Segmentation and Classification Analysis Techniques for Stroke based on Diffusion-Weighted Images

N. Mohd Saad, N. S. M. Noor, A.R. Abdullah, Sobri Muda, A. F. Muda and Haslinda Musa

***Abstract*— Diffusion-Weighted Imaging (DWI) remains the most accurate brain imaging technique for early detection of stroke. This study proposed the image analysis technique for automatically segmenting and classifying of brain stroke based on DWI. Two lesions namely acute stroke and chronic stroke are analyzed. The proposed analysis framework are pre-processing, segmentation, features extraction and classification. For segmentation, Fuzzy C-Means is used to accurately segment the stroke region. Next, the statistical parameters in spatial domain are extracted from the region of interest (ROI) as features. These features are classified using a rule-based classifier for automatic classification. The three-dimensional (3D) view is developed to enable observing directions of the gained 3D structure along three axes. The results for Jaccard, Dice, FPR and FNR of acute stroke are 0.752, 0.84, 0.049 and 0.205, respectively. The accuracy for acute stroke is 90 % and chronic stroke is 70 %. The overall sensitivity and specificity for the classification are 84.38 % and 83.33 %. In conclusion, the proposed analysis has the potential to be explored as a computer-aided tool for segmentation and diagnosis of human brain stroke.**

***Index Terms*—Diffusion-Weighted Imaging (DWI), Segmentation, Fuzzy C-Means, Correlation Template**

Manuscript received July 10, 2017; revised August 19, 2017. This work was supported in part by the Ministry of Higher Education (MOHE), Malaysia for sponsoring this work under project PJP/2016/UPM/FKEKK/CERIA/S01490 and the use of the existing facilities to complete this project.

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I. INTRODUCTION

STROKE is a major health burden in Malaysia as well as worldwide. It is also one of the top five leading causes of death in Malaysia [1]. It is estimated about 40,000 people in Malaysia suffer from stroke every year [2]. National Stroke Association of Malaysia (NASAM) stated that one of six people worldwide will suffer from the stroke in their lifetime and it is the third leading cause of adult disability [3]. Stroke is a clinical symptom that happens when the blood vessel is blocked or burst due to a blood clot.

All the oxygen and nutrient supply will be cut off causing a syndrome characterize by rapidly developing symptoms or sign of focal neurologic dysfunction due to a vascular cause [4]. Urgent treatment is needed to obtain less debilitating of stroke and for better recovery. A diagnosis of brain stroke is a crucial task and only professional neuroradiologists can perform the task. [5]. Therefore, an early detection and diagnosis is needed as the key to give successful therapy and treatment planning for brain stroke.

A dedicated computer framework such as Computer Aided Diagnosis (CAD) is needed for radiologist in providing second opinion or clinical validation towards medical images [6]. With the advantage technology of the CAD, this system is able to help radiologists to improve the accuracy of their diagnoses. Nowadays, DWI is commonly used in neuroimaging as it can consider as a proper evaluation in the most pathologic conditions [7]. This imaging technique gives high lesion contrast for the lesion differ to another magnetic resonance image (MRI) sequences [8].

DWI measures diffusion of water molecules within the tissue structure on a pixel basis. In recent stroke lesion detection, DWI has become the hallmark of MRI sequences due to its ability in reducing the diffusion water to detect the tissue of hyperintense images. Although, DWI image has good ability in visualizing the stroke lesion, but manually detection and diagnosing are very time-consuming compared to computer-aided techniques [9]. With the advance of computer-aided techniques, automatic image segmentation can be easily developed. However, a troublesome issue come out where an automatic image segmentation can provide the presence of noise and intensity inhomogeneity resulting in the larger part of utilization.

Fuzzy C-Means (FCM) is an iterative method that measures clustering by assigning different data object in each cluster [10]. It is a method where researchers likely to propose for segment medical images and it becomes more valid and reliable [9-11]. The original FCM algorithm provides good result in producing images with free noise, but the image can still be corrupted by outliner, noise and other imaging. Due to that, the FCM algorithm is modified to improve the partition of the meaningful regions [12, 13]. Xue proposed standard FCM algorithm where the images are denoise before the pixels are classified. It can reduce the noises to a certain extent, but it increased computational time and complexity [14].

The purpose of this study is to propose an image analysis technique for automatically segmenting and classifying of brain stroke based on DWI images and to visualize the brain scan in three-dimensional (3D) view. The proposed analysis is based on the FCM segmentation method, statistical parameters extracted from the segmented area and classification using rule-based classifier. Lastly, Jaccard index, Dice index, false positive rate (FPR) and false negative rates (FNR) is used to evaluate the performances of the techniques. Acute and chronic stroke lesion had been analysed through this experiment. The three-dimensional (3D) view brain is created to get a better view in the area of the stroke lesion.

II. METHODOLOGY

A. Proposed Analysis Framework

Fig 1 shows the flow process of the analysis. The framework begins with collecting the image of brain lesion from DWI followed by pre-processing the image. After that the segmentation method was applied to extract the region of interest (ROI) of the lesion. Then, the features extraction and classification were applied. Finally, 3D image of the brain stroke region is developed.

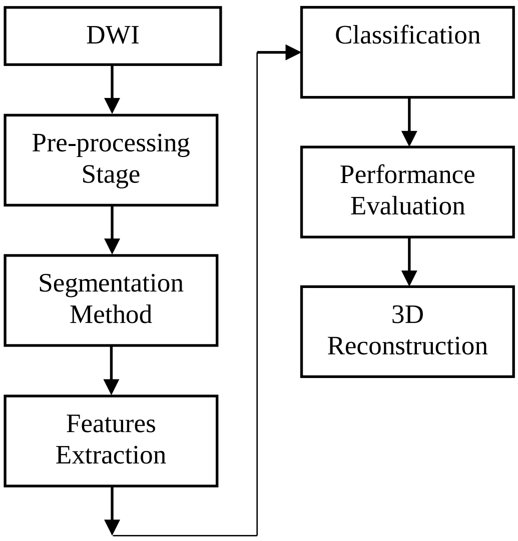

Fig 1 Flowchart of Analysis

B. Imaging Parameter

The DW-MRI images are gained from General Hospital of Kuala Lumpur using 1.5T MRI scanners Siemens Magnetom Avanto. The diffusion-weighted parameters obtained from this scanner are time echo (TE), 94ms; time repetition (TR), 3200ms; pixel resolutions, 256x256; slice thickness, 5mm; gap between each slice, 6.5 mm; of diffusion weighting known as b value, 1000s/ intensity mm2 and total number of slices, 19. The data is encoded in 12-bit DICOM (Digital Imaging and Communication in Medicine) format. The dataset consists of 30 samples of acute stroke and 20 samples of chronic stroke. Overall, 50 images were taken for this analysis.

C. Pre-processing Stage

The pre-processing stage is developed to undergo pre-processing stages to acquire better segmentation [15]. Image normalization, background removal, and image enhancement algorithms were applied to the DWI image. The intensity of these images is adjusted and the noise is removed to obtain the desired image. Fig 2 shows the normalization image and its histogram. All background pixels shown in Fig 3 are removed to improve the shape of the image histogram. Fig 4 shows the image enhancement and the histogram after applying the gamma-law transformation.

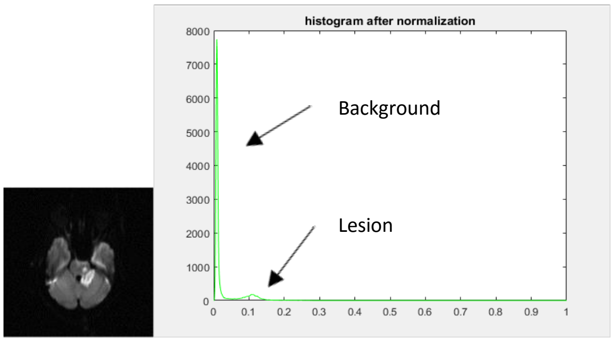

Fig 2 Image Normalization with its histogram

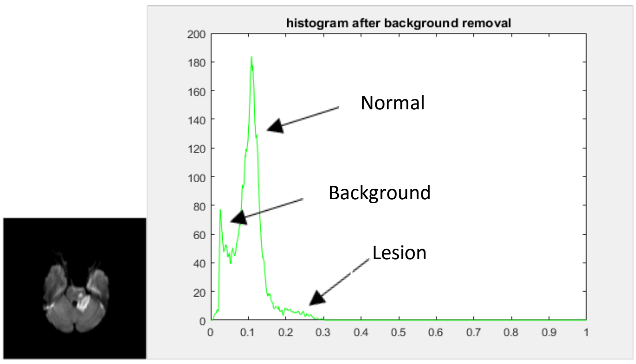

Fig 3 Image Background Removal with its histogram

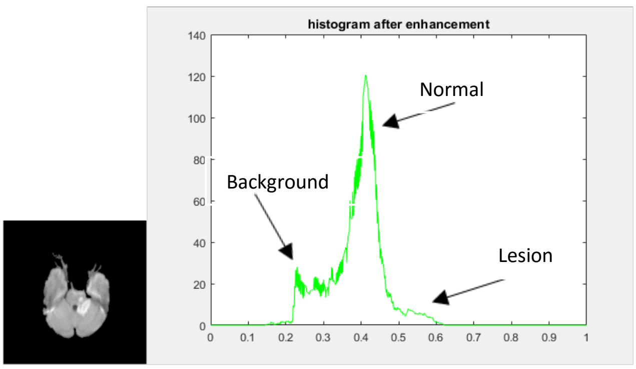

Fig 4 Image Enhancement with its histogram

D. Segmentation Method

The Fuzzy C-Means algorithm in this segmentation method begins with selecting a data point in three clusters which are the lower, middle and higher cluster. The data point will be select base in the center of each cluster. Each data point of the cluster should equal to one. The algorithm is based on minimization of the following objective function.

$$Jm = \sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^{m}\left\|x_i - c_j\right\|^2, 1 \le m \le \infty \tag{1}$$

where m (the fuzziness exponent) is any number greater than 1, N is a number of data, C is the number of clusters, u_{ij} is the degree of the membership of x_i in the cluster j, x_i is the i^{th} d-dimension centre of the cluster, c_j is the d-dimension centre of the cluster and $\|*\|$ is any norm expressing the similarity between any measured data and centre.

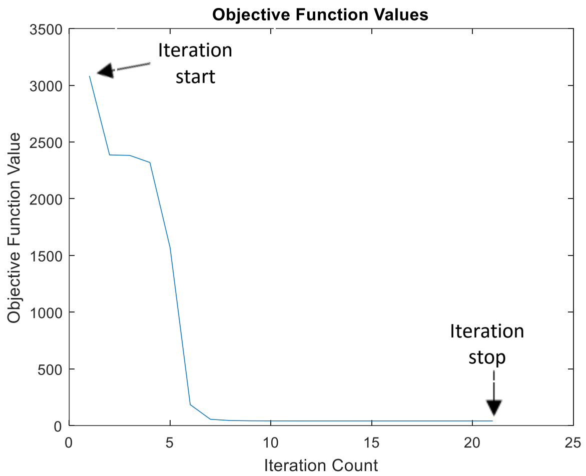

Fig 5 Objectives Function Value

Fuzzy partition works through an iterative optimization of the objective function shown above, with the membership of u_{ij} and the cluster centres c_j by:

$$= \frac{\dfrac{1}{\sum_{k=1}^{C}\left(\dfrac{\|x_i - c_j\|}{\|x_i - c_j\|}\right)}}{\dfrac{\left(\|x_i - c_j\|\right)^{\frac{2}{m-1}}}{\left(\|x_i - c_1\|\right)} + \dfrac{\left(\|x_i - c_j\|\right)^{\frac{2}{m-1}}}{\left(\|x_i - c_2\|\right)} + \ldots + \dfrac{\left(\|x_i - c_j\|\right)^{\frac{2}{m-1}}}{\left(\|x_i - c_k\|\right)}} \tag{2}$$

where $\|x_i - c_j\|$ is the distance from point i to current cluster centre j, $\|x_i - c_k\|$ is the distance from point i to the cluster centre k.

$$C_j = \frac{\sum_{i=1}^{N} u_{ij}^{m} . x_i}{\sum_{j=1}^{N} u_{ij}^{m}} \tag{3}$$

The iteration will stop when

$$\max_{ij}\left\{\left|u_{ij}^{k+1} - u_{ij}^{(k)}\right|\right\} < \varepsilon \tag{4}$$

where ε is a termination criterion between 0 and 1, whereas k is the iteration step [16]. This procedure converges to a local minimum or a saddle point J_m.

At the beginning of each iteration, the algorithm of the fuzzy membership function is computed before the values of the cluster centres is calculated. A randomize value from the cluster centre is selected in between the high and low intensity level as the unknown variable at the cluster centre and fuzzy membership function array cannot be computed directly. The estimated coveted accuracy of the cluster centres and fuzzy membership function value is shown when the iterative algorithm is exploited. At the point the refinement between two clusters at two successive iterations is less than a diminutive value of ε, the ceasing criterion for an algorithm is met.

The Morphological operation is utilized to dispense the dissonance in the image after segmentation process. To dispense the commotion and the result become more precise, both algorithms need to employ this technique. Binary area open is applied to abstract unwanted pixels less than 100 for hyperintense. BW2 = bwareaopen (BW, P) abstracts from a binary image all connected components (objects) that have pixels less than P pixels. It will engender some other binary image BW2. The value is set at 100 for hyperintense.

In DWI chronic stroke lesion image, the cerebrospinal fluid (CSF) share the similar intensity level with the stroke lesion [17]. Due to this matter, FCM method has failed to segment the lesion since the algorithm in the cluster cannot be differentiated. To improve this performance, the CSF area is removed by using the correlation template [15]. The prolong of the correlation is evaluated to which two quantitative variables, X, and Y, "go together". A positive correlation is produced when the value of x is high as the related value of y while a negative correlation is produced when the value of x is high and the related value of y is low. The correlational strength cannot judge by the eye.

The CSF characteristic is shown by comparing the abnormal image and the normal image. Three different sums of square (SS) are required to estimate a correlation coefficient which is the sums of squares for variable X, the amount of square variable Y and the sum of the square variable of XY. The total of squares for variable X is:

$$ss_{XX} = \sum\left(x_i - \bar{x}\right)^2 \tag{5}$$

The statistic keeps track of the spread of variable X. This statistic is the numerator of the variance of X $\left(s^2 x\right)$, it can be calculated as:

$$\left(s^2 x\right)(n-1) \tag{6}$$

The sum of squares for variable Y is:

$$ss_{YY} = \sum\left(y_i - \bar{y}\right)^2 \text{ or } \left(s^2 y\right)\left(n-1\right) \quad (7)$$

The sum of the cross-product ss_{xy} is:

$$ss_{XY} = \sum\left(x_i - \bar{x}\right)\left(y_i - \bar{y}\right) \quad (8)$$

This statistic is analogous to the other sums of squares except that it is used to quantify the extent to which the two variables “go together”. The correlation coefficient (r) is:

$$r = \frac{ss_{XY}}{\sqrt{\left(ss_{XX}\right)\left(ss_{YY}\right)}} \quad (9)$$

TABLE I
GUIDELINES FOR DESCRIBING CORRELATION STRENGTH

Correlation Strength	
0 < |r| < 0.3	Weak Correlation
0.3 < |r| < 0.7	Moderate Correlation
|r| > 0.3	Strong Correlation

Before performing the segmentation result, a template that use to remove CSF image is selected from numerous normal image from the clinical sample. This image is selected based on the high value of r. The equation that is used to get the result is:

$$X = P_1(X,Y) - P_2(X,Y) \quad (10)$$

where $P_1(X,Y)$ is a sample image and $P_2(X,Y)$ is a template image.

E. *Features Extraction*

Feature extraction is applied to represent the characteristic of the ROI. The features are measured directly from the ROI close regions, which are the mode, standard deviation, mean, median and mean boundary.

$$\text{Mode} = \frac{\left|\text{mod}\,e - \mu\right|}{\sigma} \quad (11)$$

$$\text{Standard Deviation} = \sqrt[s]{s^2} \quad (12)$$

$$\text{Mean} = U = \frac{\sum x}{N} \quad (13)$$

$$\text{Median} = \frac{1}{2}\left(n+1\right)^{th} value \quad (14)$$

$$\text{Compactness} = \frac{Perimeter^2}{Area} \quad (15)$$

Fig 6-8 show the scatter plots of the statistical features from the spatial domain in the ROI. The round shape indicates for the patients of chronic stroke while the diamond shape indicates the patients of acute stroke. Due to the small number of pixels counted in the segmented ROI, the feature extraction is mainly dependent on the pixel intensity and does not consider on neighbourhood pixel’s dependence.

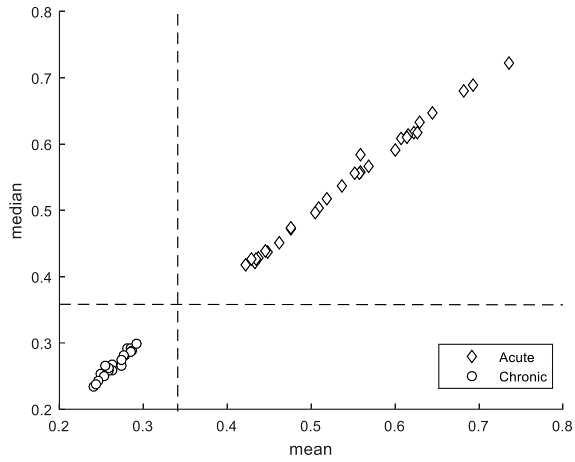

Fig 6 Median and Mean

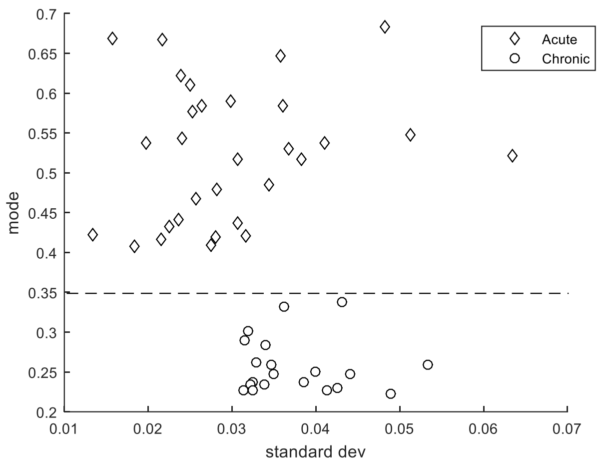

Fig 7 Mode and Standard Deviation

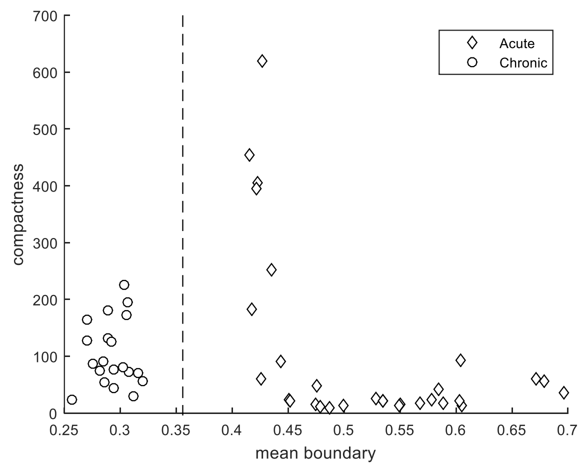

Fig 8 Compactness and Mean Boundary

F. *Classification*

The classification is determined by the rule based classifier. This classification is used to differentiate the described lesion based on the simplicity and the ability of the combination of the multi-classification of numerous features. Its application is depends on the availability of restricted amount of data. However, there must be existing of good prior information for the decision of classification can be made. The overall process of stroke classification is shown in Fig 9.

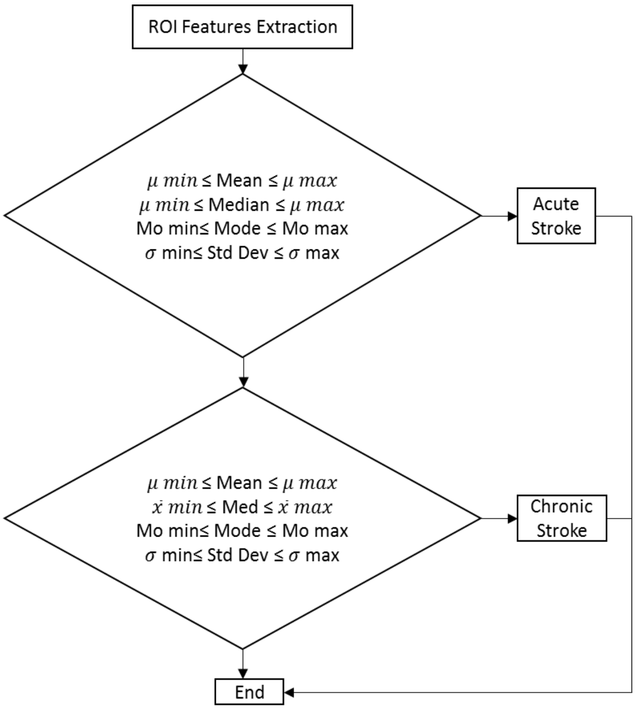

Fig 9 Rule Based Classifier

G. Performance Evaluation

The performance of the segmentation method is evaluated by using the Jaccard index, Dice index, false positive rate (FPR), and false negative rate (FNR). The performance assessment is done by comparing the ROI image from the segmentation analysis and the manual visual inspection from a neuroradiologist. The proposed method can fully segment the lesions of DWI [18]. These metrics are computed as follows:

$$\text{Jaccard } = 100 \times \frac{A \cap G}{A \cup G} \qquad (16)$$

$$\text{Dice } = 100 \times \frac{2\left|A \cap G^C\right|}{|A| \cup |G|} \qquad (17)$$

$$\text{FPR } = \frac{A \cap G^C}{A \cup G} \qquad (18)$$

$$\text{FNR } = \frac{A^C \cap G}{A \cup G} \qquad (19)$$

The average performance metrics are based on the high index of Jaccard and Dice and low FPR and FNR. The accuracy of the correct classification is evaluated using equation (20).

$$\text{Accuracy } = \frac{\sum \textit{correct classification}}{\sum \textit{number of sample}} \times 100 \qquad (20)$$

The sensitivity and specificity of a classification are defined as:

Sensitivity: The probability is positive showing that the patient has a brain stroke lesion:

$$\text{Sensitivity} = \text{TP} / (\text{TP+FN}) \qquad (21)$$

Specificity: The probability is negative showing that the patient does not have a brain stroke lesion:

$$\text{Specificity} = \text{TN} / (\text{TN+FP}) \qquad (22)$$

where true positives (TP) is patient with a brain stroke lesion and correctly classified as a positive case, true negatives (TN) is patient without brain stroke lesion and correctly classified as a negative case, false positives (FP) is incorrectly classified negative cases of patient with brain stroke lesion, and false negatives (FN) is incorrectly classified positive cases of patient without brain stroke lesion.

H. 3-Dimensional Reconstruction

3D reconstruction or modeling is designed based on the 3D analysis tool in MATLAB software. This tool can perform the process on brain images such as displaying, analyze the segmentation region and identify the location of the brain lesion. The 3D images of the brain have unique characteristics and been view in three type of axis which are sagittal, frontal and transverse. Fig 10 shows the flow process for constructing the 3D image of the brain.

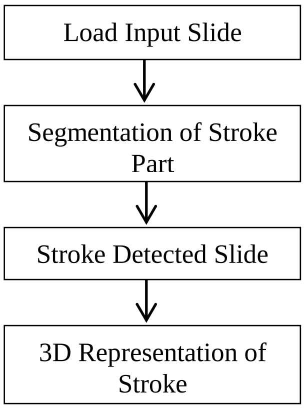

Fig 10 Flowchart of 3D view

The step is described as:

Step 1- The DWI image is loaded slice by slice using *dicomread* command.

Step 2- The area of the stroke lesion in the brain is segmented and showed using the segmentation method as explained in the section II (D).

Step 3- The output segmentation is represented by showing the brain image and stroke lesion in slice by slice 3D view for further guided in finding out exact shape and size of the brain stroke.

Step 4- A 3D view of the brain image with the stroke lesion area is shown.

III. RESULTS

A. Segmentation

The segmentation results of the original image from stroke lesion are showed in Fig 11. The manual reference image obtained from [4].

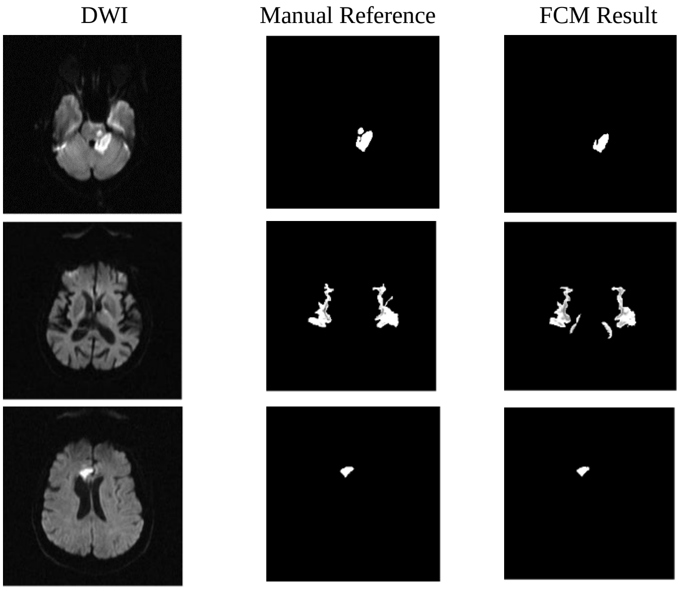

Fig 11 The segmentation results of the original image from stroke lesion

Table II shows the performance analysis and evaluation of the proposed FCM segmentation method for 30 samples of acute stroke and 20 samples of chronic stroke. The performance of the algorithm is measured using the metrics such as Jaccard index, Dice index, FPR and FNR.

TABLE II
PERFORMANCE ANALYSIS AND EVALUATION

	Acute Stroke	Chronic Stroke
Jaccard Index	0.7	0.4
Dice Index	0.84	0.53
FPR	0.049	0.284
FNR	0.205	0.273

B. Classification

The performances of the segmentation result have been test and verify to show the accuracy of the technique. The table of actual versus prediction cases in the classification of multiple classes is shown in Table III, which relates to the overall classification accuracy, sensitivity, and specificity of each class [19,20].

TABLE III
CONFUSION MATRIX FOR CLASSIFICATION

		Predicted	
Actual		Acute Stroke	Chronic Stroke
	Acute Stroke	27	3
	Chronic Stroke	5	15

From Table III, the accuracy of the stroke has been measured. The accuracy for acute stroke is 90 % and for chronic stroke is 75 %. The sensitivity of both strokes is 84.3 % and specificity is 83.33 %.

C. 3D Reconstruction

To ease the project, a proper Graphical User Interface (GUI) is designed which allow the system is used by simply clicking the buttons as shown in Fig 12. In order to work with the brain images, the user needs to enter the path directory which holds the initial DICOM (.dcm) file and MATLAB data (.mat) file by then confirms the entrance. To view the segmentation image of the brain, the user needs to choose which types of the ROI segmentation that are suitable for the brain images. After that, the user can view the 3D images and the data of the feature extraction. Fig 13 shows the images 17 slices of the brain.

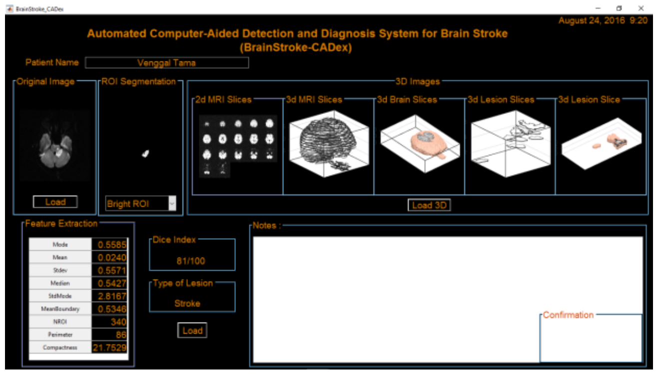

Fig 12 The main GUI

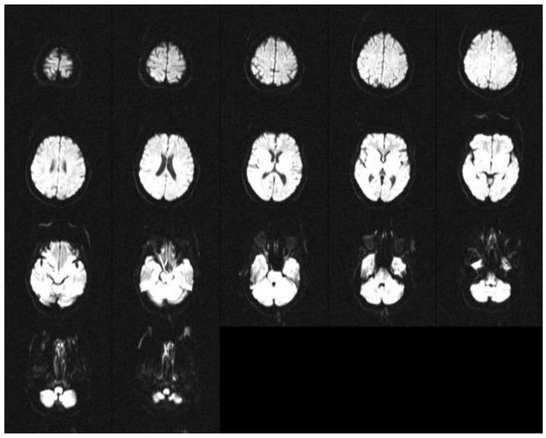

Fig 13 The segment of brain image in 2D view

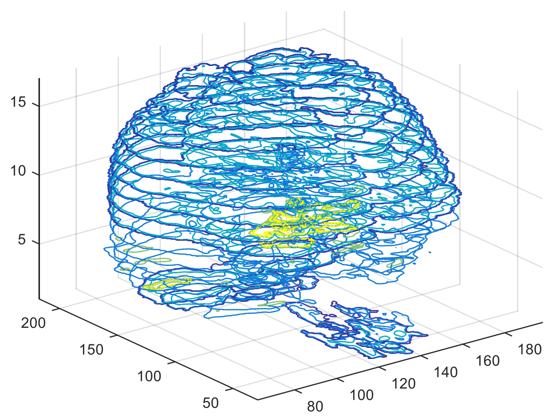

Fig 14 The outline of brain image in 3D view

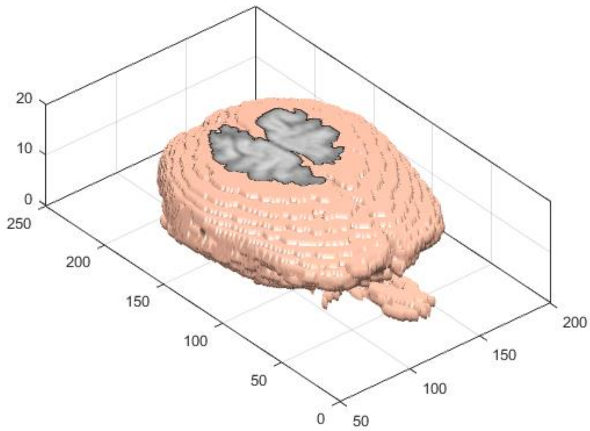

Fig 15 The brain in 3D

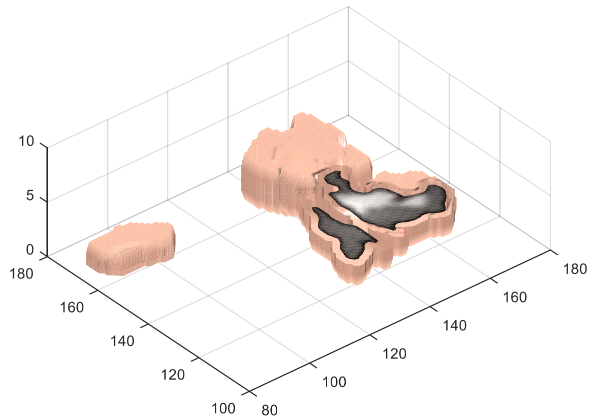

Fig 17(b) The region of blood burst or clot look like in the brain

Fig 14 and Fig 15 show the pop-up image for the 3D brain image. For Fig 14, shows the outlines of the 3D brain image. The outlines show the boundary of the brain image between normal region and abnormal region. Fig 15 shows the 3D brain image after isosurface by showing the outer of the brain lesion.

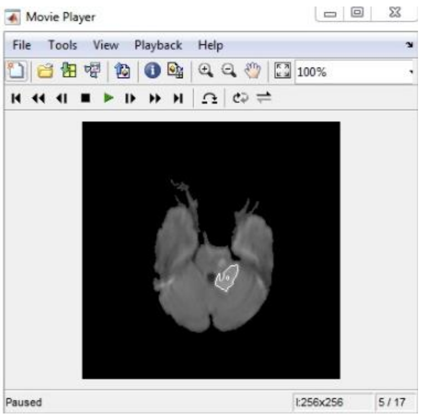

Fig 16 Movie player to show the region of stroke lesion

Fig 16 shows the pop-up movie player. The movie player plays the video by displaying 17 slices of normal and abnormal brain images. In the movie player, slice 3 until slice 8 is abnormal brain images while the other slices are normal brain images.

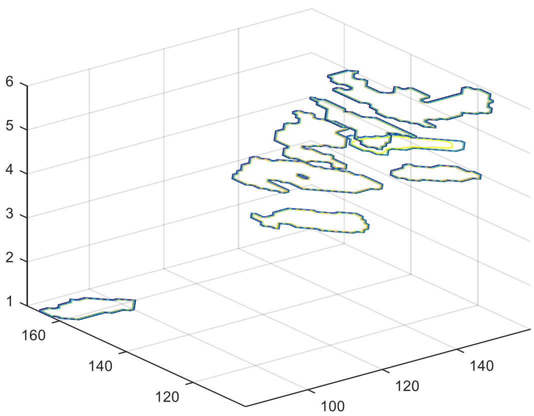

Fig 17(a) The region of blood burst or clot for each slice

Fig 17 shows the pop- up image when the 3D segmentation button is loaded. Fig 17(a) shows each slice of stroke lesion in the brain representing abnormal brain or ROI of the brain lesion. For Fig 17(b) is an image of the ROI of the brain lesion covered with the outer brain using isosurface algorithm. It has the ability to rotate and viewing the reconstruction from various angles. The illumination of the display is set in such a way to demonstrate the best contrast in the most practical angles for viewing images.

IV. Conclusion

In this study, the DWI image is used to perform the segmentation of the stroke lesion using FCM method. This segmentation method has then been compared with the manual segmentation to verify the accuracy. The results show that the FCM method is able to provide better results in segment acute stroke lesion according to the high values of Jaccard index and dice index and low values of FPR and FNR. After the image being segmented, the DWI image was able to construct in 3D showing a good view of the stroke lesion.

Acknowledgement

The authors would like to thank to the Universiti Teknikal Malaysia Melaka (UTeM), Rehabilitation Engineering & Assistive Technology (REAT) research group under Center for Robotics & Industrial Automation (CeRIA), Advanced Digital Signal Processing (ADSP) Lab for the use of the existing facilities to complete this project.

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