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ROI DETECTION AND SEGMENTATION OF MEDICAL IMAGES USING OPTIMIZED THRESHOLDING AND CLUSTERING

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ABSTRACT

Image thresholding is one of the segmentation methods to isolate Regions of Interest from the images. Maximum entropy is an image thresholding method that exploits entropy of the distribution in gray level of the image. Clustering can also be applied as an image segmentation method to group pixels based on their intensity which in turn help to identify objects of interest from the image. Fuzzy clustering has been widely applied for recognition of patterns but has the shortcomings like ability to detect a data with same super spherical shapes, sensitive to initialization and convergence into local optima. Similarly, Ostu method is a simple and time saving technique but gives improper results on the noisy images and not able to detect ROIs when much intensity deviation among pixels is detected. But these limitations can be reduced when applied with optimization techniques like PSO and QPSO. This paper discusses Maximum Entropy, Fuzzy C-Means, Ostu, MEPSO, MEQPSO, FCMPSO, FCMQPSO, OstuPSO and OstuQPSO to segment images and to find the objects of interests from the images. The experimental section of this paper shows visual validation of these techniques and its performances.

KEYWORDS: PSO, QPSO, Fuzzy C-Means, Maximum Entropy and Ostu

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INTRODUCTION

Thresholding is a simplest method of image segmentation, segments a gray image into binary image based on threshold value and it has been classified into six groups such as histogram shape methods, clustering based methods, entropy based methods ,object attribute, spatial and local methods. Clustering based methods have been generally categorized into hierarchical and partitional clustering. Hierarchical Clustering starts with a point being considered as a cluster and subsequently updating other points to the center by calculating distances and this process will be continued until all points are part of one hierarchically constructed cluster. Partitional clustering, on the other hand, performs a partition of patterns into K number of clusters, such that patterns in a cluster are more similar to each other than to patterns in different clusters. FCM is an iterative algorithm which produces partitions or clusters by minimizing sum of squared error and was developed by Dunn in 1973 [1] and modified in 1981 by Bezdek [2]. FCM as a pixel clustering method provides information better than hard clustering methods. It has been widely applied to image segmentation [3,4,5] where each data element belong to multiple clusters with reasonable degrees of membership grades which lies in the interval [0,1] and does not require any prior information about the elements in the dataset. FCM with GA and PSO[6] has been proposed to identify tumors from MRI brain image. Similarly, partitional clustering, K-means followed by Support Vector Image (SVM) proposed to study the statistical features of ROI from the mammogram [7] . A combined algorithm QPSO with Maximum Entropy demonstrated on vehicle brand images [8] and outline that QPSO improves global search ability. PSO perform well in high dimensional and mixed attribute datasets with good accuracy and the potential of PSO has been discussed in [9]. The eminent property of fuzzy clustering, allow data points to belong to more than one group, influences gene clustering [10] where a semi supervised Fuzzy clustering has been applied to know the functioning and cooperation of genes. A neuro fuzzy logic approach is applied to detect and recognize different types of brain cancer[11]. After a rich survey on PSO and QPSO, the objective function of Maximum Entropy, Fuzzy C-Means and variance between classes (Ostu) have been optimized with PSO and QPSO to find optimal threshold.For Simplicity, the terms, Maximum Entropy, Fuzzy C-means, Particle Swarm Optimization and Quantum Particle Swarm Optimization have been referred as ME,FCM,PSO and QPSO respectively. Threshold is selected by analyzing histogram of the image and a better threshold separates objects from the background with the knowledge of least square error. While in clustering, pixels representing foreground belong to one cluster and pixels representing background belong to different cluster. Generally, the average intensity of pixels is considered as a threshold.

MAXIMUM ENTROPY

Entropy based methods exploits the entropy on the distribution of gray levels, the maximum entropy being an indication of detecting objects of interest in the thresholded image. Threshold T lies in range ($0<T<L-1$, L=0, 1, 2….255) and the image is divided into two classes or two regions CO and CB based on T, where CO is the object region and CB is the background region. Shannon's entropy[12] is defined as in Eq.(1);

$$H = -\sum_{i=0}^{n} p_i \log(p_i) \qquad (1)$$

Where pi is the probability of occurrence of gray value i. The theory of maximum entropy is to select i which makes entropy as the maximum one. In order to arrive to the solution, we attempt to maximize the entropy to increase information gain. When the sum of two class entropies, the image foreground and the image background reaches its maximum then the image is said to be optimally thresholded and it is defined as in Eq.(2);

$$T_{opt} = \arg\max[H_f(T) + H_b(T)] \quad (2)$$

$$H_F(T) = -\sum_{g=0}^{T-1} \frac{p_g}{P_F} \log \frac{p_g}{P_F} \quad (3)$$

and

$$H_B(T) = -\sum_{g=T+1}^{255} \frac{p_g}{P_B} \log \frac{p_g}{P_B} \quad (4)$$

$$\text{Fitness} = H(t) = H_F(t) + H_B(T) \quad (5)$$

Solving, Eqn(2) with PSO and QPSO elaborated in next sections.

MAXIMUM ENTROPY AND PSO

Particle Swarm Optimization (PSO) is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995[13], inspired by social behavior of bird flocking or fish schooling. Intelligent optimization algorithms have been proved themselves as an effective tool to find optimal results. The system is initialized with a population of random solutions and searches for optima by updating generations. In PSO, the potential solutions, called particles, searches the whole space guided by its personal best position (pbest) and best position of the swarm (gbest). The velocity and position of the particles are updated based on their best experiences. During particles movement, every visited point will be evaluated by fitness function. And those points with highest fitness are assigned as the best positions. Then, the particles keep moving around until some stopping conditions are met. The i^{th} particle of swarm is represented as $X_i = (X_{i1}, X_{i2}, \ldots, X_{iD})$ while the velocity for i^{th} particle is represented as $V_i = (V_{i1}, V_{i2}, \ldots, V_{iD})$. The best previous position (the position giving the best fitness value) of the i^{th} particle is recorded and represented as $P_i = (P_{i1}, P_{i2}, \ldots, P_{iD})$. At each step, the particles are manipulated according to the following equations (6) and (7):

$$V'_{id} = \omega V_{id} + c_1 rand()(P_{id} - X_{id}) + c_2 rand()(P_{gd} - X_{id}) \quad (6)$$

ω represents the inertia weight to control the speed of each generation of particles, V_{id} is the velocity of i^{th} particle in dimension d. P_{id} is the best position achieved by particle i, P_{gd} is the best positions found by neighbors of particle i and c1,c2 are two positive constants known as cognitive and social components.

$$X'_{id} = X_{id} + V'_{id} \quad (7)$$

The image matrix is projected into a two dimensional feature space, PSO is applied to search over this 2D space and then convergence to global optima is monitored to extract object features. The pseudo code of PSOME is presented below;

Procedure 1

1. Generate random population of N solutions(particles);
2. For(i=0;i<popsize;i++)
3. Evaluate fitness f(X[i]) as in eqn (2);
4. Initialize the value of weight factor, ω;
5. while (termination condition is not true)
6. for(i=0;i<popsize;i++)
7. if(f(X[i])>$pbest_i$) $pbest_i$=X[i];
8. Update gbest;
9. Update(Position X[i], Velocity V[i]);
10. Evaluate f(X[i]);
11. End for Endwhile
12. If gbest(global best position)<X[i] Tseg=1; else Tseg=0;
13. Endif

The population size of particles refers the number of particles involved in obtaining solution at each iteration.

MAXIMUM ENTROPY AND QPSO

QPSO is a co-variant of popular PSO, where population of particles is depicted by a quantum behavior. Quantum theory in PSO was induced and a novel algorithm called QPSO was proposed in 2004[14][15]. Unlike PSO, QPSO needs no velocity vectors for particles and has fewer parameters to adjust[16]. It has been developed and implemented successfully in many areas such as image segmentation, clustering, pattern identification, classification etc[17]. The QPSO algorithm permits all particles to have quantum behavior and it outperforms traditional PSO and GA in terms of training speed and convergence to local minimum [18]. QPSO can be combined with thresholding methods such as 2D maximum entropy, 2D Ostu and multilevel cross entropy. In case of 2D entropy optimal solution is searched after retrieving the histogram of image. In QPSO, the state of particle is depicted by wave function $\Psi(x,t)$ instead of position and velocity. The probability of particles appearing in a certain position is obtained from the probability density function $|\Psi(x,t)|^2$ and the particle changes its position according to Eq.(8).

$$x(t+1) = p \pm \beta |mbest - x(t)| * \ln(1/u) \qquad (8)$$

Where β is the contraction expansion coefficient to control convergence speed of algorithms.

$$p = (c_1 p_{id} + c_2 p_{gd}) / (c_1 + c_2) \qquad (9)$$

Or

$$p = rand(0,1) * p_{id} + (1 - rand(0,1)) * p_{gd} \qquad (10)$$

And

$$mbest = (1/M \sum_{i=1}^{M} P_{i1}, 1/M \sum_{i=1}^{M} P_{i2}, ..., 1/M \sum_{i=1}^{M} P_{iD}) \qquad (11)$$

Where M is the population size, P_i is the pbest positions of particles and mbest is the mean of pbest positions of particles.The procedure of QPSO is given below;

Procedure 2

Initialize the population size, the positions X[i], dimensions and set P[i]=X[i];
For t= 1 to Maximum Iteration T
Compute mean best position mbest by Eq. (11);
For i = 1 to PopulationSize M
If $f(X_i)<f(P_i)$ then P[i]=X[i]; Endif;
P_g=min(f(P[i]));
For j = 1 to dimension D
Updateparticles positions $p[i][j] = rand(0,1) * P[i][j] + (1 - rand(0,1)) * P[g][j]$
if (rand(0,1)>0.5)
$X[i][j] = p[i][j] - \beta * abs(m[j] - X[i][j]) * \ln(1/u)$
Else
$X[i][j] = p[i][j] + \beta * abs(m[j] - X[i][j]) * \ln(1/u)$
Endfor j;
Endfori;
Endfor t;

QPSO has less parameters and is robust than classical PSO. Let $I=[q(x,y)]_{MXN}$ denote an image contains MxN pixels with a value of gray level ranges from 0 to 255. Each pixel in an image considered as a particle and its positions are q(x,y) , xϵ{1,2..M} and yϵ {1,2..N}. The current position of the particle is $X_i=\{x_{i1},x_{i2}..x_{id}\}$, i=1,2..MxN and D is the dimensions of the search space. And P_i is the personal best positions of particles $P_i=\{p_{i1},p_{i2}\ldots p_{id}\}$ and $P_g=\{p_{g1},p_{g2}\ldots p_{gd}\}$ the best position in the neighborhood of the particle. The optimal threshold T_{opt}, which is a gray-level value, is the food source attracting particles. In this work, the dimension of particle is considered as two, the numbers of the particle as fifteen (N=15). Each particle refers to a potential solution. The initial position of the particle is X[i], where X[i]=255*rand(1,15). Here, the generalized maximum entropy provided in Eq. (5) used as fitness function and the contraction coefficient is calculated for the T^{th} iteration as

$$\beta=(0.5)*(MAXITER-T)/MAXITER+0.5 \qquad (12)$$

The segmented image I_{seg}=

$$I_{seg} = \begin{cases} 0, & q(x,y) \le T_{opt} \\ 1, & q(x,y) > T_{opt} \end{cases} \qquad (13)$$

FCMPSO AND FCMQPSO

The FCM algorithm attempts to partition a finite collection of n elements $X=\{x_1,x_2\ldots x_n\}$ into a collection of C fuzzy clusters with respect to some given criterion and it returns list of cluster centers $C=\{c_1\ldots c_c\}$ and partition matrix U= $u_{ij} \in [0,1]$ where i=1,2..c and j=1,2..n where each element u_{ij} tell us the degree to which each element x_i belongs to c_j. The objective function of FCM is given in Eq.14 . The algorithm takes number of clusters c, the assumption partition matrix U contains values from 0 to 1 and the convergence value E as input. Thus, the objective function of FCM given in Eq. (14) is minimized when high membership values are assigned to pixels whose intensities are nearer to the centroid of particular cluster, and low membership values are assigned for the pixels whose intensities are far from centroid point.

$$\min J_{FCM}=\sum_{i=1}^{c}\sum_{j=1}^{n}\mu_{ij}^{m}d_{ij}^{2}=\sum_{i=1}^{c}\sum_{j=1}^{n}\mu_{ij}^{m}\| x_j - a_i \|^2 \qquad (14)$$

Is the membership degree of data object in cluster , where c is the number of clusters, m is the fuzzy index(m>1) which controls the fuzziness of the method.

$$a_i^{(k)} = \frac{\sum_{j=1}^{n}\left[\mu_{ij}^{(k-1)}\right]^m x_j}{\sum_{j=1}^{n}\left[\mu_{ij}^{(k-1)}\right]^m}; i = 1, 2 \ldots c \qquad (15)$$

$$\mu_{ij}^{(k)} = \left[\sum_{l=1}^{c}\left[\frac{\left[(x_j - a_i^{(k)})'(x_j - a_i^{(k)})\right]}{\left[(x_j - a_l^{(k)})'(x_j - a_l^{(k)})\right]}\right]^{1/m}\right]^{-1} \qquad (16)$$

Finally fitness function is given as

$$F = \frac{1}{J_{FCM} + 1} \qquad (17)$$

Procedure 1: FCM

(1) Set clustering number , fuzzy factor m>1,ε>0 and initialize U=[u_{ij}]
(2) Update the cluster center and membership using Eq. 15 &16 respectively.
(3) Repeat step (2), until $|J_{FCM}(t) - J_{FCM}(t-1)| \le \varepsilon$ where ε is a predefined positive number.

FCMPSO is an optimization and hybrid technique combining PSO and FCM, the Fitness function of Eq (17) is optimized according to Procedure 1 whereas in FCMQPSO , Eq(17) is optimized by Procedure 2. The Parameters set for these two methods are given in Table 1.

Ostu PSO AND OstuQPSO

Ostu is a non parametric and simple method of finding threshold of an image[19] . Let the total number of pixels are *N* with gray levels ranges from 0 to L , the probability $p_i = \frac{n_i}{N}$, where n_i is the occurrence of gray level i.

$$f_{max} = \sum_{m=0}^{k-1}\sum_{n=m+1}^{k}\omega_m\omega_n(\mu_m - \mu_n)^2 \qquad (18)$$

$$\omega_{n-1} = \sum_{i=t_{n-1}+1}^{t_n} p_i \qquad (19)$$

$$\mu_{n-1} = \sum_{i=t_{n-1}+1}^{t_n} \frac{i * p_i}{\omega_{n-1}} \quad ,1 \le n \le (k+1) \qquad (20)$$

Where k is the number of number classes
The objective function of Eq.(18) is optimized by Procedure 1 (PSO) and Procedure 2(QPSO).

EXPERIMENTAL RESULTS

The methods discussed in this paper tested on MRI images shown in Figure 1.a,Figure 2.a,Figure 3.a and Figure 4.a. The images shown in Figure 1 and figure 2 have abnormalities represented with arrow and MEPSO,MEQPSO,FCM,FCMPSO,FCMQPSO, OSTY,OstuPSO and OstuQPSO have been applied to isolate the pixels representing desired region of interest . The same methods are executed in the blood cell image shown in Figure 3.a and prostate cancer cell image of Figure 4.a. The processing results of Figure 3.a are shown in figures 3.b to 3.k. while Figures from 4.b to 4. k show the execution results proposed methods on figure 4.a. The various parameters set for these methods are given in Table 1 where fuzziness index is set to 2 for FCM based methods and parameter values of PSO are set as c1=c2=2, wmax=0.9;wmin=0.4,population size =30 and Maximum number of iterations =100. The same number of iterations is followed in all the algorithms and termination parameter is set as ε=0.001. The computation time and global best positions of QPSO based methods are mentioned in Table3 and Table 4 respectively.

Table 1
Parameters settings for FCM, FCMPSO, FCMQPSO, Maximum Entropy PSO, Maximum Entropy QPSO

Method	Parameters
MEPSO	c1=2;c2=2;wmax=0.9;wmin=0.4;popsize=20
MEQPSO	popsize=30;MAXITER=100;dimension=2;
FCM	M=2;MAXITER=100;K(Number of Classes)=3
FCMPSO	popsize=30;centroid=3;dimension=2;MAXITER=100 c1=2;c2=2;wmin=0.4;wmax=0.9;M=2
FCMQPSO	popsize=30;centroid=3;dimension=2;MAXITER=100; Beta=0.5;M=2

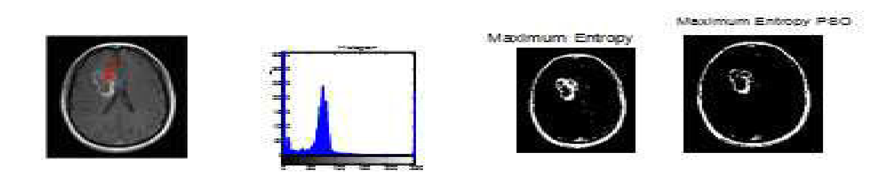
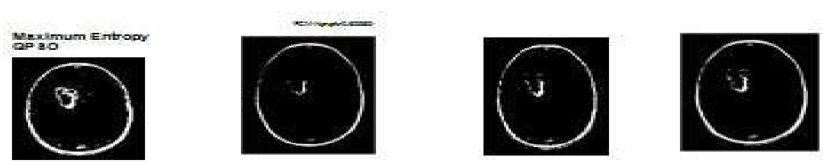


Figure 1.a. Original image   b. . Histogram   c. Maximum Entropy (threshold=92)   d. Segmentation results by PSOME (threshold=108)



e. Segmentation results by QPSOME (threshold=98   f. Fuzzy C Means   g.. FCMPSO (Classes=2)   h FCMQPSO (Classes=2)

i.Ostu (threshold=50)   j.Ostu PSO (threshold=85)   k.QPSOOstu (threshold=87)

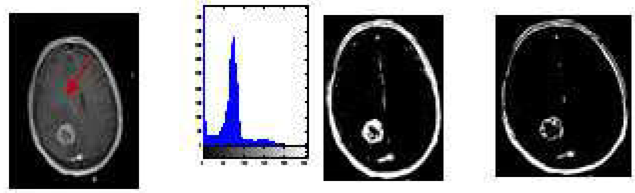
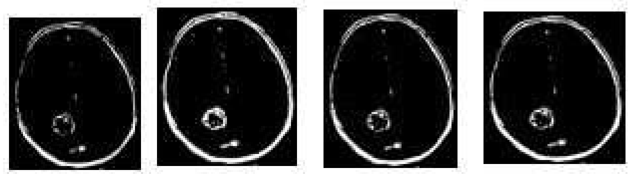
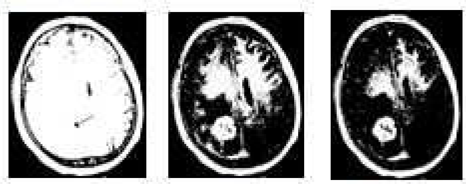


Figure 2.a.Original image | b.Histogram | c.Maximum Entropy (threshold 95) | d.Maximum Entropy PSO(threshold 131)



e. Maximum Entropy QPSO (threshold 135) | f. FCM | g. FCMPSO (classes=3) | h. FCMQPSO (classes=3)



i. Ostu (threshold=47) | j. Ostu PSO (threshold=75) | k. Ostu QPSO (threshold=80)

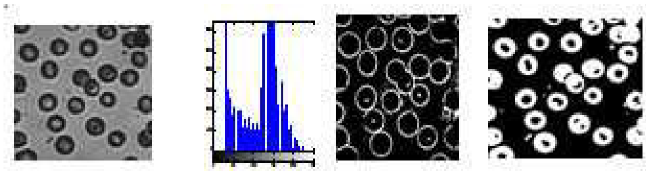
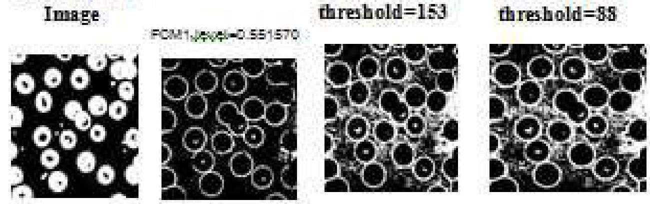
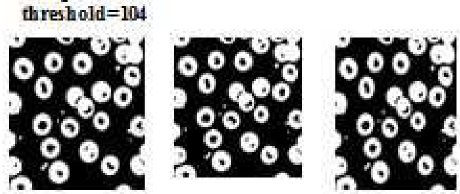


Figure 3.a Original Image | b. Histogram | c.Maximum Entropy threshold=153 | d.Maximum EntropyPSO threshold=88



e.Maximum Entropy QPSO threshold=104 | f.FCM | g. FCMPSO (classes=2) | h. FCMQPSO (classes=2)



i.Ostu (threshold=69) | j.Ostu PSO (threshold=92) | k.Ostu QPSO (threshold=90)

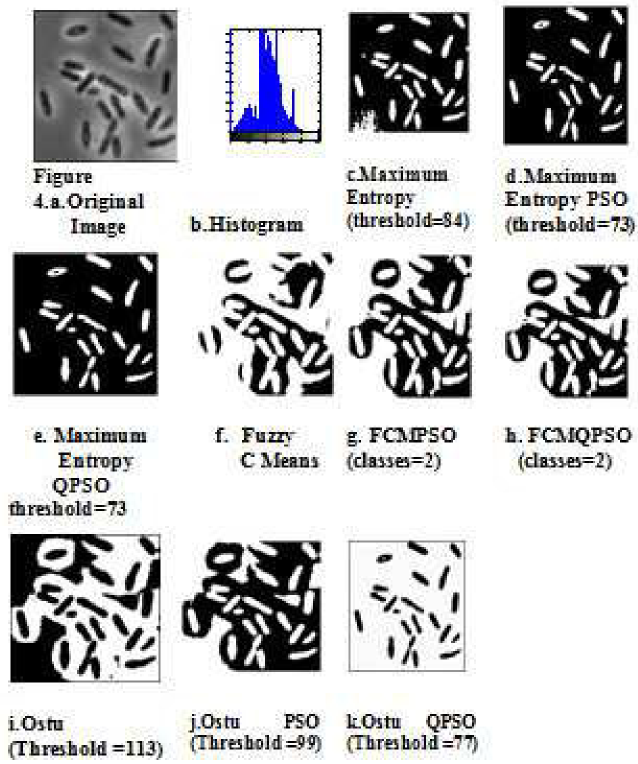


Figure 4.a. Original Image b. Histogram c. Maximum Entropy (threshold=84) d. Maximum Entropy PSO (threshold=73) e. Maximum Entropy QPSO threshold=73 f. Fuzzy C Means g. FCMPSO (classes=2) h. FCMQPSO (classes=2) i. Ostu (Threshold =113) j. Ostu PSO (Threshold =99) k. Ostu QPSO (Threshold =77)

Table 2
Global Best (GBest) positions obtained at iteration 100

Image	Ostu QPSO	FCM QPSO		ME QPSO
Figure 1.a	87	0.2894 0.0728 0.1002 0.3088	Classes=2	98
Figure 2.a	80	0.3654 0.2838 0.4155 0.2775 0.2800 0.0216 0.0239 0.3037 0.2565	Classes=3	135
Figure 3.a	90	0.3887 0.0890 0.3831 0.5063	Classes=2	104
Figure 4.a	77	0.4050 0.2915 0.4392 0.5598	Classes=2	73

Table 3
Computation Time(secs) of QPSO Ostu, QPSO FCM and QPSO ME

Image	Ostu QPSO	FCM QPSO	ME QPSO
Figure 1.a	0.48	35	3.81
Figure 2.a	0.5	90	3.74
Figure 3.a	0.46	22	3.71
Figure 4.a	0.47	15	1.1

CONCLUSION

This paper proposes intelligent optimization techniques to segment medical images and to find ROIs. The traditional thresholding methods such as FCM , Maximum Entropy and Ostu have been demonstrated and limitations are observed. Inorder to improve their performances, the objective functions of these methods are optimized using PSO and QPSO . QPSO based methods out performs PSO based methods in terms of accuracy,computation time and global convergence. Maximum Entropy and Ostu do not require prior information and are automatic thresholding methods but FCM takes number of classes as input and the computation time of FCM is higher than Maximum Entropy and Ostu. In future, we extend our work to test the applicability of proposed methods on gene expression analysis.

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