Temporal Action Proposal Generation with Background Constraint

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Abstract

Temporal action proposal generation (TAPG) is a challenging task that aims to locate action instances in untrimmed videos with temporal boundaries. To evaluate the confidence of proposals, the existing works typically predict action score of proposals that are supervised by the temporal Intersection-over-Union (tIoU) between proposal and the ground-truth. In this paper, we innovatively propose a general auxiliary Background Constraint idea to further suppress low-quality proposals, by utilizing the background prediction score to restrict the confidence of proposals. In this way, the Background Constraint concept can be easily plug-and-played into existing TAPG methods (e.g., BMN, GTAD). From this perspective, we propose the Background Constraint Network (BC-Net) to further take advantage of the rich information of action and background. Specifically, we introduce an Action-Background Interaction module for reliable confidence evaluation, which models the inconsistency between action and background by attention mechanisms at the frame and clip levels. Extensive experiments are conducted on two popular benchmarks, i.e., ActivityNet-1.3 and THUMOS14. The results demonstrate that our method outperforms state-of-the-art methods. Equipped with the existing action classifier, our method also achieves remarkable performance on the temporal action localization task.

1 Introduction

With the rapid development of mobile devices and the Internet, a massive amount of video content is being uploaded to the Internet every second. The volume of video information has far exceeded the processing capacity of the conventional manual system, thus video content analysis has attracted the extensive interest of academic and industrial communities.

One of the most active research topics in video understanding is temporal action detection, which focuses on both classifying the action instances present in an untrimmed video and localizing them with temporal boundaries. The temporal action detection task, like object detection, is divided into two parts: temporal action proposal generation (TAPG) and action recognition. Deep learning has recently been shown to significantly improve action recognition performance [Simonyan and Zisserman 2014; Lin, Gan, and Han 2019; Wu et al. 2021a]. However, the performance of the two-stage temporal action detectors in mainstream benchmarks (Jiang et al. 2014; Caba Heilbron et al. 2015a) still has much room for improvement, which is mostly influenced by the quality of proposals from temporal action proposal generation.

Hence, great efforts have been devoted to TAPG task (Lin et al. 2018, 2019). These research generally use the temporal Intersection-over-Union (tIoU) between the proposal and instance, called the action score, to evaluate the confidence of the proposal in order to develop high-quality temporal action proposals with dependable confidence scores. However, the background information is also significant but was previously overlooked. For instance, as illustrated in Figure 1, we can easily restrict false-positive proposals by detecting the background “Move a chair”. Furthermore, we can evaluate the inconsistency between the background “Move a chair” and the action “Hitting a pinata”, leading to better action score and background score of the proposal.

Motivated by above observations, we propose a general auxiliary Background Constraint idea to reduce localization errors. Specifically, we introduce a background score for the proposal’s confidence, and its supervision signal is defined

Figure 1: Illustration of the background constraint concept. We introduce a background score for the confidence of the proposal, which helps to restrict false-positive proposals.
by the temporal Intersection-over-Anchor (IoA) between
the proposal and the background. This concept can be flexi-

bly integrated into existing TAPG methods (e.g., BMN (Lin
et al. 2019), GTAD (Xu et al. 2020)) to improve the perfor-

mance in a plug-and-play fashion.

To further mine the rich information of action and
background, in this paper, we propose the Background
Constraint Network (BCNet) to generate high-quality tem-

oral action proposals. An essential component of BCNet
is the Action-Background Interaction (ABI) module, which
performs both frame-level and clip-level action-background
interaction to obtain reliable confidence scores of proposals.

To do so, we first generate action features and background
features for each frame using self-attention and difference-
attention. Sliding windows are then used to generate multi-
scale anchors from action and background features. The
clip-level interaction then discovers the complex relationships
between action-anchors and background-anchors, and
outputs the action and background scores for these anchors.
We also propose a Boundary Prediction (BP) module for
precisely locating action boundaries. To capture the com-
plex long-term temporal relationships while avoiding the in-
fluence of global noise, we aggregate the original feature se-
quence using self-attention and cross-attention mechanisms.

The output representation is then used as the global repre-
sentation for the boundary prediction task. Finally, we feed
the boundary probabilities, action scores and background
scores into the post processing module to get the final pro-
posal set.

Experimental results show the superiority of our system
on two popular datasets, i.e., ActivityNet (Caba Heilbron
et al. 2015b) and THUMOS14 (Jiang et al. 2014). Our BC-
Net achieves significant performance and outperforms existing
state-of-the-art methods on both datasets. Our contribu-
tions are summarized as follows:

• We introduce a Background Constraint concept, which
can be integrated easily with existing TAPG methods
(e.g., BMN, GTAD) and improve performance significa-

cantly.

• We propose a Background Constraint Network, which
consists of multiple attention units, i.e., self-attention,
cross-attention and difference-attention, and generates
high-quality proposals by exploiting inconsistency be-
tween action and background.

• Extensive experiments demonstrate that our method
outperforms the existing state-of-the-art methods on
THUMOS14 and achieves comparable performance on
ActivityNet-1.3, in both temporal action proposal gen-
eration task and temporal action detection task.

2 Related Work

2.1 Video Action Recognition

Action recognition is a fundamental task in the video under-
standing area. Currently, there are two types of end-to-end
action recognition methods: 3D CNN-based methods
and 2D CNN-based methods. 3D CNNs are natural extensions
of their 2D counterparts and are intuitive spatiotemporal net-
works that directly tackle 3D volumetric video data (Tran
et al. 2015; Carreira and Zisserman 2017) but have a high
computational cost. Other alternative efficient architectures,
such as TSM (Lin, Gan, and Han 2019), TEI (Liu et al.
2020), MVFNet (Wu et al. 2021a), DSANet (Wu et al.
2021b), etc, have been developed to capture temporal infor-
mation with reasonable training resources. These methods
aim to design efficient temporal modules to perform effi-
cient temporal modeling. There is also ongoing research into
dynamic inference (Wu et al. 2020), adaptive frame sam-
ping techniques (Wu et al. 2019), Korbar, Tran, and Torre-
san (2019), which we believe can complement the end-to-
end video recognition approaches.

2.2 Temporal Action Proposal Generation

Temporal action proposal generation aims to detect ac-
tion instances with temporal boundaries and confidence in
untrimmed videos. Existing methods can be mainly divided
into Top-down and Bottom-up methods. The Top-down
methods (Oneata, Verbeek, and Schmid 2014; Gao et al.
2017, Gao, Chen, and Nevatia 2018, Gao et al. 2020, Chen
et al. 2019) generate proposals using sliding windows or pre-
defined anchors. The Bottom-up methods mainly focus on evaluating “actionness”, which indicates the probability of
a potential action, for each frame or clip in a video. These
works (Shou, Wang, and Chang 2016, Zhao et al. 2017)
use snippet-wise probability to generate candidate propos-
als. BSN (Lin et al. 2018) first proposes to predict start, end
and actionness of each frame, then proposals are generated by
constructing start and end points with high probabilities,
with low confidence ones further abandoned by an evalu-
ation module. (Lin et al. 2019, Su et al. 2020, Xu et al. 2020,
Lin et al. 2020) generate all possible combinations of tem-
poral locations to evaluate confidence of proposals. (Liu et al.
2019) generates coarse segment proposals by perceiving the
whole video sequence and predicts the frame actionness by
densely evaluating each video frame. These methods eval-
uate action scores of proposals with rich clip-level context.
However, these methods fail to take full advantage of back-
ground by focusing only on the action score. In our work,
we predict the extra background score for the confidence of
proposals to reduce low-quality proposals.

2.3 Transformer and self-attention mechanism

Transformers (Vaswani et al. 2017) has achieved great suc-

cess in natural language processing. Transformer architec-
tures are based on a self-attention mechanism that summa-
rizes content from the source sequence and is capable of
modeling complex and arbitrary dependencies within a lim-
ited number of layers. Recently, many works (Dosovitskiy
et al. 2020, Carion et al. 2020, Liu et al. 2021b, Tan et al.
2021) have revealed the great potential of Transformers in the
computer vision task. Inspired by the successful application of Transformers in various fields, we intuitively take advantage of Transformers in modeling long-
range contextual information. In this paper, we utilize the
Transformer-alike structure to devise three attention units.
2.4 Background Modeling on Temporal Action Localization

Background modeling in Temporal action localization has received some attention. Several previous works (Shou, Wang, and Chang 2016; Yuan et al. 2016) generate proposals by sliding window and classify them into $C + 1$ classes for $C$ action classes plus background class. Also, several studies attempt to explicit background modeling for weakly-supervised temporal action localization. Some works (Nguyen, Ramanan, and Fowlkes 2019; Lee, Uh, and Byun 2020) try to classify background frames as a separate class. (Lee et al. 2020) formulates background frames as out-of-distribution samples. Essentially, all the above works aim to perform classification for these proposals. Unlike them, in our work, we propose a Background Constraint concept to predict an additional background score for proposal confidence evaluation. To supervise the background score, we use temporal Intersection-over-Anchor (tIoA) between the proposal and the background. Our work concentrates on utilizing the background prediction score to restrict the confidence of proposals.

3 Background Constraint Network

As shown in Figure 2, we propose a Background Constraint Network (BCNet) to generate high-quality proposals, which mainly consists of two main modules: Action-Background Interaction Module and Boundary Prediction Module. Firstly, the Action-Background Interaction (ABI) module is adopted to perform both frame-level and clip-level action-background interaction to obtain reliable confidence scores of proposals. The Boundary Prediction (BP) module is then utilized to locate the boundaries of the proposals by exploiting complex long-term temporal relationships for boundary regression.

3.1 Problem Definition

An untrimmed video $U$ can be denoted as a frame sequence $U = \{u_t\}_{t=1}^{t_u}$ with $l_u$ frames, where $u_t$ denotes the $t$-th RGB frame of video $U$. The temporal annotation set of $U$ is made up of a set of temporal action instances as $\Psi_g = \{\phi^g_n\}_{n=1}^{N_g}$ and $\varphi^b_n = (t_{s_n}, t_{e_n})$, where $N_g$ is the number of ground-truth action instances, $t_{s_n}$ and $t_{e_n}$ are the starting and ending time of the action instance $\phi^g_n$, respectively. During training phase, the $\Psi_g$ is provided. While in the testing phase, the predicted proposal set $\Psi_p$ should cover the $\Psi_g$ with high recall and high temporal overlapping.

3.2 Background Constraint

To evaluate the confidence of the proposal, existing methods primarily use the temporal Intersection-over-Union (tIoU) between the proposal and instance, called action score. The temporal Intersection-over-Union (tIoU) is used to define the label of action score, which can be computed by:

$$A_{\text{label}} = \max \left\{ \sum \frac{G_i \cap P_i}{G_i \cup P_i} \right\}_{i=1}^{n},$$

where $G_i$ is the $i$-th ground truth and $P$ is the proposal, $n$ is number of ground truth. In this paper, we propose a novel Background Constraint concept to suppress low-quality proposals (false positive proposals). Specifically, we predict a extra background score for evaluating the confidence of the proposal besides the action score. The label of the background score is generated using temporal Intersection-over-
Cross-attention to devise the self-attention unit, which consists of two sub-units in Figure 3(a). We utilize the Transformer-alike structure which consists of multiple layers. Specifically, we first use sliding window group convolutions to generate the action anchors and background anchors with different scales. Following BMN (Lin et al. 2019), we construct weight term \( w_{ij} \in \mathbb{R}^{N \times T} \) via uniformly sampling \( N \) points between the temporal region for each anchor. First, we conduct dot product in temporal dimension between \( w_{ij} \) and \( F_a \) with the shape \( C \times N \) to generate the action anchor. Then, we get action anchor sequence \( F_a^\prime \in \mathbb{R}^{L \times S} \) where \( L \) is number of clip and \( S = C \times N \). Similarly, we generate background anchors sequence \( F_b^\prime \) in the same way.

Next, the anchor sequences \( F_a^\prime \) and \( F_b^\prime \) are fed into the clip-level action-background interaction to generate action score and background score. Specifically, we first utilize two independent Self-attention Units to capture the relationships among action/background anchors, respectively. The two self-attention units output updated anchor sequence \( F_a^{c'} \) and \( F_b^{c'} \). Similar to the frame-level interaction, \( F_a^{c'} \) and \( F_b^{c'} \) are then fed into the Difference-attention Unit to obtain difference map and reweighted anchor sequence \( F_a^{\hat{c}} \) and \( F_b^{\hat{c}} \). Note that the difference map \( A_{i,j} \) represents the feature difference between \( i \)-th action anchor and \( j \)-th background anchor.

Finally, we add a clip-level predictor which encodes the \( F_a^{\hat{c}} \) and \( F_b^{\hat{c}} \) with multi-layer perceptron (MLP) and a Sigmoid layer to predict action scores and background scores.

### 3.4 Boundary Prediction Module

Long-term temporal modeling is a critical factor in proposal boundary prediction. It is natural to use self-attention mechanism to model long dependencies. However, global modeling is easy to introduce global noise then leads to the over-smoothing. To this end, we propose a Boundary Prediction (BP) module which introduces original features to alleviate this phenomenon. This module is built using the Transformer-alike structure which consists of multiple layers. Each layer contains a Self-attention Unit, a Cross-attention Unit and a feed-forward network. Specifically, we first obtain the feature \( F_i \) (\( i \) represents the input features of layer \( i \),...
if \( i = 1, F_i = F_{\alpha} \) and \( F_o \). Then, we feed them to the Self-attention Unit and generate augmented global features \( F^g_i \) and \( F^g_o \). As shown in Fig. 3(b), we use Cross-attention Unit to generate the attention map \( A(F_i, F_o) \) which represents the similarity between the aggregated feature \( F^g_i \) and the original aggregated feature \( F^g_o \) called the originality score. To get \( F_{i+1} \), we aggregate features which have high originality scores and discard features which have low originality scores.

The final output representation is then used as the global representation for the boundary prediction task. Specifically, we utilize a boundary predictor which encode the output representation with multi-layer perceptron (MLP) network and followed by a Sigmoid layer to generate boundary probability sequence.

### 3.5 Training

The overall objective of our framework is defined as:

\[
L = L_1 + L_2,
\]

where \( L_1 \) and \( L_2 \) are the objective functions of the ABI module and the BP module respectively.

**Objective of BP module.** The BP module generates the starting and ending probability sequence \( P_s, P_e \). Thus, the loss function consists of starting loss and ending loss:

\[
L_1 = L_{bd}(P_s, G_s) + L_{bd}(P_e, G_e),
\]

where \( G_s \) and \( G_e \) are the ground truth labels of boundary sequence, and \( L_{bd} \) is the binary logistic regression loss.

**Objective of ABI module.** The ABI module generates frame-level and clip-level scores: \( P^f_a, P^f_b, P^c_a, P^c_b \) and \( P^f_a, P^f_b \) are frame-level action and background classification scores. \( P^c_a \) is clip-level background classification scores. Following BMN, \( P^c_b \) is clip-level action classification scores and \( P^f_b \) is regression action scores. The loss function \( L_2 \) consists of frame-level loss and clip-level loss:

\[
L_2 = L_{frame} + L_{clip}.
\]

The frame-level loss is

\[
L_{frame} = L_c(P^f_a, G^f_a) + L_c(P^f_b, G^f_b),
\]

where \( G^f_a \) and \( G^f_b \) are the ground truth labels of action and background probability at frame-level. The clip-level loss is formulated as follows:

\[
L_{clip} = L_c(P^c_a, G^c_a) + L_r(P^c_a, G^c_a) + L_c(P^c_b, G^c_b),
\]

where \( G^c_a \) and \( G^c_b \) are the ground truth labels of action and background scores at clip-level. \( L_c \) denotes the binary logistic regression loss function and \( L_r \) is a smooth \( L_1 \) loss.

### 3.6 Inference

As mentioned above, the BP module generates boundary probability and the ABI module generates the action and background scores. Then we take the boundary probability, action scores and background scores into the Post-processing module. Firstly, we construct a proposals set \( \psi_p \) based on boundary probabilities. Second, the proposal is refined by a corresponding pre-set anchor. The proposal \( \varphi = [t_s', t_e'] \in \psi_p \) is taken as an example, we compute the temporal Intersection over Union (tIoU) between proposal \( \varphi \) and anchors, then select a matching anchor \( p_m = [t^m_s, t^m_e] \) to refine proposals. We refine the proposal as:

\[
[t_s, t_e] = \begin{cases} 
\frac{[t^s_s + t^s_e]}{2}, & \text{if } p^m_s > \alpha_1 \text{ and } p^m_e > \alpha_2, \\
[t_s', t_e'], & \text{otherwise}
\end{cases}
\]

where \( p^m_s \) is the anchor action classification score, \( p^m_e \) is the action regression score, \( \alpha_1 \) and \( \alpha_2 \) are the adjustment thresholds. Finally, we get a proposal set \( \psi_p = \{\phi_n = (t_s, t_e, p^a_t, p^b_t, p^a_m, p^b_m, p^b_m)\}_{n=1}^N \), where \( p^a_t, p^b_t \) are the starting and ending probabilities and \( p^b_m \) is anchor background score.

Following the previous practices, we also perform score fusion and redundant proposal suppression to further obtain final results. Specifically, in order to make full use of various predicted scores for each proposal \( \varphi_n \), we fuse its boundary probabilities and action-background scores of matching anchor by multiplication. The confidence score \( p^f \) can be defined as:

\[
p^f = p^a_t \cdot p^b_t \cdot p^a_m \cdot p^b_m \cdot (1 - p^b_m).
\]

Hence, the final proposal set as

\[
\psi = \{\phi_n = (t_s, t_e, p^f)\}_{n=1}^N.
\]

Moreover, we also use the Soft-NMS algorithm for post-processing to remove the proposals which highly overlap with each other.

### 4 Experiments

#### 4.1 Datasets and Evaluation Metrics

**ActivityNet-v1.3** (Caba Heilbron et al. 2015a) is a large-scale video dataset for action recognition and temporal action detection tasks. It contains 10K training, 5K validation, and 5K testing videos with 200 action categories, and the ratio of training, validation and testing sets is 2:1:1. **THUMOS14** (Jiang et al. 2014) contains 200 validation untrimmed videos and 213 test untrimmed videos, including 200 action categories. This dataset is challenging due to the large variations in the frequency and duration of action instances across videos.

**Evaluation Metrics.** Temporal action proposal generation aims to produce high-quality proposals with high tIoU, which have a high recall rate. To evaluate quality of proposals, Average Recall (AR) is the average recall rate under specified tIoU thresholds. Following the standard protocol, we use thresholds set \([0.5, 0.5:0.05:0.95]\) on ActivityNetv1.3 and \([0.5:0.05:1.0]\) on THUMOS14. To evaluate the performance of temporal action detection task, mean Average Precision (mAP) under multiple tIoU is the widely-used evaluation metric. On ActivityNet-v1.3, the tIoU thresholds are set to \([0.5, 0.75, 0.95]\), and we also test the average mAP of tIoU thresholds between 0.5 and 0.95 with step of 0.05. On THUMOS14, these tIoU thresholds are set to \([0.3, 0.4, 0.5, 0.6, 0.7]\).
Table 1: Performance comparison with state-of-the-art proposal generation methods on test set of THUMOS14 in terms of AR@AN.

| Method | AR@50 | AR@100 | AR@200 | AR@500 | AR@1000 |
|--------|-------|--------|--------|--------|---------|
| TAG    | 18.6  | 29.0   | 39.6   | -      | -       |
| CTAP   | 32.5  | 42.6   | 52.0   | -      | -       |
| BSN    | 37.5  | 46.1   | 53.2   | 61.4   | 65.1    |
| MGG    | 39.9  | 47.8   | 54.7   | 61.4   | 64.6    |
| BMN    | 39.4  | 47.7   | 54.8   | 62.2   | 65.5    |
| BSN++  | 42.4  | 49.8   | 57.6   | 65.2   | 66.8    |
| TCANet | 42.1  | 50.5   | 57.1   | 63.6   | 66.9    |
| RTD-Net| 41.1  | 49.0   | 56.1   | 62.9   | -       |
| **Ours** | 45.5  | 53.6   | 60.0   | 67.0   | 69.8    |

Table 2: Performance comparison with state-of-the-art action detection methods on test set of THUMOS14, in terms of mAP (%) at different IoU thresholds.

| Method | mAP 0.3 | mAP 0.4 | mAP 0.5 | mAP 0.6 | mAP 0.7 |
|--------|----------|----------|----------|----------|----------|
| SST    | -        | -        | 23.0     | -        | -        |
| TURN   | 44.1     | 34.9     | 25.6     | -        | -        |
| SSN    | 51.9     | 41.0     | 29.8     | -        | -        |
| BSN    | 53.5     | 45.0     | 36.9     | 28.4     | 20.0     |
| MGG    | 53.9     | 46.8     | 37.4     | 29.5     | 21.3     |
| DBG    | 57.8     | 49.4     | 39.8     | 30.2     | 21.7     |
| BMN    | 56.0     | 47.4     | 38.8     | 29.7     | 20.5     |
| G-TAD  | 54.5     | 47.6     | 38.2     | 29.8     | 20.6     |
| BSN++  | 59.9     | 49.5     | 41.3     | 31.9     | 22.8     |
| TCANet | 60.6     | 53.2     | 44.6     | 36.8     | 26.7     |
| **Ours** | 66.5  | 60.5     | 51.6     | 41.0     | 29.2     |

Table 3: Performance comparison with state-of-the-art proposal generation methods on validation set of ActivityNet-1.3 in terms of AUC and AR@AN.

| Method | AR1 (val) | AR100 (val) | AUC (val) |
|--------|-----------|-------------|-----------|
| CTAP   | -         | 73.2        | 65.7      |
| BSN    | 32.2      | 74.2        | 66.2      |
| MGG    | -         | 75.5        | 66.4      |
| BMN    | -         | 75.0        | 67.0      |
| BSN++  | 34.3      | 76.5        | 68.3      |
| TCANet | 34.6      | 76.1        | 68.1      |
| RTD-Net| 32.8      | 73.1        | 65.7      |
| **Ours** | 35.2  | 76.6        | 68.7      |

Table 4: Performance comparison with state-of-the-art action detection methods on validation set of ActivityNet-1.3, in terms of mAP (%) at different tIoU thresholds and the average mAP.

| Method     | 0.5      | 0.75     | 0.95     | Average |
|------------|----------|----------|----------|---------|
| Singh et al.| 34.5     | -        | -        | -       |
| SCC        | 40.0     | 17.9     | 4.7      | 21.7    |
| CDC        | 45.3     | 26.0     | 0.20     | 23.8    |
| R-C3D      | 26.8     | -        | -        | -       |
| BSN        | 46.5     | 30.0     | 8.0      | 30.0    |
| BMN        | 50.1     | 34.8     | 8.3      | 33.9    |
| GTAD       | 50.4     | 34.6     | 9.0      | 35.1    |
| BSN++      | 51.3     | 35.7     | 8.3      | 34.9    |
| TCANet w/ BSN | 51.9 | 34.9     | 7.5      | 34.4    |
| RTD-Net    | 46.4     | 30.5     | 8.6      | 30.5    |
| **Ours**   | 53.2     | 36.2     | 10.6     | 35.5    |

4.2 Implementation Details

**Feature Encoding.** Following previous works [Lin et al. 2019; Xu et al. 2020], we adopt the TSN (Wang et al. 2016) and I3D (Simonyan and Zisserman 2014) for feature encoding. For THUMOS14, the interval $\sigma$ is set to 8 and 5 for I3D and TSN respectively. We crop each video feature sequence with overlapped windows of size $T = 256$ and stride 128. As for ActivityNet-1.3, the sampling frame stride is 16, and each video feature sequence is rescaled to $T = 100$ snippets using linear interpolation.

**Training and Inference.** The number of layers in Boundary Prediction module is 12. Due to the limit of computation resource, we apply 1D Conv for dimension reduction, then take the features as the input to the Boundary Prediction module and Action-Background Interaction module. For each anchor, we use sampling points $N = 32$. For post-processing module, we set adjustment thresholds $\alpha_1 = 0.9$ and $\alpha_2 = 0.8$. We train our model from scratch using the Adam optimizer and the learning rate is set to $10^{-4}$ and decayed by a factor of 0.1 after every 10 epoch.

4.3 Comparison with State-of-the-arts

Here we compare our BCNet with the existing state-of-the-art methods on ActivityNet-v1.3 and THUMOS14. For fair comparisons, we adopt the same two-stream features used by previous methods in our experiments.

**Results on THUMOS14.** BCNet is compared with state-of-the-art methods in Table 1 and Table 2, where our method improves the performance significantly for both temporal action proposal generation and action detection. For the temporal action proposal generation task, results are shown in Table 1, which demonstrate that BCNet outperforms state-of-the-art methods in terms of AR@AN with AN varying from 50 to 1000. For the temporal action detection task, the proposed BCNet also achieves superior results, as shown in Table 2. The performance of our method exceeds state-of-the-art proposal generation methods by a big margin at different tIoU thresholds. Specially, BCNet based on TSN feature reaches an mAP of 51.6% at IoU 0.5. Besides, the performance of BCNet can be further boosted when it is combined with proposal post-processing methods: P-GCN (Zeng et al. 2019) and MUSES (Liu et al. 2021a). Now BCNet reaches 60.0% at IoU 0.5, outperforming all the other methods. This signifies the advantage of BCNet proposals regardless of post-processing.

**Results on ActivityNet-v1.3.** In Table 3 and Table 4, we compare the proposed BCNet with other methods on ActivityNet-v1.3, in terms of mAP (%) at different tIoU thresholds and the average mAP.
Method w/ BC 0.3 0.4 0.5 0.6 0.7
BMN* ✓ 62.5 (↑3.0) 56.3 (↑2.0) 47.6 (↑2.5) 37.2 (↑1.9) 26.3 (↑1.5)
BMN* ✓ 65.0 (↑2.1) 54.1 (↑2.0) 45.7 (↑2.2) 35.1 (↑1.8) 24.5 (↑1.3)
GTAD* ✓ 63.2 58.7 51.2 39.9 28.3
GTAD* ✓ 66.5 (↑3.3) 60.0 (↑1.3) 51.6 (↑0.4) 41.0 (↑1.1) 29.2 (↑0.9)

Table 5: The effectiveness of the Background Constraint (BC). * indicates our implementation with the publicly available code.

4.4 Ablation Study

In this section, we conduct ablation studies on THUMOS14 to verify the effectiveness of each component in BCNet.

Multi-level ABI module. We perform ablation studies to verify the effectiveness of multi-level interaction in ABI module. Frame-level interaction is designed to generate features of action and background. Here, the ablation experiment demonstrates the necessity of frame-level interaction as shown in Table 6. Compared with single-level ABI module that only has a clip-level interaction, multi-level ABI module is improved by 3.6% at tIoU 0.3.

| Frame | Clip | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 |
|-------|------|-----|-----|-----|-----|-----|
| -     | ✓    | 62.9 | 57.9 | 49.6 | 40.4 | 28.6 |
| ✓     | ✓    | 66.5 | 60.0 | 51.6 | 41.0 | 29.2 |

Table 6: The effect of ABCNet in frame-level and clip-level.

The effectiveness of Background Constraint. We perform ablation studies to verify the effectiveness of the background constraint idea. To validate the generalizability of our proposed background constraint idea, we add it to the BMN, GTAD. The experimental results are shown in Table 5 which reveals that background constraint can also significantly improve the performance of existed methods.

Architecture of ABI module. We perform ablation studies to verify the effectiveness of the architecture of ABI module. To generate reliable confidence of proposal, ABI module is designed by exploiting rich information of action and background. Our proposed ABI module consists of two key units: self-attention unit and difference-attention unit. Results are shown in Table 2. The self-attention unit can improve the performance by a large margin (almost 4.5%) at tIoU 0.5. Difference-attention unit also brings significant improvement at tIoU 0.3, as the inconsistency of action and background is captured between action and background.

| Self | Diff | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 |
|------|------|-----|-----|-----|-----|-----|
| ✓    | -    | 69.3 | 55.8 | 46.7 | 36.6 | 25.2 |
| ✓    | ✓    | 66.5 | 60.0 | 51.6 | 41.0 | 29.2 |

Table 7: The effectiveness of ABI module.

4.5 Analysis on runtime.

To verify the efficiency of our BCNet, we report the latency of our method on THUMOS14. For the fair comparisons with other models, we measure the latency under the same environment (a single NVIDIA 2080Ti GPU). We use a batch size of 1 to measure the latency on the full testing set and report the average time. As shown in Table 8, our BCNet achieve the best mAP with smallest latency (141ms v.s. 298ms, 330ms). The main reason is that our model generates fewer proposals than these methods, which helps our model run faster.

| Method | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | Latency |
|--------|-----|-----|-----|-----|-----|---------|
| BMN    | 56.0 | 47.4 | 38.8 | 29.7 | 20.5 | 330ms   |
| GTAD   | 54.5 | 47.6 | 40.2 | 30.8 | 23.4 | 298ms   |
| Ours   | 66.5 | 60.0 | 51.6 | 41.0 | 29.2 | 141ms   |

Table 8: Quantitatively analysis on latency. The smaller latency represent higher efficiency.

5 Conclusion

In this paper, we introduce a Background Constraint concept, which can be integrated easily with existing TAPG method. Based on this concept, we propose a Background Constraint Network, which consists of multiple attention units i.e., self-attention unit, cross-attention unit, and difference-attention unit, and generates high-quality proposals by exploiting inconsistency between action and background. Extensive experiments show that our model achieves new state-of-the-art performance in temporal action proposal generation and action detection on THUMOS14 and ActivityNet1.3 datasets.
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