Relocation with Coverage and Intersection over Union Loss for Target Matching

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Keywords: Target Matching, Object Detection, Deep Learning, Relocation Strategy, Loss Function.

Abstract: Target matching is a common task in the field of computer vision, which has a wide range of implements in the fields of target tracking, medical image analysis, robot navigation, etc. The tasks in these scenarios have high requirements for locating accuracy, reliability and robustness, but the existing methods cannot meet these requirements. To improve the algorithm performance in these aspects, a novel practical target matching framework is proposed in this paper. We firstly present a new bounding box regression metric called Coverage-Intersection over Union (Co-IoU) to obtain higher positioning accuracy performance compared to previous bounding regression strategies. Also, a reasonable region validation and filter strategy is proposed to reduce the false positive matches and the Region of Interest (ROI) adjustment and relocation matching strategy are innovatively present to acquire higher locating accuracy. Our experiments show that the proposed framework is more robust, accurate and reliable than the previous relevant algorithms. Besides, Coverage-Intersection over Union Loss and relocation strategy proposed in this paper can significantly improve the performance of the general object detector as well.

1 INTRODUCTION

Target matching is a basic problem in computer vision, of which purpose is to find the position of the specific target object in the whole image, it has a wide range of applications involving manufacturing, detecting edges in images, and medical image analysis (James and Alex Pappachen, 2014).

There are two common ways of target matching task. One is in template matching approach that focuses on matching the similarity of pixel information without semantics information between matching patches pairs (Hashemi et al., 2016). Another way named instance detection (Nan et al., 2019) is to take advantage of semantic information in instance templates to match and locate targets.

In template matching way, the approach based on region is more frequently used in many real-world scenarios. Normalized Cross-Correlation, NCC) is a representative template matching method (James et al., 2014), which is invariant to linear brightness and contrast changes, but it is still sensitive to rotation, scale changes, and background changes, which imposes some restrictions on deforming templates or complex backgrounds (Perveen et al., 2016). Best-Buddies Similarity (BBS) can overcome outliers (i.e., background noise, occlusion) and target nonrigid distortion (Dekel et al., 2015), but when the scale ratio of the template to the target image is small or outliers (occlusion or background clutter) cover most templates, the success rate decreases. Co-occurrence based template matching (CoTM) improves the performance of target matching (Kat et al., 2018), but is susceptible to interference from areas with similar pixel colour distribution. Quality-aware template matching (QATM) is one of the best template methods so far, and the parameters of QATM can be trained by a neural network to improve the performance of matching (Cheng et al., 2019). However, this method is still sensitive to lighting, noise, and scale changes, and the time consuming is unacceptable in many applications.

Another way in instance detection is to make use of semantic information from instance templates to solve the problem of target matching. The Target Driven Instance Detection (TDID) based on Faster RCNN (Ren et al., 2017) two-stage detector and an instance template to boost target matching

Lu, Z., Liao, J., Lv, J. and Chen, F.
Relocation with Coverage and Intersection over Union Loss for Target Matching.
DOI: 10.5220/0010191802530260
In *Proceedings of the 16th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2021) - Volume 4: VISAPP*, pages 253-260
ISBN: 978-989-758-488-6

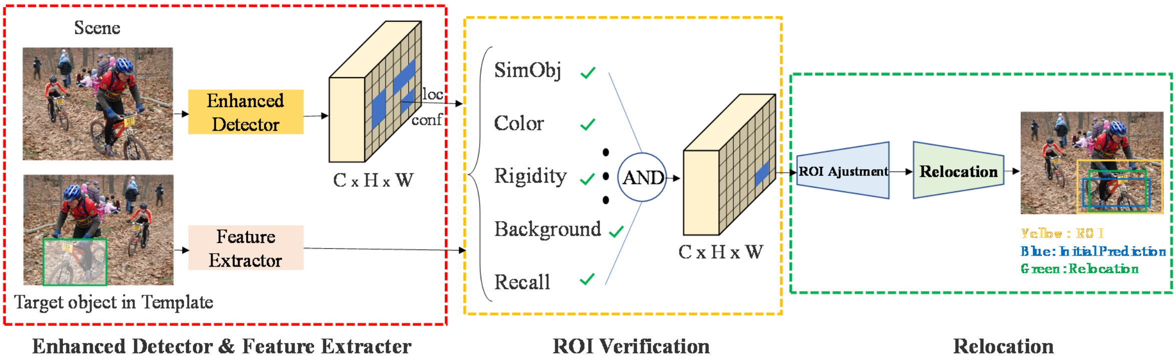


Figure 1: Pipeline of target matching framework. Enhanced Detector & Feature Extractor shows feature extracted by the enhanced detector from the target object in the scene and template. ROI Verification demonstrates the similarity metrics of the selected ROI in the patch pair feature. Relocation shows the ROI adjustment and relocation process. The blue in the final result output chart is the coarse positioning box, the yellow is the region of interest after region screening and adjustment, and the green is the output after relocation.

positioning (Ammirato et al., 2018), which improves the accuracy, but the false positives is still high. (Nan, et al., 2019) proposed a feature extraction method to measure the similarity between the matched positioning result and the instance template to filter the mismatch result, which improves the positioning reliability, but the algorithm is time-consuming. Moreover, in target detection framework, bounding box regression is a significant step to predict bounding boxes to locate the target, which can also greatly affect the final positioning` accuracy. Loss function like Intersection over Union (IoU) loss is optimized by calculating the ratio of the intersection and union between the prediction box and the real box (Rezatofighi et al., 2019), but the problem is that only two boxes that intersect can be returned. Generalized Intersection over Union (GIoU) solves the optimization problem when no intersection exists by expanding the prediction box, but this method takes too long. Distance Intersection over Union (DIoU) reduces the iteration time and improves the accuracy by adding the loss of the distance between the prediction box and the true box center (Nan, et al., 2019), but the recall rate and coverage of the regression shape can still improve.

In this paper, we present a novel target matching framework. Firstly, we design a new bounding box regression strategy called Coverage with intersection over union loss function (Coverage-IoU), based on which the detector can achieve higher locating precision in target matching tasks. Moreover, a verification strategy is present to reduce false positive in matching. And we finally propose a relocation strategy to locate in higher precision. Overall, Compared with the previous methods, the framework we proposed can improve the target locating performance without instance-level labels and shows strong robustness and fast speed in various scales, lighting, stain noise and other difficult environments, which means it is practical for the application in real-world scenes.

The contribution of our work is summarized as follows:

- A coverage-intersection over union loss, i.e., Coverage-IoU loss, is proposed by considering four geometric measures, i.e., corner points distance, coverage area, overlap area and shape recall, which better describes the regression of rectangular boxes.
- A verification strategy is presented to effectively filter regions of interest without target object, which can reduce the false positive detection rate and improve the overall performance of target matching.
- A relocation strategy is proposed to improve the performance of the target matching framework, which can reduce information loss in the neural network to acquire higher location accuracy.
- The relocation strategy and Coverage-IoU Loss proposed in this paper can be easily ported to other tasks, such as target detection, instance segmentation, and so on.

2 METHOD

The target matching framework proposed in this paper consists of three stages:

- **Enhanced Detector:**
  We first run an enhanced detector with Co-IoU loss, this stage provides candidate bounding

box detections with location and confidence, which will be verified by feature extracted from the template in the next stage.

- **Verification Tests:**
  We next predict similarity between the templates image and each proposed candidate bounding box detection in the proposed filtering strategy, which take Class similarity, co-occurrence matrix and recall into consideration.
- **Adjustment and Relocation:**
  Given the verified region of interests (ROI), we adjust the regions and relocate to achieve high locating precision.

The entire framework is shown in Figure 1.

2.1 Coverage-IoU Loss

Bounding box regressing is one of the key components in target detection, which has a great impact on the precision of locating objects. In target matching task, the output used to be (x, y, w, h) or (x_1, y_1, x_2, y_2) to represent the prediction boxes. Intersection over Union (IOU) is the most popular metric to compare the similarity between two arbitrary boxes (Eq. 1).

$$IoU = \frac{|B^{pb} \cap B^{gt}|}{|B^{pb} \cup B^{gt}|} \tag{1}$$

where B^{pb} and $B^{gt}$are the prediction positioning box and the ground truth box respectively.

Also, IOU can be used as a criterion to measure distances between bounding box predictions (Eq. 2).

$$L_{IoU} = 1 - IoU \tag{2}$$

The IoU based loss has the virtue of scale invariance, non-negativity, symmetry and triangle inequality and the identity of indiscernible target, but still has many weaknesses like optimization instability, box regression speed and so on. Thus, we propose a novel loss function to figure out these problems.

First of all, we use the distance between the two corners (upper left corner and lower right corner) of the prediction box and the target box to optimize the loss function, which can be defined as (Eq. 3).

$$L_{cd} = \frac{\rho^2(\mathbf{b}_{pl}, \mathbf{b}_{gl})}{4c^2} + \frac{\rho^2(\mathbf{b}_{pr}, \mathbf{b}_{gr})}{4c^2} \tag{3}$$

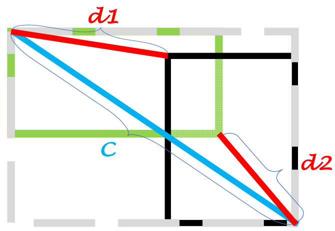


Figure 2: Schematic diagram of corner distance, in which the green rectangle is the real box, the black rectangle is the prediction box, d_1 and d_2 are the distance between the prediction box and the real box, c is the diagonal distance.

Where bpr and bpl denote right bottom corner and left top corner of B, while bgr and bgl denote right bottom corner and left top corner of B^{gt}. As shown in Figure 2, ρ (·) is the Euclidean distance, and c is the diagonal length of the smallest enclosing box covering the two boxes.

Moreover, coverage and intersection over union are added in the measurement (Eq.4 and Eq.5).

$$Co = \frac{|B^{pb} \cap B^{gt}|}{|B^{gt}|} \tag{4}$$

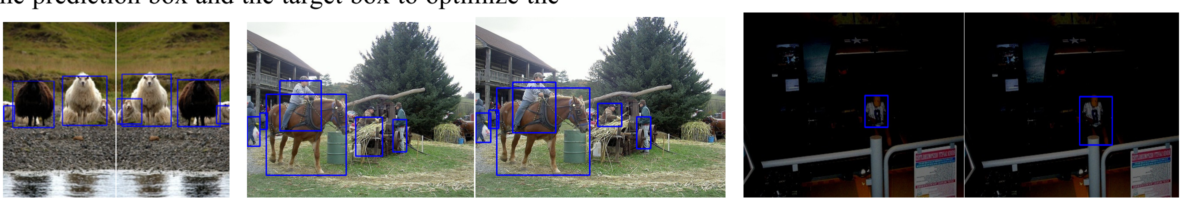
$$L_{Co} = \alpha * IOU + (1-\alpha) * Co \tag{5}$$

Where α is a positive trade-off parameter, which determines the weight of intersection over union and coverage. Generally, the higher the requirement of coverage is, the lower the value should be set. When the value is 1, the coverage ratio is not considered. In this paper, the default choice is 0.8 through experiments.

Finally, a strict shape restriction is finally added to punish the mismatch of shape, which makes the method obtain more precise positioning results with fewer iterations, and it can be met by implementing v *as* (Eq. 6).

$$v = \frac{4}{\pi^2}\left(\arctan\frac{w^{gt}}{h^{gt}} - \arctan\frac{w}{h}\right)^2 \tag{6}$$

Where v measures the consistency of shape.



L_{CIoU} $L_{Co\text{-}IoU}$ L_{CIoU} $L_{Co\text{-}IoU}$ L_{CIoU} $L_{Co\text{-}IoU}$

Figure 3: Comparison examples between the CIoU loss and Ours, the blue rectangle box is the detection result.

Thus, the final Coverage-IoU loss function is formed (Eq. 7).

$$L_{Co\text{-}IoU} = 1 - v * L_{Co} + L_{cd} \quad (7)$$

The Comparison examples between the CIoU loss and Ours are shown in Figur3. An enhanced target detector with this loss function is used to extract features, which are combined with the features extracted from the template into the next verification and filtering step to select the ROI.

2.2 Verification Tests

Since the regions predicted by the basic detector included non-target object regions, it means that the false positive ratio is relatively high and the results are not reliable. Therefore, we present verification tests to find the region of interest rather than time-consuming post-processing like matching key-points of each candidate with target. In order to properly filter the regions of interest, the verification criteria include two components: class similarity evaluation and target similarity evaluation.

Class similarity evaluation calculates the probability that two regions belong to the same category. f_t and f_r are the features extracted from the template image and candidate regions in search-image respectively. f_t and f_r can be measured as feature vectors using similarity formulas such as cosine similarity (as Eq. 8, Eq.9 below) to directly calculate the class similarity. Where μ and λ are normalization factors, and the similarity can be normalized into [0,1] intervals though taking 0.5 and 0.5 respectively.

$$\cos\theta = \frac{f_t \cdot f_r}{|f_t| \times |f_r|} \quad (8)$$

$$Sim(t \mid r) = \frac{f_t \cdot f_r}{\mu |f_t| \times |f_r|} + \lambda \quad (9)$$

Furthermore, Target similarity evaluation calculates the probability of the target object in the same category, which is consists of 3 parts: co-occurrence pixel matrix, anti-background interference metric and shape recall.

The co-occurrence pixel matrix takes colour, a certain distortion rigidity, mapping precision into account (as shown in Eq.12 below), which is calculated between the template image and candidate regions.

$$C(a,b) = \frac{\rho}{Z} \sum_{p,q} \exp\left(\frac{-d(p,q)^2}{2\sigma^2}\right)\left[I_p = a\right]\left[I_q = b\right] \quad (10)$$

Where I_p and I_q are pixel values in a and b, Z is the normalization factor and P is the edge pixel weight reduction factor, which will be applied when the edge area of the candidate area appears more frequently.

Anti-background interference reduces the impact of surrounding pixels that occur frequently in multiple areas (as Eq.10 and Eq.11 below), especially the pixels near the edge. Where ξ is the normalization factor, p is the pixel location, $h(p)$ represents the occurrence weight of pixel p, the higher the frequency of occurrence, the lower the weight.

$$M(a,b) = \frac{C(a,b)}{h(a)h(b)} \quad (11)$$

$$S_r = \xi \sum_p M\left(T_{idx}(p), R_{idx}(p)\right) \quad \forall R_{idx} \subseteq I_{idx} \quad (12)$$

Shape recall mainly measures the shape recall of the detection boxes and the template. The greater the difference, the lower the score (Eq. 12).

$$T_{recall} = \max\left(\frac{w_s h_s}{w_t h_t}, \frac{w_t h_t}{w_s h_s}\right)^{-1} \quad (13)$$

In all, the whole verification criterion is calculated by the following (Eq.13) and the candidate region with the highest score in the regions of target. If all candidate area scores are smaller than the threshold, no matching area will be outputted.

$$Conf(t \mid r) = Sim(t \mid r) \wedge S_r \wedge T_{recall} \quad (14)$$

Algorithm 1: ROIs Verification and Target Relocation.

Input: $\{R_i\}$, $i \in [1, n]$ are the set of Predictions from the enhanced base detector, n is the number of Predictions (ROIs), T is the target template.

Output: Target Region $\hat{R}$

1: Do Region of Interests verification:
2: $T' \leftarrow$ Feature Extracter(T)
3: $R_i' \leftarrow$ Feature Extracter (R_i)
4: Compute $Conf(T'|R_i') = Sim(T'|R_i') \wedge S_r \wedge T_{recall}$ %Eq.14
5: $R_S \leftarrow$ Softmax ($Conf(T'|R_i')$)
6: Do Target Relocation:
7: $R_e \leftarrow$ Region expansion(R_s)
8: $R_d \leftarrow$ Redetection (R_e)
9: $\hat{R}$ $\leftarrow$ max (Confidence (R_d, R_S))
10: Return $\hat{R}$

2.3 Region Expansion and Relocation

In the end-to-end deep learning detection method, due to the quantification error caused by pooling operations in the CNN structure, the final location results are always not accurate enough.

Figure 4: Examples of relocation, in which the blue box as the initial locating region, the green box represents the region of interest, and the red box is the output after relocation.

The Process of adjustment of regions of interests (ROIs) and relocation in this paper are proposed to solve this problem, as shown in algorithm 1. the detector based on Coverage-IoU loss is designed to be used as a guide for target matching to output ROIs, and the region of interest will be selected after verification and filtration. Then expanding the selected region of interest and finally relocation in this region to achieve high location accuracy. Due to the scale of regions of target is relatively reduced to the scale of target in relocation process, the consuming time of whole process is close to the single detector.

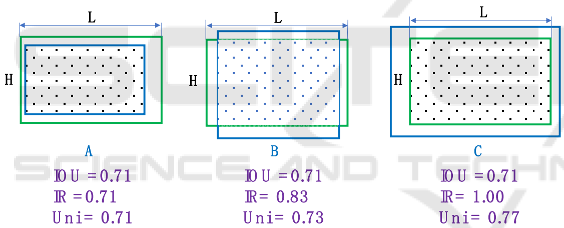


Figure 5: Comparison between IoU and Coverage-IoU loss. The green box is the ground truth, the blue detection box is the prediction box, and the dot region is the detected region of the target object.

In Coverage-IoU loss function, we add a coverage item to optimize the loss, which makes the objects in the prediction box be included in ROIs as much as possible (close to the middle), which benefits the regional expansion in this step.

As we can see from Fig.5, when the loss function is optimized, the IOU criterion can no longer be optimized when the IOU score can no longer be optimized (like A, B and C with same IoU), while Coverage loss proposed in this paper can still continue to be optimized. For many practical scenarios, matching and positioning tasks tend to be cover the target object in the prediction box as much as possible. And as shown in Figure 4, the target is more likely to be completely included and precisely located in output after relocation.

3 EXPERIMENTS

In this part, we test the performance of one of the most popular one-stage detectors (YOLOv3) based on our proposed Coverage-IoU (Joseph Redmon, 2013-2016) on Pascal VOC, which is one of the most commonly used object detection datasets. Then we take advantage of OTB template matching dataset format to build our own dataset (4 times larger than standard OTB and takes illumination, noise and angle shift into consideration) to compare the performance of our framework with other advanced methods like NCC, QATM and so on. All evaluations are based on an Intel(R) I7 7800X CPU and a GeForce GTX 2080Ti GPU.

3.1 Coverage-IoU Performance

In this experiment, we compare a single-stage detector (YOLOv3) based on Coverage-IoU loss with the detector based on other bounding box regression strategies in PASCAL VOC Dataset.

To test the improvement of the basic detector based on Coverage-IoU, we used VOC 07+12 (a combination of VOC 2007 training validation set and VOC 2012 training validation set) as the training set, which contained 16551 images from 20 classes. The test set is VOC 2007 and consists of 4952 images. We used the Darknet training tool for training, with the maximum number of iterations set to 100K. The results of each loss function are shown in Table 1 below. Average Precision (AP) is a common criterion to measure the performance of the algorithm with the change of threshold value. We used the same measure of performance AP (the average of 10 mean Average Precision across different IoU thresholds) = (AP50 + AP55 + … + AP95) / 10), AP75 (AP75, mAP@0.75) and AP90 (mAP@0.90).

This article uses the framework of darknet416.

As we can see from the Table.1, compared to $\mathcal{L}_{MSE}$, the performance of $\mathcal{L}_{IoU}$ is 7.72 points higher on AP, 18.28 points higher on AP75, and more than 4

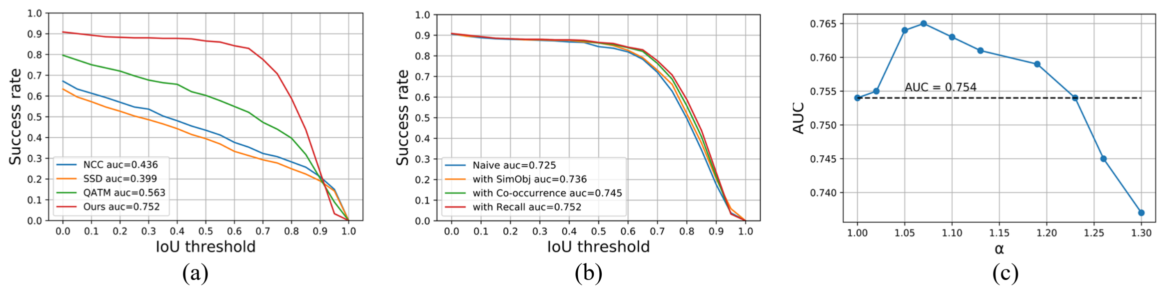


Figure 6: Performance of different Methods in AUC in MOTB. (a) Comparison among different matching and locating methods, (b) Performance of different IoU loss, (c) the influence of α on the performance of relocation.

times higher on AP90, which shows the superiority of the IoU. The loss proposed in this paper is an improvement on top of IoU. Therefore, using this method as a benchmark, we can measure the improvement of this method.

Compared with the most advanced methods, we can find in table 1 that Coverage-IoU shows a 6.96% improvement on AP, 10.20% improvement on AP75 and doubles on AP90 compared to $\mathcal{L}_{IoU}$ respectively. And it can be summarized that Coverage-IoU based detector gradually increases in proportion to other IoU based detectors (AP90 > AP75>AP) as the threshold increases, which indicates that Coverage-IoU is more suitable for the scenarios require for high locating precision.

Table 1: Quantitative comparison of YOLOv3 (Redmon and Farhadi 2018) trained using $\mathcal{L}_{IoU}$ (baseline), $\mathcal{L}_{GIoU}$, $\mathcal{L}_{CIoU}$ ($\mathcal{L}_{DIoU}$) and $\mathcal{L}_{Co-IoU}$, the results are reported on the test set of PASCAL VOC 2007.

Loss/Evaluation	AP	AP75	AP90
L_{MSE}	36.33	31.05	0.90
L_{IoU}	44.05	49.33	3.8
L_{GIoU} improv. %	46.67 5.95%	53.91 9.28%	7.54 98.42%
$L_{Co\text{-}IoU}$ improv. %	46.51 5.58%	53.87 9.20%	7.33 92.89%
$L_{Co\text{-}IoU}$ improv. %	**47.12** **6.96%**	**54.36** **10.20%**	**8.23** **116.59%**

From Figure 6(b) we can clearly see the performance of methods based on $\mathcal{L}_{IoU}$ (baseline), $\mathcal{L}_{GIoU}$, $\mathcal{L}_{CIoU}$($\mathcal{L}_{DIoU}$) and $\mathcal{L}_{Co-IoU}$ (Ours) in matching and localization task on the MOTB dataset (more details about MOTB dataset will be introduced in section 4.2), among which $\mathcal{L}_{CoIoU}$ that we proposed shows 1.3%, 2.8% and 4.7% improvement in AUC compared to $\mathcal{L}_{IoU}$ (baseline), $\mathcal{L}_{GIoU}$, $\mathcal{L}_{CIoU}$ ($\mathcal{L}_{DIoU}$) respectively, and with increasing IoU threshold, the performance of our method is consistently better than others.

3.2 Performance on MOTB Dataset

In the previous template matching paper (such as QATM, COTM), OTB dataset is one of the most commonly used datasets. It has 105 template- image pairs and about 31 scenarios for matching tests. However, the problem with OTB dataset is that the scale does not change much and the interference such as illumination, angle variation and noise is very little.

Moreover, unlike template matching tasks only focus on the shallow similarity of images patches, the templates in target matching tasks usually include specific objects, which means the internal semantics of images is also significant. So the general template datasets is not suitable for our experiments in target matching, and we set up a new dataset which has 393 image pairs in different scenarios in OTB data format, which is about four times larger than the original OTB dataset and take the variation of illumination, noise, and view angle in the actual application scenario into Consideration. Also, as a test set for target matching and positioning task, each template in the dataset include a specific target and the categories of target collected in this dataset are as same as categories in VOC Dataset to facilitate qualitative comparison of target matching and positioning.

3.2.1 Verification and Relocation

In this section, we test the effects of verification and relocation strategy on top of the detector based on Coverage-IoU in MOTB dataset.

Verification. Area Under Curve (AUC) describes the success rate of locating with the change of threshold value, which is a common criterion to measure the algorithm performance. As shown in Table 2, the AUC performance is enhanced gradually with multi verification processes. Naïve location represents the results of enhanced detector based on Coverage-IoU.

Table 2: Performance comparison among different verification strategy.

Methods /Verifications	Sim	Co-occur	Recall	AUC
Straight relocation				0.725
Feature Similarity	√			0.736
Co-occurrence Verification	√	√		0.745
Union Verification	√	√	√	**0.752**

The straight location represents directly using of shape recall to find the most matched region. Feature Similarity represents using of class probability to determine and filter regions of interests. Co-occurrence Verification takes advantage of a co-occurrence matrix considering colour, distortion, and background interference to verify ROIs. And it is clear that the union verification strategy includes all process above achieve the highest AUC improvement.

Relocation. In this paper, we use a relocation strategy to improve the location accuracy, which expands the initial location region to a certain extent and redetect again in this region of interest. Re-detection in the adjusted region of interest can reduce the loss of features by narrowing the ROI compared with detecting in the whole image.

However, the size for region of interest will affect our speed and precision to a great extent, so we have to carefully choose a suitable region expansion factor of relocation strategy (α). We have done a series of experiments on α, we set alpha varies within [1,1.3] to explore the impact of expansion factor on the performance of matching and positioning. Also, α can be selected by training the neural network, which will be our future work.

As we can see from the Figure 6(c) above, it is clear that the accuracy of location is improved with the enlargement of the region and reaches a peak at alpha is 1.07, but with the rising value of alpha, the AUC performance becomes worse due to increasing of false detection caused by fewer training pictures at these scales. To figure out this problem, we use a fusion strategy to avoid decreasing performance caused by a lack of training scale in relocation: only when the confidence of results after the relocation become higher, the predictions will be output.

3.2.2 Comparison with Other Methods

In this experiment, theαis set to 1.1 and the entire proposed target matching framework is evaluated on the MOTB dataset. Our method as well as all baseline method performance are shown in Table.3. It is clear that the method we proposed outperforms all popular methods and leads the second-best (QATM) by roughly 21% in terms of AUC score.

Also, it can be seen from Figure 6(a) that when the threshold increases from 0.5 to 0.9, the IoU is all significantly higher than the previous methods, especially when the threshold value is 0.9, there is most obvious improvement in AUC, which indicates that this method can better locate the target in high precision.

Table 3: The quantitative comparison of the localization effect of different matching methods was used. The results were tested on the MOTB data set, and the IOU performances at the thresholds of 0.5, 0.75 and 0.9 were measured respectively.

Method /Evaluation	IoU @50	IoU @75	IoU @90	AUC
SSD	44.56	28.43	18.14	30.18
NCC	50.02	35.37	19.91	35.16
QATM	80.00	61.03	39.87	60.30
Our	**96.34**	**68.01**	**52.26**	**76.25**
improv. %	**20.43**	**11.44**	**31.08**	**21.31**

3.3 Qualitative Evaluations

In this section, we demonstrate the matching performance and matching speed of proposed method through qualitative comparisons.

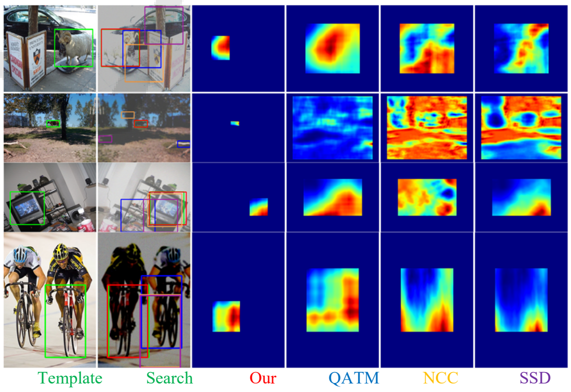


Figure 7: Qualitative matching performance comparisons.

Figure 7 provides more qualitative comparisons between our method and other matching and locating methods. These results further demonstrate the superiority of our method, which makes full use of the semantic information of the template itself to eliminate interference from other objects with shallow similar features in the background. Also, the verification strategy narrows the target area, while the relocation strategy is used to provide more accurate locations by reducing the loss of information in the neural network. As the example in the last line of Figure 7, the method proposed in this paper excludes interference from objects in same categories with similar appearance, while other methods are more susceptible to shallow features and more likely to find false target then. Or, as examples in the second and second-to-last figures, the other methods work not as well as ours when illumination is stronger or weaker than usual. And in the first line of the Figure 7 we can find that even there is only one salient target in the image (simple background and low interference), our method can also achieve a higher location accuracy than others.

Table 4: Speed test on MOTB datasets, where NCC and SSD methods can only use CPU, while QATM and the method in this paper can use GPU to accelerate the positioning effect.

Methods	**SSD**	**NCC**	**QATM**	**Ours**
Backend	CPU		GPU	
Average(*ms*)	296	321	1780	90

Finally, the matching speed is also an important criterion to measure the performance of the algorithm for practical application. Table.3 compares the average time consumed by different matching and locating methods on MOTB datasets, it is clear that the methods proposed in this paper has obvious advantages over traditional sliding window methods and QATM with GPU acceleration.

4 CONCLUSIONS

We introduced a novel target matching framework, which mainly includes Coverage- IoU based feature extractor, verification process and relocation after expanding region of interests. The idea of Coverage-IoU loss in this framework comes from that the existing IoU-loss cannot meet the coverage requirement in some scenes. The coverage, shape restriction and corner distance loss function can better describe the regression process of the bounding box and acquire more accurate position regression. Moreover, the verification strategy present here is to reduce false-positive results without the instance-level template, so as to guide the regions of interest to the target area. Finally, the inspiration of relocation strategy comes from the location errors caused by the information loss caused by pooling and other operations in the neural network, while narrowing input size and relocating in this area can reduce the position errors to achieve better performance in location accuracy. Also, the relocation strategy and Coverage-IoU Loss proposed in this paper can be easily ported to other common tasks like target detection, instance segmentation and so on.

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