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Image Segmentation using Neural Network and Modified Entropy

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Abstract

In this paper, a novel image segmentation algorithm based on fuzzy clustering and entropy analysis using space information for optical images is proposed. We adopt the general properties of Hopfield neural network (HNN) and multi-synapse neural network (MSNN) to gain the center of the clusters and the fuzzy membership degrees for solving the optimization problems. As far as the noise influence is concerned, we introduce a novel window to improve the robustness of the proposed algorithm. In the experimental analysis part, we compare our method with some state-of-the-art methodologies and adopt the well-known test image databases to conduct the experiment. The result indicates that compared to FCM and some other clustering methods, our entropy and neural network based algorithm performs better. Our approach is less time-consuming and more robust to noise.

Keywords: *Image Segmentation, Neural Network, Modified Entropy, Fuzzy Clustering*

1. Introduction

Optical image segmentation as one of the most important research areas in the community of image analysis and processing, computer vision and machine learning is becoming popular in the scientific world. The segmentation result as a prior step of many applications will directly influence the final discrimination result. Therefore, a large number of scientific institutes have conducted researches on it. The current image segmentation algorithms vary from pixel level to feature level, fuzzy clustering based algorithms have been proved to be well performed. Since Zadeh proposed fuzzy concept, Ruspini firstly proposed fuzzy c-partitions in 1969 and some researchers started to focus on fuzzy clustering algorithm. Dunn proposed the weighted c-means clustering method under the condition that m equals to be 2 in 1974, and latterly, fuzzy c-means algorithm was proposed by Bezdek. From that time, fuzzy analysis has gained lots of success and plenty of successful applications. In the research area of data mining and data science, machine learning and pattern recognition, artificial intelligence and neural science, fuzzy analysis have got great success. In 2002, ahmed, etc. [1] think bias, corrected the fuzzy c - (shorten BCFCM) and spatial neighborhood information is introduced into the objective function to overcome the disadvantage of FCM, which is sensitive to salt and pepper noise and image artifacts. In 2004, a shortcoming of computational time-consuming for BCFCM was discussed by Chen [2], they proposed modified BCFCM algorithm. In 2009, Nahla [3] propose a fuzzy kohonen clustering network to add the robustness and decrease the noise sensitiveness of the current method. Li et al. [4] studied entropy based fuzzy clustering method. They combined the entropy with fuzzy clustering method, and proposed fuzzy clustering based on entropy. Bing [5] presented a novel algorithm based on FCM and level set methods to segment images automatically. In 2013, Gong [6] proposed the local information and Kernel Metric based FCM to accurately estimate the damping extent of neighboring pixels. Wang [7] proposed a novel image

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representation method to better represent and classify the images which can be adopted by us. There are also lots of recent algorithms on image segmentation [9-17]. In this research paper, we conduct research on image segmentation using fuzzy clustering methodology based on the generalized entropy. Two typical neural networks are adopted to solve optimization related issues. Finally, spatial information is also considered when analyzing the algorithm.

The structure of this paper is organized as the following: In the second section, the traditional fuzzy clustering (FC) algorithm is introduced with other related prior knowledge. In the third section, the methodology of fuzzy analysis and generalized entropy based segmentation is discussed. In the fourth section, we conduct experiment and compare the result with other methods. In the final section, we draw the conclusion and briefly introduce our future work.

2. The Fuzzy Clustering and Related Algorithms

2.1. The Fuzzy c-means (FCM) Clustering

Clustering method attempts to organize unlabeled data into clusters or groups, such that the data within a group are more similar to each other than the ones belonging to different groups [5]. FCM is one of the commonly and generally used algorithms. We define the fuzzy clustering problems as the following description: $X=\{x_1,x_2,\cdots,x_n\}$ is defined to be the finite set of data that we will deal with, c is the number of clusters, m represents the fuzzy weight, the range of it is $1<m<\infty$. We define the cluster center to be $V=\{v_i,1\le i\le c\}$, membership degree matrix to be $U=\{\mu_{ij},1\le i\le c,1\le j\le n\}$. μ_{ij} is the fuzzy membership degree from the data point from x_j to the center of v_i. In the formula 1, we define the objective function of fuzzy c-means clustering:

$$J(U,V)=\sum_{j=1}^{n}\sum_{i-1}^{c}\mu_{ij}^{m}\left\|x_j-v_i\right\|^2 \tag{1}$$

The initial perspective of solving clustering problems will be transferred to solve the optimization problem described in formula 2.

$$\min_{U,V} J(U,V) \qquad s.t.\sum_{i=1}^{c}\mu_{ij}=1,1\le j\le n \tag{2}$$

We could get the membership degree and cluster center using the Lagrange approach as the following formula 3 and 4.

$$\mu_{ij}=\frac{1}{\sum_{l=1}^{c}\left(\frac{\left\|x_j-v_i\right\|}{\left\|x_j-v_l\right\|}\right)^{\frac{2}{m-1}}} \tag{3}$$

$$v_i=\frac{\sum_{j=1}^{n}\mu_{ij}^{m}x_j}{\sum_{j=1}^{n}\mu_{ij}^{m}} \tag{4}$$

We can find out the phenomenon from the previous two formulas that the cluster center and membership degree are relative to each other, and therefore, iterative approach as adopted by the fuzzy c-means algorithm to find out the optimal solution.

Since the FCM algorithm doesn't take into account the image spatial information, salt and pepper is sensitive to noise and image artifacts. To deal with this problem, BCFCM was proposed with the following objective function:

$$J_m^{BCFCM}\left(\mu,\alpha\right)=\sum_{j=1}^{n}\sum_{i=1}^{c}\mu_{ij}^{m}\left\|x_j-v_i\right\|^2+\frac{\alpha}{N_R}\sum_{j=1}^{n}\sum_{i=1}^{c}\mu_{ij}^{m}\sum_{x_r\in N_j}\left\|x_r-v_i\right\|^2 \tag{5}$$

In the formula 5, N_j is the set of pixels that exist in a window around x_j and N_R is the cardinality of N_j. Later, in order to reduce the computational complexity and time consumed, Chen [2] made some modification on the formula 5 to create the formula 6 as the revised objective function:

$$J_m^{CZ}\left(\mu,\alpha\right)=\sum_{j=1}^{n}\sum_{i=1}^{c}\mu_{ij}^{m}\left\|x_j-v_i\right\|^2+\alpha\sum_{j=1}^{n}\sum_{i=1}^{c}\mu_{ij}^{m}\left\|\overline{x_j}-v_i\right\|^2 \tag{6}$$

The $\overline{x_j}$ represents the mean value of the window patch around the pixel x_j (also called mean average). J_m^{CZ} is the revised new objective function. In the formula, we use the parameter α to control and adjust the neighbor influence.

2.2. The Generalized Entropy and Application

By Rudolf Clausius entropy concept, put forward to represent the uniformity of the spatial distribution of energy. In particular, more uniform distribution of energy, the greater the entropy. Later, shannon first introduces the concept of entropy, the measurement uncertainty of the information theory. In the process of fuzzy clustering, by introducing the entropy of membership degree and distance from the sample points to center, clustering process is gradually transformed from the maximum uncertainty into determination. Li [8] proposed the entropy based fuzzy clustering methodology and pointed out the novel objective function in the formula 7.

$$J_G\left(U,V\right)=\sum_{j=1}^{n}\sum_{i=1}^{c}\mu_{ij}^{m}\left\|x_j-v_i\right\|^2+\delta\cdot H\left(U,\alpha\right)\qquad \alpha>0,\alpha\neq 1 \tag{7}$$

In the formula 7, $H\left(U,\alpha\right)=\sum_{j=1}^{n}\left(2^{1-\alpha}-1\right)^{-1}\left(\sum_{i=1}^{c}\mu_{ij}^{\alpha}-1\right)$ represents the generalized entropy (GE) and we use α to represent the index of GE.

3. Image Segmentation based on Proposed Method

3.1. Modified Objective Function

We add the feature of spatial information into the entropy based fuzzy clustering methodology to generate our novel objective function:

$$J_{IM}\left(U,V\right)=\sum_{j=1}^{n}\sum_{i=1}^{c}p_j\mu_{ij}^{m}\left\|x_j-v_i\right\|^2+\delta\sum_{j=1}^{n}\left(2^{1-\alpha}-1\right)^{-1}\left(\sum_{i=1}^{c}\mu_{ij}^{\alpha}-1\right)$$
$$+\sum_{j=1}^{n}\sum_{i=1}^{c}\left(1-p_j\right)\mu_{ij}^{m}\left\|\overline{x_j}-v_i\right\|^2$$

(8)

In the formula, the statistical distribution of pixels around x_j is fornulated as $p_j = N_j^i / N_R$, N_j^i is the total number of the pixels around x_j and classified into the same cluster. $\overline{x_j}$ represents the average value of pixel which are around the point x_j, the cardinality of N_j is defined as the N_R. In order to deal with the problem of constrained optimization for the formula 8, we make use of the augmented Lagrange approach to find out the solution. The constrained condition is formulated as the following:

$$\sum_{i=1}^{c} \mu_{ij} = 1, 1 \le j \le n$$

(9)

Therefore, we could define the augmented Lagrange function (ALF) to be:

$$Z_m(U, v, \lambda) = \sum_{j=1}^{n}\sum_{i=1}^{c} p_j \mu_{ij}^m \left\| x_j - v_i \right\|^2 + \sum_{j=1}^{n}\sum_{i=1}^{c} (1 - p_j) \mu_{ij}^m \left\| \overline{x_j} - v_i \right\|^2$$
$$+ \delta \sum_{j=1}^{n} \left(2^{1-\alpha} - 1\right)^{-1} \left(\sum_{i=1}^{c} \mu_{ij}^{\alpha} - 1 \right) + \sum_{j=1}^{n} \lambda_j \left(\sum_{i=1}^{c} \mu_{ij} - 1 \right) + \sum_{j=1}^{n} \gamma \left(\sum_{i=1}^{c} \mu_{ij} - 1 \right)^2$$

(10)

$\lambda_j \left(j = 1, 2, 3, \cdots, n \right)$ stands for the Lagrange multipliers whereas γ is a huge variable. In order to solve the optimization problem of formula 10, we adopt the traditional Hopfield neural network (HNN). The structure of HNN is shown in figure 1. We use the HNN to obtain the cluster centers, while they are captured, these values will be trated as the constant value on during procedure of network transform.

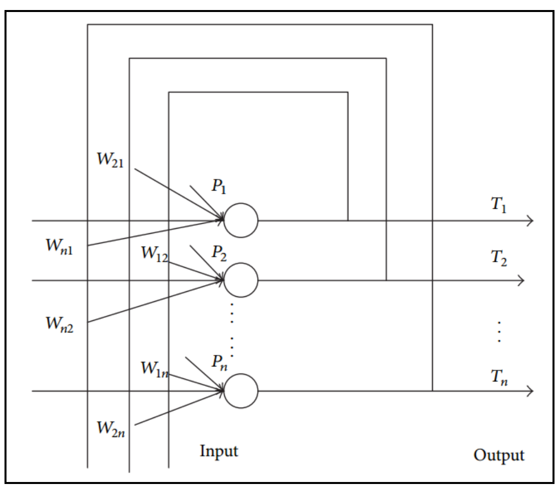

Figure 1. The Structure of Hopfield Neural Network (HNN)

3.2. Capture Cluster Centers

We can make the conclusion from the formula 10 that the function is a quadratic function about cluster center $v_i \left(1 \le i \le c\right)$. To capture the cluster centers, we ignore the fix parts under the consideration of time-consuming and efficiency. Therefore, we express the revised function as:

$$\sum_{j=1}^{n}\sum_{i=1}^{c}\left(\mu_{ij}^{m}v_i^2-2\mu_{ij}^{m}\left(p_jx_j+\overline{x_j}-p_j\overline{x_j}\right)v_i\right)$$

(11)

Notice that s denoted as the number of neurons in the network is $c\times p$. p is the demision value of the input data. We get the formula 12 according to HNN, in [8] the detailed discussions on the topic could be found.

$$NET=WV+I$$

(12)

$$NET=\begin{bmatrix} net1\\ net2\\ ....\\ nets\end{bmatrix}\quad V=\begin{bmatrix} v_1\\ v_2\\ ...\\ v_s\end{bmatrix}\quad I=\begin{bmatrix} i_1\\ i_2\\ ...\\ i_s\end{bmatrix}\quad W=\begin{bmatrix} w_{11} & w_{12} & ... & w_{1s}\\ w_{21} & w_{22} & ... & w_{2s}\\ ... & ... & ... & ...\\ w_{s1} & w_{s2} & ... & s_{ss}\end{bmatrix}$$

$$i_{(j-1)\times p+l}=2\sum_{k=1}^{n}\mu_{jk}^{m}\left(p_kx_{kl}+\overline{x_{kl}}-p_k\overline{x_{kl}}\right)\qquad j=1,2,...,c;l=1,2,...,p$$

(13)

$$w_{ji}=\begin{cases}-2\sum_{k=1}^{n}\mu_{ik}^{m} & i=j\\ 0 & otherwise\end{cases}\qquad j=1,2,...,s;i=1,2,...,s$$

(14)

$$v_j^{(g+1)}=f\left(net_j^{(g)}\right)=\begin{cases}v_j^{(g)}+\delta_v & net_j^{(g)}\geq 0\\ v_j^{(g)}-\delta_v & net_j^{(g)}\leq 0\end{cases}$$

(15)

In the formula 15, g represents the loop of g-th, and δ_v is a constant number near zero to help adjust and modify the v_j.

3.3. Capture Membership Degree

As will discuss later, our goal is to optimize the membership degree of μ in the objective function 10.We make extension of formua 10 to get the revised objective function:

$$\sum_{j=1}^{n}\sum_{i=1}^{c}\left(\left(p_jd_{ij}^{(1)}+\left(1-p_j\right)d_{ij}^{(2)}\right)\right)\mu_{ij}^{m}+\gamma\mu_{ij}^{2}$$
$$+\delta\left(2^{1-\alpha}-1\right)^{-1}\mu_{ij}^{\alpha}+\left(\lambda_j-2\gamma\right)\mu_{ij}$$

(16)

Where, $d_{ij}^{(1)}=\left\|x_j-v_i\right\|^2$ and $d_{ij}^{(2)}=\left\|\overline{x_j}-v_i\right\|^2$. We adopt the multi-synapse neural network (MSNN)to optimize membership degree μ. In the figure 2, we illustrate the basic structure of multi-synapse neural network (MSNN). In 2d for membership into a one-dimensional subscript subscript. Please note that there are more than two per weight between two neurons. In multi-synapse neural network, the transformation is defined as the following:

$\mu_{ij} \to \mu_{(j-1)c+i}$, $d_{ij} \to d_{(j-1)c+i}$. The matrix form used to express the total input of multi-synapse neural network is:

$$NET = W.U + Z.U + Y.\mathrm{U} + I$$

(17)

In addition, we define the following matrixes:

$$U_{<m-1>} = \begin{bmatrix} \mu_1^{m-1} \\ \mu_2^{m-1} \\ \cdots\cdots \\ \mu_s^{m-1} \end{bmatrix}, m > 1, where \quad U_{<1>} = U$$

(18)

$$Y_{<\alpha-1>} = \begin{bmatrix} y_1^{\alpha-1} \\ y_2^{\alpha-1} \\ \cdots\cdots \\ y_s^{\alpha-1} \end{bmatrix}, \alpha > 1, where \quad Y_{<1>} = Y$$

(19)

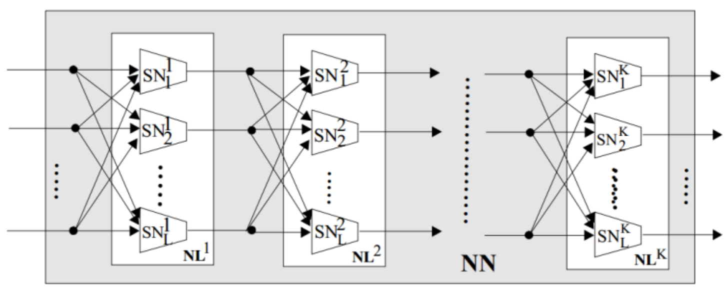

Figure 2. The Structure of Multi-synapse Neural Network

For the formula 17, the corresponding function of energy is:

$$E = -\left(\frac{1}{m}\right)U_{<m-1>}^T \cdot W \cdot U - \left(\frac{1}{2}\right)U^T \cdot Z \cdot U - \left(\frac{1}{\alpha}\right)U_{<\alpha-1>}^T \cdot Y \cdot U - U^T \cdot I$$

(20)

By comparing the formula 20 and 16, we can formulate W, Z, Y and I one by one.

$$w_{ji} \begin{cases} -m\left(p_j d_{ij}^{(1)} + (1-p) d_{ij}^{(2)}\right) & i = j \\ 0 & i \neq j \end{cases} \qquad i, j = 1, 2, \ldots, s$$

(21)

$$z_{ji} \begin{cases} -2\gamma\left(\left\lceil \frac{i}{c} \right\rceil - 1\right) \cdot c < j \leq \left\lceil \frac{i}{c} \right\rceil \cdot c & i, j = 1, 2, \ldots, s \\ 0 & others \end{cases}$$

(22)

$$y_{ji}\begin{cases}-\alpha\cdot\delta\cdot\left(2^{1-\alpha}-1\right)^{-1} & i=j \\ 0 & i\neq j\end{cases}\quad i,j=1,2,...,s$$

(23)

$$i_j = 2\gamma - \lambda_k$$

(24)

Next, we need a relationship of energy function and neural network input. Our hope is that the value of the energy function is reduced, and the iteration increases, as the objective function value. Found that the relationship between the energy function and neural network's input, we found that the matrix W and Y is symmetrical. Therefore, we modify the formula 20 to the formula 25:

$$E=-\left(\frac{1}{m}\right)U^T\cdot W\cdot U_{<m-1>}-\left(\frac{1}{2}\right)U^T\cdot Z\cdot U-\left(\frac{1}{\alpha}\right)U^T\cdot Y\cdot U_{<\alpha-1>}-U^T\cdot I$$

(25)

Through this, we canc conduct the new multi-synapse neural network, the nocel input matrix and avtivate function are:

$$NET = W\cdot U_{<m-1>}+Z\cdot U+Y\cdot U_{<\alpha-1>}+I$$

(26)

$$u_j^{(g+1)} = f\left(net_j^{(g)}\right)$$

(27)

The full expression of input of network can be expressed as:

$$net_j=\sum_{i=1}^{S}\left(w_{ji}\mu_i^{m-1}+z_{ji}\mu_i+y_{ji}\mu_i^{\alpha-1}\right)+i_j$$

(28)

At the same time, we define the energy gradient function of formula 27 to be:

$$\nabla E=-\left(\sum_{i=1}^{s}\left(w_{ji}\mu_i^{m-1}+z_{ji}u_i+y_{ji}\mu_i^{\alpha-1}\right)+i_j\right)\qquad j=1,2,...,s$$

(29)

Iterative loop termination conditions are based on membership degree value is the difference between the cycle, and finally determine a period of less than a given value ε. The detailed steps of proposed methodology is discussed as the following. (1) Initialize the value of $c,m,\gamma,\delta_v,\delta_\mu$, (2) Initialization process of v_j among the data set of x_j, the u_{ij} and γ denoted as the membership degree into the scope of [0,1] and [1,10], (3) Initiate the value of $net(0)_j=0$ and the interation counter $g=1$ in HNN, (4) Calculated the parameters in HMM (NET, I, W), (5) For $j=1\sim s$, if the condition is $net_j^{(g)}\times net_j^{(g-1)}\leq 0$, $\delta_v=\delta_v/2$, (6) For $j=1\sim s$, if the condition is $net_j^{(g)}\geq 0$, $v_j=v_j+\delta_v$ or otherwise, $v_j=v_j-\delta_v$, (7) Initiate the iteration counter g to be 1 in the proposed multi-synapse neural network, (8) Calculate the parameters for the newtwork, the parameters are: W,Z,Y,I,NET, (9) For $j=1\sim s$, if the condition is $net_j^{(g)}\times net_j^{(g-1)}\leq 0$, $\delta_\mu=\delta_\mu/2$, (10) For $j=1\sim s$, if the condition is $net_j^{(g)}\geq 0$, $\mu_j=\mu_j+\delta_\mu$ or otherwise, $\mu_j=\mu_j-\delta_\mu$, (11) For $j=1\sim s$, if the condition is $\mu_j > 1$, then $\mu_j = 1$ else if $\mu_j < 0$, then $\mu_j = 0$, (12) If $\left\| U^{(g)} - U^{(g-1)} \right\| \le \varepsilon$, exiting the algorithm else go to step 3.

4. Experiment and Analysis

In this paper, we choose test images from datasets and set the size of images to be 72×72, we control and adjust the experimental condition to be the same for all the test algorithms. We calculate the average of the pixels with 3×3 patch. Firstly, we use four images without noise to perform the algorithm we proposed. The picture Lena is downloaded from Internet and the others are built in C++ and OpenCV library. The figure 3 to figure 11 shows the result of our experiment.

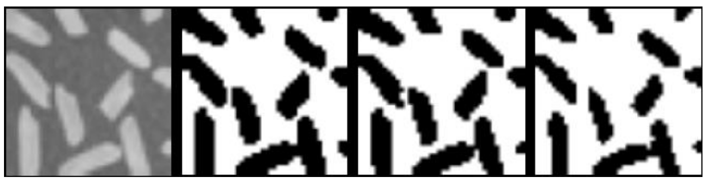

Figure 3. (a) original; (b) FCM; (c) BCFCM_ S1; (d) ISGEFCM

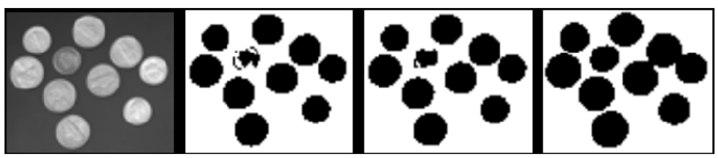

Figure 4. (a) original; (b) FCM; (c) BCFCM_ S1; (d) ISGEFCM

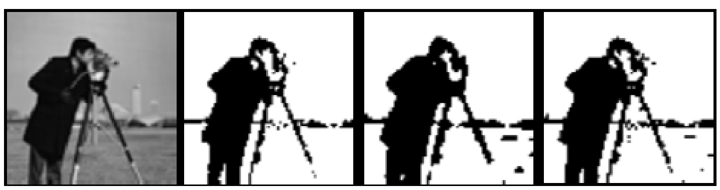

Figure 5. (a) original; (b) FCM; (c) BCFCM_ S1; (d) ISGEFCM

Figure 6. (a) original; (b) FCM; (c) BCFCM_ S1; (d) ISGEFCM

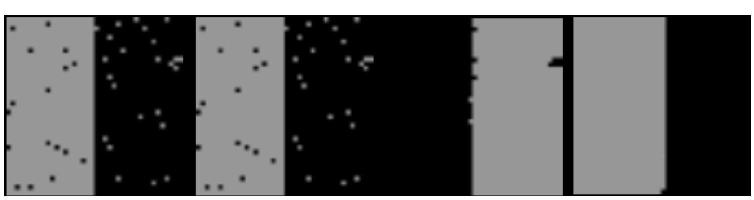

Figure 7. (a) original; (b) FCM; (c) BCFCM_ S1; (d) ISGEFCM

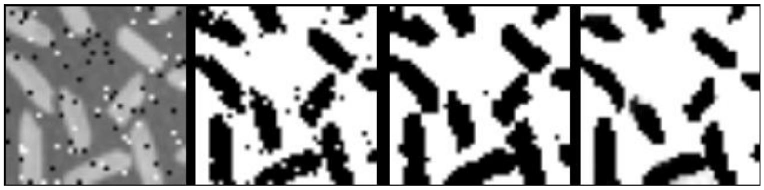

Figure 8. (a) original; (b) FCM; (c) BCFCM_ S1; (d) ISGEFCM

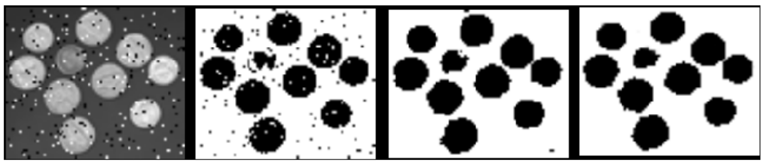

Figure 9. (a) original; (b) FCM; (c) BCFCM_ S1; (d) ISGEFCM

Figure 10. (a) original; (b) FCM; (c) BCFCM_ S1; (d) ISGEFCM

Figure 11. (a) original; (b) FCM; (c) BCFCM_ S1; (d) ISGEFCM

The first group of the experimental results show that the algorithm can keep more details and more accurate segmentation, such as the edge of the third coin in figure 2 and figure 6 the edge of the hat. A second set of results showed that FCM is invalid, noise BCFCM_S1 algorithm to remove most of the noise, and our approach, nearly all of the voice. Show that our algorithm achieves better better noise and multi-level image segmentation is similar to Figure 11. Can be concluded that our approach is robust and effective noise image segmentation and the choice of some parameters. However, we indicate that the selection of parameters is tricky and needs more experiment.

5. Conclusion and Summary

In this paper, we proposed a novel image segmentation algorithm based on modified entropy and two kinds of neural network. By adding spatial information into the algorithm, it becomes more efficient and robust. The p_j represents the pixels' distribution regulation near the x_j, therefore, we could measure and control the effect of neighbors near x_j. The experiment result indicated and proven the effective and correctness of our method.

In the future research, we plan to conduct more comparative experiment together with more state-of-the-art algorithms and introduce more optimization analysis to our current method to do more related work.

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