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AUTOMATIC SEGMENTATION OF BRAIN TUMOR MAGNETIC RESONANCE IMAGING BASED ON MULTI-CONSTRAINS AND DYNAMIC PRIOR

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Abstract- The most difficult and challenging problem in medical image analysis is image segmentation. Due to the limited imaging capability of magnetic resonance (MR), the sampled magnetic resonance images from clinic always suffer from noise, bias filed (also known as intensity non-uniformity), partial volume effects and motive artifacts. In additional, for the complex shape boundary and topology of brain tissues and structures, segmenting magnetic resonance image of brain tumor fast, accurately and robustly is very difficult. In this paper, we propose an image segmentation algorithm based on multi-constrains and dynamic prior. Through introducing a novel big scale constrain into Markov random filed model from magnetic resonance image we realize automatic segmentation under the principle of maximum a Posterior and a modified expectation-maximization algorithm according to the Bayesian frame. Finally, a set of human body detection and tracking experiments are designed to demonstrate the effectiveness of the proposed algorithms.

Index terms: Brain tumor image; magnetic resonance; segmentation;

I. INTRODUCTION

The medical image analysis has influenced many areas in neuroscience greatly in the last two decades [1-5]. With the advancement of the medical imaging technologies, neuroscientists have been increasingly interested in methodologies that can identify brain normal tissues, so as to improve the effectiveness of treatment methods against the brain disease. As the one of the most important branches of segmentation of image, the medical image segmentation is the primary and critical step for the analyzing and understanding the medical images. With the development of magnetic resonance imaging technology, it can provide d a means for imaging tissues in the brain at very high contrast and resolution in the three dimensional space. Neuroscientists are keenly interested in outlining the three main brains, i.e., grey matter, white matter and cerebrospinal fluid. All these researches that are based on morphological structure changes depend on the segmentation of magnetic resonance imaging. Thus, medical image segmentation technology provides kinds of automatic or semiautomatic extraction methods for brain structure from the multiple mode of segmentation, especially for brain tumor test.

In medical image analysis, a large number of image segmentation algorithms and methods have been put forward to realize kinds of automatic and semiautomatic image segmentation. These methods based on automatic or semiautomatic have released researchers from the burdensome manual segmentation tasks, the segmentation results of which are of certain repeatability and veracity. However, usually the veracity of these segmentation methods is worse than that of manual segmentation, for which the manual methods are in common use at present. Medical image segmentation is the most difficult problem in medical image analysis. As the imaging capability of magnetic resonance device is limited, the magnetic image often contains noise, bias filed, partial volume effect and motive artifacts. In additional, due to the complex shape, boundary and topology of brain structure, to segment the magnetic resonance image of brain tissues in a fast, accurate and robust way is of great difficulty. Besides, the segmentation of image in two dimensional spaces cannot meet the requirements of clinic and research. Thus the segmentation in three dimensional spaces becomes the mainstream gradually. The segmentation algorithms of fast, accuracy and robustness in three dimensional spaces are a pressing need of the clinic doctors and researchers. For the body tissues and structures are the structure of three dimensional spaces, and the three dimension segmentation can use the image information as sufficient as possible, the result of segmentation is more accurate and continuous in space, which can provide the information of three dimensions morphological structure, size and position for researchers.

Through several decades' development, a large number of video segmentation techniques have been developed in recent years, but it cannot meet the practical application yet. There are many reasons, concluding that some of the practical problems people faced cannot be fully expressed by mathematical models, the structures of segmentation objects are of the wide diversity, image degenerates, the segmentation cannot meet the expectation and so on, which decide that a common segmentation method couldn't possibly exist. We can only make a balance among the indexes of accuracy, fast and robustness according to the specific application. Thus, the kind of segmentation method is of great variety, such as data driven vs. model driven, region vs. boundary, automatic vs. semiautomatic, with supervision vs. without supervision, based on model vs. based on characteristic, software segmentation vs. hardware segmentation, anatomical knowledge based vs. prior probability map and so on.

For the problem of brain tumor test based on magnetic resonance image, due to the state-of-the-art of the current medical image segmentation researches, from the technology of three dimensional segmentation of view, we firstly will give an overview of current research results, especially for three dimensions. And then, aiming at the deficiencies of these methods, we provide the new algorithm based on multi-constrains and dynamic prior, to realize the image segmentation of brain tissues for brain tumor test, so as to provide a three dimensional automatic segmentation algorithm , the results of which can be closer or even better than that of manual segmentation by medical experts. The final purpose of our research is to assist the clinical diagnosis and improve the reliability and effectiveness of cure for brain tumor, with supplying a reliable tool for registration, fusion and analysis of brain medical magnetic resonance image.

II. OVERVIEW OF BRAIN MEDICAL IMAGE SEGMENTATION

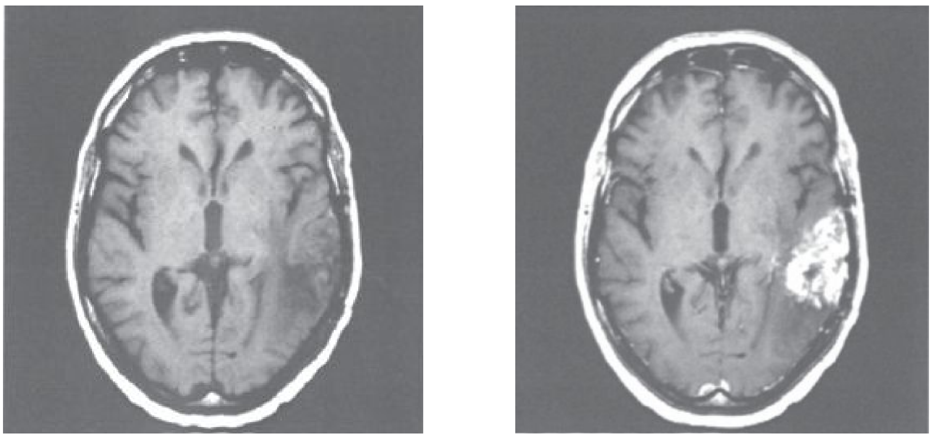
A. The Characteristic of Magnetic Resonance Imaging

Magnetic resonance imaging is a kind of medical imaging technologyes of safety and undamage, which can provide the image of body inner structure and tissues with high resolution and contrast ratio. It is founded on the theory of nuclear magnetic resonance, which can offer the detailed anatomical structure information. It can changes the contrast ratio among different interstitial fluids with various imaging sequens. It highlights the different imaging parts and produces two dimensional or three dimensional image with various modes. As the magenic resonance image can distinguish diiferent soft tissues, it is very suitable for brain tissues imaging, such as grey matter, white matter and cerebrospinal fluid. Two imaging modes are usually used for clinc imaging, i.e., T1 mode and T2 mode. The differences between two modes are reflected that the time signal during the process of magnetic resonance reconstruction is T1 or T2. The time constant value T1 and T2 for tissues in brain are shown in table 1.

Table 1. Time constant for different brain tissues

Tissues	grey matter	white matter	cerebrospinal fluid	fat	muscle
T1	850-1023	550-710	3200	200	800
T2	65-75	105-185	2000	200	63

Thus the different tissues under different imaging modes have gray values of difference, which can produce the magnetic resonance images with different contrast ratio. For example, the T1 value of fat is smaller than that of water, so the T1 weighted imaging can be used for diplaying the position of fat tissues. Similarly, the T2 time constant value is larger than that of fat, so the T2 weighted imaging can be used to display the position of water.



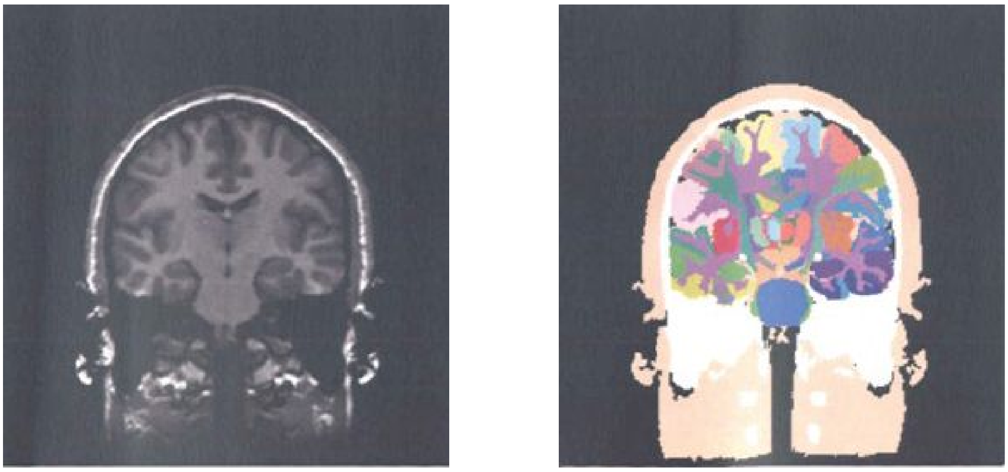
(a) (b)

Figure 1. Magnetic resonance image with enchaning: (a) picture before contrast agent injection; (b)picture after constrast agent injection.

In the magnetic resonance image, image doctor will collect the T1 weighted imaging again after the patient is injected the contrast agent, such as gadolinium complex contrast medium. This weighted imaging is called enhanced T1 weighted imaging. The contrast agent can reduce the T1 time constant of tissues which distribute around the target area. It states that it contains leaked blood in the light area in the magnetic resonance image, for the blood go through the blood brain barrier. Then comparing the T1 weighed images before and after enhancing, the enhanced brain tissues is the position of brain tumor. For the varieties of brain tumor, the manners and degrees are different each other. In figure 1, it shows the T1 weighted imaging of brain tumor before and after enhancing. The early therapeutic schedule for brain tumor usually contains excision, radiotherapy and chemotherapy. In clinic medical science, magnetic resonance aiming has been widely used for tumor diagnosis, tumor surveillance, making treatment plan and treatment outcome judgment.

B. The medical image segmentation for brain tumor

Medical image segmentation is marking each pixel or voxel as the corresponding tissues or anatomical structure. Thus, the segmentation of brain image is maring each pixle or voxel as coressponding tissues, such as white matter, gray matter and cerebrospinal fluid orcoressponding anatomical structure of brain, such as cerebral cortex substructure, encephalocoele, callosum, hippocampus, caudate nucleus and so on. In figure 2, it shows a detailed segmentation result of brain coronal based on magnetic resonance imaging.



(a) (b)

Figure 2. Segmentation magnetic resonance image: (a) coronal slice; (b) the detailed segmentation of (a).

In figure 2, different colors represent the different tissues and anatomical structure. This detailed segmentation result is done by segmenting the three main tissues patterns with automatic segmentation algorithm at first, and then each substructure is segmented manually by medical specialist. The purpose of medical image segmentation is extraction the much more abundant information for medical researchers or clinc doctor from the input medical images. The image that has been segmented is called labeled graph, each pixel or voxel of which stands for the tissues or anatomical structure. The segmentation results can be further used for tissues structure display and quantitative analysis, for example, the morphological analysis of normal tissues structure and pathological tissue structure, three dimensional diplay of form, size and position, forming the anatomical atlas and image guided surgery.

There are many different interpretations for image segmentation. However, these interpretations are more or less the same, the classical and accepted by researchers is the definition in [6] by R. M. Haralic. If we use I represents the image domain, S_k stands for the set of *k*th pixel, according to the definition by R. M. Haralic, the segmentation problem can be expessed as the formula in (1):

$$I = \bigcup_{k=1}^{K} S_k \tag{1}$$

In (1), when k is unequal to j , then $S_k \cap S_j = \Phi$ and S_k is a continuous region. For medical image segmentation, this continuous represnts a specific anatomical structure or interested region.

With the development of segmentation research and application, the researches find that the segmentation method with either-or cannot give a good performance when dealing with some specific segmentation problems. As a result, the conception of soft segmentation or called fuzzy segmentation has been proposed, the main characteristic of which is it uses the membership function to replace the characteristic function in hard segmentation. The characteristic function is usually used to describe an index of vowel in a certain set, as shown in (2) and (3).

$$\begin{cases} 0 \le m_k(j) \le 1, \ \forall k, j \\ \Sigma_{k=1}^{K} m_k(j) = 1, \forall j \end{cases} \tag{2}$$

$$\chi_k(j) \begin{cases} 1, if \ \ j \in S_k \\ 0, else \end{cases} \tag{3}$$

The main purpose of the segmentation in first level is segmenting the main three tissues, i.e., white matter, gray matter and cerebrospinal fluid. In the anatomy filed, the variety structures of brain is defined according to the border these three tissues. Therefore, in the quantitative comparison of brain morphology, the accurate segmentation of white matter, gray matter and cerebrospinal fluid is of great importance. At present, there are many methods for brain tissue segmentation, which can be divided into 5 groups.

Statistical probability Classifying based on Pixels: This method is founded on the strict mathematical statistics theory, which has a good robustness. In this method, the pixel gray statistics density function of different organizations is often expressed by Gaussian density function. And the pixel statistics density function can be expressed by parameterized Gaussian mixture model. In order to introduce the relationship among local pixels, the Markov Random Field theory was introduced, which is used for regularization of segmentation image. The Markov Random Field can be used to simulate the constraint relationship among pixels. In [7], Wells proposed a recursive statistical probability classifying method to segment the three main brain tissues and estimate the partial field of image. However, this method needs to build conditional probability density model for different organization.

Segmentation based on Region: The images regions belong to the same organization usually have similar properties, such as gray value and texture. The segmentation method based on region is to segment image by recognizing the image region with the similar properties of different organizations. Unlike many simple clustering methods, it uses the mutual relationship between neighborhood pixels in image space.

Clustering: Another kind of segmentation based on pixel is clustering algorithm, which is a kind of unsupervised classification method. This method is widely used in the pattern classification and image segmentation.

Method based on Graph Theory: The research of graph at present is hotter and relatively new. It is a kind of method based on combination optimization, which is different from the variation method, the optimization of the space by the ruler. The optimal segmentation based on graph theory is to maximize the similarity in the sub graph, minimize the similarity between sub graphs generated by segmentation, and avoid skew segmenting of the region. The performance of cut set will directly affect the quality of the segmentation results. The commonly used cut sets have Minimum cut [8], Average cut [9]，Normalized cuts [10]，and Ratio cut [11]. The applications of this method for medical image segmentation can be found in [12, 13, 17-18].

Method based on Deformable Model and Level Set: Deformable model, also known as active model, the mathematical basis of which includes geometry, physics and approximation theory. Among them, the geometry is used to express the shape of the object segmentation, physics is used to impose the shape change in space and time constraints, and optimal approximation theory provides the model to match the basic form of image data. And one of the most concerns is the

Snake Model [14], which is usually a plane curve and defines the boundary and shape of segmentation object, as shown in figure 3.

Figure 3. The white curve is a snake representing membrane of cell.

Level set method was first put forward by Osherand Serbian in literature [15], the basic idea of which is using an is surface to model the surface of segmentation object, different form the methods of above.

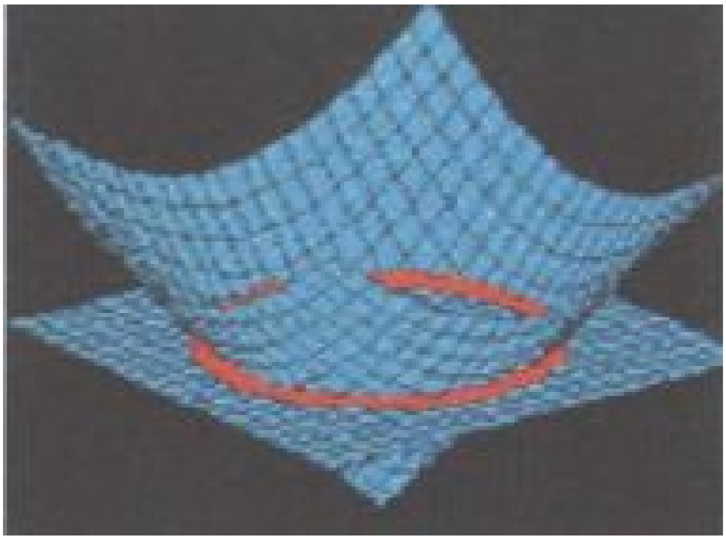


Figure 4. A level set surface.

C. Evaluation of Segmentation Algorithm

It need to identify the target object at first in image segmentation, and then do the specific segmentation. Some segmentation algorithms have some human interaction. The evaluation index of a segmentation algorithm has three: Accuracy, reliability and efficiency [16]. Accuracy is used to evaluate the results of segmentation algorithm segmentation and the extent of the gold standard in accordance with the reliability used to evaluate segmentation algorithm of segmentation result repeatability, which under the different subjective factors, the algorithm of segmentation results are consistent or consistent; Efficiency is used to evaluate the actual performance to segmentation algorithm, namely the validity.

III. AUTOMATIC SEGMENTATION OF BRAIN TUMOR MAGNETIC RESONANCE IMAGING BASED ON MULTI-CONSTRAINS AND DYNAMIC PRIOR

A. Image Segmentation of the Brain Tumors

The analysis of lesions in brain image needs to distinguish all kinds of organization structure, including normal and Daniel automatically and accurately, which must depend on the automatic image segmentation algorithm. Segmentation of medical image, especially for lesions, contributes to the diagnosis of clinical disease, radiation therapy, the lesion location and the formulation of treatment. The three dimensional segmentation of brain lesions, such as brain tumors, white matter lesions and vascular lesions, is a difficult and challenging problem.

In brain tumor segmentation problem, as the differences of location, size, shape and appearance of the tumor is much large, in additional of the changes of tissue structure caused by placeholder effect of tumor and edema phenomenon, it makes he automatic detection and segmentation brain tumor more difficult. For some kinds of brain tumor segmentation, such as polymorphic malignant gloomy, it is impossible to realize image segmentation only with the simple threshold segmentation technique. Liu et al proposed an interactive segmentation method to segment brain tumors, in order to reduce the artificial division of work. Early, Philips and others in the literature puts forward the method of using fuzzy clustering to segment brain tumors. Their research suggests that even with more modal image data, grey value distribution of brain tumor and normal brain tissue still overlap. Therefore, later researchers introduce additional prior information to various kinds of segmentation method, in order to improve the performance of segmentation algorithms. Various kinds of segmentation algorithm is used in the tumor segmentation, such as the algorithm of fuzzy clustering, statistical classification method based on pixels, dynamic surface and level set method based on deformation model, based on context constraints, the method and support vector machine method based on prior knowledge.

B. Multiple Constraint Model and Dynamic Prior for Brain Tumors

Our constraint model is founded on the following assumptions: (1) for the same kind of tissue, the changes of pixel gray value in the space is small and frequency is low; (2) for the different kinds of tissues, the changes of pixel gray value in the space is large and frequency is high; (3) image field in image space changes slowly. Normally, these assumptions in the absence of the texture image are formed. However, in the texture image, we can assume that the texture characteristic value of pixel gray value instead of pixels, the hypothesis of which is established. Therefore, the gradient of pixel gray value in the same organization will not have big mutation, and the mutations of larger amplitude will occur on different organizational boundaries. Similarly, the pixels with large gradient will be impossible existed in the same tissue area, i.e., connected pixels with the smallest gradient changes are most likely to belong to the same tissue.

The observation model without texture is shown in (4):

$$I_i = \Phi_i \mu(f_i) + n_i,\ \ i \in S,\ f_i \in L \tag{4}$$

In (4), *I* is the MR without texture. $\mu(\cdot)$ is a function, which maps a label to the grey value of an entity. And the likelihood probability of *I* is defined as:

$$\begin{aligned} &P\left(I \mid f,\theta,\Phi\right) \\ &= \prod_i \left(\frac{1}{\sqrt{2\pi\sigma_{f_i}}} \exp\left(-\frac{1}{2\sigma_{f_i}^2} \left(I_i - \Phi(i)\mu(f_i)\right)^2 \right) \right) \end{aligned} \tag{5}$$

In (5), σ represents the standard deviation.

After the anisotropic filtering operation, the image can be expressed as:

$$I_i \approx \Phi_i \mu(f_i),\ \ i \in S,\ f_i \in L \tag{6}$$

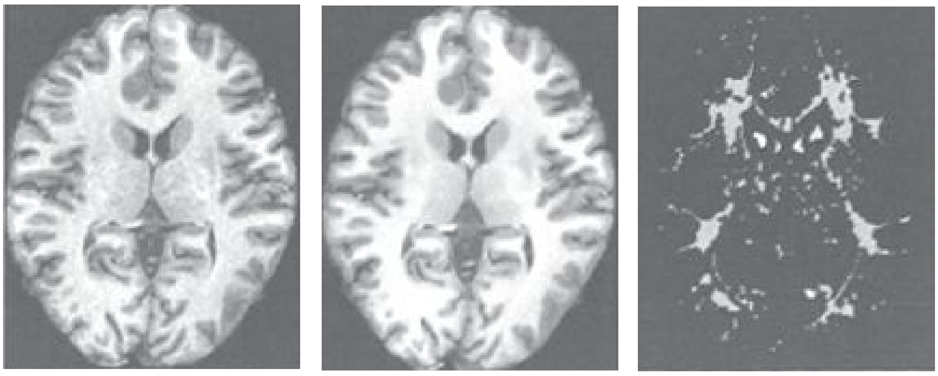
And the gradient of the image after filtering is:

$$I_i^{'} \approx \Phi_i^{'} \mu(f_i) + \Phi_i \mu^{'}(f_i),\ \ i \in S,\ f_i \in L \tag{7}$$

As the slow change of bias field, so,

$$\begin{cases} \left|\Phi_i^{'}\right| \approx 0 \\ I_i^{'} \approx \Phi_i \mu^{'}(f_i) \end{cases} \quad i \in S,\ f_i \in L \tag{8}$$

In the constraint model, the image can be divided into two parts, the first part of which is consist of $|I_i| \approx 0$. The pixels in this connected area can be treated as pixels which belong to the same kind of tissue, which is seemed as an entire part for classification. The second category is the entire pixels which do not belong to the first part. The multiple constraints model is shown in figure 5.



(a) (b) (c)

Figure 5. Pixel classification of multiple constraints model. (a) Original image; (b) filtering image; (c) constraint in a large scale.

Multiple constraints model has the following advantages:

(1) The large scale constraint is proposed for images to be segmented, which is a clustering mostly belonging to the same group of pixels. This concept is similar to the fuzzy connection degree. The connected area of pixels that mostly belong to the same kind of tissue can be treated as a large scale prior dynamic constraint, which is different from the pixel neighborhood constraint in the MRF model.

(2) As the area pixel that we define is not determined by pixel grey value but determined by the gradient value and connectivity, regional pixel can span due to partial field and the organization itself characteristics of grey value slowly changing pixel space. This feature is similar to the distinguishing features of human eyes, which makes a certain consistency of our algorithm and human eyes.

(3) Large scale constraint can change its size and shape based on the recursive segmentation results and the bias field estimation, i.e., adjusting the size and shape of pixel area belonging to the same tissue automatically. The dynamical adjusting the size and shape of large scale constraint, the size and shape of constraint in MRF neighborhood do not change. Large scale constraint can provide space region priori information for different tissue distribution in image, which can ensure the consistency and robustness of the segmentation results; the constraint in MRF can provide small scale constraint information between image pixels, which ensure the accuracy and flexibility of segmentation.

(4) The unity tag of connected area pixel can shrink the solution space of the objective function, which lids to a faster converges for algorithm.

(5) It has uniqueness for pixel division, the segmentation result of which is affected by the segmentation manner. This model can overcome the difference by the initial condition.

(6) It does not need the registration algorithm, which can avoid the registration error with the prior information of image.

C. Dynamic Prior

In the MR image, the bias field has a great influence on the segmentation result based on grey value probability statistics. Without the correction of bias field, it will lead to serious bias field algorithm segmentation failure, but the human eye can correct segmentation image containing partial field adaptively. The reason is that the analysis tool for image obtained by human eye is the brain. And the analysis of image by brain based on priori knowledge is dynamic adaptively. In order to make the priori constraints also have certain adaptability, we make the large scale constraint in multiple constraints model dynamic adjust. From the equation in (6), the large scale constraint can be adjusted according to the bias filed value, which can be called dynamic prior. Dynamic prior can express the grey value changes caused by the differences of characteristics in tissues and remove the influence of bias filed. The dynamic prior has the following features:

(1) The size and shape of dynamic is changing dynamically;

(2) The bias filed is different from each other under each position of pixel;

(3) The realization of dynamic prior is simple as adaptive threshold algorithm.

The construction steps of multiple constraints model can be expressed as following:

(1) Anisotropic Filtering of the image *I*, and obtain the filtered image *Is*;

(2) Set a gradient threshold vector *Pi* and a connected mode *conn*;

(3) Calculate the gradient of *Is*;

(4) Set an integer constant *T*, calculate the the pixel number in the connected pixel area that has been marked, and select the pixel area that the pixel number is larger than *T*;

(5) Mark the pixels in the selected connected pixel area as the region pixel, and treat the others as the general pixel. Then the pixels of image can be divided into two types, i.e., region pixels and general pixel;

(6) Treat the connected region pixel as the large scale constrain. In the large sale constraint, each pixel in the connected area has the same mark. But the mark among different connected area can be different, which is determined by all the pixel grey value in each connected area.

The construction of dynamic prior is implemented in the recursive optimization process of multiple constraints dynamic prior expectation maximization algorithm, i.e., in which multiple constraints model are reconstructed in each recursive. However, in each process of multiple constraints model construction, the estimation of bias filed changes recursively. As a result, the large scale constraint changes in each construction. By this way, the dynamic prior can be realized, can make each expectation maximization recursive can be restrained by multiple constraints dynamic prior.

D. Multiple Constraints Dynamic Prior-Expectation Maximization Algorithm

In the multiple constraints dynamic prior-expectation maximization algorithm, large scale constraint and MRF were combined into expectation maximization algorithm framework. The algorithm is robust to realize the image segmentation, parameter estimation and bias field estimation, and is not sensitive to the classification number. As the real class mark of image f and some parameters, such as Φ and θ are unknown, and the estimation problem of them are closely related. Thus, the algorithm can be implemented by two step alternate recursive progress of the class tag estimation and parameter estimation:

(1) Estimation of the class tag: obtain the estimation value of the real.

$$\hat{f}(t) = \arg\max_{f \in F} \left\{ \log\left(P\left(f \mid I, \theta(t), \Phi(t) \right) \right) \right\} \tag{9}$$

(2) Parameters estimation: estimation Φ and θ based on MAP principle and expectation maximization algorithm.

$$\begin{aligned} &\left(\hat{\theta}(t+1), \hat{\Phi}(t+1)\right) \\ &= \arg\max_{\theta,\Phi} \left\{ \log\left(P(\theta, \Phi \mid I) \right) \right\} \\ &= \arg\max_{\theta,\Phi} \left\{ E_{f \mid I, \theta(t), \Phi(t), f(t)} \left(\log\left(\frac{P(\theta, \Phi, f \mid I)}{P\left(f \mid I, \theta(t), \Phi(t), f(t) \right)} \right) \right) \right\} \end{aligned} \tag{10}$$

In MRF, the pixel is associated with the neighborhood system $N=\{N_i, i \in S\}$. In the set S, the MRF variable X of this neighborhood system must satisfy the following condition:

$$\begin{cases} P(x) > 0, \forall x \in X \\ P\left(x_i \mid x_{S-\{i\}}\right) = P\left(x_i \mid x_{N_i}\right) \end{cases} \tag{11}$$

In (11), $P(x)$ represents the probability of x=X. According to the principle of Hamersley-Clifford, the probability distribution of MRF can be expressed by that of Gibbs. Thus, the neighborhood system includes one pixel and two pixels can be expressed as:

$$\begin{cases} P(f) = \frac{1}{Z_f}\exp\left(-U(f)\right) \\ U(f) = \Sigma_{i\in S} a(f_i)\delta(f_i, I) + \Sigma_{i,j}\beta\left(I_i, I_j\right)V\left(f_i, f_j\right) \end{cases} \tag{12}$$

According to the Gaussian noise observation model and (11), (12), the MRF-MAP of f can be expressed as following:

$$\begin{aligned} \widehat{f}(t) = \arg\max_{f\in F}\{\Sigma_{i\in S}\left(\frac{\left(I_i - \Phi_i\mu_{f_i}\right)^2}{2\sigma_{f_i}^2} + \log\left(\sigma_{fi}\right)\right) \\ +U\left(f \mid \theta(t), \Phi(t)\right)\} \end{aligned} \tag{13}$$

The estimation of Φ and θ in MR image model can be obtained by expectation maximization algorithm. Due to the introduction of MRF model, the relative probability of pixel can be calculated the estimation results above. We mark the real and unknown parameters as Φ and θ, and mark the estimation value as Φ^* and θ^*.

According to the framework of expectation maximization algorithm, the MAP-expectation maximization estimation can be expressed as:

$$\begin{aligned} \left(\theta^*, \Phi^*\right) &= \arg\max_{\theta,\Phi}\left\{\log\left(P\left(\theta, \Phi \mid\right) I\right)\right\} \\ &= \arg\max_{\theta,\Phi}\left\{\log\left(\Sigma_f P\left(\theta, \Phi, f \mid I\right)\right)\right\} \\ &= \arg\max_{\theta,\Phi}\left\{\log\left(\Sigma_f \frac{P\left(\theta, \Phi, f \mid I\right)P(f \mid I, \theta', \Phi')}{P\left(f \mid I, \theta', \Phi'\right)}\right)\right\} \\ &= \arg\max_{\theta,\Phi}\left\{\log\left(E_{f\mid\theta',\Phi'}\left(\frac{P\left(\theta, \Phi, f \mid I\right)}{P\left(f \mid I, \theta', \Phi'\right)}\right)\right)\right\} \end{aligned} \tag{14}$$

In (14), Φ' and θ' stand for the estimation of Φ^* and θ^*. By the Jensen's inequation, we have:

$$\log\left(E_{f\mid\theta',\Phi'}\left(\frac{P\left(\theta, \Phi, f \mid I\right)}{P\left(f \mid I, \theta', \Phi',\right)}\right)\right) \geq E_{f\mid\theta',\Phi'}\left(\log\left(\frac{P\left(\theta, \Phi, f \mid I\right)}{P\left(f \mid I, \theta', \Phi',\right)}\right)\right) \tag{15}$$

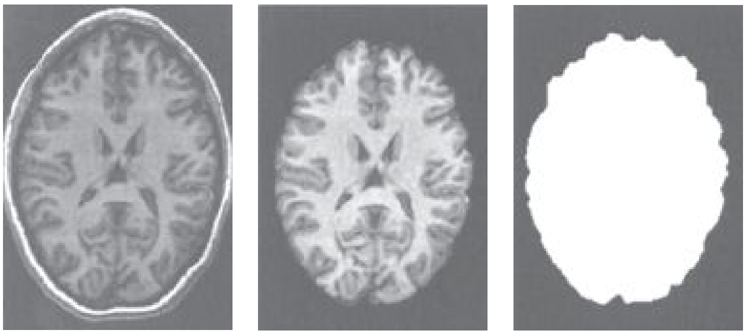
The right part of (15) has defined the lower bound of the target function; the local maximum value can be calculated by expectation maximization algorithm.

Each recursive step in expectation maximization algorithm is consisting of two parts, i.e., expectation and maximization. Due to the limited length of the paper, we omit the detailed steps of this calculate process.

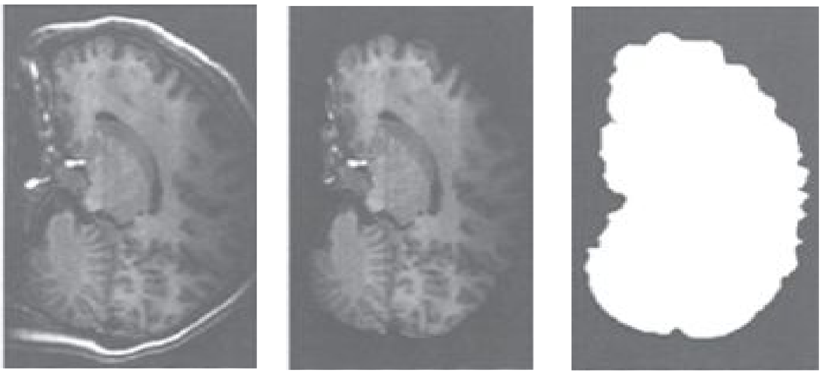
IV. EXPERIMENTS AND ANALYSIS

In order to verify the effectiveness of the segmentation algorithm that we proposed in this paper, we choose a set of clinical brain tumor MR images, including eight images. The noise in them is 1% to 9%, and the bias of them is 20% to 40%. The image mode of them is T1.

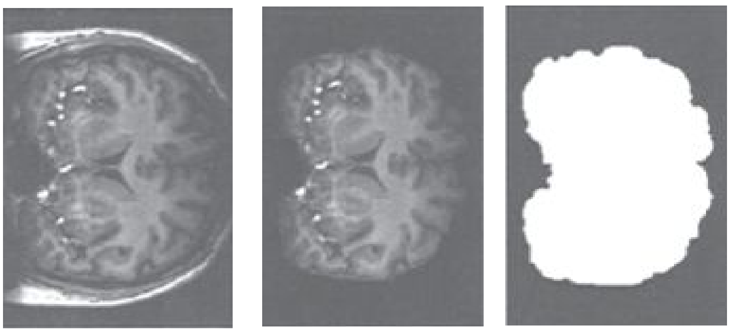
Because the purpose of our experiment is segmenting the brain tissue and organizing the brain tumor, first, we need to do the pretreatment for removing the tissues that do not belong to the brain tissue, such as skull, skin and eye. We extract the brain tissue using the fast automatic algorithm, the segmentation results of which are shown in figure 6.



(a) 3D cross section extraction results.



(b) 3D vertical plane section extraction results.



(c) 3D coronal plane section extraction results.

Figure 6. The 3D extraction results of brain tissue.

In order to analyze the segmentation results and compare, we use the Dice measure to evaluate the pixel space coverage of the segmentation results in our algorithm and that of standard segmentation (golden segmentation) results. The Dice measure takes value in the region of [0, 1], the larger value represents a better segmentation consistent degree, i.e., a better segmentation results. The definition of Dice measure is shown in (16):

$$Dice(S_1, S_2) = \frac{2|S_1 \cap S_2|}{|S_1| + |S_2|} \tag{16}$$

In (16), *S* represents a set.

The comparisons of brain MR image segmentation results based on multiple constraints dynamic prior with that of the golden segmentation algorithm are shown in table2.

Tabel 1. Segmentation results comparisons.

Number	Golden Algorithm	Our Algorithm	Dice	False Negative	False Positive
1	337297	319783	0.9592	22152	4638
2	337297	339059	0.9486	16496	18258
3	337297	720910	0.9125	37602	84450
4	337297	351534	0.9195	20590	34827
5	337297	315859	0.9550	25400	3962
6	337297	357974	0.9432	9408	30085
7	337297	367251	0.9254	33457	69807
8	337297	377429	0.9026	14758	54890

From table 2, we can see that when the noise ratio is 3% and the bias filed is ratio 20%, the Dice has the largest value, the average of which is 0.9579. When the noise ration is 9% and the bias filed is 40%, the Dice value is smallest, the average of which is 0.9080. The pixel number of false Negative and False Positive is increasing with the noise ratio and bias filed ratio. The average calculation time is 652.53 second. From the comparison with the standard algorithm, it illustrates the effeteness of our algorithm.

V. CONCLUSION

With the development of medical imaging technology, medical image has become the important basis of diagnosis and treatment for clinical medicine. The development of all kinds of the further medical image model, such as magnetic resonance image, PET, FMRI, will make an important importance growing of medical image analysis. In the brain disease diagnosis, treatment and research, especially for brain tumor, the 3D anatomy of the brain organization and structure in quantitative form has become a kind of important tools. And this research based on the on the change of organization structure relies on the segmentation of brain MR image. Segmentation of brain tissue robustly, efficiently and accurately has become an important problem in clinical and research. However, due to the complex structure of brain and the defect of imaging equipment, it is difficult do deal with this medical problem. In this paper, we propose a three dimensional automatic segmentation algorithm based on multiple constraints dynamic for brain tumor MR segmentation. In this algorithm, the segmentation, bias filed estimation and model parameter estimation are realized at the same time. We use the large scale constraint and MRF pixel neighborhood to increase the constraint for algorithm. The experiment results have shown that, the algorithm of our algorithm has the advantage of accurate segmentation and high consensus, and is insensitive with the initial value, which can deal with the brain MR image with a large bias filed ratio.

In our experiment, we only use the one dimensional feature, i.e., grey value for MR image segmentation. However, it is easily extended for the segmentation of MR image with texture information, i.e., changing the grey feature to texture information. Similarly, this algorithm can also be extended for multiple modes image segmentation, such as T1, T2, Pd and weighted MR image by using the feature of multiple modes and a proper distance measure replace the grey value, for example, Gustafson-Kessel distance measure and Euclid distance measure.

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