An Automatic Diagnostic System for CT Brain Image Classification

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Abstract

Computed tomographic (CT) images are widely used in the diagnosis of stroke. In this paper, we present an automated method to detect and classify an abnormality, into acute infarct, chronic infarct and hemorrhage at the slice level of non-contrast CT images. Designing and developing computer-assisted image processing techniques to help doctors improve their diagnosis has received considerable interests over the past years. In this paper, a CT brain image diagnostic classification system is presented which will automatically find, extract the CT brain boundary and further classify brain diseases. The system comprises a detect-before-extract (DBE) system which automatically finds the brain boundary. The proposed method consists of three main steps: image enhancement, detection of mid-line symmetry and classification of abnormal slices. A windowing operation is performed on the intensity distribution to enhance the region of interest. Domain knowledge about the anatomical structure of the skull and the brain is used to detect abnormalities in a rotation- and translation-invariant manner. A two-level classification scheme is used to detect abnormalities using features derived in the intensity and the wavelet domain.

Keywords: *Image Enhancement, Detection of midline symmetry, Image Classification, Image retrieval, Image, image Contrast stretching, Image Colorization*.

1. INTRODUCTION

Brain cell function requires a constant delivery of oxygen and glucose from the bloodstream. A stroke, or cerebro vascular accident (CVA), occurs when blood supply to part of the brain is disrupted, causing brain cells to die. Stroke is the third among the reasons for acute death [1]. It is also the first among the reasons for neurological dysfunction [1]. There are mainly two types of stroke, namely ischemic stroke and hemorrhagic stroke as shown in Fig. 1 [2]. The occurrence of Ischemic stroke is due to sudden blockage of the arteries in the brain. The blockage causes the lack of oxygen in the blood [2]. As a result, the brain cells die. On the contrary, hemorrhagic stroke is due to sudden rupture of an artery, causing the blood flowing into other brain tissue [2]**.**Brain lesion can be defined as an area of damage brain tissue due to injury or disease, and can be caused by several ways, particularly infection in the brain, abnormal grow of clusters veins, head injuries, Alzheimer's disease, multiple sclerosis and also prominent cerebral infarct or stroke [3]. According to the statistics from World Health Organization (WHO), in 2007, 15 million people suffered from stroke globally. Out of these, stroke claimed the life of 5 million, and another 5 million were permanently disabled [1].

At present, CT scans and MRI are the two brain imaging techniques mostly used in hospital to examine the brain lesion. These two techniques can effectively disclose different types of brain tissues. With the advanced technology, the images for these two imaging modalities are in DICOM format which include corresponding patient data as well as the images [4]. However, CT scan is still the prefer choice than MRI due to lower cost and wider availability [4] [5]. In addition, CT imaging can provide information especially in the acute stage. Previous works had already been proposed and implemented to detect the lesion in brain images. The proposed method consists of three steps, namely image enhancement, midline symmetry detection and abnormal classification for brain scan images [6]. In the classification process, two level classification methods are used to detect brain abnormalities by using characteristics in the intensity and wavelet domain [6]. Any tilted brain image is rotated correctly before symmetrical axis is determined [7]. After that, the area and centroid of the abnormalities are chosen as the features in the rule-based abnormalities detection [7]. The forming of midline is predicted from the brain lesion by using Linear regression model (H- MLS model) [8]. Most of the existing works on stroke detection mainly focus on

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hemorrhagic stroke without paying much attention on ischemic stroke. In this paper, early infarct detection through image colourisation is proposed to aid the radiologists in providing diagnosis to the patient. The proposed method consists of two main parts, which are image contrast stretching and image colourisation. All of the method details will be discussed in the following section.

2. IMAGE ENHANCEMENT AND NOISE FILTERING

Since the dynamic range of the Hounsfield unit (HU) values for CT images is very large (-1000 to +1000 HU), the first task is to select the appropriate range of gray level for extracting soft tissue regions. The relationship between gray level (I(x, y)) and HU given as:

$$HU = I(x, y) + \text{intercept} \quad (1)$$

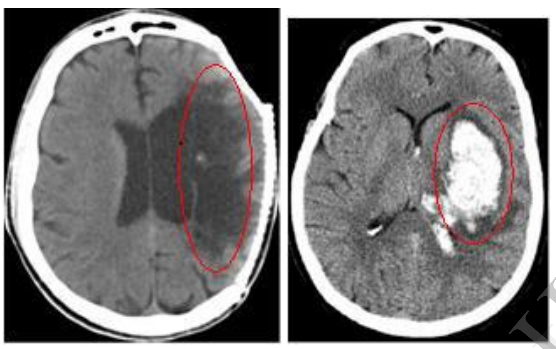

Fig. 1: Two types of stroke as indicated by red circle: (a) Ischemic stroke and (b) Hemorrhagic stroke [6]

where, the intercept value can be obtained from the meta information available in the DICOM header of CT volume data. The histogram of a given slice consists of two major peaks corresponding to the background and soft tissue pixels. Since the HU values of the soft tissue are higher than that of the background (air), the higher intensity peak will correspond to the soft tissue region [12]. A windowing operation to stretch the contrast is performed with the above peak value (P) as the center and W (set to be 120 HU) as the width of the window:

$$I_{new}(x,y)= 255 * (I_{original}(x, y) - (P - W/2))/W \text{ --------------}\rightarrow 2$$

After windowing, noise removal is performed usingWiener filtering to remove the graininess from the image. A sample image and the result of the enhancement and the denoising is shown in Fig.2

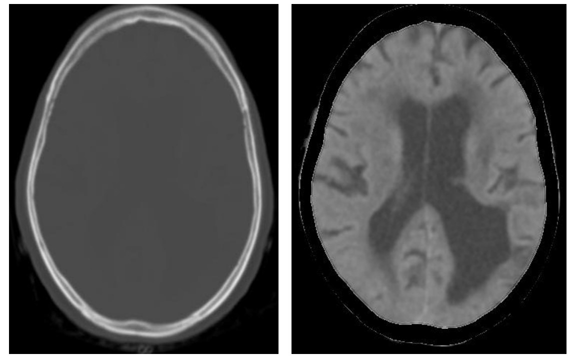

Fig 2(a) Original image,
(b)Enhanced (windowed) image

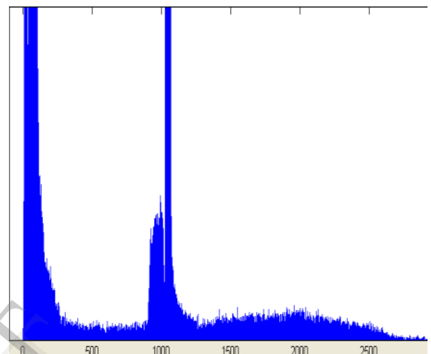

Fig 3. Histogram of the CT image in Fig. 2(a).

3. ROTATION CORRECTION AND DETECTION OF LINE OF SYMMETRY

Since our approach is to compare histograms of the two hemispheres, it is necessary to correctly identify the line of symmetry. The physical structure of the skull is used to detect the rotation angle as well as the line of symmetry. The line of symmetry ls is one that passes through the tip of the nose and bisects the horizontal line lh passing roughly through the middle of the slice. We correct for any rotation present before extracting these lines. To find ls we first search a set of slices (with high number of connected components) around the nasal cavity region. A sub-region is identified in these set of slices by locating the tip of the nose via a simple raster scan. The sub region is of size 30x512 and its horizontal projection profile is computed for every slice. The troughs in the profiles are found in either direction starting from the nose tip for each of the candidate slice. The slice which shows the steepest curve is chosen to be appropriate to detect and correct for rotation. In the axial view, the nose appears as a hill with the tip being the peak of the hill and the base being bounded by knee points of the hill. In the absence of rotation, the line passing through the tip of the nose should be orthogonal to the line connecting the base of the nose. The knee points are easily detected by determining the rate of change of the slope of the nose boundary starting from the nose tip. The deviation of the base line from the horizontal gives the rotation angle which is used to perform a correction. This preceding step can only correct for rotation in the x-y plane. It is possible that the CT volume is also rotated in the axial direction which will mean the plane of symmetry will not be perpendicular to the x-y plane. Consequently, the lines of the symmetry for each slice will not align. In order to address this problem, we determine ls for each rotation-corrected slice as follows:

lh is of same width as the horizontal projection profile of each slice and thus the required ls is the bisector of lh. A sample slice image and the result of rotation correction is shown in Fig. 4.

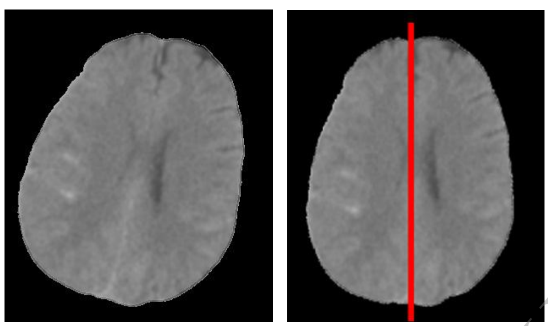

Fig. 4 (a) original image with rotation (b) rotation corrected image with the line of symmetry in red

4. DETECTION OF ABNORMAL SLICES

The detection algorithm performs a 2-level classification to identify abnormal and normal slices. Histogram features are used in the first level while wavelet-based features are used for the second level. Since the nasal slices have very little soft tissue, they have to be handled with care. In our approach, they are classified as normal in the first level and passed to the second level for analysis.

The first step differentiates the encephalic slices into three classes C1, C2 and C3 as described earlier, based on their histogram features. The ls information is used to divide a slice into two hemispheres and the histogram for the right and left hemispheres are computed and compared for similarity. The similarity metric used is the correlation coefficient which is computed on a subsample (by 5) version of the 2 Histograms. Since only the low and high indexed bins are of interest, the measure is computed only for those bins. If this measure is below a threshold the corresponding bin number is noted. If the bin number is low, the slice is classified as belonging to C1 (see Fig.5) and if the bin number is high the slice is classified as a member of C2. If the measure is below the threshold in both low and high indexed bins, the implication is that both type of abnormalities present in the slice. Therefore such slices are accorded membership in both C1 and C2. All slices with correlation measure above threshold are classified as belonging to C3.

In the second level of classification, the goal is to differentiate between normal and acute infarct cases. Histogram features are insufficient for this purpose as their grey value distributions overlap. This can be seen from the histograms shown in Fig. 6. Since the differences between the distributions are subtle, a finer analysis is required. A wavelet decomposition of the histograms is employed for this analysis. Daubechies-4 wavelet decomposition up to 5 levels are used to compute the energy distribution in the scale space. The corresponding energy values of the two histograms are compared using a simple difference of energy measure. If the difference is above a threshold, the slice is classified as belonging to C31. All other cases are classified as normal.

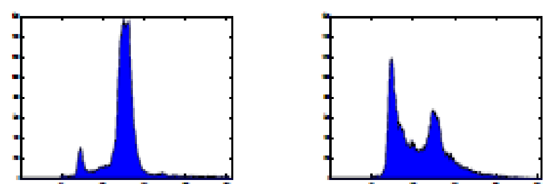

Fig.5. Histograms of a hemisphere for (a) normal and (b) with an old infarct cases.

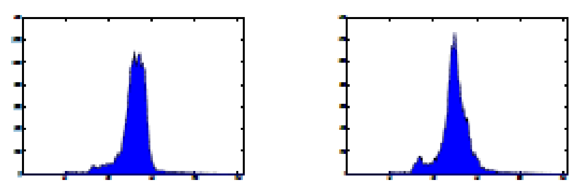

Fig. 6 Histograms of a hemisphere for (a) normal and (b) acute infarct cases.

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4.1 Image Contrast Stretching

With the advanced technology, all brain images are in DICOM format. The range of the brain image pixel is very large, corresponding to 16-bit or 65536 grayscale levels. The huge range can cause the unperceived information when the brain image is viewed without any windowing as shown in Fig. 7(a). However, most of the important brain structures are within the range of 0 to 80 in Hounsfield unit (HU). Consequently, windowing process has to be performed. Firstly, initial brain image in DICOM format has to be adjusted before conversion to Grayscale by using the equation 3. The rescale slope and rescale intercept value can be obtained from the metadata of DICOM image. This is to ensure that all DICOM image can be converted to grayscale image properly regardless of different rescale intercept on different machines.

Img= Im X rescale slope + rescale Intercept ---------------------→3

where Im is the original pixel value in DICOM format, and Img is the new pixel value in DICOM format. After that, the new HU represented by Img is converted to 8-bit greyscale value as shown in equation 2. This windowing will result in an image displaying HU from 0 to 80 only, while the remaining HU are represented by black or white colour. The windowed image is then converted to the range from 0 (black) to 255 (white). The window center (WinCenter) is set to 40 while the window width (WinWidth) is set to 80. The final greyscale image is produced and shown in Fig. 7(b).

$$grey\ img = 255 \times \frac{Img - WinMin}{WinMax - WinMin}$$

where $WinMax = WinCenter + \frac{WinWidth}{2}$

and $WinMin = WinCenter - \frac{WinWidth}{2}$

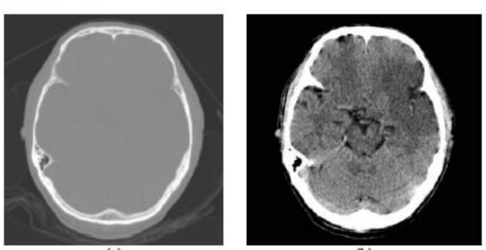

(a) (b)

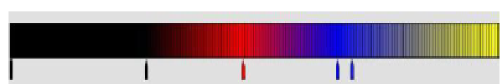
Fig. 7: A CT brain image of early infarct case: (a) image before windowing and (b) greyscale image after conversion

4.2 Image Colourisation

After converting brain image from DICOM format to grayscale, the image is then coloured. Different colours are assigned for each range of grayscale values to improve the visualization of different types of brain structures. The grayscale level can be obtained in Table 1 based on the HU for brain structures. A colour map is chosen to apply the colourisation on the brain image as shown in Fig. 8. Three basic colours are chosen, which are red, blue and yellow that form a colour wheel. Among these three colours, red colour has always been considered to be the most contrasting and prominent colour. Therefore, it is chosen for the grayscale level from 64 to 96 which covers the stroke tissue. According the blue and yellow colour, gray matter is represented by yellow colour for brighter appearance in grayscale brain image. Lastly, blue colour is chosen to cover the grayscale levels of 96 to 128. In addition, the grayscale level that falls below 64 are black, while those above 192 are white in colour. Fig. 8 shows the new colour map values to represent the grayscale levels from 0 to 255 for a CT brain image.

TABLE 1: THE RANGE OF GREYSCALE LEVELS FOR IMPORTANT BRAIN STRUCTURES

Brain Structure	Hounsfield unit range	Greyscale level
Stroke tissues	20 – 30	64 - 96
White Matter	30 – 40	96 – 128
Gray Matter	50 – 60	160 - 192


(a)

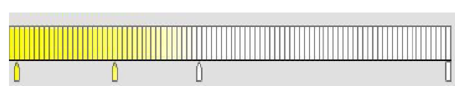

(b)

Fig. 8: (a) New colour map of 255 levels for brain image colourisation and (b) the continuation of (a)

With the proposed colour map, the visibility of early infarct area is greatly enhanced, where the stroke tissues is represented by red colour. Besides, the attention of medical practitioners is attracted to provide diagnosis if a big area of red colour appears in the brain image. However, sign of early infarct detection does not merely lie on spotting for red colour, but rather the comparison of the colour in brain symmetry. Chronic or old infarcts will be even more obvious through black colour representation. It is very hard to miss a chronic infarct in grayscale brain image. However, the infarct is more prominent

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with the aid of colours. Fig. 9 shows the early infarct area.

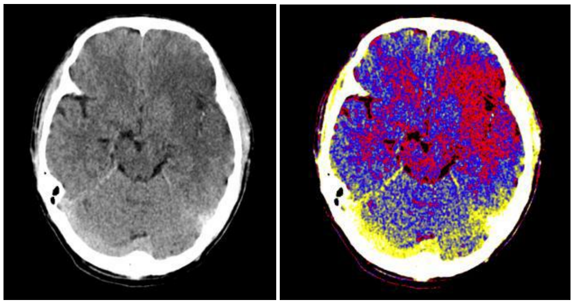

Fig. 9: A CT brain image of early infarct case: (a) the early infarct area indicated by yellow circle and (b) the early infarct area represented by red colour

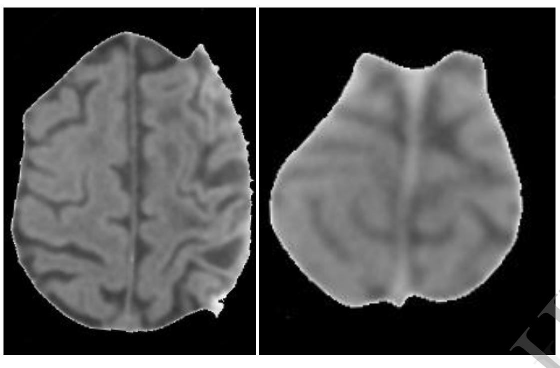

Fig. 10. Erroneous results: (a) False positive of normal (b) false positive of infarct categories

5. EXPERIMENTAL RESULTS

The performance of the method has been tested on a dataset collected from a local hospital from two different scanners: Siemens Emotion 6 and Definition CT scanners. The dataset consists of volume CT data of 15 patients (6 normal and 9 abnormal - 6 infarct; 3 hemorrhagic) cases. Number and thickness of slices vary across patients:18−31 slices and 4.8 − 6 mm, respectively. In total, there are 347 slices belonging to four main categories: 223 normal, 40 chronic infarct, 49 acute infarct and 35 hemorrhagic.
Annotation for each slice of a CT volume was provided by a senior radiologist. The classification performance of the proposed method was tested at slice and at patient (normal vs. abnormal Case) level. The performance figures are presented in terms of precision (or positive prediction value) and recall (or sensitivity). At the patient-level if any slice is found to have an abnormality the entire volume is declared to be abnormal. Table 3 shows that the algorithm has 100% recall and 90% precision at the patient-level. Table 2 presents the performance figures at the slice-level. The average precision obtained for individual category is 92% and maximum (93.3%) for hemorrhagic category. The average recall value is 90% and maximum (95.91%) for acute stroke category. In normal category, false positives were mainly due to mis-classification of slices at the boundary (in the axial direction) of the stroke. It can be seen
from Fig. 10(a) that such slices do not show characteristics of abnormality and hence are difficult to classify. False negatives in the normal category arise due to a subtle difference between normal and acute stroke categories as seen in Fig. 10(b). Some regions of nasal cavity slices also appear close to infarct type mainly due to randomness of their histograms. The mis-classification rate can possibly be
reduced with a better characterization of individual category. Colourisation of CT brain images is proposed by using simple colour map based on different Hounsfield units for different brain structures. The result shows that the early infarct detection with aid is improved by 5.5%. This is important and valuable for medical practitioner in providing treatment to patient at the early stage.

TABLE 2 PERFORMANCE FIGURES AT SLICE-LEVEL.

	Normal	Abnormal / Stroke Slices		
Patients	6	9		
Slices (groundtruth)	223	Infarct		Hemorrhage
		Chronic	Acute	
		40	49	35
True positive	205	38	47	28
False negative	18	2	2	7
False positive	17	4	4	2
Recall (%)	91.92	95.00	95.91	80
Precision (%)	92.34	90.47	92.15	93.33

TABLE 3 PERFORMANCE FIGURES AT PATIENT-LEVEL.

		Ground truth	
		Abnormal	Normal
Algorithm	Abnormal	9	0
	Normal	1	5
Recall		100%	
Precision		90%	

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6. CONCLUSIONS AND FUTURE WORKS

In this paper, we have proposed an algorithm based on contra-lateral symmetry to detect stroke affected slices in a given CT volume. The key features of our algorithm are: ability to detect all types stroke (acute, chronic infarcts and hemorrhages) even if different types are present in the same slice. The proposed approach is a unified one which helps in building a stroke analysis system that can detect and segment all types of stroke. The contra-lateral symmetry condition that we have used fails when the same type of stroke occurs symmetrically in both hemispheres. Such cases, though rare, are currently not handled by our algorithm. Initial results obtained on testing over 347 slices are very encouraging. Most of the false positives in normal category can be reduced by using the fact that strokes are usually spatially continuous. Hence, if the imaging is done with thinner slices, continuity across slices can be an indicator for abnormality. As an alternative, it is possible to include some form of spatial information in the histograms, which can help detect symmetrically occurring strokes. Such information can also help in the stroke segmentation task. Due to the Colorization technique the early infarct detection with aid is improved by 5.5%.

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