A target tracking algorithm based on ship exhaust

Mengtao Deng¹, Shitao Peng¹*, Jianbo Hu¹, Zhaoyu Qi
¹ Key Laboratory of Environmental Protection Technology on Water Transport, Ministry of Transport, Tianjin research institute for water transport engineering, M.O.T, Tianjin, 300456, China
*Corresponding author’s e-mail: pengshitao@tiwte.ac.cn

Abstract. In the field of maritime law enforcement, it is a key technology to achieve stable tracking of the black smoke exhaust of ships. Based on correlation filter tracking algorithm, a novel ship black smoke exhaust tracking algorithm is proposed. The proposed algorithm can complete the real-time tracking of ship black smoke exhaust. In addition, it can be transplanted to mobile devices, which can quickly and efficiently complete the tracking and law enforcement of the ship's black smoke, and provide convenient services for maritime law enforcement in the ship’s emission control area.

1. Introduction
Visual object tracking [1] is a research hotspot in the field of computer vision, which has important practical value and broad application prospects in military and civilian fields. Visual object tracking is to track the moving object in the video sequence, and obtain the motion information of the interested moving object, such as position, scale, and motion trajectory, so as to facilitate the next step processing and analysis of the interested object, realize the behaviour understanding of the moving object, and complete the more arduous tracking task[2], which is convenient for better service in human society.

At present, Ship exhaust tracking is an important research hotspot in the field of maritime law enforcement. However, the application of object tracking technology in the field of ship video surveillance and maritime law enforcement is not mature, and it is easily affected by external factors, such as deformation, scale variation, illumination variation, occlusion, etc. [3-4]. Ship exhaust is a non-rigid target. Most object tracking algorithms are difficult to achieve high-precision and robust tracking of exhaust. Ship exhaust tracking involves image processing, pattern recognition, artificial intelligence, and many other fields, so it has strong research value and significance.

Based on the analysis of the status of ship exhaust tracking, in this paper, based on these difficulties, a tracking algorithm of ship exhaust based on the correlation filter is proposed, which improves the robustness and effectiveness of ship exhaust tracking.

2. Ship exhaust tracking method
The flow chart of ship exhaust tracking algorithm proposed in this paper is shown in Figure 1. In the tracking process of the KCF algorithm [5], if the target is occluded for a short time and appears in the field of view again, it may lead to the drift and even the tracking failure. Therefore, the proposed algorithm uses Hamming distance to determine the confidence degree of the target tracking model in real time. If the confidence level of the target model is lower than a certain threshold, the classifier
will be stopped to update. At the same time, the template matching algorithm is used to re-locate the target and reinitialize the tracker to complete the long-term tracking of the target.

![Flow chart of ship exhaust tracking algorithm](image)

**Figure 1. Flow chart of ship exhaust tracking algorithm**

2.1. Correlation filter tracking algorithm

Ship exhaust tracking method is a tracking algorithm based on kernel correlation filter [6]. In this algorithm, ridge regression classifier is used as the core, and many samples are formed to train the classifier. The kernel function is used to calculate the similarity between the selected region and the target region, and the region with the largest response is used as the new tracking target.

2.1.1. Hog feature.

The KCF algorithm uses histogram oriented gradient feature[7-8], through the statistics and calculation of the gradient direction histogram of the local area of the image to form the image features, and then realize the description of the object features. The steps of hog feature extraction and calculation are as follows.

1. Color and gamma normalization. To reduce the influence of illumination, the image must be normalized first.

2. Calculating image gradient. gradient information can not only reflect the contour information and texture information of the image, but also can further reduce the influence of illumination. The gradient is calculated for the abscissa and ordinate of the image respectively, and the calculation method is as follows (1) and (2).

\[
G_x(x, y) = H(x+1, y) - H(x-1, y) \\
G_y(x, y) = H(x, y+1) - H(x, y-1)
\]

(1)

(2)

Where \(G_x(x, y)\) and \(G_y(x, y)\) represent the gradient values in the horizontal direction and the vertical direction respectively, and \(H(x, y)\) represents the pixel value of a certain point, then the gradient value \(G(x, y)\) direction \(\alpha(x, y)\) at the point is shown in formulas (3) and (4).

\[
G(x, y) = \sqrt{G_x(x, y)^2 + G_y(x, y)^2}
\]

(3)
\[ \alpha(x, y) = \arctan \left( \frac{G_y(x, y)}{G_x(x, y)} \right) \]  

(4)

(3) Construct directional histogram. The histogram channel voting is carried out for the pixels in the cell unit by weighted voting. Each vote has a weight, which can be calculated by the amplitude gradient of pixels.

(4) Cell units are combined into large intervals: each cell unit is combined to form a large, spatially connected region. In this way, hog features can combine the histograms of cell units in each interval into a vector. Because of the overlap between these regions, a cell unit may act on the final descriptor several times.

(5) Collect hog features: input all extracted hog features into SVM classifier to find the final decision function.

2.1.2. Kernel correlation filtering.
In practical applications, we often encounter the problem of nonlinearity, so we need to use kernel function to project the samples into the high-dimensional feature space, so that the samples become linearly separable in the high-dimensional space. The linear combination of \( W \) in high dimensional space in ridge regression is shown in formula (5).

\[ w = \sum_i \alpha_i \varphi(x_i) \]  

(5)

Where \( \varphi(x_i) \) is the function mapping the training samples to the high-dimensional feature space, the algorithm is written in the form of point product, and the kernel function is defined as shown in formula (6).

\[ k(x, x') = \varphi^T(x)\varphi(x') \]  

(6)

\( k \) is a Gaussian kernel function, or a polynomial kernel function. The point product between all sample pairs is usually stored in the \( n \times n \) kernel matrix \( K \), and \( K = k(x_i, x_j) \). The solution of ridge regression based on the least square method is shown in formula (7).

\[ \alpha = (K + \lambda I)^{-1} y \]  

(7)

Where \( K \) is the kernel matrix, \( I \) is the identity matrix and \( y \) is the expected output. Since the nuclear matrix \( K \) has the cyclic property, the discrete Fourier transform of formula (7) is carried out, and the form of formula (8) is obtained.

\[ \hat{\alpha} = \frac{\hat{y}}{k^{xx} + \hat{\lambda}} \]  

(8)

\( k^{xx} \) is the first line element of the matrix \( K = C(k^{xx}) \), which is the generating vector. Through the above method, the calculation of classifier parameters \( w \) is converted into the calculation parameter \( \alpha \), which greatly reduces the calculation amount of the algorithm.

2.2. Decision strategy of confidence degree
When the tracking target is occluded, if the target model with low confidence is used to update the classifier, the classifier will inevitably introduce the wrong model information, which will lead to the drift of the target tracking or the tracking failure [9]. When the confidence level of the target model is low, the proposed algorithm stops updating the classifier, and uses the template matching algorithm to relocate the target to complete the long-term tracking of the target.
In this part, we introduce Perceptual Hashing Algorithm and Hamming distance to judge the confidence degree of the target tracking model in real time. If the confidence level of the tracking model of the current frame is less than the threshold value $H_m$. Then the tracking model is considered to be reliable, and then the classifier is updated continuously; otherwise, the confidence of the tracking model is considered to be low, so the classifier is stopped to be updated, and the template matching algorithm is used to locate and track the target again.

2.3. Target search and relocation
When the confidence level of target tracking model is lower than a certain threshold, the method of template matching [10] is used to match and locate the target. The algorithm proposed in this paper can judge the confidence degree of the target model in real time. If the confidence level of the model is low, the template matching algorithm is used to locate the target again and reinitialize the tracker. This method can track the target in the subsequent video frames, reflecting the design of the improved algorithm Integrity.

Template matching is one of the important parts of digital image processing. According to the known template, find the image with similar size and direction with the target template from another image, and determine its coordinate position. In this paper, the square difference matching method is selected to realize the target relocation. The formula is as follows (9).

$$R(x, y) = \sum_{x', y'} [(T(x', y') - I(x + x', y + y'))^2]$$  (9)

3. Experimental results and analysis
To comprehensively evaluate the tracking accuracy and robustness of the algorithm, five groups of challenging videos are selected to test the performance of the algorithm. The hardware configuration of the experimental environment is as follows. Operating system windows10, Intel (R) core (TM) i7-10700f CPU@2.90GHz+RAM16GB. Software running environment, PyCharm Community Edition 2020.1.3 + OpenCV-Python 4.2.0. The experimental parameter $H_m$ is 0.5.

3.1. Experimental video
During the experiment, five groups of challenging ship video sequences were selected, including deformation, scale variation, occlusion, motion blur, etc. the detailed attribute description of the test video is shown in Table 1.

| Video | Frames | Resolution | Challenge |
|-------|--------|------------|-----------|
| Ship 1 | 469    | 960x544    | DEF       |
| Ship 2 | 668    | 1280x720   | DEF, SV   |
| Ship 3 | 1170   | 1280x720   | DEF, SV   |
| Ship 4 | 1305   | 1280x720   | DEF, OCC  |
| Ship 5 | 812    | 1280x720   | DEF, MB   |

3.2. Evaluation criteria
According to the general criteria of tracking algorithm, the accuracy and success rate are used as the indexes to measure the performance of the algorithm.

3.2.1. Accuracy
The average center location error (CLE) of all frames is used to represent the tracking accuracy of the algorithm in the video sequence. Generally, the Euclidean distance of 20 pixels is selected as the standard to measure the accuracy of different trackers.
3.2.2. Success rate

The success rate is also another important evaluation index to evaluate the tracking performance of the algorithm. Overlap ratio is used to represent the tracking success rate of the algorithm. The threshold range of overlap rate belongs to [0,1]. The larger the overlap ratio, the higher the tracking success rate of the algorithm.

3.3. Experimental results and discussion

To verify the effectiveness of the proposed algorithm, we use the accuracy and success rate to evaluate it. Compared with the original algorithm, the test results of mean precision, mean success rate and mean FPS on experimental video are shown in Table 2. Black bold font for best results.

Table 2. Performance comparison between the proposed algorithm and the original algorithm.

| Method     | MP   | MS   | MF   |
|------------|------|------|------|
| Improved   | 0.869| 0.834| 37.5 |
| Original   | 0.824| 0.792| 42.7 |

It can be seen from the Table 2 that the proposed algorithm has higher tracking accuracy and tracking success rate than the original algorithm, and its running speed is slightly lower than that of the original algorithm, but it basically meets the requirements of real-time performance.

Figure 2 shows the tracking results of our algorithm on five test videos. It can be seen that the ship exhaust tracking algorithm proposed has high tracking robustness and accuracy. Table 3 shows the tracking accuracy, success rate and running speed of the algorithm on five test videos. It can be found that the algorithm proposed in this paper has good tracking performance in the test video.
Table 3. Tracking accuracy, success rate and running speed of the algorithm on test video.

| Video  | Precision | Successrate | FPS  |
|--------|-----------|-------------|------|
| Ship 1 | 0.932     | 0.913       | 45.3 |
| Ship 2 | 0.871     | 0.820       | 40.6 |
| Ship 3 | 0.854     | 0.817       | 34.4 |
| Ship 4 | 0.793     | 0.768       | 30.6 |
| Ship 5 | 0.897     | 0.853       | 36.4 |

4. Conclusions

According to the characteristics of ship exhaust, in this paper, a ship exhaust tracking algorithm based on correlation filtering is proposed. The proposed method combines the model confidence determination mechanism and template matching algorithm to improve the tracking robustness and accuracy of the algorithm. The experimental results show that the proposed algorithm can not only complete the real-time tracking of ship exhaust, but also has certain adaptability to the deformation and scale variation of exhaust.

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References

[1] Meng, Z., Yang, X. (2019) Overview of target tracking algorithm. Journal of automation., 45:1244-1260.
[2] Lu, H.C., Li, P.X., Wang, D. (2018) Visual Object Tracking: A Survey. Pattern Recognition and Artificial Intelligence., 31: 61-76.
[3] Wu, Y., Lim, J., Yang, M.H. (2013) Online object tracking: a benchmark. In: 2013 IEEE Conference on Computer Vision and Pattern Recognition. Portland, OR. pp. 2411-2418.
[4] Wu, Y., Lim, J., Yang, M.H. (2015) Object tracking benchmark. IEEE Transactions on Pattern Analysis & Machine Intelligence., 37:1834-1848.
[5] Henriques, J.F., Caseiro, R., Martins, P. (2015) High-speed tracking with Kernelized correlation filters. IEEE Transactions on Pattern Analysis & Machine Intelligence., 37:583–596.
[6] Bolme, D.S., Beveridge, J.R., Draper, B.A., Lui, Y.M. (2010) Visual object tracking using adaptive correlation filters. In: 2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition. San Francisco, CA, USA. pp. 2544-2550.
[7] Wang, X., Han, T.X., Yan, S. (2009) An HOG-LBP human detector with partial occlusion handling. 2009 IEEE 12th International Conference on Computer Vision. Kyoto, Japan. pp.32-39.
[8] Xu,Y., Xu, X.L., Li, C.N. (2016) Pedestrian detection based on SVM classifier and hog feature extraction. Computer Engineering., 42: 56-60.
[9] Jiang, S.J., Ning, J.F., Cai, C. (2017) Robust Struck tracker via color Haar-like feature and selective updating. Signal Image & Video Processing., 11:1073-1080.
[10] Gao, C., Wang, F.L. (2017) License plate recognition algorithm based on template matching and local hog features. Computer system applications., 1: 122-128.