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AN IMPROVED METHOD OF AIRCRAFT RECOGNITION IN HIGH-RESOLUTION SATELLITE IMAGE USING SSOFM METHOD

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ABSTRACT
Aircraft recognition is a vital research area in recent research trends. The objective of the study is to recognize an aircraft in satellite image using sensing images matching for accurate detection and tracking. High resolution multispectral satellite images with multi angular look capability have tremendous potential applications. 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 a reconstruction-based similarity measure is proposed, which transforms the type recognition problem into a reconstruction problem. The contour tracking system provides the result with low computational complexity and better accuracy. Morphological and connected component analysis was utilized effectively for enhancing a segmented regions and contour tracking target objects. Finally the simulated result was shown that better efficiency achieved with chosen techniques and methodologies. A Novel SSOFM (statistical self-organizing feature map) type recognition approach for aircraft is proposed. In addition to making more use of the shape characteristics of different types of aircraft.

Keywords: Aircraft Recognition, Remote sensing Images, Multispectral images, SSOFM method

INTRODUCTION
The aircraft recognition is still a challenging problem; we want to further investigate how we can resolve issues in this field. Aircraft recognition is different from other natural object recognition. The number of aircraft types is limited and each type of aircraft has fixed size and shape. Considering the above characteristics, we can build a template for each type and match the test aircraft to the different types of templates. We can make more use of the shape characteristics of different types of aircraft. More importantly, we will focus on how to measure the similarity between targets and all types of templates, independent of the overall shape extraction of targets. The problem is how to measure the similarity between real target and all types of target. Since we cannot extract the contour of target ideally to obtain the characteristics of suspected target for matching, we measure the similarity between the real target and the suspected target based on the idea of discrimination through reconstructive approaches.

In conventional aircraft recognition methods, several methods are based on using rotation-invariant features after linearization. Invariant features are extracted from binary images to automatically identify six aircraft types.

An independent component algorithm is combined with invariant moments for aircraft recognition. In contour tracking is used to eliminate much noise first and then uses moment invariants to recognize the types of the aircraft. These methods always use thresholding segmentation for the overall silhouette or shape of targets, and extract rotation-invariant features such as Fourier descriptor for recognition.

However, these methods have two drawbacks: 1) obtaining the moment invariants and Fourier descriptor requires perfect extraction of silhouette or shape of each aircraft as a precondition, which is too idealistic for targets with irregular appearance caused by distortion, low SNR, and camouflage painting in satellite images; and 2) these methods do not make full use of the shape characteristics of aircraft for target representation, which reflects the prior knowledge of the aircraft target, and will greatly enhance the robustness of recognition mission.

In addition to the above kind of methods, there are also a few recognition methods that estimate the direction first after binarization and then recognize the types of aircraft. These methods estimate the direction of aircraft before representing targets that actually takes more aircraft shape characteristics, such as symmetry and fuselage characteristics, into account. These methods also require the binary image of each aircraft for direction estimation and the silhouette or contour with less fracture for target representation, which reduces the practicability of the above methods.

A novel type recognition approach for aircraft In addition to making more use of the shape characteristics of different types of aircraft, the advantage of the approach lies in that it can recognize aircraft robustly without perfect extraction of targets as a precondition, and can deal with the situation of parts missing and shadow disturbance.

The recognition approach consists of two steps: direction estimation and type recognition. In the approach, 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 SSOFM matching algorithm is proposed to solve the problem. We evaluate the method using panchromatic 0.6-m-resolution Quickbird imagery, and the experimental results illuminate that the method proposed in this letter is effective and accurate.

To evaluate the proposed aircraft recognition approach, we select seven types of aircraft occurring frequently in our image set. After direction estimation with our proposed method and alignment, the directions of aircraft are almost upright. We generate segments with four-scale segmentation, and the segmentation in each scale is based on the number of segments in an image. Now, we analyze the SSOFM matching pursuit algorithm for reconstruction.

Research Data

This study takes the IKONOS & LANDSAT5/7 high resolution remote sensing image inner city somewhere as the research objects. The research areas include road, water, buildings, tall trees, shadow with buildings shadow, trees shadow, terrain shadows and automobile, etc. This study mainly focuses on Aircrafts. IKONOS satellite image has a pan band which includes red, green and blue, near infrared multispectral bands. The PAN band spatial resolution is 0. 61 m, multispectral spectrum resolution is 2.44 m.

STATISTICAL SOFM METHOD

Self organizing Feature maps (SOFM)[1] is an unsupervised learning Neural Network method which is introduced by Kohonen(2001).This method improves the performance of the segmentation than other clustering algorithms (Al-Najdawi et al, 2012) [2,3,4]and an important self organizing property is its ability to process noisy data. Instead of using rule set, it makes the classification by a competitive learning approach that learns from input pattern. It converts high dimensional input pattern into one or two dimensional arrays of neuron units and preserves neighboring input nodes (Neurons). Each node of the map is defined by a weight vector Wij whose elements are adjusted during training. This map retains topological relationship between input neurons and its neighboring neuron. The competitive learning process consists of two steps: ordering (weight modification) and tuning (fine settings) which is selected, a winning neuron according to some criteria which is used to minimize a Euclidean distance between input vector and weight vector.[7,8]

The basic SOFM model includes an input layer and an output layer .Each input neurons is mapped through weights to every output nodes. The weights are adjustable for each iteration. Let IP=[a0,a1,a2……an-1]K be the set of n number of input nodes in Rn and which includes each ain dimension. LetOP=[b0,b1,b2……bn-1]T be the set of n number of output nodes which has two dimensions space vector and W denotes the set of weights Wj = [w0j,w1j,…….w(n- 1)j]T and represented as reference vectors. The weight vector wij represents the weight from input node i to output node j iteration h.

The weights are updated by the winning entity and finding the best matching unit is determined by the minimum of Euclidian distance to the input and neighborhood be nearer to the accessible input node. The best matching unit is found by whose distance dij is in least value. An Euclidean distance is measured by dij.

SOFM is constructed by organized set of mapping units with a two dimensional grid topology. It is based on competitive manner. For each feature vector x(t), the winning map unit(Best mapping unit) is displayed as output. The best matching unit s is defined by the difference of the input vector x(t) and the weight vectors wi for each mapping unit such as the following equation(6.8):

$$\|x(t) - w_i\| = \min_i \{\| x(t) - w_i \|\} \qquad (1)$$

The general distance is calculated by Euclidean distance formula in equation (2)

$$\|x(t) - w_i\| = \sqrt{\sum_j (x_i(t) - w_{ij})^2} \quad (2)$$

The map units have partitioned the feature space into many small regions called Voronoi regions.(Figure 6.8).After completing the partition, that result will be called Voronoi tessellation. Every map unit 'i' of this Voronoi set Xi which has those input vectorx(t) belongs to the Voronoi region of the unit i.Among the number of input vectors x(t) in the Voronoi set , 'i' is the best-matching unit as follows(Figure 6.8)

$$X = \{x(t) \mid i = \arg\min \{\| x(t) - w \|\} \forall t\}$$

$$X_i = \left\{ x(t) \mid i = \arg\min_k \{\| x(t) - w_k \|\} \forall t \right\} \quad (3)$$

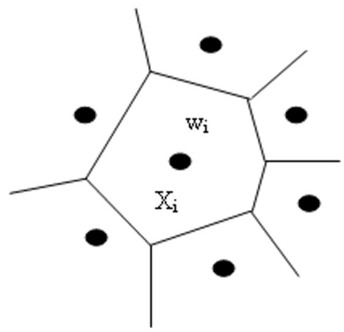


Figure 1: The Voronoi region of the map unit 'i'

TRAINING OF SSOFM NETWORK

Before segmenting the image, the SOM network should be trained in the training phase. A huge no of unclassified feature vectors are classified by SOM network. In this phase, the weight vectors of the best matching unit and their neighboring units are updated.[9] The neighborhood function Ns(t) is identified all units inside the regions in specific distance from the best matching unit. During the training process it evaluates as:

$$W_i(t+1) = \begin{cases} w_i(t) + \alpha(t)[x(t) - w_i(t)] & \text{if } i \in N_s(t) \\ w_i(t) & \text{if } i \notin N_s(t) \end{cases} \quad (4)$$

Where□(t) is the learning function (0<□(t)<1) and Ns(t) is the neighborhood function. While in the training phase, □(t) is decreased towards zero in each iteration and the radius of Ns(t) also decreases. When the training phase training phase starts Ns(t) is quite larger and it minimizes with time till it holds only the nearest neighbor of best matching unit s.

THE STATISTICAL SOFM MEASURES

The statistical SOFM is to connect a one dimensional density function to each element plane of Voronoi set of every map unit.The c-interval(confidence interval) to each one- dimensional density function is determined by SSOFM. There are many density functions available:1.Uniform density function,2.Gaussian density function 3.gamma function. This study uses Uniform density function. It is simple and easy to implement in SOFM algorithm.[10]

Let us assume SOFM with weight vectors wi and it is trained with a large number of feature vectors I(t).All feature vectors should originate from the same distribution. Each vector wi is constructed with Voronoi region and its set Xi.The weight vector wi is updated with new weight vector w`i and a C-interval(distance vector) d`i. It estimates the dimensions (d`i) and center of a hyper cube that is placed to a map unit 'i'.The estimated distribution distributes to all points inside the hypercube. The C-interval for the jth component plane of the Voronoi set Xi is denotedby the following equation:

$$w_{ij}^{t} - \frac{d_{ij}^{t}}{2}, w_{ij}^{t} + \frac{d_{ij}^{t}}{2} \qquad (5)$$

Thus, the width of the c-interval in the unit 'i' is defined by the C-interval vector d`i.

A uniform density function

If a uniform distribution is assumed for jth component plane of the Voronoi set Xi and d`i as a c-interval vector is calculated as

$$d'_{ij} = d(\max\{x\ (t)\} - \min(x\ (t)\}), \forall x(t) \in X_i \qquad (6)$$

Where the d is the C-interval(distance vector) generally in the range between 90% and 100%.The updated weight vector is assigned to be the center of the C-interval such as,

$$w_{ij}^{t} = \frac{d\ (\max\{x_j(t)\} + \min(x_j(t)\})}{2}, ¥x(t) \in Xi \qquad (7)$$

Distance function for Statistical SOFM

The non matching error pi for each feature vector x(t) and a map unit 'i' is computed.
The Hamming distance is as follows:

$$p_i = \sum_j p_{ij} \ where \quad p_{ij} = \begin{cases} 0 & if \quad (x_j(t) - w'_{ij})^2 \le (\frac{d'_{ij}}{2})^2 \\ 1 & otherwise \end{cases} \qquad (8)$$

Where w`ij is the new weight vector of jth component of a new weight vector m` ,whereasd`ij is the c-interval vector of jth component vector d`i in the mapping unit 'i'.This is successfully implemented in the SSOM algorithm. The Best matching unit s is now selected with the minimum non matching error ps.

$$p_s = \min_i \{p_i\} \qquad (9)$$

The SSOFM Algorithm

Table 1: SSOFM Algorithm

Algorithm : SSOFMalgorithm

Input : Satellite Image

Output : Shadow Detection from Segmented Image

1. Input Image
2. Create SOFM
3. (a)set input parameters X={H,S,V,Energy,Contrast ,Mean};
   (b)set int_weight_value from gray histogram ;
4. Initialize learning_rate=0.6;
5. **For**i =1 toN **do**

t=t+1

For x= 1 to X **do**

$$X_i = \left\{ x(t) \mid i = \arg\min_k \{ \| x(t) - w_k \| \} \forall t \right\}$$

$$[w_{ij}^t - \frac{d_{ij}^t}{2}, w_{ij}^t + \frac{d_{ij}^t}{2}]$$

$$d_{ij}^t = d(\max\{x_j(t)\} - \min(x_i(t)\}), \forall x(t) \in X_i$$

$$w_{ij}^t = \frac{d(\max\{x_j(t)\} + \min(x_j(t)\})}{2}, \forall x(t) \in X_i$$

$$p_i = \sum_j p_{ij} \; where \quad p_{ij} = \begin{cases} 0 & if \quad (x_j(t) - w_{ij}^t)^2 \le (\frac{d^t_{ij}}{2})^2 \\ 1 & otherwise \end{cases}$$

$$p_s = \min_i \{p_i\}$$

Endfor

End for

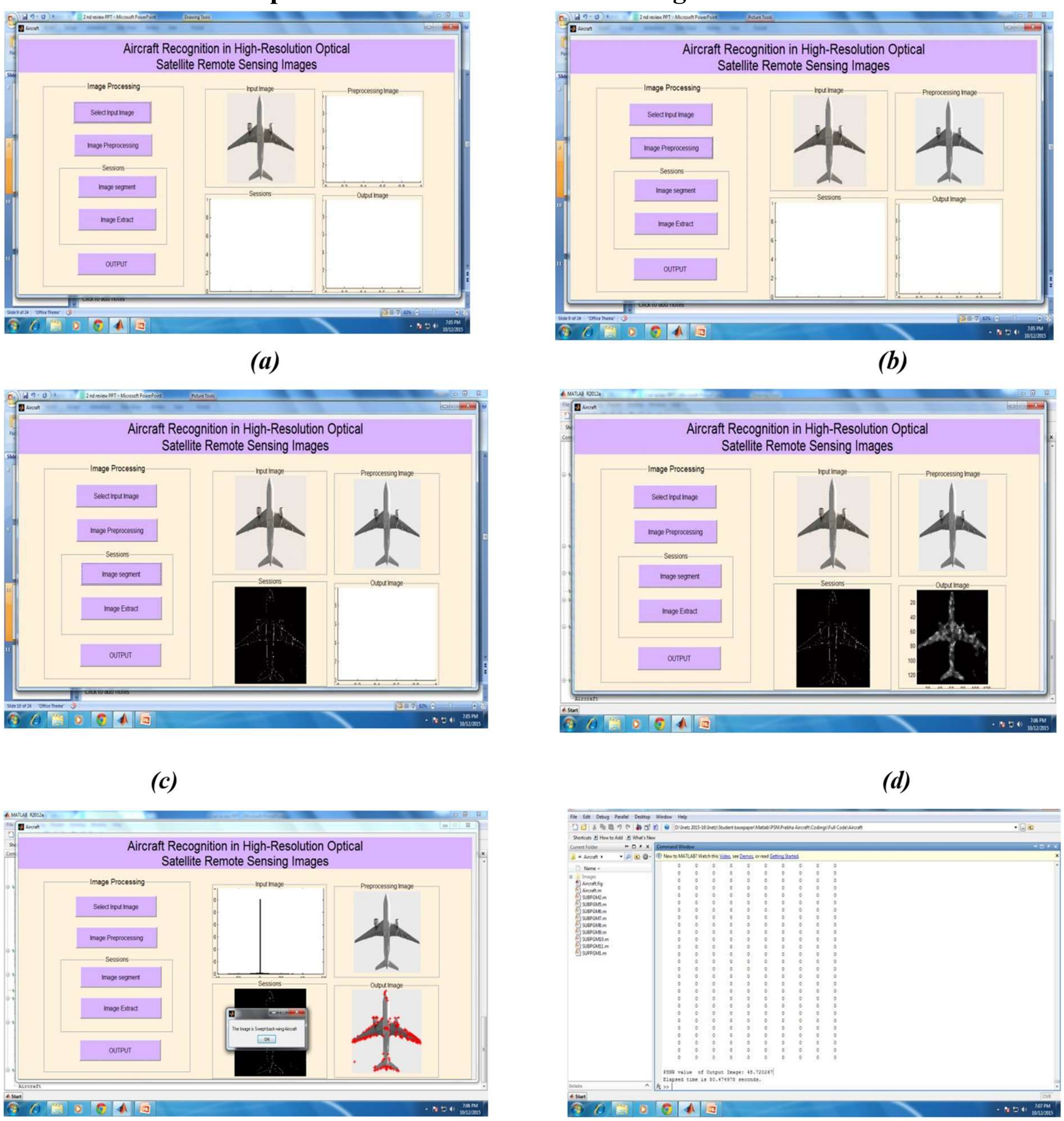
EXPERIMENTAL RESULTS

This study takes the IKONOS & LANDSAT5/7 high resolution remote sensing image inner city somewhere as the research objects. The research areas include road, water, buildings, tall trees, shadow with buildings shadow, trees shadow, terrain shadows and automobile, etc. This study mainly focuses on Aircrafts. IKONOS satellite image has a pan band which includes red, green and blue, near infrared multispectral bands. The PAN band spatial resolution is 0. 61 m, multispectral spectrum resolution is 2.44 m.

The dataset selection is utilized in this paper the currently popular IKONOS & LANDSAT5/7-Dataset [5,6] is selected, which is specifically used for remote sensing images.

As shown in Figure 2, the samples of the dataset are shown[11]. The dataset consists of four kinds of objects, which is the aircraft, the oil tank, the overpass, and the playground separately. According to the dataset, the number of aircrafts is 432. In the experiment, learning rate attenuation is adopted to adjust the learning rate. The initial learning rate is 0.001, momentum is 0.9, weight attenuation is 0.0006, and the number of iterations is 7500. As the iterations reach the 3200-generation and 34000 generation, respectively, the learning rate is adjusted to 0.1 and 0.01 of the initial learning rate, respectively. In this way, the convergence speed of loss can be adjusted[12].

Experiments results of aircrafts are given below:



(a) *(b)*

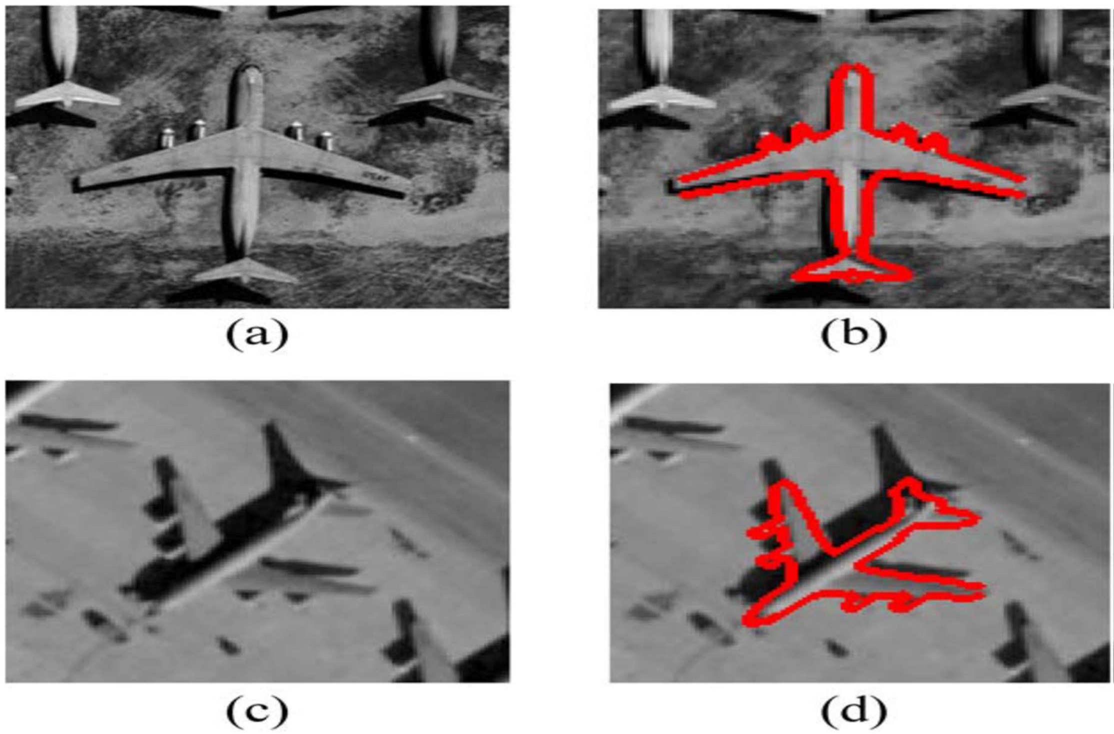
(c) *(d)*

(e) *(f)*

Figure 2: (a) Input Image (b) Image Pre-Processing (c) Image Segmentation (d)Image Extration (e) Output Image PSNR process

Target Reconstruction

After direction estimation with our proposed method and alignment, the directions of aircraft are almost upright. the template reconstruction problem to a mathematical problem and propose the method to solve the mathematical problem to represent the standard template of some type of target, the value of pixels in the target is set to be 1, and the value of pixels outside the target is set to be 0. A segment obtained by multi scale segmentation. Based on the hypothesis, the shape of target can be pieced together with the segment elements.



The Reconstruction is carried using SSOFM algorithm comparing with the template. The template matching SSOFM chooses, such that the reconstruction error is very low. If the error does not decrease after multiple iterations then the matched image is exactly identified which results in PSNR (Peak Signal to Noise Ratio) value , elapsed time & also identifies the type of aircraft wings(13,14).

TABLE1: Types of Aircraft Images with PSNR Value & Elapsed Time

Image TYPE	PSNR (VALUE)	ELAPSED TIME (SEC)
1	49.856998	52.869492
2	50.838044	28.916059
3	49.958449	17.305389
4	49.060785	18.566245
5	48.647013	11.398873
6	52.886395	23.267480
7	48.667312	25.776915

In this proposed SSFOM method compare with ACM based on ISOMAP algorithm[15], Bidirectional Feature fusion model[16] algorithms and proved that better accuracy and high performance results.IOU(Overlapping area between the overlapping are between the predicted boundary box and labelled original box ,ie the ratio of their intersection and union[16]) Curve is the one of the performance pointer to calculate the feature detection algorithm.

Image TYPE	Propesed SSOFM method		ISOMap Algorithm		BDFFDN Algorithm	
	Precision % (Quality)	IOU % (Performance)	Precision % (Quality)	IOU % (Performance)	Precision % (Quality)	IOU % (Performance)
1	90.45	86.12	78.34	80.13	84.7	72.1
2	96.2	87.33	79.32	81.54	89.41	76.43
3	97.22	85.24	67.51	79.63	91.23	75.22
4	96.74	89.53	76.72	81.67	90.12	72.24
5	95.32	92	74.42	77.86	90.22	70.45
6	96.8	86.43	72.88	82.42	89.98	75.12
7	97.33	87.72	78.92	87.27	91.11	78.59

6.CONCLUSION

In this study, an improved method for Aircraft Recognition in high-resolution satellite images using SSOFM method proposed. This technique, segments the aircraft image using the gray level satellite image with color information. Since, both the qualitative (appx 90%) and quantitative (92%) and better performance experimental results are effectively evaluated and it is seen that aircrafts are detected correctly in addition to the areas under the shadow and are illuminated. This method is not limited to remote sensing images and can be easily applied for other imagery from different sources even those with composite outdoor scenes and it can be utilized as automated method for all object detection from remote sensing images which is a difficult task. Further study can be implemented for the object compensation to get partial invariant image of the same region.

References:

[1] Kohonen.T,"The Self organizingMap",Proceedings of IEEE,vol.78,no.9,pp.1464-1480,1990.

T.Kohonen(2001),"Self-OrganizingMaps,"ComputerJournalofSpringer series in Information Sciences," vol.30,no.3,pp. 501-50

T.Kohonen(2001),"Self-OrganizingMaps,"ComputerJournalofSpringer series in Information Sciences," vol.30,no.3,pp. 501-507

T.Kohonen(2001),"Self-OrganizingMaps,"ComputerJournalofSpringer series in Information Sciences," vol.30,no.3,pp. 501-507

[2] LizyAbraham.,andM.SasiKumar,"Automaticbuildingextractionfromsatellite imagesusingartificialneuralnetworks,"Elsevier,ProcediaEngineering-ICASCE,vol.50,pp.893-903,December 2012.

T.Kohonen(2001),"Self-OrganizingMaps,"ComputerJournalofSpringer series in Information Sciences," vol.30,no.3,pp. 501-50

T.Kohonen(2001),"Self-OrganizingMaps,"ComputerJournalofSpringer series in Information Sciences," vol.30,no.3,pp. 501-50

T.Kohonen(2001),"Self-OrganizingMaps,"ComputerJournalofSpringer series in Information Sciences," vol.30,no.3,pp. 501-50

T.Kohonen(2001),"Self-OrganizingMaps,"ComputerJournalofSpringer series in Information Sciences," vol.30,no.3,pp. 501-507

[3] L. Zheng, C. Fu, and Y. Zhao, "Extend the shallow part of single shot multibox detector via convolutional neural network," International Society for Optics and Photonics, vol. 10806, Article ID 1080613, 2018.

[4] G. Cao, X. Xie, and W. Yang, "Feature-fused SSD: fast detection for small objects," International Society for Optics and Photonics, vol. 10615, Article ID 106151E, 2018.

[5] Y. Long, Y. Gong, Z. Xiao, and Q. Liu, "Accurate object localization in remote sensing images based on convolutional neural networks," IEEE Transactions on Geoscience and Remote Sensing, vol. 55, no. 5, pp. 2486–2498, 2017.

[6]. Z. Xiao, Q. Liu, G. Tang, and X. Zhai, "Elliptic Fourier transformation-based histograms of oriented gradients for rotationally invariant object detection in remote-sensing images," International Journal of Remote Sensing, vol. 36, no. 2, 2015.

[7] LeninishaShanmugam , VaniKaliaperumal,"Water flow basedgeometric active deformablemodel for roadnetwork",Elsevier,ISPRSJournal of Photogrammetry and Remote Sensing,vol.102,pp.140–147,Jan.2015.

[8] D. L. Fan, D. Liu, W. Chi, X. Liu, and Y. Li, "Improved SSD-based multi-scale pedestrian detection algorithm," Advances in 3D Image and Graphics Representation, Analysis, Computing and Information Technology, vol. 2, no. 180, pp. 109–118, 2020.

[9] Z. Huang, J. Wang, X. Fu, T. Yu, Y. Guo, and R. Wang, “DC-SPP-YOLO: Dense connection and spatial pyramid pooling based YOLO for object detection,” Information Sciences, vol. 522, pp. 241–258, 2020.

[10] M. Liu, X. Wang, A. Zhou, X. Fu, Y. Ma, and C. Piao, “UAV-YOLO: Small object detection on unmanned aerial vehicle perspective,” Sensors, vol. 20, no. 8, 2238 pages, 2020.

[11] K. Zhou, Z. Zhang, and C. Gao, “Rotated feature network for multiorientation object detection of remote-sensing images,” IEEE Geoscience and Remote Sensing Letters, vol. 18, no. 1, pp. 33–37, 2020.

[12] R. Dong, D. Xu, J. Zhao, L. Jiao, and J. An, “Sig-NMS-based faster R-CNN combining transfer learning for small target detection in VHR optical remote sensing imagery,” IEEE Transactions on Geoscience and Remote Sensing, vol. 57, no. 11, pp. 8534–8545, 2019.

[13] D. Xu and Y. Wu, “Improved YOLO-V3 with DenseNet for multi-scale remote sensing target detection,” Sensors, vol. 20, no. 15, 4276 pages, 2020.

[14] D. Xu and Y. Wu, “MRFF-YOLO: a multi-receptive fields fusion network for remote sensing target detection,” Remote Sensing, vol. 12, no. 19, 3118 pages, 2020.

[15] Xiaoqiang Zhang,Boli Xiong,Gangyao Kuang,”Aircraft segmentation in SAR images based on improved active shape model”,isprs-archivesXLII-3-2331-2018,Pg-2331-2335.

[16] Liming Zhou and Haoxin Yan,”Aircraft detection for Remote Sensing Image based on Bidirectional and Dense Feature Fusion”,Computational Intelligence and Neuro science,Vol 2021,Article ID 7618828.