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THE AUTOMATED SEGMENTATION TECHNIQUES OF T2-WEIGHTED MRI IMAGES USING K-MEANS CLUSTERING AND OTSU-BASED THRESHOLDING METHOD

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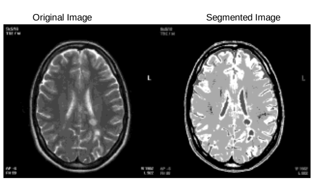
Graphical abstract



Abstract

The k-means clustering and Otsu-based thresholding of MRI images segmentation are widely used to cluster the lesions in human brain. The main objective of this paper is to employ both algorithms concept to obtain the optimum value of clusters center and threshold levels for a better segmentation process. Both segmentation approaches were used to partition the images into separate classes which are composed of pixels that have similar pre-defined feature values. The evaluation of both segmentation techniques were measured via qualitative and quantitative analysis. From the analysis of the results, it is justified that the proposed approaches are able to efficiently illustrate good segmentation results. The K-means algorithm is also successfully preserved important features of the MRI segmented images as the larger number of clustering reveals bigger grayscale intensity distribution on delineation marks of the MS lesions.

Keywords: White matter lesions, Automatic segmentation, K-means clustering, Multi threshold, grayscale intensity distribution

1.0 INTRODUCTION

Image segmentation has proven it superiority and has been applied in various fields including medical fields specifically in biomedical image analysis by various researchers. Numbers of clinical rating scale have been developed to quantify the expression of white matter (WM), but different methods deliver various degrees of reliability. In addition, semi-automated methods requiring human inputs are subjective, time consuming, laborious, error prone and vulnerable to intra- and inter-rater variability. On the other hand, the automatic technique is based on computer algorithms for segmenting and measuring WM features such as the volume, which is done by measuring the intensity of each voxel and predefined its threshold of intensity.

As there are still lag of truly reliable and fully automated method for quantitative assessment of white matter hyperintensity (WMH) on magnetic resonance imaging (MRI), Caligiuri *et al*. [1] has summarized recent works on the automatic segmentation of the WM lesions in his reviewed literature search. The review compared the large number of automated approaches that had been proposed for the segmentation of the WMH in the elderly people and patients with vascular risk factors. It is concluded that the advancement in new algorithms as well as new developments in MRI acquisition protocols should be able to help the radiologists in a way to clinically improve the evaluation of the WMH. Furthermore, the review investigated the relationship of such improvement with normal aging and pathology, and in every-day clinical practice.

In recent years, researchers have used segmentation approach based on clustering algorithm to research the image abnormality for medical analysis. Shamsi *et al*. [2] used a modified Fuzzy C-means algorithm to segment brain image. The algorithm has managed to provide better results since it is more robust to noise than the standard FCM algorithm. Vijay *et al.* [3] has compared k-means algorithm with others algorithms and gave better results for clustering medical images. However, it is a bit challenging for brain segmentation due to complex brain anatomy and structure which requires improvement in the clustering technique. Therefore, Shrivastava *et al*. [4] developed a modified k-means algorithm to cater existing problems and thus performed better in all parameters measured such as structural similarity index measure, structural content, mean squared error (MSE) and peak to signal noise ratio (PSNR).

Several clustering algorithms have been proposed to overcome the weaknesses of k-means algorithm such as the hard C-mean and the fuzzy C-means (FCM) clustering algorithms [5]. During the last decades, some researchers have modified and developed new concept of fuzziness and belonginess technique based on C-means algorithm for enhancing the segmentation techniques to improve their works. Other related work conducted by Sulaiman and Mat-Isa [6] and Zanaty [7] are intended to provide the best adaptive clustering process compared to several conventional clustering algorithms. Meanwhile, Gopal and Karnan [8] tested the segmentation technique by combining Fuzzy C Means along with metaheuristic algorithms such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). A research done by Mat Isa *et al.* [9] has proposed new clustering algorithm named as Adaptive Fuzzy Moving k-means (AFMKM) which combines the concepts of two clustering algorithms of Fuzzy Moving k-means (FMKM) and Adaptive Moving k-means (AMKM). The AFMKM algorithm works by assigning the members of the center with the largest fitness value to the nearest cluster depending on the minimum Euclidean distance. The combination properties of both algorithm has significant effect to avoid miss-clustering data into the unwanted noise cluster.

Ong *et al.* [10] proposed new automated method for WM lesions segmentation. The technique was implemented by using a novel adaptive outlier detection approach where the WM lesions were detected as the outliers in the intensity distribution. The method named as an adaptive trimmed mean algorithm and box-whisker plot were tested to detect WM lesions in the fluid-attenuated inversion recovery (FLAIR) MR images (MRIs). The results showed that the proposed method has effectively detected the WM lesion without requiring any atlas or elaboration of training procedures. Moreover, the technique was able to successfully segment various sizes and shapes of the lesions in MRIs and therefore it is able to support significant improvement on further analyzing work.

Liu and Yu [11] compared the objective function of the Otsu's method either it was equivalent to the one of the k-means method in multilevel thresholding. The result has proven that the clustering method of k-means keeps the order of the initial centroids with respect to one-dimensional data set. Meanwhile, the experiment had shown that the k-means thresholding method performed well on three dimensional (3-D) image thresholding with less computing time than the performance of the Otsu's method.

There are many works done by various researchers focusing solely on clustering or Otsu-based technique but there are smaller number of studies had combined both techniques of the k-means and Otsu-based thresholdings for overall WM segmentation. This paper will focus on the usage of two different segmentation techniques (i.e. k-means and Otsu) to segment the WM delineation of MRI Multiple Sclerosis images. Both segmentation approaches are used to class the image into separate classes composed of pixels which have similar pre-defined feature values. The evaluation of both segmentation techniques would be measured by employing qualitative and quantitative analysis. All in all, the segmentation is one of the basic technique that helps an image understanding but misclassification of the WM lesions in the images are also often to occur and causes poor delineation of the segmentation techniques.

2.0 METHODOLOGY

The aim of this study is to compare two segmentations namely as Otsu-based thresholding technique and k-means clustering method. Figure 1 shows a flowchart of the overall work proposed in this study.

The MRI brain images used in this study were downloaded from available database [12]. The MRI data were comprised of 38 subjects with Multiple Sclerosis (MS) lesions segmentation. All the images size of each slide was standardized to 512x512.

2.1 Thresholding Technique

The Otsu's method is one of the most successful methods in an image thresholding[11]. The segmentation method of the Otsu-based thresholding technique was firstly developed by Otsu himself [13]. This approach is simple since the method to select a threshold automatically from a gray level histogram has been derived from the viewpoint of discriminant analysis. Otsu's method is capable to work either for bi-level thresholding or multilevel thresholding. In the bi-level thresholding method, the pixels of the image are divided into two classes C_1 with gray levels [0, 1,… *t*] and C_2 with gray levels [*t*+1,… *L*-1] by the threshold *t*. The gray level probability distributions, w_1 and w_2 for the two classes are denoted as (1) and (2) where P_i is the probability of gray level *i* which is $P_i = 0$, the number of pixels at level *i* is denoted by $N = n_1 + n_2 + \ldots + n_L$ and *L* represents the gray levels of an image [0, 1, … *L*-1].

$$w_1 = P_r(C_1) = \sum_{i=0}^{t} P_i \tag{1}$$

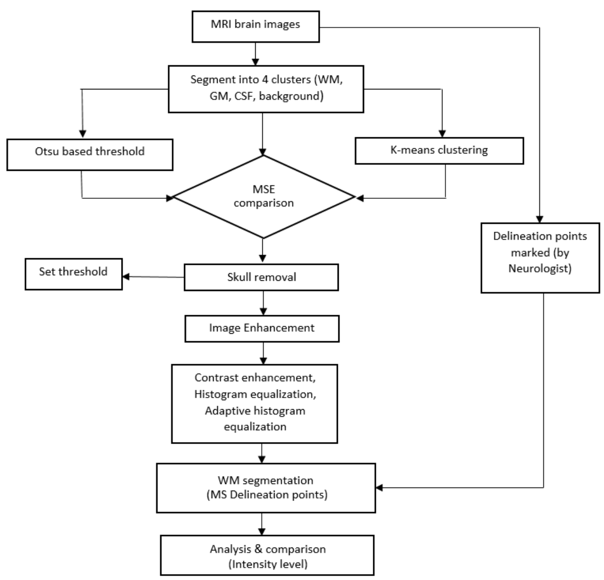


Figure 1 Flowchart for overall works of the WM segmentation

$$w_2 = P_r(C_2) = \sum_{i=t+1}^{L-1} P_i \tag{2}$$

The means of class C_1 and C_2 are calculated based on (3) and (4) respectively.

$$u_1 = \sum_{i=0}^{t} iP_i / w_1 \tag{3}$$

$$u_2 = \sum_{i=t+1}^{L-1} iP_i / w_2 \tag{4}$$

The total mean of the gray levels is denoted as U_T as in (5).

$$u_T = w_1 u_1 + w_2 u_2 \tag{5}$$

The class variance are denoted by (6) and (7).

$$\sigma_1^2 = \sum_{i=0}^{t} (i - u_1)^2 P_i / w_1 \tag{6}$$

$$\sigma_2^2 = \sum_{i=t+1}^{L-1} (i - u_2)^2 P_i / w_2 \tag{7}$$

And thus, the with-in class variance is as stated in (8) while the difference between the class variances is shown in (9).

$$\sigma_w^2 = \sum_{k=1}^{M} w_k \sigma_k^2 \tag{8}$$

$$\sigma_B^2 = w_1(u_1 - u_T)^2 + w_2(u_2 - u_T)^2 \tag{9}$$

Hence, the total variance of gray levels is as stated in (10).

$$\sigma_T^2 = \sigma_w^2 + \sigma_B^2 \tag{10}$$

Otsu's method chooses the optimal threshold, *t* by maximizing the between-class variance, which is equivalent to minimizing the within-class variance, since the total variance (the sum of the within-class variance and the between-class variance) is constant for different partitions [11].

For Otsu multilevel thresholding method, there are *M*-1 thresholds [$t_1, t_2, \ldots t_{M-1}$] that divide the pixels in the image to M classes { $C_1, C_2, \ldots C_M$ }.

$$\left\{ t_1 + t_2 .. t_{M-1} \right\} = \arg \left\{ \max_{0 \le t \le L} \left\{ \sigma_B^2 (t_1 + t_2 .. t_{M-1}) \right\} \right\}$$

$$= \arg \left\{ \max_{0 \le t \le L} \left\{ \sigma_W^2 (t_1 + t_2 .. t_{M-1}) \right\} \right\} \tag{11}$$

Where

$$\sigma_w^2 = \sum_{j=1}^{M} w_j \sigma_j^2 \tag{12}$$

$$\sigma_B^2 = \sum_{j=1}^{M} w_j (u_j - u_T)^2 \tag{13}$$

$$\sigma_j^2 = \sum_{i=t_{j-1}+1}^{t_j} (i - u_j)^2 P_i / w_j \tag{14}$$

$$u_j = \sum_{i=t_{j-1}+1}^{t_j} iP_i / w_j \tag{15}$$

$$w_j = \sum_{i=t_{j-1}+1}^{t_j} P_i \tag{16}$$

2.2 K-means Clustering Method

Another segmentation technique that has been implemented for this study was the k-means clustering method which was proposed by MacQueen [14]. This method is widely used for clustering due to its characteristics that are numerical, unsupervised, non-deterministic and iterative. It is commonly used in computer vision as a form of image segmentation. The k-means method aims to partition N data points into *k* clusters of disjointing subsets by minimizing the sum-of-squares criterion (within-class variance) as shown in (17) where x_n is a vector representing the n^{th} data point, *j* is the index of classes and $1<j<k$, and U_j is the centroid of the data points in C_j, C_j containing N_j data points.

$$J = \sum_{j=1}^{k} \sum_{n \in C_j} \left(x_n - U_j \right)^2 \quad (17)$$

The k-means clustering is done by minimizing the Euclidean distance between the data and the corresponding cluster centroid[15]. The Euclidean distance between two dimensional (2-D) vectors of *a* and *b* is given as (18).

$$d = \sqrt{(a_1 - b_1)^2 + (a_2 - b_2)^2 + ... + (a_n - b_n)^2} \quad (18)$$

Initially, the approach will partition the points in data matrix $[F(x,y)]_N$ into *k* classes with initial centroids $[ic_1, ic_2, \ldots ic_k]$ and final centroids $[cc_1, cc_2, \ldots cc_k]$. The flowchart of k-means algorithm is illustrated in Figure 2.

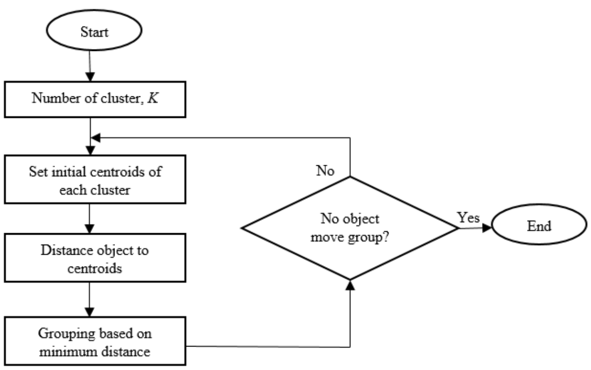


Figure 2 Flowchart of k-means algorithm

The number of cluster *k* is defined by user and the initials centroids values are set randomly where by default is 1. The iterative algorithm is used to minimize the sum of the distances of the points to the centroids and hence it is summed over all *k* clusters. Each iteration consists of reassigning points to their nearest cluster centroid, all at once, followed by recalculation of cluster centroids. In the MATLAB k-means function, a user may defined several replicates with random starting points which typically results in a solution of global minimum.

2.3 Setting Threshold Value for Skull Removal

The threshold method is also used to eliminate the skull of MRI image in order to separate out from WM, grey matter (GM) and cerebrospinal fluid (CSF). The threshold values are varied for each MRI image and therefore there is a requirement to localize the optimum threshold values in order to strip out skull evenly. Figure 3 shows the setting threshold for skull removal.

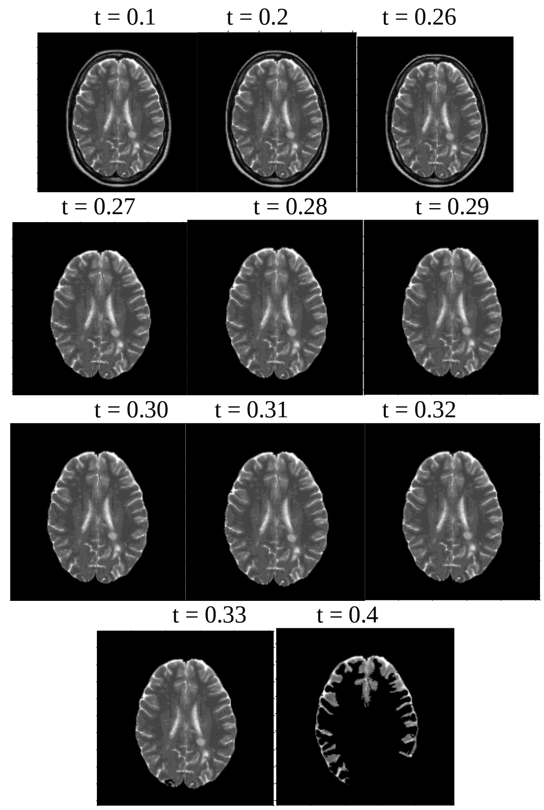


Figure 3 Setting threshold for skull removal

Initially, the conversion of the input image into grayscale format is technically programmed followed by converting this grayscale image into binary format via thresholding (Otsu-based method). The output binary image has values of 1 (white) for all pixels in the input image with luminance greater than setting level and 0 (black) for all other pixels. The level of the range is specified to be between 0 and 1, regardless of the class of the input image. In this experiment, the threshold values were tested from t = 0.1 to 0.4. The results have revealed that an optimize threshold values in accurate skull elimination were in between the range of 0.27 to 0.32. All the images were in grayscale and standardized in dimension of 512x512.

2.4 Image Gray Scale Contrast Enhancement

Image enhancement techniques is commonly conducted to enhance the contrast of the image so that the details of the entire image is able to be revealed out. Technically, the image enhancement was tested using three functions that are particularly suitable for contrast enhancement namely adjust the image intensity, histogram equalization and adaptive histogram equalization as shows in Figure 4.

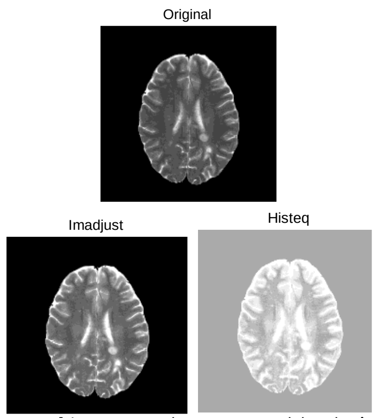


Figure 4 Image enhancement techniques

This work compares all these three techniques in enhancing the grayscale and true colour of the images. The results discovered that an adaptive histogram equalization has significantly affected the contrast enhancement compared to the other methods as proposed by Senthilkumaran and Thimmiaraja [16] whom had recommended to enhance images by histogram-based enhancement equalization methods.

3.0 RESULTS

Image segmentation is the process of grouping pixels into several homogeneous regions. This task is necessary and one of the most significant requirements in the analysis of medical images. It is one of the basic techniques that helps in an image understanding. In the MRI brain images, the common problem which is also determined as the classic problem occurring in the segmentation has to group voxels according to their tissue types. There is a need to take into account the WM, Grey Matter (GM), Cerebrospinal Fluid (CSF) and occasionally pathological tissues like the WM lesions. The analysis of the WM segmentation techniques using k-means and Otsu-based thresholding method were presented in the study. Both methods were evaluated by calculating the MSE which measured the quality change between the original and processed image in an *MxN* window size. The image quality evaluation metrics recommended by Luizou [17] are easy to compute and have clear physical meaning. Given that the evaluation metric is denoted in equation (17) where $P_{i,j}$ is the pixels in 2-D original images and $Q_{i,j}$ is the segmented images.

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(P_{i,j} - Q_{i,j}\right)^2 \qquad (17)$$

3.1 Otsu-Based Multi-thresholding Technique

Figure 5 and 6 show the segmented MRI image of 4 clusters (i.e. 3 threshold levels). The original image has been initially equalized and then segmented by using Otsu-based multi-thresholding technique. The initials threshold values were randomly selected and then they automatically performed the reduction of a grey level image into a binary image. The algorithm chooses the optimal threshold *t* by maximizing the within-class variance since the total variance is constant for different partitions.

Table 1 presents the threshold levels of each slide of the MRI image from a patient. As for the image segmentation of four clusters, the average threshold values are 44.43, 101.81 and 164.38. The average MSE is 856.71 with standard deviation of 421.66.

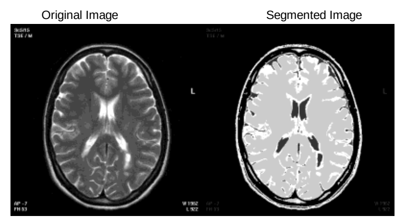


Figure 5 The original image of IM_00037 segmented into 3 threshold levels by multi-thresholding

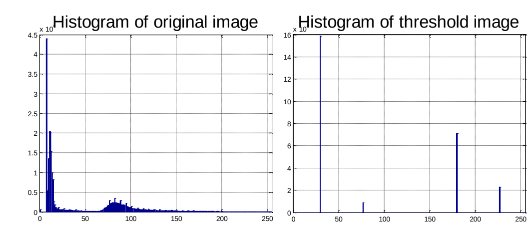


Figure 6 Histogram images of IM_00037 image

Table 1 Three threshold levels via multi-thresholding of the Otsu-based thresholding technique

MRI Slide	Threshold Levels			MSE
	t_1	t_2	t_3	
IM_00024	32	81	142	1681
IM_00025	34	85	145	1521
IM_00026	33	82	141	1600
IM_00027	32	78	136	1681
IM_00028	35	81	138	1444
IM_00029	49	116	184	576
IM_00030	48	111	183	625
IM_00031	49	109	171	576
IM_00032	48	103	158	625
IM_00033	48	103	160	625
IM_00034	47	102	162	676
IM_00035	47	104	166	676
IM_00036	48	110	177	625
IM_00037	48	111	179	625
IM_00038	47	106	165	676
IM_00039	47	106	165	676
IM_00040	49	107	164	576
IM_00041	49	112	177	576
IM_00042	49	112	178	576
IM_00043	47	110	180	676
IM_00044	47	109	181	676
Average	44.43	101.81	164.38	856.57
Std	6.50	12.23	15.82	421.66
Max	49	116	184	1681
Min	32	78	136	576

3.2 K-means Clustering Method

The MRI images have been segmented using k-means clustering method which clustered the images into four segmented area to represent WM, GM, CSF and background. Figure 7 shows the MRI image of a patient segmented into four clusters. Qualitatively, the k-means provided more details in segmented area than the thresholding method which can be visually seen in Figure 5 and 7. As an example, there is an appearance of black dots on the WM area that is visibly segmented and also the appearance of white lines around the lateral ventricles area. This is to prove that the intensity distribution using the k-means algorithm performs more accurate segmentation than the threshold technique as discussed by Liu and Yu [11]. In order to have better view on the plotted graph, Figure 8 presents the intensity distribution of each pixel into their nearest mean clusters and centroids of each cluster after applying k-means.

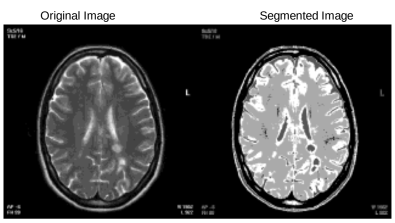


Figure 7 The IM_00037 image is segmented into four clusters via k-means clustering

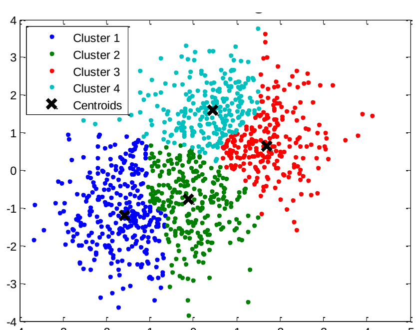


Figure 8 Graph of the intensity distribution and the clustering centroids after applying the k-means

Table 2 shows the centroids of each clusters after segmentation using the k-means method. The average centroids of each clusters are 72.1, 77.2 89.5 and 112.8. The average MSE is 2019.7 with standard deviation of 2533.2. In addition, the optimized number of iteration is 12.9.

3.3 MS White Matter Clustering

The images of the MRI MS were downloaded from available database which had been provided for the research community. In the segmentation folder there were 38 folders representing data for each patient out of overall 38 patients. In each patient folder contained the MRI TIFF images from the first and second examinations (0 months, 6-12 months). Figure 9 shows the MS lesions which had been delineated by radiologist.

Table 2 Segmentation of four clusters by k-means clustering

MRI Slide	Centroids				MSE	Iter
	C_1	C_2	C_3	C_4		
IM_00024	45	100	10	168	784	19
IM_00025	164	48	10	100	8281	19
IM_00026	10	44	157	94	3969	10
IM_00027	92	39	10	151	361	12
IM_00028	87	15	9	151	196	19
IM_00029	43	94	11	175	900	9
IM_00030	45	181	11	93	784	16
IM_00031	11	187	85	119	3844	17
IM_00032	162	79	106	11	7921	9
IM_00033	109	166	83	10	1296	6
IM_00034	79	107	10	171	36	7
IM_00035	10	81	111	185	3969	13
IM_00036	10	194	118	82	3969	8
IM_00037	97	34	161	10	196	8
IM_00038	82	10	113	175	81	21
IM_00039	10	81	169	109	3969	7
IM_00040	87	10	119	175	196	15
IM_00041	88	10	192	126	225	9
IM_00042	86	120	194	10	169	25
IM_00043	101	10	193	63	784	10
IM_00044	95	11	7	191	484	12
Average	72.1	77.2	89.5	112.8	2019.7	12.9
Std	46.3	63.1	71.4	62.8	2533.2	5.4
Max	164	194	194	191	8281	25
Min	10	10	7	10	36	6

For this automatic MS lesions segmentation, a threshold value of t = 0.3 was used to remove the brain skull. It is followed by an image enhancement that employed an adaptive histogram equalization. In order to find the intensity distribution of the WM lesions, there were three to eight clusters segmented using k-means algorithm as the k-means algorithm shown the better performance compared to Otsu-based threshold method (as presented in section 3.2).

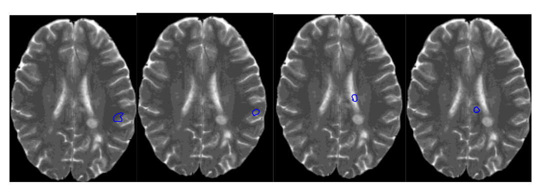


Figure 9 The MS lesions delineated by a neurologist (i.e. four lesion segmentations of the sliced image of IM 00037)

As compared to the MRI lesions which is manually delineated and marked by radiologist [20], the automatic segmentation by k-means shows a clear gray intensity distribution as seen in Figure 10. The regions in the marked lesions of the MS lines show different gray intensity level depending on the number of clusters. In this research, the automatic segmentation was tested by using the k-means algorithm which segmented the white matter into several clustering (three to eight clusters). The results show that the MS points that are manually delineated by the radiologist are consisted of only luminous region of intensity as shown in Figure 9. However, the automatic segmentation of this investigation has resulted in comprehensive segmentation in which higher clusters are usually managed to reveal a lot of details of the intensity distribution of each MS lesion delineation. As an example, three clusters segmentation as shown in the first row of Figure 10 illustrate only one and two grayscale intensity distributions on the MS lesion delineation compared to 8 clusters (last row in Figure 10). A higher cluster segmentation provided on the MS lesion delineation corresponds to bigger grayscale intensity distribution. This shows that the higher number of clusters has led to possible details in the segmentation and therefore more information of the image can be revealed.

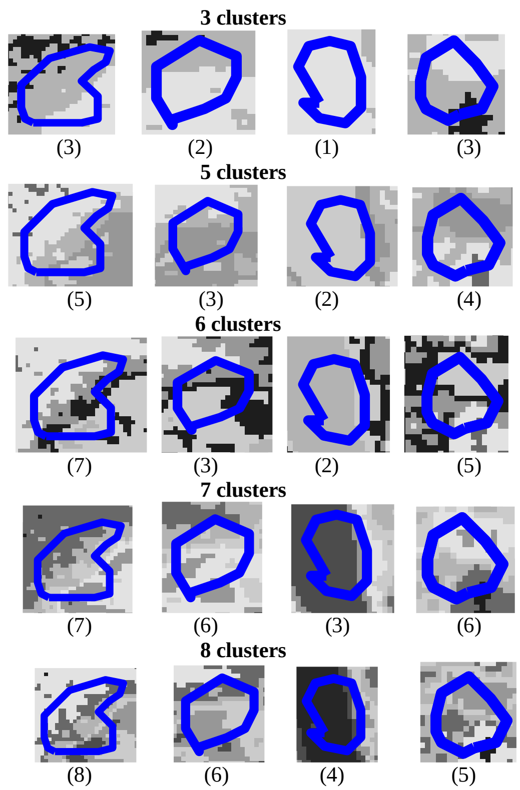


Figure 10 Clustering effect on the intensity distribution of grayscale where *( ) denoted as number of clusters in delinated area

4.0 CONCLUSIONS

This paper presents a comparison and combination of clustering algorithm named as the Otsu-based thresholding and k-means algorithm for segmentation purposes. It employs both algorithms concept to obtain the optimum value of the cluster centers for a better segmentation process. The proposed clustering algorithm is applicable to MRI brain images whereby 21 images were presented as case studies. The conclusion of this paper sees the k-means algorithm outperforms the Otsu-based threshold algorithms by successfully producing better segmented images. Although the MSE of k-means is slightly larger than the Otsu-based threshold, it shows that the k-means clustering has more clustering regions and takes the nearest mean of each pixels to be in their cluster centers. While, the Otsu-based threshold method simply classifies each pixels based on with-in class variance and between class variance. Based on the results, both qualitative and quantitative analyses have justified the conclusion that the proposed approach is able to illustrate good segmentation results efficiently. The k-means algorithm has successfully preserved important features on the MRI segmented images shown by the higher number of clustering which reveals more grayscale intensity distribution on the delineation marks of the MS lesions. The higher the cluster, the better gray intensity distribution on each MS lesions delineation. Thus, it is recommendable to expand this algorithm for the application of post image processing especially in segmenting medical images into more sophisticated and reliable technique than the current one.

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