

Temporal and Contextual Transformer for Multi-Camera Editing of TV Shows

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Abstract

The ability to choose an appropriate camera view among multiple cameras plays a vital role in TV shows delivery. But it is hard to figure out the statistical pattern and apply the intelligent processing due to the lack of high-quality training data. To solve this issue, we first collect a novel benchmark on this setting with four diverse scenarios including concerts, sports games, gala shows, and contests, where each scenario contains 6 synchronized tracks recorded by different cameras. It contains 88-hour raw videos that contribute to the 14-hour edited videos. Based on this benchmark, we further propose a new approach temporal and contextual transformer that utilizes clues from historical shots and other views to make shot transition decisions and predict which view to be used. Extensive experiments show that our method outperforms existing methods on the proposed multi-camera editing benchmark. ¹

1. Introduction

Multiview cameras provide more angles and framing in one shot which helps the viewer to relate with the story and performance in a much better way. Though it is more visually compelling than single view video, its video editing process is more tedious since it requires an experienced editor to switch among different tracks to guide the viewer.

Although intelligent video editing and creation span across shot type classification [27], cut point ranking [24], cut type recognition [25], transition type recommendation [28], etc., there are few works working on multiview video computational editing, which aims to present a nor-



Figure 1. Multi-camera editing from 6 tracks synchronized raw footage using our proposed TC-Transformer.

mal view video with shots changes automatically. The first step towards this goal is to select an appropriate view from the tracks of multiview cameras at each time step. The challenges come from two aspects: to select a suitable cutting point that transits from one shot to another shot and ensures the temporal consistency among shots in the final edited video; to pick up an appropriate view from candidate views that can well present the whole plot.

Existing methods [15, 22] basically rely on manually crafted rules or are trained on small datasets with a limited number of samples to tackle the surveillance cameras scenarios. The lack of large-scale diverse training data restrains it from real-world application in multi-camera video editing. To address this limitation, we focus on a common application domain TV shows and collect a large-scale dataset with 6 tracks raw videos and ground truth video from professional TV shows. It covers indoor and outdoor scenarios spanning concerts, sports games, gala shows and contests

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¹A shot is a series of continues frames that recorded by a camera and a track refers to the video recorded by one camera from a specific view. The dataset will be made public available in compliance with regulations.

and lasts for 88 hours which is 50 times larger than existing datasets. Taking the advantage of the above dataset, our proposed Temporal and Contextual Transformer (TC-Transformer) integrates the cutting point selection and track prediction into a unified framework that utilizes a sliding window to classify the correct view. It helps to achieve 5% ~ 6% relatively improvement over baselines.

To this end, our contribution can be summarized as follows, 1) a novel multi-camera editing dataset that contains 6 raw synchronized tracks in 88 hours recorded by professionals for the ground truth edited video made by experienced video editors. 2) a target designed approach temporal and contextual transformer that utilizes the clues of historical shots and concurrent videos from other views and solves the cutting point and view selection jointly.

Assumption: Although the paper focuses on the shot transition and view selection for TV shows, the transition effects, such as fade in/out, among different shots, which can bring more advanced performance to the final edited video, its extension to other application domains, *e.g.*, daily life videos, are out of the scope of this paper.

2. Related Work

Video Editing. Intelligent video editing tools help users to create their videos more efficiently. Some approaches tackle the textual semantics of the generated video [5, 9, 13, 26, 29]. Wang *et al.* [32] automatically search for semantic-matched shots based on the text entered by the user. Xiong *et al.* [33] develop a weakly-supervised framework that uses text as input to automatically create video sequences from a shot collection. Some researchers focus on generating various video styles based on various manually defined conditions [2, 11, 19, 20, 23]. Leaken *et al.* [18] propose a system for efficient video editing by offering a set of basic idioms. Frey *et al.* [8] develop an automatic approach that extracts editing styles in a source video and applies them to corresponding footage. Other works study the attributes and connection of individual shots [3, 24, 25]. It appears a rich set of benchmarks on shot sequence ordering, next shot selection, missing shot attributes prediction [3], cut prediction [25], *etc.* In this paper, we focus on how to create videos from multi-camera footage with the aim of following the consistency of temporal and contextual relationships.

Video Summarization. Another branch of work that shares similarities with ours is video summarization [1, 14] and video highlight detection [30] in the format of "select video clips from a large set of footage", with the main purpose of compressing information. Among the above, multiview video summarization [14] is the most related to ours. Most methods [14] study the surveillance scenario [10], and a few of them focus on social events [2]. A brief comparison of these datasets and our multi-camera editing dataset

Table 1. Comparison with existing multiview video summarization dataset.

| | Sync. | Scenarios | Duration(h) |
|----------------------|-------|------------------------------------|--------------|
| Surveillance [10] | ✗ | office, campus, road, badminton | 1.75 |
| Social [2] | ✗ | office, park, street, snowman | 1.01 |
| Multi-Camera Editing | ✓ | concert, context sports, gala show | 88.44 |

is shown in Table 1. The advantages of our new dataset lie in its synchronization, long length and clear targets to TV shows multi-camera editing. With the dataset, Hussain *et al.* [15] proposed a DB-LSTM based approach to generate a summary from multiview videos, which utilizes a lookup table in saving computational resources. Meng *et al.* [22] formulate video summarization as a multiview representative selection problem that aims to find a selection of visual elements agreeable with all views. However, all of the existing approaches target saliency detection by choosing the most noticeable parts from the video footage. Instead, our multi-camera editing aims to pick up one ideal clips from different tracks at the same timestamp in much more challenging scenarios such as concerts, gala shows, sports activities. The editing is required to achieve consistency in consecutive shots to deliver a coherent long video [16].

3. TV Shows Multi-Camera Editing Dataset

To facilitate the research in multi-camera editing, we collect a large-scale high-quality dataset TV shows Multi-Camera Editing (TVMCE) dataset, with a glimpse of it shown in Fig. 2. A demo video of the dataset is shown in the supplementary materials and we encourage readers to watch it.

Data Collection and Procedure. To make a high-quality multi-camera editing dataset for TV shows, its content, videography and editing should reach a professional level. With this in mind, we reached out to film and TV production major colleges and follow their professional production team to acquire data covering various scenarios including concert, sports, contest and gala show that happen in universities and city theaters/stadiums. These provide real-world content for us to study. With the physical content, to professionally record them is also of great importance. The videographers are professionally trained senior final-year student who are guided by professors as directors. After collecting the raw footage, The professional director need to check all raw footage and decide when to use the footage and for how long based on the specific content of the performance and some professional knowledge.

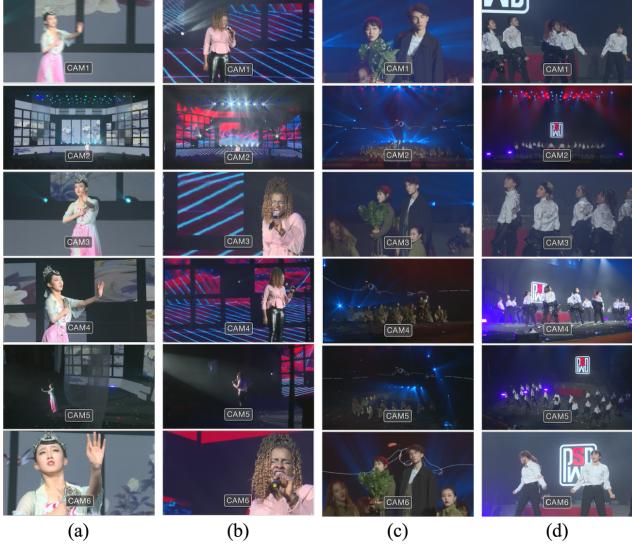


Figure 2. A glimpse of the TVMCE dataset on four different scenarios with six different synchronized tracks.

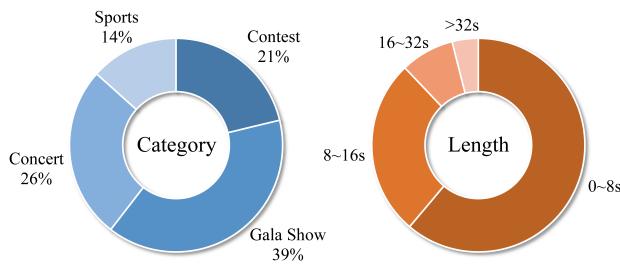


Figure 3. *Left:* Proportion of each shot category in the TVMCE dataset; *Right:* the shot length distribution of edited videos.

The collection and annotation of the TVMCE dataset require a huge cost of manpower and time with two key challenges. The first one lies on synchronization, that is to align the timestamps of each view track and every camera takes the same content from different views at any given moment. The second challenge is how to efficiently select the right track from the multiple view tracks. For an event, *e.g.*, a concert or a gala show, it usually takes 3~4 hours. This means that the director needs more than 20 hours to watch these videos, which is unacceptable. To ease the above difficulties, all different view tracks are pre-synchronized in camera settings and fed into the same screen. The editor can see all the tracks at once and make their decision, and the results are double checked by other professionals to ensure the quality. By recording the actions of these directors, we can get the annotation of which and when a track is selected.

Statistics. As shown in Figure 3, our dataset holds a balanced coverage ratio among different scenario categories

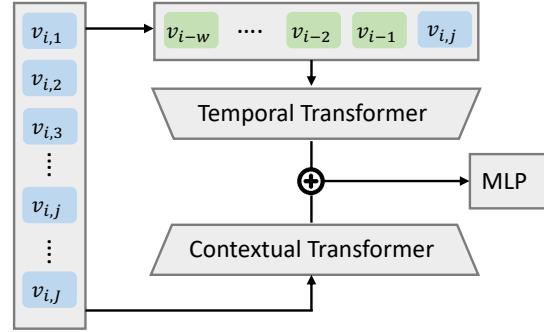


Figure 4. The framework of TC-Transformer. It contains a temporal transformer to take in historical video frames including $i-w$ -th frame to i -th frame and a contextual transformer to process all the possible candidate frames at i -th timestamp.

with 39% in gala shows and 14% in sports. Most shots in our dataset have a time duration between 0 to 8 seconds and a few shots are long shots that last longer than 32 seconds.

4. Temporal and Contextual Transformer

Problem Formulation. The raw input for multi-camera editing is the video pool V that lasts for I frames accompanying with J tracks.

$$V = \begin{bmatrix} v_{1,1} & v_{2,1} & v_{3,1} & \cdots & v_{I,1} \\ v_{1,2} & v_{2,2} & v_{2,2} & \cdots & v_{I,2} \\ \vdots & \vdots & \vdots & & \vdots \\ v_{1,J} & v_{2,J} & v_{3,J} & \cdots & v_{I,J} \end{bmatrix},$$

where $v_{i,j}$ denotes the j -th track of i -th frame. Our goal is to find a best combination of $v_{i,j}$ to form a optimal video \hat{V} such that it is consistent and rich in the content delivery.

Methodology. The brute force way is to enumerate all the possibility in the complexity of $O(I^J)$ and it has to be done offline. To overcome the above issues, we formulate this problem as a classification problem in a sliding window of length as w to make a prediction $p_{i,j}$ for $v_{i,j}$ to determine whether it is appropriate to be presented in the final output.

Inspired by the observation that professional editors select a view based on the historical decision they made and all the available views at the current time stamp. To fully utilize the above properties, we design two transformers on each frame $v_{i,j}$ to deal with temporal consistency and contextual coherence. Specifically, the temporal transformer \mathcal{T} takes $v_{i,j}$ and $i-w$ to $i-1$ -th frames as input. The contextual transformer \mathcal{C} incorporates the information from all the frames $v_{i,1}$ to $v_{i,J}$ at i -th timestamp. The outcomes of the above two transformers are finally fed into a MLP layer and the process can be formulated as below,

$$\begin{aligned} p_{i,j} = \mathcal{F}(\mathcal{T}(v_{i-w}, \dots, v_{i-1}, v_{i,j})) \\ \oplus \mathcal{C}([v_{i,1}, \dots, v_{i,j}, \dots, v_{i,J}]), \end{aligned} \quad (1)$$

where $p_{i,j} \in [0, 1]$ is the predication score of whether $v_{i,j}$ will be selected. The whole framework is trained end-to-end with binary classification loss,

$$\mathcal{L} = -y \log(p) + (1 - y) \log(1 - p), \quad (2)$$

where y is the ground truth, *i.e.*, $y = 1$ indicates $v_{i,j}$ is the selected as v_i , vice versa.

Efficient Training. The aforementioned training requires generating samples at each time step for every frame that requires heavy computational resources, since there are 5.8M frames for 88-hour footage with the fps as 24.² And it also casts difficulties in learning useful information related to multi-camera editing. To speed up the training process, we focus on shot boundaries and generate training samples using window size as 16 and step wise as 5 frames. This reduces the training samples to 24K.³

5. Experiments

5.1. Setup

Evaluation. All the baseline methods are tested on our TV Shows Multi-Camera Editing (TVMCE) dataset, which is split into 4:1 for training and test as shown in Figure 2. To evaluate the performance, we calculate the Precision and the Average Precision (AP) of selecting the right track, where the Precision is calculated by taking a concrete threshold 0.5 and the Average Precision is calculated as the weighted mean of precisions at each threshold.

Baseline. TSN [31] models long-range temporal structures with a segment-based sampling and aggregation module. SlowFast [7] is composed of a Slow pathway operating at low frame rate that captures spatial semantics, and a Fast pathway operating at high frame rate that captures motion at fine temporal resolution. ViViT [4] extracts spatio-temporal tokens from the input video and encodes them into a series of transformer layers. Video-Swin [21] advocates an inductive bias of locality and computes self-attention globally with spatial-temporal factorization.

Implementation Details. Both TSN [31] and SlowFast [7] use ResNet50 [12] as the backbone, which is pretrained on the ImageNet dataset [6]. The ViViT [4] is consisted of a spatial transformer and a temporal transformer, which use 12 transformer encoder layers. Each layer has a self-attention block of 12 heads with hidden dimension as 768. For Video-Swin [21], the dimension of the hidden layers in the first stage is set to 96, and the layer numbers of transformer block in each stage is 2, 2, 6, 2. The patch size is set to 2x4x4 and the window size is 8x7x7. Both ViViT and Video-Swin are pretrained with Kinetics-400 [17]. For

²5.8M = 66.9 × 3,600 × 24, that is all the training frames.

³24K = 4,042 × 6, that is 6 samples for each shot boundary.

Table 2. Data split of the TVMCE Dataset.

| | Train | Test | Total |
|---------------|-------|-------|-------|
| # of GT shots | 4,042 | 1,091 | 5,133 |
| Duration(h) | 66.90 | 21.54 | 88.44 |

Table 3. Overall results on TVMCE Dataset.

| Method | Precision(%) | AP(%) |
|-----------------------|--------------|--------------|
| Random | 16.66 | 16.66 |
| TSN [31] | 16.88 | 18.70 |
| SlowFast [7] | 16.70 | 16.67 |
| ViViT [4] | 17.60 | 19.83 |
| Cloud [15] | 20.38 | 20.38 |
| Video-Swin [21] | 21.20 | 20.44 |
| TC-Transformer(ViViT) | 21.29 | 20.15 |
| TC-Transformer(Swin) | 22.48 | 21.62 |

a fair comparison, all methods use a MLP block to calculate the classification score after layer normalization with the hidden dimension as 192.

5.2. Overall Analysis

The overall results are shown in Table 3. It is observed that with the training on TVMCE dataset, TSN acquires 16.88 on precision and 18.70 on AP, which performs better than a random guess. As the backbone becomes deeper and more powerful in integrating temporal information, ViViT [4] and Cloud [15] get 1% ~ 3% improvement on precision and AP. Due to the advantage on hierarchy and locality representation ability, Video-Swin [21] improves the precision from 20.38 to 21.20 and the AP from 20.38 to 20.44, which outperforms the above.

Benefited from the joint usage of temporal and contextual information, TC-Transformer achieves the highest precision accuracy 22.48 and AP 21.62 on the test set of TVMCE dataset, with 5% ~ 6% relative improvement over the baseline.

6. Conclusion

In this paper, we propose a new TV shows Multi-Camera Editing (TVMCE) dataset for multi-camera editing. It contains 88-hour raw synchronized footage recorded by 6 different cameras from different views and covers four main type of TV shows including sports, gala shows, concerts, contests. We further introduce a new method temporal and contextual transformer TC-Transformer that selects the desired frame according to its historical frames and concurrent frames from different views. The comparison on TVMCE dataset with state-of-the-art baselines shows the superiority of our TC-Transformer.

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