A Comprehensive Study on Temporal Modeling for Online Action Detection

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Abstract—Online action detection (OAD) is a practical yet challenging task, which has attracted increasing attention in recent years. A typical OAD system mainly consists of three modules: a frame-level feature extractor which is usually based on pre-trained deep Convolutional Neural Networks (CNNs), a temporal modeling module, and an action classifier. Among them, the temporal modeling module is crucial which aggregates discriminative information from historical and current features. Though many temporal modeling methods have been developed for OAD and other topics, their effects are lack of investigation on OAD fairly. This paper aims to provide a comprehensive study on temporal modeling for OAD including four meta types of temporal modeling methods, i.e. temporal pooling, temporal convolution, recurrent neural networks, and temporal attention, and uncover some good practices to produce a state-of-the-art OAD system. Many of them are explored in OAD for the first time, and extensively evaluated with various hyper parameters. Furthermore, based on our comprehensive study, we present several hybrid temporal modeling methods, which outperform the recent state-of-the-art methods with sizable margins on THUMOS-14 and TVSeries.

Index Terms—Online action detection, temporal pooling, temporal convolution, recurrent neural network, temporal attention.

I. INTRODUCTION

Online action detection (OAD) is an important problem in computer vision, which has wide range of applications like visual surveillance, human-computer interaction, and intelligent robot navigation, etc. Different from traditional action recognition and offline action detection that intend to recognize actions from full videos, the goal of online action detection is to detect an action as it happens and ideally even before the action is fully completed. It is a very challenging problem due to the extra restriction on the usage of only historical and current information except for the difficulties of traditional action recognition in untrimmed video streams.

In general, there exist two OAD tasks, i.e. spatial-temporal online action detection (ST OAD) and temporal online action detection. With online setting, the former aims to localize actors and recognize actions in space-time which is introduced in [90], while the latter is to localize and recognize actions temporally only which is systematically introduced in [15]. Our study mainly focuses on the temporal online action detection problem, and we ignore “temporal” for convenience in the rest.

As illustrated in Fig. 1 an online action detection (OAD) system mainly consists of three important parts: a frame-level feature extractor (e.g. deep Convolutional Neural Network, CNN), a temporal modeling module to aggregate frame-level features, and an action classifier. Recent works on online action detection mostly focus on the temporal modeling part, aiming to generate discriminative representations from the historical and current frame features. Inspired by the sequence modeling methods in other areas especially the Long Short-Term Memory recurrent network (LSTM) [41], various temporal modeling methods have been developed for online action detection recently. For example, Geest et al. [15] provide a LSTM-based baseline which shows superiority to the single-frame CNN model. Gao et al. [29] propose a LSTM-based Reinforced Encoder-Decoder network for both action anticipation and online action detection. Geest et al. [16] propose a two-stream feedback network, where one stream focuses on the input interpretation and the other models temporal dependencies between actions. Xu et al. [107] utilize LSTM cell to model temporal context aiming to improve online action detection by adding prediction information into observed information.

Although the above LSTM-based temporal modeling methods have significantly boosted the performance on existing OAD datasets (e.g. TVSeries [15], THUMOS-14 [44]), however, their superiority to other temporal models, e.g., naive temporal pooling, temporal convolution, and attention-based sequence models, is not discussed and remains unknown.
Moreover, the fusion of different temporal models is also rarely investigated. To address these problems, we provide a fair comprehensive study on temporal modeling for online action detection in the following aspects.

**Exploration of temporal modeling methods.** We explore four popular types of temporal modeling methods with various hyper parameters to fairly illustrate their effects for online action detection. They are namely temporal pooling, temporal convolution, recurrent neural networks, and temporal attention models. Specifically, for temporal pooling, we evaluate average pooling (AvgPool) and max pooling (MaxPool) with various sequence lengths. For temporal convolution, we evaluate traditional temporal convolution (TC), pyramid dilated temporal convolution (PDC) [58], and dilated causal convolution (DCC) [73]. For recurrent neural networks, we evaluate LSTM and Gated Recurrent Unit (GRU) with two output choices, i.e. the last hidden state and the average hidden state. For temporal attention, we evaluate naïve self-attention (NaiveSA) with a linear fully-connected (FC) layer and Softmax function, nonlinear self-attention (Nonlinear-SA) with a FC-tanh-FC-Softmax architecture, Non-local block or standard self-attention with a skip connection, and Transformer with the current frame as the query (Q) information. It is worth noting that i) we try to keep the original names of these related methods in other topics though we make adaptions for online action detection, and ii) many of these methods are introduced into online action detection for the first time to the best of our knowledge, such as TC, PDC, DCC, Non-local, etc. Overall, we extensively explore eleven individual temporal modeling methods with the off-the-shelf two-stream (TS) frame features.

The fusion of temporal modeling methods. Generally, these sequence-to-sequence methods, e.g. PDC and LSTM, can be further processed by aggregation methods to create a single representation like temporal pooling and temporal attention. Thus, we present several hybrid temporal modeling methods which combine different temporal modeling methods aiming to uncover the complementarity among them. Interestingly, we find that a simple fusion between dilated causal convolution and Transformer or LSTM improves the individual models significantly.

**Comparison with state of the arts.** We extensively compare our individual models and hybrid temporal models to existing baselines and recent state-of-the-art methods. Several hybrid temporal models outperform the best existing performance with a sizable margin on both TVSeries and THUMOS-14. Specifically, the fusion of dilated causal convolution and Transformer obtains 84.3% cAP on TVSeries, and the fusion of dilated causal convolution, LSTM, and Transformer achieves 48.6% mAP on THUMOS-14.

II. RELATED WORK

Our study is related to several other action related tasks, namely action recognition, action anticipation, temporal action detection, spatial-temporal action detection. In this section, we first briefly overview these related tasks separately and then present the recent works on online action detection.

Action recognition is an important branch of video related research areas and has been extensively studied in the past decades. The existing methods are mainly developed for extracting discriminative action features from temporally complete action videos. These methods can be roughly categorized into hand-crafted feature based approaches and deep learning based approaches. Early methods such as Improved Dense Trajectory (IDT) mainly adopt hand-crafted features, such as HOF [56], HOG [56] and MBH [97]. Recent studies demonstrate that action features can be learned by deep learning methods such as convolutional neural networks (CNN) and recurrent neural networks (RNN). For example, two-stream network [85], [99] learns appearance and motion features based on RGB frame and optical flow field separately. RNNs, such as long short-term memory (LSTM) [34] and gated recurrent unit (GRU) [11], have been used to model long-term temporal correlations and motion information in videos, and generate video representation for action classification. Some recent works also try to model temporal information within a 2D-CNN instead of using 2D-CNN as static feature extractor, e.g. both TSM [61] and TAM [23] propose an efficient approach to aggregate feature across frames inside the network.

Another type of action recognition approach is based on 3D CNNs, which are widely used for learning large-scale video datasets. C3D [21] is the first successful 3D CNN model for video classification. After that, many works extend C3D to different backbones, e.g. I3D [8] and ResNet3D [37]. In addition, some works aim to reduce the complexity of 3D CNN by decomposing the 3D convolution into 2D spatial convolution and 1D temporal convolution, e.g. P3D [76], S3D [104], R(2+1)D [22].

Action anticipation, also aka early action prediction, aiming to predict future unseen actions with historical and current information. Many works have been developed for this task in recent years. For instance, Hoai et al. [39] propose a max-margin framework with structured SVMs to address this problem. Ryoo et al. [79] formulate the action prediction problem into a probabilistic framework, which aims to maximize the posterior of activity given observed frames. Aliakbarian et al. [1] develop a multi-stage LSTM architecture that leverages context-aware and action-aware features, and introduce a novel loss function that encourages the model to predict the correct class as early as possible. Gao et al. [29] propose a Reinforced Encoder-Decoder (RED) network for action anticipation, which uses reinforcement learning to encourage the model to make the correct anticipations as early as possible. Ke et al. [51] propose an attended temporal feature, which uses multi-scale temporal convolutions to process the time-conditioned observation. The widely used datasets for action anticipation, e.g., UCF-101 [91], JHMDB-21 [43], BIT-Interaction [53], Sports-1M [48], include short trimmed videos, and the task mainly focuses on predicting the class of the current going action timely from only a small ratio of the observed part. Our task is different from action anticipation, we mainly focus on long and unsegmented video data, e.g. TVSeries, usually with large variety of irrelevant background.

Temporal action detection or localization is another hot topic which aims to temporally localize and recognize actions
by observing entire untrimmed videos. The main difference between this topic and OAD is the offline setting, i.e., post-processing is allowed for temporal action localization. In this offline setting, the whole action can be observed first. The problem has recently received increasing attention due to its potential application in video data analysis. Shou et al. [84] localize actions with three stages: action proposal generation, proposal classification and proposal regression. Xu et al. [106] transform the Faster R-CNN [78] architecture into temporal action localization. Chao et al. [10] improve receptive field alignment using a multi-tower network and dilated temporal convolutions, and exploit the temporal context of actions for both proposal generation and action classification. Lin et al. [62] generate proposals via learning starting and ending probability using temporal convolutional network, and achieve promising performance over previous methods. Zeng et al. [112] apply the Graph Convolutional Networks (GCNs) over the graph to model the relations among different proposals and learn powerful representations for the action classification and localization.

**Spatial-temporal action detection** aims to determine the precise spatial-temporal extents of actions in videos, which has attracted increasing attention recently. Early methods mainly resort to bag-of-words representation and search spatio-temporal path. In deep learning era, many works transform image-based object detection methods into this task, e.g., R-CNN [32], Faster R-CNN [78], SSD [69], etc. These adaptive methods mainly first detect actions in frame level and then link the frame-level bounding boxes into final tubes [33], [36], [75], [88]. Specially, the online setting is used in [88], [90].

**Online action detection** is defined as an online per-frame labelling task given streaming videos, which requires correctly classifying every frame. Geest et al. [13] first introduce the problem by introducing a realistic dataset (i.e., TVSeries) and some baseline results. Their later work [17] introduces a two-stream feedback network, where one stream processes the input and the other one models the temporal relations. Li et al. [60] design a deep LSTM network for 3D skeletons online action detection which also estimates the start and end frame of the current action. Xu et al. [107] propose the Temporal Recurrent Network (TRN) to model the temporal context by simultaneously performing online action detection and anticipation. Besides, Shou et al. [85] formulate the online detection of action start (ODAS) as a classification task of sliding windows and introduce a model based on Generative Adversarial Network to generate hard negative samples to improve the training of the samples.

### III. Temporal Modeling Approach

#### A. Problem Formulation

Given an observed video stream \( V = \{I_0, I_1, \ldots, I_t\} \) containing frames from time 0 to \( t \), the goal of online action detection is to recognize actions of interest occurring in frame \( t \) with these observed frames. This is very different from other tasks like action recognition and temporal action detection which assume the entire video sequence is available at once. Formally, online action detection can be defined as the problem of maximizing the posterior probability,

\[
y_t^* = \arg \max_{y_t} P(y_t | I_0, I_1, \ldots, I_t),
\]

where \( y_t \in \mathbb{R}^{K+1} \) is the possible action label vector for frame \( I_t \) with \( K \) action classes and one background class. Thus, conditioned on the observed sequence \( V \), the action label with the maximum probability \( P(y_t | I_0, I_1, \ldots, I_t) \) is
chosen to be the detection result of frame $I_t$. Generally, a pre-trained CNN model $\Phi$ is first used to extract frame-level features, e.g., the feature of $t$-th frame $f_t = \Phi(I_t; \theta) \in \mathbb{R}^d$, where $\theta$ is the fixed parameter of the model and $d$ is the dimension of feature embedding. Given the observed frame features $\{f_0, f_1, \ldots, f_t\}$, a temporal modeling module aims to aggregate discriminative information from them to better estimate the output action scores.

### B. Temporal Modeling

For online action detection, considering that faraway frames may be unrelated to the current action state, we usually input frames of a limited sequence length $L$ to the temporal modeling module, i.e., $\{f_{t-L+1}, f_{t-L+2}, \ldots, f_t\}$. For convenience, we denote the input features as $\{f_1, f_2, \ldots, f_L\}$, and assume the output of temporal modeling as $S_{out}$. Next we discuss four types of temporal modeling methods as illustrated in Fig.2.

**Temporal Pooling.** Temporal feature pooling has been extensively used for video classification [24], [47], [72], [85] which is a simple method to generate video-level representation from frame-level features. As shown in Fig.2A, we consider two temporal pooling approaches: (1) average pooling (AvgPool), i.e. $S_{out} = \frac{1}{T} \sum_{t=1}^{T} f_t$, and (2) max pooling (MaxPool) over the temporal dimension, i.e. $S_{out} = \max_{t} f_t$.

**Temporal Convolution.** Inspired by the convolutional approaches in the analysis of temporal sequential data [6], [13], [57], [58], [73] especially the WaveNet [73], we evaluate (1) traditional temporal convolution (TC), (2) pyramid dilated temporal convolution (PDC) originally used in [58], and (3) dilated causal convolution (DCC) developed in [73]. Formally, given input $F = \{f_1, f_2, \ldots, f_T\}$, our temporal convolution models output features of the same length as follows,

$$F_o = \{f_{o1}, f_{o2}, \ldots, f_{oT}\},$$

where, $f_{ot} = \sum_{t=1}^{s} f_{t+r-i} \times W_{i}^{(r)}$, $r$ is a dilation rate indicating the temporal stride to sample frames, $W \in \mathbb{R}^{d \times s}$ is a convolutional kernel, and $s$ is the kernel size. It becomes our traditional temporal convolution (i.e. conv1D without dilation) if $r = 1$. As shown in Fig.2B (a), PDC first separately conducts dilated temporal convolution with various dilation rates $\{r_1, r_2, \ldots, r_N\}$ and then concatenates the outputs in frame-wise. Formally, the output frame-level feature $f_t^{(r)}$ of PDC is defined as follows,

$$f_t^{(r)} = \text{concat}(f_{t+r_1}, f_{t+r_2}, \ldots, f_{t+r_N}) \in \mathbb{R}^{Nd}.$$

PDC uses different $r$ to cover various range of temporal context which could be better than only $r = 1$. In our study, we use three dilation rates $\{1, 2, 4\}$ to sufficiently enlarge the temporal receptive fields for PDC. As shown in Fig.2B (b), our dilated causal convolution (DCC) stacks several dilated convolutional layers with different rates. We perform ReLU after convolution, and add a residual connection to combine the input and the output of each layer. For each layer, we increase dilation rate $r$ exponentially with the depth of the network (i.e., $r = O(2^i)$ at level $i$ of the network). Specifically, we also use three dilation rates $\{1, 2, 4\}$ in order. To map the input sequence to an output sequence of the same length, we add zero padding with length $(s-1)+r$ in all layers. Formally, the output $f_t^i$ of the i-th layer and time $t$ is defined as,

$$f_t^i = \text{ReLU}(W_r^i f_t^{i-1} + b_i),$$

where $W_r^i$ and $b_i$ are parameters for dilated convolution, $W_i$ and $b_i$ are parameters to transform $f_t^{i-1}$ for the residual connection. After the temporal convolutional operation, we use average pooling to generate a single representation for classification by default.

**Recurrent Neural Network (RNN).** Recurrent Neural Network and its variants have recently been transformed from other sequence modeling topics into action classification [19], [26], [63], [72] and detection [30], [87], [107]. In contrast to temporal pooling operation which produces order-independent representations, RNN models the dependencies between consecutive frames and capture the temporal information of the input sequence. For each time step, the RNN cell receives the past step information $h_{t-1}$ and the current frame feature $f_t$, and passes the current hidden state $h_t$ into the next time step.

Specifically, we evaluate two popular recurrent cells, namely Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU). As a special RNN structure for sequence modeling, LSTM has been proven stable and powerful for modeling
long-range dependencies in various topics [33], [35], [23] and online action anticipation [29]. We illustrate LSTM in Fig 3(a) following the implementation of [35]. Formally, LSTM is formulated as follows,

\[ i_t = \sigma(W_{ri}f_t + U_{ri}h_{t-1} + V_{rc}c_{t-1} + b_i), \]
\[ g_t = \sigma(W_{rg}f_t + U_{rg}h_{t-1} + V_{rc}c_{t-1} + b_g), \]
\[ c_t = g_t c_{t-1} + i_t \tanh(W_{rc}f_t + U_{rc}h_{t-1} + b_c), \]
\[ o_t = \sigma(W_{ro}f_t + U_{ro}h_{t-1} + V_{rc}c_t + b_o), \]
\[ h_t = o_t \tanh(c_t), \]

where \( \sigma \) is the logistic sigmoid function, and \( i, g, c \) and \( o \) are respectively the input gate, forget gate, memory cell and output gate. \( h_t \) is the hidden state activation vector.

Similarly to LSTM unit, the GRU has gating units that modulate the flow of information inside the unit, as illustrated in Fig 3(b). The main difference between LSTM and GRU is that there is no separate memory cell in GRN. Formally, the GRU can be formulated as follows,

\[ r_t = \sigma(W_{rr}f_t + U_{rr}h_{t-1}), \]
\[ h_t = \tanh(W_h f_t + U_h (r_t \odot h_{t-1})), \]
\[ z_t = \sigma(W_z f_t + U_z h_{t-1}), \]
\[ h_t = (1 - z_t)h_{t-1} + z_t h_t, \]

where \( r_t \) is a set of reset gates, \( z_t \) is an update gate, and \( \odot \) is an element-wise multiplication.

Since the output of RNN is another sequence, we consider two methods to generate the final single representation \( S_{out} \). i) Following the traditional Encoder-Decoder method, we directly take the hidden state \( h_L \) at the last time step, i.e. \( S_{out} = h_L \). ii) We average the outputs of all the time steps, i.e. \( S_{out} = \frac{1}{L} \sum_{t=1}^{L} h_t \).

**Temporal Attention.** The attention mechanism [5], [64], [94], [109] allows the model to selectively focus on only a subset of frames by increasing the attention weights of the corresponding temporal feature, while ignoring irrelevant signals and noise. We evaluate four attention methods, namely naive self-attention (Naive-SA), nonlinear self-attention (Nonlinear-SA) with a FC-tanh-FC-Softmax architecture, Non-local block or standard self-attention with a skip connection, and Transformer with the current frame as the query \( Q \) information. Given a feature sequence \( F = \{f_1, f_2, \ldots, f_L\} \), the Naive-SA can be implemented by a linear fully-connected (FC) layer and Softmax function as follows,

\[ a = \text{Softmax}(W F^T + b), \]

where \( W \in \mathbb{R}^d \) and \( b \) are parameters of the FC, and \( a \in \mathbb{R}^L \) is the attention weight vector. Similar to [109], we can also add more nonlinear operation as follows (i.e. the Nonlinear-SA),

\[ a = \text{Softmax}(U_2 \tanh(U_1 F^T + b_1) + b_2), \]

where \( U_1 \in \mathbb{R}^{d_1 \times d} \) is a weight matrix, \( b_1 \in \mathbb{R}^{d_1} \) is the bias vector, and \( U_2 \in \mathbb{R}^{d_1 \times d} \) and \( b_2 \) are parameters of the second FC layer. With the attention weights, the output representation is the weighted average vector \( S_{out} = \sum_{i=1}^{L} a_i f_i \).

Transformer is another popular attention based model, which was originally proposed to replace traditional recurrent models for machine translation [29]. The core idea of Transformer is to model correlation between contextual signals by an attention mechanism. Specifically, it aims to encode the input sequence to a higher-level representation by modeling the relationship between queries \((Q)\) and memory (keys \((K)\) and values \((V)\)) with,

\[ A = \text{Attention}(Q, K, V) = \text{Softmax}(\frac{QK^T}{\sqrt{d_m}})V, \]

where \( Q \in \mathbb{R}^{L_q \times d_m}, K \in \mathbb{R}^{L_k \times d_m} \) and \( V \in \mathbb{R}^{L_k \times d_v} \). This architecture becomes standard “self-attention” with \( Q = K = V = \{f_1, f_2, \ldots, f_L\} \). Normally, we use two convolution layers followed by Batch Normalization and ReLU to generate two new features \( Q \) and \( K \) from \( F \), and the Non-local method [100] further adds a skip connection between the input and the output as follows,

\[ F' = AF + F, F' \in \mathbb{R}^{L \times d}. \]

The updated temporal feature \( F' \) is processed with average pooling by default to generate the final temporal representation \( S_{out} = \text{Avg}(F') \in \mathbb{R}^d \).

The query \( Q \) in Eq. 7 can be also a single feature vector, similar to [101] which replaces the self-attention weights by the one between local feature and long-term features, we compute the dot-product attention between current feature \( f_L \) and historical features \( \tilde{F} = \{f_1, f_2, \ldots, f_{L-1}\} \) as illustrated in Fig 2(c). This adaption is based on the assumption that the current frame is the most important one for online action detection. With this operation, an attention weight vector \( a \in \mathbb{R}^{L-1} \) is obtained and used to get the final representation as,

\[ S_{out} = a \tilde{F} + f_1, S_{out} \in \mathbb{R}^d. \]

**Training and Inference.** With the output \( S_{out} \) of temporal modeling module, we use linear FC layer with Softmax for classification, and train the whole network with cross-entropy loss. Specifically, we divide the feature sequence of a video into non-overlapped windows (size \( L \)) as the input of our temporal modeling module. At test stage, sliding window (size \( L \)) with stride 1 is used to formulate the input, and the prediction is made for the last frame.

**IV. EXPERIMENTAL CONFIGURATION**

In this section, we first introduce two widely-used OAD datasets, i.e. TVSeries and THUMOS-14, and then describe our implementation details, including unit-level feature extraction and hyperparameter settings.

### A. Datasets

TVSeries [15] is originally proposed for online action detection, which consists of 27 episodes of 6 popular TV series, namely Breaking Bad (3 episodes), How I Met Your Mother (8), Mad Men (3), Modern Family (6), Sons of Anarchy (3), and Twenty-four (4). It contains totally 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.). It is challenging with diverse actions, multiple
In each unit, the central frame is sampled to calculate the action representation. The video unit size is set to 24 frames per second. The video unit size is processed by a visual encoder to extract the unit-level representation.

In our experiments, we extract frames from all videos at 24 frames. A video chunk of a long untrimmed video is first cut into video units without overlap, each unit contains 213 untrimmed frames. To investigate the characters of the used datasets, we depict the temporal length distributions of action instances on TVSeries and THUMOS-14 in Fig.4. We observe that 70% of action instances are very short on TVSeries (i.e. 0-2s) while half of instances are longer than 3 seconds on THUMOS-14.

B. Evaluation Protocols

For each class on TVSeries, we use the per-frame calibrated average precision (cAP) which is proposed in [13].

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

where calibrated precision \(cPrec = \frac{TP}{TP + FP + I(k)}\). \(I(k)\) is an indicator function that is equal to 1 if the cut-off 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 mean cAP over all classes is reported for final performance. The advantage of cAP is that it is fair for class imbalance condition. For THUMOS-14, we report per-frame mean Average Precision (mAP) performance.

C. Implementation details

Unit-level feature extraction. Following previous work [27], [29], [62], [107], a long untrimmed video is first cut into video units without overlap, each unit contains \(n_u\) continuous frames. A video chunk \(u\) is processed by a visual encoder \(E_v\) to extract the unit-level representation \(f_u = E_v(u) \in \mathbb{R}^d\). In our experiments, we extract frames from all videos at 24 frames per second. The video unit size \(n_u\) is set to 6, i.e. 0.25 second. We use two-stream [105] network as the visual encoder \(E_v\) that is pre-trained on ActivityNet-1.3 [7]. In each unit, the central frame is sampled to calculate the appearance CNN feature, it is the Flatten 673 layer of ResNet-200 [38]. For the motion feature, we sample 6 consecutive frames at the center of a unit and calculate optical flows between them. These flows are then fed into the pretrained BN-Inception model [42], and the output of global pool layer is extracted. The motion features and the appearance features are both 2048-D, and are concatenated into 4096-D vectors (i.e. \(d = 4096\), which are used as unit-level features.

Hyperparameter setting. For the PDC model, the concatenate features are fed into an addition \(1 \times 1\) convolution to reduce the feature dimensions to 4096. For the DCC model, we use 3 dilated convolution layers, each of which is comprised of one dilated convolution with kernel size \(s = 2\), followed by a ReLU and dropout. The output dimension of the second layer is set to 2048, and thus a \(1 \times 1\) convolution is added for residual connection. Our experiments are conducted in Pytorch. We use SGD optimizer to train the network from scratch. The leaning rate, momentum and decay rate are set to \(10^{-3}\), 0.9 and 0.95, respectively. All of our experiments are implemented with 8 GTX TITAN X GPU, Intel i7 CPU, and 128GB memory.

V. Exploraton of Temporal Modeling Methods

In this section, we first present a quick comparison among the best settings of the four mentioned temporal modeling methods, and then extensively explore both individual temporal modeling methods and their combinations, and finally compare our results to the state of the arts.

A. A Quick Comparison of Temporal Modeling Methods

As mentioned in the Introduction, we totally explore eleven temporal modeling methods from four meta types, namely temporal pooling, temporal attention, RNN, and temporal convolution. For a quick glance, Table I presents the results of the best choice (i.e. the 2nd row) for each meta type. For a fair comparison, the input sequence length \(L\) is fixed as 4. Several observations can be concluded as following. First, temporal convolution (i.e. DCC) achieves the best results on both TVSeries and THUMOS-14, which indicates that discriminative information can be obtained effectively by temporal convolution. Second, temporal attention (i.e. Transformer) performs slightly better than temporal pooling (i.e. AvgPool), which demonstrates the effectiveness of attention mechanism. Third, RNN (i.e. LSTM) outperforms Transformer and AvgPool with sizable margins on both datasets, which shows that the temporal dependencies captured by LSTM is crucial for accurate online action detection. Overall, an interesting finding is that the temporal-dependent methods, i.e. temporal convolution and RNN, are superior to these temporal-independent methods for online action detection.

B. Ablation Study for Individual Temporal Modeling Method

Temporal pooling. We test two temporal pooling methods (i.e. average pooling and max pooling) with different sequence lengths. The results are shown in Fig.5. We also compare them to the baseline that uses a fully-connected (FC) layer and Softmax to generate action probabilities frame by frame.

Fig. 4. The temporal length distributions of action instances on (a) TVSeries and (b) THUMOS-14.
TABLE I
A QUICK COMPARISON AMONG THE BEST SETTINGS OF DIFFERENT META TYPES OF TEMPORAL MODELING METHODS. THE BEST CHOICE OF EACH TYPE IS PRESENTED IN THE 2ND ROW.

|                | Pooling | Attention | RNN   | Convolution |
|----------------|---------|-----------|-------|-------------|
|                | AvgPool | Transformer | LSTM  | DCC         |
| TVSeries       | 81.2    | 81.5      | 82.9  | 83.1        |
| THUMOS-14      | 41.5    | 43.3      | 45.9  | 46.8        |

The baseline model only relies on the current frame feature which obtains 79.8% (cAP) and 36.3% (mAP) on TVSeries and THUMOS-14, respectively. For temporal pooling, it is clear that average pooling consistently performs better than max pooling on both datasets. Increasing the sequence length improves both pooling methods in the beginning and degrades them dramatically after the saturation length. This can be explained by that appropriate historical information introduces useful context for online action detection while long-term historical information may introduce unrelated information and may also smooth the final representation. Another observation is that increasing the sequence length after L=4 is seriously harmful for TVSeries while not for THUMOS-14. This effect indicates a fact that each video in TVSeries contains multiple actions and numerous varied background frames while each video in THUMOS-14 only contains one action instance. Overall, the simple AvgPool method (L=4) respectively improves the baselines on TVSeries and THUMOS-14 by 1.4% and 5.2%.

RNN. We evaluate LSTM and GRU in the following four aspects: input sequence length, output strategy, hidden size, and the number of recurrent layers.

Input sequence length and output strategy. For these two factors, we vary the sequence length from 2 to 16, and evaluate two alternative output strategies including the last hidden state $S_{out} = h_{L}$ and the average hidden state $S_{out} = \frac{1}{L} \sum_{t=1}^{L} h_{t}$. The hidden size is fixed to 4096 and only one recurrent layer is used for this evaluation. Fig.6 illustrates the comparison results for LSTM and THUMOS-14 by 1.4% and 5.2%. GRU on THUMOS-14 while similarly or worse on TVSeries. This indicates that the separate memory cell in LSTM is helpful to capture more context information which is crucial for THUMOS-14 while too much context (unrelated actions or background) can degrade performance on TVSeries. Third, the effect of sequence length for both LSTM and GRU is the same as the one for pooling methods, and the best trade-off sequence length is 4 on both datasets.

Hidden size. We choose LSTM, and test different hidden sizes $D_{h} = 128, 256, 512, 1024, 2048, 4096$. The last hidden state output strategy and sequence length $L = 4$ are used for this evaluation. The results are shown in Fig.7. A clear observation is that increasing hidden size improves the final performance significantly on both datasets. In addition, it gets saturated after hidden size 2048, and the best results are respectively 82.9% and 45.9% on TVSeries and THUMOS-14 with hidden size 4096.

The number of recurrent layers. Generally, one can easily stack several recurrent layers to model the complex dependency of sequences. To this end, we evaluate the number of recurrent layers for both LSTM and GRU on TVSeries and THUMOS-14. The results are shown in Fig.8. Interestingly, adding one more layer does not bring performance gain and even dramatically degrades the performance for LSTM on both datasets. The main problem is that adding one more recurrent layer can double the number of parameters leading to overfit easily.

Temporal convolution. As shown in Table II, we compare temporal convolution models with different kernel size $s$ and dilation rate $r$, denoted as $(s, r)$. For PDC and DCC, we use temporal convolutional filters with kernel size $s = 2$ as a building block. The input sequence length is fixed to $L = 4$ for all the comparison experiments. In order to obtain output with equal length as the input, we add zero padding as it needs.
Several observations can be concluded as follows. First, the comparison between TC(2,1) and TC(3,1) indicates that the kernel size \( s = 2 \) is slightly better than \( s = 3 \) on both datasets. Second, the comparison among TC(2,1), TC(2,2), and TC(2,4) shows that different dilation rates perform similarly on both datasets. Third, both PDC and DCC which combines TC(2,1), TC(2,2), and TC(2,4) in either parallel or serial manner significantly improve the traditional TC models, and DCC performs best. This demonstrates that combining multi-dilation temporal convolution layers can capture complementary multi-scale action information.

**Temporal attention.** We compare four different attention models mentioned in Sec. II-B, i.e., Naive-SA as described in Eq. (7), Nonlocal-SA as described in Eq. (8), Non-local as described in Eq. (10), and Transformer as described in Eq. (11). As shown in Table III, several observations can be concluded as following. First, Nonlinear-SA outperforms Naive-SA by 0.8% on TVSeries and 2.6% on THUMOS-14. Compared to Naive-SA, Nonlinear-SA computes attention weights with one more nonlinear \( \tanh \) and linear FC which may be more effective for modeling the complex temporal relationships. Second, Non-local performs equally to Nonlinear-SA on both datasets, indicating that they share the similar attention mechanism more or less. Third, Transformer with current frame feature as a query performs better than Non-local by 0.6% on TVSeries and 0.9% on THUMOS-14, showing the effectiveness of our proposed design (i.e., computing the attention between current frame feature with historical features) for online action detection.

As there is a hyper parameter \( d_1 \) in Nonlinear-SA (see Eq. (9)) which can impact the final performance, we also conduct an evaluation in Table IV. We observe \( d_1 = 512 \) (1024) yield the best performance for TVSeries (THUMOS-14), and the final performance is not very sensitive to it.

### Table IV

| Dataset   | Hybrid models | TVSeries | THUMOS-14 |
|-----------|---------------|----------|-----------|
|           |               |          |           |
| TVSeries  | LSTM \oplus Transformer | 83.6     | 47.1      |
| M2        | DCC \oplus Transformer    | 84.3     | 47.1      |
| M3        | LSTM \oplus DCC \oplus Transformer | 83.0     | 48.5      |
| M4        | DCC \oplus Transformer    | 83.7     | 48.6      |
| M5        | DCC \oplus LSTM          | 83.2     | 47.9      |
| M6        | LSTM \oplus DCC \oplus AvgPool | 81.5     | 47.5      |

### Table V

| Hybrid models | TVSeries | THUMOS-14 |
|---------------|----------|-----------|
|               |          |           |
| TVSeries      | 80.6     | 42.0      |
| M2            |          |           |
| THUMOS-14     | 42.0     | 42.5      |
|               | 42.5     | 41.1      |
|               | 41.1     | 41.5      |

**C. Combination of Temporal Modeling Methods**

Generally, these sequence-to-sequence temporal models, e.g., DCC and LSTM can be further processed by aggregation methods like temporal pooling and temporal attention to generate a single representation. Thus, we present several hybrid temporal modeling methods which combine different temporal modeling methods, aiming to uncover the complementarity among them. Specifically, according to their characters, we mainly combine those temporal-dependent models and temporal-independent models as follows.

**M1** LSTM \oplus Transformer: The hidden states at all time steps are further fed into Transformer to generate a single representation, and the classification is performed on the representation.

**M2** DCC \oplus Transformer: The output of the DCC network is the same as the input sequence length, and Transformer is performed on the output sequence to generate a single representation for classification.

**M3** DCC \oplus LSTM \oplus Transformer: The output sequence is further processed by LSTM aiming to capture strong temporal dependency, and finally Transformer is used to generate the representation for classification.

**M4** LSTM \oplus DCC \oplus Transformer: The hidden states are first fed into DCC and then Transformer. This model is similar to M3 except for that it swaps the order of DCC and LSTM;

**M5** DCC \oplus LSTM: The output sequence of DCC is processed by LSTM, and then the last hidden state is used for action classification.

**M6** LSTM \oplus DCC \oplus AvgPool: This model replaces the Transformer of M3 with AvgPool to generate the final representation for classification.
D. Comparison with state-of-the-art

We compare our best results to the state-of-the-art approaches on TVSeries and THUMOS-14 in Table VI and Table VII respectively. With two-stream features, we achieve 84.3% in terms of mean cAP on TVSeries and 48.6% mAP on THUMOS-14, which outperforms the recent sophisticated-designed TRN [107] by 0.6% and 1.4%, respectively. Besides, we also present the comparison of ours with previous methods [15] for each action class on TVSeries in Fig.9. Our method can always outperform CNN and LSTM by a large margin except for action class Use computer and Write.

VI. Conclusions

In this paper, we provide a comprehensive study on temporal modeling for online action detection including four meta types of temporal modeling methods, i.e. temporal pooling, temporal convolution, recurrent neural networks, and temporal attention. We extensively explore eleven individual temporal modeling methods and explore several hybrid temporal models which combine different temporal modeling methods to uncover the complementarity among them. Based on our comprehensive study, we find that a simple fusion between dilated causal convolution and Transformer or LSTM improves the individual models significantly and also outperforms the best existing approaches on TVSeries and THUMOS-14 in Table VI and Table VII, respectively. With two-stream features, we achieve 84.3% in terms of mean cAP on TVSeries and 48.6% mAP on THUMOS-14, which outperforms the recent sophisticated-designed TRN [107] by 0.6% and 1.4%, respectively. Besides, we also present the comparison of ours with previous methods [15] for each action class on TVSeries in Fig.9. Our method can always outperform CNN and LSTM by a large margin except for action class Use computer and Write.

The results of the hybrid methods on TVSeries and THUMOS-14 are shown in Table VI. Several observations can be concluded as following. First, the best results on TVSeries and THUMOS-14 are achieved by M2 and M4, respectively. Second, combining temporal-dependent models (i.e. LSTM and DCC) with temporal-independent ones (i.e. Transformer) largely improves individual models, which indicates that they are complementary. Third, integrating LSTM into DCC ⊕ Transformer (i.e. M2→M3) degrades the performance by 1.3% on TVSeries while increases the one by 1.4% on THUMOS-14. This may be explained by that temporal dependencies are important for these long-term action instances of THUMOS-14 while harmful for the dominated short-term action instances of TVSeries.

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TABLE VI

| Method | Inputs | cAP |
|--------|--------|-----|
| CNN (De Geest et al., 2016) | 15 | 60.8 |
| LSTM (De Geest et al., 2016) | 15 | 64.1 |
| RED (Gao et al., 2017) | 29 | 71.2 |
| Stacked LSTM (De Geest and Tuytelaars, 2018) | VGG | 71.4 |
| 2S-FN (De Geest and Tuytelaars, 2018) | 17 | 72.4 |
| TRN (Xu et al., 2019) | 107 | 75.4 |
| SVM (De Geest et al., 2016) | 15 | 74.3 |
| RED (Gao et al., 2017) | 29 | 79.2 |
| TRN (Xu et al., 2019) | 107 | 83.7 |
| Ours | TS | 84.3 |

TABLE VII

| Method | mAP |
|--------|-----|
| Single-frame CNN (Simonyan and Zisserman, 2014) | 34.7 |
| Two-stream CNN (Simonyan and Zisserman, 2014) | 36.2 |
| C3D+LinearInterp (Shou et al., 2017) | 37.0 |
| Predictive-corrective (Dave et al., 2017) | 38.9 |
| LSTM (Donahue et al., 2014) | 39.3 |
| MultiLSTM (Yeung et al., 2015) | 41.3 |
| CDC (Shou et al., 2017) | 44.4 |
| RED (Gao et al., 2017) | 45.3 |
| TRN (Xu et al., 2019) | 47.2 |
| Ours | 48.6 |

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