

***AUTOMATED MIDLINE SHIFT DETECTION ON BRAIN CT IMAGES
FOR COMPUTER-AIDED CLINICAL DECISION SUPPORT***

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PREVIEW

**AUTOMATED MIDLINE SHIFT DETECTION ON BRAIN CT IMAGES
FOR COMPUTER-AIDED CLINICAL DECISION SUPPORT**

A research dissertation submitted in partial fulfillment of the requirements for the degree
of Doctor of Philosophy at Virginia Commonwealth University

by

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Abstract

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A research dissertation submitted in partial fulfillment of the requirements for the degree
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Midline shift (MLS), the amount of displacement of the brain's midline from its normal symmetric position due to illness or injury, is an important index for clinicians to assess the severity of traumatic brain injury (TBI).

In this dissertation, an automated computer-aided midline shift estimation system is proposed. First, a CT slice selection algorithm (SSA) is designed to automatically select a subset of appropriate CT slices from a large number of raw images for MLS detection. Next, ideal midline detection is implemented based on skull bone anatomical features and global rotation assumptions. For the actual midline detection algorithm, a window

selection algorithm (WSA) is applied first to confine the region of interest, then the variational level set method is used to segment the image and extract the ventricle contours. With a ventricle identification algorithm (VIA), the position of actual midline is detected based on the identified right and left lateral ventricle contours. Finally, the brain midline shift is calculated using the positions of detected ideal midline and actual midline.

One of the important applications of midline shift in clinical medical decision making is to estimate the intracranial pressure (ICP). ICP monitoring is a standard procedure in the care of severe traumatic brain injury (TBI) patients. An automated ICP level prediction model based on machine learning method is proposed in this work. Multiple features, including midline shift, intracranial air cavities, ventricle size, texture patterns, and blood amount, are used in the ICP level prediction. Finally, the results are evaluated to assess the effectiveness of the proposed method in ICP level prediction.

Novelty and Contribution

Medical data acquired practically all clinical settings contains massive amount of information but not all of this information may be relevant to a specific medical decision making process. Often simple visual inspection and traditional computational methods are incapable of extracting the hidden information behind the preliminary data, which may be instrumental in generating recommendations and predictions for both diagnosis and treatment planning. Midline shift (MLS) estimation is a vital step in clinical decision making for patients with traumatic brain injury (TBI). Computer-aided midline shift detection is crucial to assist physicians make an accurate diagnosis on the severity of TBI within a reasonable time.

In this work, an automated MLS estimation system with high accuracy is proposed to quantitatively analyze the severity of the brain injury. Using machine learning, ICP is predicted as the reference of physician decision making. This machine learning model is trained and tested using a nested crossing validation process. Novelties provided by this research include:

➤ Automated CT slice selection

Numerous raw CT slices can be acquired from one scan but not all slices are suitable for the midline shift detection. In clinical setting, physician manually chooses a few slices for diagnosis. In this work, a CT slice selection algorithm (SSA) is designed to perform the automated slice selection process in order to obtain the most suitable slices for MLS estimation. During the slice selection process, the proposed SSA algorithm automatically considers multiple anatomic information of the human brain, including the expected skull

appearance, the proper representation of intracranial region, and the topology of the ventricle system. With the significant reduction in the number of candidate slices considered for the MLS detection, the computation time needed to process the following steps is dramatically reduced.

➤ **Ideal midline detection system**

Fully considering the symmetry of the skull and anatomical features, the proposed ideal midline detection algorithm is designed to accurately identify the ideal midline on the candidate CT slices selected by the SSA algorithm. It contains two continuous processes, both of which have the assistance of the global rotation. The application of global rotation ensures accurate ideal midline detection. Exhaustive symmetric position search algorithm is used to detect the approximate ideal midline based on the row symmetry cost. Subsequently, a multiple segmentation methods based on the brain anatomical features are utilized to refine the ideal midline. Finally the brain direction is calibrated by making the detected ideal midline in vertical direction.

➤ **Dynamic window selection**

In order to further reduce the computation time involved in searching for the actual midline, a dynamic window selection method is designed by confining the region of interest in this work. Window selection algorithm (WSA) is proposed to fulfill this task on the slices selected by the SSA algorithm. The WSA algorithm not only narrows down the search for the most suitable CT slice but also confines the window in which the ventricles reside. The selected window is used as the initialization of the level set

segmentation. This process by itself can be used in other brain image processing applications as well as other similar applications.

➤ **Segmentation based on the variational level set model**

Level set method is a popular deformation model in medical image processing. Variational level set segmentation applied in this work, is a modified level set method that is designed to resolve the re-initialization limitations of the original method and reduce its sensitivity to intensity inhomogeneity of the image. In our system, the variational level set segmentation model combined with the ventricle identification process successfully extracts the contours of ventricles. Actual midline is estimated by the positions of the ventricle contours.

Compared with other segmentation methods that have been used in the MLS detection, such as the Gaussian Mixture Model (GMM), the variational level set model has proved to successfully reduce the time consumption and effectively enhance the accuracy of the segmentation.

➤ **MLS application: ICP prediction**

One of the important applications of midline shift in medical diagnosis is intracranial pressure (ICP) prediction. Elevated ICP may results in secondary complications or death via swelling and deformation of the brain tissues.

In this work, an ICP level prediction model is designed, by applying machine learning on multiple features extracted from brain CT images, including the estimated midline shift. Other features extracted from CT are included in the prediction process include

intracranial air cavities, ventricle size, texture patterns and blood amount. These features are added to other information such as demographics as important features and are used in the prediction process. The obtained results show that the proposed model can potentially be applied towards developing a clinically-useful pre-screening system for detection of elevated ICP.

PREVIEW

Chapter 1: Introduction

1.1 Motivation and background

1.1.1 Brain midline shift and its medical applications

In the United States, nearly 1.7 million cases of traumatic brain injury (TBI) are recorded annually, among which 1.365 million, i.e. nearly 80% of all cases are treated and released from an emergency department, 275,000 are hospitalized, and 52,000 die [1]. It has to be added that 26,000 lose their lives in the first two hours after injury. The majority of TBI survivors may suffer from significant physical health problems including permanent disability, which may seriously affect their lives as well as the lives of their families in both emotional and financial aspects [2, 3, 4]. TBI is considered as one of the leading causes of the death in children and young adults [5, 6]. An accurate medical diagnosis at the time of injury or soon after may dramatically alleviate the complications, avoid lifelong disability, or even save life [7, 8]. Thus, fast and accurate diagnosis is vital in TBI care.

One of the most serious problems associated with TBI is the elevation of intracranial pressure (ICP), which could lead to the deformation of brain tissue and ventricular structure thereby further complicating the injury and causing secondary complications [5]. Although invasive direct monitoring of ICP through cranial trepanation is an option to detect ICP level and its potential elevation, this invasive procedure could sometimes cause further complications [9]. Therefore, a non-invasive and cost-effective pre-

screening method to estimate ICP levels and potentially eliminate the need for invasive monitoring at least in a portion of patients would be highly desirable.

A CT scan is usually taken soon after TBI in emergency medical practice. The tissue shift and deformation shown in the scan is a vital reference for physician in medical diagnosis. One of the potential deformations, the brain midline shift (MLS), is an important index for clinicians to assess the severity of TBI and is known to be highly correlated with the ICP levels [9]. MLS greater than 5 mm can lead to sulcalfine herniation and possibly death [10].

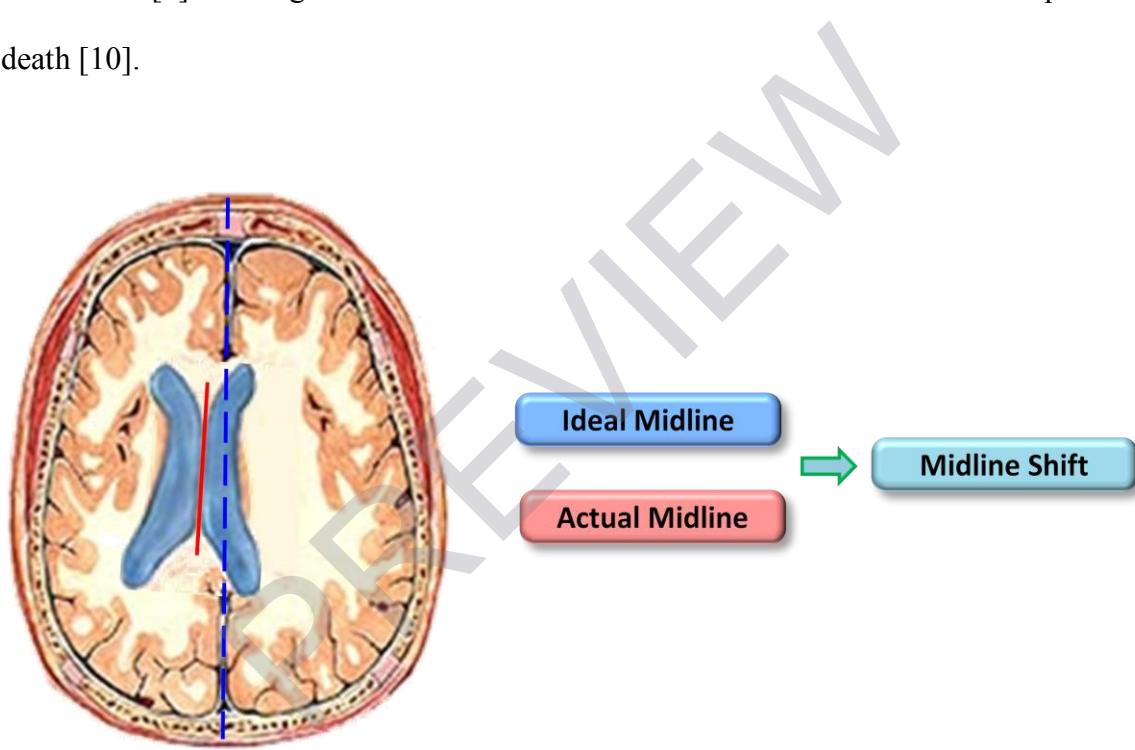


Figure 1.1 Brain midline shift. Blue dash line represents the ideal midline and red solid line represents the shifted actual midline [11].

The Midline Shift (MLS) is the degree of shift in the brain, measured roughly at about the center of the brain, which is caused by the injury or illness. As shown in Figure 1.1, the detection of MLS often involves the following two main steps: estimation of ideal midline (symmetric midline as if the injury or illness had not occurred) and detection of

actual midline (shifted midline after injury or illness). Since the ideal midline is used as reference in the MLS detection, the ideal midline estimation significantly affects the accuracy of the MLS detection. The actual midline usually is detected using the anatomic information of the brain after the injury or illness. This anatomical information includes the position of the ventricle system, which is the key clinical factor in identifying where the line resides.

1.1.2 Computed Tomography (CT) technique



Figure 1.2 CT scanner (Toshiba's High-Powered CT scanner) [12]

Computed Tomography (CT) is used in the estimation of MLS in this work, while other image modalities such as MRI could have been applied in this study as well. However, the CT is more practical system for initial TBI assessment due to its fast speed, lower

cost and high quality, and as a result, in practically all emergency medicine settings CT is the standard imaging technology used for assessment of TBI, at least for the initial assessment [13]. In addition, modern CT scanner can acquire high quality non-contrast brain CT scan in less than 10 seconds. CT scan is considered as a golden standard in assessment for acute hemorrhage and very desirable at documenting mass effect and herniation as well as effective at visualizing skull fracture [10].

As one of the important medical imaging method, CT utilizes tomography methods [14] and can provide high resolution images showing serious lesions such as intracranial hematoma, hemorrhage, and brain contusions [15]. From the emergence of CT scanning in medicine in 1970s, CT has provided the possibility of quick diagnosis of ongoing intracranial damage and the possible neurosurgical intervention afterward, which is the key to overcome life threatening events in head injured patients [16-19].

The size and number of pixels in CT image depend on the setting of the CT scanner. Smaller size of pixels combined with each other builds up higher resolution image. In CT image, the dark regions represent the tissue with a low absorption of X-ray, such as air or ventricular system in brain, while the bright regions represent the area with high absorption of X-ray, such as bone or blood. CT value measured in Hounsfield Unit (Hu) is used to describe the density of pixels in CT image. Different tissues in human body have different densities with the CT values range from -1000 Hu to 3000 Hu except for very dense materials such as dental fillings or metal implants [20]. For example, the CT value is -1000 Hu for air, -400 to -600 Hu for lung tissue, -60 to 100 Hu for fat tissue, 0 Hu for water, 40 to 80 Hu for soft tissue, and 400 to 1000 Hu for bone. Figure 1.2 is an example of CT imaging devices. Figure 1.3 shows a sample of the brain CT image.