Extraction of Cerebral Hemorrhage and Calculation of Its Volume on CT Image Using Automatic Segmentation Algorithm

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Abstract. Cerebral hemorrhage is caused by a number of factors leading to cerebral vascular rupture, which causes blood to flow into the brain tissue and then clumps together to form hematoma. If the treatment is improper for patients with cerebral hemorrhage, their lives will be in great danger. Rapid, accurate and repeatable estimation of cerebral hemorrhage is considerably important for medical diagnosis and treatments. In this paper, an automatic system is proposed to segment the regions of cerebral hemorrhage from CT images. Then the volume of cerebral hemorrhage can be calculated by extracting the regions of cerebral hemorrhage. The segmentation method proposed in this paper is based on the Otsu algorithm, Chicken swarm optimization algorithm and local recursion algorithm. Meanwhile, the results of the proposed algorithm are compared with those given by the experts.

1. Introduction
Stroke is an acute cerebrovascular disease that causes damage to brain tissue due to sudden rupture of cerebral blood vessels or obstruction of blood vessels. [1] Stroke has the characteristics of high incidence, mortality and disability rate. At the same time, the investigation shows that the death rate from stroke has risen to the highest in China. [2] Stroke apoplexy can be divided into two types: ischemic stroke and hemorrhagic stroke. [2] Accurate estimation of the volume of cerebral hemorrhage is of great significance in the treatment of hemorrhagic stroke and has important clinical value.

At present, manual and automatic segmentation are commonly applied at home and abroad to measure the cerebral hemorrhagic volume. [3-4] Manual segmentation is extremely wasteful and difficult to implement, even with non-ignorable disadvantages which are low in efficiency and high in repeatability. As far as manual segmentation is concerned, automatic segmentation is not only fast in segmentation, but also high in accuracy. However, due to the complex shape and appearance of medical images, the automatic segmentation also faces the following technical challenges. [5-7] (1) There is a gray overlap between parts with and without cerebral hemorrhage. (2) In the regions of the cerebral hemorrhage, the substantial gray level changes. As a result, how to design a robust, fast and effective segmentation algorithm for extracting the regions of the cerebral hemorrhage and calculating its volume in order to describe the degree of the cerebral hemorrhage has become an intense and difficult topic for scientific researchers. [2, 8]

Several types of method have been proposed by different researchers. Sumijan et al. proposed a method of combined thresholds to segment the regions of the cerebral hemorrhage, which uses image
features and Otsu algorithm to extract the regions of the cerebral hemorrhage. [9] Soroushmehr, S. Mohamad R., et al. developed a method of using Gaussian mixture model to obtain the region of the cerebral hemorrhage. Firstly, the algorithm used linear contrast stretching, Gray Matter Subtraction (GMS) and Total Variation (TV) to process the images of cerebral hemorrhage, and then GMM model is used to segment the images of cerebral hemorrhage. Finally, Intensity Constraint, Area Constraints and Midline Pattern Matching are used for post processing of the image. [10] Sun, Mingjie, et al. developed a method of using fuzzy clustering and threshold method. The coarse segmentation area was reconstructed in three dimensions, and then hyper volume segmentation was carried out. [11] Prakash, KN Bhanu, et al. proposed a modified distance regularized level set evolution (MDRLSE) algorithms for segmentation of the region of cerebral hemorrhage. [12] Moreover, another method is proposed in [13], which segments the regions of the cerebral hemorrhage by using Random Forests which adopts the standardized-to-template and neighborhood mean to reduce complexity and computation time.

2. The Skull Removal
The skull was removed in order to eliminate a part of the brain image, which is unfavorable to extract the region of cerebral hemorrhage. After removal, it became easier to make research and analysis. Threshold method and the left and right scanning algorithm are applied to the skull removal in this paper. Each slice was divided into the regions of bone and none-bone. The skull and some tissues outside the skull were removed by the left and right scanning algorithm. Then some noise spots appeared on the image of the skull removal, which can be eliminated by the median filter.

3. Enhanced Segmentation Algorithm

3.1. Otsu Segmentation Algorithm
Otsu segmentation algorithm uses threshold to divide an image into two parts: the target C1 and the background C2. The best threshold will be obtained when their inter class variance reaches its largest value. The discriminant is shown as follow.

\[
t = \arg\max_{t \in \text{gray}} \left[ \sigma^2_g(t) \right] = \omega_1 \left( u_1 - u_T \right)^2 + \omega_2 \left( u_2 - u_T \right)^2
\]

\[
\omega_1 = \sum_{i=1}^{I} \omega_i \sum_{j=1}^{I} p_{ij}, \quad \omega_2 = \sum_{i=1}^{I} \omega_i, \quad u_1 = \sum_{i=1}^{I} \omega_i \sum_{j=1}^{I} p_{ij} / \omega_i, \quad u_2 = \sum_{i=1}^{I} \omega_i \sum_{j=1}^{I} p_{ij} / \omega_i
\]

Where \( p_{ij} \) refers to the probability of gray level \( i \) occurrence, \( \omega_1, \omega_2, u_1, u_2, u_T \) are respectively represented as the accumulative probability of C1, the accumulative probability of C2, the average gray level of C1, the average gray level of C2, the average gray level of the whole image.

3.2. Chicken Swarm Optimization Algorithm
Chicken swarm optimization (CSO) algorithm is a random optimization algorithm that imitates the foraging behavior of natural chickens with hierarchical structure. In the chicken swarm optimization algorithm, the chicken swarm is divided into three grades, which are roosters, hens and chickens depending on the individual's ability in the process of foraging, which is full of competition and cooperation. As time changes, the role of individual also changes, and the chicks grow into big chickens.
while the adaptive range and fitness of the algorithm are improved. The algorithm is characterized as follows:

1. The chicken swarm is divided into several subgroups, each of which contains a rooster, several hens and chicks.

2. The allocation of individual roles in the chicken swarm is determined by the individual's fitness. Several individuals with high fitness are assigned as roosters and become the heads of each subgroup, while a few less adaptable individuals are assigned to chicks. For the rest of those individuals, they are assigned to hens. Hens live randomly in any chicken swarms, and the mother-child relationship between hens and chicks is determined at random.

3. Even if dominant relationship and mother-child relationship in chicken swarm have been established, these relationships will remain unchanged as long as the updated conditions are not satisfied. If the updated conditions are met, they should be reestablished.

4. In the chicken swarm, each grade has its own way of foraging. The individual follows the rooster in search for food, and the chicks are fed around the hens. The roosters have the greatest advantage in the competition of the food, the hens have the second, and the chicks have the least advantage.

When searching for the optimal solution for the optimization problem, each individual in the chicken swarm is a solution of the optimization problem. Suppose NR, NH, NC and NM represent the numbers of roosters, hens, chicks, and mother hens, respectively. In the whole chicken swarm, all the individuals are assumed to be N. The position of each individual $\mathbf{x}_{i,j}(t)$ denotes the j dimension of the i body in the t iteration value. The whole chicken swarm is divided into three types of chicken, and the location updated formula for each type of the chicken swarm is not the same.

Roosters correspond to the best fitness individuals in the chicken population. Position update equations of the roosters is as follows:

$$\mathbf{x}_{i,r}(t+1) = \mathbf{x}_{i,r}(t) \times (1 + \text{Rand}(0, \sigma^2)) \quad i \in (1,..., \text{pop}), j \in (1,..., \text{dim})$$  \hspace{1cm} (3)

Where Rand(0, \sigma^2) denote a Gaussian distribution that the mean value are 0, and the standard deviation is \sigma, \varepsilon are 1, a very small constant in order to prevent zero division error. Position update equations of hens are as follows:

$$\mathbf{x}_{i,h}(t+1) = \mathbf{x}_{i,h}(t) + c_1 \times \text{Rand} \times (\mathbf{x}_{i,r}(t) - \mathbf{x}_{i,h}(t)) + c_2 \times \text{Rand} \times (\mathbf{x}_{i,c}(t) - \mathbf{x}_{i,h}(t))$$

$$c_1 = \exp\left(\frac{f_i - f}{\text{abs}(\text{f}) + \varepsilon}\right)$$

$$c_2 = \exp\left(\frac{f_{r2} - f_i}{\varepsilon}\right)$$

Where Rand is a uniformly distributed random number between 0 and 1, r1 is the rooster in the chicken swarm of the ith hen, r2 is a randomly selected chicken from the chicken swarm which is different from the ith hen.

Position update equations of the chicks is as follow.

$$\mathbf{x}_{i,c}(t+1) = \mathbf{x}_{i,c}(t) + F \times (\mathbf{x}_{m,c}(t) - \mathbf{x}_{i,c}(t))$$ \hspace{1cm} (5)

Where m is the hen corresponding to the ith chick, $F \in (0, 2)$ is the follow coefficient that chicks follow the chick mothers to looking for food.

3.3. Local Recursive Algorithm For Chicken Swarm Optimization Based On Otsu

Local recursive algorithm can be implemented by following steps. Firstly, the whole image is segmented using the chicken swarm optimization algorithm based on Otsu, and the threshold t is generated. The pixels larger than the threshold t keeps the original gray level, and the smaller ones are 0. Then, the threshold t is determined whether it meets the recursive termination condition or not, if that condition is not met, the image will continue to be segmented by chicken swarm optimization algorithm based on Otsu(CS0). The flow chart of this algorithm is as follows.

a) Input an image that shows the skull has been removed.
b) The fitness function of the chicken swarm optimization algorithm is constructed by using the Otsu model, see formula (1).

c) Parameters of the chicken swarm optimization algorithm are set, including the maximum number of iterations M, chicken size pop, the solution space dimension dims, the number of chicken renewal G, the proportion of roosters in the whole chicken swarm scale r Percent, the proportion of hens in the scale of the whole chicken swarm h Percent, and the proportion of hens that can raise chickens the proportion of hen scale m Percent. Since the gray image pixels are between 0 and 255, the interval is regarded as the initial solution space of the function, and the initialization of the chicken swarm is generated in this interval.

d) The first threshold t approaches the optimal segmentation threshold by cooperating with roosters, hens and chickens in different subgroups.

e) The threshold t will be judged whether satisfies the local recursive termination condition. Because the pixel values of the hematoma area are higher than that of the normal brain tissue, the upper limite of threshold is regarded as the local recursive termination condition in this paper. In this paper, the initial value of upper limite of threshold is 255 gray level, and every 5 gray level decreases gradually. When the upper limite of threshold is 130 gray level, the experimental results of this algorithm are the best. So the local recursive condition of this paper is that threshold t is less than 130 gray level. If the condition is satisfied, the steps of c and d will be executed, and the solution space in the step of c is updated to between t and 255, otherwise f is executed.

f) The image will be segmented using the optimal threshold obtained from the step of e.

g) The post-processing method is used to process the segmented image and get the final segmentation image.

3.4. Post-Processing

In this paper, a post-processing method is proposed to remove the noise which contain the normal brain tissues of small amount of blood from the segmented images.

Step1: The noise from the segmented images will be filtered out by median filter that has a large parameter. At the same time, the location information that is the top, the bottom, the far left and the far right pixel points of bleeding regions of filtered image is obtained.

Step2: The post-processing method in this paper uses the position information of bleeding regions only to digging out the pixels information from the bleeding regions and nearby regions of the segmented image to generate a new image.

Step3: A median filter that has small parameter is applied to filter the noise near the bleeding regions of the new image and obtain the final segmentation result image.

3.5. Volume calculation of cerebral hemorrhage

After segmenting the regions of cerebral hemorrhage, the volume of cerebral hemorrhage is calculated. The formula for calculating the volume of cerebral hemorrhage is as following.

\[ V = \sum_{i=1}^{N} s_i \Delta h \]  \hspace{1cm} (6)

Where N represents the number of images of the bleeding slice; \( s_i \) denotes the area of i th slice image, \( \Delta h \) represents the thickness of the slice. First, the area of brain bleeding on each slice is calculated. The area of bleeding regions on each slice is obtained by multiplying the area of pixel with the number of pixels. In this paper, the row and column spacing of the pixel in the bleeding regions are 0.468mm. The number of pixels in the bleeding regions can be obtained by counting the number of pixels, whose gray value are not 0. Then, the volume of cerebral hemorrhage on each slice is obtained by multiplying the area of the cerebral hemorrhage and the layer thickness. In the end, the volume of cerebral hemorrhage on each slice accumulates the total volume of cerebral hemorrhage in the patients.
4. Experimental results and analysis

There are several CT images of 6 mm slice thicknesses from 30 patients suffered from cerebral hemorrhage shown below. Take one for example which provided by First Affiliated Hospital of Medical University Of An Hui provided the images. The performance of the experimental results in this paper and the corresponding segmentation results are shown in Figure 2.

![Figure 2. Segmentation results of 8 bleeding slices of a patient](image)

**Table 1. Comparison of segmentation results between three segmentation algorithms.**

| Slices | Slice 1 | Slice 2 | Slice 3 | Slice4 | Slice5 | The average |
|--------|---------|---------|---------|--------|--------|-------------|
| Kmean(DSC%) | 72.43 | 93.98 | 93.14 | 90.99 | 64.41 | 82.99 |
| CSOO(DSC%) | 64.48 | 90.66 | 86.60 | 76.83 | 52.96 | 74.31 |
| Our Method (DSC%) | 95.60 | 98.33 | 97.62 | 97.86 | 90.38 | 95.96 |

As shown in Table 1, the experimental results in this paper are compared with the Ground Truth, according to the results of calculation, Ours yields a higher dice similarity coefficient of 95.96%. The more accurate the segmentation of bleeding regions is, the more accurate the measurement of volume of cerebral hemorrhage would be.

**Table 2. The Volume Of Cerebral Hemorrhage To 5 Slices Of The Patient**

| Slices | Slice 1 | Slice 2 | Slice 3 | Slice4 | Slice5 |
|--------|---------|---------|---------|--------|--------|
| Ground Truth (Number of Pixel) | 2188 | 3140 | 3269 | 2823 | 1590 |
| Our Method (Number of Pixel) | 2040 | 3037 | 3117 | 2738 | 1311 |
| Slice bleeding volume Cm3 | 2.68 | 3.99 | 4.10 | 3.60 | 1.72 |
| Total bleeding volume Cm3 | | | | | 16.09 |

Table 2 shows the volume of cerebral hemorrhage of each slice and the total volume of cerebral hemorrhage of the patient. The total volume of cerebral hemorrhage of this patient is 16.09 cm$^3$. Ground truth is derived from the result of manual segmentation by doctors. Accurate calculation of the volume of cerebral hemorrhage facilitates the doctor to diagnose and treat the patient properly.

5. Summary

It is of great significance to assisting doctors in diagnosing hematoma patients to accurate segmentation of hematoma area and measurement of hematoma volume. In this paper, an automatic segmentation algorithm for cerebral hematoma in CT images is proposed. The dice similarity coefficient of this algorithm has reached to 95.96%. The algorithm proposed in paper is not only of high convenience, but
also of good robustness. Only the volume of the bleeding regions was calculated in this paper, while it is critical to obtain the location and the shape of the bleeding regions for the diagnosis of cerebral hemorrhage, in which the algorithm needs to be improved.

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