Automated brain tumor segmentation from multi-modality MRI data based on Tamura texture feature and SVM model

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Abstract. The precise segmentation of brain tumors is the most important and critical step in the diagnosis and radiotherapy of brain tumors. An automatic segmentation algorithm of brain tumor MRI image based on Tamura texture metrics and SVM model is proposed in this paper. Firstly, the local grayscale features of four modal magnetic resonance images are combined with the Tamura texture metrics, which are roughness, contrast, directionality, and regularity. In this way, the information in the image is extracted as much as possible. Then, the known samples are put into the SVM model and classifier training is performed. Finally, other brain tumor images are processed with the trained SVM model. The performance of this method is evaluated using the 2013 BRATS test data-set. The encouraging evaluation results is obtained.

1. Introduction

Brain tumor segmentation is an important task in medical image processing. Early diagnosis of brain tumors plays an important role in improving treatment possibilities and increases the survival rate of the patients. Manual segmentation of the brain tumors for cancer diagnosis, from large amount of MRI images generated in clinical routine, is a difficult and time consuming task. There is a need for automatic brain tumor image segmentation. Magnetic resonance imaging (MRI) technology has high resolution of soft tissue, can accurately describe the anatomy of the brain, and has important significance in the diagnosis, treatment and surgical guidance of brain tumors [1].

Four standard MRI modalities used for diagnosis include FLAIR, T1, T2, and T1C. Different modes provide different brain tumor information [2,3]. For example, there is a significant difference in the gray level between the image of the tumor region and the normal tissue in the FLAIR modality. The boundary texture features of the tumor region in the T1C modality are evident. In clinical practice, multimodal MRI images are combined by doctors to perform tumor segmentation. Computer-assisted software is used during segmentation to manually delineate tumor regions layer by layer. Such operations are subjective and have poor repeatability [4-5].

Common automatic or semi-automatic tumor segmentation methods are mostly based on image gray information. Such as fuzzy clustering method [6,7], level set method [8], AdaBoost iteration method [9], neural network method [10] and SVM method [11,12]. When searching for an optimal classifier, multidimensional features are used, which are suitable for multi-modal MR sequence image segmentation. In addition to gray information, texture information is also one of the inherent features of the image. When identifying the images, human never distinguish between gray information and texture information. Therefore, when identifying the images, not only the grayscale information but also the texture information is considered.
Papers [13-15] have shown that combining gray (color) information with texture information to segment the image can obtain better segmenting effect and higher robustness than those obtained with the use of only gray information or only texture information. This paper combines the gray information and texture information of MR images to propose a multi-modal-based brain tumor segmentation algorithm, in which the multi-modality MRI is firstly integrated to create high-dimensional features for each pixel, including Tamura texture features and gray features.

2. Feature extraction based on Tamura

Tamura’s research from the perspective of psychology shows that the perception of texture by human vision contains at least six components: contrast, orientation, roughness, line granularity, regularity, and degree of roughness [16]. Experiments show that the three quantitative analysis indexes of contrast, directionality and roughness are more important for the analysis of image texture. These indicators were introduced as texture information in this paper. The texture features of the four modality brain tumor images were extracted. A given brain tumor image, \( I_{k,h,w} \rightarrow \{0,1,2,\cdots,L+1 \} \), where \( k \in [1,K] \), \( h \in [1,H] \), \( w \in [1,W] \), \( K \) is the sequence of the image (hierarchy), \( H \) is the height of images, \( W \) is the width of images, and \( L \) is the pixel (voxel) gray level.

2.1 Roughness

In the paper [17], they modified the expression proposed by Tamura. This method reduces the complexity of the algorithm. Since many sequences are in one brain tumor image, which is equivalent to a combination of many images, the amount of data in the image is very large, this method is also used in this paper. The roughness of this paper is calculated as follows:

- The expression of the average gray value of pixel \((k,h,w)\) is as follows:
  \[
  A_k(h,w) = \sum_{i=0-H}^{H} \sum_{j=0-W}^{W} f(k,i,j)/(2n+1)^2
  \]
  where \( n = 1,2,3,4,5 \), \( f(k,i,j) \) is the gray value of the pixel located in the sequence \( k \), \( i \)-th row, and \( j \)-th column.

- The average grayscale variance is calculated as follows.
  \[
  E_x(k,h,w) = |A_k(h-n,w)-A_k(h+n,w)|
  \]  \[
  E_y(k,h,w) = |A_k(h,w-n)-A_k(h,w+n)|
  \]
  \( E_x \) is the calculation method in the horizontal direction, \( E_y \) is the calculation method in the vertical direction.

- The value of \( E \) is calculated, and the value of \( n \) corresponding to the maximum \( E \) value is found. This is regardless of direction, whether horizontal or vertical.
  \[
  n_{max}(k,x,y) = \max \{ E_{x,\theta}(k,x,y) | \theta \in [1,5], \theta = u,v \}
  \]

- The average roughness of the neighborhood sized \( 3 \times 3 \) is calculated as follows.
  \[
  \text{Avg}_{x,y}(k,h,w) = \sum_{i=0-H}^{H} \sum_{j=0-W}^{W} n_{max}(k,i,j)/9
  \]

- The absolute value of the difference between the roughness of the pixel \((k,h,w)\) and the average roughness is calculated. \( C^t(k,h,w) \) is the roughness measure of the pixel \((k,h,w)\).
  \[
  C^t(k,h,w) = |n_{max}(k,i,j) - \text{Avg}_{x,y}(k,h,w)|
  \]

2.2 Contrast

Contrast refers to the difference between the brightest part and the darkest part, which can be obtained by statistical analysis of the gray distribution around the pixel. The contrast of this paper is calculated as follows:
• The average grayscale value of a pixel block with a neighborhood size of $3 \times 3$ is counted, marked as $Avg_{grv}(k, h, w)$.

• The fourth moment of the neighborhood gray value is counted.
\[
M_4(k, h, w) = \sum_{i=-1}^{1} \sum_{j=-1}^{1} \frac{1}{9} f(k, i, j) - Avg_{grv}(k, h, w)^4
\]  

• The average grayscale variance for an image block sized $3 \times 3$ is calculated, the formula is as follows:
\[
M(k, h, w) = \sum_{i=-1}^{1} \sum_{j=-1}^{1} \frac{1}{8} f(k, i, j) - Avg_{grv}(k, h, w)
\]

• The contrast value of pixel $(k, h, w)$ is as follows.
\[
C^2(k, h, w) = M(k, h, w) / M_4(h, w)^{1/4}
\]

2.3 Directionality

Directionality is an important feature of an image. Some texture images have no obvious directionality, and some texture images have obvious directionality. Tamura uses directionality to measure the apparent directionality of the image.

• Calculate the gradient vector at each pixel, the modulus and direction of the vector are calculated as follows:
\[
\Delta G(k, h, w) = (|\Delta u(k, h, w)| + |\Delta v(k, h, w)|) / 2
\]
\[
\theta(k, h, w) = \arctan(|\Delta v(k, x, y)| / |\Delta u(k, h, w)|) + \pi / 2
\]

where $|\Delta u(k, h, w)|$ is the convolution of the selected image region with the operators $\begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$.

$|\Delta v(k, h, w)|$ is the convolution of the selected image region with the operators $\begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$.

• A threshold $t$ is selected in advance, and the direction angle of the pixel is $\theta(k, h, w)$.
\[
\theta(k, h, w) = \begin{cases} 0, & |\Delta G(k, h, w)| < t \\ \theta(k, h, w), & \text{otherwise} \end{cases}
\]

For images with no obvious direction, the value of $\theta$ will be flat. When the value of $k$ is smaller than the threshold $t$, we set the value of the angle to 0, $t$ is the smoothing correction parameter. There are many ways to find the threshold $t$ [17, 18]. In this paper, $t = 12$ is obtained according to the literature [18].

• The mean value of the direction angles of all the pixels is calculated.
\[
Avg_{dir}(k, h, w) = \sum_{i=-1}^{1} \sum_{j=-1}^{1} \theta(k, i, j) / 9
\]

• The direction Angle of the pixel $(k, h, w)$ subtracts the average direction Angle in equation (14), which is the measure of the degree of direction of the pixel.
\[
C^3(k, h, w) = \theta(k, i, j) - Avg_{dir}(k, h, w)
\]

The above-mentioned roughness, contrast, orientation characteristics and gray scale characteristics in four modes are normalized to an integer of 0-1. These texture feature data and gray feature data constitute a feature space for describing a brain tumor image. These texture feature data and gray scale feature data form a feature space that describes brain tumor images. For any image $I_{d\theta w}$, $I_{d\theta w}^d(d = 1, 2, \cdots, N_d)$ is assumed to be the corresponding feature matrix, where $N_d$ is the number of feature dimensions. These features include the above-mentioned roughness, contrast, directionality,
and the gray value of the center pixel. They are pixel gray value, $3 \times 3$ neighborhood pixel gray value average, $5 \times 5$ neighborhood pixel gray average difference, $5 \times 5$ neighborhood pixel gray average and $5 \times 5$ neighborhood pixel gray average difference. Because there are four modalities, so 32 features are extracted for each pixel.

3. Automated brain tumor segmentation from multi-modality MRI data based on Tamura Texture Feature and SVM

The SVM algorithm has a good generalization ability and also performs well in small sample learning. Currently, many SVM algorithms have been applied to medical image segmentation [19,20]. The classification principle of the SVM algorithm is to map the sampling sample space to a high dimensional space and establish an optimal decision hyperplane in the high dimensional space. When categorizing, the maximum distance between the two types of samples from the hyperplane is the optimal classification. In the SVM training process, the training error is the constraint condition, and the confidence range is minimized. In particular, the introduction of the kernel function is also strong for high-dimensional sample processing capabilities. Therefore, the S algorithm has better generalization ability than the traditional learning algorithm, especially in solving small sample, nonlinear and high-dimensional pattern recognition problems [21].

The MR image of brain tumor is segmented with SVM. The first step is to select the sample point, then learn the sample point, and get the optimal classifier. Finally, the classifier is used to classify the feature vectors of each pixel in the MR image. The choice of the training sample is very important and directly affects the search of the optimal classifier. Sometimes the sample selection is even more important than the method of choosing the classifier. The sampling methods mainly include: random sampling, stratified sampling, overall sampling, and systematic sampling. Sampling methods include random sampling, stratified sampling, holistic sampling and systematic sampling. Random sampling is the most commonly used method. Random sampling includes uniform sampling, simple random sampling, stratified random sampling and so on. In this paper, the uniform sampling method can be used to obtain representative samples and prevent periodic deviations. In view of the complexity of the MR sequence images, the image sampling window is set to $W_y = 7$, and new sampled images are generated every seven rows and seven columns in the image $I_{loc}$. In this way, a sequence will contain only $N_y = (HW) / W_y^2$ pixels of information, greatly improving the efficiency of the algorithm.

The flow chart of multi-modality brain tumor MRI image segmentation based on Tamura texture and SVM proposed in this paper is shown in Figure 1.

![Flow chart of multi-modality brain tumor MRI image segmentation](image)

Figure 1. Brain tumor segmentation process.

4. Experimental results and analysis

The clinical data of 30 patients (unknown patient age and gender) provided by MICCAI BRATS 2013 (https://www.virtualskeleton.ch/BRATS/Start2013) were selected as experimental data in the paper. Each of the 30 sets of data contains four modal images and the segmentation results completed by the experts. The four modes of image include FLAIR, T1, T2, and T1C images. The size of each sequence image of the data is $220 \times 220 \times 155$, and preprocessing such as shelling and registration has been completed. In order to evaluate the segmentation performance, Dice similarity coefficient (DSC), Sensitivity, and Predictive positivity value (PPV) are used to evaluate the segmentation results.
When training the network, the input is a 32-dimensional vector composed of gray values and texture information of the central pixel of the image sample and its surrounding points. The output is one-dimensional, taking 0 or 1 (0 for normal tissue and 1 for tumor tissue).

![Figure 2. H02 image raw data](image1)

![Figure 3. H02 image expert segmentation results and the segmentation results of the algorithm: (a)79th sequence expert segmentation results (b) 79th sequence algorithm segmentation results (c) 108th sequence expert segmentation results (d) 108th sequence algorithm segmentation results.](image2)

Figure 3 shows the original images of the four modalities of H02 patients. The 79th and 108th sequences were selected. From left to right are FLAIR, T1, T1C, and T2 images. Figure 3 shows the results of the expert segmentation and the results of the segmentation of this paper. It can be seen that the BP neural network after basic training can classify most normal brain tissues and tumor tissues correctly. It can be seen from the picture that in the marginal part of the tumor area. There are white tumor tissues misjudged as normal tissues while the normal tissues are misjudged as the tumor tissues. The edge part of the tumor is rough and uneven, but the segmentation precision is better from the whole, and the DSC coefficient of each layer reaches more than 90%.

![Figure 4. H06 image raw data](image3)
Figure 4 shows the original images of the four modalities of H06 patients. The 99th and 119th sequences were selected. Figure 5 shows the results of the expert manual segmentation and segmentation results of the algorithm. It can be seen from the figure that the segmentation effect of the 99th sequence is better than that of the 119th sequence. The 119th sequence of brain tumor area is shown to be disconnected. There are gaps between normal tissue and tumor tissue. These problems lead to difficulty in segmentation. The difference between the fuzzy normal tissue area and the tumor area is small, and the texture characteristics are not particularly obvious. In addition, in the training, according to the method of uniform sampling, sampling of the fuzzy region accounts for a small proportion of the input sample, so the segmentation accuracy of the brain tumor region is not high. Therefore, for the 119th sequence in Fig 4, there is a problem that the segmentation accuracy is not high. A large number of re-samplings are needed for this area. The proportion of the sample in the region to the total sample is increased, so that targeted training can be performed.

Table 1. Average segmentation results for 30 patients(%)

| Method                               | Dice    | Sensitivity | PPV      |
|--------------------------------------|---------|-------------|----------|
| SVM without Texture Feature          | 82.07±14.00 | 94.69±4.87  | 74.84±19.93 |
| Algorithm proposed in this paper     | 88.21±7.40   | 97.69±5.45  | 85.64±13.42 |

Table 1 shows a quantitative comparison of the segmentation results between the method in this paper and the method in paper[11]. The document [11] is based on the SVM algorithm without considering texture information, the kernel function of the algorithm is Gauss kernel function. It can be seen from the table that the Dice coefficient of the paper [11] method is low. In the process of extracting the gray features from multi-modal feature information, the features of different modal information that are favorable for classification are lost. These lead to a decline in the correct rate of segmentation. In this method, the texture information of the image block is considered in the multimodal information fusion process. Especially the texture information of most T1C and T2 modes can distinguish tumor points from non-tumor points, so the Tamura texture information can get a higher segmentation precision. The higher segmentation accuracy is achieved. It was obtained because the Tamura texture information was considered.

5. Conclusion
In order to achieve effective segmentation of brain tumor MR images, a segmentation method combining Tamura texture feature extraction and SVM is proposed. Firstly, local grayscale features and Tamura texture features of four modal MR images are combined in this algorithm. Enough information is extracted from the image, which can effectively overcome the individual differences of brain tumors and reduce the impact of the similar gray values of tumor margins and normal tissues. Then, the known samples are input in the SVM model for training; finally, other brain tumor images are processed with the trained SVM model. This method makes full use of the characteristics of different types of brain tumor images, taking into account not only the gray information of the images, but also the texture information of the images. The experimental results show that the proposed method has a certain degree of improvement in segmentation accuracy compared to the image segmentation method based on gray information.
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