

Automatic Midline Shift Detection in Traumatic Brain Injury

Mohsen Hooshmand^{†,§}, S.M.Reza Soroushmehr^{†,§},
Craig Williamson[‡], Jonathan Gryak[†], and Kayvan Najarian^{†,§,*}

Abstract—Fast and accurate midline shift (MLS) estimation has a significant impact on diagnosis and treatment of patients with Traumatic Brain Injury (TBI). In this paper, we propose an automated method to calculate the amount of shift in the midline structure of TBI patients. The MLS values were annotated by a neuroradiologist. We first select a number of slices among all the slices in a CT scan based on metadata as well as information extracted from the images. After the slice selection, we propose an efficient segmentation technique to detect the ventricles. We use the ventricular geometric patterns to calculate the actual midline and also anatomical information to detect the ideal midline. The distance between these two lines is used as an estimate of MLS. The proposed methods are applied on a TBI dataset where they show a significant improvement of the the proposed method upon existing approach.

I. INTRODUCTION

Traumatic Brain Injury (TBI) is a major cause of morbidity and mortality [1]. Due to its potential lifetime impact, proper diagnosis has a vital role in treatment. Clinicians use different parameters such as Midline Shift (MLS) to estimate the amount of TBI severity and outcome prediction [2]. CT classification scoring systems use MLS as one of the most decisive features to score the amount of severity [3]. MLS is the amount of brain shift due to injury [2]. It is mostly computed by locating the line between shifted ventricles in head CT scans. The actual midline is defined as the line that goes between the left and right lateral ventricles or passes through the third ventricle. It is found by performing ventricle segmentation, and then is used to estimate MLS [4]. Due to many factors, such as poor quality of CT images, the result of such segmentations are often noisy and include false positives, or missing regions. Thus, an automated and robust clinical decision support system (CDSS) can have a significant impact on optimal diagnosis.

Over the past decade, there has been a plethora of research on automatic MLS estimation as a CDSS. Liao et al. [5] estimated the amount of MLS. To do this, they considered a parametric model of shifted midline as a combination of three segments of upper and lower straight lines of the falx cerebri and a quadratic curve middle segment. To calculate the MLS from the model, the extracranial pixels are removed

and then generated a symmetry map of the brain tissue along the horizontal direction. However, as the following reasons show, their method has a low performance for most of the cases and in particular severe TBI. Their proposed approach is not fully automatic and needs manual slice selection. It first needs to rotate each slice in such a way that the ideal midline is in a vertical position. Xiao et al. [6] used the combination of a type of level set segmentation and Hugh transformation. Ideal midline detection was proposed in [7] that is based on offline and online phases. The offline phase is the model training using “scale invariant feature transform” as well as template matching. In the online phase, the features of the CT slices are compared to the offline template to locate the ideal midline. [8] used the information of lesion to estimate the amount of MLS. They proposed their method for brain images using magnetic resonance imaging (MRI). CT scans are the better choice 24h after the injury due to its availability, cost-effectiveness, shorter imaging time and easiness for injured patients. A CT image segmentation method based on a probabilistic map of ventricles and brain tissues proposed in [9]. They had used normal brain MRIs to generate the probabilistic atlas of white matter and gray matter and ventricles. However, this method is only applicable to cases without severe damage. Chen et al. [4] proposed several steps for MLS detection. In their method, the ideal midline is located by defining a measure of symmetry that calculates the symmetry of the skull with respect to a vertical line passing through the center of mass of the image. The image is rotated and the angle that yields the best symmetry is selected. The falx cerebri and anterior bone protrusion locations are also employed to make the rotation more precise. Then, the ventricles in some slices are located. This step is done by applying the Gaussian Mixture Model (GMM) [4], [10] which is a probabilistic model of K-means clustering. At the final step, the ventricles are detected using template matching and actual midline and MLS are estimated. Qi et al. [11] used a similar approach to [10] to calculate the MLS. They substituted the GMM method with a level set segmentation for locating the ventricles. In this paper, we modify the method proposed in [4] by improving the rotation, segmentation, and slice selection. The proposed method is a fully automated approach that increases detection performance. Our contribution is fourfold as follows:

- automated slice selection using head CT scan metadata;
- excluding irrelevant slices;
- rotating slices to improve the detection of the ideal midline; and

[†] Department of Computational Medicine and Bioinformatics, University of Michigan, Ann Arbor, USA

[‡] Department of Neurosurgery, University of Michigan, Ann Arbor, USA

[§] Michigan Center for Integrative Research in Critical Care (MCIRCC)

* Department of Emergency Medicine, University of Michigan, Ann Arbor, USA

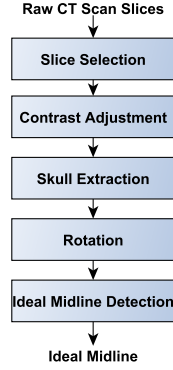


Fig. 1: IML detection phase

- using a new method for ventricle segmentation.

The rest of this paper is organized as follows. In Section II we describe the general method of MLS estimation. Our method is divided to two main phases and described in the parts II-A and II-B. In Section III we show the experimental results on brain CT images with TBI. In this section, we compare our method with available results from a previous method. Finally, Section IV concludes the paper.

II. METHOD

The MLS computation includes two main phases. In the first phase, the ideal midline shift (IML) is located. In this phase non-informative slices are excluded from the CT images and rotated to locate the IML. By locating IML, the approach goes to the next phase where the actual midline (AML) is estimated. To do this, a segmentation algorithm is applied to the selected slices. Then, a template matching is used to find the ventricles. Template images are binary images that only present ventricles. In the final step the amount of MLS is estimated using the ventricular geometric patterns. The schematic diagram of the proposed method for IML estimation is depicted in Fig. 1. Details of each step of the method are described below.

A. IML detection phase

Head CT scans have different views and types that are used for diverse diagnoses and treatments. Among the different types of images we use axial images to detect the MLS. The algorithm performs this specific slice selection automatically using the metadata available for each slice. The slice selection steps are shown in Fig. 2.

In our method, we use two different tags from metadata, “Image Type” and “Window Center”, to keep or drop a slice [12]. These tags are set by either the scanner automatically or a radiologist. Although excluding irrelevant slices is necessary for automatic analysis, the output of this stage still has non-informative slices for midline estimation. In other words, the specific slices passing this step are not useful for MLS estimation as they don’t have ventricles. To select appropriate slices for MLS estimation, subtentorial slices are identified and excluded from the chosen slices.

First, the objects smaller than a predefined threshold are removed in each slice. After dilation of each processed slice, the number of separate objects are counted and the size of the filled skull is computed. If these two criteria meet the thresholds, the slice is chosen for the next steps, otherwise marked as a subtentorial slice and discarded. This step improves the precision of the algorithm by reducing the non-informative slices. Moreover, those slices with larger area of skull in comparison to their brain tissue are excluded as well. Two samples of those slices for MLS estimation are shown in Fig. 3. The slice selection step, in addition to the automatically appropriate slice selection for IML and AML computation, reduces the redundancy of computation for the irrelevant slices. The next step of this phase is the contrast adjustment that is necessary for the following step, which extracts the skull. The skulls are used to rotate and translate the slices. The slices are rotated in a way to have the best bilateral symmetry. Using skull image of all the selected slices and stacking them helps improve the rotation calculation as compared to the method of [4]. To improve the performance of this step, two sub-steps are added. In the first stage, the rotation angle that maximizes the distance between the highest y-axis value of skull and the lowest value of skull is selected. This is due to the pseudo-elliptic shape of the head skull in the axial plane. However, as the skull is not completely elliptic, we use a different type of symmetry to find the best rotation and shift. To do this, all the extracted skulls of all chosen slices are stacked on top of each other to create one image. Then, the internal part of the stack is filled. The symmetry of the generated image is computed and the angle which has the highest vertical symmetry is picked. Then, all of the selected slices are rotated with the angles acquired in this step. Section III shows that the proposed rotation improves the whole performance of the MLS estimation. After rotation, the line that divides the rotated slices to two equal right and left partitions is marked as IML. With this step, the IML detection phase is completed.

B. AML detection phase

By finding the IML, the next phase is locating the AML. By locating both IML and AML, the MLS can be easily calculated. Clinicians usually calculate the MLS using those slices that contain the ventricles. This is due to the clear

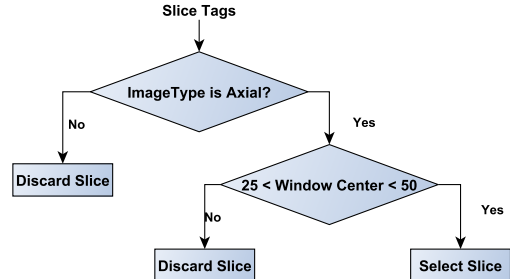


Fig. 2: Slice selection using CT scan metadata

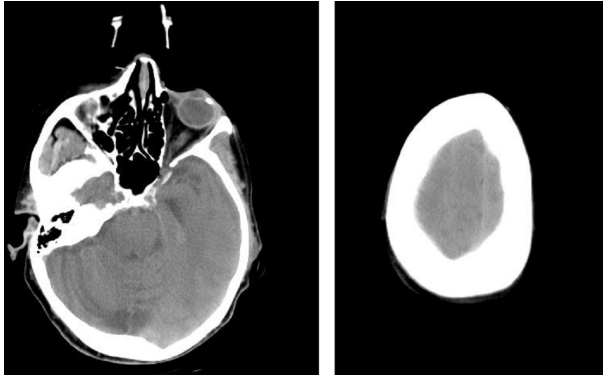


Fig. 3: Examples of slices that are dropped due to their irrelevancy for MLS estimation

visual difference between the ventricles and other tissues of the brain. By checking the amount of shift, they estimate the amount of the MLS and the severity of the TBI. Therefore, a similar method is imitated in automatic MLS estimation. To do this, we use the steps shown in Fig. 4. In the first step, the brain tissues in each image are segmented. Chen et al. [4] used a GMM based method where they segmented the brain tissues into either three or four different clusters. For clustering into three regions, they excluded the skull and suggested segmenting the brain tissue into gray matter, white matter, and ventricles. For clustering into four regions, they included skull as well as the aforementioned tissues and segmented each CT slice into four different regions. While their proposed GMM method can calculate MLS in many cases, the method often fails to segment the ventricles properly, preventing the algorithm from estimating the MLS. As mentioned before, ventricle segmentation alone is sufficient for MLS estimation. Thus our methods focuses on ventricle segmentation rather than classifying brain tissue into multiple regions as in [4]. In the results section, we use a “thresholding” method to segment the brain tissues and locate the ventricles. In addition, this method can concentrate on the ventricle segmentation and consequently reduce the computation overhead. As the ventricles are not visible in all slices, those slices that contain ventricles are passed to the next step, template matching. Using template matching proposed in [4] the ventricles are detected and matched. The slices with the matched ventricles are passed to the next step to locate the AML. The AML of each slice is then estimated. To find the final values, post-processing is performed and the median value of MLS is calculated and is considered as the MLS value at the final step.

III. RESULTS

This section compares the results of the proposed method and the method of [4]. The proposed method was implemented in “MATLAB 2016b”. An internal dataset from the University of Michigan has been used for the performance assessment. This dataset contains around 170 sets of CT scans of TBI patients. As mentioned above, all steps, from the proper slice selection to the MLS estimation, are done au-

tomatically. Table I shows the statistical comparison among different rotation methods. The clinicians’ inspected MLS and the value computed by the methods are subtracted and the mean and standard deviation of these subtraction for all participants are computed. It is clear from this table that the proposed rotation outperforms the former one. In addition, the results show that thresholding with the proposed rotation method outperforms all other combinations. Another important observation from these results is that the performance of the thresholding approach with the old rotation is lower than the combination of this segmentation algorithm with the proposed rotation. It shows that all steps are important and have a great impact on the final estimation of the MLS. This table shows a clear and sharp improvement by the proposed method in this paper.

Fig. 5 shows the impact of different rotation methods on IML detection and final MLS estimation. In both slices shown in Fig. 5, the green and red lines show correct IML, the estimated IML, respectively. The left image is acquired by the rotation method used in [4]. It is clear from the figure that the estimated IML does not coincide with the correct IML. However, the right image shows the result of the proposed algorithm, where IML of the proposed method coincide the manual one.

The amount of the MLS is a primary factor in TBI severity and outcome prediction scales, with MLS greater than $5mm$ typically representing a severe injury [2]. Therefore, we measure the performance of the proposed method using this metric and thus classify MLS values to two groups: 1) greater than $5mm$ and 2) less than or equal to $5mm$. Table II shows the comparison between the proposed method and the method of [4] in terms of sensitivity, specificity, precision, accuracy and $F1$ score. The results are generated using CT scans of 170 TBI patients from the University of Michigan database. There are 59 cases with MLS values greater than $5mm$ and 111 cases with MLS values smaller than or equal to $5mm$. As shown in Table II, the proposed method outperforms the GMM-based method [4] significantly. Therefore, it can be a proper decision support system (DSS) for clinicians. However, it needs to be more reliable to be considered as a

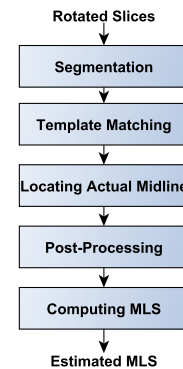


Fig. 4: AML detection phase

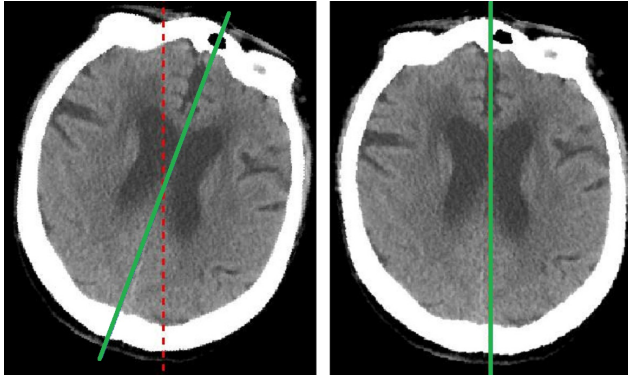


Fig. 5: Rotation comparison; left: Rotation of [4]; right: Proposed Rotation

highly trusted method.

Fig. 6 shows the comparison between the MLS estimated by [4] and the proposed method for the same selected image. The red and blue lines show IML and AML, respectively. The IML in both left and right are the same. However, their computed AML are different. The left slice shows the result of the [4]. The MLS values of the ground truth, the proposed method and the method of [4] are $8mm$, $8.09mm$ and $18.87mm$ respectively.

IV. CONCLUSION AND FUTURE WORK

MLS estimation is a significant feature that helps clinicians decide on a course of action for TBI patients. In this paper, we have proposed an automated MLS estimation by first selecting informative slices that contain ventricles. We then have proposed a rotation mechanism in which we used skull symmetry and stacking approaches. After that we have calculated the ideal midline using anatomical features. In order to estimate the actual midline we have used a simple thresholding approach to segment ventricles. We have used ventricular geometric patterns to find the actual midline. The experimental results have shown a significant improvement

TABLE I: MLS approaches comparison; mean and standard deviation of difference between the ground truth values and computed ones in mm .

Method	Mean	STD
GMM with old Rotation	5.08	4.92
Thresholding with old Rotation	3.99	4.16
GMM with new Rotation	4.66	4.22
Thresholding with new Rotation	3.78	3.74

TABLE II: Proposed method vs. [4]

Measures	Proposed	[4]
Sensitivity	0.75	0.39
Specificity	0.65	0.46
Precision	0.53	0.28
Accuracy	0.68	0.44
F1 Score	0.62	0.32

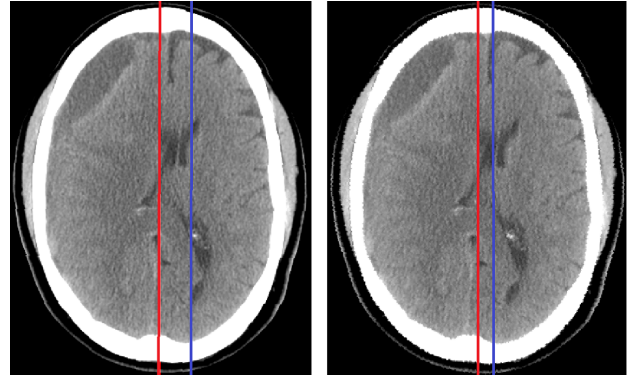


Fig. 6: MLS comparison; left: [4]; right: Proposed Approach

of the proposed method performance in comparison with the similar approach. In future work, the segmentation method template matching will be improved as it can improve the total performance of the method.

ACKNOWLEDGMENT

This material is based upon work supported by the National Science Foundation under Grant No. 1500124.

REFERENCES

- [1] R. Diaz-Arrastia and P. E. Vos, "The clinical problem of traumatic head injury," *Traumatic Brain Injury*, p. 237, 2014.
- [2] L. F. Marshall, B. M. Toole, and S. A. Bowers, "The national traumatic coma data bank," *Journal of Neurosurgery*, vol. 59, no. 2, pp. 285–288, 1983. PMID: 6864295.
- [3] E. L. Yuh, S. R. Cooper, A. R. Ferguson, and G. T. Manley, "Quantitative CT improves outcome prediction in acute traumatic brain injury," *Journal of Neurotrauma*, vol. 29, no. 5, pp. 735–746, 2012.
- [4] W. Chen, A. Belle, C. Cockrell, K. R. Ward, and K. Najarian, "Automated midline shift and intracranial pressure estimation based on brain ct images," *Journal of visualized experiments: JoVE*, no. 74, 2012.
- [5] C.-C. Liao, I.-J. Chiang, F. Xiao, and J.-M. Wong, "Tracing the deformed midline on brain CT," *Biomedical Engineering: Applications, Basis and Communications*, vol. 18, no. 06, pp. 305–311, 2006.
- [6] F. Xiao, I.-J. Chiang, J.-M. Wong, Y.-H. Tsai, K.-C. Huang, and C.-C. Liao, "Automatic measurement of midline shift on deformed brains using multiresolution binary level set method and hough transform," *Computers in Biology and Medicine*, vol. 41, no. 9, pp. 756–762, 2011.
- [7] W. Li, H. Pan, X. Xie, Z. Zhang, and Q. Han, "Simple and robust ideal mid-sagittal line (iml) extraction method for brain ct images," in *2016 IEEE 16th International Conference on Bioinformatics and Bioengineering (BIBE)*, pp. 266–273, Oct 2016.
- [8] M. Chen, A. Elazab, F. Jia, J. Wu, G. Li, X. Li, and Q. Hu, "Automatic estimation of midline shift in patients with cerebral glioma based on enhanced voigt model and local symmetry," vol. 38, no. 4, pp. 627–641.
- [9] A. Kemmling, H. Wersching, K. P. Berger, S. Knecht, C. Groden, and I. S. Noelte, "Decomposing the hounsfield unit," *Clinical Neuroradiology*, vol. 22, pp. 79–91, 2011.
- [10] W. Chen, R. Smith, S.-Y. Ji, K. R. Ward, and K. Najarian, "Automated ventricular systems segmentation in brain CT images by combining low-level segmentation and high-level template matching," *BMC Medical Informatics and Decision Making*, vol. 9, no. Suppl 1, p. S4, 2009.
- [11] X. Qi, A. Belle, S. Shandilya, K. Najarian, W. Chen, R. S. H. Hargraves, and C. Cockrell, "Automated intracranial pressure prediction using multiple features sources," in *2013 International Conference on Information Science and Applications (ICISA)*, pp. 1–4, June 2013.
- [12] D. Varma, "Managing DICOM images: Tips and tricks for the radiologist," *Indian Journal of Radiology and Imaging*, vol. 22, no. 1, pp. 4–13, 2012.