International Journal of Advanced Materials Chemistry and Physics. Volume 5, Issue 1, (2022) 16-23
http://www.cayley-nielson.com/ijamcp/

Cerebrovascular Image Segmentation Algorithm Based on FCM Based on Local Information

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Abstract

A cerebrovascular image segmentation algorithm based on fuzzy C-Means (FCM) based on local information is proposed, which is applied to the post-processing stage of cerebrovascular segmentation. The algorithm does not need to adjust parameters to balance image noise and image detail, and is able to utilize spatial information and grayscale information. Experimental results show that the FLICM algorithm reduces the misdivision of the skull and orbit. Through the comparative test of different modes, it is shown that the *Dice* coefficient of the three modes combination is higher than that of other modes, which is also better than other traditional algorithms, and the average value of the *Dice* coefficient reaches 0.6946.

Keywords: local information, FCM, image segmentation, cerebrovascular.

1. Introduction

In today's society, cerebrovascular disease has become one of the important diseases that threaten people's health and life, and the research on cerebrovascular diseases is becoming increasingly important. In addition, with the development of angiography image technology and computer technology, the use of angiography images of computer-aided diagnosis and treatment has also become a research focus and difficulty, of which the segmentation of blood vessels in cerebral angiography images is one of the key technologies of auxiliary diagnosis and treatment. Vascular segmentation refers to the separate division of the vascular part of the region in the image, which is of great significance for the diagnosis and treatment of vascular diseases. At present, due to the diversity of imaging methods and the complexity of vascular structure, although more segmentation methods for cerebral blood vessels are proposed, there is no universal and high-precision method suitable for a wide variety of contrast images. At present, researchers have done a lot of work on the study of automatic segmentation method of cerebral blood vessels based on convolutional neural networks [1-2].

Since convolutional neural networks of different modes highlight different types of features, the segmentation results may perform differently for different tissues, for example, the Gaussian mode may be better for the extraction of large blood vessel points, and the Laplace mode may have a greater advantage over small blood vessel points. Therefore, the result of combining multiple modes will have better results. However, after the experiment, the experimental results showed that there were still some misdivisions, such as the skull and orbital parts were not ideally separated. Considering the pool position of related parts such as orbit and skull, this paper uses fuzzy *C* means to post-process the segmentation results.

ISSN: 2378-9662, E-ISSN: 2381-5590 /
April, 2022

2. FCM algorithm

The basic idea of the FCM algorithm is to make the data points classified into the same class the greatest similarity between them, and the least similarity between the data of the same kind. Different from the ordinary *C* means algorithm, the FCM algorithm has a probability value description for the category to which each data point belongs, which belongs to a flexible fuzzy division. The FCM algorithm requires two parameters: the number of clusters *c* and the flexible parameter m that controls the degree of ambiguity. Assuming that there are *n* data points in common, the general number of clusters *c* should be much smaller than *n*. For flexible parameters m, this value controls the fuzziness of the algorithm, if m it is too small, the algorithm is equivalent to a hard c-means clustering algorithm (HCM), the probability value difference of each data point is small, and the clustering effect is not ideal. For the *n* data of input, the algorithm outputs a matrix of the dimension is *c* by n that represents the probability that each data belongs to each class, usually choosing the maximum value of each column as the class to which the data point belongs.[3]

Specifically, the FCM algorithm divides *n* vector $x_i(=1,2,\dots,n)$ into *c* fuzzy groups, each fuzzy group represents a similar category, and then the fuzzy group is clustered, and the loss function of the cluster is depicted by the distance of each data from the center of the fuzzy group. The difference between FCM algorithm and HCM algorithm is that FCM algorithm is divided by fuzzy, for each data point, the probability of belonging to the category is determined with the degree of membership of a value of (0,1).

The membership matrix *U* is a collection of memberships of all data, where the values are (0,1). And because of the uniformization provisions, the sum of the degree of memberships of each data point is equal to 1:

$$\sum_{\mathrm{i}=1}^{\mathrm{c}} u_{ij} = 1, \forall j = 1,\dots,\mathrm{n} \tag{1}$$

As shown in Equation (2), it is a generalized form of the loss function of FCM:

$$J(U, c_1,\dots,c_c) = \sum_{\mathrm{i}=1}^{\mathrm{c}} J_i = \sum_{\mathrm{i}=1}^{\mathrm{c}} \sum_{\mathrm{j}}^{\mathrm{n}} u_{ij}^m d_{ij}^2 \tag{2}$$

Where the value of u_{ij} is between 0 and 1, it represents the data in the *i*th row and *j*th column of the membership matrix, *c* represents the cluster center of the *i*th fuzzy group, and $d_{ij} = \|\mathrm{c_i} - x_j\|$ represents the geometric distance between the *i*th cluster center and *j*th data point: $m \in [1,\infty)$ is the flexibility index of the FCM algorithm. To find the minimum value of equation (2), construct a new objective function as follows:

$$\bar{J}(U, c_1,\dots c_c, \lambda_1,\dots,\lambda_n) = J(U, c_1,\dots c_c) + \sum_{\mathrm{j}=1}^{\mathrm{n}} \lambda_j \left(\sum_{\mathrm{i}=1}^{\mathrm{c}} \mathrm{u_{ij}} - 1\right)$$
$$= \sum_{\mathrm{i}=1}^{\mathrm{c}} \sum_{\mathrm{j}}^{\mathrm{n}} u_{ij}^m d_{ij}^2 + \sum_{\mathrm{j}=1}^{\mathrm{n}} \lambda_j \left(\sum_{\mathrm{i}=1}^{\mathrm{c}} u_{ij} - 1\right) \tag{3}$$

Where $\lambda_j, j = 1,2\dots\mathrm{n}$ are the n constrained Lagrangian multipliers of the equation (1). For all input data derivation, which is the equation (2) necessary to obtain the minimum:

$$c_i = \frac{\sum_{\mathrm{j}=1}^{\mathrm{n}} u_{ij}^m x_j}{\sum_{\mathrm{j}=1}^{\mathrm{n}} u_{ij}^m} \tag{4}$$

and

$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{d_{ij}}{d_{ki}}\right)^{\frac{2}{m-1}}} \tag{5}$$

From the two necessary conditions of (4) and equation (5), it can be seen that the fuzzy *C* means algorithm is an iterative-based algorithm. In the specific implementation process of FCM algorithm, calculate the cluster center *c* and the degree of membership matrix *U* as follows:

[1] First, the degree of membership matrix *U* is initialized, initialized with a random number between the values (0,1), and the constraints in the equation (1) are satisfied;

[2] The *i*th cluster center *c* is obtained according to the calculation method of equation (4), $i = 1,2,\ldots,c$;

[3] Find the value of the cost function according to equation (2). If its cost function value is less than a certain threshold, or the difference from the previous cost function value is less than the threshold, the algorithm ends, otherwise execution continues;

[4] Use the calculation method of equation (5) to find a new membership matrix, and return to the specific process described above in step 2 can also be changed to initialize the cluster center first, and then modify the membership matrix and cluster center according to the iterative process. In addition, in the process of iteration, the FCM algorithm does not necessarily converge to the minimum value or converge to the local minimum value, so the performance of the algorithm depends to a considerable extent on the selection of the initial value. To avoid algorithm uncertainty, you can use another fast algorithm to determine the cluster center, or initialize the algorithm with a different initial cluster center each time, run FCM multiple times, and usually use the second method to avoid the contingency of clustering.

2.1 FCM segmentation algorithm based on local information

The traditional FCM algorithm has a good segmentation effect for images that are not polluted by noise, but the segmentation effect is not ideal for images contaminated by noise. This noise sensitivity is essentially due to the fact that the spatial position information of the segmented pixels is not used, and the neighborhood information between the pixels is ignored, so the segmentation effect is not ideal for images with low signal-to-noise ratio. In the process of image segmentation, it is possible to reduce the interference of various noises and accurately classify the original image information based on a direction that needs to be improved by the standard FCM image segmentation method. For the segmentation of images based on spatial neighborhood information, many algorithms have been given in recent years, including the more classic FCMS algorithm, FCMS 1 algorithm and FCMS2 algorithm, EnFCM algorithm, FGFCM algorithm and so on.

FCMS algorithm

FCM algorithm, proposed by Ahmed et al. in 1999, mainly for the problem that the FCM algorithm does not use neighborhood information, the objective function of the FCM algorithm is added to the neighborhood pixel information, and the neighborhood pixel of the pixel is as close as possible to the central pixel in the segmentation process.

FCMS1 and FCMS2 algorithms

The FCMS algorithm has greatly improved the segmentation effect, but because the FCMS algorithm needs to calculate the neighborhood information of pixels in each iteration, the FCMS algorithm is very inefficient. In view of this problem, Zhang Daoqiang et al. proposed FCMS1 and FCMS2 algorithms, which use mean and median filtering to calculate the neighborhood information of pixels in advance, which can ensure that the efficiency of the algorithm can be effectively improved under the premise of segmentation effect.

EnFCM algorithm

The EnFCM algorithm was proposed by Szilagyi et al., which is mainly improved for the problem of low efficiency of FCM algorithm. First of all, the given image is filtered, and then a new image is constructed by using the linear combination of the filtered image and the original image, and the image is segmented based on the FCM algorithm based on the histogram of the constructed image, so that the gray level of the calculated pixel is reduced from the calculated pixel to the gray level of the calculated pixel, which greatly improves the running efficiency of the algorithm.

FGFCM algorithm

When using the EnFCM algorithm to filter the image, parameters are used to represent the influence of neighborhood information on the central pixel, so that the segmentation effect of the EnFCM algorithm is not particularly ideal. To solve this problem, Cai Weiling et al. proposed the FGFCM algorithm. The algorithm first establishes the correlation model between adjacent pixels, and then segments the image according to the EnFCM algorithm, which not only ensures a better segmentation effect but also has a high operating efficiency.

FLICM algorithm

In the FCMS algorithm, FCMS1 algorithm and FCMS2 algorithm, and EnFCM algorithm, there are preset parameters (the influence factor of neighborhood pixels on the center pixel), which effectively balances the sensitivity of the algorithm to noise and the processing of segmentation on image details. However, it is very difficult to set the value of the parameter in the relevant algorithm, and its size will directly affect the quality of the segmentation result. If the value is large, the result of the segmentation is too blurry, and if the value is small, the relevant algorithm is still sensitive to noise in the image. Although the FGFCM algorithm overcomes this and uses the correlation model of adjacent pixels to replace the constants in the EnFCM algorithm for filtering, the parameters still need to be adjusted. The adjustment of parameters directly affects the quality of the partition, but the adjustment of parameters is very difficult. In response to this situation, Stelios Krinidis and Vassilios Chatzis proposed an improved FCM algorithm based on local information (Fuzzy LocalInformation C-Means Clustering) (FLICM). Unlike the improved algorithms mentioned above, the FLICM algorithm does not contain any other parameters when utilizing neighborhood information except for the necessary parameters in the FCM series of algorithms.[4]

The objective function in the FLICM algorithm is defined as:

$$J = \sum_{\mathrm{i}=0}^{\mathrm{c}} \sum_{\mathrm{i}=0}^{\mathrm{n}} u_{ij}\, d_{ij}^{2} + G_{ij} \tag{6}$$

Where G_{ij} is the fuzzy factor, which represents the Euclidean-style distance weighted sum of the inner pixels N_k and the center of the cluster v_{ij}, reflecting the use of neighborhood information in the

FLICM algorithm, defined as：

$$G_{ij} = \sum_{j \in N_k, k \neq j}^{n} \frac{1}{d_{ik}+1} (1 - \mu_{ik})^{m} (x_K - v_i)^2 \tag{7}$$

where N_k is the collection of neighborhood locations for K, d_{jk} is the spatial position distance of pixel j and pixel k, u_{jk} is the membership of pixels relative to clustering, x_k is the gray value of pixel k, and v_i is the cluster center of cluster i.

However, the update of the cluster center and membership of the algorithm is not obtained strictly according to the principle of minimization of the objective function, but is transplanted from the FCM algorithm and the FCM algorithm as follows:

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\left\| x_j - v_i \right\|^2 + G_{ij}}{\left\| x_j - v_k \right\|^2 + G_{kj}} \right)^{\frac{1}{m-1}}} \tag{8}$$

$$v_i = \frac{\sum_{j=1}^{n} u_{ij}^{m} x_j}{\sum_{j=1} u_{ij}^{m}} \tag{9}$$

The use of FLICM algorithm has the following advantages: First, the use of G_{ij} (Fuzzy factor) does not contain other parameters other than the necessary parameters *m, C*, so there is no need to balance image noise and image detail by adjusting parameters (such as α in the EnFCM algorithm and α in the FGFCM algorithm), and the algorithm can use spatial information and grayscale information, compared to the traditional FCM algorithm, for images containing noise, the segmentation effect has been greatly improved.

3. Comparative analysis of experimental results

Because the FCM algorithm treats the input data as a set of vectors for unified processing, so more consideration should be given to the grayscale information of the image, this paper mainly uses the FLICM algorithm to remove the misdivision of the orbit in the segmented image, because the gray value at the orbit is slightly less than the vascular gray value, so the input data does not contain the spatial information of the image, and the original FCM algorithm is used to post-process the fused image. Figure. 1 shows the image processed by the FLICM algorithm. Comparing Figure. 1, it can be seen that the FLICM algorithm reduces the misdivision of the skull and orbit.

(a) Original image **(b)** Image processed by FLICM algorithm

Fig. 1. The FLICM algorithm processes the contrast image

From the above image display, although the effectiveness of the algorithm on brain CTA image segmentation can be roughly seen, and the advantages and disadvantages of each mode, the fusion results and the advantages of post-processing can be seen, the image cannot clearly analyze the quality of the proposed method, so the segmentation results of the proposed method will be quantitatively analyzed.

Experimental evaluation indicators

Usually the class of interest is positive, the other classes are negative, the prediction of the classifier on the test data set is either correct or incorrect, and the total number of occurrences of the 4 cases is recorded as:

TP – predict positive classes as positive numbers; FN – predict positive classes as negative numbers; FP – predict negative classes as positive numbers; TN – predict negative classes as negative numbers.

In order to quantitatively evaluate the segmentation effect, the *Dice* coefficient is used to describe the segmentation results. The *Dice* coefficient represents the similarity rate between the segmentation result and the standard segmentation, and is the most intuitive and key evaluation index in the experimental comparison, and the calculation is shown in the formula:

$$Dice = \frac{2TP}{FP+2TP+FN} \tag{10}$$

The result of the *Dice* coefficient is between [0,1], and the higher the *Dice* coefficient, the better the segmentation effect.

Comparison of different modal combinations

In the experiment, there are two filters to process the original image: a Gaussian filter and a Laplace filter. Gaussian filtering and Laplace filtering will extract different types of detailed information. However, these two processing methods correspond to two segmentation effects, two filtering processing modes plus the results of segmentation of the original CTA image, a total of three modes are produced for fusion comparison, so a variety of combinations will be generated. The effect of the combination of these three modes on the segmentation results will be verified in the experiment.

Since the fusion image is processed using the FLICM clustering method based on local information in post-processing, it is necessary to first verify the effect of different clusters on the segmentation result. In order to verify the effect of different clusters and different modes, a test image was randomly selected for the experiment.

As shown in Figure. 2, the *Dice* coefficient varies with the number of clusters. The three curves in the figure represent the results of each of the three modes. As can be seen from Figure. 2, when the number of clusters is greater than 20, the *Dice* coefficients of the three modes become basically stable, and when the number of clusters is less than 8, the *Dice* coefficient decreases dramatically. In addition, the Laplace mode has a larger *Dice* coefficient than the Gaussian mode and the original mode, and can basically reach a stable value of 0.75. The maximum *Dice* coefficient of gaussian mode and original mode can reach a maximum value of 0.70 at about 17 clusters, while the *Dice* coefficient of Gaussian mode will continue to decrease to about 0.63 as the number of clusters continues to grow. So the number of clusters can be selected as 20.

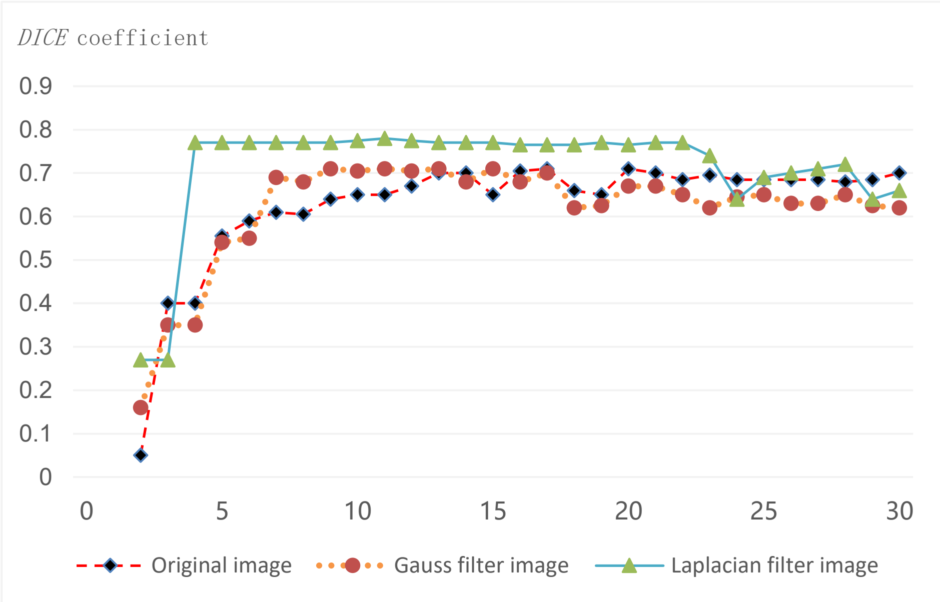

Fig. 2. Change of *Dice* coefficient with clustering number

In the experiment, 8 test data were randomly selected, and the *Dice* coefficient is shown in Table. 1 below, and the data in the table are obtained in clusters 20. "*A*" represents the original mode, "*B*" represents gaussian mode, "*C*" represents Laplace mode, and "+" represents method fusion. It can be seen from Table. 1 that the *Dice* coefficient of the "*A*+*B*+*C*" mode combination is the largest and the maximum value is also the largest; the *Dice* coefficient of the "*B*+*C*" mode combination is generally better than that of the "*A*+*C*" mode combination; the *Dice* coefficient of the "*A*", "*B*", and "*C*" single mode is smaller than that of other combination modes. Overall, the three modes are best divided, with multimodal combinations performing better than single modes.

Table. 1. *Dice* coefficients of different mode combinations

Number	1	2	3	4	5	6	7	8
A	0.5054	0.5964	0.5840	0.6363	0.5821	0.5957	0.6402	0.6902
B	0.5923	0.6132	0.6835	0.6342	0.5927	0.7105	0.6643	0.6704
C	0.6373	0.5476	0.6504	0.6525	0.6830	0.6694	0.6895	0.7588
A+*B*+*C*	0.6512	0.6002	0.7556	0.7217	0.7413	0.7526	0.7512	0.8216
A+*B*	0.6432	0.6503	0.6912	0.6711	0.6926	0.6907	0.7134	0.7231
A+*C*	0.6574	0.6183	0.6431	0.6427	0.6912	0.6833	0.7235	0.7922
B+*C*	0.6317	0.6522	0.7512	0.7431	0.7006	0.7416	0.7427	0.7937

Comparative experiments with different methods

Due to the need for experimental control, two other common CTA image segmentation algorithms are also experimented in this paper: Otsu algorithm and watershed algorithm. The basic idea of the threshold method is to calculate one or more grayscale thresholds according to the grayscale characteristics of the image, and the gray value of each pixel in the image is compared with the calculated threshold, and finally the pixels are divided into the types that meet the comparison results, the advantages of which are simple calculations, high computational efficiency, and fast speed; the basic idea of the watershed is to take the image as a geodesy topological landform, the gray value of each pixel in the image indicates the altitude of the point, and each local minimum value and its influence area are called catchment basins. The boundary of the catch basin forms a watershed, which has a good segmentation effect on the fine boundary.

Table. 2. *Dice* coefficients of different segmentation results

Method	Minimum	Maximum	Average value
CNN (Original)	0.4679	0.6542	0.5509
Otsu algorithm	0.2476	0.5217	0.3717
Watershed algorithm	0.3326	0.6715	0.4927
This article algorithm	0.6315	0.7756	0.6946

Table. 2 reflects the segmentation results of each method for 50 graphs, and it can be seen from Table. 2 that the average *Dice* coefficient of the algorithm used in this paper is significantly better than that of other algorithms, that is, the segmentation effect is the best, followed by the original CNN network, then the watershed algorithm, and finally the Otsu algorithm.

4. Conclusion

In this paper, the traditional fuzzy *C* mean algorithm and the fuzzy *C* mean algorithm with local information are introduced, and the algorithm is applied to cerebrovascular segmentation, which is mainly applied to the post-processing stage of fusion results, and related simulation experiments are carried out. Finally, two experimental comparisons were carried out, namely the comparison of different modal combinations and different methods, showing that the multimodal combination was better than the single mode, and the proposed algorithm was better than other algorithms.

Acknowledgements

Project suppored by national college students'innovation and entrepreneurship trainning program.

References

[1] Havaei M，Davy A，Warde-Farley D，et al. “Brain Tumor Segmentation with Deep Neural Networks [J]”. Medical Image Analysis 35 (2015): 18-31.

[2] Ronneberger O，Fischer P，Brox T. “U-Net: Convolutional networks for biomedical image segmentation .”

[3] X. Y. LIU. “Research on MR image segmentation algorithm and fiber tracking of human brain based on fuzzy clustering[D].” Shanghai:Shanghai Normal University (2018).

[4] X. L. Zhan. “Medical Image Segmentation Based on FLICM Fuzzy Clustering and Level Set Algorithm[D].” Baoding:Hebei University (2015).