Method of camouflage target filtering

Xiaochun Li*
Information and Navigation School, AFEU, Xi'an 710077, Shaanxi, China

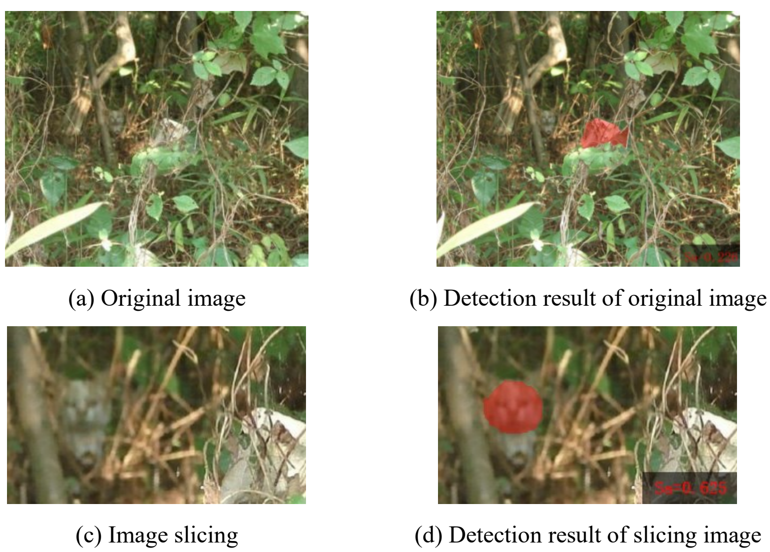
ABSTRACT

Camouflage target detection is a difficult problem in the field of target detection. The practice of camouflage target detection based on depth learning shows that the scale proportion of the targets in the image is one of the important factors that affect the detection performance. Based on the region segmentation and texture analysis, two schemes of camouflage target filtering are proposed in this paper. Experiments show that the proposed schemes improve the integrity of the target filtering significantly, it lays the technical foundation for improving the accuracy of deep recognition in the later stage.

Keywords: Target filtering, region segmentation, texture analysis, deep learning

1. INTRODUCTION

The camouflage target is one of the difficult problems in the field of target detection and recognition because of its complex background, variable shape, blurred contour boundary and similar color texture. Traditional processing methods[1-5] are difficult to fit for the complexity of camouflage targets and the characteristics of large data volume. In recent years, it has become a hot topic to explore the method of camouflage target detection and recognition based on deep learning[6-9]. But the practice shows that the scale proportion of the targets in the image is one of the important factors that affect the detection and recognition performance, see Figure 1. Scale proportion of the cat in Figure 1a is very small, deep algorithm not only can't detect the target correctly, but also can't acquire high precision target recognition. Scale proportion of the cat in Figure 1c is larger for image slicing, deep algorithm not only detect the target correctly, but also can acquire more precision target recognition Therefore, if the corresponding algorithm is designed to obtain the slice image including integrated camouflage target, the scale proportion of the targets in the image can be greatly improved which lays the technical foundation for improving the accuracy of deep recognition in the later stage.



(a) Original image (b) Detection result of original image

(c) Image slicing (d) Detection result of slicing image

Figure 1. Detection result based on depth learning.

In order to obtain slice images containing integrated targets, two schemes of camouflage target filtering proposed in this paper is introduced in the second and third sections, see the fourth section of the paper for corresponding experiment and analysis.

*chunwind@sohu.com

International Conference on Optics, Electronics, and Communication Engineering (OECE 2024), edited by Yang Yue, Proc. of SPIE Vol. 13395, 133952A · © 2024 SPIE · 0277-786X · Published under a Creative Commons Attribution CC-BY 3.0 License · doi: 10.1117/12.3048622

2 CAMOUFLAGE TARGET FILTERING BASED ON DOUBLE THRESHOLD REGION GROWTH

In practice, it is found that it is difficult to balance the requirement of camouflage target detection when the single threshold is used to segment the image, that is, how to minimize the background interference while ensuring the integrity of the target information, so as to accurately locate the camouflage target.

It is not difficult to find that high-threshold image segmentation can suppress the background effectively, low-threshold image segmentation can better retain the information of the target region in the image, so satisfactory detection results of interesting target can be obtained by combining the advantages of high-threshold and low-threshold. Based on this, camouflage target filtering scheme based on double threshold region growth is proposed in this paper as shown in Figure 2:

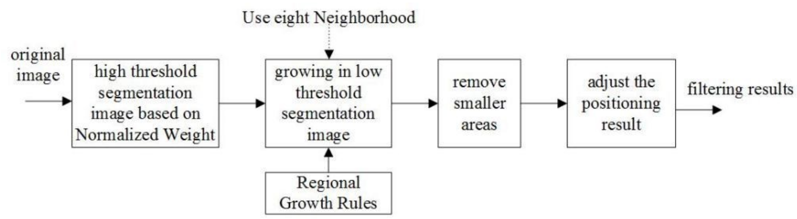


Figure 2. Camouflage target filtering scheme based on double threshold region growth.

2.1 Determination of seed points for high threshold segmentation based on normalized weight

When the image is segmented by a threshold, it represents measuring pixels of the whole image using a standard, which is equivalent to thinking that all pixels are of the same importance. Obviously, it is not reasonable, but in fact, we hope the target region in the image gets a higher weight and the background region gives a lower weight. Based on this consideration, we design the normalized weight method to determine the seed point. Normalization means that the amplitude of each pixel in the infrared image determines its weight coefficient, and the point with larger weight coefficient in the image is selected as the seed point for regional growth. mathematical expression is as follows:

$$W_1(x,y) = I(x,y)/max \tag{1}$$

Max is the maximum value of pixels in an image.

2.2 Regional growth

2.2.1 Determination of low threshold. For the design idea, the requirement of the low threshold segmentation image is that the region information of target in the image is complete, and the low threshold Tx can be obtained by multiplying the determined threshold T by using the maximum entropy threshold method by using the defined coefficient A.

2.2.2 Regional growth rules. Here, we select three regional growth rules:

Adjacency Threshold Method: An adjacency threshold is set and scan eight pixels around each seed point is scanned. If the difference between the pixel value of the seed point and the pixel value of the surrounding point is less than the adjacent threshold, it is considered to be part of the target and loop until no new seed point is generated.

Continuous Threshold Method: We can set the pixel range of the target area and scan eight pixels around each seed point. If the pixel value around the seed point is within the pixel range, it is considered to be part of the target and loop until no new seed point is generated.

Confidence Connection Threshold Method: We can calculate the expectation and standard deviation of the gray value of all pixels in the target region where the current seed point is located. If the gray value of the neighborhood pixel is within the range of the expectation (±standard deviation), it is included in the target region and determined as a new seed point, otherwise it is excluded. In the next iteration, the gray value expectation and standard deviation of the pixel are calculated based on the new target region.

2.3 Remove smaller areas and adjust the positioning result

Obviously, some connected domains with fewer pixels in the image cannot represent the target, because the proportion of the target in the image is very small, there is no sense for target detection. The connected domain with the number of pixels less than N is considered as an interference target and removed.

Next, the smallest rectangle containing each region is obtained represented by an array including the coordinates, lengths, and widths of the upper left corner of the smallest rectangle on the periphery of each connected domain. If periphery rectangles of multi targets are overlapped (see Figure3a), we think that they are different parts of the same target, and synthesize a target box, thus, the adjustment of the target positioning results can be completed (see Figure3b).

(a) Result after removing smaller areas (b) Result after adjusting positioning

Figure 3. Filtering result of camouflage target.

3. CAMOUFLAGE TARGET FILTERING BASED ON TEXTURE ANALYSIS

Observing the infrared image of camouflaged target, we find that there are different grayscale changes between the image and the background. By analyzing the texture features of the image, the obvious grayscale changes in the image can be captured. It is a feasible method to use the basic information in camouflage or concealment image to extract the texture features of the image and then achieve better filtering targets. Camouflage target filtering scheme based on texture analysis is proposed in Figure 4.

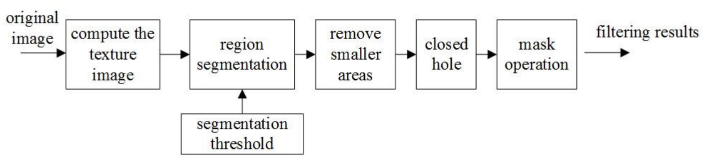


Figure 4. Camouflage target filtering scheme based on double threshold region growth.

Here, we use the maximum entropy method to segment the image. The processing of remove smaller areas is the same of above.

3.1 Computing the texture image

Because the texture feature is the region attribute of the image, the size of the region also affects the texture analysis of the image, so the study of the texture of the image must first determine the size of the observed region and the method of representing the texture information. Based on gray value of image, three methods to represent the texture information are determined.

(1) Local Entropy Value Represents Texture Information of Image

Entropy is the representation of information quantity in the image. The change of entropy value represents the change of the information quantity in the current region. The entropy value of the neighborhood around the pixel point is calculated. As the entropy value of the pixel point, the entropy change of the whole image is obtained by traversing all the pixels in the image.

Probability corresponding to each pixel value is

$$P(i) = \frac{h(i)}{\mathrm{N}} \quad \{0 \le i < K, 0 < P(i) < 1, \textstyle\sum_{i=0}^{k-1} P(i) = 1\} \tag{2}$$

where, N is the size of areas, here N=9∗9, $h(i)$ is the number of pixels in an area with a gray value i.

Gray scale entropy of gray scale image is

$$\begin{aligned} H(I) &= \textstyle\sum_{i,j} p\big(I(i,j)\big) * log_b\left(\frac{1}{p(I(i,j))}\right) \\ &= -\textstyle\sum_{i,j} p(i) * log_b(p(i)) \end{aligned} \tag{3}$$

(2) Local Standard Deviation Represents Texture Information of Image

When representing the texture of an image, we hope to reflect the change of the gray value of the local region of the image more clearly. The standard deviation can directly and clearly reflect the fluctuation range of the pixel value of target, The calculation of the neighborhood standard deviation is as follows:

$$\sigma^2 = \sum_{i=-1}^{i=1} \sum_{j=-1}^{j=1} \left(\mathrm{I(i,j)} - \bar{\mathrm{I}}(\mathrm{i,j})\right)^2 \tag{4}$$

where $\bar{I}(i,j)$ is average value of neighborhood pixel I(i,j).

(3) Local Range Represents Texture Information of Image

The size of the gray value range in the image region can also reflect the gray level change of the region, calculate the difference between the maximum pixel value and the minimum pixel value in the 3∗3 neighborhood around each pixel, assign the difference to the pixel, traverse all pixels and get the texture of the image.

3.2 Closed hole and mask operation

Closed Hole can connect the edges belonging to the same target so as to achieve complete detection of the target area by using morphological closing operation. Morphological closing operation can fill the thin cracks and holes in the image without changing the position and shape of the target. Here, size of the structure element is 10∗10.

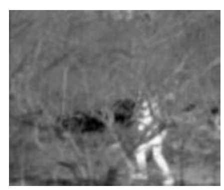
After the region segmentation, removing the interference targets and closing the hole, the target region is detected clearly. In order to reflect the change of the gray value of the target region, Masked operation on the output results is conduced, i.e. the area not belonging to the target in the original image is obscured, and the gray information of the target region is preserved.

4. EXPERIMENTAL RESULTS AND ANALYSIS

4.1 Original image

Two images were selected for algorithm analysis in the experiment, see Figure 5. The targets in both images are camouflaged targets in the jungle. There are some difficulties in the selection of targets.

(a) Original infrared image 1

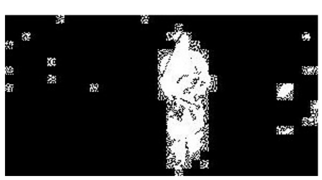


(b) Original infrared image 2

Figure 5. Original image.

4.2 Comparison of seed point selection

Results of two methods for determining seed point is showed in Figure 6. Figure 6a is the result of maximum entropy, where the pixel points with pixel value greater than zero in the output result of the maximum entropy segmentation are determined as seed points. Figure 6b is the result of normalized weight. Some of the background interference pixels are also classified as seed points by using the maximum entropy, and the seed points determined by the normalized weight method are betterly removed from the interference points. The experimental results show that good results can be obtained when the weight threshold of the normalized weight method is in the range of 0.7-0.8.



(a) Seed point selected by maximum entropy

(b) Seed point selected by normalized weight

Figure 6. Comparison of seed point selection for original image 1.

4.3 Results comparison of several regional growth rules

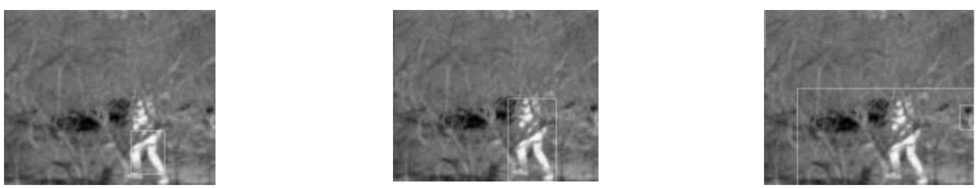
The seed point used here is determined by the normalized weight method. As shown in Figure 7, the target detection results obtained by several region growth rules are compared. Adjacent threshold method is easy to be disturbed by background, the background interference is obvious in the image, and the edge of the target is not smooth; the effect of continuous threshold method is best, the background interference is least obvious, Target edge is more continuous, and there are fewer holes inside the target; the confidence connection threshold method is more dependent on the quality of the image, and the larger or smaller area of the target in the image will affect the result. In contrast, using continuous threshold method as region growth rules is the best.

(a) Adjacency threshold (b) Continuous threshold (c) Confidence connection threshold

Figure 7. Comparison of segmentation result by different regional growth rules.

4.4 Comparison of final target filtering results

Figures 8 and 9 show final target filtering results of different original image by using two complete schemes proposed in this paper. The first column is the filtering result based on the maximum entropy algorithm. The second column is optimized filtering result by using double threshold region growth scheme. The third column is optimized filtering result by using texture analysis scheme. According to the results of maximum entropy threshold detection, the target region is artificially divided into several parts, and the detection of the target region is more complete by using double threshold region growth. The integrity of the target is the best by using texture analysis scheme.



(a) Result of maximum entropy (b) Result of double threshold region growth (c) Result of texture analysis

Figure 8. Comparison of target filtering of original image 1.

Figure 8c shows that there are two overlapping targets in final filtering results. Here, better filtering results can be obtained by using the positioning method in scheme one.

(a) Result of maximum entropy (b) Result of double threshold region growth (c) Result of texture analysis

Figure 9. Comparison of target filtering of original image 2.

5. CONCLUSION

It is very difficult to filter camouflage target from wide-area image. The author proposes two filtering schemes by designing double threshold region growth method and texture analysis method. Experiment results show that two schemes acquire better results of camouflage target filtering comparing with typical maximum entropy, and is not affected by the number of targets in wide-area image compared with clustering algorithm, therefore, recognizing accuracy of deep learning can be greatly improved by using method proposed in this paper to acquiring slice image. It can be seen that two schemes proposed in this paper provide a good pre-processing algorithm for deep learning target recognition model.

ACKNOWLEDGMENTS

This work was supported in part by the Natural Science Basic Research Program of Shaanxi under Grant 2024JC-YBQN-0699 and 2023-JC-QN-0728.

REFERENCES

[1] Song, K. and Wang, S., “Research and Implementation of Image Segmentation Algorithm,” Journal of Shenyang Institute of Engineering (Natural Science) 16(4), 71-74 (2020).

[2] Wei, G., Zhou, X. and Li, H., “Evolutionary region growing segmentation algorithm based on maximum entropy,” Journal of Jianghan University (Natural Science) 48(6), 78-83 (2020).

[3] Xu, W., [Texture Image Feature Extraction and Classification], Shanghai: East China Normal University, Doctor’s Thesis, (2017).

[4] Li, J., [Research of the Target Detection and Recognition Method for Infrared Image], Shenyang: Shenyang Ligong University, Master’s Thesis, (2012).

[5] Li, X., “Survey of research on image texture detection and feature extraction technology,” China Management Informationization 20(23), 175-178 (2017).

[6] Shi, C., Ren, B., Wang, Z., Yan, J. and Shi, Z., “Survey of camouflaged object detection based on deep learning,” Journal of Frontiers of Computer Science and Technology (12), 86-103 (2022).

[7] Pang, Y., Zhao, X., Zhang, L., et al., “Multi-scale interactive network for salient object detection,” Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, Seattle, 9410-9419 (2020).

[8] Ji, G. P., Zhu, L., Zhuge, M., et al., “Fast camouflaged object detection via edge-based reversible re-calibration network,” <https://arxiv.org/pdf/2111.03216.pdf> (5 Nov 2021).

[9] Wang, X., [Research on Camouflage Object Detection and Military Camouflage Detection Algorithm Based on Deep Learning], Changchun: Jinlin University, Master’s Thesis, (2023).