Low-Resolution Action Recognition for Tiny Actions Challenge in ActivityNet

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Abstract

Tiny Actions Challenge focuses on understanding human activities in real-world surveillance. Basically, there are two main difficulties for activity recognition in this scenario. First, human activities are often recorded at a distance, and appear in a small resolution without much discriminative clue. Second, these activities are naturally distributed in a long-tailed way. It is hard to alleviate data bias for such heavy category imbalance. To tackle these problems, we propose a comprehensive recognition solution in this paper. First, we train video backbones with data balance, in order to alleviate overfitting in the challenge benchmark. Second, we design a dual-resolution distillation framework, which can effectively guide low-resolution action recognition by super-resolution knowledge. Finally, we perform model ensemble with post-processing, which can further boost performance on the long-tailed categories. Our solution ranks Top-1 on the leaderboard.

1. Introduction

Video action recognition is an important problem in computer vision. However, current approaches mainly work on high-quality videos, which are often limited to recognize low-resolution human activities in practice. To investigate this problem, researchers often manually create low-resolution videos, by down-sampling high-resolution ones. However, such low-resolution videos cannot reflect real-world video quality. To fill this gap, Tiny Actions Challenge introduces a low-resolution action recognition task, where the benchmark is collected from real surveillance videos. Basically, this task contains two main difficulties. First, human activities are often recorded at a distance, which is far from surveillance camera. Hence, human often appear in a small resolution of video, with blurred appearance and motion information. Second, these activities are collected from the real life. Hence, their data distribution is long-tailed with heavy class imbalance.

To tackle these difficulties in this challenge, we propose a comprehensive solution for low-resolution action recognition in videos. Specifically, there are three key contributions in our main solution. First, we choose suitable video backbones for this task, and train them with data balance in order to alleviate overfitting in the challenge benchmark. Second, we design a dual-resolution distillation framework to boost low-resolution action recognition, with complementary knowledge from super-resolution network. Finally, we perform model ensemble with post-processing, which can further improve recognition performance on long-tail categories.

2. Video Backbones with Data Balance

In this challenge, we mainly choose two fundamental video backbones, including ir-CSN-ResNet152 [6] and UniFormer-Base [4], which are pretrained on Kinetics400. The main reason is that, these models share similar advantages of simple structure, light computation, less overfitting, and better accuracy on spatial-temporal representation learning. However, directly fine-tuning these models on the competition benchmark may not be preferable, since these low-resolution videos have limited action details and follow the long-tailed distribution [3].

To have a good start, we choose distinct settings for training models with these tiny action videos. First, in both the training and testing phase, we uniformly divided one video into 16 clips, and randomly selected one frame in each clip. We find that, this sampling setting works pretty well for F1-score improvement, with sufficient long-range action contexts in the video. Second, due to long-tailed distribution in this challenge, we propose to operate data balance in the

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training phase. Specifically, we first apply horizontal flip on the training videos of long-tail categories. Then, we use these flipped videos as extra training samples in these categories. As shown in Table 1, all these settings can boost video backbones for tiny action recognition.

### 3. Dual-Resolution Distillation

As mentioned before, one key problem in this challenge is that, low-resolution videos contain blurred appearance and motion of human activities. To enhance action details, we propose to transform these videos into super-resolution ones. Note that, there is no super-resolution ground truth for each low-resolution video. Hence, we use the popular RealBasicVSR [2] as a fixed generator, and directly feed low-resolution videos to generate super-resolution ones with spatial size of 224x224. Since super-resolution training videos inherit activity labels from their original low-resolution ones, we can use them to train video backbones for activity recognition.

In this work, we propose a dual-resolution distillation framework, which aims at leveraging super-resolution action knowledge to boost low-resolution recognition. First, we train a video backbone by using super-resolution videos. Second, we use this recognition network as knowledge extractor, i.e., for each low-resolution training video, we feed its corresponding super-resolution video into extractor, and generate the prediction score vector of activity categories as knowledge $k$. Finally, we feed this low-resolution video into a low-resolution recognition network. For training this network, we use two supervision signals on the prediction vector $p$, where $L_{bce}$ is the binary cross entropy loss between the prediction vector and ground truth label. $L_{kd}$ is the knowledge distillation loss (e.g., MSE) between the prediction vector $p$ and the super-resolution knowledge vector $k$.

$$L_{total} = \alpha L_{bce} + (1 - \alpha) L_{kd},$$

$$L_{kd} = \frac{1}{C} \sum_{c=1}^{C} (p_c - k_c)^2,$$

where $\alpha$ is a weight scale for loss balance. Our dual-resolution distillation flexibly leverages super-resolution information to boost low-resolution recognition, and thus leads to better performance as shown in Table 2.

### 4. Model Ensemble

We perform model ensemble to make final prediction. We find that, the models trained at the middle epochs are also useful to improve recognition. Hence, we choose 12 networks in total for model ensemble, e.g., ir-CSN x4 in Table 3 means that, we choose 4 ir-CSN models which are trained at different epochs. Furthermore, due to long-tailed distribution in this challenge, we carefully set the prediction thresholds for all the activity categories, i.e., large-sample-size categories need a higher prediction threshold, while small-sample-size categories need a lower prediction threshold. Finally, we use the prior knowledge of categories [5] to assist activity recognition in the process of model ensemble, i.e., within the same group of activities categories, it is reasonable to keep one class with the highest score. As shown in Table 3, we achieve a quite good F1 score by model ensemble and post-processing.

### 5. Training Practices

We mainly use binary cross-entropy loss to deal with multi-label classification. Additionally, we also use Asym-
metric Loss (ASL) [1], which is based on the Focal Loss, in order to further relieve the unbalanced distribution problem of this multi-label benchmark in the challenge. AdamW is chosen as optimizer, and warmup mechanism is used at the start phase of training. The initial learning rate for UniFormer is 2e-4, and this rate for ir-CSN is 1e-4. We use Cosine Annealing Warm Restarts method to schedule the learning rate. The drop path rate of UniFormer is 0.4, and the dropout rate for ir-CSN is 0.5.

6. Conclusion

In this work, we design a comprehensive solution for low-resolution activity recognition in Tiny Actions Challenge. First, we choose effective video backbones with data balance training. Second, we design a dual-distillation framework to enhance action clues from super-resolution knowledge. Finally, we perform model ensemble and post-processing to further boost recognition on such long-tailed categories in this challenge.

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