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A Novel Brain Tumor Segmentation Method for Multi-Modality Human Brain MRIs

Tianming Zhan[1], Shenghua Gu[2], Lei Jiang[3] and Yongzhao Zhan[4]

[1, 4]School of Computer Science & Communications Engineering, Jiangsu University, Zhenjiang 212013, China
[2]Jiangsu Key Laboratory of Big Data Analysis Technology, Nanjing University of Information Science and Technology, Nanjing 210044, China
[3]Petrochina Southwest Oil &Gasfield Company, Luzhou 646000, China
[1]ztm@ujs.edu.cn

Abstract

Delineating brain tumor boundaries from multi-modality magnetic resonance images (MRIs) is a crucial step in brain cancer surgical and treatment planning. In this paper, we propose a fully automatic technique for brain tumor segmentation from multi-modality human brain MRIs. We first use the intensities of different modalities in MRIs to represent the features of both normal and abnormal tissues. Then, the multiple classifier system (MCS) is applied to calculate the probabilities of brain tumor and normal brain tissue in the whole image. At last, the spatial-contextual information is proposed by constraining the classified neighbors to improve the classification accuracy. Our method was evaluated on 20 multi-modality patient datasets with competitive segmentation results.

Keywords: *Brain tumor segmentation, multiple classifier system, Spatial-contextual constraint*

1. Introduction

A brain tumor is a mass or growth of abnormal cells in human brain or close to human brain. The human brain tumor can be classified to many different types such as noncancerous (benign), and cancerous (malignant). Brain tumor treatment options depend on the type of brain tumor the patient have, as well as its size and location. However, it is a particularly time consuming task for radiologists to segment the brain tumor for location and statistical analysis. Also, in most cases the task is performed on a 3D data set by labeling the tumor slice by slice on 2D data, limiting the global perspective and potentially generating sub-optimal segmentations [1-4]. Therefore there is a need for fully automatic segmentation tools for brain tumor segmentation.

Nowadays, in clinical practice, usually multi-modality3D MRIs are used to delineate the tumor and its sub-regions. These multi-modality MRIs are generated by giving different excitation pulse sequences during MR imaging. These multi-modality MRIs can form weighted sequences to reflect the different characteristics and biological properties of tissues [5-8]. T1-weighted, T2-weighted, post-Gadolinium T1 (T1C) and FLAIR (Fluid Attenuated Inversion Recovery) weighted sequences are four commonly used MRI modalities for brain tumor extraction. Each of the modalities reveals different sub-regions in human brain. In general, an automatic segmentation method needs to consider all these MRI modalities simultaneously. Subsequently, in last few years, a large amount of research has been focused on fully automatic methods for segmenting brain tumors from multi-modality MRIs.

Even with multi-modality MRIs, brain tumor segmentation is still a challenging task because the tumors vary greatly in size and position and have a variety of shape and

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appearance properties [9-10]. Therefore, it is difficult to segment a brain tumor by using a simple unsupervised threshold. For accurately segment the brain tumor, we need to explore the characteristic and pathological process of brain tumor. On this basis, several techniques have been used to perform supervised segmentation of brain tumor in multi-modality MRIs [4-8]. However, training samples are very difficult to collect by the radiologist. This issue results in an unbalance between the high dimensionality of the MRIs and limited number of training samples [11]. One strategy to deal with this problem has been efficiently exploited by using multiple classifier system which combines the outputs from several individual classifiers according to a certain criteria [12]. However, these kinds of methods assume that data or each testing sample is independently and identically distributed and doesn't consider any spatial relationships. This is not particularly suit for medical image segmentation or classification because most voxel labels in medical image strongly depend on their neighbors. Therefore, we need to take the spatial relationship into account for accurate segmentation results.

In this paper, we propose a fully automatic technique by integrating the multiple classifier system (MCS) and spatial constraint for brain tumor segmentation from multi-modality human brain MRIs. We first use the intensities of different modalities in MRIs to represent the features of both normal and abnormal tissues. Then, the multiple classifier system (MCS) is applied to calculate the probabilities of brain tumor and normal brain tissue in the whole image. At last, the spatial regularization introduces spatial constraints to the MCS to take into account the pair-wise homogeneity in terms of classification labels and multi-modality voxel intensities. Our method was evaluated on 20 multi-modality patient datasets with competitive segmentation results.

2. Multiple Classifier System

Let $X = \{x_1, x_2, \cdots, x_n\}$ be the input multi-modality MRIs, where $x_i = [x_i^{T1}, x_i^{T2}, x_i^{PD}, x_i^{FL}]^T$ denotes a vector built by using the intensities from multi-modality MRIs and associated with an image pixel $i \in S$, $S = \{1, 2, \cdots, n\}$ is the set of integers indexing the pixels n of x. $Y = (y_1, ..., y_n) \in L^n$ is the image of labels, $L = \{1, ..., K\}$ is the set of class labels, $D = \{(x_1, y_1), ..., (x_M, y_M)\}$ is the training set, M is the total number of training samples. The goal of classification is to assign a label $y_i \in L$ to each pixel vector x_i.

According to [12], multiple classifier system combines class labels or probabilities from multiple classifiers. The final output mainly depends on the supervised classifier and the diversity among the classification results. In this paper, Naïve Bayes classifier and multinomial logistic regression classifier are chosen due to both of these two classifiers are able to generate the class labels and probabilities by training the samples selected by the radiologists.

2.1. Naïve Bayes Classifier

The naïve Bayes (NB) classifier technique [13] is based on the so-called Bayesian theorem and is particularly suited when the dimensionality of the inputs is high. Using Bayes rule, the posterior distribution can be modeled as:

$$p(y_i = k \mid x_i) = \frac{p(x_i \mid y_i = k)\, p(y_i = k)}{\sum_j p(x_i \mid y_i = j)\, p(y_i = j)} \tag{1}$$

where $p(x_i \mid y_i = k)$ is conditional probability and $p(y_i = k)$ is the prior probability of x_i belongs to j-th class which can be estimated by using training samples. In this paper, we assume that the data associated with each class are distributed according to a Gaussian distribution; then the conditional probability can be computed by using normal distribution:

$$p(x_i \mid y_i = k) = \frac{1}{(2\pi)^{1/2} \left|\Sigma_k\right|^{1/2}} \exp\{-\frac{1}{2}(x_i - \mu_k)^T (\Sigma_k)^{-1} (x_i - \mu_k)\} \tag{2}$$

Where μ_k and Σ_k are the mean value and covariance calculated by the training samples which belong to k-th class.

2.2. Multinomial Logistic Regression Classifier

Multinomial logistic regression (MLR) model [14-16] generalizes logistic regression to classification problems where the class label can take on more than two possible values. This characteristic is very useful for brain tumor segmentation, where the goal is to classify the image to several different regions.MLR technique models the posterior class distribution in a Bayesian framework. The densities $p(y_i \mid x_i)$ are modeled with the MLR, which corresponds to discriminative model of the discriminative-generative pair for $p(x_i \mid y_i)$ Gaussian and $p(y_i)$ multinomial [17]. The MLR model is formally given by:

$$p(y_i = k \mid x_i; \omega) = \frac{\exp((\omega_k)^T x_i)}{\sum_j \exp((\omega_j)^T x_i)} \tag{3}$$

Where ω is the parameters and estimated by the training samples.

2.3. Bayes Weighted Average

After the probabilities of each pixel in MRIs are obtained by NB classifier and MLR classifier, Bayesian weighted average which follows a linear opinion pool is used to produce the final probabilities as follows:

$$p(y_i = k \mid x_i) = \lambda p^{NB}(y_i = k \mid x_i) + (1-\lambda) p^{MLR}(y_i = k \mid x_i; \omega) \tag{4}$$

Where λ is a tunable parameter which controls the weights between the probability obtained by NB classifier and the probability obtained by MLR classifier. The range of parameter λ is $\lambda \in [0,1]$. If $\lambda = 1$, the classification results is same as that obtained by NB classifier, and is equal to the results obtained by MLR classifier when $\lambda = 0$. In our experiments, we select $\lambda = 0.5$, which means that the effects of NB classifier and MLR classifier to the final probability are the same.

3. Global Energy Cost Function Imposing the Spatial Constraint

The segmentation results are not accurate enough when only using the probabilities calculated in above section, because this technique only consider the image pixels as the discrete signals and without consider the spatial correlation in the whole image. In order to encourage the spatial information to improve the segmentation accuracy, we integrate the probability information and the spatial information together to propose the following optimization problem of an energy cost function:

$$\mathbf{y}^* = \arg\min \left\{ \sum_{i=1}^{n} \left(-\ln(p(y_i \mid x_i)) + \mu \sum_{j \in N_i} \left| y_i - y_j \right| \right) \right\} \tag{5}$$

Where the first term in Eq. (5) is the data term imposing the probability information which is obtained by MCS, and the second term is the total variation term which encourages the pixels in neighborhood to belong to the same class in spatial domain. Parameter μ controls the importance of spatial information.

It is very difficult to solve this total variation regularized classification model for the discrete status of y_i. In order to solve this optimization problem, we turn to graph cuts methods which are efficient tools to solve this kind of optimization problems. These methods construct our model on a graph with nodes and edges and solve the minimization of energy cost function as a maximum flow problem. In this paper, the method proposed in [18] is applied to solve our optimization problem in Eq. (5).

The whole work flow of our proposed brain tumor segmentation algorithm is provided as follows:

Step1: Selecting the training data by the radiologists;

Step2: Training NB classifier and MLR classifier by using the training samples;

Step3: Calculating the probabilities of each pixel by using NB classifier and MLR classifier;

Step4: Calculating the Bayes weighted average using Eq. (4);

Step5: Minimizing Eq. (5) to obtain the final brain tumor segmentation results;

4. Results and Discussion

We evaluate our model on the BRATS challenge data set (http://www.imm.dtu.dk/projects/BRATS2012) of 20 MRIs with brain tumor, 10 subjects are simulated data and other 10 subjects are real patient data. Each subject comprises T1, T2, FLAIR and post-Gadolinium T1 modalities. All volumes are linearly co-registered to the T1 contrast image, skull stripped, and bias correction using N3 method.

Figure 1 shows the outputs at different steps of our method for a typical subject with brain tumor. The first row shows the original images of four different modalities. We can see that the intensities of the tumor region and brain tissues are quite different in these four modalities. The second row shows the brain tumor segmentation results of each step. The left two images demonstrate the probability maps of brain tumor obtained by the NB classifier and MLR classifier, respectively. The third image demonstrated the probability map by using MCS in Eq. (4). From this result, we can see that the MCS by integrating the probabilities obtained by NB classifier and MLR classifier is able to improve the tumor segmentation result at some level. The last image in second row demonstrates the final tumor segmentation result by minimizing Eq. (5). It is clear that our method is able to detect the complete boundaries of tumor and reduce the influence of the noise by integrating the probabilities from the MCS and the TV based regularization.

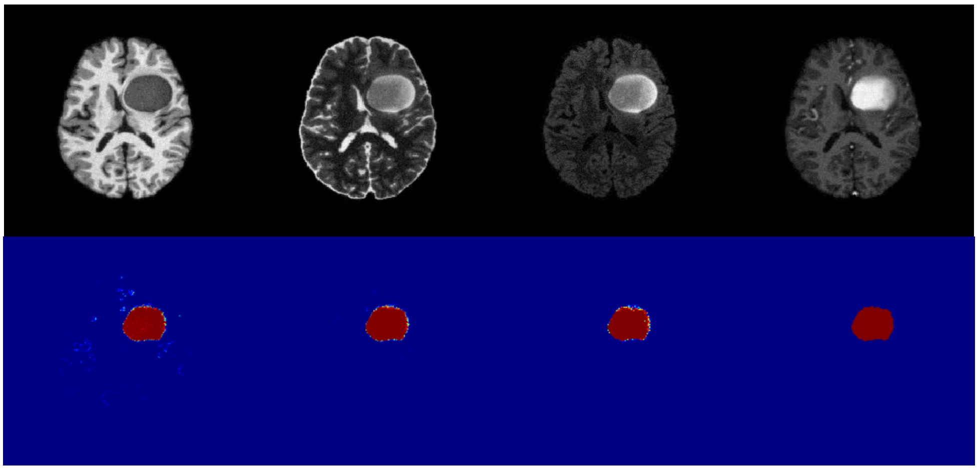

Figure 1. An Example of the Brain Tumor Segmentation Pipeline. The First Row Shows the Original Images from Four different Modalities: T1, T2, FLAIR and T1C Images from Left to Right. The Second Row Shows the Probability Maps of Brain Tumor Obtained by NB Classifier, MLR Classifier, MCS, and the Final Brain Tumor Segmentation Result of Our Method

The result of our algorithm for a real patient data is shown in Figure 2. The first row shows four T1C images from different slices of one 3D data. The segmentation results of our algorithm are demonstrated in the second row. The last row shows the corresponding segmentation of brain tumor provided by expert radiologist and used only for performance evaluation and comparison. It is clear that our brain tumor segmentation results show a high similarity to the ground truth (the third row) demonstrating the efficacy of our solution.

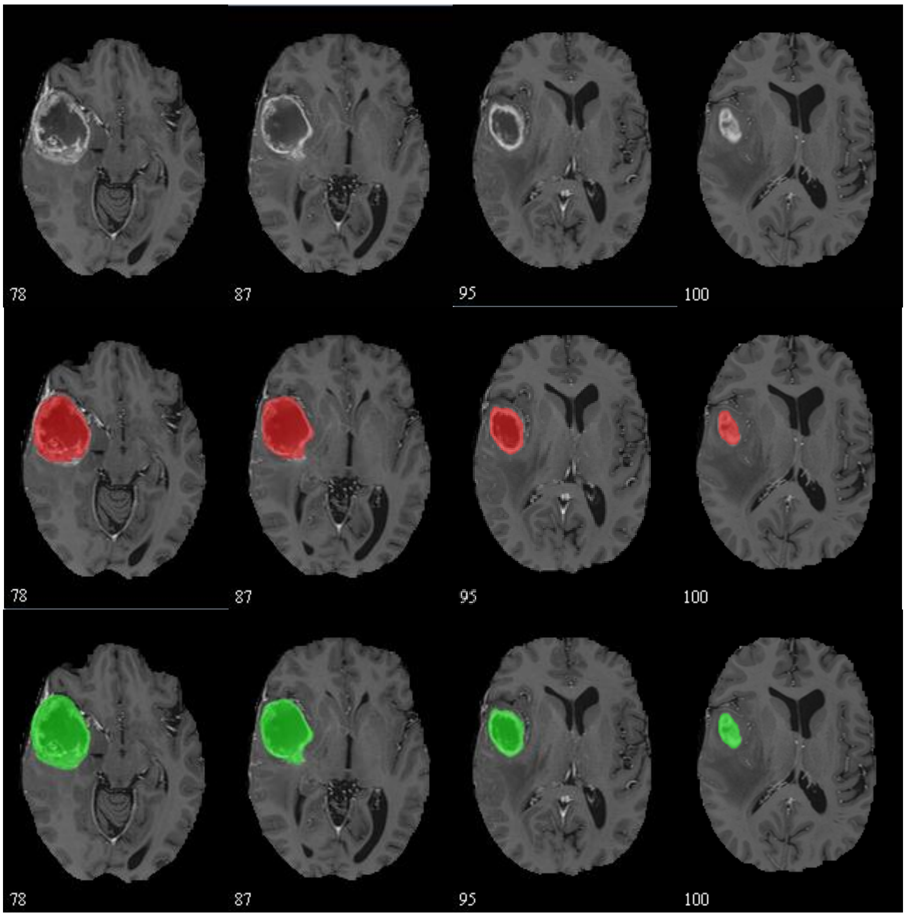

Figure 2. An Example of 3D Brain Tumor Segmentation. First Row: the T1C Images of different Slices from a Real Patient Subject. Second Row: Segmentation Results Produced by Our Algorithm. Third Row: Manual Segmentation Obtained by a Radiologist

We employed the Jaccard score to quantitatively evaluate the segmentation results obtained by the NB classifier, the MLR classifier, the MCS as well as our method in 20 subjects. Figure 3 and Figure 4 demonstrate the Jaccard Score of these four methods on simulated data and real data. As shown in these two figures, the mean JS value of the results obtained by NB classifier, MLR classifier, MCS method and our method executed on simulated data and real data are 0.79, 0.80, 0.84, 0.90, and 0.60, 0.61, 0.64, 0.79, respectively. From these results, we can see that the Jaccard scores of MCS are a litter higher than those of NB classifier and MLR classifier, which demonstrate the advantage of combination of multiple classifiers. The Jaccard scores of our method are much higher than all of those classifiers which show significant improvements by encouraging the spatial information to improve the segmentation accuracy.

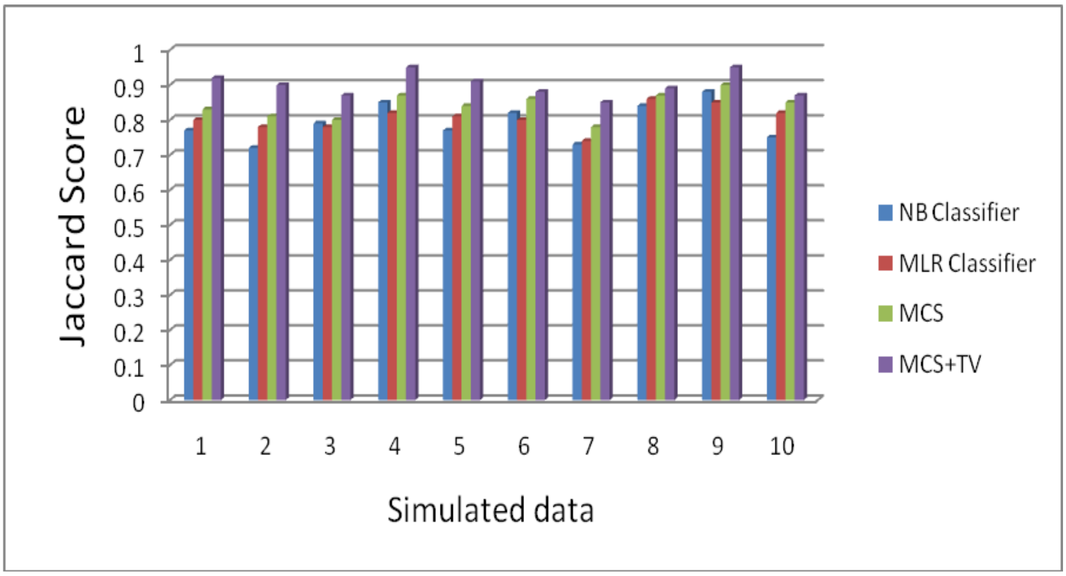

Figure 3. Jaccard Score of each Method for the 10 Simulated Subjects

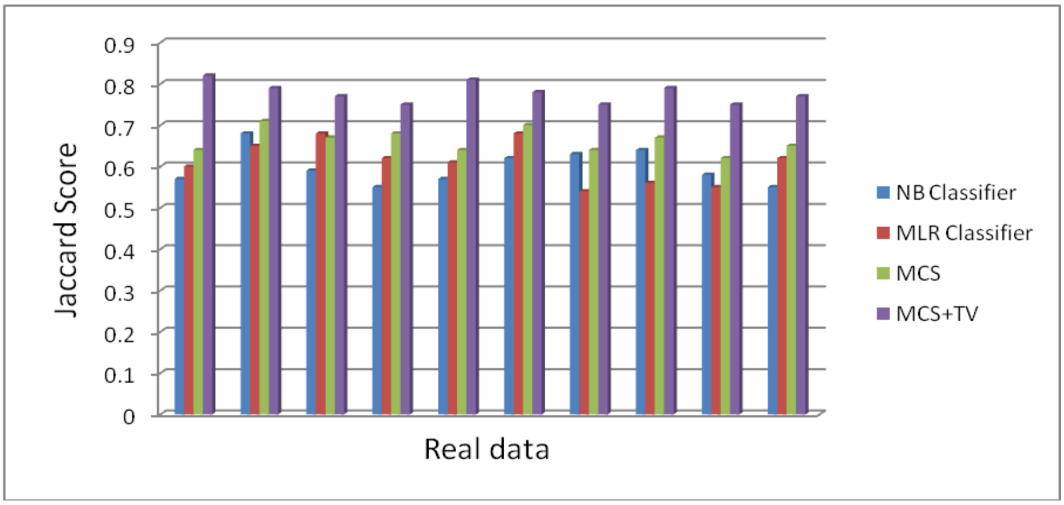

Figure 4. Jaccard Score of each Method for the 10 Real Subjects

4. Conclusions

In this paper, we presented a novel brain tumor segmentation method by using multiple classifier system and spatial constraint. Firstly, the Naïve Bayes classifier and multinomial logistic regression classifier are trained by using the training samples from the radiologists. Then, these two classifiers are applied to calculate the probability of each test pixel. After that, Bayesian weighted average from MCS is generated using linear combination of probabilities of above two different classifiers. At last, the global energy optimization function which can be solved by graph cut method is proposed by integrating the spatial-contextual information into the intensity information represented by the probability. Our method was evaluated on 20 BRATS challenge subjects; the higher Jaccard Score values demonstrate the advantage and considerable competence of our method.

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Authors

Tianming Zhan, Dr Tianming Zhan received his Ph.D. degree in Pattern recognition and intelligent system from Nanjing University of Science & Technology in 2013. His main research interests include image processing, medical image analysis, pattern recognition and numerical analysis. Correspoding author: ztm@ujs.edu.cn

Shenghua Gu, Research assistant of Jiangsu Key Laboratory of Big Data Analysis Technology, Nanjing University of Information Science and Technology. His main research interests include image processing, pattern recognition.

Lei Jiang, Research assistant of Petrochina Southwest Oil & Gasfield Company, he received his Master's degree in 2014 from University of Electronic Science and Technology of China. His main research interests include cloud computing, embedded system and smart oilfield.

Yongzhao Zhan, Professor and Ph. D Supervisor of School of Computer Science and Communication Engineering, Jiangsu University. His research interests include Human Computer Interaction, Distributed Computing, Image and Video Processing.