

BorderDet: Border Feature for Dense Object Detection

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- Name : Hossain Md Saddam
- Profile
 - July 2019, Joined Chowagiken Corporation as a ML Engineer.
 - I worked on both CV and NLP team.
- Today I am going to present a state of the art detection approach called borderDet.



- There are two types of conventional approach for the detection task which are single-stage and two-stage detection.
- BorderDet added a module call BAM on both single-stage and two stage. Its achieved state of the art result.
- In this paper BorderDet proposed a method which is called Border-Align to extract the border features which are extreme points of the border.
- With ResNet-50 backbone, this method improves single-stage detector FCOS by 2.8 AP gains (38.6 to 41.4). With the ResNeXt-101-DCN backbone, BorderDet obtains 50.3 AP, outperforming the existing state-of-the-art approaches

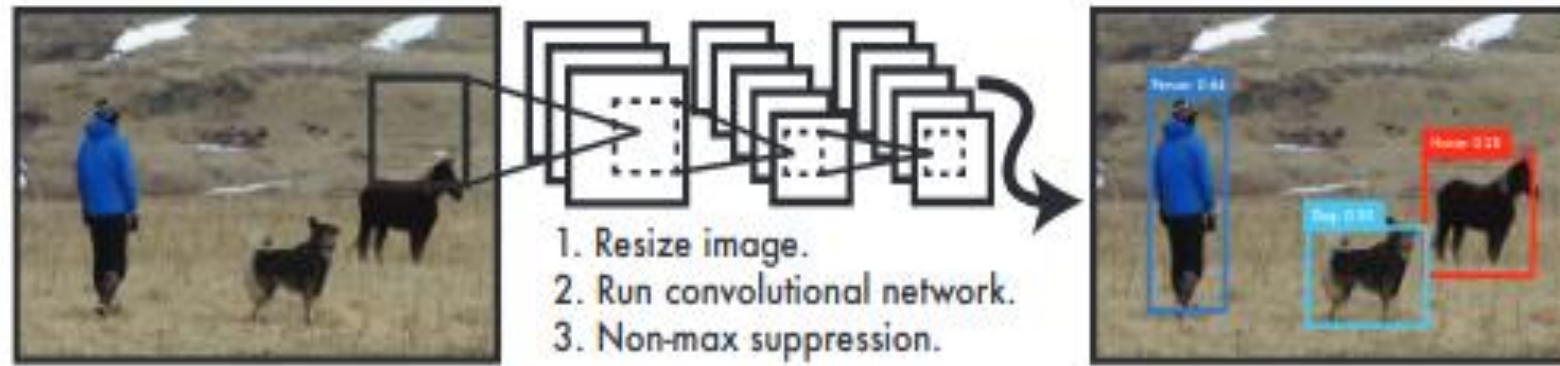
An abstract network diagram in the top right corner, featuring a complex web of interconnected nodes and lines. The nodes are represented by small dark grey circles, and the lines are thin, light blue-grey. The connections form a dense, overlapping mesh that suggests a complex system or data structure.

Established detection methods

Conventional Approach

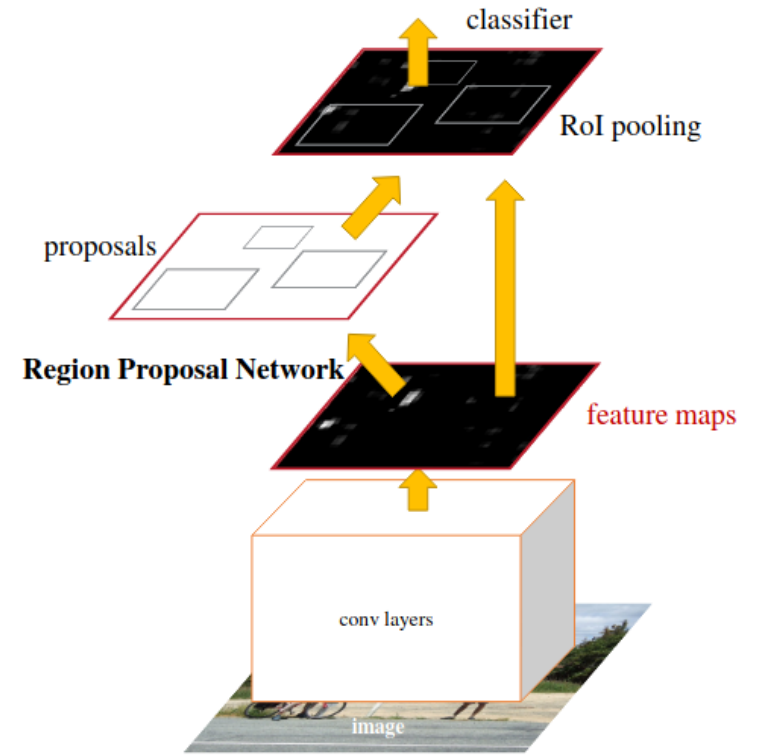
Densebox, YOLO, SSD, RetinaNet, and FCOS are the single-stage object detectors, have demonstrated the effectiveness to densely predict the classification and localization scores.

- YOLO object detection architecture



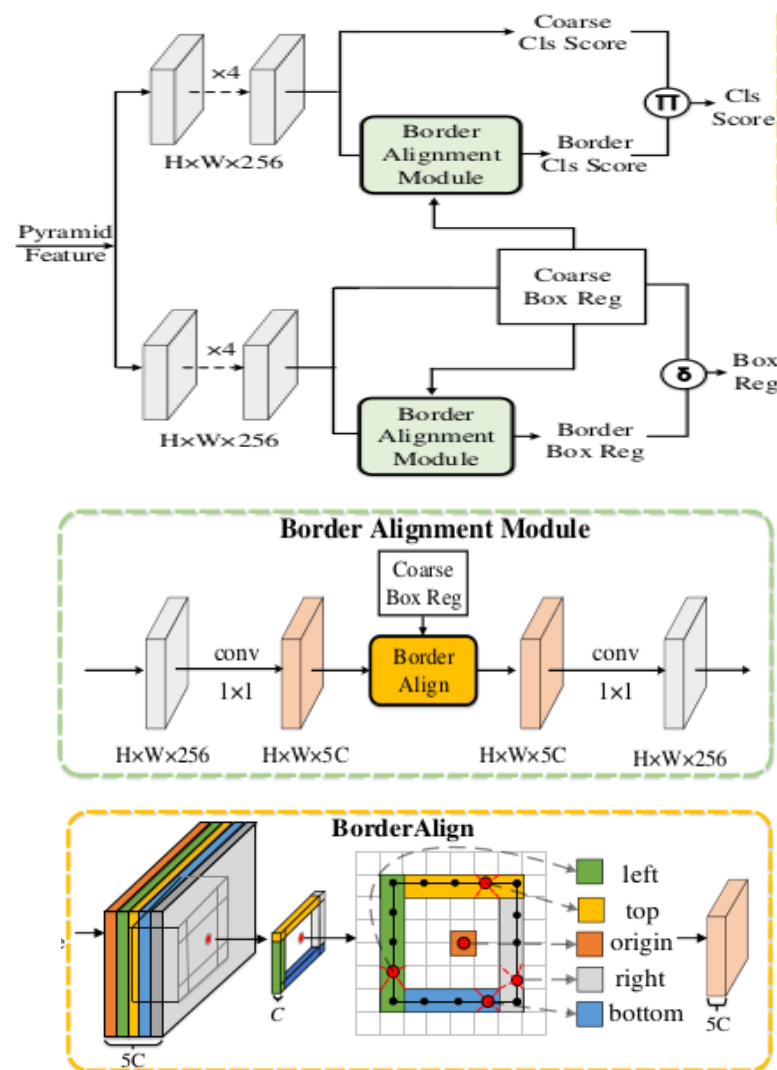
Conventional Approach

- For the two-stage, object Detectors, R-CNN series (R-CNN, Fast R-CNN, Faster R-CNN) adopt the region proposal network (RPN) that based on the sliding-window mechanism.
- To generate the initial proposals, and then a refinement stage that consists of a RoIAlign.
- R-CNN is performed to warp the feature maps of the region-of-interests (RoI) and generate the accurate predictions.



BorderDet(Single-Stage Architecture)

- Adopted a simple anchor-free object detector FCOS as baseline.
- Taking the pyramid feature maps as input. The BorderDet first predicts the coarse classification scores and coarse bounding box locations.
- The coarse bounding box locations and the feature maps are fed into the BAM to generate the feature maps which contain explicit border information.
- Finally, we apply a 1×1 convolutional layers to predict the border classification score and border locations.



BorderDet Approach(Motivation)

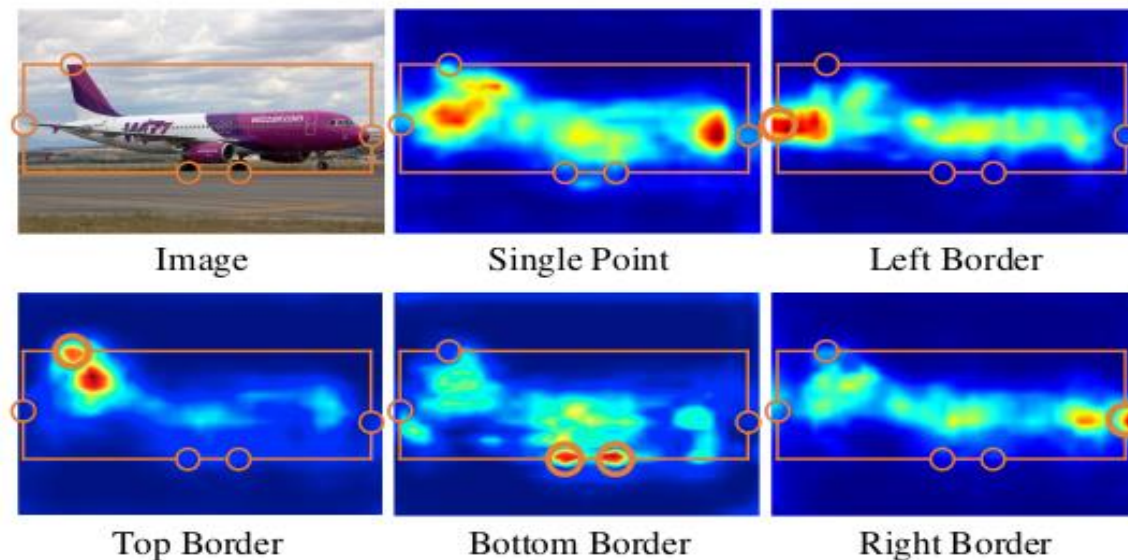
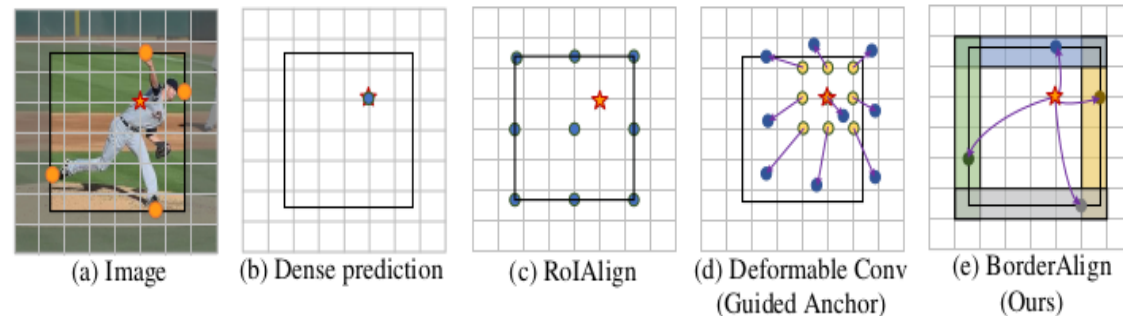


- As we can see in the table, only single point feature is not perform well compared to considering other features.
- It performs better than by 1.3 AP when consider region, border, middle border features.
- BorderDet comes into action behind this concepts.

| F_{point} | F'_{point} | F_{region} | F_{border} | F_{middle} | AP | AP_{50} | AP_{75} | AP_S | AP_M | AP_L | N |
|-------------|--------------|--------------|--------------|--------------|-------------|-----------|-----------|--------|--------|--------|-----------|
| ✓ | | | | | 38.6 | 57.2 | 41.7 | 23.5 | 42.8 | 48.9 | 0 |
| ✓ | ✓ | | | | 38.9 | 57.7 | 42.1 | 23.7 | 43.1 | 49.3 | 1 |
| ✓ | ✓ | ✓ | | | 39.9 | 58.9 | 43.4 | 24.6 | 44.1 | 50.8 | $n^2 + 1$ |
| ✓ | ✓ | | ✓ | | 39.6 | 58.5 | 43.2 | 24.2 | 43.8 | 50.4 | $4n + 1$ |
| ✓ | ✓ | | | ✓ | 39.9 | 58.7 | 43.4 | 24.8 | 44.0 | 50.4 | $4 + 1$ |

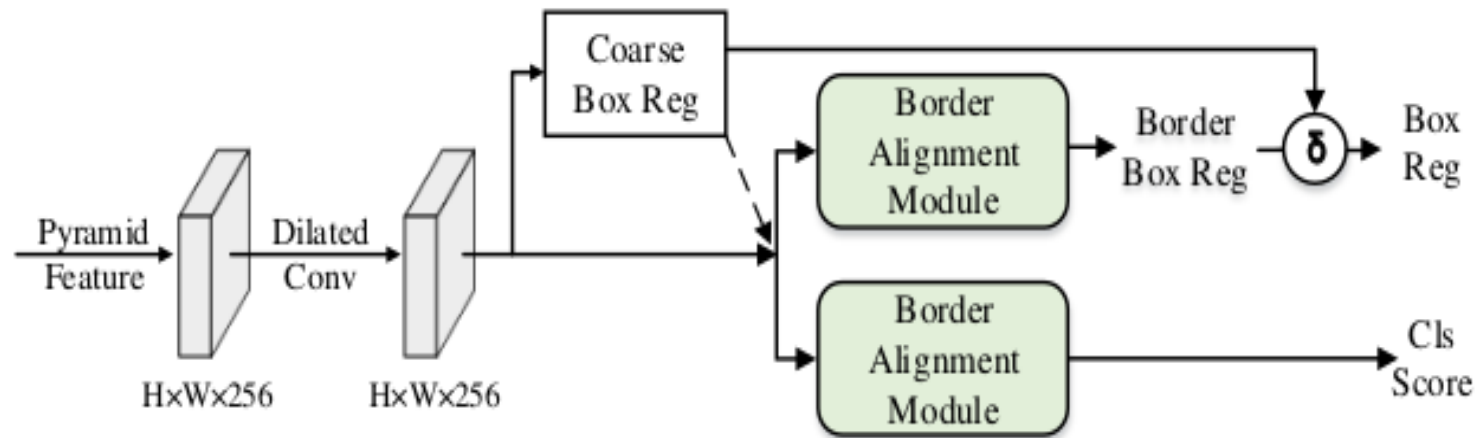
Feature Extraction

- First figure demonstrated different feature extraction strategy.
- Visualization of the border-sensitive feature maps. The orange circle on the border indicate the extreme points.



BorderRPN(two-stage)

- BorderDet method can also be served as a better proposal generator for the typical two-stage detectors.
- Added the border alignment module to RPN and denote the new structure as BorderRPN.





- BorderDet defined training loss as follows

$$\mathcal{L} = \mathcal{L}_{cls}^C + \mathcal{L}_{reg}^C + \frac{1}{N_{pos}} \sum_{x,y} \mathcal{L}_{cls}^B(\mathcal{P}^B, \mathcal{C}^*) + \mathcal{L}_{reg\{\mathcal{C}^* > 0\}}^B(\Delta, \Delta^*),$$

- In the implementation, focal loss and IoU loss are used as the classification loss and regression loss respectively, which are the same as FCOS.



- BorderDet experiments are trained on COCO trainval35k set and evaluated on COCO minival set (5K images).
- As a standard settings, It used ResNet-50 with FPN as backbone network for all the experiments.
- With an initial learning rate of 0.01, BorderDet decrease it by a factor of 10 after 60k iterations and 80k iterations respectively.
- Weight decay of 0.0001 and momentum of 0.9 are used.
- Unless specified, the input images are resized to ensure their shorter edge being 800 and the longer edge less than 1333.



- Below table demonstrated the difference between applying class-BAM and reg-BAM.
- With Border Alignment Module, the AP values are outperforming than without BAM.

| Cls-BAM | Reg-BAM | <i>AP</i> | <i>AP</i> ₅₀ | <i>AP</i> ₆₀ | <i>AP</i> ₇₀ | <i>AP</i> ₈₀ | <i>AP</i> ₉₀ |
|---------|---------|-------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|
| | | 38.6 | 57.2 | 53.3 | 46.7 | 35.3 | 16.0 |
| ✓ | | 39.7 | 58.4 | 54.8 | 48.5 | 36.2 | 15.9 |
| | ✓ | 39.7 | 57.3 | 53.3 | 47.3 | 36.9 | 18.6 |
| ✓ | ✓ | 41.4 | 59.4 | 55.4 | 49.4 | 38.6 | 19.5 |

Comparison with Other Feature Extraction Operators



- BorderAlign outperforms than other feature extraction operators by 1.0 AP at least.
- Below are the comparison of different feature extraction strategies.

| Method | AP | AP_{50} | AP_{75} | AP_S | AP_M | AP_L | fps |
|-----------------------|-------------|-------------|-------------|-------------|-------------|-------------|------|
| FCOS [21] | 38.6 | 57.2 | 41.7 | 23.5 | 42.8 | 48.9 | 18.4 |
| w/Iter-Box [5] | 39.0 | 58.0 | 42.0 | 21.8 | 42.9 | 50.7 | 18.3 |
| w/Adaptive Conv [23] | 39.6 | 58.5 | 42.8 | 22.0 | 43.5 | 51.3 | 16.8 |
| w/Deformable Conv [2] | 39.5 | 58.5 | 42.9 | 22.0 | 43.5 | 52.0 | 16.8 |
| w/RoIAlign [9] | 40.4 | 58.6 | 43.6 | 22.6 | 44.1 | 53.1 | 12.6 |
| w/ BorderAlign | 41.4 | 59.4 | 44.5 | 23.6 | 45.1 | 54.6 | 16.7 |



- BorderDet can be easily integrated with the many popular object detectors, e.g. RetinaNet and FPN.
- To prove the generalization of the BorderDet, we first add the proposed border alignment module to the RetinaNet.
- BorderDet can consistently improve the RetinaNet by 2.3 AP.
- For the two-stage method FPN, our experiments show that the proposed BorderRPN gains 3.6 AP improvement.

| Method | AP | AP_{50} | AP_{75} | AP_S | AP_M | AP_L |
|----------------|-------------|-----------|-----------|--------|--------|--------|
| Retinanet [16] | 36.1 | 55.0 | 38.4 | 19.1 | 39.6 | 48.2 |
| BD-Retinanet | 38.4 | 56.5 | 55.5 | 22.4 | 41.6 | 51.0 |
| FPN [20] | 37.1 | 58.7 | 40.3 | 21.1 | 40.3 | 48.6 |
| BD-FPN | 40.7 | 57.8 | 44.3 | 21.9 | 43.7 | 54.8 |

Comparisons with State-of-the-art Detectors



- The BorderDet, based on FCOS, ResNet-101 backbone, is the state-of-the-art methods in below table under standard setting and advanced setting.
- With the standard setting, the proposed BorderDet achieves an AP of 43.2.
- By adopting advanced settings, BorderDet reaches 50.3 AP, the state of the art among existing one-stage methods and two-stage methods.

| Method | Backbone | Iter. | AP | AP_{50} | AP_{75} | AP_S | AP_M | AP_L |
|-------------------|-----------------------|-------|------|-----------|-----------|--------|--------|--------|
| FPN [15] | ResNet-101-FPN | 180k | 36.2 | 59.1 | 39.0 | 18.2 | 39.0 | 48.2 |
| Mask R-CNN [9] | ResNet-101-FPN | 180k | 38.2 | 60.3 | 41.7 | 20.1 | 41.1 | 50.2 |
| Cascade R-CNN [1] | ResNet-101 | 280k | 42.8 | 62.1 | 46.3 | 23.7 | 45.5 | 55.2 |
| RefineDet512 [27] | Resnet-101 | 280k | 41.8 | 62.9 | 45.7 | 25.6 | 45.1 | 54.1 |
| RetinaNet [16] | ResNet-101-FPN | 135k | 39.1 | 59.1 | 42.3 | 21.8 | 42.7 | 50.2 |
| FSAF [30] | ResNet-101-FPN | 135k | 40.9 | 61.5 | 44.0 | 24.0 | 44.2 | 51.3 |
| FCOS [21] | ResNet-101-FPN | 180k | 41.5 | 60.7 | 45.0 | 24.4 | 44.8 | 51.6 |
| FCOS-imprv [21] | ResNet-101-FPN | 180k | 43.0 | 61.7 | 46.3 | 26.0 | 46.8 | 55.0 |
| CenterNet [3] | Hourglass-104 | 500k | 44.9 | 62.4 | 48.1 | 25.6 | 47.4 | 57.4 |
| BorderDet | ResNet-101-FPN | 90k | 43.2 | 62.1 | 46.7 | 24.4 | 46.3 | 54.9 |
| BorderDet† | ResNet-101-FPN | 180k | 45.4 | 64.1 | 48.8 | 26.7 | 48.3 | 56.5 |
| BorderDet† | ResNeXt-64x4d-101 | 180k | 46.5 | 65.7 | 50.5 | 29.1 | 49.4 | 57.5 |
| BorderDet† | ResNet-101-DCN | 180k | 47.2 | 66.1 | 51.0 | 28.1 | 50.2 | 59.9 |
| BorderDet† | ResNeXt-64x4d-101-DCN | 180k | 48.0 | 67.1 | 52.1 | 29.4 | 50.7 | 60.5 |
| BorderDet‡ | ResNeXt-64x4d-101-DCN | 180k | 50.3 | 68.9 | 55.2 | 32.8 | 52.8 | 62.3 |



- Paper : <https://arxiv.org/abs/2007.11056>
- Implementation: <https://github.com/Megvii-BaseDetection/BorderDet>



Thank you!