Video Relation Detection with Trajectory-aware Multi-modal Features

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ABSTRACT

Video relation detection problem refers to the detection of the relationship between different objects in videos, such as spatial relationship and action relationship. In this paper, we present video relation detection with trajectory-aware multi-modal features to solve this task. Considering the complexity of doing visual relation detection in videos, we decompose this task into three sub-tasks: object detection, trajectory proposal and relation prediction. We use the state-of-the-art object detection method to ensure the accuracy of object trajectory detection and multi-modal feature representation to help the prediction of relation between objects. Our method won the first place on the video relation detection task of Video Relation Understanding Grand Challenge in ACM Multimedia 2020 with 11.74% mAP, which surpasses other methods by a large margin.

KEYWORDS

Video Relation detection; Object trajectory detection; Relation prediction

1 INTRODUCTION

Video relation detection is to find all object trajectories and relation between them as triplet (subject, predicate, object) in a video. It bridges visual information and linguistic information, enabling the cross-modal information transformation. Comparing to other computer vision tasks like object detection and semantic segmentation, visual relation detection requires not only localizing and categorizing single object but also understanding the interaction between different objects. To capture the relation between objects, more information of the video content need to be utilized.

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2 OBJECT TRAJECTORY DETECTION

2.1 Object Detection

We choose Cascade R-CNN as our object detection model and ResNeSt101 as the network backbone. To train the object detector, we extract frames from each video to build the training set and validation set. Due to the high similarity between frames in the
We take the tracking-by-detection strategy to generate object trajectories. After that, paths of the graph represent trajectories and we can run the trajectory generation. This algorithm consists of two parts: Graph Building and Trajectory Selection. By regarding each bounding box as a node of the graph, we can link the bounding boxes that are likely to belong to the same object and from consecutive frames. After that, paths of the graph represent trajectories and we can run Dynamic Programming algorithm to pick paths that are more likely to be a object trajectory.

**Graph Building:** First, we regard each bounding box as a node and build the initial graph with no edge between them. Let $\text{category}_{t,n}, \text{conf}_{t,n}, \text{bbox}_{t,n}, \text{int}_{t,n}, \text{out}_{t,n}$ represent the object category, confidence score, bounding box, set of precursor nodes and set of successor nodes of the $nth$ bounding box in frame $t$. We set $\text{in}$ and $\text{out}$ to empty for all nodes initially. Then, for each $t(0 \leq t < T$, $T$ is the frame count) and all possible $(i, j)$ that satisfy $\text{node}_{t,i}$ and $\text{node}_{t+1,j}$ exist, if $\text{category}_{t,i}$ and $\text{category}_{t+1,j}$ are the same and the IoU of $\text{bbox}_{t,i}$ and $\text{bbox}_{t+1,j}$ is higher than a threshold, add $\text{node}_{t+1,j}$ to $\text{out}_{t,i}$ and add $\text{node}_{t,i}$ to $\text{in}_{t+1,j}$. By doing this, we link bounding boxes pair from consecutive frames that has a IoU higher than the threshold. We set the threshold to 0.2 in our experiments.

We notice that when the camera or object in the video is moving violently, the IoU of bounding boxes that belong to the same object from consecutive frames will be very low. In this case, the original seq-NMS algorithm won’t link them, causing the lost of tracking. To solve this problem, we introduce a new linking mechanism. First, for bounding boxes $B1 = (x_1, y_1, w_1, h_1)$ and $B2 = (x_2, y_2, w_2, h_2)$, we define scale_ratio and area_ratio as:

$$scale\_ratio(B1, B2) = \begin{cases} \frac{h_1}{w_1}, \frac{h_2}{w_2} > \frac{h_1}{w_1} \\ 1 \end{cases}$$

$$area\_ratio(B1, B2) = \begin{cases} \frac{w_1 h_1}{w_2 h_2}, w_1 h_1 > w_2 h_2 \\ \frac{w_1 h_1}{w_2 h_2}, w_1 h_1 \leq w_2 h_2 \end{cases}$$

Then, for each $(t_1, t_2, i, j)$ that satisfies
1) $0 \leq t_1 < t_2 \leq T, t_2 - t_1 > 1$
2) $\text{node}_{t_1,i}, \text{node}_{t_2,j}$ exist
3) $scale\_ratio(\text{bbox}_{t_1,i}, \text{bbox}_{t_2,j}) > 0.5$
4) $area\_ratio(\text{bbox}_{t_1,i}, \text{bbox}_{t_2,j}) > 0.5$

we create a path from $\text{node}_{t_1,i}$ to $\text{node}_{t_2,j}$ by interpolating nodes in each time $t(t_1 < t < t_2)$, as shown in Fig. 2. The bbox of the interpolated node is obtained by linear interpolation of $\text{bbox}_{t_1,i}$ and $\text{bbox}_{t_2,j}$. The confidence score of the interpolated node will be set to 0. By applying this linking mechanism, the trajectory generation module is more robust to violent movement of camera and objects. In our experiments, we limit $t_2 - t_1$ to be less than 8 to make a trade-off between performance and complexity.

**Trajectory Selection:** After building the graph, we can regard a full path(path that can not be extended) of the graph as a object trajectory and take sum of confidence score of nodes in the path as the score of the path. Then, we repeatedly select path with the highest score and remove the nodes of the path from the graph. We achieve this by Dynamic Programming Algorithm used in [3]. Trajectories selected by the algorithm will be returned as the trajectory detection result.

## 3 RELATION PREDICTION

Follow the scheme of [11], we first divide the video into overlapped segments with same length and perform object trajectory detection in all segments. We set segment length to 32 frames and overlap length to 16 frames in our experiments. After that, we predict the relation between all possible object pairs in the same segment.
3.1 Features

To fully capture the video context and temporal movement, we use multi-modal features, including motion feature, visual feature, language feature and location mask feature, to help the relation prediction.

**Motion Feature:** For a trajectory pair in 32 frame segment, we first calculate the location feature following method used in [13] for frame 0, 8, 16, 24 and 31. Let \( f_{\text{feat}} \) be the feature calculate for frame \( t \). To capture the relative location of the pair in the static frame, we generate static feature \( f_{\text{feat}}^{\text{static}} \) by concatenating all the features calculated for frame 0, 8, 16, 24 and 31. To capture the dynamic movement of the pair, we generate dynamic feature \( f_{\text{feat}}^{\text{dynamic}} \) by concatenating \( f_{\text{feat}}^8 - f_{\text{feat}}^0, f_{\text{feat}}^{16} - f_{\text{feat}}^0, f_{\text{feat}}^{24} - f_{\text{feat}}^0, f_{\text{feat}}^{31} - f_{\text{feat}}^0 \).

**Visual Feature:** Due to the high complexity of extracting feature from video using network like I3D[2], we choose to only extract visual feature from static frame using 2-D network. Most previous work used the object detection model to extract feature for relation prediction. However, detection model focus on the category of single object in the image. It can not capture the relation information properly. Thus, we use a scene graph generation model[14] pre-trained on Visual Genome Dataset[4] to extract feature for relation prediction to help better capturing the interaction between objects. We only use the the middle frame of the segment to extract feature. For each pair, we extract a 4096-d feature for bounding box of the subject, bounding box of the object and the union of their bounding box respectively.

**Language Feature:** For language context, we follow [13] to generate a 300-d feature for subject and object category respectively and concatenate them as the final language feature.

**Location Mask Feature:** Since coordinates only have very limited ability in representing location, we further introduce the binary mask of the bounding box to better capture the relative location of subject and object. We follow the method of [16] to generate a mask base on the bounding boxes of the subject and object in the middle frame of the segment as a input of the relation predictor.

3.2 Network Design

Using the features mentioned above as input, we design a simple neural network to predict the relation. The structure of the network is shown in Figure. 3.

After analysing the dataset, we find that about 99% of object pairs in the training set have no more than one spatial relation and one action relation. Thus, we convert the multi-label classification problem appeared in VidOR[10] Dataset to two single-label classification problem. We use focal loss[6] to supervise the spatial label and the action label separately to deal with the severe imbalance issue.

4 EXPERIMENT

In this section, we present experiment results in VidOR Dataset. We use the official evaluation code of the grand challenge to evaluate out results. More detail can be found in https://videorelation.nextcenter.org/mm20-gdc/task1.html.

4.1 Component Analysis

**Object Trajectory Detection:** We adopt Cascade R-CNN with ResNeSt101 as our object detector and Dynamic Programming algorithm with cross-frame linking mechanism as trajectory generator. To prove the effectiveness of our trajectory generation algorithm, we firstly evaluate it in the optional task Video Object Detection. Since we don’t submit our result for the optional task, we only compare our result on the validation set of VidOR Dataset with the
Table 1: Our detailed evaluation scores on VidOR test set (%)

| Method        | mAP  | R@50 | R@100 | tagging P@1 | tagging P@5 | tagging P@10 |
|---------------|------|------|-------|-------------|-------------|--------------|
| Ours(colab-buaa)| 11.74| 10.02| 12.69 | 71.36       | 56.30       | 44.59        |

result of the first place of the optional task in 2020 on the test set of VidOR Dataset. Table 2 shows that we surpass the first place of the optional task in 2020 by a large margin. Secondly, we compare the video visual relation detection results using dynamic programming with and without cross-frame linking mechanism. The results are shown in Table. 3. CFLM means cross-frame linking mechanism. We can find that cross-frame linking mechanism increases the mAP from 8.84% to 9.93%.

Table 2: Comparison with state-of-the-art methods on the optional task Video Object Detection (%)

| Method                       | mAP  |
|------------------------------|------|
| DeepBlueAI(on test set)      | 9.66 |
| ours(on validation set)      | 14.59|

Table 3: Results using different trajectory generation methods on VidOR validation set (%)

| Method     | tagging P@1 | R@50 | mAP  |
|------------|-------------|------|------|
| ours w/o CFLM | 66.59       | 8.30 | 8.84 |
| ours        | 67.43       | 9.12 | 9.93 |

Relation Prediction: We use multi-modal features to proceed relation prediction. We perform 4 experiments using our multi-modal features without language feature, motion feature, visual feature and location mask feature respectively. As shown in Table. 4, our method using all features outperforms other experiments, which shows the effectiveness of our multi-modal features. We can also find that using less feature doesn’t decrease the mAP as much as not using cross-frame linking mechanism. It means that for current dataset and methods in video relation detection, robust trajectory detection matters more.

Table 4: Results using different features on VidOR validation set (%)

| Method        | tagging P@1 | R@50 | mAP  |
|---------------|-------------|------|------|
| Ours w/o language | 66.70       | 8.98 | 9.66 |
| Ours w/o motion  | 67.18       | 9.01 | 9.86 |
| Ours w/o visual | 65.99       | 8.83 | 9.50 |
| Ours w/o mask  | 65.75       | 9.08 | 9.74 |
| Ours          | 67.43       | 9.12 | 9.93 |

4.2 Comparison with state-of-the-art

We compare our results with other methods in VidOR validation dataset. As shown in Table. 5, our method outperform other methods by a large margin, which proves the effectiveness of our method.

Table 5: Comparison with state-of-the-art methods on VidOR validation set (%)

| Method                     | tagging P@1 | R@50 | mAP  |
|----------------------------|-------------|------|------|
| RELAbuilder[18]            | 33.05       | 1.58 | 1.47 |
| MAGUS.Gamma[13]            | 51.20       | 6.89 | 6.56 |
| VRD-STGC[7]                | 48.92       | 8.21 | 6.85 |
| Ours                       | 67.43       | 9.12 | 9.93 |

We use model ensemble strategy to further improve our result for the challenge task. Tabel. 6 shows the comparison of our method and other methods in VidOR test dataset. We also outperform all other methods by a large margin.

Table 6: Comparison with state-of-the-art methods on VidOR test set (%)

| Method                     | mAP  |
|----------------------------|------|
| RELAbuilder[18]            | 0.55 |
| MAGUS.Gamma[13]            | 6.31 |
| DeepBlueAI                 | 0.24 |
| GKBU                       | 3.28 |
| Zixuan Su                  | 5.99 |
| ETRI_DGRC                  | 6.65 |
| Ours(colab-buaa)           | 11.74|

The detailed evaluation scores of our method on VidOR test set is shown in Table. 1.

5 CONCLUSION

In this paper, we propose trajectory-aware multi-modal features for video relation detection. Finally, we achieved 11.74% mAP, ranking the first place on the video relation detection task of Video Relation Understanding Grand Challenge in ACM Multimedia 2020.

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