IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received March 8, 2020, accepted March 23, 2020, date of publication March 30, 2020, date of current version April 15, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2984392

Energy Noise Detection FCM for Breast Tumor Image Segmentation

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This work was supported in part by the Natural Science Foundation of Hunan Province under Grant 2016JJ3125, in part by the Open Fund Project of Fujian Provincial Key Laboratory of Data Intensive Computing under Grant BD201808, and in part by the Degree and Postgraduate Education Reform Project of Hunan Province under Grant 2019JGYB115.

ABSTRACT The traditional fuzzy C@hyphenmeans (FCM) algorithm ignores the spatial information of pixels and is sensitive to noise images. To overcome this disadvantage, this paper proposes a fuzzy C@hyphenmeans clustering algorithm based on energy noise detection (ENDFCM) for mammographic image segmentation. Based on the weighted mean filtering, the algorithm employs the information of the spatial pixel points to enhance its noise resistance. By introducing the energy curve and designing the spatial distance, it constrains the objective function to increase its parameter adaptability. Then, it derives the new subordinate function to increase the relevance of its subordinacy, which is updated continuously during the clustering process. The experimental results show that the algorithm has better segmentation accuracy and robustness compared with the traditional FCM and its improved methods, and can accurately segment the noisy breast tumor images.

INDEX TERMS FCM, spatial information, energy curve, breast tumor, image segmentation.

I. INTRODUCTION

Breast cancer is one of the main facts that threaten women's health. Whether it can be cured depends a lot on the early discovery of breast masses. Therefore, the detection of early breast cancer is the key to breast cancer treatment in Internet of Medical Things. In order to improve the doctor's diagnosis, computer-aided diagnosis is often used in cloud-edge computing, which mainly includes three steps: tumor image segmentation, feature extraction and tumor classification. Among them, tumor image segmentation is an important part of auxiliary diagnosis. So many scholars at home and abroad have conducted extensive research on how to effectively segment breast tumor graphs. Currently available medical segmentation methods include; active contour model method, edge detection method [1], region segmentation method [2], Nyström approximation method [3], [4], machine learning classification method [5], cluster segmentation method [6], [7], neural network method [8], [9] and so on [10], [11]. The traditional fuzzy C-Means method is based on the gray-scale information of the pixel itself and ignores its spatial characteristics, and so it is sensitive to noise [12], [13]. Due to the uncertainty of imaging equipment, environment and manual operation, it is inevitable that noise is contained in breast tumor images, so that the segmentation effect of FCM is poor [14], [15].

In overcoming the defects of traditional FCM, researchers have made a series of progress [16]–[22]; Chen and Zhang [18] used spatial neighborhood information to constrain the objective function, and proposed a series of algorithms such as FCM-S to improve the segmentation accuracy, but the algorithm is not so much efficient. Kang [19] proposed an improved FCM that takes into account pixel spatial information based on adaptive weighted mean filtering images while modifying the objective function, but the algorithm ignores the details in the image. Mansheng *et al.* [20] proposed a spatial correlation based FCM to take into account the details of the image by analyzing the spatial distribution characteristics of the samples and their correlation (SCMS-FCM), The algorithm designs the influence value of the sample to improve the clustering center calculation method and the distance calculation function. Combined with the

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

neighborhood information, the fuzzy membership matrix is redefined by introducing a control parameter in the neighborhood membership summation process. but the algorithm has a large amount of computation. Huo *et al.* [21] combined the space constrained fast FCM with the Markov random field to realize the side scan sonar image segmentation (SCFMFCM). The space constraint term is added to the objective function of the algorithm to ensure the consistency of the gray value of the pixels in the neighborhood centered on i, and increase the spatial correlation of the algorithm. However, the image's detailed information is poorly preserved. Guo *et al.* [22] proposed an adaptive fuzzy C-means image segmentation algorithm based on local noise detection according to the literature [23]–[32], which calculates the neighborhood gray value. The variance is used to distinguish the noise, but the introduction of more parameters makes it easy to lose the details of the image.

Aiming at the shortcomings of NDFCM, this paper proposes a fuzzy C-means clustering algorithm based on energy noise detection (ENDFCM) to segment breast tumor images. The algorithm introduces the energy curve to achieve the parameter adaptability. The target function is updated by using the distance between samples to update the membership degree and the cluster center to improve the spatial correlation of the pixels, and the accuracy of segmentation and the retention of image's detailed information are realized. The experimental results show that the algorithm can achieve better segmentation effect for medical diagnosis of breast cancer.

The rest of this paper is organized as follows: Noise detection based FCM (NDFCM) is introduced in Section II. ENDFCM and its details are described in Section III. Section IV presents the comparative experiments and result analysis. And the conclusions are presented in Section V.

II. NDFCM ALGORITHM

A. TRADITIONAL FCM

FCM is a fuzzy clustering method based on minimum criteria. Assuming that there is a sample set $X = \{x_1, x_2, \ldots, x_n\}$, the algorithm divides the data image by calculating the cluster center v and the membership matrix u, and obtains the minimum value of the objective function J_{fcm} by adjusting the values of v and u:

$$J_{fcm} = \sum_{i=1}^{c}\sum_{k=1}^{N} u_{ik}^{m} \|x_k - v_i\|^2 \tag{1}$$

where N is the number of samples, c is the number of clusters $2 \leq c \leq N-1$, m is the fuzzy weighted index (usually taking a real number greater than 1, can control the ambiguity of the result distinction), U_{ik} means the kth The membership of the sample X_{k} in the ith class, $||.||$ represents the Euclidean distance $\sum_{i=1}^{c} \mu_{ik} = 1$.

Minimize the objective function with the Lagrangian multiplier method

$$J_{fcm} = \sum_{i=1}^{c}\sum_{k=1}^{N} \mu_{ik}^{m} \|x_k - v_i\|^2 + \lambda_1(\sum_{i=1}^{c} \mu_{i1} - 1) + \cdots + \lambda_k(\sum_{i=1}^{c} \mu_{ik} - 1) + \lambda_n(\sum_{i=1}^{c} \mu_{in} - 1) \tag{2}$$

Let $\frac{\partial J_{fcm}}{\partial u_{ik}} = 0$, $\frac{\partial J_{fcm}}{\partial v_i} = 0$, get:

$$v_k = \frac{\sum_{i=1}^{N} \mu_{ik}^{m} x_i}{\sum_{i=1}^{N} \mu_{ik}^{m}} \tag{3}$$

$$\mu_{\text{ik}} = \frac{\|x_{\text{i}} - v_k\|^{-2/(m-1)}}{\sum_{j=1}^{c} \left\|x_j - v_k\right\|^{-2(m-1)}} \tag{4}$$

B. NDFCM

In order to improve the noise immunity of FCM, Guo F. F., *et al.* use the variance of the gray level in the neighborhood to detect the noise, and use this information to balance the objective function to achieve image denoising and detail information preservation. The objective function of NDFCM is as follows:

$$J = \sum_{i=1}^{c}\sum_{k=1}^{N} \mu_{ik}^{m} \|[(1-\alpha_i)\,\xi_i + \alpha_i \bar{x}_i] - v_k\|^2 \tag{5}$$

$$\alpha_i = 1 - \sum_{j=N_i} \exp\left(\frac{-\left\|x_j - x_i\right\|}{\lambda_\alpha \max_{l \in N_i} \|x_l - x_i\|^2}\right) \Big/ N_R \tag{6}$$

where α_{i} represents the probability that pixel i is noise, ξ_{i} represents the spatial correlation between pixels, and λ_α is a given control parameter. N_{i} and N_{R} represent the corresponding neighborhood window and window size, and $\overline{x_i}$ represents the neighborhood grayscale mean. It can be seen that the greater the difference between the central pixel and the surrounding pixels, the greater the possibility of noise.

The NDFCM algorithm detects noise points by the variance of the gray levels in each neighborhood. Then, use this information to balance the noise and maintenance details in the objective function. This method improve segmentation accuracy by considering the noise intensity in each local window rather than the entire image, avoiding errors due to differences in noise intensity in different regions. The algorithm exhibits high noise stability for image data with strong noise damage.

Find the clustering center and subordinacy of the NDFCM algorithm according to equation (2) as follows:

$$u_{ik} = \frac{\|[(1-\alpha_i)\xi_i + \alpha_i \bar{x}_i] - v_k\|^{-2/(m-1)}}{\sum_{j=1}^{c} \left\|((1-\alpha_i)\xi_i + \alpha_i \bar{x}_i) - v_j\right\|^{-2/(m-1)}} \tag{7}$$

$$v_k = \frac{\sum_{i=1}^{N} u_{ik}^m \left[(1-\alpha_i)\xi_i + \alpha_i \bar{x}_i\right]}{\sum_{i=1}^{N} u_{ik}^m} \tag{8}$$

It can be seen that the NDFCM has two important parameters λ_α and ξ_i[12], and ξ_i has more constraints, and the parameter adjustment process is more complicated. In other words, the NDFCM algorithm has a strong dependence on parameters, so the selection of parameters is an important part of the algorithm. In general, the selection of ξ_i is affected by the size of the selected window, and it is heavily dependent on the type and intensity of the noise. The type and the intensity of the noise contained in the image are often unpredictable, and it takes a lot of time to adjust the parameters. And the parameters are selected in a certain range according to a fixed step size, which is easy to cause loss of image details and result in inaccurate image segmentation.

III. ADAPTIVE FCM BASED ON ENERGY DETECTION

A. ENDFCM

The NDFCM algorithm achieves better anti-noise effects by combining spatial neighborhood constraints, but this method needs to consider selecting appropriate windows to prevent the image's detailed information from getting lost when setting parameters. In order to avoid the errors caused by the window in the image segmentation process, this paper proposes an FCM algorithm based on energy noise detection based on NDFCM, and uses it to realize the initial image segmentation of breast tumors. By combining spatial information, the algorithm introduces the data information of the energy curve [10] compressed image to achieve accurate and efficient segmentation of breast tumor images.

Let $I = \{l_{ij} | 1 \le i \le m, 1 \le j \le n\}$ be the image of the size, where lij is the gray value of the image I at the pixel position (i, j). L is the maximum gray value of the image I. Define the dth order neighborhood system of (i, j) as $N_{ij}^d = \left\{(i+u, j+u) | (u, v) \in N^d\right\}$. Calculating the energy curve of the image I with a gray value of l $(1 \le l \le L)$ using the two-dimensional matrix B_x, $B_x = \left\{b_{ij}, 1 \le i \le M, 1 \le j \le N\right\}$, where $b_{ij} = 1$, if $l_{ij} > 1$, else $b_{ij} = -1$. Let $C = \left\{c_{ij}, 1 \le i \le M, 1 \le j \le N\right\}$, be another constant matrix $c_{ij} = 1$. According to the d-order neighborhood systems taking different positions, combined with the spatial context information design, the energy curve function associated with each gray value in the image is defined as follows:

$$E_l = -\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{pq \in N_{ij}^2} b_{ij} b_{pq} + \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{pq \in N_{ij}^2} c_{ij} c_{pq} \tag{9}$$

where $\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{pq \in N_{ij}^2} c_{ij} c_{pq}$ is a constant term, ensuring that the energy value $E_l \ge 0$ is greater than zero. It can be seen from equation (9) that for the image I, a two-dimensional binary matrix B_L is generated here, and when all the elements in the matrix are 1 or -1, the energy value of the gray level L will be zero (That is, all pixels of image I have gray values greater than L or less than L); otherwise, the energy value will be a positive value.

(i-1,j-1)	(i-1,j)	(i-1,j-1)
(i,j-1)	(i,j)	(i,j+1)
(i+1,j-1)	(i+1,j)	(i+1,j+1)

FIGURE 1. Neighborhood windows.

Figure 1 depicts a second order (N^2) pixel adjacent pixel (i, j) at a spatial location. In this paper, a probability formula for judging whether the pixel is a noise point is designed, and the variance reference data is obtained by using the central pixel i. First, the reference value is set, and the set reference value is compared with the calculated probability. When the calculated probability value is greater than the reference value, we say that the pixel point is a noise point, and conversely, the pixel point is not a noise point. The probability function for calculating a pixel as noise based on the energy curve is as follows:

$$\alpha_i^* = 1 - \sum_{j \in N_i} \exp \frac{-\left\|x_j - x_i\right\|^2}{\max_{l \in N_i} \left\|x_l - x_i\right\|^2 E_l \lambda} \Bigg/ \sum_{i=1}^{m}\sum_{j=i}^{n} \delta(E_l - i) \tag{10}$$

where λ is the adjustment parameter; $\delta(x) = \begin{cases} 1, & x \ne 0 \\ 0, & \text{others} \end{cases}$. It can be seen from the equation(10) that the greater the difference between the center pixel and its surrounding pixels, the more likely the pixel is to be a noise point.

In fact, the number of pixels determines the size of the image, which directly determines the calculation time of the algorithm. The traditional FCM algorithm takes a lot of manpower and material resources, sometimes even unbearable weight. Usually, the number of grey levels is smaller than that of pixels. In order to save computation time, the orginal image can be processed by a convex combination. In this paper, we use ε_i as the smoothing factor as recommended in [34]–[41].

$$\varepsilon_i = \frac{1}{1+\alpha}(x_i + \alpha \bar{x}_i) \tag{11}$$

where $\bar{x}_i$ represents the gray levels mean of the corresponding neighbourhood, and α is a control parameter, represents the control factor of the neighborhood. Specifically, the larger the value of α, the smoother the image information, and the smaller the α, the more important the details of the original image are emphasized.

On the basis of energy curve, this paper modifies the objective funtion as

$$J_{ENDFCM} = \sum_{i=1}^{N}\sum_{k=1}^{c} \mu_{ik}^{m} \left\| \left[\left(1-\alpha_i^*\right)\varepsilon_i + \alpha_i^*\bar{x}_i\right] - \nu_k \right\|^2 E_i\omega_{ik} \tag{12}$$

where ω_{ik} is the penalty factor, it is obtained as follows:

$$\omega_{ik} = \sum_{j=1}^{n_k} \frac{1}{d_{jk}} \Big/ \sum_{j=1}^{n}\sum_{j=1}^{n_k} \frac{1}{d_{jk}} \tag{13}$$

where d_{ij} denotes the sample point x_{k} and x_{j} Euclidean distance, It is worth mentioning that here ω_{ik} represents the degree of influence of the sample around the sample x_{k} on the x_{k} classification, that is, the greater the ω_{ik} value, the greater the extent to which x_{k} belongs to a certain class. Indicating the spatial correlation between the sample points around the sample point x_{k} and the x_{k} classification result, the larger ω_{ik}, the greater the correlation. The adjustment of the cluster center can be directly adjusted by adjusting ω_{ik}, and the indirect adjustment of the membership degree.

According to the method of finding the minimum value by FCM in 2.1, let $\frac{\partial J_{ENDFCM}}{\partial u_{ik}} = 0$, $\frac{\partial J_{ENDFCM}}{\partial v_i} = 0$, you can get:

$$u_{ik} = \frac{\left\|[(1-\alpha_i^*)\xi_i + \alpha_i^*\bar{\mathrm{x}}_i] - v_k\right\|^{-2/(m-1)}}{\sum_{j=1}^{c}\left\|((1-\alpha_i^*)\xi_i + \alpha_i^*\bar{x}_i) - v_j\right\|^{-2}/(m-1)} \tag{14}$$

$$v_k = \frac{\sum_{i=1}^{N} u_{ik}^{m}\left[(1-\alpha_i^*)\xi_i + \alpha_i^*\bar{x}_i\right] E_i\omega_{ik}}{\sum_{i=1}^{N} u_{ik}^{m}} \tag{15}$$

It can be seen from the above formula that after the energy curves E_i and ω_{ik} are introduced, the cluster center is readjusted, and the sample membership degree is indirectly changed by the change of the concentration center in the iterative process, and the values of E_i andω_{ik} take into account the sample. The sample distribution around the point $E_l \geq 0$, and $\omega > 0$ is a fixed value when the sample is evenly distributed. It can be known from equations (14) and (15) that after the energy curve and the penalty factor are directly introduced into the objective function, the constraint is only the cluster center. In order to improve the spatial correlation of subordinate degree, the subordinate degree shown in equation (14) is redefined as follows by weighting method:

$$u_{ik}^* = \frac{u_k\bar{u}_{ik}}{\sum_{j=1}^{c} u_{jk}\bar{u}_{jk}} \tag{16}$$

where $u_{ik}{}^{-}$ represents the mean of the membership.

B. ALGORITHM IMPLEMENTATION

The implementation steps of ENDFCM are as follows:

Step 1: Initialize each clustering parameter, including: the number of clusters c ($2 \leq c \leq n$), the iteration stop threshold ε, the fuzzy weighted index m, and the like;

Step 2: Calculate the energy curve function E_{l} according to equation (9);

Step 3: According to the traditional FCM, the cluster center and membership degree are used as the basis of the new algorithm to reduce the number of iterations of the next operation and improve the computational efficiency;

Step 4: According to the traditional FCM algorithm, find the Euclidean distance between the sample x_j and the cluster center x_{k}, and calculate ω_{ik};

Step 5: Using the formula (10) to calculate α_i^* the sample x_j;

Step 6: Calculate the membership value u according to equation (16);

Step 7: Calculate the cluster center v of the sample category according to formula (15);

Step 8: Update subordinacy and cluster center. When $\left\|V^{t+1} - V^t\right\| \leq \varepsilon$, the operation stops; otherwise $t = t+1$, jump to Step6.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

To test the effectiveness of ENDFCM, the breast tumor image in the DDSM database [33] was selected as the segmentation object. (DDSM is another resource that may be used by the mammography image analysis research community. This is a collaboration between the Massachusetts General Hospital, Sandia National Laboratories, and the University of South Florida's Department of Computer Science and Engineering. The database contains approximately 2,500 studies. Performance data for accessing mammograms and real images and for calculating automated image analysis algorithms is provided). The experimental environment is an IntelI CoreI i3 CPU, a PC with 4 GB of memory, the operating system is Windows 7, and the programming language is MATLAB (R2010b). In the segmentation process, the weighted index $m = 2$, the iteration termination threshold $\varepsilon = 10^{-4}$, and according to [13], the immune cloning algorithm is used to generate the initial cluster centers.

A. COMPARISON OF SEGMENTATION EFFECTS

Using the algorithm of this paper to segment the mammography palladium X slices in the database DDSM, this paper lists three different breast tumor images after segmentation, the salt and pepper noise with a concentration of 0.05, the mean value $u = 0.1$, the Gaussian noise with variance $\delta = 0.004$, and the mixed noise of Gauss-salt and salt were respectively added to the image to be segmented, and segmented by different segmentation algorithms. The segmentation results are shown in Fig. 2.

Fig. 2(a) is a diagram of a breast tumor to be segmented with Gaussian noise, salt and pepper noise, and Gauss-salt-salt mixed noise, respectively. Figures (b) to (f) are the segmentation effects obtained by FCM algorithm [6], fast FCM algorithm [19], SCMSFCM [20], SCFMFCM [21], NDFCM [22] and the proposed algorithm. It can be seen from the comparative results that the traditional FCM ignores the spatial feature information of the pixel and is sensitive to noise, so the segmentation effect is relatively poor. FGFCM improves the segmentation quality by introducing

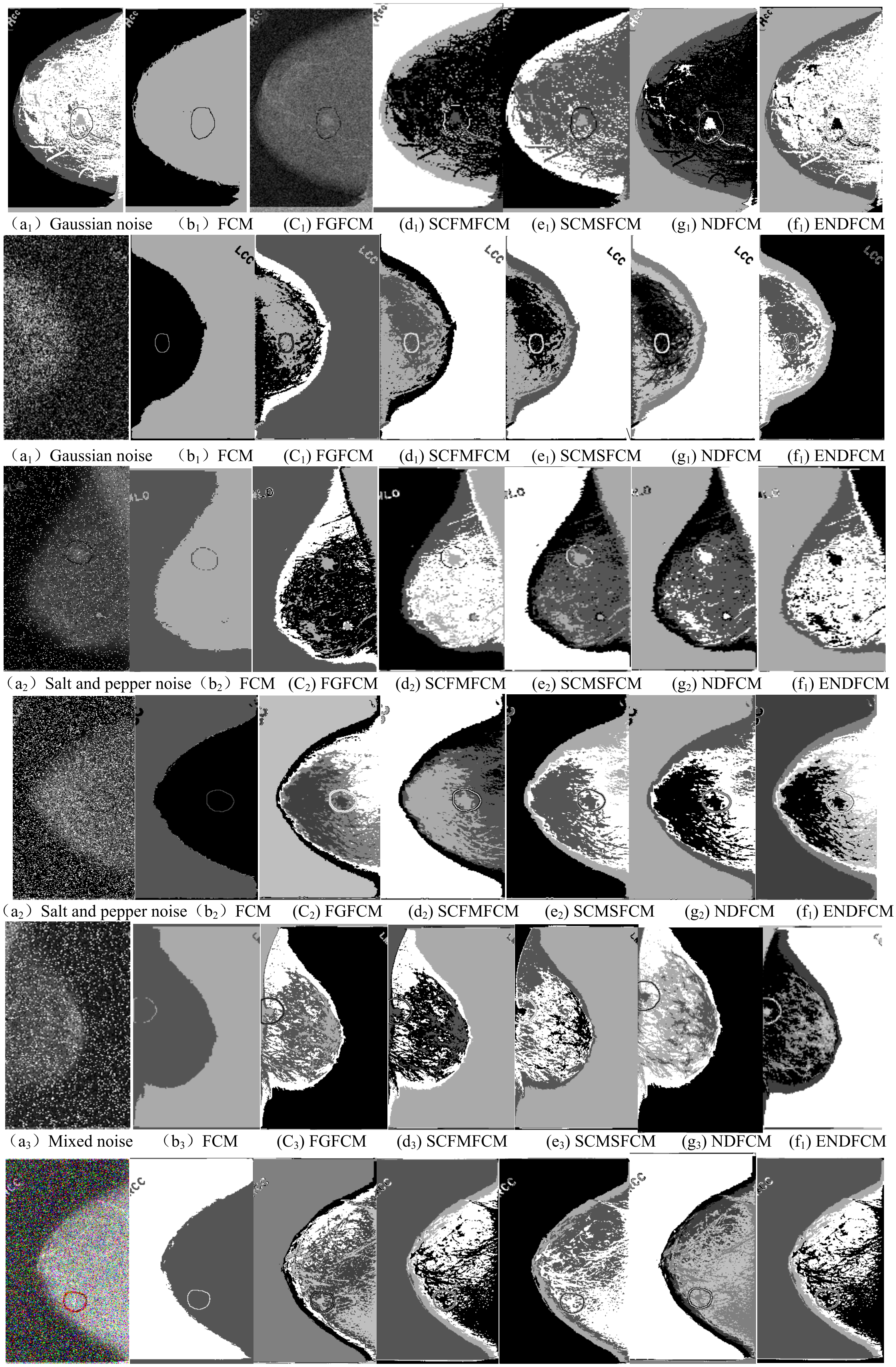

FIGURE 2. Segmentation results of different algorithms.

TABLE 1. Comparison of different clustering algorithms for segmentation image results.

Algorithms Noise	parameter	FCM	FGFCM	SCFFCM	SCMSFCM	NDFCM	ENDFCM
Gaussian noise	V_{pc}	0.8786	0.923	0.9278	0.9379	0.9407	0.952
	V_{pe}	0.2211	0.184	0.2013	0.1823	0.124	0.1729
	SA	94.0	96.68	96.2	96.79	97.46	98.56
Salt and pepper noise	V_{pc}	0.8274	0.901	0.921	0.932	0.9324	0.940
	V_{pe}	0.220	0.1823	0.182	0.172	0.171	0.170
	SA	93.89	96.5	96.51	98.79	98.76	99.6
Mixed noise	V_{pc}	0.9226	0.903	0.9019	0.915	0.901	0.917
	V_{pe}	0.1393	0.182	0.1824	0.1734	0.124	0.1734
	SA	94.67	96.61	96.63	97.58	97.23	98.57

the histogram method, but the segmentation error is larger due to the modified sampling method. SCFMFCM enhances the noise immunity of the algorithm based on Markov random field, but it causes the loss of image's detailed information. Because of the adaptive detection of noise, the segmentation effect of NDFCM is relatively good. The method of this paper introduces the energy curve based on NDFCM, fully considers the pixel space information, has relatively stronger anti-noise and detail retention, and can locate the position of the breast mass more accurately.

B. SEGMENTATION QUALITY EVALUATION

In order to verify the validity and accuracy of the ENDFCM algorithm segmentation, the segmentation results are quantitatively analyzed by using the segmentation coefficient V_{pc} [20], segmentation entropy V_{pe} [20] and segmentation accuracy (SA) respectively. V_{pc}, V_{pe} and SA are defined as follows:

$$V_{pc} = \frac{\sum_{i}^{N}\sum_{k}^{c} u_{ik}^{2}}{N} \tag{17}$$

$$V_{pe} = \frac{-\sum_{i}^{N}\sum_{k}^{c}\left[u_{ik}\log u_{ki}\right]}{N} \tag{18}$$

$$SA = \sum_{i=1}^{c} \frac{A_i \cap C_i}{\sum_{j=1}^{c} C_j} \tag{19}$$

where c represents the number of clusters, U_{ik} represents the membership of the kth sample x_k in the ith class, A_i is the ith pixel set obtained after the segmentation, and C_i represents the ith pixel set in the reference image. Here, the larger the division coefficient V_{pc}, the better the segmentation effect, and the smaller the segmentation entropy V_{pe}, the better the segmentation performance.

Table 1 is a quantitative comparison of the results of each algorithm for segmentation of images with different noisy mammographies. It can be seen from Table 1 that since the traditional FCM ignores the pixel space information and is sensitive to noise, its V_{pc} and V_{pe} values are relatively lowest, and the segmentation accuracy SA is the smallest; Compared with the traditional FCM, FGFCM and SCFMFCM have improved the segmentation quality of the algorithm to some extent by introducing the histogram method. Due to the consideration of the pixel space feature information, both V_{pc} and SA of SCMSFCM and NDFCM are increased, and V_{pe} reduced, indicating that a relatively better segmentation effect is obtained. Since the energy curve is introduced to further examine the pixel spatial characteristics, the V_{pc} of this method is relatively largest, V_{pe} is relatively smallest, and SA is relatively highest. In summary, the segmentation accuracy is SA; the algorithm in this paper is >NDFCM> SCMSFCM>SCFMFCM>FGFCM>FCM. Split entropy Vpe: The algorithm in this paper <NDFCM<SCMSFCM< SCFMFCM< FGFCM<FCM. It can be seen that the method can segment the breast tumor image relatively accurately and exhibit good segmentation performance.

C. ANTI-NOISE STABILITY ANALYSIS

To test the anti-noise stability of the ENDFCM algorithm, different concentrations of salt and pepper noise and Gaussian noise were added to the breast tumor images (as shown in Figures 3 and 4). Firstly, we consider the effect of parameters on segmentation results. In this paper, we introduce ξ_i to achieve pre-smoothing of the image, and ξ_i depends on the value of α, Therefore, the segmentation result depends on the parameter α to some extent. In Fig. 5, the effect of the parameter α on the experimental results was illustrated on the synthetic images. From Fig. 5, We can see that, whether it is salt and pepper noise or Gaussian noise, in general, as α increases, SA increases, which means that the accuracy of segmentation increases and the noise immunity becomes better. On the other hand, for α, it relies heavily on the noise intensity and variance. For Gaussian noise, α should also choose a larger value as the noise intensity increases. For salt noise, when the noise intensity is less than 0.05, the value of α increases with the noise intensity, and when the noise intensity is greater than 0.05, α seems unstable with a little disturbance.

In view of the effectiveness of SA in measuring the anti-noise of the algorithm, this paper uses SA to analyze the anti-noise stability of each algorithm. Fig. 7 shows the variation curve of V_{pc}. It can be seen from Fig. 6 that as the noise intensity increases, the segmentation accuracy SA of each algorithm decreases gradually; the SA of the

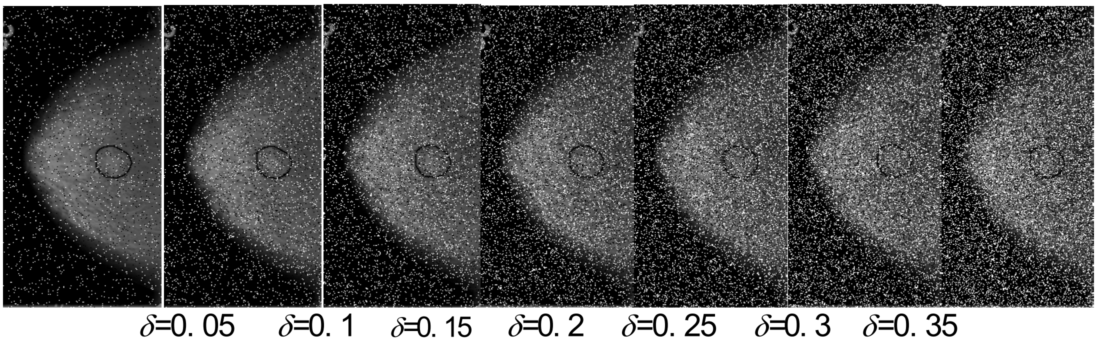

FIGURE 3. Image of breast tumor with varying degrees of salt and pepper noise.

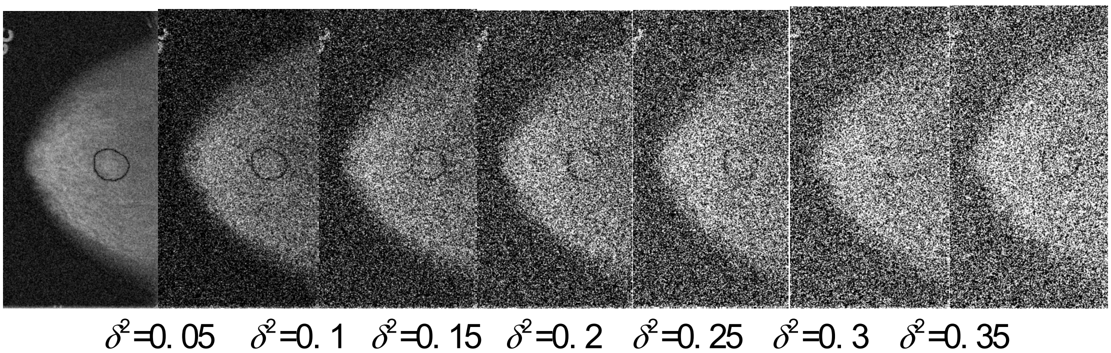

FIGURE 4. Image of breast tumor with varying degrees of gaussian noise.

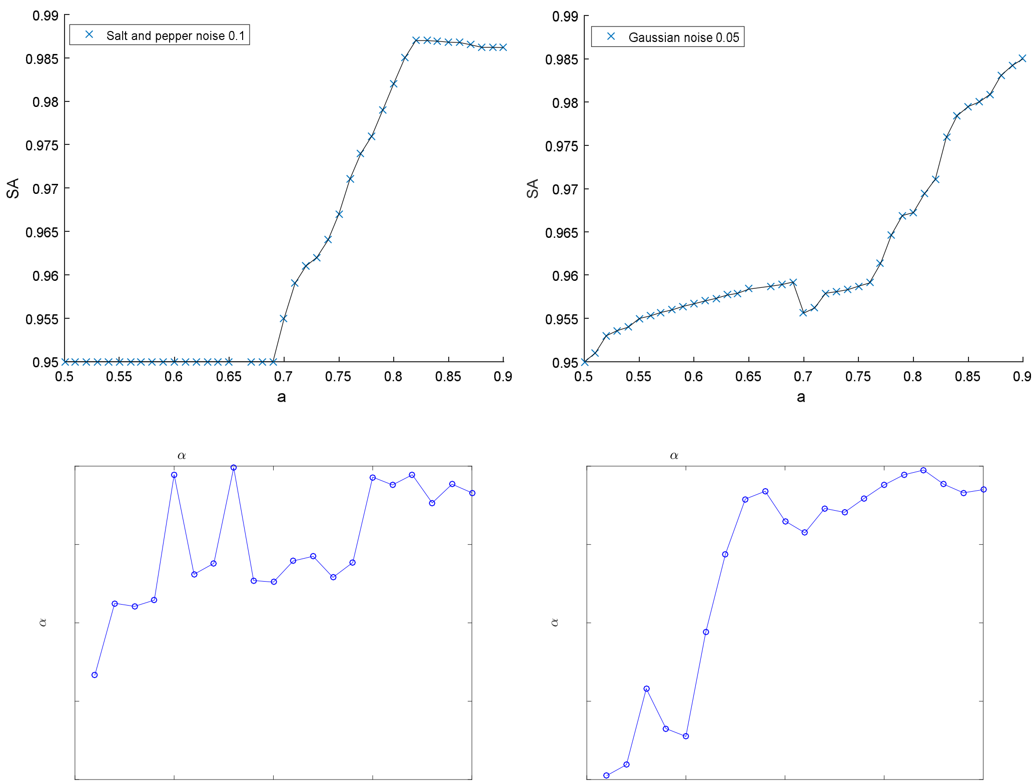

FIGURE 5. The influence of parameter α.

traditional FCM drops rapidly because the spatial correlation between pixels is not considered; FGFCM introduces the histogram method to replace the gray level with the pixel point, and uses the modified sample method to speed up

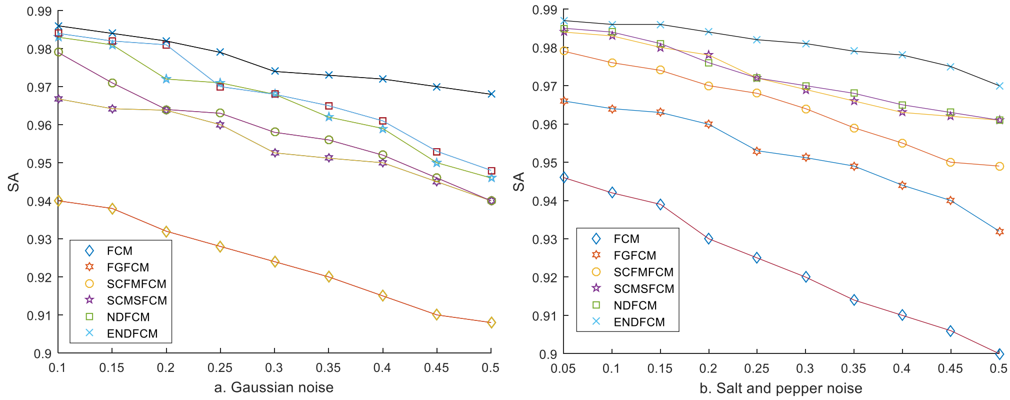

FIGURE 6. ***SA*** **variation curve of each algorithm when the noise is gradually enhanced.**

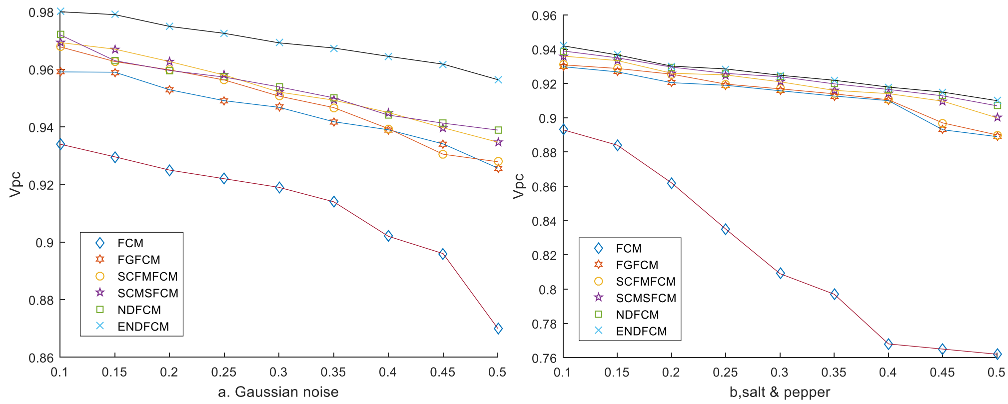

FIGURE 7. ***Vpc*** **variation curve of each algorithm when the noise is gradually enhanced.**

the algorithm's operation speed, but the algorithm accuracy is poor; The SCFMFCM algorithm uses the histogram to compress the spatial information, and combines the MRF to improve the image's noise and improve the accuracy of the algorithm. SCMSFCM and NDFCM combine pixel space information on the basis of traditional FCM algorithm, and the segmentation accuracy SA decreases relatively slowly. In this paper, ENDFCM introduces the spatial energy curve based on NDFCM, increases the spatial correlation of the algorithm, and further improves the segmentation quality of the algorithm. It can be seen that the increase of noise intensity has certain influence on the algorithm, but the impact is relatively small, indicating that the algorithm has good anti-noise stability.

V. CONCLUSION

The traditional FCM ignores the pixel space information and is sensitive to noise, when segmenting the breast tumor image, it is impossible to achieve a better segmentation effect. In this regard, this paper proposes an FCM algorithm based on energy noise detection combined with image space information and an improved algorithm is applied to image segmentation of breast tumors. The algorithm introduces a more spatially correlated energy curve to enhance the noise immunity of the algorithm. A new spatial distance constraint for the objective function is designed to achieve parameter adaptation. At the same time, the energy curve is integrated into the objective function to achieve the compression of the cluster space. A space is derived based on the new objective function. A more relevant membership function to further improve the quality of the segmentation. The qualitative and quantitative comparisons with FCM, FGFCM, SCFMFCM, SCMSFCM, NDFCM and other algorithms verify the effectiveness of the proposed algorithm. The anti-noise stability analysis shows that the performance of the algorithm does not decrease rapidly with the increase of noise intensity, it is proved that the improved algorithm has strong stability. Therefore, the ENDFCM mentioned in this paper has good anti-noise and robustness, and can accurately segment the breast tumor image, and shows good research significance and medical application prospects. However, we find that the efficiency of this method is a bit low. We will study heuristic optimization algorithm to improve its efficiency in the future.

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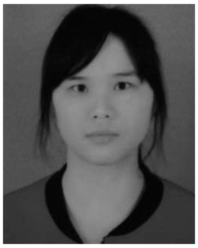

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