Brain Tissues Segmentation in MR Images based on Level Set Parameters Improvement

Mohammad masoud Javidi[1]andMajid Hajizade[2]and Mehdi Jafari Shahbazi[3]

ShahidBahonarUnivresity of Kerman,Kerman,Iran.
[1,2]Department of Computer Science ,Faculty of Mathematics and Computer,ShahidBahonar University of Kerman,Kerman,Iran.
[3]Department Of Electronic Engineering , College of Technical and Engineering , Kerman Branch , Islamic Azad University , Kerman , Iran

Abstract

this paper presents a new image processing technique for brain tissue segmentation, precisely,in order to recognize brain diseases. Automatic level set(ALS) is a powerful method for segmenting brain tissues in MR images that uses spatial Fuzzy C-Means (SFCM) to set initial contour near the object's boundaries in order to increasing the speed of algorithm. Themethod efficiency depends on selecting the optimized amounts of controlling parameter. In this paper, the ALSis improved by optimal regulating of controlling parameters. The proposedmethod contains two phases. In the first phase,the initial contour of ALS determined via the SFCM and image features are extracted. Then, the optimal controlling parameters of ALS are determined by a genetic algorithm.By applying image features and optimal controlling parameters to the generalized regression neural network(GRNN), a neural system is trained. In the second phase, the initial contour is specified and image features are extracted as inputs to trained neural network from phase1. Thus, the outputs of neural network are used as ALS controlled parameters. The resultsshow that the accuracy of proposed ALS is improvedabout 1.4 %with respect to the ALS method. The proposed ALS not only retains the speed but also has a higher accuracy.

Keywords

Automatic level set, spatial FCM clustering, genetic,generalized regression neural network.

1. INTRODUCTION

Brain is the body control center and one of the most important organs in the body, so the health of this organ is essential. There are a lot of diseases which threaten the brain health and cause a lot of irreparable damages such as *multiple sclerosis* (MS). However, the recognition of the brain diseases is a vital for remedy and medical treatment. Progress in technology has caused various imaging modalities(like CT, XRAY, MRI, US, PET, and SPET) in order to image from different organs in the body. Mentioned imaging techniques play important roles in recognizing the illness. *Magnetic resonance image* (MRI) is used to study brain tissues because there is a higher resolution between different tissues and it also has a higher safety in contrast with other modalities.

Extracting the *gray matter* (GM), *white matter* (WM), and *cerebrospinal fluid* (CSF)regions is the most important and challenging phase in analyzing the brain MRI. After extracting the considered tissues, their structural features (like size, appearance, and shape)are analyzed and finally different diseases can be recognized.

There area lot of methods available for MRI brain image segmentations[1]–[3]. The presented methods are divided into three classes; including manual, semi-automatic, and automatic[4]. Due to the complexity of brain tissues, noise, and poor contrast of brain MRI, the manual segmentation of brain tissues is time consuming with a high error rate. Therefore, most of the presented methods are implemented in an interactional experiment and semi-automatic[5]. In semi-automatic algorithms, the initial segmentation and controlling parameters are characterized by the radiologist. Semi-automatic methods depend on the observation and the interacting of the experts during implementation. Thus,automatic methods are useful for brain tissue segmentation.

Since in medical images the transitional regions between different tissues are not crisp[6], in [7]–[9],*fuzzy inference systems* (FIS) are used for image segmentation. FCM clustering is an unsupervised technique, first proposed by Bezdek[10]. In traditional FCM, pixel intensity is used for image segmentation, but in SFCM, with respect to adjacent pixel correlation, the neighborhood pixel intensity is also used. This strategy enhances the noise effects[11]–[13].

The active models or deformable models are popular methods inmany applications. Deformable models are divided into two groups: parametric and nonparametric. Level set is the subset of deformable models and unlike the snake,it is a nonparametric model of that. Level set were first introduced by Osher and Sethian[14]. It is an effective and efficient method for medical image segmentation [15], [16]. Level set has some advantages and disadvantages; such that topology is changeable but the computations are high and the speed is low. One of the biggest challenges in implementing of the level set methods is to keep the level set function close tothe signed distance function. To overcome this challenge the level set function need to re-initialized to the signed distance function periodically.This procedure lead to an stable level set function, but it increases the computational complexity which causes the speed reduced.In [17], a variational level set formulation is used, where its speed has increased due to elimination of costly re-initialization procedure. However this variational formulation has some controlling parameters that obtained by try and error. Also the initial segmentation determines by the user and therefor this method is a semi-automatic. In order to solve this problem,the integrated techniques presented [4], [15]. In the proposed method in [15], the initial segmentation done by fuzzy clustering whose results enhanced by morphological operations and then the variational level set implemented for the final segmentation. An automatic segmentation method also proposed in [4] which the initial segmentation and also the regulation of controlling parameters done by SFCM and the variational level set used for final segmentation.Nevertheless, the exact and optimally determination of the amount of controlling parameters affects the algorithm efficiency. In this paper,an automatic method is proposed that initial segmentation done by SFCM and variational level setimplemented for final segmentation whose controlling parameters are regulated precisely and optimally. The proposed method for optimally adjusting controlling parametershas two phases. In the first phase, the image features are extracted and the optimal amount of the level set controlling parameters are obtained by genetic algorithm. Then, a learning process will run by using generalized regression neural network.In the secondphase, theperformance of the automatic level set has been evaluated whose controlling parameters have been regulated by the neural network resulted from the first phase. The obtained results show that besides retaining the speed, the accuracy of the proposed automatic level set method has also improved.

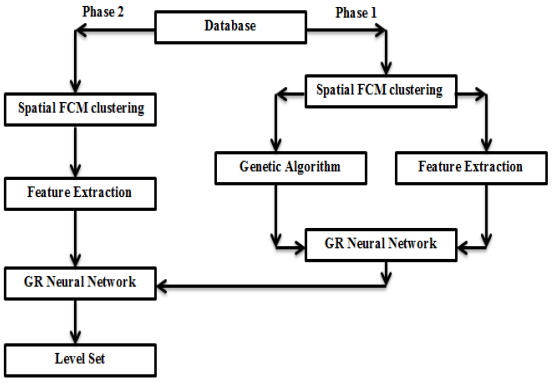
The remaining sections of this paper are organized as follow. The proposed method is explained in Section2. Experimental results are reported in Section 3 and finally the conclusion is expressed in Section4.

2. PROPOSED METHOD

The block diagram of the proposed algorithm is shown in Figure I. The method is implemented in two phases. In the first phase, by applying extracted features as input and optimal ALS controlling parameters (yielded by genetic algorithm)as the target the GRNNis trained. The aim of the second phase is to evaluate the performance of the automatic level set whose controlling parameters are adjusted optimally. Therefore,by extracting features and applying them to the trained neural network, the values of ALS controlling parameters are determined. Finally, the level set method,according to the optimal parameters, is implemented and itsperformanceis evaluated. The results show that the accuracy of the automatic level set has improved with respect to other existing methods.

The spatial FCM clustering process is explained in part A. the automatic level set is expressed in part B. In part C, the extracted features are introduced and finally in part D and E the genetic algorithm and the generalized regression neural network are explained, respectively.

Figure 1. Proposed method.



A. Spatial FCM Clustering

The main idea of FCM clustering is to distribute data within the clusters in a way that the data within the same clusters are sufficiently similar and the data in different clusters are sufficiently different. In the standard FCM clustering, the center of each subclassv_i and membership function u_{ij} are computed from the (1) and (2)subject to condition (3)in order to optimize (4)[11].

$$v_i = \frac{\sum_{j=1}^{n} u_{ij}^{m} x_j}{\sum_{j=1}^{n} u_{ij}^{m}} \qquad (1)$$

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\| x_j - v_i \|^2}{\| x_k - v_i \|^2} \right)^{\frac{2}{m-1}}} \qquad (2)$$

$$\sum_{i=1}^{c} u_{ij} = 1 , \ \forall j = 1, \ldots n \qquad (3)$$

$$J = \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{m} d_{ij}^{2} = \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{m} \| x_j - v_i \|^2 \qquad (4)$$

where x_i is the specific image pixel, u_{ij} represents the membership of the j[th] pixel to the i[th] cluster, v_i is the centroid of i[th] cluster, $\|.\|$ denote a norm metric, and m is a parameter that controls the fuzziness of the obtained segmentation results. In this paper, SFCM is used in order to perform the initial segmentation and to set the initial contour of the automatic level set. In SFCM, unlike FCM, the spatial information is used for membership function computation as

$$h_{ij} = \sum_{k \in NB(x_j)} u_{ik} \qquad (5)$$

where NB(x_j) is a square window 5×5 in the spatial domain with x_j as center. h_{ij} also shows the membership of the j[th]data in the i[th] cluster v_i.If a large number of neighbors of a pixel belongs to one cluster, the spatial function of that pixel will be larger. Finally, the spatial function is used to compute the membership function as[13]

$$u_{ij} = \frac{u_{ij}^{p} h_{ij}^{q}}{\sum_{k=1}^{c} u_{kj}^{p} h_{kj}^{q}} \qquad (6)$$

where p and q are the parameters that control the importance of u and h, respectively.

B. LevelSet

The automatic level set method, whose controlling parameter values are optimized, is used for final brain MRI segmentation. Level set starts with a closed boundary (initial contour) and deformsstep by stepwith operations such as shrinking and expanding, according to the image restrictions. The level set is defined by Lipschitzfunction $\phi(x, y): \Omega \to R$ on an image, where $\phi(x, y)$ is called the level set function and is defined by the Γ boundary as

$$\begin{cases} \phi(t, x, y) < 0 & (x, y) \text{ is inside } \Gamma(t) \\ \phi(t, x, y) = 0 & (x, y) \text{ is at } \Gamma(t) \\ \phi(t, x, y) > 0 & (x, y) \text{ is outside } \Gamma(t) \end{cases}. \qquad (7)$$

On the other hand, $\Gamma(t)$ ischaracterized by a particular level which is usually the zero level of the function $\phi(t, x, y)$ at time t. In general, $\Gamma(t)$ evolves according to the following *nonlinear partial differential* (PDE) equation

$$\begin{cases} \dfrac{\partial \phi}{\partial t} + F\,|\nabla \phi| = 0 \\ \phi(0, x, y) = \phi_0(x, y) \end{cases}. \qquad (8)$$

In the standard level set, the initial contour (ϕ_0) is determined by the user. In addition, that method has some disadvantages. For example, since the standard level set function converts the two-

dimensional segmentation to three-dimensional, the computational complexity is increased. Also, because of the periodically re-initialization of the level set function, during evolution, the speed of this method is low.Here, a variationallevel set formulation is used in which by eliminating re-initialization procedure the speed of the algorithm is increased. Evolution equation of the level set is [17]

$$\frac{\partial \phi}{\partial t} = \mu\zeta(\phi) + \xi(\mathrm{g}, \phi) \qquad (9)$$

wherethe first term $\zeta(\phi)$ is called the penalty term which keeps the level set function close to the signed distance function and prevents its deviation

$$\zeta(\phi) = \Delta\phi - div\left(\frac{\nabla\phi}{|\nabla\phi|}\right). \qquad (10)$$

The second term $\xi(\mathrm{g}, \phi)$, like standard level set method,attract ϕ towards the variationalboundary

$$\xi(\mathrm{g}, \phi) = \lambda\delta(\phi) div\left(\mathrm{g}\frac{\nabla\phi}{|\nabla\phi|}\right) + \upsilon \mathrm{g}\delta(\phi) \qquad (11)$$

where g isthe edge detection function that stopsthe level set evolution near the optimal solution. Itis defined as

$$\mathrm{g} = \frac{1}{1 + |\nabla(G_\sigma * I)|^2}. \qquad (12)$$

In theproposed method, user interaction for determination of the initial contour of the level set is eliminated and it is determine by SFCM method which has been explained in the previous part.Therefore, ϕ_0 is initialized by

$$\phi_0(x, y) = -4\varepsilon(0.5 - B_k),\ B_k = R_k \geq b_0,\ b_0 \grave{o} (0,1) \qquad (13)$$

where R_k is the image, resulted from SFCM method, and ε is a constant regulating the Dirac function that is defined as

$$\delta_\varepsilon(x) = \begin{cases} 0, & |x| > \varepsilon \\ \frac{1}{2\varepsilon}\left[1 + cos\left(\frac{\pi x}{\varepsilon}\right)\right], & |x| \leq \varepsilon \end{cases}. \qquad (14)$$

Therefore, the level set function starts from an arbitrary binary region

$$\phi_0(x, y) = \begin{cases} C, & \phi_0(x, y) < 0 \\ -C, & otherwise \end{cases}. \qquad (15)$$

Finally, the evolution of the level set is

$$\phi^{k+1}(x, y) = \phi^k(x, y) + \tau\left[\mu\zeta\left(\phi^k\right) + \xi\left(\mathrm{g}, \phi^k\right)\right] \qquad (16)$$

There are some controlling parameters in(16)that are shown in Table I.

TABLE I. AUTOMATIC LEVEL SET CONTROLLING PARAMETERS

parameter	***Significance***
σ	Controlling the spread of gaussian smoothing function
C	Controlling the gradient strength of initial level set function
ε	Regulating for dirac function
μ	Weighting coefficient of the penalty term
λ	Coeffecient of the contour length for smoothness regulation
ν	Artificial ballon force
τ	Time step of level set evolution
b_0	Threshold for convert fuzzy to crisp

The final segmentation results strongly depend on these parameter values. The method for optimally adjusting these controlling parameters is shown in Figure I. The exact and optimal values of the level set controlling parameters are obtained by the generalized regression neural network. This network has been trained in the first phase by applying the extracted features of the images as the input and the optimal values of controlling parameters as the output, which is obtained by the genetic algorithm.

C. Feature Extraction

In the proposed method extracted features are as the input of neural network. These are divided in 3 categories:

- Pixel value measurements features.
- Shape measurements feature.
- Zernike features.

The used pixel and shape features are mentioned in Table II.

TABLE II. PIXEL AND SHAPE MEASUREMENT FEATURES

Shape measurement features	Pixel value measurement features
Area	Max intensity
Centroid	Min intensity
Bounding box	Mean intensity
Major axis length	-
Minor axis length	-
Eccentricity	-
Orientation	-
Convex area	-
Filled area	-
Euler number	-
Equive diameter	-
Solidity	-
Extent	-
Perimeter	

For Zernike feature extraction, the radial polynomials, Zernike basis function and finally Zernike moments are computed[18]. For image with $N \times N$ size, the discrete form of the Zernike moments is expressed as

$$Z_{n,m} = \frac{n+1}{\lambda_N} \cdot \sum_{c=0}^{N-1} \sum_{r=0}^{N-1} f(x,y) V^{*}_{n,m}(x,y) \qquad (17)$$

where n is the order of the radial polynomial and m is the repetition of the azimuthal angle to satisfy the following constraints

$$\begin{cases} n \geq 0 \\ |m| \leq n \\ n - |m| = 2k \end{cases} . \qquad (18)$$

In this work the following Zernike moments are used

$$\{Z_{n,m} \mid n = m \quad , 1 \leq n \leq 20\} . \qquad (19)$$

More details on computing Zernike moments can be found in[18], [19].

D. Genetic Algorithm

The *genetic algorithm* (GA) belongs to a class of population-basedstochastic algorithms that are inspired from principles of natural evolution known as evolutionary algorithms. GA is based on the principles of "survival of fittest", as in the natural phenomena of genetic inheritance and Darwinian strife for survival. It was first introduced by john Holland in[20]. In the proposed method, GA has been used in the first phase to find the optimal values of the ALS controlling parameters. GA works with a population of chromosomes (individuals or solutions). Each chromosome has 8 gens, containing real numbers, which show different controlling parameters.

First, the initial population (called the first generation) of 30 chromosomes are randomly produced. In each generation, two different parents are selected, by roulette wheel selection method, from the current population to swap information between them to generate two new offspring by crossover operation as

$$c1 = b \times p1 + (1-b) \times p2$$
$$c2 = (1-b) \times p1 + b \times p2 \qquad (20)$$

where p1 and p2 vectors are two parent's chromosome and b is a random number between 0 and 1.

The idea behind the roulette wheel selection method is that the individuals with higher fitness have more probability of selection. So a fitness function is defined to compute the fitness value.Fitness function computes the ALS segmentation accuracy for each chromosome.

Then, the mutation is applied. In order to perform the mutation operator the new child is produced quite randomly from the search space. Rudolph in [21] proved that in a genetic algorithm, in each production of the new generation if the best chromosome (expert person) of the previous generation transfers to the new generation the algorithm will be converged. Therefore, in GA some chromosomes are transferred to the next generation, which its rate is 0.5. The crossover rate is 0.85 and the mutation rate is 0.1.

E. Generalized regression neural network

Nowadays computational intelligence such as neural network, inspired from the human's brain,has an important rule to solve the problems in different fields. *Radial basis function* (RBF) neural network is the special kind of neural networks which creates mapping from the input space to the output space. The *generalized regression neural network* (GRNN) is an enhance of the RBF neural network which differs from it at the third layer as shown in Figure 2. GRNN is a third layer neural network, based on nonlinear regression theory that is able to estimate the nonlinear functions. GRNN is less sensitive with respect to the unstable inputs and it can be trained more quickly. GRNN has an input layer, a radial basis, and a special linear layer, in which the number of neurons of the radial basis layer is equal to the input size.

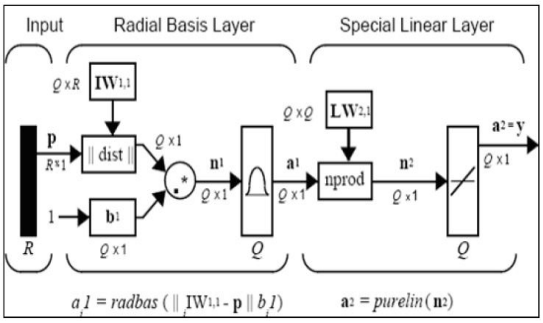


Figure 2. GRNN structure.

In GRNN the radial basis function related to the i^{th} neuron in the radial basis layer is computed by

$$G_i = \exp\left(\frac{\gamma X - X_i^2}{\sigma^2}\right) \qquad (21)$$

where $\|.\|$ is the Euclidean norm metric, σis the spread rate of the radial basis function (is chosen 0.5), X_i is the ith learning pattern vector, and γis the constant coefficient equals to 0.5.

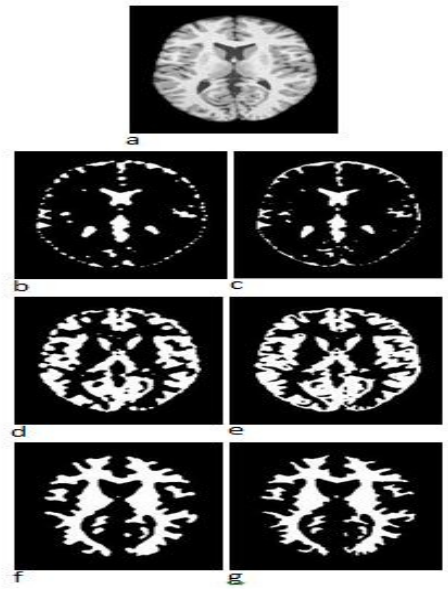


Figure 3. Segmentation results: a) main brain MRI, b) CSF tissue, Lee algorithm, c)CSF tissue, poposed method, d)GM tissue, Lee algorithm, e)GM tissue, poposed method, f)WM tissue, Lee algorithm, g)WM tissue, poposed method.

3. EXPERIMENTAL RESULTS

The Brain Web MRI database is used to evaluate the performance of the proposed algorithm. The method has been implemented by MATLAB software.Database contains 270 MRI which are randomly divided in a way that 70% of images are used in the first phase in order to establish the neural network and 30% of images are used in the second phase in order to evaluate the proposed method.The method is compared with Lee *et al.* method[4]. Three criterions including accuracy, specificity, and sensitivity areused for evaluation purposes as [22]

$$Accuracy = (TP + TN) / (TP + TN + FP + FN) \quad (1.1)$$

$$Specificity = TN / (TN + FP) \quad (1.2)$$

$$Sensitivity = TP / (TP + FN). \quad (1.3)$$

The obtained results are shown in Table III. As it is clear from this table, the proposed algorithm has a better efficiency compared to the automatic level set Lee *et al.*

TABLE III. EVALUATION OF METHODS

Algorithm	Criteria		
	Accuracy	***Specificity***	***Sensitivity***
Our method	97.03	98.24	87.94
Lee method	95.66	97.47	82.20

4. CONCLUSION

Automatic level set method is a powerful and quick method for brain tissue segmentation. Since the segmentation accuracy in this method strongly depends on the ALS controlling parameters, a new algorithm is presented to choose the best values. The proposed method contained two phases. In the first phase, the genetic optimization algorithm was used to find the optimal values of controlling parameters and GRNN was used to learn them. In the second phase, image features were extracted and applied to the neural network yielded from the first phase. Level set was implemented by the extracted values of controlling parameters from neural network. Experimental results showed that automatic level set, whose controlling parameters have been accurately adjusted had better performance. Therefore, the proposed level set not only retained the speed but also extracted the brain tissues more accurately.

In the future work, our goal is to use other optimization and classification algorithms in order to find optimal values of controlling parameters to yield a higher accuracy for brain tissue segmentation.

REFERENCES

[1] D. L. Pham, C. Xu, and J. L. Prince, “Current methods in medical image segmentation 1,” Annu. Rev. Biomed. Eng., vol. 2, no. 1, pp. 315–337, 2000.

[2] A. W.-C. Liew and H. Yan, “Current methods in the automatic tissue segmentation of 3D magnetic resonance brain images,” Curr. Med. Imaging Rev., vol. 2, no. 1, pp. 91–103, 2006.

[3] M. A. Balafar, A. R. Ramli, M. I. Saripan, and S. Mashohor, “Review of brain MRI image segmentation methods,” Artif. Intell. Rev., vol. 33, no. 3, pp. 261–274, 2010.

[4] B. N. Li, C. K. Chui, S. Chang, and S. H. Ong, “Integrating spatial fuzzy clustering with level set methods for automated medical image segmentation,” Comput. Biol. Med., vol. 41, no. 1, pp. 1–10, 2011.

[5] K. Levinski, A. Sourin, and V. Zagorodnov, “Interactive surface-guided segmentation of brain MRI data,” Comput. Biol. Med., vol. 39, no. 12, pp. 1153–1160, 2009.

[6] K. C.-R. Lin, M.-S. Yang, H.-C. Liu, J.-F. Lirng, and P.-N. Wang, “Generalized Kohonen’s competitive learning algorithms for ophthalmological MR image segmentation,” Magn. Reson. Imaging, vol. 21, no. 8, pp. 863–870, 2003.

[7] S. Shen, W. Sandham, M. Granat, and A. Sterr, “MRI fuzzy segmentation of brain tissue using neighborhood attraction with neural-network optimization,” Inf. Technol. Biomed. IEEE Trans. On, vol. 9, no. 3, pp. 459–467, 2005.

[8] M.-S. Yang, Y.-J. Hu, K. C.-R. Lin, and C. C.-L. Lin, “Segmentation techniques for tissue differentiation in MRI of ophthalmology using fuzzy clustering algorithms,” Magn. Reson. Imaging, vol. 20, no. 2, pp. 173–179, 2002.

[9] D.-Q. Zhang and S.-C. Chen, “A novel kernelized fuzzy c-means algorithm with application in medical image segmentation,” Artif. Intell. Med., vol. 32, no. 1, pp. 37–50, 2004.

[10] J. C. Bezdek, Pattern recognition with fuzzy objective function algorithms. Kluwer Academic Publishers, 1981.

[11] H. Yousefi-Banaem, S. Kermani, O. Sarrafzadeh, and D. Khodadad, "An improved spatial FCM algorithm for cardiac image segmentation," in Fuzzy Systems (IFSC), 2013 13th Iranian Conference on, 2013, pp. 1–4.
[12] W. Cai, S. Chen, and D. Zhang, "Fast and robust fuzzy c-means clustering algorithms incorporating local information for image segmentation," Pattern Recognit., vol. 40, no. 3, pp. 825–838, 2007.
[13] K.-S. Chuang, H.-L. Tzeng, S. Chen, J. Wu, and T.-J. Chen, "Fuzzy c-means clustering with spatial information for image segmentation," Comput. Med. Imaging Graph., vol. 30, no. 1, pp. 9–15, 2006.
[14] S. Osher and J. A. Sethian, "Fronts propagating with curvature-dependent speed: algorithms based on Hamilton-Jacobi formulations," J. Comput. Phys., vol. 79, no. 1, pp. 12–49, 1988.
[15] B. N. Li, C. K. Chui, S. H. Ong, and S. Chang, "Integrating FCM and level sets for liver tumor segmentation," in 13th International Conference on Biomedical Engineering, 2009, pp. 202–205.
[16] N. Paragios, "A level set approach for shape-driven segmentation and tracking of the left ventricle," Med. Imaging IEEE Trans. On, vol. 22, no. 6, pp. 773–776, 2003.
[17] C. Li, C. Xu, C. Gui, and M. D. Fox, "Level set evolution without re-initialization: a new variational formulation," in Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on, 2005, vol. 1, pp. 430–436.
[18] A. Tahmasbi, F. Saki, H. Aghapanah, and S. B. Shokouhi, "A novel breast mass diagnosis system based on Zernike moments as shape and density descriptors," in Biomedical Engineering (ICBME), 2011 18th Iranian Conference of, 2011, pp. 100–104.
[19] A. Tahmasbi, F. Saki, and S. B. Shokouhi, "Classification of benign and malignant masses based on Zernike moments," Comput. Biol. Med., vol. 41, no. 8, pp. 726–735, 2011.
[20] J. H. Holland, Adaptation in natural and artificial systems: An introductory analysis with applications to biology, control, and artificial intelligence. U Michigan Press, 1975.
[21] G. Rudolph, "Convergence analysis of canonical genetic algorithms," Neural Netw. IEEE Trans. On, vol. 5, no. 1, pp. 96–101, 1994.
[22] M. Jafari and S. Kasaei, "Automatic Brain Tissue Detection in Mri Images Using Seeded Region Growing Segmentation and Neural Network Classification.," J. Appl. Sci. Res., vol. 7, no. 8, 2011.