A High-Performance Object Proposals based on Horizontal High Frequency Signal

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Abstract—In recent years, the use of object proposal as a preprocessing step for target detection to improve computational efficiency has become an effective method. Good object proposal methods should have high object detection recall rate and low computational cost, as well as good localization quality and repeatability. However, it is difficult for current advanced algorithms to achieve a good balance in the above performance. For this problem, we propose a class-independent object proposal algorithm BHL. It combines the advantages of window scoring and superpixel merging, which not only improves the localization quality but also speeds up the computational efficiency. The experimental results on the VOC2007 data set show that when the IOU is 0.5 and 10,000 budget proposals, our method can achieve the highest detection recall and an average mean best overlap of 79.5%, and the computational efficiency is nearly three times faster than the current fastest method. Moreover, our method is the method with the highest average repeatability among the methods that achieve good repeatability to various disturbances.

Index Terms—object proposals, object detection, Binarized, HL Frequency, Border merge

I. INTRODUCTION

Fig. 1: Comparison of the most advanced general object proposal methods on the VOC2007 data set [1] when the proposal is $10^{4}$ and the overlap threshold $IOU \geq 0.5$. Our approach achieves the best performance between recall (DR), repeatability and computational efficiency, and MABO is similar to that of the most advanced methods. All competition results are generated by public code (see the details in our experiment section).

USING sliding Windows to extract densely overlapping detection boxes and then analyze them is a popular strategy in object detection methods [2]. However, in general object detection tasks, in order to obtain good detection accuracy, a large number of potential windows need to be detected. For example, images of $W \times H$ pixels, the number of potential windows can reach $O(W^2H^2)$, so that most of the computing resources are wasted on useless potential windows. In recent years, a variety of general object proposal schemes have been proposed and attracted extensive attention, based on the visual attention mechanism of the human eye. The general object proposal can be accurately generated under the premise that the type of the detected object is uncertain, which can reduce the number of search windows in the preprocessing stage of object detection and recognition, thereby greatly reducing the computational time. This scheme has been adopted by mask R-CNN [3], faster R-CNN [4], Cascade R-CNN [5] and other excellent target detection algorithms [2]. The results show that the object proposal scheme can be successfully applied to complex computer vision systems as a data preprocessing step. Among them, Sel.search [6], Edgeboxes [7] and BING [8] have the most advanced performance. Object proposal as a pre-processing step for other algorithms must meet the highest possible object detection recall rate in the shortest possible time to avoid missed detection and improve real-time performance. Among them, only BING [8] can achieve optimal performance in terms of recall rate and computational efficiency, which is why BING is widely used in various image detection [9].

However, the localization quality of the proposals generated by BING is not high, and the recall rate also drops rapidly when the overlap threshold IOU is stricter. Although Sel.search [6], MCG [12] and other super-pixel merging methods can achieve better performance in localization quality, but at the cost of great calculation time. The problems of these two types of methods can be summarized as low efficiency and poor localization quality. For this problem, we have proposed a solution that can significantly improve the localization quality and computational efficiency, while also improving the recall rate and the robustness to noise interference. Specifically, our main work and contributions:

- We propose to use horizontal high frequency features (HL) to describe closed contours: HL features have better objectness measuring and lower computational complexity than NG features, which makes our algorithms have higher recall rates and higher computational efficiency. The test results in Pascal VOC2007 [1] show that the calculation of HL feature is only one eighth of NG feature, while the recall rate of HL feature is higher than NG feature.
- We propose an efficient eight-neighbor edge tracking and bounding box growth algorithm to merge window borders.
containing different parts of the same object: by iteratively merging neighborhood boxes with the same attributes, the merged proposal box is closer to the real area. On the VOC2007 data set, using this strategy we can make the BIHL algorithm improve the localization quality by 8.7% without reducing the recall rate, and the calculation time is only 0.04ms.

II. PROPOSED APPROACH

In this section, we will describe our method of generating an object proposal. The implementation process of the algorithm is shown in Figure 3.

First, for each test image I, downsampling is performed according to a series of fixed ratios \( P_{ds} \), where \( (m, n) \) respectively represent the ratio of image line and column downsampling.

\[
P_{ds} (m, n) = \left[ 2^m, 2^n \right], \begin{cases} 
  \text{if } m \in \{0, 1, 2, 3\}, |n - m| \leq 2 \\
  \text{if } m = 4, n = 3 
\end{cases}
\]

(1)

Secondly, for each downsampled image \( I_{ds(m,n)} \), we calculate its horizontal high-frequency HL feature map \( I_{Fds(m,n)} \) and traverse each feature map \( I_{Fds(m,n)} \) with a fixed-size search template. We limit the maximum downsampling ratio during downsampling, which reduces the number of times the search template traverses the image. Since each downsampled image needs to be traversed using a search template, the less the number of downsamplings, the smaller the amount of computation. Although the area of the window we initially generated cannot contain large objects, we don’t need to worry about this, because we have adopted a border merging strategy for these proposals, and generated a high-quality window that approximates the real area of the object by tracking the edge of the object. These new proposals include large-scale objects. The border merging strategy is an iterative fusion process. The main purpose of this strategy is to improve the poor quality of the window scoring method, which is an insurmountable defect. Since our border merging process only processes a small number of window borders with the same attributes, the amount of calculation is almost negligible compared to other steps of the algorithm, which we will introduce later. Third, for each region of the search template traversal, we use a binarized classifier to score it, and perform non-maximum suppression and border merging based on the scored results.

In Figure 2, the thresholds \( T_c \) and \( T_{mval} \) are set to filter out background interference.

A. HL frequency feature and Object proposal

Objects are usually rich and complex in color and texture, so the method of using color and gradient features such as BING has a higher recall rate at a lower overlap threshold, but the localization quality is lower. And as the overlap threshold increases, its recall rate will drop dramatically. Frequency signals have good ability to extract image structure information, and has a wide range of applications in image processing field. We have found that this feature of frequency can be applied to the feature extraction of the object proposal generation method to achieve good results.

Calculation method: for the downsampled image \( I_{ds(m,n)} \), first use the high pass filter \( f_h \) defined in equation 2 to convolute the image in the row direction in steps of 2, and then use the low pass filter \( f_l \) defined in equation 3 to deconvolute the image in the column direction in the same steps, then the horizontal high frequency feature map \( I_{Fds(m,n)} \) can be obtained.

\[
f_h = [-1 1] / 1.41 \quad (2)
\]

\[
f_l = [1 1] / 1.41 \quad (3)
\]

As shown in Table I, the HL feature requires only a few basic operations to achieve. We counted all the required basic operands and compared it with BING’s NG feature.

| Feature | + | - | * | / | \text{abs} | \text{max} | \text{min} |
|---------|---|---|---|---|----------|----------|----------|
| HL 5wh 1.5wh 2wh 1.5wh | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| NG 7wh 20wh+5w+4w+4w+4w+4wh+4w-4h 14wh | 4wh 3wh |

The basic operands of HL feature are only 1 / 8 of NG feature, so theoretically, the computing efficiency of HL feature is much higher than NG feature.

We use the HL as the metric feature of objectness. Calculate the horizontal high-frequency HL feature map \( I_{Fds(m,n)} \) on a series of downsampled images, and then a sliding window is used to traverse each 8 * 8 scale region on the feature map in steps of 1 to obtain the 64 dimensional HL feature \( hl \) of the corresponding region. Then we binarize each \( hl \) feature and use the binary SVM classifier to calculate the classification score.

B. Binarized

1) HL feature binarization: The binarized expression of the HL feature \( f_s \) is as shown in Eq. (4), and the first \( N_g \) binary bits are used to approximate the 64-dimensional HL frequency feature \( hl \) [8], Where \( k \) represents a binary bit.

\[
f_s = \sum_{k=1}^{N_g} 2^{8-k} hl_k \quad (4)
\]
2) Classifier binarization: Literature[8][20] explains that binary approximation of classifier has the advantage of accelerating feature extraction and classification process. In order to improve the computational efficiency, we refer to [8] [20] using a set of basic vectors to approximate the SVM classifier model \( w_{hl} \).

\[
 w_{hl} \approx \sum_{i=1}^{N} \lambda_i \nu_i 
\]

Using this approximation, we can effectively compute the dot product \( \langle w_{hl}, f_s \rangle \) using only bitwise operations. Where: \( \nu_i \) can be represented by a binary vector, \( \nu_i = 2\nu_i^+ - 1 \), \( \nu_i^+ \in \{0, 1\}^D \). The following cross-expression can be obtained:

\[
\langle w_{hl}, f_s \rangle \approx \sum_{i=1}^{N} \lambda_i \sum_{h=1}^{N} 2^{s-h}(2\nu_i^+ - \lfloor h_k \rfloor)
\]

Where \( \lambda_i \in R \) represent the calibration coefficients, \( N_a \) represents the number of decomposition basis vectors.

C. Non-maximum suppression and Boxes Merging

Using the Eq.6 to traverse the feature map \( F_{F_{decay}(m,n)} \), a classifier score matrix \( M \) can be generated, and each element value of the matrix \( M \) represents the objectness score of the \( 16 \times 2^m \times 2^n \) region of the corresponding original image. where \( (m,n) \) respectively represent the ratio of image line and column downsampling. In this paper, the non-maximum suppression algorithm is used to filter the background region where the score is less than 0 in \( M \) and suppress the window with the overlap ratio greater than 87.5%. The proposal box coordinates and scores after the non-maximum suppression are stored in the container \( V \), and the merge strategy proposed by us is used to merge the borders.

1) Bounding box merge: The proposal generated by a fixed-size search template on a series of downsampled images is likely to not well surround the object instance, resulting in a lower quality of the final generated proposal boxes. In order to solve this problem, we propose a fast and effective eight-neighborhood edge tracking and border growth algorithm to merge box borders containing different parts of the same object. Our method only fuses a small number of box borders with the same attributes, which takes almost no time. We merge the bounding boxes after non-maximum suppression. The merging process is based on the principle that the scores and positions are similar. The steps to implement the algorithm are as follows:

- Create an all-one matrix \( M_1 \). The proposals stored in the container \( V \) are projected into \( M_1 \) according to the score from high to low, and the matrix value of the projected coordinates in \( M_1 \) becomes 0, and the projection point is used as a seed point \( A \) to be grown;
- In \( M_1 \), judge whether the value of 8 fields around the current seed point \( A \) is 0, if not, set 0, if 0, it means that the point has been grown by the previous seed point \( B \), then judge whether the difference between the serial number of \( A \) in \( V \) and the serial number of \( B \) in \( V \) is less than the threshold value \( T_{x1} \), if less than, fuse the two seed points, otherwise, as a new seed point;
- If there is seed point \( B \) on the coordinate point when proposal \( C \) is projected to \( M_1 \), judge whether the difference between the serial number of \( C \) in \( V \) and the serial number of \( B \) in \( V \) is less than the threshold value \( T_{x2} \). If it is less than the threshold value, fuse the two seed points, otherwise, delete proposal \( C \);
- We limit the maximum length of \( V \) to 1100, and stop growing when there is no proposal in the container \( V \).

2) Performance evaluation: In order to verify the performance of the merge strategy, we tested the recall rate (DR), localization quality (MABO) and computation time (Time) when using the merging strategy and disabling the merge strategy on the VOC2007 dataset [1].

According to Table II, the recall rate does not change when the BIHL algorithm adopts the merge strategy, while the localization quality has greatly improved, and the merge strategy only accounts for about 3% of the calculation time (0.05ms). When BING adopted our merger strategy, the localization quality improved by 9.3%.

III. EXPERIMENT

To verify the validity and superiority of the proposed method, we tested our method in the public dataset Pascal VOC2007 [1] and the Pascal VOC2007 synthetic interference dataset [2] with 297,120 test images [2], and compared it with the best typical method in the last decade: MCG[12], Sel.Search(Sel.S)[6], Rand.Prim(R.P)[13], MTSE (ME)[17], Endres(E)[11], LOP[14], Kantalankila (R1)[16], Rigor (Rr)[15], Objectness(Obj)[18], BING[8], EdgeBox (EB)[7], Rahtu (Ru)[19], Uniform(U)[2], RPN[4], VOC2007 contains 20 object categories, including 9,963 natural images with annotated labels. We trained using a training data set consisting of 2501 images and tested on a test data set consisting of 4952 images. The VOC2007 Interference Dataset [2] is a repeatability test set synthesized by adding scaling, rotation, illumination variation, JPEG artefacts, blurring, and salt&pepper noise in the VOC2007 test set[1]. The four key evaluation indicators of the general object proposal methods are recall rate, computational efficiency, localization quality, and repeatability[2]. The recall rate evaluates whether it is possible to use as few object proposals as possible including as many objects as possible in the image. Computational efficiency evaluates whether the speed of the object proposal method is significantly faster than the detector itself, so as to improve the computational efficiency of the detector. Repeatability evaluates whether the performance of the object proposal method remains stable on similar or slightly different images. Localization quality evaluates the validity of the generated object proposal. Therefore, we also mainly test and compare four aspects: (1) object detection recall

1. https://github.com/batra-mlp-lab/object-proposals.
2. http://3dimage.ee.tsinghua.edu.cn/cxz/mtse
3. http://3dimage.ee.tsinghua.edu.cn/cxz/mtse
4. https://github.com/endernewton/tf-faster-rcnn.
(DR), (2) mean average best overlap (MABO), (3) computing time, and (4) repeatability. Because these methods have been optimized for the Pascal VOC2007 dataset [1], we only use their default parameter settings. It is worth noting that the VOC2007 data set is labeled with simple samples and difficult samples. In this paper, the comparison is made under the condition of selecting all difficult samples and simple samples.

A. Recall

When the detection and recognition algorithm uses box generated by the object proposal method as a candidate window, whether the object proposal method can contain all the interested objects in the test image is the most critical criterion to measure their performance. We evaluate by calculating the maximum recall rate that can be achieved under a fixed overlapping thresholds (IoU) and the number of proposals is less than 10,000 [2]. In the experiment we used the overlapping thresholds $IOU \geq 0.5$ to calculate the recall rate. The experimental results are shown in Table 3.

B. MABO

In order to evaluate the quality of our object proposals, Mean average best overlap (MABO) is used to measure the ability of how well the proposals generated by a method can localize object instances [2].

In Table III, we summarize the recalls and MABOs for each method at different overlap thresholds when the number of proposals is less than , and underline the top 3 methods in performance. Our method, BIHL, achieves the highest recall rate in all methods at $IOU \geq 0.5$. The MABO of our method is slightly lower than that of some segmentation method and superpixel merging method. But when the localization quality reaches 80%, the performance of the proposed algorithm depends more on the computational efficiency, detection recall rate and repeatability to perturbation.

C. Proposal Repeatability

By referring to the evaluation method of Jan Hosang et al. [2], we compared BIHL with other most advanced algorithms, and the results are shown in figure 3.

In Table III we summarize the average repeatability of all state-of-the-art methods. The repeatability of various perturbation is generally poor with RPN[4] and segmentation methods and superpixel merging methods. The average repeatability of BIHL is second only to BING[8]. However, as shown in Figure 3, BING are very sensitive to scaling, but BIHL can still achieve good performance. This shows that BIHL is the method with the highest average repeatability among the state-of-the-art methods that maintain good repeatability to various perturbation.

D. Computational Time

Table III shows the computational time of all advanced methods on the PASCAL VOC2007 test set containing 4952 images [1]. RPN[4] runs on GTX 1080Ti GPU and 2.20 GHz Intel Xeon E5-2630 v4 CPU. Other methods only run on Intel Xeon E5-2630 v4 CPU. The time shown here is the average time of all images of the PASCAL VOC2007 test set[1], including all steps from reading the image to outputting the proposals. In general, segmentation-based methods and superpixel merging methods run relatively slowly. For example, the fastest method Rand. Prim[13] also requires 1.54 s, while the slowest method Endres[11] requires 150s. Edge-based methods are usually less computationally intensive. For example, the slowest method Rahtu[19] only requires 5.47 s, and the fastest BING[8] of them can reach 0.004 s. The three variants of our method, except for the difference in accuracy and proposal budget, run at almost the same speed, 0.0015s per image, which is the most efficient method of all current methods, which is nearly 3 times faster than BING [8].

IV. CONCLUSION

In this paper, we propose a new object proposal algorithm (BIHL), which can generate high quality proposals in a very effective way. The advantages of the algorithm are mainly brought by two parts: (1) HL frequency feature, (2) bounding box merging. BIHL has a minimal computational complexity and good objectness measurement ability, which make our algorithm achieve the best performance of the recall rate and computational efficiency in all object proposal algorithms on the VOC2007 dataset, and the average optimal overlap rate (MABO) reaches 79.5%. At the same time, BIHL is the method with the highest average repeatability among the state-of-the-art methods that maintain good repeatability to various perturbation. The code will be published in https://github.com/JiangChao2009/BIHL.
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