CONFIDENCE GUIDED ENHANCING BRAIN TUMOR SEGMENTATION IN MULTI-PARAMETRIC MRI

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ABSTRACT

Enhancing brain tumor segmentation for accurate tumor volume measurement is a challenging task due to the large variation of tumor appearance and shape, which makes it difficult to incorporate prior knowledge commonly used by other medical image segmentation tasks. In this paper, a novel idea of confidence surface is proposed to guide the segmentation of enhancing brain tumor using information across multi-parametric magnetic resonance imaging (MRI). Texture information along with the typical intensity information from pre-contrast T1 weighted (T1pre), post-contrast T1 weighted (T1post), T2 weighted (T2), and fluid attenuated inversion recovery (FLAIR) MRI images are used to train a discriminative classifier at pixel level. The classifier is used to generate a confidence surface, which gives a likelihood of each pixel being a tumor or non-tumor. The obtained confidence surface is then incorporated into two classical methods for segmentation guidance. The proposed approach was evaluated on 19 groups of MRI images with tumor and promising results have been demonstrated.

Index Terms— Multi-parametric MRI, Brain Tumor, Segmentation, Learning, Appearance Feature.

1. INTRODUCTION

Brain tumor segmentation is an important application in medical diagnostics, as it provides medical experts the information associated to lesions, which is essential for treatment planning and response assessment. The process of manual segmentation of tumors by medical experts is a tedious and time consuming task. On the other hand, automated quantitative analysis of tumors is a very useful but challenging task due to the complexity of medical images and the variation of anatomical structures. In addition, the limitations of the current imaging process result in high degree of appearance similarity between normal regions and the tumor.

In clinical practice, physicians analyze multi-parametric magnetic resonance imaging (MRI), typically consisting of pre-contrast T1 weighted (T1pre), post-contrast T1 weighted (T1post), T2 weighted (T2), and fluid attenuated inversion recovery (FLAIR), to measure the enhancing tumor size using their prior knowledge. To assist measuring the volume of enhancing brain tumors, Kanaly et al. [1] proposed a semi-automatic approach by asking users to manually define regions of interest covering the tumors but with minimal inclusion of normal tissues. In the existing automatic approaches [2], intensity and the prior probabilities of tissues through atlases are used to generate the models for tumor segmentation. However, the enhancement of non-tumor regions along with the tumor regions may significantly affect the performance of tumor detection and segmentation. Using atlases for tumor detection requires accurate non-rigid registration of atlases to the patient images [2], where such a registration itself is difficult to obtain [3].

In the past several years, scientists working on computerized medical imaging have been trying to improve the performance of automatic tumor segmentation by using machine learning methods. For example, Menze et al. [4] applied a generative model based on an improved multivariate EM algorithm for tumor segmentation on multi-model image volumes. Ruan et al. [5] identified tumor regions by training a Support Vector Machine (SVM) on mean and variance extracted from small patches of multi-parametric MRI images. In an adaptive training framework proposed by Zhang et al. [6], multi-kernel SVM was trained to do tumor classification. Markov Random Fields [7] and SVM based Conditional Random Fields [8] have also been used for tumor segmentation. However, the importance of tumor appearance features was not well exploited, which may limit the performance of those methods on enhancing tumor segmentation.

In this paper, we propose to use both intensity and texture features extracted from multi-parametric MRI for tumor detection, which is then applied for guiding the tumor segmentation. The contributions of our work are two-fold: 1) Besides intensity information, image textures are introduced for tumor detection by exploiting the fact that normal brain tissues often have different structures than the lesions due to the effect of angiogeneses. 2) The other contribution is that a confidence surface is generated from the tumor detection result and is used to guide the segmentation as a new form of prior knowledge.

The rest of the paper is organized as follows. In Section 2, the method of detecting tumors using intensity and texture features extracted from multi-parametric MRI images is presented. Section 3 gives the details of confidence surface generation and confidence guided segmentation. Validation and discussion of the proposed methods are presented in Section 4. Section 5 concludes the paper.

2. TUMOR DETECTION AND LOCALIZATION

Distinguishing the enhanced non-tumor regions from the actual tumor might be a simple task for a medical expert, since oncologists

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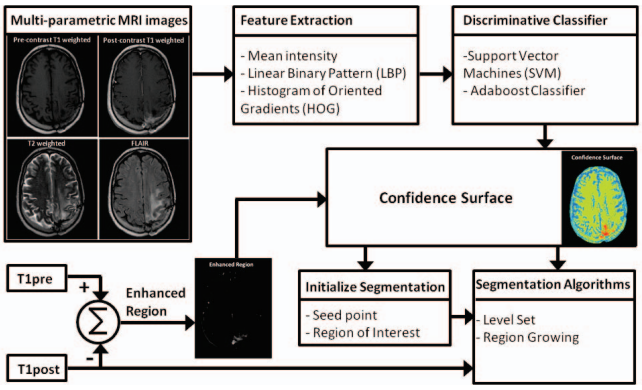


Fig. 1. Overview of our proposed tumor detection framework.

can use the information from multi-parametric MRI combined with their years of experience while manually segmenting the tumors. However, it is a big challenge for any automatic tumor detection or segmentation algorithm. In this paper, we attempt to incorporate this expert knowledge and experience of oncologists by training discriminative models on intensity and texture features across multi-parametric MRI images for brain tumor detection and segmentation.

2.1. Feature extraction

For classification based detection or segmentation, the feature descriptors play an important role. In our work, texture feature descriptors are used, which are complementary to intensity features due to their illumination invariant nature. The used feature descriptors include Mean Intensity (MI), Local Binary Pattern (LBP) [9], and Histograms of Oriented Gradient (HOG) [10], which are extracted from a spatial neighborhood of $n \times n$ pixels. The MI feature is computed to represent the average intensity information, which is very useful in measuring enhancement. To deal with intensity variation, the LBP feature [9] is extracted, which is a very powerful texture feature descriptor. It has been successfully used in face recognition and human detection. It encodes 256 possible texture patterns at each pixel, providing an efficient representation of texture. The HOG feature [10], which has been successfully used in object detection and recognition, is also computed to characterize the gradient information in the neighborhood. The orientations of gradients computed vertically and horizontally are quantized into 9 bins and are weighted with their magnitude. The histogram of these weighted orientations is considered as our HOG descriptor.

2.2. Classification based Detection

The proposed detection approach is depicted in the upper part of Fig. 1. To speed up the detection process, a mask is first generated for the enhanced region, obtained by the difference of T1pre and T1post images. Then MI, LBP and HOG features are only computed within the enhanced region mask from each of the T1pre, T1post, T2, and FLAIR images. After extracting the features from each image, a feature vector is generated by concatenating all those features together. The obtained feature vectors are then input into two well known classification approaches, SVM [11] and AdaBoost [12], for tumor pixel classification.

3. CONFIDENCE GUIDED SEGMENTATION

During segmentation, a confidence surface is generated from the tumor classification results and used to guide the following tumor segmentation. The details of the method are presented in this section.

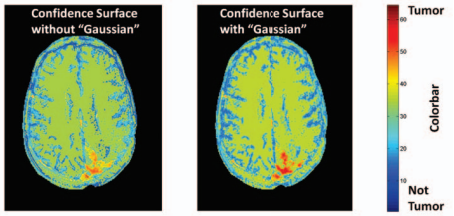


Fig. 2. Confidence surface before and after applying 2D Gaussian.

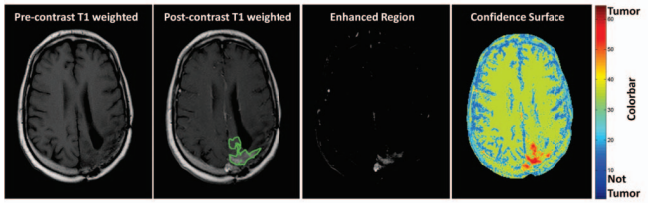


Fig. 3. T1pre and T1post images, the enhanced region, and the generated confidence surface. The green contour shows the ground truth of the tumor.

3.1. Confidence Surface Generation

The confidence surface C_s is constructed based on the classification output scores of the designed classifier. Since the confidence surface generated by the classification output is noisy as shown in Fig. 2, we smooth it using a 2D Gaussian. For each pixel, its confidence is propagated to the neighborhood by using Gaussian distribution.

$$C_s(x) = \frac{1}{N} \sum_{i=1}^{N} p(x; \mu_i; \Sigma_i), \quad (1)$$

where N is the total number of enhanced pixels, $p(x; \mu_i; \Sigma_i)$ is a 2D Gaussian distribution for a pixel i with a standard deviation defined by the classification score of that particular pixel. An example of the generated confidence surface is shown in Fig. 3, together with the delineated ground truth image.

3.2. Segmentation Methods

Most of the existing segmentation approaches are built on the fact that the tumor region is enhanced with the administration of contrast enhancement agent, when compared to normal regions. Hence, they only consider the change of intensity of a tumor on the contrast enhanced image. However, in practice, some normal tissue may have similar intensity levels with the enhancing tumors, since those regions may also get enhanced with the use of contrast agent. In such cases, the automatic segmentation methods may fail, which results in the segmentation of a larger region than the actual tumor region. On the contrary, if any noise appears within the tumor region or if the contrast enhancement of the tumor is not uniformly distributed, the segmentation method may not be able to extract the complete tumor region. Therefore, we propose to use the constructed confidence surface C_s, as a prior to guide the segmentation process. The proposed approach makes use of the classification confidence computed using not only intensity but also texture information to guide the segmentation of tumor on T1post image to achieve increased segmentation accuracy. The overview of the proposed segmentation approach is shown in the lower part of Fig. 1.

In order to demonstrate the effectiveness of using confidence guidance, the confidence surface is incorporated into two classical segmentation methods, level set [13] and region growing [14], to guide the segmentation. The input to each modified segmentation method consists of the generated confidence surface and the T1post MRI image. In the following paragraphs, we summarize the two segmentation methods that have been used throughout this work. For each of these methods, we used the points with highest confidence as seeds to initialize the segmentation process automatically.

Level set based Segmentation: The level set [13] model can delineate the object boundaries in a given image based on level set evolution. The contour is evolved by minimizing the energy functional. In the original version, the energy functional is defined by using regional intensity and contour curvature. In the proposed method, a new force term coming from the confidence surface is added, which tries to separate the confidence surface into two regions in the same time, denoting tumor and non-tumor. The new energy functional is defined as

$$\begin{aligned} F(c_1, c_2, C) &= \mu \cdot Length(C) \\ &+ \int_{\Omega} |u_0(x,y) - c_1|^2 dxdy + \int_{\bar{\Omega}} |u_0(x,y) - c_2|^2 dxdy \\ &+ w_1 \int_{\Omega} |p(x,y) - p_1|^2 dxdy + w_2 \int_{\bar{\Omega}} |p(x,y) - p_2|^2 dxdy \end{aligned} \quad (2)$$

where Ω and $\bar{\Omega}$ denote the regions inside and outside the segmentation curve C. $p(x,y)$ is the confidence value of pixel (x,y), and p_1 and p_2 represent the average of confidence values inside and outside the tumor region, respectively. μ, w_1 and w_2 are positive weighting parameters.

Region Growing based Segmentation: Region growing [14] is a pixel-based image segmentation method, which checks the neighbor pixels of the initially provided seed region and iteratively adds the neighbor pixels to the region to be grown if a measure of similarity $S(x,y)$ is smaller than a threshold. After adding a pixel, the mean intensity of the grown region is updated. In the original version of the algorithm, the similarity $S(x,y)$ is only based on the difference in pixel intensities. In our proposed method, the similarity $S(x,y)$ is weighted by the confidence of that pixel being a tumor, according to the confidence surface. This helps the region to grow to the pixels with similar intensities and also with high confidence of being a tumor. In our setup, the similarity measure is defined as $S(x,y) = |I(x,y) - c|(1 - p(x,y))$, where $p(x,y)$ is the probability of a pixel being a tumor, $I(x,y)$ is the intensity of pixel (x,y), and c is the mean intensity of the current region. The pixels in the neighborhood of a current boundary pixel with the minimal $S(x,y)$ is included into the region.

4. EXPERIMENTS

In our experiments, 19 groups of multiparametric MRI images from 11 subjects were used for validating the proposed methods. Each group consists of a T1pre, a T1post, a T2, and a FLAIR image. Tumor regions manually delineated by a physician were considered as the ground truth. All the multi-parametric MRI images for one patient are aligned in our experiments before tumor detection. We provide quantitative results based on leave-one-out cross validation strategy. In this framework, we leave all the slices belonging to one subject for testing and consider the slices of the remaining subjects for training.

In our work, the true positive rate (TPR) and false positive rate (FPR) are used to quantitatively measure the tumor detection performance. The Dice similarity score (DSS) [15] is employed to measure the segmentation accuracy. Let A and B denote the ground truth and the detected tumor region, respectively. Define a, b and c as the number of pixels enclosed by A, B, and their intersecting area, respectively. Then DSS can be computed as $DSS = 2c/(a+b)$.

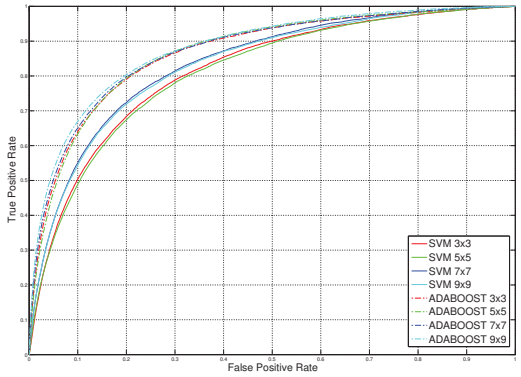


Fig. 4. ROC curves for tumor detection with different neighborhood sizes $n = \{3, 5, 7, 9\}$ for both AdaBoost and SVM.

4.1. Experimental Setup

For training the classifiers, all the pixels inside the labelled tumors were considered as positive samples and the enhanced pixels from the non-tumor regions were taken as negative samples. The trained classifiers were tested on enhanced regions of testing subjects and the average true positive and false positive rates for pixel classification were computed for performance evaluation based on cross validation. In the proposed framework, the features are extracted from $n \times n$ image patches. To understand the influence of neighborhood size on the performance of detection, we tested with $n = \{3, 5, 7, 9\}$ and found that setting larger neighborhood size $n = 9$ helps to achieve better performance as shown by the receiver operating characteristic (ROC) curves in Fig. 4. The larger patches can capture more information in a larger neighborhood, however that will result in a more intensive computational load. In addition, it can be seen that, by using the same features, AdaBoost performed better than the SVM classifier in terms of the area under curve. Thus, in the rest of the experiments, AdaBoost with features extracted from 9×9 image patches was used for tumor detection and segmentation guidance.

The parameters used in the segmentation methods are set as follows. For the level set based methods, μ was set to be 0.2 and $w_1 = w_2$ were set as 1.25. For the region growing based method, the thresold was set to be the standard deviation of the tumor region pixel intensities multiplied by 0.7.

4.2. Segmentation Results

Fig. 5 shows some examples of the segmentation results obtained by using different segmentation methods. It can be seen that by using the confidence surface more accurate segmentation results were obtained. Compared with the original segmentation approaches, the confidence surface guided methods are able to distinguish most of the normal tissues enhanced by the administration of contrast agent from the enhancing tumor tissues. Although some structure like the blood vessels cannot be excluded, the results obtained by using the proposed methods get much closer to the ground truth.

The quantitative evaluation results of each tested segmentation method measured using DSS are shown in Table 1. The improve-

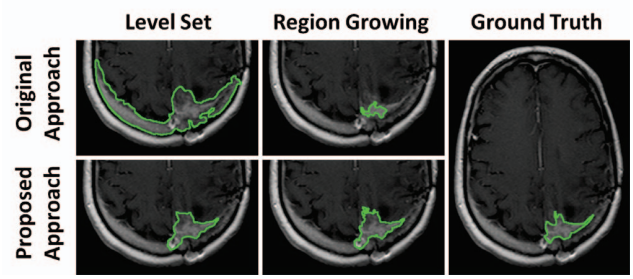


Fig. 5. Segmentation results using the two segmentation methods on the same subject for a direct comparison of the original approach and the proposed approach. The green contours show the segmented tumor regions.

Table 1. The average Dice similarity scores (DSS) and the standard deviations of the results obtained using the original and the proposed segmentation methods.

Method	Level set	Region growing
Original	0.30±0.27	0.29±0.22
Conf. guided	0.68±0.13	**0.69±0.14**

ment can be clearly seen when the confidence surface is used for guiding the segmentation. For both the segmentation methods, the performance has been significantly improved with much higher DSS values after incorporating the confidence surface generated from tumor detection (Student's t-test with $p < 0.01$). The best performance was obtained by using the confidence guided region growing method. It is worth noting that the DSS values are not very high due to the fact that the enhancing tumor is usually not very big. In some cases, the difference of just several pixels in the labelling results can cause low DSS values.

4.3. Discussion

The main power of the proposed method comes from the introduction of using image texture features for tumor detection rather than just using the intensity information. The main motivation of using regional appearance feature descriptors is based on the fact that normal brain tissues have different appearances on multi-parametric MRI from the lesions due to the effect of angiogeneses, although the former may also be enhanced sometimes to have similar intensities.

Fig. 6 shows the weights of each feature extracted from different parametric images in the trained AdaBoost classifier. It can be seen that the MI features from the T1pre and T1post images still play the

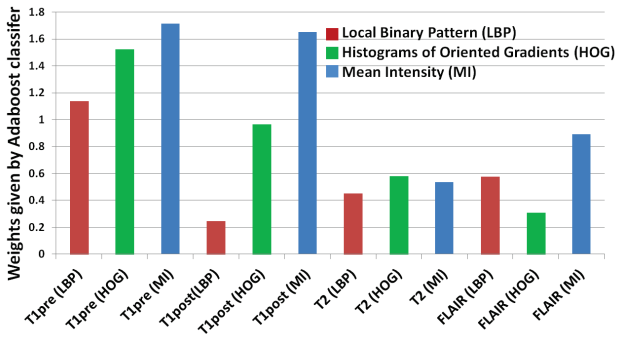


Fig. 6. The weights of each feature extracted from different parametric images in the trained AdaBoost classifier.

most important role in tumor detection, which is expected since we are dealing with enhancing brain tumors. On the other hand, the HOG features from T1pre and T1post images and the LBP feature from T1pre image have larger weights than the MI feature from T2 and FLAIR images. It suggests that the used feature descriptors are able to capture useful texture information beside the intensity, which is very important for accurate detection.

5. CONCLUSION

In this paper, a confidence guided enhancing brain tumor segmentation framework is presented. The proposed approach can effectively exploit the texture information from multi-parametric MRI. The detection results are incorporated into segmentation through the introduction of confidence surface. The proposed framework provides a new way for adding expert knowledge into image segmentation through a learning based approach, which leads to an automatic enhancing brain tumor labelling tool to assist radiologists. The quantitative experiments proved the significant improvement on the two classical segmentation methods. In our future work, we will investigate the incorporation of confidence surface into more sophisticated segmentation methods to achieve better segmentation performance.

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