**Cross-modal Consensus Network for Weakly Supervised Temporal Action Localization**

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**ABSTRACT**

Weakly supervised temporal action localization (WS-TAL) is a challenging task that aims to localize action instances in the given video with video-level categorical supervision. Previous works use the appearance and motion features extracted from pre-trained feature encoder directly, e.g., feature concatenation or score-level fusion. In this work, we argue that the features extracted from the pre-trained extractors, e.g., I3D, which are trained for trimmed video action classification, but not specific for WS-TAL task, leading to inevitable redundancy and sub-optimization. Therefore, the feature re-calibration is needed for reducing the task-irrelevant information redundancy. Here, we propose a cross-modal consensus network (CO2-Net) to tackle this problem. In CO2-Net, we mainly introduce two identical proposed cross-modal consensus modules (CCM) that design a cross-modal attention mechanism to filter out the task-irrelevant redundant information using the global information from the main modality and the cross-modal local information from the auxiliary modality. Moreover, we further explore inter-modality consistency, where we treat the attention weights derived from each CCM as the pseudo targets of the attention weights derived from another CCM to maintain the consistency between the predictions derived from two CCMs, forming a mutual learning manner. Finally, we conduct extensive experiments on two commonly used temporal action localization datasets, THUMOS14 and ActivityNet1.2, to verify our method, which we achieve the state-of-the-art results. The experimental results show that our proposed cross-modal consensus module can produce more representative features for temporal action localization.

**CCS CONCEPTS**

- Computing methodologies → Activity recognition and understanding

**KEYWORDS**

Weakly supervised learning, Temporal action localization, Feature re-calibration, Mutual learning

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1 INTRODUCTION

Temporal action localization is a task to localize the start and end timestamps of action instances and recognize their categories. In recent years, many works [30, 51, 52, 54] put effort into the fully
supervised manner and gain great achievements. However, these fully supervised methods require extensive manual frame/snippet level annotations. To address this problem, many weakly supervised temporal action localization (WS-TAL) methods [13, 14, 25, 38, 50] are proposed to explore an efficient way to detect the action instances in the given videos with only video-level supervision which is more easily obtained by the annotator.

As other weakly supervised video understanding tasks like video anomaly detection [8, 40] and video highlight detection [10], most existing WS-TAL methods develop their framework based on the multiple-instance learning (MIL) manner [13, 19, 20, 23, 50]. These methods firstly predict the categorical probabilities for each snippet and then aggregate them as the video-level prediction. Finally, they perform the optimization procedure using the given video-level labels. Among them, some works [19, 23, 32, 50] introduce an attention module to improve the ability to recognize the foreground by suppressing the background parts. For action completeness modeling, Islam et al. [12] utilize an attention module to drop the most discriminative parts of the video but focus on the less discriminative ones. With regards to feature learning, most of WS-TAL methods [13, 35] mainly apply a contrastive learning loss for each snippet and then aggregate them as the video-level prediction. Intuitively, they perform the optimization procedure using the given video-level labels.

The aforementioned methods use the original extracted features that contain the task-irrelevant information redundancy [8, 21, 43, 44] to produce predictions directly for each snippet. However, as the features extracted from trained for another task, i.e., trimmed video action classification, which introduces redundancy inevitably, their performances are restricted to the quality of extracted features and only acquire sub-optimization [8, 21]. Intuitively, performing feature re-calibration for task-specific features is a way to tackle this problem. Instead of finetuning the feature extractor [2, 8, 48] with high time and computation cost, we explore to re-calibrate the features in a more efficient manner. In this work, our intuition is simple: the RGB and FLOW features contain modality-specific information (i.e., appearance and motion information) from different perspectives of the given data. Therefore, we can filter out the redundancy contained in a certain modality with the help of global context information from itself and the local context information from different perspectives of different modalities (Figure 1).

As discussed above, the inconsistency between pre-trained task with the target one leads to inevitable task-irrelevant information in the extracted features denoted as redundancy, which restricts the optimization, especially under weak supervision. Previous works pay less attention to this problem but use the features directly. Here, we aim to re-calibrate the features in the very beginning by leveraging information from two different modalities (i.e., RGB and FLOW features). In this work, we develop a Cross-modal Consensus NETwork (CO\textsubscript{2}-Net) to re-calibrate the representations of each modality for each snippet in the video. CO\textsubscript{2}-Net contains two identical cross-modal consensus modules (CCM). Specifically, two types of modal features are fed into both CCMs, one of them acts as the main modality and the other one serves as the auxiliary modality. In CCM, we obtain the modality-specific global context information from the main modality and the cross-modal localized focused descriptor from the auxiliary modality. Then we aggregate them to produce a channel-wise descriptor that can be used to filter out the task-irrelevant information redundancy. Intuitively, with the global information of the main modality, CCM can use the information from different perspectives of the auxiliary modality to determine whether a certain part of the main modality is task-irrelevant information redundancy. Thus we obtain the RGB-enhanced features and FLOW-enhanced features from two CCMs after filtering the redundancy in original RGB features and FLOW features, respectively. Then we utilize these two enhanced features to estimate the modality-specific attention weights, respectively, and apply mutual learning loss on these two estimated attention weights for mutual promotion. In addition, we also apply the top-k multiple-instance learning loss [13, 20, 35] that is widely used to learn the temporal class activation map (T-CAM) for each video.

Finally, we conduct extensive experiments on two public temporal action localization benchmarks, i.e., THUMOS14 dataset [15] and Activity1.2 dataset [7]. In our experiments, we investigate and discuss the effect of our proposed cross-modal consensus module with other feature fusion manners (e.g., additive and concatenate function). The experimental results show that our CO\textsubscript{2}-Net achieves the state-of-the-art performance on two public datasets, which verify its efficacy for temporal action localization. To summarize, our contribution is three-fold:

- As far as we know, it is the first work to investigate multi-modal feature re-calibration and modal-wise consistency via mutual learning for temporal action localization.
- We propose a framework, i.e., CO\textsubscript{2}-Net, for temporal action localization to explore a novel cross-modal attention mechanism to re-calibrate the representation for each modality.
- We conduct extensive experiments on two public benchmarks, where our proposed method achieves the state-of-the-art results.

2 RELATED WORKS

Weakly Supervised Temporal Action Localization. Weakly supervised temporal action localization provides an efficient way to detect the action instances without overload annotations. Many works mainly tackle this problem using the multiple-instance learning (MIL) framework [12, 13, 19, 20, 24, 25, 32]. Several works [13, 35] mainly aggregate snippet-level class scores to produce video-level predictions and learn from video-level action labels. In this formulation, background frames are forced to be mis-classified as action classes to predict video-level labels accurately. To address such a problem, many works [12, 19] apply an attention module in their framework to suppress the activation of background frames to improve localization performance. Lee et al. [19] introduces an auxiliary class for background and proposes a two-branch weight-sharing architecture with an asymmetrical training strategy. Besides, MIL-based methods only focus on optimizing the most discriminative snippets in the video [5, 8]. For action completeness modeling, some works [12, 27] adopt the complementary learning scheme that drops the most discriminative parts of the video but focuses on the complementary parts. Also, several works [33, 52] attempt to optimize their framework under a self-training regime.
In this work, instead of feature extractor finetuning, we attempt to filter out the task-irrelevant redundancy from the specific modality via a novel re-calibration way, which we make a consensus between the global context from itself and the local context information from another modality, while the aforementioned works treat the multiple modalities information equally.

3 METHOD

Video is a typical type of multimedia that can be translated into multiple modalities that represent the information from different perspectives of different modalities.

3.1 Problem Formulation

We first formulate the WS-TAL problem as follows: suppose \( V \) denotes a batch of data with \(|V|\) videos and corresponding video-level categorical labels \( \mathcal{Y} \), where \( \mathcal{Y} = \{y^{(1)}, ..., y^{(|V|)}\} \) and \( y^{(i)} = \{y_1^{(i)}, ..., y_C^{(i)}\} = \{0, 1\}^C \) for \( i \)-th video, where \( C \) means the number of category. The goal of WS-TAL is to learn a function that simultaneously detects and classifies all action instances temporally with precise timestamps as \((t_s, t_e, c, y)\) for each video, where \( t_s, t_e, c, y \) denote the start time, the end time, the predicted category and the confidence score for corresponding action proposal, respectively.

3.2 Pipeline

Feature Extraction. Following recent WS-TAL methods [12, 35], we construct CO2-Net upon snippet-level feature sequences extracted from non-overlapping video volumes, where each volume contains 16 frames. The features for appearance modality (RGB) ...
and motion modality (optical flows) are both extracted from pretrained extractors, i.e., I3D [3]. The features for appearance and motion modality are 1024-dimension for each snippet. For i-th video with T snippets, we use matrix tensors \(X_{RGB} \in \mathbb{R}^{T \times D}\) and \(X_{FLOW} \in \mathbb{R}^{T \times D}\) to represent the RGB and FLOW features of the whole video, respectively, where D means the dimension of the feature vector.

**Structure Overview.** Figure 2 shows the whole pipeline of our proposed CO2-Net. Both RGB and FLOW features are fed in two identical cross-modal consensus modules. In each CCM, we select one of the two modalities as the main modality that will be enhanced by removing the task-irrelevant information redundancy with the help of the global context of itself and cross-modal local-focused information from another (auxiliary) modality. Thus we can obtain the more task-specific representation for each modality. Then, the enhanced representation is utilized to produce attention weights that indicate the probabilities of each snippet being foreground through an attention unit that consists of two convolution layers. We aggregate two attention weights generated by enhanced features from two CCMs respectively to produce final attention weights that can be used in the testing stage. And we also fuse the two enhanced features and feed them into a classifier to predict the categorical probabilities for each snippet.

### 3.3 Cross-modal Consensus Module

In this work, we employ a cross-modal consensus module to filter out the task-irrelevant information redundancy for each modality before the process of downstream learning task. The proposed cross-modal consensus module is constructed by a global-context-aware unit and a cross-modal-aware unit to distinguish the information redundancy and filter out them via a channel-wise suppression on the features. As shown in Figure 3, we treat the appearance modality (RGB features) as the main modality and the motion modality (FLOW features) as the auxiliary to feed in our proposed cross-modal consensus module, while the same workflow is performed when the roles of the two modality are exchanged. For the convenience of expression, we take RGB features as the main modality features as an example in the rest of the article.

As the features are extracted from a encoder that pretrained on some large datasets not related to WS-TAL task, thus the features may contain some task-irrelevant misleading redundancy that restricts the localization performance. Given the main modality and the auxiliary modality, instead of directly concatenating them, we aim to design a mechanism to filter out the task-irrelevant information redundancy in the main modality. Motivated by the self-attention mechanism [42] and squeeze-and-excitation block [11], we develop a similar manner, named cross-modal attention mechanism, to distinguish the information redundancy and filter out them.

In the global-context-aware unit, we first squeeze modality-specific global context information into a video-level feature \(X_g \in \mathbb{R}^L\), which is aggregated from the main modality \(X_{RGB}\), using an average pooling operator \(\psi(\cdot)\) on temporal dimension. Then, we adopt a convolution layer \(F_G^G\) to fully capture channel-wise dependencies and produce modality-specific global-aware descriptor \(M_G^G\). The process is formulated below:

\[
\begin{align*}
X_g &= \psi(X_{RGB}), \\
M_G^G &= F_G^G(X_g).
\end{align*}
\]  

(1)

As multiple modalities provide information from different perspectives, we can leverage the information from the auxiliary modality to detect the task-irrelevant information redundancy in the main modality. Thus, in the cross-modal-aware unit, we aim to capture the cross-modal local-specific information from the auxiliary modality features \(X_{FLOW}\). Here, we introduce a convolution layer \(F_L^L\) that embed the features of the auxiliary modality to produce a cross-modal local-focused descriptor \(M_L^L\) as follows:

\[
M_L^L = F_L^L(X_{FLOW}).
\]  

(2)

Here, we obtain channel-wise descriptor \(M\) for feature re-calibration by multiplying modality-specific global-aware descriptor \(M_G^G\) with cross-modal local-focused descriptor \(M_L^L\). Finally, the task-irrelevant information redundancy is filtered out via a cross-modal attention mechanism as follows:

\[
M = M_G^G \otimes M_L^L, \\
\overline{X}_{RGB} = \sigma(M) \otimes X_{RGB},
\]  

(3)

where \(\sigma(\cdot)\) is a Sigmoid function, while the “\(\otimes\)" means element-wise multiplication operator. Remarkably, \(M_G^G\) and \(M_L^L\) can be treated as “Query” and “Key” in the self-attention module [42]. Instead of using a softmax operator, we apply a Sigmoid function to produce channel-wise re-calibration weights to enhance the original main modality features \(X_{RGB}\).

### 3.4 Dual Modal-specific Attention Units

After obtaining the enhanced features, we attempt to produce modality-specific temporal attention weights that indicate the snippet-level probabilities of being foreground. Here, following...
previous works [12, 19], we feed the enhanced features into the attention unit $F^A_{RGB}$ for modality-specific attention weights:

$$A_{RGB} = F^A_{RGB}(\overline{X}_{RGB}).$$

(4)

where $F^A_{RGB}(\cdot)$ is the attention unit for RGB with three convolution layers, which is same with the attention unit for FLOW $F^A_{FLOW}$.

As we have two CCMs in the proposed CO2-Net, we obtain the RGB-enhanced features $\overline{X}_{RGB}$ and modality-specific attention weights $A_{RGB}$ from one CCM that treats the appearance modality as the main modality and motion modality as the auxiliary modality, while we also gain the FLOW-enhanced features $\overline{X}_{FLOW}$ and modality-specific attention weights $A_{FLOW}$ from another CCM, in which the roles of two modalities are opposite to the former CCM.

After obtaining the enhanced features (i.e., $\overline{X}_{RGB}$ and $\overline{X}_{FLOW}$) and modality-specific attention weights (i.e., $A_{RGB}$ and $A_{FLOW}$). We first fuse two attention weights:

$$A = \frac{A_{RGB} + A_{FLOW}}{2}.$$  

(5)

We think that the two modality-specific attention weights produced by two enhanced features respectively have different emphasis on the video, while the fused attention weights $A$ can better represent the probability of snippet being foreground because it made a trade-off between the two modality-specific attention weights. Finally, We concatenate two types of enhanced features, i.e., $\overline{X}_{RGB}$ and $\overline{X}_{FLOW}$, to form $\overline{X}$ and feed it into a classifier that contains three convolution layers to produce the temporal class activation map (T-CAM) $S \in \mathbb{R}^{T \times (C+1)}$ for the given video, where the $(C+1)$-th class is the background class.

3.5 Optimizing Process

Constraints on Attention Weights. Here, we have obtained two modality-specific attention weights (i.e., $A_{RGB}$ and $A_{FLOW}$) and a fused attention weights $A$. Then we first apply mutual learning scheme on two modality-specific attention weights:

$$L_{ml} = \alpha \delta(A_{RGB}, \phi(A_{FLOW})) + (1 - \alpha) \delta(A_{FLOW}, \phi(A_{RGB})).$$

(6)

where $\phi(\cdot)$ represents a function that truncates the gradient of input, while $\delta(\cdot)$ means a similarity metric function and $\alpha$ is a hyperparameter. In Eq. 6, we treat $A_{RGB}$ and $A_{FLOW}$ as pseudo-labels of each other (as shown in Figure 4), so that they can learn from each other and align the attention weights. Here, we adopt mean square error (MSE) as function $\delta(\cdot)$ in Eq. 6. Besides MSE, we also discuss others similarity metric functions (i.e., Jensen-Shannon (JS) divergence, Kullback-Leibler (KL) divergence and mean absolute error (MAE)) that is applied in Eq. 6 in Section 4.4. In addition, we can find that the distribution of attention weights should be opposite to the probability distribution of the background class in $S$:

$$L_{oppo} = \frac{1}{3} (||A_{RGB} + s_{c+1} - 1|| + |A_{FLOW} + s_{c+1} - 1|| + |A + s_{c+1} - 1||),$$

(7)

where $|\cdot|$ is an absolute value function, and $s_{c+1}$ is the last column in the T-CAM $S$ that represents the probabilities of each snippet being background. And we also utilize a normalization loss $L_{norm}$ to make the attention weights more polarized:

$$L_{norm} = \frac{1}{3} (||A_{RGB}||_1 + ||A_{FLOW}||_1 + ||A||_1),$$  

(8)

where $||\cdot||_1$ is a L1-norm function.

Constrains on T-CAMs and Features. In order to better recognize the background activity, we apply the attention weights $A$ to suppress the background snippets in T-CAM $S$ and obtain suppressed T-CAM $\overline{S}$:

$$\overline{S} = A \otimes S.$$  

(9)

In this work, we apply the widely used top-k multiple-instance learning loss [35] on T-CAM $S$ and $\overline{S}$, denoted as $L_{mil} = L_{mil}^{org} + L_{mil}^{sup}$. Also, we apply the co-activity similarity loss $L_{cas}$ [35] on fused features $\overline{X}$ and suppressed T-CAM $\overline{S}$ to learn better representations and T-CAM. Because we utilize the suppressed T-CAM in the testing stage in Section 3.6, we only apply $L_{cas}$ on suppressed T-CAM.

Final Objective Function. Finally, we aggregate all aforementioned objective functions to form the final objective function for whole framework optimization:

$$L = L_{mil} + L_{cas} + L_{mil}^{sup} + \lambda_1 L_{oppo} + \lambda_2 L_{norm},$$

(10)

where $\lambda_1$ and $\lambda_2$ are hyperparameters. Our framework can learn more robust representation to produce more accurate T-CAM by optimizing that final objective function.

3.6 Temporal Action Localization

At the testing stage, we follow the process of [12]. Firstly, we calculate the video-level categorical probabilities that indicate the possibility of each action class happened in the given video. Then we set a threshold $r$ to determine the action classes that would be localized in the video. For the selected action class, we threshold the attention weights $A$ to drop the background snippets and obtain the class-agnostic action proposals by selecting the continuous components of the remaining snippets. As we said in Section 3.1, a

Both the top-k multiple-instance learning loss and co-activity similarity are widely used in current WS-TAL methods. They are not the main contributions in this work, so that we do not detail them in our paper. More details of them can refer to [35].
candidate action proposal is a four-tuple: \((t_i, t_e, c, \gamma)\). After obtaining the action proposals, we utilize the suppressed T-CAM \(\mathcal{S}\) to calculate the class-specific score \(\gamma\) for each proposal using Outer-Inter Score [38]. Moreover, we use multiple thresholds to threshold the attention weights to enrich the proposal set with proposals in different levels of scale. Further, we remove the overlapping proposals using soft non-maximum suppression.

## 4 EXPERIMENTS

In this section, we conduct extensive experiments on two public temporal action localization benchmarks, i.e., THUMOS14 [15] and ActivityNet1.2 dataset [7], to investigate the effectiveness of our proposed framework. In addition, we conduct ablation studies to discuss each component in \(\text{CO}_2\)-Net and visualize some results.

### 4.1 Datasets and Metrics

We evaluate our proposed approach on two public benchmark datasets, i.e., THUMOS14 dataset [15] and ActivityNet1.2 dataset [7], for temporal action localization. THUMOS14. There are 200 validation videos and 213 test videos of 20 action classes in THUMOS14 dataset. These videos have diverse length and those actions frequently occur in the videos. Following the previous works [12, 35], we use 200 validation videos to train our framework and 213 test videos for testing. ActivityNet1.2. ActivityNet1.2 dataset is a large temporal action localization dataset with coarser annotations. It is composed of 4,819 training videos, 2,383 validation videos and 2,489 test videos of 20 action classes. We cannot obtain the ground-truth annotations for the test video, because they are withheld for the challenge. Therefore, we utilize validation videos for testing [12, 13].

**Evaluation Metrics.** In this work, we evaluate our method with mean average precision (mAP) under several different intersections of union (IoU) thresholds, which are the standard evaluation metrics for temporal action localization [35]. Moreover, we utilize the official released evaluation code\(^3\) to measure our results.

### 4.2 Implementation Details

In this work, we implement our method in PyTorch [34]. In the very beginning, we apply I3D networks [3] pretrained on Kinetics-400 [17] to extract both RGB and FLOW features for each video, following previous work [13, 35]. We sample continuous non-overlapping 16 frames from video as a snippet, where the features for each modal of each snippet are 1024-dimension. In the training stage, we randomly sample 500 snippets for THUMOS14 dataset and 60 snippets for ActivityNet1.2 dataset, while all snippets are taken during testing. For fair comparisons, we do not finetune the feature extractor, i.e., I3D. The attention unit is constructed with 3 convolution layers, whose output dimensions are 512, 512 and 1 while the kernel sizes are 3, 3 and 1. The classification module contains 3 temporal convolution layers. Between each convolution layer, we use Dropout regularization with possibility as 0.7.

For each hyperparameters, we set \(\lambda_1 = \lambda_2 = 0.8\) for the last two terms of regularization in the final objective function, \(\beta\), to obtain the best performance for both two datasets. In the training process, we sample 10 videos in a batch, in which there are 3 pairs of videos and each pair contains the same categorical tags for co-activity similarity loss \(\mathcal{L}_\text{cas}\). We deploy Adam optimizer [18] for optimizing, in which the learning rate is 5e-5 and weight decay rate is 0.001 for THUMOS14, while 3e-5 and 5e-4 for ActivityNet1.2 dataset. All experiments are run on a single NVIDIA GTX TITAN (Pascal) GPU.

### 4.3 Comparison With State-of-the-art Methods

We first compare our proposed \(\text{CO}_2\)-Net with current weakly supervised state-of-the-art methods and several fully supervised methods. We report the results in Table 1 and Table 2. From Table 1, we can find that our method outperforms all weakly supervised methods in all IoU metrics on the THUMOS14 dataset, while even comparable with fully supervised methods at low IoU region. Compared with those native early fusion methods (e.g., HAM-Net [12] and UM [20]) and late fusion methods (e.g., TSCN [52]), our method gains a significant improvement. For example, The results on “AVG mAP (0.1:0.7)” of \(\text{CO}_2\)-Net vs. that of UM is 44.6% vs. 41.9%. These results show that using the information from different modalities to reduce the task-irrelevant information redundancy can benefit the temporal action localization. In addition to this, we also compare our method with several fully supervised, we can find that the results produced by our \(\text{CO}_2\)-Net are even comparable with those fully supervised methods in terms of metrics with low IoU, i.e., mAP@IoU0.1 and mAP@IoU0.2. Moreover, our method even outperforms some fully supervised methods, e.g., S-CNN [59] and BSN [22]. These results validate the effectiveness of our proposed method.

With regard to the results of ActivityNet1.2 dataset reported in Table 2, we can find that our method is still better than the current SOTA methods on the whole. However, We cannot obtain the same improvement on ActivityNet1.2 dataset as it we do in the THUMOS14 dataset, because ActivityNet1.2 dataset has only 5 action instances per video, compared with THUMOS14 dataset which has around 15 action instances per video. Additionally, we find that the annotations of ActivityNet1.2 are coarser than those in THUMOS14 dataset. Taking all these into account, we recognize that the THUMOS14 dataset is more suitable for temporal action localization task than ActivityNet1.2 dataset (as discussed in [13]). Therefore, we mainly use the former to verify our method in the following.

### 4.4 Ablation study

In this work, we propose a cross-modal consensus module to re-calibrate the representations and produce the enhanced features, and a mutual learning loss to enable two CCMs can learn from each other. Also, our final objective function consists of several components. Here, we first conduct the ablation studies to investigate the effect of each object functions. Then we discuss different kinds of combination of main and auxiliary modalities in the cross-modal consensus module. Finally, we also illustrate the results of different multi-modal fusion methods as well as SE-attention [11] that replace the CCM in \(\text{CO}_2\)-Net to verify the effectiveness of CCM.

**Effect of each component of final objective function.** Each component in the final objective function (Eq. 10) performs important role in our framework to help to learn the feature representations and final predictions. To verify the effectiveness of each

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\(^3\)http://github.com/activitynet/ActivityNet
Table 1: Comparisons of CO₂-Net with other methods on the THUMOS14 dataset. AVG is the average mAP under multiple thresholds, namely, 0.1:0.5:0.1, 0.1:0.7:0.1 and 0.1:0.9:0.1; while † means additional information is adopted in this method, such as action frequency or human pose. * indicates that the results are obtained by contacting the corresponding authors via email.

Table 2: Comparison of our algorithm with other methods on the ActivityNet1.2 dataset. AVG means average mAP from IoU 0.5 to 0.95 with 0.05 increment.

Table 3: Ablation studies of our algorithm in term of average mAP under multiple IoU thresholds as {0.1:0.7:0.1}.

Table 4: Ablation studies of different types of mutual learning loss in term of average mAP under multiple IoU thresholds from 0.1 to 0.7 with interval as 0.1.
Table 5: Comparisons of different kinds of combination for the main modality and the auxiliary modality in our cross-modal consensus module. “Global” means that a convolution layer after global pooling is adopted to capture modality-specific global context, while “Local” means a convolution layer without global pooling but local-focused.

| Method     | mAP@IoU | AVG |
|------------|---------|-----|
|            | 0.1     | 0.3 | 0.5 | 0.7 |
| Local Local| 68.1    | 52.6| 36.3| 13.2| 43.0 |
| Local Global| 70.0   | 54.1| 37.5| 12.3| 44.0 |
| Global Local| 70.1    | 54.5| 38.3| 13.4| 44.6 |

Table 6: Comparisons with other multi-modal early fusion methods (i.e., addition and concatenation), SSMA [41] and SE-attention [11] in CO2-Net in term of average mAP under multiple IoU thresholds [0.1:0.7:0.1].

| Method                      | Avg mAP | Add | Concat | SSMA [41] | SE [11] | CCM |
|-----------------------------|---------|-----|--------|-----------|---------|-----|
|                            | 39.9    | 39.5| 38.0   | 43.0      | 44.6    |

Figure 5: The illustration of the action localization results predicted by our full method and several variant methods on several video samples. Action proposals are represented by green boxes. The horizontal and vertical axes are time and intensity of attention, respectively. The method “Ours + CCM” means our full method CO2-Net.

In this work, we explore feature re-calibration for action localization to reduce the redundancy. A cross-modal consensus network is proposed to tackle this problem. We utilize a cross-modal consensus module to filter out the information redundancy in the main modality with the help of information from different perspectives of the auxiliary modality. Also, we apply a mutual learning loss to enable two cross-modal consensus modules to learn from each other for mutual promotion. Finally, we conduct extensive experiments to verify the effectiveness of our CO2-Net and the results on ablation studies show that our proposed cross-modal consensus module can help to produce more representative features that would boost the performance of WS-TAL.

5 CONCLUSION

In this work, we explore feature re-calibration for action localization to reduce the redundancy. A cross-modal consensus network is proposed to tackle this problem. We utilize a cross-modal consensus module to filter out the information redundancy in the main modality with the help of information from different perspectives of the auxiliary modality. Also, we apply a mutual learning loss to enable two cross-modal consensus modules to learn from each other for mutual promotion. Finally, we conduct extensive experiments to verify the effectiveness of our CO2-Net and the results on ablation studies show that our proposed cross-modal consensus module can help to produce more representative features that would boost the performance of WS-TAL.

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