

3D Filtering for Injury Detection in Brain MRI

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Abstract

This paper introduces a brain injury detection approach, using 3D filtering technique, for the images acquired by the magnetic resonance imaging (MRI) technique. The proposed method uses the symmetry property of brain MRI on both 2D images and 3D volumetric information of the MRI sequences. The approach consists of two key steps: (1) each slice of a brain image is segmented into different parts using a region growing algorithm, and a symmetry affinity matrix is computed, (2) non-symmetric regions are extracted, and they are further used to detect brain injury. The Kalman filter is explicitly used in step (2) to filter out the non-injury regions in 3D. Experiments are carried out to indicate the high efficiency of the method to detect the brain injuries.

1. Introduction

Detecting regions of interest (ROIs) [1, 2], including the brain injury, from the images acquired by the medical imaging devices, has been attracting intense research attention for the reason of its useful application in computer aided diagnosis, which significantly accelerates and improves the clinical decision. The magnetic resonance imaging (MRI) outperforms other medical imaging techniques like CT and PET by its higher discriminative display of the detailed brain functional areas in different planes.

A properly designed injury detection method for MRI should exploit specific property that efficiently discriminates between injury and non-injury brain parts. Most commonly used properties are image features like gray scale, shape and texture [7], which provide cues to different functional areas of the brain. Dependent on prior knowledge, such properties are difficult to acquire, if not impossible, to perform automatic detection covering a wide range of injury categories and imaging devices and their parameters. To solve this problem, this paper presents an automatic injury detection method using the symmetry

as the fundamental property, based on the assumption that the injuries constitute non-symmetric areas whereas the healthy brain shows a highly symmetric structure. This method is free from prior knowledge since it exploits symmetry property. Furthermore, the Kalman filter [3], which is a well-known tracker and smoother, is applied in this paper to extract both the non-symmetric regions and the injury parts. The Kalman filter is used for the reason of its robustness to noisy observations and providing a smoothed tracked trajectory. We formulate the non-symmetric region extraction as a tracking problem, which regards the 2D MRI scans as a volumetric sequence of frames having close relations with each other. The *true* state of tracking we need to know is the non-symmetric region properties, and the Kalman filter is able to formulate a smoothed state estimation which rejects the symmetric regions as noisy observations. For injury detection, the state variable of Kalman filter is changed to the properties discriminating injury and non-injury.

This paper makes the following contributions:

- (1) The method is free from prior knowledge since it uses symmetry as an automatic injury detection property. The hypothesis is that injury regions (2D/3D) are asymmetric which can be further refined.
- (2) A 3D filtering approach based on Kalman filter is applied to extract the injury regions from MRI scans. The results are shown on the data collected from the same patient at two different times and they are compared with previous work.

The remaining of the paper is organized as follows. In section 2, the technical realization of the proposed method is described. Experimental results are shown in section 3. Conclusions are made in section 4.

2. Technical Approach

The overall system is summarized in Fig 1. The image segmentation by region growing provides the segmented brain parts which contain coherent region properties like gray scale and texture. The symmetry property extraction basically obtains symmetry affinity matrix for both 2D image slices and 3D volumetric

sequence. From the brain segments and symmetry affinity matrix, non-symmetric regions are extracted by Kalman filter using the 3D filtering. They are further used to detect brain injury.

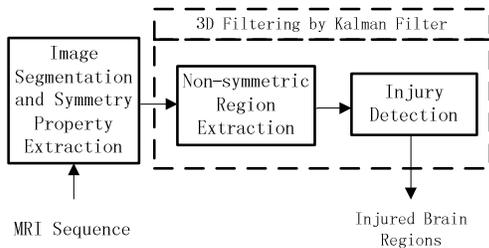


Fig 1. The overall diagram of the proposed method.

2.1. Image Segmentation and Symmetry Property Extraction

In order to partition brain into functional parts, images are segmented by a region growing algorithm, which examines the neighboring pixels of the ‘seed point’ and determines if a pixel should be added to the seed point by region similarity criteria. The region similarity criteria used are gray scale and texture coherences. Furthermore, since the brain is highly symmetric, we continue to enforce symmetry as another similarity criterion. By using symmetry integration, the naturally symmetric parts in a brain are segmented more symmetrically. The segmentation results are displayed in Fig 2(b). The symmetry property in this paper serves two objectives:

- (1) It is used in symmetry-based image segmentation.
- (2) It is applied to non-symmetric region extraction.

For both purposes, a symmetry affinity matrix defines the symmetry property. The global symmetric constellations of features [6] is used to detect the reflective symmetry axis for brain. Based on the axis, the symmetry affinity matrix is computed by the curvature of gradient vector flow (CGVF) [5]. If the two points have non-symmetric fields based on the axis, their CGVF should be highly different, indicating a larger symmetry affinity value. As shown in Fig 2(c), the red areas in symmetry affinity matrix contain non-symmetric parts with high symmetry affinity values. We compute the mean symmetry affinity value of the region, and use it as a region feature to detect the injury.

2.2. 3D Filtering by Kalman Filter

After obtaining the brain segments and symmetry affinity matrix of the brain image, the Kalman filter is used to detect the brain injury. The Kalman filter is regarded as a highly efficient tracker and smoother

that is widely used in image filtering, video tracking and pattern recognition. The Kalman filter addresses the problem of estimating the state x of a controlled process given the measurement z_k in the k th image frame as shown below,

$$\hat{x}_k = \hat{x}_k^- + K_k (z_k - H\hat{x}_k^-) \quad (1)$$

where \hat{x} is the system state to be tracked, and the prior state estimate \hat{x}^- is updated as follows,

$$\hat{x}_k^- = \hat{x}_{k-1} + Bu_k \quad (2)$$

and the measurement gain is computed as,

$$K_k = P_k^- H^T (HP_k^- H^T + R)^- \quad (3)$$

where P and R refer to covariance of the measurement and update noise, respectively. H is the controlling matrix indicating the trajectory of the state x , and B is the controlling matrix of the user input. The state variable x in this paper refers to the region properties to be filtered and detected for the injury. The input vector u is set to zero due to no control input in our system. The brain injury detection is described in the following two subsections.

2.2.1. Non-symmetric region extraction

This process uses the Kalman filter to track regions from all MRI scans in a MRI sequence as 3D data, and filter out the symmetric regions and extracts the non-symmetric regions that contain the injury. The Kalman filter regards the mean symmetry affinity value of region as the state variable x , and it is the state to be tracked and filtered. The starting regions for tracking are extracted using the following procedures:

- (1) Symmetry affinity matrices in sequence are added up to form a 3D symmetry affinity volume matrix.
- (2) A local window searches within affinity volume to find out the position having the highest 3D symmetry affinity density. This position is the highest non-symmetric location having most of the injury regions.
- (3) The regions containing the above positions are used as the first several regions for tracking. Since most of these regions correspond to real brain injury regions, the tracking process can converge to the state of the real injury.

The tracking trajectory shown as the blue solid line in Fig 3, converges to the smoothed state estimation, which is the symmetry affinity of the real injury region we need to track, and the highly noisy observations shown by the dashed line far below 20% of the estimation, are filtered out as the symmetric regions. The extracted non-symmetric regions are shown in Fig 2 (d). The results in the same sequence are obtained by

a single tracking process. By these proposed steps, all the injury is included in the non-symmetric regions.

2.2.2. Injury Detection

The injury detection obtained only from the non-symmetric regions rejects the redundancy and improves the accuracy of detection. In this step, the state variable of Kalman filter tracking is changed from the mean symmetry affinity of the region to the mean gray value and the 2D position of the region. Thus, a 3-dimensional state vector x in equation (1) is obtained. The filtering procedure is similar to as stated before. The smoothed state estimation is the mean gray value and 2D position of the real injury regions. The noisy state observations of regions 20% away

from the smoothed trajectory are rejected as the non-injury. The final detected injury is shown in Fig 2(e).

3. Experimental Results

3.1. Datasets

The datasets we used are two MRI sequences A and B, taken at different time from the same patient, provided by Loma Linda University Medical Center. Example images are shown in Fig 2(a). Each sequence has 20 MRI scans. Two MRI scans have different angle, brightness, size and intensity. In our case, registration is not required since sequences are analyzed separately.

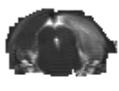
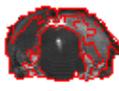
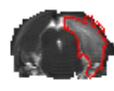
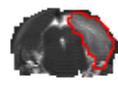
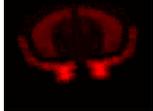
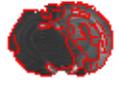
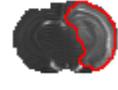
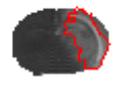
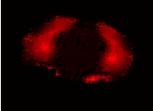
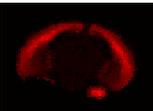
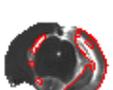
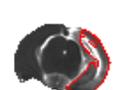
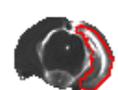
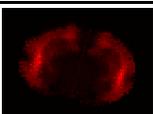
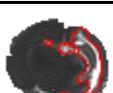
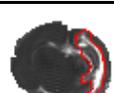
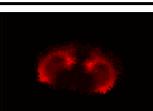
MRI#	(a)Original	(b) Segmentation	(c)Symmetry Affinity	(d)Non-symmetric Regions	(e) Injury Detection (this paper)	(f) Injury (ground-truth)	(g) Error Rate
A9							8.95%
A10							8.83%
A12							10.24%
A14							11.57%
B9							7.16%
B10							8.34%
B12							8.82%
B14							10.19%

Fig 2. The results of the proposed method for 2 different MRI sequences taken at different time for the same patient.

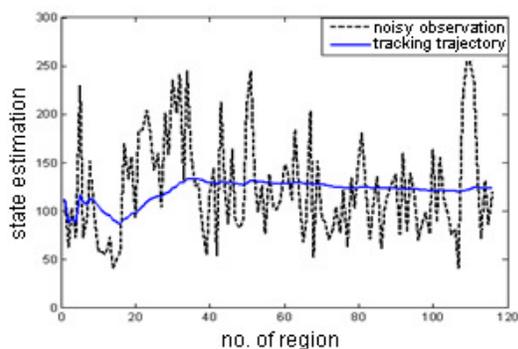


Fig 3. State estimation using the Kalman filter.

3.2. Injury Detection by the Proposed Method

Fig 2 displays the injury detection results for MRI sequences #A and #B for different steps of the proposed approach. The injury detected by our method in Fig 2(e) is compared to the ground-truth injury in Fig 2(f). It can be seen that the injury is visually close to the ground-truth with small variations in the boundary area. By finding the overlap and non-overlap area compared to the ground-truth, the percentage of non-overlap area determines the error rate, as shown in Fig 2(g). Since the sequences are among the challenging cases, the error rate shown in Fig 2(g) is satisfactory. The error rate in sequence #A is higher because the injury has more diffused boundary as can be seen in image #A12 in Fig 2, so it is challenging for image segmentation to detect the injury boundary. Table 2 shows the results of the two MRI sequences with 20 MRI frames for each. Our method obtains an overall volumetric error rates below 10%, a promising results under these challenging injury detection conditions. The MRI sequences #A is scanned 2 days prior to #B, so its injury is more severe with a higher percentage of injury. The proposed method is compared to the method in [4], an automatic MRI injury detection method published recently. The method proposed in this paper has a better error rate as shown in Table 1. The advantages of this paper over the work in [4] are that in the final discrimination between injury and non-injury, the proposed method not only uses symmetry and gray scale as features like the work in [4], but it also uses 2D position as an additional feature. As a result, the injury detected in [4] has more noisy non-injury regions near the boundary of real injury. Furthermore, the Kalman filter is more robust to track the real state of injury which also leads to lower error rate.

Table 1. Results of the proposed method and comparison.

MRI #	Total Brain Volume	Total Injury Volume	Injury Volume (Ground-Truth)	% of Injury	Error Rate (this paper)	Error Rate (work in [4])
A	83296	16033	17260	19.25%	9.82%	11.21%
B	78572	14398	15106	18.32%	8.64%	9.17%

4. Conclusions

This paper provided a brain injury detection method for MRIs. The 3D filtering technique is explicitly used to detect non-symmetric and injury regions using Kalman filter tracking and state estimation. Both the qualitative and quantitative results on the data from the two MRI sequences showed that the computed injury closely approximates the ground-truth. In the future we will evaluate the approach on larger datasets.

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