Scholar Publishing Group
Machine Learning Theory and Practice
https://doi.org/10.38007/ML.2022.030104
ISSN 2790-0983 Vol. 3, Issue 1: 27-34

Infrared Laser Image Feature Localization Technology Based on Decision Tree Algorithm

Xiangdong Ma*

Heilongjiang Shicheng Education Consulting Office, Harbin 150040, China

450999502@qq.com

**corresponding author*

Keywords: Decision Tree Algorithm, Infrared Image, Laser Image, Feature Localization

Abstract: Because infrared small target image has the characteristics of low signal-to-clutter ratio, small size of target and no obvious shape structure and texture information, it is difficult to detect small target in infrared system. Therefore, it is of practical significance to study the key and difficult points of infrared detection. This paper mainly studies the feature localization technology of infrared laser image based on decision tree algorithm. This paper first analyzes the basic theory of feature image matching, focusing on the performance of the classical edge feature extraction, point feature extraction and description methods. In this paper, the decision tree method is applied to the field of infrared dim small target detection, considering the perspective of image segmentation, to explore the ability of decision tree to express infrared image targets.

1. Introduction

Due to the infrared image imaging distance and the influence of atmospheric transmission, infrared weak small targets detection areas there are still many difficult problems, such as infrared weak small targets is usually a very weak signal, and the size is very small, the lack of structural characteristics, and so on, led to the image background of infrared dim-small target easily drown, liable to be ignored, in the test This is particularly deadly in infrared image processing. Therefore, it is difficult to study how to apply the target detection algorithm in the field of infrared imaging and adapt to the characteristics of infrared images [1-2]. Because of the particularity of this task, the general object detection algorithms are not effective in this task. In addition, with the application of infrared detection means in many fields, in order to enhance the universality of the algorithm, it is of great significance to study the detection algorithm of small and weak targets that can meet the real-time performance [3-4]. In addition to the military field, it has application value in many other fields. For example, in medical imaging pathology analysis, sea rescue and other tasks, infrared dim small target detection technology helps people to obtain a lot of valuable information [5].

Since 1990s, with the development of computers, neural networks have been migrated to infrared dim small target detection task. The most representative two-stage target detection algorithm in neural networks is Faster R-CNN. The two-stage target detection is mainly aimed at the general target detection scene, which refers to the detection using two steps: Firstly, the candidate region is framed through the anchor frame, and then the location and category information of the target are finally predicted based on the candidate region through parameter sharing [6-7]. In addition, most infrared dim dim target detection has certain confidentiality, and there is no benchmark public data set with a large amount of data, which leads to the failure to explore the network algorithm based on deep learning with good performance in this field. At present, there is a lack of public benchmark data sets for research in the field of infrared dim small target detection, and the current neural networks are all trained on some specific public data sets with good results. If they are directly migrated to the infrared dim small target detection task, the detection effect is not as good as expected [8-9]. The fundamental reason lies in the small size of dim and small targets in infrared images and few structural features, which are easy to lose only features in the network downsampling and lack of partial feature supervision. Therefore, it is necessary to redesign the network structure based on the current neural network construction module to achieve the characteristics of infrared images [10]. Despite deep learning has such a broad range of applications in image processing, but the deep learning can sometimes be too much of a good thing, some tasks needed in traditional image processing technology has been able to achieve detection, the general image processing algorithm is higher, the same operation can be performed in any image, and the depth of the neural network has some limitations in this regard, Therefore, it is necessary to study traditional image processing algorithms [11].

In this paper, the algorithm is mainly oriented to the static infrared image, aiming to improve the accuracy of infrared image feature localization.

2. Infrared Image Feature Localization Based on Decision Tree Algorithm

2.1. Basic Theory of Feature Image Matching

The core of the target localization technology based on feature image matching is the feature matching algorithm with good performance. The performance of the feature matching algorithm directly determines the performance of the target localization technology. Feature matching is divided into three parts: feature extraction, feature description and similarity measurement. In order to obtain the target positioning method of image matching with good performance, various classical feature extraction and description methods need to be studied and analyzed [12].

An edge is the beginning or end of an area, extracted according to sudden changes in color, gray or texture. Through the extraction of edge features, each individual in the image can be distinguished. Classical edge feature extraction methods include Roberts operator, Sobel operator, Prewitt operator, Laplacian operator, LOG operator and Canny operator [13]. Image edge feature extraction is realized by derivation. According to the different derivation methods, it can be divided into the edge feature extraction method based on first order differentiation and the edge feature extraction method based on second order differentiation. According to the principle of the algorithm, the Canny operator should belong to the edge feature extraction method based on the first order differential, but because the Canny operator has been summarized and improved, with complex processing flow, it is a good practical edge detection algorithm. When calculating the gradient, in order to pursue the gradient closer to the real partial derivative, scholars adopted different calculation methods and realized different edge feature extraction methods [13]. The essential difference of various edge feature extraction methods lies in the different convolution templates used.

When the photoelectric equipment works normally, visible and infrared images taken will have obvious noise, blurred boundary and small gray difference between individual regions, which requires higher requirements for edge feature extraction algorithm [14]. Infrared image than visible light image is clear, the image of individual regional gray level difference is very big, the requirements of the low to the edge feature extraction operator, general performance edge feature extraction operator can obtain better edge character, grayscale image left half of the individual area close to the part of the gray level differences also exist in the individual area of the part, There are certain requirements for feature extraction operators [15].

The edge feature extraction performance of this kind of algorithm is poor when the gray level of individual regions is close to each other. For the left part of the visible image, this kind of algorithm almost does not extract the edge feature, and for the left part of the infrared image, most of the edge features obtained is in the gray level difference. Among the three classical first-order differential edge feature extraction algorithms, the Roberts operator has the worst effect, and the edge extracted from the right half of the test image also has edge fracture. The effect of Sobel and Prewitt operators is similar, which can well extract the edge features in the case of large gray difference of individual regions, but the edge fracture is still obvious, and the effect is still not ideal [16-17].

Feature extraction and description are the basis of point feature matching. Different extraction and description methods make point feature matching methods have different anti-noise, anti-rotation, anti-scale change ability and calculation speed. Features include corner points, center points and high curvature points of the image. Corner points are the most commonly used point features, which are the collection of pixels with sudden changes in gray level and have certain invariance in the image. Classical point feature extraction methods include Harris, SUSAN, FAST, SIFT and SURF operators. Among them, Harris, SUSAN and FAST operators use gray information to extract point features, while SIFT and SURF operators use curvature to extract point features [18].

2.2. Decision Tree Algorithm Feature Localization

The decision tree algorithm divides the data into different subregions after all the data is input into the space. The decision tree classification algorithm extracts several sub-region classification tree models from the given training samples. At the same time, decision tree is a top-down recursive strategy, which is a tree structure composed of a root node, multiple branch nodes and a series of terminal leaf nodes. The middle node is the label representing the branching results of the decision tree, and the branch node represents the branching algorithm leading to the formation of these branching results. The root node is the node at the highest level of the decision tree.

The root node to each leaf nodes can form a top-down classification rules and the classifying each sample under test, only need to start from the root node, in the each branching node branch testing, the corresponding node branch recursive layer to the next node, then the node test again and has been growing to the leaf node, The data attributes contained in the leaf nodes are the classification of the final decision tree. Therefore, the internal nodes represent tests for different attributes, and each leaf node stores a portion of the object to be tested.

This paper selected the ID3 improved algorithm... C4.5 algorithm, different from ID3 algorithm which uses information gain to select attributes, uses information gain rate to select attributes, and uses pruning to reduce the occurrence of overfitting.

Suppose a random variable X takes the value {X1, Xn), each of which has the probability {P1, Pn). Then the entropy of X can be defined as follows.

$$Entropy(S) = \sum_{i=1}^{c} - p_i \log_2 p_i \tag{1}$$

It is defined as: for each feature in the system, the information increase brought by this feature to the system, that is, the information gain, can be obtained by calculating the difference between the information amount of the system when it exists and the information amount when it disappears. The expression is as follows:

$$Gain(S, A) = Entropy(S) - \sum_{v \in V(A)} \frac{S_v}{S} Entropy(S_v) \tag{2}$$

In C4.5 algorithm, information gain rate is used to select the growth of attribute branches. Information gain rate is composed of information gain and split information and its expressions with split information are as follows:

$$GainRatio(S, A) = \frac{Gain(S, A)}{SplitInfor\ mation(S, A)} \tag{3}$$

$$SplitInfor\ mation(S, A) = -\sum_{i=1} \frac{|S_i|}{|S'|} \log_2 \frac{|S_i|}{|S'|} \tag{4}$$

Where is the set of all samples, V(A) is the set of all values of attribute A, v is an attribute value, Sv is the set of examples in which attribute A value is v. In this paper, S is all infrared images in the training set.

3. Feature Localization Experiment of Infrared Laser Image

3.1. Evaluation Index

In order to reflect the performance of the network more comprehensively, Recall index and OKS (Object Keypoint Similarity) index are used to quantitatively evaluate the effectiveness of the network. In this paper, OKS is used to evaluate image key points. OKS is generated by Intersection over Union (IOU) index in object detection, which is the similarity degree of key points calculated by the actual marking value and the predicted value of key point location.

Recall rate, also known as recall rate, measures the key point recognition rate in this paper, that is, whether the same type of key points will be identified as other key points. Its expression is shown as follows, where TP stands for positive example prediction becomes positive example in the network, FN stands for positive example prediction becomes negative example in the network.

3.2. Experimental Setting

In this paper, the preprocessed image is trained. The input image size is 1920×1080, the batch_size is set to 1, and the optimizer uses Adam. As the number of iterations increases, the learning rate will decrease to half of the original one.

3.3. Network Comparison

In order to verify the effectiveness and superiority of the proposed decision tree in locating key points on infrared images, the experiment is carried out through infrared images, and the experimental comparison between Mask-RCNN, ResNet-101 and the proposed algorithm is carried out on data sets, and the performance of the network is quantitatively evaluated through the average accuracy, OKS index and recall index.

4. Analysis of Experimental Results

4.1. Training Process Data Comparison

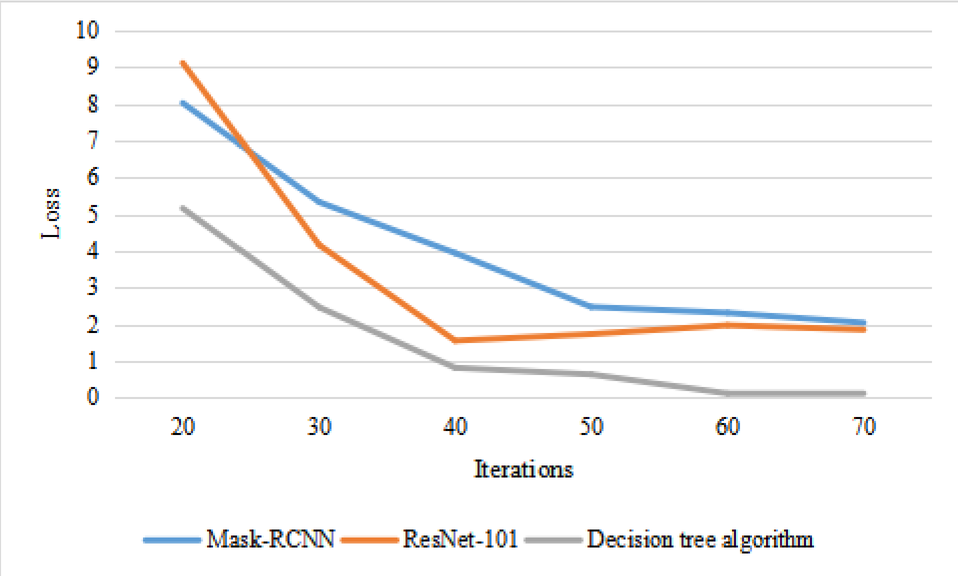

Figure 1. Loss value in network training

The dataset is trained through several iterations, and the comparison results with the loss values of multiple networks are shown in FIG. 1. In the training process, the loss values of the network in this paper will not change drastically after each training. Although the loss value of other networks also decreases slowly, the loss value of other networks is unstable and difficult to converge quickly and stably. As can be seen from the figure, the loss value of the network in this paper gradually decreases. After 60 iterations, the loss value of this network is lower than that of other networks, and finally converges.

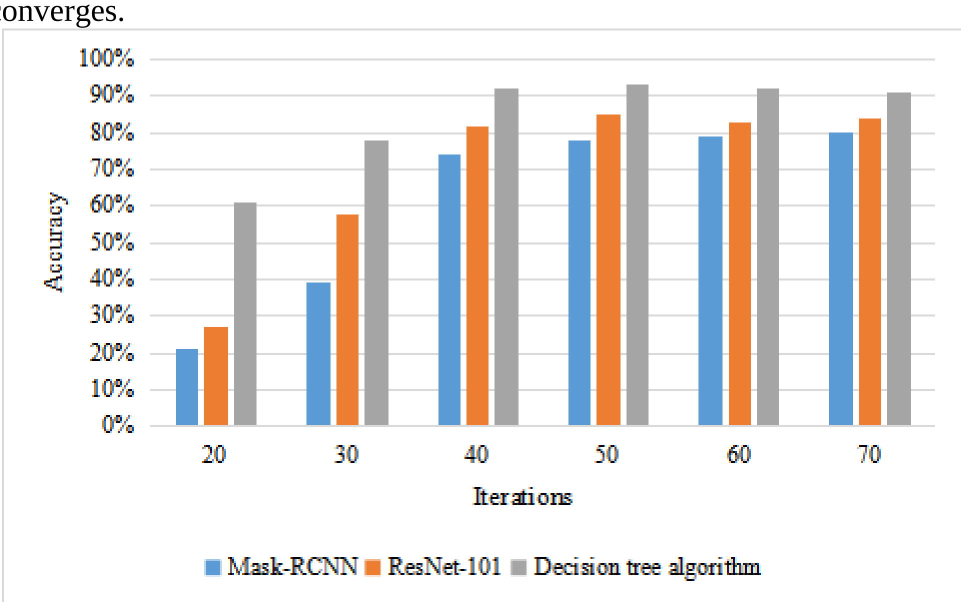

Figure 2. Accuracy during network training

Figure 2 shows the positioning accuracy of key points using different networks under the infrared image dataset during training. As can be seen from the figure, although the accuracy of ResNet-101 network increases faster in the initial training, the network in this paper can achieve higher accuracy.

4.2. Localization Comparison of Different Images

Table 1. Comparison of accuracy of key point positioning test in different networks

	Figure 1	Figure 2	Figure 3	Figure 4
Mask-RCNN	82.4	81.6	84.5	83.7
ResNet-101	87.9	89.3	88.4	84.7
Decision tree	92.8	93.1	95.6	94.4

Table 1 shows the comparison of key point accuracy of the network in the test set, excluding the case of missing key point detection. It can be seen from the table that the average accuracy of the network in this paper on this dataset is as high as 93.9%. When compared with specific key points, the accuracy of most key points of the proposed network is higher than that of other networks.

Table 2. Comparison of recall rate of key point positioning in different networks

	Figure 1	Figure 2	Figure 3	Figure 4
Mask-RCNN	81.9	82.4	83.2	80.1
ResNet-101	85.7	86.8	86.5	85.6
Decision tree	91.4	92.5	88.4	90.5

Table 2 shows the recall rate of key point positioning in different networks in the test set, in which the calculation of recall rate includes the missed detection of key points. As can be seen from the table, the average recall rate of the network in this paper is 90.7%, indicating that the network can accurately identify and classify key points, and its accuracy is lower than that of the test set. This is because there is the problem of missing key points in the detection.

Table 3. Experimental comparison of OKS performance of different networks

	AP	AP50	AP75	APL
Mask-RCNN	80.5	89.1	83.5	83.4
ResNet-101	82.2	90.7	84.5	84.7
Decision tree	85.4	94.1	88.5	88.3

As shown in Table 3, compared with the above mentioned networks, the proposed network has a better effect on AP75 and AP50.

5. Conclusion

With the development of science and technology, infrared observation technology has been widely used in many fields because of its high detection accuracy, strong robustness and better concealment. However, the research of this technology is complicated and difficult, because there are many interference factors in the infrared background, such as imaging distance, atmospheric radiation, imaging noise and so on. This article will the decision tree method is applied to the infrared weak small targets detection field, considering the Angle of image segmentation, explore the decision tree of infrared image target expression ability, combined with the feature of infrared small target image size and structure, the characteristics of less to gm's decision tree is improved, exploring in increase feelings of wild while maintaining network figure of the resolution of the image segmentation.

Funding

This article is not supported by any foundation.

Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

References

[1]Munoz P, van Dijk P W L, Geuzebroek D, et al. Foundry developments toward silicon nitride photonics from visible to the mid-infrared. IEEE Journal of Selected Topics in Quantum Electronics, 2019, 25(5): 1-13. https://doi.org/10.1109/JSTQE.2019.2902903

[2]Gonzalez-Val C, Pallas A, Panadeiro V, et al. A convolutional approach to quality monitoring for laser manufacturing. Journal of Intelligent Manufacturing, 2020, 31(3): 789-795. https://doi.org/10.1007/s10845-019-01495-8

[3]Zaitsev V Y, Matveyev A L, Matveev L A, et al. Strain and elasticity imaging in compression optical coherence elastography: the two‐decade perspective and recent advances. Journal of biophotonics, 2021, 14(2): e202000257. https://doi.org/10.1002/jbio.202000257

[4]Tittl A, Leitis A, Liu M, et al. Imaging-based molecular barcoding with pixelated dielectric metasurfaces. Science, 2018, 360(6393): 1105-1109. https://doi.org/10.1126/science.aas9768

[5]Mathurin J, Pancani E, Deniset-Besseau A, et al. How to unravel the chemical structure and component localization of individual drug-loaded polymeric nanoparticles by using tapping AFM-IR. Analyst, 2018, 143(24): 5940-5949. https://doi.org/10.1039/C8AN01239C

[6]Bang S, Park S, Kim H, et al. Encoder–decoder network for pixel‐level road crack detection in black‐box images. Computer‐Aided Civil and Infrastructure Engineering, 2019, 34(8): 713-727. https://doi.org/10.1111/mice.12440

[7]Petit Y, Danto S, Guérineau T, et al. On the femtosecond laser-induced photochemistry in silver-containing oxide glasses: mechanisms, related optical and physico-chemical properties, and technological applications. Advanced Optical Technologies, 2018, 7(5): 291-309. https://doi.org/10.1515/aot-2018-0037

[8]Nguyen P H, Arsalan M, Koo J H, et al. LightDenseYOLO: A fast and accurate marker tracker for autonomous UAV landing by visible light camera sensor on drone. Sensors, 2018, 18(6): 1703. https://doi.org/10.3390/s18061703

[9]Auner G W, Koya S K, Huang C, et al. Applications of Raman spectroscopy in cancer diagnosis. Cancer and Metastasis Reviews, 2018, 37(4): 691-717. https://doi.org/10.1007/s10555-018-9770-9

[10]Khairullina E, Mosina K, Choueiri R M, et al. An aligned octahedral core in a nanocage: Synthesis, plasmonic, and catalytic properties. Nanoscale, 2019, 11(7): 3138-3144. https://doi.org/10.1039/C8NR09731C

[11]Schnell M, Mittal S, Falahkheirkhah K, et al. All-digital histopathology by infrared-optical hybrid microscopy. Proceedings of the National Academy of Sciences, 2020, 117(7): 3388-3396. https://doi.org/10.1073/pnas.1912400117

[12]Zabatani A, Surazhsky V, Sperling E, et al. Intel® realsense™ sr300 coded light depth camera. IEEE transactions on pattern analysis and machine intelligence, 2019, 42(10): 2333-2345. https://doi.org/10.1109/TPAMI.2019.2915841
[13]Perez-Guaita D, Kochan K, Batty M, et al. Multispectral atomic force microscopy-infrared nano-imaging of malaria infected red blood cells. Analytical chemistry, 2018, 90(5): 3140-3148. https://doi.org/10.1021/acs.analchem.7b04318
[14]Fanizza E, Mastrogiacomo R, Pugliese O, et al. NIR-Absorbing Mesoporous Silica-Coated Copper Sulphide Nanostructures for Light-to-Thermal Energy Conversion. Nanomaterials, 2022, 12(15): 2545. https://doi.org/10.3390/nano12152545
[15]Kirsch M, Lorenz S, Zimmermann R, et al. Integration of terrestrial and drone-borne hyperspectral and photogrammetric sensing methods for exploration mapping and mining monitoring. Remote Sensing, 2018, 10(9): 1366. https://doi.org/10.3390/rs10091366
[16]Kukkala V K, Tunnell J, Pasricha S, et al. Advanced driver-assistance systems: A path toward autonomous vehicles. IEEE Consumer Electronics Magazine, 2018, 7(5): 18-25. https://doi.org/10.1109/MCE.2018.2828440
[17]Petay M, Cherfan M, Bouderlique E, et al. Multiscale approach to provide a better physicochemical description of women breast microcalcifications. Comptes Rendus. Chimie, 2022, 25(S1): 553-576. https://doi.org/10.5802/crchim.210
[18]Isensee K, Kröger-Lui N, Petrich W. Biomedical applications of mid-infrared quantum cascade lasers–a review. Analyst, 2018, 143(24): 5888-5911. https://doi.org/10.1039/C8AN01306C