Research Article

Recognition and Volume Measurement of Intracranial Hematoma through CT Images under Intelligent Recognition Algorithm

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In order to realize the automatic recognition of intracranial hematoma and accurate measurement of hematoma volume in patients with ICH (intracerebral hemorrhage), the FCM algorithm (fuzzy c-means algorithm) was improved in this study, and a new level set segmentation algorithm based on FCM was obtained, FCRLS (fuzzy c-means regularized level set). Then, 120 ICH patients were used as the research objects, and the FCRLS algorithm was evaluated by the recall, precise, and F_1 -score values to evaluate the effect of intracranial hematoma recognition. The CT images of 48 patients with intracranial hematoma were used as the data set of the FCRLS algorithm. The hematoma was segmented, and the DSC (Dice similarity coefficient) value and running time were used to evaluate the segmentation results of the algorithm. At the same time, the LS (level set) algorithm and the FCM algorithm were introduced for comparison. The results show that the recall value of the FCRLS algorithm is 0.89, the precise value is 0.94, the F_1 -score value is 0.91, the Dice coefficient is 94.81%, and the running time is 14.48 s. Compared with the LS algorithm and the FCM algorithm, the above five indicators have significant differences ($P < 0.05$). Hematoma volume measurement found that the average error of FCRLS algorithm from expert measurement results was 5.62%, which was statistically significant compared with LS algorithm and FCM algorithm ($P < 0.05$). In summary, the FCRLS algorithm can accurately identify the cerebral hematoma area of ICH patients, has an ideal segmentation effect on the hematoma, and can accurately measure the true volume of the hematoma, which is worthy of clinical application.

1. Introduction

At present, acute cerebrovascular disease is at the forefront of all fatal diseases. According to China's 2008 government health report, the incidence of acute cerebrovascular disease has reached as high as 20% [1, 2]. Acute cerebrovascular disease is also called stroke, including ischemic stroke and hemorrhagic stroke. According to pathological reasons, hemorrhagic stroke includes nontraumatic hemorrhagic stroke and intracerebral hemorrhage (ICH) [3, 4]. The common causes of ICH are hypertension and aneurysm. Affected by these two causes, intracerebral hemorrhage occurs and a large amount of blood flows into the brain tissue. When blood accumulates in the brain to a certain volume, it is called cerebral hematoma. The hematoma continuously compresses the brain tissue, causing brain

dysfunction in the patient. In severe cases, the brain tissue of the patient will die, and eventually it will even endanger the life of the patient [5, 6].

In the clinical diagnosis of cerebral hemorrhage, the physician's clinical treatment plan mainly relies on cranial computer tomography (CT) and magnetic resonance imaging (MRI) [7]. CT is currently the most widely employed imaging method in ICH clinical diagnosis and treatment. CT refers to tomographic imaging, with high resolution, good lesion display, and clear anatomical relationship. In addition, ICH shows high density shadow on CT. Therefore, CT is the first choice for the diagnosis of ICH [8]. With the development of computer technology, computer aided diagnosis technology has been widely accepted in the medical industry. Automatic segmentation calculation technology is replacing manual as the main means of medical image

recognition and segmentation [9, 10]. There are two steps for computer technology to identify the ICH measurement volume. First, intelligent recognition algorithm is adopted to segment and extract the hematoma of ICH patients. Second, the volume calculation equation is adopted to measure the volume of the hematoma [11, 12]. However, due to the individual differences in the tissues and organs of ICH patients, the hematoma of the patients presents irregularities and complex variability, and automatic detection and segmentation technologies are faced with many difficulties [13]. Based on such situation, a novel image segmentation algorithm FCRLS was established, which can automatically identify and segment ICH in patients, aiming to provide a theoretical basis for the clinical treatment of ICH patients.

2. Materials and Methods

2.1. Research Object. In this research, 120 patients, who were confirmed to be ICH by pathology or clinical follow-up, were deemed as the research objects, who were admitted to the hospital from January 2017 to May 2020. CT was performed for each patient. Among the 120 patients, 81 were males and 39 were females. The average age of the patients was 64 ± 10.11 years. This research had been approved by the Medical Ethics Committee of the Hospital. The patient and his family members were aware of the research situation and had signed the informed consent forms.

Inclusion criteria were defined as follows: (1) patients older than 18 years of age, (2) patients who were confirmed to be ICH after CT scan according to the *Chinese Guidelines for the Diagnosis and Treatment of Cerebral Hemorrhage (2014)*, (3) head CT scan showed that the cerebral hemorrhage was located on the supratentorial basal segment area, and (4) patients with complete clinical data.

Exclusion criteria were defined as follows: (1) patients with cerebellar or brainstem hemorrhage, (2) patients with traumatic cerebral hemorrhage, (3) patients with severe lung infection, blood system disease, or coagulation dysfunction, (4) patients with severe infection during hospitalization or with persistent high fever, (5) patients who cannot be scanned by CT, and (6) patients with incomplete clinical data.

2.2. CT Image Preprocessing of ICH Patients. When CT scan is performed on a patient, due to various constraints and interferences such as imaging equipment, imaging environment, and patient's brain tissue, it is inevitable that CT images will suffer a certain degree of degradation during the acquisition and transmission process. It may cause missing or incorrect image information, which will have a significant impact on the results of image segmentation [14]. Therefore, before image segmentation, it is necessary to preprocess images and boundary blurs. Blurry boundaries in CT images of ICH patients are mainly caused by the insignificant differences between the brain tissues of the patients [15]. Therefore, while the original image information is preserved, the difference between regions on the CT image is enhanced to solve the boundary blur problem. Assuming that the point

$P_i = (m_i, n_i)$ is discussed, the method of processing image edge blur is as follows:

$$(m_i, n_i)' = \alpha(m_i, n_i) + \beta_R \sum_{(m_R, n_R) \in N_R} |(m_R, n_R) - (m_i, n_i)|, \quad (1)$$

$$(m_R, n_R) \in N_R,$$

where $(m_i, n_i)'$ is the pixel after image processing, α is the retention coefficient of the pixel in the center of the area, β is the gray value difference coefficient of the area, N_R is the neighborhood pixel set of (m_i, n_i) , and (m_R, n_R) is the neighborhood pixel. The above image processing method retains the gray value of the central pixel of the original image and then superimposes the difference with the central pixel by calculating the difference with the neighboring pixel. It utilizes the update of the gray value of the central pixel to improve the edge blur of CT images.

Aiming at the noise generated by equipment and instruments when the CT image is collected, the median gray value of the pixels in the image area is adopted to eliminate the noise points. The calculation process is expressed by the following equation:

$$(m_i, n_i)' = \text{med}\{(m_R, n_R)\}, \quad (m_R, n_R) \in N_R. \quad (2)$$

From equation (2), the gray value of the pixel after replacement is close to the gray value of other normal pixels in the image. Therefore, the processed image not only retains the original information of the image but also avoids the influence of image edge blur during the denoising process. This image preprocessing method retains the original information of the image while increasing the difference between regions, thereby improving the definition of the image edge. In addition, the noise points of the image are eliminated on the premise of avoiding the blur of the image edge.

2.3. Implement of FCRLS Automatic Segmentation Algorithm. Due to the irregular boundaries of CT images and the unobvious location of the lesion in patients with ICH, FCM was adopted to perform initial clustering and segmentation of CT images of ICH patients in this work. Then, according to the clustering results, the distance regularization level set model was initialized, and the accurate segmentation of CT images was finally completed.

The FCM algorithm is widely adopted in medical image segmentation. FCM is originated from the K-means clustering algorithm, which minimizes the function through multiple iterations to complete the clustering process. Its calculation method is expressed by the following function:

$$f = \sum_{x=1}^K \sum_{y=1}^H \|i_y - v_x\|^2. \quad (3)$$

In the above equation, f represents the cost function of the algorithm, K represents the clustering category, $H = N_m \times N_n$, i_y represents the pixel value of the image, and v_x represents the x th cluster center. K-means clustering algorithm can only classify image pixels into a certain

category, which is more difficult in actual calculations. The FCM algorithm introduces a membership function μ_{xy} to represent the fuzzy membership of the y th pixel and the x th cluster center. The function expression is as follows:

$$f = \sum_{y=1}^H \sum_{x=1}^C \mu_{xy}^l \|i_y - v_x\|^2. \quad (4)$$

In the above equation, C represents the clustering level, l represents the weight index of the fuzzy membership of the algorithm, μ_{xy}^l represents the membership function, and μ_{xy}^l should meet the following conditions:

$$\begin{aligned} \forall x, y, \sum_{x=1}^C \mu_{xy} &= 1, \\ \mu_{xy} &\in [0, 1], \\ \sum_{y=1}^H \mu_{xy} &> 0. \end{aligned} \quad (5)$$

For μ_{xy}^l and v_x , the following function is adopted to solve them, and the minimum value of the objective function is calculated:

$$\begin{aligned} \mu_{xy} &= \frac{\|i_y - v_x\|^{-(2/l-1)}}{\sum_{k=1}^C \|i_y - v_k\|^{-(2/l-1)}}, \\ v_x &= \frac{\sum_{n=1}^H \mu_{xy}^l i_y}{\sum_{y=1}^H \mu_{xy}^l}. \end{aligned} \quad (6)$$

FCM algorithm can realize the preliminary accurate segmentation of the image, but it does not consider the edge information and spatial domain of the image when segmenting the image. Moreover, affected by image noise, the segmentation effect of some images with blurred boundaries and uneven grayscale is poor [16]. When FCM algorithm is employed to segment the brain CT images of ICH patients, it is often difficult to obtain the expected results. To solve this, the LS function is initialized according to the clustering results after the initial segmentation and clustering of the FCM algorithm. The initialization level set function is represented by the following function:

$$\phi'(m, n) = -4\varepsilon(0.5 - P_k), \quad (7)$$

where P_k represents a binary image and ε is a Dirac function parameter, which will affect the image segmentation result. The parameters of different medical images are also different. The function of the distance regularization term in the energy functional corresponding to this LS algorithm is the single-potential hydrazine function. This kind of function will cause the curve evolution to be inaccurate in the calculation process of the level calculation method [17]. The calculation equation of the unipotent hydrazine function is as follows:

$$R_H(\phi) \triangleq \int_{\Omega} h(|\nabla\phi|) dm. \quad (8)$$

When $x = 1$, the minimum value of the function area can be obtained according to the gradient descent flow equation as follows:

$$\frac{\partial\phi}{\partial g} = \phi \operatorname{div} [d_h(|\nabla\phi|) \nabla\phi] dm. \quad (9)$$

The above equation is a diffusion equation. When $\nabla\phi$ is close to 0, the diffusion rate becomes infinite, and the calculation accuracy of the algorithm will be greatly affected. The distance regularized level set evolution (DRLSE) model is adopted to solve this problem. The energy functional of the DRLSE model for image segmentation is as follows:

$$\varepsilon(\phi) = \mu R_H(\phi) + \gamma S_e(\phi) + \nu U_e(\phi), \quad (10)$$

where μ , γ , and ν are the coefficients of each energy term, $\mu R_H(\phi)$ is the internal energy term, And $\gamma S_e(\phi)$ and $\nu U_e(\phi)$ are the external energy term, and the calculation equations of $S_e(\phi)$ and $U_e(\phi)$ are expressed by the following function:

$$S_e(\phi) = \int_{\Omega} e\delta(\phi) |\nabla\phi| dm dn, \quad (11)$$

$$U_e(\phi) = \int_{\Omega} eH(-\phi) dm dn. \quad (12)$$

In equations (11) and (12), e represents the edge indicator function, δ represents the Dirac function, and H represents the Heaviside function, and its expression is as follows:

$$H(m) = \begin{cases} \frac{1}{2} \left[\frac{m}{\varepsilon} + \frac{1}{\pi} \sin\left(\frac{\pi m}{\varepsilon}\right) \right], & |m| \leq \varepsilon, \quad |x| \leq \varepsilon, \\ 0, & x < -\varepsilon, \\ 1, & x > \varepsilon. \end{cases} \quad (13)$$

Substituting equations (12)–(14) into (10), we can calculate the energy functional, and the following equation is obtained:

$$\varepsilon(\phi) = \mu \int_{\Omega} h_2(|\nabla\phi|) dm + \gamma \int_{\Omega} e\delta_e(\phi) (|\nabla\phi|) dm + \nu \int_{\Omega} eH_e(-\phi) dm. \quad (14)$$

First, the derivative of ϕ is calculated, and the steepest descent algorithm is adopted to minimize the function to get the following equation:

$$\frac{\partial\phi}{\partial g} = \mu \operatorname{div} [d_{h_2}(|\nabla\phi|) \nabla\phi] + \gamma \delta_e(\phi) \operatorname{div} \left(e \frac{\nabla\phi}{|\nabla\phi|} \right) + \nu e \delta_e(\phi). \quad (15)$$

The finite difference method is adopted to discretize the function to get the iterative equation:

$$\begin{aligned} \phi^{t+1}(m+n) = & \phi^t(m+n) + \tau [\mu \operatorname{div} [d_{h_2}(|\nabla \phi^t|) \nabla \phi^t] \\ & + \gamma \delta_\varepsilon(\phi^t) \operatorname{div} \left(e^{\frac{\nabla \phi^t}{|\nabla \phi^t|}} \right) + \nu \delta_\varepsilon(\phi^t)]. \end{aligned} \quad (16)$$

The above equation is transformed to get a new iterative model of LS segmentation algorithm based on FCM:

$$\begin{aligned} \phi^{t+1}(m+n) = & \phi^y(m+n) + \tau [\mu \operatorname{div} [d_{h_2}(|\nabla \phi^y|) \nabla \phi^y] \\ & + \gamma \delta_\varepsilon(\phi^y) \operatorname{div} \left(e^{\frac{\nabla \phi^y}{|\nabla \phi^y|}} \right) + G(R_t) \nu \delta_\varepsilon(\phi^y)]. \end{aligned} \quad (17)$$

FCRLS algorithm takes into account the spatial domain of CT image when segmenting images, which makes the segmentation results of manual initialization more stable (Figure 1). Moreover, the high adaptive ability of the LS algorithm makes the evolution speed of the segmentation curve gradually slower as it approaches the true boundary of the lesion during automatic image segmentation, making the outline of the lesion smoother. In addition, due to the introduction of the DRLSE model, the segmentation result of the improved algorithm is more stable and the evolution result is more accurate.

2.4. Detection of the Recognition Effect of FCRLS Algorithm on Intracranial Hematoma. The brain CT images of the 120 ICH patients participating in this work were analyzed using different algorithms, to determine whether there was hematoma in the brain of the patients. The hematoma area manually drawn by two radiologists was set as the gold standard. Then, FCM algorithm and LS algorithm were employed to compare with the FCRLS algorithm of this research. The automatic segmentation algorithm was more accurate in identifying the hematoma. When the segmentation result was basically the same as the area manually segmented by the expert, it was judged as a valid positive. When the hematoma area segmented by the algorithm was too far from the area manually segmented by the expert, it was judged as invalid positive. When the expert determined that there was no hematoma area in the patient's CT and the hemorrhage area was not recognized during the algorithm segmentation, it was judged as valid negative. When the algorithm segmented some images with more pseudonoise, resulting in the incomplete boundary of the segmented region and output meaningless images, it was judged as invalid negative. The result that there was a hematoma that the algorithm did not detect was called false positive. The result that there was no hematoma but the algorithm detected the area of hemorrhage was called false negative. Then, precise, recall rate (Recall), and F_1 value (F_1 -score) were used to evaluate the accuracy of different algorithms in identifying hematoma in ICH patients. The calculation equations were as follows:

$$\begin{aligned} \text{Precise} &= \frac{TP}{FP + TP}, \\ \text{Recall} &= \frac{TP}{FN + TP}, \\ F_1 &= \frac{2(\text{Recall} \times \text{Precise})}{\text{Recall} + \text{Precise}}. \end{aligned} \quad (18)$$

In the above equations, TP meant true positive, FP meant false negative, FN meant false positive, and F_1 was the harmonic mean of Precise and Recall.

2.5. Detection of Segmentation Effect of FCRLS Algorithm. Dice similarity coefficient was adopted to evaluate the ICH segmentation effect of brain CT images of ICH patients. DSC can accurately reflect the overlap between the area automatically segmented by the algorithm and the real area of ICH. In this research, the manual segmentation results of two radiologists were set as the gold standard to measure the DSC value of different segmentation algorithms. The calculation equation is as follows:

$$\text{DSC} = \frac{2 \times |M \cap N|}{|M| + |N|}, \quad (19)$$

where M represented the area manually segmented by experts, that is, the real area, and N represented the area automatically segmented by different segmentation algorithms.

2.6. ICH Volume Measurement. After the CT image segmentation of ICH patients was completed, the ICH volume was measured according to the segmentation results. The calculation equation is as follows:

$$V = \sum_{i=1}^G S_i \Delta d, \quad (20)$$

where G represented the number of ICH lesion layers, S_i represented the area of the lesion in the i th layer, and Δd represented the thickness of the lesion slice. The slice thickness in this research was 8 mm, the image matrix size was 512×512 , and the pixel size was 0.2364 mm^2 . When the volume of the patient's hematoma was measuring, first, the hematoma area of each slice based on the segmentation results of different segmentation algorithms was calculated. The hematoma area of each slice was the number of pixels in the hematoma multiplied by the pixel size. Then, the area of sliced hematoma was multiplied with the slice thickness to get the volume of single sliced hematoma. Finally, the volume of the hematoma at all levels was added to obtain the patient's ICH volume.

2.7. Statistical Analysis. SPSS19.0 software was employed for data processing. Mean ($\bar{x}$) was how measurement data were expressed, which were tested by two independent samples t -test. χ^2 test was adopted to test count data. Pearson analysis

FIGURE 1: FCRLS algorithm automatic segmentation steps. (a) Original image, (b) segmentation result, and (c) extraction of region of interest.

was adopted to analyze the parameter correlation. $P < 0.05$ indicated statistically considerable difference.

3. Results

3.1. Evaluation of Different Algorithms on the Recognition Effect of Intracranial Hematoma. First, two radiologists manually delineated the brain CT images of the 120 ICH patients who participated in the research, to determine whether there was ICH. Among them, 48 patients were judged by experts to have ICH, and 72 patients were judged to have no hematoma. The results were set as the gold standard. Then, FCM algorithm, LS algorithm, and FCRLS algorithm were adopted to segment and judge 120 patients' CT images. Recall, Precise, and F_1 -score of the segmentation results of different algorithms were calculated. It was found that the Recall, Precise, and F_1 -score of the FCM algorithm was 0.69, 0.73, and 0.71, respectively. Those of the LS algorithm was 0.72, 0.76, and 0.74, respectively. Those of the FCRLS algorithm was 0.89, 0.94, and 0.91, respectively. Compared with the above three indicators, the difference was statistically significant ($P < 0.05$) (Figure 2). Moreover, FCRLS algorithm had better effect on the identification and judgment of ICH in patients versus FCM algorithm and the LS algorithm.

3.2. Evaluation of Different Algorithms for Segmentation of Intracranial Hematoma. After ICH identification of ICH patients, 48 brain CT images of the patients judged by experts to contain hematoma were segmented by different segmentation algorithms (Figures 3 and 4). The expert manual segmentation results were deemed as the gold standard. It was clear that compared with FCM algorithm and LS algorithm, the segmentation effect of FCRLS algorithm was more ideal.

3.3. DSC Comparison of Different Segmentation Algorithms. The Dice similarity coefficient can evaluate the segmentation accuracy of different algorithms very well. After the DSC of

the FCM, LS, and FCRLS algorithms was compared, the results showed that the Dice coefficient of the FCM algorithm was 76.18%, that of LS algorithm was 84.22%, and that of the FCRLS algorithm was 94.81%. Compared with the Dice coefficients of the three algorithms, the difference was statistically significant ($P < 0.05$) (Figure 5). It was evident that the FCRLS algorithm had better segmentation effect.

3.4. Comparison of Algorithm Running Time. When the brain CT images of ICH patients were segmented, the running time of the three algorithms was counted. The average running time of segmentation of FCM algorithm was 20.02 s, that of LS algorithm was 18.44 s, and that of FCRLS algorithm was 14.48 s. Compared with the average running time of the three algorithms, the difference was statistically significant ($P < 0.05$) (Figure 6). Apparently, FCRLS algorithm had relatively shorter running time, indicating that the FCRLS algorithm improved the segmentation speed while improving the segmentation accuracy.

3.5. Comparison of Volume Measurement Results of Different Segmentation Algorithms. After segmentation, the patient's hematoma volume was measured according to the segmentation results of different algorithms, with the hematoma volume calculated by the expert's manual segmentation as the gold standard. The hematoma volume of 48 ICH patients was measured and compared with expert measurement results. It was found that the average error between the hematoma volume measurement result of FCM algorithm and the expert measurement result was 16.44%, the average error between LS and expert result was 12.31%, and the average error between FCRLS algorithm and expert result was 5.62%. Compared with the average segmentation error of the three algorithms, the difference was statistically significant ($P < 0.05$) (Figure 7). Obviously, FCRLS algorithm had better measurement results, and the measured hematoma volume was closer to the actual volume of the patient's ICH.

FIGURE 2: Comparison of recognition effects based on different algorithms (* indicates that the difference is statistically significant).

FIGURE 3: Brain CT images of ICH patient.

4. Discussion

To study the adoption of intelligent recognition algorithms in ICH recognition and hematoma volume measurement in ICH patients, FCM algorithm was improved, and the DRLSE model was introduced to improve the algorithm segmentation effect. Then, FCM algorithm and LS algorithm were compared with the FCRLS algorithm proposed. 120 cases of patients who were identified as ICH by pathology or clinical

follow-up were taken as the research objects, and CT was performed on the brain of the patients. Then, different algorithms were employed to judge whether there was hematoma in the brain of ICH patients. With expert judgment results as the gold standard, Recall, Precise, and F_1 -score values were compared to evaluate the recognition effect of the algorithms. It was found that the Recall, Precise, and F_1 -score of FCRLS algorithm were 0.89, 0.94, and 0.91, respectively, which were higher than the FCM algorithm and

FIGURE 4: The segmentation results of different algorithms.

FIGURE 5: Comparison of Dice coefficients of different segmentation algorithms (* indicates that the difference is statistically significant).

FIGURE 6: Comparison of running time of different segmentation algorithms (* indicates that the difference is statistically significant).

FIGURE 7: Comparison of hematoma volume measurement errors of different segmentation algorithms (* indicated that the difference was statistically significant).

the LS algorithm, suggesting that the FCRLS algorithm was more accurate for ICH identification of ICH patients. After the recognition, 48 images containing hematoma were adopted to analyze the segmentation effects of different algorithms. Comprehensive evaluation was implemented regarding the DSC value and algorithm running time. The result revealed that the FCRLS algorithm had better segmentation effect, the DSC value was higher than the FCM algorithm and the LS algorithm, and the algorithm running time was lower than them. The reason was that the FCRLS algorithm can accurately and quickly identify the edge of the lesion so that the FCRLS algorithm greatly reduced the segmentation time while improving the segmentation accuracy, and this was similar to the findings of Kavitha et al. [18]. Finally, the hematoma volume was measured based on the segmentation results of different algorithms. It was found that the hematoma volume measurement based on the FCRLS algorithm was relatively more accurate. The error with the actual volume was only 5.62%, which showed that the measurement result of the FCRLS algorithm was more accurate.

5. Conclusion

The effect of FCRLS algorithm on the recognition and segmentation of hematoma was evaluated in this work. The results showed that the FCRLS algorithm can more accurately identify the ICH condition of ICH patients, and it was also more accurate for hematoma image segmentation and hematoma volume measurement. This algorithm has promising adoption prospect in the treatment of ICH. This automatic segmentation algorithm is worthy of clinical promotion. This work also provides a theoretical basis for the treatment of ICH patients. However, there are few cases in this research and no evaluation of the clinical treatment effect has been made. These shortcomings make it requires more in-depth research with more data in future work.

Data Availability

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

Conflicts of Interest

The author declares no conflicts of interest.

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