International Journal of Application or Innovation in Engineering & Management (IJAIEM)
Web Site: www.ijaiem.org Email: editor@ijaiem.org
Volume 3, Issue 7, July 2014 **ISSN 2319 - 4847**

MRI Image Segmentation Using Shannon and Non Shannon Entropy Measures

Varshika Pandey[1], Vipin Gupta[2]
1Research Scholar (Department of Electronics and Communication Gyan Vihar University), 2Assistant Professor, Electronics and Communication Department Gyan Vihar University, Jaipur, India

ABSTRACT
Image Segmentation is a vital tool in medical field that enable professionals to detect their patient's problems and help them to get proper diagnosed. In this article, an entropy based approach for image segmentation is discussed to highlight tumour in MRI images. Magnetic Resonance Imaging (MRI) is a process, in which pixel values are based on radiation absorption. In the proposed approach we have selected threshold values on the basis of different entropy measures such as Shannon, Renyi, Harvard Charvart , Kapur and Vajda entropy measures to segmentize an MRI image indicating tumour. The gray level co-occurrence and probability matrix are utilized as basis functions for proposed methodology. Simulation results for different entropy measures depicts that Non Shannon Entropy measures give more promising results as compared to classical Shannon based approach, thus can be used to detect human body tumours using MRI images.
Keywords: Image Segmentation, Co-occurrence and Probability matrix, Shannon Entropy, Renyi Entropy, Harvard Charvart Entropy, Kapur Entropy, and Vajda Entropy.

1. INTRODUCTION

Segmentation is the process to dicotise an image into distinct images with homogenous properties such as gray level, colour, texture, brightness, and contrast. The role of segmentation is to subdivide the objects into an image; in case of medical image segmentation the aim is to:

- Study anatomical structure
- Identify regions of Interest i.e. locate tumour, lesion and other abnormalities
- Measure tissue volume to measure growth of tumour(also decrease in size of tumour with treatment)
- Help to plan how to treat prior to radiation therapy

In this paper we have focused on one of the problems in image segmentation in medical fields when dealing with the MRI images indicating tumour. MRI stands for Magnetic Resonance Imaging which is a safe and a painless test that uses a magnetic field and radio waves to produce detailed pictures of the body's organs and structures. Through MRI Images we are able to locate the problem with the body tissues or tumours if any in the body. MRI creates two dimensional image of thin slice of a body.

In [1] the fully automatic approach for segmenting the brain from head magnetic resonance MR images has been discussed which works even in the presence of radio frequency. The method uses an integrated approach which use anisotropic filters and snake contouring techniques.

In [2] the automatic segmentation of structures from Basal Ganglia and a new methodology based on Stacked Sparse Auto Encoders (SSAE) is proposed. Moreover two approaches including 2D and 3D features of images are included and then the results are compared based on that they saw that SSAE improves the result.

It is the purpose of this paper to investigate and present a comparative study of different entropy measures for threshold selection purpose in MRI image segmentation problems using co-occurrence matrix. Here we compute the threshold for each gray plane using the minima of each entropy measures (Shannon, Renyi, Havrda-Charvat, Kapur and Vajda), which in turn is computed via the co-occurrence matrix and use it for segmentation. The simulation results are also presented using different entropy measures. It is seen that the threshold values obtained from these plots is dependent on the particular definition of the entropy chosen, which in turn affects the segmentation results. It is seen that Non Shannon Entropy measures gives better results as compared to the Shannon entropy measures.The rest of the paper is organized as follows. Section II describes the definitions of several entropy measures which are evaluated for threshold selection in image segmentation problems. Simulation results are presented in section III. Section IV of this paper presents us the conclusion.

2. PROPOSED METHOD

The methodology to segmentise the image using the Gray Level Co-occurrence matrix (GLCM) and probability matrix is discussed. In this paper we have extent this image in non Shannon entropy measures such as (Renyi, Harvard Charvart, Vajda, and Kapur) on MRI images.

We have calculated the gray co-occurrence matrix C_{m1m2} for each channel in Gray Images.

The probability function $p_{m1m2}=C_{m1m2}/MN$ is then calculated from gray co-occurrence matrix.

Entropy functions for each entropy are defined below in the interval t € [0, 1, 2, 3 ..... L-2].

The minima points are obtained from the graph plotted against from the entropy versus gray level plot (t).

Gray Co-occurrence matrix:- It is a matrix or a distribution that is defined over an image to the distribution of co-occurring values at a given offset. Mathematically a GLCM 'C' matrix is defined over an image n*m image I, parameterized by an offset (Δx, Δy), as:

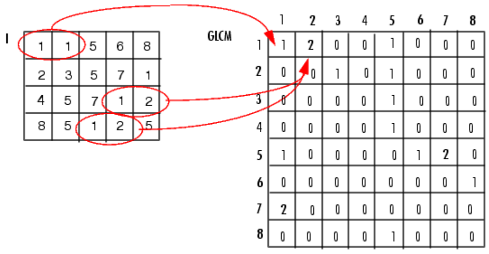
$$C?x?y(i,j) = \sum_{p=1}^{n}\sum_{q=1}^{m}\begin{cases}1, \text{if } I(p,q)=i \text{ and } I(p+\Delta x, q+\Delta y)=j\\ 0, \text{otherwise}\end{cases}$$

Where I and j are the Image intensity values of the images, p and q are the spatial positions in the image I and offset (Δx, Δy) depends on the direction used θ and the distance over which the matrix is computed Offset parameterization makes GLCM more sensitive to rotation. Syntax of the GLCM can be give by any of the of three:

GLCM= graycomatrix [I]

GLCM= graycomatrix [I, parameter1, value1, parameter2, vauel2…]

[GLCM, SI]= graycomatrix(….)



Probability Matrix:- It is a normalized GLCM over all offsets or directions under the consideration.

Entropy:- Entropy is the measure of degree of randomness that can be used to characterize the texture of the input image. Entropy is defines as .

There are different types of entropies as:

a). **Shannon Entropy:-** Shannon entropy provides an absolute limit on the best possible lossless compression of a signal under constraint. Shannon Entropy is defined as

$$H_s(P_{m1m2}) = -\sum_{m1}\sum_{m2} p_{m1m2}\log p_{m1m2}$$

where pm1 and pm2 are probability density functions in 2-D random variable [3]. In this paper we have computed the values of pm1m2 from the entries of the GLCM.

b). **Renyi Entropy:-** Renyi Entropy generalizes the Shannon Entropy, this entropy is also important in quantum information where it can be used as a measure of entanglement. It is defined as the entropy of the order of ∝, where ∝≥0 and ∝≠1, is defined as

$$H_r(p_{m1m2}) = \frac{1}{1-\alpha}\log\sum_{m1}\sum_{m2}(p_{m1m2})^{\alpha}$$

c).**Harvrda-Charvat:-** This entropy is used for statistical physics and modified by Dracozy. This entropy is defined as the function of ∝ and mathematically as

$$H_{hc}(p_{m1m2}) = \frac{1}{2^{\alpha-1}}\sum_{m1}\sum_{m2}p_{m1m2}^{\alpha} - 1$$

d). **Kapur Entropy:-**This entropy is defined by $H_k(p_{m1m2})$ of order of α and type β and is defined as [4]:

$$H_k(p_{m1m2}) = \left(\frac{\sum_{m1}\sum_{m2}p_{m1,m2}^{\alpha+\beta-1}}{\sum_{m1}\sum_{m2}p_{m1,m2}^{\beta}} - 1\right)(2^{1-\alpha}-1)^{-1}$$

e). **Vajda Entropy:-** It is the special case of Kapur Entropy where β=1 is taken and Vajda measures $H_v(p_{m1m2})$ it is preferred over Kapur's Entropy as it calculations are faster and it is defined as :

$$H_v(p_{m1,m2}) = \left(\frac{\sum_{m1}\sum_{m2}p_{m1,m2}^{\alpha}}{\sum_{m1}\sum_{m2}p_{m1,m2}} - 1\right)(2^{1-\alpha}-1)^{-1}$$

Above we have discussed the Entropies and their mathematical representation. The main approach of this paper is to select threshold from entropy function of the above entropies which will calculate the minimum value of threshold. The entropy function of given Entropies are as follows.

Table 1. Entropy Function

Entropy	Entropy Function Entropy(t)
Shannon	$-\sum_{m_1=0}^{t}\sum_{m_2=t+1}^{L-1} p_{m_1m_2}\log p_{m_1m_2} - \sum_{m_1=t+1}^{L-1}\sum_{m_2=0}^{t} p_{m_1m_2}\log p_{m_1m_2}$
Renyi	$\frac{-\log\sum_{m_1=0}^{t}\sum_{m_2=t+1}^{L-1}(p_{m_1m_2})^{\alpha}}{1-\alpha} - \frac{-\log\sum_{m_1=t+1}^{L-1}\sum_{m_2=0}^{t}(p_{m_1m_2})^{\alpha}}{1-\alpha}$
Havrda-Charvat	$\frac{1}{2^{1-\alpha}-1}\left(\sum_{m_1=0}^{t}\sum_{m_2=t+1}^{L-1} p_{m_1,m_2}^{\alpha}-1\right)+ \frac{1}{2^{1-\alpha}-1}(\sum_{m_1=t+1}^{L-1}\sum_{m_2=0}^{t} p_{m_1,m_2}^{\alpha}-1)$
Kapur	$\sum_{m_1=0}^{t}\sum_{m_2=t+1}^{L-1}(\frac{p_{m_1,m_2}^{\alpha+\beta-1}}{p_{m_1,m_2}^{\beta}}-1)(2^{1-\alpha}-1)^{-1}+ \sum_{m_1=t+1}^{L-1}\sum_{m_2=0}^{t}(p_{m_1,m_2}^{\alpha+\beta-1})-1(2^{1-\alpha}-1)^{-1}$

The above entropies are calculated for each t ∈ [0, 1, 2 , 3….L-2] on the basis of the Gray Co-occurrence Matrix Cm1m2 which in turn is used to calculate the probability density function pm1m2. This Pm1m2 plays a vital role which represents an image.

Steps:-

1) Let I(x,y) be a given image.
2) C_{m1m2} represents the co-occurrence matrix for a specified neighbourhood.
3) Then $$P_{m1m2} = \frac{\sum C_{m1m2}}{\sum \text{All 8 neighbourhoods}}$$

Apply, Entropy functions given by table 1 on this P_{m1m2} where t varies from 0 to L-2

For t=0 to L-2

V(t)= Entropyfun($P_{m1m2,}$ t)

End.

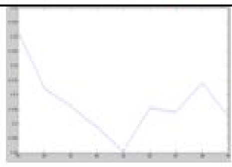
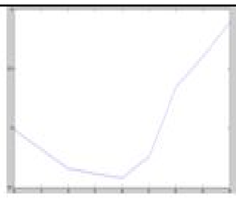
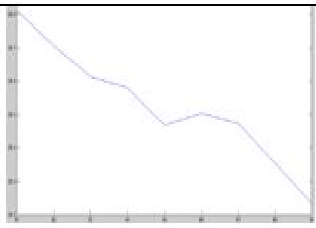
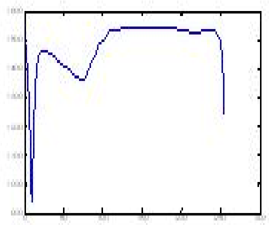
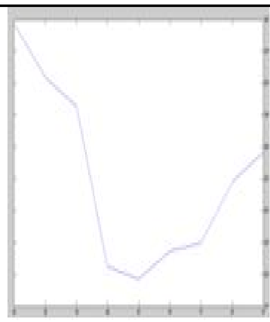
Find out all localised minima's.

Find the minimal localised minima; find its generating t values which represent the optimal threshold values.

3. SIMULATION RESULTS

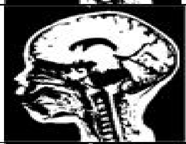
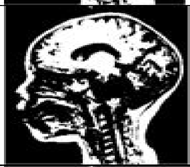
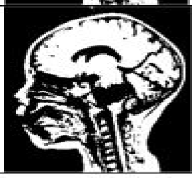
The experiment is conducted on 12 to 15 MRI Images on 2.60 GHz Intel core i5 processor running on windows 8.The average computation time comes out to be 0.5 seconds. The entropy versus gray value plots for the different entropy functions is represented by below figures for a few select MRI Images.

Table 2. Entropy Graph

Entropy	Graphs
Shannon	
Renyi	
Harvrd Charvat	
Vajda	
Kapur	

The threshold values for Shannon and Non Shannon measures is tabulated as below

Table 3. MRI images with Threshold Values

Entropy	Image	Value
Shannon		210
Renyi		78
Havrda Charvat		85
Kapur		60
Vajda		65

4. CONCLUSION:

of entropy chosen which in turn affects the segmented result. Further the segmented results show that the clarity best obtained is from Harvrda-Charvat Entropy Function which will help in identification of tumours and will provide the pro treatment to the patients and thus, they can be cured. After studying different entropy functions on the given MRI image, the thresholds values obtained depend on particular definition

REFERENCES

[1] Alberto Martino Gonzalez, Laura Igual Munoz, 'Segmentation Of Brain MRI Structures with Deep Machining Learning' Master In Artificial Intelligence

[2] M.Stella Attkins,Blair T Mackiewich 'Fully Automatic Segmentation of the Brain in MRI' IEEE Transactions on Medical Imaging Vol 17 No 1 February 1998

[3] KK Sharma, Neeraj Sharma, Shobha Sharma 'Comparison Of Shannon And Non Shannon Entropy Measures For Threshold Selection in Image Segmentation Problems' 2012 International Conference On Electronics Computer Technology

[4] Chun Yuan, Shagli Liang, "Segmentation of Color Image Based on partial Differential Equations," Fourth International Symposium on Computational Intelligence and Design, 2011.

[5] Baljit Singh Khehra, Amar Pratap singh Pharwaha, "Digital Mammogram Segmentation using Non-Shannon Measures of Entropy ,"Proceeding of the world congress on Engineering 2011 Volume II WCE 2011,july 6-8, 2011, London, U.K.

[6] Anil K. Jain, Fundamentals of digital image processing, Prentice- Hall of India, New Delhi, 2010

[7] Kapur, J.N.: Generalized entropy of order α and type β. Math. Seminar, Delhi,

[8] G.C. Patni and K.C. Jain, "Axiomatic Characterization of Some non- additive measures of Information," Metrika, Band 24, 1977, Seite 23- 34, Physica-Verlag, Wien.

[9] P.K. Sahoo, P.K., Wilkins, C., et al., "Threshold selection using Renyi's entropy," Pattern Recognition, vol. 30, pp. 71–84, 1997.

Vipin Gupta received B. Tech degree from Shri Balaji College of Engineering and Technology Jaipur and done his M. Tech from MNIT jaipur. He is currently an Assisstant Professor in Suresh Gyan Vihar University and is pursuing PhD from Poornima University Jaipur.

Varshika Pandey got enrolled in dual degree programme in Suresh Gyan Vihar University and received B. Tech in 2013 and is currently pursuing M. Tech from the Suresh Gyan Vihar University.