QAHOI: Query-Based Anchors for Human-Object Interaction Detection

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Abstract

Human-object interaction (HOI) detection as a downstream of object detection task requires localizing pairs of humans and objects and recognizing the interaction between them. Recent one-stage approaches focus on detecting possible interaction points or filtering human-object pairs, ignoring the variability in the location and size of different objects at spatial scales. In this paper, we propose a transformer-based method, QAHOI (Query-Based Anchors for Human-Object Interaction detection), which leverages a multi-scale architecture to extract features from different spatial scales and uses query-based anchors to predict all the elements of an HOI instance. We further investigate that a powerful backbone significantly increases accuracy for QAHOI, and QAHOI with a transformer-based backbone outperforms recent state-of-the-art methods by large margins on the HICO-DET benchmark.

1 Introduction

Human-object interaction (HOI) detection has recently received increasing attention as a field with great potential applications. HOI detection approaches need to extract the semantic relationships between humans and objects and predict a set of (human, object, action) triplets within an image. Specifically, an HOI instance is a pair of human and object bounding boxes, and a corresponding action class represents the relationship between them. HOI detection can be divided into two parts: human-object pair detection and interaction recognition.

To achieve high efficiency, one-stage approaches [5, 9, 7, 19, 3, 14, 17, 6, 15] detect human-object pairs and recognize the corresponding action class in parallel. A commonly adopted way is to make use of the interaction point, which is the intersection of human and object boxes [9, 17, 15], and a matching process is required to match the interaction point with a pair of human and object boxes. Although interaction points combine the HOI instance detection and recognition together, there are mainly two drawbacks such as the semantic features are ambiguous when the interaction point is far apart from the human and object, and the lack of a multi-scale architecture which is commonly used in object detection.

To extract the semantic features between the human-object pairs with more contextual information and less irrelevant local information, Transformer [16] is introduced into HOI detection [7, 19, 3, 14]. As query embeddings in the transformer decoder represent HOI instances and incorporate object detection and interaction recognition together, the transformer-based HOI detection methods also can be seen as query-based methods which belong to the one-stage approach. However, the transformer-based methods [7, 19, 3, 14] are built upon the CNN backbone, and the multi-head attention used in transformer suffers from a quadratic complexity with the growth of the feature map size. Besides, the training of the high complexity transformer suffers from slow convergence, and pre-training the model in object detection task and fine-tuning in HOI detection task are always used to obtain a fine result.

In this paper, we proposed a transformer-based method, which leverages a hierarchical backbone to extract multi-scale context features, and a deformable transformer [18] to encode the multi-scale semantic features and decode the HOI instances. The reference points in the deformable transformer decoder act as the anchors for aggregating the HOI embeddings from the multi-scale context features. With the base location of anchors and corresponding HOI embeddings, an interaction detection head can predict the HOI instances directly. As the anchors are used throughout the HOI embeddings’ decoding and the final prediction process, we call our method Query-Based Anchors for HOI detection, QAHOI. Furthermore, with the efficient attention mechanism of the deformable transformer, QAHOI with a large transformer-based backbone can be trained from scratch and outperform recent state-of-the-art methods by large margins.

2 Method

Our purpose is to address the drawbacks in the recent one-stage approaches that lack a multi-scale architecture and suffers from a poor CNN backbone for the HOI detection task. The deformable DETR [18] develops the deformable multi-scale attention module to reduce the complexity of attention in DETR to the linear complexity with the spatial size, which achieves a multi-scale transformer-based object detector. Our proposed method, QAHOI, further improves this idea.
to solve HOI detection as a dense prediction problem. QAHOI adapts the deformable transformer decoder to an HOI instance detector by using the query embeddings to generate anchors and decode the HOI information. The overall architecture of QAHOI is shown in Figure 1.

### 2.1 Multi-Scale Feature Extractor

To improve the model’s expression ability, QAHOI constructs a multi-scale feature extractor by combining a hierarchical backbone and a deformable transformer encoder [18] as shown in Figure 1. The hierarchical backbone extracts four stages’ feature maps for the deformable transformer encoder, which is well designed for processing multi-scale feature maps. Specifically, given an image of size $3 \times H \times W$, QAHOI uses the last three stages’ feature maps $x_1 \in \mathbb{R}^{2C_s \times \frac{H}{4} \times \frac{W}{4}}$, $x_2 \in \mathbb{R}^{4C_s \times \frac{H}{8} \times \frac{W}{8}}$ and $x_3 \in \mathbb{R}^{8C_s \times \frac{H}{16} \times \frac{W}{16}}$ of the backbone. The $1 \times 1$ convolution is used to project the feature map $x_1$, $x_2$ and $x_3$ from dimension $C_s$ to dimension $C_d$. Then, the multi-scale feature maps $x_1$, $x_2$ and $x_3$ are flattened and concatenated to $N_S$ vectors with $C_d$ dimensions as the input of the deformable transformer encoder, where $N_S$ is the sum of pixel numbers of the three feature maps from the backbone. A fixed positional encoding is used to indicate the scale level of the input. The deformable transformer encoder extracts the semantic feature $S \in \mathbb{R}^{N_S \times C_d}$ in a multi-scale manner and provides it for the deformable transformer decoder to decode the HOI instances.

### 2.2 Predicting HOI with Query-Based Anchors

According to the deformable DETR, the query embeddings of the deformable transformer decoder in QAHOI are split equally into two parts, one as the HOI query embeddings $Q_{HOI} \in \mathbb{R}^{N_q \times C_d}$ and the other as the positional embeddings $Q_{pos} \in \mathbb{R}^{N_q \times C_d}$, and the anchors $P \in \mathbb{R}^{N_q \times 2}$ are generated from positional embeddings $Q_{pos}$ via a linear layer. With the HOI query embeddings and the anchors, the HOI embeddings $E \in \mathbb{R}^{N_q \times C_d}$ are decoded by the deformable transformer decoder’s attention mechanism with the source of the encoded semantic feature from the deformable transformer encoder. The decoding process of the deformable transformer decoder is shown in Figure 2. The self-attention of the HOI query embeddings are calculated by the multi-head attention module [16] with the positional embeddings, and the anchors aggregate the semantic feature from the output of the deformable transform encoder to calculate the multi-scale deformable attention [18] with the HOI query embeddings.

QAHOI implements a simple interaction head which is similar to the QPIC [14], and the difference is that QAHOI combines each HOI embedding with a certain anchor. Hence, QAHOI feeds the decoded HOI embeddings into the interaction head to predict the HOI instances. Figure 3 shows the predicting process of the interaction head in QAHOI. Following the deformable DETR, each anchor $(p_x, p_y)$ of the anchor set $P \in \mathbb{R}^{N_q \times 2}$ acts as the base point for...
the bounding boxes of a pair of a human and an object. Thus, the human and object boxes $B^h, B^o \in \mathbb{R}^{N_q \times 4}$ predicted by the FFN in the interaction head are composed of $\{d_x, d_y, w, h\}$, where $d_x$ and $d_y$ denote the offsets between the anchor and the box’s center, and $w$ and $h$ denote the box’s width and height. Then, the final bounding boxes $\hat{B}^h, \hat{B}^o$ are composed of $\{d_x + p_x, d_y + p_y, w, h\}$. Finally, the object class of the object boxes $O \in \mathbb{R}^{N_q \times K_o}$ and the action class of the HOI instances $A \in \mathbb{R}^{N_q \times K_a}$ are combined with the human and object bounding boxes $\hat{B}^h, \hat{B}^o$ to construct the output HOI instances.

2.3 Training and Inference

Following the training procedure of the QPIC [14], the ground-truth set is padded with $\phi$ (no pairs) to the size of $N_q$, and the Hungarian algorithm [8] is used to match all of the $N_q$ predictions with the ground-truth set. For the loss calculated on the matched pairs, the QPIC’s loss function is based on the DETR [1], and because QAHOI implements the deformable DETR [18], we follow the Deformable DETR to calculate the Focal Loss [10] of the object class, which is different from the QPIC. For the anchors derived from the query embeddings, because the query embeddings are learnable parameters, the positions of the anchors are learned during training and fixed during inference.

2.4 Top K Scores and HOI NMS

QAHOI requires sufficient anchors to extract multi-scale features. In general, the number of anchors far exceeds the number of HOI instances in an image. For the HICO-DET dataset, 96% of the images contains less than 10 HOI instances. QAHOI filters the results in two steps. Firstly, the HOI instances with the top $N_t$ object class scores are selected. Then, an HOI Non-Maximal Suppression (NMS) is used to filter out the final results. The HOI NMS is calculated based on the IoU of humans and objects between HOI instances and the HOI score. The HOI score is obtained by multiplying the object score and the action score, $c_{\text{HOI}} = c_o \cdot c_a$. And a combined IoU of human and object between an HOI instance $i$ and $j$ is calculated as:

$$\text{IoU}(i, j) = \text{IoU}(B_i^{(h)}, B_j^{(h)}) \cdot \text{IoU}(B_i^{(o)}, B_j^{(o)})$$

(1)

The same as the object detection task, a threshold $\delta$ is used to remove HOI instances with low scores for each action category based on the IoU.

3 Experiments

3.1 Experimental Setting

Dataset. We conduct the experiments on the HICO-DET [2] dataset, which contains 47,776 images (38,118 in the training set and 9,658 in the test set). HICO-DET has 117 action classes and 80 object classes (the object classes same as the MS-COCO [11] dataset), and the action classes and the object classes constitute 600 HOI classes. Based on the number of instances of the 600 HOI classes in the dataset, these HOI classes are divided into three categories: Full (all of the HOI classes), Rare (138 classes with less than 10 instances), and Non-Rare (462 classes with 10 or more than 10 instances). We report the results (in Table 1) on the Default setting (with unknown objects) and the Known Object setting (without unknown objects) of the HICO-DET.

Metric. The mean average precision (mAP) is used to evaluate the predicted HOI instances. For a true positive HOI instance, the intersection over union (IoU) between the predicted human bounding box and the ground-truth human bounding box is higher than 0.5, and the IoU between the predicted object and the ground-truth object bounding box is also higher than 0.5. As usual, we report the mAP on the Full, Rare, and Non-Rare categories of the HICO-DET.

Implementation Details. For the backbone, we train QAHOI with Swin-Transformer [12] pre-trained on ImageNet-20K as our best model. Specifically, we use Swin-Tiny and Swin-Base pre-trained on ImageNet-1K, and Swin-Base and Swin-Large pre-trained on ImageNet-22K. Following the setting of the Deformable DETR, the deformable transformer encoder and decoder both have 6 layers ($N_l = 6$), the number of the query embeddings is $N_q = 300$, and top $N_t = 100$ HOI instances are selected by object scores. In the NMS process, $\delta = 0.5$ is used to filter the HOI instances by the combined IoU. We use the AdamW [13] optimizer with the backbone’s learning rate of $10^{-5}$ and other’s $10^{-4}$, and the weight decay of $10^{-4}$. We train the model for 150 epochs with a batch size of 16 (two images per GPU, 8 GPUs), and the learning rates of the backbone and others are decayed at 120 epochs.

3.2 Comparison with State-of-the-Arts

The results compared with the state-of-the-art methods on the HICO-DET are shown in Table 1. We use QAHOI with the Swin Transformer as our best model to compare with other state-of-the-art methods. Compared with recent one-stage approaches, with the multi-scale feature maps and multi-scale deformable attention, even we do not train a detector on the MS-COCO dataset, which is beneficial for the object detection part of the model, QAHOI with Swin-Large backbone still outperforms the state-of-the-art one-stage method, QPIC with 5.88 mAP (relatively 19.7%). We found that the better the performance of the pre-trained backbone in the classification task became, the further improvement in accuracy we achieved in the HOI detection. The mAP of QAHOI with Swin-Base backbone pre-trained on ImageNet-20K is 4.1 (rel-
An additional low-QAHOI on the HICO-DET dataset. Following the deformable DETR’s weight which is trained on the MS-COCO dataset and fine-tuning the weights of the detector.

Table 1: Comparison with state-of-the-art on HICO-DET.

| Method         | Backbone | Detection | Full | Rare | Non-Rare | Full | Rare | Non-Rare |
|----------------|----------|-----------|------|------|----------|------|------|----------|
| QAHOI          | Swin-Base| (1)       | 24.37| 22.44| 30.83    | 24.21| 17.51| 27.21    |
| QAHOI          | Swin-Base| (2)       | 24.63| 22.49| 31.06    | 24.58| 17.66| 27.37    |
| QAHOI          | Swin-Base| (3)       | 24.68| 22.47| 31.11    | 24.71| 17.71| 27.40    |
| QAHOI          | Swin-Base| (4)       | 24.70| 22.48| 31.14    | 24.73| 17.73| 27.43    |
| QAHOI          | Swin-Base| (5)       | 24.72| 22.49| 31.15    | 24.75| 17.75| 27.45    |
| QAHOI          | Swin-Base| (6)       | 24.73| 22.50| 31.16    | 24.76| 17.76| 27.46    |
| QAHOI          | Swin-Base| (7)       | 24.74| 22.51| 31.17    | 24.77| 17.77| 27.47    |
| QAHOI          | Swin-Base| (8)       | 24.75| 22.52| 31.18    | 24.78| 17.78| 27.48    |
| QAHOI          | Swin-Base| (9)       | 24.76| 22.53| 31.19    | 24.79| 17.79| 27.49    |

Table 3. Ablation study of the filtering steps. QAHOI with Swin-Tiny is used as the base method.

| Ablations         | Backbone   | Detection | Full | Rare | Non-Rare | Full | Rare | Non-Rare |
|-------------------|------------|-----------|------|------|----------|------|------|----------|
| Full Rare Non-Rare| base       | 26.46    | 20.82| 28.44|
| + topk scores     | 26.70      | 20.89    | 28.43|
| + NMS              | 26.47      | 22.44    | 30.27|

3.4 Conclusion and Future Work

In this paper, we propose a transformer-based one-stage method for HOI detection, which leverages a hierarchical backbone and transformer encoder to extract the multi-scale semantic feature, a transformer decoder to decode the HOI embeddings and an interaction head to predict the HOI instances. The transformer decoder and the interaction head leverage the query-based anchors to decode the HOI embeddings and predict the HOI instances. Transformer-based backbones with the attention mechanism show a great advance for HOI detection, and the query-based anchors are also flexible in detecting the HOI instances. In the future, we will develop our method with better object detectors and further reduce the training cost.
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