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Characterization of Brain Glioma in MRI using Image Texture Analysis Techniques

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Abstract: ***This study aimed to characterize brain glioma in magnetic resonance images using image texture analysis techniques in order to recognize the tumor and surrounding tissues by means of textural features. This is an analytical case control study was conducted in radiation oncology department at radiation and isotopes center of Khartoum (RICK), which included 100 patients underwent MRI for brain (50 with brain glioma and the rest with normal scan), FLAIR, T2, T1, and T1 with contrast sequence was performed then the image extracted as DICOM images and then converted to TIFF format which used as input data for an algorithm generated using IDL (interactive data language) for textural features extraction. Three basic textural features types was used to classify the brain images using five different window sizes (3x3, 5x5, 10x10, 15x15, and 20x20 pixels) which are first order statistics (FOS), second order statistics, and diagonal features, to recognizes 4 different classes (brain gray and white matter, tumor, background and CSF); further analysis and image segmentations was performed to remove background from the images for purpose of image enhancement. The extracted feature classified using linear discriminant analysis. The result showed that the classification accuracy, sensitivity and specificity according to window sizes was (99.5%, 98.4% and 100%), (98.5%, 95.7% and 100%), (99.1%, 98.8% and 99.3%), (98.1%, 94.3% and 100%), and (96.1%, 90.0% and 98.8%) respectively for brain glioma. This study implies that 3x3 window gives a higher classification accuracy while the most significant features for classification includes; difference average of SGLD, mean and entropy of FOS.***

Keywords: Brain Glioma, SGLD, Texture Analysis, Brain MRI.

1. Introduction

Medical imaging represents the utilization of technology in biology for the purpose of noninvasively revealing the internal structure of the organs of the human body. It is a way to improve the quality of the patient's life thro ugh a more precise and rapid diagnosis, and with limited side-effects, leading to an effective overall treatment procedure. Al-Kadi 2009. Hassan et.al 2015, stated that the primary tumours of the central nervous system (CNS) are relatively uncommon, accounting for only 2% of cancer deaths (Symonds et.al 2012).

The overall annual incidence is around 7 per 100 000 population, giving approximately 4400 people newly diagnosed with a brain tumour in the UK each year (Symonds et.al 2012). Many type of tumors arising from the brain tissue, overall, about 80% of CNS tumours are primary and 20% secondary. However, the proportions depend exactly on how the patient population is gathered. Approximately 200 new CNS cases are seen per year, and only 6% are due to metastases. Intrinsic tumours (i.e. those arising within the brain substance) which are Glial tumours, (Astrocytoma, Oligodendrogliomas, Oligoastrocytoma, Glioblastoma (GBM)), Ependymomas, Medulloblastoma, Germinoma/ teratoma and Lymphoma (primary CNS lymphoma–PCNSL). Extrinsic tumours of the brain covering, Meningioma, Other tumours, Pituitary adenoma and Craniopharyngioma, Acoustic (vestibular) schwannoma, Skull base chordoma and chondrosarcoma and Cerebral metastases that come from outside the brain. Glioma 58%, Meningioma 10%, Pituitary and Cranio 9%, Acoustic 5%, Ependymoma 3%, Lymphoma 2%, Other 7%. According to the WHO 2000 classification the glioma according to pathological examination was categorizes into Grade I (3%), Grade II (15%), Grade III (15%) and Grade IV (67%). Radiotherapy is one of the most affected method that used to eradicate the tumors of brain the fundamental principles of radiotherapy (RT) planning and treatment delivery apply to CNS tumours. (Symonds et.al 2012).

2. Texture Features

In this paper texture is defined as the spatial variation of pixel intensities, which is a definition that is widely used and accepted in the field. The main image processing disciplines in which texture analysis techniques are used are classification, segmentation and synthesis. (Pietikainen, 2000). Synthesizing image texture is important in three-dimensional (3D) computer graphics applications where the goal is to generate highly complex and realistic looking surfaces. Fractals have proven to be a mathematically elegant means of generating textured surfaces through the iteration of concise equations (Pentland, 1984).

Many textural features has been used in this study which are FOS, SGLD (second order) and diagonal feature. Although our understanding of the cognitive process of human vision is constantly expanding much has been learned from experiments in the visual perception of digital image information (Bruce et al, 2003). Such work is vital, particularly in medical imaging where the misinterpretation of image information can have a serious impact on health (ICRU, 1999).

First-order Texture Analysis measures use the image histogram, or pixel occurrence probability, to calculate texture, (Press, 1998), based on image histogram which include: variance; coarseness; skewness; kurtosis; energy; and entropy. Second order statistics also based on calculation of GTSDM elements according to co-occurrence matrix, (Haralick et al., 1973). Which include the following texture: Angular second moment, Contrast, Correlation and etc… which calculated using different window size.

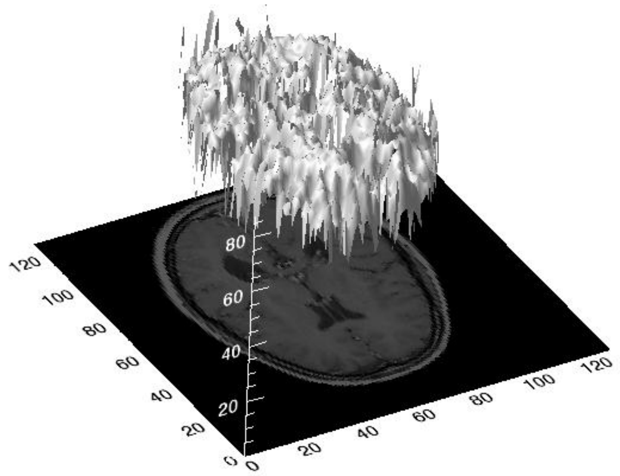

Figure 1: Three-dimensional textured intensity surface representation of a medical image. (Lower): Two-dimensional MR image of the brain. (Upper): Pixel values of the MR image plotted on the vertical axis to produce a 3D textured surface. (Esgiar et al., 2002).

3. Review in Literature

This traditional approach has been used extensively to describe different image textures by unique features and has found application in many disparate fields such as: discrimination of terrain from aerial photographs (Conners & Harlow, 1980); in vitro classification of tissue from intravascular ultrasound (Nailon, 1997); identification of prion protein distribution in cases of Creutzfeld-Jakob disease (CJD) (Nailon & Ironside, 2000); classification of pulmonary emphysema from lung on high-resolution CT images (Uppaluri et al., 1997; Xu et al., 2004; Xu et al., 2006); and identifying normal and cancerous pathology (Karahaliou et al., 2008, Zhou et al., 2007; Yu et a., 2009). Higher-order approaches have been used to localize thrombotic tissue in the aorta (Podda, 2005) and to determine if functional vascular information found in dynamic MR sequences exists on anatomical MR sequences (Winzenrieth, 2006).

4. Material and Method

An analytical case control study conducted in radiation oncology department at radiation and isotopes center of Khartoum (RICK) for 100 patient underwent MRI for brain (50 with brain glioma and the rest with normal scan), FLAIR, T2, T1, and T1 with contrast sequence was performed then the image extracted as DICOM images and TIFF format was used as input data for algorithm generated using IDL (interactive data language) image processing program for purpose of textures extraction, three basic textural method used to classify the brain using five different window sizes (3x3, 5x5, 10x10, 15x15, and 20x20) which are FOSs, second order statistics, and diagonal features, for three different classes (brain gray and white matter, tumor and CSF);

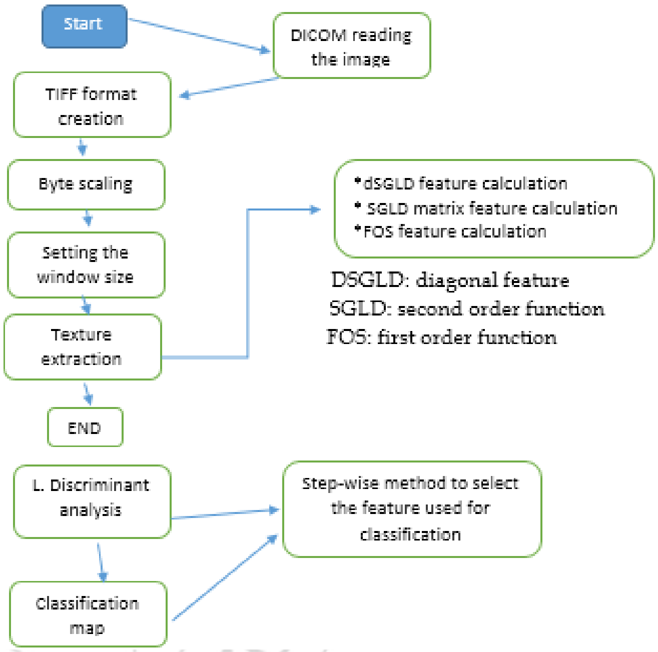

Figure 2: Block diagram demonstrating the steps used to classify the brain tissue using IDL.

5. Result Presentation

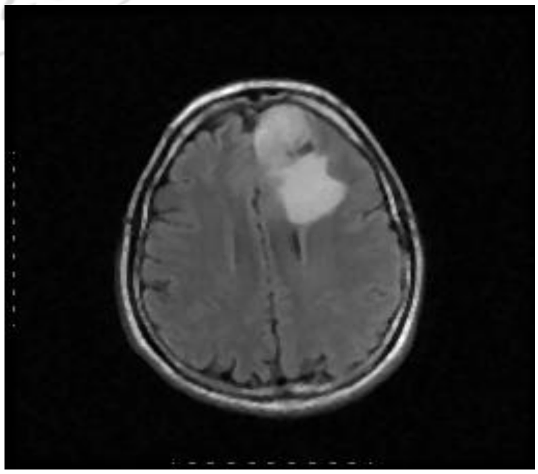

Figure 3: The orginal FLAIR image for brain with brain tumor

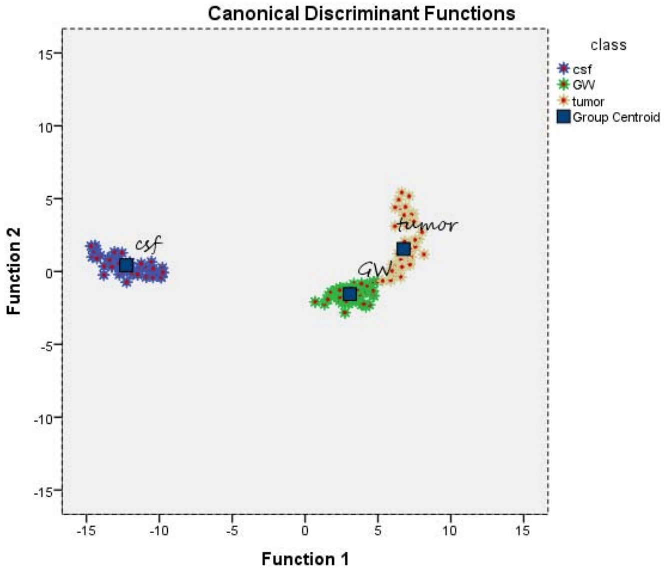

Figure 4: classification Map that created using linear discriminant analysis function.

Table 1: Showed the window size related to its calcification accuracy and the test sensitivity and specificity.

Window size	*Calcification accuracy (%)*	*Sensitivity (%)*	*Specificity (%)*
3x3	99.5	98.4	100
5x5	98.5	95.7	100
10x10	99.1	98.8	99.3
15x15	98.1	94.3	100
20x20	96.1	90.0	98.8

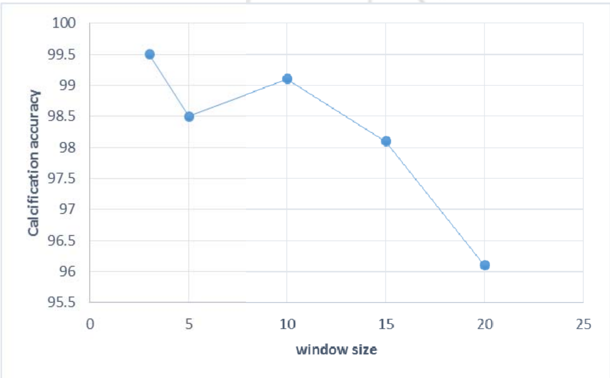

Figure 5: Showed the scatter plot for the window sizes relative to the classification accuracy of each window used for texture calculation.

Table 2: Showed the classification accuracy result using linear discriminant function, in which 99.5% of original grouped cases correctly classified.

DF	*Class*	*Predicted Group Membership*			*Total*
		CSF	GW	Tumor	
Count	CSF	**55**	0	0	55
	GW	0	**79**	0	79
	Tumor	0	1	**63**	64
%	CSF	**100**	0.0	0.0	100.0
	GW	0.0	**100**	0.0	100.0
	tumor	0.0	1.6	**98.4**	100.0

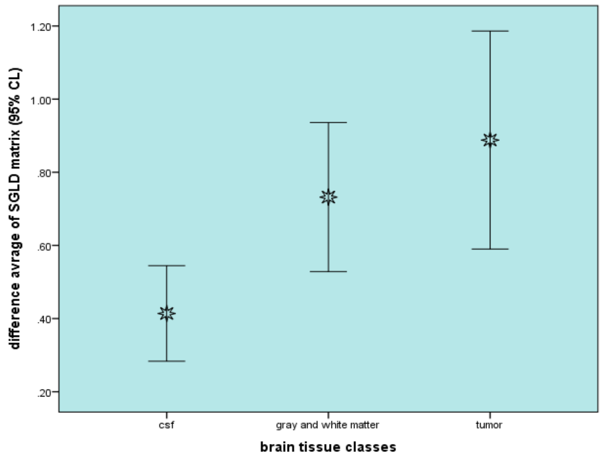

Figure 6: Simple error bar graph showed the classification based on difference average of SGLD.

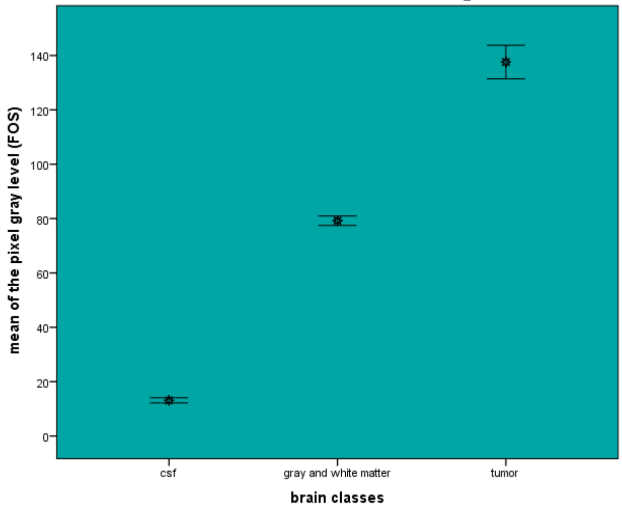

Figure 7: Simple error bar graph showed the classification based on mean from the first order statistics.

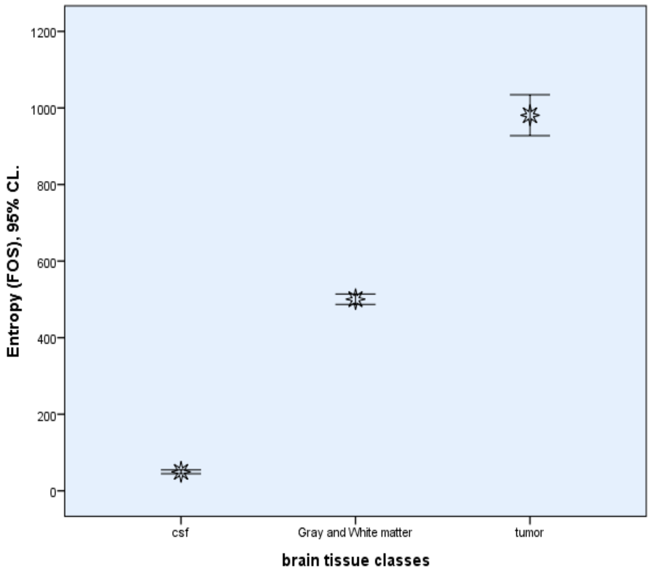

Figure 8: Simple error bar graph showed the classification based on entropy from FOS.

Table 3: Fisher's linear discriminant functions that created using selected feature presented here:

Classification Function Coefficients			
Selected feature	Class		
	CSF	GW	GLIOMA
Diff average	1.416	2.532	1.809
Mean	8.456	23.582	25.716
Entropy	-.993	-2.747	-2.969
(Constant)	-32.175	-248.544	-315.083

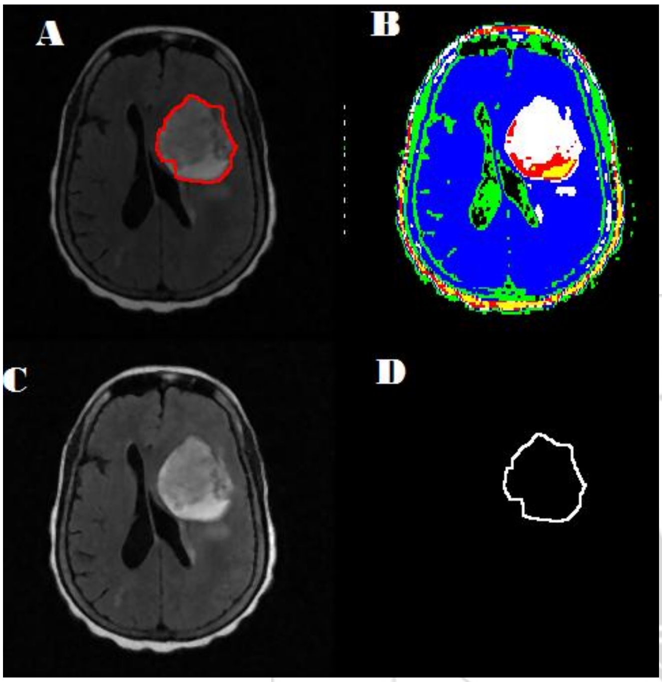

Figure 9: Demonistrate a hetrogenous brain mass [A] GTV definition based on tumor intensity profile, [B] Classification map based on intensity of brain tissue, [C] the orginal FLAIR image, [D] tumor margin drwon by algorithm generated IDL program that can be used as radiotherapy GTV.

6. Discussion and Analysis

MRI scan composed from different imaging sequences which aims to differentiate between different brain tissue according to its intensities and presence of proton in those tissue, so any sequence having its own pixels intensities, this study was done on all brain sequences even with contrast images for brain glioma which having a heterogeneous enhancement rather than ring one for metastatic brain disease in order to select the sequence with higher classification accuracy for purpose of discriminations, FLAIR images as in (fig. 1.) was selected.

Fig. 4. Demonstrate classification Map that created using linear discriminant analysis functions where the three different tissue classes of brain gray and white matter, CSF and glioma. Are clearly seperated according to calculated texture at P<0.05, and CL=95%. Also there was some similarty noted between tumor and brain tissue possibly due to good tissue differentiation especially for small size (early stage) tumors in which cancer tissue relatively simillar to the tissue of orgin morphologicaly. But CSF were clearly discriminated because it has a small pixles intensity and low MR intensity signals, same result noted by difference avarage based classification as in fig. 6.

Different window sizes was used in this study to calcuulate the texture including digonal feature which are 3x3, 5x5, 10x10, 15x15 and 20x20 in which the clasiification accuracy inversly related to the window size possible because of small dynamic range images, the higher classification accuracy noted in 3x3 window which equal to 99.5% of orginal classes was discriminated, sensitivity of 98.4% and spacificity of 100%. as in table (1), fig. 5.

Table (2): Showed the classification accuracy result using linear discriminant function, in which 99.5% of original grouped cases correctly classified for 3x3 window generated using step-wise technique to select the most significant feature that can be used for perpose of tumor charatrization which are: difference avarage of SGLD, mean and entropy from first order statistics.

First order here was excellently used to classify the brain tissue and glioma better than the second order and diagonal feature which is also excluded because of higher similarity noted, Aggarwal and Agrawal (2012), stated that the Variance is a measure of the histogram width that measures the deviation of gray levels from the Mean. Skewness is a measure of the degree of histogram asymmetry around the Mean and Kurtosis is a measure of the histogram sharpness, mean of histogram gray level was clearly differentiate the signal difference between the three classes as in fig. 7. And the same differentiations noted when we applying entropy from first order statistics. Fig. 8.

One of the most important aims of this study was to draw the GTV for brain glioma as final study result based on both extracted texture and intensity profile relative brain tissue and generation of classification map as in fig. 9. Which demonistrate a hetrogenous brain mass [A] GTV definition based on tumor intensity profile, [B] Classification map based on intensity of brain tissue, [C] the orginal FLAIR image, [D] tumor margin drwon by algorithm generated IDL program that can be used as radiotherapy GTV. Respectively. The delineated GTV was compared to barrittee et.al 2009 and ICRU report No. 83. In which Most planning is based on CT, because this delivers exact patient geometry and position without distortion, and because CT density is required for accurate dosimetry calculation. Typically, MRI does not have to be performed in the treatment position, provided suitable image co-registration software is available. Because its provide better visualization and tumor detection, While MRI is in general the better modality for showing tumour, CT is extremely useful to determine the extent of bone involvement, or the extent of a non-invasive tumour which is limited by bone. GTV outlined here is clearly match with ICRU-83 as the visible contrast enhancing edge of tumour fig. 9, shown most clearly on MRI, using T1W with gadolinium contrast. GTV G I-II = mass+ areas of peritumoural oedema, G II–IV= contrast-enhancing edge of the tumour in T1 weight images as stated by Hassan and gar-elnabi 2015, Moreover in the next view years the using of MR spectroscopy, PET-MR, PET-CT, will give clear result in tumor planning. This study resulted in definition of GTV based on its pixels properties.

7. Conclusion

Texture analysis depending on the relative pixels intensity of brain tissues that acquired during MR imaging i.e. resonance acquired from imaging procedure could serves the diagnostic field and overcoming the visual diagnosis that comes with different interpretation and also would have promising future to avoid invasive technique if the base line for individual tissues being determined and algorithmic aided computer have been applied.

Also this study overcome the problem of using different window sizes to calculate the texture in which 3x3 window having a higher classification accuracy was noted. Also for future radiotherapy planning a development of computer program to outline GTV for brain glioma and its surrounding peritumoural edema was clearly developed which can solve problem of using co-registration program and image fusion process.

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