Shape-Adaptive Selection and Measurement for Oriented Object Detection

Liping Hou, Ke Lu, Jian Xue*, Yuqiu Li

1 University of Chinese Academy of Sciences, Beijing 100049, China
2 Peng Cheng Laboratory, Shenzhen 518055, China
{houliping17, liyuqiu20}@mails.ucas.ac.cn, {luk, xuejian}@ucas.ac.cn

Abstract
The development of detection methods for oriented object detection remains a challenging task. A considerable obstacle is the wide variation in the shape (e.g., aspect ratio) of objects. Sample selection in general object detection has been widely studied as it plays a crucial role in the performance of the detection method and has achieved great progress. However, existing sample selection strategies still overlook some issues: (1) most of them ignore the object shape information; (2) they do not make a potential distinction between selected positive samples; and (3) some of them can only be applied to either anchor-free or anchor-based methods and cannot be used for both of them simultaneously. In this paper, we propose novel flexible shape-adaptive selection (SA-S) and shape-adaptive measurement (SA-M) strategies for oriented object detection, which comprise an SA-S strategy for sample selection and SA-M strategy for the quality estimation of positive samples. Specifically, the SA-S strategy dynamically selects samples according to the shape information and characteristics distribution of objects. The SA-M strategy measures the localization potential and adds quality information on the selected positive samples. The experimental results on both anchor-free and anchor-based baselines and four publicly available oriented datasets (DOTA, HRSC2016, UCAS-AOD, and ICDAR2015) demonstrate the effectiveness of the proposed method.

Introduction
The detection of arbitrarily oriented objects is a fundamental yet challenging task in computer vision, and can be applied in a wide range of scenarios, such as remote sensing (RS) images and text scenes. Because using horizontal bounding boxes (HBBs) cannot accurately calibrate the position of arbitrary-oriented objects and can also easily be affected by non-maximum suppression (NMS), using oriented bounding boxes (OBBs) has become a popular positioning approach and has made significant progress. Existing oriented object methods based on a deep convolutional neural network (CNN) mostly focus on the problems of the huge scale variations of objects and complex backgrounds but pay little attention to the large aspect ratio variations of objects.

As reported in ATSS (Zhang et al. 2020), the selection of positive and negative samples plays a critical role in detection performance, and is also the essential difference between anchor-based and anchor-free methods. Existing sample selection strategies are mainly divided into fixed and dynamic strategies. Although the simplicity and intuitiveness of fixed label assignment strategies make them a popular choice, they ignore the actual shape and content of the intersecting region of objects, particularly for oriented object detection. As shown in Fig. 1 (a) and (b), anchor-based methods (e.g., RetinaNet (Lin et al. 2017b)) use the max intersection over union (IoU) value (MaxIoU, for simplicity) between proposals and objects, and anchor-free method (e.g., FCOS (Tian et al. 2020)) uses k-nearest distance (K-Nearest for simplicity) between a point and the object’s center for sample selection. The developers of ATSS proposed a sample selection strategy using dynamic IoU thresholds, which is shown in Fig. 1 (c). In other recent works, researchers have proposed dynamic sample selection or anchor learning strategies (Yang et al. 2018a; Kim and Lee 2020; Zhang et al. 2020). Although these strategies are more efficient than fixed assignment strategies, they have the following problems: (1) the oriented object shape information (e.g., large aspect ratio) is overlooked; (2) selected positive
samples are processed in a uniform manner without considering their quality; and (3) there are limited applications to insertable architectures, for example, some dynamic anchor learning or selection strategies cannot be used for anchor-free architectures. Therefore, to avoid the aforementioned problems and further optimize the entire process, two shape-adaptive strategies for arbitrary-oriented object detection are proposed in this study for dynamically selecting samples and evaluating the quality of positive samples.

Specifically, for the purpose of adaptively selecting samples, the shape-adaptive selection (SA-S) strategy is proposed, which uses the object shape information effectively, and the object shape information is focused on the aspect ratio, which is calculated as the ratio of the long edge to the short edge in this study. The proposed SA-S strategy is designed to calculate optimal IoU thresholds for the objects with different shapes, so it is suitable for both anchor-based and anchor-free methods which adopt IoU threshold to assign labels.

Furthermore, considering that the selected positive samples have different qualities and potentials, a shape-adaptive measurement (SA-M) strategy is designed to add quality information to them. The SA-M strategy measures the positive sample’s quality using a new concept, that is, the normalized shape distance, which combines the center and shape of the object to calculate the distance of the sample point relative to the object. Additionally, a boundary-center loss function is elaborated based on an anchor-free architecture for keypoint learning. The main contributions of this study are as follows.

1. A novel dynamic SA-S strategy is proposed, which selects positive samples according to the shape and characteristics distribution of objects.
2. A new SA-M strategy is proposed, which evaluates the quality of the selected positive samples. Additionally, the new concept of the normalized shape distance is designed, which eliminates the effect of the object shape on the estimation of relative object distances.
3. Sufficient experiments were conducted to prove that the proposed dynamic sample selection and measurement strategies can be embedded into both anchor-free and anchor-based methods to achieve significant improvements in detection performance.

The experimental results demonstrated that the proposed method was superior to other state-of-the-art methods on the benchmark datasets DOTA (Xia et al. 2018), UCAS-AOD (Zhu et al. 2015), HRSC2016 dataset (Liu et al. 2017), and ICDAR2015 (Karatzas et al. 2015).

**Related Work**

**Oriented Object Detection**

Representation of object in object detection has been dominated by HBBs for several years, whose cornerstone is the horizontal anchor (Ren et al. 2015; Lin et al. 2017b). With the growing demand for the detection of objects with arbitrary orientation, such as text and targets in remote sensing scenes, oriented object detection methods (Yang et al. 2018b, 2021c,d) have attracted much attention. There are five types of detection methods for oriented object detection: (1) generating oriented region proposals directly (Azim et al. 2018; Ding et al. 2019); (2) regressing the angle parameters based on horizontal region proposals (Yang et al. 2019a; Zhang, Lu, and Zhang 2019; Yang et al. 2020b); (3) using the mask prediction of the mask branch to locate the object area (Li et al. 2020); (4) regressing the angle parameters (Yang et al. 2021b; Han et al. 2021); and (5) predicting angles using a classification method (Yang and Yan 2020; Yang et al. 2021a; Yang, Yan, and He 2020). Although the anchor-based methods mentioned above have obtained promising detection results, some limitations remain, such as too many hyperparameters, overlapping calculations, and complex post-processing.

To overcome the shortcomings of anchor-based methods, anchor-free methods have become a new research focus in recent years. Horizontal object representations based on anchor-free methods can be summarized as keypoint-based methods (Zhou, Zhuo, and Krahenbuhl 2019; Duan et al. 2019), pixel-based methods (Tian et al. 2020), and point set-based methods (Yang et al. 2019b). Many excellent studies have emerged recently that explore the effective representation using anchor-free methods for oriented object detection. O2Det (Wei et al. 2020) detects a pair of corresponding middle lines. PolarDet (Zhao et al. 2021), and P-RSDet (Zhou et al. 2020) represent the oriented objects using the polar method in the polar coordinate system.

**Sample Selection for Object Detection**

Classical anchor-based detectors, for example, RetinaNet (Lin et al. 2017b), select positive and negative samples based on the fixed MaxIoU matching strategy, which adopts the IoU value (anchor with ground-truth box) as a matching metric. Many excellent dynamic sample selection strategies have been proposed recently. MetaAnchor (Yang et al. 2018a) is a type of anchor function that generates adaptive anchors from arbitrary customized prior boxes. DAL (Ming et al. 2021b) dynamically assigns anchors according to a defined matching degree, which can comprehensively evaluate the localization potential of the anchors. FreeAnchor (Zhang et al. 2021) is a learning-to-match approach that allows objects to dynamically select anchors under the maximum likelihood principle. PAA (Kim and Lee 2020) is a novel anchor assignment strategy that adaptively separates anchors into positive samples and negative samples for a ground-truth bounding box in a probabilistic manner.

Although these adaptive strategies achieve dynamic sample selection, most of them ignore object shape information and the differentiation between the selected positive and can only be applied to either the anchor-free or anchor-based methods.

**The Proposed Method**

The oriented anchor-free method RepPoints is used as a baseline example to introduce the proposed method, and the pipeline is illustrated in Fig. 2. RepPoints is constructed with a backbone network, initial detection head, and refinement.
Figure 2: Pipeline of the proposed method. The SA-S strategy dynamically selects samples based on the shape of the object for the refinement detection head, and then SA-M strategy measures the quality of positive samples in the initial detection head and refinement detection head. Boxes represent the predicted point sets for a clear visualization, where solid boxes and dashed boxes represent positive and negative samples, respectively. $\mu$ and $\sigma$ denote the mean and standard deviation of the IoU values between the proposal predictions and the ground-truth box.

**Shape-adaptive Selection (SA-S)**
- Dynamic IoU Threshold $T_{\text{IoU}}$
- Normalized shape distance
- Quality Information

**Shape-adaptive Measurement (SA-M)**
- $\mathcal{L}_{\text{cls}}$
- $\mathcal{L}_{\text{reg}}$
- $\mathcal{L}_{\text{bc}}$

**Initial detection head**
- Input FPN
- Distribution Characteristics
- Shape Information

**Refinement detection head**
- Ground-truth center
- Positive samples

**Table 1: Pilot experiments for the relationship between pre-defined IoU threshold and the aspect ratio of the object on DOTA.**

| $\gamma_m$ | AP | PL | RA | BC | SP | SV | TC | LV | HA |
|-----------|----|----|----|----|----|----|----|----|----|
| 0.5, 0.4 | 87.78 | 71.26 | 72.36 | 68.85 | 75.55 | 89.60 | 55.72 | 48.38 |
| 0.4, 0.3 | 87.48 | 67.68 | 82.54 | 70.36 | 78.12 | 90.78 | 58.72 | 60.93 |
| 0.3, 0.2 | 80.81 | 67.16 | 76.88 | 69.01 | 78.47 | 90.84 | 58.69 | 60.25 |
| 0.1, 0.1 | 79.07 | 66.82 | 77.95 | 65.66 | 63.12 | 90.07 | 59.64 | 67.58 |

The Motivation

First, the motivation for conducting pilot experiments to show the relationship between a reasonable IoU threshold and the aspect ratio of the object is presented, and experimental results are listed in Table 1. $T_{\text{IoU}}$ represents the predefined IoU threshold containing positive and negative threshold. $\gamma_m$ represents the mean aspect ratio of all objects in one category, and AP is the average precision. It can be seen in Table 1 that while the aspect ratio of the object is larger, the performance is better with a low IoU threshold. This may be because the IoU value has different sensitivities to localization errors under different shapes.

Therefore, because the traditional IoU-based sample selection strategy uses the same predefined IoU threshold for all objects, mining high-quality samples for multi-class object detection is ineffective, particularly when a wide variety of object shapes exists. Motivated by the above experimental results and analysis, two shape-adaptive strategies are proposed, SA-S and SA-M, for dynamically selecting and measuring the samples, respectively.

**Shape-Adaptive Selection**

The IoU-based selection strategy is used in the refinement detection head of RepPoints. However, the IoU-based strategy ignores the object shape and processes all objects using the same fixed rule, which may be applicable to most objects, but some objects with special shapes are ignored.

To optimize the selection process, an SA-S strategy is proposed that adaptively adjusts the IoU threshold according to the shape and characteristics distribution of objects to select samples. Inspired by the ATSS (Zhang et al. 2020), the mean and standard deviation of objects are adopted to dynamically calculate the IoU threshold. For the $i$-th ground-truth box, the IoU threshold $T_{\text{IoU}}^i$ for selecting samples is calculated as:

$$T_{\text{IoU}}^i = f(\gamma_i) \ast (\mu + \sigma), \quad (1)$$
is calculated as:

\[ \gamma_i = \frac{1}{J} \sum_{j=1}^{J} \mathcal{I}_{i,j}, \quad \sigma = \sqrt{\frac{1}{J} \sum_{j=1}^{J} (\mathcal{I}_{i,j} - \mu)^2}, \]

where \( J \) is the number of candidate samples, and \( \mathcal{I}_{i,j} \) is the IoU value between the \( i \)-th ground-truth box and the \( j \)-th prediction. \( \gamma_i \) represents the aspect ratio of the ground-truth box corresponding to the prediction and is calculated as the ratio of the long edge to the short edge. According to the above analysis, the weight should decrease as the aspect ratio increases so that elongated objects are assigned a low IoU threshold. A monotonic decreasing function is designed for the weighting factor that depends on the object’s aspect ratio. \( f(\gamma_i) \) is the weighting factor function of the object and is calculated as:

\[ f(\gamma_i) = e^{-\frac{\gamma_i}{\omega}}, \quad (2) \]

where \( \omega \) is a weighted parameter that defaults empirically to 4. A larger \( \omega \) usually achieves better performance when a dataset contains a large number of elongated objects. Positive samples are selected using a general assignment strategy, which selects candidates whose IoUs are greater than or equal to the threshold \( \mathcal{T}_i^{\text{IoU}} \).

**Shape-Adaptive Measurement**

Compared with the points located inside the object, the points located near the boundaries of the object contain more information about the clutter background, and even nearby objects. Therefore, the points located inside the object, particularly the points located around the center of the object, are more representative of the object’s features than the points located close to the boundaries of the object. Processing all positive samples in the same manner would lead to the misjudgment of some high-quality samples. Points inside the object that are far from the center of the object are likely to be suppressed by background points that are closer to the center of the object. The above analysis leads to the conclusion that the detection potential of each point is strongly related to the shape of the object and not only the distance of each point from the object center.

To optimize this process, an SA-M strategy is proposed to evaluate and add quality information to each positive sample. The quality of a positive sample is estimated using its position relative to the object, which is called the normalized shape distance in this study. A function is elaborated to calculate the normalized shape distance using the distance from the sample to the corresponding object’s center and the shape information of the object. Specifically, each ground-truth box is described as five parameters \((x, y, w, h, \theta)\), where \((x, y)\), \(w, h\) denote the center coordinates, width, and height of the ground-truth box, respectively, and \(\theta\) represents the angle of box following (Han et al. 2021). The normalized selection of \((w, h)\) on the \(x\) or \(y\)-axis is determined by the angle. The normalized shape distance \(\Delta d_{ij}\) from the \(j\)-th sample point to the \(i\)-th object’s center is calculated as:

\[ \Delta d_{ij} = \begin{cases} \sqrt{\frac{(x_i-x_j)^2}{w_i^2} + \frac{(y_i-y_j)^2}{h_i^2}} & \text{if } 0 \leq \theta_i \leq \pi/2 \\ \sqrt{\frac{(x_i-x_j)^2}{h_i^2} + \frac{(y_i-y_j)^2}{w_i^2}} & \text{otherwise} \end{cases} \]

Then, the quality \(\bar{Q}_{ij}\) of the positive sample is calculated after obtaining the normalized shape distance:

\[ \bar{Q}_{ij} = e^{-\Delta d_{ij}}, \quad (4) \]

For the selected positive samples, a distinction is established in terms of quality and the influence of inappropriate process for selecting positive samples is eliminated.

**Loss Functions**

**Boundary-Center Loss** An isolated point with a large deviation greatly affects the quality of the convex hull (calculated from predicted point set) and has a negative influence on precise localization. To address this problem, a boundary-center loss is proposed in this study. The left-most, right-most, top-most and bottom-most point are selected from the point set, and a mean center point is calculated by the average \(x\) and \(y\) coordinates of all the points in the point set. The five points’ coordinates of prediction and ground-truth box are represented by \(p_i\) and \(g_i\), where \(i = (1, 2, ..., 5)\), is the index of the selected five points. The boundary-center loss \(L_{bc}\) is used to constrain the boundary and center points, and defined as:

\[ L_{bc} = \sum_{i=1}^{5} L_{\text{smooth}}(p_i, g_i), \quad (5) \]

where \(L_{\text{smooth}}\) is the smooth \(L_1\), which is defined as

\[ \text{smooth}_1(t) = \begin{cases} 0.5t^2 & \text{if } |t| < 1 \\ |t| - 0.5 & \text{otherwise} \end{cases} \]

The smooth \(L_1\) distance of the five points from the predicted point set and ground-truth bounding box is calculated using \(\text{smooth}_1(||p_i - g_i||)\), which is defined in (6), and \(||p_i - g_i||\) is the \(L_2\) distance between the two \(i\)-th points.

**Total Loss** The total loss is calculated as:

\[ L = \lambda_1 L^c + \lambda_2 L^L + \lambda_3 L^2, \quad (7) \]

where \(L^c, L^L,\) and \(L^2\) represent the classification loss, initial detection head loss, and refinement detection head loss, respectively. \(\lambda_1, \lambda_2,\) and \(\lambda_3\) are weighting coefficients, which are empirically set to 1.0, 0.375, and 1.0, respectively. For the \(i\)-th object, the classification loss is denoted as:

\[ L_i^c = \frac{1}{N^+} \sum_{p_j \in P^+} Q_{ij} \sum_{ij} \bar{Q}_{ij} L_{ij}^{c_{ij}}, \quad (8) \]

where \(j, N^+, \) and \(P^+\) respectively represent the index, total number, and the set of the predicted convex hulls, respectively. The classification loss \(L_i^{c_{ij}}\) adopts the focal loss (Lin et al. 2017b). \(Q_{ij}\) is the quality measurement, and the scale-adaptive weight is assigned to each positive sample on the basis of \(Q_{ij}\). \(p_j\) represents the predicted convex hull that is calculated using the predicted point sets.

In the initial detection head, the regression loss is defined as:

\[ L_i^L = \frac{1}{N^+} \sum_{p_j \in P^+} \bar{Q}_{ij} \sum_{ij} \bar{Q}_{ij} L_{ij}^{c_{ij}} + L_{bc}, \quad (9) \]

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The regression loss for the convex hull $L_{\text{reg}}^\text{reg}$ adopts the GIoU loss (Rezatofighi et al. 2019) and is calculated as:

$$L_{\text{reg}}^\text{reg} = \frac{1}{N} \sum_{j} \bar{Q}_{ij}^\prime \sum_{ij} \hat{Q}_{ij}^\prime L_{ij}^\text{reg}$$

where $\hat{Q}_{ij}^\prime$ is the quality measurement for each positive sample in the refinement detection head. Regression loss $L_{\text{reg}}^\text{reg}$ also adopts GIoU loss.

**Experiments and Discussions**

The results of experiments conducted on four typical publicly available datasets containing oriented objects, that is, DOTA (Xia et al. 2018), HRSC2016 (Liu et al. 2017), UCAS-AOD (Zhu et al. 2015), and ICDAR2015 (Karatzas et al. 2015) are summarized to evaluate the effectiveness of the proposed method. The details of the datasets, method implementations, evaluation metrics, and experimental results are presented in the following subsections.

**Datasets**

**DOTA** (Xia et al. 2018) is a public, large aerial image dataset for oriented object detection that contains 15 categories, and objects in a wide variety of scales, orientations, and shapes: plane (PL), baseball diamond (BD), bridge (BR), ground track field (GTF), small vehicle (SV), large vehicle (LV), ship (SH), tennis court (TC), basketball court (BC), storage tank (ST), soccer ball field (SBF), roundabout (RA), harbor (HA), swimming pool (SP), and helicopter (HC). DOTA contains 2,806 aerial images and 188,282 instances. The size of each image is in the range of 288 to 8,115 pixels in width, and 211 to 13,383 pixels in height. This dataset contains three subsets, which are the training set (1/2), validation set (1/6), and testing set (1/3), and the ground truth of the test set is not publicly accessible. All images in the training and validation sets were split into blocks of 1024×1024 pixels, with an overlap of 200 pixels for the training dataset.

**HRSC2016** (Liu et al. 2017) contains 436 images for training, 181 images for validation, and 444 images for testing. The image size ranges from 300×300 to 1,500×900 pixels. The dataset contains ships with arbitrary aspect ratios and orientations. All images were resized to 800×512 for training and testing.

**UCAS-AOD** (Zhu et al. 2015) is an aerial image dataset for oriented car and airplane detection that contains 1,510 images with approximately 659×1280 pixels and 14,596 instances. For the experiments in this study, the dataset contained 1,057 randomly selected images for training and 302 images for testing.

**ICDAR2015** (Karatzas et al. 2015) is a challenging dataset for scene text detection and recognition that contains 1,000 images for training and 500 images for testing and is used for the detection of arbitrarily oriented text.

**Implementation Details**

The baselines were an anchor-free method RepPoints (Yang et al. 2019b) and an anchor-based method S$^2$A-Net (Han et al. 2017a) for oriented object detection. They both consisted of a backbone for feature extraction and two detection heads for predicted results refinement. FPN (Lin et al. 2017a) with ResNet50 (He et al. 2016) was used as the backbone to extract features, unless special notes were provided. The framework was trained using the SGD optimizer, where the initial learning rate, momentum, and weight decay were 0.01, 0.9, and 0.0001, respectively. The framework was trained respectively for 12, 36, 120, and 240 epochs on the DOTA, HRSC2016, UCAS-AOD, and ICDAR2015 datasets, respectively. The numbers of the points in a point set in RepPoints and the anchors at each position in S$^2$A-Net were set to 9 and 1, respectively. The weighted parameter $\omega$ in (2) was empirically set as 4 on DOTA, UCAS-AOD, and ICDAR2015. Considering that the HRSC2016 dataset contains a large number of elongated ships, $\omega$ was set as 14 on it. Additionally, all experiments were performed using MM Detection-1.1 (Chen et al. 2019) and PyTorch-1.3/1.2 on 2 Titan V GPUs with 11G memory and 4 Tesla V GPUs with 32G memory, while the operating system is Ubuntu 16.04. Experiments were performed more than twice and stable values were taken as final results. Data augmentation consisted of random flipping and random rotation. The experimental results for the baseline and “ours” shown in Table 5, 7, and 8 used multi-scale training and data augmentation for a fair comparison with other methods.

**Ablation Study**

To analyze the effectiveness of the proposed method when other conditions were fixed, a series of controlled variable comparison experiments were performed. The impact of the individual structure proposed in this paper was studied on DOTA and HRSC2016, and the results are shown in Table 2. The results demonstrate that each of the proposed structures achieved different degrees of improvement for detection performance on all datasets.

**Effect of Shape-Adaptive Selection.** Table 3 shows the improvements of 7.65%, 12.28%, and 15.66% were achieved for the classic large aspect ratio categories, BR, HA, and HC, respectively, which demonstrates that the dynamic SA-S strategy was effective for objects with large aspect ratios. The mAP significantly increased by 3.64% when the SA-S strategy was used, which confirms the effectiveness of the SA-S strategy.

Also, the shape-adaptive idea can be applied to other sample selection strategies to further improve detection performance. As Table 4 shows, “MaxIoU-SA (ours)” repre-
Table 2: Ablation study results for each structure based on RepPoints on the DOTA and HRSC2016 datasets. “BCL” denotes the boundary-center loss, and “I” and “SI” indicate the individual improvement and the total improvement in mAP values for this structure compared with the baseline, respectively.

| Dataset | BCL SA-S | SA-M | mAP(%) | I | SI |
|---------|---------|------|--------|---|----|
| DOTA    | × × ×   |      | 70.25  |   |    |
|         | √ × ×   |      | 70.96  | +0.71 | +0.71 |
|         | √ √ ×   |      | 74.60  | +3.64 | +4.35 |
|         | √ √ √   |      | 74.92  | +0.32 | +4.67 |
| HRSC2016| × × ×   |      | 75.11  |   |    |
|         | √ × ×   |      | 77.38  | +2.27 | +2.27 |
|         | √ √ ×   |      | 87.01  | +9.63 | +11.90 |
|         | √ √ √   |      | 88.60  | +1.59 | +13.49 |

Table 3: Results of the SA-S strategy for objects with large aspect ratios based on RepPoints on DOTA.

| Sample Selection          | BR   | HA   | HC   | mAP(%) |
|---------------------------|------|------|------|--------|
| MaxIoU                    | 43.07| 60.93| 44.41| 70.96  |
| ATSS (Zhang et al. 2020)  | 50.51| 63.68| 51.21| 72.10  |
| SA-S (ours)               | 52.72| 73.21| 60.07| 74.60  |

Table 4: Performance of the SA-S and SA-M strategies on anchor-free and anchor-based methods on HRSC2016.

| Based Method              | Sample Selection | mAP(%)  |
|---------------------------|------------------|---------|
| RepPoints (anchor-free)   | MaxIoU           | 75.11   |
|                           | MaxIoU-SA (ours) | 82.96   |
|                           | ATSS (Zhang et al. 2020) | 78.07   |
|                           | SA-S & SA-M (ours) | **88.60 (+13.49)**   |
| S²A-Net-D (anchor-based)  | MaxIoU           | 80.26   |
|                           | MaxIoU-SA (ours) | 84.54   |
|                           | ATSS (Zhang et al. 2020) | 88.68   |
|                           | SA-S & SA-M (ours) | **88.91 (+8.65)**   |

Table 5: Comparison of the mAP values of different rotation methods on HRSC2016.

| Method                     | Backbone | mAP  |
|---------------------------|----------|------|
| RRD (Liao et al. 2018)    | VGG16    | 84.30|
| Rol-Transformer (Ding et al. 2019) | R-101 | 86.20 |
| RSDet (Qian et al. 2021)  | R-101    | 86.50|
| Gliding Vertex (Xu et al. 2020) | R-101 | 88.20 |
| BBAVec (Yi et al. 2021)   | R-101    | 88.60|
| R³Det (Yang et al. 2021b) | R-101    | 89.26|
| CSL (FPN) (Yang and Yan 2020) | R-101 | 89.62 |
| DAL (Ming et al. 2021b)   | R-101    | 89.77|
| **Ours (RepPoints-based)**| R-101    | 90.00|
| **Ours (S²A-Net-based)**  | R-101    | **90.27**|

adaptive idea could also be adopted in other fixed sample selection strategies, and further improved mAP. S²A-Net-D denotes one of the baseline structures of S²A-Net, which uses deformable convolution to replace the alignment convolution layer and was described in (Han et al. 2021) in detail. The results demonstrated that the proposed strategies boosted mAP on the anchor-free baseline RepPoints and anchor-based baseline S²A-Net-D by 13.49% and 8.65%, respectively.

Effect of Boundary-Center Loss. According to the results in rows 6 and 7 in Table 2, an mAP improvement of 2.27% was obtained after the boundary-center loss was added. The boundary-center loss suppressed low-quality predicted convex hulls by constraining the boundary corner and mean center points to optimize the detection results under the guidance of spatial information.

Comparisons with State-of-the-art Detectors

Results on HRSC2016. The ship objects in HRSC2016 had large aspect ratios. Experiments performed on HRSC2016 verified the superiority of the proposed shape-adaptive method. As shown in Table 5, the object detection performance of the proposed method was superior to that of the other methods, and achieved 90.27% mAP based on S²A-Net.

Results on DOTA. As shown in Table 6, the anchor-based methods remained the most popular and high-performing detectors on the DOTA dataset. The proposed method based on RepPoints achieved 74.92% mAP with the R-50-FPN (i.e., ResNet50-FPN) backbone without any tricks (e.g., data augmentation). The proposed method based on S²A-Net with the RX-101-FPN backbone achieved the best performance with respect to the mAP values compared with all the one-stage and two-stage methods. The proposed method achieved comparable performance with other methods with fewer calculations and less inference time. Notably, because of the different backbones (e.g., R-50/101/152 (He et al. 2016), RX-101 (Xie et al. 2017), and H-104 (Newell, Yang, and Deng 2016)), different input image configurations, and
Table 6: Comparison of different detectors of mAP values on the OBB-based task of the DOTA-v1.0. ‘*’ indicates that multi-scale training/testing was used in the method. “BB” represents “ Backbone”. Values with underlines indicate that the best mAP values are achieved compared to all methods. “Ours-RP” means the implementation of our method based on RepPoints, and “Ours-S” means the implementation of our method based on S^2-A-Net. The references of the methods involved in the comparison are listed below: GSDet (Li, Wei, and Zhang 2021), RADET (Li et al. 2020), Ours (RepPoints-based). Table 7: Comparison of the AP with state-of-the-art methods on UCAS-AOD. The references of the methods involved in the comparison are listed below: YOLOv3 (Redmon and Farhadi 2018), RetinaNet (Lin et al. 2017b), Faster-RCNN (Ren et al. 2015), RoI-Transformer (Ding et al. 2019), RIDet-Q (Ming et al. 2021a), RoI-Transformer (Ding et al. 2019), RIDet-O (Ming et al. 2021a) and DAL (Ming et al. 2021b).
| Method                  | P    | R    | F-measure |
|------------------------|------|------|-----------|
| RRPN (Ma et al. 2018)  | 82.2 | 73.2 | 77.4      |
| SCRDet (Yang et al. 2019a) | 81.3 | 78.9 | 80.1      |
| RRD (Liao et al. 2018) | 85.6 | 79.0 | 82.2      |
| DAL (Ming et al. 2021b) | 84.4 | 80.5 | 82.4      |

| anchor-based:          |
|-----------------------|
| S2A-Net (baseline)    | 80.4 | 78.2 | 79.3      |
| Ours (S2A-Net-based)  | 81.4 | 78.8 | 80.1      |

| anchor-free:           |
|-----------------------|
| RepPoints(baseline)   | 74.2 | 72.1 | 73.2      |
| Ours (RepPoints-based)| 86.0 | 81.8 | 83.9      |

Table 8: Comparison of the performance of different methods on ICDAR2015. “P” is “Precision” and “R” is “Recall”. (Liao et al. 2018), thereby demonstrating the robustness of the proposed method in different scenarios.

Conclusions

In this study, two novel shape-adaptive strategies were proposed: SA-S and SA-M, for oriented object detection. These strategies dynamically select samples and adaptively assign quality weights to the selected positive samples. The proposed SA-S strategy dynamically selects high-quality candidate samples as positive samples, considering the shape and characteristics distribution of objects. The SA-M strategy adds quality information to different positive samples. The shape-adaptive strategies outperform in terms of the oriented object detection performance when there was a wide aspect ratio variation between objects. Extensive experiments were conducted on both anchor-free and anchor-based baselines and four publicly available datasets, and the results demonstrate that the proposed method achieves state-of-the-art performance and can be easily embedded into other detectors to improve detection performance. The source code of the paper will be available publicly at https://github.com/houliping/SASM.

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