

A Review on Aircraft Detection Techniques and Feature Extraction Using Deep Learning

Riya Bhalara¹, Rupal J Shilu², Debolina Nandi³

Atmiya University, Rajkot

Corresponding author: Riya Bhalara

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ABSTRACT- For object detection, the two-stage proposal has been achieving the highest correctness, whereas the one-stage proposal has the advantage of high efficiency. Detecting objects in unstructured environments is one of the most challenging tasks. Airplane recognition is a difficult undertaking in high goal far off detecting pictures because of its variable sizes, colours, complex backgrounds. Aircraft location procedures centers in extricating the general shape highlights of airplane for identification, which is excessively hopeful for focuses in far off detecting images. In this paper, different airplane location procedures and highlight extraction calculations were considered.

Keywords- PSF (Point spread Function), Edge box, CNN, RPN, Deep learning, Object detection, R-CNN, SSD, YOLO

I. INTRODUCTION

Convolutional Neural Networks (CNNs) have accomplished extraordinary outcomes in various fields of recognition, detection and grouping particularly in PC vision[9]. Item discovery, i.e. distinguishing the areas and classifications of various article occurrences in a single picture, is a fundamental issue in a huge assortment of uses. For example, autonomous and self-driving vehicles. Late advances in object identification are driven by the accomplishment of the Locales with CNN highlights strategy. Plane recognition is utilized in numerous fields. For example, picture surveillance, status observing, far off detecting examination and in other mechanical or common fields[1].

II. RELATED WORK

This area presents a survey on different methods utilized for airplane detection and acknowledgment utilizing satellite pictures.

A. An Improved Faster R-CNN For Small Object Detection

In this paper, Changqing Cao proposed an improved algorithm based on faster region- CNN

(Faster R-CNN) for small object detection[1]. The two-phase detection idea is utilized : In the positioning stage, an improved loss function based on intersection over Union for bounding box regression is proposed and use of bilinear interpolation to improve the regions of interest pooling operation to solve the problem of positioning deviation and in the recognition stage, the use of multi-scale convolution feature fusion to make feature map contain more information and the use of improved non- maximum suppression (NMS) algorithm to avoid loss of overlapping objects. The object detection algorithm generates a large number of region proposals. Each region proposal has a corresponding score which may cause false detection results and may result in some missed overlapping objects.

B. Convolutional Neural Network Based Real-Time Object Detection And Tracking For Parrot AR Drone 2

In this paper, Ali Rohan uses an Parrot AR Drone 2 for the application of this paper. The Convolutional Neural Network method is used for object detection and target tracking[7]. Author aims an proposal to detect and track the target object, moving or still, using SSD object detector. A CNN dependent on SSD design is prepared to recognize a solitary class. In case of single class detection, the training of CNN requires a particular proposal and it is different from the normal training of the network. For this, Ali Rohan implemented a training method using positive (i.e images with object) and negative images (i.e images with no object). Also, SSD is selected because it aims to combine the performance of YOLO with the correctness of region-based detectors [6]. SSD provides higher correctness for object detection than YOLO. The drone sends the images at a constant frequency of 30Hz. These images are received and processed in PC through CNN for object detection. The figurings dependent on a few emphases display that the effectiveness accomplished for target

following is 96.5%. The object detection results show that CNN detects and classifies object with a high level of correctness 98%.

C. An Adaptation Of CNN For Small Target Detection In The Infrared

Dong Zhao proposes a novel learning method for infrared small target detection under various sky complex cloud backgrounds. The Convolutional Neural Network (CNN) is adapted to extract hidden features of small targets from infrared pictures with a proposed strategy for enormous measure of preparing information age. The Point Spread Function (PSF) is employed to model, small target data and artificially generate positive samples. The random background image patches are selected as the negative samples. CNN[8] is adapted after generating a large number of positive samples. The proposed detection problem is converted into pattern classification problem, and is different from traditional small target background suppression algorithm. The experiment results show that the adapted method can reduce false alarm rate of target detection.

D. Drone Detection Using Convolutional Neural Networks with Acoustic STFT Features

In this paper, Yoojeong Seo proposed an proposal that rely on short time Fourier transform (STFT) of received signal to distinguish drone from motor-based devices with similar harmonic features to a drone in an urban environment[3]. The acoustic signal is fetched using Yeti Pro microphone. The acoustic data undergoes preprocessing method where data is segmented into frames of 20ms and each frame is overlapped with adjacent frames. The CNN model consists of a convolution layer, a pooling layer, an active layer and fully connected layer which is used for detection of drones. The detection rate is 98.97% and false alarm rate is 1.62%. This is based on the NASA study [4] indicating that humans can sufficiently distinguish the acoustic properties of drones even though they have similar harmonic features.

E. An Aircraft Target Detection Method Based on Regional Convolutional Neural Network for Remote Sensing Images

In this paper deep residual network is used to extract the features of aircraft targets and the size of different aircraft targets are analysed. K-means is used to cluster different sizes. Based on these representative sizes of the aircrafts, the Aircraft Targets Region Proposal Network (ATRPN) is

proposed to synthesize geometric features of different aircrafts[13]. Deep residual network[11] is used as a feature extracting network with ATRPN as the candidate box generation network[12]. And based on Faster R-CNN detection algorithm, ATRPN R-CNN remote sensing image aircraft target detection method is proposed. This method extracts the aircraft target feature as a frontend from ResNet-50 residual network and then connect ATRPN candidate box generation network for detecting aircraft target and positioning.

F. Automatic Target Detection in Satellite Images using Deep Learning

In this paper, an objective framework for satellite imagery is proposed which utilizes EdgeBoxes and Convolutional Neural System (CNN) for characterizing objective and non-target objects. The edge data of targets in satellite imagery contains unmistakable and succinct attributes[10]. EdgeBox calculation is applied on input pictures after that geometric separating is done to choose military targets among the object proposals. CNN is a profound learning classifier with a high learning limit and an ability of naturally taking in ideal highlights from preparing information. It is invariant to minor rotations and shifts in the target object. Then after jCNN jis used jto jextract jfeatures jof jobjects jand jthen jclassifies jwhether jit jis ja jaircraft jor jnon-aircraft. jThe jdataset jcontains j500 jaircraft jpatches, j5000 jnon-aircraft jpatches jand j26 jtest jimages jtaken jfrom jGoogle jEarth. jResize jthe jpatches jto j32x32 jand juse jthem jto jtrain jthe jCNN. j

G. Detection and Classification of Land Mines from Ground Penetrating Radar Data Using Faster R-CNN

Venceslav Kafedziski proposed use of Faster R-CNN Inception v2 network for land mine detection, localization and classification. The image dataset used for training and testing the R-CNN network consists of GPR B-scans obtained both by gprMax based simulations and from real measured GPR data. TjThe gprMax software for generating B-scan images, especially for AT mines dataset. Using gprMax software, 48 B-scans is simulated, containing mines and other objects. In different simulations, the simulated mines differ in their sizes and properties, and the media in which they are buried also differ. The training set consists of 204 objects with hyperbolic signatures and 48 AT mines, and the test set consists of 75 objects with hyperbolic signatures and 24 AT mines. To test the detection process, authors used 25

additional images that don't contain any objects. Object detection algorithms may be accompanied by classification algorithms. The method performance is evaluated using Confusion matrices and ROC curves. Faster R-CNN uses object detection algorithm that eliminates the selective search algorithm and lets the network learn the region proposals[2]. Instead of using selective search algorithm on the feature map to identify the region proposals, a separate network (Region Proposal Network – RPN) is used to predict the region proposals[5].

III. CONCLUSION

Aircraft detection is a challenging task in remote sensing images due to its variable sizes, colors, complex backgrounds. Aircraft detection using CNN gives better results compared to other techniques. After training the remote sensing image aircraft target detection method on the data set and the experimental results show that the detection method has higher detection correctness in many different scenes including different aircraft targets.

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