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Automated Detection of Lesions in Patients with Traumatic Brain Injury using Brain CT Images: Concept Note and Proposed Method

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Abstract

Accurate and early interpretation of CT scan images in TBI patients reduces the critical time for diagnosis and management. As mentioned in other studies, automated CT interpretation using the feature extraction method is a rapid and accurate tool. Despite several studies on the machine and deep learning employing algorithms for automated CT interpretations, it has its challenges. This study presents a concept note and proposes a feature-based computer-aided diagnostic method to perform automated CT interpretation in TBI. The method consists of preprocessing, segmentation, and extraction. We have described a simple way of classifying the CT scan head into five circumferential zones in this method. The zones are identified quickly based on the anatomic characteristics and specific pathologies that affect each zone. Then, we have provided an overview of different pathologies affecting each of these zones. Utilizing these zones for automated CT interpretation will also be a helpful resource for concerned physicians during the odd and rush hours.

Keywords

- ► automated image analysis
- ► segmentation
- ► CT scan brain
- ► traumatic brain injury

Introduction

Traumatic brain injury (TBI) refers to the neuropathological changes and brain dysfunction due to any injury to the head. TBI has emerged as a silent epidemic predominantly affecting the young and productive population and adds to the mortality, morbidity, and societal burden.[1] CT head plain is the investigation of choice in patients with a head injury. The complexity and dynamic nature of TBI necessitate prompt and accurate identification of pathology on CT images and subsequent appropriate management for optimal outcome. Therefore, it is crucial to have facilities for CT scans, and at the same time, it is essential to have personnel trained to accurately interpret the CT image findings. Imaging is an important clinical tool used in the management of patients with brain injury. The objectives of the present study are to propose an algorithm for automated image segmentation and interpretation of CT scans of the brain and propose an algorithm for identification and categorization of the abnormal CT findings in patients with TBI.

Characteristics of Brain Pathology to be Identified

Important pathological findings on the CT brain are tabulated in ►**Table 1**.[2] Each can be categorized based on the CT as shown earlier based on the zones described have characteristic appearance as illustrated below. For example, on CT imaging, the acute EDH appears as a well-defined, hyperdense, biconvex, extra-axial collection. It is usually

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Table 1 Based on lesion characteristics,[2] proposed zones on CT imaging

Zone	Definitions	Probable lesions
Zone I	Extracranial including scalp	Scalp lacerations Swelling
Zone II	Skull	Various fractures
Zone III	Just inside the skull Including dura mater, subdural space, sub-arachnoid space and adjacent brain parenchyma	Extradural hemorrhage (EDH) Subdural hemorrhage (SDH, acute and chronic) Subarachnoid hemorrhage (SAH) Surface contusions
Zone IV	Cerebral gray and white matter, outside the central ventricular region	(Intracerebral hemorrhage (ICH) Cerebral contusion Cerebral, edema
Zone V	Central ventricular regions and adjacent brain parenchyma	Intraventricular hemorrhage (IVH) Contusions

associated with an overlying skull fracture. Mass effect with sulcal effacement and midline shift is frequently seen. Because the EDH is located in the potential space between the dura and inner table of the skull, it rarely crosses cranial sutures because the periosteal layer of the dura is firmly attached at sutural margins. However, at the vertex, where the periosteum that forms the outer wall of the sagittal sinus is not tightly attached to the sagittal suture, the EDH can cross midline. An important imaging finding that predicts rapid expansion of an arterial EDH is the presence of low-attenuation areas within the hyperdense hematoma (the so-called "swirl sign"), thought to represent active bleeding. It is an ominous sign that needs to be followed closely.[3,4]

The Proposed Method for Automated CT Interpretation

We propose image segmentation algorithms that can be applied for the precise detection of TBI pathology (►**Table 1**). Such detection can be helpful in further quantitative analysis of critical characteristics, such as the size or volume of the lesion. Our proposed method is divided into three main stages: **image preprocessing, brain segmentation, and hydrocephalus segmentation.**

Image Preprocessing

Each image from the input dataset will be normalized to a common intensity range in this step. For brain segmentation, pixel intensities will be transformed to Hounsfield units[1] (range from -1024 to ~3071). According to the DICOM specification, every pixel in the image will be scaled. After scaling image intensities, using other DICOM header information, such as *Window width* and *Window center,* pixel intensities will be transformed from signed to unsigned values without quality changes. In the case of CT images, 12 bits are sufficient to cover a whole range of intensities. The data are shifted when using unsigned shorts, so all CT intensities become positive numbers ranging from 0 to 4095 ($g_m i_n = 0$, $g_{max} = 4095$).

Brain Segmentation

The second step will be aimed at the extraction of the whole brain. This step is necessary for further quantitative assessment of the disease progress. Pixel transformation performed in the previous step significantly increased the image's contrast. As a result, the skull area and the CT scanner tube elements could be easily removed by suppressing (setting to zero) any pixel in the image above 95% of the maximum pixel intensity value. The selected threshold will be chosen empirically based on observing the distribution of pixel intensities after their transformation. After removing the skull and CT tube, extraction of the whole brain area was possible. For this purpose, the 2D segmentation algorithm based on region growing was applied. This method requires the selection of the initial seed point. It was decided to locate the seed at the center of each cross-section as it is always contained in the brain area. The desired region originates from the exact location of this point. Then, the region grows from the seed point to adjacent points depending on the selected threshold. Threshold value determines the scope of permissible difference of intensity between intensity of the candidate pixel and an average intensity of pixels already classified into the region. In the present method, we propose five zones on the CT scan from outside to inside and different pathologies described on each zone. These zones are described in ►**Table 1** along with the corresponding lesions. The normal unsegmented CT brain plain image is shown in ►**Fig. 1A**. ►**Fig. 1B** and **1C** shows the segmented zone 1 corresponding to the scalp and skull. The proposed five zones are shown in ►**Fig. 2**.

Advantages and Challenges

The advantage of developing this algorithm is prompt identification of pathology on CT scan by a primary physician and nonneurosurgeon. Early and accurate CT scan interpretation will facilitate the timely transfer of TBI patients to a center equipped with facilities for TBI care and allow for the appropriate treatment initiation at the first point of contact. The main disadvantage of this

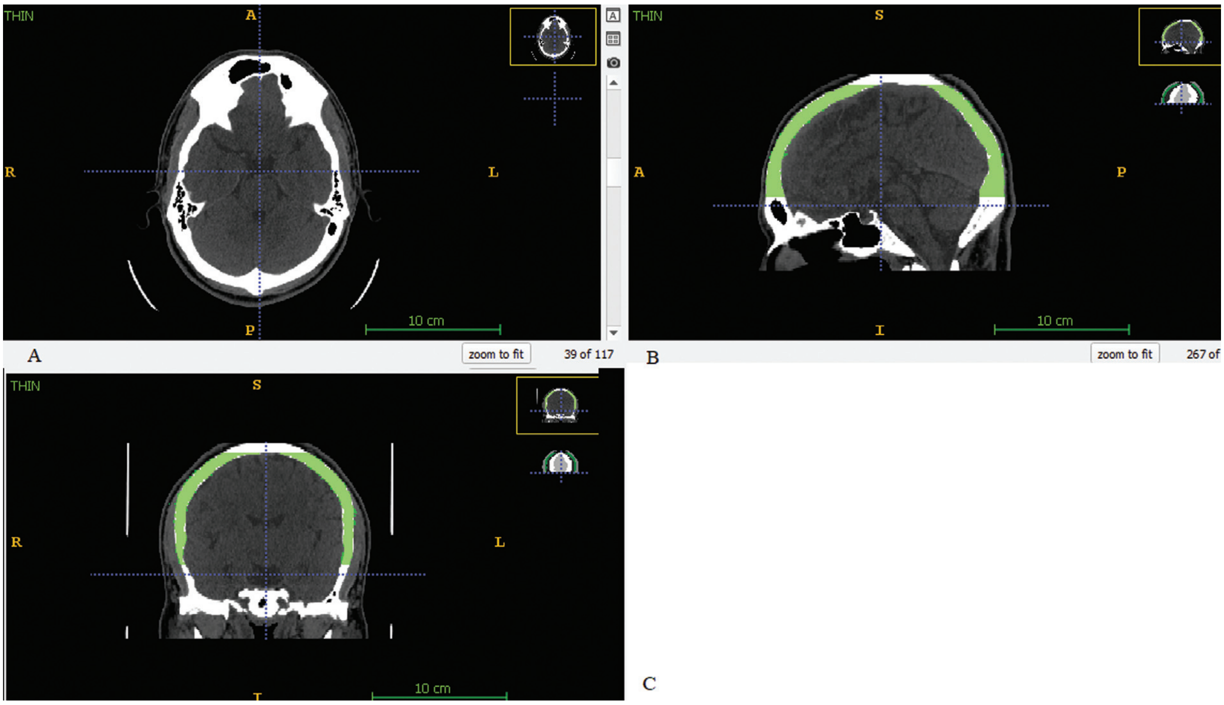

Fig. 1 **(A):** Normal unsegmented plain CT brain. **(B)** Segmented zone of scalp and skull in sagittal view. **(C)** Coronal View.

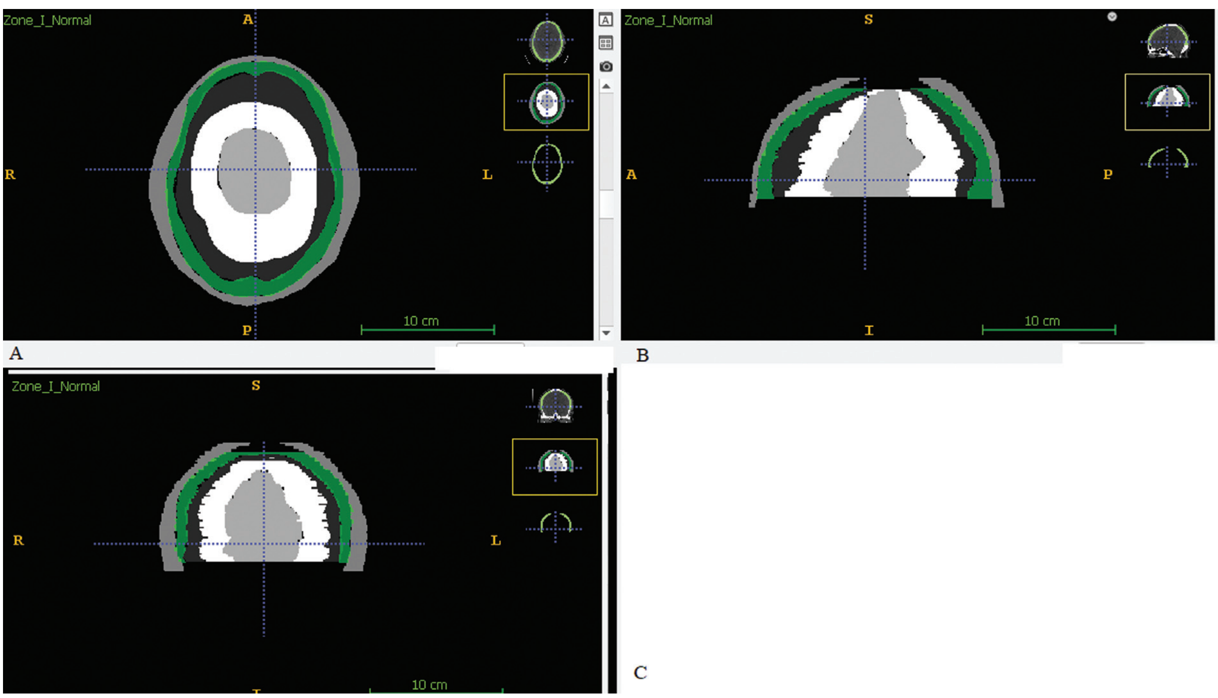

Fig. 2 Proposed five zones from outside to inside comprising scalp as zone 1, skull as zone II, subdural space as zone III, cerebral gray matter as zone IV, central ventricular regions and adjacent parenchyma as zone V.

approach is that seeded region-growing algorithms may not clearly define the boundaries of the stroke region. Moreover, to date, only a single study has addressed the problem of detecting both hemorrhagic and ischemic strokes in a given CT volume.[5] It is worth mentioning, however, that the availability of a high-quality template does not in itself ensure a successful spatial normalization.[6]

Conclusion

Rapid advancements in medical imaging technology have resulted in accurate and early diagnosis of many diseases conditions, better management planning, and improved outcomes in neurosurgical practice.[7] Several authors have developed algorithms for automated analysis and segmentation of CT images to interpret the findings as an adjunct to manual image reading.[7–12] The present article presents a conceptual analysis to explore the feasibility of automated image analysis and segmentation to interpret the CT images in patients with TBI.

Conflict of Interest
None declared.

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