Ship Target Detection Algorithm for Maritime Surveillance Video Based on Gaussian Mixture Model

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Abstract. The paper presents a vessel target detection algorithm to achieve the maritime visual surveillance, which aims to reduce the influence of clutter that exists in the background and improve the reliability of ship target detection. In the proposed detector, the main steps including background modeling, model training and updating and the segmentation of foreground, are all based on Guassian Mixture Model (GMM). By exploiting the characteristics of GMM, we simply determine whether new pixels, in the video, belong to the foreground. Having modeled surveillance region, we roll out the moving ship detection using background subtraction, segmenting the ship target by the continuity of the adjacent frames. The target precision rate of the algorithm is 97.29% and the false alarm probability is 22.83% in the experiments. Comparing with other algorithms, the results show that this algorithm can not only improve target precision rate, but also reduce false alarm probability, and greatly overcome the influence of large amount of clutter on the detection of moving ship objects in video background, effectively restraining the influence of the noise from the dynamic scenario transformation.

1. Introduction

The current maritime surveillance systems are based on space-borne Synthetic Aperture Rader (SAR), High Frequency Surface Wave Rader (HFSWR), regular ship-based radars, and air-/space-borne optical sensors [1]-[3]. The SAR equipment can operate continuously under all-weather conditions at the expense of limited image. However, maritime video surveillance, an important part of the vessel traffic service, can provide more intuitive image includes moving ship information and makes up the deficiency of AIS (Automatic identification System) and radar, which has become an effective and feasible mode for maritime authorities to manage ship traffic [4][5]. Ship detection and continuous tracking are the basis of many follow-up studies, such as video motion analysis and behavior understanding, which has resulted in the visual maritime surveillance become a research hotspot of intelligence traffic.

At present, the current maritime surveillance tools are mainly installed the channel, cruise ships, bridges, near the water-gate to acquire surveillance video image which can be used for ship target detection. Comparing with other monitoring systems, the maritime video surveillance has the following characteristics: the maritime images contain horizon consists of sea surface and sky; Background clutter: maritime video surveillance includes a lot of shaking ripples and light spots; Camera shaking results in a non-linear change in the state of the target; Illumination variations: different seasons, time periods, illumination intensity and direction affect the detection of ship targets directly. All these factors make it difficult to ship target detection.
Some scholars have proposed detection techniques for ship based on maritime video surveillance images. These methods mainly include AFDM (adjacent frame difference method) [6], optical flow method [7], background modeling and subtraction [8]. While AFDM has a strong adaptability to the change of illumination, scale and other testing environment, it is easy to detect holes in the ship targets detection when dealing with the texture of the target pixel of the moving ship and the change of the color gradation. Optical flow method can independently detect the objects of the moving ship, don't need to know in advance video ship targets motion scene, but this method needs a large number of calculations and has poor anti-noise performance, which is difficult to meet the requirements of real-time detection. Background subtraction method can effectively obtain the complete region of the ship targets. The key of this is to obtain the background image of video surveillance scene and maintenance updates.

Background modeling plays a significant role in ship target detection by using the background subtraction. N Friedman established a single Gaussian distribution model [9], believing that each pixel value in the video image approximately obeyed Gaussian distribution and by using the obtained pixel value to estimate Gaussian distribution parameters. The new pixels, in the video, which did not match the Gaussian distributions were regarded as background, otherwise the foreground. In the video scene of the target detection of the actual moving ship, the background exists the water ripples with dynamic shaking, and this single-Gaussian distribution model has no significant effect on dynamic scenes detection. C Stauffer proposed the GMM (Gaussian Mixture Model) to replace the single Gaussian distribution to estimate the background [10], and successfully solved the approximate periodic motion of the background, such as the shaking leaves and corrugation, and could also adapt to the change of illumination. W C Hu constructed the background image using the median of the first n frames of images, and proposed the corresponding background updating method to realize the automatic detection of illegal target intrusion in mariculture zone [11]. A Borghgraef and W Y Wang pre-introduced target information to be detected [12][13]. Based on the pixel subtraction of the background to obtain the ship target image, and then to update and assessment. Running Mean Updating Background (RMUB) was used to obtain the foreground image by constructing the background model [14], reducing the "empty" phenomenon in moving target detection, but it was sensitive to illumination change, while initializing the update background phase was slow, background learning was lagged behind, causing the foreground target be detected to background.

In view of the above analysis, GMM can adapt to the changing of complex background. Therefore, GMM is used to detect the target of moving ship. Finally, the reliability of the algorithm is verified by experiments.

2. Moving ship target detection
The maritime surveillance video images are collected by the infrared thermal imager or infrared high definition camera installed on the ship, gate, bridge et al. It usually includes four parts: sky, ship, sea surface and fixed object, among which the sky, sea and fixed objects are marked as the background, while ship is marked as the foreground. In this paper, GMM is used to detect the target of moving ship. The detection processes include background modeling, model training and updating and the segmentation of foreground.

2.1. Background modeling
GMM can approximate the probability density distribution of arbitrary shape, fitting the background distribution of the real scene, and it is widely used to moving target detection [15]. The change of pixel value \(x'\) captured in the image of time \(t\) is considered as a stochastic value. \(K\) Gaussian functions are used to fit the gray distribution of the pixel value \(x'\). The probability of \(x'\) is written as:

\[
P(X') = \sum_{i=1}^{K} \omega_i \eta(X', \mu_i, \Sigma_i)\tag{1}\]
Where: \( K \) is the total number of Gaussian distributions, with the ranging from 3 to 5; \( \omega_k(t) \) \((0 \leq \omega_k(t) \leq 1, \sum_{k=1}^{K} \omega_k(t) = 1)\) is the normal weight of component \( k \) at time \( t \); \( \mu_k(t) \) and \( \Sigma_k(t) \) are the mean and covariance matrix at time \( t \). The Gaussian probability density function \( \eta \) is defined as:

\[
\eta = \frac{1}{(2\pi)^{D/2} |\Sigma|^{1/2}} \exp \left\{ -\frac{1}{2} (x - \mu(t))^T \Sigma^{-1} (x - \mu(t)) \right\}
\]

(2)

2.2. Model training and updating

Model matching is to compare the pixel point \( I(x,y) \) observed in the current frame image with the established GMM. If the equation (3) is satisfied, it is considered that the pixel point \( I(x,y) \) of the current frame matches the established GMM, otherwise, the pixel does not match.

\[
|I'(x,y) - \mu_k(t)| \leq 2.5 \sigma_k^{-1}
\]

(3)

Where: \( \sigma_k^{-1} \) is the variance of component \( k \) at \( t-1 \) time.

Model matching must update model parameters in real time. Updating method sees the equation (4).

\[
\begin{align*}
\mu_k^{t+1} &= (1-\alpha) \mu_k(t) + \sigma_k(t) x' \\
\sigma_k^{t+1} &= (1-\rho) \sigma_k(t) + \rho (\mu_k(t) - x')^2 \\
\omega_k^{t+1} &= (1-r) \omega_k(t) + r M_k(t)
\end{align*}
\]

(4)

Where: \( \alpha \) is update parameter, according to [13], the value is 0.02; \( \rho \approx \alpha/\omega \); \( r \) is updated parameter for weight; \( M_k(t) \) is a value that model matched is 1, otherwise 0.

Keeping 3 Gaussian components arrange from big to small. When the model does not match, the current frame pixel appears new distribution, and the mean \( \mu_k(t) \) of the current frame is used; besides, initializing a larger variance and a smaller weight. The new Gaussian distribution model replaces the last Gaussian distribution in the original sequence, and the remaining two Gaussian distributions keep the same mean and variance. Updating the weight according to equation (5).

\[
\omega_k^{t+1} = (1-r) \omega_k(t)
\]

(5)

2.3. The segmentation of foreground

In the GMM model parameter learning phase, the Gaussian distribution with a large weight describes a large probability of background pixel value, otherwise a small probability of foreground pixel value. The Gaussian distribution is sorted by the value of \( \omega_k(t) / \sigma_k(t) \) from mid-size to small. If \( l_i, l_2, ..., l_m \) means that each Gaussian distribution are arranged according to the value of \( \omega_k(t) / \sigma_k(t) \) from big to small at \( t \) time and the first \( n \) Gaussian distributions are satisfied with equation (6), then first \( n \) Gaussian distributions are the background distribution and the rest are the foreground distributions.

\[
\sum_{k=1}^{n} \omega_k(t) \geq T
\]

(6)

Where: \( T \) general value is 0.7~0.8, here is 0.75.

3. The experimental results and analysis

In order to evaluate the detection performance of GMM, the target precision rate (TPR) and false alarm probability (FPR) are selected as the evaluation criterion [3].

In view of different complex sea conditions, in this paper, a large number of experimental tests are carried out to compare GMM with conventional detection method: AFDM and RMUB, to verify the reliability of GMM in the detection of moving ship targets. All experiments are using MATLAB programming language, the computer configuration: Windows10, Intel(R) 1.8GHz, memory 8GB of memory. The resolution of the image: 432 \times 240.
In the experiments, a total of 1037 images of two scenarios are selected as experimental test samples. Scenario one is a surveillance video with a total of 207 frames, which indicates the detection background with the change of illumination and dynamic swaying water ripples during the day, another one contains both dynamic swaying water ripples and fixed objects with a total of 830 frames.

In order to deeply analyze the segmentation rules of the target pixels and the background pixels in surveillance video, this paper presents a method of pixel value analysis for a specific pixel point \( I(x,y) \). Using \( X' \) to represent RGB color component at time \( t \), \( X' = (x', y', z') \). The change of surveillance video image means the change of three RGB color component values, which means RGB values at the same location are replaced by new values. This paper chooses two different observation points in scenario 1, \( I_1 (235,398) \) and \( I_2 (169,245) \).

Table 1 indicates the characteristics of variation at \( I_1 \) and \( I_2 \). In the scenario, there are no moving ship target though the point \( I_1 \), and only one passes through point \( I_2 \). The RGB component changes and RGB 3D distribution of point \( I_1 \) and \( I_2 \) are shown in figure 1 and figure 2 respectively.

As is shown table 1, the mean, variance and standard deviation of the sample point are relatively small, when there is no moving ship target though the point \( I_1 \). The mean value increased suddenly, when there is moving ship target passes by the sample point, while the variance and standard deviation are larger than those without moving targets.

**Table 1.** Mean, variance and standard deviation of pixel sample points

| Scenario | Points | Coordination | Frames | Target state | Mean | Variance | Standard deviation |
|----------|--------|--------------|--------|--------------|------|----------|-------------------|
| Scenario 1 | \( I_1 \) | (235,398) | 1-269 | No | 92.56 | 18.98 | 4.35 |
|          |        |              |        | Yes | 141.56 | 341.22 | 18.47 |
|          |        |              |        | No | 108.64 | 4.64 | 2.15 |
| Scenario 1 | \( I_2 \) | (169,245) | 87-166 | No | 110.27 | 1.66 | 1.28 |
|          |        |              |        | Yes | 141.56 | 341.22 | 18.47 |
|          |        |              |        | No | 108.64 | 4.64 | 2.15 |

(1) No moving ship target in scenario 1

The change of the pixel value of the observation point keeps stable when there is no moving ship target in scenario 1, as is shown in figure 1 (a), and the change trend of RGB 3D distribution presents a ellipsoid shape, as is shown in figure 2 (a).

(2) A few number of moving ship targets

RGB color components are suddenly increasing and then return to the original value when the moving target appears in scenario 1, as is shown in figure 1 (b). RGB color components of target points are far away from the center of the model, as is shown in figure 2 (b).

![Changes of RGB component at \( I_1 \) and \( I_2 \) in scenario 1](image-url)

(a) Changes of RGB component at \( I_1 \) (b) Changes of RGB component at \( I_2 \)
Figure 2. RGB 3D distribution at $I_1$ and $I_2$ in scenario 1

Figure 3 shows some experimental results in scenario 1, figure 3 (a, f) show the original the images of 20th and 198th in the maritime surveillance video, the second to fourth column represent that the saliency maps of target extracted by using AFDM, RMUB as well as GMM; see figure 3 (b, c, d, g, h, i). The fifth column indicates the detection results by using the GMM; see figure 3 (e, j). In the initial detection stage, the three methods achieve good detection results. The water ripples are detected to foreground in the sea-surface; see figure 3 (b, c, d). With the detection goes deep, AFDM and RMUB are difficult to avoid the background of water ripples detect as foreground; see the figure 3 (b, c). However, the ship target achieves better detection performance by using GMM in sea-surface, avoiding the complex both the water ripples and light spot are detected to background; see figure 3 (i).

Figure 3. Detection result under the change of illumination during the day. (a, f) Original images; (b, g) Saliency maps of AFDM; (c, h) Saliency maps of RMUB; (d, i) Saliency maps of GMM; (e, j) Detection results of GMM

Figure 4 shows some experimental results in scenario 2. The first column is the original image of frames 51 and 162 in the surveillance video. The second to the fourth column represents the saliency maps of moving ship extracted by using AFDM, RMUB and GMM under the environment of dynamic swaying water ripples and stationary objects. The fifth column indicates the result of using GMM for the detection of moving ship target. In the initial detection stage, as shown in figure 4 (b, c, d), the detection effect of GMM is similar to AFDM, but the detection results of GMM and AFDM are better than the RMUB. In terms of reducing the influence of wave effect, GMM is similar to RMUB, both of them are obviously superior to that of AFDM. With the detection goes deeper, though AFDM and RMUB can improve the detection effect, there are massive loss of detection targets, as shown in figure 4 (g, h). Although the coastal sea wave background is detected as foreground by the GMM algorithm, the target area of the moving ship is distinct and has a clear texture, as shown in figure 4 (i). The TPR and FAR of GMM algorithm is 94.58% and 24.36% respectively, which is superior to the other two methods, as shown in table 2.
Figure 4. Detection results of three kinds of methods under the environment of dynamic swaying water ripple and stationary objects. (a, f) Original image; (b, g) Saliency maps of AFDM; (c, h) Saliency maps of RMUB; (d, i) Saliency maps of GMM; (e, j) Detection results of GMM.

In order to verify the effectiveness of the GMM as a whole, using the AFDM, RMUB and GMM to deal with the monitor video in the three scenarios separately, which is conducted under the same simulation environment. In this paper, we calculate the $TPR$ and $FAR$ of different methods in different scenarios respectively, the results in shown in table 2.

| Sequence | $P_{TPR}$ | $P_{FPR}$ |
|----------|-----------|-----------|
| Scenario 1 | 87.40% | 34.20% | 67.10% | 21.30% |
| Scenario 2 | 77.87% | 58.43% | 31.80% | 24.36% |

As shown in table 2, GMM is better than AFDM and RMUB. From the statistical results, The $TPR$ of GMM is 97.29%, higher than the other two methods. The $FPR$ of GMM is 22.83%, lower than the other two methods. The reason why there is the $FPR$ is that the ship size is smaller and also there is some significant disturbance that caused by the impact of the sea wave. In complex sea conditions, when background has fixed object marks and shaking water ripples, the performance of GMM algorithm is better than that of the other two methods.

4. Conclusion

In this paper, the moving target is detected by ship surveillance video under three scenarios. The detection result shows that the average detection rate of the three methods, AFDM, RMUB and GMM, are similar. GMM is slightly higher than AFDM and RMUB. However, the $FPR$ of the three detection methods is quite different. The $FAR$ of GMM is 22.83%. The $FAR$ of AFDM and RMUB is 46.31% and 49.45% respectively. The results show that GMM has better detection results compared with traditional detection method, such as AFDM and RMUB, and has strong anti-interference ability. GMM can achieve good results regardless of whether the background is relatively fixed, or the noise interference caused by light, or the ripple of a large amount of shaking.

The next step is to study the influence of weather condition, blocked moving targets under other conditions, such as poor visibility, etc., to design and develop an easier and more practical background model to reduce the influence of dynamic scenario change on the detection of moving ship.

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