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Brain Tumor Segmentation using Multi Level Thresholding using Fuzzy Entropy

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Abstract*: *In image processing field, image processing technique is used to distinguish the object from its image scene at pixel level. The image segmentation process is the significant task in the processing of image field as well as in image analysis. The most difficult task in the image analysis field is the automatic separation of object from its background. To alleviate this problem several image segmentation process is introduced are gray level thresholding, edge detection method, interactive pixel classification method, neural network approach and segmentation based on fuzzy approach This chapter presents the multilevel set thresholding method using partition of fuzzy approach on brain image histogram and theory of entropy. The fuzzy entropy method is applied on multi-level brain tumor MRI image segmentation method. The threshold of brain MR image is obtained by optimized the entropy measure. In this method, Differential Evolution technique is used to find the best solution.

Keywords-Segmentation, Thresholding, Fuzzy Entropy

I. INTRODUCTION

A single thresholding based method is used for MRI brain image segmentation but the distinguishable of various brain tissues particularly Gary matter, white matter and cerebrospinal fluid is difficult because of different intensity for different tissue. So, the appropriate threshold value for MRI brain image segmentation is difficult.

The several research activities are done by fuzzy c means clustering (FCM) algorithm. The objective function of FCM is fuzzy membership and cluster centroids. The FCM provides bad clustering approach due to presence of noise in the input signal which leads to reduce the border between the real clusters The threshold value for more than one-level thresholding based image segmentation is obtained by increasing the total entropy value by optimization technique of Genetic algorithm is used. But these approaches provide lacks in their statistical evaluation and computation time is high.

This chapter overcomes the multilevel thresholding segmentation problem by introducing fuzzy-entropy based multi-level image segmentation process where differential evolution method is used to optimize the thresholding approach. This optimization technique overcomes the GA and PSO optimization method in multi-level threshold image segmentation .Threshold may be done by global or local thresholding technique but these method is computational expensive. So optimization technique is needed to optimize the objective function which produces result as the reduction of computation time. Due to this optimization technique, the objective function is maximized by optimal threshold and it discriminate the foreground and background brain image is segmented.

II. FUZZY ENTROPY

Fuzziness is the collective features of objective things and individual thinking. The efficient way of researching and dealing out fuzzy phenomenon is a fuzzy set theory. Fuzzy entropy measures the level of fuzziness in a fuzzy set using entropy made by fuzzy set theory. So, the measurement of fuzziness in a fuzzy set is called fuzzy entropy and is an important key factor in fuzzy system such as fuzzy neural network system, fuzzy decision making system, fuzzy control system, fuzzy pattern recognition system and fuzzy management system.The measurement of fuzziness in fuzzy set is done by Shannon entropy and distance between fuzzy set method.

2.1 Concept of Fuzzy Entropy

Let us consider $I = \{(i,j): i = 0,1,2,..,M-1; j = 0,1,2,\ldots,N-1\}$ where width of image is represent by M, height of the image is given by N, gray level of the image is denoted by L. Let us consider the two threshold t1 and t2 it used to divide the original image I into three regions are r1a, r2a and r3a. The r1 is the regions covers the pixel and it intensity value is smaller than t1. The pixel has the intensity between t1 and t2 is the region r2. The pixel has the intensity is greater than t2 is the region r3.

The unknown probabilistic partition of original image is given by and their probability distribution is:

P_1=P(r1a); P_2=P(r2a); P_3=P(r3a)

The membership function of three region r1a, r2a and r3 and it require six parameter. The values of t1 and t2 threshold are based on membership function.

Let the pixel grade with gray value of k belongs to three region such as black, dust and white equivalent to their conditional probability.

$$\mu_{1a}(k) = \begin{cases} 1 & k \le u_1 \\ 1 - \frac{(k-u_1)^2}{(w_1-u_1)*(v_1-u_1)} & u_1 < k \le \\ \frac{(k-u_1)^2}{(w_1-u_1)*(w_1-v_1)} & v_1 < k \le w \\ 0 & k > w_1 \end{cases}$$

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$$\mu_{2a}(k)=\begin{cases} 0 & k\le u_1 \\ \frac{(k-u_1)^2}{(w_1-u_1)*(v_1-u_1)} & u_1<k\le v \\ 1-\frac{(k-w_1)^2}{(w_1-u_1)*(w_1-v_1)} & v_1<k\le \\ 1 & w_1<k\le u_2 \\ 1-\frac{(k-u_2)^2}{(w_2-u_2)*(v_2-u_2)} & u_2<k\le \\ \frac{(k-w_2)^2}{(w_1-u_2)*(w_2-v_2)} & v_2<k\le w \\ 0 & k\le w_2 \end{cases}$$

$$\mu_{3a}(k)=\begin{cases} 0 & k\le u_2 \\ \frac{(k-u_2)^2}{(w_2-u_2)*(v_2-u_2)} & u_2<k\le v \\ 1-\frac{(k-w_2)^2}{(w_2-u_2)*(w_2-v_2)} & v_2<k\le \\ 1 & k>w_2 \end{cases}$$

- Above mentioned equations are assumed $0\le u_1<v_1<w_1<u_2<v_2<w_2\le$

III. MULTI-LEVEL FUZZY ENTROPY

This section describes about the multi level fuzzy entropy. First describes the multi-level Shannon entropy method.

3.1 Multi-level Shannon Entropy (MLSE)

Consider discrete finite set of n distribution of probability are where

$$Pd=(pd_1,pd_2,p3,\dots,pd,$$

$$\Delta_n=\{(pd_1,pd_2,p3,\dots,pd_n)|pd_i\ge 0, i=1,2,\dots,n, n\ge 2, \textstyle\sum_{i=1}^{n} pd_i=1\}$$

. The MRI brain image segmentation entropy is defined as:

$$TE(P)=-\textstyle\sum_{i=1}^{n} I$$

Where I represent the gray level of MRI digital image. The normalized histogram for brain image is defined as P. Partition the normalized histogram into n classes for n-1 thresholds (t).

3.2 Multi-Level Fuzzy Entropy (MLFE)

Set A is a classical, it is defined by a collection of element which can either belong or not belong to set A. It is the simplification of classical set. Element in this set is partially belongs to set A. In this proposed framework, trapezoidal membership function is utilized for computing the n brain MR image segmented regions membership through unknown fuzzy parameter area.

The maximum fuzzy entropy (MFE) of brain MR image segmentation of n-level segmentation is given as:

$$MFE_1=-\sum_{i=0}^{L-1}\frac{pd_i*\mu_1(i)}{Pd_1}*In\left(\frac{pd_i*\mu_1(i)}{Pd_1}\right)$$

$$Pd_1=\textstyle\sum_{i=0}^{L-1} pd_i*\mu_i(i), Pd_2=\sum_{i=0}^{L-1} pd_i*\mu_2(i),\dots,Pd_n=\sum_{i=0}^{L-1} pd_i*\mu_n(i)$$

The total entropy is maximized for attaining the best possible value of parameter.

$$\varphi(r_1,s_1,\dots,r_{n-1},s_{n-1})=Argmax([MFE_1(t)+MFE_2(t)+..+MFE_n(t)])$$

The above equation is needed to optimize globally to bring down the computational time of proposed MR brain image segmentation.

3.3 Differential Evolution

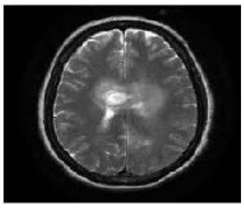
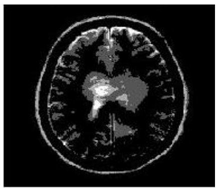
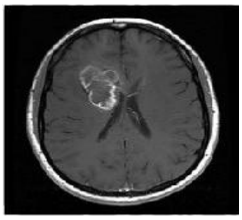
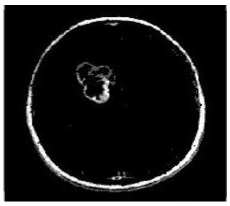
DE optimizes a problem by improving a candidate solution based on the given measure of quality introduced by Storn in 1997. The Dimensional vector d consists ith individual of population at generation (time) t .The population member is changed for each generation to create a donor vector. The donor is used to discriminate the various differential evaluation schemes. The earliest variants of differential evaluation are called as differential evaluation/rand/1 scheme is used to create the donor vector for each segmentation. In this scheme three types of parameter vectors and each vector is not equal to each other.The donor vector is multiplied with scalar function S to differentiate with each other.

The heterogeneous population is increased by binomial crossover operation. This operation is take place on d variable whenever a random number is taken between 0 and 1 is within Cr value. The trail vector is introduced for each target vector then the uniform random number generator is defined for the jth evaluation. The selection process is performed on finally to represent next generation.(t=t+1). Then the target vector is replaced by better trial vector in next generation.

$$\vec{M}_I(t+1)\begin{matrix} = & \vec{T}_I(t)\ if\ f\left(\vec{T}_I(t)\right)>f\left(\vec{M}_I(t)\right) \\ = & \vec{M}_I(t)\ if\ f\left(\vec{T}_I(t)\right)\le f\left(\vec{M}_I(t)\right) \end{matrix}$$

IV. RESULT AND DISCUSSION

The experiments and performance evaluation are carried on MRI brain images collected from difference modalities. The proposed systems are evaluated and compared multilever fuzzy entropy with multilevel shannon entropy and was implemented with Matlab R2012 in a windows XP system with Pentium 4 CPU 3GHZ and 2GB RAM

Original Image	Segmented Image
	
	

The figure illustrates the qualitative of multi level fuzzy entropy with differential evaluation for different MR brain image segmentation. The segmentation image is obtained for 3rd level thresholding segmentation. The combination of fuzzy entropy with differential evaluation provides better performance than other optimization technique such as genetic algorithm.

Comparison of SSIM between Shannon entropy and fuzzy level entropy

Image	2nd level thresholding		3rd level thresholding	
	MLSE	MLFE	MLSE	MLFE
Image 1	0.6245	0.8564	0.7123	0.9345
Image 2	0.4672	0.6734	0.5416	0.7819
Image 3	0.5671	0.6987	0.6017	0.7123
Image 4	0.7612	0.9213	0.8012	0.9981
Image 5	0.6713	0.8912	0.7123	0.9012
Image 6	0.6891	0.9871	0.7204	0.9989
Image 7	0.7613	0.8971	0.8125	0.9001

The above table provides the comparison between Multi level Shannon Entropy and Multi level fuzzy entropy in terms of SSIM for seven MR brain tumor images. From the table observed that MLFE provides better segmentation compared to MLSE. The better results are obtained by the combination of fuzzy entropy with differential evaluation optimization technique.

V. CONCLUSION

It can be concluded for this phase that Multi level fuzzy entropy using thresholding techniques proves better segmentation compared to multi level Shannon entropy. This is established through image quality metrics of structural similarity index metrics. The better approach is obtained through differential evaluation optimization technique algorithm.

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