R-C3D: Region Convolutional 3D Network for Temporal Activity Detection

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Abstract

We address the problem of activity detection in continuous, untrimmed video streams. This is a difficult task that requires extracting meaningful spatio-temporal features to capture activities, accurately localizing the start and end times of each activity, and also dealing with very large data volumes. We introduce a new model, Region Convolutional 3D Network (R-C3D), which encodes the video streams using a three-dimensional fully convolutional network, then generates candidate temporal regions containing activities, and finally classifies selected regions into specific activities. Computation is saved due to the sharing of convolutional features between the proposal and the classification pipelines. The entire model is trained end-to-end with jointly optimized localization and classification losses. R-C3D is faster than existing methods (569 frames per second on a single Titan X Maxwell GPU) and achieves state-of-the-art results on THUMOS’14 (10% absolute improvement). We further demonstrate that our model is a general activity detection framework that does not rely on assumptions about particular dataset properties by evaluating our approach on ActivityNet and Charades.

1. Introduction

Activity detection in continuous video is a challenging problem that requires not only recognizing, but also precisely localizing activities in time. Existing state-of-the-art approaches address this task as detection by classification, i.e. classifying temporal segments generated in the form of sliding windows [13, 20, 24, 37] or via an external “proposal” generation mechanism [10, 35]. These approaches suffer from one or more of the following major drawbacks: they do not learn deep representations in an end-to-end fashion, but rather use hand-crafted features [33, 34], or deep features like VGG [28], ResNet [8], C3D [32] etc., learned separately on image/video classification tasks. Such off-the-shelf representations may not be optimal for localizing activities in diverse video domains, resulting in inferior performance. Furthermore, current methods’ dependence on external proposal generation or exhaustive sliding windows leads to poor computational efficiency. Finally, the sliding-window models cannot easily predict flexible activity boundaries.

In this paper, we propose an activity detection model that addresses all of the above issues. Our Region Convolutional 3D Network (R-C3D) is end-to-end trainable and learns task-dependent convolutional features by jointly optimizing proposal generation and activity classification. Inspired by the Faster R-CNN [21] object detection approach, we compute fully-convolutional 3D ConvNet features and propose temporal regions likely to contain activities, then pool features within these 3D regions to predict activity classes (Figure 1). The proposal generation stage filters out many background segments and results in superior computational efficiency compared to sliding window models. Furthermore, proposals are predicted with respect to predefined anchor segments and can be of arbitrary length, allowing detection of flexible activity boundaries.

Convolutional Neural Network (CNN) features learned end-to-end have been successfully used for activity recog-
nition [14, 27], particularly in 3D ConvNets (C3D [32]), which learn to capture spatio-temporal features. However, unlike the traditional usage of 3D ConvNets [32] where the input is short 16-frame video chunks, our method applies full convolution along the temporal dimension to encode as many frames as the GPU memory allows. Thus, rich spatio-temporal features are automatically learned from longer videos. These feature maps are shared between the activity proposal and classification subnets to save computation time and jointly optimize features for both tasks.

Alternative activity detection approaches [4, 17, 18, 29, 39] use a recurrent neural network (RNN) to encode a sequence of frame or video chunk features (e.g., VGG [28], C3D [32]) and predict the activity label at each time step. However, these RNN methods can only model temporal features at a fixed granularity (e.g., per-frame CNN features or 16-frame C3D features). In order to use the same classification network to classify variable length proposals into specific activities, we extend 2D region of interest (RoI) pooling to 3D which extracts a fixed-length feature representation for these proposals. Thus, our model can utilize video features at any temporal granularity. Furthermore, some RNN-based detectors rely on direct regression to predict the temporal boundaries for each activity. As shown by results in object detection [7, 31] and semantic segmentation [2], using a regression-only framework to predict object boundaries does not work well in practice compared to “proposal based detection”.

We perform extensive comparisons of our approach to state-of-the-art activity detection methods using three publicly available benchmark datasets - THUMOS’14 [12] sports activities, ActivityNet [9] human activities on Youtube, and Charades [26] in-the-wild daily activities. We achieve new state-of-the-art results on THUMOS’14 and Charades, and improved results on ActivityNet when using only C3D features. Our code will be made publicly available to support further research progress.

To summarize, the main contributions of our paper are:

- an end-to-end activity detection model with combined activity proposal and classification stages that can detect arbitrary length activities;
- fast detection speeds (5x faster than current methods) achieved by sharing fully-convolutional C3D features between the proposal generation and classification parts of the network;
- extensive evaluations on three diverse activity detection datasets that demonstrate the general applicability of our model.

2. Related Work

Activity Detection There is a long history of activity recognition, or classifying trimmed video clips into fixed set of categories [11, 15, 19, 27, 33, 42]. Activity detection also needs to predict the start and end times of the activities within untrimmed and long videos. Existing activity detection approaches are dominated by models that use sliding windows to generate segments and subsequently classify them with activity classifiers trained on multiple features [13, 20, 24, 37]. Most of these methods have stage-wise pipelines which are not trained end-to-end. Moreover, the use of exhaustive sliding windows is computationally inefficient and constrains the boundary of the detected activities to some extent.

Recently, some approaches have bypassed the need for exhaustive sliding window search to detect activities with arbitrary lengths. [4, 17, 18, 29, 39] achieve this by modeling the temporal evolution of activities using RNNs or Long Short Term Memory (LSTM) networks and predicting an activity label at each time step. The deep action proposal model in [4] uses LSTM to encode C3D features of every 16-frame video chunk, and directly regresses and classifies activity segments without the extra proposal generation stage. Compared to this work, we avoid recurrent layers, encoding a large video buffer with a fully-convolutional 3D ConvNet, and use 3D RoI pooling to allow feature extraction at arbitrary proposal granularity, achieving significantly higher accuracy and speed. The method in [41] tries to capture motion features at multiple resolutions by proposing a Pyramid of Score Distribution Features for activity detection, however their model is not end-to-end trainable and relies on handcrafted features.

Aside from supervised activity detection, a recent work [36] has addressed weakly supervised activity localization from training data labeled only with video level class labels by learning attention weights on shot based or uniformly sampled proposals. The framework proposed in [22] explores the uses of a language model and an activity length model in a detection pipeline. Spatio-temporal activity localization [38, 40] have also been explored to some extent. We only focus on supervised temporal activity localization in this work.

Object Detection Activity detection in untrimmed videos is intrinsically related to object detection in images. The inspiration for our work, Faster R-CNN [21], extends R-CNN [7] and Fast R-CNN [6] object detection approaches, incorporating RoI pooling and a region proposal network. Compared to recent object detection models e.g., SSD [16] and R-FCN[3], Faster R-CNN is a general and robust object detection framework that has been deployed on different datasets with little data augmentation effort. Like Faster R-CNN, our R-C3D model is also designed with the goal of easy deployment on varied activity detection datasets. It avoids making certain assumptions based on unique characteristics of a dataset, such as the UPC model for ActivityNet [18] which assumes that each video contains a single activity class. We show the effectiveness of our
model on three different types of activity detection datasets, the most extensive evaluation to our knowledge.

3. Approach

We propose a Region Convolutional 3D Network (R-C3D), a novel convolutional neural network for activity detection in continuous video streams. The network, illustrated in Figure 2, consists of three components: a shared 3D ConvNet feature extractor [32], a temporal proposal stage, and an activity classification and refinement stage. To enable efficient computation and end-to-end training, the proposal and classification sub-networks share the same C3D feature maps. The proposal subnet predicts variable length temporal segments that potentially contain activities, while the classification subnet classifies these proposals into specific activity categories or background, and further refines the proposal segment boundaries. A key innovation is to extend the 2D RoI pooling in Faster R-CNN to 3D RoI pooling which allows our model to extract features at various resolutions for variable length proposals. Next, we describe the shared video feature hierarchies in Sec. 3.1, the temporal proposal subnet in Sec. 3.2 and the classification subnet in Sec. 3.3. Sections 3.4 and 3.5 detail the optimization strategy during training and testing respectively.

3.1. 3D Convolutional Feature Hierarchies

We use a 3D ConvNet to extract rich spatio-temporal feature hierarchies from a given input video buffer. It has been shown that both spatial and temporal features are important for representing videos, and a 3D ConvNet encodes rich spatial and temporal features in a hierarchical manner. The input to our model is a sequence of RGB video frames with dimension $\mathbb{R}^{3 \times L \times H \times W}$. The architecture of the 3D ConvNet is taken from the C3D architecture proposed in [32]. However, unlike [32], the input to our model is of variable length. We adopt the convolutional layers (from conv1a to conv5b) of C3D, so a feature map $C_{conv5b} \in \mathbb{R}^{512 \times \frac{H}{16} \times \frac{W}{16}}$ (512 is the channel dimension of the layer conv5b) is produced as the output of this sub-network. We use $C_{conv5b}$ activations as the shared input to the proposal and classification sub-networks. The height ($H$) and width ($W$) of the frames are taken as 112 each following [32]. The number of frames $L$ can be arbitrary and is only limited by memory.

3.2. Temporal Proposal Subnet

To allow the model to predict variable length proposals, we incorporate anchor segments into the temporal proposal sub-network. The subnet predicts potential proposal segments with respect to anchor segments and a binary label indicating whether the predicted proposal contains an activity or not. The anchor segments are pre-defined multiscale windows centered at $(L/8)$ uniformly distributed temporal locations. Each temporal location specifies $K$ anchor segments, each at a different fixed scale. Thus, the total number of anchor segments is $(L/8) \times K$. The same set of $K$ anchor segments exists in different temporal locations, which ensures that the proposal prediction is temporally invariant. The anchors serve as reference activity segments for proposals at each temporal location, where the maximum number of scales $K$ is dataset dependent.

To obtain features at each temporal location for predicting proposals with respect to these anchor segments, we first add a 3D convolutional filter with kernel size $3 \times 3 \times 3$ on top of $C_{conv5b}$ to extend the temporal receptive field for the temporal proposal subnet. Then, we downsample the spatial dimensions (from $\frac{H}{16} \times \frac{W}{16}$ to $1 \times 1$) to produce a temporal only feature map $C_{tpm} \in \mathbb{R}^{512 \times 1 \times 1 \times 1}$ by applying a 3D max-pooling filter with kernel size $1 \times \frac{H}{16} \times \frac{W}{16}$. The 512-dimensional feature vector at each temporal location in $C_{tpm}$ is used to predict a relative offset $\{\delta c_i, \delta l_i\}, i \in \{1, \cdots, K\}$ to the center location and the length of each anchor segment $\{c_i, l_i\}, i \in \{1, \cdots, K\}$. It also predicts the binary scores for each proposal being an activity or background. The proposal offsets and scores are predicted by adding two $1 \times 1 \times 1$ convolutional layers on top of $C_{tpm}$.

**Training:** For training, we need to assign positive/negative labels to the anchor segments. Following the standard practice in object detection [21], we choose a positive label if the anchor segment 1) overlaps with some ground-truth activity with Intersection-over-Union (IoU) higher than 0.7, or 2) has the highest IoU overlap with some ground-truth activity. If the anchor has IoU overlap lower than 0.3 with all ground-truth activities, then it is given a negative label. All others are held out from training. For proposal regression,
the anchor segment is transformed with respect to a nearby ground truth activity segment using the coordinate transformations described in Sec. 3.4. We sample balanced batches with a positive/negative ratio of 1:1.

3.3. Activity Classification Subnet

The activity classification stage has three main functions: 1) selecting proposal segments from the previous stage, 2) three-dimensional region of interest (3D RoI) pooling to extract fixed-size features for selected proposals, and 3) activity classification and boundary regression for the selected proposals based on the pooled features.

The proposal subnet outputs a set of candidate proposal segments with associated scores. Some activity proposals highly overlap with each other and some have a low proposal score indicating low confidence. Following the standard practice in object detection [5, 21] and activity detection [24, 39], we employ a greedy Non-Maximum Suppression (NMS) strategy to eliminate highly overlapping and low confidence proposals. The NMS threshold is set as 0.7.

The selected proposals can be of arbitrary length. However, we need to extract fixed-size features for each of them in order to use fully connected layers for further activity classification and regression. We design a 3D RoI pooling layer to extract the fixed-size volume features for each variable-length proposal from the shared convolutional features $C_{conv5b} \in \mathbb{R}^{512 \times (L/8) \times 7 \times 7}$ (shared with the temporal proposal subnet). Specifically, in 3D RoI pooling, an input feature volume of size, say, $l \times h \times w$ is divided into $l_s \times h_s \times w_s$ sub-volumes each with approximate size $\frac{l}{l_s} \times \frac{h}{h_s} \times \frac{w}{w_s}$, and then max pooling is performed inside each sub-volume. In our case, suppose a proposal has the feature volume of $l_p \times 7 \times 7$ in $C_{conv5b}$, then this feature volume will be divided into $1 \times 4 \times 4$ grids and max pooled inside each grid. Thus, proposals of arbitrary lengths give rise to output volume features of the same size $512 \times 1 \times 4 \times 4$.

The output of the 3D RoI pooling for selected proposals is fed to a series of two fully connected layers. Finally, the proposals are classified to activity categories by a classification layer and the refined start-end times for these proposals are given by a regression layer. The classification and regression layers are also two separate fully connected layers and for both of them the input comes from the aforementioned fully connected layers (after the 3D RoI pooling layer).

Training: We need to assign an activity label to each proposal predicted by the proposal subnet for training the classifier subnet. An activity label is assigned if the proposal has the highest IoU overlap with a ground-truth activity, and at the same time, the IoU overlap is greater than 0.5. A background label (no activity) is assigned to proposals with IoU overlap lower than 0.5 with all ground-truth activities. Training batches are chosen with positive/negative ratio of 1:3.

3.4. Optimization

We train the network by optimizing both the classification and regression tasks jointly for the two subnets. The softmax loss function is used for classification, and smooth L1 loss function [6] is used for regression. Specifically, the objective function is given by:

$$\text{Loss} = \frac{1}{N_{cls}} \sum_{i} L_{cls}(a_{i}, a_{i}^{\text{*}}) + \lambda \frac{1}{N_{reg}} \sum_{i} a_{i}^{\text{*}} L_{reg}(t_{i}, t_{i}^{\text{*}}) \quad (1)$$

where $N_{cls}$ and $N_{reg}$ stand for batch size and the number of anchor/proposal segments, $\lambda$ is the loss trade-off parameter and is set to a value 1. $i$ is the anchor/proposal segments index in a batch, $a_{i}$ is the predicted probability of the proposal or activities, $a_{i}^{\text{*}}$ is the ground truth, $t_{i} = \{ \delta c_{i}, \delta l_{i} \}$ represents predicted relative offset to anchor segments or proposals. $t_{i}^{\text{*}} = \{ \delta c_{i}, \delta l_{i} \}$ represents the coordinate transformation of ground truth segments to anchor segments or proposals. The coordinate transformations are computed as follows:

$$\begin{align*}
\delta c_{i} &= (c_{i}^{*} - c_{i})/l_{i} \\
\delta l_{i} &= \log(l_{i}^{*}/l_{i})
\end{align*} \quad (2)$$

where $c_{i}$ and $l_{i}$ are the center location and the length of anchor segments or proposals while $c_{i}^{*}$ and $l_{i}^{*}$ denote the same for the ground truth activity segments.

In our R-C3D model, the above loss function is applied for both the temporal proposal subnet and the activity classification subnet. In the proposal subnet, the binary classification loss $L_{cls}$ predicts whether the proposal contains an activity or not, and the regression loss $L_{reg}$ optimizes the relative displacement between proposals and ground truth. In the proposal subnet the losses are activity class agnostic. For the activity classification subnet, the multiclass classification loss $L_{cls}$ predicts the specific activity class for the proposal, and the number of classes are the number of activities plus one for the background. The regression loss $L_{reg}$ optimizes the relative displacement between activities and ground truths. All four losses for the two subnets are optimized jointly.

3.5. Prediction

Activity prediction in R-C3D consists of two steps. First, the proposal subnet generates candidate proposals and predicts the the start-end time offsets as well as proposal score for each. Then the proposals are refined via NMS with threshold value 0.7. After NMS, the selected proposals are fed to the classification network to be classified into specific activity classes, and the activity boundaries of the predicted proposals are further refined by the regression layer. The localization prediction in both proposal subnet and classification subnet is in the form of relative displacement of center point and length of segments. In order to get the start time
and end time of the predicted proposals or activities, inverse coordinate transformation to Equation 2 is performed.

Our model accepts variable length input videos. However, to take advantage of the vectorized implementation in fast deep learning libraries, we pad the last few frames of short videos with blank frames, and break long videos into buffers (limited by memory only). The predicted activities are post-processed by NMS at a lower threshold (0.1 lower than the mAP evaluation threshold) to get the final activity predictions.

4. Experiments

We evaluate R-C3D on three large-scale activity detection datasets - THUMOS’14 [12], Charades [26] and ActivityNet [9]. Sections 4.1, 4.2, 4.3 provide the experimental details and evaluation results on these three datasets. Results are shown in terms of mean Average Precision - mAP@α where α denotes different Intersection over Union (IoU) thresholds, as is the common practice in the literature. Section 4.4 provides the detection speed comparison with state-of-the-art methods.

4.1. Experiments on THUMOS’14

The THUMOS’14 activity detection dataset contains over 24 hours of video from 20 different sport activities. The training set contains 2765 trimmed videos while the validation set and the test set contain 200 and 213 untrimmed videos respectively. This dataset is particularly challenging as it consists of very long videos (up to a few hundreds of seconds) with multiple activity instances of very small duration (up to few tens of seconds). Most videos contain multiple activity instances of the same activity class. In addition, some videos contain activity segments from different classes.

**Experimental Setup:** We divide 200 untrimmed videos from the validation set into 180 training and 20 held out videos to get the best hyperparameter setting. All 200 videos are used as the training set and the final results are reported on 213 videos in the test set. Since the GPU memory is limited, we first create a buffer of 768 frames at 25 frames per second (fps) which means approximately 30 seconds of video. Our choice is motivated by the fact that 99.5% of all activity segments in the validation set (used here as the training set) are less than 30 seconds long. These buffers of frames act as inputs to R-C3D. We can create the buffer by sliding from the beginning of the video to the end, denoted as the ‘one-way buffer’. An additional pass from the end of the video to the beginning can be used to increase the amount of training data as a data augmentation strategy, denoted as the ‘two-way buffer’. We initialize the 3D ConvNet part of our model with C3D weights trained on Sports-1M and finetuned on UCF101 released by the author in [32]. We allow all the layers of R-C3D to be trained on THUMOS’14 with a fixed learning rate of 0.0001.

The number of anchor segments K chosen for this dataset is 10 with specific scale values of [2, 4, 5, 6, 8, 9, 10, 12, 14, 16]. The values are chosen according to the distribution of the activity durations in the training set. At 25 fps and temporal pooling factor of 8 (C_{tpn} downsamples the input by 8 temporally), the anchor segments correspond to segments of duration between 0.64 and 5.12 seconds\(^1\). Note that, the predicted proposals or activities are relative to the anchor segments but not limited to the anchor segment boundaries, enabling our model to detect variable-length activities.

**Results:** As a sanity check, we first evaluate the perform-
mance of the temporal proposal subnet (ref Section 3.2). A predicted proposal is marked as correct if it has IoU with a ground truth activity of more than 0.7, otherwise it is considered incorrect. With this binary setting, precision and recall values for the temporal proposal subnet are relatively high - 85% and 83% respectively.

In Table 1, we present a comparative evaluation of the activity detection performance of our end-to-end model with existing state-of-the-art approaches in terms of mAP at IoU thresholds 0.1-0.5 (denoted as α). For both the one-way buffer setting and the two-way buffer setting we achieve new state-of-the-art for all five α values. In the one-way setting, mAP@0.5 is 27.0% which is an 8% absolute improvement from the state-of-the-art. The two-way buffer setting further increases the mAP values at all the IoU thresholds with mAP@0.5 reaching as far as 28.9%. Our model comprehensively outperforms the current state-of-the-art by a large margin (28.9% compared to 19.0% as reported in [24]). The CDC framework [23], developed concurrently with our model, predicts frame-by-frame dense labels and has recently reported 23.3% mAP@0.5 for the THUMOS’14 dataset. Our model still performs significantly better than this very recent approach.

The Average Precision (AP) for each class in THUMOS’14 at IoU threshold 0.5 for the two-way buffer setting is shown in Table 2. For per-class AP, our model outperforms the other three baselines in most classes and it shows significant improvement (by more than 20% absolute AP) for activities e.g., Basketball Dunk, Cliff Diving, and Javelin Throw. For some of the activities, our method is only second to the best performing ones by a very small margin (e.g., Billiards or Cricket Shot). Figure 3(a) shows some representative qualitative results from two videos in this dataset.

### 4.2. Experiments on ActivityNet

The ActivityNet [9] dataset consists only of untrimmed videos and is released in three versions. We use the latest release (ActivityNet 1.3) which has 10024, 4926 and 5044 videos containing 200 different types of activities in the train, validation and test sets respectively. Except for only a few, most videos contain activity instances of a single class covering a great deal of the video. Compared to THUMOS’14, this is a large-scale dataset both in terms of the number of activities involved and the amount of video. Researchers have taken part in the ActivityNet challenge [1] held on this dataset. The performance of the participating teams is evaluated on test videos for which the ground truth annotations are not public. In addition to evaluating on the validation set, we show our performance on the test set after evaluating it on the challenge server.

**Experimental Setup:** Similar to THUMOS’14, we keep the length of the input buffer to be 768 but, as the videos are long, we sample frames at 3 fps to fit it in the GPU memory. This makes the duration of the buffer approximately 256 seconds which covers over 99.99% activities in the training split. The considerably long activity durations in ActivityNet prompt us to set the number of anchor segments K to be as high as 20. Specifically, we chose the following scales - [1, 2, 3, 4, 5, 6, 7, 8, 10, 12, 14, 16, 20, 24, 28, 32, 40, 48, 56, 64]. Thus the shortest anchor segment is of duration 2.7 seconds and the longest one is of duration 170 seconds, which covers 95.6% of all activities in the training set.

Considering the vast domain difference of the activities between Sports-1M and ActivityNet, we finetune the Sports-1M pretrained 3D ConvNet model [32] with the training videos of ActivityNet at 3 fps on the activity classification task. We initialize the 3D ConvNet part of our model with these finetuned weights. ActivityNet being a large scale dataset, the training takes more epochs. As a speed-efficiency trade-off, we freeze the first two convolutional layers in our model during training. The learning rate is kept fixed at 0.0001 for the first 10 epochs and then it is decreased to 0.00001 for 5 further epochs. Based on the improved results on the THUMOS’14 dataset, we choose the two-way buffer setting with horizontal flipping of frames for data augmentation.

**Results:** In Table 3 we show the performance of our model and compare with existing published approaches. The results are shown for two different experimental settings. In the first setting, only the training set is used for training and the performance is shown for either the validation or test data or both. In the second setting, training is performed on both training and validation sets while the performance is shown on the test set. The table shows that the proposed method does achieve a performance better than methods not using handcrafted features e.g., UPC [18]. UPC is the most fair comparison as it also uses only C3D features. However, it relies on a strong assumption that each video in ActivityNet just contains one activity class. Our approach obtains an improvement of 4.3% on the validation set and 4.5% on the test set over UPC [18] in terms of mAP@0.5 without any such strong assumptions. When both training and validation sets are used for training, the performance improves further by 1.6%.

|                | train data | validation | test     |
|----------------|------------|------------|----------|
| G. Singh et. al. [30] | train      | 34.5       | -        |
| G. Singh et. al. [30] | train+val  | -          | 36.4     |
| B. Singh et. al. [29] | train+val  | -          | 28.8     |
| UPC [18]        | train      | 22.5       | 22.3     |
| R-C3D (ours)    | train      | 26.8       | 26.8     |
| R-C3D (ours)    | train+val  | -          | 28.4     |
### Experimental Setup

The dataset consists of 7985 train and 1863 test videos. The videos are recorded by Amazon Mechanical Turk users based on provided scripts. Apart from low illumination, diversity and casual nature of the videos containing day-to-day activities, an additional challenge of this dataset is the presence of a large number of temporally overlapping activities. This is achieved by the ability of the proposal subnet to produce possibly overlapping activity proposals and is further facilitated by region offset regression.

### Activity Detection Speed

In this section, we compare our model with two others in terms of detection speed, as shown in Table 5 results. S-CNN [24] uses a time-consuming sliding window strategy without requiring any manually-designed postprocessing.
Figure 3. Qualitative visualization of the predicted activities by R-C3D (best viewed in color). Figure (a) and (b) show results for two videos each in THUMOS’14 and ActivityNet. (c) shows the result for one video from Charades. Groundtruth activity segments are marked in black. Predicted activity segments are marked in green for correct predictions and in red for wrong ones. Predicted activities with IoU more than 0.5 are considered as correct. Corresponding start-end times and confidence score are shown inside brackets.

Table 5. Activity detection speed at test time.

| Method                  | FPS  |
|-------------------------|------|
| S-CNN [24]              | 60   |
| DAP [4]                 | 134.1|
| R-C3D (ours on Titan X Maxwell) | 569  |
| R-C3D (ours on Titan X Pascal) | 1030 |

strategy and predicts at 60 fps. DAP [4] incorporates a proposal prediction step on top of LSTM and predicts at 134.1 fps. Our R-C3D model constructs the proposal and classification pipeline in an end-to-end fashion, which is significantly faster at 569 fps on a Titan-X GPU Maxwell. On the upgraded Titan-X GPU Pascal, our test speed reaches an even higher 1030 fps. The speedup of R-C3D over DAP may come from the fact that the LSTM recurrent architecture in DAP takes time to unroll, while R-C3D directly accepts a wide range of frames as input and operates on the shared features in both the proposal and classification subnets.
5. Conclusion

We introduce R-C3D, the first end-to-end temporal proposal classification network for activity detection in untrimmed videos. We evaluate our approach on three large-scale data sets with very diverse characteristics, and demonstrate that it can detect activities faster and more accurately than existing models based on 3D Convnets. Additional features can be incorporated into our model to further boost the activity detection result. One future direction may be to incorporate R-C3D with hand-engineered motion features for improved activity prediction without sacrificing the speed.

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