |
| CSN [25]         | BMN [18]        | 11.00                   | 10.34                   | 9.46                   | 8.29                   | 6.71                   | 9.16                     | 19.46                   | 17.79                  | 15.87                  | 13.62                  | 10.90 | 15.53      |
| ViViT [1]        | CSN [25]        | 18.47                   | 17.21                   | 15.56                  | 13.38                  | 10.58                  | 15.04                    | 26.44                   | 24.55                  | 22.30                  | 19.82                  | 16.25 | 21.87      |
| ViViT [1]        | ViViT [1]       | 30.09                   | 27.59                   | 25.81                  | 22.80                  | 19.26                  | 25.11                    | 26.44                   | 24.55                  | 22.30                  | 19.82                  | 16.25 | 21.87      |

(c) Action detection results for Noun.

2.4. Generation of Detection Results

To detect actions, it would be convenient if the BMN [18] can directly output both scores for the candidate proposals as well as the predictions of the verb and noun category for the corresponding proposals. However, we observe that when we use the candidate-level features extracted by the BMN network to perform both proposal evaluation task and classification, the performance is terrible. We suspect that there is some optimization conflict in the classification and the proposal evaluation tasks.

Since the accuracy of the feature extraction backbone ViViT (pre-trained on Kinetics700 and fine-tuned for EPIC-KITCHENS-100 action recognition task) can achieve 47.4% with 3 × 10 views in the validation set, we directly use its classification predictions. Specifically, we save all the predictions during the feature extraction process as we have mentioned before. Empirically, we show in Table 1 that, when we use ViViT [1] or CSN [25] features as the clip-level features and the candidate-level features of BMN to perform classification, the performance is worse than simply using the classification results generated directly by ViViT or CSN. Furthermore, when ViViT classification is used, a 6.85% performance improvement is observed over the CSN classification results. This is mainly due to the higher accuracy of ViViT in action recognition task. In our experiments, we do not use any ensemble strategy, which provides a simple and strong baseline for EPIC-KITCHENS-100 dataset.

To generate detection results, for each proposal generated by BMN, we sample the classification results in time range covered by the proposal with 10 uniform temporal location. The sampled classification results are averaged to get the prediction of respectively verb and noun for the proposal.
positional action detection results are obtained by fusing verb, noun scores and proposals.

3. Conclusion

In this report, we propose a stronger baseline for Ego-Centric Action Detection. We adopt a sliding window strategy to alleviate the problem that the temporal duration of proposals is too short to be detected efficiently. In addition, we also found that the conflict when the classification task and the proposal task coexist in the same network. Separating the two has significantly improved the performance. These two problems are inevitable in EPIC-KITCHENS-100 temporal action detection, how to solve these problems elegantly is still worthy of further study.

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References

[1] Anurag Arnab, Mostafa Dehghani, Georg Heigold, Chen Sun, Mario Lučić, and Cordelia Schmid. Vivit: A video vision transformer. arXiv preprint arXiv:2103.15691, 2021.

[2] Yueran Bai, Yingying Wang, Yunhai Tong, Yang Yang, Qiuyue Liu, and Junhui Liu. Boundary content graph neural network for temporal action proposal generation. arXiv preprint arXiv:2008.01432, 2020.

[3] Gedas Bertasius, Heng Wang, and Lorenzo Torresani. Is space-time attention all you need for video understanding? arXiv preprint arXiv:2102.05095, 2021.

[4] Navaneeth Bodla, Bharat Singh, Eric Noland, Chloe Hillier, and Andrew Zisserman. A short note on the kinetics-700 human action dataset. arXiv preprint arXiv:1907.06987, 2019.

[5] Joao Carreira, Eric Noland, Chloe Hillier, and Andrew Zisserman. A short note on the kinetics-700 human action dataset. arXiv preprint arXiv:1907.06987, 2019.

[6] Jiyang Gao, Zhenheng Yang, Kan Chen, Chen Sun, and Ram Nevatia. Turn tap: Temporal unit regression network for temporal action proposals. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 6202–6211, 2019.

[7] Jianwen Jiang, Yu Cao, Lin Song, SZY Li, Z Xu, C Gan Q Wu, C Zhang, and G Yu. Human centric spatio-temporal action localization. ActivityNet Workshop on CVPR, 2018.

[8] Tianwei Lin, Xiao Liu, Xin Li, Errui Ding, and Shilei Wen. Boundary-matching network for temporal action proposal generation. In Proceedings of the IEEE International Conference on Computer Vision, pages 3889–3898, 2019.

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

[10] Antoine Miech, Jean-Baptiste Alayrac, Lucas Smaira, Ivan Laptev, Josef Sivic, and Andrew Zisserman. End-to-end

[11] Joao Carreira and Andrew Zisserman. Quo vadis, action recognition? a new model and the kinetics dataset. In IEEE Conf. Comput. Vis. Pattern Recogn., pages 6299–6308, 2017.

[12] 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. arXiv preprint arXiv:2006.13256, 2020.

[13] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. arXiv preprint arXiv:2010.11929, 2020.

[14] Tengda Han, Weidi Xie, and Andrew Zisserman. Self-supervised co-training for video representation learning. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 6202–6211, 2019.

[15] Tianwei Lin, Xiao Liu, Xin Li, Errui Ding, and Shilei Wen. Bmn: Boundary-matching network for temporal action proposal generation. In Proceedings of the European Conference on Computer Vision (ECCV), pages 3628–3636, 2017.

[16] Jianwen Jiang, Yu Cao, Lin Song, Zhiwu Qing, Xiang Wang, Yutong Feng, Shiwei Zhang, Jianwen Jiang, Zhurong Xia, Mingqian Tang, Nong Sang, and Marcelo Ang. Towards training stronger video vision transformers for epic-kitchens-100 action recognition. arXiv preprint arXiv:2106.05058, 2021.

[17] Ziyuan Huang, Shiwei Zhang, Jianwen Jiang, Mingqian Tang, Rong Jin, and Marcelo Ang. Self-supervised motion learning from static images. arXiv preprint arXiv:2104.00240, 2021.

[18] Tianwei Lin, Xiao Liu, Xin Li, Errui Ding, and Shilei Wen. Stronger video vision transformers for epic-kitchens-100 action recognition. arXiv preprint arXiv:2106.05058, 2021.
learning of visual representations from uncurated instructional videos. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 9879–9889, 2020.

[22] Zhiwu Qing, Haisheng Su, Weihao Gan, Dongliang Wang, Wei Wu, Xiang Wang, Yu Qiao, Junjie Yan, Changxin Gao, and Nong Sang. Temporal context aggregation network for temporal action proposal refinement. *arXiv preprint arXiv:2103.13141*, 2021.

[23] Zhiwu Qing, Xiang Wang, Yongpeng Sang, Changxin Gao, Shiwei Zhang, and Nong Sang. Temporal fusion network for temporal action localization: Submission to activitynet challenge 2020 (task e). *arXiv preprint arXiv:2006.07520*, 2020.

[24] Zhaofan Qiu, Ting Yao, and Tao Mei. Learning spatio-temporal representation with pseudo-3d residual networks. In *Int. Conf. Comput. Vis.*, pages 5533–5541, 2017.

[25] Du Tran, Heng Wang, Lorenzo Torresani, and Matt Feiszli. Video classification with channel-separated convolutional networks. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 5552–5561, 2019.

[26] Du Tran, Heng Wang, Lorenzo Torresani, Jamie Ray, Yann LeCun, and Manohar Paluri. A closer look at spatiotemporal convolutions for action recognition. In *IEEE Conf. Comput. Vis. Pattern Recog.*, pages 6450–6459, 2018.

[27] Xiang Wang, Baiteng Ma, Zhiwu Qing, Yongpeng Sang, Changxin Gao, Shiwei Zhang, and Nong Sang. Chr-net: Cascade boundary refinement network for action detection: Submission to activitynet challenge 2020 (task 1). *arXiv preprint arXiv:2006.07526*, 2020.

[28] Xiang Wang, Shiwei Zhang, Zhiwu Qing, Yuanjie Shao, Changxin Gao, and Nong Sang. Self-supervised learning for semi-supervised temporal action proposal. *arXiv preprint arXiv:2104.03214*, 2021.

[29] S Xie, C Sun, J Huang, Z Tu, and K Murphy. Rethinking spatiotemporal feature learning for video understanding (2017). arxiv preprint. *arXiv preprint arXiv:1712.04851*, 2017.

[30] Mengmeng Xu, Chen Zhao, David S Rojas, Ali Thabet, and Bernard Ghanem. G-tad: Sub-graph localization for temporal action detection. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 10156–10165, 2019.

[31] Shiwei Zhang, Lin Song, Changxin Gao, and Nong Sang. Glnet: Global local network for weakly supervised action localization. *IEEE Transactions on Multimedia*, 22(10):2610–2622, 2019.

[32] Hang Zhao, Antonio Torralba, Lorenzo Torresani, and Zhicheng Yan. Hacs: Human action clips and segments dataset for recognition and temporal localization. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 8668–8678, 2019.

[33] Daquan Zhou, Bingyi Kang, Xiaojie Jin, Linjie Yang, Xiaochen Lian, Zihang Jiang, Qibin Hou, and Jiashi Feng. Deepvit: Towards deeper vision transformer. *arXiv preprint arXiv:2103.11886*, 2021.