Automated Analysis of CT Slices for Detection of Ideal Midline from Brain CT Scans

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***Abstract*—Midline shift detection with high accuracy is crucial in quantitatively analyzing the severity of a brain injury in clinical environments. Accuracy of the estimated ideal midline (IML) significantly affects the accuracy of the computed midline shift. In this work, a two-step process, which consists of computed tomography (CT) Slice Selection Algorithm (SSA) and IML detection, is proposed to automatically estimate the IML in brain CT images. SSA is designed for automatic slice selection. Skull fracture level and intracranial area are used as vital features in the selection. Using skull symmetry and anatomical features, IML detection accurately estimates the position and rotation angle of the IML before calibrating. Experimental results of the multi-stage algorithm were assessed on 1762 CT slices of 40 patients. The accuracy of the proposed system is 91.6%, which makes it viable for use under clinical settings.**

Keywords-ideal midline;IML; midline shift; MLS; CT slice; SSA; mid-sagittal plane

I. INTRODUCTION

In the United States alone, nearly 1.7 million cases of Traumatic Brain Injury (TBI) are recorded annually [1]. Midline Shift (MLS), which is the shift in the brain's midline, is a common aftermath due to the head injury. It is an important index for clinicians to assess the severity of TBI. MLS greater than 5 mm can lead to sufalcine herniation and possibly death [2]. Ideal midline is the symmetric midline of the brain without injury or illness. Estimating Ideal Midline (IML) [2] is a vital step in MLS calculation.

Skull symmetry and anatomic features have been widely used to detect the IML in last two decades [3, 4, 5]. Ruppert et al. extracted the mid-sagittal plane (MSP) based on bilateral symmetry maximization [6]. Chen et al. used a combination of bone symmetry and anatomical features in CT images for detection of IML [7]. This method works effectively and accurately on a single CT slice, but does not consider the connection among CT slices. Furthermore, all the methods above mentioned [3, 4, 5, 6, 7] cannot automatically select the proper slices before analysis. In practice, dozens of CT images can be acquired in one patient's brain scan. It is crucial to choose a few appropriate slices that contain clear anatomical features and limited noise, to be used for MLS quantification. Prior to this work, no automated method to perform this task existed.

In this work, we propose a two-step algorithm for automated detection of the IML. As the first step, a CT Slice Selection Algorithm (SSA) is proposed to select appropriate slices from a large number of raw CT images. SSA proposed in this work realizes the real automated slice selection which is the initial step for automated IML detection. We did not find any existing automated method to perform this task. The second step focuses on the IML detection through anatomical features extracted from the selected slices and the consideration of the connection among CT slices. A database of 1762 CT slices of 40 patients with TBI cases were used for this study. As shown later, the proposed algorithm yields highly desirable accuracy and efficiency when tested against this dataset.

The rest of this paper is organized as follows: the methodology is introduced in Section II. The results are presented and discussed in Section III. The work is summarized in Section IV.

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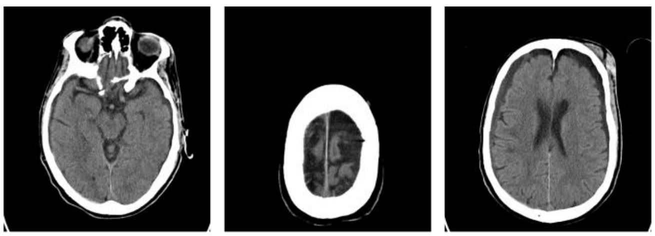
II. Methodology

2.1 *CT Slice Selection Algorithm* (*SSA*)

Among the dozens of raw CT images acquired from a single patient, only a few are useful for the physician in a diagnosis that includes midline estimation. Some images taken from the lower section of the head contain too much interference/noise from other organs, such as the eye and nose in the top image in Figure 1-a. Some images capture a small intracranial area because the scan position is too close to the calvaria, as seen in Figure 1-b. From the viewpoint of anatomical features, the ideal CT slices usually contain integrated skull bone and larger intracranial area, such as Figure 1-c. Therefore, CT slice selection should ideally be based on the above mentioned features.



(a) (b) (c)

Figure 1. Three raw CT slices from one patient's head CT scan.

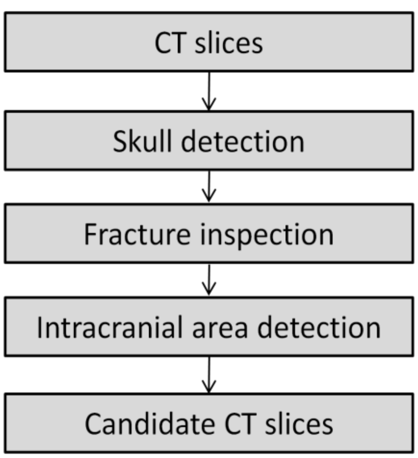


Figure 2. Flowchart of CT Slice Selection Algorithm (SSA).

The CT Slice Selection Algorithm (SSA) was designed to effectively select a few appropriate CT slices from a large number of images. As the flowchart shows in Figure 2, this algorithm analyzes every slice by examining multiple anatomic features.

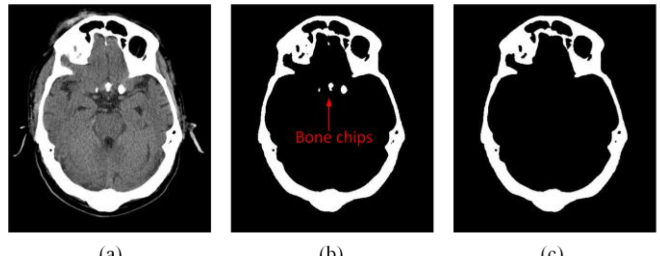


Figure 3. Skull detection process. (a) Raw CT slice (b) Detected bones B with little bone chips (c) Detected skull.

As the first step in SSA algorithm, skull detection is implemented on every raw CT slice. Using a threshold method, potential bone pixels can be extracted from the raw image. In this study, based on experimentation, the value for the threshold is set to 250 (out of 255), which lies within the common range for bone intensity within CT images. Using the connected component algorithm (CCA) [8], the discrete bone chips can be removed (Figure 3-b). Bone pixels form a certain number of connected regions. We choose the one containing the largest number of elements as the candidate skull (Figure 3-c).

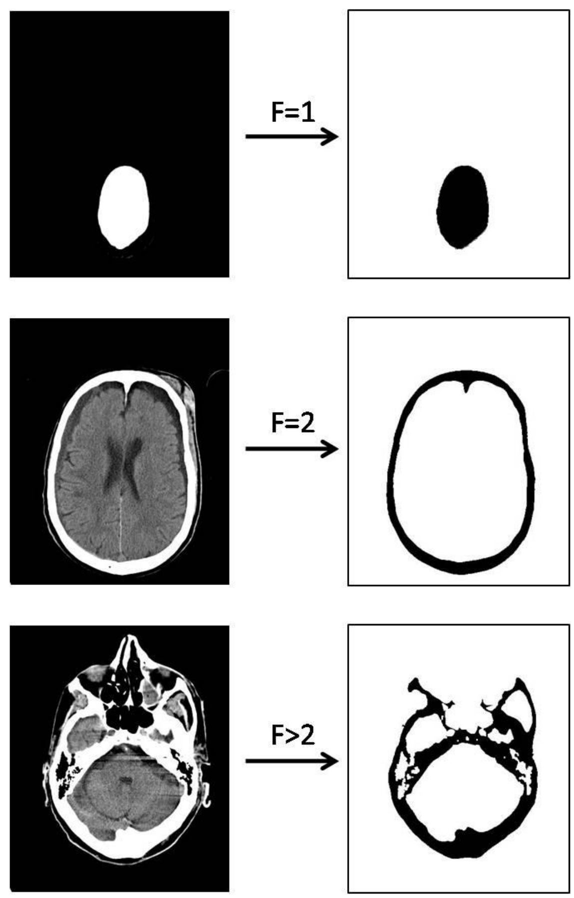


Figure 4. Skull fracture inspection. The left three images are the raw CT images while the right three images show the detected skull.

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The second step in the SSA algorithm is skull fracture inspection to remove slices with either skull fractures or partial skull. Such "non-integrated" skull affects IML identification since symmetry value calculation, through the exhaustive symmetric position search, is sensitive to skull contour. We define a new measure, called skull fracture level F, to estimate the integrity of the skull. Skull fracture level F is defined by the number of isolated regions separated by the skull. To prevent any small holes in the skull from affecting the calculation, a minimum threshold (of 200 pixels in this work) is set for the area of those isolated regions. If the computed skull fracture level F is equal to 2, it implies that the skull is integrated and ideal for the following steps of detection. An example is the middle slice in Figure 4. If the skull fracture level is not equal to 2, the image cannot be used in detection of IML due to either an inappropriate scan position or a serious fracture in the skull. Examples are the top and bottom slices in Figure 4. After skull fracture inspection, all images with $F\neq 2$ are removed from the slice subset.

Based on clinical experience, CT slices with larger intracranial area generally contain more information for IML detection. Hence, in the third step of the SSA algorithm, the intracranial area is calculated and sorted for all remaining slices. After skull fracture inspection, every CT image should contain only two dark regions, which are separated by the detected skull. An example is the middle-right image in Figure 4. In order to calculate intracranial area, the intracranial region has to be distinguished from the region outside of the skull. This can be achieved using the coordinate of the skull's mass-center. The image moment m_{pq} of the order $p+q$ can be defined as below,

$$m_{pq} = \sum_{j=1}^{n}\sum_{i=1}^{m} i^p \cdot j^q \cdot \Gamma_{ij}, \quad (p = 0,1; q = 0,1) \tag{1}$$

where Γ_{ij} with the value of either 1 or 0 represents the intensity of the element at the ith row and jth column in the detected skull matrix Γ. The coordinate of the mass center (x, y) of the identified skull can be obtained by

$$\begin{cases} x = \dfrac{m_{10}}{m_{00}} \\ y = \dfrac{m_{01}}{m_{00}} \end{cases} \tag{2}$$

Thus the region containing the coordinate of the skull mass center (x, y) is the intracranial region. The intracranial area of all remaining slices is calculated and sorted in descending order. The first λ slices with larger intracranial areas are selected as the candidate slices for IML detection. This number of λ is a variable that depends on the number of slices for one patient or on physician's requirement. In this work, we choose λ=3 candidate slices for the detection that follows.

2.2 Ideal midline detection

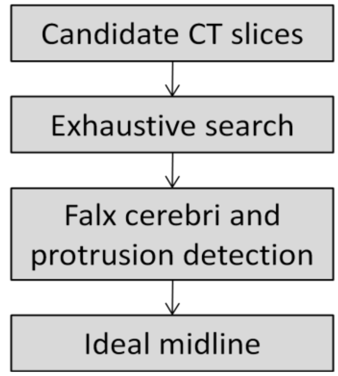


Figure 5. Flow chart of ideal midline detection

After slice selection is performed using SSA algorithm, all candidate slices are appropriate for IML detection. Ideal midline detection consists of an exhaustive search as well as falx cerebri and protrusion detection, as shown in Figure 5.

To find the approximate IML, we use the exhaustive symmetric position search algorithm, which was developed in a prior work by our research group [9]. The row symmetry is defined as the difference in distance between each side of the skull edge and the current approximate midline. The CT image is rotated around the mass center of the skull, which is calculated by (2). The symmetry cost S_θ of the image at each rotation angle θ is calculated as the sum of all row symmetry in the resulting image as follows.

$$S_\theta = \sum_{i=1}^{m} \left| l_i - r_i \right| \tag{3}$$

where m is the number of rows in the image with the rotation angle θ (in this study ; $-45°<\theta<+45°$) and measures l_i and r_i are the distance between the edge of the skull on the left or right side, respectively, and the current approximate midline at the ith row. More details can be found in [9]. Finally, the rotation angle θ with the minimum symmetry cost S_θ determines the rotation direction of the midline of the brain on each particular CT slice.

$$\theta_k = \arg\min_{\theta_{kj}} [S_{\theta_{k1}}, S_{\theta_{k2}}, \cdots S_{\theta_{kl}}],\ (1 \le k \le \lambda) \tag{4}$$

where θ_k is the rotation angle of the midline on the kth slice and $S_{\theta_{kl}}$ is the symmetry cost of the kth slice at the rotation angle θ_{kj}. Then, the kth candidate slice is calibrated to the vertical direction by rotating the skull by -θ_k angle.

In addition, the accuracy of approximate IML can be improved by utilizing other features of the skull and the brain. Thus, following the approximate IML estimation using exhaustive search, brain anatomical features, such as the position of the falx cerebri and protrusion of skull bone, are used to refine the position of the IML. Here, we use the algorithm proposed in our previous work [9, 10]. The falx cerebri is a strong arched fold of dura mater that descends vertically in the longitudinal fissure between the left and right cerebral hemispheres. In this work, we use edge detection method and Hough transform to execute the detection. Additionally, a bone protrusion located in the anterior section of the skull is used in the refinement. To locate the lowest point of the protrusion curve, the derivative of the curve is calculated in a limited neighborhood area (10-15 pixels in this work). The local minimum point *a* is determined by

$$x_a = \arg\max_{x}[\Re(x+w)+\Re(x-w)-2\cdot\Re(x)] \quad (5)$$

where the function $\Re(x)$ is the extracted curve of the interior bone edge and *w* is the neighborhood width. Using the detected falx cerebri and the bone protrusion, we can obtain the refined rotation angle φ_k of the midline in the *k*th slice. Therefore, the rotation angle for the *k*th slice should be $\phi_k=\theta_k+\varphi_k$.

It is worth notice that those obtained rotation angles may be different for different slices. However, since the patient usually keeps the same gesture during CT scan, the slices in one CT scan should have the same rotation angle. In order to fully consider the connection among slices, we use a global rotation angle ϕ given by (6).

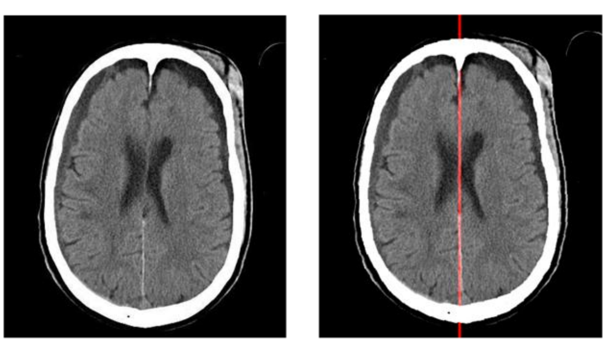
$$\phi = median[\phi_1,\phi_2,\cdots,\phi_\lambda], \quad (6)$$

As shown in (6), it is the median value of the rotation angles of all λ slices after CT slice selection.

Lastly, each slice is calibrated to the vertical direction. Therefore, during the IML detection process, the IML is centered by the mass center of the skull and rotated by an angle of $-\phi$ from the original position in the slice.

III. RESULTS AND DISCUSSION

The SSA algorithm is primarily based on the anatomical characteristics of the skull and closely simulates the process of manual CT slice selection and decision making in IML by physicians. In our database, all CT slices selected by the SSA algorithm have been found to be acceptable for IML detection by physician's approval. Result of the IML detection is displayed in Figure 6. It can be noticed that the detected IML is accurately located in the middle of the skull. Additional, the direction of the skull is calibrated by moving the IML to vertical direction.



(a) (b)

Figure 6. The ideal midline detection on a candidate slice selected by the SSA algorithm. (a) Original CT slice, (b) ideal midline is detected and the skull direction is calibrated.

This database contains original 1762 axial CT scan slices acquired across 40 patients with cases of both mild and severe Traumatic Brain Injuries (TBI). Collaborating physicians manually labeled the IML. With a strict definition of accuracy, which is an allowed error of three pixels in the horizontal direction and 2 degrees of the rotation angle, accuracy of our algorithm is 91.6% and the mean value of the error δ in horizontal direction is only 2.4 pixels as shown in TABLE I.

We have evaluated our method using a previous work designed by some authors of this paper [9] as baselines. With the same criteria, the accuracy of this work is 6% higher and the mean value of horizontal error is 17% smaller than the method in [9].

TABLE I. COMPARISON ON THE ACCURACY OF IML ESTIMATION

Method	Our method	Method in [9]
Number of patients	40	40
Accuracy	91.6%	85.7%
Mean value of error δ	2.4	2.9

The improvement on accuracy shows that the implementation of global rotation angle after IML detection greatly enhances the accuracy on skull rotation calibration by fully considering the connection among slices.

IV. SUMMARY AND FUTURE WORK

In this work, we developed a system with the combination of the SSA algorithm and the ideal midline (IML) detection process to identify the IML using CT scans of patients with head injuries. The proposed SSA algorithm is used to closely simulate the process of manual selection of CT slice by physicians. Fully considering the symmetry of the skull and anatomical features, IML detection algorithm with the adjustment of global rotation can accurately identify the IML on the candidate CT slices selected by the SSA algorithm. The obtained results show high accuracy (91.6%) and a potential for the system to be implemented in clinical settings. In the future, more work can focus on the actual midline detection which is the shifted midline after brain injury or illness. Then IML detection can be used the midline shift estimation which is one of the key index in TBI assessment in clinical practice.

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