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A GMM-Based Segmentation Method for the Detection of Water Surface Floats

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ABSTRACT Gaussian Mixture Model (GMM) is a widely used approach for the background subtraction and the moving objects detection. However, the classical GMM probably detects incorrectly and cannot deal with the shadows with a pixel-level and time-domain classification, and thus it cannot monitor the water surface floats effectively. To solve this problem, an improved GMM-based automatic segmentation method (IGASM) is proposed to detect the water surface floats in this paper, where the background updating strategy is improved to segment the water surface floats more effectively. Besides, the GMM results are mapped into an HSV color space, and a light-shadow discriminant function is applied to solve the problems of light and shadow. Then, a morphological method is used to smooth the extracted foregrounds. Finally, Graph Cuts algorithm is applied to optimized the segmentation results according to the spatial information of video images. Experimental results demonstrate that IGASM can detect the water surface floats quickly and accurately, and the influences of light, shadows and ripples of water surface can be eliminated as much as possible.

INDEX TERMS Background subtraction, Gaussian mixture model, graph cuts, light-shadow discriminant function, video segmentation, water surface floats.

I. INTRODUCTION

With the rapid development of industrialization, the human beings have caused serious pollutions to the environments. Especially, there are a large number of garbage floating on lakes, rivers and pools, which always worsen the water quality and bring harms to the humans. Besides, these water surface floats will seriously damage the ecological environment and the regional economy [1], [2], e.g., the water landscapes in many scenic spots are affected by these floats. At present, the detection of water surface floats typically depends on the arrangement of manual inspections, which requires a large amount of human and material resources. The automatic detection [3], [4] of water surface floats has become an important topic. In this regard, some cameras are firstly assigned around the water area, and then the moving objects are detected through the videos taken by these cameras. However, the existing detection techniques [5]–[7] are not very satisfactory, due to the fact that the water surface floats always move slowly and remain stationary chronically. For example, the floats on lakes have stayed on the lake shore for a long period, and the GMM algorithm may identify the floats as the background by mistake. Moreover, the captured background images are also affected by in dynamic environments, such as the variations of weather and light. Note that the classical GMM algorithm considers the difference of pixel's characteristics in time-domain when extracting the foreground objects, whereas the spatial information of video images is ignored [8], which gives rise to the detection inaccuracy of water surface floats.

To this end, this paper proposes an improved GMM-based automatic segmentation method (IGASM) for the detection of water surface floats. This method first establishes a background model based on Gaussian mixture model, and detect light and shadow by a light-shadow discriminant function in an HSV color space. IGASM can segment the stationary water surface floats through a new strategy of updating background models. In addition, some morphological operations are used to smooth the extracted foregrounds. Finally, by combining Graph Cuts algorithm, IGASM optimizes the segmentation results according to the spatial information of video images.

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The paper is organized as follows: in Section II, we introduce some existing foreground segmentation methods and the related works of water surface floats detection. The classical GMM algorithm is described in Section III. We propose the improved GMM-based automatic segmentation method in Section IV. Experimental results are reported in Section V. Some conclusions are drawn in Section VI.

II. RELATED WORKS

Video segmentation has been a focus of computer vision and image processing, and it plays a key role in some fields such as the target classification, tracking and recognition [9], [10]. In recent years, some related works have been proposed, such as the optical flow [11], temporal difference [12] and background subtraction [13]–[15]. Stauffer *et al.* propose the GMM [16], an adaptive background mixture model for the real-time tracking, where each pixel is modeled as a mixture of Gaussians and is classified based on whether the Gaussian distribution which represents it most effectively is considered part of the background model. Boykov *et al.* propose the Graph Cuts [17] which needs the user to mark certain pixels as "object" or "background" to provide hard constraints for segmentation and applies the "graph cuts" to find the globally optimal segmentation of the image with these hard constraints and some soft constraints incorporated both boundary and region information.

Although tremendous success has been achieved, the detection of the water surface floats is still a challenging problem. Compared with the segmentation of ordinary objects, the main difficulty in the segmentation of water surface floats is due to their dynamic motion characteristics. For example, the floats may either be constantly moving under the forces of current and wind, or be stationary on the shore for a long time. This brings great challenges to the construction of background model. If the background model with a shorter update period is used, the long-time stationary floats are probably integrated into the background and will be hardly detected and segmented. If the background model with a longer update period is used, the impact on dynamic scene changes such as light changes and surface waves cannot be well handled. Zheng *et al.* [18] propose a method to extract the moving objects on water surface, where a decision method based on Mahalanob Distance was applied to segment the water surface in the image according to the statistic information of the water region in HSI (Hue-Saturation-Intensity) color space. This method can extract the water surface moving targets stably, but it cannot segment the stationary objects and cannot deal with the light changes and shadows caused by floats. Reference [19] calculates the intensity and time probability maps of each input image frame and separates the floating wood objects from the water surface with respect to brightness and temporal variation features. This method can effectively overcome the influences of background changes, and extract the floating wood objects in videos quickly. In [20], a method is proposed to monitor the abnormal water surface based on ART (Adaptive Resonance Theory). This method extracts the image features from HSI color space by using Gaussian-Hermite invariant moments, and can effectively detect the abnormal areas of water surface. However, this method does not consider the relationship between adjacent frames, and thus it cannot guarantee the segmentation accuracy.

These segmentation methods mentioned above classify the pixels from either the temporal aspect or the spatial aspect. Actually, the spatial-temporal features of the pixels are indispensable. With regard to the water surface floats, the traditional methods are not ideal, especially for the stationary floats. In a more robust and efficient segmentation system, both spatial information and temporal information of the images should be taken into account jointly for the detection of water surface floats.

This paper designs an improved GMM-based automatic segmentation method for the detection of water surface floats. By improving the background updating strategy, a long-term stable and background model is constructed to solve the problem that the stationary floats integrated with the background are hard to be detected. A light-shadow discriminant function is provided to solve the problems of light and shadow. Finally, the spatial information in video images is utilized to optimize the segmentation results.

III. ADAPTIVE GAUSSIAN MIXTURE MODEL

In essence, the video segmentation technology is a problem of binary classification. That is, to find out whether the pixel of current frame falls into the foreground state or the background state.

The basic idea of GMM is that the color information between pixels is not correlated, and the processing of each pixel is independent with each other. The color of each pixel is represented by the superposition of K Gaussian distributions (usually K is between 3 and 5). If we consider the color X presented by the pixels as a random variable, and then at time $T = 1, 2, \ldots, t$ the pixel value of the image is equal to the sampling value of the random variable X. A mixture of K Gaussian distributions is used to fit the pixel values, and a Gaussian mixture background model is constructed. Then, the distance between the current pixel values and the Gaussian mixture model is calculated to judge the foreground and background.

Suppose that the recent history of each pixel is $\{x_1, x_2, \ldots, x_t\}$, and then the probability of observing the current pixel value is expressed as:

$$P(x_t) = \sum_{i=1}^{K} \omega_{i,t} \cdot \eta\left(x_t, \mu_{i,t}, \Sigma_{i,t}\right) \tag{1}$$

where K is the number of distributions, currently, from 3 to 5 are used. $\omega_{i,t}$ denotes an estimate of the weight of the i-th Gaussian in the mixture at time t, $\mu_{i,t}$ denotes the mean value of the i-th Gaussian, $\Sigma_{i,t}$ is the covariance matrix of the i-th Gaussian, and $\eta(\cdot)$ is a Gaussian probability density function:

$$\eta(x, \mu, \Sigma) = \frac{1}{(2\pi)^{1/2} \cdot |\Sigma|^{\frac{1}{2}}} \cdot e^{-\frac{1}{2}(x-\mu)^T \cdot \Sigma^{-1} \cdot (x-\mu)} \tag{2}$$

When a new observation point x_{t+1} arrives, each new pixel value is compared with the mean values of the existing K Gaussian distributions, until a match is found. The match is defined as a pixel value within a β standard deviation:

$$\left\| x_{t+1} - \mu_{i,t} \right\| \leq \beta \cdot \Sigma_{i,t}^{\frac{1}{2}} \tag{3}$$

where β is a constant (β is set to 2.5). If the matched distribution is the background model distribution, and then the pixel belongs to the background, otherwise, it belongs to the foreground.

If none of the K distributions match the current pixel value, and then the distribution with the least prior weight is replaced with a new distribution with the current value as its mean value. The prior weight of the K distributions (at time $t+1$) denoted by $\omega_{i,t+1}$ is updated as follows:

$$\omega_{i,t+1} = (1-\alpha) \cdot \omega_{i,t} + \alpha \cdot M_{k,t} \tag{4}$$

where a is a learning rate, and $M_{k,t}$ is 1 for the model which matched and 0 for the others. After this approximation, the prior weight is renormalized.

The parameters of μ and Σ for unmatched distributions will remain the same. These parameters of the distribution which matches the new observation will be updated as follows:

$$\mu_{i,t+1} = (1-\rho) \cdot \mu_{i,t} + \rho \cdot x_{t+1} \tag{5}$$

$$\Sigma_{i,t+1} = (1-\rho) \cdot \Sigma_{i,t} + \rho \cdot (x_{t+1} - \mu_{i,t+1}) \cdot (x_{t+1} - \mu_{i,t+1})^T \tag{6}$$

where ρ is written as:

$$\rho = \alpha \cdot \eta(x, \mu, \Sigma) \tag{7}$$

Finally, we will determine which distributions are most likely to become the background model. Generally, the Gaussians are ordered according to the value of ω/σ in a descending order, and the first B distributions will be chosen as the background model, where

$$B = argmin_b\left(\sum_{k=1}^{b} \omega_{i,k} > T\right) \tag{8}$$

IV. AUTOMIC SEGMENTATION METHOD BASED ON IMPROVED GMM ALGORITHM

In this paper, the approach is consisted of four parts: (1) Obtaining the rough segmentation results of water surface floats by an improved GMM algorithm. (2) Using a light-shadow discriminant function to remove the light and shadow pixels existing in the segmentation results. (3) Smoothing by morphological operations to remove the noise. (4) Taking the results of the above steps as the input and using Graph Cuts algorithm to optimize the segmentation results.

A. IMPROVED GMM ALGORITHM

In order to reduce the cost of matrix inversion, the Stauffer algorithm claims that the RGB components of the pixel x_t have the same variances, and the covariance matrix is expressed as:

$$\Sigma_{i,t} = \sigma_i^2 \cdot I \tag{9}$$

Actually, the change of one component (e.g., the color changes from dark red to vermilion) does not indicate that the pixel has transformed from the background to the foreground. Therefore, in the IGASM authors applied that the variance of each color component is represented and updated respectively.

$$\Sigma_{i,t} = \begin{bmatrix} \sigma_{r,t}^2 & & \\ & \sigma_{g,t}^2 & \\ & & \sigma_{b,t}^2 \end{bmatrix} \tag{10}$$

Besides, in the classical GMM algorithm, the stationary floats may gradually be merged into the background, resulting in some undetectable cases. For example, when the floats first appear in the monitoring range, which is detected successfully, however, if its value cannot match any background distributions, and then a new distribution will be generated to replace the original model with the least prior weight. According to (4), (5) and (6), the prior weight ω will be increased and the variance σ^2 will be decreased gradually over time. When the ratio of ω/σ exceeds that of the original background model, the GMM algorithm mistakenly takes it as "background", which leads to the detection failure.

To this end, this paper improves the updating strategy of the GMM algorithm, and a light-shadow discriminant function is used to divide the foreground pixels into two parts: with regard to those "false" foreground pixels caused by the light and shadow, we update their distribution parameters by the original updating strategy; with regard to those "real" foreground pixels, we will not update their distribution parameters to prevent them from being merged into the background.

Figure 1 shows that the ratio of ω/σ increases continuously in GMM, whereas it remains stable in IGASM, which indicates that with the new updating strategy the improved algorithm can effectively prevent the stationary water surface floats from being merged into the background and can maintain a long-term stable background.

B. LIGHT-SHADOW DISCRIMINANT FUNCTION

For the background subtraction algorithms, the light and the shadow caused by the foreground objects are always vital problems. In the process of extracting foreground objects, the detection accuracy will be affected due to the large similarity between shadow pixels and foreground objects. Besides, the sudden changes of light may also interfere with the detection results. Therefore, a robust and efficient segmentation method should be designed to solve this problem.

The HSV color space (*H, S, V*) uses Hue, Saturation and Value to describe the color characteristics [21]. In this paper,

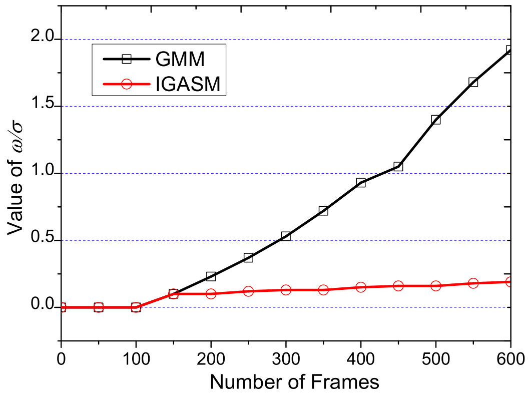


FIGURE 1. **Variation curves of ω/σ in GMM and IGASM.**

the HSV color information is applied to detect the light and shadow because it reproduces the human visual behavior better and it is more sensitive to brightness changes caused by light and shadow [22]. Unlike the real foreground pixels, the component V varies greatly in light and shadow pixels, whereas the changes of components H and S usually should fall into a preset interval [23].

In HSV color space, (h_1, s_1, v_1) and (h_2, s_2, v_2) represent the current pixel value and the background pixel value, respectively. The light-shadow discriminant function is given as follows:

$$L(x, y) = \begin{cases} 1, & \text{if} \frac{|v_1 - v_2|}{v_2} \geq T_V \text{ and } |s_1 - s_2| < T_S \\ & \text{and } |h_1 - h_2| < T_H \\ 0, & \text{otherwise} \end{cases} \tag{11}$$

where $L(x, y)$ denotes the pixel of light and shadow, T_V is the threshold of V, which is related to the intensity of light. A stronger light gives rise to a larger T_V. Typically, the value is about 0.2.T_S and T_H denote the thresholds of components S and H, respectively, and the typical values are $T_S = 0.13$ and $T_H = 0.15$.

This discriminant function solves the problems of light and shadow effectively and removes the light and shadow pixels which are mistakenly considered as the foreground pixels. Through this function, the real foreground pixels are obtained, as illustrated in Figure 2 (e) and (f).

C. SMOOTHING AFTER SEGMENTATION

Although we have obtained the original water surface floats segmentation result, some unexpected objects such as the speckle noise or disturbance blocks needs to be removed. Thus, the morphological approach has been introduced to solve this problem [24]. In this paper, an open operation is applied to remove the noise and disturbance blocks. The open operation is a fundamental morphological approach in the image processing, which makes an erosion of the image before dilating it. The process is denoted by $A \circ B$, and it is expressed as:

$$A \circ B = (A \otimes B) \oplus B \tag{12}$$

where A is the original image. B is a structuring element, which commonly selects the "diamonds" with a size of 3×3. "$\otimes$" denotes the operator of erosion, and "$\oplus$" denotes the operator of dilation. Thus, the expression of "$(A \otimes B) \oplus B$" denotes the dilation of A by B.

The open operation breaks off the narrow and removes the small interference blocks in the image, making the contour of the object much smooth. Figure 3 (b) shows the small disturbance blocks after the segmentation. It mistakes the ripple on the water surface as a part of foreground object. Through the open operation, a smoother and clearer contour of the water surface floats is obtained, as illustrated in Figure 3 (c).

D. ACCURATE SEGMENTATION BY GRAPH CUTS

After the previous processing, the segmented water surface floats may be smaller than the real ones. Besides, to judge whether a pixel belongs to the foreground or not, the characteristics of the surrounding pixels will be examined. The Graph Cuts algorithm segments the image with some additional spatial information such as gray level, region information and boundary information, which have been ignored in previous works. In this paper, Graph Cuts algorithm is exploited to improve the segmentation accuracy.

In Graph Cuts, we define $A = (A_1, \ldots, A_p, \ldots, A_{|P|})$ to be a binary vector whose element (such as A_p) specify assignments to pixel p in P. Each A_p can be either an "object" or a "background." The energy cost function $E(A)$ is expressed as:

$$E(A) = \alpha R(A) + B(A) \tag{13}$$

where α is an influencing component, $R(A)$ is the "region" properties of A and assumes the individual penalties for assigning the pixel p to "object" and "background." $B(A)$ combines the "boundary" properties and is interpreted as a penalty for a discontinuity among the pixels. $E(A)$ denotes the energy cost function, and it achieves the minimum value when all the pixels in the graph are correctly classified into the categories of "object" or "background."

According to the characteristics of Graph Cuts algorithm, it can be technically combined with the segmentation method, and thus the algorithm steps are given as follows: first, we use the foreground and background pixels obtained from the previous operations as an input to the Graph Cuts algorithm. Then, we build an undirected graph model and construct an energy function with these foreground and background hints. Finally, to reduce the energy consumption, the minimum cut algorithm is used to solve the global optimal segmentation.

Figure 4(b) shows that the segmentation of the floats is smaller than the real ones without using the Graph Cuts. For the Graph Cuts algorithm segments the image with spatial information, whereas GMM classifies the pixels with temporal information, the combination of the two methods (i.e., the usage of spatial-temporal information) can improve

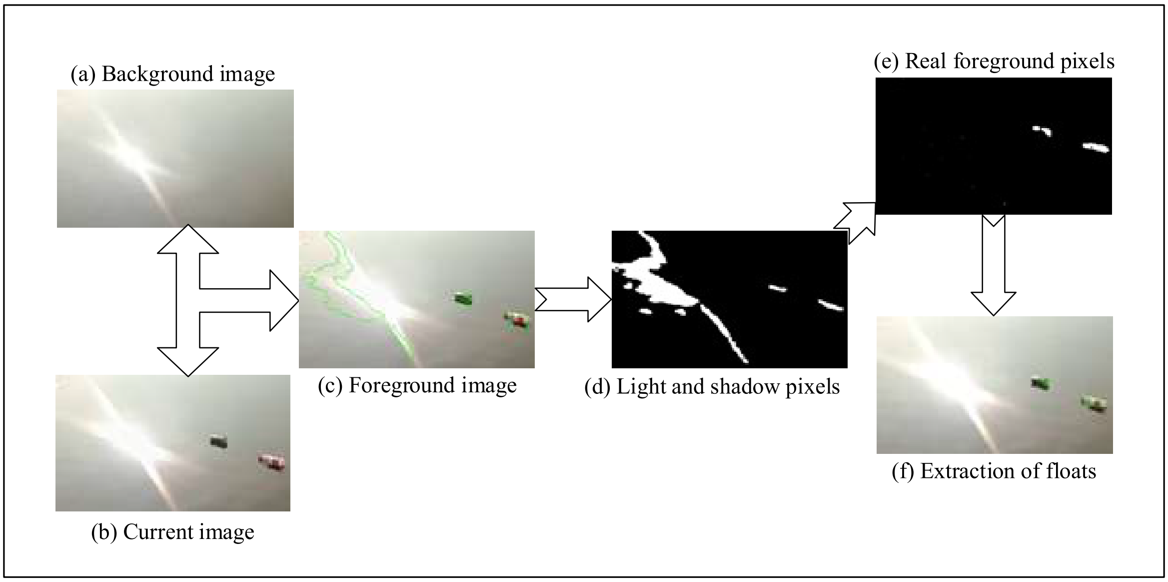


FIGURE 2. Scheme of the light and shadow elimination.

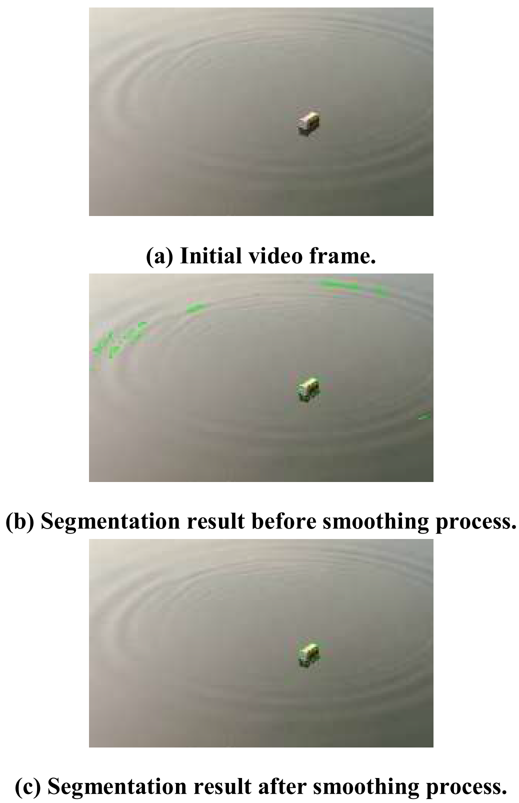


FIGURE 3. Smoothing process after segmentation.

the segmentation accuracy, and an example result is shown in Figure 4 (c).

E. DESCRIPTION OF IGASM

In this section, an improved GMM-based automatic segmentation method (IGASM) is proposed, and the detailed steps are provided as follows:

Step 1 : The video frames are imported at a sampling rate of 30 frames per second.

Step 2 : According to the imported video frames, if the background model can be constructed, and then Step 4 is carried out; otherwise, Step 3 is carried out.

Step 3 : The background model is initialized through GMM (200 video frames are typically required for this initialization), and then return to Step 1.

Step 4: The foreground pixels are separated from the background pixels according to formula (3).

Step 5 : The light-shadow discriminant function is applied to eliminate the pixels of light and shadow by (10), and then the foreground objects are obtained.

Step 6 : The background model is updated with the improved updating strategy.

Step 7 : The segmentation results are smoothed via the open operation, and the "diamonds" are selected as the structural elements to deal with the interference of the water surface ripples.

Step 8 : The segmentation results are further optimized by Graph Cuts.

Step 9 : The contours of the water surface floats in the video frames are identified.

The pseudocode of this method is present as Algorithm 1.

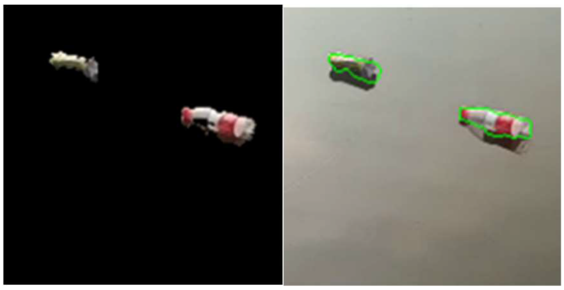
V. EXPERIMENTAL RESULTS AND ANALYSIS

A. WORK TOOLS AND SOURCE VIDEOS

In this section, in order to validate the performance of the proposed method IGASM, some simulation experiments are carried out on a laptop. Six videos of 900 frames are sampled for the experiments of IGASM. The video frames have the size of 640 × 480 and are generated with a camera and the light changes in all test videos, especially in video 1 and video 2. These experiments are completed on the computer

(a) Initial video frame.

(b) Segmentation result without Graph Cuts.



(c) Segmentation result with Graph Cuts.

FIGURE 4. An example of segmentation results.

Algorithm 1 Improved GMM-Based Automatic Segmentation Method (IGASM)

```
Input: video frame: frame;
Output: floating objects: obj;
frame ← capture.read()
while (frame) {
  if ( ! background model) {
    background model ← GMM(frame)
    Continue;
  }
  else {
    obj ← GMM background subtraction(frame, 0)
    bkg ← GMM background subtraction(frame, 1)
    obj ← obj−light-shadow detection(obj)
    obj ← morphology open operation(obj, diamond)
    obj ← Graph Cuts(obj, bkg)
  }
    show (obj, frame)
}
```

with Intel Core^{TM}i5-6300HQ and 8GB RAM. The average computing time for handling each frame is 310 ms and it can be used smoothly in the online scenario. The parameter K of the Gaussian mixture model is set to 3, and the learning rate α is set to 0.06.

B. EVALUATION RESULTS

To evaluate our work, we introduce the foreground detection accuracy ξ and the light-shadow discrimination accuracy η proposed by Prati *et al.* [25] to evaluate the segmentation results. ξ and η are defined as:

$$\begin{cases} \xi = \dfrac{T_o}{T_o + F_o + U_o} \\ \eta = \dfrac{T_s}{T_s + U_s} \end{cases} \tag{14}$$

where T_o denotes the number of the foreground pixels which have been correctly detected and T_s denotes the number of the light and shadow pixels which have been correctly detected. Likewise, U_o and U_s denote those that have not been detected. F_o denotes the number of pixels which have been mistakenly detected as the foreground pixels. The evaluation results of GMM and IGASM are shown in Table 1.

TABLE 1. Water surface floats segmentation for videos.

Video	GMM		IGASM	
	ξ(%)	η(%)	ξ(%)	η(%)
1	65.91	11.30	87.28	85.72
2	56.88	25.82	79.27	69.75
3	71.66	46.08	86.84	91.31
4	68.03	36.19	89.71	81.78
5	85.43	55.87	92.49	94.53
6	74.52	49.16	90.32	88.63

The results in Table 1 illustrate that IGASM can effectively detect the floats on the water surface and eliminate the light and shadow well. Compared with GMM, the IGASM has a better segmentation performance, especially in the scenes where the light changes dramatically and both the foreground detection accuracy and light-shadow discrimination accuracy are much higher than those of GMM.

Besides, the F_1 score and recall rate R are used to measure the balance and integrity of the segmentation results. The definition of the two measures are given as follows:

$$\begin{cases} F_1 = \dfrac{2T_o}{F + T_o - TN} \\ R = \dfrac{T_o}{T_o + U_o} \end{cases} \tag{15}$$

where F is the total number of pixels in the video frame, TN is the number of background pixels which have been segmented correctly. Both the F_1 score and recall rate R fall into the numerical interval [0, 1].

Figure 5 shows that IGASM has much higher F_1 scores in all source videos, compared with MTEA proposed in [18] and IGMT proposed in [20], which indicates that IGASM has a

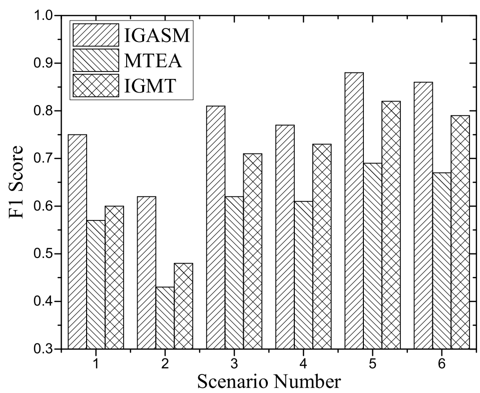


FIGURE 5. Comparison of F_1 score in different algorithms.

better performance in terms of the segmentation of the water surface floats in different scenarios.

In Figure 6, the segmentation result dealt by the Graph Cuts algorithm has a larger recall than those without the assistance of Graph Cuts, which indicates that the Graph Cuts algorithm can be well combined with the improved GMM algorithm to solve the incomplete segmentation problem of the water surface floats and improve the accuracy and integrity of the segmentation results.

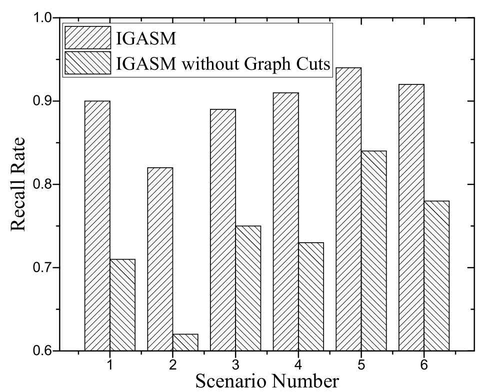


FIGURE 6. Recall rate comparison between IGASM and IGASM without Graph Cuts.

VI. CONCLUSION

Based on GMM algorithm, this paper proposes an automatic segmentation method for the detection of water surface floats. By improving the updating strategy, the stationary floats can be successfully detected, while a light-shadow discriminant function is used to solve the problems of light and shadow in the segmentation results as well. Then, the open operation is applied to smooth the contour and Graph Cuts algorithm, and thus the accuracy of the segmentation results can be further improved. Experimental results show that IGASM exhibits a preferable performance in the segmentation of water surface floats, especially in the scenarios where the light changes dramatically and the water surface floats remain stationary.

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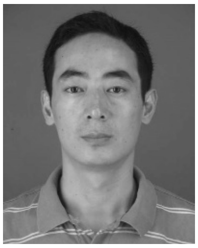

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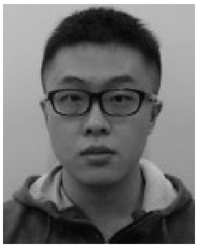

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