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一、美国《工程索引》(Ei Compendex)　　收录 1 篇

1. Accession number: 20221912089857
   Title: Student Ability Portrait Construction Research Based on Big Data
   Authors: Bo, Yu (1); Wang, Can (1); Li, Lin (1); Lu, Xuming (1)
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   Source: Proceedings - 2022 International Conference on Big Data, Information and Computer Network, BDICN 2022; Pages: 156-160; Issue date: 2022
   Conference: 2022 International Conference on Big Data, Information and Computer Network, BDICN 2022
   Document type: Conference article (CA)

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证明人：

大连理工大学图书馆

2022 年 8 月 29 日

ISSN: 1574-017X

EISSN: 1875-905X

Mobile Information Systems

An Internation Journal

Publishers-Hindawi Limited

Volume. 2022

Cycle-Quarterly

Mobile Information Systems

VOLUME 2022

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Hindawi
Mobile Information Systems
Volume 2022, Article ID 8333054, 8 pages
https://doi.org/10.1155/2022/8333054

Research Article

Image Segmentation Algorithm of Colorimetric Sensor Array Based on Fuzzy C-Means Clustering

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Received 21 June 2022; Revised 14 July 2022; Accepted 22 July 2022; Published 21 August 2022

Academic Editor: Gopal Chaudhary

In the real world, the boundaries between many objective things are often fuzzy. When classifying things, they are accompanied by ambiguity, which leads to fuzzy cluster analysis. The most typical in fuzzy clustering analysis is the fuzzy C-means clustering algorithm. The fuzzy C-means clustering algorithm obtains the membership degree of each sample point to all the class centers by optimizing the objective function, so as to determine the category of the sample point to achieve the purpose of automatically classifying the sample data. Based on fuzzy C-means clustering, this paper analyzes the image segmentation algorithm of the chroma sensor array. The fuzzy C-means (FCM) algorithm for colorimetric sensor array image segmentation is an unsupervised fuzzy clustering and recalibration process, which is suitable for the existence of blur and uncertainty in colorimetric sensor array images. However, this algorithm has inherent defects; that is, it does not combine the characteristics of the current colorimetric sensor array diversity and instability, does not consider the spatial information of the pixels, and only uses the grayscale information of the image, making it effective for noise. The image segmentation effect is not ideal. Therefore, this paper proposes a new colorimetric sensor array image segmentation algorithm based on fuzzy C-means clustering. Through the image segmentation effect test, the image segmentation algorithm proposed in this paper demonstrates an overall optimal segmentation accuracy of 96.62% in all array point image segmentation, which can effectively and accurately achieve the target extraction of colorimetric sensor array images.

1. Introduction

Under the social and economic development, color as an optical property closely related to material chemical information and capable of objective measurement has attracted more and more attention from researchers in various countries, which has led to the widespread application of computer vision in analytical chemistry [1]. At present, sensors have been able to detect volatile substances, biological samples, ions, and small organic molecules and have the advantages of fast response, high selectivity, and high specificity. Based on colorimetric sensor arrays, in the visualization bionic nose technology, the effective segmentation of the sensor unit determines the reliability of feature extraction information, which is the premise and key of computer vision recognition. The higher the accuracy of sensor unit segmentation, the more valuable and meaningful the information extracted from the feature information will be; otherwise, the extracted information will become meaningless. The current colorimetric sensor array is mainly based on manual segmentation. The methods are inefficient, reproducible, and easy to introduce human error. In order to overcome the above shortcomings, segmentation methods based on image threshold, region growing, artificial neural network, and cluster analysis have been proposed and applied to array image segmentation. The Otsu algorithm based on image threshold is the most commonly used method. The algorithm is convenient and widely used, but it is mainly based on gray threshold segmentation. It is easily affected by image noise and illumination environment and produces incorrect segmentation results [2, 3]. The image segmentation algorithm for region growing also shows good overall performance in colorimetric sensor array segmentation, but this method can easily introduce wrong boundaries. For high-dimensional color images with different features, the time complexity of the algorithm is a problem to overcome [4]. The artificial neural network method can achieve effective segmentation of complex information images, but its network layer design lacks theoretical basis, it takes time to train and learn large samples before segmentation, and it is also inseparable from the algorithm complexity limit [5, 6]. For the segmentation algorithm of cluster analysis, its basic principle is to classify similar pixel points in the feature space of the image into a class, especially the fuzzy C-means (hereinafter referred to as FCM) image segmentation algorithm based on feature space clustering. It does not directly indicate whether a pixel belongs to a certain class. Finally, by continuously iterating the membership degree and the cluster center, the objective function value is reached. In the smallest case, the optimal image segmentation is achieved [7, 8]. The main difficulty lies in how to effectively determine the initial clustering conditions [9]. The fuzzy membership degree theory proposed by the FCM algorithm matches the characteristics of image information ambiguity very well, considering that the array image is a two-dimensional lattice image with different color information, and segmentation using image information is the main segmentation method of the FCM algorithm [10, 11].

Innovation points of this paper: (1) by introducing the differential curvature operator, it can make the blurred division effect more realistic than the actual image, retain the parameters in the image, and reduce the influence of external factors. This paper constructs the spatial function correlation parameters that can be adaptive and proposes the DCFCM algorithm. It is proved that the improved algorithm can suppress noise and protect edge details adaptively and has a good fuzzy division effect. (2) By introducing the idea of nonlocal mean filtering into the FLICM algorithm, the fuzzy factor is improved. In this paper, the noise immunity and image processing are preserved, and the processing steps are reduced by weighting the information that affects the blurring factor so that it can adaptively adjust the weight of local information and nonlocal information in the flat region and the edge region and make its structural information more targeted to adjust the membership degree of the target pixel. (3) In this paper, a kind of based on fuzzy c-means clustering color sensor array image segmentation algorithm is proposed. First, the initial clustering is determined by the histogram information under grid analysis, and then color information is introduced into the objective function to achieve accurate segmentation of the color sensor array. This paper compares the Otsu algorithm for segmentation of different types of dot matrix images, and the traditional FCM algorithm has better overall segmentation accuracy, for the color sensor array feature extraction provides an effective method for image segmentation.

The first part of this paper introduces the fuzzy theory foundation and the standard fuzzy C-means clustering segmentation algorithm theory. The second part introduces the important operation process of the experiment and the tools needed, including the data collection method during the experiment. The last part of this article, research conclusion, shows the final conclusion: compared with the traditional FCM algorithm and the current commonly used RGB_Otsu algorithm, this paper designed the H&I_FCM in all array point image segmentation algorithm which shows the overall optimal segmentation accuracy of 96.54%, more can adapt to different light environment and pollution spots, and can effectively and accurately realize the colorimetric sensor array image segmentation.

2. Proposed Method

2.1. Related Work. FCM method is very sensitive to noise. Usually, local spatial information is introduced into the objective function to improve the robustness of FCM. Tao proposes an FCM algorithm that is faster and more robust, an optimised algorithm. First, the local spatial information of the image is integrated into our FRFCM through the introduction of morphological reconstruction operation to ensure noise resistance and image detail retention. Secondly, the cluster center is replaced by local membership filtering based on the pixel space neighbors only. Compared with the latest algorithm, it does not need to calculate the distance between the neighbor of the pixel and the clustering center. In addition, because the spatial filter can effectively improve the pixel membership, it is effective for noise image segmentation. His experiments on composite and real-world images show that compared with the latest image segmentation algorithm, it shows that there are obvious differences in noise and color processing between the spatial filter synthetic image and the real-world image, which greatly improves the pixel membership [12, 13]. Gu used the density functional theory (DFT) to calculate the performance of CSA sensor at B3LYP/ LANL2DZ in the methanol phase. Combined with the ground structure, he calculated the binding energy representing the binding sensitivity of CSA sensor to VOCs. His results showed that CoPc was sensitive to trimethylamine (*L1*), followed by acetone (*L4*) and formaldehyde (*L6*), while O, N, ethanol (*L2*), propane (*L3*), and ethyl acetate (*L5*) were not easily detected by CoPc. His theoretical research has certain guiding significance for the design and detection of CSA sensors [14, 15]. Shang found that FCM has poor robustness to noise, which often leads to unsatisfactory segmentation effect of noisy images. In addition, FCM algorithm is very sensitive to the selection of the initial cluster center. To solve these problems, he proposed to clone kernel space FCM (CKS_FCM). Cloning kernel space improves segmentation performance in several ways. The real experimental results and synthetic SAR images shown in his research show that the method he studied can generate high precision and noise and obtain more robustness [16, 17]. In the image segmentation based on clustering analysis, Wang applied spatial constraints to reduce noise but retain details. Based on fuzzy the C-means (FCM) method, to increase the detail and reduce the noise generated in the image, he proposes an image segmentation algorithm with internal kernel noise. In his proposed algorithm, two additional images based on the local information obtained from the original image through smoothing and sharpening filters are introduced to construct a multidimensional gray vector instead of the original one-dimensional gray. Then, the kernel method is used to enhance its robustness. Robustness can enhance the nature features in an image, placing the image maliciously modified to stabilize its image properties. In addition, he modified the target function by using penalty terms representing the diversity between local pixels. Compared with NNcut (Nystrom standardized cut) and FLICM (fuzzy local information C-means), the segmentation accuracy reaches nearly 99%. His experimental results and parameter adjustments on natural and medical images have proved that it has good flexibility and robustness in processing noise and details [18, 19].

2.2. FCM Image Segmentation Algorithm Based on Weighted HI Component. Suppose that a data set $X = \{x_1, x_2, ..., x_n\}$ containing n samples is divided into c subclasses $(2 \le c \le n)$, where x_i represents a certain sample in the data set $(1 \le i \le n)$, and the FCM algorithm is essentially in equation (1). Under conditional constraints, the unsupervised classification method is completed by iteratively optimizing the objective function value in equation (2).

$$\sum_{k=1}^{c} u_{ik} = 1, \quad \le u_{ik} \le 1, \tag{1}$$

$$J_{FCM} = \sum_{i=1}^{n} \sum_{k=1}^{c} u_{ik}^{m} \|x_i - v_k\|^2. \tag{2}$$

In (1) and (2), v_k represents the cluster center of the kth subclass of c subclasses; u_{ik} is the fuzzy membership degree of the ith subsample of the data set to the kth subclass; m represents the FCM algorithm. By the degree of ambiguity, the smaller the value, the closer the property of the FCM algorithm to the hard clustering algorithm. M represents the ambiguity of the FCM algorithm. The higher the value of m, the less correlation between the nature of the algorithm and the clustering algorithm. In this paper, m takes the value of 2; x_i represents the norm of a sample to its cluster center, which is used in the mainstream research of the current FCM algorithm. The 2-dimensional norm, i.e., the Euclidean distance, is no exception. Because of the HCS color space, the H component of the image has a circular cycle characteristic. In this paper, the influence on the segmentation accuracy is considered through the introduction of the H component, and the weight of the H component in different algorithms is compared, and its calculation formula is

$$D(H_i, v_{HK}) = \left(\frac{H_{\max}}{2} - \left| |H_i - v_{HK}| - \frac{H_{\max}}{2} \right| \right). \tag{3}$$

In formula (3), $H_{\max}$ is the maximum value of the H component, and when the H component is in 8 bit data format, the maximum value is 255. $D(I_i, v_{Ik})$ is the similarity distance between the ith sample to be classified and the cluster center v_{IK} in the I component. The calculation formula is

$$D(I_i, v_{Ik}) = |I_i - v_{Ik}|. \tag{4}$$

The H component and I component cluster center vector $V = \{v_{Hk}, v_{Ik}\}$ can also be determined according to

$$v_{Hk} = \frac{\sum_{i=1}^{n} u_{ik}^{m} H_i}{\sum_{i=1}^{n} u_{ik}^{m}}, v_{Ik} = \frac{\sum_{i=1}^{n} u_{ik}^{m} I_i}{\sum_{i=1}^{n} u_{ik}^{m}}. \tag{5}$$

2.3. Standard Fuzzy C-Means Clustering Segmentation Algorithm

2.3.1. Cluster Analysis. The richness of the world lies in the differentiation between things. In the process of human transformation of nature, the idea of "things gather together, people divide by group" subtly guides people's behavior. According to some proposed similarity criterion, the process of dividing the object under study into multiple categories is called clustering. These objects can refer to specific physical objects or abstract objects in mathematical models. Cluster analysis refers to the theoretical study of mathematical methods in the clustering process, abstracting, and interpreting the model, and clustering is the core of cluster analysis. In cluster analysis, clustering is performed according to certain criteria, and this criterion is the similarity between individuals. When studying a complex object, various possible measurements can be made on its features. The various measured values are formed into a vector form. The n feature vectors are composed of n-dimensional vectors. The vector is equivalent to a point in the feature space, and the feature vector in the entire sample can be regarded as many points in the feature space. In the process of clustering, the distance function between these points and points in the feature space can be used as the measure of individual similarity, and the distance is used as the basis of individual classification. The feature space similarity value and the value of the cluster label are compared and judged. The closer the value is, the higher the similarity is, and vice versa. The smaller the distance is, the higher the similarity is. Various practical physical meanings are abstracted into the concept of distance. The purpose of this mathematical abstraction is to facilitate the subsequent classification. In addition, the cluster analysis is based on the difference between different objects, according to the distance function for the classification between individuals, so whether this classification method is effective and the distribution pattern of the individual's feature vector has a great relationship, this is also the case. Therefore, when clustering a specific object, it is very important whether the selected feature vector is appropriate.

The general steps of clustering are shown in Figure 1: the feature vector is a feature that represents a recognized object with a component. The similarity between the same class of patterns and the difference between different classes of patterns are mainly reflected in these components features. By clustering the characteristics, properties, chemical information, attributes, etc., of things, the differences of things are reflected. Therefore, proper identification of the recognition object feature is an important part of the cluster. Since in many practical problems, the most important features are often not readily available, and the choice of feature vectors is called one of the most difficult tasks of clustering. The feature space similarity measure is an important part, which

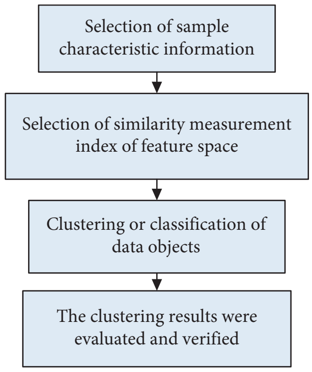

Figure 1: General clustering steps.

directly affects the results of clustering and selects different scales according to different classification objects. Distance is a measure that uses a wide range of similarities, and there are many types of distances. Each type of distance has its own advantages and disadvantages and needs to be correctly selected based on the characteristic information of the sample. The data are clustered or classified, that is, through the previously selected feature vectors and similarity measures, and then classified according to certain clustering criteria. The selection of clustering criteria is an important part of this work. The commonly used clustering criteria are threshold criteria and function criteria. When the clustering criteria are determined, cluster the data according to this criterion.

The final step is to evaluate the clusters. The evaluation cluster is judged by selecting the appropriate function value according to the threshold standard. For example, in the clustering analysis method with threshold criteria, the classification results need to be judged to guide the threshold selection. In the function-based cluster analysis method, the result of classification will directly affect the judgment and evaluation of standard function.

2.3.2. Colorimetric Sensor Array Image Segmentation Algorithm Based on Fuzzy C-Means Clustering. In the FCM algorithm, the order of class center and subordinate level is adjusted iteratively to achieve the goal of convergence. The fuzzy C-means algorithm is a resilient fuzzy segmentation method, which is a new hard clustering method. The FCM algorithm essentially finds the least weight at the edge points of the image. The smallest weight can judge the value of the objective function sought by the algorithm and compare whether it meets the demand range under the algorithm, thus achieving the classification of the target. According to the objective function, we can get

$$J = \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{m} d_{ij}^{2}. \tag{6}$$

Here, C is the number of cluster centers preset; u_{ij} needs to satisfy $0 \le u_{ij} \le 1$ and $\sum_{i=1}^{c} u_{ij} = 1$ constraints; m is the preset blur factor, which is the parameter that controls the degree of blurring and requires m to be greater than 1. When $m = 1$, the FCM algorithm degenerates into a hard C-means clustering algorithm, which also includes a membership function, but the membership is fixed. According to the previous research experience, m generally takes 2 segments better; $d_{ij} = \|x_j - v_i\|$ is the Euclidean distance from the jth pixel to the ith gray value, where x_j is the gray value of the jth pixel, and v_i is the ith gray value of the cluster center point.

The physical meaning of the objective function J is the sum of the weighted distances between each pixel point and each subcluster center in the target image. The smallest Euclidean distance between each pixel point and a cluster center is the largest Euclidean distance from other cluster centers, so the theoretical basis of the FCM algorithm is to find suitable cluster centers.

The formula for dividing the j th pixel into the k th class is as follows:

$$k = \arg\max\left\{u_{ij}, i = 1, 2, \ldots, C\right\}. \tag{7}$$

Since the membership degree has a constraint $\sum_{i=1}^{c} u_{ij} = 1$, it is necessary to use Lagrange when calculating the minimum value of the objective function.

The Japanese operator obtains a minimum objective function and gives the following functions:

$$J = \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{m} d_{ij}^{2} + \sum_{j=1}^{n} \lambda_j \left(\sum_{i=1}^{n} u_{ij} - 1\right). \tag{8}$$

Based on $\partial J/\partial u_{ij} = 0$, you can get

$$u_{ij} = \left(\frac{-\lambda_j}{m d_{ij}^{2}}\right)^{1/m-1} = \frac{\left(-\lambda_j\right)^{1/m-1}}{\left(m d_{ij}^{2}\right)^{1/m-1}}. \tag{9}$$

According to formula (9) and constraint $\sum_{i=1}^{c} u_{ij} = 1$, you can get

$$\left(-\lambda_j\right)^{1/m-1} = \frac{1}{\sum_{k=1}^{c}\left(1/m d_{kj}^{2}\right)^{1/m-1}}. \tag{10}$$

Bringing (10) into (9) gives

$$u_{ij} = \left[\sum_{k=1}^{c}\left(\frac{d_{ij}^{2}}{d_{kj}^{2}}\right)^{1/m-1}\right]^{-1}. \tag{11}$$

Based on $\partial J/\partial v_i = 0$, you can get

$$v_i = \frac{\sum_{j=1}^{n} u_{ij}^{m} x_j}{\sum_{j=1}^{n} u_{ij}^{m}}. \tag{12}$$

(11) and (12) are membership degree and cluster center update formulas, respectively. When seeking the minimum objective function, the member matrix and cluster center must be continuously updated according to (11) and (12) until the minimum value is obtained. When the membership degree is calculated according to (11), if d_{ij} is 0, the membership degree value belonging to this class is 1, and the membership degree value belonging to other classes is 0. The standard FCM algorithm usually stops iterating when the difference in pixel membership before and after two

iterations is less than a certain threshold because membership updates are related to the cluster center and the algorithm works easily when the initial cluster center is wrong. A local optimum is reached; it is also possible to set a maximum number of iterations and stop iterating once this number is reached.

Through the above derivation analysis, the process of segmenting images by the FCM algorithm can be summarized into the following main steps:

(1) Initializing the membership degree u_{ij} of the pixel and making it satisfy $u_{ij} \in [0, 1]$ and $\sum_{i=1}^{c} uij = 1$

(2) Calculating the cluster center v_i of the pixel according to formula (12), where $i = 1, 2, C$

(3) Calculate a new membership degree u_{ij}^{new} according to equation (11) and record the previous membership degree as u_{ij}^{old}

(4) If $\max\left\{|u_{ij}^{\text{old}} - u_{ij}^{\text{new}}|\right\} < \varepsilon$, go to step (5); otherwise, go to step (2)

(5) Classify each pixel in the image according to equation (7) and output the classified image

It can be known from the objective function of equation (8), it is known that getting the minimum value requires ensuring that the membership degree of the cluster center in the target image is as large as possible, and the membership degree belonging to other cluster centers is as small as possible. However, (8) also shows that, in the process of clustering, the FCM algorithm considers only the distance between the gray value of each pixel and each cluster center, and the gray values of each pixel are independent of each other. The farther the distance between the gray value of the pixel and the center of each cluster is, the more times the subsequent iterative calculation will be performed. The smaller the example, the less the number of iterations, which is more conducive to the judgment of the threshold. The influence between adjacent pixels is not considered, so when the FCM algorithm is used to segment the NMR brain image of Gaussian noise pollution, a large error occurs. Moreover, from the convergence of the objective function, when the initial value of the initial cluster center value is not properly selected, it is easy to fall into the local optimum in the iterative process.

3. Experiments

3.1. Experimental Design. This paper experimentally designs a colorimetric sensor array image segmentation algorithm based on fuzzy C-means clustering for image segmentation. The specific flowchart is shown in Figure 2. The performance of the image segmentation algorithm was obtained by testing the effect of image segmentation on 180 array point images. In the test, in addition to the proposed weighted HI component FCM image segmentation algorithm, the Otsu threshold segmentation algorithm (abbreviated as RGB_Otsu algorithm) is commonly used in RGB color space of array images, and the traditional FCM algorithm (I_FCM algorithm) containing only I components are used.

In order to evaluate the advantages and disadvantages of various algorithms, we introduce the segmentation accuracy

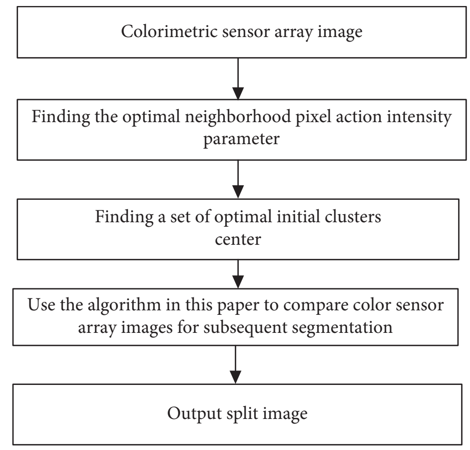

Figure 2: Flow chart of the image segmentation algorithm designed in this paper.

rate SA to quantitatively analyze the segmentation results of each algorithm. In operation, SA refers to the ratio of the correctly divided pixel points to the sum of the resulting image pixels. Through experiments, the researchers of colorimetric sensor arrays manually segmented the 180 images of 60×60 array points and processed the results as standard images. Then, using improved FCM, I_FCM and RGB_Otsu algorithms, all array point images were realized. The segmentation is performed, and the segmentation result is evaluated according to the average segmentation precision SA of each type of image. In each algorithm, the number of clusters, the fuzzy index, and the convergence parameters are the same, c is 4, m is 2, and the convergence parameter is 0.02; the FCM algorithm and the neighborhood radius in the I_FCM algorithm are 1. In the RGB_Otsu algorithm, the nonlocal search window has a radius of 2.

In this experiment, all image segmentation tests are based on 1.7 GHz CPU frequency, 4 GB memory computer, and MATLAB 2014a platform under 64 bit Windows8 operating system.

3.2. Experimental Data Collection. The experimental data collected in this paper are collected by a 1024×768 resolution camera, and a total of 5 6×6 array size 24 bit colorimetric sensor array true color images are acquired. After meshing, a total of 180 array point images are obtained (resolution is 60×60). These 180 array point images are divided into three categories according to illumination and noise conditions: 127 normal images, 36 uneven illumination or blurred images, and 17 images with contaminated spots.

4. Discussion

4.1. Image Segmentation Algorithm for Colorimetric Sensor Array Based on Fuzzy C-Means Clustering

4.1.1. Evaluation of Segmentation Accuracy of Different Algorithms. Figure 3 shows the typical segmentation results of the array point image under the segmentation algorithm. Table 1 shows the statistical results of the segmentation

Figure 3: Schematic diagram of typical segmentation results for array points.

accuracy of the three algorithms in image segmentation of all array points. Figure 4 is obtained from Table 1. It can be seen intuitively that, in the normal array point image segmentation, the segmentation precision of the three algorithms is comparable; in the image segmentation of array points with uneven illumination or blur, since improved FCM considers the hue information, it is 90.80%, the segmentation accuracy is the highest among the three, and the I_FCM and RGB_Otsu segmentation precisions are relatively close. In the array point image segmentation with contaminated spots, I_FCM has the highest segmentation accuracy of 96.51%, but improved FCM segmentation accuracy is also as high as 96.28%, and RGB_Otsu has the lowest segmentation accuracy. Overall, compared to the other two image segmentation algorithms, improved FCM shows 96.62% of the overall optimal segmentation accuracy in all array point image segmentation, especially under the influence of light environment and pollution spots, and it still has a good segmentation effect.

Table 1: Statistical results of dot image segmentation accuracy of colorimetric sensor arrays (%).

Array point type	Improved FCM	I_FCM	RGB_Otsu
Normal	97.81	97.79	97.80
Uneven or blurred light	89.99	82.77	78.89
With contaminated spots	95.39	93.28	89.79
All array points	96.55	93.89	94.21

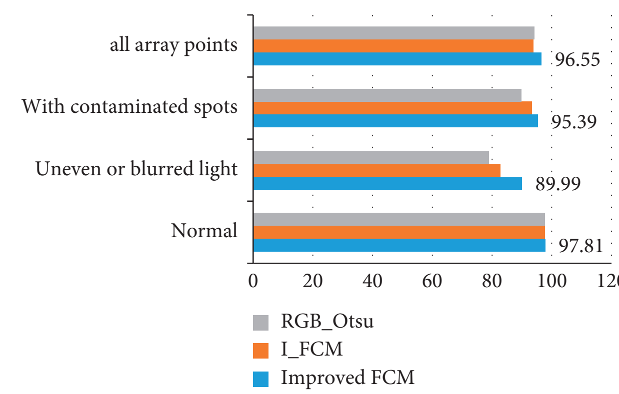

Figure 4: Statistical results of dot image segmentation accuracy for colorimetric sensor arrays (%).

4.1.2. Evaluation of Segmentation and Segmentation Accuracy of Different Weight Systems. In order to evaluate the influence of the introduction of H component on the segmentation accuracy, the segmentation precision of three different types of array points under different weight coefficients, H component, is calculated under the improved FCM algorithm. The weight coefficient of the H component ranges from 0 to 1, which is the value. The interval is 0.1.

As shown in Figure 5, in the image segmentation of three different types of array points, as the weight of the H component increases in the objective function, the initial segmentation accuracy is improved, but in the later stage, as the specific gravity of the H component increases, the segmentation accuracy will decrease, even lower than the FCM algorithm segmentation accuracy of simple I. Due to the discontinuity of the H component, its proportion in image segmentation should not be too large, so it needs to be occupied by the H component with a reasonable weight coefficient formula. The proportion is assigned. By referring to the weight distribution formula proposed by Rajaby, the proportion of I component is further increased by the square sum method, and W_H is controlled within a reasonable horizontal range.

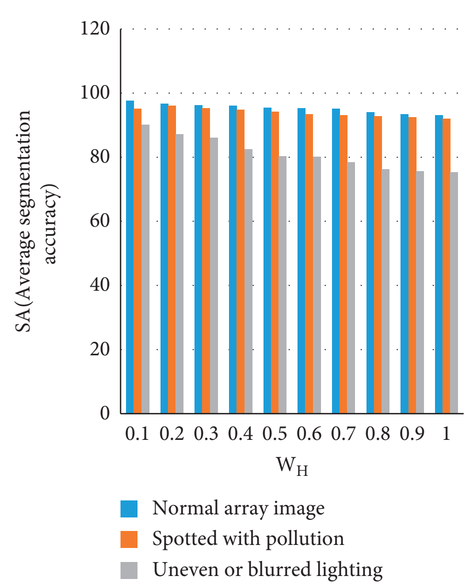

Figure 5: Segmentation accuracy of the improved FCM algorithm with different weight values.

4.1.3. Running Time Evaluation. Time complexity is an important indicator for evaluating the quality of an algorithm. If the image segmentation is not performed within the predetermined time, it means that the amount of calculation

Table 2: Comparison of runtime results.

Image type	Project	Improved FCM	I_FCM	RGB_Otsu
Array point image	(s)	0.071	0.034	0.046
Array image		2.003	0.981	0.998

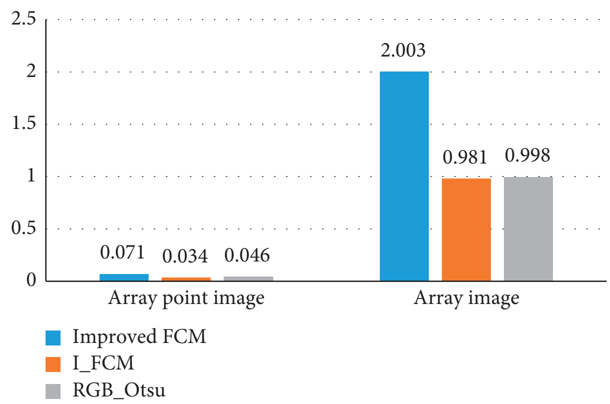

Figure 6: Run time comparison results.

is large, and the algorithm is also unqualified. If it is within the predetermined time, it means that the algorithm is satisfactory. For an excellent image segmentation algorithm, in addition to excellent segmentation results, its transit time must be controlled within an acceptable level. Therefore, this paper is divided into images. The average running time of the three algorithms in the five array images and the 180 array point images after meshing is calculated in the test. The statistical results are shown in Table 1.

Run time comparison results are shown in Table 2. Figure 6 is produced by Table 2. The average runtime can be seen from Figure 6. In the image segmentation operation, improved FCM has the longest running time, I_FCM has the shortest running time, and RGB_Otsu is moderate. The improved FCM has the longest running time and the shortest running time of I_FCM. If the running time is relatively short, I_FCM will not be able to run, and RGB_Otsu cannot be obtained. In fact, both I_FCM and RGB_Otsu are single-channel image segmentation, but the running time of I_FCM is obviously better than RGB_Otsu. The running time of improved FCM is due to the use of dual-channel image information in segmentation and involves the calculation of W_H and W_I, so it is reasonable that its running time is the most time-consuming of the three, but its running time is in an acceptable horizontal range.

4.1.4. Algorithm Average Similarity Evaluation. It can be seen from Figure 7 that the average distortion degree of the clustering result generated by the IFCM algorithm is smaller than that of the algorithm III when the clustering result is analyzed, and the average similarity is correspondingly larger than that of the algorithm III, and it is not required to be artificially set. λ_i^j value can be adjusted automatically. When the effect of interval size on clustering exceeds 2.5, the average distortion curve and average similarity curve of

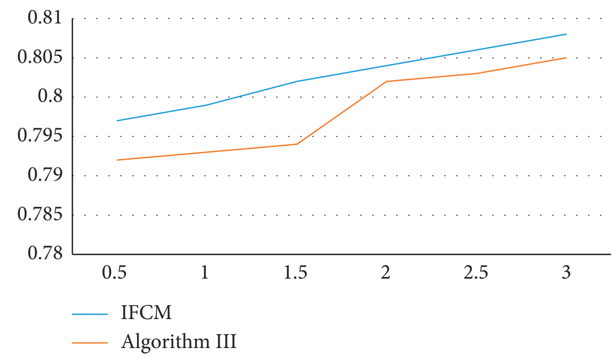

Figure 7: IFCM average similarity comparison chart.

IFCM tend to be gentle, that is to say, the interval size has little effect on the clustering result, which fully demonstrates the adaptive of λ_i^j. When segmenting images from colorimetric sensor arrays, the color information from the sensor unit is the basis for the subsequent feature analysis, and the excellent segmentation accuracy guarantees the correctness of the information extraction. Therefore, the segmentation accuracy should be the more important aspect in the algorithm design.

5. Conclusions

Color as an optical property closely related to material chemical information and capable of objective measurement has attracted more and more attention from researchers in various countries, which has led to the widespread application of computer vision in analytical chemistry. In this paper, a colorimetric sensor array image segmentation algorithm based on fuzzy C-means clustering is proposed. Firstly, the initial clustering condition is determined by meshing the histogram information analysis. Compared with the Otsu algorithm and traditional FCM algorithm, this algorithm has better overall segmentation accuracy than different types of array point image segmentation, which provides a way for feature extraction of colorimetric sensor arrays.

Combined with the image segmentation effect test results, this paper can draw the following conclusions: compared with the traditional FCM algorithm and the currently used RGB_Otsu algorithm, the improved FCM image segmentation algorithm designed in this paper shows 96.62% in all array point image segmentation. The overall optimal segmentation accuracy can adapt to the influence of different illumination environments and speckle pollution and can effectively and accurately segment the image of the colorimetric sensor array.

In the colorimetric sensor array image segmentation, the color information of the sensor unit is the basis for the subsequent feature analysis, and the excellent segmentation accuracy ensures the correctness of the information extraction. Therefore, the segmentation accuracy should be the more important aspect in the algorithm design. This topic has achieved certain results, but there are still many places in the work that can be improved and continue to be studied in depth. The future work is mainly the determination of parameters. Clustering results for input parameters: very sensitive; parameters are often difficult to determine. In the algorithm proposed in this paper, a parameter α is introduced, but the judgment and the value of this parameter need to be further investigated.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflicts of interest.

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