Discerning Generic Event Boundaries in Long-Form Wild Videos

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Abstract

Detecting generic, taxonomy-free event boundaries in videos represents a major stride forward towards holistic video understanding. In this paper we present a technique for generic event boundary detection based on a two stream inflated 3D convolutions architecture, which can learn spatio-temporal features from videos. Our work is inspired from the Generic Event Boundary Detection Challenge (part of CVPR 2021 Long Form Video Understanding- LOVEU Workshop). Throughout the paper we provide an in-depth analysis of the experiments performed along with an interpretation of the results obtained. The code for this work can be found at https://github.com/rayush7/GEBD

1. Introduction

It is a natural tendency of humans to perceive videos as a composition of events like making breakfast, attending class, watching a movie etc. These events could further be segmented into a sequence of shorter temporal units as studied in cognitive psychology [19]. Event boundaries comprise of instances of greater change in action, cases indicating completeness of specific goals and sub-goals, occasions where predictability collapses etc. Event boundary detection has a plethora of significant applications in complex action recognition, video summarisation, video editing and ad-cue points detection for YouTube videos. In the last few years tremendous advancements have been made in action anticipation [12, 1], temporal action detection [5, 6], segmentation [9, 10] and parsing [13, 14]. However only limited progress has been made when it comes to detecting event boundaries in long form videos due to unavailability of proper task definition and annotations.

In this direction, the generic event boundary detection challenge was organised in the Long Form Video Understanding Workshop at CVPR 2021 to further investigate this task. The challenge uses the newly proposed Kinetics- GEBD [15], which contains the largest number of boundaries (around 32x ActivityNet, 8x EPIC-Kitchens-100). The boundaries have open vocabulary, contain generic event changes, are in the wild and adhere to human perception diversity. The challenge aims at predicting the timestamps where an event boundary is most likely to occur. The train, validation and test dataset each contained nearly 20,000 videos of duration 10 secs. Each video was annotated by 5 annotators separately for event boundaries and every annotator was given a F1-consistency score (an indicator of annotator rating) as explained in [15]. The evaluation protocol used is the relative distance (Rel.Dis) whereas the official metric for the challenge is F1@5%, which is defined as the F1 score computed with 5% threshold. Rel.Dis is the error between detected and ground-truth timestamps, divided by the length of the whole video.

2. Related Work

Video understanding encapsulates various tasks like action recognition, action anticipation, action detection, temporal action detection, video summarisation, event boundary detection, etc. Shot Boundary Detection [16, 17] is a long-standing problem to detect shot transitions (zooming in/out, fading in/out effect, camera shot change) in videos which are added during video editing. Although in this task shot boundaries have very well defined vocabulary making them significantly easier than generic event boundary detection.

Temporal Action Detection involves the task of detecting the start and end of action instances in an untrimmed, long video. There have been many standard datasets including THUMOS [7], ActivityNet [3] to address this problem. However all of these have predefined action classes and a fixed norm to define the beginning and end of actions. Some of the works in this direction include [5, 6]. Temporal Action Segmentation refers to the task of labelling the instances of actions in every frame of the video. Some well known
Temporal Action Parsing [14] focuses on identifying tempo-
flow stream to incorporate motion cues. We use I3D in two
and further, to boost performance it also exploits an optical
RGB ConvNet to learn about temporal patterns from
and has been trained on
Kinetics 400
I3D [4] model, which seemed to be computationally efficient
detecting such changes. To this end, we decided to exploit
diverse scenarios for boundary detection.

To envision what will be the best approach to tackle such
level of details in both space and time. Thus it is difficult
to classify whether the frame at time-stamp \( t \) is a boundary
or background.

**Baseline:** We considered a ResNet50 backbone trained
on ImageNet which was fine-tuned with Pairwise Boundary classifier (PC) [15] as baseline\(^1\). The input to PC is a
concatenation of two vectors which are an average of feature representation of \( m \) frames before and after time-stamp \( t \).

**Reproducibility:** We trained our model on 2 NVIDIA
GeForce RTX 2080Ti GPUs for 16 epochs and batch size of
16 using the Adam [8] optimiser. The learning rate was
chosen to be 0.0001 which decayed by 0.1 after every 10
epochs.

### 3. Method

The objective here is to localise moments into short tem-
poral segments from a long video sequence, where the bound-
aries for such short segments are often triggered by changes
in background, activity, persons, etc., i.e. it has different
level of details in both space and time. Thus it is difficult
to envision what will be the best approach to tackle such
diverse scenarios for boundary detection.

We hypothesise that motion could play a crucial role in
detecting such changes. To this end, we decided to exploit
I3D [4] model, which seemed to be computationally efficient
and has been trained on Kinetics 400 and made publicly
available. I3D is a two stream network which relies on 3D
ConvNet to learn about temporal patterns from RGB stream
and further, to boost performance it also exploits an optical
flow stream to incorporate motion cues. We use I3D in two
settings:

- **Fine-tuned I3D:** In this, we considered (1) only RGB
(2) both RGB + Flow streams. We used the pre-trained
I3D and fine-tuned it for binary classification.

- **Fixed feature extractor:** Under this regime, we
use I3D as a fixed feature extractor, i.e. we
consider the output from the penultimate layer before last the Conv3d layer and further aug-
ment the network with two non-linear layers

| Model       | F1 Score@5% | Precision@5% | Recall@5% |
|-------------|-------------|---------------|-----------|
| Baseline \(^2\) [15] | 52.11       | 60.44         | 45.81     |
| RGB        | 51.39       | 48.20         | 55.04     |
| RGB+Flow   | 51.26       | 47.96         | 55.06     |
| RGB\(_{fixed}\) | 50.72       | 42.44         | 63.03     |

### 4. Results and Discussion

The results obtained using different strategies (as ex-
plained in Section 3) for training the I3D [4] model are
shown in Table 1 and Table 2 for the validation and test dataset respectively. To our surprise, the I3D model trained using
only RGB images performed the best on the test dataset,
achieving an F1@5% score of 66.05, even outperforming
the I3D model trained using both RGB and optical
flow, which achieved an F1@5% score of 65.95 on the
validation set. The I3D model, when used as a fixed feature
extractor, obtained an F1@5% score of 63.23 on the test
dataset. On the validation set, both the I3D model trained
on RGB only, and the one trained on RGB with optical flow
gave results comparable to the baseline score of 52.11 [15].
In all our experiments we used the annotations correspond-
ing to the annotator with highest F1-consistency score as
groundtruth annotation for every video based on the weights
given results comparable to the baseline score of 52.11 [15].

In order to interpret our results, we carried out a class
based analysis of boundaries detected by our model. Figs. 2a
and 2b highlight 10 classes in KineticsGEBD with the high-
est and lowest mean success for correctly detected bound-
aries for such short segments are often triggered by changes
in background, activity, persons, etc., i.e. it has different
level of details in both space and time. Thus it is difficult
to classify whether the frame at time-stamp \( t \) is a boundary
or background.

1Input format as followed in PyTorch

2Our baseline results were lower compared to [15], which was probably
because we only had availability to 17,159 training, 15,176 validation and
17,254 test videos.
Figure 1: Event Boundary detection for a video in gymnastics tumbling, folding clothes, using computer and shooting goal (soccer) classes (top to bottom) in KineticsGEBD (val set)

Figure 2: Top 10 classes in KineticsGEBD (Val set) with highest mean (Fig2a) and lowest mean (Fig2b) success for correctly detected boundary.
aries by our model respectively. We believe that classes like gymnastics, tumbling and folding, clothes have well understood the definition of boundaries and hence our model detects them consistently, whereas classes like using computer and shooting goal (soccer) have no precise and closed vocabulary for boundaries, making it difficult for our model to detect them. This is clearly illustrated in Fig. 1.

An important point to observe is that we are using the Farneback algorithm to calculate optical flow as it is computationally efficient. However, it is less accurate, which could be a possible explanation for the inferior performance. Furthermore, our model does not explicitly learn changes in brightness or changes in camera angle or shots, which also justifies lack of performance in such cases. Lastly, Rel.Dis measures the discrepancy between the detected timestamp and the ground truth timestamp (if event boundary is a range then it is represented using the middle timestamp). However in research problems like hard cut shot boundary detection and gradual transition shot boundary detection, predictions within a window of time around the groundtruth timestamp are considered a correct prediction. We suggest incorporating such adjustments to the evaluation protocol would be more insightful and interpretable. An even more intricate version of this task would be to detect generic boundaries along with identifying semantic implications associated with them.

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