HRDNET: HIGH-RESOLUTION DETECTION NETWORK FOR SMALL OBJECTS

Ziming Liu∗‡, Guangyu Gao∗†, Lin Sun† and Zhiyuan Fang∗

∗Beijing Institute of Technology, Beijing, China; †Magic Leap, Inc., CA, USA; and ‡Inria, Université Côte d’Azur, Sophia Antipolis, France.

liuziming.email@gmail.com; guangyugao@bit.edu.cn; sunlin@cs.stanford.edu; zy_fang@outlook.com

ABSTRACT

Small object detection is a very challenging yet practical vision task. With deep network-based methods, the contextual information of small objects may disappear when the network goes deeper. An intuitive solution to alleviate this issue is to increase the input resolution, however, it will aggravate the large variant of object scale and introduce unbearable computation cost. To leverage the benefits of high-resolution images without bringing up new problems, we propose a High-Resolution Detection Network (HRDNet) which takes multiple resolution inputs with multi-depth backbones. Meanwhile, we propose the Multi-Depth Image Pyramid Network (MD-IPN) and Multi-Scale Feature Pyramid Network (MS-FPN). The MD-IPN maintains multiple position information using multiple depth backbones. Specifically, high-resolution input will be fed into a shallow network to reserve more positional information and reduce computational costs, while low-resolution input will be fed into a deep network to extract more semantics. By extracting various features from high to low resolutions, the MD-IPN can improve the performance of small object detection and maintain the performance of middle and large objects. Additionally, MS-FPN is introduced to align and fuse multi-scale feature groups generated by MD-IPN to reduce the information imbalance. Extensive experiments are conducted on the COCO2017 and the typical small object dataset, VisDrone 2019. Notably, our HRDNet achieves the state-of-the-art on these two datasets with significant improvements on small objects.

Index Terms— Small Object Detection, High-resolution Images, Image Pyramid, Deep Neural Network

1. INTRODUCTION

With the advances of deep learning, object detection achieves the remarkable progress. According to whether the proposals are generated by an independent learning stage or directly and densely sample possible locations, object detection can be classified into two-stage or one-stage models. Compared to two-stage detectors [1, 2], one stage methods [3, 4] are less complex and faster with some precision loss. Recently, lots of anchor-free detectors are proposed, e.g., CornerNet [5], FCOS [6], FSAF [7], which create some low-level abstractions of the images like lines, circles, and then ‘iteratively combine’ them into some objects. However, these methods are still struggling with small objects.

Those above-mentioned methods can benefit from the deep and powerful network with multi-level features fusion, e.g., using feature pyramid network (FPN), but also it will introduce more computations. While high-resolution images reserve more detail information, they are helpful for the small object detection. However, they also introduce new issues, such as that, it will degrade the performance of large objects and bring in unaffordable computation cost. We focus on the trade-offs between large and small object detection and high performance and low computational complexity.

In this paper, we propose a novel High-resolution Detection Network (HRDNet), which includes a Multi-Depth Image Pyramid Network (MD-IPN) and a Multi-Scale Feature Pyramid Network (MS-FPN), as shown in Figure 1. The core idea of the HRDNet is to use a deep backbone to process low-resolution images while using a shallow backbone to process high-resolution images. The advantage of extracting features from high-resolution images with the shallow and tiny network has been demonstrated in [8]. With HRDNet, we can not only get more details for a small objects from high-resolution images, but also guarantee the efficiency and effectiveness by integrating multi-depth and multi-scale deep networks.

The MD-IPN can be regarded as a variant of the image pyramid network with multiple streams. MD-IPN is dealing with the trade-offs between large and small object detection, as well as high performance and low computational complexity. We extract features from the high-resolution image using a shallow backbone network. Because of its weak representation power, we also need deep backbones to obtain robust semantic features by feeding low-resolution images in. Thus, the inputs of the MD-IPN form an image pyramid with a fixed decreasing ratio of \( \alpha \in [0, 1] \). The output of MD-IPN is a series of multi-scale feature groups, while each group contains multi-level feature maps.

The multi-scale feature groups extend the standard feature
Fig. 1. Overall structure of HRDNet with MD-IPN and MS-FPN. The input is an image pyramid with \( N \) images (\( N = 3 \) here), and the decreasing ratio is \( \alpha \). The outputs of MD-IPN are \( N \) groups feature pyramids, and the decreasing ratio of each feature pyramid is 2. MS-FPN fuses these features into one feature pyramid \( \{ F'_0, F'_1, F'_2, F'_3, F'_4 \} \), which is used for object detection.

2. RELATED WORK

The state-of-the-art object detection methods include one-stage models, e.g., RetinaNet [3], Yolo-v3 [9], Center net [10], FSAF [7], Corner net [5], EfficientDet [11] and two-stage models, e.g., Faster R-CNN [2], Cascade R-CNN [1] etc. Nevertheless, our HRDNet is a more fundamental and general framework for most of detection models, such as RetinaNet and Cascade R-CNN.

2.1. Small object detection

The detection performance is largely bounded by small object detection. Therefore, there are many researches specializing in small object detection. For example, [12] proposed oversampling and copy-pasting small objects to solve such a problem. Perceptual GAN [13] generated super-resolved features and stacked them into feature maps of small objects to enhance the representations. DetNet [14] maintained the spatial resolution and has a large receptive field to improve small object detection. SNIP [15] resized images to different resolutions and only train samples which is close to ground truth. SNIPER [16] is proposed to use regions around the bounding box to remove the influence of background. Unlike these methods, we combine both image pyramid and feature pyramid together, with which it not only effectively improves the detection performance of small targets, but also ensure the detection performance of other objects.

2.2. High-resolution detection

Some studies already explored to do object detection on high-resolution images. [8] proposed a fast tiny detection network for high-resolution remote sensing images. [17] proposed an attention pipeline to achieve fast detection on 4K or 8K videos using YOLO v2 [18]. However, these works did not fully explore the effect of high-resolution images for small object detection, which is what we concentrate on.

2.3. Feature-level imbalance

To capture the semantic information of objects from different scales, multi-level features are commonly used for object detection. However, they have serious feature-level imbalance because they convey different semantic information. Feature
Pyramid Network (FPN) [19] introduced a top-down pathway to transmit semantic information, alleviating the feature im-
balance problem in some degree. Based on FPN, PANet [20] 
involved a bottom-up path to enrich the location information 
of deep layers. The Libra R-CNN [21] revealed and tried to 
deal with the sample level, feature level, and objective level 
imbalance issues. Pang et al. [22] proposed a light weighted 
module to produce featured image pyramid features to aug-
ment the output feature pyramid. While these methods only 
focus on multi-level features, we proposed a new module 
called Multi-scale FPN to solve the imbalance not only from 
multi-level features but also from multi-scale feature groups.

3.1. MD-IPN

The MD-IPN is composed of N independent backbones with 
various depth to process the image pyramid. We term each 
backbone as a stream. HRDNet can be generalized to more 
streams, but for better illustration, we mainly discuss the two-
stream HRDNet and three-stream HRDNet. Figure 1 presents 
an example of three-stream HRDNet. Given an image I with 
resolution $R$, the high-resolution image ($I_0$ with $R$) is 
processed by a stream of shallow CNN ($S_0$), and the lower-
resolution images ($I_1$ and $I_2$ with $\alpha R$ and $\alpha^2 R$, and $\alpha = 0.5$,) 
is processed by streams of deeper CNN ($S_1$ and $S_2$). Gener-
ally, we can build an image pyramid network with N inde-
pendent parallel streams, $S_i, i = \{0, 1, \ldots, N - 1\}$.

We use $\{I_i\}_{i=0}^{N-1}$ to represent the input images with differ-
ent resolutions given the original image $I_0$ with the highest 
resolution. The outputs of the multi-scale image pyramid are 
N feature groups $\{G_i\}_{i=0}^{N-1}$. Each group $G_i$ contains a set 
of multi-level features $\{F_{i,j}\}$, where $i \in \{0, 1, \ldots, N - 1\}$ is the 
multi-scale index and $j \in \{0, 1, \ldots, M - 1\}$ is the multi-level 
index. For example, in Figure 1, N and M are 3, 4 respective-
ly, and the relation can be formulated as $G_i = S_i(I_i) = 
\{F_{i,0}, F_{i,1}, F_{i,2}, F_{i,3}\}, \text{where } i \in \{0, 1, \ldots, N - 1\}$.

3.2. MS-FPN

Feature pyramid network (FPN) is one of the key compo-
nents for most object detection algorithms. It combines low-
resolution, semantically strong features with high-resolution, 
semantically weak features via a top-down pathway and lat-
eral connections. In our HRDNet, the MD-IPN generates 
multi-scale (different resolution) and multi-level (different hi-
erarchy of features) features. To deal with the multi-scale hi-
erarchy features, we also proposed the Multi-Scale FPN (MS-
FPN). Different from FPN, semantic information propagates 
not only from high-level features to low-level features but also 
from deep stream (low-resolution) to shallow stream (high-
resolution). Therefore, there are two directions for the com-
putation of the multi-scale FPN. The basic operation in multi-
scale FPN is same as traditional FPN, i.e., $1 \times 1$ Convolution, 
$2 \times$ up-sampling and sum-up.

In this way, the highest resolution feature, i.e., $F_{0,0}$, not 
only maintain the high-resolution for small object detection 
but also combine semantically strong features from multi-
scale streams. Our novel MS-FPN can be formulated as 
$F_{i,j} = \text{Conv}(F_{i,j}) + U_p(F_{i,j+1})$ if $i = N-1$, $F_{i,j} = 
\text{Conv}(F_{i,j}) + U_p(F_{i,j+1}) + U_p(F_{i+1,j})$ if $i \neq N-1$. 

Fig. 3. The change of AP, AP75 over different input's res-
olution. The HRDNet used here is a two-stream version with ResNet18+101 backbone.
Table 1. Performance Comparison of Cascade R-CNN and HRDNet with different resolution’s input. The HRDNet here is a two streams version, and † means that it is trained on patch images as mentioned in Section 4.1.

| model          | resolution | pedestrian | people | bicycle | car | van | truck | tricycle | awning-tri | bus | motor | mAP  |
|----------------|------------|------------|--------|---------|-----|-----|-------|----------|------------|-----|-------|------|
| Cascade R-CNN  | 1333 × 800 | 37.9       | 27.7   | 13.3    | 74.3| 44.6| 34.7  | 24.6     | 13.2       | 52.4| 38.3  | 36.1 |
| Cascade R-CNN  | 2660 × 1600| 51.5       | 38.0   | 20.2    | 80.0| 48.0| 32.4  | 28.2     | 12.1       | 44.8| 47.5  | 40.3 |
| HRDNet         | 2000 × 1200| 49.6       | 49.5   | 47.9    | 34.7| 30.4| 36.9  | 30.4     | 15.3       | 46.7| 48.7  | 41.9 |
| HRDNet         | 2660 × 1600| 55.8       | 42.4   | 23.1    | 51.2| 42.1| 41.0  | 34.3     | 16.3       | 59.7| 53.8  | 46.1 |
| HRDNet †       | 2660 × 1600| 56.7       | 45.1   | 27.7    | 51.3| 43.0| 37.6  | 18.8     | 56.9       | 56.4| 47.8  |

The $F_{i,j}$ is the feature in level $j$ and stream $i$ in Figure 2. The $Up(\cdot)$ operation is $2 \times$ up-sampling. The $Conv(\cdot)$ is $1 \times 1$ convolution. Finally, MS-FPN outputs the final feature group $G = \{F_{0}, F_{1}',...F_{l}',...\}$. $F_{i}'$ is calculated by $F_{i}' = Conv(F_{0,i})$, where $F_{0,i}$ is the features in Group $G_{0}$, i.e., the outputs of the highest resolution stream.

4. EXPERIMENTS

4.1. Experiment details

Datasets. We conduct experiments on two typical small object detection data sets: VisDrone2019 [23] and COCO2017 [24]. The VisDrone2019 dataset consists of 288 video clips formed by 261,908 frames and 10,209 static images, covering a wide range location, environment, objects, and density. The resolution of VisDrone2019 is ranging from 960 to 1360. COCO is the most common benchmark for object detection, and we trained our model on the COCO training set and tested it on the COCO validation set. In COCO, most images’ resolution is 500-800 px, which will be resized to 1333 × 800 or 1000 × 600 in the training stage, but 960-1360 px in VisDrone2019 [25] dataset.

Training. We use SGD optimizer with a mini-batch 2 for each GPU. The learning rate starts from 0.02 and decreases by 10 at epoch 7 and 11 with totally 15 epochs. The weight decay is $1 \times 10^{-4}$. The linear warm-up strategy is used with warm-up iterations of 500, and the warm-up ratio of 1.0/3. The linear interpolation is applied for the image pyramid. The resolution decreasing ratio $\alpha$ is 0.5. To fit the high-resolution images from VisDrone2019 into the GPU memory, we equally cropped each original image in VisDrone2019 training set into four patches which are not overlapped. In this way, we obtained a new training set with such cropped images.

Inference. Same resolution as training is used for inference. The NMS IOU threshold is 0.5, and the threshold of confidence score is 0.05. Without especially emphasizing, three scales are applied for the multi-scale test.

4.2. Ablation Studies

The effect of image resolution. Extensive ablation studies on the VisDrone2019 dataset are conducted to illustrate the effect of input image resolution for detection performance. Table 1 shows that the performance has a significant improvement with the increase of image resolution. Higher resolution leads to better performance under the same experimental settings. The detection of small objects show more improvements. Importantly, HRDNet performs much better than the SOTA Cascade R-CNN with the same resolution as the input.

Interestingly, when the resolution of input increases, single backbone model, i.e., Cascade R-CNN, suffers dramatically decrease (1.1-7.6%) for categories with relatively large size, i.e., truck, awning-tricycle and bus. On the contrary, significant performance increase (1.5-2.5%) can be observed from HRDNet. Simply increasing the image resolution without considering the severe variant of object scale is not the ideal solution for detection, let alone small object detection.

Explore the optimal image resolution. Is it true higher resolution leads to better performance? Does it have the optimal resolution for detection? In this part, we will present the effect of image resolution for object detection. Figure 3 shows the change of the Average Precise ($AP_{0.05:0.95}$, $AP_{75}$) with different resolutions. The resolution starts from 2666 (long edge) with 400 as the stride. HRDNet achieves the best performance when the resolution is $3800 \times 2800$ px.

Fig. 4. Comparison of the simple FPN (A), multi-scale FPN aligned with depth (B) and resolution (C). Each column is one stream in MD-IPN, and each row refers to the depth of backbone. The blue and gray blocks are those features been fused and features to be fused respectively. The red arrows is a basic fusing operation described in subsection 2.3.

Table 2. The comparison of three different MS-FPNs.

| style          | AP   | AP50 | AP75 |
|----------------|------|------|------|
| ResNet10+18    |      |      |      |
| simple FPN     | 28.8 | 49.5 | 28.8 |
| aligned by resolution | 28.7 | 49.6 | 28.7 |
| aligned by depth | 28.9 | 49.9 | 28.7 |
| ResNet18+101   |      |      |      |
| aligned by resolution | 31.8 | 54.0 | 32.3 |
| aligned by depth | 32.0 | 54.3 | 32.5 |
Table 3. The speed (items/s) and the number of parameters (M) are obtained on a same machine with one Nvidia GTX 2080Ti GPU and Intel(R) Xeon(R) Silver 4210 CPU. Here is a two stream HRDNet using MS-FPN aligned with depth.

| model   | backbone       | resolution | params   | speed | AP50 |
|---------|----------------|------------|----------|-------|------|
| Cascade | ResNet18       | 1333       | 56.11M   | 9.9   | 36.1 |
| Cascade | ResNet18       | 2666       | 56.11M   | 5.4   | 40.3 |
| Cascade | ResNet18       | 3800       | 56.11M   | 2.5   | 42.6 |
| HRDNet  | ResNet10+18    | 3800       | 62.44M   | 3.7   | 49.2 |
| HRDNet  | ResNet18+101   | 3800       | 100.78M  | 2.8   | 53.3 |
| HRDNet  | ResNeXt50+101  | 3800       | 152.22M  | 1.5   | 55.2 |

Table 4. The comparison of HRDNet and Model Ensemble. The models here follow the design of Cascade R-CNN.

| model                  | backbone       | resolution | AP   | AP50 | AP75 |
|------------------------|----------------|------------|------|------|------|
| Single Backbone        | ResNeXt50      | 3800       | 32.7 | 54.6 | 33.6 |
| Single Backbone        | ResNeXt101     | 1900       | 30.4 | 51.0 | 31.1 |
| Model Ensemble         | ResNeXt50+101  | 3800×1900  | 32.9 | 55.1 | 33.5 |
| HRDNet                 | ResNeXt50+101  | 3800×1900  | 33.5 | 56.3 | 34.0 |

Table 5. The comparison with SOTA models on visdrone2019 DET validation set. † results are obtained with the same environment. + + denotes multi-scale test.

| model                  | backbone       | resolution | AP   | AP50 | AP75 |
|------------------------|----------------|------------|------|------|------|
| †Cascade R-CNN [1]     | ResNet50       | 2666       | 24.10| 42.90| 23.60|
| †Faster R-CNN [2]      | ResNet50       | 2666       | 23.50| 43.70| 22.20|
| †RetinaNet [3]         | ResNet50       | 2666       | 15.10| 27.70| 14.30|
| †FCOS [6]              | ResNet50       | 2666       | 16.60| 28.80| 16.70|
| HFEA [26]              | ResNeXt101     | -          | 27.10| -    | -    |
| HFEA [26]              | ResNeXt152     | -          | 30.30| -    | -    |
| DSOD [27]              | ResNeXt50      | -          | 28.80| 47.10| 29.30|
| HRDNet                 | ResNeXt10+18   | 3800       | 25.68| 49.15| 25.90|
| HRDNet                 | ResNeXt18+101  | 2666       | 28.33| 49.25| 28.16|
| HRDNet                 | ResNeXt18+101  | 3800       | 31.39| 53.29| 31.63|
| †HRDNet++              | ResNeXt50+101+152 | 3800     | 34.35| 56.65| 35.51|
| †HRDNet++              | ResNeXt50+101  | 3800       | 35.51| 62.00| 35.13|

Table 6. The state of the art performance on COCO test-dev, the input resolution of HRDNet ResNet101 stream is same as other models above, i.e. 1333 × 800, while the input of ResNet 152 stream is a 2× smaller image. ‘++’ denotes that the inference is performed with multi-scales.

| model                  | backbone       | AP   | AP5 | APF | APF,M | APF,L |
|------------------------|----------------|------|-----|-----|--------|--------|
| Faster R-CNN + FPN [19]| ResNet101      | 36.2 | 18.2| 39.0| 46.2   |
| DeNet-101(wide) [28]   | ResNet101      | 35.8 | 12.3| 36.1| 50.8   |
| CoupleNet [29]         | ResNet101      | 34.4 | 13.4| 38.1| 50.8   |
| Mask-RCNN [30]         | ResNet101      | 39.8 | 22.1| 43.2| 51.2   |
| Cascade-RCNN [1]       | ResNet101      | 42.8 | 23.7| 43.5| 55.2   |
| CSRNet++ [15]          | ResNet101      | 43.4 | 27.2| 48.5| 54.9   |
| SNP/PearsonNet [16]    | ResNet101      | 43.3 | 27.1| 44.7| 56.1   |
| SFDNet [14]            | ResNet101      | 43.2 | 25.1| 46.5| 55.2   |
| SSD51 [4]              | VGG-16         | 28.8 | 10.9| 31.8| 41.5   |
| RetinaNet++ [3]        | ResNet101      | 39.1 | 21.8| 42.7| 50.2   |
| RetinaNet++ [32]       | ResNet101      | 38.4 | 16.6| 39.9| 51.4   |
| M2Det900               | VGG-16         | 41.0 | 22.1| 46.5| 53.8   |
| ContextNet51 [5]       | Hourglass-104  | 40.5 | 19.4| 42.7| 53.0   |
| FCOS [8]               | ResNet101      | 42.1 | 25.6| 44.9| 52.0   |
| FSAF [7]               | ResNet101      | 42.9 | 26.6| 48.2| 52.7   |
| ContextNet511 [10]     | Hourglass-104  | 44.9 | 25.6| 47.4| 57.4   |
| HRDNet++               | ResNet101+152  | 47.4 | 32.1| 58.5| 55.8   |

How to design the multi-scale FPN. MS-FPN is designed to fuse multi-scale feature groups. Here, we consider three different styles, including simple FPN, multi-scale FPN aligned by depth, multi-scale FPN aligned by resolution, as shown in Figure 4, to demonstrate MS-FPN’s advantage. A simple FPN is to apply standard FPN to each multi-scale group of HRDNet and fuse the results of each FPN. New connections between multi-streams are introduced for multi-scale FPN, as shown in Figure 2. We conducted two groups experiments with ResNet10+18 and ResNet18+101 backbone. The first experiment in Table 2 shows that the multi-scale FPN is better than the simple FPN. Both experiments demonstrate that MS-FPN aligned with depth performs better than those aligned with resolution. Therefore, we adopt MS-FPN aligned with depth in our architecture.

Efficient and Effective HRDNet. We illustrate the number of parameters and running speed of proposed HRDNet, comparing with the state-of-the-art single backbone baseline. The results are shown in Table 3 prove that HRDNet can achieve much better performance with a similar number of parameters and even faster running speed.

Comparison with model ensemble. To further demonstrate that the improvement of HRDNet is not due to more parameters, we compared a two-stream HRDNet with the ensemble of two backbone models under the same experimental setting (Table 4). The ensemble models fuse the predicted bounding boxes and scores before NMS (Non-Maximum Suppression) and then perform NMS. We found that the single backbone models with high-resolution input always perform better than those with low-resolution even it is processed by a stronger backbone. HRDNet performs better than the ensemble model, thanks to the novel multi-scale and multi-level fusion method. They further prove that our designed MS-FPN is essential for HRDNet.

4.3. Comparison with the state-of-the-art methods

VisDrone2019: We compare HRDNet with the SOTA methods to demonstrate the advantage of our model and technical contributions. Table 5 shows that HRDNet achieves the best performance on VisDrone2019 DET validation set. Notably, our model obtains more than 3.0% AP improvement with ResNeXt50+101 compared to HFEA (ResNet152).

COCO2017: Besides the experiments on VisDrone2019, we also conduct experiments on the COCO2017 test set to prove our method works well on a larger scale, complicated and standard detection dataset. Table 6 shows that HRDNet achieves state-of-the-art results, and > 4.9% APsmall improvement compared with most recent algorithms.

5. CONCLUSION

In this paper, we propose the HRDNet with well-designed MD-IPN and MS-FPN to solve the issues which are not
considered in others for small objects. HRDNet achieves the state-of-the-art on small object detection dataset, VisDrone2019, at the same time, we outperform with a large margin on COCO.

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