A Video Summarization Method Using Temporal Interest Detection and Key Frame Prediction

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Abstract—In this paper, a Video Summarization Method using Temporal Interest Detection and Key Frame Prediction is proposed for supervised video summarization, where video summarization is formulated as a combination of sequence labeling and temporal interest detection problem. In our method, we firstly built a flexible universal network frame to simultaneously predicts frame-level importance scores and temporal interest segments, and then combine the two components with different weights to achieve a more detailed video summarization. Extensive experiments and analysis on two benchmark datasets prove the effectiveness of our method. Specifically, compared with other state-of-the-art methods, its performance is increased by at least 2.6% and 4.2% on TVSum and SumMe respectively.

Index Terms—Video summarization, universal network frame, temporal interest detection, sequence labeling

I. INTRODUCTION

With the rapid development of the mobile networks, the self-media era has come and results in massive video data. Hence the computer vision technology that can efficiently browse and watch videos is urgently required [1][2].

A good video summary will concisely describe the original video on the basis of time consistency and integrity constraints, distill its important events into a short viewable summary, and remove redundant information as much as possible within the restricted time ratio [3][4].

In the past few years, video summarization has received more and more attention [5][6][7]. The current work explores the supervised learning method of video summarization [8][9][10][11]. These methods use training data composed of ground-truth labels manually generated with human preferences. Supervised learning methods are often superior to unsupervised methods because they can implicitly learn human preferences.

Predicting the frame-level importance scores using different deep learning networks is now the mainstream method of video summarization [3][8][9]. The subtask of temporal consistency is merged into the prediction of the frame-level importance score. But without temporal consistency constraints, the prediction scores of video frames in the same semantic segment can’t accurately represent the importance of the corresponding segment. The temporal interest proposals strategy proposed by [4] greatly improved the shortcomings of the current methods. The interest detection framework firstly tries to solve the temporal consistency problem of video summaries through temporal interest detection.

However, this kind of interest segment detection has two disadvantages as below: (1) The evaluation form is relatively single, and all the frames in same segment are given the same importance score. (2) The importance score predicted by this method is not necessarily accurate because of the error caused by the detection. There may be unimportant frames in the interest segment because this segmental assignment method is given a higher score.

Based on the above two methods, we formulate video summarization as a combination of sequence labeling and temporal interest detection problem. Different from the existing methods, we separate the subtask of temporal consistency problem from the prediction of frame-level importance scores, and refine the importance scores of each frame under the constraints of temporal interest segments. The main innovations and contributions of our video summarization method are as follows:

(1) The video summarization is firstly formulated as a combination of sequence labeling and temporal interest detection problem.

(2) Based on our problem formulation, a universal network frame is firstly proposed to simultaneously predicts frame-level importance scores and temporal interest segments, and then combine the two components with different weights to achieve a more detailed video summarization.

(3) The convolutional sequence network, long short-term memory (LSTM) and self-attention mechanism are successfully used in our universal framework. And our general framework can be flexibly adapted to other effective models.

II. METHOD

In this section, we first introduce the problem formulation, and then elaborate our model architecture and strategies.

A. Problem Formulation

We formulate video summarization as a combination of sequence labeling and temporal interest detection problem, where the input is a sequence of video frame-level features, and the output are importance scores of interest segments with their location in video (associated center and segment length offsets) [4] and the frame-level importance scores [12] indicates the probability of the frame being selected as a key frame. Finally, we combine the frame-level importance scores and the interest
segments scores with different contribution weights to obtain the final score of each frame. Then a certain post-processing technique is used to convert the final scores into shot-level scores and generating summary video with a length budget.

B. Feature Extraction

Consider a video with $T$ frames. Each frame is preprocessed and expressed as a feature vector. We denote the frames in the video as $\{F_1, F_2, ..., F_T\}$, where $F_i$ is the feature vector of the $i$-th frame. Following [3], we uniformly down-sample the videos to 2 fps. Then we take the output of the pool5 layer in the pretrained GoogleNet [13] as the feature descriptor for each video frame. The dimension of this feature descriptor is 1024.

**Fig. 1. The architecture of the universal network frame**

C. Universal Network Frame

Fig. 1 shows the overall architecture of our universal network frame. The temporal feature sequence was fed into the base model, self-attention mechanism [4], convolutional sequence networks [8] and LSTM [3] in this paper, to capture and extract long-range representations. There is an optional process that is using the summation over the long-range representation and original spatial feature as final representation. We then exploit a temporal pooling layer to pool long-range features and final representation was fed into fully connected layers that defined as the decoder to predicts the frame-level importance scores. DP-LSTM, using LSTM [3] as base model, has same architecture as DP-Attention, what’s different is that we use long-range representations only as the final representation.

**Based on the general framework, temporal interest detection and key frame prediction with self-attention mechanism (DP-Attention), LSTM (DP-LSTM) and convolutional sequence networks (DP-CSN) were developed to verify the effectiveness of our method.**

Specifically, For DP-Attention, the base model was verified as self-attention model [4][9], using the summation over the long-range representation and original spatial features as the final representation. The combination of the multi temporal scaled pooling features and final representation was fed into fully connected layers that defined as the decoder to predicts the frame-level importance scores. DP-LSTM, using LSTM [3] as base model, has same architecture as DP-Attention, what’s different is that we use long-range representations only as the final representation.

**For DP-CSN, Fig. 3 shows the detailed components. The fully convolutional encoder applies 1D convolution on the temporal sequence, the first two convolutional layers (conv1 and conv2) consist of multiple temporal convolution layers where each temporal convolution is followed by a batch normalization and a ReLU activation. We add a temporal**
maxpooling next to each convolution layer, which means the features’ temporal length output from conv2 becomes 1/4 of the original feature temporal length after two maxpooling operations. Each of conv3 and conv4 consists of a 1×1 temporal convolution, followed by ReLU and dropout.

The temporal shortened multi scale pooling features and long-ranged features are mapped into original temporal length after deconvolution operation by deconv1. Then the two sorts of features were fed to classification and regression module and deconv2 respectively for prediction.

Following [4] we adopt the temporal interest proposals generation strategy for the universal network frame, which provide a dense sampling of temporal interest proposals with pre-defined multi-scale intervals that accommodate interest variations in length.

To balance the efficiency and effectiveness, we specify 4 proposals whose durations are 4, 8, 16, and 32 just like [4], multi temporal scale pooling has same scales as the corresponding interest proposals’ durations. What’s different is that we do multi temporal scale pooling on the output features from conv4 of DP-CSN, because the temporal length is 1/4 of the original length, which the receptive field was expanded, correspondingly, to make the proposal generation strategy to be temporally invariant, we scale the pooling size to 1/4 of the original anchor size as 1, 2, 4 and 8. Our experiments result will show that the strategy could better extract the correlation characteristics between frames, especially on SumMe dataset.

D. Learning

We adopt multi-task loss to jointly train the model. Formally, the objective function is written as follows:

\[ L_{\text{total}} = L_{\text{cls}} + \lambda_1 L_{\text{reg}} + \lambda_2 L_{\text{pre}} \]  

Where \( L_{\text{cls}} \) represents the classification loss of the predicted interest segment, \( L_{\text{reg}} \) represents the regression loss of the active interest segment, and \( L_{\text{pre}} \) represents the prediction loss of the frame-level importance score. \( \lambda_1 \) and \( \lambda_2 \) are used as a hyperparameter to balance the weights of these three loss functions to achieve the optimal effect.

Specifically, focal loss [14] is used to help more accurate detection of interesting segments, in the form:

\[ L_{\text{cls}} = -\frac{1}{N} \sum_{n=1}^{N} (1-p_n)^\gamma \log(p_n) \]  

\[ p_n = \frac{\exp(x_i(\text{class}))}{\sum_j \exp(x_j(f_j))} \]  

Where \( N \) represents the total number of predicted segments (including positive and negative segments), and \( p_n \) represents the probability that the \( n^{\text{th}} \) segment is correctly classified for the ground-truth interest segment labels, which is actually represented by the softmax function. \( \gamma \) is an hyperparameter that is artificially set, we set it to 1.

The regression loss \( L_{\text{reg}} \) is the positioning regression for the positive interest segment, and the specific form is expressed as follows:

\[ L_{\text{reg}} = \frac{1}{N_{\text{pp}}^{\gamma}} \sum_{i=1}^{N_{\text{pp}}^{\gamma}} \left( \frac{1}{Q_{\text{pp}}^{\gamma}} \sum_{q=1}^{Q_{\text{pp}}^{\gamma}} \text{smooth}_\gamma(t_q - t_q^*) \right) \]  

\[ \text{smooth}_\gamma(x) = \begin{cases} 0.5x^2 & \text{if } |x|<1, \\ |x| - 0.5 & \text{otherwise} \end{cases} \]  

The predicted location offset \( t_i = (\delta c_i, \delta l_i) \) contains center position and length offsets between generated segments and pre-defined proposals. The ground truth location offset \( t_i^* = (\delta c_i^*, \delta l_i^*) \) is computed as follows:

\[ N_{\text{pos}} \text{ represents the number of positive interest segments, } \]  

\[ t_i(t_i^*) \text{ represents the predicted (ground-truth label) } i^{\text{th}} \text{ group of positioning regression, each group contains } Q \text{ parameters. The regression loss of positioning regression is calculated by the } \text{smooth}_\gamma \text{ loss, and the expression is shown in (5)}. \]

Specifically, the predicted location offset \( t_i = (\delta c_i, \delta l_i) \) contains center position and length offsets between generated segments and pre-defined proposals. The ground truth location offset \( t_i^* = (\delta c_i^*, \delta l_i^*) \) is computed as follows:

\[ \delta c_i^* = (c_i^* - c_i)/l_i, \delta l_i^* = \ln(l_i^*/l_i) \]  

For the prediction loss of frame-level importance scores, the weighted focal loss is used because the categories of temporal important frames and non-important frames are extremely unbalanced. The specific form is as follows:

\[ L_{\text{pre}} = -\frac{1}{T} \sum_{i=1}^{T} \omega_i (1 - p_i)^\gamma \log(p_i) \]  

Where \( T \) represents the total number of temporal frames, \( \omega_i \) represents the category weight of the ground-truth classification of the \( i^{\text{th}} \) frame, \( \omega_i = \frac{\text{median-freq}}{\text{freq}_i} \), \( \text{freq}_i \) represents the number of frames with ground-truth label divided by the total number of frames in videos, and \( \text{median-freq} \) is simply the median of the computed frequencies. \( p_i \) indicates the probability that the \( i^{\text{th}} \) frame is classified with the ground-truth label, as shown in equation (3).

E. Post-Processing Strategy for Key-Shot Selection

In the testing stage, we generate the refined segments by using the predicted offsets. Following [4], we perform the non-maximum suppression (NMS) on the refined proposals to remove the redundant and low-quality segments. The output form after the execution is that each frame in corresponding temporal segment of the video is assigned an importance score. The higher the score, the greater the degree of human interest.

We combine the frame-level importance scores and the interest segment scores with different contribution weights \( \alpha \) to obtain the final more detailed frame-level prediction scores to generate the video summary. The specific form is expressed as follows:

\[ \alpha_i S_i + \alpha_1 S_i = S_{\text{f}} \quad s.t. \quad \alpha_i + \alpha_1 = 1 \]  

Where \( S_i \) represents the interest segment score of the frame, \( S_{\text{f}} \) indicates that the frame-level important score, and \( S_{\text{f}} \) is final score of the frame.

The strategy has several advantages:(1) It can refine the frame-level prediction scores on the basis of the interest detection segment; (2) The method can be used to check and balance each other and improve the robustness and stability of
the model; (3) The final score preference can be flexibly adjusted through the contribution coefficient $\alpha$.

Finally, the Kernel Time Segmentation (KTS) algorithm [15] was adopted to segment the video sequence into video shots, the shot-level importance score is calculated by averaging the final scores in the same shot as the shot-level importance score. We produce the summaries under the constraint that the total length of selected shots is no more than 15% of the original video length for a fair comparison with previous methods.

III. EXPERIMENTS

In this section, we first introduce the datasets used in the experiment and its evaluation criteria. The details and settings of the experiment will be discussed in the second section. Finally, we show and analyze the experimental results.

A. Datasets and Evaluation

We evaluate our method on two public benchmark datasets: SumMe [16] and TVSum [12]. The SumMe dataset contains 25 videos, covering various events (sports, holidays, etc.) and the length is 1.5 to 6.5 minutes. The TVSum dataset contains 50 YouTube videos in 10 different categories (making sandwiches and repairing vehicle tires, etc.). The length of the videos in this dataset is usually 1 to 5 minutes. Following previous work [16], we use 39 videos from the YouTube dataset [17] and 50 videos from the Open Video Project (OVP) dataset [17][18] to augment the training data. In the YouTube dataset, there are videos composed of news, sports, and cartoons. OVP dataset including different types of videos such as documentaries or cartoons.

We use three settings as suggested in [3][8] to evaluate our method. (1) Canonical: We use the standard 5-fold cross validation (5FCV), i.e., 80% of videos for training and the rest for testing. (2) Augmented: We still use the 5FCV but we augment the training data in each fold with OVP and YouTube. (3) Transfer: for a target dataset, e.g. SumMe or TVSum, we use the other three datasets as the training data to test the transfer ability of our model.

Following [8], to compute F-score as the metric to assess the similarity between automatic summaries and ground truth summaries. We follow the standard approach described in [16][19] to calculate the metric for videos that have multiple ground-truth summaries.

B. Experiments

In this subsection, we describe implementation details and present experimental results. Finally, the analysis was provided.

1) Implementation Details

For the settings of hyperparameters in equation (2), $\lambda_1$ is set as 1, while $\lambda_2$ is set as 2, our model is more focused on the classification loss of the frame-level importance score. The non-maximum suppression threshold is set as 0.5 for DP-Attention and DP-CSN, and 0.2 for DP-LSTM. The contribution weights for the interest segment score and the non-maximum suppression threshold is set as 0.5 for DP-classification loss of the frame-level importance score.

2) Results and Comparisons

We compared our models, DP-Attention, DP-LSTM and DP-CSN with the most advanced video summarization methods on SumMe and TVSum. These methods are divided into two categories: (1) conventional methods include Video MMR[20], Live-Light [21], ERSUM [22], MSDS-CC [23], and (2) deep learning based methods include vsLSTM [3], dppLSTM [3], SUM-GAN[24], AVS[25], SASUM [26], DR-DSN [27], TSTN [11], FCSN [8], VASNet [9] and DSNet [4]. The comparison results are shown in Table I and Table II.

It can be clearly observed from Table I that the results on canonical tests of all our models on the two basic datasets are

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### Table I

| Method                  | SumMe | TVSum | Params |
|-------------------------|-------|-------|--------|
| Video MMR [20]          | 26.6  | -     | -      |
| Live-Light [21]         | -     | 46.0  | -      |
| ERSUM [22]              | 43.1  | 59.4  | -      |
| MSDS-CC [23]            | 40.6  | 52.2  | -      |
| vsLSTM [3]              | 37.6  | 54.2  | 2.63   |
| dppLSTM [3]             | 38.6  | 54.7  | 2.63   |
| SUM-GAN [20]            | 39.1  | 51.7  | 295.86 |
| SUM-GAN [20]            | 41.7  | 56.3  | 295.86 |
| A-AVS [25]              | 43.9  | 59.4  | 4.40   |
| M-AVS [25]              | 44.4  | 61.0  | 4.40   |
| SASUM [22]              | 40.6  | 53.9  | 44.07  |
| SASUM [22]              | 45.3  | 58.2  | 44.07  |
| DR-DSN [27]             | 41.4  | 57.6  | 2.63   |
| DR-DSN [27]             | 42.1  | 58.1  | 2.63   |
| TS-STN [11]             | 46.1  | 60.0  | 16.18  |
| VASNet [9]              | 49.7  | 61.4  | 7.35   |
| FCSN [8]                | 48.8  | 58.4  | 116.49 |
| DSNet [4]               | 50.2  | 62.1  | 8.53   |
| DP-CSN (Ours)           | 52.3  | 63.2  | 79.87  |
| DP-LSTM (Ours)          | 50.6  | 63.5  | 8.53   |
| DP-Attention (Ours)     | 51.9  | 63.7  | 4.33   |

### Table II

| Methods                  | SumMe | TVSum |
|--------------------------|-------|-------|
|                          | C     | A     | T     |
|                          | C     | A     | T     |
| vsLSTM [3]               | 37.6  | 41.6  | 40.7  | 54.2 | 57.9 | 56.9 |
| dppLSTM [3]              | 38.6  | 42.9  | 41.8  | 54.7 | 59.6 | 58.7 |
| SUM-GAN [24]             | 41.7  | 43.6  | -     | 56.3 | 61.2 | -    |
| DR-DSN [27]              | 42.1  | 43.9  | 42.6  | 58.1 | 59.8 | 58.9 |
| A-AVS [25]               | 43.9  | 44.6  | -     | 59.4 | 60.8 | -    |
| M-AVS [25]               | 44.4  | 46.1  | -     | 61.0 | 61.8 | -    |
| FCSN [8]                 | 48.8  | 50.2  | 45.0  | 58.4 | 59.1 | 57.4 |
| VASNet [9]               | 49.7  | 51.1  | -     | 61.4 | 62.4 | -    |
| DSNet [4]                | 50.2  | 50.7  | 46.5  | 62.1 | 63.9 | 59.4 |
| DP-CSN (Ours)            | 52.3  | 53.6  | 46.5  | 63.2 | 63.3 | 57.6 |
| DP-LSTM (Ours)           | 50.6  | 50.8  | 46.1  | 63.5 | 63.3 | 58.9 |
| DP-Attention (Ours)      | 51.9  | 51.8  | 46.1  | 63.7 | 63.9 | 58.5 |

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The results showed that our method was able to achieve competitive performance on both datasets, particularly in the Augmented setting. Further analysis and discussion will be provided in the final section.
significantly better than other methods. Compared with the other state-of-the-art methods, the F-score on TVSum and SumMe have increased by at least 2.6% and 4.2% respectively. For Table II, it also has significant improvement in augmented and transfer tests. DP-CSN especially achieved significant effect on SumMe dataset compared with the other methods, which the effect on augmented is at least 5.9% higher than the other state-of-the-art methods. For TVSum dataset, DP-Attention achieves the best result. The transfer test are slightly lower than the best results in table, however, considering the randomness of the neural network parameter learning results, the performance is basically the same.

In addition, we choose DP-CSN as a representative model to test the diversity of our method on two datasets as shown in table III. 

C. Analysis

Through the comparison of experimental results, several key observations are summarized:

(1) We prove that our formulate strategy for video summarization is superior to other methods.

(2) Furthermore, all our models achieved significantly better performance on the two basic datasets than other state-of-the-art methods, which means the general network frame we proposed for video summarization based on our formulation strategy is effective for most mainstream deep learning models.

(3) Finally, we have reason to believe that converting other mainstream networks for video summarization into our framework can also get a certain effect.

IV. Conclusion

A video summarization method using Temporal Interest Detection and Key Frame Prediction is proposed. Unlike the existing methods, we firstly formulate the problem as a combination of sequence labeling and temporal interest detection problem and built a flexible universal network frame to simultaneously predicts frame-level importance scores and temporal interest segments, and then combine the two components with different weights to achieve a more detailed video summarization. The experimental results prove the superiority of our problem formulation and the universal validity of the general framework.

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