Dynamic Changes of Multiple Sclerosis Lesions on T2-FLAIR MRI using Digital Image Processing

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***Abstract*—Multiple Sclerosis (MS) is a complex autoimmune neurological disease affecting the myelin sheath of the nerve system. In the world, there are about 2.5 million patients with MS, in South and East Asia the ratio of MS is high. This disease affects young and middle-aged people. The MS is a fatal disease, and the numbers and volumes of MS lesions can be used to determine the degree of disease severity and track its progression. The detection of multiple sclerosis is a critical problem in MRI images because MS is described as frequently involves lesions, it can be appeared on a scan at one time-point and not appeared in subsequent time points. Also, MS on the T2 FLAIR MRI image is more often manifested by the presence of focal changes in the substance of the brain and spinal cord, which complicate their dynamic control according to MRI data. The detection and extraction of the MS lesions features are not just a tedious and time-consuming process, but also required experts and trained physicians, so the computer-aided tools become very important to overcome these obstacles. In this paper, we present a novel computer-aided approach based on digital image processing methods for enhancing the structures, removing undesired signals, segmenting the MS lesions from the background, and finally measuring the size of MS lesions to provide information about the current status of MS, which represent MS lesions that are either new, increasing or shrinking. The accuracy of the proposed methodology was 96%, according to the results presented in data. The lack of accuracy is related to some errors in segmentation.**

Keywords*—Multiple sclerosis; T2-FLAIR; magnetic resonance imaging; digital image processing; image segmentation

I. Introduction

Multiple Sclerosis (MS) is a chronic autoimmune disease in which the myelin sheath in the fibers of the cerebral nerve and spinal cord is affected by demyelination. The demyelination is a formation of foci MS which destroys the myelin of the white matter of the brain and spinal cord. MS disease targets young and middle-aged people. The absence of timely diagnosis and treatment leads to disability and loss of working capacity due to the simultaneous damages of various parts of the nerve system. Patients with MS have multiples symptoms such as weakness [1], fatigue, blurred vision, and bladder symptoms. The exact cause of the disease (MS) is still unknown; some interested researchers connect the disease with genetic and environmental causes[2].

In the world, there are about 2.5 million patients with MS [3]. In some regions of Europe, the incidence of multiple sclerosis is quite high and is in the range of 8-7 cases per million [4]. In large industrial areas and cities, it is higher. According to epidemiological studies and research in the field of diagnosis and treatment of demyelinating [5] diseases, South and East Asia are in a zone of a high probability of demyelinating diseases.

The diagnostic by a neurologist allows evaluating the clinical manifestations of the disease. Magnetic resonance imaging (MRI) is used to visualize the location of MS and assess the morphological features of the affected areas [6]. The characteristics of metabolic processes of foci multiple sclerosis are investigated using positron emission tomography (PET)[7]. It is important to note that neurological sometimes cannot diagnosis the MS; this condition is called a radiologically isolated syndrome. In this case, the effectiveness of treatment and diagnosis is determined only by MRI.

Generally, MRI is a non-invasive medical imaging technique that comprises of a strong magnetic field, radiofrequency wave, and computer. The output of this technique is high-quality images of anatomical structures of the brain. The most common MRI modes are T1-weighted, T2-weighted, and T2-Flair images[8]. Fig. 1 shows the brain tumor on the T2-FLAIR and T2- weighted modes.

In this study, the T2-FLAIR image is used because MS lesion has vague boundaries and low contrast in T1-weighted and T-2 weighted [9]. Also, T2-FLAIR shows MS lesion brighter than other modes[10]. MRI images are characterized by the presence of random noises and fuzzy boundaries in the process of their formation. Moreover, T2-FLAIR is a very complicated biomedical object for analysis because it is achieved with the help of special procedures and equipment to visualize real biological objects that have certain properties that make their analysis difficult.

Multiple sclerosis on T2-FLAIR [11] is more often manifested by the presence of multiple changes in the substance of the brain and spinal cord, which complicates their dynamic control according to MRI data. The absence of timely diagnosis and treatment leads to disability and loss of working capacity due to the simultaneous damages of various parts of the nerve system. The location and volume of MS lesions are important in determining the degree of treatment progress [12].

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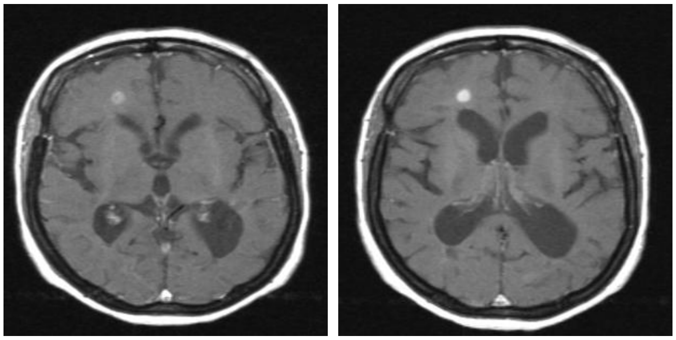


(a) (b)

Fig. 1. Brian Tumor on different MRI modes a) T2-Weighted, b) T2-FLAIR.

The Radiologists and clinical experts manually measure the parameters of the MS lesions, and the accuracy of their results depend on their training and experience. The detection and extraction of the foci MS features are not just a tedious and time-consuming process, but also required experts and trained physicians, so the computer-aided tools become very important to overcome these obstacles. All published MS computer-aided approaches were applied on different data, mostly not calibrated, and their outputs were usually not directly comparable, making difficult the choice of the most effective method adopted to a clinical application. The MS is a fatal disease, and the information about MS lesions can be used to determine the degree of disease severity and track its progression. In this paper, we proposed a computer-aided tool that provides information about the current status of MS lesions (such as shrinking, growing, or presenting of a new one) using digital image processing techniques.

The research paper is organized as follows: Section 2 presents the critical analysis and comparison of recent related literature with our research work, Section 3 describes the proposed methodology and the stepwise illustrations, Section 4 outlines the result and discussion, and at last Section 5 concludes the paper with brief recommendations for future work.

II. Literature Review

Medical imaging is a non-intrusive technique applied in the medical field where the internal organs can be viewed without opening up of human body surgically. An MRI is a technique of medical imaging that produces images by an absorbed and emitted radio frequency signal from the human body [13]. In clinical practice, T1-weighted and T2-weighted are mostly used, but there are also other modes such as T2 FLAIR, which used to suppress the signal of the cerebrospinal fluid to get a better visualization of various multiple sclerosis [14]. Despite that, MRI has superior quality as a method for the clinical diagnosis of MS lesions, as well as understanding the size and location of the diseases.

The process of MRI image formation and storing interferes with random signals and noises that disrupt the intensity distribution of the image creating fuzzy boundaries. Different methods are being used for pre-processing MRI images. Generally, there are two techniques for noise reduction in medical images, the first is by increasing the acquisition (computational load and cost of the biomedical equipment) and the second one is by applying some processing techniques to remove or reduce the noises, which usually requires less acquisition time and can reduce the computational load. Gupta et al.[15] reviewed several linear and non-linear filtering algorithms for denoising digital images. In their study, the main goal was smoothing and enhancing the visual quality of the images. In their approach, the median filter was adopted due to flexibility and multiple-uses. It preserves most details and can remove most kinds of noises, such as impulse and Rician noises. Also, Kaur et al. [16] reviewed the noise characteristics in MRI images and applied different nonlinear filters to reduce Rician noise. As known, Noises are undesirable information [16] or random signals that cause damages by producing unreal boundaries, objects, and indistinct backgrounds[17], so the reduction of noises are mandatory in the medical image processing.

The uniformity of intensity distribution creates fuzzy boundaries, which lead to the need for filtration to remove the noises and segmentation to separate the lesions from the background of the images. Tanya et al. [18] improved a 3D segmentation approach using a convolutional neural network (CNN) to process four voxel-based uncertainties. Their results showed that filtering based on uncertainty greatly enhanced the accuracy of small MS lesions detection (around 40% of the dataset). Moreover, their result of segmentation provides clinicians or radiologists with information permitting them to assess whether to accept or reject lesions of high uncertainty quickly.

The location and volume of MS lesions are important in determining the degree of treatment progress. Ghribi et al.[19] suggested some recent segmentation (semi-automatic and automatic) methods. They gave a brief review of some directed methods to MS segmentation. However, no one of them can be regarded as a model approach. Many MS segmentation methods have been proposed in the last few years [20] to develop new techniques that give hopeful results.

In the MRI brain white mater images, segmenting of the MS is an essential process before therapy or surgical planning. Ameli et al. [21] presented a study of multiple sclerosis segmentation algorithms. In their study, they explored thirteen segmentation methods on the 53 MS cases. They gathered a database of 53 MS patients. The results of their study still trailing human expertise on both detection and delineating criteria.

Many multiple sclerosis segmentation methods based on intensity distributions such as thresholding method [22] and Mixtures of Gaussians can be implemented with the distribution of the intensity to differentiate between normal and infected tissues [23]. Recently, Schmid et al. [24] introduced a pipeline segmentation of FLAIR hyperintense white matter lesion changes between two points. Their method segmented significant changes in white matter lesions. The result of using their approach leads to more coherent results. The limitation of their work that they cautioned that their algorithm was validated using high-quality MRI data in the early stage of MS. Hence it may not work well with other situations.

Roy et al.[25] presented details of the longitudinal white matter lesion segmentation of MS challenge that was mentioned during the 2015 international symposium on biomedical imaging. Different lesion segmentation algorithms evaluated their submitted results. Their experiment shared a rich data set, collaborated and comprised of various avenues of research, reviewed the refinement of the evaluation metrics.

Over the past few years, the convolution neural network (CNN) gained a lot of interest in classifying MS lesions after the segmentation process. Roy et al. [26] proposed a CNN approach to separate the white matter lesions from multi-contrast MRI. Their approach divided into two paths: the first contains multiple parallel convolutional filters, and the second produces a thresholding function for binarization of images. Their approach scored a 90.48 in the International Symposium on Biomedical Imaging challenge.

Aslani et al. [27] introduced an automated method for segmenting MS lesions from multi-modal brain magnetic resonance images. Their approach based on a deep-end to end 2D CNN. They included a down-sampling path that can encode information from multiple modalities. The volume [28] of MS lesions can be used to determine the degree of disease severity and track its progression. Therefore, the segmentation of MS in white matter plays an essential role in understanding the nature of the dynamic behaviors of MS and helps to investigate the progression of the disease. The MS lesions are small in terms of size and indistinct borders. In T2 FLAIR may possess low resolution and often has imaging artifacts. Multiple sclerosis observed with high inter-rater variability according to Carass et al. [29].

The mentioned studies above have been organized a competition in MS lesion filtering, segmenting, and measuring. All multiple sclerosis approaches are evaluated on different datasets, mostly not determining the size and location of the lesions. Also, their results are making difficult the choice of the most relevant method adapted to clinical use.

Multiple sclerosis is described as frequently involves lesions. It can appear on a scan at one time-point and not appeared in subsequent time points. Determining the MS at one scan without reference to other scans may cause errors in the estimation of damaged tissue. The damaged tissues (MS lesions) have an indistinct correlation, and they change their location during treatments. Multiple sclerosis on MRI is characterized by the presence of multiple changes (shrinking or growing) in the substance of the brain and spinal cord, which complicates their dynamic control according to MRI data. Thus, there is an apparent need to investigate the dynamic changes of multiple sclerosis lesions on T2-FLAIR MRI using digital image processing. In this paper, we proposed a comparable methodology for overcoming the problem of dynamic changes in MS lesions by selecting the most relevant digital image processing methods to provide information about the current status of MS, which represent MS lesions that are either new, increasing or shrinking.

III. Proposed Methodology

In this study, around 38 scans before and after a month of treatment for each one of 55 MS cases from different real clinical cases were gathered and presented in DICOM format. For retrieving the images, neurologists, and neurosurgeons were consulted to differentiate between diseased and healthy (normal) images. Various processes were performed on the selected images based on a novel digital image processing methods for enhancing the structures, removing undesired signals, segmenting the MS from the background, and finally measuring the size of MS lesions to provide information about the current status of MS, which represent MS lesions that are either new, increasing or shrinking. Fig. 2 illustrates the stages of different processes of the proposed methodology

A. *Documentation*

In this paper, T2 FLAIR mode is used. The registration of images was performed on a Siemens magnetic resonance imaging machine with a field strength of 1.5 T.

B. *Pre-Processing Stage*

During formation and transformation in various devices, medical images can be distorted and degraded by different random signals or errors. The first step in digital image processing is the enhancement by eliminating noisy information.

- Image Enhancement

This stage is essential to distinguish the lesions and enhance the quality of images. In this section, spatial filters were used because we are dealing with additive noises, and we need to have direct results. Linear and non-linear filters such as median, Gaussian, and Laplacian smooth the images by averaging the value of pixels. For example, median filter denoise images from the impulse noise by determining the position of the impulse and replace it with median value while keeping other pixels of the image intact[30].

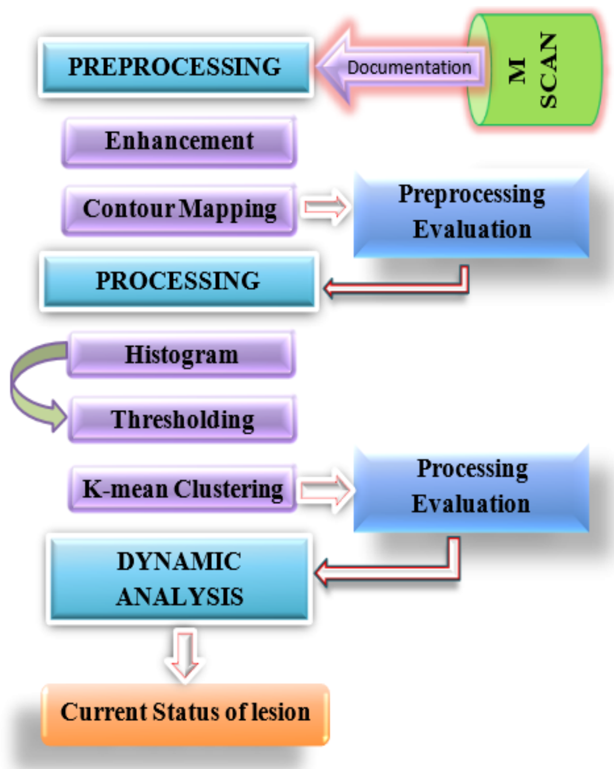


Fig. 2. Schematic Diagram of the Proposed Methodology.

- Contour Mapping

Contour is a graph that shows the 3D image in the 2D plane. It plots two variables, variable on the Y-axis and a response variable Z as contours [31]. In this section, we analyzed the results of the pre-processing stage by using a contour mapping technique to draw the intensity structure of MS lesions before and after the pre-processing stage. The goal of this step is to evaluate the enhancement of MS structures on the T2-FLAIR images.

C. Processing (Segmentation) Stage

Segmentation plays an important role in many medical diagnostics, and the result of segmentation influences the entire analysis. The following points contain detailed information related to the proposed segmentation methods.

- Histogram

In this section, the histogram was proposed to study the distribution of the image ingredients and also to select the thresholding value to separate the lesions from the normal tissues [32].

- Threshold Method

The meaning of segmentation in MRI medical images is dividing an image into a set of meaningful, homogenous, non-overlapping regions. One of the effective ways for separating the interest is the Threshold method [33].

$$I(x,y) = \begin{Bmatrix} 1, if\ f(x,y) > T \\ 0, if\ f(x,y) \leq T \end{Bmatrix} \quad (1)$$

The output of image I(x,y) depends on the T. The main logic in this method is the selection of a threshold value (T). The selection of threshold value (T) in this method was made using the histogram of the intensity distribution.

- K-means Clustering Method

Clustering is a technique for splitting the image into clusters of pixels. The pixels in each cluster must have similar attributes and vary from other clusters. In this method, there are not common pixels between clusters. In other words, one pixel can only belong to one cluster only[34]. K-means clustering algorithm (formula 2) has two phases: determining the number of clusters (k=5) is first, and the second one is taking each point of the cluster, which has the nearest centroid from the respective data point.

$$C_k = \frac{1}{k} \sum_{y \in C_k} \sum_{x \in C_k} p(x,y) \quad (2)$$

Where k is the number of selected clusters. Although k-means has a great advantage of being easy to implement, it has some drawbacks. The quality of the final clustering results depends on the arbitrary selection of initial centroid.

In this section, we examined the threshold and k-means clustering methods by comparing the size of MS lesions after segmentation with the results that done automatically (manually) by radiologists without segmentation. The goal of this section is to select the most optimal method to separate MS lesions.

D. Dynamic Analysis

In this section, a quantitative assessment of pathological changes was carried out by calculating [35] the size of the MS in each slice after and before the treatment to investigate and evaluate the dynamic changes (shrinkage or growth) of MS lesions. The expression that was used to calculate the size of the lesions after segmentation is:

$$S_o = \sum_{i=1}^{n} (N_p * h_p * w_p) \quad (3)$$

Where So is the calculated area of MS, Np is the number of segmented pixels on i slice; hp and wp are the height and width (pixel dimensions), respectively. We should fix the filtration and segmentation methods (do not change from image to image), to get accurate and useful results.

IV. Result and Discussion

A. Pre-Processing Results and Discussion

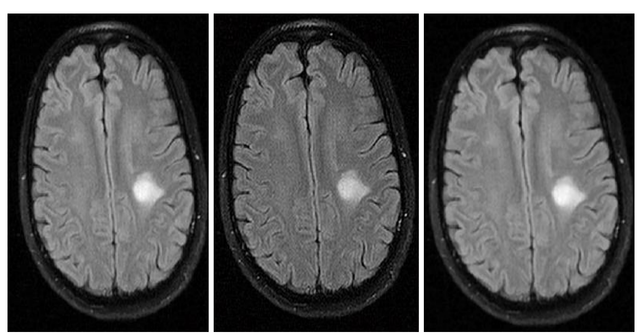
The basic ideas of the most enhancing filters (such as Laplacian or median) are based on the fact that dark and light pixels are found to be adjacent (next to each other) on the borders. The spatial filters were implemented to denoise and improve the quality of the images. Fig. 3 demonstrates that Laplacian (masks center -8) and Sobel filters highlight the edges of the objects, reinforce the boundaries between the light and dark pixels of the images. The Gaussian and Median remove unnecessary noises and smooth the borders on the images, which will reduce the lack of accuracy in the segmentation, shown in Fig. 4. Generally, the essential task of filters is smoothing, denoising, sharpening and emphasizing borders.

The output of this stage is the finer details of the images. Besides, the noises were reduced to the minimum degree from these images. Also, the MS lesions zones are clear and made it detectable as compared to raw images.

B. Contour Mapping

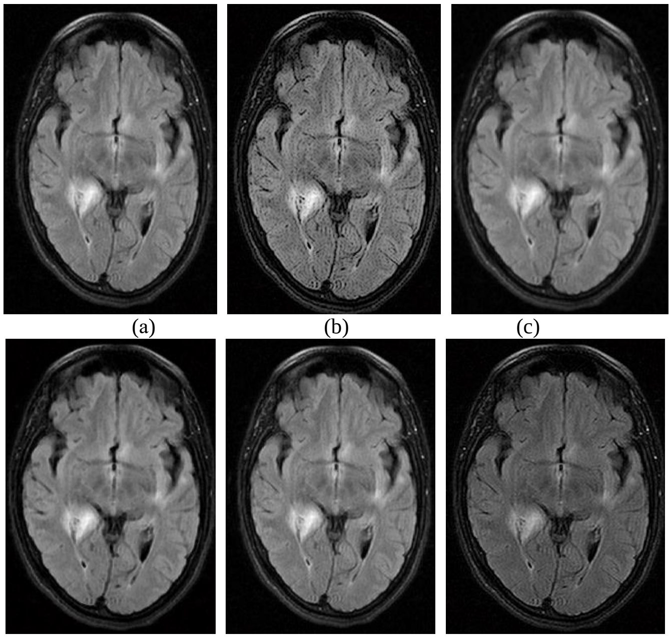
The contour method allows for mapping the intensity distribution. The numerical values represent the intensity values of images as groups of pixels corresponding to the normal and pathological brain tissues.

Fig. 5 presents the results of using the contour mapping method on the T2-FLAIR MS image. The results show that normal brain tissue has an intensity of pixel ranging from 250 to 300, and pathological has intensity higher than 350.



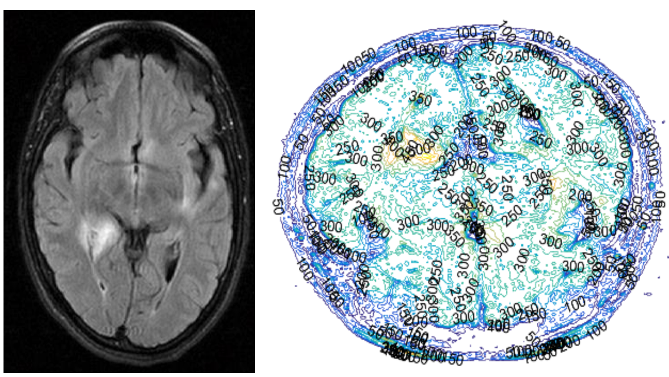
(a) (b) (c)

Fig. 3. Spatial Filters with T2 FLAIR MRI Images: (a) Original Image, (b) Image with Gaussian Filter, (c) Image with Median Filter.



(a) (b) (c) (d) (e) (f)

Fig. 4. Spatial Filters with T2 FLAIR MRI Images: (a) Original Image, (b) Image with Laplace Filter (-4 mask), (c) Image with Gaussian filter, (d) Image with Median Filter, e) Image with Laplace Filter (-8 Mask), (f) Image with Averaging Filter.



(a) (b)

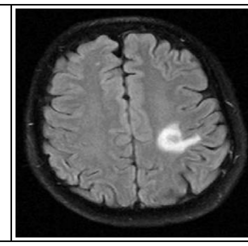
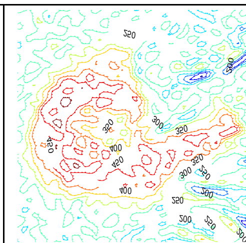
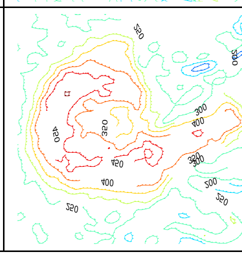
Fig. 5. Result of using Contour Mapping Method: (a) Original Image, (b) Contour of Image.

C. Results and Discussion of Pre-Processing Evaluation

In this section, we suggest the contour method to study the results of filtration on T2 FLAIR MS images and also to map the lesions. The purpose of this section is to evaluate the results of the pre-processing stage on MS lesions structures and compare them with the structures of the same lesions before preprocessing.

Table I demonstrates that the structures of multiple sclerosis lesions after the pre-processing stage have noticeable values. Also, it can be judged that the MS lesions before and after having varied constructions. The MS lesion has after pre-processing observable constructions and clear intensity distributions. The use of filtering in this paper (with T2-FLAIR) was mandatory to give accurate and optimal results for the following steps.

TABLE. I. EVALUATION OF MS LESIONS BEFORE AND AFTER PRE-PROCESSING

Original image of a patient with Multiple sclerosis	
The changes in the structure of the MS lesion before and after pre-processing	
Before pre-processing	
After pre-processing	

D. Processing (Segmentation) Results and Discussion

The meaning of segmentation in medical imaging is dividing an image into a set of meaningful, homogenous, non-overlapping clusters (regions or classes). Each region has similar attributes (such as intensity, depth of pixels, or textures) and should be different from other regions.

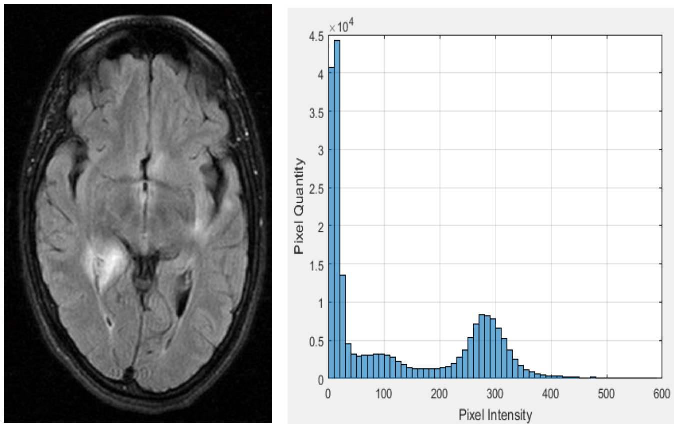
- Histogram

Histogram of an image provides a visual interpretation of the intensity distribution over an image. It can be used in many digital image processing applications, such as study the result of filtering techniques by tracking the intensity distribution over the image. Another use for the histogram is a binarizing image (segmentation) and determine the borders between different image components. In this section, we used the histogram method for the logical selection of thresholding segmentation values. Fig. 6 shows the histogram representation of normal and abnormal tissues.

The result of the histogram shows that the normal tissues have larger peaks than multiple sclerosis. The distribution of the MS tissues locates above 350. The histogram helped us easily to set the value of thresholding segmentation method.

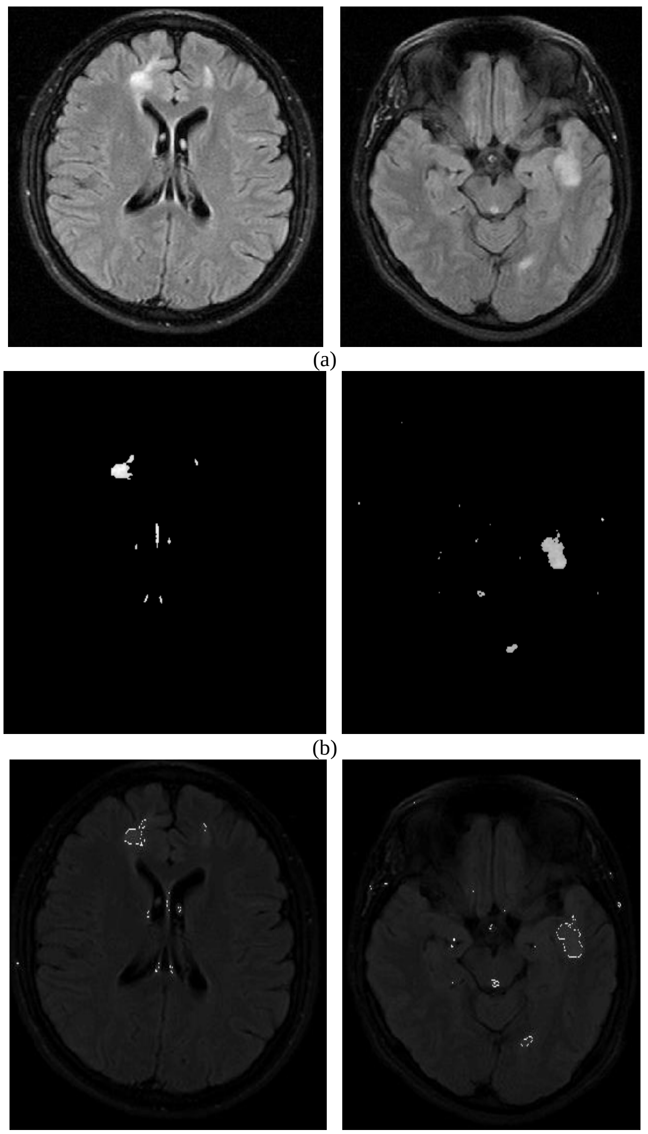
- Thresholding method

The histogram helped us easily to set the value of the thresholding segmentation method. The optimal thresholding segmentation value is T=350. Fig. 7 shows the result of segmentation using the thresholding method.



(a) (b)

Fig. 6. Histogram of the MRI Image (a) Original Image, (b) Histogram Representation of Normal and Abnormal Tissues,



(a)

(b)

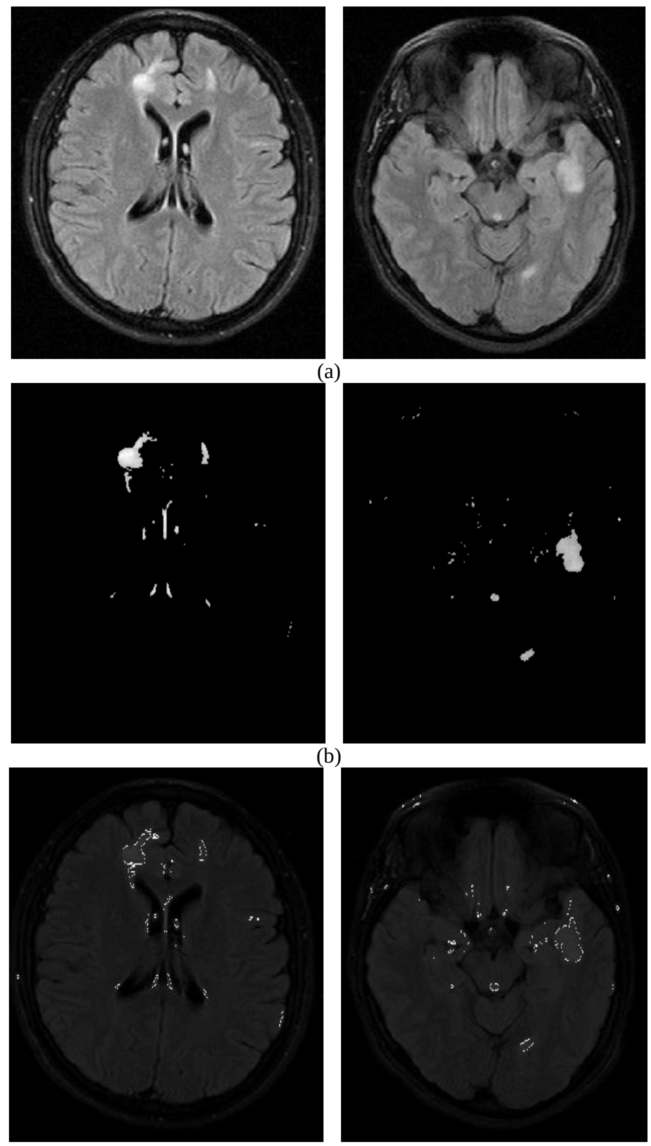
(c)

Fig. 7. Result of Thresholding Segmentation Method: (a) Original Image, (b) Segmented Image, (c) Mapping the Segmented Image with the Original Image.

- K-means clustering method

Clustering is a technique for splitting the image into clusters of pixels. The pixels in each cluster must have similar attributes and vary from other clusters. In this method, there are not common pixels between clusters, and we set the number of clusters equal to five (k=5). Fig. 8 shows the result of segmentation using the K-means clustering method.

All segmentation methods convert a given image into a grayscale image, then separate the infected tissues from healthy tissues by binarizing the image. The selection of the thresholding and k-means clustering methods was based on flexibility and popularity. Both methods successfully separated the MS lesions from the background.



(a)

(b)

(c)

Fig. 8. Result of K-means Clustering Segmentation Method: (a) Original Image, (b) Segmented Image, (c) Mapping the Segmented Image with the Original Image.

E. Results and Discussion of Processing Evaluation

The segmentation methods play a major role in determining the size and real boundaries of multiple sclerosis lesions. It can give accurate or sometimes misguided results. In this section, we evaluate the proposed segmenting methods to select a suitable method for the following steps. The accuracy and reliability of the results were confirmed by the data presented in the physician's (automatic evaluation by specialists) calculation.

TABLE. II. EVALUATION OF MS LESIONS SIZE WITH THRESHOLDING AND K-MEAN CLUSTERING SEGMENTATION METHODS

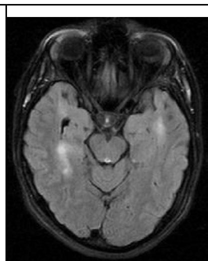
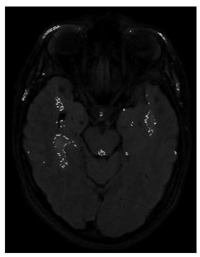
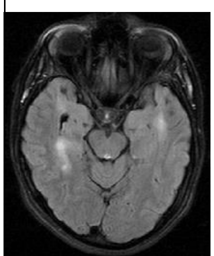
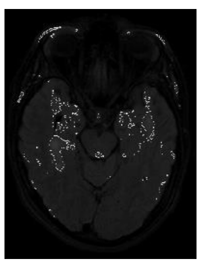
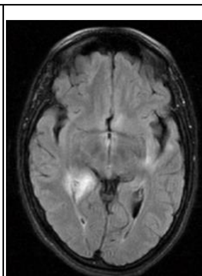
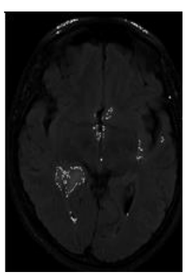
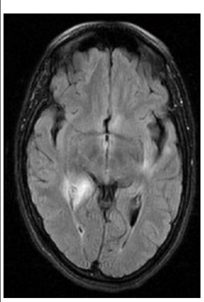
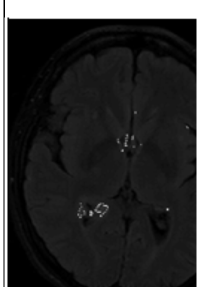
Method	**Original Image**	**Segmented Image**	**Size of MS,mm**
Patient no 1. is a woman, 43 years old, estimating MS lesion size was (2557,85) mm²			
With threshold method			2214.72
With k-means clustering method			2135.52
Patient no 2. is a man, 27 years old, estimating MS lesion size was (1800,52) mm²			
With thresholdmethod			1375.2
With k-means clustering method			1140.4

Table II presents the changes in MS lesion size with different segmentation methods and illustrates that the thresholding method approximately determined the boundaries of the MS area and gave a satisfactory result, whereas the k-means clustering method provided critical results. The separation of multiple sclerosis lesions from healthy tissues using segmentation methods is a real challenging task. The results of using thresholding and k-means clustering were optimistic, according to the presented data. In this paper, we selected thresholding as a method to segment the lesions because of the flexibility, accuracy, and capability of handling big dimensionality.

F. Results and Discussion of Dynamic Analysis of MS Lesions

Multiple sclerosis (MS) is described as frequently involves lesions. It can be appeared on a scan at one time-point and not appeared in subsequent time points, as shown in Fig. 9. Determining the MS at one scan without reference to other scans may cause errors in the estimation of damaged tissue. The damaged tissues (MS Lesions) have an indistinct correlation, and they change their location during treatments.

In this section, we investigate the accuracy of the implemented methodology using 38 scans divided equally as 19 scans before and 19 scans after a month of treatment for each one of 55 MS cases. Also, we fixed the filtering (Laplacian and Median) and segmenting (thresholding) methods for all scans. Then the obtained results were calibrated with the results of the automatic evaluation (done by specialists) of MS lesions that are either new, increasing, or shrinking. In the following, we present the evaluation results of two real clinical patients.

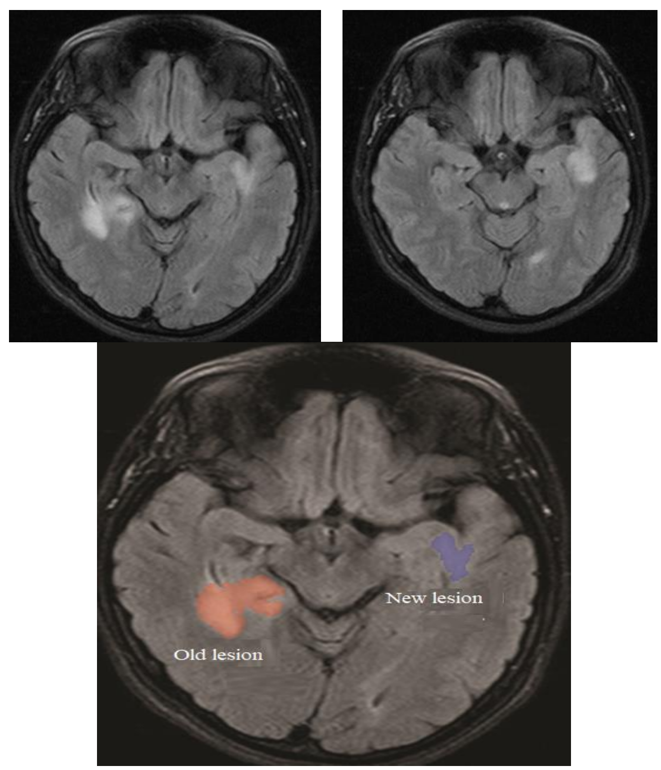


Fig. 9. Dynamic Changes of MS Lesions During Treatment.

- First Patient

The first case is a woman, 45 years old, the result of MRI scans show that she has most likely pseudotumor of the demyelinating disease in the left parietal lobe, as shown in Fig. 10.

The results of automatic evaluation by specialists before and after one month of treatment for the MS lesion size are presented in Table III, and the results of MS dynamic changes after and before treatment for the MS lesion size using our proposed methodology are shown in Table IV.

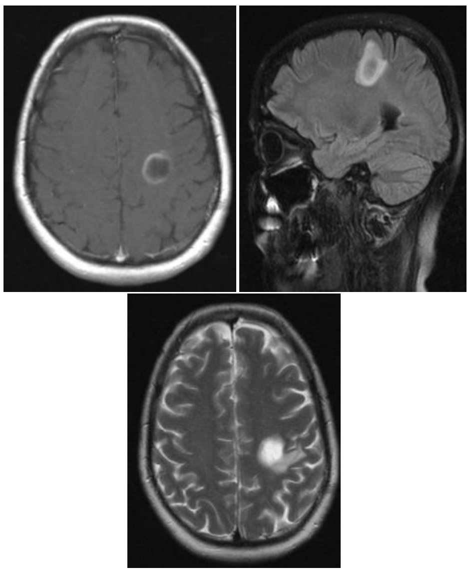


Fig. 10. MS Lesion in different Slices: Patient no.1.

TABLE. III. RESULTS OF THE AUTOMATIC EVALUATION OF DYNAMIC CHANGES OF MS LESIONS: PATIENT NO 1

Slice No.	**Size of MS lesion (mm^2)**	
	Before Treatment	*After One Month of Treatment*
1	0	0
2	0,10	0
3	0	0
4	0	0
5	1360,9	1209,3
6	0	0
7	10	0
8	0	0
9	1442,4	0
10	190,77	198,48
11	0	0
12	0	0
13	0,15	0
14	0	0
15	611,32	830,8
16	0	0
17	0	0
18	8	0
19	1510,8	1050,8
Total area, S_o	5116,4	3289,4

TABLE. IV. RESULTS OF DYNAMIC MS LESIONS CHANGES USING THE PROPOSED METHODOLOGY: PATIENT NO.1

Slice No.	***Size of MS lesion (mm^2)***	
	Before Treatment	*After One Month of Treatment*
1	0	0
2	0	0
3	0	0
4	0	0
5	1460,9	1169,3
6	0	0
7	0	0
8	0	0
9	1472,6	0
10	190,08	204,8
11	0	0
12	0	0
13	0	0
14	0	0
15	598,32	838,8
16	0	0
17	0	0
18	0	0
19	1491,8	1000,8
Total area, S_o	5213,52	3213,26

- Second Patient

The second case is a woman, 32 years old, the results of her MRI scans illustrate that she has an acute and chronic demyelinating disease, as shown in Fig. 11.

The results of automatic evaluation by specialists before and after one month of treatment for the MS lesion size are presented in Table V, and the results of MS dynamic changes after and before treatment for the MS lesion size using our proposed methodology are shown in Table VI.

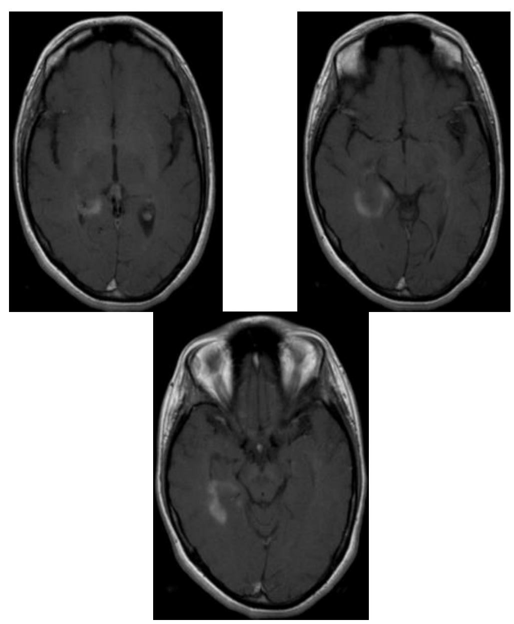


Fig. 11. MS Lesion in different Slices: Patient no.2.

TABLE. V. RESULTS OF THE AUTOMATIC EVALUATION OF DYNAMIC CHANGES OF MS LESIONS: PATIENT NO 2

Slice No.	Size of MS (mm^2)	
	Before Treatment	*After One Month of Treatment*
1	0	0
2	838,8	221,04
3	854,64	1854
4	0	129,6
5	0	0
6	0	0
7	743,04	1386
8	800,64	322,56
9	185,04	52,56
10	190,77	198,48
11	0	0
12	300,24	749,52
13	1748,2	676,8
14	517,68	175,68
15	0	0
16	0	0
17	1218,2	1864,1
18	414,72	713,52
19	152,64	5,06
Total area, S_o	7773,84	8150,4

TABLE. VI. RESULTS OF DYNAMIC MS LESIONS CHANGES USING THE PROPOSED METHODOLOGY: PATIENT NO 2

Slice No.	Size of MS lesions (mm^2)	
	Before Treatment	*After One Month of Treatment*
1	0	0
2	738,6	221,04
3	554,54	1454
4	0	100,6
5	0	0
6	0	0
7	641,03	1289
8	602,55	212,65
9	135,4	46,51
10	0	0
11	0	0
12	199,2	678,47
13	1600,34	800,89
14	420,47	578,6
15	0	0
16	0	0
17	1122,2	1746,02
18	512,71	811,24
19	255,24	6,02
Total area, S_o	7080.0	8237.0

All tables show appearing of new and disappearing of old multiple sclerosis lesions after or before the treatment. For example, slices number 2 (patient no. 1) and slice number 4 (patient no. 2). Atrophy and growth of the multiple sclerosis lesions were presented in the results of the proposed methodology as the slices number 5, 7, 9, 10, 13, 15, and 19 in Table IV. Also, the slices number 2,3,7,8,9 ,12,13,14,17,18 and 19 in Table VI. The results of the proposed methodology (Table IV and Table VI) were calibrated with the results of the automatic evaluation (Table III and Table V) for the same slices in both cases. The result of calibration shows that the errors between automatic evaluation and proposed methodology for patient no. 1 before and after treatment are nearly 1.89% and 2.31%, respectively. The patient no. 2 had 8.9% before treatment and 1.06% after one month of treatment.

In this paper, the proposed methodology used T2-FLAIR MRI scans to measure and investigate MS lesion shrinking, growing, and appearing of a new one in 55 MS cases. The result shows that shrinkage of lesions presented in 29 cases, whereas 19 cases showed more severe growth in old lesions. Also, new lesions presented in 7 cases. The accuracy of the proposed methodology was 96%, according to the results presented in data. The lack of accuracy is related to the errors of filtration and segmentation.

V. CONCLUSION

The selected MRI images were T2-FLAIR because these types of images show distinct boundaries of multiple sclerosis and have acceptable contrast. In this paper, the use of spatial filters was mandatory to detect and enhance the visuality of MS lesions. The results of spatial filters were tested using the contour method. The results of the contour method showed that MS lesions after filtration have observable construction and clear intensity distribution. The segmentation methods play a major role in determining the size and real boundaries of multiple sclerosis lesions. It can give accurate or sometimes misguided results. The thresholding method (with T=350) approximately determined the boundaries of the MS area and gave a satisfactory result. Whereas the k-means clustering method with (k=5) provided critical results. In this paper, we selected thresholding as a method to segment the lesions because of the flexibility, accuracy, and capability of handling big dimensionality. The size of MS lesions was measured using the quantitative method after fixing the filtration and segmentation methods. The evaluation of the proposed methodology was done using T2 FLAIR MRI scans to measure and investigate MS lesion shrinking, growing, and appearing of a new one in 55 MS cases. The result shows that shrinkage of lesions presented in 29 cases, whereas 19 cases showed more severe growth in old lesions. Also, new lesions presented in 7 cases. The accuracy of the proposed methodology was 96 %, according to the results presented in data. The lack of accuracy is related to some errors in segmentation. The proposed method can be used for filtering, segmenting, and tracking the information about the current status of MS, which represent MS lesions that are either new, increasing or shrinking. The improvement of accuracy will be better with more data. This approach can be used in diagnostics room for automatic decisions in critical multiple sclerosis cases.

VI. CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

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