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FEATURE-BASED BRAIN MID-SAGITTAL PLANE DETECTION BY RANSAC

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ABSTRACT

Mid-sagittal plane passes through the border between the two hemispheres of a brain, which are roughly symmetric. Image-based detection of mid-sagittal plane has applications to a number of computer and human tasks, such as image registration and diagnosis. The problem requires robust methods to inherent asymmetries between the two hemispheres, pathalogical abnormalities that further degrade the hemispheric symmetry, and degradations in image quality. Furthermore, it is desirable to have a computationally feasible method because mid-sagittal plane detection is often a pre-processing step that is followed by more compute-intensive algorithms. In this paper, we introduce a novel feature-based mid-sagittal plane detection algorithm for MR brain images. The proposed method is robust even in the presence of very large abnormalities, can cope with outliers in the detected features, and is very fast. Its robustness to abnormalities stems from its hierarchical operation. A 3-D MR data is first processed as 1-D image lines, then as 2-D slices, and finally 3-D volume. This makes it possible to detect the mid-sagittal plane as long as two image lines are not affected by pathalogical abnormality, which is a significant improvement over the literature. Furthermore, the use of outlier-robust RANSAC algorithm for fitting a mid-sagittal line to the detected feature points in each slice provides robustness to the inaccuracies in the detected feature points.

1. INTRODUCTION

The brain of a healthy subject exhibits a rough bilateral symmetry with respect to the interhemispheric fissure that bisects the brain. This fissure is commonly referred to as anatomical mid-sagittal plane (MSP). Figure 1 shows the location of the mid-sagittal plane for a 2-D slice as a white line. As it can be observed from the figure, the two hemispheres are not perfectly symmetic. The inherent deviations from the symmetry are caused by normal morphological differences between the hemispheres. For example, in most subjects, the right frontal and the left occipital lobes are larger than their respective counterparts. In addition to the inherent factors that apply to all, patients with abnormalities, such as tumors and lesions, will have large asymmetries between two brain hemispheres. In this paper, we are concerned with robust detection of the mid-sagittal plane in magnetic resonance (MR) brain images independently from morphological differences between the brain hemispheres, and the existence and the severity of pathalogical abnormalities.

The detection of the MSP is essential for both human-based and automated brain image analysis. The MSP location can be employed to estimate the head orientation. Because non-optimal head position during scanning may cause the same brain organ to appear in different slices for the right and left hemispheres, making a diagnosis may be difficult. By computing the MSP, the volumetric data can be resampled to elucidate the normal and pathalogical asymmetries. For the automated brain image analysis, both low- and high-level applications can benefit from the MSP detection. At the low-level, the computed MSP parameters replace the rotational and translational parameters in the registration of two volumes; hence, it makes the registration problem simpler. For the high-level image analysis, because a large amount of asymmetry may indicate a pathological abnormality, mid-sagittal plane may serve as a reference to evaluate the hemisphere symmetry for computer-aided detection (CAD) purposes.

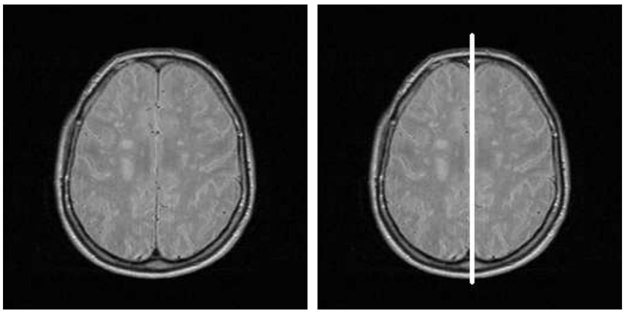

Figure 1: The mid-sagittal plane location for the brain MR slice on the left is shown as a white line on the right

The existing methods for MSP detection follow either a feature-based or a symmetry-based approach. In the feature-based approach, the aim is to directly determine the interhemispheric fissure from its intensity and textural features. In [2], Brummer proposes a 3-D extension of Hough transform by observing that MSP appears as long lines in the coronal view. His approach involves detection of lines from the edge maps of 2-D brain image scans, and then fitting a plane to the detected MSP line candidates. In [6], Marais et al. use linear snakes to extract fissure lines in each slice, and then fit a plane to these lines by orthagonal regression. In general, feature-based methods are robust to abnormalities and morphological interhemispheric differences because they do not assume symmetry. The existing approaches, however, are sensitive to the outliers in the extracted features.

In the symmetry-based approach, mid-sagittal plane is defined as the one that maximizes the similarity between the brain and its reflection. The methods following this approach [1, 5, 7, 8, 3, 4] first define a parameter space that describes the MSP, a similarity measure, such as cross-correlation, to assess the interhemispheric symmetry in the selected feature space, such as intensity or edges [5], and a search method and search criteria to find the parameters that maximize the similarity measure. The main problems with this type of approaches are their sensitivity to asymmetries and the computational cost that results mainly from the search step. Their main advantage is the generalizability of the methods to other medical image modalities, such as CT and PET [7].

In this paper, we propose a feature-based MSP detection algorithm that uses RANSAC to find interhemispheric fissure in each slice and the MSP in the 3-D. Our main contributions are: 1) The use of RANSAC to estimate MSP lines from feature points provides robustness to outliers, which the existing feature-based algorithms lack, 2) we propose a novel model-based feature-point detection method that results in robust detection of MSP even in the presence of very large-sized abnormalities, and 3) a significant improvement in the computational speed of MSP detection compared to even the feature-based algorithms.

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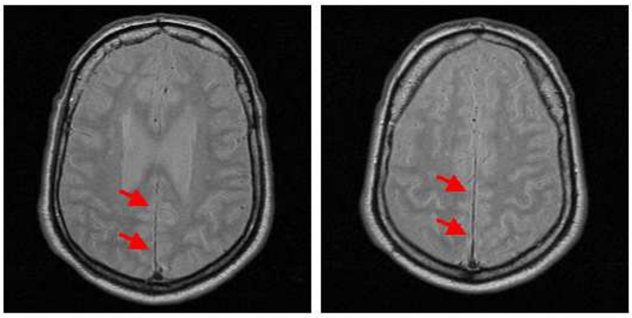

Figure 2: Interhemispheric fissure appears hypo-intense (dark) in PD images (arrows point to the fissure)

2. PROPOSED ALGORITHM

Our aim is to detect the MSP of a brain from its volumetric MR data. This 3-D data corresponds to the axial view of the brain and are composed of multiple 2-D slices. The proposed algorithm first analyzes each 2-D slice independently to detect the feature points that correspond to the interhemispheric fissure. This process involves model-based analysis of the intensity profile along each image line (1-D row-by-row image intensity analysis) to determine whether the profile includes the fissure, and if it includes, to detect its position. After that, RANSAC fits a line to the detected feature points for each slice. As in the first step, each slice is analyzed independently from the others. Finally, the third stage integrates slice lines to determine the optimal MSP plane. In the following, we first explain the model-based feature point detection in each image line. After that, Section 2.2 introduces RANSAC-based line fitting to the detected feature points for each slice. Finally, Section 2.3 explains the detection of the MSP from the slice lines.

2.1 Line-based feature point extraction

Interhemispheric fissure appears hypo-intense (darker) in the proton density (PD) MR images as shown in Figure 2. Although the fissure is not visible in all slices, distinguishable intensity patterns occur along the image rows wherein the fissure appears. Figure 3 shows a typical row-projection of intensity for the rows having the fissure. The row-projection of intensity shows a peak followed by a local minimum in both left and right sides. Anatomically, both peaks (points 1 and 5 in Figure 3) refer to the skull region, and the minima (points 2 and 4 in Figure 3) correspond to the background that fills the region between the skull and the intracranial region. Between the left and the right minimum, brain tissues, e.g., white matter, gray matter, and cerebrospinal fluid, exist and the PD intensity shows less variation. The fissure location is noticeable as a local intensity minimum that is located almost equidistant to the left and the right minimum (point 3 in Figure 3). Because low intensity projection values may stem from other factors than the existence of the fissure, the detection of local minima alone would not suffice. In the following, we explain a unified method that not only detects those points but also verifies whether the row projection fits the anatomical model or not.

Among the feature points, we first detect the peaks and valleys on the right and the left sides. These points are detected by first adaptively defining an intensity level to compensate for the MR intensity variations from one scan to another. This value is defined as the average intensity value of the processed row. After that, we identify the regions where positive and negative crossings of this intensity level occurs. For example, if we compute the average intensity level as 200 for the projection in Figure 3, point 1 can be defined as the maximum value between the first positive and the first negative gradients that cross intensity level 200. Point 2, on the other hand, is defined as the minimum between the location of the negative gradient found when searching for point 1 and the next positive gradient that passes through intensity value 200. The peak and the valley on the right side, i.e., points 5 and 4, respectively, are defined similarly and detected by scanning the projection from right to left. We also verify the conformance of the detected points to the projection model shown in Figure 3. The model indicates that the points 1 and 2 should be to the left of the points 4 and 5, i.e., $x_1 < x_2 < x_4 < x_5$ where x_n indicates the x-coordinate of the n^{th} point. This is verified after independently computing these locations. If this is not the case, it is concluded that the line is not a valid MSP hypo-intense line.

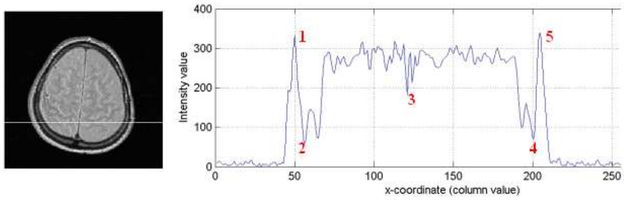

Figure 3: Row intensity projection (right) along the highlighted row (left) shows five landmarks than indicate the existence and the location of the fissure

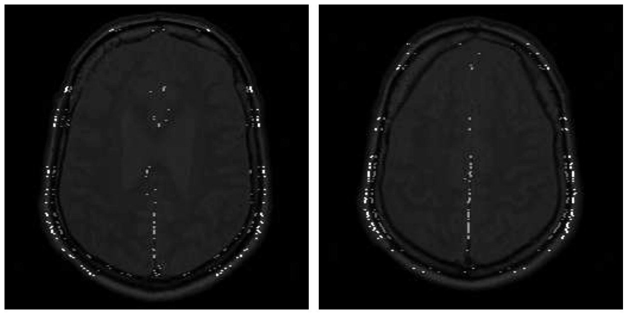

Figure 4: The detected five feature points for each line that fits the proposed model

After the computation of the peaks and valleys, we first define the search interval for point 3 from the locations of the other points. Basically, we compute the distance between point 1 and point 5 and define half of it as the length of the interval, shown as $\triangle$ in Eqn. 1. The window center, W_c, is assigned as the mean of point 1 and point 5 coordinates. After that, x_3 is tentatively assigned according to Eqn. 6 as the coordinate of the minimum intensity value in the defined interval. As a result, a minimum is located whether or not the projection fits the model. The projection model, shown in Figure 3, indicates that point 3 should be roughly equidistant to points on the left and the right. To impose this constraint, we validate the tentative x_3 value by computing its distance to the window center. This distance value is compared with a threshold value that is computed in Eqn.6 as the higher of the quarter of the window length and five (a fixed value of five is used to handle the cases when the window is very small). This model constraint considerably reduces the number of outlier feature points (approximately 30-40% of initial points can be eliminated). In Figure 4, the remaining features after this step are shown. In some slices, almost all of the resulting feature points (point 3s) perfectly align with the MSP line. In the next section, we explain how to robustly fit a line by RANSAC to these feature points.

$$\triangle = (x_5 - x_1) \times 0.5 \quad (1)$$

$$D_{thr} = max(5, 0.25 \times \triangle) \quad (2)$$

$$W_c = (x_1 + x_5) \times 0.5 \quad (3)$$

$$W_l = W_c - 0.5 \times \triangle \quad (4)$$

$$W_r = W_c + 0.5 \times \triangle \quad (5)$$

$$x_{3cand} = \tilde{x} | I(\tilde{x}) \leq I(x), \forall x \in [W_l, W_r] \quad (6)$$

$$x_3 = \begin{cases} x_{3cand} & | x_{3cand} - x_c | \leq D_{thr} \\ -1 & otherwise \end{cases} \quad (7)$$

2.2 Slice-based mid-sagittal line detection

Given the feature points, we would like to fit a line to point 3s in each slice. Because the random sampling consensus (RANSAC) algorithm is a robust model-fitting algorithm to a number of points even in the presence of significant amount of outliers, we use RANSAC for mid-sagittal line detection. Compared to the Hough transform, which is used by edge-based mid-sagittal plane detection methods, RANSAC provides robustness to the outliers in the feature points and can compute the line parameters in a very speedy manner. In general, RANSAC can be summarized as follows:

Assume:

- The parameters can be estimated from N data items (In our case, N = 2 for a line)
- There are M data items (feature points) in total.

Then, the steps of the algorithm:

1. select two data items (feature points) at random
2. estimate the line parameters: slope and the intersect
3. evaluate the fit of the line to M data items
4. if the current line has a better fit than the best one found so far, accept the current as the best line
5. repeat L times

We modified steps 1 and 3 in the above general framework. Step 1 chooses two feature points at random. This is not the optimal solution because it does not utilize the domain knowledge. In our case, most of the outlier feature points lie in the upper half of the image. As a result, we choose two feature points for parameter estimation only from the lower half of the image.

Step 3 evaluates the fit of the model. We define three measures for this:

- Average distance, D_{avg}, from the line to W_c of each slice
- The number of inliers, N_i: the number of feature points that are close to the computed line (we assign the feature points having distance less than three pixels as inliers)
- The percentage of inliers, P_i: the number of inliers divided by the total number of feature points in a slice

We only use D_{avg} to measure the fitness value of the current line. The line with the smallest D_{avg} value is accepted as the best line for that particular slice. The other two parameters, the number of inliers N_i and the percentage of inliers P_i, of the best-fitting line are used in the next section.

2.3 Volume-based mid-sagittal plane (MSP) computation

Up to this stage, we independently computed a line for each slice having sufficient number of feature points. As explained in the previous sections, hypo-intense fissure regions do not appear in all slices. As a result, some slices will have a better line fit than the others. To select the most accurate lines, we use the parameters N_i and P_i that are computed in the line computation stage by RANSAC. We define the best slice line as the one having N_i greater than some small number, such as ten, and the largest P_i value. The constraint on N_i is added to make sure that enough number of feature points have been detected for the slice with the largest P_i value. After the selection of the best slice, we compute the inliers to this line in each slice and re-compute the line to fit these feature points in the least-squares sense.

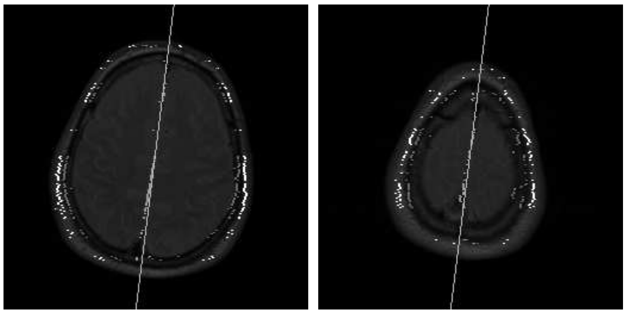

Figure 5: The detected feature points and the MSP for an oriented head

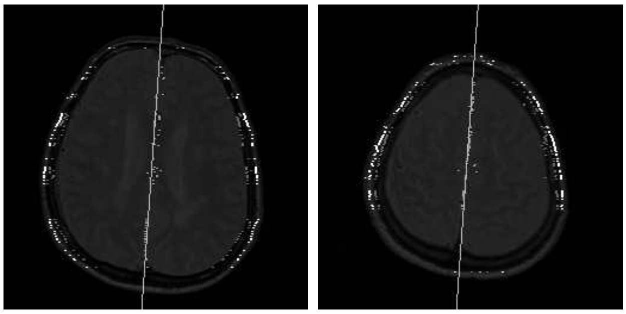

Figure 6: The detected feature points and the MSP for an oriented head

2.4 Analysis of the computational requirement

Compared to the feature-based methods that use edges, we use a model to select at most a single point for each image row. Because we also determine whether the row-projection fits the model, our method is robust to noise and pathological abnormalities. For the same reason, we detect much less number of feature points than the edge-based approaches. We only detect the feature points that are relevant to the problem. This not only increases the speed of the algorithm but also reduces the inaccuracies in the detection. The number of feature points can at most be as many as image height value per slice. In practice, because of the background region and the disappearance of the hypo-intense region in some regions, the number of feature points is approximately one quarter of the image height per slice. This significantly speeds up the algorithm.

3. RESULTS

In the following, we show some results on a data set obtained from Leiden University Medical Center (LUMC). The dataset consists of 30 subjects with atherosclerotic risk factors (mean age 77.4 ∓ 3.4y). MRI was performed on a Philips Intera 1.5T whole body scanner at LUMC. We used dual-spin echo weighted images (TR/TE1/TE2: 3000/27/120 ms, FLIP: 90^o) with a FOV 220mm, 3mm slice thickness, no slice gap and 256×256 matrix. The proposed algorithm was able to detect the MSP line accurately in all of the cases. Figures 5- 8 show several of the results with the detected feature points. The results demonstrate the robustness of the algorithm to the head orientation, Figures 5 and 6 , and to the existence of abnormalities, such as white matter lesions in Figures 7 and 8. In addition to this, we also added artificial lesions and rotated the dataset to demonstrate the robustness of the proposed method. In Figure 9, the dataset was rotated 25 degrees for the slice on the left. For the slice on the right, a large lesion that is visible in two thirds of the brain has been added. The MSPs were detected accurately in both cases. Because the proposed method identifies the dark fissure line,

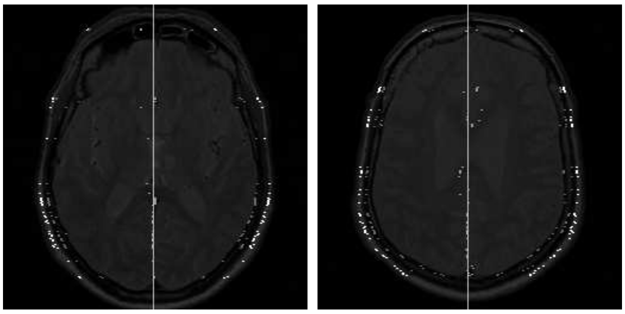

Figure 7: The detected feature points and the MSP in the presence of abnormalities

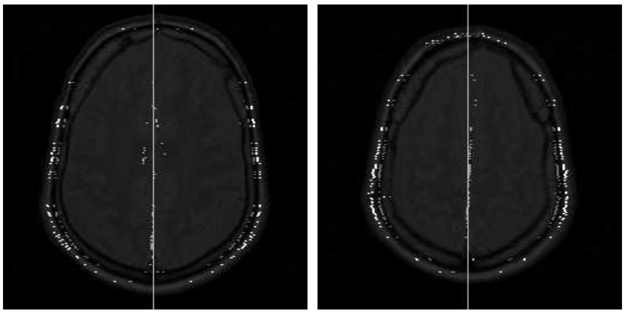

Figure 8: The detected feature points and the MSP in the presence of abnormalities

we added a large lesion directly on the fissure line to further test the algorithm. The results of that experiment have been shown in Figure 10. The MSP was detected accurately by the features detected correctly in slices that have smaller lesion.

4. CONCLUSIONS

We have introduced a novel feature-based brain mid-sagittal plane detection algorithm. The hierarchical approach and the explicit model of the intensity projection make the algorithm robust to abnormalities and outliers in the detected feature points. Because only relevant feature points are detected and processed further by RANSAC, the algorithm is also very fast. The algorithm also adaptively changes the intensity-based thresholds; hence, it should be robust to the applied MR protocol. One limitation of the proposed algorithm is that it currently requires the availability of the axial PD contrast to be able to detect the MSP. Because PD is one of the common contrasts in a typical brain MR scan, this is not a very limiting condition. Furthermore, intensity projections for other contrasts, such as T1 and T2, can also be modeled to identify the fissure points. Our initial experiments on this topic indicate that similar performance values can be obtained with other contrasts as well.

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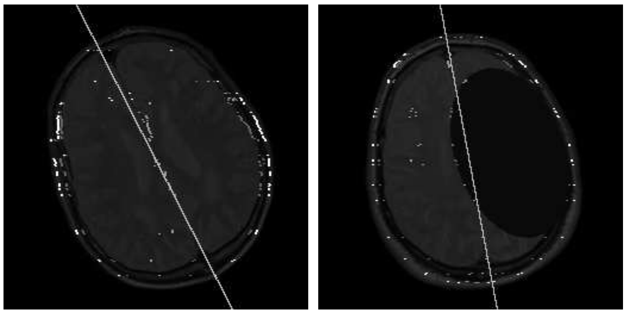

Figure 9: The results demonstrating the robustness of the proposed algorithm to head orientation and large-sized abnormalities

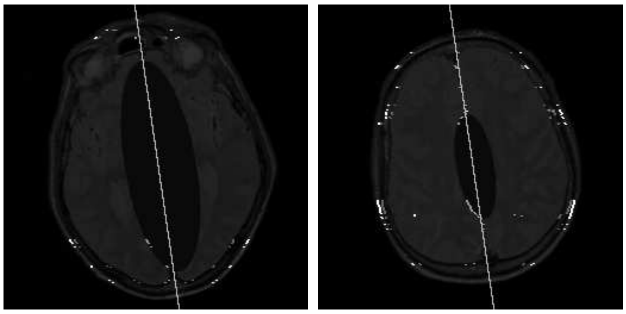

Figure 10: The MSP detected in the presence of abnormalities on the fissure

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