Objectness-Guided Open Set Visual Search and Closed Set Detection

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Abstract

Searching for small objects in large images is currently challenging for deep learning systems, but is a task with numerous applications including remote sensing and medical imaging. Thorough scanning of very large images is computationally expensive, particularly at resolutions sufficient to capture small objects. The smaller an object of interest, the more likely it is to be obscured by clutter or otherwise deemed insignificant. We examine these issues in the context of two complementary problems: closed-set object detection and open-set target search. First, we present a method for predicting pixel-level objectness from a low resolution gist image, which we then use to select regions for subsequent evaluation at high resolution. This approach has the benefit of not being fixed to a predetermined grid, allowing fewer costly high-resolution glimpses than existing methods. Second, we propose a novel strategy for open-set visual search that seeks to find all objects in an image of the same class as a given target reference image. We interpret both detection problems through a probabilistic, Bayesian lens, whereby the objectness maps produced by our method serve as priors in a maximum-a-posteriori approach to the detection step. We evaluate the end-to-end performance of both the combination of our patch selection strategy with this target search approach and the combination of our patch selection strategy with standard object detection methods. Both our patch selection and target search approaches are seen to significantly outperform baseline strategies.

1. Introduction

Artificial intelligence (AI) approaches relying on deep learning (DL) and primarily using deep convolutional neural networks (CNNs) have recently shown great success at numerous tasks. In problems such as image classification [14, 12], object detection [21, 19], image segmentation [16, 22] and application areas such as medical diagnostics [5, 16], AI approaches can meet or exceed human capabilities. Among other things, current AI/DL research addresses issues such as open set recognition [24, 9] (one of the foci of this study), privacy [26], adversarial attacks [6], low-shot learning [18, 4], and AI bias [3]. This study is specifically focused on the task of using CNNs for detecting objects, where much progress has been made through algorithms such as Yolo or Fast(er)-RCNN [21, 19, 20, 23]. However, most object detection work has thus far relied on the assumption that the target objects occupy a significant fraction of the search area. We consider instead the situation where objects may be several orders of magnitude smaller than the image size (e.g., images with thousands of pixels per side and relevant objects spanning only tens of pixels). This occurs frequently in remote sensing applications, notably in satellite imagery (e.g., vehicles in a parking lot) and microscopy images (e.g., synapses in electron microscopy imaging of brain tissue [27]). Most machine vision techniques operate on images on the order of a few hundred pixels per side, for example the $224 \times 224$ pixel images of ImageNet [7]. Processing very high resolution (vHR) images requires additional computation, time, and money, particularly in streaming applications. To be useful, approaches to this problem must efficiently manage trade-offs among computational cost, memory, and performance in an application-specific manner.

Thoroughly searching such data sources for objects at
varying scales motivates the development of unconventional approaches. Standard techniques relying on convolutional neural networks involve processing sliding windows of full images. The computational cost of this process increases quadratically with the size of the image, incurring large memory and computational footprints that eventually become prohibitive. In practice, the computational budget may be fixed, leading to choices about how to prioritize window selection.

Further, a given architecture may struggle to reason across sufficiently diverse scales, leading to potential neglect of target candidates. We thus have two goals for this work: (1) to achieve high performance for object search and detection in vHR images and (2) to develop methods that scale according to data and computational constraints.

To address these issues, we sought an efficient approach to more efficiently “look” for objects belonging to classes of interest (Figure 1). Recent work [30] has tackled aspects of this problem using deep reinforcement learning (DRL). We instead address it through an approach that identifies regions of high potential objectness. We use a probabilistic interpretation of object detection in vHR images whereby predicted objectness maps act as priors for detection algorithms, allowing us to perform search in a maximum-a-posteriori setting. In this work, we examine two different detection scenarios: (1) closed-set object detection, whereby we search efficiently for instances of a fixed number of pre-identified object classes, and (2) open-set target-guided search, where the algorithm must find instances of a target class defined by only a single image.

2. Related Work

Numerous works have addressed the problem of object detection in visual data through the use of convolutional neural networks. R-CNN [11] and Fast-RCNN [10] rely on selective search to identify proposal regions, while Faster-RCNN [21] jointly identifies proposal regions and their classes. The YOLO family of algorithms [19, 20, 2] use a learned policy being used to make the low- vs. high-resolution determination. The DRL agent is trained to choose which regions of an image to process at low resolution and which regions to process at high resolution in order to best balance efficiency with detection performance.

Here we provide an alternative approach that allows flexible sampling of HR windows (also referred to as glimpses) as an alternative to a fixed-grid approach. Furthermore, we develop an approach for estimating objectness from low-resolution (LR) gist images that then guides our glimpse-sampling approach. Finally, we demonstrate how this approach can be used for open-set search in a MAP framework.

3. Methods

We discuss complementary approaches to object detection in vHR overhead images. In particular, we address object detection in closed and open-set scenarios, using estimates of objectness from LR gists to guide the search and detection processes.

3.1. Efficient Closed-Set Detection

3.1.1 Objectness Estimation

We first develop an approach that allows our model to examine the full scene at low resolution (and with low computation cost), producing a saliency map to guide subsequent high-resolution object detection. Specifically, we train a deep neural network (DNN) to produce a density map of objectness; that is, a map that encodes the likelihood of regions containing objects from the classes we wish to detect. In practice, given a high-resolution ground-truth class-level semantic segmentation, $S_c$, we generate a binary segmentation $S_b$ by converting the class-level labels to binary labels that represent the presence or absence of an object.

To train the prediction model, we generate LR gist images $I_g$ from the original vHR image $I_{vHR}$ (e.g., we resize a 4000x4000 image to 128x128) and similarly scale $S_b$ to get a gist mask $S_g$ of fixed dimensions, $(w_{gist}, h_{gist})$. For conve-
nience and following common practice, we assume images are square (i.e., \( w_{\text{gist}} = h_{\text{gist}} = d_{\text{gista}} \)). The scale factor, \( \alpha \), is defined as

\[
\alpha = \frac{d_{\text{gista}}}{d_{\text{HR}}}. \tag{1}
\]

As a result of the downsampling, we expect the gist images to lose some class-level information and potentially even reduce small objects beyond recognition (e.g., one pixel). However, our intent is to produce density maps that capture object likelihood rather than a true segmentation. We find that the gist images still preserve sufficient context to support those predictions (e.g., textures, co-occurring larger objects, etc.).

Using the gist images, we train a U-Net \([22]\) to produce objectness density maps \( \pi \) from the gist images. We define our training loss to be the binary cross-entropy

\[
L_{\pi} = -\sum_{i,j \in S_x} y_{ij} \log(\pi_{ij}) - (1 - y_{ij}) \log(1 - \pi_{ij}). \tag{2}
\]

Here \( y_{ij} \) is the true objectness value at pixel \((i, j)\) and \( \pi_{ij} \) is the objectness prediction at that same location.

In case ground-truth segmentation is unavailable, an alternative is to convert bounding box annotations to Gaussian densities of the same shape and normalized to have a peak of 1 at the center. Supplemental experiments demonstrated this to be an effective alternative when high-quality ground truth is sparse.

### 3.1.2 Region Selection

Given the objectness maps as a prior, we seek to select a set of high-resolution regions to glimpse over. While there are many strategies for performing the selection, our general process is as follows. We first define the appropriate glimpse image dimensions, as determined by the downstream object detector. Assuming square input images as before, we use \( d_{\text{glimpse}} \) to denote the final glimpse resolution. From this definition, we can determine the corresponding size of a glimpse in the gist image via \( d_{\text{glimpse}} = \text{ceil}(\alpha \cdot d_{\text{glimpse}}) \).

Given the glimpse size relative to the gist image, we seek to define a policy for sampling glimpses that maximizes the detection of objects of interest. We initially focus on rule-based policies that are deterministic and interpretable. Our simple yet effective policy is described in Algorithm 1. The method iteratively samples glimpses that maximize the total available objectness. This strategy allows for glimpses to overlap each other, but can be easily modified by increasing or decreasing the \( \beta \) term (for instance, \( \beta = -(d_{\text{glimpse}})^2 \) prevents any glimpse overlap).

#### Algorithm 1: Glimpse Selection Policy

**Result:** Selection of a set of glimpses

**Input:** \( \pi : \) Objectness map prior of dimension \( d_{\text{gista}} \)

\( d_{\text{glimpse}} : \) Glimpse dimension in HR image-space

\( \alpha : \) Gist scaling factor

\( n_{\text{glimpse}} : \) Maximum number of glimpses

\( \beta : \) Objectness penalty term [default=0]

**Output:** \( G : \) Set of selected glimpse locations

1. Compute \( d_L_{\text{glimpse}} = \text{ceil}(\alpha \cdot d_{\text{glimpse}}) \);
2. Compute \( \sigma = \frac{d_{\text{glimpse}}}{4} \);
3. Generate Gaussian kernel, \( k \) with width \( \sigma \) and dimension \( d_{\text{glimpse}} \);
4. Compute \( \pi' = \text{conv}(\pi, k) \);
5. \( G = \{\} \);
6. for \( i = 1 : n_{\text{glimpse}} \) do
7. \( \) Generate \( S_{\pi'} \) according to \([5]\);
8. Compute \( p_{x,y} \) according to \([5]\);
9. Add \( p_{x,y} \) to \( G \);
10. Reset objectness at glimpse location
11. \( \) \( \pi' = \pi + \sum_{p_{x,y} \in G} p_{x,y} \text{Glimpse Dimension in LR} \)
12. end
13. return \( G \)

At each step in the loop in Algorithm 1, we search for where to glimpse next so that the sampled glimpse maximizes the total objectness contained within it. To speed up this search, we first compute an integral image of the current map \( \pi' \):

\[
S_{\pi}(i,j) = \sum_{i' \leq i, j' \leq j} \pi(i',j') \quad \forall \ i,j \tag{3}
\]

From this table, we can easily search for the glimpse with maximum objectness by simply summing over shifted (according to \( d_{LR} \)) versions of \( S_{\pi} \) and finding the location of the maximum. Using Python-style notation to illustrate indexing \( S_{\pi} \) for the four shift operations, the glimpse with maximum objectness over all search locations \((x, y)\) can be found according to:

\[
p_{x,y} = \arg \max_{x,y} (S_{\pi}[:-d_{LR}:-d_{LR}] + S_{\pi}[d_{LR}:-d_{LR}:]) - (S_{\pi}[:-d_{LR},d_{LR}:] + S_{\pi}[d_{LR},-d_{LR}:]) \tag{4}
\]

#### 3.2. Open-Set Object Detection - Target-Guided Search

We consider now the task of target-based, open-set search. In this setting the goal is to search the image for
tiles (sub-images) that support the presence of a desired target object, while relying on only a single example image of that target (which we denote here as o).

Consider a set of candidate search locations obtained by tiling the original image into a set of sub-image tiles and denote their coordinates as (i, j). To achieve the goal of optimal open-set search, we use as criteria the likelihood $l_o(i, j)$ that the specific target object be found at that location. We estimate this likelihood by comparing the network embedding representations $f$ of the exemplar object image $o$ and the tile $T(i, j)$:

$$l_o(i, j) = \cos(f(T(i, j)), f(o)). \quad (5)$$

We use the second-to-last layer of ResNet50 as the embedding function $f(.)$ in computing this deep similarity $l_o(i, j)$.

We further consider a refined approach that uses maximum a posteriori (MAP) criteria, wherein we interpret the objectness probability $\pi_{i,j}$ (in Eq. (2)), integrated over a specific tile (at coordinates (i, j)), as a prior that any object of interest be present in that tile. The resulting a-posteriori probability $p_o(i, j)$ that the target object is present in the tile is then:

$$p_o(i, j) = l_o(i, j)\pi_{i,j}. \quad (6)$$

We use these above metrics to obtain a rank ordering by deep similarity of tiles to visit. Our search policy is chosen simply to visit tiles in decreasing order for either $l_o(i, j)$ or $p_o(i, j)$. We call global searches ordered by likelihood $l_o(i, j)$ G-ML-MSTR (“global search / searching for most similar to reference”) and global searchers ordered by a-posteriori probability $p_o(i, j)$ G-MAP-MSTR.

4. Experiments

4.1. Data

To test our objectness-based approach, we run an evaluation on the DOTA/iSAID overhead dataset [33, 32] which consists of 2806 overhead images ranging in size from 800x800 to 4000x4000. In order to test the ability of our method to find objects that are small relative to the size of the image, we narrow our evaluation to six object classes: small vehicle, large vehicle, plane, helicopter, ship, and storage tank (henceforth referred to as DOTA6).

We train all core models on the DOTA training split and evaluate on the images of the validation split. Of the 458 images in the validation split, we test on only those containing at least one instance of the objects in DOTA6.

Figure 4 shows performance averaged across all DOTA6 classes. Note that while the oracle detector represents best case performance, it is still unable to achieve perfect precision since there are cases where sampled glimpses contain partial objects that fail to meet the IoU detection threshold.

4.2. Closed-set Objectness-guided Detection

4.2.1 Objectness U-Net

We use a U-Net architecture based on four downsampling and four upsampling blocks, where each block down-/upsamples the input feature map by a factor of two and then passes the result through two blocks of {convolution, batch normalization, ReLU}. Inputs to the U-Net model also pass through a similar block before undergoing downsampling. At each downsampling block, the number of channels is doubled starting at 64 and ending at 512. Upsampling blocks concatenate the upsampled feature maps with the maps from the skip connection (achieving twice the original number of channels at the corresponding level in the downsampling path) and produce feature maps with 512 chan-
nels at the lowest point of the U-Net down to 64 channels at the highest point. Our U-Net accepts inputs of dimensions 128x128x3 and returns a 1-channel objectness prediction of dimension 128x128.

Segmentation masks for the DOTA6 labels were converted to a binary map and our U-Net was trained via backpropagation using ADAM [13] optimization with a standard Binary Cross Entropy loss (Eq. (2)) between the objectness prediction and ground-truth mask.

4.2.2 Baseline Object Detectors

In this work, we use a trained YOLOv3 detector operating on 512x512 tiles. Because we do not make any algorithmic modifications to the HR-detector architecture itself, the quality of the detection results hinges on our algorithm’s ability to select HR glimpses to evaluate. As such, our baselines were established to measure the quality of the glimpse selection. We implemented several policies to sample glimpses either from a fixed grid or flexibly (allowing possible overlap of glimpses). Baselines are described in Table 1.

| Policy   | Description                                                                 |
|----------|-----------------------------------------------------------------------------|
| grid     | Glimpses spaced uniformly with possible overlap for large $n_{hr}$           |
| grid_fixed| Non-overlapping tiles ordered randomly                                      |
| random   | Overlapping glimpses whose coordinates are sampled uniformly                |
| entropy  | Glimpses sampled according to entropy (highest to lowest)                   |
| unet     | Objectness-guided search according to Algorithm I                          |
| unet_fixed| Objectness-guided (highest to lowest) search of non-overlapping tiles       |

Table 1. Glimpse selection policies

within a sampled high-resolution glimpse. In so doing we decouple the effects of the glimpsing and object detection strategies.

Additionally, in order to address computational efficiency, we evaluate detection performance considering cases with a fixed HR glimpse budget. Results are shown in Figure 3. We determine true/false detections following the standard practice of using an Intersection-over-Union (IoU) threshold of 0.5 between predicted and true bounding boxes.

4.3. Open-Set Detection - Target Guided Search

We again use DOTA6 to evaluate our open-set search strategies against the following baselines: a naive global sliding window and local searches in predefined regions maximizing similarity to the target tile, similarity to the initial location, and similarity to the current tile. The local search is motivated by the observation that objects of interest tend to cluster in specific regions (e.g. cars clustered in
a parking lot).

The sequences of search trajectories that these approaches generate are compared – for illustrative purposes – in the lower panels of Figures 6, 8, and 7. In the top panes of these figures, we plot the recall value as a function of the number of search steps. Here we define recall in terms of the ground truth locations and assuming that the algorithm recognizes an object when it lands upon it (i.e., oracle detection).

An overall comparison of the different strategies over a set of N=11 images is provided in Figure 5. It can be seen that the best performance is achieved by the global ML and MAP-guided approaches, with a clear benefit being observed when the prior \( \pi(i,j) \) in used in the selection of the next tile.

![Figure 5](image.png)

**Figure 5.** Performance (recall) comparison aggregated over all images for all proposed methods against all baselines described. The y-axis is recall, the x-axis is the normalized number of looks (where 1 indicates that all tiles in the image have been searched and explored.)

5. Discussion

Several observations can be made about our approaches and results.

In the closed-set paradigm, we find that conventional object detectors, such as YOLOv3, exhibit poor performance in the overhead domain. This is likely due to the differences in object scale and density in overhead imagery compared to the ground-level, natural images for which they were developed. The situation is further complicated by the inherent variability of the DOTA dataset, which was gathered from a variety of sensors and under a variety of imaging conditions. DOTA therefore contains significant variation in both image resolution and Ground Sample Distance (GSD).

In both the closed set object detection and open set target-guided search tasks, our objectness maps provide a strong prior for improving the efficiency of the search. The objectness prior improves recall for closed-set detection, particularly in the first few glimpses. This attribute is important given typical computational budgets and because of the absence of other detection methods for vHR overhead imagery. In open set target-guided search, we see that global searches using similarity to the reference representation solidly outperform the baselines. A noticeable gain is also seen when including the objectiveness prior in that approach.

While we made considerable improvements over baseline methods, closed set object detection and open set search in overhead imagery remain areas ripe for future research. Areas of future work may include extensions of the current work in both the closed and open set settings by using objectness along with reinforcement learning and, when carrying out open set search in the context of applications in autonomy and robotics applications, the use of Bayesian filtering to improve smoothness of search trajectories.

6. Conclusion

This study examines both closed-set object detection and open-set target search. It proposes a method for predicting pixel-level objectness from low resolution gist images used subsequently for evaluation at high resolution and also in a Bayesian approach for open-set visual search that aims to find all objects in an image of the same type as a given target reference. This work shows the benefits of the objectness-guided approach for improving the efficiency of vHR image
processing. This is true both for selecting HR glimpses and for incorporation as a prior in open set target search. Both approaches are shown to improve performance when compared to baseline methods.

Figure 7. (top) performance comparison of MSTR-ML with other baseline approaches: recall vs normalized number of looks. (bottom) illustration of the search trajectory using MSTR-ML.

Figure 8. (top) performance comparison of MSTR-ML with other baseline approaches: recall vs normalized number of looks. (bottom) illustration of the search trajectory using MSTR-ML.
References

[1] Amit Banerjee and Philippe Burlina. Efficient particle filtering via sparse kernel density estimation. *IEEE Transactions on Image Processing*, 19(9):2480–2490, 2010.

[2] Alexey Bochkovskiy, Chien-Yao Wang, and Hong-Yuan Mark Liao. YOLOv4: Optimal Speed and Accuracy of Object Detection. *arXiv*:2004.10934 [cs, eess], Apr. 2020.

[3] Philippe Burlina, Neil Joshi, William Paul, Katia D Pacheco, and Neil M Bressler. Addressing artificial intelligence bias in retinal disease diagnostics. *arXiv preprint arXiv:2004.13515*, 2020.

[4] Philippe Burlina, William Paul, Philip Mathew, Neil Joshi, Katia D Pacheco, and Neil M Bressler. Low-shot deep learning of diabetic retinopathy with potential applications to address artificial intelligence bias in retinal diagnostics and rare ophthalmic diseases. *JAMA ophthalmology*, 138(10):1070–1077, 2020.

[5] Philippe M Burlina, Neil Joshi, Katia D Pacheco, TY Alvin Liu, and Neil M Bressler. Assessment of deep generative models for high-resolution synthetic retinal image generation of age-related macular degeneration. *JAMA ophthalmology*, 137(3):258–264, 2019.

[6] Nicholas Carlini and David Wagner. Adversarial examples are not easily detected: Bypassing ten detection methods. In *Proceedings of the 10th ACM Workshop on Artificial Intelligence and Security*, pages 3–14, 2017.

[7] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei. Imagenet: A large-scale hierarchical image database. In *CVPR09*, 2009.

[8] Adam Van Etten. You only look twice: Rapid multi-scale object detection in satellite imagery. *CoRR*, abs/1805.09512, 2018.

[9] Chuanxing Geng, Sheng-jun Huang, and Songcan Chen. Recent advances in open set recognition: A survey. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2020.

[10] R. Girshick. Fast r-cnn. In *2015 IEEE International Conference on Computer Vision (ICCV)*, pages 1440–1448, 2015.

[11] Ross Girshick, Jeff Donahue, Trevor Darrell, and Jitendra Malik. Rich feature hierarchies for accurate object detection and semantic segmentation. *arXiv:1311.2524 [cs]*, 2014. arXiv: 1311.2524.

[12] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016.

[13] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014.

[14] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. *Communications of the ACM*, 60(6):84–90, 2017.

[15] W. Liao, X. Chen, J. Yang, S. Roth, M. Goesele, M. Y. Yang, and B. Rosenhahn. Lr-cnn: Local-aware region cnn for vehicle detection in aerial imagery. *ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences*, V-2-2020:381–388, Aug 2020.

[16] Mike Pekala, Neil Joshi, TY Alvin Liu, Neil M Bressler, D Cabrera DeBuc, and Philippe Burlina. Deep learning based retinal oct segmentation. *Computers in Biology and Medicine*, 114:103445, 2019.

[17] Katie Rainey, Shibin Parameswaran, Josh Harguess, and John Stastny. Vessel classification in overhead satellite imagery using learned dictionaries. In Andrew G. Tescher, editor, *Applications of Digital Image Processing XXXV*, volume 8499, pages 741 – 752. International Society for Optics and Photonics, SPIE, 2012.

[18] Sachin Ravi and Hugo Larochelle. Optimization as a model for few-shot learning. 2016.

[19] Joseph Redmon, Santosh Kumar Divvala, Ross B. Girshick, and Ali Farhadi. You only look once: Unified, real-time object detection. *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 779–788, 2015.

[20] Joseph Redmon and Ali Farhadi. Yolov3: An incremental improvement, 2018. cite arxiv:1804.02767Comment: Tech Report.

[21] Shaoqing Ren, Kaiming He, Ross B. Girshick, and Jian Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 39:1137–1149, 2015.

[22] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical image computing and computer-assisted intervention*, pages 234–241. Springer, 2015.

[23] W. Sakla, G. Konjevod, and T. N. Mundhenk. Deep multi-modal vehicle detection in aerial isr imagery. In *2017 IEEE Winter Conference on Applications of Computer Vision (WACV)*, pages 916–923, 2017.

[24] Walter J Scheirer, Anderson de Rezende Rocha, Archana Sapkota, and Terrance E Boulf. Toward open set recognition. *IEEE transactions on pattern analysis and machine intelligence*, 35(7):1757–1772, 2012.

[25] Jacob Shermeyer and Adam Van Etten. The effects of super-resolution on object detection performance in satellite imagery. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) Workshops*, June 2019.

[26] Reza Shokri, Marco Stronati, Congzheng Song, and Vitaly Shmatikov. Membership inference attacks against machine learning models. In *2017 IEEE Symposium on Security and Privacy (SP)*, pages 3–18. IEEE, 2017.

[27] Shin-ya Takemura, C Shan Xu, Zhiyuan Lu, Patricia K Rivlin, Toufiq Parag, Donald J Olbris, Stephen Plaza, Ting Zhao, William T Katz, Lowell Umayam, et al. Synaptic circuits and their variations within different columns in the visual system of drosophila. *Proceedings of the National Academy of Sciences*, 112(44):13711–13716, 2015.

[28] Mingxing Tan, Ruoming Pang, and Quoc V. Le. Efficientdet: Scalable and efficient object detection. In *The IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2020.

[29] Tianyu Tang, Shilin Zhou, Zhipeng Deng, Huanxin Zou, and Lin Lei. Vehicle detection in aerial images based on region
convolutional neural networks and hard negative example mining. *Sensors*, 17(2):336, 2017.

[30] Burak Uzkent, Christopher Yeh, and Stefano Ermon. Efficient object detection in large images using deep reinforcement learning. *2020 IEEE Winter Conference on Applications of Computer Vision (WACV)*, pages 1813–1822, 2020.

[31] A. Van Etten. Satellite imagery multiscale rapid detection with windowed networks. In *2019 IEEE Winter Conference on Applications of Computer Vision (WACV)*, pages 735–743, 2019.

[32] Syed Waqas Zamir, Aditya Arora, Akshita Gupta, Salman Khan, Guolei Sun, Fahad Shahbaz Khan, Fan Zhu, Ling Shao, Gui-Song Xia, and Xiang Bai. isaid: A large-scale dataset for instance segmentation in aerial images. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*, pages 28–37, 2019.

[33] Gui-Song Xia, Xiang Bai, Jian Ding, Zhen Zhu, Serge Belongie, Jiebo Luo, Mihai Datcu, Marcello Pelillo, and Liangpei Zhang. Dota: A large-scale dataset for object detection in aerial images. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2018.