SYMMETRY-INTEGRATED INJURY DETECTION FOR BRAIN MRI

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ABSTRACT

This paper presents a new brain injury detection approach in images acquired by magnetic resonance imaging (MRI). The proposed approach is based on the fact that the anatomical structure of a 2D brain is highly symmetric, while most of the injury in the brain generally indicates asymmetry. The approach starts from symmetry integrated region growing segmentation of the brain images using the symmetry affinity matrix, and candidate asymmetric regions are initially extracted using kurtosis and skewness of symmetry affinity matrix. An Expectation Maximum classifier with Gaussian mixture model is used explicitly to classify asymmetric regions into injury and non-injury. Experimental results are carried out to demonstrate the efficacy of the approach for injury detection.

Index Terms — *Symmetry, Segmentation, Kurtosis, Skewness, Symmetry Affinity*

1. INTRODUCTION

Compared to traditional medical imaging techniques like CT and PET, magnetic resonance imaging (MRI) is the most recently applied technique most commonly used in radiology to visualize the structure and function of the body. It provides detailed images of the body in any plane with higher discrimination. Computer-aided diagnosis on brain MRI requires automatic extraction of regions-of-interest (ROI), such as injured regions/volumes or other abnormal tissues. State-of-the-art ROI extraction techniques can be mainly divided into two classes: tissue classification [1, 2] and abnormality/target extraction [3]. The tissue classification approaches start with brain segmentation based on prior information of tissue, and extract ROIs from classified tissue. Large amount of training data is needed for these approaches in order to obtain satisfactory classification results. Abnormality/target extraction approaches generally use digital subtraction between slices, seed growing or feature matching to detect ROIs. For accurate subtraction, this requires more strict normalization and registration of different MRI slices [4]. The ROI extraction results are highly dependent on the quality of preprocessing and prior knowledge. In our method, we overcome the above limitations to a great extent by integrating symmetry information in ROI extraction. This idea comes from the observation that most of the ROIs are asymmetric with their mirror regions against the symmetry axis. Since the brain structure is highly symmetric, we are able to detect ROIs by eliminating symmetric tissues. By integrating symmetry, we overcome the limitations of other approaches and this paper makes the following contributions:

(a) We do not consider any prior information for detecting asymmetric ROIs. We eliminate symmetric tissue without further classifying it by a large amount of training data;

(b) We need only a small number of examples of injury tissues for final classification of asymmetric regions. These contributions save a large amount of computation time for ROI extraction with high quality of results.

2. TECHNICAL APPROACH

The overall diagram of our method is given below:

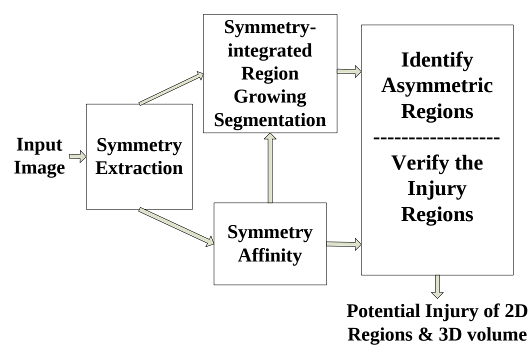

Fig. 1 Diagram of the overall method.

Our system for injury detection is based on exploiting symmetry of the brain. We use symmetry in various ways in the following two key steps of our system:

(a) Symmetry-integrated image segmentation;

(b) Asymmetry detection by kurtosis and skewness of symmetry affinity matrix.

With symmetry integrated into region growing segmentation, step (a) enhances the symmetric level of brain tissues in segmentation results. In step (b), for each region, kurtosis and skewness of its symmetry affinity value are computed and they are further used in extracting asymmetric regions from segmented parts. Finally, the injured regions and volumes are classified as normal or injured.

2.1. Symmetry-integrated Segmentation

Symmetry-integrated image segmentation is the first step that separates a brain slice into different parts, providing candidate regions for asymmetric region extraction. We use global symmetric constellations of features in [5] to detect the dominant reflective symmetry axis for brain, as in Fig 3. (b). Based on the axis, a symmetry affinity matrix is computed by curvature of gradient vector flow (CGVF) [6]. If the two points have globally symmetric fields by axis, their curvatures of GVF have closer values. Therefore, larger affinity in the image indicates asymmetric regions. The symmetry affinity matrix is further used to build the new symmetry constraint for pixel aggregation in a region growing approach for image segmentation, as follows:

$$\delta_{symmetry}(i,j) = \frac{\frac{\pi}{2} + actan(\sqrt{(1+C_i)(1+C_j)})}{\pi} + \frac{1 + |\sqrt{C_i} - \sqrt{C_j}|}{2} \quad (1)$$

Let us consider unlabeled pixel i that is going to or not going to be grown into labeled neighboring region j during region growing. C_i and C_j are symmetry affinities of pixel i and region j. The first term of equation (1) indicates that if both patterns i and j indicate low symmetry affinities (highly symmetric) with regard to their symmetric counterparts, they are more likely to be aggregated by decreasing the constraint $\delta_{symmetry}(i,j)$. The second term favors lower criterion for similar symmetry affinities. The symmetry constraint is combined with gray scale and texture to build an aggregation constraint as follows:

$$\delta(i,j) = \delta_{symmetry}(i,j) \times (\delta_{gray}(i,j) + \delta_{texture}(i,j)) \quad (2)$$

Based on the aggregation constraint, pixel i will be aggregated into neighbored region j if $\delta(i,j)$ between them is below a threshold δ_m. As the symmetry constraint enforced, since symmetric parts will lower $\delta_{symmetry}(i,j)$, segmentation will outline more complete and integrated symmetric regions. This procedure will improve the accuracy of asymmetric region extraction used in the next sub-section.

2.2. Asymmetric Region Extraction

The asymmetric region extraction basically classifies segmented regions into symmetric and asymmetric regions. We provide a new method using kurtosis and skewness of symmetry affinity matrix to detect asymmetric regions. For a sample of n values the sample kurtosis and skewness are given by following:

kurtosis:
$$g_4 = \frac{\mu^4}{\delta_2^2} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^4}{(\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2)^2} \quad (3)$$

skewness:
$$g_3 = \frac{\mu^3}{\delta_2^{1.5}} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^3}{(\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2)^{1.5}} \quad (4)$$

Based on definition of kurtosis, higher kurtosis value means sharper and narrower peak of distribution. Kurtosis property has been applied to detect the abnormality based on the reason that kurtosis measures the deviation of a distribution from the background [7]. We use kurtosis of symmetry affinity matrix to detect asymmetric regions, based on the observation that the asymmetric regions (brighter) in the symmetry affinity matrix can be regarded as abnormal target contrast to the background. For each region a kurtosis value of its symmetry affinities is computed using eq. (3). Larger kurtosis of a region means more deviation in its symmetry affinity distribution, which leads to potential asymmetry. The skewness is another cue for asymmetry detection. Once we know the mean symmetry affinity value of a region, the negative skewness means that the distribution is left-tailed to its mean value. Since zero symmetry affinity means perfect symmetry, negative skewness means that the region affinity shows more asymmetry property. The asymmetric region detection can be expressed as follows:

(a) Discard symmetric regions whose mean symmetry affinities are quite low; note that highly symmetric regions will have a low affinity.

(b) For each of the remaining regions, compute its kurtosis minus skewness g=(g4-g3) from eq. (3) (4), and build a histogram for this value. A higher g indicates more asymmetric of the region. A threshold Ω is found to partition the histogram to extract final asymmetric regions.

2.3. Brain Injury Extraction

After symmetry integration in the above two steps, we make sure that almost all the injury regions are included in the asymmetric parts. Post-processing procedures are performed to further eliminate noisy regions. First, small isolated regions with areas below 15 pixels are discarded. Second, very small regions in larger region boundaries, quantifying 10% of the region size, are removed automatically. Still a limited number of asymmetric regions remain for possible injuries. An Expectation Maximum (EM) classifier with Gaussian Mixture Model (GMM) is used to classify the remaining asymmetric regions into two classes: injury vs. non-injury by the asymmetric information from 3D MRI sequences, along with the gray-scale value of a region. Regions with larger 3D asymmetric volumes are classified as injury. At this stage, unsupervised classification is realized without a prior training model.

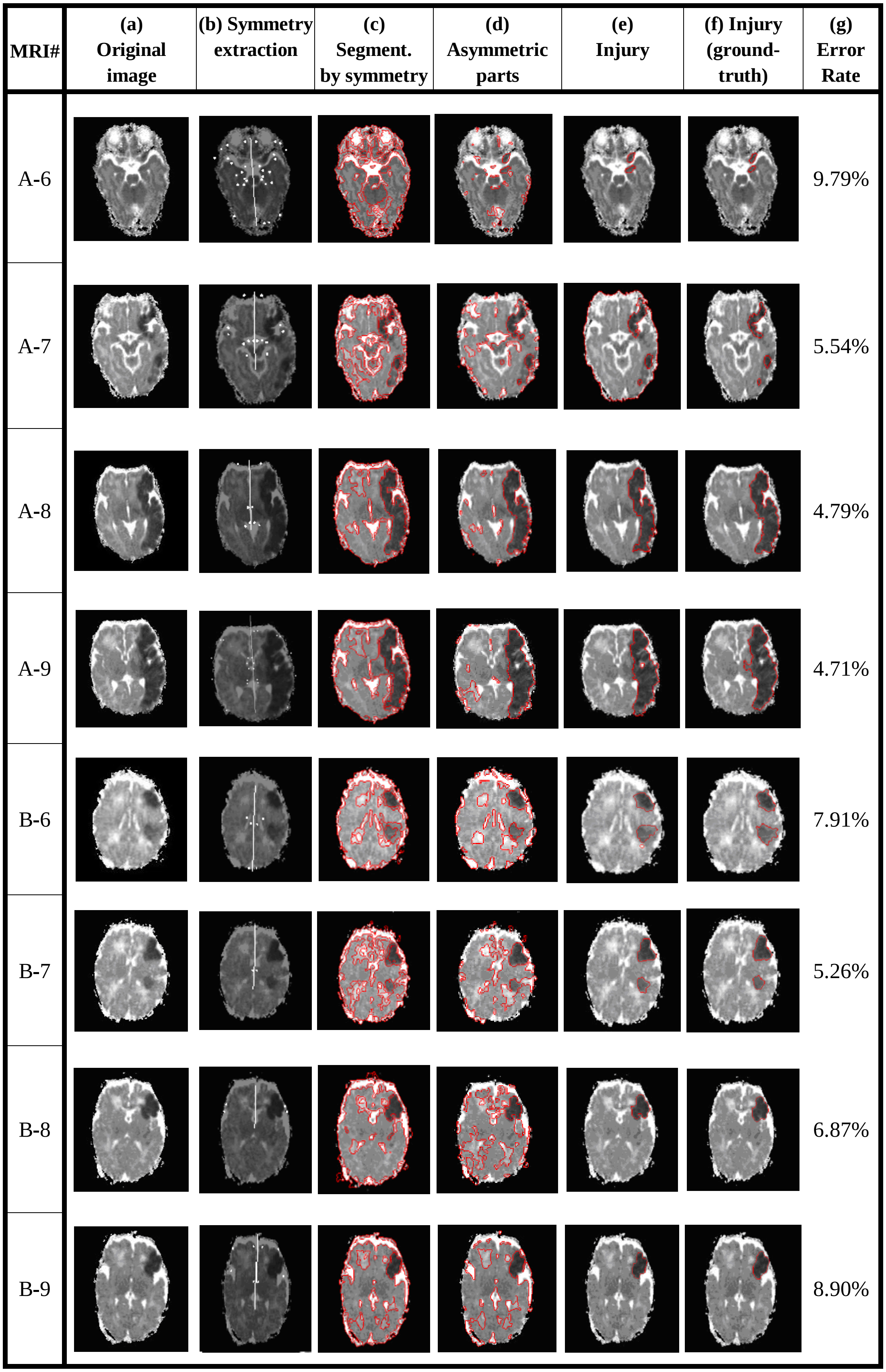

Fig 2. Example results from MRI sequences of patient #A and #

3. EXPERIMENTAL RESULTS

3.1. Datasets and Parameters

The dataset is composed of two sequences of MRI slices from two patients #A and #B, provided by The Loma Linda University Medical Center, at Loma Linda, CA. Some sample slices are shown in Fig 2. Slices in each MRI sequence are collected from different projection layers for the same patient. The two patients suffer from brain injury in different functional areas of the brain. Major parameters are composed of pixel aggregation threshold for region growing segmentation, and the kurtosis minus skewness histogram cut threshold Ω, stated in section 2.2, for asymmetry detection. Their values are 0.024 and 0.22, respectively, in our experiments.

3.2. Experimental Results

We run our algorithms on MRI sequences of slices for the two patients. In order to guarantee the comparability of results, all slices in the same sequence use the same set of parameters. Example slices and the results of each step (see Fig. 1) are shown in Fig 2. The final injured regions in Fig 2(e) are compared to the ground-truth injury in 2(f), by finding the percentage of overlapped and non-overlapped area. The overlapped area is the total number of injury pixels that are overlapped between our injury detection and its ground-truth injury, and it is divided by the area of ground-truth injury to generate the true positive rate. The non-overlapped area is the non-overlapped number of injury pixels of our detection method with regard to the ground-truth injury. The non-overlapped area divided by ground-truth injury area, determines the error rate, as in Fig 2(g). The overall error rate for patient #A by our method is 5.34%, and 9.74% for patient #B, as shown in Table 1 & 2. We compare our method to Bianchi's [8] Apparent Diffusion Coefficient (ADC) Image Maps method, which is also an automatic brain injury detection method, using the same datasets. As shown in Table 1 & 2, our method reaches lower error rates compared to the referenced method. Also for our results the total volume, injury volume and percentage of injury are all closer to the ground-truth data.

Methods	Total Volume	Injury Volume	Percentage of Injury	Error Rate
Our method	83142	14196	17.07%	5.34%
ADC Image Maps	112970	16593	14.69%	14.73 %
Ground-truth injury	83957	14864	17.70%	NA

Table 1. Statistical results of injury --- A comparison of detection methods for patient #A.

Methods	Total Volume	Injury Volume	Percentage of Injury	Error Rate
Our method	76474	3736	4.89%	9.74%
ADC Image Maps	112113	3965	3.54%	17.12%
Ground-truth injury	77381	3452	4.46%	NA

Table 2. Statistical results of injury --- A comparison of detection methods for patient #B.

4. CONCLUSION

This paper provides a new injury detection method for brain MRIs. A symmetry-integrated image segmentation is applied to ensure that the symmetry property is preserved in the segmentation results. Kurtosis and skewness are used with a symmetry affinity matrix to extract potential asymmetric regions. Brain injury is finally extracted using a classifier based on Gaussian mixture model for potential asymmetric regions. The quantitative results on the data from the two patients show that the volume of the computed injury closely approximates the ground-truth. In the future we will evaluate the approach on larger datasets.

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5. REFERENCES

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