AUTOMATIC BRAIN TUMOR DETECTION IN MAGNETIC RESONANCE IMAGES

Sahar Ghanavati[1], *Junning Li*[1], *Ting Liu*[1], *Paul S. Babyn*[2], *Wendy Doda*[2], *GeorgeLampropoulos*[1]

[1] AUG Signals Ltd., Toronto, ON., Canada
[2] Hospital for Sick Children, Department of Medical Imaging, University of Toronto, ON., Canada

ABSTRACT

Automatic detection of brain tumor is a difficult task due to variations in type, size, location and shape of tumors. In this paper, a multi-modality framework for automatic tumor detection is presented, fusing different Magnetic Resonance Imaging modalities including T1-weighted, T2-weighted, and T1 with gadolinium contrast agent. The intensity, shape deformation, symmetry, and texture features were extracted from each image. The AdaBoost classifier was used to select the most discriminative features and to segment the tumor region. Multi-modal MR images with simulated tumor have been used as the ground truth for training and validation of the detection method. Preliminary results on simulated and patient MRI show 100% successful tumor detection with average accuracy of 90.11%.

Index Terms— Brain Tumor, Automatic Detection, MRI, Shape Deformation, Gabor Filters, AdaBoost

1. INTRODUCTION

Detection and accurate localization of tumor in brain scans is the first step in treatment/surgery planning and in tumor change detection. Magnetic Resonance Imaging (MRI) is widely used to visualize brain structures such as white matter, grey matter, and ventricles and to detect abnormalities. In general, different MRI sequences with different contrast properties are acquired for better visualization of abnormalities, and the tumor segmentation is performed manually by radiologists. However, manual segmentation is a time-consuming and subjective process.

A semi-automated tumor segmentation was proposed by Koompairojn et al. to overcome these difficulties [1]. This method requires the manual segmentation of tumor contour in one MR slice. The manually segmentated contour is then propagated sequentially through all MR slices. However, Computer-Aided Diagnosis (CAD) systems can involve in brain tumor detection in another way: automatically assessing the probability of abnormality and then, highlighting the potentially abnormal regions for radiologists for further inspection. As a result, the probability of overlooking the tumor and the effort of manual examination of the whole 3D image are reduced. For this purpose, the CAD system should have the capability of fully automated segmentation of tumors. Many proposed automatic tumor detection techniques are based on fusion of complimentary information of different MRI modalities [2]. Classification methods such as neural network and support vector machine (SVM), and extraction of features, including shape-based and texture-based, were proposed for automatic tumor segmentation [3, 4]. Ahmed et al. showed that fusion of selected features extracted from multi-modal MRI improves the accuracy of tumor segmentation [5]. Xuan et al. proposed to use AdaBoost classifier to perform selection and fusion of intensity, symmetry and texture features extracted from multi-modal MRI [6].

We propose an automatic algorithm for tumor detection by fusing the complimentary information of different MRI modalities including T1, T2, and T1 with gadolinium contrast agent (Gad) that are commonly used for clinical diagnosis. These modalities have different contrast characteristics and can provide better visualization of abnormalities. We investigate the efficacy of shape deformation feature along with intensity, symmetry and texture features extracted from each image. The AdaBoost classifier is used to find the best combination of features for classification of image voxels into tumor and normal. A set of MR images with simulated tumor is used for the training and validation of the classifier. Preliminary results on simulated and patient data demonstrate the potential of this tumor detection technique for clinical applications.

2. METHODOLOGY

The workflow of our proposed method is shown in Figure 1. Each MRI in the training set is first pre-processed to minimize the intensity bias and to remove the non-brain tissue. The pre-processing also includes multi-modality within-subject registration and co-registration to a standard template for cross-subject comparison. Next, four types of features (i.e., intensity, symmetry, shape deformation, and texture features) are extracted from the pre-processed images. Feature selection and fusion are performed using AdaBoost. For new subjects, only the selected features computed in the training process will be extracted and tumor will be detected using the trained classifier.

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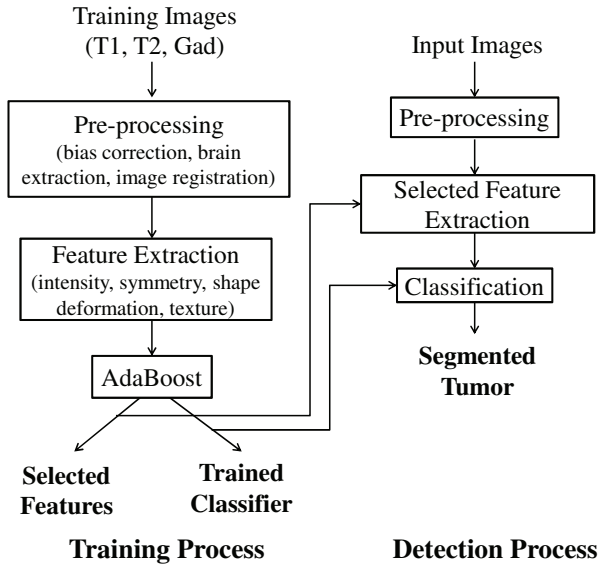


Fig. 1. Automatic detection workflow.

2.1. Data Pre-processing

The MRI intensity is inhomogeneous mainly due to the radio-frequency (RF) field non-uniformity and eddy currents resulted from switching gradient fields in the imaging system. Different imaging parameters and devices also affect the intensity distribution. The images are first corrected for the intensity inhomogeneity using an automatic method known as Non-parametric Non-uniform intensity Normalization (N3) [7]. The non-brain tissue such as skull and eyes is removed automatically from each image using Brain Extraction Tool (BET) [8]. Different MRI modalities of each subject are co-registered using a multi-modality multi-resolution registration method based on mutual information. The images of all subjects are then transformed to a common coordinate system by affine registration to a symmetric MR template (McConnell Brain Imaging Center, Montreal Neurological Institute). Finally, the images are normalized using histogram matching to the MR template (T1 template for T1 and Gad images and T2 template for T2 images), in order to minimize the range of intensity variation of the same tissue among different subjects. All the training and test images go through these pre-processing steps prior to the feature extraction and detection process.

2.2. Feature Extraction

Four types of features are extracted from each MRI: intensity, symmetry, shape deformation, and texture based on Gabor filters. Figure 2 shows the four features extracted from a T1-weighted MRI with simulated tumor and the result of thresholding the feature images.

2.2.1. Intensity

Intensity is the most straightforward feature that has been widely used for tumor segmentation in MRI. However, it is not sufficient for robust and accurate tumor detection due to tumor intensity variation and overlap with the intensity of normal tissues.

2.2.2. Symmetry

The normal brain has a high degree of symmetry between the two hemispheres. However, the presence of tumor typically results in asymmetry in brain anatomy. This asymmetry is used as a feature to detect the tumor in MRI. The symmetry plane in MRI is detected by the registration-based method proposed by Tuzikov et al. which has shown to be robust for pathological MR images [9]. The image and its reflection through the symmetry plane are subtracted. The normal tissue is not perfectly symmetric. So a binary mask is created from the subtracted image and small sparse regions of asymmetry are eliminated using morphological filters. The subtracted image is masked with this binary image to form the final symmetry feature.

2.2.3. Shape Deformation

Tumor growth results in brain anatomical deformation in the structures surrounding the tumor. This anatomical deformation is used as a feature for tumor detection. MRIs are registered to the symmetric template using a 3D non-rigid Demons registration algorithm. The magnitude of the deformation vector field resulted from the registration is calculated and normalized to form the shape deformation feature.

2.2.4. Texture

Texture is an important characteristic of the image, describing the spatial pattern of the neighboring pixels' intensities, and is commonly used in image segmentation [6]. A multi-channel filtering approach using a bank of 3D Gabor filters with different orientations and spatial frequencies is employed to extract texture feature vectors from each MRI. A 3D Gabor function is defined as a complex sinusoidal wave aligned with X-axis at a particular frequency and orientation, modulated by a 3D Gaussian envelope:

$$g(x,y,z) = e^{j(2\pi fx+\phi)} e^{-(\frac{x^2}{2\sigma_x^2}+\frac{y^2}{2\sigma_y^2}+\frac{z^2}{2\sigma_z^2})} \quad (1)$$

Different orientations of Gabor filters are achieved through 3D rotation. In order to cover the spatial frequency of the image, MR images are filtered using a bank of Gabor filters consisting of twelve orientations (four rotations, i.e., 0, $\frac{\pi}{4}$, $\frac{\pi}{2}$, and $\frac{3\pi}{4}$, about X, Y, and Z axes) and four frequencies ($4\sqrt{2}$, $8\sqrt{2}$, $16\sqrt{2}$ and $32\sqrt{2}$ cycle/image width). To increase the robustness, the final texture of each pixel is calculated as

the absolute averaging of a nonlinearly transformed Gabor-filtered images within a window (W) of size $M \times M$, as shown in Equation 2

$$e(x,y,z) = \frac{1}{M^2} \sum_{(x\prime,y\prime,z\prime)\in W} |\Psi(f(x\prime,y\prime,z\prime))| \qquad (2)$$

, where $(f(x,y,z))$ is the Gabor-filtered image, $\Psi(t) = tanh(\alpha t)$ is the nonlinear transformation. The value of nonlinearity parameter, α, is set to 0.25 which causes the transformation to behave as a blob detector. The size of the window, M, is calculated based on the Gabor filter frequency [10].

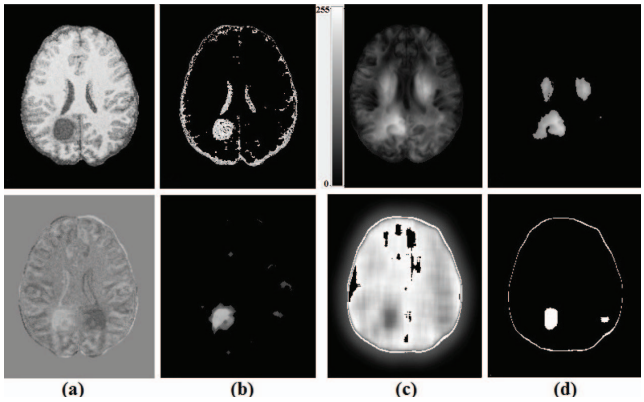


Fig. 2. Features extracted from a T1 MRI with simulated tumor. Top row: (a) Normalized intensity, (b) Thresholded intensity feature, (c) Deformation field magnitude, (d) Thresholded deformation feature; Bottom row: (a) Subtraction of image and reflected image through symmetry plane, (b) Thresholded and filtered symmetry feature, (c) Windowed Gabor-filtered image with freq. $2\sqrt{2}$, dir. X and rotation 0, (d) Thresholded texture feature.

2.3. Classification

The performance of the tumor detection method depends on the discriminating power of the features. Not all the features provide useful information for detection of tumor. For example, many texture features based on Gabor filters were extracted from each image but only a few of them can be used to segment the tumor. AdaBoost is a classifier that selects and combines the most discriminative features during the learning process [11]. In each iteration, training examples are reweighted and the weights of misclassified data points are increased, so that the next classifier is forced to focus on these examples. A weak classifier is computed based on only one selected feature that best discriminates the classes in that iteration. The final classifier consists of the weighted weak classifiers:

$$H(x) = sign(\sum_{t=1}^{T} \alpha_t h_t(x)) \qquad (3)$$

where $h_t(x)$ is the weak classifier on the selected feature in iteration t and α_t is its weight in that iteration.

3. EXPERIMENTS AND RESULTS

3.1. Simulated Data

We used five sets of T1, T2 and Gad MR images with simulated tumors with different size, shape, location, and contrast generated by TumorSim software (Utah Center for Neuroimage Analysis). Four of the data sets contain one tumor and one data set contains two tumors. Images are of size $255 \times 255 \times 181$ with isotropic resolution of 1 mm and each voxel in the images is labeled as normal or tumor. The benefit of using simulated data is the availability of known tumor regions that can be used as the ground truth for evaluating the performance of the algorithm. The images were preprocessed as aforementioned and the four types of features were extracted from the images to be used as the training data set for the classification. A leave-one-out validation was performed on the images. The result of the tumor detection and the ground truth are shown in Figure 3. The tumor was detected in 100% of cases.

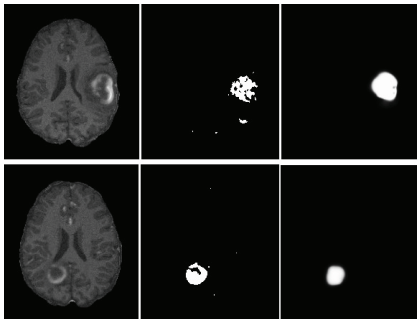


Fig. 3. Result of leave-one-out validation on two simulated data. Left: Original Gad image; Middle: Segmented tumor using our method; Right: The ground truth.

To investigate the efficacy of the shape deformation feature, it was excluded from the training data feature vector and the same leave-one-out validation was performed. The average accuracy (true positive rate) and specificity (1- false positive rate) were calculated for both experiments and the result is shown in Table 1. Both the accuracy and specificity are improved slightly by inclusion of shape deformation feature. The deformation of tumor neighboring structures results in a larger area to be highlighted as high probability of tumor in the shape deformation feature. This in turn results in better segmentation at the edges of the tumor and higher classification accuracy.

Table 1. The effect of shape deformation feature on the classification result. Case 1: validation with intensity, symmetry, shape deformation, and texture features. Case 2:validation with intensity, symmetry, and texture features.

	accuracy	specificity
Case 1	90.11%	92.26%
Case 2	89.12%	91.19%

3.2. Patient Data

A preliminary study was performed on a set of multi-modal MRI from a patient with tumor (Hospital for Sick Children, Toronto). The training was performed using the five simulated data sets. Figure 4 shows the patient's Gad MRI and the result of our automatic tumor detection technique. It can be seen that the classifier can detect the tumor. However, the volume of the detected tumor is smaller than the actual tumor's volume and there are noisy regions in the detection result. In order to improve the accuracy and robustness of the proposed method the training data set needs to be expanded to include more patient images.

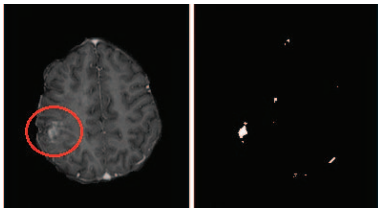


Fig. 4. Result of tumor detection on a patient data. Left: Original Gad image with the tumor marked with a red circle; Right: Segmented tumor using our method.

4. CONCLUSION

We have developed an automatic tumor detection algorithm using multi-modal MRI. The preliminary results show 100% detection rate in all of our test sets including simulated and patient data with an average accuracy of about 90%. Our results also show that the shape deformation feature can improve the segmentation accuracy.

Currently, we are validating our method on multiple healthy and pathological patient data with variable tumor characteristics. These segmented real data will be included in the training data set in order to improve the classification performance. We will employ our registration technique and tumor detection algorithm to detect tumor changes which is essential for monitoring tumor growth/shrinkage, response to treatment over time, and evaluation of surgical outcome.

5. REFERENCES

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