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Characterization of Multiple Sclerosis Lesionin MR Imaging Using Texture Analysis

*Simaa Hamid, Mohamed E. M. Gar-Elnabi, Suhaib Alameen
College Of Medical Radiological Sciences, Sudan University Of Science and Technology,Khartoum, Sudan

Abstract:*In this paper we classify of brain tissue using Gray Level Run Length Matrix (GLRLM) to extract classification features from MR images. The techniques used here included elven features to define Multi Sclerosis, White Matter, Grey Matter and CSF were classified further using linear discriminate analysis. The results of the classification showed that the Multi sclerosis tissue classified well from the rest of the tissue although it has characteristics mostly similar to surrounding tissue, several texture features were introduced using Higher Order Statistic. The GLRLM and its features seem very useful in texture classification, and the classification accuracy of multi sclerosis 96.9 %, white matter 93.8 %, grey matter 92.6% and the CSF 100%. Texture parameter from FLAIR images can assess brain inflammatory activity with sufficient accuracy to be considered as a potential alternative to enhancement MR images.*

Keywords:*Multi Sclerosis, White matter, Grey matter, GLRLM, Higher Order Statistics,*

I. Introduction

Multiple sclerosis (MS) is the most common autoimmune disease of the central nervous system, with complex pathophysiology, including inflammation, demyelination, axonal degeneration, and neuronal loss. Within individuals, the clinical manifestations are unpredictable, particularly with regard to the development of disability [1]. And it's one of the most common causes of neurological disability in young adults. However, different observations in perfusion imaging studies in MS have challenged the interpretation of abnormal perfusion as a reactive phenomenon to inflammation. The occurrence of demyelinating lesions is not inevitably coupled to the presence of a local preceding inflammatory reaction [2,3].

The use of magnetic resonance imaging (MRI) to study the disease has much improved the noninvasive detection of pathology and the study of disease progression, especially in following the evolution of MR-visible white matter (WM) lesions, most of which are clinically silent. Conventional T2-weighted images have been used to assist diagnosis and follow the course of MS, as WM lesions are particularly conspicuous on these images. However, WM lesions do not appear to account for much of the disability associated with MS and pathological changes [4] and quantitative MR abnormalities [5,6] including decreased magnetization transfer ratio (MTR) have been seen in normal-appearing brain tissue (NABT), both in white (NAWM) and gray (NAGM) matter.

Texture analysis refers to a set of processes applied to characterize spatial variations of pixel's gray levels in an image. Texture analysis which is used to quantify pathological changes that may be undetectable by conventional MRI techniques, has the potential to detect the subtle changes in tissues & supports early diagnosis of MS.

Conventional MR examination usually includes fluid attenuated inversion recovery (FLAIR) and T2-weighted (T2-W) imaging for lesion load delineation, together with contrast enhanced (CE) T1-weighted (T1-W) imaging to detect foci of brain blood barrier (BBB) disruption due to local inflammation. Diffusion-weighted imaging (DWI), from which mapping of the apparent diffusion coefficient (ADC) is derived, may give additional information about cell loss and/or ultrastructural disorganization within diseased parenchyma. Though diffuse involvement of the CNS with the MS disease process has been highlighted by histopathological studies, acute inflammatory foci occur, which may be assessed either by the a posteriori demonstration of lesion size enlargement and/or de novo lesion appearance on serial T2-W images at the chronic phase, or by contemporary contrast-enhancement on T1-W images of a single examination at acute phase [7].

The visual texture of ROIs was analyzed using the run length matrix (RLM) [8,9] , eleven texture parameters describing the distribution of runs of gray levels in the image were estimated with the same computation parameters.

The RLM method [10,11] quantifies image texture. Basically, a gray level run dictates the number of times two or more pixels having the same value in a preset direction, and the RLM is the matrix of run-length frequency occurring in an image in each (generally 4) direction considered. Features derived from RLM represent fine (long runs) or coarse texture (short runs) of an image.

II. Material and Metods

This study approved by Modern Medical Center and Army Hospital (Toshiba 1.5 Tesla, PHILIPS 1.5 Tesla) for 110 Patients.

Gray level run length matrix:

The Gray Level Run Length Matrix is a statistical texture characterization method [12,13,14]. This method consists in counting the number of pixel segments having the same intensity in a given direction, then representing the results in a matrix. A direction (0°, 45°, 90° or 135°) and a number of gray levels are decided on beforehand.

The value contained in the matrix's (l,n) square is equal to the number of segments of length l and gray level n. This implies that the matrix's number of columns is dynamic, as it is determined by the length of the longest segment.

By design, this calculation is symmetrical and consequentially, it is unnecessary to consider the four complementary directions (180°, 225°, 270° or 315°, in this example 8 possible directions between a given pixel and its neighbors are taken into account). Figure 4 shows an example of the calculation of a Run Length Matrix:

Image

1	2	3	4
1	3	4	4
3	2	2	2
4	1	4	1

=>

Gray Level (i)	Run Length (j)			
	1	2	3	4
1	4	0	0	0
2	1	0	1	0
3	3	0	0	0
4	3	1	0	0

Figure 1. example of the calculation of a run length matrix for a 4×4 image in 0^0 direction and for4 gray levels.Once the matrix obtained, 11 indexes are calculated [15] to determine the vector that characterizes the texture. To establish our model, the matrix for a given gray level and for four directions was calculated. Then, for each index, the average value of the four directions was taken.

III. Results And Discussion

In this paper were features extracted from MRI images using GLRLM . and this features showed significant correlation with the predefined classes (Multiple sclerosis, White matter, Grey matter, CSF) they included elven features (Short Run Emphasis SRE, Long Run Emphasis LRE Gray-Level Nonuniformity GLN, Run Length Nonuniformity RLN, Run Percentage RP , Low Gray-Level Run Emphasis LGLRE, High Gray-Level Run Emphasis HGLRE, Short Run Low Gray-Level Emphasis SRLGLE, Short Run High Gray-Level Emphasis SRHGLE, Long Run Low Gray-Level Emphasis LRLGLE, Long Run High Gray-Level Emphasis LRHGLE). All these feature were calculated for all images and then the data were ready for discrimination which was performed using step-wise technique in order to select the most significant feature that can be used to classify the Multi sclerosis in MR imaging and the results show that:

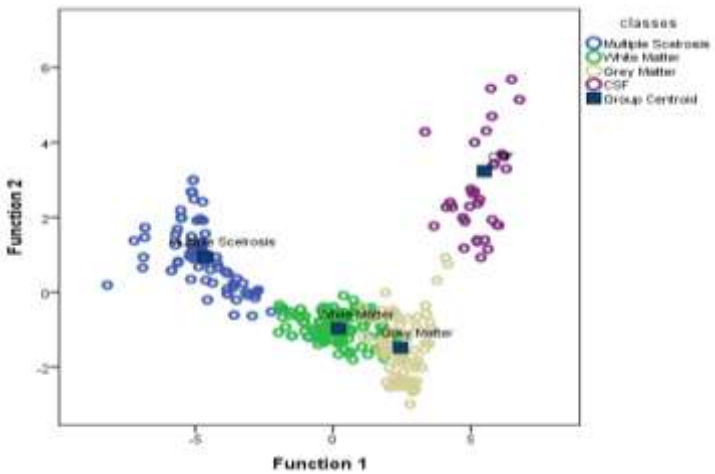

Fig 1. show Scatter plot generated using discriminante analysis function for four classes represents: Multi Sclerosis, White Matter, Grey Matter and CSF

Table 1: Showed the classification accuracy of the Multi sclerosis using linear discriminant analysis:

Classes		Predicted Group Membership				Total
		HCC	Liver	Spine	Ribs	
	Multiple Sclerosis	96.9	3.1	0	0	100%
	White Matter	.0	93.8	6.2	.0	100%
	Grey Matter	.0	6.2	92.6	1.2	100%
	CSF	.0	.0	.0	100	100%
Total classification accuracy = 95.2%						

Table 1. show classification score matrix generated by linear discriminante analysis and classification accuracy of 95.2%. The classification accuracy of Multi Sclerosis 96.9% , White Matter 93.8%, Grey Matter and CSF showed a classification accuracy of 92.6%, 100% respectively.

Fig 1. error bar plot for the SRE selected by the linear stepwise discriminate function as a discriminate feature

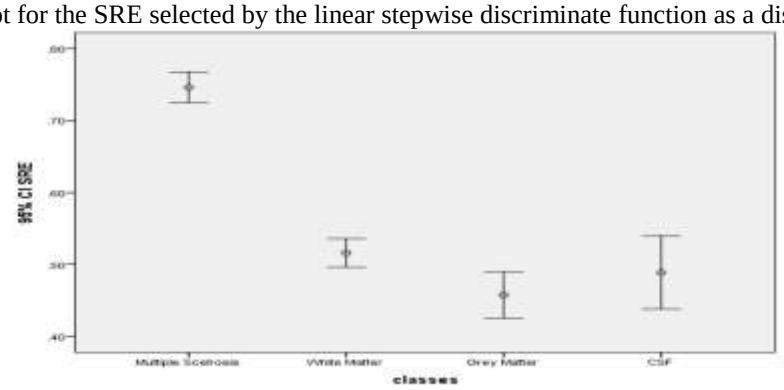

Figure 1. show error bar plot for the CI SRE textural features that selected by the linear stepwise discriminate function as a discriminate feature where it discriminate between all features. From the discriminate power point of view in respect to the applied features the SRE can differentiate between all the classes successfully.

Fig 2. error bar plot for the LRE selected by the linear stepwise discriminate function as a discriminate feature

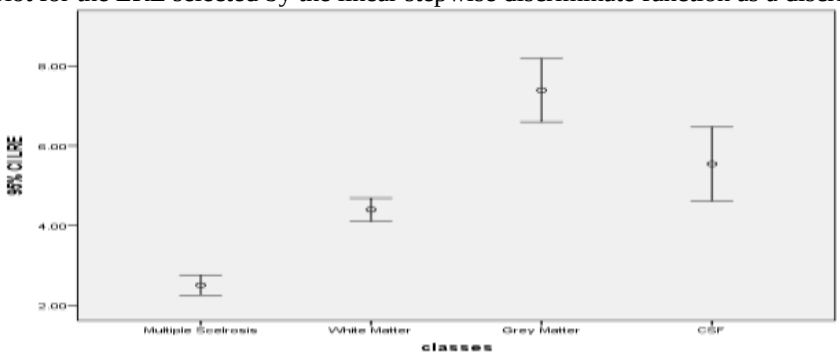

Figure 2. show error bar plot for the CI LRE textural features that selected by the linear stepwise discriminante function as a discriminante feature where it discriminate between all features.

Fig 3. error bar plot for the GLN selected by the linear stepwise discriminate function as a discriminate feature

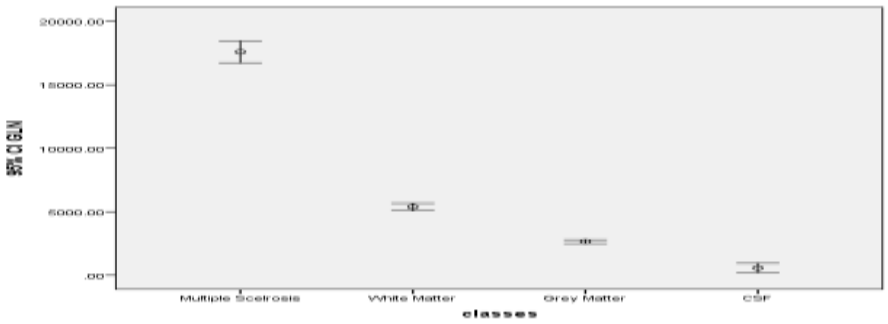

Figure 3. show error bar plot for the CI GLN textural features that selected by the linear stepwise discriminante function as a discriminante feature where it discriminate between all features.

Fig 4. error bar plot for the RLN selected by the linear stepwise discriminate function as a discriminate feature

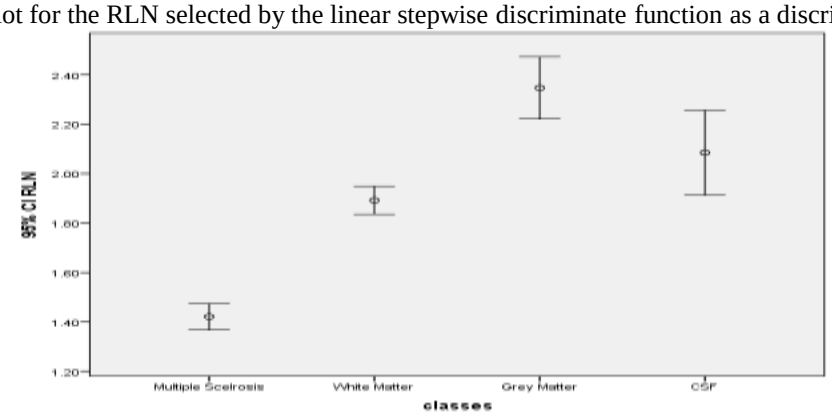

Figure 4. show error bar plot for the CI RLN textural features that selected by the linear stepwise discriminante function as a discriminante feature where it discriminate between all features.

Fig 5. error bar plot for the LRHGE selected by the linear stepwise discriminate function as a discriminate feature

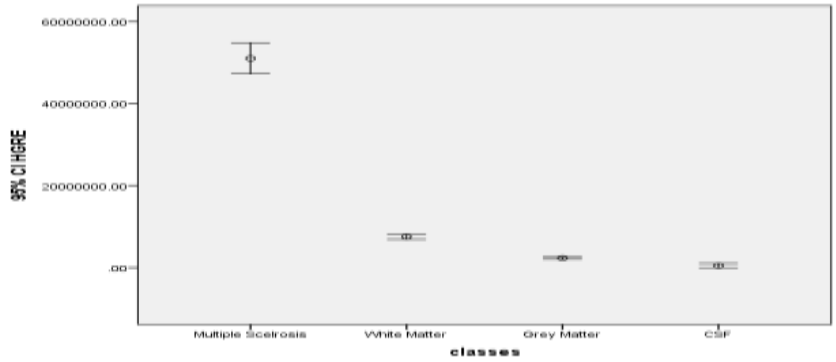

Figure 5. show error bar plot for the CI HGRE textural features that selected by the linear stepwise iscriminante function as a discriminante feature where it discriminate between all features.

Fig 6. error bar plot for the LRHGE selected by the linear stepwise discriminate function as a discriminate feature

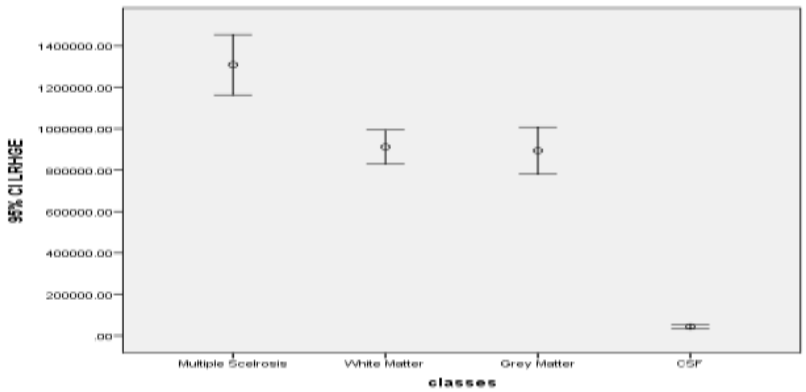

Figure 6. show error bar plot for the CI LRHGE textural features that selected by the linear stepwise discriminante function as a discriminante feature where it discriminate between all features.

IV. Conclusion

The classification of brain tissues to Multi Sclerosis, White and Grey matter and CSF in MR Images and the features of the classified regions of the whole images as raw data were classified furthers using linear discriminate analysis. The classification processes were carried out using Interactive Data Language (IDL) program as platform for the generated codes The result of the classification showed that the Mutli Sclerosis areas were classified well from the rest of the tissues although it has characteristics mostly similar to surrounding tissues. Using Linear discrimination analysis generated a classification function which can be used

to classify other image into the mention classes as using the following multi regression equation; where the vote will be for the class with a higher classification score:

Multiple Sclerosis= (SRE*2353.165) + (LRE*-196.241) + (GLN*0.50) + (RLN*1806.964) + (RP*576.982) + (LGRE*5.326) + (SRLGE*38.913) + (SRHGE*-0.002) + (LRLGE*-140.838) -2182.928

White matter = (SRE*2348.024) + (LRE*-196.957) + (GLN*0.046) + (RLN*1809.336) + (RP*562.166) + (LGRE*5.718) + (SRLGE*50.645) + (SRHGE*-0.002) + (LRLGE*-142.703) -2134.997

Grey matter= (SRE*2411.959) + (LRE*-199.825) + (GLN*0.45) + (RLN*1847.108) + (RP*541.391) + (LGRE*5.326) + (SRLGE*67.667) + (SRHGE*-0.002) + (LRLGE*-149.386) -2198.448

CSF = (SRE*2400.578) + (LRE*-199.487) + (GLN*0.41) + (RLN*1827.355) + (RP*524.756) + (LGRE*5.921) + (SRLGE*56.742) + (SRHGE*-0.002) + (LRLGE*-180.027) - 2148.454

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