MR Brain Image Segmentation using Bacteria Foraging Optimization Algorithm

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***Abstract* --The most important task in digital image processing is image segmentation. This paper put forward an unique image segmentation algorithm that make use of a Markov Random Field (MRF) hybrid with biologically inspired technique Bacteria Foraging Optimization Algorithm (BFOA) for Brain Magnetic Resonance Images The proposed new algorithm works on the image pixel data and a region/neighborhood map to form a context in which they can merge. Hence, the MR brain image is segmented using MRF-BFOA and the results are compared to traditional metaheuristic segmentation method Genetic Algorithm. All the experiment results show that MRF-BFOA has better performance than that of standard MRF-GA**

Keyword - Magnetic Resonance Image (MRI), Brain Tumor, Brain Image Segmentation, Markov Random Field, Bacteria Foraging Optimization Algorithm (BFOA)

I. INTRDUCTION

Brain tumor is one of the major reasons for the increase in mortality among humans. A tumor can be more precisely defined as an abnormal growth caused by cells reproducing themselves in an uncontrolled fashion. This year 2012, an estimated 22,910 adults (12,630 men and 10,280 women) in the United States will be diagnosed with primary malignant tumors of the brain and spinal cord. It is estimated that 13,700 adults (7,720 men and 5,980 women) will die from this disease this year [26]. Medical imaging is a mandatory tool for improving the diagnoses, understanding and treatment of a vide variety of diseases including cancer. Detection of brain tumor requires high-resolution brain MRI. Most Medical Imaging Studies and detection conducted using MRI, Positron Emission Tomography (PET) and Computed tomography (CT) Scan. Now a days MRI systems are very important in medical image analysis. MRI has a multidimensional nature of data provided from different sequential pulses magnetic resonance imaging (MRI) can provide detailed information about disease and can identify many pathologic conditions, giving an accurate diagnosis.

The Segmentation of an image is the process of separation of the image into regions of similar structure and behavior. The main purpose many image processing applications is to extract important features from the image and provides description, interpretation, or understanding of the scene can be provided by the machine. Segmentation of tumor region from the brain Magnetic Resonance Images is an critical but time-consuming task performed by Radiologists and Medical Experts

There are many algorithms used to divide the brain images into tumors, edema and necrotic tissues from the MR Image. Several authors suggested various algorithms for segmentation [12-19]. Siyal et al described a new method on Fuzzy C-means for segmentation purpose [20] . Phillips,W.E et al described Application of fuzzy C-Means Segmentation Technique for tissue Differentlation in MR Images of a hemorrhagic Glioblastoma Multiforme[21]. S. Murugavalli1 et al , A high speed parallel fuzzy c-mean algorithm for brain tumor segmentation [22]. S. Murugavalli1, An Improved Implementation of Brain Tumor Detection Using Segmentation Based on Neuro Fuzzy Technique [23], Jayaram K et al described Fuzzy Connectedness and Image Segmentation[24].Kannan et aln describe Segmentation of MRI Using New Unsupervised Fuzzy C mean Algorithm[25]

The rest of this paper is organized as follows. Section II describes the preprocessing and enhancement process. Section III deals with the segmentation of MR images using MRF hybrid with BFOA algorithm. Section IV compares the result of MRF-GA with the proposed MRF hybrid with BFOA. Section V gives the conclusion for the paper.

II. PREPROCESSING AND ENHANCEMENT PROCESS

A. Image Acquisition

To access and use the real medical images for carrying out research is a very difficult due to various technical problems. The MRI data for the research is obtained from the Brain Web Database at the McConnell Brain ImagingcenteroftheMontrealNeurologicalInstituteMNI),McGillUniversity.(http://www.bic.mni.mcgill.ca/brainweb). A sample T1 weighted images of size 181x217x36 are taken and used for enhancement and segmentation purpose. T1- weighted images shows water darker and the fat brighter. The images are acquired in MINC format and which is converted to the JPEG format before the processing. Fig1. shows the image after acquisition.

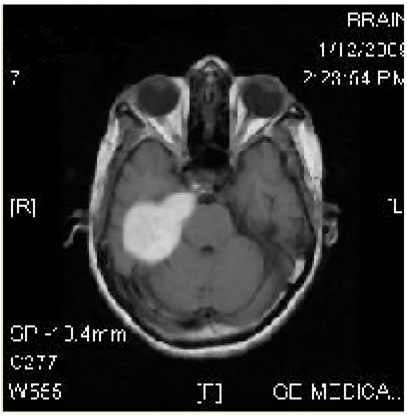

Fig. 1. Acquired T1 weighted MR Image

B. Removal of film artifacts and skull portions

The acquired MRI brain image consists of lot of film artifacts and label which includes patient name, age and marks for identification on the MRI. These film artifacts are removed using tracking algorithm .The tracking algorithm starts from the first row and first column, the intensity value of the pixels are analyzed using the threshold value of the film artifacts. If the pixel intensity value is greater than that of the threshold value then that pixel intensity is made to zero and removed from MRI. The high intensity values of film artifacts are removed from MRI brain image. Separate threshold values are set for the labels and the skull region so that both the unwanted parts of the MRI image can be removed. Fig. 2 shows the image after removing the artifacts.

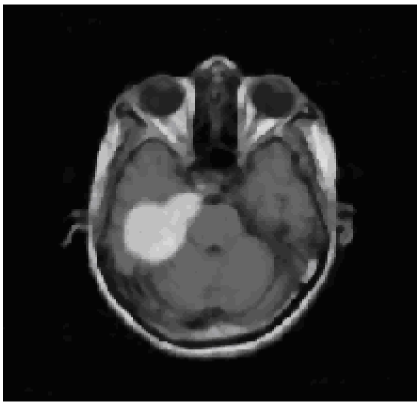

Fig. 2. Image after removing the artifacts

C. MRI image enhancement using Histogram Equalization and Center Weighted Median Filter

Image enhancement techniques are used to improve the visual appearance of Magnetic Resonance Image (MRI) by eliminating high frequency components from the images. Image Enhancement can be done by applying various types of filters like low pass filter, Median filter, Gaussian Filter, Sobel filter etc. on images. The proposed system describes that the image enhancement is done using Histogram Equalization and Center Weighted Median Filter for removing high frequency components such as impulsive noise, salt and pepper noise, etc [27-28]. The MRI brain image is histogram equalized and then the center weighted median filter is applied.

The center weighted median (CWM) filter is a type of weighted median filter which gives more weight only to the central pixel of each window. This filter can preserve the fine image details while suppressing additive white and impulsive-type noise. When comparing the properties of the CWM filter with other median filters it is very clear that the CWM filter along with Histogram Equalization can outperform other median filters

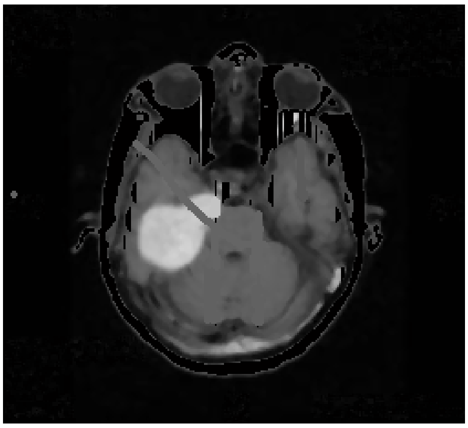

Fig. 3. Enhanced image

III. SEGMENTATION USING MRF-BFOA

Segmentation is the process of separating portions of the image for performing further image analysis. The task of segmentation of brain MRI images is to obtain the suspicious region probably the tumor to assist radiologists for diagnosis. Image segmentation techniques use different methodologies like Region-based approach, morphological operation, fuzzy approaches and stochastic approaches for MRI image segmentation. Local thresholding is used by setting threshold values for sub-images. It requires selection of a window size and threshold parameters [1-6]

Edge detection is a traditional method for segmentation. Many operators like Roberts gradient, Sobel gradient, Prewitt gradient and Laplacian operator etc. can be used to detect the edges. Image segmentation can also be done using the morphological operations such as erosion, top-hat transformation etc. It is good in dealing with geometrically analytic aspects of image analysis problems.[7-11]. Stochastic approaches have also been used to segment tumors. The watershed transformation for segmentation considers the gradient magnitude of an image as a topographic surface. Pixels having the highest gradient magnitude intensities correspond to watershed lines, which represent the region boundaries. Vast range of algorithms are available to segment the portion of images, some of them were discussed above.

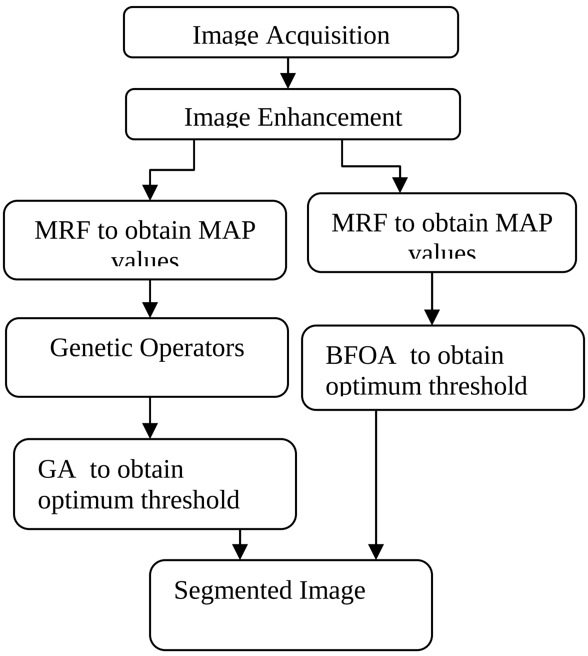

Fig. 4. The proposed Segmentation Process

A. *Markov Random Field (MRF) model*

Markov Random Field (MRF) model was used to deal with the spatial relations between the labels obtained in an iterative segmentation process. The process-assigning pixel labels iteratively. The MRF is used to compute the MAP value of each kernel. The metaheuristic algorithm BFOA is implemented to obtain the optimum labels by minimizing the MAP values. The intensity value corresponding to the central pixel of the kernel that holds the optimum label is used as the threshold value for segmentation.

The MRF is used for segmenting the image by providing and analyzing optimal labels of the pixels. The optimum label is that which minimizes the MAP estimate

B. Segmentation using MRF-GA

Genetic algorithms are based on natural selection discovered by Charles Darwin. This Algorithm uses natural selection of fittest individuals for optimizing the problem. Optimization for the problem can be implemented through natural exchange of genetic material between parents. Offsprings are created from parent genes by allowing only the fittest individuals to breed. In our perspective of Genetic Algorithm, genetic material is replaced by strings of bits and natural selection replaced by fitness function to find the optimal solution. The two main operation for the matting of parents is by cross-over and mutation operations [33].

Divide the image into kernels of size 3 x 3 and assign labels for each kernel using the principle of Markov Random Field iteratively and apply the crossover and mutation operation to find the optimum label among the kernels. The central pixel of the corresponding kernel will be the threshold value. The image is then segmented using this value as threshold.

C. Segmentation using MRF-BFOA

Bacteria Foraging Optimization Algorithm (BFOA) was proposed by Passino. This algorithm is based on the application of group foraging strategies of a swarm of E.coli bacteria in multi-optimal function optimization. Bacteria search for nutrients in a manner to maximize energy obtained per unit time Foraging is the method for locating, handling and ingesting food. During foraging activity of the real bacteria, movement is achieved by a set of tensile flagella. Flagella help an E.coli bacterium to tumble or swim, which are two basic operations performed by a bacterium at the time of foraging [29-30]

D. Prime steps in Bacteria Foraging Optimization Algorithm

1. *Chemotaxis*: This process simulates the movement of an E.coli cell through swimming and tumbling via flagella. An E.coli bacterium can move in two different ways. It can swim for a some period of time in the same direction or it may tumble .

2. *Swarming*: Swarming is termed as a group behavior of E.coli bacteria in which the cells arrange themselves in a form of a ring by moving up the nutrient gradient. The cells when stimulated by a high level of succinate, release an attractant aspertate, which helps them to aggregate into groups and thus move as concentric patterns of swarms with high bacterial density

3. *Reproduction:* The health of Bacteria can be calculated using the objective function. If the objective function yields a high value such bacteria are the least healthy bacteria and finally they die. The bacteria which yield lower value are the healthier ones which split into two separate bacteria, which are then placed in the same location. This is how the swarm size is constant.

4. *Elimination and Dispersal:* Gradual or sudden changes in the local environment like rise of temperature, where a bacterium population lives may kill or disperse a group of bacteria that are currently in a region with a high concentration of nutrient gradients.

E. Algorithm

The algorithm for our implementation is as follows:

Read the MRI image stored in a two dimensional matrix. Pixels with same gray value are labeled with same number. For each kernel in the image, the posterior energy U (x) is calculated. [Kernel is a 3×3 window of neighborhood pixels]

$U(x) = \{\sum [(y-\mu)^2 / (2 * \sigma^2)] + \sum \log(\sigma) + \sum V(x) \}$

where, y is the intensity value, μ is the mean value of the kernel, σ is the standard deviation, V is the potential function for set of all kernels over the image, and x is the label of the pixel. If x_1 is equal to x_2 in a kernel, then $V(x) = \beta$, otherwise 0, where β is positive constant. The posterior energy values of all the kernels are stored in a separate matrix [31-32]..

Bacteria Foraging Optimization is used to minimize the posterior energy function. The procedure is as follows:

[Step 1] Initialize parameters *p, S, Nc, Ns, Nre, Ned, Ped, C(i)(i=1,2…S),* ^{i} .
[Step 2] Elimination-dispersal loop: l=l+1
[Step 3] Reproduction loop: k=k+1
[Step 4] Chemotaxis loop: j=j+1
[a] For i =1,2…S take a chemotactic step for bacterium i as follows.

i) Create a solution matrix (Sol) to store the labels of all the pixels, posterior energy values of all the pixels, and a flag column to mention whether the pixels is selected by the bacteria or not.

ii) Initialize the Matrix Sol with zeros.

iii) Store the labels and the energy function values in Sol.

[b] Compute fitness function, J (i, j, k, l).

Let, J (i, j, k, l) = J (i, j, k, l) + J_{cc} (^{i} (j, k, l),P(j, k, l))

(i.e. add on the cell-to cell attractant–repellant profile to simulate the swarming behavior) . where J_{cc} is the cell to cell signaling and it is taken as a random number between 1 to -1

[c] Let Jlast=J (i, j, k, l) to save this value since we may find a better cost via a run.

[d] Tumble: generate a random vector

(i) p with each element m (i),m 1,2,..., p, = a random number on [-1, 1].

[e] Move: Let

$$^{i}(j+1,k,l) = {}^{i}(j,k, l) + C(i) \frac{i}{Sqrt(^{T}(i) \quad (i))}$$

This results in a step of size C(i) in the direction of the tumble for bacterium i.

[f] Compute J (i, j +1, k, l) and let

J (i, j + 1, k, l) =J (i, j, k, l) + Jcc (^{i} (j+ 1, k, l), P(j+ 1, k, l))

[g] Swim

i) Let m=0 (counter i for swim length).

ii) While m< Ns (if have not climbed down too long).

• Let m=m+1.

• If J (i, j +1, k, l) < Jlast (if doing better), let Jlast = J (i, j +1, k, l) and let

$$^{i}(j+1,k,l) = {}^{i}(j,k, l) + C(i) \frac{i}{Sqrt(\Delta^{T}(i)\ \Delta(i))}$$

i) The minimum value from the set, assign as local minimum (Lmin).

ii) Compare this local minimum (Lmin) with the global minimum (Gmin), if Lmin is less than Gmin, assign Gmin = Lmin.

And use this ^{i} (j + 1, j,k) + to compute the new J (i, j +1, k, l) as we did in [f]

• Else, let m= Ns. This is the end of the while statement.

[h] Go to next bacterium (i+1) if i S (i.e., go to [b] to process the next bacterium).

[Step 5] If j < Nc, go to step 4. In this case continue chemotaxis since the life of the bacteria is not over.

[Step 6] Reproduction:

[a] For the given k and l, and for each i = 1,2,..., S ,

Let Jhealth = J(i, j, k, l) where j is from 1 to N_c + 1

be the health of the bacterium i (a measure of how many nutrients it got over its lifetime and how successful it was at avoiding noxious substances). Sort bacteria and chemotactic parameters C(i) in order of ascending cost Jhealth (higher cost means lower health).

[b] The Sr bacteria with the highest Jhealth values die and the remaining Sr bacteria with the best values split (this process is performed by the copies that are made are placed at the same location as their parent).

[Step 7] If k < Nre, go to step 3. In this case, we have not reached the number of specified reproduction steps, so we start the next generation of the chemotactic loop.

[Step 8] Elimination-dispersal: For i = 1,2..., S with probability Ped, eliminate and disperse each bacterium (this keeps the number of bacteria in the population constant). To do this, if a bacterium is eliminated, simply disperse another one to a random location on the optimization domain. If l < Ned, then go to step 2; otherwise end.

[Step 9] The Gmin has the optimum label which minimizes the posterior energy function. Store the pixels has the optimum label in a separate image, that is the segmented image

IV. RESULT AND ANALYSIS

Select the image pixels, which are having optimum label, are stored as a separate image. This image is the segmented image of brain MR image.

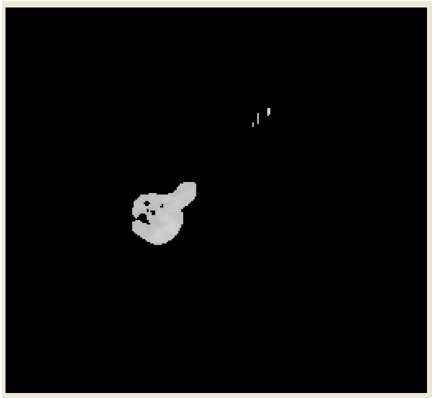

Fig. 5. Segmentation result using MRF-BFOA

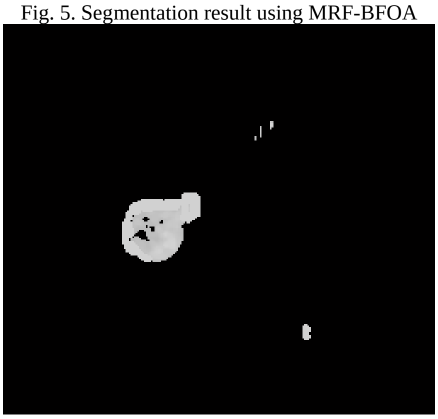

Fig. 6. Segmentation result using MRF-GA

For comparison, the same image was tested using the meta-heuristic segmentation methods such as the genetic algorithm. As can be seen, the proposed method is more efficient than the other methods.

TABLE 1

Comparison between MRF-GA and MRF-BFOA

	Segmentation using MRF-GA	Segmentation using MRF-BFOA
Adaptive threshold	179.20	185.30
Number of segmented cells	1016	878
Execution time	33.55	31.21

The above table shows that the MRF- BFOA outperform MRF-GA for the segmentation of tumor regions in the brain MRI images. Both algorithms are implemented using MATLAB 7 on T2 weighted MRI images from the online Brain Web Database. The kernel size selected for both implementation is 3 x 3

V. CONCLUSION

In this paper, the population based image segmentation approach was presented. The approach used for segmentation is the Bacteria foraging optimization of the E.coli bacteria. The improved accuracy rate according to the experimental results is due to better characterization of natural brain structure. Experiments on MRI images show that the segmentation result of the proposed method has higher accuracy compared to existing algorithms.

REFERENCES

[1] Aaron Lefohn, Joshua Cates, Ross Whitaker,: "Interactive GPU-Based level sets for 3D Brain Tumor Segmentation",April 16,2003.
[2] Ahmed Saad, Ben Smith,Ghassan Simultaneous Segmentation, Kinetic Parameter Estimation and Uncertainty Visualization of Dynamic PET Images", MICCAI 2007.
[3] Albert K.W.Law,F.K.Law,Francis H.Y.Chan,:"A Fast Deformable Region Model for Brain Tumor Boundary Extraction",IEEE ,oct 23, USA,2002.

[4] Amini L, Soltanian-Zadeh H, Lucas.C,:"Automated Segmentation of Brain Structure from MRI", Proc. Intl.Soc.Mag.Reson.Med.11(003.

[5] ErikDam,Marcoloog,Marloes Letteboer,:"Integrating Automatic and Interactive Brain tumor Segmentation", Proceedings of the 17th International Conference on Pattern Recognition (ICPR'04), IEEE Computer Society.

[6] Duan Haibin, Wang Daobo, Zhu Jiaqiang and Huang Xianghua, "Development on ant colony algorithm theory and its application," Control and Decision, Vol. 19, No. 12, Dec. 2004.

[7] P.S. Shelokar, V.K. JayRaman and B.D. Kulkami, "An ant colony clustering approach for clustering", ANALYTICAL CHMICAL ACTA 509, 2004, pp.187- 195.

[8] M. Dorigo, Mauro Birattari and Thomas Stiitzle, "Ant Colony Optimization artificial Ants as a Computational Intelligence Technique", Computational Intelligence magazine, Nov. 2006, pp.28-39.

[9] J. Liu, Y.Y. Tang, "Adaptive image segmentation with distributed behavior-based agents," IEEE Transactions Pattern Analysis and Machine Intelligence 21, June 1999, pp. 544-551.

[10] H. He, Y. Chen, "Artificial life for image segmentation," International Journal of Pattern Recognition and Artificial Intelligence 15 (6), 2001, pp. 989-1003.

[11] Hongmin Cai,Ragini Verma, Yangming Ou,Seung-koolee,Elias R.Melhem,Christos Davatzaikos,:"Probabilistic Segmentation of brain tumors Based on Multi-Modality Magnetic Resonance Images",IEEE,ISBI 2007

[12] Alirezaie, J., M.E. Jernigan and C. Nahmias,."Neural Network based segmentation of MagneticResonance Images of the Brain", IEEE Trans. Nuclear Science, 1997, 44 (2): 194-198.

[13] Bezdek, J.C.,. "Cluster validity with fuzzysets", Cybernetics, 1974, 3: 58-73.

[14] Chunyan Jiang,Xinhua Zhang,Wanjun Huang,Christoph Meinel.:"Segmentation and Quantification of Brain Tumor,"IEEE International conference on Virtual Environment,Human-Computer interfaces and Measurement Systems, USA, 12-14, July 2008.

[15] DeSieno, D.,. "Adding a conscience to competitive learning", Proceeding of IEEE the Second International Conference on Neural networks(ICNN88) 1988, 1: 117- 124.

[16] Fu, K.S. and J.K. Mui,." A survey on image segmentation", Pattern ecognition, 1981, 13: 3-16.

[17] Gonzalez, R.C. and R.E. Woods, "Digital image processing, Pearson Education", 2002.

[18] Haralick, R.M. and L.G. Shapiro,. "Survey ,image segmentation techniques", Computer Vision, Graphics Image Process, 1985, 29: 100-132[9]

[19] HanShen,WilliamSandham,MalcolmGranet,Annette Sterr.:"MRI Fuzzy Segmentation of Brain Tissue Using Neighbourhood Attraction with Neural-Network Optimization",IEEE Transcations on Information Technology in BiomedicineVol.9,No.3,Sep 2005.[22]

[20] Siyal M.Y,Lin yu,:"An Intelligent modified fuzzy C-means based algorithm for bias estimation and Segmentation of brain MRI",Elsevier,Pattern Recognition Letters,26,2005.

[21] Phillips,W.E, Velthuizen R.P, Phuphanich S, L.O, Clarke L.P, Silbiger ,:"Application of fuzzy C-Means Segmentation Technique for tissue Differentlation in MR Images of a hemorrhagic Glioblastoma Multiforme ", Pergamon,Megnetic Resonance Imaging, Vol.13, 1995.

[22] S. Murugavalli1 , V. Rajamani," An Improved Implementation of Brain Tumor Detection Using Segmentation Based on Neuro Fuzzy Technique" Journal of Computer Science 3 (11): 841-846, 2007

[23] S. Murugavalli1 , V. Rajamani," "A high speed parallel fuzzy c-mean algorithm for brain tumor segmentation", BIME Journal, Volume (06), Issue (1), Dec., 2006.

[24] Jayaram K.Udupa,Punam K.Saha,:"Fuzzy Connectedness and Image Segmentation", Proceedings of the IEEE,vol.91,No 10,Oct 2003.

[25] Kannan S.R,:"Segmentation of MRI Using New Unsupervised Fuzzy C mean Algorithm",ICGST,2005.

[26] American Cancer Society's publication, Cancer Facts & Figures 2012.

[27] T. Sun, M. Gabbouj and Y. Neuvo, "Center weighted median filters: some properties and application in image processing," Signal Processing, vol. 35, pp. 213-229, 1994.

[28] B. R Dobrin, T. G. Campbell and M. Gabbouj, "A fast algorithm for running computation of center weighted rank order filters," Proc. of IEEE Winter work shop on Nonlinear Digital Signal Processing, Tampere, Finland, Jan. 17-20, 1993.

[29] T. Logeswari and M. Karnan, "An improved implementation of brain tumor detection using segmentation based on soft computing" Journal of Cancer Research and Experimental Oncology Vol. 2(1) pp. 006-014, March, 2010.

[30] Hongwei Mo, Yujing Yin, "Image Segmentation Based on Bacterial Foraging and FCM Algorithm" International Journal of Swarm Intelligence Research, 2(3), 16-28, July-September 2011.

[31] L. N. Decastro, F. J. Von Zuben, and Idea Group Pub et al. "Recent Developments In Biologically Inspired Computing." IGI Publishing, Hershey, PA, USA, 2004.

[32] K. M. Passino. Biomimicry of bacterial foraging for distributed optimization and control. IEEE Control Systems Magazine, 22: 52–67, 2002.

[33] B. M. Baker and M. A. Ayechew, " A genetic algorithm for the vehicle routing problem", Computers & Operations Research, 30(5): 787–800, 2003.