Mid-Sagittal Plain Detection and Correction Based Wavelet Transfrom and Principle Component Analysis

Ali M. Hasan
Al-Nahrain University- College of Medicine- Baghdad, Iraq
a.hasan4@edu.salford.ac.uk

Abstract— The Mid-Sagittal Plain (MSP) of Brain is an important initial step in brain image analysis because of providing an initial estimation for the brain, pathology assessment and tumor detection. The human brain is divided into two hemispheres and these hemispheres are approximately bilateral symmetry around the MSP, that's mean that most of structures in one side of the brain have a counterpart on the other side with similar shape and location. This paper presents a technique for detecting and correcting the MSP of brain from magnetic resonance images (MRI) by using Principle component analysis (PCA) method that computes the distinctive principle axes that are orthogonal to each other, and determine the orientation of the patient's head instead of depending on measuring symmetry to identify the MSP of brain.

Keywords-component; Magnetic resonance image (MRI); Principle compnent analysis (PCA); Mid-Sagittal Plain (MSP)

I. INTRODUCTION

The advances in medical imaging techniques provide facilities of internal visualization of brain. These medical images are used for diagnosing and visual interpretation by clinicians. The MSP identification is an important initial step in brain image analysis because of providing an initial estimation for the brain, pathology assessment and tumor detection [1, 2]. The human brain is divided into two hemispheres and these hemispheres are approximately bilateral symmetry around the MSP, that's mean that most of structures in one side of the brain have a counterpart on the other side with similar shape and location. The two hemispheres are separated by the longitudinal fissure that represents a membrane between the left and right hemispheres filled with CSF and it can be used to recognize the two hemispheres visually [3]. The two hemispheres separation process in the axial MRI brain scanning images can be done by recognizing the MSP along the longitudinal fissure which can be used as a reference for asymmetry analysis. The MSP of the brain has the same orientation of the patient's head. The symmetry of brain is an important indicator about the normality and abnormality of brain such that most pathology such as tumors, bleeding and stroke in the human brain can be determined by a symmetry based analysis of MRI brain scanning images. However, the growth of tumor cells can destroy the symmetry and curve the MSP of brain [4]. The MSP extraction methods can be divided into two groups [3, 5]; Content-based method is based on seeking a plane that maximizes a symmetry measure between both sides of brain [3, 5-9]. The major obstacle preventing this methods from wide adoption in realistic neuro-application is the difficulty of measuring symmetry and identifying the MSP of the brain for the pathological patients e.g. the air pockets and the presence of lesions should be ignored when computing the axis of symmetry [4]. Shaped-based method uses the geometric landmarks or topological features of the head such as inter-hemispheric fissure to extract and detect the orientation of MSP of the brain which denotes the symmetry plane [5, 10]. All parallel axial slices, the inter-hemispheric fissure lines are parallel with the same orientation of patient's head [11]. In this study, the concentration will be on shape-based method to determine the orientation of the patient's head instead of depending on measuring symmetry to identify the MSP of brain. The proposed method is based essentially on using PCA method to compute the distinctive principle axes that are orthogonal to each other. Those axes are used to characterize the patient's head by representing the spatial distribution of the mass. Such that any plane of symmetry in a body is orthogonal to a principle axis [5, 12].The remainder of the paper is organized as follows, in Section 2, we review some related work and introduce the contribution of this research. In Section 3, material and methods are described. The experimental results are discussed in Section 4. Finally, the conclusions are drawn in section 5.

II. RELATED WORKS

The Mid-Sagittal Plane (MSP) of the brain is a plane that separates it into two halves known as the two hemispheres of the brain. Identifying this plane is considered important for many automated systems that measures the similarity between the two hemispheres. Therefore, the detection of MSP is a topic that has been investigated for decades [13]. Liu, et al. [4] , Liu and Collins [14] and Ardekani, et al. [7] proposed an automated algorithm for detecting the MSP based on the symmetry axis that should have the same orientation of the patient's head. Hence, the process is that of searching for the orientation of the reflection line that maximizes the cross-correlation between the original image and the rotated image. Bergo, et al. [10] proposed an automated method for detecting the longitudinal fissure, which is clearly visible in T1-w images. The author assumed that the MSP contains a maximal area of

Cerebrospinal fluid (CSF), which appeared as a low intensity area. Therefore, the proposed method was based on searching of a sagittal plane that minimized the intensity mean. Ruppert, et al. [3] proposed an algorithm for extracting the MSP by searching the plane that maximizes a bilateral symmetry measure. The bilateral symmetry measurement was based on extracting the edge features from the MRI brain image. Then measuring the similarity using the correlation between the left and right hemispheres with respect to a candidate cutting plane. Jayasuriya and Liew [1] proposed an automated algorithm for detecting the MSP of the brain by exploiting the property that the longitudinal fissure in T1-w images appears as a dark area. A set of lines were drawn in multiple angles to analyze the intensity along these lines. The best possible line that fits the inter-hemispheric fissure which represents the angle of the MSP to the vertical axis was chosen. Nabizadeh and Kubat [15], Ray, et al. [16] and Saha, et al. [17] separated the brain into two hemispheres by finding the longest diameter that represents the MSP of the brain. Their algorithm included separating the brain from the background, finding the brain center, finding the brain's borderline, determining the lengths of all possible brain diameters and assign the longest diameter as the MSP of the brain. The previous works have shown different techniques for detecting MSP of the brain as summarized in Table 1. However, the intensity-based analysis methods (symmetry, fissure) might not be the optimal solution to identify the MSP, because they are sensitive to any pathological conditions that could induce asymmetries and displacement of anatomical structures of the brain [4, 13, 14].

In this study, the emphasis is on estimating the orientation of the skull that is identical to the reflection line and passes through the MSP of the brain [11, 14].

III. MATERIAL AND METHODS

The main objective of this research is to investigate the use of orientation of the skull to detect the MSP of brain and correct it. The proposed method includes the following steps; background segmentation, orientation determination, geometrical transformation, and centralize patient's head in the center of MRI slice. The flow chart of the proposed method is shown in Fig. 1.

A. Data Collection

The same dataset of MRI brain scans that was used in [12, 18], is used in this study. The dataset was collected were collected by using a SIEMENS MAGNETOM Avanto 1.5 Tesla scanner and PHILIPS Achieva 1.5 Tesla scanner.

B. Image Denosing

The removal of noise from noisy data to obtain the unknown signal is known as denoising. Magnetic resonance (MR) images are usually corrupted by random noise that makes a small random modification of the intensity in an individual or small groups. These modifications may be lead to erroneous

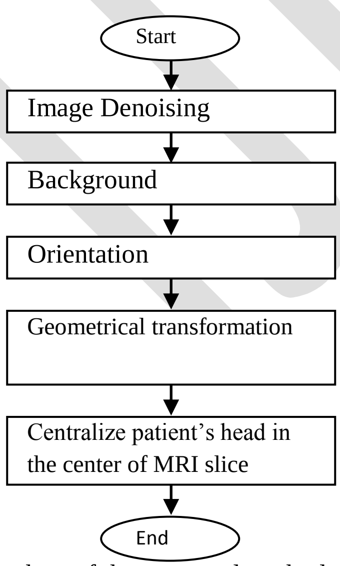

Figure 1: Flow chart of the proposed method.

segmentation and feature extraction. Recently, wavelet transform has been used significantly as a popular method in various applications for data analysis and image processing. Several algorithms based wavelet transform has been proposed for denoising of MRI images [19]. In this study, a wavelet transform based bilateral filter as described in [19] is used to denoise the MRI images. First, the MRI images are decomposed into multi-level to extract the approximation and the detailed sub-bands as shown in Fig. 2. Then, bilateral filter is used to denoise the approximation sub-band to improve the visibility of MRI images with preserving relevant edge features. Finally, inverse wavelet transform is performed to reconstruct the denoised MRI images.

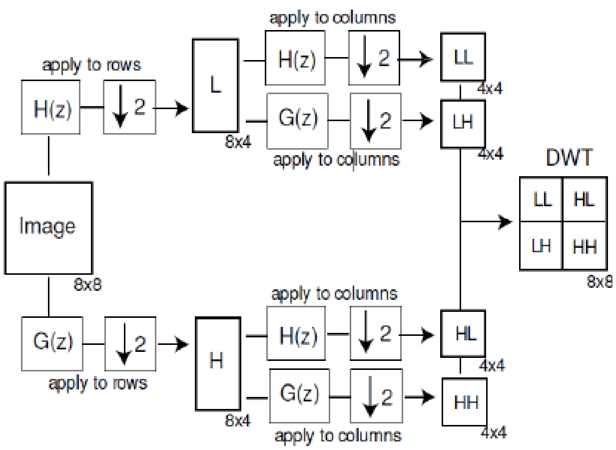

Figure 2: MRI image decomposition by two-dimensional wavelet transform.

Table 1: Summary of existing MSP methods.

Method	Features
Junck, et al. [20]	Symmetry/ Intensity cross correlation
Liu and Collins [14]	Symmetry/ Intensity cross correlation
Ardekani, et al. [7]	Symmetry/ Intensity cross correlation
Liu [5]	Symmetry/ Intensity cross correlation
Bergo, et al. [10]	Symmetry/ Intensity cross correlation
Ruppert et al. (2011)	Symmetry/ Intensity cross correlation
Prima and S. [21]	Symmetry/ Intensity cross correlation
Tuzikov, et al. [22]	Symmetry/ Intensity cross correlation
Jayasuriya and Liew [1]	Fissure/ Minimized the intensity mean
Hu and Nowinski [11]	Fissure/ Local symmetry index
Ray, et al. [16]	Longest diameter
Saha, et al. [17]	Longest diameter
Nabizadeh and Kubat [15]	Longest diameter

C. **Background Segmentation**

Due to the prior knowledge that the background intensity values of MRI brain slices is always approach to zero. Therefore, it is important to eliminate and exclude this part of MRI image from implementation because it normally has much higher number of pixels without meaningful information than the brain region [23]. In this study, histogram thresholding method is used as a simplest segmentation method to segment the background of MRI brain slice based on thresholding the intensity values by a specific threshold *T* value. Such that, if the intensity value of pixel is greater than *T* then the pixel is considered as brain region, otherwise is considered as background [24]. The *T* can be determined as either manually which is specified by user or automatically by using different approaches [25-28]. In this study, it is noted that the histograms of two different MRI T2-w images' have approximately the same shape of distributions [29] as shown in Fig. 3. Therefore, *T* value is selected experimentally and set to 0.1 after the effect of a range of threshold values 0.05, 0.1, 0.2, and 0.3 had been manually observed. Consequently, if an intensity value of pixel is less than 0.1, it is considered as a background. This histogram thresholding is implemented by using *im2bw* function with specific value of threshold in MATLAB Image Processing Toolkit [30]. Then it is followed by implementing a set of morphological operators in sequence to remove any holes that may be available in the head region. There are many morphological operators but only two operators are essential and can be combined in many ways to produce more complex morphological operators which can solve different problems in image analysis. These two operators are dilation and erosion. The dilation is an operation that is used to increase the size of objects which are located in the foreground or appeared as white pixels in binary images. While, the erosion is an operation that is used to increase the size of background objects and decrease the foreground objects in binary images [25, 31, 32]. Additionally, holes filling morphological operator is used to fill holes that are defined as a background region of a binary image and surrounded by connected borders of foreground regions [27, 33, 34]. In this study, the deficiencies of segmentation process are overcome by dilating the segmented MRI brain scanning image using dilation morphological operator.

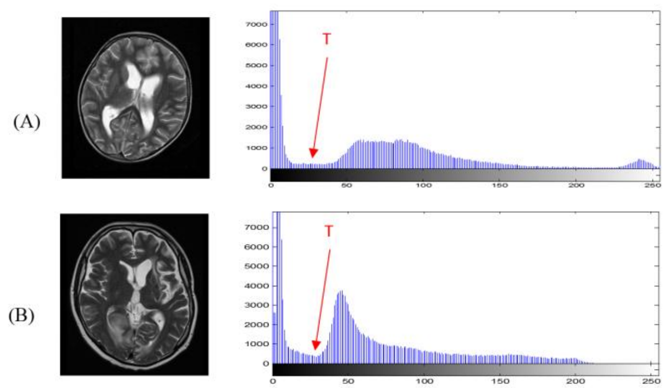

Figure 3: T2-w MR images of two different patients and corresponding histograms.

Then the internal holes are filled using holes filling morphological operator. Consequently, a binary mask with one's denotes the patient's head, and zero's denotes the background. This mask is then multiplied with the original slice image to produce a new slices image without background. Fig. 3 shows an example of how the MRI image is segmented, dilated and holes filled.

The PCA method essentially attempts to transfer the coordinate of original data to a new coordinate system. Such that the maximum variation in the data comes to lie on the first coordinate, it is known the first principal component. The second maximum variation in the data lies on the second coordinate and so on.

The most common steps that are followed by radiologists and clinicians in MRI units and specifically in MRI Unit of Al-Kadhimiya Teaching Hospital, include positioning and aligning the patient's head inside the head coil according to the laser light indicator, and using sponges to support and minimize the head tilt and rotation. This gives better MRI image quality [35]. Due to all brain slices in the same scan have the same symmetry axis orientation [4], it is possible to detect the degree of skewness to the left or right by using single slice in axial viewing instead of using all brain slices in context of reducing computational complexity. In this study, we assume that the patient's head may be skewed only either left or right.

Let D is an original two-dimensional data with two observations that are plotted on X and Y coordinates. The PCA is used to map linearly these coordinates into new X' and Y' coordinates, where X' extends along the direction of the maximum variation of given data and Y` is perpendicular on X` extends along the direction of the minimum variation of given data as shown in Fig. 4 [36]. In this study, D represents the coordinates of pixels in foreground part of the segmented MRI brain image, such that X=[X_1, X_2, …., X_n], and Y=[Y_1, Y_2, ….., Y_n]. These coordinates are normalized by subtracting the mean from each one according to following Eq. 1, and Eq. 2:

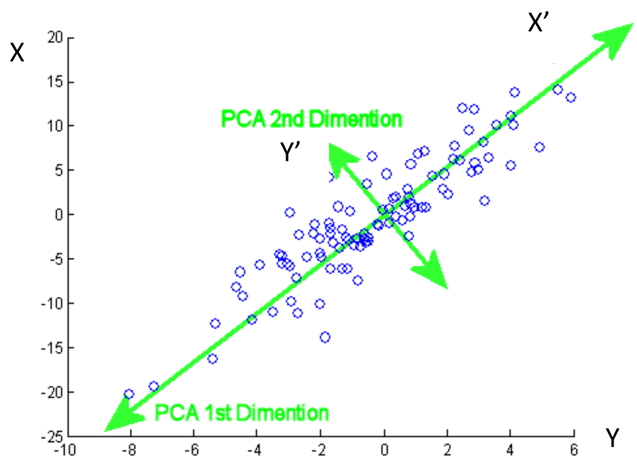

Figure 4: Remapping the axes (X, Y) of original data into new axes (X', Y').

$$\bar{X} = \frac{1}{n}\sum_{i=1}^{n} X_i \qquad (1)$$

$$\bar{Y} = \frac{1}{n}\sum_{i=1}^{n} Y_i \qquad (2)$$

The covariance matrix (cov) that is symmetrical and semi-positive definite matrix, is used to measure to which extent that these coordinates are linearly related as given in Eq. 3.

$$cov(x,y) = \frac{1}{(n-1)}\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y}) \qquad (3)$$

If the given data has *m* dimensions, the covariance matrix is an *m* by *m* matrix [36, 37]. Then the eigenvectors and eigenvalues can be calculated by using the following Eq. 4 and Eq. 5 respectively. Where, the eigenvectors and eigenvalues include useful information about the new coordinates of the given data [38]. Each eigenvector points in the direction of a new coordinate axis. The desirable coordinate that has the highest eigenvalues, represents the axis that includes the most variation in the given data. It is also known the first principle component. This means that the required new coordinate X`-axis passes through the maximum variation of given data and points from the original central point to the first principle component [32, 36]:

$$|cov - \lambda I| = 0 \qquad (4)$$

$$cov.V = \lambda V \qquad (5)$$

Where λ is the eigenvalues of the covariance matrix, *I* is the identity matrix and *V* is the eigenvectors matrix.

Then, the angle θ between the X-axis and X'-axis represents the degree of skewness of patient's head during the MRI test as shown in Fig. 5. It could be calculated by using Eq. 6:

$$\theta = \tan^{-1}\frac{V_2}{V_1} \qquad (6)$$

Where, V_1 and V_2 are the eigenvectors values which are related to the maximum eigenvalues.

The main shortcut of PCA that is not efficient to distinguish between the axis of symmetry and axis of orientation. However, it is still interesting approach because of simplicity and the low processing time [9].

The PCA algorithm is implemented by using *princomp* function in MATLAB Image Processing Toolkit [30].

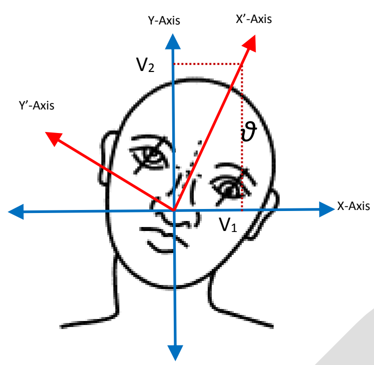

Figure 5: Original and new coordinates of brain.

D. Geometrical Transformation

Geometrical transformation techniques are widely used in computer graphic and image analysis. They help to eliminate the geometric distortion that occurs within image capturing [32]. They can be used to estimate the unknown pixels by interpolation of input pixels and rotate the object around a fixed point known as the center of rotation [39]. A geometric transformation includes two basic steps. First, the pixel coordinates transformation that is used to map the coordinates of the input pixel to the new position in the output image. Second, the brightness interpolation that is used to compute the brightness value in the new image by interpolating the brightness of several input pixels in the neighborhood [32]. There are two types of interpolation techniques; nearest neighbor interpolation and bilinear interpolation [27, 39]. After the angle θ is computed in the previous step, which represents the wobble of patient's head with respect to the horizontal axis of the input image. It becomes easily to correct and rotate the patient's head by using *Geometric Rotator system object* in MATLAB Image Processing Toolkit [30].

E. Centralize Patient's Head in the Centre of MRI slice

The proposed algorithm for extracting texture features in this study is based essentially on measuring symmetry between the two hemispheres of brain. As well as, the MSP of brain is positioned in the middle of the patient's head and the centroid of patient's head is identical with the MSP of brain [4]. Therefore, it becomes easily to make the MSP of brain identical exactly in the middle of MRI brain scanning image by shifting patient's head either left or right using Eq. 7, and Eq. 8:

$$g_x = \frac{1}{N}\sum_{i=1}^{N} x_i \qquad (7)$$

$$g_y = \frac{1}{N}\sum_{i=1}^{N} y_i \qquad (8)$$

Where, N is the number of pixels in the segmented patient's head, and g_x and g_y are the coordinates of centroid. Then the patient's head is shifted by number of pixels that is equal to the difference between g_y and 256 which represent the coordinates of middle line of MRI brain image.

IV. Experimental Results

The proposed algorithm is implemented using MATLAB 2014, and applied on a dataset of MRI brain scans used in [12, 18] and includes T2-weighted images of 165 patients. To evaluate the proposed algorithms used in this study, a set of examples will be implemented using this algorithm.

Since all MRI brain slices have the same MSP orientation [14], the MSP detection and correction algorithm is implemented on a single slice to determine the orientation instead of using all slices to avoid computational complexity. The preferable slice is the bony structures slice which is located in the lower of the brain, and contains the largest number of pixels. It provides more accurate detection rate compared to slices higher in the brain (at the tip of the head) which has ovals or near-circular shape [4].

To compare with an expert clinician delineation, the MSPs of 50 MRI slices from the collected dataset were manually identified by an expert clinician from MRI Unit in Al-Kadhimiya Teaching Hospital. These MRI slices were given to the expert after correcting and aligning the MSPs of these slices. The proper location of the fitted line was drawn with the mouse by the expert. Figure 6, shows mean squared error (MSE) distribution between manual and our algorithm delineation of MSPs. Consequently, 92% of the computed MSPs are matched approximately to clinician's delineation within MSE≤3º.

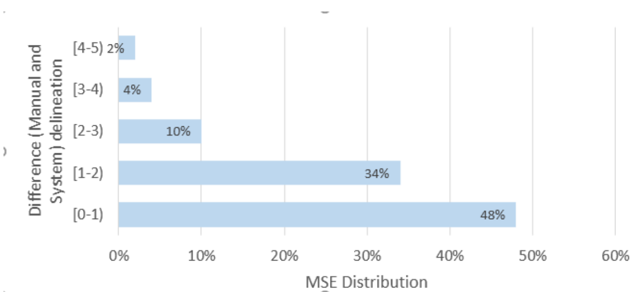

Figure 6: Distribution of MSE between manual and our algorithm.

For further evaluation, the given MRI brain slice in Fig. 7 was resampled and rotated with yaw angles from -10º to 10º in 2.5º intervals using Geometric Rotator system object in MATLAB Image Processing Toolkit [30]. Table 1 demonstrates the result of detecting and computing yaw angles of the given MRI brain slices in Fig. 7 and comparing our results with [14] and [40]. Our algorithm can identify the yaw angle of resampled MRI brain slice with minimum mean squared error (MSE) compared to [14, 40]. Figure 8, shows a comparison of actual and detected yaw angles using our algorithm and the proposed algorithms in [14, 40].

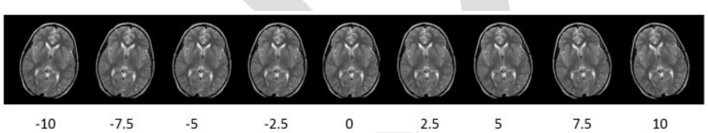

Figure 7: Resampling of one slice from the axial MRI brain scanning image with varied rotate angles.

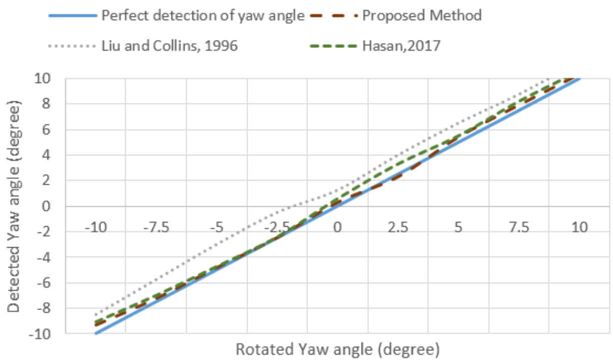

Figure 8: Comparison between actual and detected yaw angles in given MRI brain slice.

V. Conclusion

We have proposed a fast, and accurate method for the MSP estimation in MRI brain scans. This method exploits the orientation of patient's head to locate and identify the MSP. It is based on automatic segmentation of the patient's head and elimination of background. The algorithm works on both normal and pathological brain scans

Table 1: Numerical results of detecting yaw angle.

Yaw Angle	-10°	-7.5°	-5°	-2.5°	0°	2.5°	5°	7.5°	10°	MSE
[40]	-9.08°	-7°	-4.74°	-2.43°	0.58°	3.3°	5.5°	8.21°	10.57°	0.35°
[14]	-8.5°	-5.75°	-3°	-0.5°	1.25°	4°	6.5°	8.75°	11.25°	2.5°
Proposed Method	-9.28°	-7.2°	-4.8°	-2.45°	0.3°	2.3°	5.4°	7.9°	10.3°	0.067°

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