Deep Learning Methods of Small Object Detection

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Remote sensing methodology has been increasingly applied in fields such as forest fire detection, iceberg detection, ship detection, floating object detection, and agriculture monitoring. Synthetic aperture radar (SAR) images can be used to construct two-dimensional images, which can be further reconstructed into multidimensional images if necessary. When the SAR focuses on the target application, such as biomass detection in the forest, ship detection in the ocean, and vehicle count on land, it comprises many small objects. Detecting these small images is less effortless than general object detection in typical images.

SAR image ACF detector Region of Interest object detection

1. Introduction

Remote sensing is a technique used to acquire data such as temperature, photographs, growth, pressure, and fire without direct contact with the target material. Remote sensing methodology has been increasingly applied in forest fire detection, iceberg detection, ship detection, floating object detection, agriculture monitoring, gathering pictures of the earth, etc. [1]. Many methods and tools such as radars are commonly used to capture remotely sensed image datasets [2], of which SAR image datasets have been playing a vital role. SARs can be used to construct two-dimensional images, which can be further reconstructed into multidimensional images if necessary. When the SAR focuses on the target application, such as biomass detection in the forest, ship detection in the ocean, and vehicle count on land, it comprises many small objects [3]. Detecting these small images is less effortless than general object detection in typical images. Specifically, observing ships or any biomass-detecting objects in applications such as marine surveillance has been challenging. The reason behind the difficulty is the number of pixels available in the small objects in a large image [4].

Over the past decade, new techniques have been developed for small object detection in remote sensing images. Due to image processing and definition complexity, detecting icebergs and ships still needs improvement. This detection technique has been studied for a long time. Deep learning (DL) has made rapid progress in the computer vision field.

2. DL Methods of Small Object Detection

The CNN, a deep feed-forward artificial neural network, shows its different characteristics depending on the problem types it is applied to. CNN plays many roles in detecting ships but can detect only small objects.

Unsupervised machine learning (ML) approaches such as principle component analysis (PCA) and the k-method have been used to discriminate between ships and icebergs. However, ML has to be extended to DL when a large dataset volume is there. Many remote sensing researchers have used CNN differently for their problems. A research-implemented solution was introduced for marine surveillance systems to discriminate between ships and icebergs [1]. They utilized four Conv2D layers and three dense layers with a 3 × 3 convolutional filter. They had a fully connected layer with 256 fully connected neurons. The authors used the pseudo-labeling approach since, in their dataset, only a small amount of labels were available. The transfer learning approach tackled the same problem, transferring the knowledge gained through a labeled SAR dataset to an unlabeled SAR dataset with future, present, and past information [2].

To classify icebergs and ships in multispectral satellite images, a C-Core dataset was used [3]. Two different CNNs were implemented with 561,217 and 1,134,081 parameters, respectively. Finally, those results were compared with support vector machine (SVM) results, and it was concluded that CNN had superior results in detecting ships. Iceberg detection was accomplished with the help of CNN, and it showed improved efficiency with the assistance of the Region of Interest (ROI), Sift, Surf, Threshold, and Transfer Learning [4]. Sidelobes were also included since the reflection of sidelobes may suppress large ships [5]. A constant false alarm rate was used to detect objects in ROI, followed by a parallel CNN, and in this approach, the parallel algorithm trained the model [6]. Moreover, a constant false alarm rate was also used after despeckling SAR images in supervised reinforcement learning [7].

SAR images is where CNN brought dominant accuracy results. The accuracy was improved by improving the features of objects in the training process [8]. The single-shot detector (SSD) is also used for object detection. Two major types of algorithms are widely available for object detection. Some algorithms such as RCNN, FRCNN, and Mask RCNN come under the first technique. There is a variety of CNN processing. Two detection stages occur. In the first stage, the region type of objects is expected to detect the object, and then objects are detected in those regions. The second technique is the fully convolutional approach. The you only look once (YOLO) approach and SSD are examples of this technique. These algorithms' networks are capable of detecting images in a single pass. SSD works with the help of two components. SSD components are the backbone model and the single shot (SS) head.

VGG 16 was used as the backbone architecture [9], and the SSD method was treated as a baseline detector with a set of layers for the detection of objects. In this work, layers of SSD are responsible for specific scale objects. Large objects can be detected in the deeper layer, and small objects can be spotted in the shallow layer with lightweight objects [10]. Since SSD cannot detect tiny objects, the image pyramid network helped the model improve SSD's performance. Since there was a need for oriented object information, in place of a conventional region proposal, network-oriented candidate region networks were used. At the same time, the feature fusion network (FFN) enhanced spatial information. This FFN is used for fusing IPN layers with SSD layers.

YOLO is a deep learning method that does not require dividing the images into blocks; the entire image can be looked at once. This speedy network is specifically designed for real-time object detection such as traffic signals, locating persons, finding animals, etc. It shows high accuracy with the help of three essential components: residual blocks, bounding box regression, and intersection over union, which are responsible for detecting, predicting, and locating, respectively. In [11], YOLO v2 was implemented to detect ships in marine environments with feature separation and feature alignment, which outperforms conventional neural networks with deeper layers. However, the number of parameters handled was still increased. To avoid this hyperparameter issue, they reduced the number of layers.

Tiny YOLO V3 [12] was used to detect small objects in aerial imagery, unlike conventional YOLO, which needs a large memory volume for better accuracy. However, tiny YOLO v3 needs a small amount of memory, even though there is a tradeoff between accuracy and memory. Another study [13] used conventional YOLO based on Darknet-53. Three-level pyramids were utilized for feature map creation. The Adam optimizer was implemented since the study used a small-size dataset. Finally, the model produced high precision. The generative adversarial network is a deep learning architecture that has the potential to work in both supervised and semi-supervised modes.

GAN is composed of two models: generative and discriminative models. The generator model uses the network, which generates images by adding random objects [14] and produces an input image that is similar to the actual image. The discriminator attempts to classify whether the generated image the generator generates looks like the actual input image. A super-resolution network was integrated with a cycle model based on GAN residuals [15]. Feature pyramid networks are networks [16] designed explicitly as feature extractors. They create high-quality multi-scale feature maps, which are significantly better than conventional feature extractors utilized in the CNN. Feature pyramid networks use two different pathways: bottom-up and top-down pathways [17].

More ship detection research solutions were recently proposed over the SAR imagery dataset. A method was developed with the DL algorithm for a SAR image dataset [18]. In this work, various proactive solutions and their mitigated risk were analyzed. An improved method was developed for detecting ships with SAR images [19]. A pre-training technique was adopted with DL, especially for scarcely labeled SAR image datasets. A novelty was achieved with a coarse-to-fine method for detecting ships with an optical remote sensing (OSR) image dataset [20]. In this work, ResNet was used alongside discrete wavelet transform (DWT) to achieve higher accuracy for detecting ships as a state-of-the-art method. Yet another approach was initiated to detect small ship-like objects in complex SAR datasets, and a hybrid method model was created alongside intersection over union loss prediction [21]. Here, shape similarity was identified for small-ship object detection. A ship detection technique was developed with a spatial SAR dataset with a shuffle group for a large scale [22]. This work introduced enhancement with the DL algorithm for ship detection.

A refinement network with feature balancing was used for multi-scale ship detection, and it was developed as an anchor-free method [23]. The DL algorithm used a SAR dataset for feature balancing in ship identification. A high-resolution ship detection mechanism was designed for a SAR dataset with large quantities [24]. This work developed a scattering and critical point-guided network with a core DL algorithm. Dense attention feature aggregation with CNN detected the ship over a SAR image dataset [25]. In this work, CNN was used anchor-free and featured dense attention. The modified mechanism with DL was used to develop a model for ship detection, and it was called a CenterNet++ mode [26]. A SAR image dataset was used for the seamless detection of the ship.

A lightweight ship detection mechanism was introduced with YOLO v4, achieving high-speed detection of the ship over a SAR image dataset [27]. This work used three channels of Red, Green, and Blue (RGB) SAR images and achieved precise results. Recently, a target signature-based ship indicator was developed for complex signal kurtosis alongside a SAR image dataset [28]. This work introduced signals for complex image detection. A model was used to identify the ships on a high-resolution SAR image dataset tested with the DL algorithm [29]. This method was equipped with adaptive hierarchical detection. A lightweight neural network (NN)-based solution was recently introduced to detect ships over SAR image datasets [30]. This work tested a multi-scale ship identification mechanism for space-borne SAR images. Yet another work was developed for SAR-image-based ship detection, and it was technically named U-net [31]. In this work, the efficacy was achieved and tested for a low-cost ship detection model.

A few more works have introduced ship detection techniques with neural-network-based models [32][33][34][35]. A work discussed multiple downsampling for small objects with weaker features of small objects. Here, YOLOv5 was introduced to overcome irrelevant context. Feature enhancement was achieved with YOLOv5 with discriminative features of smaller objects [36]. Recently, GAN was used with ResNet 50 architecture with a feature pyramid network (FPN) to detect multi-class objects alongside the image enhancement process for a SAR dataset [37]. GAN was used to detect small, as well as medium-sized, objects. Yet another work used FPN with CNN for scale sequence feature detection over small objects. Scale-sequence-based FPN introduced considerable accuracy in detecting small objects [38].

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