Texture Description of low grade and high grade Glioma using Statistical features in Brain MRIs

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Abstract— Low grade and High grade Gliomas are tumors that originate in the glial cells. The main challenge in brain tumor diagnosis is whether a tumor is benign or malignant, primary or metastatic and low or high grade. Based on the patient's MRI, a radiologist could not differentiate whether it is a low grade Glioma or a high grade Glioma. Because both of these are almost visually similar, autopsy confirms the diagnosis of low grade with high-grade and infiltrative features. In this paper, textural description of Grade I and grade III Glioma are extracted using First order statistics and Gray Level Co-occurance Matrix Method (GLCM). Textural features are extracted from 16X16 sub image of the segmented Region of Interest(ROI) .In the proposed method, first order statistical features such as contrast, Intensity , Entropy, Kurtosis and spectral energy and GLCM features extracted were showed promising results. The ranges of these first order statistics and GLCM based features extracted are highly discriminant between grade I and Grade III. In this study which gives statistical textural information of grade I and grade III Glioma which is very useful for further classification and analysis and thus assisting Radiologist in greater extent.

Index Terms—Glioma, Region of Interest, First order statistics, Grey Level Co-occurance matrix, Texture.

I. INTRODUCTION

Gliomas are not a specific type of cancer but are a term used to describe tumors that originate in glial cells. Glial cells are the building-block cells of the connective, or supportive, tissue in the central nervous system [2, 12]. Gliomas are classified into four grades that reflect the degree of malignancy. Grades I and II are considered low-grade and grades III and IV are considered high-grade. Grades I and II are the slowest-growing and least malignant; grade I tumors are generally considered borderline between benign and malignant. Grade III tumors are considered malignant and grow at a moderate rate. Grade IV tumors, such as glioblastoma multiforme, are the fastest-growing and most malignant primary brain tumors [2].The most frequently encountered challenge in brain

tumor diagnosis is the differential diagnosis of a solitary intra-axial brain tumor. It is always problematic to judge whether a tumor is benign or malignant, primary or metastatic, [12] and low or high grade. Despite some characteristic MR imaging findings, it can be difficult, sometimes even impossible, to distinguish between these tumors, and, in such cases, gross tumor resection or stereotactic biopsy is required for precise diagnosis. Another problematic issue is preoperative grading of glial tumors by noninvasive techniques. The clinical presentation of brainstem gliomas is often non-specific and misleading. Radiological imaging is imperative to demonstrate a brainstem lesion but, is not always capable of detecting the true nature of the lesion. Based on the patient's MRI, a radiologist could not differentiate whether it is a low grade glioma or a high grade glioma. Because both of these are almost visually similar, autopsy confirms the diagnosis of low grade with high-grade and infiltrative features [15].

The intrinsic appearance of a Glioma on a magnetic resonance image should say something about how well-behaved or aggressive the tumor is or will be in the not so distant future[2]. A very useful way to characterize the appearance of the tumors on MRI is to analyze their texture. When an oncologist describes a tumor from its MR image, he/she may talk about the irregularity of the tumor borders or heterogeneity of the tumor itself.

Most texture analysis frameworks developed regarding brain tumors deal with tumor segmentation or tissue characterization [9]. These tumors are pathologically composed of poorly differentiated (i.e. anaplastic) and heterogeneous cancerous cells. Well-differentiated cells are one that grow and specialize normally in healthy tissues.

Magnetic Resonance Imaging (MRI) is a common medical imaging technology used to visualize a patient's brain[14]. The most common MRI modalities used to assess gliomas are Fluid Attenuated Inversion Recovery (FLAIR), T1 and T2-weighted modalities.
T1-weighted modalities highlight fat tissue in the brain and FLAIR and T2-weighted modalities highlight tissue with higher concentration of water. T1-weighted scans are usually followed by post-contrast T1-weighted scans taken after the patient is injected with a contrast agent, which is

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usually gadolinium. The contrast agent enables clinicians to locate areas of contrast enhancement on the brain scans, which is an increased T1 signal intensity in post-contrast T1-weighted scans. Contrast enhancement is indicative of disruption in the blood-brain barrier. This abnormality is typically seen in brain tumors and other brain diseases. In general, edema, border definition and tumor heterogeneity are best observed on FLAIR and T2-weighted images [2].

Texture refers to properties that represent the surface or structure of an object and is defined as something consisting of mutually related elements [5, 8].The texture is very important cue in region based segmentation of images. Texture features play a very important role in computer vision and pattern recognition. Texture Applications include industrial inspection, estimation of object range and orientation, shape analysis, satellite imaging, and medical diagnosis. Texture analysis is based upon mostly, four ways, Structural approach, Statistical approach, Model based approach, and Transform based approach. Structural approaches [6] represent texture by well defined primitives (micro textures) and a hierarchy of spatial arrangements (macro texture) of those primitives [1]. This method is elementary and is mostly useful for moderate and highly periodic textures. One way of characterizing texture is by calculating a set of local statistical properties of the pixel grey level intensity, measuring variations in a surface such as smoothness, coarseness and regularity [5]. Out of these, Co-occurance matrix based approach is giving better results but it has limitation of large memory storage requirement, added complexity, and time requirement. The main statistical features used in this study are First order statistics, contrast, spectral energy, kurtosis, entropy and second order Statistics GLCM features.

For some typical applications, particularly in the medical image processing, segmentation based on gray level does not give the desired results; in such applications, segmentation based on textural feature methods gives more reliable results; therefore, texture-based analysis is extensively used in analysis of medical images[2,10] Image analysis based on texture feature of an image is still a complex and challenging problem, and hence texture feature based technique is the approach we have selected for analysis of medical images.

This paper is organized as follows. Section II provides a brief overview of texture description of low grade (Grade I) and high grade (Grade IV) using first order statistical features such as average intensity (mean), average contrast (standard deviation), smoothness, Entropy, Kurtosis and spectral energy and GLCM features. In section III the details about experimental results and discussion will be presented. Finally, a conclusion about the obtained results is carried out in section IV. It is possible to measure these intuitive properties using texture analysis and differentiate with low grade and High grade glioma.

A. Background

In medical imaging, different methods of texture description and classification are available in literature [1,3,6,10,11,14,16].Texture description and classification of malignant and benign tissues in mammograms using spectral analysis [2] statistical features [3] and statistical inter pixel relationship matrices like Grey-Level Co-occurance Matrix (GLCM) [2,4,8] are available. Statistical and GLCM based Texture description of normal and abnormal liver lesions in ultrasound images, texture analysis and characterization of Bone mass using curvlet transform [8, 11] in Computed Tomography (CT) images are also reviewed.

In this paper texture description of low grade (grade I) and High grade (grade III) Glioma are studied using 1) first-order statistics and 2) second-order statistics that are computed using spatial gray-level co-occurrence matrices (GLCMs).

II. METHODS AND MATERIALS

This paper, only T2 weighted brain MRI data is considered. In the proposed method, segmentation of Region of Interest (ROI) and texture description using statistical features were calculated on fifty sets of MRI data. Out of this, thirty sets are of high grade Glioma(grade III) Fig.2.2 and twenty of them are low grade Glioma (Grade I) Fig.2.1.

In this study, MRI images are collected from Radiology department of Sree Chitra Institute of Medical Sciences and Technology (SCIMST). The images are grey scale images. The selected images for test are histo-pathologically tested and the radiologists have tested and have confirmed the presence of the disease.

The focal lesions are generally of diameter less than 5cm. which could be represented as a small region of grid size 80x80 pixels maximum, Thus the abnormal region is
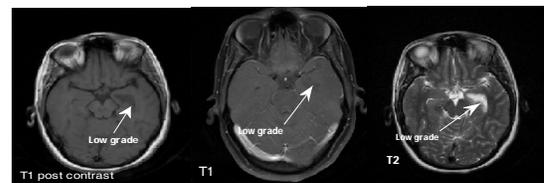

Figure 2.1: MRI scans of a low grade glioma tumor. T1-weighted image after the injection of contrast agent, A T1-weighted image, and T2-weighted image
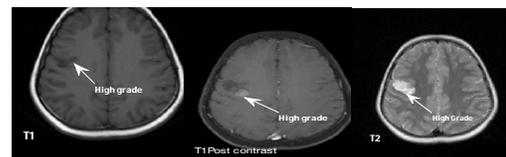

Figure 2.2: MRI scans of a high grade(third grade) glioma tumor. A T1-weighted image, T1-weighted image after the injection of contrast agent, T2-weighted image
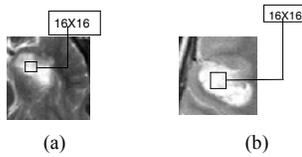
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Figure2.3selection area for feature extraction
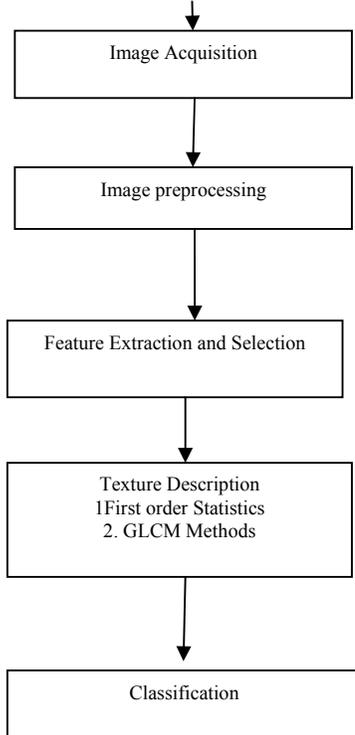(a) low grade Glioma (b) High grade Glioma

Figure2.4 The proposed method of
texture description and classification in
low grade and high grade Glioma

suitably segmented[8] and from this region a sub image of size 16x16pixels with 16 bit resolution is chosen for accurate analysis. An important approach for describing a region Fig.2.3 is to quantify its texture content.

The following are the feature selection methods were more preferred for texture description. Hence these features are extracted. The textural parameters used in our experiments are based on the following methods:
1. Moments of gray level histograms of a local area-First order statistics
2. Gray level co-occurrence matrix method (GLCMM)-Second order statistics

B. First-order statistics

   Basic statistics are used on regions of interest on raw or texture images to characterize their textural properties. For any region of interest, the mean(average Intensity) and the standard deviation(Average Contrast) of the gray values in the region can be used to measure the spread of gray values

of the pixels within that region. One class of such measures is based on statistical moments. Here statistical moments such as Mean, Standard deviation, Entropy,Kurtosis and Spectral energy are calculated from the segmented ROI using "(1)".The expression for n^{th} moment about mean is given by

$$\mu n = \sum_{i=0}^{L-1} (zi-m)^n P(Zi) \qquad (1)$$

Where Zi is a random variable indicating intensity.P(z) is the histogram of the intensity levels in a region, L is the no.of possible intensity levels and mean"(2)" can be calculated using" (1) "

$$m = \sum_{i=0}^{L-1} z_i p(z_i) \qquad (2)$$

 Another useful statistics used here are entropy [4] and kurtosis[3] which can be used on regions of interest from both raw and texture images. Given a region of interest in a grayscale image, entropy is a function of pixel intensities (or probabilities), which measures uncertainty in the region of interest. If the histogram of the region, which describes the frequency distribution of the gray values, is taken to be a probabilistic distribution, then the entropy computed using the histogram is a measure of the region's randomness.

$$e = -\sum_{i=0}^{L-1} p(z_i)\log_2 p(z_i) \qquad (3)$$

   Second and third moments describes the degree of asymmetry of the distribution (skewness), and an expression involving the second and fourth moments describes the ratio between the spread in the middle part of the distribution and the spread in the tails (kurtosis). Energy is a measure of how uniform the texture is. Entropy is negatively correlated to energy and is a measure of randomness. Contrast is also negatively correlated with homogeneity. Due to these correlations, in our experiments we choose to use only energy and contrast.

C. Gray Level Co-occurrence Matrices (GLCM), Second Order Statistics

The basic statistical tools, introduced earlier, extract first order statistics. First order statistics are measures that do not take into account the location of gray values relative to each other. The Gray Level Co-occurrence Matrices (GLCM) use second order statistics. The central idea behind GLCMs is that gray values of pairs of pixels and their relative positions characterize certain textural properties. GLCM are constructed by observing pairs of image cells distance'd' from each other and incrementing the matrix position corresponding to the grey level of both cells. This allows us to derive four matrices for each given distance: P $(0^0, d)$, P $(45^0, d)$, P $(90^0, d)$, P $(135^0, d)$.
    For instance, P $(0^0, d)$ is defined as follows:

$$p((0^0),d(a,b)) = \left| \{((k,l),(m,n)) \in D : \right.$$
$$k-m=0, |l-n|=d, f(k,l)=a, f(m,n)=b\} \right| \qquad (4)$$

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Where each '*P*' value is the number of times that:

$f(x_1; y_1) = i$, $f(x_2, y_2) = j$, $\left| x_1 - x_2 \right| = d$ and $y1 = y2$ append simultaneously in the image.

A co-occurrence matrix contains the frequency of a certain pair of pixels repetition in an image. According to the previous formula"(4)" the parameters needed are as follows:

Number of grey levels: Normally, it is used a grayscale image of 256 grey levels, which means a high computational cost because all possible pixel pairs must be taken into account. The solution is to generate the matrix reducing the number of grayscales, and so the number of possible pixel combinations. The co-occurrence matrix is always square with the same dimensionality as the number of grey-levels chosen.

Distance between pixels (d): the co-occurrence matrix stores the number of times that a certain pair of pixels is found in the image. Normally the pair of pixels is just neighbours, but the matrix could also be computed analyzing the relation between non consecutive pixels. Thus a distance between pixels must be previously defined Angle (θ): Similarly to the distance it is necessary to define the direction of the pair of pixels. The most common directions are 0^0, 45^0, 90^0, 135^0, and its symmetric equivalents.

The configurations of the co-occurrence matrix used in our experiments include $d = 1$ and $\theta = 0$ since these values are sufficient to cover uniformity of disease features. Each element of the GLRLM (i ,j) specifies the estimated number of times a picture contains a run of length j, for gray level i, in the direction of angle θ [1]. Twenty one features were extracted from the method including multiple values of some features .The proposed descriptors used for characterizing co- occurrence matrices of size 16 x 16, that are given below

1) Auto Correlation,
2) Contrast,
3) Cluster Prominence
4) Dissimilarity
5) Energy
6) Entropy:
7) Sum of squares: Variance
8) Sum variance,
9) Sum entropy,
10) Difference entropy,

Main descriptors defined using GLCM method is Energy, Entropy, Contrast, Homogeneity, and Maximum Probability, and correlation. The other descriptors are derived from these.

$$ Energy = \sqrt{\sum_{i=1}^{n}\sum_{i=1}^{n} p_{i,j}^2 } \qquad (5)$$

Energy" (5)" a measure of uniformity in the range [0,1].Uniformity is 1 for a contrast image. The term '$p_{i,j}$ ' is the i,j th term of Co-occurrence matrix (C)divided by the sum of the elements 'C'.

$$ Entropy = -\sum_{i=1}^{n}\sum_{j=1}^{n} p_{i,j} \log p_{i,j} \qquad (6)$$

Entropy "(6)"measures the randomness of the elements of 'C'. The entropy is 0,when all '$P_{i,j}$'s are 0 and is maximum when all '$P_{i,j}$'s are equal.

$$ Contrast = \sum_{i=1}^{n}\sum_{j=1}^{n} p_{i,j}(i-j)^2 \qquad (7)$$

Contrast " (7)" is a measure of intensity contrast between a pixel and its neighbour over the entire image. The range of values is 0 (when C is constant) to $(k - 1)^2$

$$ Homogenity = \sum_{i=1}^{n}\sum_{j=1}^{n} \frac{p_{i,j}}{i+(i-j)^2} \qquad (8)$$

Homogeneity "(8)" measures the spatial closeness of the distribution of elements in 'C' to the diagonal. The range of values is [0,1], with the maximum being achieved when C is a diagonal matrix.

$$ Maximum \Pr obability = \max_{(i,j)} p_{i,j} \qquad (9)$$

Maximum Probability measures the strongest response of 'C'. The range of values is [0, 1]

$$ Correlation = \sum_{i=1}^{n}\sum_{j=1}^{n} \frac{(i-m_r)(j-m_c)}{\sigma_r \sigma_c} \qquad (10)$$

Where $\sigma_r \neq 0; \sigma_c \neq 0$

Correlation "(10)"is a measure of how correlated a pixel is to its neighbour over the entire image.

Due to inverse correlations of Entropy and Energy, Homogenity and Contrast, here constructed two co-occurrence matrices and applied each second order statistic to both matrices and then used the average of the two results. Therefore, two values, one for energy and one for contrast, are returned for the GLCM texture results.

III. RESULTS AND DISCUSSIONS

In this work, thirty sets of High grade Glioma and twenty sets of Low Grade Glioma are used for texture description. Each MRI volume has 19 to 22 axial slices (T2 weighted) of the brain. A tumor usually spans across many slices. Texture extraction from every slice of a patient repeated over all slices can be computationally intensive and thus time consuming and unnecessary .Here we finally decided to choose, for each scan volume, the slice that contains the largest area of the segmented tumor, together with the slice immediately above and the slice immediately below.

It is found that the best features for discriminating Low grade and High grade Glioma are the features of GLCM constructed at direction of 0° and using first statistical descriptors. In order to effectively use the first order and second order statistical descriptors, each slices are cropped and only 16x16 sub-images fully contained in the interior of the segmented area (Fig.3.1) are considered. The range

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of values of contrast, intensity and entropy, Kurtosis, and spectral energy (Firsr order statistics) and GLCM based features of Low grade and High grade Glioma of 16x16 sizes are shown in Table 1 and Table 2 respectively.

For High grade Glioma, using first order statistical descriptors the contrast, intensity and entropy ,Kurtosis, and spectral energy ranges are 40.5 ± 20, 170 ± 20, 5.445 ± 0.5405, 175 ± 50, $(8.5 \pm0.08)*10^{+11}$ respectively. Similarly for Low grade Glioma, the contrast, intensity and entropy ranges are 11.5 ± 0.5, 220 ± 5.64, 6.5 ± 0.422 , 5.5 ± 1.5, $(5.5 \pm0.08)*10^{+11}$, respectively. It is also observed that the values of contrast, intensity, entropy and Kurtosis for low grade and high grade Gliomas are highly discriminated. This has proven the usefulness of the five texture descriptors in differentiating the low grade and high grade tissues. From the Table 1.it is found that for low grade Glioma intensity and Entropy are high and Spectral energy and kurtosis are low when compared with High grade Glioma.
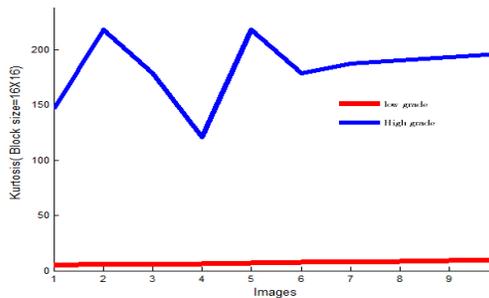

Figure 3.2 Kurtosis value using 16x16 tile pixels
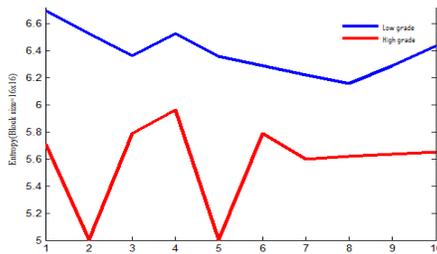

Figure 3.3. Entropy value using 16x16 tile pixels
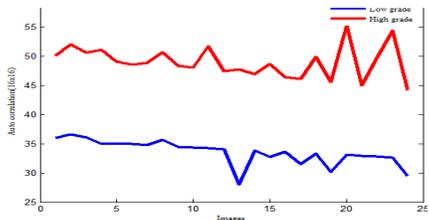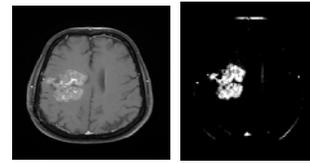

Figure 3.4. Autocorrelation value using 16x16 tile pixels

3a.   3b

Figure 3.1a. Shows original image (grade 3 Glioma). 3b. Segmented Image

It is also observed that, contrast, intensity and energy, are three significant texture descriptors, but entropy and Kurtosis are shown to be the most effective discriminator as shown in Fig 3.2 and Fig. 3.3.

Second order statistical features are computed using GLCM method. Out of the twenty one features computed (as mentioned in section II C) ten features discriminate between low grade and high grade Glioma. The range of values of Auto correlation, Contrast, Variance, Sum variance, Entropy, Sum Entropy, Difference entropy, Dissimilarity, Energy and Cluster prominence for low grade and High grade Glioma is shown in Table 2. From the Table 2, it is found that Entropy, Dissimilarity and Contrast are high, and Auto correlation, Variance and Energy are low for Low grade Gliomas with respect to grade III. Contrast increases means the region is not homogeneous. Detection is done based on textural descriptors obtained from features extraction process. From these features as shown in Fig.3.4 Auto correlation is the most discriminant feature between low grade and high grade Glioma. This has proven the usefulness of these first order and second order texture descriptors mentioned above are differentiating between low grade and high grade Glioma.

IV. CONCLUSION

In this paper texture description of low grade and high grade Glioma using first order and GLCM based second order statistics are considered. For each texture analysis method in our framework, it is intuitive as to what they individually measure in an image. Using first order statistical descriptors the contrast, intensity and entropy, Kurtosis, and spectral energy ranges for High grade and low grade Glioma are computed and best feature are identified. It is observed that the ranges of these five descriptors are highly differentiable between low (grade I) and high grade (grade III) Glioma. Twenty one GLCM based texture descriptors are also computed for better results, of which ten descriptors are differentiable between low (grade I) and high grade (grade III) Glioma. Based on these first and second order statistical descriptors further classification and Analysis of high grade and low grade glioma is possible. This approach has potential for further development for classification and analysis and thus assisting Radiologist in greater extent.

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TABLE 1.TEXTURE DESCRIPTION USING FIRST ORDER STATISTICS

Texture Type	Auto Correlation	contrast	Dissimilarity	Variance	Energy	Entropy	Sum entropy	Cluster Prominence	Sum variance	Difference entropy
Low Grade	35±1.8	0.35±0.025	2.16±0.09	35.5±0.9	0.135±0.008	0.325±0.05	110.5±11	100±50	11.5±0.5	0.633±0.043
High Grade	50±1.8	0.24±0.025	1.8±0.06	50±0.5	0.215±0.004	0.235±0.006	158±3	50±5	14±0.3	0.558±0.02

TABLE 2. TEXTURE DESCRIPTION USING GLCM METHOD

Texture Type	Average Intensity	Average Contrast	Entropy	Kurtosis	Spectral Energy
Low Grade	220±5.64	11.5±0.5	6.5±0.422	5.5±1.5	$(5.5 ±0.08)*10^{+11}$
High Grade	170±20	40.5±20	5.445±0.5405	175±50	$(8.5 ±0.08)*10^{+11}$

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