Segmentation of Brain Stroke Lesions using Marker-based Algorithms in CT images

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***Abstract*— The computed tomography has huge role in the assessment of the hemorrhagic lesions of the brain. Physicians widely use CT to delineate the size and magnitude of the bleeding. In the medical image processing, the separation and detection of the objects is very crucial issue. The water-based segmentation (subdivision) is an approach that use to detect the closely contact margins tissues within the images. Manual outlining of the stroke in CT images considers as subjective operation that takes long time with less accuracy. In this study, the lesions were detected firstly and followed by Contrast augmentation and Segmentation. The suggested technique was evaluated to endorse its achievability and efficiency. These techniques attained 0.97 + 0.01, 0.98 + 0.02 and 0.991 + 0.01 (P = 0.001) for sensitivity, specificity and operating curve analysis, respectively. The analysis of the results images showed that the proposed approach is effective in detecting of the smaller lesions which might missed by using other segmentation methods. (*Abstract*)**

Keywords*— *Stroke, Image Segmentation, Watershed Transformation, Image Enhancement

I. INTRODUCTION

In cognitive neuroscience, neuropsychological studies of people with strokes are widely used to enhance our incomprehensive brain function. Studying the parallels between anomalous behavior and actual brain damage offers insight into the nature of the function [1]. Accurate diagnosis of stroke injuries thus represents a key step towards systemic and functional neuropsychological research. The stroke type is generally divided into two classes: (1) blood vessel hemorrhagic stroke failure; and (2) ischemic stroke or blood supply damaging ischemic infarction. Less common chemical strokes can cause any type of stroke [2]. Computer tomography (CT) and magnetic resonance imaging (MRI) are two modal approaches, which are widely used in stroke lesion evaluations. CT is the preferred treatment in the acute stroke unit that typically provides dosage, cost and reduced exclusion from critical rhea imaging while it is not unusual in stroke patients participating in MR-Anatomical image clinical research protocols (usually weighted images T1 and T2). On the other hand, ischemic stroke was observed earlier by MR imagery and then done with a negative CT scan. Blooding is a bright (hyper-intensive) region, which during the CT scanning contrasts sharply with its surroundings. In addition, an ischemic stroke appears to be a dark (hypo-intensive) region, as opposed to the surrounding area, depending on the time of the stroke [3] [4].The latest lesion detection technique usually involves manual delineation by trained professionals of abnormal brain tissue, but it does have a range of disadvantages (Ashton et al. 2003). In addition to the time-consuming approach, tissue lesions and non-lesions are consistently interfering, particularly at the brain frontier and around the ventricle. This manual approach also causes variations across the customer [5] [6]. In addition, manual delineation in chronic stroke patients outside of the injury should not typically be seen in permanent stroke-induced degeneration, although this degeneration can lead to clinical deficits in the patient. Combined with manual editing, automated hypo or hyperactive intensive areas will dramatically reduce delineation times but the results remain operator-dependent. Recently, complete methods have been proposed to reduce intersubjective variation in brain delineation procedures and to allow for the analysis of large CT data sets [7]. While multiple segmentation algorithms for lesions were built in MR images, only a few methods have been proposed for CT scans for stroke lesions. The bulk of CT scans are used for identifying hemorrhagic strokes. Considering that the hemorrhagic stroke tends to be lighter than ordinary tissue, it was proposed that unregulated "fuzzy clustering" techniques could be used to identify hemorrhagic candidates along with expert systems and morphological procedures to differentiate between different affected regions and pictorial objects. Unlike hemorrhagic image processing technology, ischemic identification of strokes was far less well recognized for their more complex existence. Regional seated increasing algorithms were used to divide the CT image into a uniform set of intensities. Input to an ex-pert frame based on rules was subsequently given for the axis of symmetry as factors such as luminosity, magnitude, texture, and relative position [8]. The main drawback is that the seeded algorithms can't clearly define the stroke field boundaries. In addition, only one study in a given CT amount reported hemorrhagic and ischemia strokes. In this experiment, the lesioned tissue was detected by comparing the intensity of the image in both hemispheres, showing that the sensitivity of one hemisphere is substantially different. This technique is faulty as it is impossible to identify symmetric abnormalities on both sides of the brain centerline. However, restricted symmetrical abnormalities are likely, based on clinical evidence [9]. An alternative method for defining the hemorrhogenic and esthetic stroke is a contrast between the CT image strength of a patient and the images of a group of subjects to differentiate individual voxels. This technique has also been used in the study of MR images but never for CT images. The first high-resolution CT simulation requiring precise spatial measurements of the single brains on the same template image [10]. Nevertheless, a prototype of high quality does not guarantee sufficient spatial standardization. Classic algorithms are used to balance affinity and/or nonlinear warping of a prototype's picture brain. Problems that occur when atypical regions of hypo-or hyperactive

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intensity are present in the healthy brain. In this case, advanced approaches such as cost-function masking or surface-based registration technique can avoid the presence of strokes from having a negative impact on the normalization of prejudicial lesions over or under fitting ([11]. In this study, a method was establish that accurately normalizes CT-images from stroke to stroke, and then compares the template region with hypothermic or extremist signals within the CT-image community. Visual incidents superimposed on CT brain scans without lesion and CT images of patients with strokes demonstrate this strategy. My approach can automatically detect stroke lesions and thus provide a quick and efficient method for clinical application and study..

II. Materials and Methods

A gray-sized histogram is similar to the determination of a particular diagnostic test level by dividing an image into two groups or clusters (Section 10.2.1). In this case, we try to divide the correct amount of pixels in the front and the background. There are two pixel classes in which k is a threshold value, class 0 with value [0, k], and class 1 with value [k+1, L-1] if the pixels is [0, L-1] and the histogram is bimodal.

The class probabilities are.

$$p(C_0) = \sum_{i=0}^{k} \mathrm{P(i)} = \omega_0\,(k) = \omega\,(k) \tag{1}$$

$$p(C_1) = \sum_{i=k+1}^{L-1} \mathrm{P(i)} = \omega_1\,(k) = 1 - \omega\,(k) \tag{2}$$

The class means are

$$\mu_0(k) = \sum_{i=k+1}^{L-1} \mathrm{i}P(i|C_0) = \frac{1}{\omega_0\,(k)} \sum_{i=0}^{k} iP(i) \tag{3}$$

$$\mu_1(k) = \sum_{i=k+1}^{L-1} \mathrm{i}P(i|C_1) = \frac{1}{\omega_1\,(k)} \sum_{i=0}^{k} iP(i) \tag{4}$$

And the individual class variances are

$$\sigma_0{}^2(k) = \frac{1}{\omega_1\,(k)} \sum_{i=k+1}^{L-1} [\mathrm{i} - \mu_0(\mathrm{k})]^2\, P(i) \tag{5}$$

$$\sigma_1{}^2(k) = \frac{1}{\omega_1\,(k)} \sum_{i=k+1}^{L-1} [\mathrm{i} - \mu_0(\mathrm{k})]^2\, P(i) \tag{6}$$

A. Method description

The CT scan images were registered into the system coordinator. The subdivision of the images were done in three phases. The first phase was pre-segmentation procedures, which included conversion of the images format into grayscale and double that made them easy for system to read and to manipulate. Then the adaptive histogram was applied for image augmentation. The noise reduction processes, which used were sharpen and log transforms. The second phase included edge recognition using Sobel method then computation of both foreground and background. The third phase included application of watershed-based algorithm and visualization of the results. Stroke segmentation carried out into two phases. The first phase was the classification of the normal brain tissues and the lesion with same intensity. The second phase was boundary The entire framework is built using MATLAB software package. The testing of this framework and processing of stated results were done on a computing system having an Intel i5 fifth generation processor without any special purpose GPU. With this configuration, the framework took on an average about 1-1.5 minutes to analyze a single patient CT series containing about 70 to 80 slices. The database contains respective CT images in DICOM (Digital Imaging and Communication in Medicine) format. They are converted into 8-bit gray scale images (Step 1 of Figure 2). For segmentation of stroke, marker-controlled watershed algorithm was implemented. This method was selected on basis of the fact that Skull CT scan consists of a continuous connected stroke with only some small parts of it other than the stroke, being separated from the main body. Hence, Image segmentation is an ideal method to detect these isolated strokes. Its implementation in medical image analysis has been limited due to possibility of over-segmentation and being noise sensitive. Processing the image to give it apriority knowledge of which region we want to segment, significantly improves the algorithm efficiency. Since watershed algorithm performs segmentation by drawing ridgelines around local minimums in image, we modify the image such that stroke and normal regions become local minimums. It is done as follows: Firstly, `Opening by reconstruction' technique and subsequently `Closing by reconstruction' technique is applied with `disk' structuring element of size 8. Here, a `disk' shape is used as a mask as it somewhat relates to hemorrhage morphology. The size 8 was fixed after experimentation with different sizes. This helps to flatten out the regional maximums present inside image objects pertaining to stroke and normal parts. Further foreground object marker (i.e. stroke region) is found out by finding regional maximums in image. This process provides both foreground and background markers (i.e. normal region) present in image (Step 4 of Figure 2). They are distinguished using adaptive thresholding technique. The image is modified such that uniform regional minimums are present at the location of computed foreground and background markers in the image. This in effect makes the stroke boundary, a continuous regional maximum. This helps the watershed algorithm to draw ridgelines along stroke's boundary and hence segment it. Regional maximums are computed using `imregionalmax' function present in Image Processing toolbox available in MATLAB software. Further, a mask is created identical to the shape created by the watershed ridgelines (Steps 5 and 7 of Figure 2). The segmented region is then extracted from the image with help of this mask, by keeping all the pixels inside and on the mask same and blacking out the pixels outside the mask (Step 8 of Figure 2).

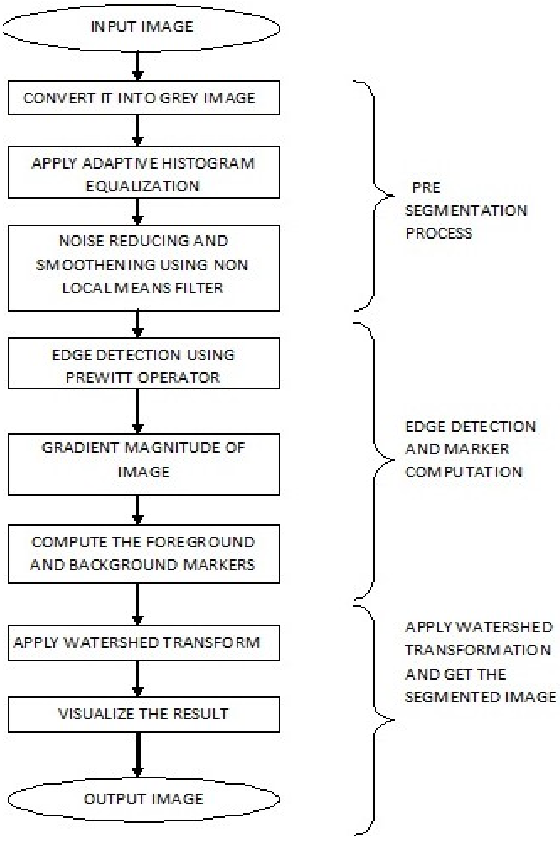

Fig.1. Flowchart of an Improved Marker Controlled Watershed Transformation

III. THE RESULTS

This study conducted to study colour stroke CT image using colors segmentation filters of MatLab software package. The sample of this study was 20 patients with different age distribution and body mass index.

A. EXPERIMENTAL RESULTS

The proposed algorithm is implemented on various test images.

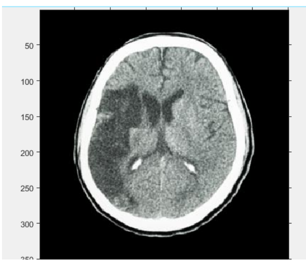

Fig.2: Pears Original Image

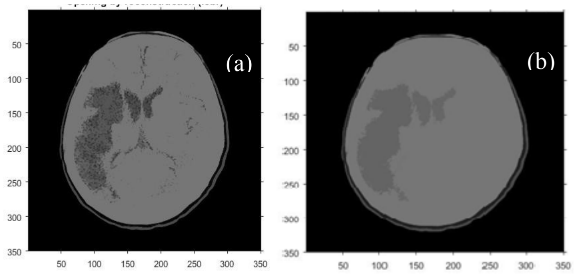

Figure 3: Watershed Markers (a) Basic Method (b) Proposed Method

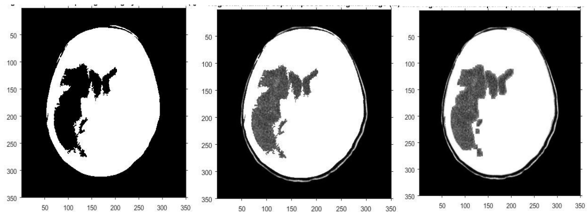

Fig. 4: Segmented Image the proposed segmentation method

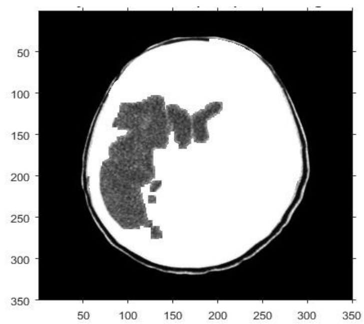

Fig. 5: Markers and Object boundaries superimposed on original image

TABLE1: THE QUANTITATIVE RESULTS WERE ANALYZED FOR PREFORMING THE TASK OF STROKE DETECTION IN THE DATA.

Physician	**Sensitivity**		**Specificity**		**Precision**		**Accuracy**	
	Pre-	***Post -***	***Pre-***	***Post -***	***Pre-***	***Post -***	***Pre-***	***Post-***
GT1	0.98	0.71	0.92	0.90	0.94	0.89	0.93	0.92
GT2	0.94	0.81	0.97	0.93	0.99	0.86	0.84	0.94
GT3	0.94	0.86	0.91	0.89	0.93	0.85	0.83	0.91
GT4	0.91	0.84	0.93	0.87	0.93	0.84	0.90	0.95
GT5	0.91	0.83	0.94	0.88	0.91	0.82	0.88	0.91
Mean	0.87	0.93	0.81	0.93	0.89	0.94	0.85	0.92

The mean improvement in reclamation sensitivity, precision, accuracy and performance is 12.6%, 4 %, 8.8 % and 5. 4 %. Such values contribute to our initial goals. Improvement in mean sensitivity shows that the window helps to accurately detect stroke lesions in data and increases true positive (stroke slices) identification. The marginal shift in specificity indicates that the difference does not affect normal detection of data.

IV. CONCLUSION

The traditional watershed transformation approach has a problem of over segmentation. To solve the problem a new algorithm was proposed which gave good results when compared to traditional results. This experimental study was conducted in the form of a water-based parallel calculation algorithm in CT images in order to test an effective brain stroke segmentation process. As well as exploring the use of the new non-linear method in CT images to enhance, contrast of soft tissue through automated stroke extraction. The image processing uses filters mainly to eliminate high image frequencies, i.e. to glut images, or low frequencies, i.e. to improve or detect image boundaries. Because of various factors, the pictures are usually poor. To avoid errors and degradation, the researcher used pre-processing images, including enhancement and noise. Different non-linear filters for smoothing have been developed. While their properties and area of application have been extensively studied, Fourier cannot evaluate them automatically. Researchers implemented anisotropic filtration and median filtering. Testing was carried out with anisotropic and median filtering algorithms.

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