Symmetry Plane Detection in Neuroimages based on Intensity Profile Analysis

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Abstract— Symmetry plane identification is a critical initial step in brain image analysis, either done manually or automatically. Automatic extraction of the symmetry plane can provide an initial estimate for brain image registration, pathology assessment and disease diagnosis. This paper presents a novel technique for extracting the mid plane from volumetric magnetic resonance images (MRI). It is a theoretically simple approach that utilizes anatomical and radiological properties. The method is straight-forward to implement without the need for any prior segmentation. The efficacy of the proposed method was tested on brain MRI while investigating the robustness against rotation, intensity non-uniformity, noise and pathology. The method was compared with a cross-correlation based technique and the results show the viability of the approach.

Keywords- Medical image analysis; brain symmetry; mid-sagittal plane; inter-hemispheric fissure; MRI

I. INTRODUCTION

Advances in neuroimaging techniques have facilitated in vivo visualization of brain. When utilizing these images for diagnosis, visual interpretation is still the common practice used in clinical settings. The research in brain image analysis can improve accurate diagnosis of brain disorders by providing quantitative measures.

The human brain exhibits approximate bilateral symmetry. The two brain hemispheres which have similar shapes are connected by corpus callosum. In the boundary between the two hemispheres is the longitudinal or inter-hemispheric fissure, which is a dark, deep groove (See Fig. 1). Although real separation surface is not perfectly planar, mid-sagittal plane (MSP) is commonly considered as a plane passing through this boundary. Knowing the exact location of the MSP has many applications. In brain image registration, mid-sagittal plane detection is a key step. It can bring different images into a common coordinate system like Talairach-Tournoux [1]. On the other hand, symmetrical plane helps identifying brain pathologies like stroke or tumor by comparing to healthy regions of the brain. It is necessary for radiologists to analyze brain images taken from several patients or different modalities in a standard neuroanatomical space. Mid-sagittal plane is usually taken as the reference plane and is located manually by a neuroanatomy expert. However, manual methods are operator dependent and accurate reproducibility is hard to achieve. Therefore, a robust and accurate automatic technique can be useful not only in research, but in clinical practice. However, detecting the symmetry plane is difficult due to various noise artifacts, pathologies and tilted head scans. The goal is to have robust

estimates even in the tilted, pathological and noisy brain images.

Figure. 1. T1-Weighted MRI: Axial View of the Brain.
(Two slices at different locations)

Due to the high contrast between different soft tissues and non-use of radiation, MRI has widely been used for studies of brain abnormalities. Falx cerebri can be clearly seen in MRI images as a hyper-dense, pencil-thin line (see Fig.1). It is one of the toughest meninges and it descends vertically in the longitudinal fissure between the cerebral hemispheres. Even though inter-hemispheric fissure (IF) actually has a zigzag configuration, it is most often simplified as a planar surface. The IF contains cerebral spinal fluid (CSF) that gives a weak MR signal on T1-weighted images [2,3]. Therefore, image intensity in this region is generally low.

Based on these anatomical and radiological properties, we present a method for locating mid-sagittal plane in T1-weighted MRI images.

II. RELATED WORK

A number of automatic methods have been proposed to identify symmetry plane or mid-sagittal plane (MSP) of the brain. These methods either depend on a similarity-measure or they take an approach based on landmark detection. In the former, MSP is defined as the plane that maximizes a symmetry criterion. In these methods ([4-10]), a search is performed to find the plane that maximizes the similarity measure. Usually, the image is reflected across the initial plane and cross-correlation is used to measure the similarity between the original and the reflected images. These methods also rely on an initial plane computed by principal axis of inertia or edge detection. Since a similarity criterion is considered in this approach, they do not perform well

when the brain image contains asymmetry due to pathology. Another disadvantage is the high computational cost.

In the second approach, a landmark is chosen (usually, the longitudinal fissure) and then MSP is defined around this region based on intensity or texture properties. In [11], Brummer presented a MSP detecting technique based on a 3D variant of the Hough transform (HT). A series of 2D HTs are performed on standard coronal or trans-axial scans to get straight lines. MSP is considered as the major plane appearing in the scans. In the method by Smith and Jenkinson [12], average brain radius is estimated using image histogram and a symmetry score is calculated for all possible mid-plane orientations. Then, for each resulting line, the symmetry score for all lines perpendicular to this mid-plane is calculated and finally from the peak score value, MSP is estimated. Hu and Nowinski [13] presented a method in which they defined MSP as a plane formed from inter-hemispheric fissure line segments. By minimizing a local symmetry index around the mass centre, fissure line segments are localized on pre-determined axial slices. After removing outliers with the help of histogram, MSP is estimated using least square error fit. In the method by Volkau et al. [14], Kullback-Leibler (KL) measure is computed on sagittal slices by comparing each slice to a reference slice. By using the slice that gives the maximum KL measure, MSP is estimated. Etkin [15] proposed feature-based method for detecting MSP. For each slice of the volumetric image, row by row image intensity analysis is performed and a line is fitted using RANSAC (Random Sample Consensus). It is implemented on MR axial PD images. In [16], MSP is estimated by detecting falx cerebri in CT images. However, falx cerebri may not be visible in all scans.

These landmark based methods are generally robust to brain asymmetries caused by pathologies. The existing methods, however, can be sensitive to the outliers.

Although a variety of works has been done in addressing the issue of MSP detection, still there is no method commonly accepted as the best. For an algorithm to be used in clinical setting, it has to be fast, robust and accurate [2,13]. Existing techniques leave significant room for better applicability and accuracy.

In our approach, we consider the MSP as the plane that best fits the boundary between the two hemispheres. Our method does not present limitations with respect to the initial orientation of the image or the asymmetry present.

III. METHODOLOGY

Our algorithm for detection of MSP is based upon the fact that the longitudinal fissure (LF) is the only major plane that appears darkest in T1-weighted MRI images. Our goal is to extract the MSP of a brain from its volumetric MRI data consisting of stacks of 2D slices. 3D data is first processed as individual 2D slices assuming that MSP is a planar surface.

Inter-hemispheric fissure appears dark and dense in T1-weighted MR images. Although it is not clearly visible in all slices, intensity profile of each slice has a distinct intensity pattern along where the fissure is present. By exploiting this property, we analyzed the intensity profile along lines drawn

in multiple angles. Best possible line that fits the inter-hemispheric fissure is estimated. Each 2D slice is analyzed independently and finally the mode is taken as the angle of the MSP to vertical axis.

Angle is measured anticlockwise from the orientation to the vertical axis where the angle is taken as 0° .

For computational efficiency and robustness towards local minima, a multi-scale approach was applied by reducing the resolution of the original image. An approximate location of the MSP was computed from images of lower resolution and then it was estimated more precisely in images with higher resolution. We found that sub-scaling to 1/4 of the original image is the lowest resolution that still reliably gives a line which is close to the final solution.

The procedures are as follow:

1. Read the brain volume data.
2. **For** each slice **do**
3. Compute the centroid of the image
4. Sub-scale the image slice to give an image with lower resolution.
5. **For** each sub-scale **do**
6. Rotate a straight line that passes through the centroid from 0° to 180° in 1° intervals:
7. **For** each angle θ **do**
8. Compute the intensity score by summing the intensity values along the line and keep track of the angle
9. **End for**
10. Choose the angle θ_0 with the minimum score
11. **End for**
12. On the original image, perform a localized search around θ_0 , between -5° and 5° by measuring the intensity score
13. Estimate the best-fit line by taking the minimum intensity score
14. **End for**
15. Estimate the best plane for the 3D volume by taking the mode of the angles obtained from all slices.

For illustration, a distribution plot of intensity scores at each angle is shown in Fig.2.

The optimal angle can be located within 1° accuracy. By estimating the best-fit plane, the algorithm succeeded in disconnecting the two hemispheres of all the images. Our approach has a key advantage of insensitivity to smooth intensity variation which is a common problem in MR images. We also found that the method works well for lower resolution images as well.

Figure 2. Distribution plot of the intensity score at each angle

IV. EXPERIMENTAL RESULTS

The dataset comprises of 12 T1-weighted axial MR scans of normal and pathological cases. The MRI datasets were chosen from IBSR (<http://www.cma.mgh.harvard.edu/> and BrainWeb (<http://www.bic.mni.mcgill.ca/brainweb/>). A subset of the data obtained from the above image databases was also used in [5]. The size of each image volume was $181 \times 217 \times 181$ voxels and slice thickness was 1mm. Phantom data from BrainWeb were used to analyze the effect of noise and intensity non-uniformity in the final results. The robustness of the algorithm to the orientation of the image was also checked. For all data used in this study, good results could be obtained under qualitative judgment. We also performed a quantitative evaluation comparing with a commonly used existing technique. Some of the results obtained are shown in Fig.3-Fig.6.

Figure 3. Left: Normal brain, Right: 30° rotated image.

Figure 4. Images with Asymmetry.
Left: Minor lesion, Right: Major lesion.

Figure 5. Noise Effect: Left: 3% Noise Right: 9% Noise

Figure 6. INU Effect: Left: 20% INU Right: 40% INU

V. EVALUATION

Our results were visually inspected by an expert and were judged to be consistently correct. 90% of the cases were scored as highly accurate.

Although our approach is not based on a similarity score, considering the property that the brain is approximately symmetrical along the MSP, below we provide a quantitative comparison with other similarity based techniques.

A. Comparison with Other Techniques

Since cross-correlation is one of the most commonly used techniques in MSP detection algorithm, we used this for evaluating the performance of our method. The correlation coefficient between two images A and B can be calculated as:

$$cc = \frac{\sum_i (a_i - \bar{a})(b_i - \bar{b})}{\sqrt{\sum_i (a_i - \bar{a})^2} \sqrt{\sum_i (b_i - \bar{b})^2}} \quad (1)$$

Where a and b are the intensity values in the i -th pixel and $\bar{a}$ and $\bar{b}$ are the respective means of the entire image.

For each image we rotated our estimated line in varying angle ranging from -5° to 5° and computed the cross-correlation as described in [9]. The line that gave the maximum value of cross-correlation was compared with the line estimated by our method. Two lines coincided in one third of the cases. In the rest, our approach showed visually better results (See Fig.7-Fig. 9), even though its cc score was slightly lower. The results show the superiority of our method compared with the cross-correlation based approach. In particular, our method is robust to large pathological asymmetry and noise. Since our method performs calculations on each slice and then taking the mode of the results give accurate results, it is insensitive to pathologies that normally reside in a small part of the brain.

Fig. 7. Normal brain MSP projections on axial slices. Left: Proposed method($cc=0.9315$). Right: Maximum $cc=0.9338$

Fig. 8. Noisy image MSP projections on axial slices. Left: Proposed method($cc=0.8043$). Right: Maximum $cc=0.8370$

Fig. 9. Pathological image MSP projections on axial slices. Left: Proposed method($cc=0.8106$). Right: Maximum $cc=0.8205$

B. Quantitative Evaluation

If the symmetry is perfect, we expect that the histograms of intensity distribution on the left and right hemispheres will be exact replica of each other. Hence, the degree of dissimilarity between the two hemispheres separated by the estimated symmetry plane can be computed on the corresponding histograms using the Bhattacharyya distance (BD):

$$B_D = 1 - \sum \sqrt{H_1 * H_2} \quad (2)$$

where H_1 and H_2 are the two intensity histograms. This similarity score is in the range of 0 and 1, where 0 means that the histograms are perfectly similar.

TABLE I. COMPARISON OF COMPUTED BD VALUES

Image	B_D (Our Method)	B_D (cc Method)
Image1	0.1395	0.1358
Image2	0.0896	0.0896
Image3	0.1405	0.1405
Image4	0.0308	0.0315
Image5	0.1044	0.1081
Image6	0.0895	0.1002
Image7	0.2832	0.2832
Image8	0.0879	0.0867
Image9	0.1040	0.1059
Image10	0.0921	0.0994
Image11	0.0376	0.0452
Image12	0.0241	0.0339

Based on this BD measure (See Table 1), a paired t -test was performed to find out the statistically significant difference between the mean of our method (mean = 0.102, stdev = 0.068) and that of cross-correlation based method (mean = 0.105, stdev = 0.066). The results (Degrees of freedom=11, t -value $t = 2.267$, p -value $p = 0.045$ and the

probability value for 95% confidence level $\alpha = 0.05$) indicate that we have a statistically significant lower (better) mean value at 95% confidence level.

Fig. 10. Midline shift [17].

VI. CONCLUSION AND FUTURE WORK

We have presented a novel but simple technique for detecting the mid-sagittal plane in MR images. The method exploits both anatomical and radiological properties of the inter-hemispheric fissure in T1-weighted MR brain images. It does not require any pre-processing step like removal of extra-cranial tissues. The method is robust with respect to noise, intensity non-uniformity and orientation. The algorithm achieved good results on pathological images in our experiment. However, in severe pathological images, inter-hemispheric fissure can deviate from its mid-plane, resulting in a surface that cannot be assumed as a plane anymore (See Fig. 10). This is a limit of all existing approaches including ours. Although some initial steps have been taken in this direction on non-brain images [18], the problem is yet to be solved.

Our future work involves dealing with the case of non-planar inter-hemispheric fissure. More quantitative validation on a “gold standard” dataset defined manually by a group of neuroanatomy experts will also be considered.

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