Abstract—In this paper, a method based on neighborhood information is proposed, which adjusts the parameters by using a method of chi square with Gauss weighted distance and the self-adaptability of shared neighbor weighting. And by integrating the nearest neighbor weighted adaptive method, each pixel is automatically given a scale parameter to reduce the need to adjust the parameters. Gauss weighted local neighborhood information is introduced in this paper, to construct the similarity matrix directly on the original image. At the same time, based on the existing graph-cut image segmentation method it is necessary to construct a better network graph by using the maximum flow minimum cut. So, NJW algorithm is replaced by a improved Graph cut which combines the multi-scale analysis method, to improve the efficiency of the original segmentation method and enhance the clinical usability.

Keywords—medical image segmentation, local neighborhood information, multi-scale, chi square.

I. INTRODUCTION

Medical image processing is based on the results of medical image segmentation, such as bone segmentation and angiography system reconstruction. And according to the bone segmentation method, the characteristics of spine MRI and CTA images were analyzed by 2D image and 3D body data, then different segmentation methods can be proposed. Two contents are included in this paper. Firstly, a new fast segmentation technique for spine images is presented, and, it solves the disadvantage that the segmentation result is less ideal when the method is used to segment the spine image, and the problem of manually adjusting the parameters is Shl; secondly, the neighborhood information in graph cut is introduced, to be used to replace the NJW algorithm in the literature [2], and synthesize the Multi-scale analysis method, improve the speed of the document [2] segmentation method and enhance the clinical usability.

II. THE PRESENT SITUATION AND PROBLEMS OF IMAGE SEGMENTATION BASED ON GRAPH THEORY AND MULTI-SCALE SEGMENTATION

Multi-scale segmentation method means, after sampling the original image at different scales, processing it on the basis of sampling, and then mapping back to the original image, in order to achieve the purpose of increasing speed.

After studying the multi-scale image segmentation algorithm of Shi et al [1], we found that, although it can improve the segmentation speed, more parameters need to be adjusted manually, and it is not easy to operate. Only the gray level information and the interference contour are used as the classification feature, and the segmentation information is not taken into account. But the segmentation effect of the spinal MR image is not ideal, so it is improved in this paper.
III. METHODS OF IMPROVEMENT

Inspired by the last section of Shi et al.’s multi-scale segmentation algorithm, the speed of segmentation can be improved. The neighborhood information of the pixel is introduced, and the similarity algorithm in the Graph cut method [2] is improved. The NJW algorithm [3] in Reference [2] is replaced, and the multi-scale analysis method is integrated to improve the efficiency of the method in order to enhance the clinical usability.

The pixel similarity algorithm in Reference [2] is shown in Equation (1).

$$W_{ij} = e^{-\chi^2(v_i,v_j) / \sigma_i \sigma_j}$$  \hspace{1cm} (1)

In Equation (1), $\sigma_i = d(v_i,v_k)$ and $\sigma_j = d(v_j,v_k)$.

A local scale parameter $\sigma_j$ is calculated for each data point $v_j$, where $v_k$ represents the kth nearest neighbor of point $v_j$, so $\sigma_j$ represents the Euclidean distance of the point $v_j$ to its kth nearest neighbor.

Let each point $v_j$ specify a specific scale parameter $\sigma_j$, which allows automatic adjustment of the similarity between two points based on the local statistics information of the surrounding points $v_j$ and $v_j$.

The gray value of all the pixels in the neighborhood is used instead of the gray value of a single pixel, [3] weighted by the Gaussian function. Thus, the chi-square distance [2] between two nodes (pixels) $v_j$ and $v_j$ in the image is expressed as Equation (2).

$$d^2(v_i,v_j) = \frac{1}{2} \sum_{k=1}^{n} W_k \frac{(v_i(k) - v_j(k))^2}{v_i(k) + v_j(k)}$$  \hspace{1cm} (2)

$$\sum_{k=1}^{n} W_k = 1, W_k \geq 0$$

$v_{i(k)}$ represents the gray value of the kth pixel in the 5 × 5 neighborhood of a node, and $w_k$ is the feature weight.

The graph similarity algorithm in Graph cut algorithm is shown in Equation (3).

$$b_{(p,q)} = e^{-\frac{(f_{p} - f_{q})^2}{2\sigma^2}} \frac{1}{\text{dist}(p,q)}$$  \hspace{1cm} (3)

Edge $\{p,q\}$, i.e., the similarity algorithm of the pixels $p$ and $q$ is the simple 4 or 8 neighborhood [4], so the literature [2] is more comprehensive for the use of neighborhood information.

There are two types of edges for each pixel $P$ in the Graph cut: neighboring links (N-links) and terminal links (t-links). Any point $p$ each has two t-links, which are expressed as $\{p, St\}$, and $\{p, T\}$ and connect it to the terminal node. In this section, the pixel similarity algorithm which is used by the method in Reference [2] replaces the calculation of the $\{p,q\}$ weight of the edge n-links in the graph cut.

That is to say, the pixel similarity algorithm in the Graph cut algorithm is replaced by Equation (4).

$$W_{ij} = e^{-\chi^2(v_i,v_j) / \sigma_i \sigma_j}$$  \hspace{1cm} (4)

IV. EXPERIMENTS

The experimental data presented in this chapter are provided by Guangzhou Southern Hospital, which uses 3.0T magnetic resonance and collects 100 MR images. The parameters are resolution 0.5859mm, layer thickness 4mm, size is 512 × 512 pixels, layer spacing 0.4mm. MRI is divided into four categories, including T1-weighted healthy human spine images and patient spine images, T2-weighted healthy human spine images and patient spine images. In this paper, the algorithm is compared with the more classical algorithm, including NJW algorithm, Gamio algorithm, Shi algorithm. Analysis shows the advantages of the proposed algorithm. The results of the manual division of the experts can be a measure of the standard, and then its accuracy can be quantitatively analyzed.

The hardware environment used in the experiment is as follows: processor Intel Core Duo (2.53 GHz), machine memory size 2G. The software environment is Windows 7 system. Processing software: Matlab 2008a and Visual Studio 2008.

(Experiment 1): T1-weighted images of patients with natural vertebral body

The parameters are set as in the NJW algorithm, $\sigma=0.2$, $C=35$; in the Gamio algorithm, $\sigma=0.45$, $C=35$.

Figure 1. Gold Standard: the left side of the vertebral body contoured manually by the expert and the vertebral body on the right

Figure 2. The left side of the vertebral body contoured manually by the expert and the vertebral body on the right

From Figure 1 and Figure 2, the first line is the edge of the vertebral body, the second line is the resulting vertebral body, and the third line is compared with the manual segmentation
edge.

(Experiment 2): T1-weighted images of the patient's vertebral lesions

The parameters are set as in the NJW algorithm, $\sigma=0.05$, $C=65$; in the Gamio algorithm, $\sigma=0.15$, $C=40$.

Figure 3. Gold Standard: the left side of the vertebral body contoured manually by the expert and the vertebral body on the right

Figure 4. The left side of the vertebral body contoured manually by the expert and the vertebral body on the right

From Figure 3 and Figure 4, the first line is the edge of the vertebral body, the second line is the resulting vertebral body, and the third line is compared with the manual segmentation edge.

(Experiment 3): T2-weighted images of patients with natural vertebral body

The parameters are set as in the NJW algorithm, $\sigma=0.1$, $C=38$; in the Gamio algorithm, $\sigma=0.12$, $C=40$.

Figure 5. Gold Standard: the left side of the vertebral body contoured manually by the expert and the vertebral body on the right

Figure 6. The left side of the vertebral body contoured manually by the expert and the vertebral body on the right

Figure 7. Gold Standard: the left side of the vertebral body contoured manually by the expert and the vertebral body on the right

Figure 8. The left side of the vertebral body contoured manually by the expert and the vertebral body on the right

From Figure 5 and Figure 6, the first line is the edge of the vertebral body, the second line is the resulting vertebral body, and the third line is compared with the manual segmentation edge.

(Experiment 3): T2-weighted images of patients with natural vertebral body

The parameters are set as in the NJW algorithm, $\sigma=0.18$, $C=40$; in the Gamio algorithm, $\sigma=0.35$, $C=35$.

Figure 7. Gold Standard: the left side of the vertebral body contoured manually by the expert and the vertebral body on the right

Figure 8. The left side of the vertebral body contoured manually by the expert and the vertebral body on the right

From Figure 7 and Figure 8, the first line is the edge of the vertebral body, the second line is the resulting vertebral body, and the third line is compared with the manual segmentation edge.

(Experiment 4): T2-weighted images of patients with vertebral lesions, vertebral degeneration, intervertebral disc herniation

The parameters are set as in the NJW algorithm, $\sigma=0.1$, $C=50$; in the Gamio algorithm, $\sigma=0.1$, $C=40$. 
From Figure 9 and Figure 10, the first line is the edge of the vertebral body, the second line is the resulting vertebral body, and the third line is compared with the manual segmentation edge.

Through the above experiments, we can see that the improved algorithm proposed in this chapter can accurately segment the vertebral body, smoothly and clearly. The results are close to those in Reference [2], and satisfactory results can be achieved. And the segmentation of vertebral body contour and vertebral body shape are closer to the manual segmentation results.

1) Analysis of Four Algorithm Results

Experimental comparison of four kinds of segmentation algorithms is shown in Table 1.

| method               | image | Dice   | ME    | HD   |
|----------------------|-------|--------|-------|------|
| NJW algorithm        | 12    | 0.901617 | 0.008217 | 3.3  |
|                      | 14    | 0.912605 | 0.006710 | 4.5  |
|                      | 16    | 0.947509 | 0.004051 | 1.7  |
|                      | 18    | 0.886505 | 0.008152 | 4.2  |
|                      | 20    | 0.957979 | 0.004467 | 1.7  |
| Gamio algorithm      | 12    | 0.92693  | 0.006344 | 2    |
|                      | 14    | 0.894051 | 0.007881 | 2    |
|                      | 16    | 0.891325 | 0.007866 | 1.7  |
|                      | 18    | 0.860596 | 0.010296 | 2.8  |
|                      | 20    | 0.902853 | 0.010391 | 2.2  |
| Algorithm of literature [2] | 12    | 0.964549 | 0.003132 | 2    |
|                      | 14    | 0.94315  | 0.002842 | 1.7  |
|                      | 16    | 0.969118 | 0.002293 | 1.4  |
|                      | 18    | 0.962901 | 0.002724 | 1.7  |
|                      | 20    | 0.950673 | 0.003147 | 1.7  |
| Improved Method      | 12    | 0.954549 | 0.003342 | 1.8  |
|                      | 14    | 0.94315  | 0.002643 | 1.5  |
|                      | 16    | 0.969118 | 0.002643 | 1.5  |
|                      | 18    | 0.952901 | 0.00276  | 1.6  |
|                      | 20    | 0.950673 | 0.003147 | 1.7  |

2) Four algorithm variable settings and time analysis

| method                | Gray-scale information | Location Information | Interference contours | Weights | Num-ber of clusters | time /s |
|-----------------------|------------------------|----------------------|-----------------------|---------|---------------------|--------|
| NJW                   | Yes                    | No                   | No                    | No      | Yes (C)             | 51.47  |
| Gamio                 | Yes                    | No                   | No                    | No      | Yes (C)             | 53.29  |
| Reference [2]         | No                     | No                   | No                    | No      | Yes (C)             | 57.01  |
| This chapter          | No                     | No                   | Yes (λ)               | No      |                     | 13.25  |

※ "Yes" means that the parameters need to be set manually, "no" means that you do not need to manually press the setting.

The improved method not only manually adjusts the parameters less than NJW and Gamio, but also the execution time is minimal. In the case where the NJW and Gamio methods are less efficient, the results are close to those of the algorithm in Reference [2], and satisfactory results can be achieved.
V. CONCLUSIONS

In this paper, the Gauss weighted local spatial neighborhood information is improved to the Graph cut, which is used to replace the NJW algorithm in Reference [2] and to synthesize the multi-scale analysis method to improve the speed of the method in Reference [2], which increases clinical availability. But the information collection is not comprehensive enough, which led to the increase of speed, nevertheless the effect has declined slightly. Further study of sampling methods needs to better utilize the original image information.

ACKNOWLEDGMENT

This research is finance supported by 2017-2020 China National Natural Science Fund (51679058); 2013-2016 China Higher Specialized Research Fund (PhD supervisor category) (20132304110018)

REFERENCES

[1] Shi dianguo, Gray-based image segmentation based on graph theory, Wuhan University of Technology, 2009. (in Chinese)

[2] Zheng qian, Study on medical image segmentation method and its application, Southern Medical University, 2014. (in Chinese)

[3] Shi J, Malik J, “Normalized cuts and image segmentation”, IEEE Transactions on Pattern Analysis and Machine Intelligence, 1997, pp.888-905.

[4] Hu chunhai, Zheng weitao, Zhou qian, Cheng shuhong, “Generalized image segmentation algorithm based on multi-scale analysis”, Journal of Yanshan University, Vol.01, 2012, pp.39-43. (in Chinese)

[5] Carballido Gamio J, Belongie S J, Majumdar S, “Normalized cuts in 3-D for spinal MRI segmentation”, IEEE Transactions on Medical Imaging, Vol.23, No.1, 2004, pp.36-44.

[6] Jarvis R A, Patrick E A, “Clustering Using a Similarity Measure Based on Shared Near Neighbors”, IEEE Transactions on Computers, 1973, Vol.C-22, No.11, 1973, pp.1025-1034.

[7] Hendrickson B, Leland R W, A multilevel algorithm for partitioning graphs, supercomputing conference, 1995, pp.28-28.

[8] Liu yi, Based on the image of the interactive image segmentation algorithm. Nanjing University of Science and Technology, 2013. (in Chinese)

[9] Shi J, Malik J, “Normalized Cuts and Image Segmentation”, IEEE Transactions on Pattern Analysis & Machine Intelligence, Vol.22, No.8, 2000, pp.888-905.

[10] Cour T, Bénédit F, Shi J, “Spectral Segmentation with Multiscale Graph Decomposition”, Vol.2, No.2, 2005, pp.1124-1131.

[11] Wang bosh, “Digital image processing technology research progress”, Engineering Technology: Full version, No.9, 2016, pp.00128-00128. (in Chinese)

[12] Luo huaqin, Study on Adaptive Scaling Algorithm Based on Nearest Neighbor Paths, Harbin Engineering University, 2012. (in Chinese)

[13] Jayasree. M, Narayanan N K, Image segmentation based on multiple means using class division method, International Conference on Industrial Instrumentation and Control, IEEE, 2015, pp.1264-1267.

[14] Chen wen, “Progress and development trend of medical imaging technology”, Journal of Practical Medical Imaging, Vol.17, No.3, 2016, pp.254-257. (in Chinese)

[15] Fan tiej, “No-field nuclear magnetic resonance system knee joint imaging technique and clinical application observation”, The world’s latest medical information Abstract: continuous electronic journals, Vol.16, No.64, 2016, pp.232-232. (in Chinese)

[16] Jiao pengpeng, “Comparative analysis of typical segmentation algorithms in medical images”, Information Technology, No.2, 2015, pp.82-84. (in Chinese)

[17] Qi ji, Zhao deqiang, Li yika, “Conclusion on the concept of vertebral artery type cervical spondylosis”, Journal of Cervical and Lumbar, Vol.38, No.1, 2017, pp.5-8. (in Chinese)

[18] Jayasree. M, Narayanan N K, “Image segmentation based on multiple means using class division method International Conference on Industrial Instrumentation and Control”, IEEE, 2015, pp.1264-1267.

[19] Carballido Gamio J, Belongie S J, Majumdar S, “Normalized cuts in 3-D for spinal MRI segmentation”, IEEE Transactions on Medical Imaging, Vol.23, No.1, 2004, pp.36-44.

[20] Zelnik-Manor L, “Self-tuning spectral clustering. Advances in Neural Information Processing Systems”, No.17, 2004, 1601—1608.

[21] Krishnamurthy S, Narasimhan G, Rengasamy U, “Three-dimensional lung nodule segmentation and shape variance analysis to detect lung cancer with reduced false positives”, Proceedings of the Institution of Mechanical Engineers Part H Journal of Engineering in Medicine, Vol.230, No.1, 2016, pp.58-70.

[22] Ng A Y, Jordan M I, Weiss Y, “On Spectral Clustering: Analysis and an algorithm”, Proceedings of Advances in Neural Information Processing Systems, No. 14, 2002, pp.849–856.

[23] Lombaert H, Sun Y, Grady L, et al, “A Multilevel Banded Graph Cuts Method for Fast Image Segmentation”, Tenth IEEE International Conference on Computer Vision. DBLP, Vol. 1, 2005, pp.259-265.

[24] Parveen R, Todd-Pokropek A, “Classification of MRI Brain Tissues Using Fuzzy Estimation”, IEEE Nuclear Science Symposium Conference Record. IEEE, 2002, pp.613-2619.

[25] Nanthagopaul A P, Rajamony R S, “Classification of benign and malignant brain tumor CT images using wavelet texture parameters and neural network classifier”, Journal of Visualization, Vol.16, No.1, 2013, pp.19-28.

[26] Adalsteinsson D, Sethian J A, “A Fast Level Set Method for Propagating Interfaces”, Journal of Computational Physics, Vol.118, No.2, 1995, pp.269-277.

[27] Behrens S, Automatic Level Set Based Cerebral Vessel Segmentation and Bone Removal in CT Angiography Data Sets, Pattern Recognition. 2013, pp.237-242.

[28] Cour T, Bénédit F, Shi J, “Spectral Segmentation with Multiscale Graph Decomposition”, Vol.2, No.2, 2005, pp.1124-1131.

[29] Song Y, Bao X, Liu Z, et al, An Improved Brain MRI Segmentation Method Based on Scale-Space Theory and Expectation Maximization Algorithm, Advances in Multimedia Information Processing – PCM 2015. Springer International Publishing, 2015, pp.516-525.