Streaming Video Model

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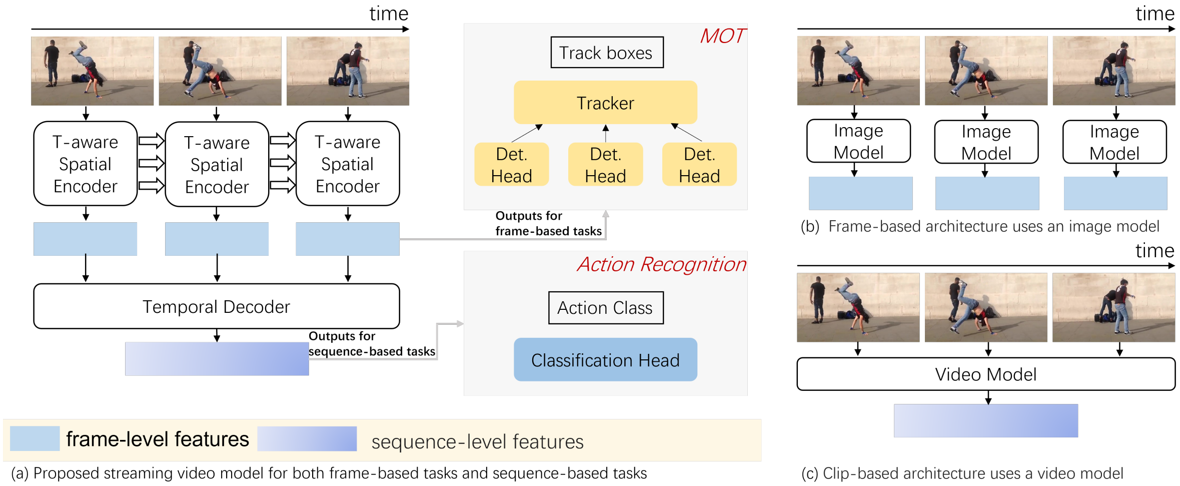

(a) Proposed streaming video model for both frame-based tasks and sequence-based tasks

(b) Frame-based architecture uses an image model

(c) Clip-based architecture uses a video model

Figure 1. Illustration of the proposed streaming video model with a comparison to conventional frame-based architecture and clip-based architecture. (a) The two-stage streaming video model gracefully serves different types of video tasks through a unified architecture. The output of the temporal-aware (T-aware) spatial encoder serves the frame-based tasks, such as MOT, while the output of the temporal decoder serves the sequence-based tasks, such as action recognition. (b) Frame-based architecture, which uses single image model to independently extract spatial features for each frame, is widely used in the frame-based video tasks. (c) Clip-based architecture, which uses video model to produce the spatiotemporal features for an entire clip, is widely used in the sequence-based video tasks.

Abstract

Video understanding tasks have traditionally been modeled by two separate architectures, specially tailored for two distinct tasks. Sequence-based video tasks, such as action recognition, use a video backbone to directly extract spatiotemporal features, while frame-based video tasks, such as multiple object tracking (MOT), rely on single fixed-image backbone to extract spatial features. In contrast, we propose to unify video understanding tasks into one novel streaming video architecture, referred to as Streaming Vision Transformer (S-ViT). S-ViT first produces frame-level features with a memory-enabled temporally-aware spatial encoder to serve the frame-based video tasks. Then the frame features are input into a task-related temporal decoder to obtain spatiotemporal features for sequence-based tasks. The efficiency and efficacy of S-ViT is demonstrated by the state-of-the-art accuracy in the sequence-based action recognition task and the competitive advantage over conventional architecture in the frame-based MOT task. We believe that the concept of streaming video model and the implementation of S-ViT are solid steps towards a unified deep learning architecture for video understanding. Code will be available at https://github.com/yuzhms/Streaming-Video-Model.

1. Introduction

As a fundamental research topic in computer vision, video understanding mainly deals with two types of tasks. The sequence-based [9, 56] tasks aim to understand what is happening in a period of time. For example, the action

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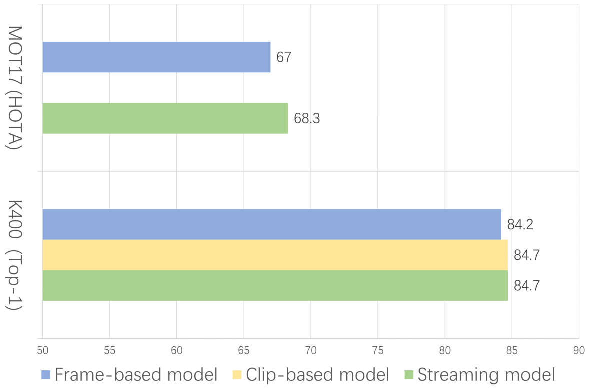


Figure 2. Comparison on video modeling paradigm on both the sequence-based action recognition task and frame-based multiple object tracking task. The proposed streaming model achieves higher performance than the frame-based model on both tasks while has no loss compared to clip-based model on the sequence-based task. The clip-based model can not be directly used in frame-based tasks.

recognition task classifies the object action in a video sequence into a set of predefined categories. The frame-based tasks [11, 31, 72], on the other hand, aim to look for key information in a certain point of time in a video. For example, the multiple object tracking (MOT) task predicts the bounding boxes of objects in each video frame. Although both types of tasks take a video as input, they are handled very differently in computer vision research.

The different treatment of these two types of tasks is mainly reflected in the type of backbone network used. The action recognition task is usually handled by a clip-based architecture, where a video model [1], which takes a video clip as input and outputs spatiotemporal features, is used. In the video object segmentation (VOS), video object detection (VOD), and multiple object tracking (MOT) tasks, however, a frame-based architecture [14, 21] is often adopted. The frame-based architecture employs image backbone to generate independent spatial features for each frame. In most tracking-by-detection MOT solutions, these features are directly used as the input to the object detector.

Both types of treatment have their respective drawbacks. On the one hand, the clip-based architecture processes a group of video frames at one time, which puts great pressure on the processor's memory space and processing power. As a result, it is difficult to handle long videos or long actions effectively. In addition, the summarized spatiotemporal features extracted by a video backbone usually lack sufficient spatial resolution to be used for dense prediction tasks. On the other hand, the frame-based architecture does not consider surrounding frames in the process of spatial feature extraction. As a result, the features do not contain any temporal information or an out-of-band mechanism is in need to gather additional temporal information. We believe that a video frame should be treated differently from a single image and that temporal-aware spatial features are more powerful for solving frame-based video understanding tasks.

In this paper, we propose a unified architecture to handle both types of video tasks. The proposed streaming video model, as shown in Fig.1, circumvents the drawbacks of the conventional treatment by a two-stage design. Specifically, it is composed of a temporal-aware spatial encoder, which extracts temporal-aware spatial feature for each video frame, and a task-related temporal decoder, which transfers frame-level features to task-specific outputs for sequence-based tasks. When compared with frame-based architecture, the temporal-aware spatial encoder in streaming video model leverages additional information from past frames, so that it has potential to obtain more powerful and robust features. When compared with clip-based architecture, our model disentangles the frame-level feature extraction and clip-level feature fusion, so as to alleviate the computation pressure while enabling more flexible use scenarios, such as long-term video inference or online video inference.

We instantiate such a streaming video model by building the streaming video Transformer (S-ViT) based on the vision Transformer [14]. S-ViT is featured by self-attention within a frame to extract spatial information and cross-attention across frames to make the fused feature temporal-aware. Specifically, for the first frame of a video, S-ViT extracts exactly the same spatial feature as a standard image ViT, but it stores keys and values of every Transformer layer in a memory. For subsequent frames in a video, both intra-frame self-attention and inter-frame cross-attention [54] with the stored memory is calculated. S-ViT borrows ideas from triple 2D (T2D) decomposition [74] and limits the cross-attention region within patches with the same horizontal or vertical positions. This decomposition reduces the computational cost and allows S-ViT to handle long histories. The output of this stage can directly be used by the frame-based video tasks. For sequence-based tasks, an additional temporal decoder, implemented by a temporal Transformer, is used to gather information from multiple frames.

We evaluate out S-ViT model on two downstream tasks. The first task is the sequence-based action recognition. We get 84.7% top-1 accuracy on Kinetics-400 [23] dataset and 69.3% top-1 accuracy on Something-Something v2 [20] dataset, which is on par with the state-of-the-art, but at a reduced computation expenditure. The second task is MOT, which operates on video frames in a widely adopted tracking-by-detection framework. We show that introducing temporal-aware spatial encoder creates comparative advantage over a frame-based architecture under a fair setting on MOT17 [40] benchmark.

We summarize the contributions as follows. First, we propose a unified architecture, named streaming video model, for both frame-based and sequence-based video understanding tasks. Second, we implement a T2D-based streaming video Transformer and demonstrate how it can be used to serve different types of video tasks. Third, experiments on action recognition and MOT tasks show that our unified model could achieve state-of-the-art results on both types of tasks. We believe that the work presented in this paper is a solid step towards a universal video processing architecture.

2. Related Works

Video models and video tasks. Video understanding is a fundamental research topic in computer vision. There are mainly two kinds of tasks, one of which, named sequence-based tasks [9, 56], aims to understand what is happening over a period of time, and the other, named frame-based tasks [11, 31, 72], aims at capture the detail information at a certain point of time. Due to the fact that the inputs are quite different for these two types of tasks, different families of models are developed independently.

For sequence-based tasks, clip-based models with 3D (width, height, and time) video input are used. 3D convolutional neural networks (CNNs) [9, 17, 45, 50–52, 64] once were popular in the past decade, and video vision Transformer [1, 3, 6, 16, 36, 68, 74] are emerging models in recent years. Thanks to the attention mechanism in Transformer [54], video vision Transformers have better capability to model long-range spatiotemporal correlations and thus achieve higher performance than CNN-based methods. For frame-based tasks, frame-based models with 2D (width and height) image input are used. The common models includes ResNet [21], CSPNet [55], and Swin Transformer [35]. Such models are adopted in the same way they are for images. And they do not encode any temporal-related information. In this paper, we propose a unified architecture to handle both types of tasks.

Long-term video models and online video models. As the clip-based models require all frames as input at once, they have difficulty with long videos. A series of works termed long-term video models [60, 61] are proposed to handle long videos. Building on top of clip-based models, some memory designs are used to extend the temporal coverage. Long-term feature banks [60] augment 3D CNNs with auxiliary supporting information extracted over the entire video. MeMViT [61] augmented multi-scale vision Transformer with cached memories using attention-based designs. There is also a series of methods termed online video models [24, 30, 78]. The temporal shifted module (TSM) [30] proposes to shift part of the channels along the temporal dimension to exchange temporal information, resulting in an efficient and online video model. MoViNets [24] leverages the neural architecture search (NAS) technique, the causal convolution [53], to build an efficient and causal video model for mobile devices.

Our streaming video model does not fall into these two model families as we target unifying frame-based and sequence-based tasks, so it is versatile for any kinds of video inputs. On the contrary, long-term video models and online video models are still clip-based models, where the former aims at extending the temporal context and the latter aims at efficient and causal video model inference.

Vision Transformer. Motivated by the success in NLP [54], Vision Transformers (ViTs) [14] have made great progress in computer vision. Different from previous dominant CNN architectures, ViTs treat an image as a set of visual words and model their correlation with the attention operation. ViTs have already led a paradigm shift in various vision tasks, including image recognition [35], object detection [8], semantic segmentation [10], action recognition [3], etc. In this work, we build our streaming video Transformer based on the vanilla vision Transformer [14] and a corresponding video adaptation mechanism triple 2D decomposition [74].

Multiple object tracking. Tracking by detection [4, 73] is one of the dominant paradigms in multiple object tracking (MOT). These method first utilize powerful detectors to obtain detection results in each single frame and then associate defections over time to construct tracking trajectories. The association can be done by using location, motion, and appearance clues or directly solved using transformer architecture as set-prediction [70]. We follow a simple yet effective association method called ByteTrack [72] in this paper and use a ViT-based detector to produce detection results. The key feature of the proposed method is the incorporation of a temporal-aware mechanism during the detection feature extraction stage. While some prior works investigate the utilization of temporal information in MOT [12, 65, 77], infusing it at the early feature extraction stage is infrequent.

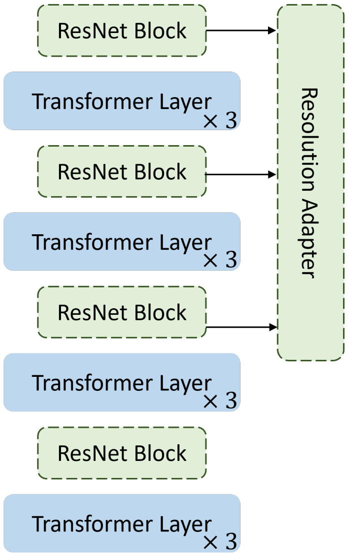
3. Method

We build a streaming video model, named S-ViT, based on vision Transformer (ViT) [14]. In this section, we will first introduce the background of each S-ViT component. Then, we will describe our architecture and model in details. Finally, we will provide the implementation details.

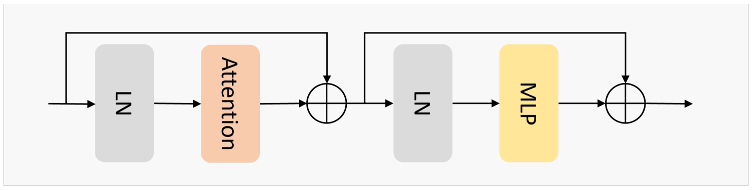
3.1. Background

Let us first review the vision transformer and its extension to frame-based video tasks and sequence-based video tasks.

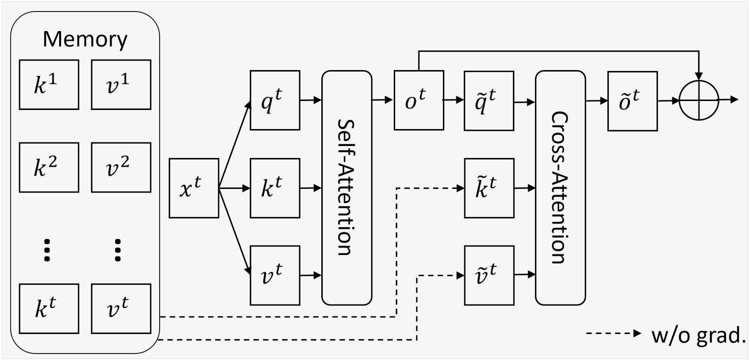
Vision Transformer. Vision Transformer (ViT) is first proposed to process image inputs $X \in \mathbb{R}^{H \times W \times 3}$, where H and W denote the height and width, and 3 is the number



(a) Temporal-Aware Spatial Encoder



(b) Transformer layer



(c) Streaming T2D attention

Figure 3. Illustration of streaming video Transformer. (a) The architecture of temporal-aware spatial encoder. (b) The scheme of a Transformer layer. (c) Detailed structure of streaming T2D attention.

of RGB channels. ViT first embeds an image into N non-overlapping patches $X_p \in \mathbb{R}^{N \times C}$, where C is the number of channels. Then, a positional embedding is added to obtain the input Z^0 to the first Transformer layer:

$$Z^0 = X_p + e, \tag{1}$$

where $e \in \mathbb{R}^{N \times C}$ is the learnable positional embedding.

The key components in ViT are L Transformer layers which are composed of a self-attention (SA) block, layer normalization (LN) layers, and a multi-layer perception (MLP) block, as shown in Fig.3-(b). Denote Z^{l-1} and Z^l as the input and output of the l^{th} Transformer layer, the computation implemented by this layer can be written as:

$$Y^l = \mathrm{MSA}(\mathrm{LN}(Z^{l-1})) + Z^{l-1}, \tag{2}$$

$$Z^l = \mathrm{MLP}(\mathrm{LN}(Y^l)) + Y^l. \tag{3}$$

ViT for frame-based video tasks. Most frame-based video tasks, such as VOS, VOD, and MOT, need multi-scale feature maps. ViT is a non-hierarchical architecture that only maintains a single-scale feature map, which makes it difficult to be plugged into existing frameworks. For example, most detection frameworks utilize the ResNet-style multi-stage architecture that has feature maps of stride 4, 8, 16, and 32, but the plain ViT only has a feature map of stride 16. To solve this resolution misalignment problem, we develop a simple resolution adaptor (RA) to transfer the single-scale feature to multi-scale features, as shown in Fig.3-(a). The RA is implemented by a set of up-sample and down-sample (de-)convolutions. We found such direct adaptation works well in our video dense prediction tasks. Our implementation is similar to the prior work ViTDet [28] that built a simple feature pyramid network (FPN) for image object detection. The difference is that our resolution adaptor does not replace the original sophisticated feature pyramid network (e.g. the PAN [34] in YOLOX [19]) but serves as a plugged-in module on top of the backbone to bridge the resolution mismatch. Besides the multi-scale architecture, plain ViT also has a high computation cost due to the quadratic complexity in self-attention [54]. We solve this issue by using windowed self-attention [35] and convolutional cross-window propagation blocks [21], which are the same as ViTDet.

ViT for sequence-based video tasks. Classical clip-based video models need to model the spatiotemporal feature jointly. Although our model does not follow the clip-based paradigm, the spatiotemporal feature learning mechanics in existing works are profitable in the streaming model's design. From this perspective, we build our streaming video model from a SOTA clip-based video model named T2D-ViT [74]. The T2D-ViT extends ViT from an image model to a clip-based video model by introducing temporal attention. Concretely, given an input video tensor $Z \in \mathbb{R}^{N_h \times N_w \times N_t \times C}$, besides calculating the XY attention inside each frame, T2D-ViT also calculates the XT temporal attention within the same $y \in \{1, 2, ..., N_h\}$ index and the TY temporal attention within the same $x \in \{1, 2, ..., N_w\}$ index.

The central idea of T2D-ViT is the decomposition of static appearance and dynamic motion. Therefore, it shares the same spirit with our streaming video model in that the spatial modeling in the current frame and the temporal modeling among nearby frames are disentangled. Due to the efficiency and effectiveness of T2D-ViT, we adopt a similar XT and TY temporal attention in our S-ViT model, which will be introduced in the next section.

3.2. Streaming Video Model

Fig.1-(a) gives an overview of the proposed streaming video Transformer. Given an input sequence, at each timestamp, the temporal-aware spatial encoder module first encodes the spatial information within the current frame; then it fuses information from previous timestamps. The output of this module is frame-level features, which can be utilized for frame-based tasks like multiple object tracking. On top of the temporal-aware spatial encoder, an optional temporal decoder is appended to generate video-level features. Such video-level features are used for sequence-based tasks like action recognition.

The core design in our streaming video Transformer is the temporal-aware spatial encoder with streaming T2D attentions. The architecture of temporal-aware spatial encoder is shown in Fig.3-(a), which is composed of multiple Transformer layers and optional ResNet Blocks and the resolution adaptor. The ResNet Block and the resolution adaptor are used for frame-based video tasks which needs multi-scale feature maps. The Transformer layer is composed of Attention layer and MLP block with skip connection and layer normalization, as shown in Tab.3-(b). We use the streaming T2D attention, which introducing temporal-aware spatial features by leveraging memorized histories.

Fig.3-(c) illustrates the implementation of streaming T2D attention. First, we compute the spatial self-attention from the input x_t:

$$q_t = x_t W_q; k_t = x_t W_k; v_t = x_t W_v, \tag{4}$$

$$o_t = \text{Attention}(q_t, k_t, v_t), \tag{5}$$

where W_q, W_k, and W_v are projection matrices for queries, keys and values, respectively. Then, we maintain a memory pool to store the historical information. During each frame's forward process, we put the keys and values in the self-attention into the memory pool. Concretely, in the forward pass of the first frame, the memory pool only contains the keys and values of the first frame itself. And in the forward pass of the t-th frame, the memory pool contains all keys and values from the past timestamps. Formally speaking, the memory used for frame t is

$$\tilde{k}^t = [\text{sg}(k^1), \text{sg}(k^2), ..., \text{sg}(k^{t-1}), \text{sg}(k^t)], \tag{6}$$

$$\tilde{v}^t = [\text{sg}(v^1), \text{sg}(v^2), ..., \text{sg}(v^{t-1}), \text{sg}(v^t)]. \tag{7}$$

Here the sg stands for `stop gradient`. We generate another temporal query $\tilde{q}^t$ from the output of spatial self-attention o_t by a separate transformation matrix $\tilde{W}_q$ and then compute the cross attention on $\tilde{q}^t$, $\tilde{k}^t$, and $\tilde{v}^t$:

$$\tilde{o}^t = \text{Attention}(\tilde{q}_t, \tilde{k}_t, \tilde{v}_t). \tag{8}$$

Notice that the cross-attention here is calculated within the XT and TY data planes to improve the efficiency and effectiveness. Using the TY attention as an example. Given inputs $\tilde{q}_t \in \mathbb{R}^{N_w \times N_t \times C}$ and $\tilde{k}_t, \tilde{v}_t \in \mathbb{R}^{T \times N_w \times N_t \times C}$, we split them along the horizontal axes to get $\{\tilde{q}_t^1, \tilde{q}_t^2, ..., \tilde{q}_t^{N_w}\}$, $\{\tilde{k}_t^1, \tilde{k}_t^2, ..., \tilde{k}_t^{N_w}\}$, and $\{\tilde{v}_t^1, \tilde{v}_t^2, ..., \tilde{v}_t^{N_w}\}$. The attention is calculated among queries, keys, and values with the same horizontal axis. Similarly, XT attention is calculated among queries, keys, and values with the same vertical axis. The outputs of XT and TY attention are fused into o_t with learnable per-channel weights initialized to $1e - 4$. The introduction of T2D attention decrease the computational complexity of cross attention part from $O(N_w^2 N_h^2 T)$ to $O(N_w^2 N_h T + N_w N_h^2 T)$, which makes our temporal attention module light-weight and therefore applicable for long histories.

3.3. Implementation Details

We implement our S-ViT based on the ViT-B [14] model, which has 12 layers of Transformer. To support multi-scale features, we manually split the network into 4 stages, with 3 layers for each stage. In the frame-based video tasks, we use windowed attention with the window size of 14×14 to reduce the heavy computation cost from the global self-attentions. Four ResNet blocks are appended at the end of each stage, respectively, for cross-window feature propagation. The CLIP [46] pre-trained weights are used as the initialization. For parameters that did not exist in the ViT-B model, we randomly initialized them.

For the action recognition task, we use four temporal transformer layers as the temporal decoder. A text-generated classifier [63] is applied for the Kinetics-400 [23] dataset and a learnable linear classifier for the something-something v2 [20] dataset following T2D-ViT. On the multiple object tracking task, we use the YOLOX-style [19] detection head and the ByteTrack [72] tracker.

4. Experiments

4.1. Experimental Setup

We evaluate our method on two video tasks, namely the video action recognition and the multiple object tracking. For video action recognition, we conduct experiments on two widely used benchmark, i,e., Kinetics-400 [23] and Something-Something v2 [20]. For multiple object tracking, we use MOT17 [40] dataset for evaluation with additional data sources MOTSynth [15] and CrowdHuman [48].

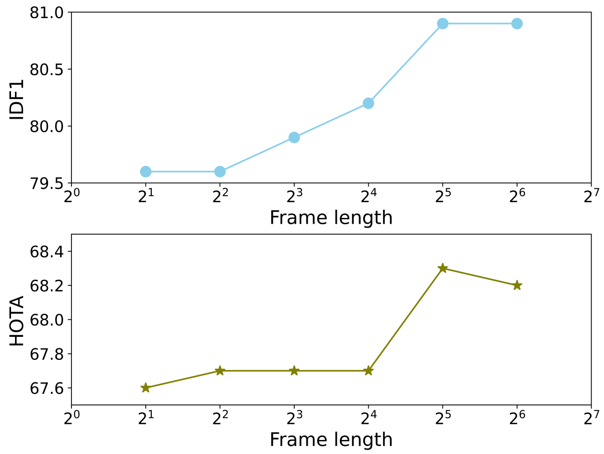


Figure 4. Comparison of the performance of S-ViT with different test-time memory length.

Kinetics-400 (K400) [23] is a large-scale video action recognition dataset collected from YouTube. It contains 234584 training videos and 19760 validation videos. The video in K400 is trimmed to around 10 seconds. We use the sparse sampling [41] and randomly resized cropping to sample 16 frames with 224 × 224 resolution to form a video clip. We use the same data augmentation and regularization as in X-CLIP [41], including random horizontal flip, color jitter, random grayscale, label smoothing, Mixup [71], and CutMix [69]. In the inference phase, we adopt the multi-view testing with four temporal clips and three spatial crops. The top-1 and top-5 classification accuracy on the validation set are reported as evaluation metrics.

Something-Something V2 (SSv2) [20] is another large-scale action recognition dataset which focus more on temporal modeling. The labels are like ”Pulling something from left to right”, so it is crucial to learn motion information. The training set contains 168.9K training videos and the validation set contains 24.7K validation videos. We use segment-based sampling from [30] to sample 32 frames with 224 × 224 resolution. The augmentation and regularization in SSv2 include random augmentation [13], repeated augmentation [22], random erasing [75], Mixup [71], and CutMix [69], which follow the practice in MViT [16].

MOT17 [40] is a multiple object tracking dataset that contains 7 training sequences and 7 test sequences. The total frame number is only 11k, so it is not enough to train our S-ViT model. We use the CrowdHuman [48] dataset and the MOTSynth [15] dataset to expand the training data. CrowdHuman contains 19.4k images in crowd human scenarios, and MOTSynth contains 764 synthetic video sequences with 1.3m frames generated from Grand Theft Auto V. We conduct our experiments with combinations of different data sources and discuss the influence in Sec.4.2. The data augmentation and regularization include Mosaic [5] and Mixup [71], which follow the practice in ByteTrack. The input image size is 1440 × 800 with the shortest side ranging from 576 to 1024 during multi-scale training. We use the CLEAR [2] metrics for evaluation, including multiple object tracking accuracy (MOTA), high order tracking accuracy (HOTA) [38], and IDF1, to evaluate different aspects of tracking and detection performance. We also report the raw statics such as FP, FN, and IDs. As there are no labels for the testing set of MOT17, we split the training set by using the first half of each video for training and the last half for validation in our ablation studies, following [76]. We report test results when compared with other methods.

Training configurations. We train our S-ViT model using the AdamW [37] optimizer. The training epoch for action recognition on K400 and SSv2 is set to 30 with 5 epochs of warmup. A cosine learning rate schedule with the maximum learning rates of 1e-5 and 5e-5 are used for K400 and SSv2 respectively. The training epoch for multiple object tracking is set to 10 with 1 epoch of warmup. The learning rate is set to 2.5e-4 with a cosine annealing schedule. More details can be found in the supplementary.

4.2. Results on Multiple Object Tracking

The most important advantage of our S-ViT model for frame-based video tasks is its ability to extract temporal-aware spatial features. We design controlled experiments on the MOT17 dataset to demonstrate the effectiveness of the streaming video model and also ablate the influence of some newly introduced factors.

Effectiveness of streaming video model. Tab.1 shows the comparison between our streaming video model and the frame-based video model. Our streaming video model outperforms the frame-based video model by 0.6 MOTA, 2.5 IDF1, and 1.3 HOTA, which clearly demonstrates the effectiveness of temporal-aware spatial features.

Influence of test-time memory length. One flexibility of our streaming video Transformer is that we can use arbitrary memory length in the test phase without model retraining. Intuitively, using longer history helps our model to extract robuster features. As shown in Fig.4, longer test-time memory length indeed improves the tracking performance. Specifically, the 32-frame model gets 1.3 higher IDF1 and 0.7 higher HOTA than the 2-frame model.

Ablation study on training datasets. The paradigm switch from a frame-based video model to a streaming video model also involves a transition of training datasets. In multiple object tracking, it is common practice to involve additional data sources, as the MOT17 only has seven training sequences. An image pedestrian detection dataset called CrowdHuman is used in many prior works. However, as the CrowdHuman dataset only contains still images, it cannot provide useful temporal information, which is needed

Table 1. Comparison of the frame-based video model and streaming video model on MOT17 half-validation set.

Method	MOTA ↑	IDF1 ↑	HOTA ↑	FP ↓	FN ↓	IDs ↓
frame-based	79.0	78.4	67.0	10248	23058	564
streaming	79.6	80.9	68.3	9507	22956	453

Table 2. Comparison of training datasets for streaming video model training on MOT17 half-validation set. MOT17 is a video dataset. MOTS is short for MOTSynth, which is a synthetic video dataset. CH is short for CrowdHuman, which is an image dataset.

Dataset	MOTA ↑	IDF1 ↑	HOTA ↑	FP ↓	FN ↓	IDs ↓
MOT17	69.9	73.6	61.6	18837	29016	750
+CH	78.0	78.0	65.7	9966	25065	549
+MOTS	77.4	78.1	66.2	11742	24279	555
+MOTS +CH	79.6	80.9	68.3	9507	22956	453

by our streaming video model. We thus introduce another synthetic video dataset, MOTSynth, to train our streaming video model. The drawback of using MOTSynth is that it has a domain gap with real images because it is generated from a video game. We evaluate the different combinations of these data sources and present the results on Tab.2. The first row shows the results of using MOT17 alone. The HOTA of this model is only 61.6% and we observe severe over-fitting during training. The second row and the third row show the results of adding CrowdHuman and MOTSynth, respectively. In order to use CrowHuman in our streaming video model, we duplicate frames to form a video. It is clear that both additional data sources help our model achieving higher performance on MOT17. Finally, in the last row, we use all three data sources and achieve the highest performance of 68.3 HOTA, showing the importance of using both the video data sources and the real-world data sources.

4.3. Results on Action Recognition

We present the action recognition results of S-ViT on Tab.3 with a comparison of the frame-based model and the clip-based model. The frame-based model here is implemented with a spatial encoder and a temporal decoder, and the streaming model further upgrades the spatial-encoder's temporal awareness. The only difference between them is whether to use temporal awareness in spatial encoder. Our streaming video model achieves a 0.5% top-1 accuracy gain and a 1.0% top-1 accuracy gain over the frame-based model on K400 and SSv2, respectively, thanks to the temporal-aware spatial encoder. It is also surprising to see that our streaming video model achieves similar top-1 and top-5 accuracy on K400 when compared with the clip-based model but reduces the GFLOPs by 14%. The streaming video model only uses the history information to compute the cross-attention, while the clip-based video model uses both the history and the future. The same performance of these two models indicates that future information may not be necessary for sequence-based video task, and we have the opportunity to build a causal video model without sacrificing the performance on some kind of dataset. On SSv2, we observe a notable performance loss that may be related to the fine-grained category definition in SSv2. For example, knowing future information may help to distinguish the class "opening something" from the class "pretending to open something without actually opening it."

Table 3. Comparison of the frame-based video model, clip-based video model, and streaming video model on K400 and SSv2.

Method	GFLOPs	K400		SSv2	
		Top-1	Top-5	Top-1	Top-5
frame-based	282	84.2	96.7	68.3	91.6
clip-based	397	84.7	96.7	70.5	92.6
streaming	340	84.7	96.8	69.3	92.1

Table 4. Comparison to the state-of-the-art on Kinetics-400. #Frames denotes the total number of frames used during inference which is #frames per clip × # spatial crop × # temporal clip.

Method	#Frames	GFLOPs	Top-1	Top-5
Methods with CNN				
R(2+1)D [52]	16x1x10	75	72.0	90.0
SlowFast + NL [18]	16x3x10	234	79.8	93.9
X3D-XXL [17]	16x3x10	144	80.4	94.6
Methods with Transformer				
TokenLearner [47]	64x3x4	4076	85.4	96.3
ViViT-L FE [1]	32x3x1	3980	83.5	94.3
MViTv2-L (312 ↑) [29]	40x3x5	2828	86.1	97.0
TimeSformer-L [3]	96x3x1	2380	80.7	94.7
Video-Swin-L (384 ↑) [36]	32x5x10	2107	84.9	96.7
MTV-L [68]	32x3x4	1504	84.3	96.3
MTV-B [68]	32x3x4	399	81.8	95.0
Uniformer-B [27]	32x3x4	259	83.0	95.4
MViTv2-B [29]	32x1x5	225	82.9	95.7
Video-Swin-S [36]	32x3x4	166	80.6	94.5
Methods with CLIP-B pre-trained ViT				
ActionCLIP-B/16 [58]	32x3x10	563	83.8	96.2
EVL ViT-B/16 [33]	32x3x1	592	84.2	-
X-CLIP-B/16 [41]	16x3x4	287	84.7	96.8
ViT-B w/ ST-Adapter [42]	32x3x1	607	82.7	96.2
Text4Vis-B/16 [63]	16x3x4	-	83.6	96.4
T2D-B [74]	16x3x4	395	84.7	96.7
Streaming Video Model				
S-ViT (**Ours**)	16x3x4	340	84.7	96.8

4.4. Benchmark Evaluation

In this section, we compare the performance of S-ViT with state-of-the-art methods on both the action recognition task and the multiple object tracking task. Results of action recognition on K400 and SSv2 are shown in Tab.4 and Tab.5, respectively. Results of multiple object tracking on the MOT17 test set are shown in Tab.6.

Kinetics-400. In Tab.4, we report the comparison of our streaming video model and previous clip-based models on K400. Among all the compared models, our S-ViT achieves competitive performance with relatively low GFLOPs. Specifically, we get a 2.9% top-1 accuracy gain over MTV-B [68] and a 0.8% top-1 accuracy gain over EVL ViT-B/16 [33] with lower GFLOPs. Even compared with the state-of-the-art models X-CLIP-B/16 [41] and T2D-B [74], our S-ViT still gets competitive performance. It is worth noting that our model is a streaming video model that extracts features frame by frame and does not use future information in the temporal-aware spatial encoder. So it is quite a success that we do not lag behind clip-based video models, showing the opportunity of using streaming video models on sequence-based tasks.

Something-Something V2. Tab.5 presents results of S-ViT compared to SOTA methods on SSv2. Consistent with our findings on K400, our streaming video model showcases considerable proficiency on this motion-focused dataset, demonstrating its potential to operate as a general video action recognition model for diverse datasets.

MOT17. We report multiple object tracking results on MOT17, as shown in Tab.6. Among all the compared methods, our S-ViT attains top performance and only underperforms ByteTrack, which utilizes the strong YOLOX detector with COCO [32] pre-training. S-ViT uses a pure ViT backbone and does not use any detection pre-training. Further tuning of the ViT-based detection architecture may improve the performance of our method, but it is beyond the scope of streaming video model in this paper. Nevertheless, our S-ViT achieves the highest performance among all Transformer-based methods, outperforming TransMOT [12] by 1.4 MOTA, 0.8 IDF1, and 0.3 HOTA.

Table 5. Comparison to the state-of-the-art on SSv2.

Method	#Frames	GFLOPs	Top-1	Top-5
Methods with CNN				
TSM [30]	16x1x1	66	63.3	88.5
MSNet [25]	16x1x1	67	64.7	89.4
SELFYNet [26]	16x1x1	67	65.7	89.8
TDN [57]	16x1x1	132	66.9	90.9
Methods with hierarchical Transformer				
Video-Swin-B [36]	32x3x1	321	69.6	92.7
UniFormer-B [27]	32x3x1	259	71.2	92.8
MViT-B-24 [16]	32x3x1	236	68.7	91.5
MViTv2-S [29]	32x3x1	65	68.2	91.4
MViTv2-B [29]	32x3x1	225	72.1	93.4
Methods with cylindrical Transformer				
TimeSformer-HR [3]	16x3x1	1703	62.5	-
ViViT-L [1]	16x3x4	903	65.4	89.8
MTV-B (320p) [68]	16x3x4	930	68.5	90.4
Mformer-L [44]	32x3x1	1185	68.1	91.2
EVL ViT-B/16 [33]	32x3x1	682	62.4	-
ViT-B w/ ST-Adapter [42]	32x3x1	652	69.5	92.6
T2D-B [74]	32x3x2	397	70.5	92.6
Streaming Video Model				
S-ViT (**Ours**)	32x3x2	340	69.3	92.1

Table 6. Comparison to the state-of-the-art on the MOT17 test set.

Method	MOTA ↑	IDF1 ↑	HOTA ↑	FP ↓	FN ↓	IDs ↓
Methods with CNN						
CenterTrack [76]	67.8	64.7	52.2	18,498	160,332	3,039
QDTrack [43]	68.7	66.3	53.9	26,589	146,643	3,378
TraDeS [62]	69.1	63.9	52.7	20,892	150,060	3,555
FairMOT [73]	73.7	72.3	59.3	27,507	117,477	3,303
CorrTracker [59]	76.5	73.6	60.7	29,808	99,510	3,369
Unicorn [67]	77.2	75.5	61.7	50,087	73,349	5,379
ByteTrack [72]	80.3	77.3	63.1	25,491	83,721	2,196
Methods with Transformer						
MeMOT [7]	72.5	69.0	56.9	37,221	115,248	2,724
TransCenter [66]	73.2	62.2	54.5	23,112	123,738	4,614
MOTR [70]	73.4	68.6	57.8	-	-	2,439
Trackformer [39]	74.1	68.0	-	34,602	108,777	2,829
TransTrack [49]	75.2	63.5	54.1	50,157	86,442	3,603
GTR [77]	75.3	71.5	59.1	26,793	109,854	2,859
TransMOT [12]	76.7	75.1	61.7	36,231	93,150	2,346
S-ViT (**Ours**)	78.1	75.9	62.0	39,063	82,704	1,983

5. Conclusion

In this work, we propose the idea of streaming video models that aim to unify the treatment of both frame-based and sequence-based video understanding tasks, which in the past were handled by separate models. We present an implementation named streaming video Transformer and conduct comprehensive experiments on multiple benchmarks. Our model achieves competitive performance on the sequence-based action recognition datasets compared to existing clip-based methods. Our model also achieves a significant performance gain on the frame-based multiple object tracking task compared to the previous practice of frame-based models. To the best of our knowledge, this is the first deep learning architecture that unifies video understanding tasks.

In the future, we will apply S-ViT to more video tasks including single object tracking, video object detection, and long-term video localization. Besides, we will continue to improve S-ViT by upgrading its components, such as the detection head.

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