IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received October 7, 2019, accepted November 18, 2019, date of publication December 2, 2019,
date of current version December 23, 2019.

*Digital Object Identifier 10.1109/ACCESS.2019.2956988*

# Algorithm of Adaptive Fast Clustering for Fish Swarm Color Image Segmentation

**LONGQING SUN, BING LUO, TING LIU, YAN LIU, AND YAOGUANG WEI**
College of Information and Electrical Engineering, China Agricultural University, Beijing 100083, China

Corresponding author: Longqing Sun (sunlq@cau.edu.cn)

This work was supported by the National Key Research and Development Plan for the 12th Five-Year Plan under Grant 2015BAD17B04-5.

**ABSTRACT** Fish swarm image segmentation provides an easy to understand and analyze representation for behavior monitoring feature extraction and image information analysis, accurate and effective image segmentation is the basis of fish shoal monitoring. In this paper, algorithm of adaptive fast clustering for fish swarm color image segmentation was proposed by combining the fish swarm hypoxia image features and K-Means++ algorithm. In the RGB color space, the color information of the channel with the maximum average brightness is retained, the others compensation was zero, the generated new image replaced the original. The fish color library was constructed using the gray distribution statistics of the fish swarm targets and background. The pixel probability distribution value in each gray scale range of the normalized gray histogram of the newly generated image is calculated, and combine with the fish group target gray scale reference statistic, the clustering value is determined by two traversing. According to the reserved channel information, the corresponding cluster fish swarm color library is selected for color clustering. The clustering result is processed by threshold transformation to finally realize fish swarm image segmentation. Experiment showed that the average range of structural similarity of our algorithm was [0.93, 1], and the average range of peak signal-to-noise ratio was [44, 50], the running time of the algorithm in this paper is 56% shorter than K-Means ++ algorithm and 71% shorter than the fuzzy clustering algorithm when processing the same images, which could met the requirements of image segmentation quality and accuracy for fish behavior detection.

**INDEX TERMS** Image segmentation, color compensation, color library, cluster value, K-Means++.

## I. INTRODUCTION

Reasonable regulation of aquaculture water environment is crucial to the healthy growth of fish swarm [1]–[3]. It is one of the effective ways to accurately control the aquaculture water environment by effectively and accurately extracting fish targets and analyzing and identifying the relationship between behavior characteristics and environmental factors [4]–[6].

In recent years, many scholars have done a lot of research on image clustering and image segmentation [7]–[11]. Image clustering is the clustering of a color image into several clusters in the image, and each cluster corresponds to the target in the image. An image can get several color classes through the color clustering of the image, and each color class may correspond to several consecutive color blocks in space. Image segmentation is to divide an image into several regions with the same characteristics. Especially under complex conditions, the hard clustering image segmentation based on K-Means and soft clustering based on fuzzy clustering is studied deeply in theory and practice [12]–[17].

Hong *et al.* [18] determined the clustering number by the number of gray histogram peaks in the K-Means clustering process, and the fish image segmentation was realized by combining the mathematical morphology method. Guoqiang *et al.* [19] used Matlab clustering analysis tool, took the B plane of grouper image as input matrix, conducted clustering segmentation on it, and the extraction of complete grouper was realized from complex seawater background. Vij *et al.* [20] used watershed and K-Means segmentation technology to complete color image segmentation, which effectively reduced the occurrence of easy over-segmentation in watershed. Saha *et al.* [21] proposed a multi-focus image fusion algorithm based on source image edge information and K-Means segmentation, so that the segmentation

The associate editor coordinating the review of this manuscript and approving it for publication was Gangyi Jiang.

results have good sharpness and minimum fusion artifacts. Namburu *et al.* [22] introduced rough set and K-Means clustering to eliminate the influence of image noise on segmentation accuracy. Patil *et al.* [23] estimated the number of clusters using edge clustering to realize automatic segmentation of color images. Kazanskiy *et al.* [24] proposed image segmentation with complex hyperspectral method based on pixel spatial proximity, which combined support vector machine and K-Means++ to obtain high accuracy. Arthur and Vassilvitskii [25] proposed a central-based clustering algorithm, which effectively ensured the distance between the initial clustering centers as far as possible and improved the accuracy. Condat [26] proposed a new method of data clustering and image segmentation. Firstly, k regions were fixed to reduce the operation cost of unnecessary. However, this method relied on the discretization of search space, and a limited number of candidates must be specified to determine k centroid. Zheng *et al.* [27] set the value of the image brightness component to a specific, and which used the equivalence relation between the threshold value and the connected domain number to conduct adaptive segmentation, avoiding the interactive input of K value.

Classical fuzzy clustering assigns data to multiple clusters at different degrees of membership but irrelevant data are also allocated to some clusters that do not relate to them. Chowdhary *et al.* [28] bound possibilities method with fuzzy c-mean to resolve this issue after applying intuitionistic fuzzy histogram hyperbolically algorithm in initial preprocessing phase in the mammogram images. Dougherty *et al.* [29] proposed a core-based locally adaptive fuzzy C-Means and probability de-fuzzing classification method, which eliminated the influence of local intensity non-uniformity and noise and improved the accuracy of image segmentation and classification. Chowdhary and Acharjya [30] proposed hybrid possibilistic exponential fuzzy c-mean segmentation approach, exponential FCM intention functions are recalculated and that select data into the clusters. Which solves the well-known fuzzy segmentations like fuzzy c-means (FCM) assign data to every cluster is not realistic in few circumstances. Li *et al.* [31] used multi-channel information and spatial information of fish image to segment, which overcame the problem that traditional Fuzzy C-Means clustering algorithm was sensitive to noise, so as to improve the robustness of the algorithm. Chowdhary and Acharjya *et al.* [32] proposed a novel intuitionistic possibilistic fuzzy c-mean algorithm, possibilistic fuzzy c-mean and intuitionistic fuzzy c-mean are hybridized to overcome the coincident cluster problem, reduces the noise and brings less sensitivity to an outlier. Wan *et al.* [33] proposed the fuzzy c-means (FCM) algorithm and its improved have been proven to be effective in image segmentation, but the methods are not adaptable to process fish swarm images owing to the intrinsic speckle noise. Fuzzy c-means clustering algorithm can determine which clustering category the current data are by assigning membership weight and calculating probability percentage [34], [35]. The algorithm is of high complexity, which consumes a lot of computing resources and is especially sensitive to the noise of image segmentation [36], [37]. The K-Means algorithm with a high complexity and is sensitive to noise and abnormal points [38], [39]. In both soft clustering algorithm and hard clustering algorithm, the clustering value is determined manually, in addition, the algorithm has high complexity and low operating efficiency, making it difficult to meet the real-time segmentation of specific targets.

For the above reasons, we presented algorithm of adaptive fast clustering for fish swarm color Image segmentation. The algorithm flow chart is shown in the figure 1 below:

From the flow chart, firstly, channel separation is carried out on the original image. Through histogram analysis, the channel that contributes the most to the fish swarm target is selected. After color compensation of reserved channel image, a new image is obtained for subsequent segmentation. According to the pixel probability distribution values in each gray scale interval of the normalized histogram of the newly generated image and the benchmark probability statistics of fish swarm, the cluster value of clustering is screened out through two traversal. According to the reserved channel information, the established fish swarm color database is selected to complete the color clustering. The threshold transformation of clustering results is made to achieve the segmentation of fish swarm targets.

## II. MATERIALS AND METHODS

### A. IMAGE DATA ACQUISITION

The data came from the agricultural Internet of things engineering technology research center of China agricultural university. In this paper, we selected 60 crucian (5-7cm) with small individual and clustering habit were as experimental fish. Before data collection, crucian had been living in water for 2 months and had fully adapted to the cultivation environment. The size of the fish tank was 120*120*100cm, the water level was 70cm, and the indoor temperature was about 15 degrees. The device of image acquisition is HIKVISION camera, which was used for video image acquisition, with resolution of 1024*768 pixels, bit depth of 24 bits and 24 frames /s. The image acquisition dates used in this experiment are from February 26, 2019 to March 2, 2019, the camera saves an image everyone minute and collects a total of 7,200 images. The figure 2 is the diagram of the experimental device. In the figure, the dissolved oxygen content in the water is monitored by the Multi3420 sensor, the camera is used for image collection, and the results are transferred to the local computer via local area network for storage.

### B. COLOR CLUSTERING SEGMENTATION ALGORITHM

K-Means++ is a center clustering algorithm. In the process of image clustering, clusters are composed of objects with close Euclidean space distance, and compact and independent are taken as the final goal. Suppose the group of pixels in the image is represented as follows:

$$\{\mathrm{x}_i/(\mathrm{R}_i, \mathrm{G}_i, \mathrm{B}_i)\}_i^N \tag{1}$$

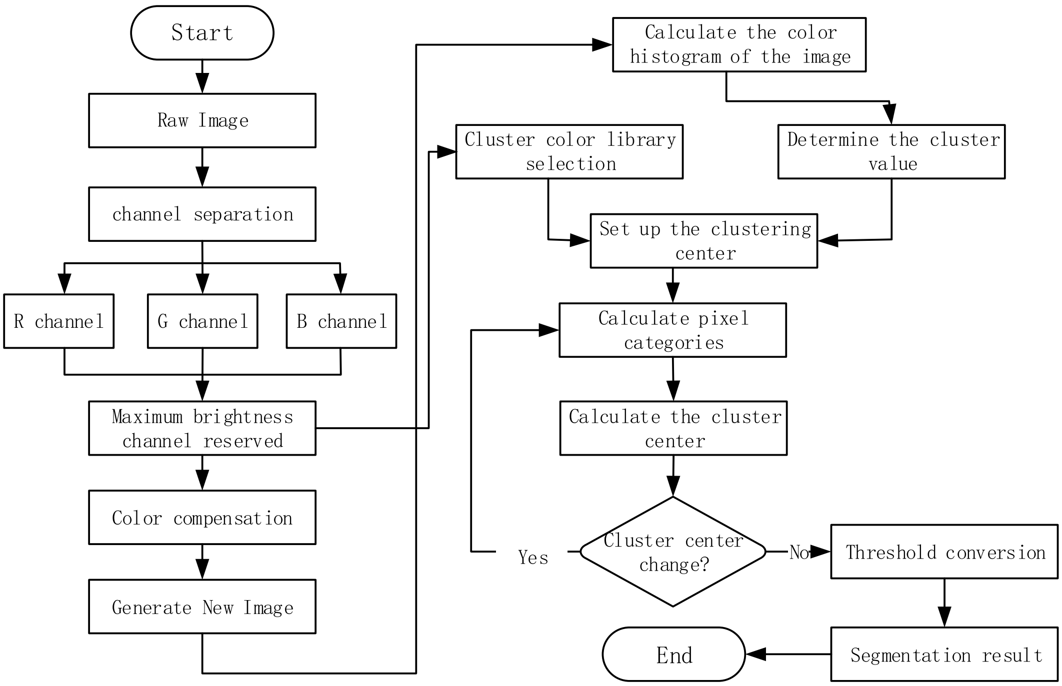


**FIGURE 1.** The algorithm flow chart.

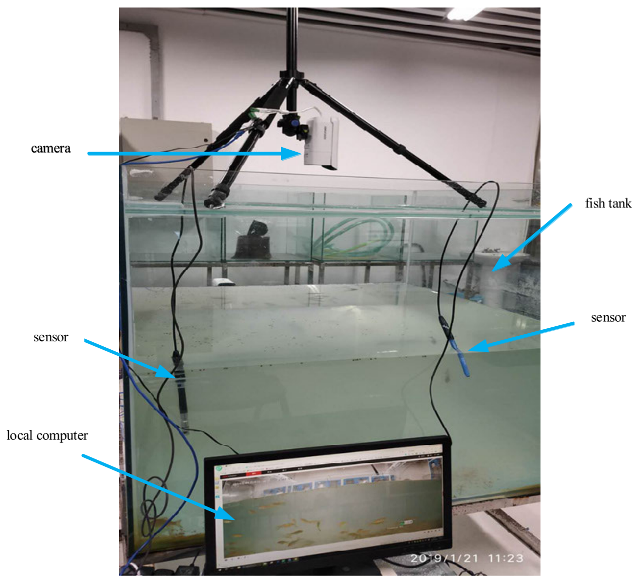


**FIGURE 2.** The experimental equipment.

$N$ is the total number of pixels. $x_i \in R^3$, It means that every sample element was a 3 dimensional vector. Randomly select k cluster center of mass, $\lambda_1, \lambda_2 \cdots \lambda_k \in R^3$, Without considering the spatial position of the points, the formula of $d_{ij}$ for the color similarity of two pixels can be calculated according to the principle of close color value, as follows:

$$d_{ij} = \sqrt{(\mathrm{R}_i - \mathrm{R}_j)^2 + (\mathrm{G}_i - \mathrm{G}_j)^2 + (\mathrm{B}_i - \mathrm{B}_j)^2} \quad i, j \in N \quad (2)$$

Until the following formula is satisfied:

$$o_i := \arg\min ||x_i - \lambda_j||^2 \quad i,\ j = 1, 2 \cdots k \qquad (3)$$

where, $o_i$ represents the nearest point between sample $x_i$ and $k$ clustering centers. $\lambda_j$ is the guess for the sample center of the same class. After the end of clustering, each point is replaced by the center point of the cluster.

### C. THE ESTABLISHMENT OF FISH COLOR LIBRARY

In order to analyze the influence of different channel on image brightness and contrast, we randomly selected 5000 fish images, conducted channel separation operation on them, and counted the average of gray distribution in different channels. In the Figure 3, (a) represents the average normalized histogram of the gray-scale image of the R channel, (b) represents the average normalized histogram of G channel. Figure (c) represents the average normalized histogram of B channel. From the figure 2, we can refer to the brightness and contrast features of different channels intuitively. The peak position of the histogram indicates the overall brightness. If the image is brighter, the peak of the histogram appears in the right part of the histogram. If the image is dark, the peak of histogram is displayed in the left part makes dark details difficult to distinguish. If there is just a small non-zero value in the middle of the histogram, the contrast is low. If the distribution of non-zero values is very much and uniform, the image contrast is higher. It can be seen from figure (a) (b) (c) that the channel G is of high brightness, compared with the average brightness and contrast of channel R and channel B. G channel image contributes the most to fish target.

In the process of color clustering, it is necessary to build a corresponding color library based on the features of the target images. In this paper, the fish shoal color library $L_i$, $i = 0, 1, 2$ is constructed according to the contribution of

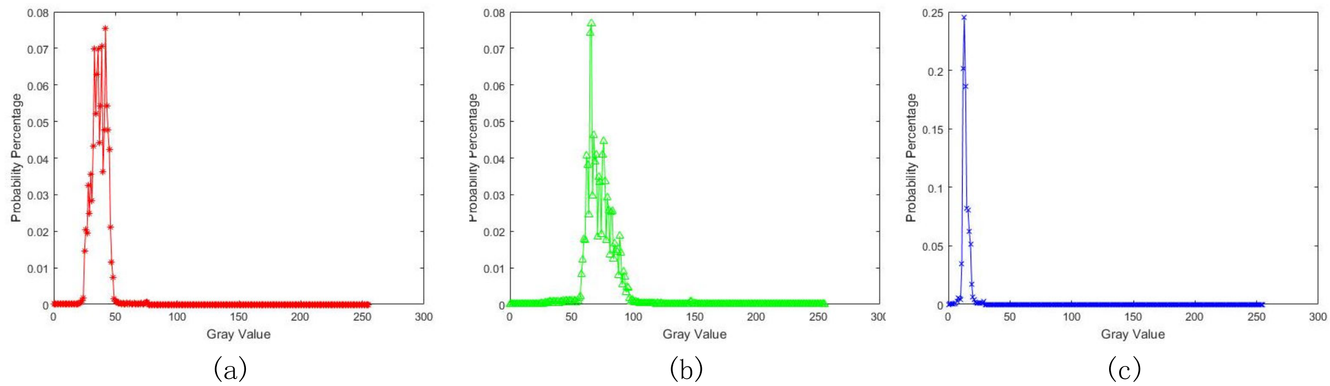


**FIGURE 3.** The average value of gray histogram of different channels.

**TABLE 1.** Partial information of fish swarm color $l_1$ library.

| R_P | G_P | B_P | R_P | G_P | B_P |
|---|---|---|---|---|---|
| 0 | 50 | 0 | 0 | 54 | 0 |
| 0 | 51 | 0 | 0 | 55 | 0 |
| 0 | 52 | 0 | 0 | 56 | 0 |
| 0 | 53 | 0 | 0 | 57 | 0 |

different channel images' brightness. The color library consists of three parts. $L_0$ is the fish swarm color library that only retains the brightness information of R channel image; $L_1$ is only retains the brightness information of G channel image; $L_2$ only retains the brightness information of B channel image. For example, when the average brightness of G channel image is the maximum, $L_1$ is constructed based on the G channel image. The grayscale value range in $L_1$ library is [0, 255], and the grayscale compensation of the remaining two channels is zero. Table 1 shows the color information in the $L_1$ library:

Where, R_P represents the grayscale values of R channel pixels, G_P represents the values of G channel, B_P represents the B channel.

### D. K-MEANS ALGORITHM

K-means algorithm is a clustering algorithm based on partition, which has been widely used in image segmentation. The steps of the algorithm are as follows:

Step 1: $K$ samples were randomly selected from the data set as the initial clustering center;

$$\mathrm{O}=\{\mathrm{o}_1,\mathrm{o}_2, \ldots, o_k\} \tag{4}$$

where, $\mathrm{o}_1,\mathrm{o}_2, \ldots, o_k$ represent randomly selected cluster center, O represents the set of cluster center.

Step 2: For each sample $x_i$ in the data set, the distance from it to $K$ clustering centers is calculated and divided into the corresponding classes of the clustering center with the smallest distance;

Step 3: For each category $\mathrm{o}_i$, its clustering center is recalculated as follows:

$$\mathrm{o}_i = \frac{1}{|o_i|}\sum\nolimits_{x\in o_i} x \tag{5}$$

where, the sample set is $x$, $i = 1, 2\ldots.N$, $N$ is the total number of pixels.

Step 4: Repeat steps 2 and 3, until the cluster center is no longer changed.

### E. FISH SWARM IMAGE SEGMENTATION ALGORITHM

#### 1) FEATURE IMAGE GENERATION

In the RGB color space, the channel with the maximum average brightness in the three channel images is taken as the target channel, and the others with lower are compensated to zero, and the generated new image replaces the original. The three components of a color image are represented by vectors form:

$$\mathrm{Im}\, g(\mathrm{x}, y) = [\mathrm{R(x, y); G(x, y); B(x, y)}] \tag{6}$$

$\mathrm{Im}g(\mathrm{x, y})$ is the pixel value of any point, where (x, y) represents the position coordinates, R(x, y) is the brightness value at the (x, y) pixel point of R channel, G(x, y) represents the brightness value of G channel, B(x, y) represents the brightness at the (x, y) pixel point of B channel. In order to get the most obvious fish swarm feature image, channel separation is carried out for the three-color image, and the channel feature with the maximum average brightness is retained. The others are compensate to zero, and the generated feature image is represented by Seg(x, y).

$$\mathrm{Seg(x, y) = Img(x, y)^{*}M}_i\mathrm{(i = 0, 1, 2)} \tag{7}$$

where, Img(x, y) represents original images. $M_i$ is different compensation operations: $M_0$ means that the brightness information of the R channel will be retained and the others will be zero; $M_1$ means G channel will be retained and the remaining will be compensated to zero; $M_2$ means B channel will be retained and the others will be compensated to zero.

#### 2) DETERMINATION OF CLUSTER VALUE OF FISH SWARM COLOR CLUSTERING

K-Means++ algorithm can ensure the distance between clustering centers as far as possible, but cluster values are determined according to manual experience [25]. The larger the cluster value, the smaller the image segmentation, the higher the time complexity, and the larger number of irrelevant regions can be easily segmented. If the clustering value is too low, incomplete and over segmentation will occur. Choosing the right cluster number has a significant impact on the segmentation. The steps of cluster value selection algorithm in this paper are described as following:

Step 1: set the gray interval. Set the gray image of fish swarm after color compensation is Segray(x, y), where (x, y) is the spatial coordinate, including the grayscale of $c_0, c_1 \cdots c_{255}$. In this paper, the images are divided into $T$ gray intervals according to the gray level to form a new pixel space $R'$, denoted as:

$$R' = \{r_1, r_2, \cdots, r_T\} \tag{8}$$

For each small grayscale interval, the number of pixels is:

$$\mathrm{r}(\mathrm{c}_i, \mathrm{c}_j) = ||\mathrm{Segray}(\mathrm{x}, \mathrm{y}, \mathrm{c}_i) + \mathrm{Segray}(\mathrm{x}, \mathrm{y}, \mathrm{c}_{i+1}) + \cdots + \mathrm{Segray}(\mathrm{x}, \mathrm{y}, \mathrm{c}_j)||(\mathrm{i} < \mathrm{j}) \tag{9}$$

where, R' is the new pixel space, ||*|| means the norm of the sum between the number of pixels in the grayscale interval of $\mathrm{c}_i$ and $c_j$, Segray(x, y, $\mathrm{c}_i$) refers to the number of pixels whose gray value is $\mathrm{c}_i$, (x, y) is the spatial coordinate, $r(\mathrm{c}_i, \mathrm{c}_j)$ represents the total number of pixels between the grayscale interval of $\mathrm{c}_i$ and $\mathrm{c}_j$.

Step 2: traverse the pixels and calculate the total number of pixels in each gray interval. Take any $r_t \in R$ and calculate the total number of pixels in the gray scale interval according to the above formula. Count the percentage of pixels of each gray interval in the total number of pixels, which is represented by $p_t, t = 1, 2, 3 \cdots T$.

$$p_t = \frac{(\mathrm{x}, \mathrm{y})(\mathrm{c}_i, \mathrm{c}_j)}{N}, \quad t = 1, 2, 3 \cdots T \tag{10}$$

In the formula, (x, y) is the spatial coordinates of pixels, $r(\mathrm{c}_i, \mathrm{c}_j)$ represents the total number of pixels in the $\mathrm{c}_i$ and $c_j$. $N$ is the total number of pixels in the image, and $t$ is a positive integer.

Step 3: Sort the pixel distribution probability values of each grayscale interval in step2. In order to select the grayscale interval distribution that has more influence on the target, the benchmark probability value is set as $p_0$. By traversing the probability value of each pixel distribution, we can find the probability distribution value satisfying the following equation:

$$p_t = \frac{(\mathrm{x}, \mathrm{y})(\mathrm{c}_i, \mathrm{c}_j)}{N} > \mathrm{p}_0, \quad t = 1, 2, 3 \cdots T \tag{11}$$

The pixel distribution satisfying the gray range of the above equation is very helpful for foreground segmentation. We consider the color information as a category. After traversing all, the cluster value K is determined as follows:

$$K = \sum_{1}^{T} (\frac{(\mathrm{x}, \mathrm{y})(\mathrm{c}_i, \mathrm{c}_j)}{N} > \mathrm{p}_0) \tag{12}$$

where, (x, y) is the spatial coordinate of pixel, $(\mathrm{c}_i, \mathrm{c}_j)$ represents the grayscale interval of $\mathrm{c}_i$ and $c_j$. $N$ is the total number of pixels, and $p_0$ is the base probability value.

#### 3) CLUSTERING SEGMENTATION FISH COLOR LIBRARY SELECTION

Through the brightness analysis of different channels of Img(x, y), different color compensation methods are adopted, and a new color compensation image Seg(x, y) is generated to replace the original image. $M_i$ represents different compensation operations, where $i = 0, 1, 2$.

If $i = 0$ represents the color compensation by $M_0$ operation, then the generated image will be color clustering by R library.

$$\mathrm{Seg}(\mathrm{x}, \mathrm{y}) = \mathrm{Img}(\mathrm{x}, \mathrm{y})^{*}\mathrm{M}_0 \tag{13}$$

If $i = 1$ represents the color compensation by $M_1$ operation, and the generated images be color clustering by G library.

$$\mathrm{Seg}(\mathrm{x}, \mathrm{y}) = \mathrm{Img}(\mathrm{x}, \mathrm{y})^{*}\mathrm{M}_1 \tag{14}$$

If $i = 2$ represents the color compensation by $M_2$ operation, the result will be color clustering by B library.

$$\mathrm{Seg}(\mathrm{x}, \mathrm{y}) = \mathrm{Img}(\mathrm{x}, \mathrm{y})^{*}\mathrm{M}_2 \tag{15}$$

#### 4) IMAGE COLOR CLUSTERING

According to the determined cluster value K and the fish swarm color library $L_i$, $i = 0, 1, 2$. K-Means ++ algorithm is used to cluster images. A sample point is randomly selected from the cluster color library $L_i$ as an initial center of mass $o_1$, and the remaining center of mass satisfies the following conditions:

$$o_x = l_y \in L_i, x = 1, 2, \cdots, \mathrm{K}; \mathrm{y} = 0, 1 \cdots 255; \ \mathrm{i} = 0, 1, 2 \tag{16}$$

Calculate the distance between each sample point in $L_i$ and $o_1$, the probability as follows:

$$\frac{D(l_y)^2}{\sum_{l_y \in L_i} D(\mathrm{L}_i)^2} \tag{17}$$

$D(\mathrm{L}_i)$ is the distance from each sample point to the nearest center. Select the point with the highest probability as the next initial center of mass. Repeat this step until K initial centers are selected. The sample point is $l_y$ in the color library.

## III. EXPERIMENTAL RESULTS AND DISCUSSION

In the experiment, the experimental platform is desktop, Intel(R)Core(TM)i7-6700 CPU@3.40GHZ 3.41GHZ,8GB. The experimental environment is windows10, Matlab and Python.

### A. EVALUTION OF EXPERIMENTAL SEGMENTATION EFFECT

#### 1) SEGMENTATION RESULTS UNDER DIFFERENT ENVIRONMENTS

In the culture process, the increase of the floating impurities, the color of water and the change of illumination will bring more noise interference, which will challenge the

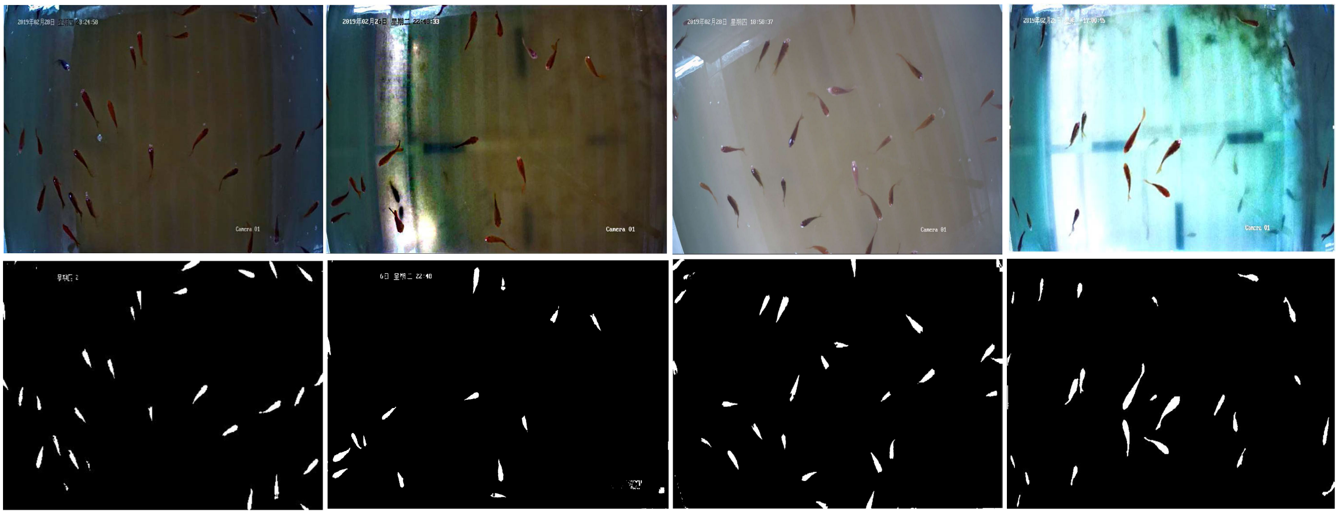

**FIGURE 4.** Image segmentation effect of fish hypoxia for the different aquaculture process.

image segmentation of fish schools. In order to verify the robustness of the algorithm to the image segmentation of fish hypoxia, we randomly selected 100 fish hypoxia images in different environments for segmentation experiments. The segmentation result of some images is shown in figure 4: In different aquaculture environments, our algorithm could clearly segment the target from the image, and the result was complete and clear. It suggests that our algorithm is robust.

### 2) COMPARISON OF DIFFERENT ALGORITHMS

In order to verify the segmentation effect of the proposed algorithm, we used a representative fuzzy clustering algorithm (FCM) and the traditional K-Means++ algorithm for comparison experiments. 100 images collected were segmented by our algorithm and others, and the results were used as the basis for later comparative analysis. Figure 5 presents the results of different segmentation algorithm. In the figure, (a) is the original image, (b) is the image by using our algorithm, (c) is the segmentation result of K-Means ++ algorithm, (d) is the segmentation image of FCM algorithm.

It can see from the results of (c) are fuzzy and incomplete, with poor edge sensitivity and insignificant boundary segmentation. The segmentation in (d) show over-segmentation of the reflective region, a lot of inappropriate and excessive segmentation cannot meet the actual requirements well. It can be seen from the results of (b) that the boundary between the target and the background is bright and the segmentation is complete. Compared with the other algorithm, we achieved effective and accurate segmentation of images.

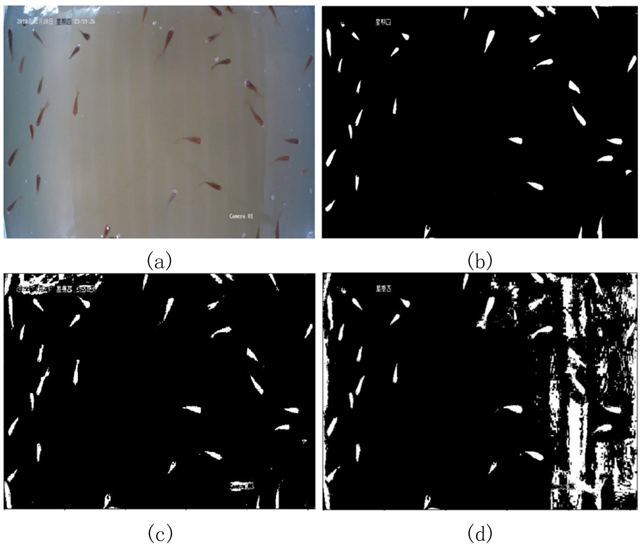

**FIGURE 5.** Comparison segmentation effect of different algorithm.

## B. EVALUATION OF ALGORITHM SEGMENTATION

### 1) STRUCTURAL SIMILARITY

The structural similarity (SSIM) reflects the similarity between the segmentation and the standard image, the value range is [0, 1], the larger the value, the higher the similarity between the segmentation effect and the reference image, the higher the segmentation precision, and the better the effect. Where, the reference image is a binary target segmentation image that is manually calibrated by agricultural experts. When the value is 1, indicating that the segmentation effect is exactly the same as the reference image. This index can measure the distortion degree of the image structure and has certain universality.

$$\sigma_{fg} = \frac{1}{MN-1}\sum_{i=1}^{MN}(f_i-\mu_f)(g_i-\mu_g) \tag{18}$$

$$SSIM(\mathrm{f},\mathrm{g}) = \frac{(2\mu_{\mathrm{f}}\mu_{\mathrm{g}}+C_1)(2\sigma_{fg}+\mathrm{C}_2)}{(\mu_f^2+\mu_g^2+\mathrm{C}_1)(\sigma_f^2+\sigma_g^2+\mathrm{C}_2)} \tag{19}$$

In the formula, sigma $\sigma_{\mathrm{fg}}$ is the covariance of $f$ and $g$, which is the measurement of the structural information of image structure attribute. $MN$ is the total number of pixels. $\sigma_{\mathrm{f}}$ and $\sigma_{\mathrm{g}}$ are standard deviations of $f$ and $g$ respectively. Where,

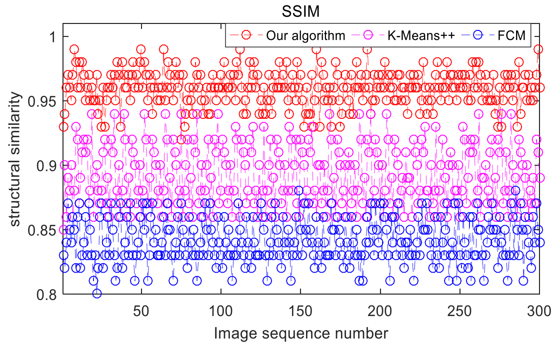


**FIGURE 6.** Structural similarity.

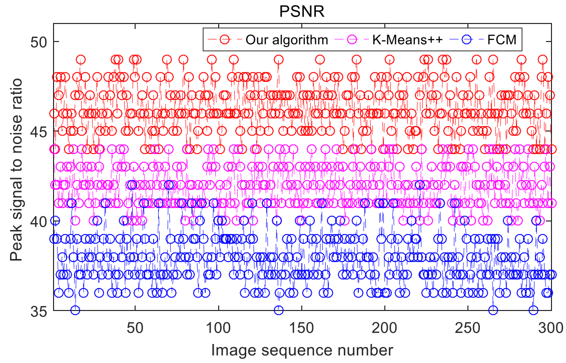


**FIGURE 7.** Peak signal to noise ratio.

$\mu_f$ and $\mu_g$ represent the gray values of segmentation result image $f$ and reference $g$ respectively, and are measures of the brightness of image structure information. $SSIM(f, g)$ is the structural similarity value between $f$ and $g$.

In order to analyze the segmentation performance of different segmentation methods for a given image, this paper presented the structural similarity values of 300 images obtained by different algorithms. It can be seen from the figure 6 that the average range of structural similarity of the algorithm in this paper [0.93, 1]. Compared with others, our algorithm has the highest accuracy, which indicated that the quality of segmentation image was high.

### 2) PEAK SIGNAL-TO-NOISE RATIO

Peak signal to noise ratio (PSNR) is an error sensitive image quality evaluation, the value range is [0,100]. The higher value, less distortion and the higher quality. The specific calculation formula is as follows:

$$PSNR = 10\lg \frac{(A-1)^2 MN}{\sum_{i=1}^{M}\sum_{j=1}^{N} ||g(i,j) - f(i,j)||^2} \tag{20}$$

where, g(i, j) is the gray value of the standard at the coordinate of (i, j), f(i, j) is the gray value of the segmented image at the coordinate of (i, j), $MN$ is the image size, and $A$ is the total gray level.

In order to analyze the performance of different algorithms in a given image, this paper statistics the peak signal-to-noise ratio obtained by using different methods to segment 300 images, as showed in figure. 7. It can be seen from the figure that the average range of peak signal-to-noise ratio of the proposed algorithm was [44-50], which was significantly higher than FCM and K-Means++ algorithm. It indicated that our algorithm had higher reliability and better effect.

### 3) ANALYSIS OF ALGORITHM RUNNING EFFICIENCY

In order to further analyze the segmentation efficiency of different algorithms, 300 fish shoal images collected were randomly divided into three groups. Each group of 100 images for segmentation experiment, all images are 1024*768. The average segmentation time of the three different algorithms is shown in the table below:

**TABLE 2.** Average execution time statistics.

| Group number | Average segmentation time / ms | | |
|---|---|---|---|
| | K-Means++ | FCM algorithm | Our algorithm |
| 1 | 107116.8 | 156558.2 | 46672.4 |
| 2 | 115885.4 | 172631.0 | 49764.8 |
| 3 | 108947.6 | 170858.3 | 48766.1 |
| Average | 110649.9 | 166682.5 | 48401.1 |

**TABLE 3.** Comparison of time and space complexity.

| | K-Means++ | Our algorithm |
|---|---|---|
| Time complexity | O(I*N*K*M*3) | O(I*N*K*M) |
| Space complexity | O(N*M*3) | O(N*M) |

In the table 2, the running time of the algorithm in this paper is 56% shorter than K-Means ++ algorithm and 71% shorter than the fuzzy clustering algorithm when processing the same images. Therefore, the running time complexity of our algorithm is less than the traditional algorithm, and the segmentation efficiency is improved.

The following table compares the time and space complexity of our algorithm and the traditional K-Means ++ algorithm.

In the table 3, K is cluster value, M is the number of fields of each element, N is the number of pixel points in each channel image, I is the number of iterations. After K is selected as the cluster value, I iteration is set, then the time complexity of traversing N pixel points in a single channel is I*N*K*M, and the space complexity is N*M. Therefore, when all three channels are traversed, the time complexity and space complexity are respectively: I*N*K*M*3 and N*M*3. Therefore, the time complexity and space complexity of our algorithm is improved compared with the traditional k-means ++ algorithm.

### 4) ANALYSIS OF ALGORITHM SEGMENTATION ACCURACY

In order to accurately evaluate the segmentation accuracy of the algorithm, 100 images are randomly selected for segmentation, and the segmentation results of the image are compared with the standard reference images marked by agricultural experts. The average accuracy, over-segmentation rate and under-segmentation rate of image segmentation of the three algorithms are statistically analyzed. The results are shown in the following table:

**TABLE 4. Segmentation accuracy evaluation of different algorithms.**

| Evaluation index | Our algorithm | K-Means++ | FCM |
|---|---|---|---|
| Acc_Seg | 92.27% | 85.21% | 78.64% |
| Over_Seg | 1.90% | 7.16% | 17.12% |
| Under_Seg | 10.75% | 9.45% | 11.39% |

In table 4, *Acc_Seg* represents the segmentation accuracy, *Over_Seg* represents the over-segmentation rate, and *Under_Seg* is the under-segmentation rate. *Acc_Seg* refers to the percentage of the area that is accurately divided to the real area in the reference image. The higher the ratio, the more accurate the segmentation; *Over_Seg* refers to the ratio of the pixel points of the segmentation result outside the reference image area; *Under_Seg* is the ratio of the pixel points in which the segmentation result is missing inside the reference image area. The above three indicators are calculated as follows:

$$Acc\_Seg = (1 - \frac{|R_{seg} - T_{seg}|}{R_{seg}}) \times 100\% \tag{21}$$

$$Over\_Seg = \frac{O_{seg}}{R_{seg} + O_{seg}} \tag{22}$$

$$Under\_Seg = \frac{U_{seg}}{R_{seg} + O_{seg}} \tag{23}$$

where, $R_{seg}$ represents the reference area of the segmented image manually drawn by the expert. $T_{seg}$ represents the real area of the image obtained by algorithm segmentation. $O_{seg}$ is the number of pixels that should not be included in the segmentation result, but actually the number of pixels in the segmentation result. $U_{seg}$ is the number of pixels that should be included in the segmentation result, but the number of pixels that are actually not in the segmentation result. $|R_{seg} - T_{seg}|$ is the number of pixels that are incorrectly split.

It can be seen from the table that the algorithm has a lower over-segmentation rate and higher accuracy than the comparison algorithm. Among them, under the same conditions, the over-segmentation rate of the proposed algorithm is only 26.54% and 11.11% of the K-Means++ algorithm and the FCM algorithm, respectively, showing better segmentation performance. Therefore, our algorithm for fish image segmentation has good versatility and effectiveness, is a practical and promising algorithm of image segmentation.

### *C. PARAMETER SELECTION OF ALGORITHM*

#### 1) GRAY INTERVAL NUMBER SELECTION

Gray distribution of the target image has continuity, and the change of pixel gray value between adjacent valleys of the gray histogram has continuity, so that the number of valleys in the normalized histogram is more suitable as the number of the gray interval. In this paper, the number of valleys of normalized histogram was regarded as the number of gray scale interval. Experiment show that the number of gray interval determined by the algorithm not only guarantees that each gray interval had enough pixel points, but also reduced the impact of external environment noise on the segmentation target and improved the accuracy of segmentation.

**TABLE 5. Average iou values of image segmentation results with different benchmark probabilities.**

| $P_0$(%) | R_IOU | G_IOU | B_IOU |
|---|---|---|---|
| 0 | 0.78 | 0.72 | 0.77 |
| 0.2 | 0.80 | 0.79 | 0.81 |
| 0.4 | 0.84 | 0.84 | 0.85 |
| 0.6 | 0.90 | 0.89 | 0.89 |
| 0.8 | 0.92 | 0.91 | 0.90 |
| 1.0 | 0.95 | 0.94 | 0.93 |
| 1.2 | 0.90 | 0.89 | 0.88 |
| 1.4 | 0.87 | 0.88 | 0.85 |
| 1.6 | 0.83 | 0.86 | 0.84 |
| 1.8 | 0.80 | 0.83 | 0.82 |
| 2.0 | 0.79 | 0.80 | 0.79 |

#### 2) DETERMINATION METHOD OF BASE PROBABILITY VALUE

The gray interval was divided according to the number of valleys in the gray histogram of each image, and calculates the probability distribution of the number of pixels in each gray interval respectively. The statistical formula is as follows:

$$p_t = \frac{(\mathrm{x, y})(\mathrm{c}_i, \mathrm{c}_j)}{N}, \quad t = 1, 2, 3 \cdots T \tag{24}$$

In the formula, (x,y) is the spatial coordinates of pixels, $r(\mathrm{c}_i, \mathrm{c}_j)$ represents the total number of pixels in the grayscale interval of $\mathrm{c}_i$ and $c_j$. $N$ represents the total number of pixels in the image, and $t$ is a positive integer. To determine the basic probability $p_0$ in the clustering process, we counted 1000 images and calculated the average IOU of segmentation results under different benchmark probability values. IOU is a measure of image segmentation performance. Given a set of images, IOU measures the similarity between the segmentation region and the real region of the objects existing in the set of images, and is defined by the following equation:

$$IOU = \frac{SR \cap GT}{SR \cup GT} \tag{25}$$

where, IOU represents the intersection and union ratio of segmented and reference image that is a binary target segmentation image manually calibrated by agricultural experts. *SR* and *GT* represent segmentation result and reference image respectively.

In the field of image segmentation, if the results are completely consistent with the original image, then the IOU is 1. The higher the IOU, the higher the segmentation accuracy is considered.

Table 5 was the average IOU values of 1000 images under different benchmark probabilities. As shown in table 3, when $p_0 < 0.01$, as the value of $p_0$ decreases, the average IOU values decrease, when $p_0 > 0.01$, as the $p_0$ increases, the average IOU values decrease, when $p_0 = 0.01$, the average IOU values reaches about 95%, which can meet the requirements of image segmentation. Therefore, this paper adopts the base probability value of 0.01.

In table 5, $P_0$ represents benchmark probability, R_IOU represents the average IOU value of image segmentation results retaining R channel information, G_IOU represents the average IOU value of image segmentation results retaining G channel information, B_IOU represents the average

**TABLE 6. Optimal k-value distribution statistics in the segmentation of 500 images.**

| Method | K=3 | K=4 | K=5 | K=6 | K=7 | K=8 | K=9 |
|---|---|---|---|---|---|---|---|
| Manual | 4 | 26 | 136 | 192 | 108 | 23 | 11 |
| Our | 3 | 29 | 141 | 198 | 102 | 20 | 7 |

Note: Manual represents the determination of cluster value by repeated trial and error. Our represents the clustering cluster value determined by the method in this paper.

IOU value of image segmentation results retaining B channel information.

### 3) CLUSTER VALUE DETERMINATION ANALYSIS

In order to verify the validity of the method to determine K. The artificial trial was compared with the method in this paper to determine K, and the segmentation experiment was carried out for 500 images. In the process of manually determining the cluster value, when the IOU between the result and the reference image reaches the maximum, record the number of K value. The K is output and saved when using our algorithm. The reference image is a binary target segmentation image manually calibrated by agricultural experts.

It can be seen from the table 6 that the cluster values determined in this paper were consistent with the results determined by manual. This showed that the cluster value determination algorithm in this paper is effective.

## IV. CONCLUSION

Based on K-Means++ algorithm, this paper presented algorithm of adaptive fast clustering for fish swarm color Image segmentation. The main conclusions were as follows:

1) Through channel color compensation, a new image was generated to replace the original and reduced a large number of complex noise.
2) Aiming at the features of color clustering and fish hypoxia images, an independent fish cluster color library is constructed by using the gray distribution statistics of fish swarm and background target. Which reduced the time of clustering and improved the efficiency.
3) The clustering value was determined adaptively through the valley number of normalized histogram, so as to avoid the inefficiency and invalid segmentation brought by artificial experience.
4) The average range of structural similarity of our algorithm was [0.93, 1], and the average range of peak signal-to-noise ratio was [44-50]. Compared with the other methods, the quality and accuracy were significantly improved.
5) Experiment showed that the running time of the algorithm in this paper is 56% shorter than K-Means ++ algorithm and 71% shorter than the fuzzy clustering algorithm when processing the same images.

In our algorithm, the color information of the fish swarm was retained to the maximum extent. Although the method eliminated a lot of irrelevant noise, it also caused a loss to the pixel information.

## REFERENCES


[1] H. Liu, H. Li, H. Wei, X. Zhu, D. Han, J. Jin, Y. Yang, and S. Xie, "Biofloc formation improves water quality and fish yield in a freshwater pond aquaculture system," *Aquaculture*, vol. 506, pp. 256-269, May 2019.

[2] N. H. Y. Nhi, C. T. Da, T. Lundh, T. T. Lan, and A. Kiessling, "Comparative evaluation of Brewer's yeast as a replacement for fishmeal in diets for tilapia (Oreochromis niloticus), reared in clear water or biofloc environments," *Aquaculture*, vol. 495, pp. 654–660, Oct. 2018.

[3] B. B. Gonçalves, N. F. Nascimento, M. P. Santos, R. M. Bertolini, G. S. Yasui, and P. C. Giaquinto, "Low concentrations of glyphosate-based herbicide cause complete loss of sperm motility of yellowtail tetra fish Astyanax lacustris," *J. Fish Biol.*, vol. 92, no. 4, pp. 1218–1224, 2018.

[4] J. Zhao, W. Bao, F. Zhang, S. Zhu, Y. Liu, H. Lu, M. Shen, and Z. Ye, "Modified motion influence map and recurrent neural network-based monitoring of the local unusual behaviors for fish school in intensive aquaculture," *Aquaculture*, vol. 493, pp. 165–175, Aug. 2018.

[5] A. Ibrahim, A. Ahmed, S. Hussein, and A. E. Hassanien, "Fish image segmentation using Salp swarm algorithm," in *Proc. Int. Conf. Adv. Mach. Learn. Technol. Appl.*, 2018, pp. 42–51.

[6] A. Issac, M. K. Dutta, B. Sarkar, and R. Burget, "An efficient image processing based method for gills segmentation from a digital fish image," in *Proc. 3rd Int. Conf. Signal Process. Integr. Netw. (SPIN)*, Feb. 2016, pp. 645–649.

[7] K. Zhang, L. Zhang, K.-M. Lam, and D. Zhang, "A level set approach to image segmentation with intensity inhomogeneity," *IEEE Trans. Cybern.*, vol. 46, no. 2, pp. 546–557, Feb. 2016.

[8] S. Niu, Q. Chen, L. D. Sisternes, Z. Ji, Z. Zhou, and D. L. Rubin, "Robust noise region-based active contour model via local similarity factor for image segmentation," *Pattern Recognit.*, vol. 61, pp. 104–119, Jan. 2017.

[9] A. Fakhry, T. Zeng, and S. Ji, "Residual deconvolutional networks for brain electron microscopy image segmentation," *IEEE Trans. Med. Imag.*, vol. 36, no. 2, pp. 447–456, Feb. 2017.

[10] M. Drozdzal, G. Chartrand, E. Vorontsov, M. Shakeri, L. D. Jorio, A. Tang, A. Romero, Y. Bengio, C. Pal, and S. Kadoury, "Learning normalized inputs for iterative estimation in medical image segmentation," *Med. Image Anal.*, vol. 44, pp. 1–13, Feb. 2017.

[11] A. S. Milas, K. Arend, C. Mayer, M. A. Simonson, and S. Mackey, "Different colours of shadows: Classification of UAV images," *Int. J. Remote Sens.*, vol. 38, nos. 8–10, pp. 3084–3100, 2017.

[12] J. Zheng, D. Zhang, K. Huang, and Y. Sun, "Adaptive image segmentation method based on the fuzzy c-means with spatial information," *IET Image Process.*, vol. 12, no. 5, pp. 785–792, 2018.

[13] H. Liu, F. Zhao, and V. Chaudhary, "Pareto-based interval type-2 fuzzy c-means with multi-scale JND color histogram for image segmentation," *Digit. Signal Process.*, vol. 76, pp. 75–83, May 2018.

[14] M. C. Bakkay, S. Chambon, H. A. Rashwan, and C. Lubat, "Automatic detection of individual and touching moths from trap images by combining contour-based and region-based segmentation," *IET Comput. Vis.*, vol. 12, no. 2, pp. 138–145, 2018.

[15] Y. Li, H. Lu, L. Zhang, J. Zhu, S. Yang, X. Hu, X. Zhang, Y. Li, B. Li, and S. Serikawa, "An automatic image segmentation algorithm based on weighting fuzzy C-means clustering," *J. Image Graph.*, vol. 158, no. 12, pp. 27–32, 2007.

[16] F. Zhao, J. Fan, H. Liu, R. Lan, and C. W. Chen, "Noise robust multiobjective evolutionary clustering image segmentation motivated by the intuitionistic fuzzy information," *IEEE Trans. Fuzzy Syst.*, vol. 27, no. 2, pp. 387–401, Feb. 2019.

[17] G. Xia, H. Sun, L. Feng, G. Zhang, and Y. Liu, "Human motion segmentation via robust Kernel sparse subspace clustering," *IEEE Trans. Image Process.*, vol. 27, no. 1, pp. 135–150, Jan. 2018.

[18] Y. Hong, Q. Duan, D. Li, and J. Wang, "An improved K-Means clustering algorithm for fish image segmentation," *Math. Comput. Model.*, vol. 58, nos. 3–4, pp. 790–798, 2013.

[19] M. A. Guoqiang, T. Yunchen, L. Xiaolan, X. Kezhi, and X. Su, "Color image segmentation of live grouper fish with complex background in seawater," *Appl. Mech. Mater.*, vol. 743, no. 4, pp. 293–302, 2015.

[20] S. Vij, S. Sharma, and C. Marwaha, "Performance evaluation of color image segmentation using K means clustering and watershed technique," in *Proc. 4th Int. Conf. Comput. Commun. Netw. Technol. (ICCCNT)*, Jul. 2013, pp. 1–4.

[21] K. Saha, P. Shah, S. N. Merchant, and U. B. Desai, "A novel multi-focus image fusion algorithm using edge information and K-mean segmentation," in *Proc. 7th Int. Conf. Inf. Commun. Signal Process. (ICICS)*, Dec. 2009, pp. 1–5.
[22] A. Namburu, S. K. Samayamantula, and S. R. Edara, "Generalised rough intuitionistic fuzzy C-means for magnetic resonance brain image segmentation," *IET Image Process.*, vol. 11, no. 9, pp. 777–785, 2017.
[23] R. V. Patil and K. C. Jondhale, "Edge based technique to estimate number of clusters in k-means color image segmentation," in *Proc. 3rd Int. Conf. Comput. Sci. Inf. Technol.*, Jul. 2010, pp. 117–121.
[24] N. L. Kazanskiy, P. G. Serafimovich, and E. A. Zimichev, "Spectral-spatial classification of hyperspectral images with k-Means++ partitional clustering," *Proc. SPIE, Opt. Technol. Telecommun. Int. Soc. Opt. Photon.*, vol. 9533, Mar. 2015, Art. no. 95330M.
[25] D. Arthur and S. Vassilvitskii, "K-means++: The advantages if careful seeding," in *Proc. 18th Annu. ACM-SIAM Symp. Discrete Algorithms*, 2007, pp. 1027–1035.
[26] L. Condat "A convex approach to K-means clustering and image segmentation," in *Proc. Int. Workshop Energy Minimization Methods Comput. Vis. Pattern Recognit.* Cham, Switzerland: Springer, 2017, pp. 220–234.
[27] X. Zheng, Q. Lei, R. Yao, Y. Gong, and Q. Yin, "Image segmentation based on adaptive K-means algorithm," *EURASIP J. Image Video Process.*, vol. 2018, Dec. 2018, p. 68.
[28] C. L. Chowdhary and D. P. Acharjya, "Breast cancer detection using intuitionistic fuzzy histogram hyperbolization and possibilitic fuzzy c-mean clustering algorithms with texture feature based classification on mammography images," in *Proc. Int. Conf. Adv. Inf. Commun. Technol. Comput.*, 2016, p. 21.
[29] A. W. Dougherty and J. You, "A Kernel-based adaptive fuzzy c-means algorithm for M-FISH image segmentation," in *Proc. Int. Joint Conf. Neural Netw. (IJCNN)*, May 2017, pp. 198–205.
[30] C. L. Chowdhary and D. P. Acharjya, "Clustering algorithm in possibilistic exponential fuzzy c-mean segmenting medical images," *J. Biomimetics Biomater. Biomed. Eng.*, vol. 30, pp. 12–23, Jan. 2017.
[31] J. Li, D. Lin, and Y.-P. Wang, "Segmentation of multicolor fluorescence *In-Situ* hybridization (M-FISH) image using an improved fuzzy c-means clustering algorithm while incorporating both spatial and spectral information," in *Proc. IEEE Int. Conf. Bioinf. Biomed. (BIBM)*, Nov. 2015, pp. 413–416.
[32] C. L. Chowdhary and D. P. Acharjya, "Segmentation of mammograms using a novel intuitionistic possibilistic fuzzy C-mean clustering algorithm," in *Nature Inspired Computing*. 2018.
[33] L. Wan, T. Zhang, Y. Xiang, and H. You, "A robust fuzzy c-means algorithm based on Bayesian nonlocal spatial information for SAR image segmentation," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 11, no. 3, pp. 896–906, Mar. 2018.
[34] D.-Q. Zhang and S.-C. Chen, "A novel kernelized fuzzy C-means algorithm with application in medical image segmentation," *Artif. Intell. Med.*, vol. 32, no. 1, pp. 37–50, 2004.
[35] K. S. Tan and N. A. M. Isa, "Color image segmentation using histogram thresholding—Fuzzy c-means hybrid approach," *Pattern Recognit.*, vol. 44, no. 1, pp. 1–15, 2011.
[36] J. C. Bezdek, R. Ehrlich, and W. Full, "FCM: The fuzzy c-means clustering algorithm," *Comput. Geosci.*, vol. 10, nos. 2–3, pp. 191–203, 1984.
[37] W. Yan, S. Shi, L. Pan, G. Zhang, and L. Wang, "Unsupervised change detection in SAR images based on frequency difference and a modified fuzzy c-means clustering," *Int. J. Remote Sens.*, vol. 39, no. 10, pp. 3055–3075, 2018.
[38] S. Madhukumar and N. Santhiyakumari, "Evaluation of k-Means and fuzzy C-means segmentation on MR images of brain," *Egyptian J. Radiol. Nucl. Med.*, vol. 46, no. 2, pp. 475–479, 2015.
[39] D. S. Modha and W. S. Spangler, "Feature Weighting in $k$-Means Clustering," *Mach. Learn.*, vol. 52, no. 3, pp. 217–237, 2003.


**LONGQING SUN** was born in Hubei, China. He received the master's degree in engineering from China Agricultural University. He is currently an Associate Professor with China Agricultural University and the Deputy Director of the Key Laboratory of Agricultural Information Standardization of the Ministry of Agriculture and Rural Areas. He is mainly engaged in research and development of agricultural informatization. He is dedicated to the integration of agricultural Internet of Things technology, and animal behavior intelligent analysis.

**BING LUO** was born in Henan, China. He is currently pursuing the master's degree with the College of Information and Electrical Engineering, China Agricultural University. His research focuses on the use of computer image processing technology.

**TING LIU** was born in Shanxi, China. She is currently pursuing the master's degree with China Agricultural University. She mainly studies intelligent livestock farming.

**YAN LIU** was born in Shandong, China. He is currently pursuing the master's degree in computer science and technology with China Agricultural University. He mainly studies intelligent aquaculture.

**YAOGUANG WEI** was born in Henan, China. He is currently an Associate Professor with China Agricultural University. His research directions are advanced agricultural sensing technology research and agricultural production intelligent control technology research.