Harmony Search Optimization Algorithm Based Multilevel Thresholding for MRI Brain Images

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Abstract— *Segmentation is a partitioning portion of an image. The fundamental idea of thresholding is to choose an optimal gray level threshold value for separating objects from the background based on their gray level distribution. Segmentation is very difficulty of medical images. The harmony search is a evolutionary algorithm which is motivated in musicians improvise new harmonies while playing. In this thesis is used a Multilevel Thresholding (MT) algorithm based on the harmony search optimization algorithm. The approach combines the good search capabilities of harmony search optimization algorithm with objective functions recommended by the multilevel thresholding methods of Otsu's and Kapur's. The proposed algorithm, the original brain image is converting to gray scale image and calculate the histogram of the image. The random samples will be taken from the inside of the histogram image. That samples put up the each harmony in the Harmony Search Algorithm (HSA) background, while its quality is evaluated considering the objective function that is working by the Otsu's or the Kapur's method. The set of aspirant solutions are evaluated by the objective functions and HSA operators until the best possible solution is found. These approach is generates a multilevel thresholding algorithm which is can efficiently identify the threshold values for a Magnetic Resonance Imaging (MRI) brain image within a minimum number of iterations. The quality of output image is measured by Peak Signal to Noise Ratio (PSNR) and Jaccard's Similarity Coefficient.*

Keywords— **Thresholding, Niblack, Sauvola, PSNR, Jaccarrd**

1. INTRODUCTION

Image processing is an essential part of signal processing in which input and output are taken as image or image parameters. An image is two dimensional function of $f(x, y)$ where x, y are spatial coordinates called as pixels and amplitude of $f(x, y)$ at any pair of coordinates (x, y) is called the intensity or gray level of image at that point. Image is basically processed in spatial and frequency domain. Spatial domain refers to the image plane itself, it is based on the straight manipulations of the pixels in the image. Frequency domain refers to an image which is processed in the form of sub bands and it is applicable to all transformations such as Discrete Wavelet Transform (DWT), Discrete Fourier Transform (DFT) [1].

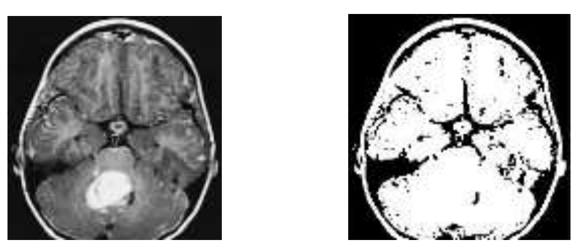
Thresholding method can be chosen manually according to a priori information or routinely by image information. Thresholding is a simple for image segmentation it separating the pixel which is white as objects and black as a background. Thresholding technique is convert the gray scale image into binary image, it select a proper threshold value *T*, whether *T* is constant to separate the pixel into objects from background. If pixel intensity is greater than or equal to threshold value $f(x, y) \geq T$, it considered the object, otherwise the pixel belong to background. Selection of the threshold value the thresholding methods is divided into two types, global and local thresholding. In Global thresholding methods can be unsuccessful when the background clarification is uneven. In local thresholding, multiple thresholds ate used to recompense for uneven illumination. Threshold value chosen is classically done interactively though it is possible to derive automatic threshold value selection algorithm [13].

TYPES OF THRESHOLDING

1.1 Global Thresholding

Histogram of the image $f(x, y)$ is collected of light as an object and dark as background. The intensity pixel value of the object and background are grouped into two modes. In global thresholding, a thresholding value *T* is separate the object and background. The state for choosing threshold *T* is given as follows:

$$g(x,y) = \begin{cases} 1, iff(x,y) > T \\ 0, iff(x,y) \leq T \end{cases}$$



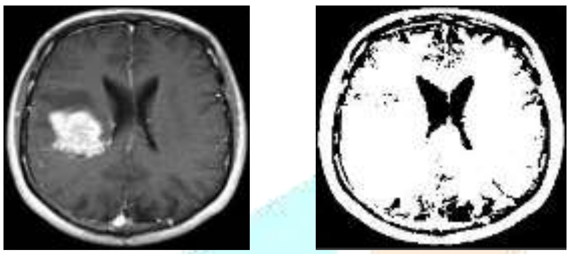
(a) (b)

Figure 1. a) Original Image b) Using Global Thresholding

1.2 OTSU THRESHOLDING METHOD

The Otsu thresholding method, is a differentiate analysis method. The threshold operation is regarded as the splitting of the pixels of an image into two classes *D0* and *D1* (e.g., objects and background) at gray-level t, i.e., $D0 = \{0,1,2,\dots,t\}$ and $D1 = \{t+1, t+2, \dots, L-1\}$. As stated in, let σ_w^2, σ_w^2 and σ_T^2 be the within the class variance, between-class variance, and the total variance, respectively. An optimal threshold can be resolute by minimizing one of the following (equivalent) condition functions with admiration to t [17]:

$$\lambda = \frac{\sigma_B^2}{\sigma_W^2}, \eta = \frac{\sigma_B^2}{\sigma_T^2}, \kappa = \frac{\sigma_T^2}{\sigma_W^2}$$



(a) (b)

Figure 2.3. a) Original Image b) Using Otsu Technique

1.3 RIDLER CALVARD TECHNIQUE

The Ridler and Calvard algorithm uses an iterative clustering approach. First step compute the threshold value (e.g. mean image intensity).Pixels above and below the threshold are assigned to the object and background classes correspondingly. Then the mean of pixels in the object class is computed as μ_F and for the background as μ_B. Using these two mean values, an improved threshold T_1 is computed as [19]:

$$T_1 = \frac{\mu_S + \mu_F}{2}$$

(a) (b)

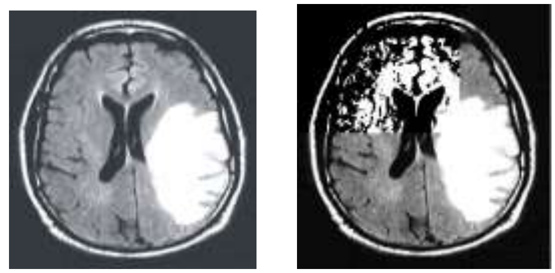
Figure 2.a) Original Image b) Using Ridler Calvard Technique

A. Local Thresholding

Global thresholding method is not appropriate solution whenever the background clarification is uneven. In local thresholding technique, appropriate solution for background illumination is uneven. The threshold value T depending upon gray levels of $f(x, y)$ and some local image properties of adjacent pixels such as mean or variance.

The threshold technique with a locally varying threshold function $T(x, y)$ is given by

$$g(x,y) = \begin{cases} 1 \; if \; f(x,y) \geq T(x,y) \\ 0 \; if \; f(x,y) < T(x,y) \end{cases}$$



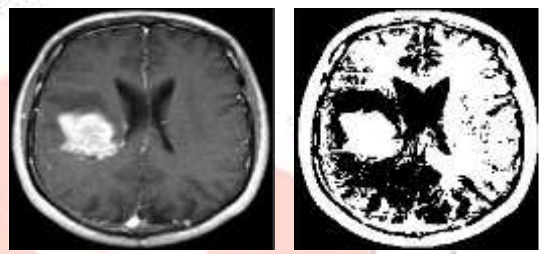
(a) (b)

Figure 3. a) Original Image b) Using Local Thresholding

1.4 BERNSEN'S TECHNIQUE

Bernsen's technique is developed by Bernsen's, it is local thresholding technique. Local threshold value is computed through local contrast. The local threshold value for each pixel (x, y) is computed by the relation.

$$T(x,y) = \frac{Imax + Imin}{2}$$



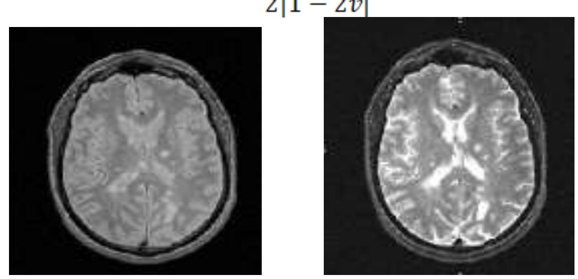
(a) (b)

Figure 4. a) Original Image b) Using Bernsen's Technique

1.5 LAAB (Local Adaptive Automatic Binarization)

Local adaptive automatic binarization is proposed by T.R Singh et al. It is converting to gray scale image into binary image routinely without using any threshold value T by adapting the pixel contained by local region surroundings. In this algorithm is an automatic binarization with local adaptation. Local mean of $m(x, y)$ of pixel intensity value and local region is help for local adaption because is carried out within a local window size of $w \times w$. The automatic binarization is designed as:

$$b(x,y) = \frac{|1-2v| - (1-2v)}{2|1-2v|}$$



(a) (b)

Fig. 5 a) Original Image b) Using LAAB Technique

B. Adaptive Thresholding

Adaptive thresholding technique is used to when the images are captured under without lightning situation and it is necessary to segment a lighter foreground from its background or when gray level value not constant of the background and object disparity varies within an image. This method allows the threshold value *T* to change based on the gradually unreliable function of location in the image or on local neighboring hood information. Threshold *T* based on the spatial coordinated (*x*, *y*) pixels [16].


(a) (b)

Fig. 6 a) Original Image b) Using Adaptive Thresholding

PROPOSED TECHNIQUES

2.1 INITIALIZE THE PARAMETERS OF HSA

In step 1, HSA parameters are initialized as follows [23]:

1. Harmony memory size (HMS) is the number of solutions that are stored in the Harmony Memory. Harmony Memory Size is related to the population size in genetic algorithms.

2. Harmony Memory Considering Rate (HMCR) is used during the improvisation procedure to choose whether the variables of the solution must take the value of any one in Harmony Memory. HMCR takes a value in the range [0, 1]. It is similar to the crossover rate in genetic algorithms. For example, if Harmony Memory Considering Rate (HMCR) is 0.9 it meaning that the probability of choosing the value of the variable from HM is 90%; even as the probability of selecting a value randomly as of the domain of the variable is 10%, i.e. (1 – HMCR). In case, the region of the variable refers to all the feasible shift patterns that Harmony Search Algorithm (HSA) can select from. Choosing a random value for the variable at probability of (1 – HMCR) is related to the mutation operation in genetic algorithms.

3. Pitch Adjusting Rate (PAR) is also used during the improvisation procedure to make a decision whether the variable of the solution must be distorted to a neighbor value. Pitch Adjusting Rate takes a value in the range [0, 1]. The amount of transform is determined by the bandwidth to shift the solution from one neighbor to another. The value of the bandwidth is arbitrarily select from its domain, and used to modify one shift pattern for a nurse. For case, if PAR is 0.3 it meaning the probability of altering the variable value is 30%; whilst 70%, i.e. (1 – PAR), is the probability of maintenance the variable without any change. PAR is related to a local search algorithm which agrees only improving solutions.

4. The maximum Number of Improvisations (NI) in the search corresponding number of iterations in HSA.

In this process, it investigates the appropriate values for Harmony Search Algorithm parameters including HMS, HMCR, PAR and NI.

2.2 Between—Class Variance (OTSU'S METHOD)

Otsu's is a nonparametric technique for thresholding it proposed by Otsu that segment image measure based on the employs the maximum variance value of the different classes [24]. It is captivating the intensity levels *L* as of a gray scale image or from every component of a RGB (red, green, and blue) image, the intensity values probability distribution is calculated as follows:

$$Ph_i^c = \frac{h_i^c}{NP}, \sum_{i=1}^{NP} Ph_i^c = 1, c = \begin{cases} 1,2,3 \ \ if \ \ RGB\ Image \\ 1\ if Gray\ scale\ Image \end{cases} \quad \cdots (3.6)$$

Where *i* is a definite intensity level ($0 \leq i \leq L - 1$), c is the constituent of the image. In *c* is depends on if the image is gray scale or RGB whereas the total number of pixels in the image is denoted as the Number Improvisation. h_i^c (histogram) of the image is the number of pixels that respective to the i intensity level in *c*. The histogram is normalized contained by a probability distribution Ph_i^c . Bi-level is the simplest segmentation of two classes are defined as:

$$C_1 = \frac{Ph_1^c}{\omega_0^c(th)}, \ldots, \frac{Ph_{th}^c}{\omega_0^c(th)} \quad and \quad C_2 = \frac{Ph_{th+1}^c}{\omega_1^c(th)}, \ldots, \frac{Ph_L^c}{\omega_1^c(th)}, \quad \cdots (3.7)$$

Where C_1 and C_2 classes are probability distributions, of $\omega_0(th)$ and $\omega_1(th)$ as it is given by Eq. (3.8).

$$\omega_0^c(th) = \sum_{i=1}^{th} Ph_{i,}^c \qquad \omega_1^c(th) = \sum_{i=th+1}^{L} Ph_i^c \quad \cdots (3.8)$$

In μ_0^c and μ_1^c that define the classes and It is necessary to compute mean levels using Eq. (3.9). Once individual's values are calculated, the Otsu variance between classes σ^{2^c} is calculated using Eq. (3.10) as follows:

$$\mu_0^c = \sum_{i=1}^{th} \frac{iPh_i^c}{\omega_0^c(th)}, \qquad \mu_1^c = \sum_{i=th+1}^{L} \frac{iPh_i^c}{\omega_1^c(th)}$$

$$\sigma^{2^c} = \sigma_1^c + \sigma_2^c$$

Observe that for both equations, Eqs. (3.9) and (3.10), *c* depends on the type of image. In Eq. (3.10) the number two is part of the Otsu´s variance operator and does znot characterize on proponent in the mathematical logic. Likewise σ_1^c and σ_2^c in Eq. (3.10) are the variances of C_1 and C_2 classes are distinct as:

$$\sigma_1^c = \omega_0^c(\mu_0^c + \mu_T^c)^2, \sigma_2^c = \omega_1^c(\mu_1^c + \mu_T^c)^2,$$

Where $\mu_T^c = \omega_0^c\mu_0^c + \omega_1^c\mu_1^c$ and $\omega_0^c + \omega_1^c = 1$. Depends on the values σ_1^c and σ_2^c, Eq.(3.12) given the objective function.

$$J(th) = \max\left(\sigma^{2^c}(th)\right),\ 0 \le th \le L - 1, \quad \cdots (3.12)$$

Where $\sigma^{2^c}(th)$ is the Otsu´s variance for a given threshold (*th*) value. Hence, the optimization difficulty is compact to determine the intensity level (*th*) that maximizes Eq. (3.12).

Otsu's method is functional for a single module of an image. In such case RGB images, it is required to single module images needs to separation in the image. The bi-level thresholding is described the extensive of multiple thresholds. Original image separate the possible *k* classes and calculate the *k* variances and their corresponding elements is based on the k thresholds using Eq. (3.5). The objective function *J*(*th*) in Eq. (3.12) can thus be rewritten for multiple thresholds as follows:

$$J(TH) = \max\left(\sigma^{2^c}(\mathrm{TH})\right), \quad 0 \le \mathrm{th_i} \le \mathrm{L} - 1, \quad \mathrm{i} = \quad \cdots ($$

Here $TH = [th_1, th_2, \ldots, th_{k-1}]$, is a vector have multiple thresholds and the variances are calculated throughout Eq. (3.14) as follows.

$$\sigma^{2^c} = \sum_{i=1}^{k} \sigma_i^c = \sum_{i=1}^{k} \omega_i^c(\mu_i^c - \mu_T^c)^2, \quad \cdots (3.14)$$

Here, it represents and definite class, ω_i^c and μ_j^c are correspondingly the probability of incidence and the mean of a class. In multilevel threshold, such values are obtained as:

$$\omega_0^c(th) = \sum_{i=1}^{th1} Ph_i^c$$

$$\omega_1^c(th) = \sum_{i=th_1+1}^{th2} Ph_i^c$$

$$\vdots \qquad \vdots$$

$$\omega_{k-1}^c(th) = \sum_{i=th_k+1}^{L} Ph_i^c \quad \cdots (3.11)$$

and, for the mean values:

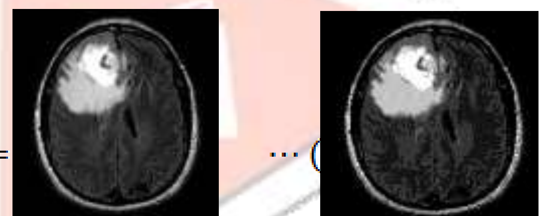
$$\mu_0^c = \sum_{i=1}^{th_1} \frac{iPh_i^c}{\omega_0^c(th_1)}$$

$$\mu_1^c = \sum_{i=th_1+1}^{th_2} \frac{iPh_i^c}{\omega_0^c(th_2)} \quad \cdots (3.16)$$

$$\vdots \qquad \vdots$$

$$\mu_{k-1}^c = \sum_{i=th_1+1}^{L} \frac{iPh_i^c}{\omega_k^c(th_k)}$$

Like a bi-level thresholding, for the Multilevel Threshold using the Otsu's method *c* corresponds to the image works, RGB *c* = 1, 2, 3 and gray scale *c* = 1.



(a) (b)

Fig. 7 a) Original Image b) Using Otsu's Method

2.3 *Entropy Criterion Method (KAPUR'S METHOD)*

Kapur method is proposed by Kapur et al. It is another nonparametric method that is used to establish the optimal threshold values. Kapur method is based on the entropy criterion and probability distribution of the histogram image. That this kapur method to get the optimal threshold value *th* that it is maximum of the overall entropy. Density and separability of entropy measured by among classes. In this logic, when entropy has the highest value the optimal *th* value properly separates the classes. The objective function kapur's method is distinct as [24]:

$$J(th) = H_1^c + H_2^c, \quad c = \begin{cases} 1,2,3 \text{ if RGB Image} \\ 1 \text{ if Gray scale Image} \end{cases} \quad \cdots (3.15) \quad \cdots (3.17)$$

Where the H_1 and H_2 are defined as the entropies is computed by the following model:

$$H_1^c = \sum_{i=1}^{th} \frac{Ph_i^c}{\omega_0^c} \ln\left(\frac{Ph_i^c}{\omega_0^c}\right), H_2^c = \sum_{i=th+1}^{L} \frac{Ph_i^c}{\omega_1^c} \ln\left(\frac{Ph_i^c}{1}\right), \quad \cdots(3.18)$$

In probability distribution of the intensity levels Ph_i^c which is obtained using Eq.(3.6). $\omega_0(th)$ and $\omega_1(th)$ are probability distributions for C_1 and C_2 classes. $ln(\cdot)$ stands for the natural logarithm. Like to the Otsu's method, the entropy-based approach can be extensive for multiple threshold values; for such a case, it is important to divide the image into *k* classes using the related number of thresholds. Under such situation the new objective function is distinct as:

$$J(TH) = max\left(\sum_{i=1}^{k} H_i^c\right), c = \begin{cases} 1,2,3 \text{ if } RGB \ Image \\ 1 \text{ if } Gray\,Scale\,Image \end{cases} \quad \cdots(3.19)$$

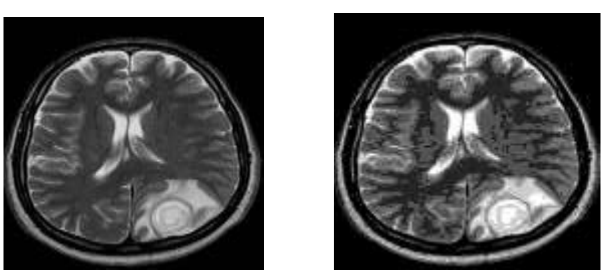
Where $TH = [th_1, th_2, \ldots, th_{k-1}]$, is a vector that contains the multiple thresholding values. Every entropy is calculated individually with its relevant *th* value, so Eq. (3.20) is extended for *k* entropies.

$$H_1^c = \sum_{i=1}^{th_1} \frac{Ph_i^c}{\omega_0^c} \ln\left(\frac{Ph_i^c}{\omega_0^c}\right),$$

$$H_2^c = \sum_{i=th_1+1}^{th_2} \frac{Ph_i^c}{\omega_1^c} \ln\left(\frac{Ph_i^c}{\omega_1^c}\right), \quad \cdots(3.20)$$

$$H_k^c = \sum_{i=th_k+1}^{L} \frac{Ph_i^c}{\omega_{k-1}^c} \ln\left(\frac{Ph_i^c}{\omega_{k-1}^c}\right)$$

The $(\omega_0^c, \omega_1^c, \ldots, \omega_{k-1}^c)$ is the values of the probability happening of the *k* classes are obtained using Eq. (3.15) and the probability distribution Ph_i^c with Eq. (3.9).To conclude, it is important to use Eq. (3.5) to divide the pixels into the related classes.

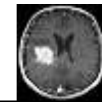
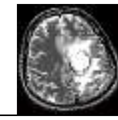
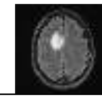
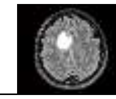
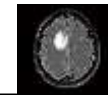
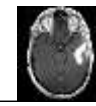
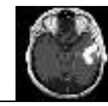
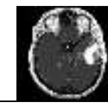
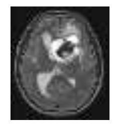
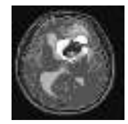
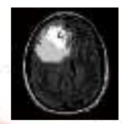
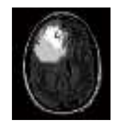
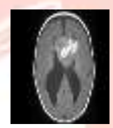
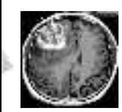


(a) (b)

Figure 3.2. a) Original Image b) Using Kapur's Method

3 RESULT AND DISCUSSION

Images	Original	Using Otsu	*Using*

	image		*Kapur*
Image 1			
Image 2			
Image 3			
Image 4			
Image 5			
Image 6			
Image 7			
Image 8			

(a) (b) (c)

Fig. 8 a)Original Image b) Using Otsu's with HSMA c) Using Kapur's with HSMA

Table 1
Result after applying the Harmony Search Optimization Algorithm using Otsu's function to the MRI brain image

Images	K	Threshold value	PSNR	Jaccard	Time
Image 1	6	23 60 90 123 169 219	59.06	0.20	8.9
Image 2	6	24 66 103 134 171 216	59.16	0.20	10.77
Image 3	6	23 48 75 97 117 169	58.49	0.50	15.97
Image 4	6	28 68 99 136 177 220	61.23	0.10	19.01
Image 5	6	12 37 68 101 146 208	59.75	0.04	11.41
Image 6	6	19 46 76 120 169 220	63.99	0.43	12.82

Image 7	6	7 38 82 112 141 196	59.16	0.07	11.77
Image 8	6	29 61 94 123 162 215	58.45	0.19	12.51

Table 2
Result after applying the Harmony Search Optimization Algorithm using Kapur's function to the MRI brain image

Images	k	Threshold value	PSNR	Jaccard	Time
Image 1	6	59 90 118 155 201 224	59.23	0.25	7.05
Image 2	6	17 48 80 125 168 210	59.27	0.22	10.41
Image 3	6	33 78 114 144 178 213	61.15	0.52	14.68
Image 4	6	12 50 99 137 175 214	62.02	0.14	12.95
Image 5	6	30 71 107 138 169 202	59.93	0.32	9.63
Image 6	6	49 74 108 143 179 215	65.64	0.56	6.01
Image 7	6	22 54 106 138 172 214	59.63	0.22	8.56
Image 8	6	33 64 94 125 158 205	58.48	0.21	8.31

4 CONCLUSIONS

In this paper, multilevel thresholding based on the Harmony search optimization algorithm is used. Harmony Search Optimization Algorithm use some objective functions that can be proposed by the multilevel thresholding methods of Otsu's and Kapur's thresholding methods. Otsu's and Kapur's Multithresholding technique to gives the multi thresholding value for MRI brain images. The performance of these two methods is compared using Jaccard's Similarity Coefficient and Peak Signal to Noise Ratio for MRI brain images. The Experimental result shows the Kapur method produces the better results than the Otsu thresholding method. Kapur method is gives the better result for MRI brain images.

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