Abstract

Most work on temporal action detection is formulated as an offline problem, in which the start and end times of actions are determined after the entire video is fully observed. However, important real-time applications including surveillance and driver assistance systems require identifying actions as soon as each video frame arrives, based only on current and historical observations. In this paper, we propose a novel framework, Temporal Recurrent Network (TRN), to model greater temporal context of a video frame by simultaneously performing online action detection and anticipation of the immediate future. At each moment in time, our approach makes use of both accumulated historical evidence and predicted future information to better recognize the action that is currently occurring, and integrates both of these into a unified end-to-end architecture. We evaluate our approach on two popular online action detection datasets, HDD and TVSeries, as well as another widely used dataset, THUMOS’14. The results show that TRN significantly outperforms the state-of-the-art.

1. Introduction

As we go about our lives, we continuously monitor the social environment around us, making inferences about the actions of others that might affect us. Is that child running into the road or just walking towards the sidewalk? Is that passerby outstretching his hand for a punch or a handshake? Is that oncoming car turning left or doing a U-turn? These and many other actions can occur at any time, without warning. We must make and update our inferences in real-time in order to be able to react to the world around us, updating and refining our hypotheses moment-to-moment as we collect additional evidence over time.

In contrast, action recognition in computer vision is often studied as an offline classification problem, in which the goal is to identify a single action occurring in a short video clip given all of its frames [3, 5, 9, 18, 36, 51]. This offline formulation simplifies the problem considerably: a left turn can be trivially distinguished from a U-turn if the end of the action can be observed. But emerging real-world applications of computer vision like self-driving cars, interactive home virtual assistants, and collaborative robots require detecting actions online, in real-time. Some recent work [11, 12, 17, 35] has studied this problem of online action detection, but the restriction on using only current and past information makes the problem much harder.

Here we introduce the novel hypothesis that although future information is not available in an online setting, explicitly predicting the future can help to better classify actions in the present. We propose a new model to estimate and use this future information, and we present experimental results showing that predicted future information indeed improves the performance of online action recognition. This may seem like a surprising result because at test time, a model that predicts the future to infer an action in the present
observes exactly the same evidence as a model that simply infers the action directly. However, results in cognitive science and neuroscience suggest that the human brain uses prediction of the future as an important mechanism for learning to make estimates of the present [2, 8, 15, 16]. Our findings seem to confirm that the same applies to automatic online action recognition, suggesting that jointly modeling current action detection and future action anticipation during training forces the network to learn a more discriminative representation.

In more detail, in this paper we propose a general framework called Temporal Recurrent Network (TRN), in which future information is predicted as an anticipation task and used together with historical evidence to recognize action in the current frame (as shown in Fig. 1). To demonstrate the effectiveness of our method, we validate TRN on two recent online action detection datasets (i.e., Honda Research Institute Driving Dataset (HDD) [32] and TVSeries [11]) and a widely used action recognition dataset, THUMOS’14 [24].

Our model is general enough to use both visual and non-visual sensor data, as we demonstrate for the HDD driving dataset. Experimental results show that our approach significantly outperforms baseline methods, especially when only a fraction of an action is observed. We also evaluate action anticipation (predicting the next action), showing that our method performs better than state-of-the-art methods even though anticipation is not the focus of this work.

2. Related Work

Action and Activity Recognition. There is extensive work in the literature on action and activity recognition for videos of various types and applications, from consumer-style [50] and surveillance videos [39], to first-person videos from wearable cameras [26, 29, 30]. Early work used hand-crafted visual features, such as HOG [27], HOF [27], and MBH [43], and motion features, such as improved dense trajectories [42], while most recent methods use deep convolutional networks. Simonyan and Zisserman [37] propose a two-stream convolutional network that uses both RGB frames and optical flow as inputs [44], while others including Tran et al. [41] and Carreira et al. [4] avoid pre-computing optical flow by learning temporal information in an end-to-end manner using 3D convolution. Recurrent neural networks (RNNs), such as long short-term memory (LSTM) [22] and gated recurrent unit (GRU) [7] networks have also been widely adopted to capture temporal dependencies [14] and motion information [48]. However, most of these methods focus on trimmed videos and cannot be directly applied to long video sequences that contain multiple actions and a wide diversity of backgrounds.

Offline Action Detection. Offline methods observe an entire video and estimate the start and end moment of each action. Many of these methods are inspired by region-based deep networks from object detection [33] and segmentation [19]. Shou et al. [36] propose S-CNNs to localize actions in untrimmed videos by generating temporal action proposals, and then classifying them and regressing their temporal boundaries. TCN [9] performs proposal ranking but explicitly incorporates local context of each proposal. R-C3D [47] improves efficiency by sharing convolutional features across proposal generation and classification. SST [3] avoids dividing input videos into overlapping clips, introducing more efficient proposal generation in a single stream, while TURN TAP [18] builds on this architecture. TAL-Net [5] improves receptive field alignment using a multi-scale architecture that better exploits temporal context for both proposal generation and action classification. CDC [34] makes frame-level dense predictions by simultaneously performing spatial downsampling and temporal upsampling operations. But the above work assumes all video frames can be observed, which is not possible in the online task that we consider here.

Early Action Detection. Our work is also related to early action detection, which tries to recognize actions after observing only a fraction of the event. Hoai et al. [21] propose a max-margin framework using structured SVMs for this problem. Ma et al. [31] design an improved technique based on LSTMs and modify the training loss based on an assumption that the score margin between the correct and incorrect classes should be non-decreasing as more observations are made.

Online Action Detection. Given a live video stream, online action detection tries to detect the actions performed in each frame as soon as it arrives, without considering future context. De Geest et al. [11] first presented a concrete definition and realistic dataset (TVSeries) for this problem. They later [12] proposed a two-stream feedback network, with one stream focusing on input feature interpretation and the other modeling temporal dependencies between actions. Gao et al. [17] propose a Reinforced Encoder-Decoder (RED) network and a reinforcement loss to encourage recognizing actions as early as possible. RED was designed for action anticipation – predicting actions a few seconds into the future – but can be applied to online detection by setting the anticipation time to 0. Shou et al. [35] identify the start time of each action using Generative Adversarial Networks and adaptive sampling to distinguish ambiguous backgrounds, and explicit temporal modeling around transitions between actions for temporal consistency.

In contrast to all of this existing online action detection work which only focuses on current and past observations, we introduce a model that learns to simultaneously perform online action detection and anticipation of the immediate future, and uses this estimated “future information” to improve the action detection performance of the present.
3. Online Action Detection

Given a live video stream that contains one or more actions, our goal is to recognize actions of interest occurring in each video frame. Unlike most prior work that assumes the entire video is available at once, this online action detection problem requires us to process each frame as soon as it arrives, without accessing any future information. More formally, our goal is to estimate, for each frame $t$ of an image sequence, a probability distribution $p_t = \{p_t^0, p_t^1, p_t^2, \cdots, p_t^K\}$ over $K$ possible actions, given only the past and current frames, $\{I_1, I_2, \cdots, I_t\}$ (where $p_t^0$ denotes the “background” probability that no action is occurring).

3.1. Temporal Recurrent Network (TRN)

To solve this problem, we introduce a novel framework called Temporal Recurrent Network (TRN). The main idea is to train a network that predicts actions several frames into the future, and then uses that prediction to classify an action occurring. This framework anticipates the future via a temporal decoder, and incorporates that predicted information to improve online action detection.

**Algorithm 1 Workflow of TRN Cell**

**Input:** image feature $x_t$ and previous hidden state $h_{t-1}$

**Output:** probabilities $p_t$ and current hidden state $h_t$

1. Initialize $\overrightarrow{h}_{t-1}$ with $h_{t-1}$ embedded by an FC layer
2. Initialize $\overleftarrow{h}_{t-1}$ with all zeros
3. for $i = 0 : I_{t}$ do
   4. Update $\overrightarrow{h}_t$ using $\overleftarrow{h}_{t-1}$ and $\overrightarrow{h}_{t-1}$
   5. Compute $f_t$ and $g_t$ using $\overrightarrow{h}_t$
   6. Update $\overleftarrow{h}_t$ using $\overrightarrow{h}_t$
4. end for
7. Compute future context features $\overrightarrow{x}_t$ as Eq. (1)
8. Update $h_t$ with STA($h_{t-1}$, $[x_t, \overrightarrow{x}_t]$)
9. Compute $p_t$ as Eq. (2)
We now describe each component of a TRN cell in detail, as summarized in Alg. 1.

The temporal decoder works sequentially to output the estimates of future actions and their corresponding hidden states \( \{ \tilde{h}_t, \tilde{h}_t^1, \ldots, \tilde{h}_t^\ell \} \) for the next \( \ell_d \) time steps, where \( h_i^t \) for \( i \in [0, \ell_d] \) indicates the hidden state at the \( i \)-th time step after \( t \). The input to the decoder at the first time step is all zeros. At other time steps \( t \), we feed in the predicted action scores \( \tilde{\tau}_t^{-1} \), embedded by a linear transformer.

The future gate takes hidden states from the decoder and models the feature representation of future context. For simplicity, our default future gate is an average pooling layer, but other fusion operations such as non-local (NL) blocks \(^{45}\) could be used. More formally, the future context feature \( \tilde{x}_t \) is obtained by averaging and embedding the hidden state vector, \( \tilde{h}_t \), gathered from all decoder steps,

\[
\tilde{x}_t = \text{ReLU}(W_f^T \text{AvgPool}(\tilde{h}_t) + b_f) \tag{1}
\]

The spatiotemporal accumulator (STA) takes the previous hidden state \( h_{t-1} \) as well as the concatenation of the image feature \( x_t \) extracted from \( I_t \) and the predicted future feature \( \tilde{x}_t \) from the future gate, and updates its hidden states \( h_t \). It then calculates a distribution over candidate actions,

\[
p_t = \text{softmax}(W_c h_t + b_c), \tag{2}
\]

where \( W_c \) and \( b_c \) are the parameters of the FC layer used for action classification.

As we can see, in addition to the estimated action of the current frame \( t \), TRN outputs predicted actions for the next \( \ell_d \) time steps. In order to ensure a good future representation and jointly optimize online action detection and prediction, we combine the accumulator and decoder losses during training, i.e. the loss of one input sequence is

\[
\sum_\ell (\text{loss}(p_t^i, \ell_t) + \alpha \sum_i^\ell \text{loss}(\tilde{p}_t^i, \ell_{t+i})), \tag{3}
\]

where \( p_t^i \) indicates the action probabilities predicted by the decoder for step \( i \) after time \( t \), \( l_t \) represents the ground truth, \( \text{loss} \) denotes cross-entropy loss, and \( \alpha \) is a scale factor. We optimize the network using offline training in which labels of both current and future frames are used. At test time, our model uses the predicted future information without accessing actual future frames, and thus is an online model.

4. Experiments

We evaluated our online action detector against multiple state-of-the-art and baseline methods on three publicly-available datasets: HDD \(^{32}\), TVSeries \(^{11}\), and THUMOS’14 \(^{24}\). We chose these datasets because they include long, untrimmed videos from diverse perspectives and applications: HDD consists of on-road driving from a first-person (egocentric) view recorded by a front-facing dashboard camera, TVSeries was recorded from television and contains a variety of everyday activities, and THUMOS’14 is a popular dataset of sports-related actions.

4.1. Datasets

HDD \(^{32}\) includes nearly 104 hours of 137 driving sessions in the San Francisco Bay Area. The dataset was collected from a vehicle with a front-facing camera, and includes frame-level annotations of 11 goal-oriented actions (e.g., intersection passing, left turn, right turn, etc.). The dataset also includes readings from a variety of non-visual sensors collected by the instrumented vehicle’s Controller Area Network (CAN bus). We followed prior work \(^{32}\) and used 100 sessions for training and 37 sessions for testing.

TVSeries \(^{11}\) contains 27 episodes of 6 popular TV series, totaling 16 hours of video. The dataset is temporally annotated at the frame level with 30 realistic, everyday actions (e.g., pick up, open door, drink, etc.). The dataset is challenging with diverse actions, multiple actors, unconstrained viewpoints, heavy occlusions, and a large proportion of non-action frames.

THUMOS’14 \(^{24}\) includes over 20 hours of video of sports annotated with 20 actions. The training set contains only trimmed videos that cannot be used to train temporal action detection models, so we followed prior work \(^{17}\) and train on the validation set (200 untrimmed videos) and evaluate on the test set (213 untrimmed videos).

4.2. Implementation Details

We implemented our proposed Temporal Recurrent Network (TRN) in PyTorch \(^{1}\), and performed all experiments on a system with Nvidia Quadro P6000 graphics cards. To learn the network weights, we used the Adam \(^{25}\) optimizer with default parameters, learning rate 0.0005, and weight decay 0.0005. For data augmentation, we randomly chopped off \( \Delta \in [1, \ell_c] \) frames from the beginning for each epoch, and discretized the video of length \( L \) into \( (L - \Delta) / \ell_c \) non-overlapping training samples, each with \( \ell_c \) consecutive frames. Our models were optimized in an end-to-end manner using a batch size of 32, each with \( \ell_c \) input sequence length. The constant \( \alpha \) in Eq. (3) was set to 1.0.

4.3. Settings

To permit fair comparisons with the state-of-the-art \(^{11, 17, 32}\), we follow their experimental settings, including input features and hyperparameters.

\(^{1}\)The code will be made publicly available upon publication.
HDD. We use the same setting as in [32]. Video frames and values from CAN bus sensors are first sampled at 3 frames per second (fps). The outputs of the Conv2d, 7h, 1x1 layer in InceptionResNet-V2 [40] pretrained on ImageNet [13] are extracted as the visual feature for each frame. To preserve spatial information, we apply an additional 1 × 1 convolution to reduce the extracted frame features from 8×8×1536 to 8×8×20, and flatten them into 1200-dimensional vectors. Raw sensor values are passed into a fully-connected layer with 20-dimensional outputs. These visual and sensor features are then concatenated as a multimodal representation for each video frame. We follow [32] and set the input sequence length ℓ_e to 90. The number of decoder steps ℓ_d is treated as a hyperparameter that we cross-validate in experiments. The hidden units of both the temporal decoder and the STA are set to 2000 dimensions.

TVSeries and THUMOS’14. We use the same setting as in [17]. We extract video frames at 24 fps and set the video chunk size to 6. Decisions are made at the chunk level, and thus performance is evaluated every 0.25 seconds. We use two different feature extractors, VGG-16 [38] and two-stream (TS) CNN [46]. VGG-16 features are extracted at the fc6 layer from the central frame of each chunk. For the two-stream features, the appearance features are extracted at the Flatten,673 layer of ResNet-200 [20] from the central frame of each chunk, and the motion features are extracted at the global_pool layer of BN-Inception [23] from precomputed optical flow fields between 6 consecutive frames. The appearance and motion features are then concatenated to construct the two-stream features. The input sequence length ℓ_e is set to 64 due to GPU memory limitations. Following the state-of-the-art [17], the number of decoder steps ℓ_d is set to 8, corresponding to 2 seconds. As with HDD, our experiments report results with different decoder steps. The hidden units of both the temporal decoder and the STA are set to 4096 dimensions.

4.4. Evaluation Protocols

We follow most existing work and use per-frame mean average precision (mAP) to evaluate the performance of online action detection. We also use per-frame calibrated average precision (cAP), which was proposed in [11] to better evaluate online action detection on TVSeries,

\[ cAP = \frac{\sum_k cPrec(k) * I(k)}{P}, \]

where calibrated precision \( cPrec = \frac{TP}{TP + FP/w} \), \( I(k) \) is 1 if frame \( k \) is a true positive, \( P \) denotes the total number of true positives, and \( w \) is the ratio between negative and positive frames. The advantage of cAP is that it corrects for class imbalance between positive and negative samples.

Another important goal of online action detection is to recognize actions as early as possible; i.e., an approach should be rewarded if it produces high scores for target actions at their early stages (the earlier the better). To investigate our performance at different time stages, we follow [11] and compute mAP or cAP for each decile (10 percent interval) of the video frames separately. For example, we compute mAP or cAP on the first 10% of the frames of the action, then the next 10%, and so on.

4.5. Baselines

We compared against multiple baselines to confirm the effectiveness of our approach.

CNN baseline models [37, 38] consider online action detection as a general image classification problem. These baselines identify the action in each individual video frame without modeling temporal information. For TVSeries and THUMOS’14, we reprint the results of CNN-based methods from De Geest et al. [11] and Shou et al. [34]. For HDD, we follow Ramanishka et al. [32] and use InceptionResNet-V2 [40] pretrained on ImageNet as the backbone and finetune the last fully-connected layer with softmax to estimate class probabilities.

LSTM and variants have been widely used in action detection [32, 49]. LSTM networks model the dependencies between consecutive frames and jointly capture spatial and temporal information of the video sequence. For each frame, the LSTM receives the image features and the previous hidden state as inputs, and outputs a probability distribution over candidate actions.

Encoder-Decoder (ED) architectures [6] also model temporal dependencies. The encoder is similar to a general LSTM and summarizes historical visual information into a feature vector. The decoder is also an LSTM that produces predicted representations for the future sequence based only on these encoded features. Since there are no published results of ED-based methods on HDD, we implemented a baseline with the same experimental settings as TRN, including input features, hyperparameters, loss function, etc.

Stronger Baselines. In addition to the above basic baselines, we tested three types of stronger baselines that were designed for online action detection on TVSeries and THUMOS’14. Convolutional-De-Convolutional (CDC) [34] places CDC filters on top of a 3D CNN and integrates two reverse operations, spatial downsampling and temporal upsampling, to precisely predict actions at a frame-level. Two-Stream Feedback Network (2S-FN) [12] is built on an LSTM with two recurrent units, where one stream focuses on the input interpretation and the other models temporal dependencies between actions. Reinforced Encoder-Decoder (RED) [17] with a dedicated reinforcement loss is an advanced version of ED, and currently performs the best among all the baselines for online action detection.
4.6. Results

### 4.6.1 Evaluation of Online Action Detection

Table 1 presents evaluation results on HDD dataset. TRN significantly outperforms the state-of-the-art, Ramanishka et al. [32], by 5.4%, 2.8%, and 8.1% in terms of mAP with sensor data, InceptionResnet-v2, and multimodal features as inputs, respectively. Interestingly, the performance gaps between TRN and [32] are much larger when the input contains sensor data. Driving behaviors are highly related to CAN bus signals, such as steering angle, yaw rate, velocity, etc., and this result suggests that TRN can better take advantage of these useful input cues. Table 2 presents comparisons between TRN and baselines on TVSeries. TRN significantly outperforms the state-of-the-art using VGG (mcAP of 3.0% over 2S-FN [12]) and two-stream input features (mcAP of 4.5% over RED [17]). We also evaluated TRN on THUMOS’14 in Table 3. The results show that TRN outperforms all the baseline models (mAP of 1.9% over RED [17] and 2.8% over CDC [34]).

**Qualitative Results** are shown in Fig. 3. In Fig. 3a, we visualize and compare the results of TRN, and compare with Ramanishka et al. [32] on HDD. As shown, u-turn is difficult to classify from a first-person perspective because the early stage is nearly indistinguishable from left turn. With the help of the learned better representation and predicted future information, TRN differentiates from subtle differences and “look ahead” to reduce this ambiguity. As shown in Table 1, TRN beats the baseline models on most of the actions using multimodal inputs, but much more significantly on these “difficult” classes, such as lane branch and u-turn. Qualitative results also clearly demonstrate that TRN produces not only the correct action label, but also better boundaries. Fig. 3b and 3c show promising results on TVSeries and THUMOS’14. Note that TVSeries is very challenging; for example, the drinking action in Fig. 3b by the person in the background in the upper left of the frame is barely visible.

### 4.6.2 Ablation Studies

**Importance of Temporal Context.** By directly comparing evaluation results of TRN with CNN and LSTM baselines, we demonstrate the importance of explicitly modeling temporal context for online action detection. LSTMs
capture long- and short-term temporal patterns in the video by receiving accumulated historical observations as inputs. Comparing TRN and LSTM measures the benefit of incorporating predicted action features as future context. CNN-based methods conduct online action detection by only considering the image features at each time step. Simonyan et al. [37] build a two-stream network and incorporate motion features between adjacent video frames by using optical flow as inputs. Table 3 shows that this motion information provides 1.5% improvements. TRN-TS also takes optical flow as inputs and we can clearly see a significant improvement (83.7% vs. 75.4%) on TVSeries.

Future Context: An “Oracle” Study. To demonstrate the importance of using predictions of the future context, we implemented an “oracle” baseline, RNN-offline. RNN-offline shares the same architecture as RNN but uses the features extracted from both the current and future frames as inputs. Note that RNN-offline uses future information and thus is not an online model; the goal of this experiment is to show: (1) the effectiveness of incorporating future information in action detection, given access to future information instead of predicting it; (2) and the performance gap between the estimated future information of TRN and the “real” future information of RNN-offline. To permit a fair comparison, the input to RNN-offline is the concatenation of the feature extracted from the current frame and the average-pooled features of the next $\ell_d$ frames (where $\ell_d$ is the same as the number of decoder steps of TRN).

The results of RNN-offline are 41.6%, 85.3%, 47.3% on HDD, TVSeries, and THUMOS’14 datasets, respectively. Comparing RNN-offline with the RNN baseline, we can see that the “ground-truth” future information significantly improves detection performance. We also observe that the performance of TRN and RNN-offline are comparable, even though TRN uses predicted rather than actual future information. This may be because TRN improves its representation during learning by jointly optimizing current and future action recognition, while RNN-offline does not. We also evaluated TRN against ED-based networks, by observing that ED can also improve its representation by jointly conducting action detection and anticipation. Thus, comparisons between TRN with ED and its advanced version [17] measure how much benefit comes purely from explicitly incorporating anticipated future information.

Figure 3: Qualitative results of our approach and baselines on HDD, TVSeries, and THUMOS’14 datasets. The vertical bars indicate the scores of the predicted class. (Best viewed in color.)
Table 4: Online action detection results when only portions of action sequences are considered, in terms of cAP (%). For example, 20%-30% means that the first 30% of frames of the action were seen and classified, but only frames in the 20%-30% time range were used to compute cAP.

| Portion of video | CNN [11] | LSTM [11] | VGG | TRN | SVM [11] | RED [17] | ED [17] | TRN |
|------------------|----------|-----------|-----|-----|----------|----------|--------|-----|
| 0%-10%           | 61.0     | 61.0      | 61.2| 61.1| 61.2     | 61.2     | 61.3   | 61.5|
| 10%-20%          | 61.0     | 61.0      | 61.2| 61.1| 61.2     | 61.2     | 61.3   | 61.4|
| 20%-30%          | 61.2     | 61.2      | 61.3| 61.3| 61.5     | 61.4     | 61.4   | 61.5|
| 30%-40%          | 61.2     | 61.2      | 61.3| 61.3| 61.5     | 61.4     | 61.4   | 61.5|
| 40%-50%          | 61.3     | 61.3      | 61.4| 61.4| 61.4     | 61.4     | 61.4   | 61.4|
| 50%-60%          | 61.4     | 61.4      | 61.4| 61.4| 61.4     | 61.4     | 61.4   | 61.4|
| 60%-70%          | 61.4     | 61.4      | 61.4| 61.4| 61.4     | 61.4     | 61.4   | 61.4|
| 70%-80%          | 61.4     | 61.4      | 61.4| 61.4| 61.4     | 61.4     | 61.4   | 61.4|
| 80%-90%          | 61.4     | 61.4      | 61.4| 61.4| 61.4     | 61.4     | 61.4   | 61.4|
| 90%-100%         | 61.4     | 61.4      | 61.4| 61.4| 61.4     | 61.4     | 61.4   | 61.4|

Table 5: Action anticipation results of TRN compared to results of TRN with decoder steps $\ell$. Table 6: Online action detection and action anticipation results of TRN with decoder steps $\ell_d = 4, 6, 8, 10$.

4.6.3 Evaluation of Different Stages of Action.

We evaluated TRN when only a fraction of each action is considered, and compared with published results [11] on TVSeries. Table 4 shows that TRN significantly outperforms existing methods at every time stage. Specifically, when we compare TRN-TS with the best baseline SVM-FV, the performance gaps between these two methods are roughly in ascending order as less and less of the actions are observed (the gaps are 6.5%, 6.4%, 6.3%, 7.3%, 7.9%, 8.6%, 9.7%, 10.5%, 11.2% and 11.8% from actions at 100% observed to those at 10% observed). This indicates the advantage of our approach at earlier stages of actions.

4.6.4 Evaluation of Action Anticipation.

We also evaluated TRN on predicting actions for up to 2 seconds into the future, and compare our approach with the state-of-the-art [17] in Table 5. The results show that TRN performs better than RED and ED baselines (mcAP of 75.7% vs. 75.1% vs. 74.5% on TVSeries and mAP of 38.9% vs. 37.5% vs. 36.6% on THUMOS’14). The average of anticipation results over the next 2 seconds on HDD dataset is 32.2% in terms of per-frame mAP.

5. Conclusion

In this paper, we propose Temporal Recurrent Network (TRN) to model greater temporal context and evaluate on the online action detection problem. Unlike previous methods that consider only historical temporal consistencies, TRN jointly models the historical and future temporal context under the constraint of the online setting. Experimental results on three popular datasets demonstrate that incorporating predicted future information improves learned representation of actions and significantly outperforms the state-of-the-art. Moreover, TRN shows more advantage at earlier stages of actions, and in predicting future actions. More generally, we believe that our approach of incorporating estimated future information could benefit many other online tasks, such as video object localization and tracking, and plan to pursue this in future work.
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