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Surface-to-air missile sites detection agent with remote sensing images

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Improvement and development in satellite and aerial photography have resulted in the rapid growth of the quantity and quality of remote sensing images, which are commonly used in military intelligence gathering, navigation, damage assessment, surveying, and mapping. Finding military facilities such as surface-to-air missile sites (SAMSs) from massive amounts of high-resolution remote sensing images, has attracted considerable research interest globally. However, existing map interpretation is mainly conducted by human experts; therefore, it is time consuming and often suffers from low detection accuracy.

Han [1] proposed a type of SAMSs detection strategy, wherein it was revealed that SAMSs are considerably small to be searched for and assumed that they are deployed for protecting the airport or harbor. Thus, after preprocessing remote sensing images, he adopted mean filtering to decrease the noise. Then, Hough transformation is applied in straight line detection to find airport runways. After employing artificial feature extraction, the SAMSs nearby airports are located. However, Han's strategy possesses some limitations. First, although these traditional image processing algorithms are simple and efficient, they are incapable of processing large-scale remote sensing images, especially small targets in the complex background such as SAMSs. Second, since there are remarkable differences in SAMSs globally, the generalization abilities of artificial extracted features are weak. Third, Han's strategy aims at the SAMSs nearby airports or harbors, which may fail to find those hidden in mountain areas or other places.

Moreover, a large number of intelligence agents are needed to view all the images of the relevant areas in conventional map interpretation, which is time consuming and inefficient. Apart from that, the accuracy will also decrease as intelligence agents' working time increases. Therefore, it will help considerably to introduce automatic detection through deep learning methods to the advantage of the intelligence gathering. However, collecting remote sensing images with data annotations is the main difficulty.

Owing to the above limitations, we propose a detection framework based on deep learning approaches and conduct SAMSs dataset. Then, we select a sliding window when searching SAMSs to cover all areas. Convolutional neural networks (CNNs) have achieved great success in many computer vision tasks [2, 3]. For example, the region-based convolutional neural network (RCNN) has significantly improved the accuracy of object detection in comparison with traditional methods [3]. Therefore, many object detection studies are based on this framework.

As shown in Figure 1(b), the working flow of the detection agent comprises two parts, namely training and searching. In the training part, we conduct an SAMSs dataset of different countries and compare two typical algorithms' performance, you only look once v3 (YOLO-v3) [4] and Faster RCNN [5]. In the searching part, we search an area of approximately 6000 km^2 leveraging on the trained model. After judging the detection results, some confirmed and suspected SAMSs are indicated on the map. Finally, these confirmed results will be returned to SAMSs dataset to optimize the model incrementally.

SAMSs dataset. We collected 1332 SAMSs images from Google Map[1)] and annotated them with LabelImg[2)]. In general, SAMSs have a diameter of no more than 200 m, which means that all images need to be in high resolution; otherwise, we could not distinguish them in huge pictures. Consequently, the ground sample distance is from 0.15 to 0.6 m. Figure 1(a) shows two typical SAMSs, Patriot and Hawk[3)]. The shooting angle of remote sensing images is from top to bottom, resulting in that each target could face in all directions. Therefore, data augmentation is crucial in improving detection accuracy. By utilizing translation, flipping, scaling and rotation, the size of the dataset was increased to 10443.

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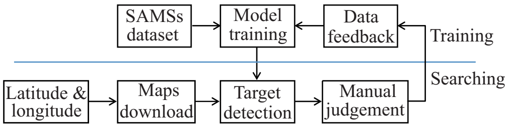
1) Google Map is a web mapping service developed by Google. It offers satellite imagery and street maps, among others.
2) LabelImg is a graphical image annotation tool. https://github.com/tzutalin/labelImg.
3) Patriot and Hawk are two kinds of medium-range surface-to-air missiles.

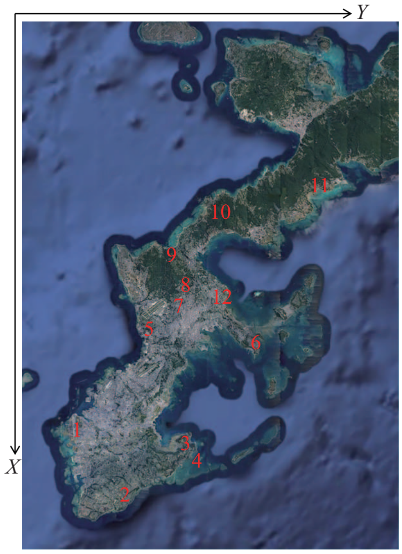
(a)



(b)

Model	Precision (%)	Rate (fps)
YOLO-v3	32.05	27
Faster R-CNN (VGG16)	85.90	4
Faster R-CNN (VGG16-DA)	87.18	4
Faster R-CNN (Resnet101)	82.05	4
Faster R-CNN (Resnet101-DA)	91.02	4

(c)



(d)

(e)

Figure 1 (Color online) (a) SAMSs dataset; (b) working flow of detection agent; (c) detection results of different models. "DA" means data augmentation; (d) searching area and target locations; (e) some searching results.

Model training. YOLO-v3[4)] and Faster RCNN[5)] take the SAMSs dataset as input. For Faster RCNN, we adopt the pre-trained VGG16 [6] and Resnet101 [7] models to extract features. Since all the images are of high resolution, coordinates error caused by location error of bounding box can be ignored. As a result, we pay more attention to the classification precision. The detection results are showed in Figure 1(c). Although YOLO-v3 is six times faster than Faster RCNN in remote sensing images for the detection task, we prefer higher accuracy.

Area searching. Figure 1(c) shows that combining Faster RCNN with Resnet101 model and data augmentation could get the highest accuracy. Therefore, this strategy is adopted to search for a specific area. First, we convert longitude and latitude into tile coordinates, which are index to Google Map and then, crawl map data. After downloading the map data, all the images will be detected by the trained model. Afterward, we check all output results to find if they contain SAMSs. As shown in Figure 1(d), we search this area of approximately 6000 km^2 comprising more than 40000 remote sensing images. To speed up detection, images full of the ocean will be skipped. Therefore, the model automatically selects 100 undetermined targets. After manual verification, we find 10 confirmed and 2 suspected SAMSs. Figure 1(e) shows 4 SAMSs results. More detection results could be referred to our PowerPoint and attached video.

Deep learning approaches with the trained model could filter out obvious results. The number of images which need humans to judge reduces from 40000 to 100. Automatic detection and manual verification could be finished in 3 hours. Thus, the proposed detection agent is able to significantly reduce the intelligence agents' workload.

Data feedback. Owing to the particularity of military installations, every country's SAMSs are infrequent in the dataset. Once some new SAMSs are confirmed, these images will be added to the dataset to increase positive samples. In this way, we can get a higher probability to find new SAMSs when searching in an unknown area. Furthermore, negative samples are necessary as well. Most of these 100 undetermined images are false positive containing similar buildings, farmland, and parking lots. Consequently, negative samples feedback could reduce the false alarm probability and increase the overall performance of the SAMSs detection agent.

4) YOLO. https://github.com/AlexeyAB/darknet.
5) RCNN. https://github.com/jwyang/faster-rcnn.pytorch.

Conclusion and significance. Herein, we propose a new framework for the target detection agent in remote sensing images and construct an SAMSs dataset consisting of images from different countries. After inputting the longitude and latitude, the agent could transform coordinates, download map data, cover all areas using the pre-trained detector, present undetermined targets to intelligence agents, and automatically add confirmed targets to dataset fully. Furthermore, taking advantage of the detection agent, intelligence agents could investigate thousands of square kilometers of land per hour. The agent could be easily extended to other detection tasks, such as fighter aircraft, airport, and early warning radar, which depends on the input dataset. In addition, this system could not only be applied as an off-line detector to process map data but also be deployed on the airplane or satellite to monitor the specific area in real-time.

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Supporting information Videos and other supplemental documents. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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