Visual Spatio-Temporal Relation-Enhanced Network for Cross-Modal Text-Video Retrieval

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Abstract

The task of cross-modal retrieval between texts and videos aims to understand the correspondence between vision and language. Existing studies follow a trend of measuring text-video similarity on the basis of textual and video embeddings. In common practice, video representation is constructed by feeding video frames into 2D/3D-CNN for global visual feature extraction or only learning simple semantic relations by using local-level fine-grained frame regions via graph convolutional network. However, these video representations do not fully exploit spatio-temporal relation among visual components in learning video representations, resulting in their inability to distinguish videos with the same visual components but with different relations. To solve this problem, we propose a Visual Spatio-Temporal Relation-Enhanced Network (VSR-Net), a novel cross-modal retrieval framework that considers the spatial-temporal visual relations among components to enhance global video representation in bridging text-video modalities. Specifically, visual spatio-temporal relations are encoded using a multi-layer spatio-temporal transformer to learn visual relational features. We align the global visual and fine-grained relational features with the text feature on two embedding spaces for cross-modal text-video retrieval. Extensive experimental are conducted on both MSR-VTT and MSVD datasets. The results demonstrate the effectiveness of our proposed model. We will release the code to facilitate future researches.

1. Introduction

Recent years have witnessed an exponential growth of multimedia data (e.g., video, image, and text), which increases the demands for effectively and accurately retrieving useful information across different modalities. Being one of these challenging tasks, cross-modal text-video retrieval aims to retrieve the video given a text query, which requires measuring the semantic similarity between a sentence and a video. Video data are distinct from images due to the temporal dependencies among frames and the additional dynamic relationships among objects, resulting in the inability of existing video retrieval techniques to distinguish videos with the same visual components but with different relations. Figure 1 shows such an example. Given the text query “A woman breaks the two bacon slices into pieces and lays them on the tomatoes”, the existing retrieval systems are likely to consider both (a) and (b) as positive examples, since both of them contain the same motion (“laying”) and objects (“bacon slices”, “tomatoes”) with the text query. However, example (b) is indeed a false positive, as it presents “a woman lays tomatoes on the green leaves” (with bacon slices on the kitchen table). This example suggests that ignoring the visual relations (i.e., object relations) presented in videos could lead to inaccurate retrieval results. Therefore, capturing higher-level spatio-temporal visual relations in videos is crucial to distinguish similar videos.

This paper investigates the problem of cross-modal text-
video retrieval. In the literature, many efforts have been devoted to learning better video representations, in order to improve the performance of text-video retrieval. Based on the granularity of feature representations, existing works can be roughly categorized into global and fine-grained feature-based methods. Global feature-based methods typically use global representations to represent entire video and sentence, which usually ignore local details. Such approaches work well in a simple cross-modal retrieval scenario, where only a single object is presented in the video or text query. For more realistic cases that involve complex natural scenes, the performance of these methods is usually unsatisfactory. In contrast, fine-grained feature-based methods pay attention to local details and perform matching by detecting objects in videos and texts. With fine-grained modeling, the performance of cross-modal text-video retrieval has been significantly improved. Nevertheless, the existing efforts can only capture simple visual relations by graph convolutional network (GCN) [7, 26] or utilize an attention mechanism [5, 34] as a cross-modal interaction module to delve into high-level correspondences. As GCN-based video modeling is handcrafted, it depends heavily on expert knowledge and empirical feedback, which may not be able to effectively mine and models the high-level fine-grained visual relations. Attention-based models, on the other hand, selectively align the key information presented in different modalities. As the fine-grained visual relations are also ignored by attention-based methods, the performance of these attention-based methods is still unsatisfactory.

To further improve the performance of cross-modal text-video retrieval, this paper studies this problem from the perspective of spatio-temporal relation modeling for videos. Generally, there are two major obstacles in modeling the spatio-temporal relation. First, videos contain diverse compositional objects with complex mutual interactions, and the objects/relations bear different aspects of importance when grounded with textual entities. These objects and interactions increase the difficulties in capturing higher-level fine-grained visual contents. Second, fine-grained relation modeling captures considerable fragmented information, which will overlook contextual information. Therefore, determining how to use multi-granularity visual information and complement such information in spatial and temporal dimensions to represent videos is of great importance.

To address the two problems, we propose a Visual Spatio-Temporal Relation-Enhanced Network (VSR-Net) that enhances visual representation with spatio-temporal relations among components. We present an overview of VSR-Net in Figure 2. Specifically, for videos, our VSR-Net attempts to extract two types of features — global visual features and fine-grained relational features. For global visual features, we directly adopt the widely used 2D/3D-CNN (i.e., InceptionResNetV2 [27], I3D [3]). For fine-grained relational features, we use pre-trained Faster-RCNN [22] to extract regional features (i.e., features of bounding boxes). Then, a multi-layer spatio-temporal transformer is employed for learning higher-level semantical relational features. This type of transformer separately captures fine-grained local spatial relations and long-term temporal relations among local spatial relations. To cover different levels of semantics, we align the global visual and fine-grained relational features with the text feature on two embedding spaces. Lastly, the similarity between videos and texts is measured in both embedding spaces and then summed to obtain the final similarity score. In this way, the global visual information and fine-grained relational information in a video can be utilized for cross-modal text-video retrieval.

Our contributions are summarized as below:

- We propose a novel text-video matching model called VSR-Net, which augments global video representation with fine-grained relational features and aligns the global visual and fine-grained relational features with the text feature on two embedding spaces for cross-modal text-video retrieval.
- We present a multi-layer spatio-temporal transformer module to learn higher-level fine-grained relations for visual regions and capture cross-modal semantic alignments accurately.
- We conduct extensive experiments on two standard benchmarks and verify the effectiveness of our proposed method. We have released our codes\(^1\) to facilitate further researches (the website is anonymous).

2. Related Work

2.1. Text-video Retrieval

According to the granularity of feature representations, we roughly divide existing works into two groups: global feature-based and fine-grained feature-based methods.

**Global feature-based methods** [6, 17, 20, 36] are mainly based on learning a joint embedding space where visual and textual correlations are maximized. For the video representation, they focused only on leveraging the global feature of the video. Miech et al. [17] publish a large-scale video description dataset to learn video-text representations. They find that models pretrained on HowTo100M can be successfully transferred by fine-tuning on the different datasets. Dong et al. [6] adopt three branches, i.e., mean pooling, bi-GRU, and CNN to encode sequential videos and texts and learn a hybrid common space for video-text retrieval.

\(^1\)https://https://github.com/Lionel-Hing/VSR-Net
Figure 2. The overall framework of our proposed VSR-Net. First, we extract fine-grained relational and global visual features for videos. The fine-grained relations are represented by local regional features using a multi-layer spatio-temporal transformer. The global visual features are represented by 2D-CNN and 3D-CNN features using a temporal transformer. Then, we extract textual features by BERT. Finally, both video and relational features are leveraged to align with textual features on two embedding spaces for cross-modal text-video retrieval. Among them, T-Block denotes a transformer block.

Patrick [20] present a generative objective to improve the instance discrimination limitations of contrastive learning to improve performance in text-video retrieval.

**Fine-grained feature-based methods** [5, 7, 32, 34], which utilize local semantic information from language or video and then formulate the retrieval task. Chen et al. [5] propose a hierarchical graph reasoning model, which decomposes text into events, actions, and entities, and aligns texts with videos at three levels for video-text matching. Feng et al. [7] construct fully-connected semantic correlation graphs for videos and learn semantic reasoning by using the novel random walk rule-based graph convolutional networks for video-text retrieval. Wu et al. [34] develop hierarchical alignment networks for cross-modal matching on three semantic-level (i.e., frame-word, clip-phrase, and video-sentence) representations.

Recent studies have also explored rich multimodal information (e.g., motion, audio, and speech) [8, 14, 18, 31] or large-scale dataset (e.g., HowTo100M) pre-training [15, 20, 23] to improve the performance of cross-modal retrieval. **Different from these works**, our study aims to enhance visual representation with spatio-temporal relations between components for improving the performance of cross-modal text-video retrieval. Our paradigm does not contradict pre-training or multimodal feature learning-based frameworks. Instead, both pre-training and multimodal feature learning modules can be directly integrated into our framework to further improve its performances.

### 2.2. Visual Relation Understanding

Prior efforts have shown the importance of incorporating visual relationships into video understanding and are effective in several downstream applications, such as visual relationship detection [21, 25], object recognition [30, 33], and video captioning [19, 38]. For instance, Qian [21] constructs fully connected spatial-temporal graphs for videos and proposes a novel video relation detection model to pass the message and carry out reasoning in these graphs. Wang et al. [30] propose a novel graph representation that has variant relationships between objects in a long-range video and obtains a significant gain in action recognition. Pan et al. [19] propose a spatial-temporal graph network to perform video captioning by exploiting object interactions. However, modeling object spatio-temporal relations in the video is still not thoroughly investigated. Most studies have built visual relation graphs and adopted the GCN [13] to extract visual relation graph features. Massive graph construction and graph feature extraction are hand-crafted, complex and time-consuming. Recently, the transformer [28] has shown great superiority in understanding 1, 2 and 3-dimensional signals (e.g., natural language processing and computer vision), and has strong interpretability, strong representation capabilities. Therefore, our work adopts a multi-layer spatio-temporal transformer to learn spatio-temporal relations further digging into object interactions. Notably, we validate in the experiments that under a strict memory budget, our approach can surpass many related methods.
3. Method

Figure 2 depicts our VSR-Net architecture. Our model consists of three modules: 1) video embedding learning, which involves extracting video global features; 2) relation embedding learning, which involves extracting fine-grained relational features; 3) text embedding learning, which involves extracting video global features; 2) relation embedding learning, which involves extracting fine-grained relational features; 3) text embedding learning, which involves extracting textual and video features with triplet ranking loss.

3.1. Video Embedding Learning

Given a long video clip, we sample T video frames from it with the same temporal duration between every two frames. For frame-level features, we first use 2D-CNN to extract appearance features and 3D-CNN to extract motion features. Then, we concatenate 2D and 3D features and apply a pointwise linear layer to obtain global visual features \( F_v \in \mathbb{R}^{d_v} \). Finally, we feed the result to standard multi-layer transformer block [28] and an attention-aware feature aggregation layer [9] to obtain its video embedding, which is denoted as \( F_v \in \mathbb{R}^{d_v} \).

3.2. Relation Embedding Learning

In addition to having global visual features, the proposed framework learns the relation features from the video to enhance cross-modal retrieval. The introduction of spatio-temporal relation among objects in the video equips the model with the ability to identify the fine-grained differences of video with similarity. To capture the visual relations from the video, we first adopt the pre-trained Faster RCNN [1] to detect frame-level region proposals and select the top N region proposals with the highest detection confidence to represent each frame. Prior efforts [30,33] focus on abstracting frame-level region proposals as fully connected spatial-temporal graphs and using GCN to learn relational features. However, computing all pair-wise relations across all video frames would be inefficient in creating a video as a fully connected graph. In recent years, pure transformer-based models have shown promising performance due to their strong representation capabilities. As a central piece of transformer, self-attention comes with a flexible mechanism to deal with variable-length inputs. It can be understood as a fully connected layer where the weights are dynamically generated from pairwise relations from inputs, which conveys refreshing solutions to process visual relations. Inspired by these pioneering efforts, to capture higher-level visual relations from the video, we use a multi-layer spatio-temporal transformer architecture to learn the relation embeddings. In the following, the basic components used in the transformer and the transformer used in the module are presented in detail.

Transformer Block. The Transformer consists of multi-head self-attention (MSA), multi-Layer perceptron (MLP), and layer-norm (LN). In the self-attention module, the inputs \( X \in \mathbb{R}^{n \times d} \) are linearly transformed to three parts, i.e., queries \( Q \in \mathbb{R}^{n \times d_q} \), keys \( K \in \mathbb{R}^{n \times d_k} \), and values \( V \in \mathbb{R}^{n \times d_v} \), where \( n \) is the sequence length, \( d, d_q, d_k, d_v \) are the dimensions of inputs, queries (keys) and values, respectively. The scaled dot-product attention is applied on \( Q, K, V \):

\[
\text{SA}(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V.
\]

With \( \text{SA}(Q, K, V) \), MSA is defined as:

\[
\text{MSA}(Q, K, V) = \text{Concat}(\text{head}_1, \cdots, \text{head}_M)W^O,
\]

where \( \text{head}_i = \text{SA}(QW^Q_i, KW^K_i, VW^V_i) \).

Where \( QW^Q_i, KW^K_i, VW^V_i \) are projections of different heads, \( W^O \) is another mapping function. The MLP is applied between self-attention layers for feature transformation and non-linearity:

\[
\text{MLP}(X) = \text{GELU}(XW_1 + b_1)W_2 + b_2,
\]

where \( W_1 \in \mathbb{R}^{d \times d_m} \) and \( W_2 \in \mathbb{R}^{d_m \times d} \) are weights of the two fully-connected layers respectively, \( b_1 \in \mathbb{R}^{d_m} \) and \( b_2 \in \mathbb{R}^{d} \) are the bias terms, and GELU [10] is the activation function. Layer normalization [2] is a key part in transformer for stable training and faster convergence, and LN is applied over each sample \( x \in \mathbb{R}^d \) as follows:

\[
\text{LN}(x) = \frac{x - \mu}{\eta} \odot \gamma + \beta,
\]

where \( \mu, \eta \in \mathbb{R} \) are the mean and standard deviation of the feature respectively, \( \odot \) is the element-wise dot, and \( \gamma, \beta \in \mathbb{R}^d \) are learnable affine transform parameters.

Multi-layer spatio-temporal transformer for relation embedding learning. We suppose that a set of object proposals \( Y^t = \{y^n_t\}_{n=1}^N \) are in frame \( t \), where \( y^n_t \in \mathbb{R}^{d_e} \) is the feature vector of the n-th proposal and \( N \) is the top N region proposals. We propose a multi-layer spatio-temporal transformer architecture to learn local relational information in a video. In this multi-layer spatio-temporal transformer, we have two data flows in which one flow operates across the frame and the other processes the object proposals inside each frame. We view each frame tensor \( Y^t_0 \) as a sequence of object proposal embeddings:

\[
Y^t_0 = \left[ y^{t,1}_0, \cdots, y^{t,2}_0, \cdots, y^{t,N}_0 \right].
\]

For the object proposal embeddings, to capture spatial relations among visual objects, we utilize a multi-layer transformer block to explore the interaction pattern in spatial (frame) between object proposals:

\[
Y^t_{l'} = Y^t_{l-1} + \text{MSA}\left(\text{LN}\left(Y^t_{l-1}\right)\right),
\]

where \( l \) is the layer number.
where \( l = 1, 2, \ldots, L \) is index of the \( l \)-th layer, and \( L \) is the total number of layers. The updated features after multi-layer transformer block are forwarded to an average pooling layer, which calculates the mean of all the proposal features and leads to a \( 1 \times d^e \) dimensions representation. All frame tensors after transformation are

\[
Z_0 = \left[ Y_{L}^{1''}, Y_{L}^{2''}, \ldots, Y_{L}^{L''} \right].
\]

This process builds the relationship among proposals by computing interactions between any two proposals. For the frame level, we create the object proposal embedding memories to store the sequence of frame-level representations \( Z \). Similar to the object proposal level processing, we use the standard multi-layer transformer block for transforming the frame embeddings:

\[
Z_t = Z_{t-1} + \text{MSA} \left( \text{LN} \left( Z_{t-1} \right) \right),
\]

\[
F_r = Z_t' + \text{MLP} \left( \text{LN} \left( Z_t' \right) \right).
\]

This temporal transformer block is used for modeling temporal relation among frame embeddings. Finally, we apply an attention-aware feature aggregation layer [9] to obtain the final relation embedding, denoted as \( F_r \in \mathbb{R}^{d_r} \).

### 3.3. Text Embedding Learning

For learning the contextual relations between the words in the video description sentence \( s_t \), we use a BERT language representation model to encode the word sequence, and it applies the bidirectional training of transformer [28] to language modeling. It includes 12 layers of transformer blocks. Each block has 12 attention heads, and the hidden size is 768. Here, we take the hidden state of the per-token outputs of the last 2 layers to represent the information of the entire input sentence \( F_s \in \mathbb{R}^{d_t} \). Finally, we transform each sentence representation \( F_s \in \mathbb{R}^{d_t} \) into a text embedding feature \( F_t \in \mathbb{R}^{d_t} \) by using a pointwise linear layer and an attention-aware feature aggregation layer [9].

### 3.4. Joint Embedding Learning

The purpose of joint embedding learning between video and textual features is to perform similarity comparisons. For a given video \( V_i \), the proposed framework extracts two types of embedding features — video embeddings \( F_v \) and relation embeddings \( F_r \). We calculate the similarity between videos and sentences in both embedding spaces. Specifically, for a given sentence \( T_i \), the similarity score with \( V_i \) is obtained by summing the cosine similarities between its text embedding features \( F_t \) and such two types of video embedding features, where \( 0 \leq \lambda \leq 1 \) is a hyper-parameter to balance the importance of two similarity scores. Based on the defined similarity score, we use a hinge-based triplet ranking loss to encourage the similarity score of matched video and sentence to be larger than those of mismatched ones:

\[
L_r = [\delta - S(V_i, T_i) + S(V_i, T_j)]_+ + [\delta - S(V_i, T_i) + S(V_j, T_i)]_+,
\]

where \( 0 < \delta \leq 1 \) is the margin, the operator \([x]_+ = \max(x, 0)\), and \( S(\cdot, \cdot) \) is the similarity function. \((V_i, T_i)\) represents the positive pair, while \((V_i, T_j)\) and \((V_j, T_i)\) represent the negative pairs available in the mini-batch.

### 4. Experiments

#### 4.1. Dataset

**MSR-VTT.** The dataset is constructed by [35]. It contains 10,000 unique Youtube video clips with 20 different text captions. Following the settings in [16, 35, 37], we adopt three kinds of evaluation settings. For the 1K-A test set [37], we use 7k train-val videos [17] and 9k train-val videos for training [8] and report results.

**MSVD.** The dataset is constructed by [4]. It contains 1,970 clips from YouTube. Each video clip has around 40 descriptions in multiple languages. Following previous work [29], there are 1,200 clips for validation, and 670 clips for testing.

#### 4.2. Experiment Setting

**Implementation Details.** We sample 26 video frames from it with the same temporal duration between every two frames. In our experiments, the ILSVRC-2012-CLS [24] pre-trained InceptionResNetV2 [27] is adopted to extract 1536-D 2D features and the Kinetics [11] pre-trained I3D [3] to extract 1024-D 3D features. The number \( N \) of regions within a frame is 36, identical to [1]. The dimension \( d \) of region features extracted from ResNet-101 is 2048-D. The dimensionality of video-embedding vectors \( F_v \) and relation-embedding vectors \( F_r \) are set as 1024-D. For each sentence, we use pre-trained BERT to extract 1536-D word embedding and apply a pointwise linear layer and an attention-aware feature aggregation layer [9] to obtain 1024-D text-embedding vectors.

We implement our proposed model using PyTorch\(^2\). We train for 60 epochs using Adam optimizer [12] with a mini-batch size of 64 and a learning rate of 0.0001. As for the layer number \( L \) of transformer block, we set it to 4 and 2 on the MSR-VTT and MSVD datasets, respectively. In addition, the trade-off parameter \( \lambda \) in Eq. (11), the margin \( \delta \) in Eq. (12) are set to 0.5 and 0.2, respectively. Training our model from scratch on MSR-VTT takes about 4 hours on 4

\(^2\)http://www.pytorch.org
Table 1. Performance of introducing visual relations (VR) for cross-modal retrieval. The evaluations are done on 1K-A test set for MSR-VTT.

| Method            | Text-to-Video | Video-to-Text |
|-------------------|---------------|---------------|
|                   | R@1  | R@5  | R@10 | MedR | R@1  | R@5  | R@10 | MedR |
| dataset split from [8] |      |      |      |      |      |      |      |      |
| VG                | 30.3  | 66.6  | 78.0  | 3    | 29.4  | 65.0  | 78.5  | 3    |
| VR_{st}           | 29.9  | 63.4  | 76.0  | 3    | 31.8  | 62.9  | 76.2  | 3    |
| VG + VR_{m}       | 32.7  | 66.0  | 79.4  | 3    | 32.9  | 67.0  | 79.6  | 3    |
| VG + VR_{s}       | 33.8  | 69.3  | 82.9  | 2    | 36.2  | 72.4  | 84.3  | 2    |
| VG + VR_{t}       | 33.7  | 67.5  | 81.7  | 3    | 34.0  | 70.2  | 82.7  | 2    |
| VSR-Net           | 37.2  | 73.8  | 85.0  | 2    | 40.2  | 76.1  | 86.2  | 2    |

Figure 3. Qualitative examples of the text-video tasks: In (a), (b), we show retrieval ranks of VSR-Net and the variant VG on MSR-VTT dataset. Given a textual description as a query, we retrieve the most relevant video ranked from left to right. True positives are bounded in green boxes.

GeForce RTX 2080 Ti GPUs. For further details on hyper-parameters and model complexity, we refer the interested reader to the supplementary material.

Evaluation Metrics. We employ the widely used median retrieval rank (MedR) and recall rate at top K (R@K) for assessing retrieval accuracy. MedR measures the median rank position among where true positives are returned. R@K measures the fraction of true positives being ranked at top K returned results. Therefore, lower MedR scores indicate higher performance; in contrast, higher R@K scores indicate better performance.

4.3. Effects of Relations

We experimented with variants of our model to verify the effectiveness of introducing visual relations for text-video retrieval:

- **VG**. We only utilize the pre-trained 2D and 3D CNNs to extract the global features of the whole video as video embedding learning.
- **VG + VR_{m}**. We apply the avg-pooling features of all regionals without using the features extracted by multi-layer spatio-temporal transformer as relation embedding learning.
- **VG + VR_{s}**. We only utilize regional visual spatial relation features as relation embedding learning and global features as video embedding learning.
- **VG + VR_{t}**. We only utilize regional visual temporal relation features as relation embedding learning and global features as video embedding learning.
- **VR_{st}**. We only utilize regional visual spatio-temporal relation features as relation embedding learning.
Table 2. Cross-model retrieval comparison with state-of-the-art methods on MSR-VTT (1K-A test).

| Method                  | Text-to-Video |         |         | Video-to-Text |         |         |
|-------------------------|---------------|---------|---------|---------------|---------|---------|
|                         | R@1 | R@5  | R@10 | MedR  | R@1 | R@5  | R@10 | MedR  |
| Data split from [17]    |     |       |       |       |     |       |       |       |
| Miech et al. [17]       | 12.1 | 35.0  | 48.0  | 12    | -   | -    | -    | -    |
| STG [26]                | 15.5 | 39.2  | 50.4  | 10    | -   | -    | -    | -    |
| TCE [36]                | 17.1 | 39.9  | 53.7  | 9     | -   | -    | -    | -    |
| DualEncoding [6]        | 21.6 | 49.5  | 62.3  | 6     | 27.8| 48.7 | 58.7 | 6    |
| VSR-Net                 | 32.9 | 67.1  | 82.3  | 3     | 34.3| 70.4 | 82.7 | 2    |
| Data split from [8]     |     |       |       |       |     |       |       |       |
| CE [14]                 | 20.9 | 48.8  | 62.4  | 4     | 20.6| 50.3 | 64.0 | 5.3  |
| MMT [8]                 | 24.6 | 54.0  | 67.1  | 4     | 24.4| 56.0 | 67.8 | 4    |
| SUPPORT-SET [20]        | 27.4 | 56.3  | 67.7  | 3     | 26.6| 55.1 | 67.5 | 3    |
| T2VLAD [31]             | 29.5 | 59.0  | 70.1  | 4     | 31.8| 60.0 | 71.1 | 3    |
| VSR-Net                 | 37.2 | 73.8  | 85.0  | 2     | 40.2| 76.1 | 86.2 | 2    |

Table 3. Cross-model retrieval comparison with state-of-the-art methods on MSVD.

| Method                  | Text-to-Video |         |         | Video-to-Text |         |         |
|-------------------------|---------------|---------|---------|---------------|---------|---------|
|                         | R@1 | R@5  | R@10 | MedR  | R@1 | R@5  | R@10 | MedR  |
| Mithun et al. [18]      | 16.1 | 41.1  | 53.5  | 9     | 23.4| 45.4 | 53.0 | 8    |
| CE [14]                 | 19.8 | 49.0  | 63.8  | 6     | -   | -    | -    | -    |
| ViSERN [7]              | 18.1 | 48.4  | 61.3  | 6     | 24.3| 46.2 | 59.5 | 7    |
| SUPPORT-SET [20]        | 23.0 | 52.8  | 65.8  | 5     | 27.3| 50.7 | 60.8 | 5    |
| VSR-Net                 | 23.7 | 54.5  | 68.4  | 4     | 26.0| 55.7 | 69.2 | 4    |

We explore these model variants on the MSR-VTT (9K test), as shown in Table 1. We omit the results on MSVD because of space limitations, but they show similar trends to MSR-VTT. From the results, we have the following observations. First, as expected, on both text-to-video and video-to-text, our VSR-Net, VG + VR_s, and VG + VR_t significantly outperforms VG alone. The result verifies the significance of introducing visual relation representation. Second, compared with VG + VR_m, the performance of our VSR-Net verifies that the multi-layer spatio-temporal transformer can capture the fine-grained local relational features. Third, compared with two variants of models (i.e., VG and VR_{st}) that only use either global visual features or fine-grained local relational features, our model considers both global and fine-grained local relational features to achieve the best performance. This verifies the effectiveness of aligning the global visual and fine-grained relational features with text features on two embedding spaces. Notably, global visual features and fine-grained relational features are highly complementary, and their combination leads to an improvement far beyond the performance of the global visual features alone. Moreover, compared with VG + VR_s and VG + VR_t, our VSR-Net achieves substantially better performance, which reveals the complementarity of the spatial and temporal relation features.

Figure 3 shows two examples of text-to-video retrieval results between the model with and without visual spatio-temporal relations. Figure 3 (a) shows examples of a few test videos from the MSR-VTT dataset: the sentence describes two objects (“pitcher” and “catcher”), and the action (“throw a ball”) in a short-term segment, which requires accurate spatio-temporal grounding. Comparing VSR-Net to its variant VG, our model successfully retrieves the correct video, which contains all spatio-temporal relationships and entities described in the sentence. The second and third videos only lacks “falls sideways” action, and the fourth and fifth videos do not contain “hit backwards” and “falls sideways” actions. In the bottom example, the VG model also retrieves similar scenes in the video. However, we observe that videos involving related elements are only ranked as the true positive in the top 3 position. The performance of VG indicates that removing the fine-grained spatio-temporal relationships hurts the expressiveness of the video representation and further degrades the retrieval performance. Another example is showed in Figure 3 (b), which indicates that our models identify the relevant objects “man with baseball hat”, and the action “playing guitar” and successfully ranks the correct video at the top. Without visual relations, the video contains the objects “man”, “hat”, and “guitar” and the action “talking” will be ranked at the top.
1. A small boy is playing a ball with a dog.
2. A dog is playing with baby.
3. A dog is playing with balls.

1. A man is applying cheese on the bread slices.
2. Someone sprinkled cheese on the bread slices.
3. A man is spreading butter on garlic bread.

Figure 4. Video-to-text retrieval examples on MSVD testing set with top 3 retrieved text sentences. True positives are green text sentence.

instead. Moreover, Figure 4 also provides qualitative results on video-to-text retrieval from MSVD dataset. The top example contains a scene, which is “A small boy is playing a ball with a dog”. Comparing these results, we observe that the variant VG retrieves a list of sentences involving related objects “baby”, “dog”, which cannot capture the fine-grained spatio-temporal information in the video. Our model not only identifies the relevant objects “small boy”, “ball”, and “dog” but also captures the relationships between them. Analogously, in the bottom example, by capturing the positional relations “A man”, between “cheese”, and “bread” in the query video, the model ranks the correct captions at the top. Again, it verifies the effectiveness of the fine-grained spatio-temporal relation features for cross-modal retrieval in both directions.

4.4. Performance Comparison

To demonstrate the effectiveness of the VSR-Net solution, we compared it to several state-of-the-art baselines: (1) RNN-based methods: DualEncoding [6], TCE [36], (2) Multimodal Fusion methods: Mithun et al. [18], CE [14], MMT [8], (3) GCN-based methods: ViSERN, [7], STG [26], and (4) other methods: Miech et al. [17], SUPPORT-SET [20], T2VLAD [31]. Note that for fair comparisons, we directly cited the results from their original papers without pre-training on HowTo100M [17].

The quantitative results on MSR-VTT and MSVD are presented in Table 5 and Table 3, respectively. On MSR-VTT, we observe that for all data partitions, our proposed method consistently outperforms all compared methods in all evaluation metrics by a large margin, including CE [14], MMT [8], and T2VLAD [31], which use expert features (e.g., object, motion, face, scene, sound, and speech). Moreover, our VSR-Net significantly outperforms recent spatio-temporal relation-based method (STG [26]) in all evaluation metrics, especially, boosts the text-video retrieval quality by a margin of 31.9% in R@10. This condition reveals that modeling the spatial-temporal visual relations by a multi-layer spatio-temporal transformer to enhance global video representation has a strong impact on the performance of text-video retrieval. On MSVD, our proposed method outperforms recent state-of-the-art methods in terms of most indicators. Note that among all these methods, ViSERN [7] uses only fine-grained video features to compute the similarity between the video and text. Analogously, we also observe that VSR-Net outperforms the fine-grained feature-based method ViSERN [7] by a great margin. This reveals that jointly modeling the global and fine-grained video representation plays a significant role in text-video retrieval, contributing to more powerful representation. Notably, on MSVD, the performance of our model is not as outstanding. We summarize the following reasons for this: (1) The size of the MSVD dataset is smaller than the MSR-VTT dataset. The transformer has the property of lacking structural bias making it prone to overfitting for small-scale data. (2) Each video clip in MSVD corresponds to a larger number and more abstract description.

5. Conclusions

This work contributes to a novel learning method for cross-modal text-video retrieval. We claim that video representation should learn not only from global features but also from fine-grained spatio-temporal relationships for cross-modal text-video retrieval. To fulfill this target, we design the Visual Spatio-Temporal Relation-Enhanced Network (VSR-Net) to capture fine-grained local relational and global visual information for cross-modal text-video retrieval. Extensive experimental results on two benchmarks have demonstrated the effectiveness and superiority of our proposed method. Besides, we still face an inherent computational burden of attention in processing long-length video
Table 4. Comparison with different models in terms of model size and computation overhead at the inference stage.

| Model       | Parameters (M) | FLOPs (G) |
|-------------|----------------|-----------|
| MMT [8]     | 133.4          | 12.64     |
| DualEncoding [6] | 95.9        | 3.64      |
| VSR-Net     | 31.48          | 10.33     |

Figure 5. Performance of text-to-video retrieval with different layers number of transformer blocks.

Figure 6. Evaluation of different weight combination of the global and relation similarities.

with more complex fine-grained relations. Therefore, we leave computational optimization of the multi-layer spatio-temporal transformer as future works.

A. Model Complexity

We compare our method with opened-source methods in terms of model size and computation overhead at the inference stage. As shown in Figure 5, since the performance of using one layer of transformer block outperforms MMT by a large margin, we only calculate the model size and computational overhead of using one layer of transformer block. Analogously, we also observe that our VSR-Net with one layer of transformer block outperforms DualEncoding by a great margin on the MSR-VTT 1K-A test set [17]. Notably, we omit the text-video retrieval results of VSR with a layer of transformer block on the MSR-VTT 1K-A test set [17] due to space limitations, which show similar trends to the MSR-VTT 1K-A test set [8]. In addition, we conclude that for each additional layer of transformer block, the computational cost will increase by $8.29$ GFLOPs and the parameters will increase by $25.19$M. Following [6], we measure the number of FLOPs required for a text-video pair. As shown in Table 4 and Figure 5, we have two main observations: 1) our VSR-Net with one layer of transformer block achieves $83.3\%$ text-to-video recall@10 accuracy on the MSR-VTT 1K-A test set, which is $16.2\%$ higher than MMT, with fewer parameters and lower computational cost. 2) our VSR-Net with one layer of transformer block is smaller and slightly slower than DualEncoding.

B. Additional Experiments

We provide additional experimental comparisons with state-of-the-art baselines on MSR-VTT (Full test set and 1K-B test set). Tables 5 report the performance comparison results. We observe that the results are in line with the conclusions of the main work. Hence, the proposed VSR-Net model is effective in cross-modal text-video retrieval.

C. Attention Visualization

To intuitively observe the effectiveness of introducing spatio-temporal relations, we visualize the attention map to infer the value of the spatio-temporal relational features. We select 2 clips, including a positive example in text-to-video retrieval and a positive example in video-to-text retrieval, from MSR-VTT and MSVD. In Figure 7, we show the original frames and attention maps. As can be seen, our VSR-Net learns to value core parts with intensely semantic relations such as “pitcher + catcher” in “throwing a ball”, “boy + dog” in “walking a dog”. Furthermore, the regions of four salient people are highlighted separately in the left part of Figure 7.

D. Parameter Sensitivity

We carry out experiments to explore how the layer number of transformer block $L$ and the trade-off parameter $\lambda$ affect the retrieval performance. Notably, we omit the video-text retrieval results on the two datasets due to space limitations, which show similar trends to text-video retrieval. First, we analyze the influence of the hyperparameter, that is, the layer number of transformer block on the MSR-VTT 1K-A test set [8], and MSVD datasets. Figure 5 presents...
Table 5. Cross-model retrieval comparison with state-of-the-art methods on MSR-VTT (Full test and 1K-B test).

| Method            | Text-to-Video |                    |                    |                    | Video-to-Text |                    |                    |                    |
|-------------------|---------------|--------------------|--------------------|--------------------|---------------|--------------------|--------------------|--------------------|
|                   | R@1 | R@5 | R@10 | MedR | R@1 | R@5 | R@10 | MedR |
| Full test set     |     |     |      |      |     |     |      |      |
| STG [26]          | 8.3 | 23.7| 33.9 | 28   |     |     |      |      |
| HGR [5]           | 9.2 | 26.2| 36.5 | 24   | 15.0| 36.7| 48.8 | 11    |
| DualEncoding [6]  | 11.6| 30.3| 41.3 | 17   | 22.5| 47.1| 59.8 | 7     |
| T2VLAD [31]       | 12.7| 34.8| 47.1 | 12   | 20.7| 48.9| 62.1 | 6     |
| VSR-Net           | 18.6| 45.6| 61.1 | 7    | 20.4| 49.7| 63.8 | 6     |
| 1K-B test set     |     |     |      |      |     |     |      |      |
| CE [14]           | 18.2| 46.0| 60.7 | 7    | 18.0| 46.0| 60.3 | 6.5   |
| MMT [8]           | 20.3| 49.1| 63.9 | 6    | 21.1| 49.4| 63.2 | 6     |
| DualEncoding [6]  | 23.0| 50.6| 62.5 | 5    | 25.1| 52.1| 64.6 | 5     |
| T2VLAD [31]       | 26.1| 54.7| 68.1 | 4    | 26.7| 56.1| 70.4 | 4     |
| VSR-Net           | 33.6| 68.7| 82.7 | 3    | 38.0| 72.4| 85.7 | 2     |

Caption: a pitcher throws a ball which is hit backwards and chased by the catcher while the umpire falls sideways.

Caption: a small boy is playing a ball with a dog.

Figure 7. Visualization of attention on sample clips from the MSR-VTT and MSVD datasets. The odd row presents original frames, and the even presents corresponding attention maps.

the results across the layer number of transformer block on the two datasets by Recall@10; note that Recall@1 and Recall@5 present the same trend, in which performances increase until certain numbers (4 and 2 for MSR-VTT and MSVD datasets, respectively) and then become stable. This result is due to the model’s capability of capturing the spatio-temporal relations of the deepest layer numbers.

Moreover, the influence of the hyperparameter $\lambda$ in Eq. (11) is revealed in Figure 6. We assign different trade-off parameter $\lambda$ to the two scores (i.e., $VR_{st}$ and $VG$) to observe their influence on the matching performance on the two datasets. By analyzing the results shown in Figure 6, we have the following observations: 1) The leftmost part of Figure 6 shows the results when $VR_{st}$ accounts for 0, that is, when the proportion of $VG$ is 1, which means that we remove the visual relations module from our model (i.e., $VG$). We can observe that when the visual relations module is removed, the retrieval performance is reduced by a large margin over the two datasets. This condition shows the positive effect of comprehensively introducing visual relations for text-video retrieval. 2) Increasing the proportion of $VR_{st}$ substantially boosts the performance of model. Our model performs best performance on the two datasets when $\lambda = 0.5$. Therefore, we argue that $VR_{st}$ and $VG$ occupy the same contribution to the overall similarity. We conclude that the two similarities work together to obtain the best retrieval performance in a cooperative manner.

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