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An adaptive clustering segmentation algorithm based on FCM

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Abstract: The cluster number and the initial clustering centers must be reasonably set before the analysis of clustering in most cases. Traditional clustering segmentation algorithms have many shortcomings, such as high reliance on the specially established initial clustering center, tendency to fall into the local maximum point, and poor performance with multithreshold values. To overcome these defects, an adaptive fuzzy C-means segmentation algorithm based on a histogram (AFCMH), which synthesizes both main peaks of the histogram and optimized Otsu criterion, is proposed. First, the main peaks of the histogram are chosen by operations like histogram smoothing, merging of adjacent peaks, and filtering of small peaks, and then the values of main peaks are calculated. Second, a new separability measure η is defined and a group of main peaks with the maximum value of η serve as the optimal segmentation threshold value. The values of these main peaks are employed for initializing of the initial clustering center. Finally, the image is segmented by the weighted fuzzy C-means clustering algorithm. The experiment results show that, compared with existing algorithms, the proposed method not only avoids the oversegmentation phenomenon but also has a significantly shorter computing time than the traditional segmentation algorithm based on mean shift. Therefore, the proposed algorithm can obtain satisfactory results and effectively improve executive efficiency.

Key words: Clustering, fuzzy C-means, Otsu algorithm, histogram, image segmentation, separability measure

1. Introduction

Segmentation algorithms are involved in virtually all computer vision systems, at least in a preprocessing stage, up to practical applications in which segmentation plays a most central role: they range from medical imaging to object detection, traffic control systems, and video surveillance, among many others [1]. Image segmentation is the process of improving visual sense by partitioning the image into several different areas of interest according to the given rules [2]. Since the effects of subsequent operations are directly affected by the segmentation results, it is vital to select the appropriate image segmentation method. According to the general principle on which the segmentation is based, a taxonomy of the different segmentation algorithms is built that distinguishes the following categories: edge-based algorithms [3], thresholding techniques [4], region-based approaches [5], and certain theory-based algorithms (e.g., the Markov random field) [6]. Among them, the image segmentation algorithm based on a threshold value is one of the fundamental techniques in image segmentation, because it has advantages of simplicity and reliability [7]. In addition, the fuzzy C-means (FCM) clustering segmentation algorithm [8] has multithreshold values, strong adaptability, and easy realization, and it has been widely used in the field of image segmentation. However, the FCM clustering algorithm is a supervised algorithm. Before

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the algorithm is executed, the initial cluster number and clustering center must be set [9], which can only be obtained through prior knowledge of the sample points and experimental results. Errors in the cluster number will affect the effect of subsequent clustering, while nonideal selection of the initial clustering center will cause the final clustering process to become trapped in the local extreme point, influencing the convergence rate of the algorithm. Thus, one of the key steps in the clustering algorithm is selecting a suitable initial clustering center and cluster number. In order to attain the initial clustering center adaptively, the mean shift-based feature space analysis technique was introduced in the literature [10]. The complete solution toward autonomous image segmentation is to combine a bandwidth selection technique with top-down task-related high-level information. The only user-set parameter is the resolution of the analysis and either gray level or color images are accepted as input. However, the obtained cluster number is too high and oversegmentation is prone to happen. An unsupervised texture image segmentation method based on wavelet multiscale analysis and MS was proposed in the literature [11]. The adaptive multiscale segmentation is realized by applying a mean shift (MS) cluster algorithm to features generated by a wavelet pyramid. As a result, the unsupervised texture segmentation method does not require either training or prior knowledge of the number of textures. The center of a homogeneous texture is analyzed by using features in coarse resolution, and its border is detected in finer resolution so as to locate the boundary accurately. However, wavelet analysis is used for coarse segmentation, and then the MS algorithm is adopted for further segmentation. Hence, the algorithm has a relatively long computation time.

Due to the poor performance of traditional segmentation algorithms on large images, several improved FCM algorithms that use a histogram are proposed, instead of the gray function, to find centers of the gray level [12,13]. The image histogram is used to reduce the time cost of the fuzzy clustering segmentation process; however, these algorithms are sensitive to noise. In order to solve the problem of poor antinoise of the traditional FCM algorithm in image segmentation, two-dimensional FCM clustering algorithms for image segmentation have been proposed [14,15]. The fitness function containing neighbor information is set up based on the gray information and the neighbor relations between the pixels described by the improved two-dimensional histogram. However, such algorithms require manual selection of parameters α. Moreover, they are not suitable for multitarget segmentation. The rationality of attribute weights determination is an important issue in the weighted fuzzy clustering algorithms. A FCM algorithm that can obtain attribute weights and clustering results simultaneously is proposed with the interval constraints [16,17]. The algorithms can prevent the iterative calculation from falling into unnecessary local minima under the supervision of the decision maker's experience and preference.

In general, the peak value of the histogram can be used as a class center. In the literature [18], an optimal threshold value segmentation approach based on a 2D gray-level histogram is presented. The optimal segmentation curve on the 2D gray-level histogram is a quadratic curve. Furthermore, the optimal segmentation threshold value can be obtained by analyzing the curve. Wang et al. [19] put forward an automatic detection technique for segmentation threshold value and peaks in a gray-level histogram. In accordance with the intuitionistic features of the histogram, the peaks of the histogram are considered as a watershed, and each valley includes two neighbor peaks and a bottom point. The water level is elevated from the bottom point until every valley is filled. Valleys with the largest amount of water are obtained, and the bottom of these valleys becomes a segmentation threshold value. Although adaptive segmentation of an image can be achieved by using peak points in the histogram, there may be too many of these peak points compared with the cluster number of the partitioned image. Therefore, it is infeasible to initiate the clustering center directly via peak point values.

Another threshold selection method from gray-level histograms for image segmentation based on the Otsu criterion [20] is proposed without other a priori knowledge. An optimal threshold is selected by the discriminant criterion so as to maximize the separability of the resultant classes in gray levels. When the cluster number is two and the Otsu criterion is satisfied, it means that the intraclass samples are the most concentrated while the interclass samples are the most scattered, which corresponds to the lowest misclassification rate. However, when the cluster number is over two, the Otsu criterion does not correspond to the minimum misclassification rate. Thus, initiating a clustering center by the Otsu parameters may lead to poorer clustering results, which is the reason for the poor multithreshold value characteristic of the Otsu algorithm [20].

In view of the above reasons and to find the accurate initial clustering center and cluster number, in this paper, a coarse classification is carried out through calculation of main peaks of the histogram at first. Second, correlation between intraclass and interclass samples is considered, the separability measure η is redefined, and a set of main peaks with the largest η is adopted as the initial clustering center. Finally, the weighted FCM algorithm is employed for clustering segmentation of the image. The proposed algorithm avoids the oversegmentation phenomenon in other algorithms under the premise of good segmentation accuracy and efficiency. It also overcomes the drawbacks of overreliance on a particularly set initial clustering center and tendency to fall into the local extreme point in the classic FCM algorithm. Therefore, an unsupervised FCM algorithm is realized.

2. Histogram analysis

A histogram is a statistical model of an image, reflecting the distribution of the number of pixels in an image at each intensity value found in that image. The peaks of the gray-level histogram indicate the high appearance frequency of the gray-level's pixels, whereas the valleys indicate the low appearance frequency of the gray-level's pixels. In the process of image clustering segmentation, the peak value can be used as the initial clustering center. However, the final cluster number is normally less than the peak number, so some pseudopeaks should be removed while the rest of the peaks should remain in accordance with certain guidelines. For an image whose total pixel number is N, if a pixel with gray-level i corresponds to the frequency H_i of a histogram, the discriminant for the peaks and the valleys is as follows:

$$\begin{array}{l} \text{if } H_i < H_{i-1} \ \ \&\& \ \ H_i < H_{i+1}, \text{ pixel with gray-level } i \text{ is valley} \\ \text{if } H_i > H_{i-1} \ \ \&\& \ \ H_i > H_{i+1}, \text{ pixel with gray-level } i \text{ is peak} \end{array} \tag{1}$$

The subsequent operations are to identify the main peaks in all these peak points, and the calculation of the main peaks is as follows:

2.1. Smoothing of the histogram

Some pulses often appear in the histogram, as shown in Figure 1a. These peaks are the first kind of pseudopeaks and need to be eliminated. Smoothing of the histogram method is employed for filtering out these pulses, and the histogram is smoothed by calculating the mean of every five gray values. Figure 1b shows the histogram after smoothing, and it can be observed that the basic shape of the histogram remains unchanged and many sharp points of the pulses are filtered out.

2.2. Merging of adjacent peaks

After histogram smoothing, many sharp points of the pulses are filtered out, but there are still many residual peak points, requiring the merging of adjacent peaks. As shown in Figure 1b, there exist multiple peaks when gray-level value ranges from 150 to 200. Commonly, the width of the main peak is rather large; when the distance between the gray-level value of the ith peak and the $(i + 1)$th peak is less than the given width d, the adjacent peaks should be merged. Therefore, according to Figure 1b, there is only one main peak when the gray-level value ranges from 150 to 200.

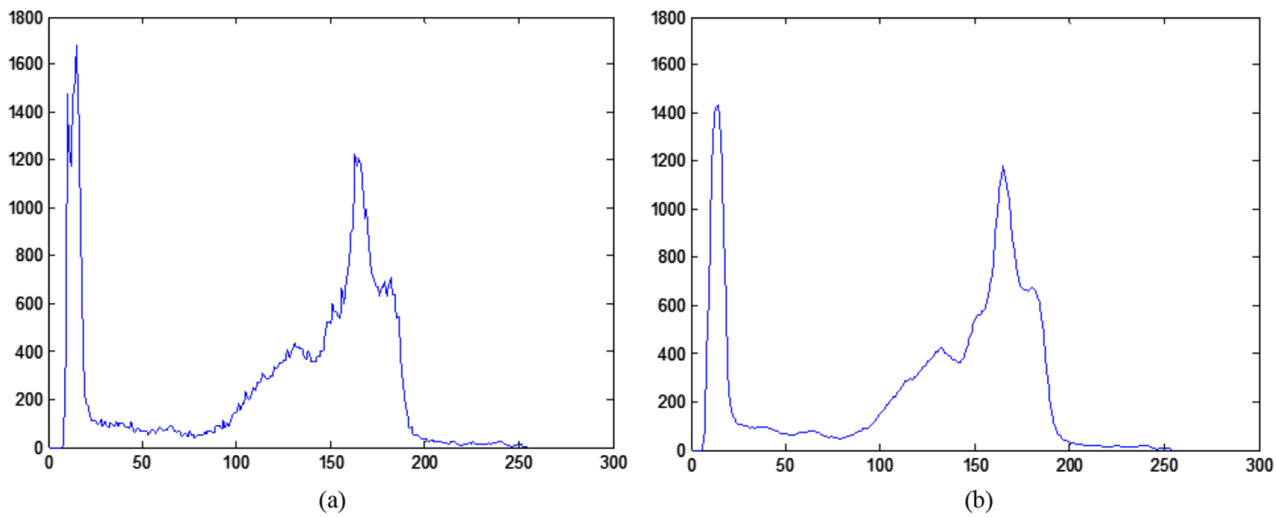

Figure 1. Comparison of smoothing effect of the histogram: a) original histogram, b) histogram after smoothing.

2.3. Filtering of small peaks

After merging of adjacent peaks, the number of peaks is reduced, but a small quantity of the pseudopeaks still exist. As shown in Figure 1b, peaks whose gray-level value is in the range of 20 to 100 have a low peak height and a small peak area S, and they should be removed. If V_j is the gray-level value of the jth valley point, then the peak area is:

$$S = \sum_{i = V_j}^{V_{j+1}} H_i \tag{2}$$

Through the aforementioned three steps, the number of candidate sets of main peaks of gray-level histogram is reduced. Experimental testing revealed that the number of main peaks is more than 5 and less than 10 in most cases, which is consistent with the requirements of the subsequent clustering. If the number of main peaks is too small, even less than the required minimum class number of image segmentation, it will directly lead to accuracy reduction in the final segmentation. Similarly, if the number of main peaks is too large, it will increase the selection randomness of the clustering centers, which is unfavorable for the determination of class number and execution efficiency of the algorithm.

3. Adaptive FCM segmentation algorithm based on histogram

3.1. Traditional Otsu algorithm

The Otsu algorithm [20], also known as the maximal variance between clusters method, uses the measure of statistical discriminant analysis and classifies data by the standard of variance between clusters. When the cluster number is two and the maximum variance between the clusters is satisfied, the corresponding data separation between clusters and classification is optimum.

Assume image I has N pixels and its gray level is 256. If a segmentation threshold value Th is selected, pixels of the image can be divided into two clusters, C_1 and C_2, according to the gray-level value. Suppose the gray-level value of cluster C_1 is in the range of 0 to Th and the gray-level value of cluster C_2 ranges from Th to 255. It can be inferred from the histogram that the gray-level mean value of the total pixels in the image is $m_G = \sum_{i=0}^{255} ip_i$, where p_i is the appearance probability of a pixel whose gray-level value is i. The mean value of the gray level of cluster C_1 is $m_1 = \sum_{i=0}^{Th} ip_i$ and the probability that the sample points are divided into cluster C_1 is $P_1 = \sum_{i=0}^{Th} p_i$. Similarly, the mean value of the gray level of cluster C_2 is $m_2 = \sum_{i=Th+1}^{255} ip_i$ and the probability that the sample points are divided into cluster C_2 is $P_2 = \sum_{i=Th+1}^{255} p_i$. Thus, the variance between these two clusters can be defined as:

$$\sigma_B^2 = P_1(m_1 - m_G)^2 + P_2(m_2 - m_G)^2 \tag{3}$$

With the change in the value of *Th*, the variance between clusters varies accordingly. The background pixel set and foreground pixel set, partitioned by various variances between clusters, are also different. When the selected value of *Th* gradually moves close to the optimal value, the variance between clusters also increases gradually. A larger variance between clusters indicates a bigger segmentation difference of the background and foreground and better separability among pixels. Therefore, the largest variance between clusters means the smallest error probability of segmentation, namely the best segmentation results. Furthermore, the Otsu algorithm is a single threshold value segmentation algorithm, while generally multithreshold value segmentation approaches are used in image segmentation. Hence, the separability measure on the basis of this method can be extended to the field of multithreshold value segmentation. Under the condition that there are L clusters $(C_1, C_2, \ldots, C_L)$, the multithreshold value of the variance between clusters is defined as:

$$\sigma_B^2 = \sum_{k=1}^{L} P_k(m_k - m_G)^2 \tag{4}$$

3.2. Selection of the initial clustering centers

As mentioned above, the single threshold segmentation method can only be used for a binary image. However, the more commonly employed technique in image segmentation is multithreshold segmentation. The classic Otsu algorithm has a poor multithreshold value performance; if the data are still divided by the standard of cluster number with the largest variance between clusters and its corresponding threshold value, then segmentation accuracy does not necessarily increase with the larger variance between clusters, because when the sample points are adequately dispersed, the obtained cluster number is bigger and the variance between clusters is larger. Although larger variance between clusters represents better separability of the samples between clusters, good aggregation cannot be guaranteed in each cluster. Therefore, large deviation exists in accordance with the standard of the classic Otsu algorithm, affecting the effect of subsequent segmentation.

To ensure the accuracy of classification, a new discriminant criterion is adopted and the concept of variance within a cluster is introduced, which is shown in Eq. (5):

$$\sigma_{in}^2 = \sum_{k=1}^{L} P_k \sigma_k^2 \tag{5}$$

Here, σ_k^2 is variance within the kth cluster, and σ_{in}^2 is the global variance within clusters.

Dispersion of interclass samples should be higher in the correct classification result, and better aggregation of intraclass samples should be guaranteed. This requires the minimum variance within a cluster on the basis of larger variance between clusters. The correlation of intraclass and interclass is considered here, and the separability measure criterion η is given as:

$$\eta = \frac{\sigma_B^2}{\sigma_{in}^2} \tag{6}$$

By adopting the ratio of variance between clusters and variance within a cluster as the measurement criterion, both the affiliation and global information of the samples are considered, avoiding the problem of ignoring the intraclass sample information when considering the interclass information. When separability measure η reaches its maximum value, the comprehensive performance of separability of interclass data and aggregation of intraclass data is the optimum. Therefore, the threshold value with the maximum η can be employed for image segmentation.

The other reason for the poor performance of the classic Otsu algorithm is its low execution efficiency. When only a single threshold value is used, the optimal threshold value can be obtained with up to 256 times of traversal; when double threshold values are used, it will be up to 256^2 times of traversal; as for the triple threshold values, it will be up to 256^3 times of traversal, and so on. Thus, the Otsu algorithm has very low execution efficiency under the condition of multiple thresholds. To solve this problem, a nonglobal traversal method is adopted here, i.e. just the η corresponding to the main peaks of the histogram will be calculated. Therefore, the scope of traversal has been greatly reduced. In addition, in most cases, the optimal segmentation threshold value is near the gray-level value of the main peaks, meaning that the deviation is very small.

3.3. Neighborhood weighted FCM segmentation algorithm

Since neighborhood information of the pixel space is not fully considered in the classic FCM algorithm, the FCM algorithm [8] will be replaced by neighborhood weighted FCM (NWFCM) algorithm [21] in this section. The main idea of this method is to replace the Euclidean distance in the traditional FCM algorithm with the neighborhood weighted distance. Its objective function is:

$$J_m = \sum_{n=1}^{N} \sum_{j=1}^{c} (u_{nj})^m d_N^2(x_n,\ v_j) \tag{7}$$

Here, m is the fuzzy factor, which is usually set to 2, and $d_N(x_n, v_j)$ is the neighborhood weighted distance:

$$d_N(x_n,\ v_j) = \sum_{r \in N_n} w_{nr} d(x_r,\ v_j) \tag{8}$$

Suppose that $\Omega = \{x_1, x_2, x_3, \ldots, x_N\}$ is the total sample space, u_{nj} is the membership of the nth sample belonging to the jth class ($1 \le n \le N$, $0 \le j \le c$, and $u_{nj} \le 1$), w_{nr} is the weight of sample x_r in neighborhood N_i of any x_n, and $d(x_r, v_j) = \sum |\{x_r\}_q - v_j|$ is the Euclidean distance from the qth sample point $\{x_r\}_q \in \boldsymbol{N}_\mathbf{i}$ to clustering center v_j. The neighborhood weighted FCM algorithm is used to divide these samples into c classes according to the minimum objective function, under the condition of $\sum_{j=1}^{c} u_{nj} = 1$. The clustering center v_j and membership function u_{nj} are updated based on the Lagrange multiplier method until the proposed algorithm converges:

$$u_{nj} = \frac{d_N^{-2/(m-1)}(x_n, v_j)}{\sum_{j=1}^{c} d_N^{-2/(m-1)}(x_n, v_j)} \tag{9}$$

$$v_j = \sum_{n=1}^{N} (u_{nj})^m x_i \Big/ \sum_{n=1}^{N} (u_{nj})^m \tag{10}$$

The Euclidean distance in the original algorithm is replaced by the neighborhood weighted Euclidean distance in the NWFCM segmentation algorithm, overcoming the difficulty in dealing with the tiny difference among various classes in the classic FCM algorithm. In addition, utilization of the image spatial information is improved and a better segmentation result is obtained. Compared with the classic FCM algorithm, the proposed approach has better noise resistance. Thus, the NWFCM segmentation algorithm is adopted for the final clustering segmentation.

Based on the previously discussed techniques, an adaptive FCM segmentation algorithm based on a histogram (AFCMH) is proposed in this paper. First, peak points in the histogram are filtered out through smoothing of the histogram, merging of adjacent peaks, and filtering of small peaks and the value of main peaks is calculated. Second, a new separability measure η is defined. Then a set of main peaks with the maximum η is used as the optimal segmentation threshold value, and the clustering center is initiated based on the value of these main peaks. Finally, the image is partitioned via the weighted FCM-clustering algorithm. The implementation steps of the AFCMH are as follows:

Input: An image with total N pixels, neighborhood weight matrix $\mathbf{W}$ of the pixels, and iterative precision is $\varepsilon = 0.01$.

Output: Membership matrix $\mathbf{u}$.

Step 1: The main peaks of histogram are obtained through the following operations: smoothing of histogram, merging of adjacent peaks with $d = 20$, and filtering of small peaks.

Step 2: Separability measure η is calculated by substituting each value of the main peaks into Eqs. (4) to (6). A set of main peaks with the maximum η is selected as the initial segmentation threshold value.

Step 3: The clustering center v_0 and membership u_0 are initialized using the initial segmentation threshold value obtained in Step 2. Set the initial iteration number $T_0 = 0$.

Step 4: The membership function and clustering center are updated via Eqs. (9) and (10), and let $T = T + 1$.

Step 5: The objective function J_m is calculated using Eq. (7). It is deemed that the calculation is converged and the proposed algorithm is terminated if the difference of the objective function is less than the given iterative precision ε between two adjacent iterations. Otherwise, return to Step 4.

4. Experimental results

The hardware environment of the proposed algorithm consists of a PC with a 2.1 GHz Intel Pentium B950 CPU and 2 GB memory. Let fuzzy factor $m = 2$ and iterative precision $\varepsilon = 0.01$. The effectiveness of the proposed algorithm is validated by comparison of the segmentation results among the AFCMH algorithm with the traditional FCM algorithm and the MS algorithm.

In the first experiment, a standard Lena image and coin image are selected. The image segmentation results are compared with the classic MS algorithm [10], as depicted in Figure 2. For the Lena image, the experimental results suggest that too many details are preserved in the segmentation algorithm based on MS, leading to too many classes in the final segmentation. Similarly, for the coin image, since the discrimination between the object and the background is very small, visual perception of the foreground object is affected. The cluster number obtained by AFCMH is consistent with the common subjective judgment of humans, avoiding the problem of too many classes and the oversegmentation phenomenon in the MS algorithm.

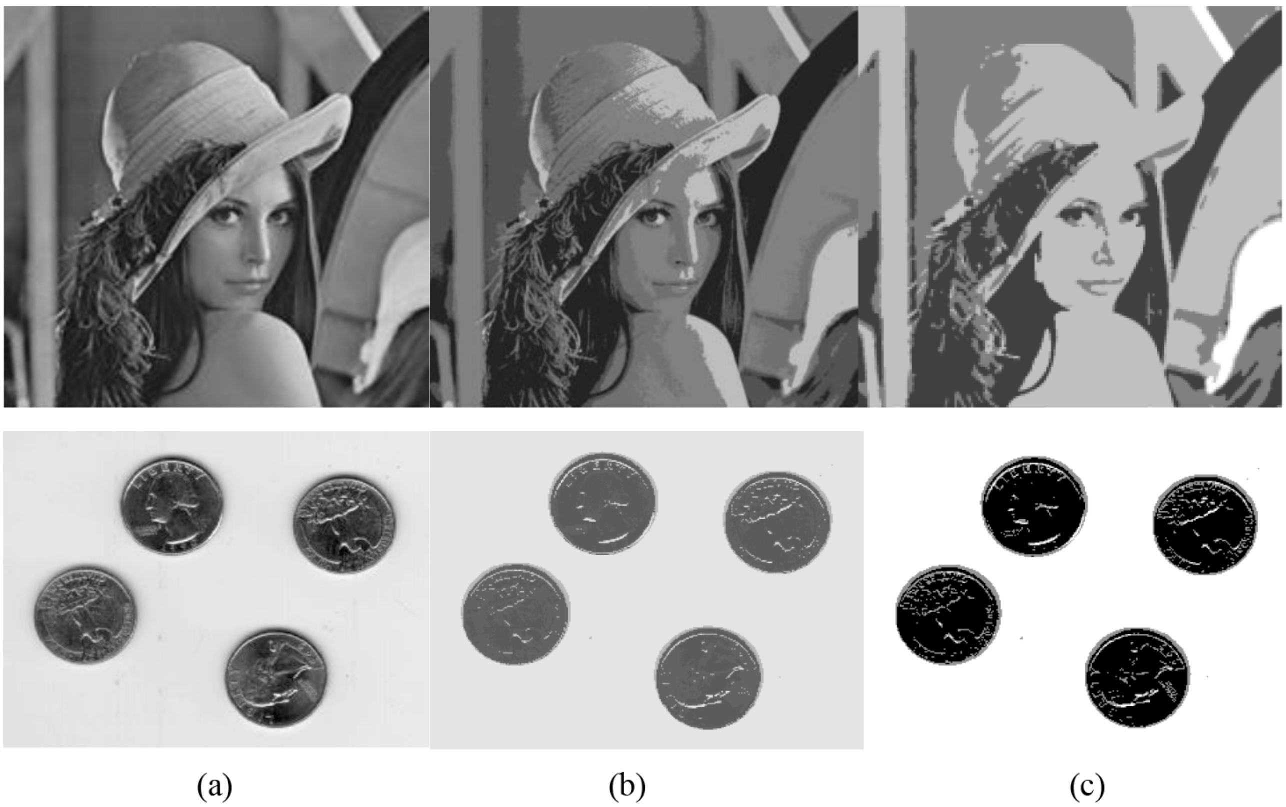

Figure 2. Comparison of segmentation results between the AFCMH and MS algorithms: a) original image, b) MS algorithm, c) AFCMH algorithm.

In the second experiment, several images from the Berkeley Library are selected. The image segmentation results are compared with the classic MS algorithm [10] and the enhanced FCM (EnFCM) algorithm [22]. The objective function of EnFCM is:

$$J_m = \sum_{i=1}^{M} \sum_{j=1}^{c} r_i u_{ij}^m \left(\varepsilon_i - v_j \right)^2 \tag{11}$$

Here, M is gray levels of the image, ε_i is a linear weighted pixel with gray value i, and r_i is the number of pixels with gray value i.

The results of the second experiment are shown in Figure 3. It can be inferred from the experimental results that the EnFCM algorithm and the MS algorithm have poor resistance to the noise segmentation in the small circle images, and some noise still exists in the segmentation results. For the next two natural images, the EnFCM algorithm and MS algorithm also have oversegmentation, resulting in poor segmentation results. The AFCMH algorithm avoids oversegmentation and ensures segmentation accuracy.

Table 1 is the comparison of the computation time of the cluster number of the AFCMH algorithm with the MS and EnFCM algorithms. Because of comprehensive consideration of spatial information in the NWFCM, the AFCMH algorithm needs more computing time than EnFCM. However, the execution efficiency is better than that of the MS algorithm, since the initial clustering center and cluster number are established via the nonglobal traversal method in the AFCMH algorithm. Moreover, the MS algorithm is influenced by the bandwidth parameters during execution. When the setting of bandwidth is nonideal, too many objects will be segmented and too many classes will be obtained, leading to the oversegmentation phenomenon. However, specific main peaks of the histogram are chosen as the initial clustering centers in the AFCMH algorithm, which can avoid the aforementioned problems in the MS algorithm.

Table 1. Comparison of the segmentation efficiency and classes of the presented algorithm (AFCMH) with the MS algorithm and the EnFCM algorithm.

Image	Algorithm	Time (s)	Classes
Lena	EnFCM algorithm	0.34	4
	AFCMH algorithm	1.23	4
	MS algorithm	7.86	7
House	EnFCM algorithm	0.13	4
	AFCMH algorithm	0.57	4
	MS algorithm	6.51	6
Circle	EnFCM algorithm	0.15	3
	AFCMH algorithm	0.32	3
	MS algorithm	2.16	5

Partition coefficient V_{pc} [23] and partition entropy V_{pe} [24] were selected to measure the reliability of segmentation. The definitions are given as follows:

$$V_{pc} = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{c}(u_{ij})^2 \tag{12}$$

$$V_{pe} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{c}u_{ij}\log(u_{ij}) \tag{13}$$

Better clustering results usually correspond to a smaller V_{pe} with a greater V_{pc}. Table 2 shows the different metrics of the AFCMH algorithm with the EnFCM algorithm [22] and the MS algorithm. The V_{pe} of AFCMH is smaller than that of both the EnFCM and the MS algorithm, while the V_{pc} is greater than that of the EnFCM and the MS algorithm, so the AFCMH algorithm performs better than the EnFCM algorithm and the MS algorithm.

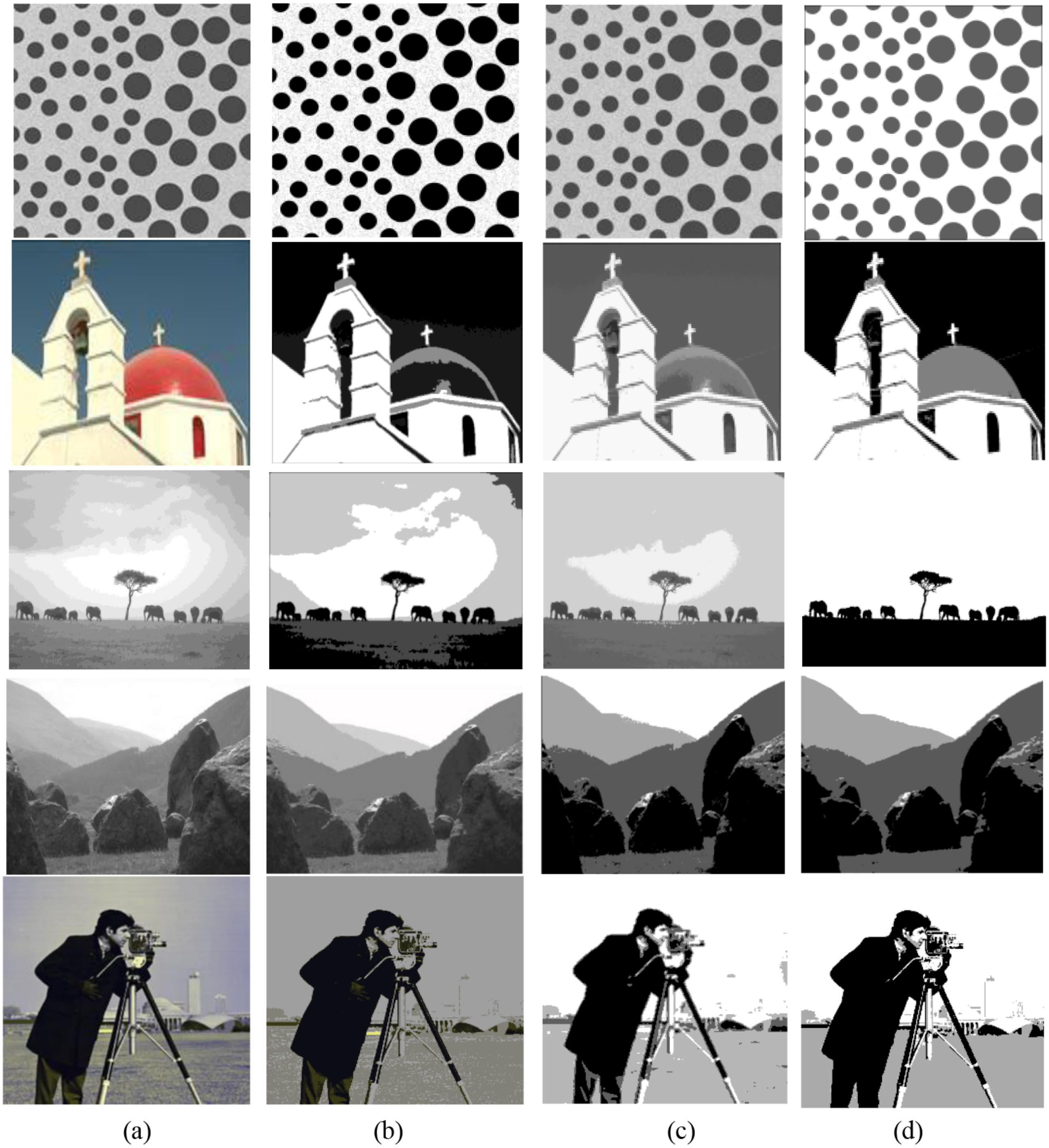

Figure 3. Comparison of three kinds of algorithms in image segmentation: a) original image, b) EnFCM algorithm, c) MS algorithm, d) AFCMH algorithm.

5. Conclusion

In this paper, an adaptive FCM segmentation algorithm based on the main peaks of the histogram and the optimized Otsu criterion is proposed. The proposed method can realize unsupervised acquisition of the initial

Table 2. Comparison of the V_{pc} and V_{pe} of the AFCMH algorithm with the EnFCM algorithm and the MS algorithm.

Image	Algorithm	V_{pc}	V_{pe}
Lena	MS algorithm	0.462	0.733
	EnFCM algorithm	0.715	0.561
	AFCMH algorithm	0.782	0.398
House	MS algorithm	0.645	0.590
	EnFCM algorithm	0.704	0.447
	AFCMH algorithm	0.778	0.387
Circle	MS algorithm	0.371	0.963
	EnFCM algorithm	0.563	0.785
	AFCMH algorithm	0.793	0.422

clustering center and reduce human intervention. The adopted separability measure, which synthesizes main peaks of the histogram and the optimized Otsu criterion, overcomes the drawback of the poor multithreshold value characteristic in the classic Otsu algorithm. The experimental results demonstrate that the computation time of cluster number in the AFCMH algorithm is less than that of the MS algorithm. The oversegmentation phenomenon in the MS algorithm can also be avoided, resulting in satisfactory segmentation results. However, the AFCMH algorithm is essentially based on threshold value segmentation, so there is the problem of lack of smoothness in part of the segmentation boundary. The focus of ongoing study is improving smoothness of the segmentation boundary.

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