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T-C3D: Temporal Convolutional 3D Network for Real-Time Action Recognition

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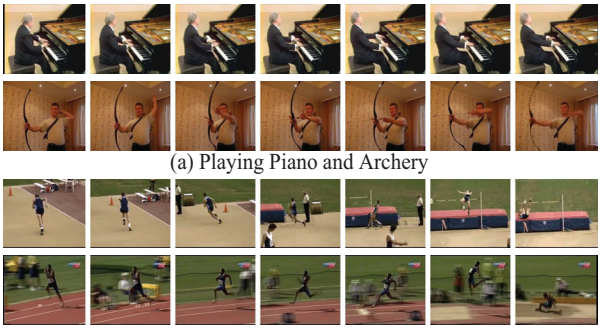
Abstract

Video-based action recognition with deep neural networks has shown remarkable progress. However, most of the existing approaches are too computationally expensive due to the complex network architecture. To address these problems, we propose a new real-time action recognition architecture, called Temporal Convolutional 3D Network (T-C3D), which learns video action representations in a hierarchical multi-granularity manner. Specifically, we combine a residual 3D convolutional neural network which captures complementary information on the appearance of a single frame and the motion between consecutive frames with a new temporal encoding method to explore the temporal dynamics of the whole video. Thus heavy calculations are avoided when doing the inference, which enables the method to be capable of real-time processing. On two challenging benchmark datasets, UCF101 and HMDB51, our method is significantly better than state-of-the-art real-time methods by over 5.4% in terms of accuracy and 2 times faster in terms of inference speed (969 frames per second), demonstrating comparable recognition performance to the state-of-the-art methods. The source code for the complete system as well as the pre-trained models are publicly available at https://github.com/tc3d.

1 Introduction

Video-based action recognition is to enable the computers to recognize the human actions automatically in real-world videos. It has attracted considerable attention from the academic community (Simonyan and Zisserman 2014; Tran et al. 2015) to industry applications such as video classification (Karpathy et al. 2014) and behavior analysis in public security systems (Wang and Schmid 2013). The task of human action recognition in videos, however, is still very challenging due to several reasons. First, the video is naturally an information-intensive media with a number of complexities, e.g., scale variations, cluttered background, viewpoint changes, camera motions, and so on. Second, unlike action recognition in a still image, video-based action recognition should have the ability of characterizing both short-term small motions and long-term temporal evolutions of appearances. Some actions can be reliably distinguished through the motion computed from consecutive frames (i.e., short-term motions), but there are also certain similar actions that require the overall features of long-term video (i.e., long-term motions), where the short-term information on short clips is almost the same.



(a) Playing Piano and Archery

(b) High Jump and Long Jump

Figure 1: Example videos from four classes of UCF101. Some actions can be reliably distinguished through the motion computed from consecutive frames. However, certain similar actions require the overall features of the video to identify since the short-term information on a clip is almost the same. For example, in (a), we can identify the "Playing Piano" and "Archery" with sequential frame. While in (b), "High Jump" and "Long Jump" can be accurately recognized only when the overall information is obtained.

To illustrate the above issues, we show some example videos from UCF101 (Soomro, Zamir, and Shah 2012) dataset in Figure 1. As shown in Figure 1, "Playing Piano" and "Archery" can be easily recognized through the appearance information of a static frame or small motion between continual frames. However, sometimes short clips are not sufficient for distinguishing similar classes (high jump vs long jump). In this situation, the video-level representations must be taken into consideration. Therefore, it is important to exploit the complementary nature of the single static image, the short and long-term temporal evolution, and the video-level representations, which, however, is a great challenge in video processing. Last but not least, due to the highly complex nature of the videos, it often requires expensive computational cost to deal with a video. In practice, this is often the most critical bottleneck for video-based ac-

tion recognition, and most existing methods are hard to be applied to large-scale datasets or real-time situations.

In the last decade, extensive research has been done on video-based action recognition, which includes hand-engineered descriptor-based methods and action representations with deep learning. The former mainly consists of feature extraction, feature encoding, and classification, which predominantly focuses on designing discriminative and powerful video descriptors with local spatial-temporal features. However, the performance of hand-crafted descriptors is not satisfactory. Unlike the methods with hand-crafted descriptors, most deep learning methods make use of convolutional neural networks (CNNs) to capture individual image-level appearance and exploit the temporal characteristic in videos. Unfortunately, most of the impressive deep learning based approaches cannot be deployed for real-time process due to their high computation burden (e.g., optical flow).

To solve the above issues, we seek to take the advantages of a deep 3-dimensional convolutional neural network (3D-CNN) to represent both the image-level information and motion information between consecutive frames. Therefore, our method can significantly reduce the computational complexity compared to the two-stream based methods since it avoids extracting the optical flow. Furthermore, we use the entire video information to distinguish the similar actions by a temporal encoding method. Owing to this encoding method, our approach obtains fast inference speed and achieves high performance compared to other 3D-CNN based methods. Lastly, we explore many alternatives for our T-C3D to build up the good architecture for action recognition. In this step, we also gain some interesting findings that might benefit future research on the related subjects. For example, we observe that pre-training the 3D-CNN on a clean but small dataset is more critical than a large but noisy dataset to improve the performance. Experiments on two challenging datasets demonstrate that T-C3D significantly boost the performance and obtain comparable performance with the state-of-the-art action recognition methods under the real-time requirement. More specially, our proposed method achieves 91.8% and 62.8% accuracy on UCF101 and HMDB51, respectively, at the speed of 969 fps.

The contributions of this paper are as follows:

- We propose a real-time 3D-CNN based action recognition architecture to learn video representation at a multitude of granularity. The learned features are able to model not only the temporal evolution of appearance between short clips but also the overall temporal dynamics of the entire video.
- We propose a temporal encoding technique with aggregation functions to model characteristics of the entire video, which considerably improves the recognition performance.
- We only employ RGB frames as the input of CNN to process action recognition at real-time while achieving comparable performance to the state-of-the-art methods.

2 Related Work

Action recognition has been widely explored in the last decade. We briefly group previous works related to ours into two categories: 1) action recognition with hand-engineered features, and 2) CNNs for action recognition.

To depict the temporal motion in videos for action recognition, many works try to devise effective features. Early researches propose some video representations which are derived from the image domain and extended to measure the temporal dimension of 3D volumes, such as 3D Histogram of Gradient (HOG3D) (Klaser, Marszałek, and Schmid 2008) and 3D Scale-Invariant Feature Transform (SIFT-3D) (Scovanner, Ali, and Shah 2007). Besides, several works focus on designing local spatio-temporal features. In particular, Wang et al. (Wang and Schmid 2013) propose a state-of-the-art hand-crafted feature named Improved Dense Trajectories (IDT), which extracts several descriptors (HOG, HOF and MBH) and tracks them in a dense optical flow field. However, some features designed by human beings are not discriminative enough to model the video. Part of them are too computationally expensive to process at real-time despite the impressive performance.

Since deep CNN brings significant progress in image recognition, researchers extend CNN for action recognition in video (Piergiovanni, Fan, and Ryoo 2017; Michael et al. 2017; Liu et al. 2015; Gan et al. 2016a). According to different convolutional architectures, neural networks for action recognition fall into two types: one-stream based methods and two-stream architecture approaches.

As to the one-stream CNNs, networks always pay more attention to spatial information. Several works (Tran et al. 2015; 2017; Varol, Laptev, and Schmid 2017) employ 3D convolution operator with the input of a short clip to model the temporal motion in video. However, this kind of methods have not yet significantly outperformed the traditional methods for action recognition in video. This is partly due to lack the capacity to model long-term features utilizing 3D-CNN. The other reason might be underachieving large-scale video datasets comparable in size and variety to ImageNet. The appearance of large-scale and well-labeled video datasets, like Sports-1M (Karpathy et al. 2014) and Kinetics (Kay et al. 2017), bring the opportunities to promote researches in this area. Motivated by above observations, we extend 3D-CNN with temporal encoding framework to model the entire video character and pre-train the network on a large-scale and clean dataset to fully unleash the potential of 3D-CNN.

The two-stream architecture is proposed in (Simonyan and Zisserman 2014) where spatial net captures single RGB image appearance and temporal net depicts the motion among a short clip with the input of ten optical flow maps. This might be the first work demonstrates that the deep model is more accurate than hand-engineered features, such as dense trajectories-based representation. Recently several attempts (Girdhar et al. 2017; Wang et al. 2016) have been made to improve the two-stream network from different aspects. Very recently, Kar et al. (Kar et al. 2017) describe an adaptive temporal pooling method that learns to pool discriminative and informative frames and discards majority of the redundant and non-discriminative frames in the

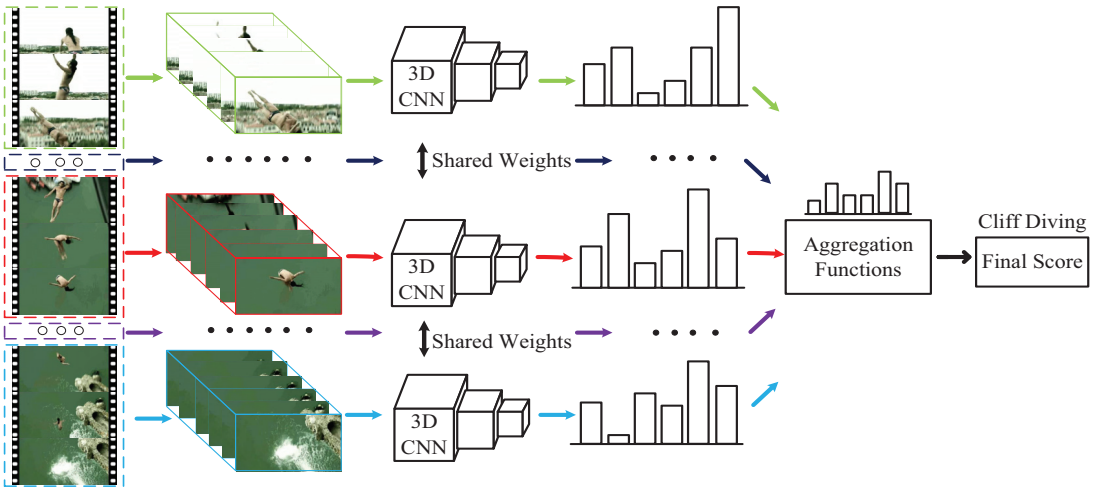


Figure 2: The proposed T-C3D architecture for real-time video action recognition.

video. The approach proposed in (Girdhar et al. 2017) provides an end-to-end trainable architecture for spatiotemporal video feature aggregation, where the inherent visual vocabularies (VLAD) are learned directly from the loss function. Despite good performance, all of two-stream based methods are too computationally expensive to meet the real-time requirement due to the heavy calculation of optical flows.

For real-time action recognition, Zhang et al. (Zhang et al. 2016) replace the optical flow with motion vectors to deploy the algorithm at real-time. This method transfers knowledge from high quality optical flow to motion vector encoding representation. While this work accelerates the speed of deep learning methods for action recognition, it is cumbersome owing to the calculation of optical flow during the training phase. Besides, the performance is not really superior. Compared with it, our approach totally avoids calculating the optical flow and only requires RGB frames to train the network. Meanwhile, our model can achieve a superior recognition performance and a faster speed.

3 Temporal 3D Convolutional Network

Figure 2 illustrates the framework of the proposed T-C3D network. Each input video is firstly divided into S parts. Then several frames are selected from each part to make up a clip. Next, S clips represented the entire video are fed into the 3D-CNNs respectively. The 3D-CNN extends the 2D-CNN at the temporal dimension, which is more suitable for capturing the three-dimensional data feature of video. The 3D-CNNs on all clips share the same weights. Furthermore, the feature maps or class scores of different clips are fused by an aggregation function to yield segmental consensus, which is a video-level prediction. Compared with previous works, T-C3D calculates the loss value with the video-level score rather than the clip-level or single frame prediction. The weight parameters are also updated and optimized by the video-level loss. Thus, T-C3D can model the overall video information. In summary, the pipeline mainly includes the following steps: 1) generating the clips of a video, 2) feeding the clips to 3D network, and 3) obtaining the video-level final scores by aggregating the features of the clips. The overall process is end-to-end trainable. Next, we will describe the proposed temporal encoding model and each part in detail.

3.1 Temporal Encoding Model

Videos are naturally hierarchical structured media because a video can be decomposed into spatial static single frames, temporal parts consisting of short temporal between consecutive frames, and long-term temporal evolution of entire videos. Motivated by this observation and given the real-time requirement, we design a novel real-time architecture for action recognition. First, we replace heavy calculation features (e.g., optical flow and IDT) with 3D-CNN to model the short-term temporal motion, making the framework extremely faster owing to the only requirement of RGB frames. Then, the temporal encoding method is introduced to characterize the overall information of an entire video, which can dramatically boost the classification accuracy.

To characterize the overall video feature, we introduce the temporal encoding method. Formally, given a video V, we uniformly divide it into S parts $\{P_1, P_2, P_3, ..., P_s\}$ in temporal dimension. Then, a sequence of frames are chosen from Pi to form the a clip Ci. Next, S feature maps are obtained by feeding forward the 3D-CNN with each clip. Combining S clips features with aggregating functions gains the video-level features. Finally, video-level features derive the ultimate class scores. Different from previous works, T-C3D optimizes and updates its parameter through the video-level score rather than the clip-level prediction. The process can be formulated as Equation 1:

$$Y_v = H(Q(F(C_1; W); F(C_2; W); ...; F(C_s; W))), \quad (1)$$

in which Y_v represents the final class score of the video v, $F(C_s, W)$ is the function describing the 3D-CNN with weights W, and yields feature map of clip C_s, such as last convolutional layer, fully connected layer, and probability of

all action categories. The aggregation function Q fuses the output from multiple clips to obtain a discriminative representation of the entire video. Based on this representation, the prediction function H produces the probability values of each action category for the whole video. Specially, in our work, the output of F is the last fully connected layer while H is the widely used softmax function. Multiple alternatives of aggregation function Q are exploited in the Section 4.4.

The differentiability of temporal encoding method allows T-C3D to be easily optimized using back propagation. Based on standard categorical cross-entropy loss, the final loss function regarding the segmental consensus $G = Q(F(C_1; W); F(C_2; W); ...; F(C_s; W))$ is formulated as

$$L(y, G) = \sum_{i=1}^{N} y_i (G_i - \log \sum_{j=1}^{N} \exp G_j), \tag{2}$$

where N is the number of action classes and y_i is the ground truth label concerning class i. S is a hyperparameter and we perform hyperparameter search to evaluate the effects of the value of S in next section. More importantly, the aggregation function Q is of significant importance because it not only integrates the clips' information into video-level feature but also determines the differentiability of the whole pipeline. In our experiments, we extensively study multiple differentiable aggregation function alternatives, such as mean pooling, max pooling, and attention pooling. Differentiable aggregation functions allow us to realize the multiple clips to jointly update the network weights W with standard back-propagation algorithms. In the back-propagation process, the gradients of network weights W concerning to the loss value L can be formed as

$$\frac{\partial L(y, G)}{\partial W} = \frac{\partial L}{\partial W} \sum_{s=1}^{S} \frac{\partial Q}{\partial F(C_s)} \frac{\partial F(C_s)}{\partial W}, \tag{3}$$

where S is number of clips adopted by T-C3D. In Equation 3, the weights are optimized through the segmental consensus G derived from all clip-level prediction. Updated parameters in this manner, T-C3D learns network weights from the overall video rather than a single clip. Next, we will introduce the implementation of the model in detail.

3.2 Video Components Generation

Different from the still images, videos are dynamic and with varying sequences. To exploit the good manners to model the overall video, we first uniformly divide the video into several parts in the temporal dimension. Then a clip is constituted by sampling several frames from each part with two popular sample schemes. The first scheme uniformly divides the video snippet generated in the previous step into a certain number of fragments and randomly selects one frame from each fragment to constitute the final clip. The second method randomly chooses a certain number of consecutive frames from the snippet to construct the final clip. In essence, the first sampling approach randomly selects non-consecutive frames distributed evenly throughout the video to represent the whole video. The second method uniformly chooses S clips from the entire video and each clip consists of a certain number of sequential frames. In next section, we give the comparison on classification accuracy of these two different down-sampling methods.

3.3 3D Convolutional Neural Network

Different from 2D-CNN's outstanding achievement on various visual tasks in still images, 3D-CNN is likely to fit for the videos which can be considered as the expansion of images in the temporal dimension. Convolutional 3D Network (C3D) (Tran et al. 2015) is one of the typical works that employ the 3D-CNN to extract both the spatial information and temporal cues with the input of sixteen raw RGB frames. However, sixteen raw RGB frames cannot model the long-term information. Then, Long-term Temporal Convolutions (LTC) (Varol, Laptev, and Schmid 2017) improve the C3D by feeding 3D-CNN with longer continuous RGB frame sequences and corresponding optical flow maps, ranging from 20 to 100 frames. All above works demonstrate that 3D-CNN is a promising direction for video-based action recognition. In our work, we extend the aforementioned 3D-CNN works from the following aspects.

Firstly, inspired by the amazing image classification accuracy obtained by the deep residual CNN, we adopt a deeper 3D-CNN network with residual block. More specially, we employ the 3D ResNet with 17 convolutional layers and one fully connected layer according to previous work on ConvNet architecture search (Tran et al. 2017). Experiments demonstrate that the deeper residual 3D-CNN can extract richer and stronger spatio-temporal feature hierarchies from the given multiple frames.

Secondly, pre-training the parameters of CNN (Gan et al. 2015; 2016b; Liu, Liu, and Ma 2017; Ma 2017) on a large-scale dataset has been proven greatly crucial for various visual tasks, e.g., object detection, image classification, semantic segmentation, and so on. For 3D-CNN, previous works such as LTC have shown that 3D models pre-trained on Sprots-1M achieve higher classification accuracy than the models trained from scratch. In this paper, we first follow the strategy introduced in C3D and pre-train our model on Sports-1M. Although Sports-1M has over than one million videos, it contains amounts of noise since it is not manually labeled. Very recently, Kay (Kay et al. 2017) et.al propose a large-scale and clean dataset, called Kinetics, which covers 400 human action categories with at least 400 video clips for each action. To activate the neuron in the 3D-CNN as much as possible, we make efforts to train the 3D-CNN on Kinetics with the temporal encoding method. Experiments show that pre-training on Kinetics significantly boosts the performance.

3.4 Aggregation Functions

As mentioned above, aggregation functions is a very curial component in the T-C3D framework. In this subsection, we provide a detailed description and insightful analysis of four aggregation functions, including average pooling, max pooling, weighted pooling, and attention pooling.

Average Pooling. In this aggregation function, we adopt average pooling to fuse the 3D-CNN output of the sampled

clips, i.e., $g_i = \frac{1}{S}\sum_{s=1}^{S} F_s^i$, where F_s^i is the i^{th} element of $F_s = F(C_s; W)$. The basic assumption of average pooling is to utilize the activations of all clips for action recognition and employ their mean responses as the overall video prediction. From this perspective, average pooling is able to jointly depict sequences of clips and obtain the visual feature from the entire video. However, some videos may contain noisy sequences that are irrelevant with the actions, in this case, averaging over these noisy clips cannot accurately model the action character, possibly leading to degradation of the recognition performance.

Maximum Pooling. Another widely used aggregation method is maximum pooling, where we perform a maximum operation over these clip-level outputs, i.e., $g_i = \max_{i\in\{1,2,\ldots,S\}} F_s^i$. The basic intuition of max pooling is to select the most discriminative clip for every action category and represent the whole video with this strongest response. Intuitively, it focuses on a single clip without taking the activations of other clips into consideration. In some cases, a single clip is not discriminative enough to capture the entire video information. To some degree, T-C3D degrades to the previous works which train the network with one clip per video when employing the max pooling. Therefore, this aggregating function drives the T-C3D to represent the entire video just with single clip, which violates the T-C3D's assumption of modeling overall video.

Weighted Pooling. The goal of this aggregation function is to produce a set of linear weights to perform an element-wise weighted linear fusion among the outputs of each clip. Specifically, the aggregation function is defined as $\sum_{s=1}^{S} \omega_s F_s^i$, where ω_s is the weight for the s^{th} clip. In our experiments, both the network weights W and the fusion weights ω are optimized simultaneously. We introduce this aggregation function based on the fact that action always consists of several phases and these different phases may have different influences in identifying action classes. This function combines the merits of both maximum pooling and evenly pooling, having ability of jointly depicting sequences of relevant clips while decreasing the bad effects of noisy clips. Specially, we adopt a convolutional layer with the kernel of $S \times 1$ to implement the function.

Attention Pooling. This aggregation function has the same goal as the weighted pooling method. It borrows the memory attention mechanism of a kind of end-to-end trainable memory network (Sukhbaatar et al. 2015) for our feature aggregation. The intuition therein is to employ a neural model to read external memories through a differentiable addressing/attention scheme. In our work, we consider the outputs of each clip as the memory and cast feature weighting as a memory addressing procedure. Formally, let F^s be the 3D-CNN feature map of s^{th} clip, then the aggregation module filters them with a kernel q via dot product, producing a sequence of corresponding weights e_s. Then a softmax function operates on them to generate positive parameters ω_s with $\sum_{s=1}^{S} \omega_s = 1$. These two steps can be formulated as the Equation 4 and Equation 5 respectively

$$e_s = q^T F_s, \tag{4}$$

$$\omega_s = \frac{\exp e_s}{\sum_{j=1}^{S} \exp e_j}. \tag{5}$$

Obviously, this aggregation module essentially chooses one point inside of the convex hull spanned by all the feature maps.

4 Experiments

In this section, we first describe the benchmark datasets and implementation details of the proposed framework: T-C3D. Then, we compare the performance and speed of our method with the state-of-the-art methods. After this, we explore various alternatives for learning T-C3D networks, such as generating snippets strategy, aggregation function, and weight initialization scheme.

4.1 Datasets and Evaluation Protocol

We empirically evaluate our T-C3D approach on the two public benchmark datasets for action recognition: UCF101 (Soomro, Zamir, and Shah 2012) and HMDB51 (Kuehne et al. 2011). The UCF101 dataset is a widely used benchmark which consists of 101 action categories with 13,320 videos in about 27 hours. The majority of video clips in UCF101 have the 320×240 pixels spatial resolution and 25 frames per second (FPS) frame rate. Each action class has at least 100 video samples. HMDB51 dataset is a large collection of realistic videos from various sources, such as web videos and movies. This dataset is composed of 51 action categories with 6,766 video clips in all. A split in HMDB51 includes 3,570 training and 1,530 test instances, while each split in UCF101 contains around 9,500 training and 3,700 test video samples. For both datasets, we adopt the three standard training/testing splits provided in original works as the evaluation scheme and report the mean accuracy over these three splits. Following (Li et al. 2016), the exploration study for training T-C3D is only conducted on the first split of UCF101. As for speed evaluation, we adopt FPS as metric and conduct experiments on a CPU (E5-2640 v3) and a K40 GPU.

4.2 Implementation Details

For both datasets, each video is sampled to generate the clips to feed the network. Following (Tran et al. 2017), every clip contains eight frames and each frame in the clip is resized to 128×171 from the original spatial resolution. Then every frame subtract the mean value of the training data to center the input data. Moreover, to reduce the effect of severe overfitting and learn powerful features from T-C3D, we adopt two types of data augmentation techniques. Firstly, we horizontally flip frames with 50 probability. Secondly, we extend the random crop with scale jittering and aspect ratio jittering techniques that are commonly used in still image classification. Specially, we randomly select the width and height of the cropped region on three scales 1, 0.875, and 0.75, generating more training instances. Then all the cropped regions

are resized into 112×112. Namely, the network employs an $8 \times 112 \times 112$ input, the largest that can fit within GPU memory limits and maintain a large enough mini-batch.

The network parameters are learned in an end-to-end fashion with the mini-batch stochastic gradient descent algorithm, where the momentum is set to 0.9 and the batch size is set to 8. The pre-trained models on Sport-1M and Kinetics are utilized to initialize network weights. We randomly initialize the last fully connected layer and add a dropout layer after the global pooling layer with high dropout ratio (set to 0.8 in experiments) to prevent over-fitting. On UCF101, the initial learning rate is 0.005 and decreased to its 1/10 every 8,000 iterations. The whole optimization procedure is stopped at 20,000 iterations. For HMDB51, the training scheme is the same as that of UCF101, except that the iteration numbers are adjusted according to the number of training instances.

During the testing phase, to balance the speed and classification accuracy, we investigate both multi-scale testing strategy and only a single center crop to predict the action category. More specifically, the feed forward process of CNN is performed by GPUs when evaluating the speed.

4.3 Comparison with The-State-of-The-Art Methods

Table 1 shows the comparison of our architecture with current state-of-the-art methods including:

1) **Hand-engineered feature methods:** IDT encoded with Fisher Vector (Wang and Schmid 2013), DT encoded with Multi-view super vector (MVSV) (Cai et al. 2014), and Motion Vector (MV) encoded with Fisher Vector;

2) **One-stream methods:** C3D (Tran et al. 2015), Res3D (Tran et al. 2017), Slow Fusion (Karpathy et al. 2014), and Temporal Segment Network (TSN) with input RGB (Wang et al. 2016);

3) **Two-stream methods:** original two-stream method (Simonyan and Zisserman 2014) with shallow and deep CNN models, Two-stream+LSTM (Yue-Hei Ng et al. 2015), LTC (Varol, Laptev, and Schmid 2017), AdaScan (Kar et al. 2017), ActionVLAD (Girdhar et al. 2017), TDD+FV (Wang, Qiao, and Tang 2015) and TSN (Wang et al. 2016), and Enhanced MV (Zhang et al. 2016).

Compared with hand-crafted features-based methods, T-C3D outperforms the most discriminative hand-engineered feature (IDT) encoded with the robust encoder (FV). Moreover, it achieves the best accuracy among one-stream methods that use only RGB input on both datasets. TSN (RGB) and Slow Fusion belong to 2D-CNN based approaches. They are both inferior to T-C3D since 2D-CNN might be unsuitable for extracting the spatial-temporal information of videos. Although TSN can achieve more impressive performance of 87.3% at real-time on split 1 of UCF101 when using RGB and RGB Difference, it still obtain lower accuracy and the higher computational cost compared with our method. Finally, T-C3D attains higher accuracy than the two-stream methods with very deep CNN architectures. More specially, it achieves competitive performance to the state-of-the-art methods or even outperforms some recently proposed extended works of two-stream framework when per-training on the Kinetics dataset. Despite superior performance on both datasets, TSN is computational expensive (5 fps) and far from the real-time requirements. Note that the improved algorithm of two-stream also can be applied to further enhance T-C3D. For speed evaluation, it should be noticed that T-C3D beats all the real-time models on the accuracy by a large margin while achieving the fastest speed. Our fast version can achieve the 969 FPS.

Table 1: Comparison of performance and speed with the state-of-the-art methods on UCF101 and HMDB51 (mean accuracy across 3 splits). TS stands for Two-stream architecture methods.

	Method	UCF101	HMDB51	FPS
Hand-crafted Feature	IDT+FV	85.9	57.2	2
	DT+MVSV	83.5	55.9	N/A
	MV+FV	78.5	N/A	133
One-stream (RGB)	C3D	82.3	51.6	314
	C3D(3nets)	85.2	N/A	<314
	Slow Fusion	65.8	N/A	N/A
	Res3D	85.8	54.9	N/A
	TSN(RGB)	85.1	51.0	N/A
Two-stream (Based)	TS(VGG-M)	88.0	59.4	14
	TS(Resnet50)	91.7	61.2	<14
	TS+LSTM	88.6	N/A	<14
	LTC	91.7	64.8	<14
	AdaScan	89.4	54.9	<14
	ActionVLAD	92.7	66.9	<14
	TDD+FV	90.3	63.2	<14
	TSN	94.2	69.4	5
	Enhanced MV	86.4	N/A	390
T-C3D	Ours(Sports1M)	89.4	58.6	220
	Ours(Kinetics)	**92.5**	**62.4**	**220**
	Ours(Fast)	**91.8**	**62.8**	**969**

Table 2: Comparison of sampling methods on split 1 of UCF101 dataset.

Sampling Methods	Accuracy
Consecutive Sampling	89.5
Non-Consecutive Sampling	89.2

4.4 Exploration Study

In this subsection, we conduct exploration study of the T-C3D from the following four aspects: 1) sampling methods for generating snippets, 2) the number of snippets sampled from a video, 3) aggregation functions, and 4) parameter initialization schemes. In this empirical study, we conduct all experiments on the split 1 of UCF101 dataset with the proposed framework.

Evaluation on sampling methods. We investigate the effects of two sampling methods described in Section 3.2. Table 2 summarizes the results. We can observe that sampling consecutive frames is more suitable for learning the 3D-CNN parameters than sampling frames evenly from the whole video. The latter methods can get the whole video information with non-consecutive frames, the two adjacent

Table 3: Exploration of different aggregation functions for T-C3D on split 1 of UCF101 dataset.

Aggregation Functions	Accuracy
Max pooling	88.1
Average pooling	89.4
Weighted pooling	89.1
Attention pooling	89.5

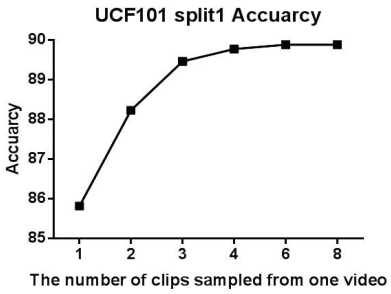


Figure 3: Recognition accuracy (%) on split 1 of UCF101. The performance is improved when increasing the number of clips sampled from the video.

frames sampled by this method might last across a long period of time. The 3D-CNN possibly lacks the capability of capturing the large motion features.

Evaluation on aggregation functions. The results of different aggregation functions are summarized in Table 3. The attention aggregation function achieves the best performance, and average pooling obtains quite similar performance. This conclusion possibly suggests that on clean datasets with fewer scale variations and cluttered background, the simple aggregation module can result in better recognition accuracies. In this sense, we exploit average pooling for the aggregation function in later experiments.

Evaluation on snippets number. We study extensively the impact of the number of clips sampled from one video. Figure 3 obviously shows that increasing the number of clips can result in better performance. Note that the model weights are updated without the temporal encoding method when the number of clips is 1. It is easily concluded that temporal encoding method is benefit for increasing the classification accuracy. Besides, when the number of clips increases from 4 to 6 or 8, the performance saturates. Given the trade-off between training time and accuracy, we set the number of clips to 3 as the default setting.

Evaluation on parameter initialization. In Table 4, we find that pre-training the weight parameters of T-C3D on a large-scale dataset can get better performance. Sports-1M with the ground truth is not well labelled has less accuracy, although it have more training samples and more categories. Thus, the quality seems to be more important than quantity when choosing the datasets to initialize the parameter.

Evaluation on the balance between speed and accuracy. We also make efforts to find the trade-off between the performance and the speed. According to Table 5, feeding forward the network with 5 crops and mirror (multi-scale) brings a slight improvement on performance but a serious deceleration. Aggregating all clips of a video is a good choice which balances the accuracy and computational cost. Moreover, sampling S clips per video also obtains an impressive performance in an extremely fast speed. S is number of clips adopted by T-C3D.

Table 4: Evaluation of different parameter initialization schemes for T-C3D on split 1 of UCF101 dataset.

Parameter Initialization	Accuracy
Training on scratch	68.3
Pre-train on Sports-1M	89.5
Pre-train on Kinetics	92.5

Table 5: Comparison of speed and accuracy based on different clip numbers and multi-scale strategies for T-C3D on split 1 of UCF101 dataset.

Parameter Initialization	Accuracy	FPS
All clips per video (multi-scale)	92.8	45
S clips per video (multi-scale)	92.2	197
All clips per video	92.5	220
S clips per video	91.8	969

5 Conclusion

We present T-C3D, an end-to-end trainable framework to take advantage of the temporal encoding method and deep 3D-CNN to learn the overall temporal information of a video. By feeding consecutive frames to network, T-C3D extracts the complementary information on spatial information from a single image and motion features between sequential frames. T-C3D captures the overall temporal dynamics of the whole video through the temporal encoding method. Owing to the capacity to model multiple granularity features of videos, our approach achieves competitive performance to the state-of-the-art methods. Furthermore, T-C3D does not require heavy computational process so that it processes videos in a speed of very faster than real-time, which makes it possible to deploy action recognition algorithms on mobile devices. In the future, we will extend T-C3D for online processing where the system performs recognition as the frames are received instead of presenting the entire video.

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