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AUTOMATIC DETECTION OF ISCHEMIC STROKE LESION USING TEXTURAL ANALYSIS FROM BRAIN CT IMAGES

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ABSTRACT
Stroke lesion quantifying and characterizing is still an open challenge. This method diagnosis the stroke lesion accurately which helps the radiologist fast and proper treatment so that death rate due to brain stroke can be reduced. The method contains three main modules: preprocessing, segmentation and feature extraction. Pre-processing module removes noise and artifacts and abnormal region is extracted in segmentation module. The image is subdivided into four regions to find the region that has the possibility for inclusion of abnormal area. The abnormal portion which contains stroke lesion is characterized with statistical features using first-order histogram. The paper proposes a self-constructed, effective algorithm to support ischemic stroke lesion detection and feature extraction based on CT images.

KEYWORDS: Ischemic Stroke, Computed Tomography (CT), Brain Segmentation, Statistical Features, Infarct.

INTRODUCTION
Ischemic stroke is a condition in which brain stops working due to an obstruction of the blood supply to the brain and which resulting the subsequent death of brain tissue and eventual necrosis.

Ischemic stroke is the third leading cause of death in industrialized countries[1] and it may lead to long-term disability.[2] Ischemic stroke can be classified into two categories they are thrombotic (throm-BOT-ik) and embolic (em-BOL-ik). Thrombotic stroke forms a blood clot (thrombus) in an artery that supplies blood to the brain. Embolic stroke occurs when, blood clot within artery but in this case clot (emboli) can be found somewhere other than brain itself. With both types of ischemic stroke, the blood clot or plaque blocks the flow of oxygen-rich blood to a portion of the brain. According to the World Health Organization, each year 15 million people worldwide who suffer from a stroke, of these 6 million people die each year and another 5 million are permanently disabled.[3] One in six people worldwide will have a stroke in their lifetime. Stroke can take the life of people in every six seconds.

Advanced neuro-imaging techniques play a crucial role in the diagnosis of stroke for brain imaging. Either MR (Magnetic Resonance Imaging) or CT (Computed Tomography) imaging[4] have been normally recommended for detection of stroke. In clinical practice due to wider availability, lower cost and sensitiveness for early diagnosis, CT imaging is preferred over MRI for detection of stoke. Its diagnosis often involves assessing the strokes presence, location, extent, evolution and other factors.

Early and accurate diagnosis of stroke lesion is the key factor for implementing successful therapy and treatment planning.[5]

Lesion segmentation has been performed for improvement of diagnosis process which is a very challenging task and helps the radiologist to make proper and accurate treatment. Manual segmentation is a tedious and time consuming task and is non-reproducible.[6]

In this paper, we propose an automatic ischemic stroke lesion segmentation algorithm using texture analysis from CT images. Development of robust and accurate segmentation techniques of this algorithm have been provided the facility of longitudinal monitoring and analysis of stroke lesions which evolve over time.[7]

Related Work
Various computer-aided diagnosis (CAD) systems have been developed to locate, segment and quantify the stroke lesion area that assist physicians in the diagnosis

and treatment of stroke patients.[8–10] CT and MRI are the two modalities are widely used for stroke detection. Most existing work on stroke detection mainly focuses on hemorrhagic stroke detection.

Previously, Fuk Hay Tang et al[11] introduced CAD scheme for detection of ischemic strokes where circular regions had been selected with varying radii in symmetrical portions of brain but it might ignore the actual infected region. Thomas M.H Hope[12] predicted the severity of cognitive impairments after stroke but the position of the lesion had not given importance.

Uˇsinskas et al. analyzed 18 joint textural features for detection of ischemic stroke patterns in CT slices, but the automated thresholding for each image, at the time of this study, was not completed.[13] Lin and Liu[14] developed a neural network technology based on artificial intelligence which had been used to fabricate a prediction model to detect recurrent stroke. Mayank Chawla et al.[15] introduced an algorithm of two-level classification scheme for detection of stroke using features derived in the intensity and the wavelet domain. Histogram shapes had been used to detect the abnormalities but acute and normal cases were indistinguishable. Lee et al.[16] developed a method which enables radiologists to find the stroke area quickly by analyzing the edge of the brain tissue, the main disadvantage of this method was prolonged CT scanning of patient which may cause of delay of medical treatment for acute stroke patients and can result in progression of the stroke. Hema Rajini et al.[17] applied different classifiers like K-Means, SVM, ANN, decision tree to find out the efficiency and accuracy of those classifiers in terms of early and automatic detection of stroke. Zhang et al.[18] proposed that in brain image analysis, object boundary definition is an important task. 3D Active Volume (AVM) which has been proposed currently can able to incorporate both gradient and regional information to enhance robustness. Performance of the segmentation process of this model depends on the position, shape, size of the initialization, especially for data with complex texture. Vinay et al.[19] detected ischemic strokes by applying Fuzzy methods on CT images. Ushani Balasooriya[20] developed an intelligent system by using fuzzy and watershed algorithms with neural networks to classify strokes.

Some problem still exists in identifying the brain stroke area. New stroke area cannot be distinguished properly from the old one. Diversity of human brain tissue, leads the role of difficulty in proper diagnosis of stroke area. All these problems are responsible to create the delay in fast and accurate treatment. To overcome these problems and also accurately and quickly detect the affected stroke area, an automatic ischemic stroke detection algorithm has been developed.

METHODOLOGY

The proposed method is demonstrated in Figure 1.

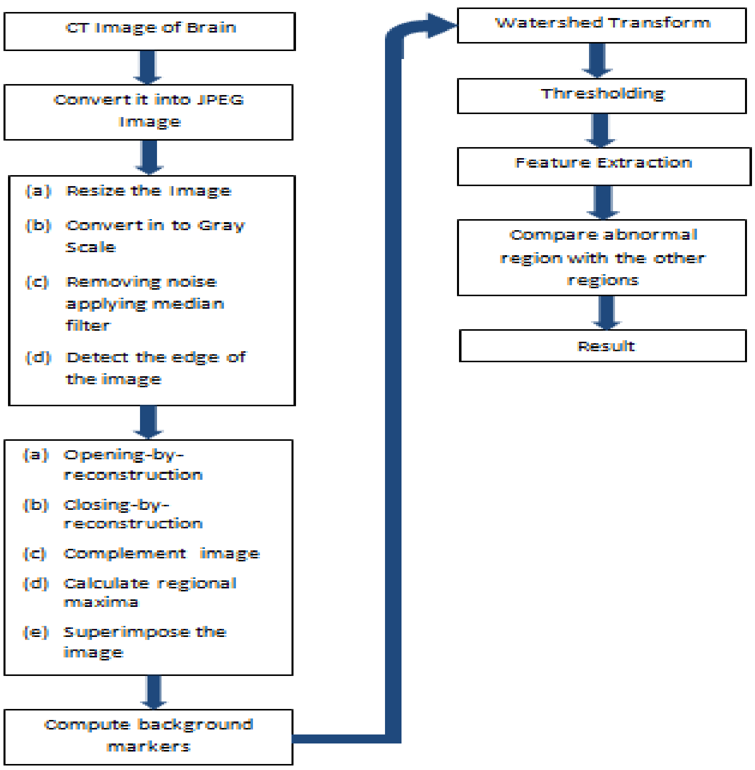

Fig 1: Block Diagram of Proposed Method

The block diagram as shown in Fig 1 represents the different steps of preprocessing, segmentation and feature extraction techniques. The details descriptions of each technique are as follows:

Description of the Proposed Method

The entire design of the system consists of three major modules such as (a) Preprocessing, (b) Segmentation, and (c) Feature Extraction. The steps of each module are as follows:

- Real time data sets of CT images have been converted in to a jpeg first.
- In the next step, image has been preprocessed for removing the artifacts noise etc., clear image has been produced which will be then processed in the segmentation module.
- In segmentation module the region of interest i.e. stroke lesion is identified and isolated from the other part of the brain image.
- In feature extraction module, Image is divided in to four symmetric regions and texture features are computed for each region.
- Finally in the last step the abnormal region has been detected by analyzing the statistical features.

Detail Description of Three Modules

Image Preprocessing:

- Image resizing (256 X 256) has been performed in order to fit the system with the user interface.
- Covert it into gray scale image
- After enhancing the intensity of gray scale image a median filter of window [3 X 3] has been applied for removing the noise from the CT image.
- Then edge detection operation has been taken place on the resulting image.

Fig. 2.1 Original Image

Fig 2.2 Gray Scale Image

Fig. 2.3 Adjusted Image

Fig. 2.4 Filter Image

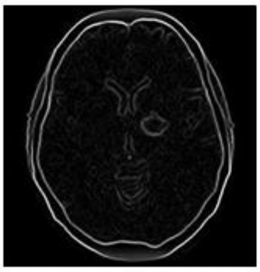

Fig. 2.5 Edge-Detected Image

Fig 2: Preprocess Images

Morphological Operations

Reconstruction based opening and closing have been used instead of standard opening and closing, as they are more effective for removing small blemishes without affecting the overall shapes of the objects.

a) The morphological techniques which are used as follows
- Opening-by-reconstruction
- Closing-by-reconstruction
- Complement the image
- Calculate regional maxima
- Superimpose the image

b) Compute the background markers
c) Watershed Transformation to localize the stroke lesion
d) Threshold segmentation with a threshold value 50
e) Visualize the result
f) Finally removing the back ground noise.

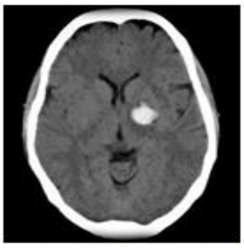

Fig. 3.1 Reconstructed Image followed by Opening

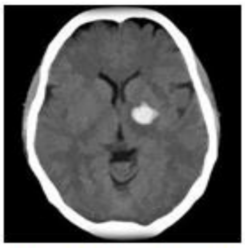

Fig. 3.2 Reconstructed Image followed by Closing

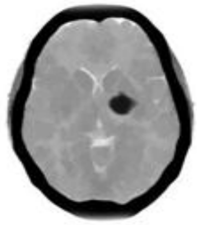

Fig. 3.3 Negative of Reconstructed Image

Fig 3: Images for Morphological Operations

Segmentation Module

Watershed Segmentation Algorithm

Watershed algorithm, firstly computing the gradient magnitude of the input image and then computing the watershed of the gradient magnitude, finally superimpose the gradient on the original one.

Thresholding

Thresholding is basic and most representational algorithm in image segmentation. In local thresholding process, a threshold value (T) is first set, if the image intensity is less than fixed threshold value T, then each pixel in image has replaced with a black pixel or a white pixel if the image intensity is greater than that constant threshold value. Threshold method is applied to segment the stroke region from the brain tissue.

Fig. 4.1 Region Maxima

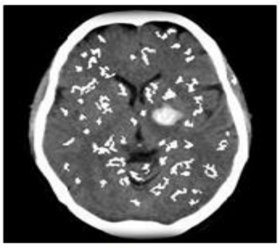

Fig. 4.2 Super Impose Region Maxima

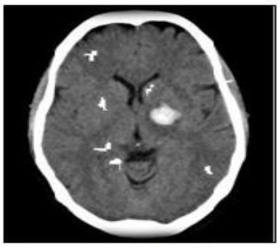

Fig. 4.3 Modified Region Maxima

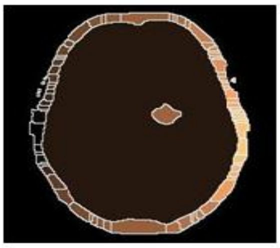

Fig. 4.4 Watershed Segmentation of Stroke

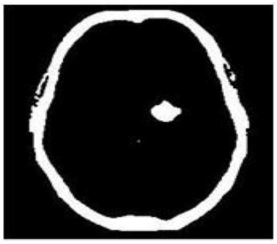

Fig. 4.5 Threshold Segmentation

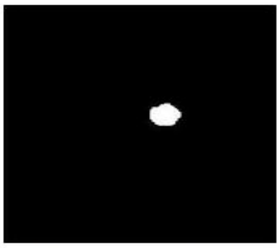

Fig. 4.6 Isolated Stroke Lesion

Fig 4: Segmented Images

Feature Extraction

It captures visual content of images for indexing and retrieval. Textures are calculated from an individual pixel and do not consider pixel neighbor relationships. In this work, intensity histogram has been extracted from the given input image. The histogram of intensity levels is a simple summary of the statistical information of the image and the gray-level histogram is calculated from the individual pixels. First-order statistical information about the image (or sub image) can be obtained from the histogram.

Methodology of Feature Extraction Module

Feature Extraction Module consists of five major steps

- Image is divided into four quadrants (regions)
- Histogram and pixel values have been computed for each quadrants
- Compare each region with respect to predefined criteria
- Statistical features have been calculated for all four regions
- Identified the abnormal regions based on the value of texture features.

Experiment Results

The experiment results obtained from the proposed method is demonstrated below.

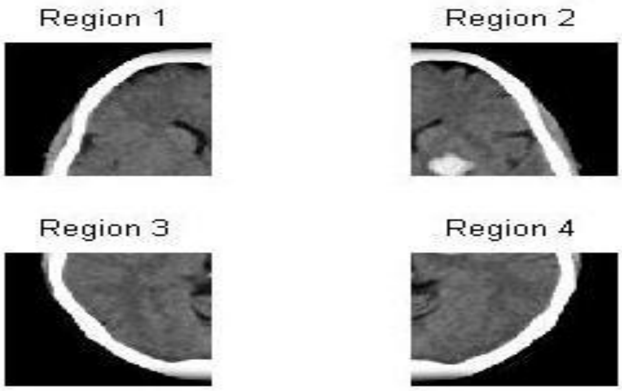

Fig 5: Division the CT Image in to four Regions

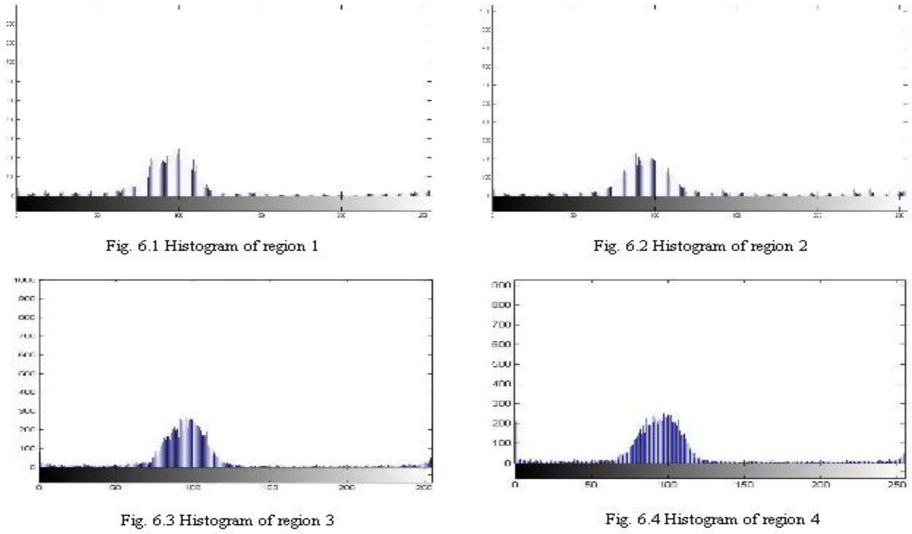

Fig 6: Histogram of four regions

Fig 5 illustrates the four quadrants of the brain CT image, one of these parts includes abnormal area and the other parts contain the normal areas and Fig 6 demonstrates their related histograms. According to its histogram and pixel value, region that may contain abnormal area is detected from the other regions. As shown in Fig 6.3 only region (2) has the possibility for inclusion of abnormal area.

Texture Analysis

First-order texture measures are calculated from the original image values. Features such as mean, standard deviation, variation, skewness and kurtosis, entropy are calculated.

Let random variable I represents the gray levels of image region. The first-order histogram $P(I)$ is defined as:

$$P(I) = \frac{\text{number of pixels with gray level I}}{\text{total number of pixels in the region}}$$

These statistics are defined by the following equations in the below table 1.

Table 1 First Order Features

Moment	Definition	Formulae
Mean	The mean is the average value of all pixels in an image.	$\mu = \sum_{i=1}^{G-1} ip(i)$
Standard Deviation	It is the measurement of the average contrast	$\sigma = \sqrt{\sum_{i=0}^{G-1} (1-\mu)^2 (p(i))}$

Variance	It determines the intensity variation around the mean	$\sigma^2 = \sum_{i=1}^{G-1} (1-\mu)^2(p(i))$
Skewness	It measures symmetries of the histogram around the mean	$\sigma^{-3} = \sum_{i=1}^{G-1} (1-\mu)^3(p(i))$
Kurtosis	Kurtosis is the fatness of the histogram	$\sigma^{-4} \sum_{i-1}^{G-1} (1-\mu)^4(p(i))$
Entropy	It measures the disorder or complexity of an image	$-\sum_i \sum_j g_{ij}\, log_2 g_{ij}$

Table 2 represents the values of first order statistical features for different regions. Variance depends on the mean value and the mean value is low for stroke region, as the dark part represents the stroke area, mean shows the brightness part in the image. Skewness and Kurtosis show a lower value for the normal part. Standard deviation and entropy show the lower value for abnormal part and higher value for normal parts.

Table 2 Evaluation of abnormal region using Statistical Feature

Moment	Region 1	Region 2	Region 3	Region 4
Mean	18.4250	18.0237	18.4665	19.2953
SD	6.1657	6.1189	6.1882	6.3165
Variance	38.0157	39.8976	38.29	37.4409
Skewness	-1.4664	-1.4951	-1.4775	-1.4945
Kurtosis	3.4510	3.5618	3.4924	3.5346
Entropy	2.3509	2.2984	2.3422	2.3134

CONCLUSION

This paper proposes an ischemic stroke detection system using a computer-aided diagnostic ability based on automated segmentation method and feature extraction method. The proposed algorithm exhibits promising performance with capabilities of delicate automatic segmentations for stroke detection.

This method presents the efficient approach for identifying and detecting the stroke lesions from the input CT images. Intensity information along with neighbourhood relationships and histograms of brain images help in building a stroke analysis system that can detect and segment stroke area successfully. Statistical features have significantly increased the performance and accuracy of the proposed method. Normal and abnormal parts of the brain have been detected by comparing these different features. This automatic detection of stroke lesion system assists the radiologists to identify the haemorrhage and infarct regions in the human brain and to arrive at a faster and accurate decision without any treatment delay.

The key feature of this system is to detect not only the stroke lesion but also other brain abnormalities like tumour, abscess and lesion etc.

Future work may improve upon this method by revising the histogram normalization and neural network will be used as classifier to identify the different kind of stroke like acute, chronic infarcts and hemorrhages. Further, there is enough room for research by introducing the three dimensional domain with necessary algorithms in our future research.

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