

Low-Fidelity End-to-End Video Encoder Pre-training for Temporal Action Localization

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Temporal action localization (TAL) is a fundamental yet challenging task in video understanding. Existing TAL methods rely on pre-training a video encoder through action classification supervision. This results in a task discrepancy problem for the video encoder – trained for action classification, but used for TAL. Intuitively, end-to-end model optimization is a good solution. However, this is not operable for TAL subject to the GPU memory constraints, due to the prohibitive computational cost in processing long untrimmed videos. In this paper we resolve this challenge by introducing a novel low-fidelity end-to-end (LoFi-E2E) video encoder pre-training method. Instead of always using the full training configurations for TAL learning, we propose to reduce the mini-batch composition in terms of temporal, spatial or spatio-temporal resolution so that end-to-end optimization for the video encoder becomes operable under the memory conditions of a mid-range hardware budget. Crucially, this enables the gradient to flow backwards through the video encoder from a TAL loss supervision, favourably solving the task discrepancy problem and providing more effective feature representations. Extensive experiments show that the proposed LoFi-E2E pre-training approach can significantly enhance the performance of existing TAL methods. Encouragingly, even with a lightweight ResNet18 based video encoder in a single RGB stream, our method surpasses two-stream ResNet50 based alternatives with expensive optical flow, often by a good margin.

1. Introduction

Video analysis has recently become an important area of research, encompassing multiple relevant problems such as action recognition [9, 14], temporal action localization [1, 8, 13, 20, 50, 51], and video question answering

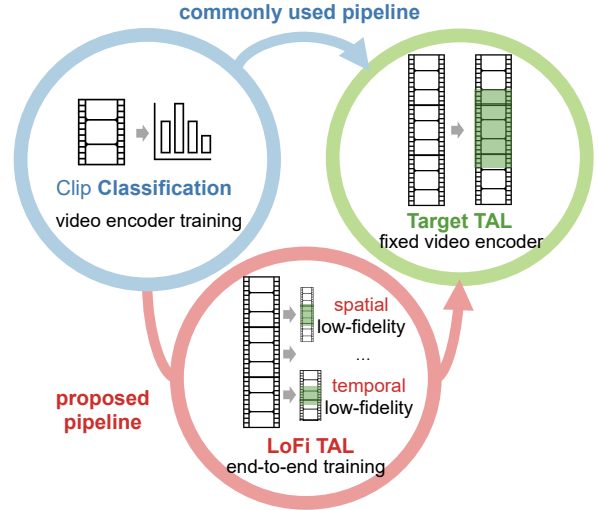


Figure 1. A typical temporal action localization (TAL) model is composed of a video encoder and a TAL head. For model optimization two stages are often involved: (1) pre-training the video encoder on a large video classification dataset with action classification task’s supervision (*top-left circle*), and (2) training the TAL head on the target action localization dataset (*top-right circle*) whilst freezing the video encoder. This standard training method leads to a task discrepancy issue with the video encoder – trained for video classification but used for TAL. To overcome this limitation, we introduce an extra stage in-between that optimizes both the video encoder and the TAL head end-to-end at a low temporal and/or spatial resolution (*i.e.*, low-fidelity) subject to the same GPU memory constraints (*bottom-middle circle*).

[22, 28]. Among those, temporal action localization (TAL) [1, 20] is a fundamental yet challenging task, as natural videos are not temporally trimmed. Given an untrimmed video, TAL aims to identify the start and end points of all action instances and recognize their category labels simultaneously. A typical TAL pipeline is based on deep

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CNNs composed of two modules: a video encoder and a TAL head. Video encoders are often shared across different TAL pipelines (e.g., G-TAD [51], BC-GNN [4]), by taking a specific off-the-shelf action classification model (e.g., C3D [43], I3D [9], TSM [30]), with differences only in the TAL head. Instead of short (e.g., 10 seconds) trimmed video clips as in action recognition, TAL’s input videos are characterized by much longer temporal duration and bigger data volume, *i.e.*, raw videos without any manual trimming. This causes unique computational challenges that remain unsolved particularly in model optimization.

In standard optimization of a TAL model, two stages are often involved:

1. First, pre-training the video encoder on a large source video classification dataset (e.g., Kinetics [25]) and optionally on the clip version of the target dataset under *action classification supervision*;
2. Second, training the TAL head on the target action localization dataset (e.g., ActivityNet [20]) under *TAL task supervision*, whilst freezing the video encoder’s parameters.

With this standard training method, however, the video encoder is only optimal for action classification but not for the target TAL task. Trained to be invariant to all the short segments of an action instance (as designed in the first stage), the video encoder has inferior sensitivity to action temporal boundaries which a TAL model aims to detect. We call this a *task discrepancy problem*. Consequently, the final TAL model could suffer from suboptimal performance since feature representation generally plays a critical role in deep learning.

Intuitively, *end-to-end optimization* of video encoder and TAL head could simply solve the above limitation with the vanilla training method. Unfortunately, it is not that straightforward for TAL model optimization. As mentioned above, model training is severely restricted by the large input size of untrimmed videos and subject to the memory constraint of GPUs. This is why the two-step training method as described above becomes the most common and feasible choice for optimizing a TAL model in practice. Regardless, we believe that solving this limitation of the TAL training design bears a great potential for improving TAL performance.

In this work, we present a simple yet effective *low-fidelity end-to-end* (LoFi-E2E) video encoder pre-training method particularly designed for more effective TAL model optimization. This eliminates the above task discrepancy issue (video classification vs. TAL) when training the video encoder. This is achieved by introducing a surprisingly simple strategy with a novel stage of optimizing both the video encoder and the TAL head end-to-end using a lower temporal and/or spatial resolution (*i.e.*, low-fidelity) in the mini-

batch construction. As compared to the standard training method, our proposed training strategy does not increase the GPU memory standard (often a hard constraint for many practitioners). Crucially, with our LoFi-E2E training the gradients back-propagate to the video encoder from a temporal action localization loss whilst conditioned on the target TAL head, enabling the learning of video encoders sensitive to the temporal localization objective.

We make the following **contributions** in this work. **(I)** We investigate the limitations of the standard optimization method for TAL models, and consider that the task discrepancy problem with the video encoder would harm the performance of existing TAL models. This is caused by complex model design and the GPU memory constraints jointly. Despite a potentially significant ingredient, video encoder optimization is largely ignored by existing TAL methods without systematic investigation. **(II)** To improve TAL model optimization, we present a novel, simple, and effective *low-fidelity end-to-end* (LoFi-E2E) video encoder pre-training method. **(III)** Extensive experiments show that the proposed LoFi-E2E yields a new state-of-the-art performance when combined with off-the-shelf TAL models (e.g., G-TAD [51]) despite using a lightweight ResNet18-based video encoder and merely RGB video frames without the need of computationally expensive optical flow, thus also enjoying far superior inference efficiency.

2. Related Work

Temporal action localization (TAL) models: *Temporal action localization* models can be grouped by architectural design pattern in two categories, one-stage and two-stage architectures. The former type, one-stage methods, either predict temporal action boundaries or generate proposals, and classify them within the same network [4, 10, 19, 35, 31, 49, 51, 53]. The latter type, two-stage models, generate sets of action proposals (e.g., segments) [7, 13, 15, 21, 34]. An auxiliary head is used for classification of each proposal into an action class [32, 41, 42, 54, 57]. In this work, rather than introducing a novel model design, we focus on the training of generic TAL models, with a particular focus on the video encoder. This is a relatively less investigated aspect in the TAL literature.

Video encoders in TAL: The video encoder is an indispensable part of a TAL model [31, 46, 51]. One of the most common video encoders used in existing TAL methods [4, 31, 32, 51] is a two-stream Temporal Segment Network (TSN) [46]. Concretely, these works use two TSN networks, one with a ResNet50 [18] backbone trained on RGB video frames, and the other with a BN-Inception backbone [23] trained on optical flow. Other alternative video encoder choices include two-stream I3D model [9] (see [17, 54]) and Pseudo-3D [40] (see [35]).

Due to the large per-video input size in the TAL problem, the video encoder must be fixed when training the TAL portion of the model to avoid GPU memory issues. Typically, it is pre-trained using a cross-entropy loss for *action classification* on a large-scale video classification dataset such as Kinetics [25, 55]. An optional step is to further pre-train it on the foreground segments of the target TAL dataset [31, 51, 12, 39]. This brings a mismatch between training and inference for the video encoder, which we call a task discrepancy problem. More specifically, although trained to distinguish the content of different action classes, the video encoder is less sensitive to action temporal boundaries, making it less effective for TAL task. In fact, due to their inherent design CNNs have limited localization capabilities [36], unless they are augmented with specialized localization-specific layers [33]. Additionally, the action classification task focuses only on the foreground content whilst ignoring per-class background segments including the transition between foreground and background. In this paper we propose a novel low-fidelity end-to-end video encoder pre-training method to solve this limitation with existing TAL methods.

Pre-training in video analysis: While current TAL literature mostly relies on pre-training through supervised learning, the rapid advancement of self-supervised learning makes it a promising alternative [3, 5, 37, 38, 47]. A large body of research has focused on finding effective temporal-related pretext tasks, from frame ordering learnt through triplets of frames [38], to sorting the frames of a sequence [27], distinguishing whether sequences are played forward or backwards [47] or through playback speed-related pretext tasks [5, 52, 45, 24]. These methods exploit video-specific characteristics to force the network to focus on some sort of semantic content within video, inducing representations capturing long-term temporal semantic relations, but force invariance to or ignore the relative positioning of the snippets within the action instances. They are thus not suited for pre-training the video encoder of a TAL model.

Very recent works [2, 50] have exploited some of the aforementioned techniques for better pre-training of action localization models. For example, localization-tailored data augmentation and classification is adopted by [50]. However, these works introduce a large amount of extra video data and additional stream networks, both of which are expensive in terms of memory and computation. In contrast, our method aims to improve TAL modelling directly without the need for learning from extra training video data and using an expensive second network, nor relying on optical flow obtained at high computational cost.

3. Method

A Temporal Action Localization (TAL) model takes as input a long untrimmed video with a varying number of frames. For design convenience, a varying-length video is often decomposed into a sequence of *snippets* of fixed-length L . The definition of a snippet is the same as in action recognition, where first a segment of consecutive frames (e.g., 64) is selected and then sub-sampled with stride r (e.g., stride 8 to obtain 8-frame snippets). To represent a snippet, one first applies a video encoder to extract frame-level feature vectors and then averages them to obtain the snippet-level feature representation [7, 13, 16, 32]. The resulting snippet feature sequence is denoted as $X \in \mathbb{R}^{C \times L}$, where C is the feature dimension of each snippet, and L is the number of snippets.

In the training set, each video is associated with a set of action instance annotations Ψ at the segment level each including the start time, the end time, and the action class label. The objective is to train a TAL model that can accurately localize all the target action instances in a given untrimmed video. To that end, the model output predicts a varying number of action instances Φ each with predicted temporal boundaries, action class, and confidence score.

3.1. Model Training Procedure

Our training method for any TAL model consists of three stages as depicted in Figure 2: **(1)** First, we pre-train the video encoder by action classification supervision on a large video dataset (e.g., Kinetics [25]). **(2)** Second, we conduct low-fidelity end-to-end (LoFi-E2E) pre-training of the video encoder using a TAL head on the target dataset (Sec. 3.2). This is under TAL supervision with the objective loss function derived from the ground-truth Ψ and model prediction Φ . To this end, we propose to reduce the mini-batch configuration in terms of the spatial and temporal resolution of the video otherwise end-to-end optimization cannot satisfy the GPU memory constraint. This is a critical step since the *target task* of action localization supervision can be used to optimize the video encoder on the *target dataset*. **(3)** Last, we freeze the already end-to-end pre-trained video encoder and re-train the TAL head of choice on the target dataset at full fidelity. Note that in this setup we cannot perform end-to-end optimization of the final TAL model, limited by the hardware memory constraint. Next, we will detail the proposed LoFi-E2E training.

3.2. Low-Fidelity Training Configurations

We consider two main dimensions of input video data: *temporal dimension* and *spatial dimension*. Formally, we define the *full fidelity* (configuration) of mini-batch for the model training as

$$\Omega_f = L \times H \times W \quad (1)$$

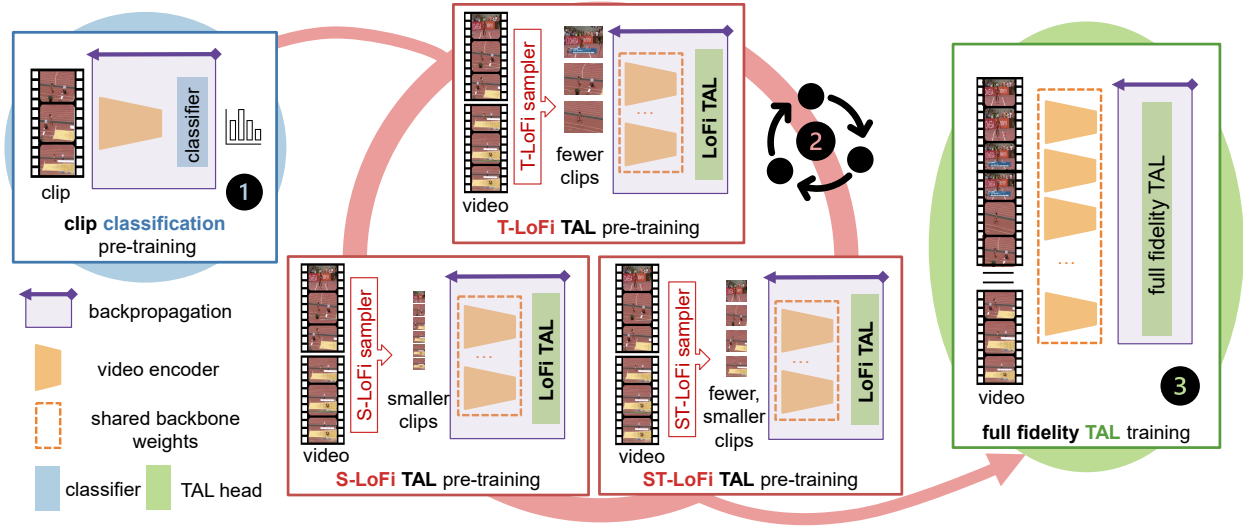


Figure 2. **Schematic overview of the proposed TAL model training procedure.** Three stages are involved during model training: (1) Pre-training the *video encoder* under action classification task’s supervision on an auxiliary video dataset (e.g., Kinetics [25]); (2) Low-fidelity (low mini-batch configuration in the spatial, temporal, or spatio-temporal resolution of training videos) end-to-end pre-training of the *video encoder* together with the TAL head under TAL task’s supervision on the target dataset; This is the key stage introduced in this paper for resolving the task discrepancy problem without memory overhead increase. (3) Fine-tuning the TAL head in the full fidelity configuration under TAL task’s supervision on the target dataset.

where L specifies the temporal resolution, and $H \times W$ refers to the 2D spacial resolution. Under the full fidelity with a certain memory size constraint, only the TAL head can be trained whilst leaving the video encoder frozen. In order to enable the video encoder to be optimized end-to-end together with the TAL head under the TAL task’s supervision for resolving the task discrepancy issue, we design four low-fidelity configurations for the mini-batch.

(I) Spatial Low-Fidelity (S-LoFi) In the first configuration, we lower the spatial resolution of the input videos by a factor of r_s at both spatial dimensions as:

$$\Omega_s = L \times \frac{H}{r_s} \times \frac{W}{r_s} \quad (2)$$

With smaller spatial feature maps, this could effectively reduce the memory consumption of the video encoder’s feature maps which in turn creates space to enable the learning of the video encoder.

(II) Temporal Low-Fidelity (T-LoFi) In the second configuration, we instead consider temporal resolution reduction in the following form:

$$\Omega_t = \frac{L}{r_t} \times H \times W \quad (3)$$

where $r_t > 1$ is the scaling factor. This corresponds to a smaller number of snippets being taken as input by the TAL head, finally outputting less predictions in case that the candidates per time location remains. This would reduce the memory demands by the localization module.

(III) Spatio-Temporal Low-Fidelity (ST-LoFi) In the third configuration, we apply a (typically smaller) reduction in both temporal and spatial resolutions concurrently. Similarly, this reduction is formulated as:

$$\Omega_{st} = \frac{L}{r_t} \times \frac{H}{r_s} \times \frac{W}{r_s} \quad (4)$$

In this setup, memory saving can be shared between the temporal and the spatial dimensions.

(IV) Cyclic Low-Fidelity (C-LoFi) Each of the above three LoFi configuration is used in isolation. To further explore their complementary benefits, we propose to apply them jointly. To that end, we adapt the recently proposed multigrid training strategy [48], originally designed for speeding-up action recognition training. Specifically, we form a sampling grid with the three LoFi configurations and cycle through them repeatedly. We integrate both the short and long cycle strategies [48]. In particular, the long cycle changes the values of r_t and r_s at the beginning of the

epoch, and cycling through the configuration **I** to **III** after c_l epochs. Instead, the short cycle changes r_t and r_s after c_s batches cycling through the configuration **I** to **III**.

It is important to note however some practical differences with the original multigrid training. Contrary to the original multigrid method, we shift the reduction in input resolution between the temporal and the spatial dimensions so that the *per-video* memory usage remains (approximately) constant. Thus, the batch size also remains constant throughout, and the pre-training never experiences the full resolution setting (*i.e.*, the full fidelity).

We compare the four strategies in Section 4.3. By default, we use the C-LoFi design with the long cycle strategy.

3.3. An Instantiation of LoFi-E2E

Off-the-shelf TAL model: In this study, we adopt the state-of-the-art TAL method G-TAD [51]. Other alternatives [31] can be similarly adopted without further considerations. Relying on graph convolution [26], G-TAD is composed by a stack of GCNeXt blocks to obtain context-aware features. In each GCNeXt block, there are two graph convolution streams to model two types of contextual information. One stream operates with temporal neighbors, and the other adaptively aggregates semantic neighbors in the snippet feature space. At the end of all GCNeXt blocks, G-TAD extracts a set of sub-graphs based on pre-defined temporal anchors. With the sub-graph of interest alignment layer, SGAlign, it represents each sub-graph by a feature vector, which is further used as input of multiple fully-connected layers to predict the final action predictions.

To train G-TAD with our LoFi-E2E, we select one of the proposed low-fidelity variants and apply the original TAL loss function to optimize both the video encoder and the TAL head. To avoid finetuning with an under-trained head, the G-TAD weights at this stage are initialized using the standard pre-training strategy, same as the video encoder.

Implementation details: We use ResNet-based TSM [30] as the video encoder due to its good accuracy-cost trade-off and reasonable memory requirements compared to 3D-based alternatives. For the full fidelity setting (Eq. (1)), we follow the standard G-TAD protocol and represent each video by $L = 100$ snippets. The full spatial resolution is $H \times W = 224 \times 224$. We keep the other hyper-parameters (*e.g.*, the number of GCNeXt layers) the same as in the default G-TAD configuration. However, the number of anchor proposals can be reduced when L is less. Concretely, we enumerate all the possible combinations of start and end as the anchors, *e.g.*, $\{(t_s, t_e) \mid 0 < t_s < t_e < L; t_s, t_e \in \mathcal{N}; t_e - t_s < L\}$.

For LoFi-E2E training, we use an SGD optimizer. The batch size is 16 for all the training methods and input patterns. The weight decay is 10^{-4} and we set the momentum

to 0, which is standard for fine-tuning [29]. The learning rate is 0.1, and it is decayed by 0.5 in every 5 epochs.

When we train G-TAD on full fidelity, we keep the same training methods as shown in the G-TAD paper, except that we perform a learning rate search within the set $\{0.0002, 0.0005, 0.001, 0.002, 0.005\}$. We follow the rest of the common post-process for TAL as specified in the original G-TAD paper, including the application of soft-NMS [6] with a threshold of 0.84. We select the top-100 prediction for the final evaluation.

Hardware and software settings: For LoFi-E2E training, we use 4 NVIDIA V100 GPUs, each with 32GB memory. Under this setting, the memory constraint is 128GB, which constitutes a mid-range computational budget. We further show a low-budget option that can be trained on a single V100 GPU. We implemented our method using PyTorch¹.

4. Experiments

4.1. Experimental setup

Datasets: We use *Kinetics400* [25] as the auxiliary video classification dataset for initial pre-training of the video encoder. For model performance evaluation, we use two popular temporal action localization benchmarks. (1) *ActivityNet-v1.3* [20] contains 19,994 temporally annotated untrimmed videos with 200 action categories. In the standard evaluation protocol, these videos are divided into the training/validation/testing sets by the ratio of 2:1:1. (2) *Human Action Clips and Segments (HACS-v1.1)* [56] is a recent temporal action localization dataset. It contains 140K complete segments on 50K videos in 200 action categories (the same ones as ActivityNet-v1.3).

Evaluation metrics: We adopt the mean Average Precision (mAP) rate at specified IoU thresholds as the main evaluation metrics. Following the standard evaluation setting, a sets of IoU thresholds, $\{0.5, 0.75, 0.95\}$ are reported, as well as the average mAP over 10 different IoU thresholds $[0.5 : 0.05 : 0.95]$.

4.2. Pre-training Methodology Comparisons

Setting: In this set of experiments, we directly compare different methodologies for pre-training the video encoder.

To compare with our proposed LoFi-E2E, we first consider the most widely used pre-training method that pre-trains the video encoder by action classification task on an auxiliary dataset (*Kinetics400* in our case). We name this method as *Action Classification Pre-training (ACP)*. To

¹We will release our code.

Table 1. **Comparing TAL results of different video encoder pre-training methods.** ACP: Action Classification Pre-training, ACP+: further fine-tuning ACP on the target dataset using a classification task using positive action segments.

Metric	0.5	0.75	0.95	Average
Dataset	ActivityNet-1.3			
<i>ImageNet</i>	48.45	32.40	6.89	32.16
ACP	49.64	34.16	7.68	33.59
ACP+	49.87	34.58	7.85	33.84
LoFi-E2E (ours)	50.40	35.42	8.88	34.43
Dataset	HACS-1.1			
<i>ImageNet</i>	31.74	19.64	5.67	20.18
ACP	35.68	22.79	6.51	23.00
ACP+	36.31	22.96	6.62	23.31
LoFi-E2E (ours)	37.47	24.36	7.08	24.62

adapt the video encoder to the target dataset, it can be further trained through an action classification task on a clip version of the target TAL dataset, using each positive segments as a training instance. We name this variant **ACP+**.

In this experiment, we train our model using the cyclic low-fidelity (C-LoFi) configuration with the long cycle strategy. Other configurations will be evaluated in Section 4.3. To demonstrate the effect of video encoder pre-training, we also take into account an ImageNet pre-trained video encoder, which uses no video data. We refer to this baseline as *ImageNet pre-training (ImageNet)*.

Results: The results by different video encoder pre-training methods are reported in Table 1. We make the following observations. **(1)** Without pre-training on a related auxiliary dataset, the model performance could be significantly degraded. This indicates the significance of video encoder and its pre-training on large, relevant video data. **(2)** With action classification based pre-training on the target video data, the performance indeed improves to some degree. This means that solving the data distribution shift between the auxiliary dataset and the target dataset is useful. **(3)** Importantly, the biggest performance changes come from the proposed LoFi-E2E method which instead solves the task discrepancy issue by pre-training the video encoder with TAL task. This indicates that although auxiliary video data is similar to target data in distribution, the task-level differences would still pose obstacles harming the model performance, confirming our motivation and hypothesis of this study; Once this obstacle is properly tackled with our low-fidelity pre-training, more significant performance gain can be then rewarded. Overall, this verifies the efficacy of the proposed method in pre-training the video encoder.

4.3. LoFi-E2E Design Comparisons

Setting: We examine different low-fidelity (LF) configurations. We use the setting as: $r_t = 4$ for T-LoFi, $r_s = 2$ for S-LoFi (note that this is applied in both spatial dimensions, thus being comparable to T-LoFi), $r_s = \sqrt{2}$, $r_t = 2$ for ST-LoFi, and $c_s = 16$ for C-LoFi’s shirt/long cycle strategy. We include the standard pre-training strategy (*i.e.*, ACP) to provide a baseline and facilitate comparisons.

Results: The results for ActivityNet-v1.3 and HACS-1.1 are shown in Table 2. We provide the following observations: **(1)** Each of our proposed LoFi configurations can improve the model training similarly. This suggests that spatial and temporal dimensions both are good selections for low-fidelity manipulation. **(2)** Integrating our LoFi configurations into a more advanced cyclic training strategy produces some further, although moderate, improvement. In particular, the long cycle produces the best overall performance for both datasets.

4.4. Comparison with State-of-the-Art

Setting: Following video encoder pre-training evaluation, we further conduct a system-level performance comparison with previous state-of-the-art methods. Whilst ResNet50-based (R50) methods are a common backbone choice for video encoder, for our method we still use a more lightweight ResNet18 (R18) due to its higher efficiency in computation and memory. Furthermore, compared to the popular architecture design in two streams (one for RGB and one for optical flow), our method only uses RGB frames, avoiding the excessive costs derived from computing optical flow and running a second forward pass.

Results: The results of our method are compared with existing alternatives in Table 3 for ActivityNet-v1.3 and Table 4 for HACS-1.1. It is evident that our method can achieve the best performance among all the competitors, despite the single stream input modality and a much lighter video encoder backbone. This clearly demonstrates that tackling the pre-training of the video encoder is of particular importance for TAL, and that existing efforts towards improving the TAL head model has led to neglecting of a key model component. On ActivityNet-v1.3, it is encouraging to see that with a stronger pre-trained video encoder by our method and a shallower architecture, optical flow can be favourably eliminated without performance sacrifice (actually even enjoying better performance). This result is crucial since how to get rid of optical flow for more efficient action analysis itself is an important research problem [11].

Table 2. **Comparing different low-fidelity configurations.** Dataset: ActivityNet-v1.3 and HACS. ACP: Action Classification Pre-training. TR: Temporal Resolution; SR: Spatial Resolution.

Design	TR	SR	ActivityNet 1.3				HACS 1.1			
			0.5	0.75	0.95	Avg	0.5	0.75	0.95	Avg
ACP	-	224x224	49.64	34.16	7.68	33.59	35.68	22.79	6.51	23.00
S-LoFi	100	112x112	50.47	34.71	7.57	34.12	37.16	24.23	6.84	24.25
T-LoFi	25	224x224	50.28	35.21	8.09	34.32	37.30	24.18	7.07	24.36
ST-LoFi	50	158x158	50.36	34.79	7.59	34.12	37.13	24.27	7.08	24.36
Short C-LoFi	Batch-level Cycle		50.57	35.12	8.14	34.38	37.63	24.45	6.95	24.60
Long C-LoFi	Epoch-level Cycle		50.40	35.42	8.88	34.43	37.47	24.36	7.08	24.62

Table 3. **Comparing TAL results with state-of-the-art methods on ActivityNet-1.3 validation set.** “*” indicates RGB-only Kinetics400 pre-trained TSM video encoder without fine-tuning. OF: Optical Flow. R18/50: ResNet-18/50.

Method	OF	Arch.	#Par	0.5	0.75	0.95	Avg
SCC [19]	✗	C3D	79M	40.00	17.90	4.70	21.70
CDC [41]	✗	C3D	79M	45.30	26.00	0.20	23.80
R-C3D [49]	✗	C3D	79M	26.80	-	-	-
BSN [32]	✓	R50	23M	46.45	29.96	8.02	30.03
P-GCN [54]	✓	I3D	25M	48.26	33.16	3.27	31.11
BMN [31]	✓	R50	23M	50.07	34.78	8.29	33.85
BC-GNN [4]	✓	R50	23M	50.56	34.75	9.37	34.26
G-TAD [51]	✓	R50	23M	50.36	34.60	9.02	34.09
G-TAD*	✗	R18	12M	49.64	34.16	7.68	33.59
+ LoFi-E2E	✗	R18	12M	50.40	35.42	8.88	34.43

Table 4. **Comparing TAL results with state-of-the-art methods on HACS-1.1 validation set.** “*” indicates RGB-only Kinetics400 pre-trained TSM video encoder without fine-tuning. OF: Optical Flow. R18/50: ResNet-18/50. 2S.: 2-stream.

Method	OF	Arch.	#Par	0.5	0.75	0.95	Avg
SSN [57]	✓	2S	12M	28.82	18.80	5.32	18.97
G-TAD*	✗	R18	12M	35.68	22.79	6.51	23.00
+ LoFi-E2E	✗	R18	12M	37.47	24.36	7.08	24.62

4.5. Using Different Video Encoders

Setting: Our LoFi-E2E method can be used in combination with different video encoders, as long as the backbone is end-to-end trainable. We compare the performance gains of our default encoder, ResNet18-based TSM, with a 3D-based alternative, an 18-layer R(2+1)D encoder [44]. Note that the default spatial resolution for R(2+1)D, as defined by the authors, is 112×112 pixels. We thus use our T-LoFi setting, maintaining the default spatial resolution for both networks. This test is conducted on ActivityNet-v1.3.

Results: The results are given in Table 5. It can be observed that with either TSM-R18 or R(2+1)D as video en-

Table 5. **Ablation on different video encoders.** The performance improvement from using our LoFi pre-training does not depend on the video encoder’s backbone. Dataset: ActivityNet-v1.3. TAL head: G-TAD. R18: ResNet18.

Method	0.5	0.75	0.95	Average	Gain
TSM-R18	49.64	34.16	7.68	33.59	-
+ LoFi-E2E	50.28	35.21	8.09	34.32	+0.73
R(2+1)D	49.65	34.11	8.66	33.55	-
+ LoFi-E2E	49.84	34.73	8.64	34.21	+0.66

coder, our method can similarly and consistently improve the performance of the state-of-the-art G-TAD. This verifies that our LoFi-E2E method is generally effective and useful in training TAL models.

4.6. Performance-Hardware Budget Trade-off

Setting: So far we have provided results with a fixed computational budget of 4 GPUs. Given the flexibility of our LoFi-E2E method, we can further study the model performance trade-off under different hardware (GPU memory) budget cases. For a low budget configuration, we define a configuration so that the whole training procedure can fit in a single V100 GPU (32GB)². In this case, the temporal resolution needs to be lowered to 25 snippets and the spatial resolution to 112×112 pixels. Then we consider a fixed GPU budget of 4 V100 GPUs (128G). Under this setting, we compare our T-LoFi configuration with an alternative configuration: using a lower spatial resolution (112^2) in exchange for a larger video backbone, a ResNet-50.

Results: The performances of our method under different budget settings are compared in Table 6. Comparing the first two rows, our method can still comfortably outperform the standard action classification pre-training (ACP) baseline under the low computational budget setting. When we set the GPU memory budget to 128G, as shown in the last two rows, it is found that lowering the spatial resolution for

²Admittedly, a V100 GPU is still a high-end GPU, having 32GB of memory. The current on-demand hourly rate at AWS is 3.06USD.

using a deeper video encoder (ResNet-50) leads to a slightly worse trade-off in Average-mAP; Besides, in the inference cost perspective, using a ResNet18-based video encoder offers a clear advantage.

Table 6. **Trade-off analysis between performance and budget (GPU memory) on ActivityNet-1.3 validation set.** TR: Temporal Resolution. SR: Spatial Resolution. R18/50: ResNet-18/50.

TR/SR	Arch.	GPU	0.5	0.75	0.95	Avg
ACP	R18	–	49.64	34.16	7.68	33.59
25/112 ²	R18	32G	50.01	34.46	8.38	33.99
25/224 ²	R18	128G	50.28	35.21	8.09	34.32
25/112 ²	R50	128G	50.07	35.31	8.03	34.23

4.7. Effectiveness of End-to-End Training

Setting: While our proposed method effectively closes the domain and task gaps for TAL, it still has to sacrifice input spatial and/or temporal resolution. Thus, although arguably less damaging in terms of final performance, there still exists a gap between train-time and test-time settings. To evaluate the exact benefit for TAL from end-to-end training, we train G-TAD using 25 snippets in the following two settings: 1) using a video encoder pre-trained on Kinetics400 (*i.e.*, ACP baseline) and 2) using end-to-end training.

Results: The resulting performances are compared for both ActivityNet-v1.3 and HACS-1.1 in Table 7. We can see that, while the overall performance is significantly lower due to the lack of temporal resolution, the accuracy improves significantly on both datasets, namely 1.19 and 1.45 in terms of Average-mAP.

Further, our method then would proceed by using the end-to-end trained backbone as a frozen video encoder to train the full-fledged 100-snippet G-TAD model on top of it (*i.e.*, full fidelity). The results corresponding to this strategy have been reported in Table 1, with an improvement of 0.84 and 1.62 (LoFi-E2E vs. ACP) in terms of full resolution performance for ActivityNet-v1.3 and HACS-1.1 respectively. Indeed, the performance improvement of our LoFi-E2E is a bit lower than that of intact end-to-end training. However, this difference is relatively small, meaning that the remaining train-vs-test gap in spatio-temporal resolution has a small impact.

Finally, we note that higher gains are achieved on HACS-1.1 than on ActivityNet-v1.3. We hypothesize that this is due to the larger amount of training data available on HACS-1.1, resulting in more benefits from our LoFi-E2E in video encoder pre-training.

4.8. Comparison to Self-Supervised Learning

We compare our method to two representative video self-supervised learning (SSL) methods in Table 8: Arrow of

Table 7. **Performance on LoFi setting (25 snippets, 224² res.) for the video encoder pre-trained on Kinetics vs end-to-end training.** ANET: ActivityNet-v1.3; HACS: HACS-1.1.

Method	Dataset	0.5	0.75	0.95	Avg	Gain
K400	ANET	45.75	32.05	4.80	31.02	-
E2E	ANET	47.52	33.30	5.31	32.21	(+1.19)
K400	HACS	29.28	17.95	4.05	18.49	-
E2E	HACS	31.08	19.74	4.29	19.94	(+1.45)

Table 8. **Comparison to self-supervised learning methods.** Dataset: ActivityNet-v1.3.

Method	0.5	0.75	0.95	Average
ACP	49.64	34.16	7.68	33.59
Arrow [47]	44.14	28.87	5.90	28.82
Speed [5]	44.50	29.52	6.14	29.39
ACP+Arrow	49.79	34.48	7.70	33.72
ACP+Speed	49.84	34.11	7.50	33.75
LoFi-E2E	50.40	35.42	8.88	34.43

Time [47] and SpeedNet [5]. Both competitors are trained on Kinetics400. As we can see, without action classification label information both SSL methods in isolation are clearly inferior for the TAL task. When combined with the standard action classification pre-training (ACP) along the feature representation dimension, only slight performance gains can be achieved despite doubling the computational cost in video encoding. This suggests their marginal complementary benefit. Overall, this test indicates that the proposed LoFi-E2E optimization is superior over recent SSL alternatives in pre-training TAL’s video encoder.

5. Conclusion

In this work we have presented a simple and effective low-fidelity end-to-end (LoFi-E2E) video encoder pre-training method for achieving more effective TAL models. This is motivated by an observation that in existing TAL methods the video encoder is merely pre-trained by action classification supervision on short video clips, lacking desired optimization w.r.t. the target temporal localization supervision. Indeed, end-to-end model optimization itself is not novel. However, this is non-trivial to conduct for training a TAL model, due to large per-video size that would easily overwhelm the GPU memory, rendering it infeasible in practice. To overcome this obstacle, we propose to reduce the mini-batch construction configurations in the temporal and spatial dimensions of training videos so that end-to-end optimization becomes operable under the same memory condition. Extensive experiments demonstrate that our method can clearly improve the performance of existing off-the-shelf TAL models, yielding new state-of-the-art per-

formance even with only RGB modality as input and a more lightweight backbone based single-stream video encoder on two representative TAL benchmarks. Further, in-depth ablation studies have also been conducted to break down the performance benefits from different training steps and mini-batch configurations.

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