Journal of Innovative Optical Health Sciences
Vol. 11, No. 6 (2018) 1850037 (9 pages)
© The Author(s)
DOI: 10.1142/S1793545818500372

World Scientific
www.worldscientific.com

J. Innov. Opt. Health Sci. 2018.11. Downloaded from www.worldscientific.com
by 2001:250:4000:420b:e17e:45b8:4836:5cc4 on 12/25/18. Re-use and distribution is strictly not permitted, except for Open Access articles.

Study on threshold segmentation of multi-resolution 3D human brain CT image

Ling-ling Cui* and Hui Zhang
The First Hospital Affiliated to Jinzhou Medical University
Jinzhou 121001, P. R. China
**cuilingling1@sina.cn*

Received 12 July 2018
Accepted 11 September 2018
Published 19 October 2018

In order to effectively improve the pathological diagnosis capability and feature resolution of 3D human brain CT images, a threshold segmentation method of multi-resolution 3D human brain CT image based on edge pixel grayscale feature decomposition is proposed in this paper. In this method, first, original 3D human brain image information is collected, and CT image filtering is performed to the collected information through the gradient value decomposition method, and edge contour features of the 3D human brain CT image are extracted. Then, the threshold segmentation method is adopted to segment the regional pixel feature block of the 3D human brain CT image to segment the image into block vectors with high-resolution feature points, and the 3D human brain CT image is reconstructed with the salient feature point as center. Simulation results show that the method proposed in this paper can provide accuracy up to 100% when the signal-to-noise ratio is 0, and with the increase of signal-to-noise ratio, the accuracy provided by this method is stable at 100%. Comparison results show that the threshold segmentation method of multi-resolution 3D human brain CT image based on edge pixel grayscale feature decomposition is significantly better than traditional methods in pathological feature estimation accuracy, and it effectively improves the rapid pathological diagnosis and positioning recognition abilities to CT images.

Keywords: Multi-resolution; 3D human brain CT image; segmentation; feature extraction; recognition.

1. Introduction

With the development of digital image processing technology, the application of 3D digital image processing technology to medical image analysis can improve medical pathological diagnosis and analysis capabilities. Human CT images are images

*Corresponding author.

This is an Open Access article published by World Scientific Publishing Company. It is distributed under the terms of the Creative Commons Attribution 4.0 (CC-BY) License. Further distribution of this work is permitted, provided the original work is properly cited.

J. Innov. Opt. Health Sci. 2018.11. Downloaded from www.worldscientific.com
by 2001:250:4000:420b:e17e:45b8:4836:5cc4 on 12/25/18. Re-use and distribution is strictly not permitted, except for Open Access articles.

of human organs imaged by CT light scanning technology. Analyzing CT images can realize pathological diagnosis and localization of human organs. Through high-resolution 3D image processing technology, image feature extraction is improved based on the CT image analysis, thus realizing rapid localization and analysis of human pathological features.[1] CT image analysis plays an important role in pathological analysis of human bones and brain. In the detection of brain diseases, it is required to perform high-resolution recognition and feature extraction to the 3D human brain CT images and analyze the 3D human brain CT image for pathological diagnosis through the singular feature point location analysis method. The recognition of 3D human brain CT images is based on threshold segmentation, and accurate localization of human brain diseases is achieved through image segmentation and edge contour feature extraction. Therefore, it is of great importance to study threshold segmentation methods of multi-resolution 3D human brain CT image in recognition of human brain CT image, and more and more attentions have been paid to the research of image processing methods.[2,3]

In traditional methods, 3D human brain CT image segmentation and feature detection are mainly performed through the ultrasonic echo detection method and edge contour feature segmentation method.[4] The Harris corner point detection technology is adopted for CT image feature location and the adaptive feature decomposition method for 3D human brain CT image reconstruction, which has achieved good resolution and recognition capabilities. However, the method is complex and time-consuming. In Ref. 5, a threshold segmentation method of multi-resolution 3D human brain CT image based on texture superpixel edge segmentation is proposed. In this method, dynamic enveloping contour decomposition method is adopted to perform block segmentation of CT images, and the feature matching method is adopted to reconstruct and recognize the dynamic feature points of the 3D human brain CT images, so as to improve the pixel matching ability of the images. However, this method has the problems of excessive computing overhead and low accuracy of feature decomposition in the threshold segmentation of multi-resolution 3D human brain CT images, practicality is not strong. In Ref. 6, a feature segmentation algorithm of 3D human brain CT image based on bright spot distribution detection is proposed. In this method, an active contour model for 3D human brain CT images is constructed, and threshold denoising and filtering are performed on the images, and with the corner detection method, the abrupt point detection of the CT images is performed, which improves the ability to rapidly search and locate the disease cause points of the CT images. However, this method is easy to be affected by local disturbance points in CT image segmentation, resulting in poor segmentation accuracy of images and proneness to excessive segmentation, it makes the final research result deviate. In Ref. 7, an improved image segmentation method is proposed to realize accurate diagnosis of human brain diseases. In this method, initial segmentation is carried out to the region-of-interest of image with lesions in a human brain CT image based on the FCM clustering principle, and a network diagram is constructed for the 3D CT image with enhanced filter based on the grayscale and spatial information, and then the network diagram is segmented based on the graph cutting theory. In this way, the image with lesions in the human brain CT image is segmented. Experimental results show that this proposed method can effectively improve the diagnostic accuracy of human brain diseases. However, the segmentation process in this method is more complex, the current medical level is difficult to achieve, so its operability is poor. In Ref. 8, a fast 3D reconstruction algorithm of multi-resolution cone-beam CT image based on wavelet transform is proposed. In this algorithm, wavelet transform of corresponding scale is performed on collected projection images, and wavelet coefficients of corresponding scales are selected to perform FDK reconstruction, and then corresponding low-resolution 3D image data can be obtained, thus high-resolution 3D image data can be obtained, it improves the diagnostic efficiency. Experimental data shows that this method can be adopted to not only obtain 3D image data with different resolutions, but also generate high-resolution 3D image data with the same resolution and similar precision compared with the traditional FDK algorithm, and the reconstruction speed can be increased by more than 1 times. However, this method cannot provide sufficient segmentation accuracy and the obtained data is not accurate enough. The practical application of this method is of little significance.

In order to solve the problem of threshold segmentation accuracy and accuracy of traditional

J. Innov. Opt. Health Sci. 2018.11. Downloaded from www.worldscientific.com
by 2001:250:4000:420b:e17e:45b8:4836:5cc4 on 12/25/18. Re-use and distribution is strictly not permitted, except for Open Access articles.

methods is not high, a threshold segmentation method of multi-resolution 3D human brain CT image based on edge pixel grayscale feature decomposition is proposed in this paper. In this method, first, original 3D human brain image information is collected through CT scanning technology and CT image filtering is performed to the collected information through the gradient value decomposition method and edge contour features of the 3D human brain CT image are extracted. Then, the threshold segmentation method is adopted to segment the regional pixel feature block of the 3D human brain CT image to segment the image into block vectors with high-resolution feature points, and the 3D human brain CT image is reconstructed with the salient feature point as center to realize high-resolution identification and segmentation of the CT image and achieve accurate location and recognition of singular feature points. Finally, the experimental results show that the method can effectively improve the threshold segmentation accuracy and recognition accuracy of multi-resolution human brain CT images, and the whole has more advantages.

2. Pixel Feature Acquisition and Denoising Preprocessing of 3D Human Brain CT Image

2.1. *Acquisition of 3D human brain CT image*

In order to perform threshold segmentation to a 3D human brain CT image, pixel features are collected through the 3D template matching method, and adaptive feature decomposition is performed to the collected 3D human brain CT image. During acquisition of pixel features of the 3D human brain CT image, a coordinate system is constructed as follows:

$$\begin{cases} x = R\sin\eta\cos\phi & 0 \le \phi \le 2\pi, \\ y = R\sin\eta\sin\phi & 0 \le \eta \le \pi, \\ z = R\cos\eta & R = D/2, \end{cases} \tag{1}$$

where η represents the template matching value of the 3D human brain CT image in a polar coordinate system and ϕ represents the deviation angle of lesion feature points in the 3D human brain CT image. Laplacian sharpening template matching method is used to acquire real-time 3D human brain CT images and extract the feature information of 3D human brain motion images. According to the extracted information, a test set and a training set of three-dimensional human brain motion images are constructed, and the characteristic quantities of various damage states of three-dimensional human brain are analyzed.[9] A pixel set of 3D human brain CT image acquisition output is given as follows:

$$\begin{aligned} &J_1(W_i) \\ &\quad = \sum_{r=1}^{t}\sum_{p=1}^{k_1} \|W_i^T x_{ir} - W_i^T x'_{irp}\|^2 A_{irp} \\ &\quad = \sum_{r=1}^{t}\sum_{p=1}^{k_1} \mathrm{tr}(W_i^T x_{ir} - W_i^T x'_{irp})(W_i^T x_{ir} - W_i^T x'_{irp})^T A_{irp} \\ &\quad = \sum_{r=1}^{t}\sum_{p=1}^{k_1} \mathrm{tr}(W_i^T[(x_{ir} - x'_{irp})(x_{ir} - x'_{irp})^T A_{irp}]W_i) \\ &\quad = \mathrm{tr}\left(W_i^T\left[\sum_{r=1}^{t}\sum_{p=1}^{k_1}(x_{ir} - x'_{irp})(x_{ir} - x'_{irp})^T A_{irp}\right]W_i\right) \\ &\quad = \mathrm{tr}(W_i^T H_1 W_i), \end{aligned} \tag{2}$$

where

$$H_1 = \sum_{r=1}^{t}\sum_{p=1}^{k_1}(x_{ir} - x'_{irp})(x_{ir} - x'_{irp})^T A_{irp}. \tag{3}$$

The seed point matching method is adopted to divide the 3D human brain CT image into 3×3 pixel blocks in the 8-neighborhood pixel feature space. The imaging region of the 3D human brain CT image is defined to be $M \times M$, and it is set to be $3 * 3$ in this paper. The image block feature quantities in the x-direction and y-direction of the 3D CT imaging edge scale are calculated, and then the 3D human brain CT image corner information is obtained,[10] which can be simplified in the following form with $J_2(W_i)$.

$$\begin{aligned} &J_2(W_i) \\ &\quad = \sum_{r=1}^{t}\sum_{q=1}^{k_2} \|W_i^T x_{ir} - W_i^T x_{irq}\|^2 B_{irq} \\ &\quad = \mathrm{tr}\left(W_i^T\left[\sum_{r=1}^{t}\sum_{q=1}^{k_2}(x_{ir} - x_{irq})(x_{ir} - x_{irq})^T B_{irq}\right]W_i\right) \\ &\quad = \mathrm{tr}(W_i^T H_2 W_i), \end{aligned} \tag{4}$$

where

$$H_2 = \sum_{r=1}^{t}\sum_{q=1}^{k_2}(x_{ir} - x_{irq})(x_{ir} - x_{irq})^T B_{irq}. \tag{5}$$

J. Innov. Opt. Health Sci. 2018.11. Downloaded from www.worldscientific.com by 2001:250:4000:420b:e17e:45b8:4836:5cc4 on 12/25/18. Re-use and distribution is strictly not permitted, except for Open Access articles.

According to pixel sampling of the 3D human brain CT image, H_1 and H_2 are deduced, which are taken as the training set for edge contour feature extraction and template matching of the 3D human brain CT image.[11] The 3D human brain CT image is divided into t blocks, and feature separation is performed on the x axis and y axis according to the correlation feature information of the imaging region, which is represented as follows:

$$y_i = W_i^T M_i = [y_{i1}, y_{i2}, \ldots, y_{it}], \tag{6}$$

$$y_T = W_i^T M_T = [y_{T1}, y_{T2}, \ldots, y_{Tt}], \tag{7}$$

where M_i and M_T are feature subspace components after rotation transformation W_i. According to the above image acquisition results, information acquisition and data set construction of the 3D human brain CT images are realized,[12] on which neighborhood search and feature matching of the 3D human brain CT image are performed to improve the recognition capability of the image.

2.2. *Image denoising*

The gradient value decomposition method is adopted to perform CT image filtering to the collected image, and the contour features of the 3D human brain CT image are extracted.[13] The denosing algorithm of CT image is the threshold denoising method. The prior information of the previous CT image is given,[14] and then the wavelet projection mapping method is adopted to obtain the edge pixel feature quantity, the original image as follows:

$$W_i = (H_1 - H_2)\omega = \lambda\omega, \tag{8}$$

$\{w_1, w_2, \ldots, w_{d_i}\}$ is adopted to represent the edge grayscale pixel set of the 3D human brain CT image, and the size relationship of the feature values is set to $\{\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_{d_i}\}$. Feature matching is performed according to the energy level within the neighborhood at the pixel level, and then d_i feature values are obtained. $\{\lambda_j | j = 1, 2, \ldots, d_i\}$ represents the grayscale binary component of the 3D human brain CT image, where d_i represents the difference in feature sets of 3D human brain operation information. Through the autocorrelation feature matching method. Among them, the grayscale pixel point of the image is obtained to be $\{\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_{d_i} > 0 \geq \lambda_{d_i+1} \geq \lambda_{d_i+2} \geq \cdots \geq \lambda_d\}$. $W = \{w_1, w_2, \ldots, w_{d_i}\}$ is adopted to represent the grayscale vector set of the 3D human brain CT image within the affine invariant region W_i. The gradient value decomposition method and threshold denoising are adopted to obtain a denoised output image as follows:

$$\begin{gathered} x(n) = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} X(k) \exp(j2\pi kn/N), \\ n = 0, 1, \ldots, N-1, \end{gathered} \tag{9}$$

where $X(k)$ is the image gamma for filtering output and $\exp(j2\pi kn/N)$ is the template scale factor. Through cascade wavelet denoising, the positioning frame of the 3D human brain CT image is obtained as follows:

$$e = \frac{1}{|\nabla u|}\left(\frac{\partial u}{\partial y} i - \frac{\partial u}{\partial x} j\right), \quad f = \frac{1}{|\nabla u|}\left(\frac{\partial u}{\partial x} i + \frac{\partial u}{\partial y} j\right). \tag{10}$$

According to the affine invariant moment of the 3D human brain CT image, I_x is set to be the grayscale pixel sequence of a single-sample 3D human brain CT image. $x = P, N$. Through adaptive feature decomposition, the active contour of the image is obtained, and Laplace enhancement processing is performed to the image through the template matching method to improve the information representation ability of the CT image.[15]

3. Optimization of Threshold Segmentation Algorithm of CT Image

3.1. *Edge contour feature extraction of 3D human brain CT image*

The gradient value decomposition (GVD) method is used to filter the collected images to extract the edge contour features of 3D human brain CT images.[16] The expression of edge contour sharpening template output of the 3D human brain CT image is

$$\begin{aligned} S_c &= [S_0, \ldots, S_{Q-1}]_{\text{binary}} \\ &= \left[\sum_{i}^{Q-1} S_i \times 2^i\right]_{\text{Dec}}, \end{aligned} \tag{11}$$

J. Innov. Opt. Health Sci. 2018.11. Downloaded from www.worldscientific.com
by 2001:250:4000:420b:e17e:45b8:4836:5cc4 on 12/25/18. Re-use and distribution is strictly not permitted, except for Open Access articles.

$$S_i = \sum_{j}^{W\times W} I_x^j, \tag{12}$$

where Q is the weight of the 3D human brain CT image block and W is the local region contour feature. The covariance matrix for constructing the distribution of edge contour features of the 3D human brain CT image is

$$C = O^T O \begin{bmatrix} \sum H_x(t)H_x(t) & \sum H_x(t)H_y(t) \\ \sum H_y(t)H_x(t) & \sum H_y(t)H_y(t) \end{bmatrix}. \tag{13}$$

Scale decomposition is performed in the active contour search area, and then the information enhancement output of the 3D human brain CT image is obtained as follows[8]:

$$O = USV^T, \tag{14}$$

where U is a $N \times N$ training sample set matrix for the 3D human brain CT image; V is a 2×2 grayscale histogram matrix and S is a $N \times 2$ local information subspace matrix. Through the structured feature transformation method, the grayscale histogram distribution matrix of the 3D human brain CT image is obtained as follows:

$$f_R(z) = \begin{pmatrix} f_x(z) \\ f_y(z) \end{pmatrix} = \begin{pmatrix} h_x * f(z) \\ h_y * f(z) \end{pmatrix}, \tag{15}$$

where $f(z)$ is the geometric feature invariant vector of the 3D human brain CT image and $*$ is convolution operation. 3D human brain CT image block processing is performed in the active contour lasso region, and the edge contour feature extraction output of the 3D human brain CT image is obtained as follows:

$$O_i = U_i S_i V_i^T = U_i S_i [v_1, v_2]^T, \tag{16}$$

$$v_1 = [v_{11}, v_{12}]. \tag{17}$$

In this way, the edge contour features of the 3D human brain CT image are extracted. The threshold segmentation method is adopted to segment the regional pixel feature block of the 3D human brain CT image to improve feature matching capability and information enhancement capability of the image.[17]

3.2. *3D human brain CT image and image threshold segmentation*

Block fusion of the 3D human brain CT image is performed through the template matching method, and the characteristic decomposition equations of the 3D human brain CT image are obtained and described as follows:

$$\begin{cases} p_{\mathrm{th}}^{(b_{\mathrm{int}})} = C_t \sum_{x_i \in w} k(\|x_i\|)\delta(h(x_i) - b_{\mathrm{int}}), \\ p_{te}^{(b_{\mathrm{ine}})} = C_e \sum_{x_i \in w} k(\|x_i\|^2)\mathrm{his}_{x_i}\delta(v_{x_i} - b_{\mathrm{ine}}), \end{cases} \tag{18}$$

where $C_t = C_e = \frac{1}{\sum_{x_i \in w} k(\|x_i\|^2)}$, which represents the grayscale pixel state feature set of the CT image and $b_{\mathrm{ine}} \in [1, M]$ represents the visualization reconstruction output result of the 3D human brain image. The following binary function is adopted to represent the high-resolution pixel reconstruction output of the CT image:

$$I(u,v) = \left(\frac{1}{2} + \frac{1}{4}\left(\cos\left(\frac{\pi u^2}{R}\right) + \cos\left(\frac{\pi v^2}{R}\right)\right)\right) \times 255, \tag{19}$$

where R represents a specification constant. In analysis of the 3D human brain CT image, set $R = 1000$. Threshold segmentation of the 3D human brain CT image is performed through scale decomposition and template matching method, and the segmentation scale is obtained as follows:

$$\begin{aligned} &E(\phi, f_1, f_2) \\ &\quad = \mu \int \frac{1}{2}(|\nabla\phi| - 1)^2 dx + v \cdot \mathrm{Length}(C) \\ &\qquad + \lambda_1 \int \left[\int K_\sigma(x-y)|I - f_1(x)|^2 H(\phi) dy\right] dx \\ &\qquad + \lambda_2 \int \left[\int K_\sigma(x-y)|I - f_2(x)|^2 (1 - H(\phi) dy)\right] dx, \end{aligned} \tag{20}$$

where $\lambda_1, \lambda_2, \nu, \mu$ are the state factors of lesion feature points in the CT image, representing the edge pixel set of the image. K_σ is the standard deviation of threshold segmentation and σ is the RGB vector set of histogram. σ is selected to perform neighborhood matching to improve the feature matching ability in segmentation process. Finally, the image is segmented into block vectors with high-resolution feature points through the RGB decomposition method, and the 3D human brain CT image is

J. Innov. Opt. Health Sci. 2018.11. Downloaded from www.worldscientific.com by 2001:250:4000:420b:e17e:45b8:4836:5cc4 on 12/25/18. Re-use and distribution is strictly not permitted, except for Open Access articles.

reconstructed with the salient feature point as center. The reconstruction output is obtained as follows:

$$\begin{aligned} &E(\phi, f_1, f_2) \\ &\quad = \lambda_1 \int \left[\int K_\sigma(x-y)|I - f_1(x)|^2 H(\phi) dy \right] dx \\ &\qquad + \lambda_2 \int \left[\int K_\sigma(x-y)|I - f_2(x)|^2 (1 - H(\phi)) dy \right] dx, \end{aligned} \tag{21}$$

$$\begin{aligned} &E_{\mathrm{RGB}}(\phi, f_1^G, f_2^G) \\ &\quad = \lambda_1 \int \left[\int K_\sigma(x-y)|I^G - f_1^G(x)|^2 H(\phi) dy \right] dx \\ &\qquad + \lambda_2 \int \left[\int K_\sigma(x-y)|I^G - f_2^G(x)|^2 (1 - H(\phi)) dy \right] dx, \end{aligned} \tag{22}$$

where I^G represents the sparse solution of the 3D human brain CT image, and f_1^G and f_2^G represent the gradient value segmentation pixel differences. Based on the difference characteristics of pixels, pathological analysis is performed.

4. Simulation Experiment Analysis

In order to test the application performance of the model designed in this paper in 3D human brain CT image segmentation and high-resolution feature localization of diseased spots, a simulation experiment was conducted. The specific flow chart is shown in Fig. 1.

The experimental parameters are as follows: The experiment was designed with Matlab 7. In parameter setting, the smoothing parameter of the gradient value segmentation was set to be 2.2; the sharpening curvature parameter of the 3D human brain CT image 1.25; the number of search iterations $K = 50$; the sliding matching coefficient of grayscale histogram 1.14; the image threshold segmentation scale 2; the panel parameter of 3D reconstruction $\beta = 2.8$: the segmentation scale of super-pixel neighbor point $a = 0.56$; the size of template matching 20*20 and the neighbor size of lesion feature point 2.5.

According to the above simulation environment and parameter settings, 3D human brain CT image threshold segmentation was simulated and designed, and the original collected 3D human brain CT image is obtained as shown in Fig. 2.

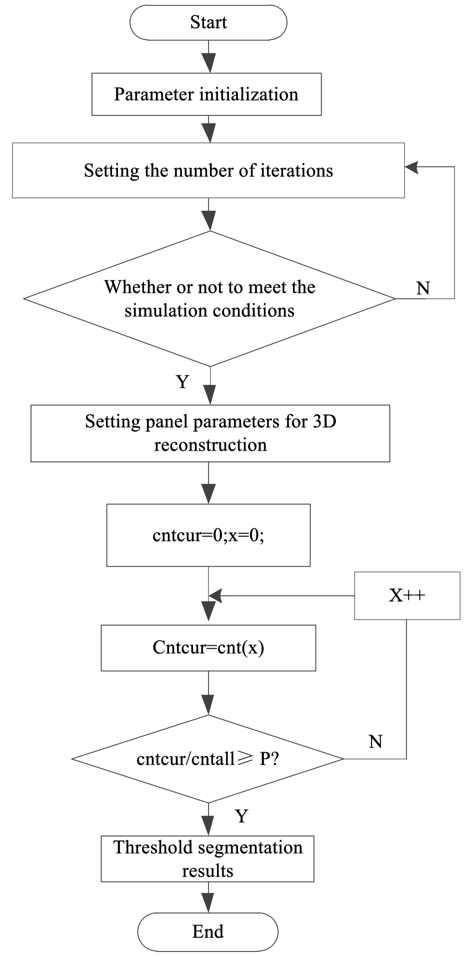

Fig. 1. Experimental flow chart.

The collected image shown in Fig. 2 is taken as the research object to perform CT image filtering, and contour features of the 3D human brain CT image are extracted to realize information

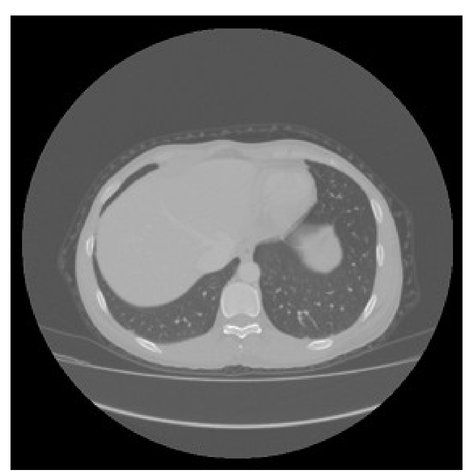

Fig. 2. Original 3D human brain CT image.

J. Innov. Opt. Health Sci. 2018.11. Downloaded from www.worldscientific.com
by 2001:250:4000:420b:e17e:45b8:4836:5cc4 on 12/25/18. Re-use and distribution is strictly not permitted, except for Open Access articles.

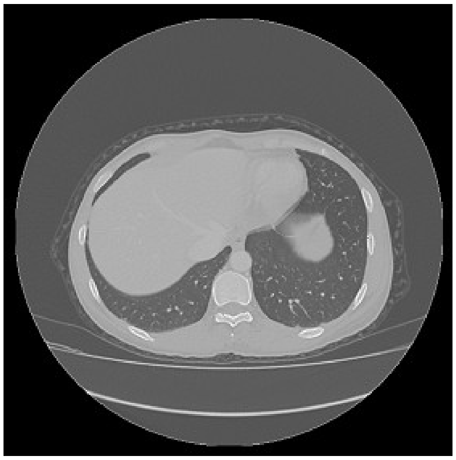

Fig. 3. Enhancement result of 3D human brain CT image.

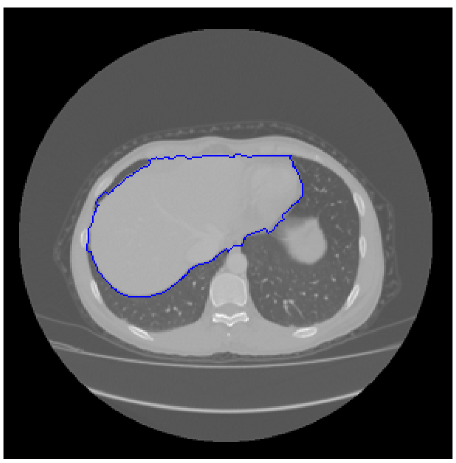

Fig. 4. Block segmentation result of CT image.

enhancement. The image enhancement result is obtained as shown in Fig. 3.

On the basis of image filtering and information enhancement processing, the threshold segmentation method is adopted to perform segmentation of the 3D human brain CT image region pixel feature block. As shown in Fig. 4, the segmentation results of pixel feature blocks in 3D human brain CT images are presented.

Analysis of Fig. 4 shows that when the method proposed in this paper is adopted for block segmentation of 3D human brain CT image, Image recognition ability is stronger. Based on this, the segmentation is continued and the segmentation results are shown in Fig. 5.

Analysis of Fig. 5 shows that when accurate location and identification of feature points of lesion in the CT image is achieved through threshold

Fig. 5. Image threshold segmentation result.

segmentation of the 3D human brain CT image, the peak signal to noise of the output image is relatively high. In order to compare the performance, the pathological estimation performance of CT images was compared with Propos method and Traditional method. The comparison results are obtained as shown in Fig. 6.

Analysis of Fig. 6 shows that when the signal to noise ratio is 0, the accuracy of pathological feature estimation provided by traditional methods can reach 80%, while the accuracy of it provided by the method proposed in this paper can reach 100% regardless of the signal to noise ratio, it can be seen that the accuracy of this method is more accurate; with the increase of signal to noise ratio, accuracy provided by the method proposed in this paper is

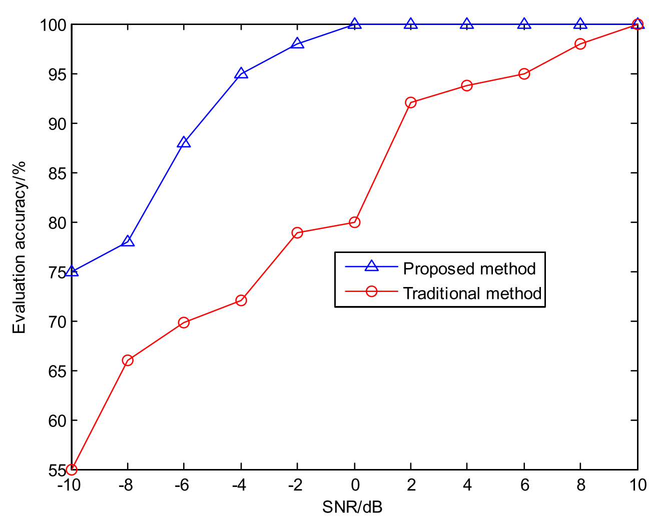

Fig. 6. Comparison of pathological feature estimation performance of CT image.

J. Innov. Opt. Health Sci. 2018.11. Downloaded from www.worldscientific.com by 2001:250:4000:420b:e17e:45b8:4836:5cc4 on 12/25/18. Re-use and distribution is strictly not permitted, except for Open Access articles.

stable at 100%, and the traditional method can provide accuracy of 100% only when the signal-to-noise ratio reaches 10. Therefore, the method proposed in this paper is more stable.

So, when the method proposed in this paper is adopted to perform threshold segmentation of 3D human brain CT images, the rapid pathological diagnosis and localization recognition abilities of human brain CT images are improved.

5. Conclusion

In the detection of brain diseases, it is required to perform high-resolution recognition and feature extraction to 3D human brain CT images and analyze the 3D human brain CT images for pathological diagnosis through the singular feature point location analysis method to realize accurate localization of human brain diseases through image segmentation and edge contour feature extraction.

(1) A threshold segmentation method of multi-resolution 3D human brain CT image based on edge pixel grayscale feature decomposition is proposed in this paper. Original 3D human brain image information is collected through CT scanning technology, and CT image filtering is performed to the collected information through the gradient value decomposition method.
(2) The edge contour features of the 3D human brain CT image are extracted, and the threshold segmentation method is adopted to segment the regional pixel feature block of the 3D human brain CT image. And then the 3D human brain CT image is reconstructed with the prominent feature points as the center to realize the high resolution recognition and accurate segmentation of the CT image.
(3) Study shows that the method proposed in this paper can improve the threshold segmentation precision and recognition accuracy of multi-resolution 3D human brain CT images and can improve the ability of feature extraction and pathological analysis to human brain CT images.
(4) Human brain CT technology can detect the fine structure of the human brain without damage, and the details are exquisite. Because of the complexity of human brain tissue and the influence of camera, it is difficult to present the medical images clearly. CT image segmentation has been the focus and difficulty of scientists. In this paper, the threshold segmentation method of multi-resolution human brain CT image is studied, and the problems of low threshold segmentation accuracy and recognition accuracy and low segmentation speed of CT image are solved. It provides a strong support for people to explore the internal structure of human brain and examine human encephalopathy. In the research and clinical diagnosis and treatment of the brain, this method can extract and analyze the tissues of normal or lesion areas, observe the relationship between blood vessels and lesions, so that the relevant medical staff can make further research and diagnosis on the results of segmentation, increase the accuracy of clinical diagnosis, and improve the diagnosis. The level of treatment is good.
(5) Acquisition of research results is not the ultimate goal of scientific research, but should also be applied to clinical practice, through teaching and other means to strengthen the promotion of research results, so that research results truly serve medical diagnosis, and serve the people.
(6) The future research direction is to future improve the threshold segmentation accuracy and recognition accuracy of human brain CT images and the CT image segmentation speed based on this paper.

References

1. L. Songlin, J. Yong, G. Yong, Z. Xiaoling, C. Guolong, "Moving target tracking algorithm based on improved Camshift for through-wall-radar imaging," *J. Comput. Appl.* **38**(2), 528–532 (2018).
2. P. Ferrara, T. Bianchi, "Image forgery localization via fine-grained analysis of CFA artifacts," *IEEE Trans. Inf. Forensics Security* **7**(5), 1566–1577 (2012).
3. L. Tengfei, J. Weili, "Automatic line segment registration using Gaussian mixture model and expectation-maximization algorithm," *IEEE J. Selected Topics Appl. Earth Observat. Rem. Sens.* **7**(5), 1688–1699 (2014).
4. L. Siwei, P. Xunyu, Z. Xing, "Exposing region splicing forgeries with blind local noise estimation," *Int. J. Comput. Vis.* **110**(2), 202–221 (2014).
5. L. Xiao, G. Baozhen, L. Qijun, L. Yunpeng, T. Qingguo, "Acquisition of camera dynamic extrinsic

J. Innov. Opt. Health Sci. 2018.11. Downloaded from www.worldscientific.com
by 2001:250:4000:420b:e17e:45b8:4836:5cc4 on 12/25/18. Re-use and distribution is strictly not permitted, except for Open Access articles.

parameters in free binocular stereo vision system," *J. Comput. Appl.* **37**(10), 2888–2894 (2017).

6. Z. Quangui, C. Feng, L. Zhiqiang, "Human action recognition based on coupled multi-Hidden Markov model and depth image data," *J. Comput. Appl.* **38**(2), 454–457 (2018).
7. D. Suijuan, "Simulation study on accurate diagnosis of pathological region of human brain CT," *Comput. Simul.* **347**, 294–297 (2017).
8. W. Zheng, Q. Wang, Y. Wang *et al.*, "Threshold segmentation of pulmonary subsolid nodules on CT images: Detection and quantification of the solid component," *Chin. J. Lung Cancer* **20**(5), 341–345 (2017).
9. H. Min, C. Xu, L. Dengwang, "Multiresolution cone-beam CT image fast 3D reconstruction algorithm based on wavelet transform," *J. Electron. Inf.* **3910**, 2437–2441 (2017).
10. Z. Moghaddam, M. Piccardi, "Training initialization of hidden markov models in human action recognition," *IEEE Trans. Automat. Sci. Eng.* **11** (2), 394–408 (2014).
11. C. Chimhundu, T. Mutsvangwa, Refinement of threshold intensity-derived segmentations of bone from CT via statistical shape models, *Su Biomed. Eng. Conf.* (2016).
12. B. B. Amor, J. Su, A. Srivastava, "Action recognition using rate-invariant analysis, of skeletal shape trajectories," *IEEE Trans. Pattern Anal. Mach. Intell.* **38**(1), 1–13 (2016).
13. Q. Y. Tan, H. Leung, Y. Song *et al.*, "Multipath ghost suppression for through-the-wall-radar," *IEEE Trans. Aerospace Electr. Syst.* **50**(3), 2284–2292 (2014).
14. G. Gennarelli, F. Soldovieri, "Multipath ghosts in radar imaging: Physical insight and mitigation strategies," *IEEE J. Selected Topics Appl. Earth Observat. Remote Sensing* **8**(3), 1078–1086 (2014).
15. C. Xiu, F. Ba, "Target tracking based on the improved Camshift method," *Proc. 2016 Chin. Control and Decision Conf. (CCDC 2016)*, Piscataway, NJ, pp. 3600–3604, IEEE, 2016.
16. L. Zhang, T. Z. Qiao, "An binary segmentation algorithm for infrared image," *Infrared Tech.* **36**(8), 649–651 (2014).
17. M. Donadieu, F. Y. Le, A. Lecocq *et al.*, "Metabolic voxel-based analysis of the complete human brain using fast 3D-MRSI: Proof of concept in multiple sclerosis," *J. Magnet. Reson. Imaging* **44**(2), 411–419 (2016).
18. P. G. Liu, Y. Y. Liu, M. Pan *et al.*, "Research of image process and phase segmentation of 3D sandstone samples based on micro-CT tomogram," *Sci. Tech. Eng.* (2017).