COMPARISION OF NORMAL Vs HERNIATED CERVICAL IMAGES USING GRAY LEVEL TEXTURE FEATURES

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ABSTRACT

Texture is one of the significant characteristic for the analysis of many types of images because it provides a rich source of information about the image. Also it contributes a key to understand basic mechanisms that underlie human visual perception. An image texture is a set of metrics calculated in image processing designed to quantify the identified texture of an image. An image texture gives us information about the spatial arrangement of color or intensities in an image or selected region of an image. Texture classification is one of the domains in the field of texture analysis. Texture feature calculations use the contents of the GLCM to give a measure of the variation in intensity at the pixel of interest. In this paper four statistical feature of texture called Energy ,Entropy, Contrast and Homogeneity are calculated from gray level Co-occurrence matrix (GLCM) of normal and herniated (abnormal) cervical MRI images from various patients with Disc Degeneration Diseases. It is found that the contrast feature is the best to differentiate between normal and herniated. The entropy feature for herniated cervical image is always less than that of normal cervical image. The homogeneity feature for herniated image is also less than that of normal cervical image.

Keywords : Cervical Image, Texture Features, GLCM

I.INTRODUCTION

The neck is the start of the spinal column and spinal cord. The Spinal Column is made up of 33 bones stacked on one after another called the vertebrae. Out of 33,the neck contains seven of these, known as the cervical vertebrae. They are the smallest and uppermost vertebrae in the body. The cervical spine is comprised of seven vertebrae: C1, C2, C3, C4, C5, C6, and C7. These vertebrae begin at the base of the skull and extend down to the thoracic spine. The cervical vertebrae have cylindrical bones that lie in front of the spinal cord and stack up one on top of the other to make one continuous column of bones in the neck. C1, the top vertebrae called the Atlas, is only the cervical vertebrae do not have a vertebral body. Instead, it is shaped more like a ring. The atlas connects to the occipital bone above to support the base of the skull. This connection is the atlas-occipital joint. The second, C2 called the axis, has a large bony protrusion that points up from its vertebral body, and fits into the ring-shaped atlas above it. The atlas is able to rotate around the axis, with the help of atlanto axial joint. Cervical vertebrae C3 through C6 are known as typical vertebrae because they share the same basic characteristic with most of the vertebrae throughout the spine. A herniated disc occurs when a disc in the spine is compressed and breaks open, leaking the inner disc fluid into the spinal canal. A herniated disc is caused by severe compression in the spine, usually due to general wear and tear or injury. A herniated disc occurs when the gel-like center of a spinal disc ruptures through a weak area in the tough outer wall, similar to the filling being squeezed out of a jelly doughnut. Neck or arm pain, numbness or tingling may result when the disc material touches or compresses a spinal nerve. Herniated discs are most common in people in their 30s and 40s, although middle aged and older people are slightly more at risk if they're involved in strenuous physical activity. Only about 8% of herniated discs occur in the neck region.

II. Gray Level Texture Features – A Review

Image comparison/classification can be done using statistical method of examining textures that considers the spatial relationship of pixels. Gray-level co-occurrence matrices (GLCM) have been introduced by Haralick et. al.[1] for analysis of textures. Generally, second order statistics are extracted from gray level co-occurrence matrices and used for analysis of gray-level textures.

We utilize and extend the co-occurrence matrices for describing spatial relationships between different types of features going beyond intensity values. These second order statistics are accumulated into a set of 2D matrices, P(r, s|d), each of which measures the spatial dependency of two gray levels, r and s, given a displacement vector d = (d, θ) = (dx, dy).

The number of occurrences (frequencies) of r and s, separated by distance d, contributes the $(r, s)^{th}$ entry in the co-occurrence matrix P(r, s|d).

A co-occurrence matrix is given as:

$$P(r, s|d) = \|\{((x1, y1), (x2, y2)) :$$

$$I(x1, y1) = r, I(x2, y2) = s\}\|$$

where $(x1, y1), (x2, y2) \in w \times h$,

$(x2, y2) = (x1 \pm dx, y1 \pm dy)$

and $\|.\|$ is the cardinality of a set.

Texture features, such as energy, entropy, contrast, and homogeneity are then derived from the co-occurrence matrix. The advantage of GLCM is that the histograms of the image and its rotation image are the same , and another is that the size of storage place for histogram is lower than the storage size of the image .

Among statistical methods, the gray level co-occurrence matrix (GLCM) is extensively applied in texture description [2], and the results from the co-occurrence matrices are better than those of other texture discrimination methods [3].

Energy: Energy gives the sum of square elements in GLCM. It is fully different from entropy. When the window is proficient orderly, energy value is high. The square root of Angular Second Moment (ASM) texture character is used as Energy. Its range is [0 1]. Since constant image its value is 1.It is given by

$$Energy = \sum_{i,j=0}^{N-1} \left(P_{ij}\right)^2$$

Entropy : Entropy measures the disorder of an image and it achieves its largest value when all elements in P matrix are equal. When the image is not texturally uniform many GLCM elements have very small values, which imply that entropy is very large. Therefore, entropy is inversely proportional to GLCM energy.

$$Entropy = \sum_{i,j=0}^{N-1} -\ln\left(P_{ij}\right)P_{ij}$$

Contrast: Measures the local contrast of an image. The Contrast is expected to be low if the gray levels of each pixel pair are similar, given by:

$$Contrast = \sum_{i,j=0}^{N-1} P_{ij}\left(i-j\right)^2$$

Homogeneity: It Measures the local homogeneity of a pixel pair. The Homogeneity is expected to be large if the gray levels of each pixel pair are similar, given by:

$$Homogeneity = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+\left(i-j\right)^2}$$

In this paper, cervical (MRI) images of normal and herniated (diseased) image is used for calculating the GLCM values. To interpret an image, the variations in the intensity values must be analyzed. In this paper, images are quantized into 32 gray levels for various combinations of direction and distance values. Nine features are calculated for each normal image and it is shown in Table 1. In the same way nine features are calculated for the herniated cervical image with changing the direction and distance value and are shown in Table 2**.** In Table 3 & Table 4, find the average values of all features of normal and herniated image respectively.

III. LITERATURE STUDY

Gray level co-occurrence matrices (GLCM) have been introduced by Haralick for analysis of textures. Generally, second order statistics are extracted from gray level co-occurrence matrices and used for analysis of grey-level textures.

T. Reed and H. Wechsler, [4] Segmentation of textured images and gestalt organization using spatial or spatial-frequency representations, performed a comparative study on various spatial and spatial-frequency representations and concluded that the Wigner distribution had the best joint resolution.

P. Ohanian and R. Dubes, [5] Performance evaluation for four classes of textural features, they compared the fractal model, co-occurrence matrices, the MRF model, and Gabor filtering for texture classification.

Singh and Singh [6] compared seven spatial texture analysis techniques. In this method, the image was segmented into a binary stack depending on the number of gray levels in the image. Then geometrical measurements of the connected regions in each stack were taken as texture features.

Drimbarean and Whelan [7] presented a comparative study on color texture classification. The local linear filter based on Discrete Cosine transform (DCT), Gabor filters, and co-occurrence matrices were studied along with different color spaces, such as RGB and *L*a*b**. The result states that color information was important in characterizing textures.

D. He and L.Wang [8] considers a texture image a composition of texture units and uses the global distribution of these units to characterize textures. Each texture unit comprises a small local neighborhood, e.g. 3 × 3, and the pixels within are thresholded according to the central pixel intensity. Pixels brighter or darker than the central pixel are set to 0 or 2 respectively, and the rest of the pixels are set to 1. These values are then used to form a feature vector for the central pixel, the frequency of which is computed across the image to form the texture unit spectrum.

IV. RESULTS AND DISCUSSION

In this experiment, 24 cervical images (MRI) are used for comparison. Out of 24 cervical images, 12 images are normal cervical images and the remaining 12 images are herniated cervical images. Normal cervical Images are denoted by N1, N2 and N3. Herniated (Diseased) cervical images are represented by H1, H2 and H3. Due to processing complexity, all the images are resized into 100 × 100. Further all the images are quantized into 32 gray levels. Gray level Co-occurrence Matrices (GLCM) are calculated for the different combinations of directions($\boldsymbol{\theta}$) and distances(d). From the GLCMs, the statistical texture features namely energy, entropy, contrast and homogeneity are calculated as shown in Table 1 & Table 2. The feature table shows that most of the normal cervical image's texture features are smaller in values compare with the herniated cervical images.

The contrast and homogeneity texture features are prominent in distinguishing the normal and herniated cervical images. The average of each texture features calculated for each Normal and herniated cervical image with different combinations of directions(θ)=(0^o,45^o,90^o) and distances (d)=1,2,3. The average of each texture features for normal and herniated cervical images are shown in Table 3 & Table 4 respectively. Homogeneity value performs better in differentiating normal and herniated cervical image with respect to average values. Figure 1 shows the contrast values of Normal(N1) and herniated(H1) cervical image with different combinations of directions(θ)=(0^o,45^o,90^o) and distances (d)=1,2,3.

$(\boldsymbol{\theta}, \boldsymbol{d})$	ENERGY			ENTROPY			CONTRAST			HOMOGENEITY		
	N1	N2	N3	N1	N2	N3	N1	N2	N3	N1	N2	N3
(0^o,1)	0.2676	0.3472	0.3062	-0.0023	-0.0027	-0.0025	0.0126	0.0200	0.0189	0.0006	0.0006	0.0006
(0^o,2)	0.2061	0.2902	0.2331	-0.0018	-0.0021	-0.0019	0.0303	0.0439	0.0340	0.0005	0.0005	0.0005
(0^o,3)	1.7148	2.5469	1..9455	-0.0139	-0.0172	-0.0152	0.3494	0.4754	0.3796	0.0049	0.0048	0.0050
(45^o,1)	0.2387	0.3250	0.2770	-0.0019	-0.0024	-0.0022	0.0184	0.0295	0.0253	0.0006	0.0005	0.0006
(45^o,2)	0.1819	0.2683	0.2118	-0.0015	-0.0017	-0.0017	0.0405	0.0578	0.0414	0.0005	0.0005	0.0005
(45^o,3)	1.5256	2.3098	1.7123	-0.0123	-0.0140	-0.0137	0.4427	0.6040	0.4416	0.0044	0.0043	0.0045
(90^o,1)	0.3191	0.4025	0.3782	-0.0028	-0.0032	-0.0033	0.0069	0.0115	0.0076	0.0007	0.0007	0.0007
(90^o,2)	0.2534	0.3607	0.3041	-0.0022	-0.0027	-0.0026	0.0172	0.0277	0.0162	0.0006	0.0006	0.0006
(90^o,3)	0.2266	0.3346	0.2658	-0.0019	-0.0025	-0.0024	0.0207	0.0355	0.0201	0.0005	0.0005	0.0006

Table 1: GLCM features of Normal Cervical Image with gray levels(n)=32, different directions(θ)=(0^o,45^o,90^o) and distances (d)=1,2,3

(θ, d)	ENERGY			ENTROPY			CONTRAST			HOMOGENEITY		
	H1	H2	H3	H1	H2	H3	H1	H2	H3	H1	H2	H3
(0°,1)	0.6936	0.4250	0.3582	-0.0031	-0.0028	-0.0018	0.0178	0.0010	0.0014	0.0006	0.0008	0.0007
(0°,2)	0.6022	0.2663	0.2311	-0.0026	-0.0008	-0.0003	0.0393	0.0035	0.0042	0.0005	0.0006	0.0006
(0°,3)	0.5329	0.2084	0.1858	-0.0024	-0.0003	-0.0001	0.0499	0.0071	0.0074	0.0005	0.0006	0.0005
(45°,1)	0.6724	0.2756	0.2555	-0.0030	-0.0008	-0.0006	0.0234	0.0028	0.0032	0.0005	0.0006	0.0006
(45°,2)	0.5733	0.1818	0.1706	-0.0025	0.0000	-0.0001	0.0430	0.0098	0.0092	0.0005	0.0005	0.0005
(45°,3)	0.4951	0.1510	0.1377	-0.0023	0.0000	-0.0001	0.0542	0.0144	0.0151	0.0004	0.0005	0.0004
(90°,1)	0.7681	0.3638	0.3441	-0.0034	-0.0021	-0.0018	0.0095	0.0014	0.0014	0.0006	0.0007	0.0007
(90°,2)	0.7209	0.2470	0.2265	-0.0031	-0.0008	-0.0004	0.0226	0.0046	0.0043	0.0006	0.0006	0.0006
(90°,3)	0.6860	0.2074	0.1845	-0.0029	-0.0005	-0.0001	0.0323	0.0081	0.0077	0.0005	0.0005	0.0005

Table 2: GLCM features of Herniated Cervical Image with gray levels(n)=32, different directions(θ)=(0°,45°,90°) and distances (d)=1,2,3

Normal Images	MEAN			
	ENERGY	ENTROPY	CONTRAST	HOMOGENEITY
N1	0.5482	-0.0045	0.1043	0.0015
N2	0.7984	-0.0050	0.1450	0.0014
N3	0.4098	-0.0051	0.1094	0.0015

Table 3: Average of each Texture features calculated for each Normal Cervical image with different combinations of directions(θ)=(0°,45°,90°) and distances (d)=1,2,3

Herniated Images	MEAN			
	ENERGY	ENTROPY	CONTRAST	HOMOGENEITY
H1	0.6383	-0.0028	0.0324	0.0005
H2	0.2585	-0.0009	0.0059	0.0006
H3	0.2327	-0.0006	0.0060	0.0006

Table 4: Average of each Texture features calculated for each Herniated Cervical image with different combinations of directions(θ)=(0°,45°,90°) and distances (d)=1,2,3

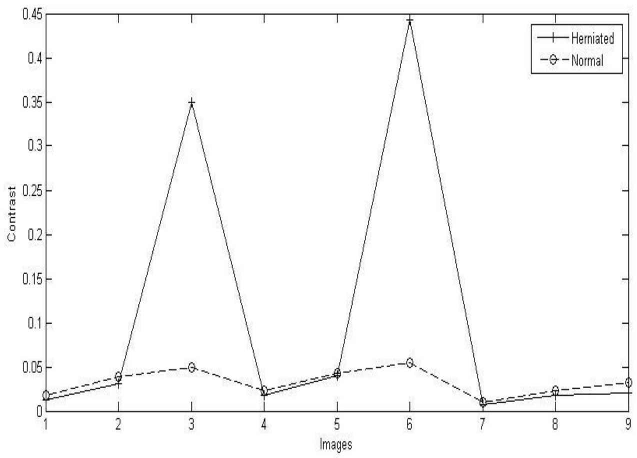

Fig. 1: Normal Vs Herniated Image using Contrast feature

V.CONCLUSION

This paper presents the comparison of normal image with herniated image using texture features. The combination of contrast and homogeneity values of cervical images may provide better result in classifying as normal and herniated cervical images. In future, the texture features called energy, entropy, contrast and homogeneity may be calculated and compared with different bucket sizes or gray levels. Also, these features may be used in machine learning algorithms to develop the knowledge about normal and herniated cervical images and classify them.

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