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An improved K-means clustering algorithm for fish image segmentation[☆]

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ABSTRACT

Fish contour extraction from images is the foundation of many fish image applications such as disease early warning and diagnostics, animal behavior, aquatic product processing, etc. In order to improve the accuracy and stability of fish image segmentation, we propose a new fish images segmentation method which is the combination of the K-means clustering segmentation algorithm and mathematical morphology. Firstly, the traditional K-means clustering segmentation algorithm has been improved for fish images. The best number of clusters is determined by the number of gray histogram peaks, and the cluster centers data is filtered by comparing the mean with the threshold decided by Otsu. Secondly, the opening and closing operations of mathematical morphology are used to get the contour of the fish body. The experimental results show that the algorithm realized the separation between the fish image and the background in the condition of complex backgrounds. Compared with Otsu and other segmentation algorithms, our algorithm is more accurate and stable.

1. Introduction

Fisheries production has been one of the pillar industries of China's agricultural production. But fish diseases are increasingly prevalent and seriously threaten fishery production. In order to quickly and accurately prevent and treat fish diseases, image analysis technology is introduced into fish disease diagnosis systems by researchers. Fish image segmentation is the basic step in the fish image feature extraction. At the same time, fish image segmentation can be applied in the fields of aquatic products processing, fish identifying and classifying, fish behavior, etc. It has become one of the main research topics in recent years.

Fish image processing comprises fish image preprocessing and fish image analysis. Image preprocessing is to eliminate noise, suppress background noise and highlight the target area of the image. The technologies in image preprocessing include image segmentation and contour extraction. Image segmentation is one of the most important parts of image processing and machine vision, which is the premise of image analysis and pattern recognition. This paper does research on the fish image segmentation in complex backgrounds.

There are many image segmentation methods, such as threshold segmentation, image-domain based segmentation, statistical analysis methods and artificial neural network methods. It has been widely used for target segmentation in crop

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diseases. The clustering algorithm applied to image segmentation theory is on the basis of the aggregation of image pixels in the feature space, Tan Zhicun [1] proposed an improved genetic K-means clustering algorithm for the image segmentation method. Cor J. Veenman [2] thought that image segmentation could be realized step by step through several scales of the clustering. Ng, H.P. [3] proposed a combination of K-means clustering and an improved watershed segmentation algorithm for medical image segmentation. Hu Jing [4] proposed an improved fuzzy C-means clustering algorithm for fish lesion segmentation.

Literature on fish image segmentation is listed below: Sun Xueyan [5] used the edge detection method of Gaussian Laplace filtering, that can easily detect false edges and is noise-sensitive. In the cyprinid diseased fish image feature extraction algorithm, Wang Yan [6] proposed a dual-threshold difference between the shadow method. It applies to the image of a simple background, whose gray histogram has two peaks. The segmentation methods used in the above literature have certain limitations, and especially in complex background situations the results corresponding to fish image segmentation are often ineffective. This paper proposes a method based on K-means clustering and mathematical morphology image processing to solve the difficulty of fish image segmentation in the complex background.

The main contributions of the paper include:

(1) The optimal number of clusters according to the image gray histogram peaks' number is used to improve the tradition K-means algorithm in order to solve the uncertainty of the number of clusters.
(2) The initial cluster centers are filtered in the K-means clustering algorithm to solve the randomness of the initial cluster centers.

2. Methods

In this paper we use the K-means clustering algorithm for image segmentation, improvement measures were respectively proposed for the two shortcomings of the randomness of clusters' number and initial cluster centers. The segmented image is handled with morphological processing in order to get the complete contour. The improved algorithm realized the separation between fish image and background in the condition of a complex background. Compared with other segmentation algorithms, the results are of high accuracy and stability.

2.1. *K-means clustering segmentation algorithm*

K-means clustering supposed by Mac Queen [7,8] is an unsupervised classification algorithm based on a clustering technique. It divides data into a predetermined class K on the basis of minimizing the error function. The K-means clustering algorithm is a partitioning algorithm of the feature space clustering algorithms, which is widely used.

The K-means clustering algorithm steps are as follows:

Step 1: Randomly select from the data set of k points as initial cluster centers.
Step 2: Respectively calculate the distance of each sample to the cluster centers, the sample is placed under the sample from the nearest class.
Step 3: According to the clustering results, recalculate the cluster center. The calculation method is to take the arithmetic mean of all the elements as the new clustering center.
Step 4: According to the new center, re-cluster all the elements of the data set.
Step 5: Repeat Step 4 until the clustering does not change.
Step 6: Output the result.

Assuming that there are N data points in total, they have to be divided into k clusters. The K-means clustering algorithm is to minimize J:

$$J = \sum_{n=1}^{N} \sum_{k=1}^{K} \|x_n - \mu_k\|^2 \gamma_{nk}. \tag{1}$$

If the data points are classified into the closest center, we will get the minimum value of J. When data point n is classified into *cluster* (k), γ_{nk} is 1, and 0 otherwise. We can adopt an iterative approach to get the minimum value of J: firstly, we fix μ_k and select the optimal γ_{nk}. The next step is to fix γ_{nk} and seek the best μ_k. We get the derivative of J to μ_k, and make the derivative equal zero. When we get the smallest J, μ_k should be met:

$$\mu_k = \frac{\sum_n \gamma_{nk} x_n}{\sum_n \gamma_{nk}}. \tag{2}$$

The value of μ_k should be the mean of all the data points in *cluster* (k). We always get the minimum value of J during each iteration, so J will continue to reduce (or remain unchanged), but does not increase, which guarantees the k-means will eventually reach a minimum.

What affect the K-means clustering results are mainly two factors [9]: one is the choice of the value of clusters k, the other one is the initial cluster centers.

The number of clusters k values is often determined by people's prior knowledge [10]. If the specified number of clusters is too large, the image will be split too small, and the time complexity is high, which affects the efficiency of the program

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running. On the contrary, if the number of clusters is too small, the target will be split incompletely or over-segmentation will appear. Therefore, selecting an appropriate number of clusters is very important for good image segmentation results.

The K-means clustering algorithm largely depends on the initial cluster centers [11]. The shortcomings of a random selection of the initial cluster centers is that if the classification of the initial cluster centers is seriously deviated from the global optimum classification [12], the algorithm may fall into the local optimum value. When the number of clusters is relatively large, this disadvantage appears more frequently. And under this condition the image must be processed in several rounds of clustering, so that it is possible to achieve satisfactory results.

If we use the K-means clustering algorithm to segment an image several times, the results are different with the changes of the initial cluster centers. The stability of the initial cluster centers has great impact on the segmentation results' quality.

2.2. Improved K-means clustering segmentation algorithm

The improved K-means clustering segmentation algorithm of this paper obtained the number of clusters and chose the best initial cluster centers.

2.2.1. The value of clustering number

In order to solve the uncertainty of the number of clusters, this paper proposes the number of image histogram peaks (or troughs) as the number of clusters in the K-means clustering algorithm. The main basis is that the K-means clustering segmentation algorithm is a clustering process based on image gray values and histogram peaks and troughs which respond to the image gray level distribution changes. So this paper takes the number of histogram peaks (or troughs) as the number of clusters. If the image histogram has k peaks, then the number of image clusters using the K-means clustering algorithm is k.

Steps in calculating the histogram peaks: firstly, smooth the image histogram, then do the derivative operation to the fitting curve and get peaks of the curve, and make a reasonable choice according to the given distance threshold. If the point adjacent to the peak point is less than the threshold for the distance it will be discarded, and finally we mark the peak point on the histogram to calculate the peak number as the number of clusters. We calculated the distance of each pair of adjacent peak and valley points. The threshold value is the average of all calculated distances:

$$peakDis = \frac{\sum_{i=0}^{M} dis(i)}{M}. \tag{3}$$

In the formula, $dis(i)$ is the distance between adjacent peak and valley points, and M is the number of the distance.

2.2.2. Initial clustering centers

For the randomness of the k-means clustering algorithm initial cluster centers, we improved the algorithm to select a threshold determined by Otsu as the filtering basis of initial cluster centers.

This is proposed by Nobuyuki Otsu [13] and is an adaptive threshold method. The basic principle is based on the image histogram to separate the target and the background according to the calculated threshold. The threshold is the gray value which makes the greatest difference in gray level between the target and the background.

P_A, P_B is the probability of occurrence. $\omega_A,\ \omega_B$ is the mean gray of A and B. ω_0 is the mean gray of the whole image. A, B are the two regional between-class variance:

$$\sigma^2 = p_A\left(\omega_A - \omega_0\right)^2 + p_B\left(\omega_B - \omega_0\right)^2. \tag{4}$$

The method takes the between-class variance of the two types as the criterion. And it takes t^* that makes σ^2 the largest as the best appropriate threshold. The greater the difference between classes, the smaller the differences within the class, using Otsu can obtain the better result.

The calculation of Otsu is simple and it has low time complexity. However if we use the method of Otsu in fish image segmentation directly, there will be the phenomenon of incomplete segmentation. Within the target class, there is a large difference. The abdomen of the fish is white, while the fish tail, the back of the fish and the fins are mostly dark. Taking into account the actual facts that the difference between background and target is large for fish images, we use a threshold determined by Otsu as the filtering basis of initial cluster centers.

The basic steps are as follows:

(1) Calculate the optimal segmentation threshold *level* by using Otsu.
(2) Use the K-means clustering algorithm to select the initial cluster centers randomly.
(3) Calculate the mean of the cluster centers and get the difference *dif* between the mean and *level*.
(4) Make comparison between *dif* and the given threshold T, if greater than the threshold, repeat (2) and (3); less than the threshold, get the value of the initial cluster centers.

2.3. Mathematical morphology

Mathematical morphology is one of the mathematical tools for image analysis on the basis of structural elements. The idea [14] is using some form of structural elements to measure and extract the corresponding shape in the image in order

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Fig. 1. High back crucian carp [16].

Fig. 2. Common carp.

to achieve the purpose of image analysis and recognition. The basic operations [15] of mathematical morphology include erosion, dilation, opening operation and closing operation:

$$\text{Erosion formula}: A \ominus B = \{x | B + x \subseteq A\} \tag{5}$$

$$\text{Dilation formula}: A \oplus B = \{x | B + x \neq \emptyset\} \tag{6}$$

$$\text{Opening operation}: A \circ B = \{A \ominus B\} \oplus B \tag{7}$$

$$\text{Closing operation}: A \cdot B = \{A \oplus B\} \ominus B. \tag{8}$$

Binary morphological dilation and erosion can be transformed into a collection of logical operators. It is used to segment the binary image, refine, extract the skeleton, fill the area, and extract the edge.

Edge extraction:

$$\beta(A) = A - (A \ominus B). \tag{9}$$

Using erosion to A by structure element B, letting A minus erosion result, we will get the edge of target A.

In the fish contour extraction process, we use the opening operation for separation of target and background, connect the fracture zone with the closing operation, use area fill to fill holes, and adopt boundary extraction for fish contours. Given the shape of the fish, we selected a radius of five disk-shaped structural elements.

3. Algorithm realization

The steps of the improved K-means clustering segmentation algorithm proposed by this paper are as follows: firstly enter the original images, and convert the images to grayscale. Secondly use the improved K-means clustering algorithm for segmentation, and get the results of image segmentation. Thirdly adopt mathematical morphology to obtain the boundary of the fish body. Finally get contour images of the fish.

This paper selects carp images as test data. The test image is shown in Figs. 1 and 2.

3.1. *K-means clustering segmentation algorithm*

3.1.1. *The selection of cluster number*

According to the image histogram, we determine the number of clusters. As shown in Figs. 3 and 4, the gray histogram peaks are marked.

According to the star-shaped markers, Fig. 1 has 9 peaks, so the resultant number of clusters k is 9. Fig. 2 has 8 peaks, so the cluster number is 8.

In order to discuss the impact of different k values for the segmentation results, we randomly selected three groups of different k, $k = 2$, $k = 6$ and the value of k is determined by the peaks' number in this paper. The segmentation results are listed respectively. Comparative results are shown in Figs. 5 and 6.

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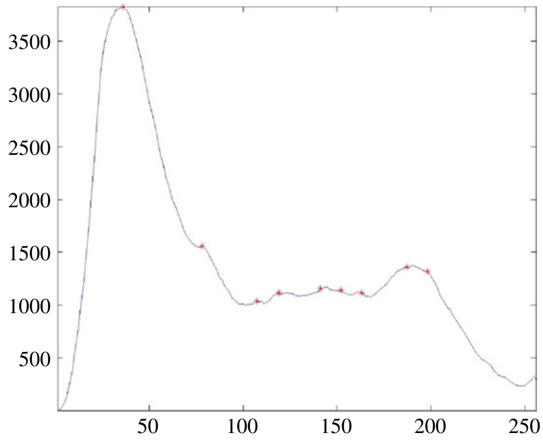

Fig. 3. Gray histogram of high back crucian carp.

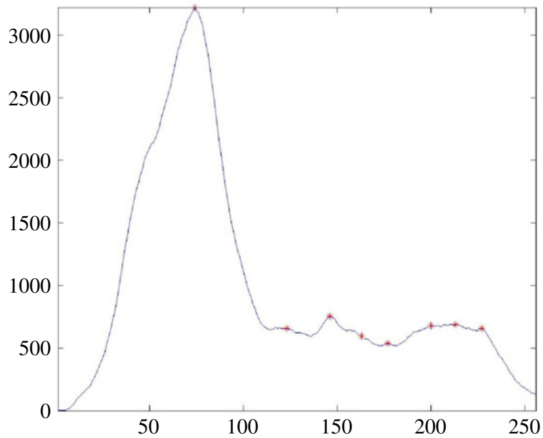

Fig. 4. Gray histogram of common carp.

Fig. 5. Segmentation results of Fig. 1. (a) $k = 2$, (b) $k = 6$ and (c) $k = 9$ (peaks' number of Fig. 3).

Fig. 6. Segmentation results of Fig. 2. (a) $k = 2$, (b) $k = 6$ and (c) $k = 8$ (peaks' number of Fig. 4).

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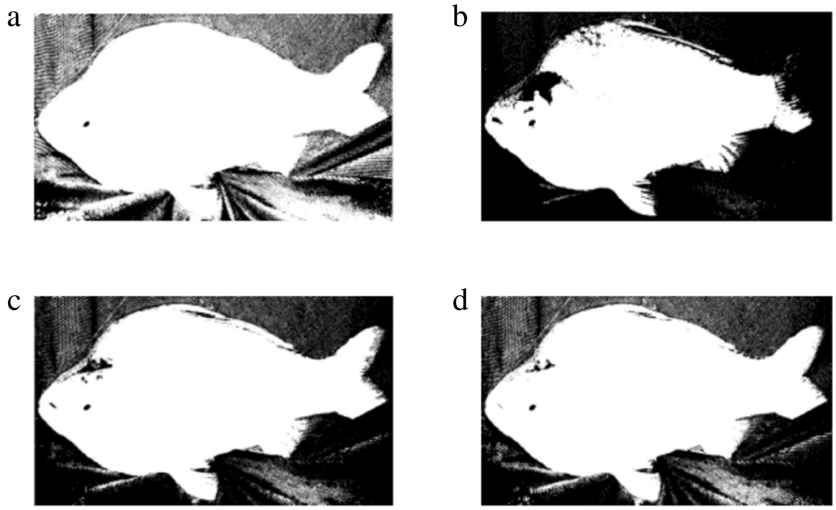

Fig. 7. The contrast of initial cluster centers to improve before and after (a) mean of random cluster center equals 90, (b) mean of random cluster center equals 151, (c) mean of selected cluster center equals 110, (d) mean of selected cluster center equals 108.

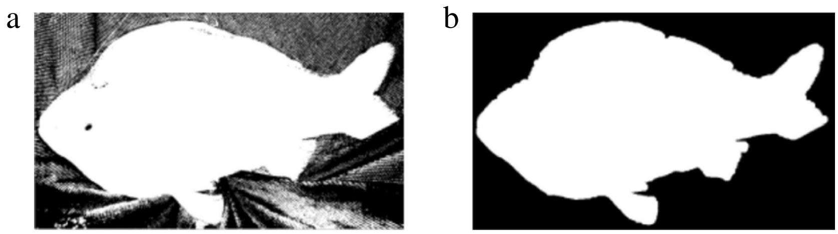

Fig. 8. The result of opening operation. (a) Image segmentation result. (b) The result of opening operation.

By contrast, a more complete target can be achieved by the improved method, taking histogram peaks as the number of clusters.

3.1.2. The selection of initial cluster center

After the number of clusters is determined, we get the threshold determined by Otsu to select the initial cluster centers aimed at solving the problem of instability of the clustering results. The mean of the cluster center can obtain a better segmentation result near the threshold.

For example, in Fig. 1 the threshold value which is decided by Otsu is 109. The mean of the cluster center can obtain a better stable segmentation result near the threshold.

In order to discuss the impact of different initial cluster centers for the segmentation results, we listed different segmentation results of random cluster centers and the stable cluster centers which are selected by the threshold. Different segmentation results' contrast is shown in Fig. 7.

Segmentation results using the improved algorithm is more complete and more stable clustering results. When the segmentation algorithm is unimproved, the results with the selection of initial cluster centers are quite different. Therefore the segmentation is very unstable, and there are large areas of over-segmentation and under-segmentation parts.

3.2. Mathematical morphology algorithm

As the image background is relatively complex, there are still many noise points after the segmentation. Through closing and opening operations of mathematical morphology, area filling and border extraction, we can get a more complete outline of the fish.

The effect of the opening operation and closing operation is shown in Figs. 8 and 9.

The boundary extraction effect is shown in Fig. 10.

3.3. Fish contour extraction results

According to the obtained contour lines and gray image, the contour image is shown in Fig. 11.

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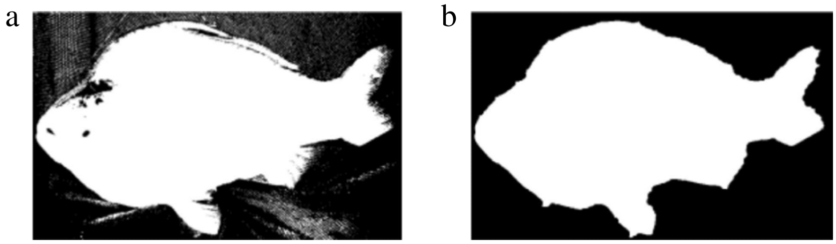

Fig. 9. The result of closing operation. (a) Image segmentation result. (b) The result of closing operation.

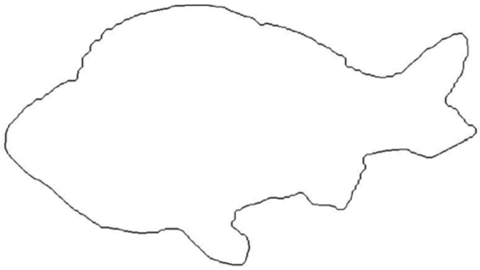

Fig. 10. The effect of boundary extraction.

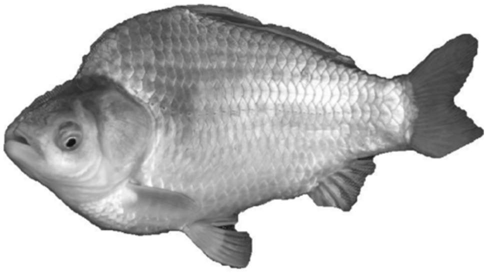

Fig. 11. Fish contour image.

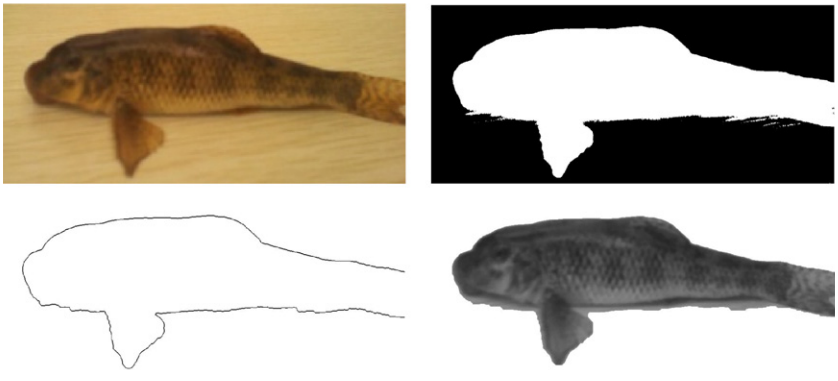

Fig. 12. Segmentation process of test image.

In order to verify the algorithm, we choose images of different backgrounds as test data. Experiment results are shown in Figs. 12 and 13.

4. Analysis of segmentation results

In order to analyze the segmentation results, we compared our improved K-means clustering algorithm for image segmentation with Canny edge detection, Otsu, level set segmentation, EM clustering segmentation algorithm and traditional K-means clustering segmentation algorithm. Experimental results showed that: using the Canny edge detection,

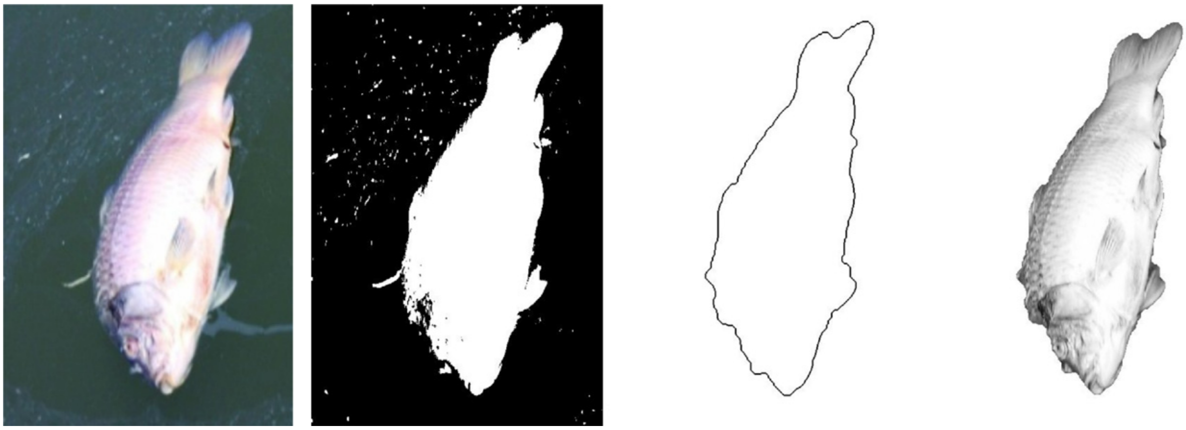

Fig. 13. Segmentation process of test image.

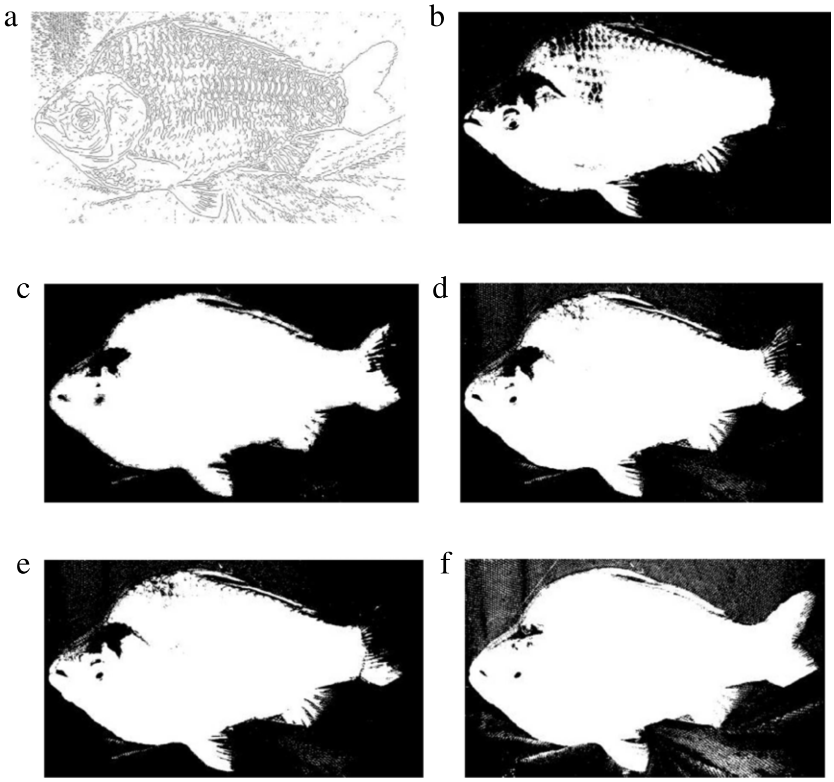

Fig. 14. The contrast of segmentation algorithm. (a) Canny edge detection. (b) Otsu segmentation. (c) Level set segmentation. (d) EM clustering segmentation. (e) Traditional K-means clustering segmentation. (f) Improved K-means clustering segmentation.

the result will get a lot of pseudo-edges in complex backgrounds. Using the Otsu algorithm, the split images obtained a large area of under-segmentation. Level set segmentation and EM clustering segmentation of fish is not complete. Using the improved K-means clustering algorithm, the target image is more complete (see Fig. 14).

5. Conclusion

This paper improved the K-means clustering segmentation algorithm. Firstly, reasonable peaks were chosen in the fitting curve of the gray histogram. The clusters' number is decided by the number of peaks. Secondly, the initial cluster centers were filtered by the threshold of Otsu. Thirdly, the opening operation, closing operation, area filling and border extraction in mathematical morphology are used to process the image after clustering. Ultimately the fish image contour extraction is obtained. Experimental results show that this method applies to the extraction of fish contours in complex backgrounds. The segmentation results are more stable and accurate compared with other segmentation algorithms.

This paper discussed the effects of the number of clusters in the K-means clustering segmentation algorithm to the segmentation results. Experimental results showed that the selection of histogram peaks' number is reasonable. This paper also discussed the effects of the randomness of the initial cluster centers to the segmentation results. If the selection is seriously deviated from the optimal global classification, segmentation results will be a large area of the deviation. Experimental results proved the effectiveness of filtering according to the threshold decided by Otsu.

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