International Journal of Engineering Research and General Science Volume 6, Issue 2, March-April, 2018
ISSN 2091-2730

AIRCRAFT RECOGNITION IN REMOTE SENSING IMAGES BASED ON CONVOLUTIONAL NEURAL NETWORKS

Abin O. Bright [1], J.Blessy[2]
PG Student M E Applied Electronics[1]
Assistant Professor[2]
Department Of Electronics and Communication Engineering
Narayanaguru College of Engineering Manjalumoodu, KanayaKumari, Tamil Nadu, India

Abstract— Automatic aircraft recognition is a challenging task. Conventional methods always extract the overall shapes of aircraft at first and then represent the aircraft based on the extracted shape with different features for recognition. The major problem of these methods is that they have a high requirement on shape extraction, which is too idealistic for targets in Remote sensing images. To address these challenges, propose a new aircraft recognition framework, which can be divided into three processes: region proposal, classification, and accurate aircraft localization process. First, a region proposal method is used to generate candidate regions with the aim of detecting all objects of interest within these images. Then, generic image features from a local image corresponding to each region proposal are extracted by a combination model of 2-D reduction convolutional neural networks (CNNs). Haar cascade method is used to classification of aircraft. To improve the location accuracy, introduces an unsupervised score based bounding box regression (USB-BBR) algorithm, combined with a non-maximum suppression algorithm to optimize the bounding boxes of regions that detected as objects. Experiments show that the dimension-reduction model performs better than the retrained and fine-tuned models and the detection precision of the combined CNN model is much higher than that of any single model. The proposed USB-BBR algorithm can more accurately locate objects within an image. Compared with traditional features extraction methods, such as elliptic Fourier transform based histogram of oriented gradients and local binary pattern histogram Fourier, the proposed localization framework shows robustness when dealing with different complex backgrounds.

Keywords— Aircraft recognition, Convolutional neural networks (CNN), unsupervised score-based bounding box regression (USB-BBR), Haar Cascade method.

INTRODUCTION

To recognize the types of aircraft is very important. Identification of the activity patterns of aircraft, detect the unusual trends of aircraft, and make judgment through type recognition. However, aircraft recognition with high-resolution space borne Remote sensing images is a challenging task. It is still difficult to distinguish targets of some types from the others. In conventional aircraft recognition methods, several methods are based on using rotation-invariant features after binarization.

Currently, there is small demand for accurate localization in the remote sensing field. The majority of studies focuses on detection rather than localization (the two processes have been confused by some people). Aircraft detection in remote sensing images faces far more challenges because of more complex background information they contain than that of natural images. Remote sensing images offer information about the texture, shape, and structure of ground objects, and they can be used for precise object identification. However, in addition to providing ample information for object detection, they also present information redundancy problems. Moreover, because of noise interference, weather, illumination intensity, and other factors, object detection in remote sensing images is a troublesome issue.

In this paper, focus on accurate localization of detected objects rather than simple object detection. Based on this aspect, use object localization to summarize this paper. In this paper, we tackle the feature extraction problem for aircraft detection in remote sensing images using convolutional neural network (CNN) models. CNN relies on the specific layer structure to learn the essential features of input images, thus avoiding the effort of designing a feature extraction strategy. In addition, CNN models have a wide range of application. CNNs with deeper layer structure tend to have better learning abilities. In this paper, the feature extraction strategy is based on CNN models with a deep layer that can describe objects in remote sensing images. Finally, propose a new aircraft localization framework for remote sensing images that can detect, classifying and locate objects accurately by using Haar cascade and unsupervised score based bounding box regression (USB-BBR) method.

RELATED WORK

Qichang Wu, Hao Sun, Xian Sun, Daobing Zhang, Kun Fu, and Hongqi Wang have proposed a targets in high-resolution remote sensing images. Automatic aircraft recognition is a challenging task. Conventional methods always extract the overall shapes of aircraft at first and then represent the aircraft based on the extracted shape with different features for recognition. The major problem of these methods is that they have a high requirement on shape extraction, which is too idealistic for targets in satellite images. In this paper, propose a new aircraft recognition approach that can recognize aircraft robustly without perfect extraction of silhouette or shape of aircraft as a precondition, and can deal with the situation of parts missing and shadow disturbance. Specifically, a direction estimation method is proposed first to align aircraft to a same direction. Then, a reconstruction-based similarity measure is proposed, which transforms the type recognition problem into a reconstruction problem. Finally, a jigsaw matching pursuit algorithm is proposed to solve the reconstruction problem. The main advantage of the method lies in that the method can recognize aircraft robustly and excludes the target overall shape extraction phase, which is usually included in the traditional recognition methods and is not practical due to disturbing background. Experimental results show that our recognition method yields a good performance

Yu Li, Xian Sun, Hongqi Wang, Hao Sun, and Xiangjuan Li(2010) have proposed contour-based spatial model which can detect geospatial targets accurately in high resolution remote sensing images. To detect the geospatial targets with complex structures, each image was partitioned into pieces as target candidate regions using multiple segmentations at first. Then, the automatic identification of target seed regions is achieved by computing the similarity of the contour information with the target template using dynamic programming. Finally, the contour-based similarity was further updated and combined with spatial relationships to figure out the missing parts a CBS model has been proposed to solve the problem of detecting geospatial targets present in high resolution remote sensing images accurately and automatically. Multiple segmentations are employed to produce candidate target regions. According to their contour similarities, the seed regions are identified. Spatial relationship is utilized to obtain missing parts of the target instances. They use dynamic programming to calculate shape similarities efficiently since it utilizes the ordering information between contour points. Experiments with aircraft as example target demonstrate the precision, robustness, and effectiveness of the proposed method. The CBS model is a global shape model, which captures the global characteristic of targets

PROPOSED METHOD

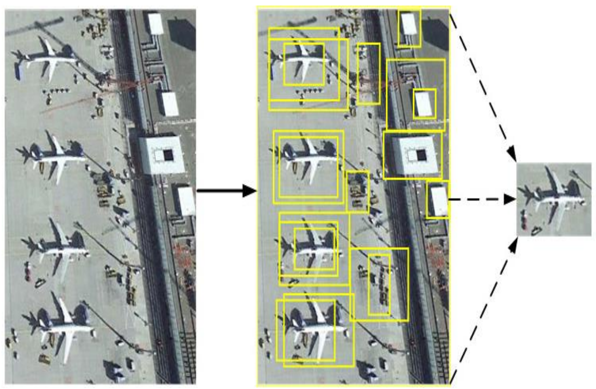
The proposed aircraft localization framework follows a pipeline approach. Which can be divided into three processes: region proposal, classification, and accurate aircraft localization process. First, when dealing with a test image, use a selective search algorithm to generate category independent possible regions. Then, all these candidate regions are sent to a combined model consists of 2-D reduction CNNs. Class labels and classification scores for each candidate region are an average output of two CNN models. Finally, perform an accurate object localization process to address these classified regions. For accurate aircraft localization, the propose method using the unsupervised score-based bounding box regression (USB-BBR) method to improve box localization precision after using the non-maximum suppression (NMS). For classification Haar cascade method is using. In this section, present our design for each procedure. The proposed object localization framework is shown in Resulted figure.

REGION PROPOSAL

Traditionally, a sliding window technique has been used for aircraft detection; however, the sliding window technique is an exhaustive search method and is computationally expensive. Recently proposed a selective search algorithm that produces object regions by taking the underlying image structure into account. The selective search algorithm yields a completely class-independent set of locations. It also generates fewer locations, which simplifies the problem because the sample variability is lower. More importantly, it frees up computational power, which can then be utilized for more robust machine learning techniques and more powerful appearance models.

Aircraft can occur at any scale within an image because of the diverse means for acquiring images. Moreover, images at the same scale may be different sizes. Therefore, we collect images that share approximately the same image with the aim of acquiring all the similar objects at one scale. Then, apply the selective search algorithm to address the objects that have different sizes within an image.

The experiments also indicate that the greater the number of candidates, the higher the recall will be. While the recall value may be different for remote sending images, in any image classification task, it is a key factor that influences both the CNN detection result and the accuracy of object localization.



Proposed aircraft localization framework. Fig. 1 Test image. Fig. 2 Selective search method produces most of the candidate object regions from the test image and adds some candidate regions extracted from low region density areas, where the selective search method generates few regions

FEATURE EXTRACTION

A CNN model consists of convolution layers, pooling layers, and full connection layers. A convolution layer has several filters and generates different feature maps using these filters on local receptive fields in the maps of the previous layer or input. The filter size can be $n \times n$ (where n is smaller than the input size). Weights are shared between convolution layers. The pooling layer uses filters to generalize the brief representation of the convolution layer to reduce the number of parameters. There are several pooling types; these include max pooling and average pooling. The pooling operation provides a form of translation invariance. The feature becomes more complex and global as the layers become deeper.

In this paper, the CNN models chosen to extract features are Alex Net and Google Net due to their superior performance. To retain more information for back propagation, for both the Alex Net and Google Net networks, add a 64-D inner product layer before the last inner-product layer. For Alex Net, we reduce the dimension of the second full-connection layer from 4096 to 64, and for Google Net, add a 64-D layer after the last convolutional layer. Moreover, the two CNNs are combined to detect objects simultaneously and the result of this combined CNN models is the averaged outputs of the two CNN models

To perform feature extraction, first extract image patches from the candidate regions generated by the region generation process. Then, normalize the image patches to 227 × 227 to fit the input dimensions of the CNN models and use them as input to the CNN to extract features. The last layers of the CNN models are softmax classification layers. For the combined CNN model, need to perform forward propagations of the two CNN models. After forward propagation, the two CNN models produce classification results of these candidate regions. The regions will have class labels and class scores after forward propagation. For examples, assume that the candidate region is b and that the class label and classified scores for the entire set of classes computed by model A are lA and sA, while the class label and classified scores for the entire set of classes computed by model B are lB and sB. The class score S of the model combination is the average of sA and sB, while the class label L of the model combination is the label according to the maximum of S.

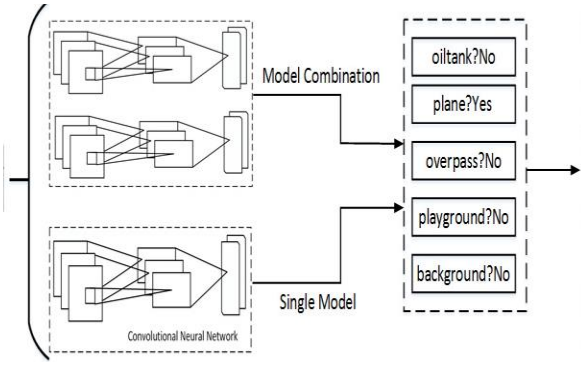


Fig. 3 CNN is applied to extract the features from these candidate regions. Fig. 4 Classification results of the regions. We used two approaches to obtain the classification results of candidate regions: one is a single model strategy and the other is a model combination strategy that averages the outputs of two CNN models.

ACCURATE AIRCRAFT LOCALIZATION

To produce the optimum bounding box for locating the object, propose method a two-stage object accurate localization method: NMS and USB-BBR. The NMS method is mainly used to eliminate region overlap. The USB-BBR method to reduce the location errors. All the scored regions are allocated into different groups; each group belongs to one object that needs to be detected. For a set of scored candidate regions $B = \{b1, b2, \ldots, bn\}$ where n is the total number of regions in the set, the regions in B are first sorted by their area in ascending order. The next step is to classify the regions of B into m groups, where a group $G = \{G1, G2, \ldots, Gm\}$. The grouping begins with the first sorted region, computing the overlap area ratio of the first sorted region to that from the rest of B. If the overlap area ratio is greater than or equal to a given threshold, the two regions are classified into the same group; otherwise, only the first sorted region is classified into the group. The group process completes when all the regions in B have been computed.

Though this grouping process, each object that needs to be detected may have a group of scored regions. The goal is to regress the regions of each group Gk, namely, to produce the optimum bounding box for locating the object. Assume that $Ik = (xk , yk, wk , hk)T$ is the regressed bounding box of Gk, where (xk, yk) is the center coordinate of Ik and (wk , hk) are the width and height of Ik , respectively. Thus, the goal is to obtain Ik. For bki Gk, $Dki = (xki,, yki, wki , hki)T$ corresponds to the i th scored region in Gk. Given $ci = Ik - Dki$, we can obtain Ik by

$$L(Ik) = \text{argmin} \sum_{i=0}^{n} u_i \, c_i^T \, c_i$$

where ui is the region score bki in Gk .

Algorithm 1 USB-BBR

Input: The full set of regions $B = \{b1, b2, \ldots, bn\}$, a

threshold δ, where $0 < \delta < 1$, a max iteration, t, and

an iteration step s, where $0 < s < \delta$

Set: $G = \{b1, b2, . . . , bm\}$ $(m = n)$

Set: $R = \{b1, b2, . . . , bm\}$

$I = \emptyset$

while $t > 0$ and $\delta > 0$ **do**

sort the elements of G in ascending order by the corresponding region areas of R

$i = 0$

while $G \neq \emptyset$ **do**

$i = i + 1$

get the area a of r which is the first element of R

get the first element G' of G

$G'i = G'$

remove G' from G

get L (the length of G)

for $j = 1, 2, . . . , L$ **do**

get the overlap area *overa* between $r\ j$ and r

if $overa/a \geq \delta$ **then**

$Gi = G'i \cup G\ j$

remove $G\ j$ from G

end if

end for

end while

$m = i$

$G = \{G1, G2, . . . , Gm\}$ $(G1 = G'1, G2 = G2, . . . , Gm = G'm)$

update the elements of R according to G

$t = t - 1$

$\delta = \delta - s$

end while

obtain the final region grouping set $G = \{G1, G2, . . . , Gm\}$

International Journal of Engineering Research and General Science Volume 6, Issue 2, March-April, 2018
ISSN 2091-2730

for $k = 1, 2, \ldots, m$ **do**

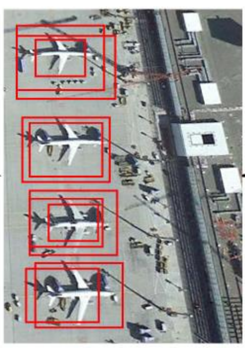
$Ik = argmin\_li=1\ ui\ cTi\ ci$ (l is the length of Gk)

append Ik to I

end for

Output: I

The first iteration regression result of G is denoted as $R = \{r1, r2, \ldots, rm\}$, computed by (1). The regions in R may belong to the same object, so using an iterative process to update G. Each iteration uses a descending threshold and the same grouping method to update G by comparing the overlap area ratio of regions in R. Then, R is computed from the updated G. The grouping results occur in the next update iteration, and the iteration process completes when it reaches a specified maximum number of iterations or the threshold is less than or equal to 0.The I is computed by the final grouping set, G. The threshold for the overlap area ratio decreases as the iteration time increases. The USB-BBR algorithm is solved by the least-squares method. Algorithm 1 describes the process of USB-BBR. Fig. 7 shows the USB-BBR process. After sorting the classified regions in B, the grouping process begins moving from the first sorted region to the last one. All regions are divided into three groups by computing their overlap area ratio. Then, the regression optimal region of each group is computed. The regression result of B is R. The regions in R may still belong to the same object, so we use an iterative process to update G and R. The final regression result is computed when the iterative update process completes. Here, I is the regression result computed by the final grouping set.



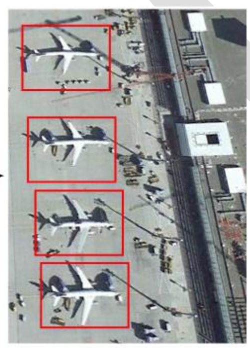


Fig. 5 Classification results of the candidate regions. Fig. 6 Final detection results after the accurate object localization process using USB BBR.

AIRCRAFT CLASSIFICATION

Haar cascade classifier consists of a list of stages, where each stage consists of a list of weak learners. The detected aircrafts in question by moving a window over the image. Each stage of the classifier labels the specific region defined by the current location of the window as either positive or negative – positive meaning that an object was found or negative means that the specified aircrafts was classified in the image. If the labelling yields a negative result, then the classification of this specific region is here by complete and the location of the window is moved to the next location. The classifier yields a final verdict of positive, when all the stages, including the last one, yield a result, saying that the object is found in the image.

A true positive means that the aircrafts in question is indeed in the image and the classifier labels it as such – a positive result. A false positive means that the labelling process falsely determines, that the aircrafts are located in the image, although it is not. However, each stage can have a relatively high false positive rate, because even if the n-th stage classifies the non-object as actually being the object, then this mistake can be fixed in n+1-th and subsequent stages of the classifier. Finally aircrafts was classified according to their shapes. In Haar cascade method the final output will mention according to the structure. In output it is shown in various colours.

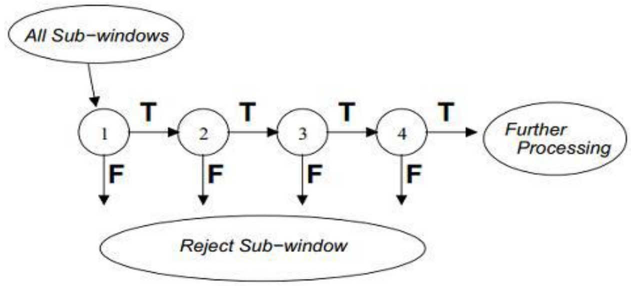


Fig. 7 Aircraft Classification Based on Haar Cascade Method

EXPERIMENTS AND RESULTS

The proposed framework on detection performance. For the proposed aircraft localization framework, used a large data set to train the CNN models and applied model fine-tuning to initialize the weighs. Also used a model combination method when classifying candidate regions, and the accurate object localization process to enhance the location precision. Systematically analyses the performance effects caused by these strategies.

Table 1. Final output accuracy, recall, precision is detected

Type	Accuracy	Recall	Precision
RED	94.2%	0.9603	0.9235
GREEN	94.5%	0.9302	0.9333
BLUE	95.0%	0.9403	0.9001

FEATURE EXTRACTION AND CLASSIFICATION

The results show that weight initializations play a crucial role in the learning ability of CNN models, and the model combination strategy can improve the precision value to a certain extent. Namely, the fine-tuned model can increase the learning performance of CNN models and the detection precision of a combination mode is higher than that of a single model.

To deal with the problem of several regions corresponding to one object, we used the USB BBR algorithm after NMS. The detection results of using the GoogleNet-finetune model. Compared with the result from using a CNN with NMS, using a CNN with USB-BBR can greatly increase the localization precision, because the process optimizes several regions into one region; consequently, the location accuracy is much higher

Table 2. Details of the Transformation of positive Training Samples

Type	Argument
Translation Transform	$dw = 0.1w$ $dh=0.1h$
Scale Transform	$ds=(0.8,0.9,1.1,1.2)$
Rotation Transform	$d0= 90°, 180°,270°$

The above table shows the translation transform, scale transform and rotation transform of an aircraftThe rotation transform typically performs 90°, 180°, and 270° rotation; however, when there are few instances of a class, the angle of rotation deceases to increase the number of rotations. When the IoU was greater than or equal to 0.5 compared with a ground-truth region chosen during the first positive sample collection process, the region became a positive sample; otherwise, when the IoU was less than 0.3 with the ground-truth region, the region became a negative sample The ratio of positive samples selected from the first and second positive data set sources is 5:1, and the positive samples from the second part of the positive data set were used to enhance the adaptability of the CNN models. All the CNN data set samples were resized to 227 × 227.

REGION PROPOSAL AND UNSUPERVISED SCORE-BASED BOUNDING BOX REGRESSION

Fig.8 shows a portion of the comparison detection results both with and without the USB-BBR method. The first column is the detection result without using the bounding box regression method and the second column is the detection result using the USB-BBR method. As Fig.9 shows, the USB-BBR has better localization precision. Therefore, the USB-BBR method can increase the detection localization precision. Comparative detection results both with and without USB-BBR

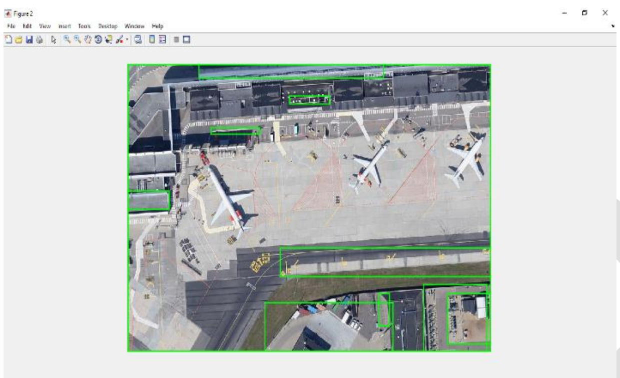


Fig.8 Comparative detection results both with and without USB-BBR. The first column shows the detection results without USB-BBR.

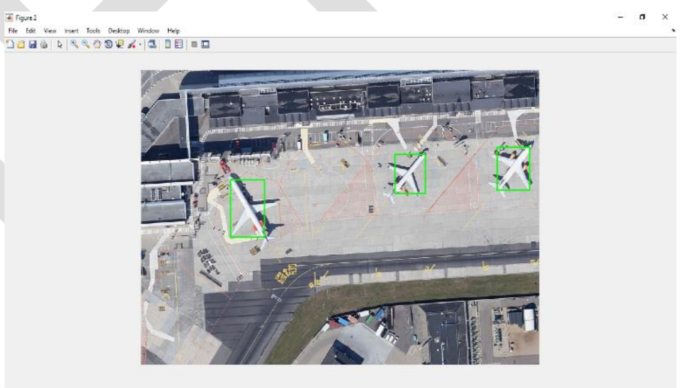


Fig. 9 The second column shows the detection results with USB-BBR.

CLASSIFICATION OF AIRCRAFT

The final output of aircraft recognition and classification by using CNN and Haar cascade method it will show on the below fig.10 the classified output mention in various colors and it is classified according to the shape and structure of the aircraft. The recalling and precision values are better than existing method. Haar cascade method is also used for feature extraction of aircraft.

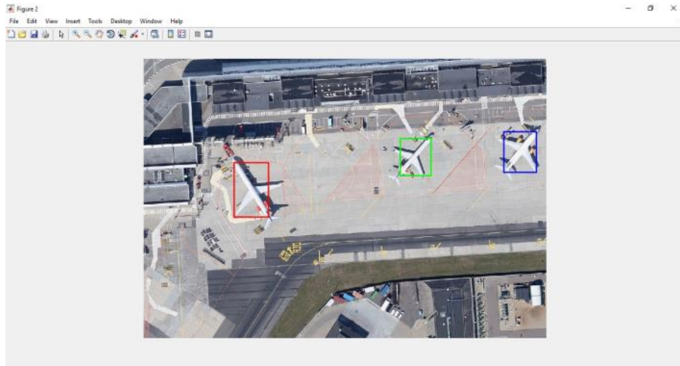


Fig. 10 By using Haar cascade method final output showed in various colors

CONCLUSION

Proposed aircraft localization framework based on CNN in remote sensing images. The framework uses the CNN and Haar models to extract object features and obtain classification results. In the first stage, used a selective search method to generate the major part of the candidate object regions. In the second stage, designed a dimension reduction model using trained models to initialize the network weights and then use it to extract features and classify the aircraft to different categories by using Haar cascade method. Also tested a retrained model and a fine-tuned model. In the third stage, the proposed a new USB-BBR algorithm, as part of the accurate object localization process, to obtain better detection localization precision, and used NMS to decrease the number of overlapped regions. The addition of the USB-BBR method can help to obtain an optimal bounding box for each group of classified regions. In addition, investigated the influences of different sizes of training data sets, different weight initialization methods, and different model combinations on detection performance. These results can help guide other researchers to obtain good results. The results of the experiments indicate that the proposed localization framework is both simple and robust. In further work, the aim is to enhance this framework and improve its detection and localization performance using GPS technology and the features describe of the objects

REFERENCES:

1. P. Agrawal, R. Girshick, And J. Malik, 2014, “Analyzing The Performance OfMultilayer Neural Networks For Object Recognition,” In Proc. Eur. Conf.Comput. Vis., Pp. 329–344.
2. H. Azizpour, A. S. Razavian, J. Sullivan, A. Maki, and S. Carlsson, Sep. 2015, “Factors of transferability for a generic convnet representation,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 38, no. 9, pp. 1790–1802.
3. Y.L. Boureau, J. Ponce, and Y. Lecun, 2010, “A Theoretical Analysis of Feature Pooling In Visual Recognition,” In Proc. Int. Conf. Mach. Learn., Pp. 111–118.
4. G. Cheng and J. Han, 11–28 Mar. 2016, “A Survey on Object Detection in Optical Remote Sensing Images,” Isprs J. Photogram. Remote Sens., Vol. 117.
5. G. Cheng, J. Han, P. Zhou, And L. Guo, Dec. 2014, “Multi-Class Geospatial Object Detection And Geographic Image Classification Based On Collection Of Part Detectors,” Isprs J. Photo Gramm. Remote Sens., Vol. 98, Pp. 119–132.
6. G. Cheng, P. Zhou, and J. Han, Dec. 2016, “Learning Rotation-Invariant Convolutional Neural Networks for Object Detection in Vhr Optical Remote Sensing Images,” Ieee Trans. Geosci. Remote Sens., Vol. 54, No. 12, Pp. 7405–7415.
7. G. E. Dahl, T. N. Sainath, And G. E. Hinton, May 2013, “Improving Deep Neural Networks For Lvcsr Using Rectified Linear Units And Dropout,” In Proc. Ieee Int. Conf. Acoust., Speech Signal Process. (Icassp), Pp. 8609–8613.
8. Dean Et Al., 2012, “Large Scale Distributed Deep Networks,” In Proc. Neural Inf. Process. Syst. (Nips), Pp. 1–11.
9. A. Grubb and J. A. Bagnell, Oct. 2013, “Stacked Training for Overfitting Avoidance in Deep Networks,” In Proc. Int. Conf. Mach. Learn., P. 1
10. J. Han Et Al., Mar. 2014, “Eficient, Simultaneous Detection Of Multi-Class Geospatial Targets Based On Visual Saliency Modelling And Discriminative Learning Of Sparse Coding,” Isprs J. Photogram. Remote Sens., Vol. 89, Pp. 37–48.
11. J. Han, D. Zhang, G. Cheng, L. Guo, And J. Ren, Jun. 2015, “Object Detection In Optical Remote Sensing Images Based On Weakly Supervised Learning And High-Level Feature Learning,” Ieee Trans. Geosci. Remote Sens., Vol. 53, No. 6, Pp. 3325–3337.
12. A.G. Howard, 2013, “Some Improvements on Deep Convolutional Neural Network Based Image Classification.” Unpublished Paper. [Online]. Available: Https://Arxiv.Org/Abs/1312.5402
13. Y. Huang, L.Zhang, P. Li, and Y. Zhong, 2010, “High-Resolution Hyper-Spectral Image Classfication with Parts-Based Feature and Morphology Profile in Urban Area,” Geo-Spatial Inf. Sci., Vol. 13, No. 2, Pp. 111–122.

14. T. Ishii, R. Nakamura, H. Nakada, Y. Mochizuki, And H. Ishikawa, May 2015, “Surface Object Recognition With Cnn And Svm In Landsat 8 Images,” In Proc. Iapr Int. Conf. Mach. Vis. Appl., Pp. 36.
15. Jiang, L. Cao, M. Cheng, C. Wang, and J. Li, Oct. 2015, “Deep Neural Networks-Based Vehicle Detection In Satellite Images,” In Proc. Int. Symp. Bioelectron. Bioinf, Pp. 184–187.
16. Krizhevsky. (2014), “One Weird Trick For Parallelizing Convolutional Neural Networks.” [Online]. Available: Https://Arxiv.Org/Abs/1404.5997
17. Y. Li, X. Sun, H. Wang, H. Sun, and X. Li, Sep. 2012 “Automatic Target Detection in High-Resolution Remote Sensing Images Using A Contour-Based Spatial Model,” Ieee Geosci. Remote Sens. Lett. Vol. 9, No. 5, Pp. 886–890
18. Mahendran and A. Vedaldi. 2014, “Understanding Deep Image RepresentationsBy Inverting Them.” Unpublished Paper. [Online]. Available: Https://Arxiv.Org/Abs/1412.0035
19. Paine, H. Jin, J. Yang, Z. Lin, and T. Huang, 2013, “Gpu Asynchronous Stochastic Gradient Descent to Speed Up Neural Network Training.” Unpublished Paper. [Online]. Available: Https://Arxiv.Org/Abs/1312.6186
20. S. Razavian, H. Azizpour, J. Sullivan, and S. Carlsson, Jun. 2014, “Cnn Features Off-The-Shelf: An Astounding Baseline for Recognition,” In Proc. Cvpr, Pp. 806–813.
21. Shao, W. Yang, G. Liu, and J. Liu, Jul. 2012, “Car Detection From High Resolution Aerial Imagery Using Multiple Features,” In Proc. Ieee Int. Geosci. Remote Sens. Symp. (Igarss), Pp. 4379–4382.
22. H. Sun, X. Sun, H. Wang, Y. Li, and X. Li, Jan. 2012, “Automatic Target Detection In High-Resolution Remote Sensing Images Using Spatial Sparse Coding Bag-Of-Words Model,” IEEE Geosci. Remote Sens. Lett, Vol. 9, No. 1, Pp. 109–113.
23. J. R. R. Uijlings, K. E. A. Van De Sande, T. Gevers, and A. W. M. Smeulders, Apr. 2013, “Selective Search for Object Recognition,” Int. J.Comput. Vis., Vol. 104, No. 2, Pp. 154–171.
24. Z. Xiao, Q. Liu, G. Tang, and X. Zhai, 2014, “Elliptic Fourier Transformation Based Histograms Of Oriented Gradients For Rotationally Invariant Object Detection In Remote-Sensing Images,” Int. J. Remote Sens., Vol. 36, No. 2, Pp. 618–644.
25. F. Zhang, B. Du, and L. Zhang, Apr. 2015, “Saliency-Guided Unsupervised Feature Learning For Scene Classfication,” Ieee Trans. Geosci. Remote Sens., Vol. 53, No. 4, Pp. 2175–2184.
IJERGS