Identification of acute intracranial bleed on computed tomography using computer aided detection

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Abstract. Intracranial haemorrhage can be life threatening. Timely detection of acute intracranial haemorrhage in an emergency room is essential so that the patient can be given medical attention without delay. This has led to the use of Computer Aided Detection (CAD) systems which can help to pick up and prioritize patients with high risk of bleeding. A CAD for identification of acute intracranial haemorrhage in Computed Tomography (CT) on a per patient basis was developed in this project. The CAD is aimed to be a triage tool which determines the priority of image being read by radiologists. It was developed and validated using 119 and 108 volumes of brain CT images respectively. The volumes were first registered to standard Montreal Neurological Institute (MNI) space. Slices close to the base and top of the skull that tend to contribute to false positives were omitted. Then, the volumes were analysed by a fully automated CAD program developed in MATLAB. The algorithm involved multiple thresholding and symmetry detection in 3D to detect acute intracranial haemorrhage. The evaluation took around 5s per volume. On a per patient basis, the CAD achieved sensitivity of 75.0%, specificity of 83.8%, and accuracy of 80.6% in the validation set.

1. Introduction
Approximately 7 million individuals every year in the world suffer from traumatic brain injuries caused by various reasons [1]. It is a life-threatening medical condition where immediate treatment is crucial as it can cause internal brain bleeding, leading to disability and death. Correctly identifying haemorrhage or bleeding in the brain is critical to make fast and reliable treatments and diagnostic decisions for providing better care to brain injury patients. However, internal bleeding is typically only picked up by imaging modalities such as computed tomography (CT) scans, and the manual assessment of these medical images by radiologists. Manual assessment of images is a time consuming and tedious task. Furthermore, the availability of radiologists for immediate diagnosis cannot always be expected as many emergency cases occur outside office hours. This has led to the use of Computer Aided Detection (CAD) systems which can help to automatically pick up and prioritize high risk patients.

CAD began to be applied widely for the detection of abnormalities in medical imaging in the 1980s [2]. For brain CT image analysis, various detection methods have been proposed. The most common segmentation approached have been using thresholding [3] and active contours [4]. Aside from that, there are also approaches using knowledge-based classification [3], feature extraction [5], symmetrical
axis detection [6], Otsu multi-thresholding [7], fuzzy C-mean clustering [4], and histogram analysis [1]. In this paper, a fully automatic CAD system was developed for identification of acute intracranial haemorrhage in CT on a per patient basis for purposes of triage.

1.1. Intracranial haemorrhage

Intracranial haemorrhage happens when blood vessels within the brain bursts, causing bleeding inside the confines of the skull. It can be classified into extracerebral and intracerebral haemorrhage. They are further divided into epidural haemorrhage (EDH), subdural haemorrhage (SDH), subarachnoid haemorrhage (SAH), intraparenchymal haemorrhage (IPH) and intraventricular haemorrhage (IVH). The type of haemorrhage depends on the location of the bleed and appears differently in CT images [8]. SAH is usually thread-like, small and punctate in CT images. According to the Brain Aneurysm Foundation, SAH accounts for between 0.01 and 0.08 percent of visits to the emergency room [9]. This type of haemorrhage is not considered in this project.

2. Materials and Methods

The data consists of 227 volumes of non-contrast CT images from University of Malaya Medical Centre (UMMC) including 223 volumes of adults, 3 volumes of children and 1 infant. Slice thickness varied between 1.25 mm to 3.0 mm; reconstruction diameter (field of view) varied between 179 mm to 350 mm. The volumes were divided randomly into two data sets, namely training set and validation set. The training set contains a total of 119 volumes where 54 volumes contain at least one acute intracranial bleed. The validation set contains 108 volumes where 40 of them contain at least one acute intracranial bleed. Diagnosis of all cases was made by a radiologist. The diagnosis is taken as the gold standard for this work. All volumes were anonymized and the study has been approved by the medical ethics committee of UMMC (MECID. NO:201412-864).

2.1. Method

The volumes were registered or realigned to standard Montreal Neurological Institute (MNI) space using the Insight Segmentation and Registration Toolkit (ITK). The target volume was a CT brain template published by Rorden [10]. The registration allowed a reasonable knowledge of which slices would correspond to specific locations in the brain. Then, the registered volumes were analysed by using a CAD program developed in this study. The CAD program was written in MATLAB R2018b (The MathWorks, Inc., Natick, MA, USA).

2.1.1. CAD program.

The algorithm was run on a Personal Laptop with Intel® Core™ i5-8250U CPU @ 1.60 GHz 1.80 GHz processor, running on Windows 10 operation system with 8.00 GB RAM. The program started with selection of slices namely slices 15 to 85 where the slices close to the skull base and tip of the head were omitted. Then the intracranial region of the brain was extracted by thresholding at the density of brain and acute intracranial bleed with 10 HU tolerance (from 10 HU to 100 HU). The scalp and other noise were eliminated by only retaining the biggest central object of each slice. The first detection of bleed was done by thresholding at the acute bleed density with 5 HU tolerance and 10 HU tolerance for lower bound and upper bound respectively (from 45 HU to 100 HU). The second detection of bleed was done by using the symmetrical property of features in CT brain images. The extracted brain was split and mirrored through the midsagittal plane. Image subtraction was done between the two halves. A binary mask was created by thresholding the result volume from 20 HU to 60 HU, an estimation of the difference between acute bleed density with normal brain density. Erosion and dilation morphological operations were done throughout to eliminate tiny fragments. The first and second bleed detections were combined, only the regions where both detections agreed with each other would be picked up as suspected bleed. Bleed in this study is defined as hyperdense regions with a volume of at least 600 mm³ which was empirically determined from analysis of the training set.
3. Results and Discussion
The performance of the algorithm was evaluated on a per patient as opposed to per lesion basis. The summary of the CAD evaluation for both training and validation set are shown in Table 1.

Table 1. Summary of algorithm evaluation

|                      | Training set (n=119) | Validation set (n=108) |
|----------------------|----------------------|-------------------------|
| Sensitivity (%)      | 85.2                 | 75.0                    |
| Specificity (%)      | 86.2                 | 83.8                    |
| Accuracy (%)         | 85.7                 | 80.6                    |

The sensitivity of the algorithm shows the algorithm’s ability to pick up patients with bleeds whereas the specificity shows the algorithm’s ability to rule out patients without bleeds. The algorithm takes an average of about 5 seconds per volume for evaluation, not including the initial registration to MNI space.

The results show that the detection is fast (average of 5 seconds per volume). Figure 2 shows an example of bleed successfully detected by the algorithm.

3.1. False positive cases
False positive cases in this study are mostly contributed by the density near the skull. The areas near the skull appears brighter or denser compared to normal brain tissue due to cupping artefacts. These denser brain regions fall within the threshold tolerance and failed to be eliminated since most of them are not symmetric (Figure 3(a)).

Besides, streak artefact also contributed to some false positive cases. This might be caused by the patient movement or dense bone regions which degrades the quality of the CT images (Figure 3(b)).

3.2. False negative cases
In some cases, acute intracranial bleed is initially detected but were too small and were thus erroneously omitted (Figure 3(c)). The threshold of the bleed volume in this study was set to $600 \text{ mm}^3$. The thresholding, morphological, and intersection operations could all contribute to this error.

![Figure 3](image-url)

**Figure 3.** Example of (a) image which the area near the skull appears denser, (b) image degraded by streak artefacts, and (c) small bleed that the algorithm fails to pick up. The original image is displayed on top whereas image at the bottom shows overlay of the bleed detected (red area)

4. Conclusions
A CAD program for fully automatic detection of acute intracranial haemorrhage in CT has been developed. This program involves the registration of volumes and bleed detection in 3D using both intensity thresholding and symmetry. The sensitivity, specificity and accuracy of the algorithm for the validation set was 75.0%, 83.8% and 80.6% respectively.

5. References
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