Particle Swarm Optimization on Follicles Segmentation to Support PCOS Detection

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***Abstract*— Polycystic Ovary Syndrome (PCOS) is the most common endocrine disorders affected to female in their reproductive cycle. PCO (Polycystic Ovaries) describes ovaries that contain many small cysts/follicles. This paper proposes an image clustering approach for follicles segmentation using Particle Swarm Optimization (PSO) with a new modified non-parametric fitness function. The new modified fitness function use Mean Structural Similarity Index (MSSIM) and Normalized Mean Square Error (NMSE) to produce more compact and convergent cluster. The proposed fitness function is compared to a non-parametric fitness function proposed by previous research. Experimental results show that the proposed PSO fitness function produce more convergent solution than previous fitness function especially on ultrasound images. This paper also investigates the influence of contrast enhancement to the performance of PSO image clustering and the extracted follicular size. The experimental result shows that PSO image clustering which preceded by contrast enhancement produce larger intra-cluster distance, intra-cluster distance and quantization error than PSO image clustering which not preceded by contrast enhancement. PSO with contrast enhancement produce closer Region of Interest (ROI) toward to the reference ROI which manually identified by doctor.**

Keywords—follicles; cysts; Particle Swarm Optimization; image clustering

I. INTRODUCTION

Currently, medical images in digital form are often used for medical records of patients in a hospital service (mobility) [2]. Polycystic Ovary Syndrome (PCOS) is a common endocrine system disorder among women of reproductive age which can be detected by diagnosis on ultrasound image [1]. The main features include chronic anovulation, hyperandrogenaemia, insulin resistance and the presence of enlarged ovaries containing numerous small follicles [18]. Historically, the detection of polycystic ovary required visualization of the ovaries at laparotomy and histological confirmation following biopsy [8]. In recent years, transabdominal and/or transvaginal ultrasound have become the most commonly used as diagnostic methods for the identification of polycystic ovary (PCO). Based on international consensus [3], the PCO should have at least one of the following: either 12 or more follicles measuring 2-9 mm in diameter or increased ovarian volume (>10 cm^3). If there is evidence of a dominant follicle (>10 mm) or a corpus luteum, the scan should be repeated during the next cycle.

In ultrasound assessment, the follicles on PCO images can be identified as dark region, the darker area than surrounding. Currently, it is detected manually by doctor vision. So it hard to distinguish follicles or other objects (such as intestine, blood vessels), since follicular size in ovary is very small. This paper proposes an automatic follicles detection to help doctor to identify the cysts and to reduce the burden of doctor diagnosis.

Image segmentation is a fundamental process in several image processing and computer vision applications. It can be considered as the first low-level processing step in image processing and pattern recognition [7]. Image segmentation is defined as the process of dividing as image into disjoint homogenous regions. These homogenous regions should represent objects or parts of them [10]. There are many techniques for image segmentation in the literature, such as thresholding, edge-based, region growing and clustering. Thresholding techniques using scanline for follicles segmentation have already implemented by Mehrotra *et al.* [14] and Rihana *et al.* [17], while Hiremath *et al.* [15] used edge based method for follicles detection. Maryruth *et al.* [12] also implemented region growing for follicles segementation. Other study conducted by Ashika Raj [6] implemented Fuzzy C-Means Clustering for ovarian follicle detection on PCOS.

In this paper, Particle Swarm Optimization (PSO) is used on clustering process for follicles segmentation. PSO for image clustering have already implemented by Omran [13], and Wong *et al.* [11]. Omran proposed two parametric fitness functions and onenon-parametric fitness function. Wong *et al.* proposed two new improved parametric fitness functions. The experimental result of their experiments showed that PSO can perform better than K-Means algorithm by generating more compact clusters and larger inter-cluster separation. Since PSO using a random method, the results are not completely the same in each run. So finding the convergent solution is the important work. This paper proposed a new modified non-parametric fitness function using MSSIM and MSE to produce more compact and convergent cluster especially on ultrasound images.

The rest of the paper is organized as follows. Section II explains the process of follicle detection and PSO algorithm. Section III describes our approach in PSO image clustering; the new modified fitness function also will be described in this

section. Section IV explains the experimental result. Conclusion and Future Work are provided in Section V and VI.

II. METHODOLOGY

Fig.1. illustrates the process of follicle detection proposed in this paper.

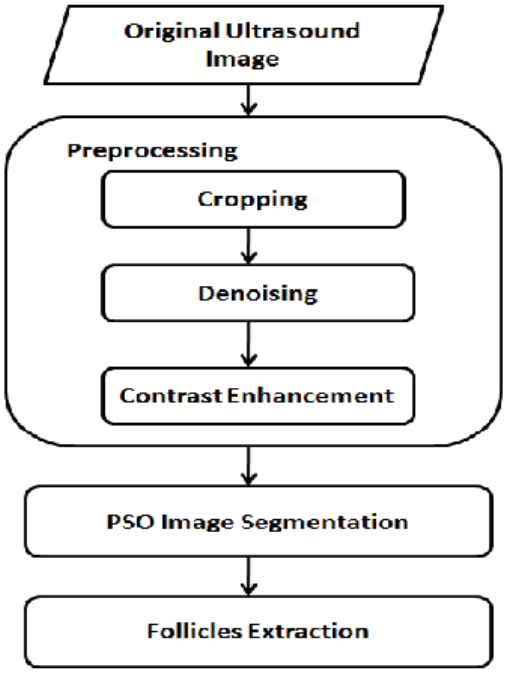

Fig. 1. Block diagram of Follicle Detection

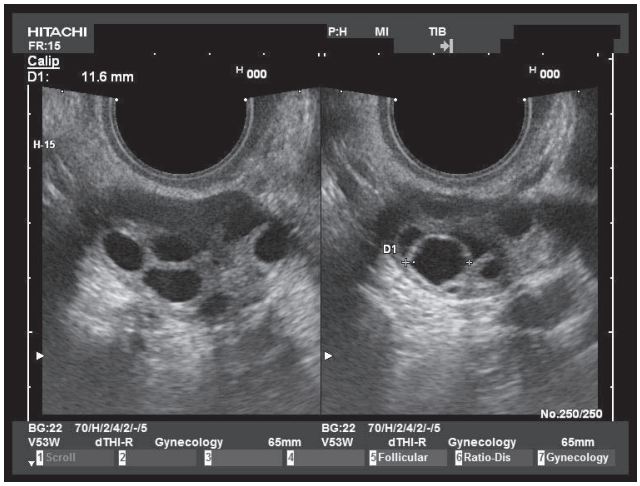

Fig. 2. Polycystic Ovary

A. Image Preprocessing

Image preprocessing is an important step to prepare the PCO ultrasound images before clustering algorithm applied. This paper used cropping, denoising and contrast enhancement in the preprocessing step.

- Cropping

  Since the PCO ultrasound images used in this paper consist of two ovaries that might be taken using different depth of probe, so it should be cropped into left and right ovary. The cropping process also can reduce unimportant area of the images.

- Denoising

  Common noises that affect digital images are Gaussian noise, Poisson noise, Salt and Pepper noise, but in ultrasound image a new type of noise occur, which called Speckle noise. Speckle noise is a multiplicative noise which difficult to remove. The speckle noise worsens the edges of image [16]. This paper use wavelet thresholding method for speckle noise denoising.

- Contrast Enhancement

  Contrast enhancement makes the dark area in the images more clear and distinct, it allows for areas of lower local contrast to gain a higher contrast. This paper use histogram equalization for the contrast enhancement, it accomplishes this by effectively spreading out the most frequent intensity values on the histogram.

B. Particle Swarm Optimization

Swarm Intelligence (SI) originated from the study of colonies, or swarms of social organisms. Studies of the social behavior of organisms (individuals) in swarms prompted the design of very efficient optimization and clustering algorithms. Particle Swarm Optimization (PSO) is an evolutionary computation technique developed by Kennedy and Eberhart in 1995 [9]. PSO is a stochastic optimization approach, modeled on the social behavior of birds flocks [5]. It is a population-based search procedure where the individuals, referred to as particles, are grouped into a swarm. Each particle in the swarm represents a candidate solution to the optimization problem.

Each particle has the following information in the problem space [5]:

- x_i , the position of the current particle
- v_i , particle velocity
- y_i, best position of the particle which has the best fitness value
- *Pbest* (personal best) position associated with particle *i* is the best position visited by particle so far. If denotes the fitness function, then the personal best position of the particle at time step t is denoted as:

$$y_i(t+1) = \begin{cases} y_i(t) iff\big(x_i(t+1)\big) \geq f(y_i(t)) \\ x_i(t+1) iff(x_i(t+1)) < f(y_i(t)) \end{cases} \quad (1)$$

There are two approaches for PSO, which is the local best (*lbest*) and global best (*gbest*) [5]. The difference is in the neighborhood topology used for the exchange of information among particles. For *gbest* models, the best particle is determined from the whole swarm. If the best position particle is denoted by vector $\hat{y}$, then :

$$\hat{y}(t) \in \{y_0, y_1, \dots, y_s\}$$
$$f(\hat{y}(t)) = \min\{f\big(y_0(t)\big), f\big(y_1(t)\big), \dots, f(y_s(t))\} \quad (2)$$

where s is the number of particle in the swarm

While in the *lbest* model, the population is divided into several particle populations overlap in the particle environment. For each neighbor N_j, best particle referred to as the best particle adjacency, which is defined as :

$$N_j = \{y_{i-l}(t), y_{i-l+1}(t), \dots, y_{i-1}(t), y_i(t), y_{i+1}(t), \dots, y_{i+l-1}(t), y_{i+1}(t)\} \quad (3)$$

$$\hat{y}_j(t+1) \in N_j | f\left(\hat{y}_j(t+1)\right) = \min\{f(y_i)\}, \forall y_i \in N_j \quad (4)$$

Adjacency is usually determined using particle index, although the topology adjacency also used. *Gbest* PSO is a special case of *lbest* when the environment is the entire population (*l*=*s*). If PSO *lbest* has a great diversity of the *gbest* PSO, the PSO *lbest* will be slower than the *gbest* PSO. Image clustering in this study use the *gbest* PSO model.

For each iteration on *gbest* PSO algorithm, v_i dan x_i updated as follow:

$$v_i(t+1) = \omega v_i(t) + c_1 r_1(t)(y_i(t) - x_i) + c_2 r_2(t)\left(\hat{y}(t) - x_i(t)\right) \quad (5)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (6)$$

where ω is inertia weight, c_1 and c_2 are constant velocity. The equation above consists of 3 components :

- Term of inertia, which is used to store the previous velocity. Inertia weight controls the influence of the previous velocity. Large inertia weight supports exploration, while small inertia weight supports exploitation.
- Cognitive component, $y_i(t) - x_i$, which represents the particle itself experiences where the direction of the best solution.
- Social component, $\hat{y}(t) - x_i(t)$, which represents the entire population beliefs in which way the best solution is.

PSO algorithm performs repetitive applications in updating the above equation to certain iteration is reached, or until the change in velocity is close to zero. Quality is measured by using a particle fitness function which reflects the optimization solution.

C. PSO Based Image Clustering

On Image clustering using PSO algorithm, there are some terms [11] :

- N_b : number of spectral band on image
- N_p : number of pixel image
- N_c : number of spectral class (defined by user)
- z_p : component N_b on pixel p
- m_j : mean cluster j

The most common performance measurement is error quantization [11], which is defined as:

$$J_c = \frac{\sum_{j=1}^{N_c}\left[\sum_{\forall z_p \in C_j} d(z_p, m_j)\right]/|C_j|}{N_c} \quad (7)$$

where :

$$d(z_p, m_j) = \sqrt{\sum_{k=1}^{N_b}(z_{pk} - m_{jk})^2} \quad (8)$$

In the image clustering context, a particle represent N_c mean cluster. That means x_i consist of $x_i = (m_{i1}, \dots, m_{ij}, \dots, m_{iN_c})$ where m_{ij} refers to *j*-th cluster centroid vector of *i*-th particle. So, swarm represents the number of candidate image clustering.

Omran *et al.* [13] introduced image clustering using *gbest* PSO algorithm, where the quality of each particle is measured by using a fitness function :

$$f(x_i, Z_i) = w_1 \bar{d}\max(Z_i, x_i) + w_2\left(z_{max} - d_{min}(x_i)\right) \quad (9)$$

where z_{max} is maximum value of pixel image (for example $z_{max} = 2^8 - 1$ for 8 bit image), Z_i is matrix represents location of particle i in the pixel cluster. Each element z_{ijp} indicates if pixel z_p locates on cluster C_{ij} particle *i*. Constant ω_1 dan ω_2 are user defined constant.

$\bar{d}\max(Z_i, x_i) = \max_{j=1,\dots,N_c}\{\sum_{\forall z_p \in C_{ij}} d(z_p, m_{ij})/|C_{ij}|\}$ is the average of maximum Euclidean distance of particle to the its associated class, and $d_{min}(x_i) = \min_{\forall j1, j2, j1 \neq j2}\{d(m_{ij1}, m_{ij2})\}$ is minimum Euclidean distance for each pair cluster. $|C_{ij}|$ on the equation above is cardinality of cluster set C_{ij}.

In this term, the fitness function has some simultaneous objectives:

- Minimized intra-distance between pixel and its cluster mean, which is calculated by $\bar{d}_{\max}(Z_i, x_i)$
- Maximized inter-distance among clusters, which is calculated by $d_{min}(x_i)$.

To improve the performance of PSO clustering, Omran *et al.* [13] modified the fitness function in equation 9 by using quantization error (*Je*) in equation 7.

$$f(x_i, Z_i) = w_1 \bar{d}_{\max}(Z_i, x_i) + w_2\left(z_{max} - d_{min}(x_i)\right) + w_3 J_e \quad (10)$$

Besides these two parametric fitness functions, Omran [13] also introduce a non-parametric fitness function, so the users do not need to define the weight for each term.

$$f(x_i, Z_i) = \frac{\bar{d}_{\max}(Z_i, x_i) + J_e}{d_{min}(Z_i, x_i)} \quad (11)$$

Man To Wong *et al.* [11] proposed two new modified parametric fitness function using other weighted quantization error (Je_2) and Mean Square Error (MSE) as follow :

$$f(x_i, Z_i) = w_1 \bar{d}_{\max}(Z_i, x_i) + w_2\left(z_{max} - d_{min}(x_i)\right) + w_3 Je_2 \quad (12)$$

And

$$f(x_i, Z_i) = w_1 \bar{d}_{\max}(Z_i, x_i) + w_2\left(z_{max} - d_{min}(x_i)\right) + w_3 MSE \quad (13)$$

where $$Je_2 = \left\{\sum_{j=1}^{N_c}\left[\left(\sum_{\forall z_p \in C_{ij}} \frac{d(z_p, m_{ij})}{|C_{ij}|}\right) \cdot \left(\frac{|C_{ij}|}{N_o}\right)\right]\right\} \quad (14)$$

N_o is total number of data vectors to be clustered

$$MSE = \frac{1}{n}\sum_{j=1}^{K}\sum_{z_p \in C_j}(z_p - m_j)^2 \quad (15)$$

The PSO algorithm for image clustering as follows [11]:

1. Initialize each particle to contain N_c randomly selected cluster mean.
2. For t=1 to t_{max}(maximum number of iterations)
   (a) For each particle i
      i. For each pixel z_p
         - Calculate $d(z_p, m_{ij})$ for all cluster C_{ij}
         - Assign z_p to C_{ij} where $d(z_p, m_{ij}) = \min_{\forall c=1,\dots,N_c}\{d(z_p, m_{ic})\}$
      ii. Calculate fitness function $f(x_i(t), Z_i)$
   (b) Update the personal best and the global best position $\hat{y}(t)$
   (c) Update cluster centroid using equation (5) and (6)

The advantage of using PSO is a parallel search of the optimal clustering. The population based search reduces the effect of initial conditions, especially on a relatively large population.

D. Follicles Extraction

In this paper, the geometrical features of each dark region that recognized by PSO clustering algorithm will be extracted. These features are MeanIntensity, Area, BoundingBox, Perimeter, Centroid, Diameter, Extent, Eccentricity, MajorAxisLength, MinorAxisLength, ConvexArea, ConvexHull, EulerNumber, FilledArea, Orientation and Solidity.

III. Proposed Approach in PSO Image Clustering

To improve the convergence solution of PSO image clustering, this paper proposes a new modified non-parametric fitness function using MSSIM [19] and NMSE [4] as follow:

$$f(x_i, Z_i) = \frac{2NMSE}{MSSIM+1} \tag{16}$$

where :

$$NMSE = \frac{\sum_{j=1}^{M}\sum_{k=1}^{N}[F(j,k)-\hat{F}(j,k)]^2}{\sum_{j=1}^{M}\sum_{k=1}^{N}[F(j,k)]^2} \tag{17}$$

$$MSSIM(X,Y) = \frac{1}{M}\sum_{j=1}^{M} SSIM(x_j, y_j) \tag{18}$$

$$SSIM(x,y) = \frac{(2\mu_x\mu_y+C_1)(2\sigma_{xy}+C_2)}{(\mu_x^2+\mu_y^2+C_1)(\sigma_x^2+\sigma_y^2+C_2)} \tag{19}$$

In this term, the proposed fitness function has some simultaneous objectives:

- Minimized error of segmented image compared to original image in term of pixel values.
- Maximized similarity of segmented image compared to original image in term of HVS assessment. SSIM is consistent to human eye perception [19].

Since value range of NMSE is [0..1] and MSSIM is [-1..1], so for making both terms have a same value range and weight, NMSE should be multiplied by 2 and MSSIM value should be added by 1.

In order to investigate the effectiveness of the proposed method, two sets of experiments were conducted. PSO parameters that used in both experiments as follow:

- Cognitive component=2.5
- Social component=2.5
- Inertia weight=1.4
- Number of cluster (k) = 5
- Swarm size (s) = 70.

A. Set-up I

In this experiment we compared the performance of the proposed non parametric fitness function (equation 16) and the previous non parametric fitness function proposed by Omran (equation 11). PSO clustering algorithm with both fitness function has been applied on five grayscale images: PCO image 1, PCO image 2, Lenna, Pepper and Airplane. In this experiment we did not use contrast enhancement at the preprocessing step.

Since PSO algorithm used a random method when initialize its particle, so each experiment should be run at least 20 times. The average and standard deviation of intra-cluster distance, inter-cluster distance and quantization error generated by these experiments will be used as evaluation criteria to analyze the convergence of both fitness functions.

B. Set-up II

In this experiment we investigate the influence of contrast enhancement to the performance of PSO image clustering algorithm with our proposed fitness function (equation 16) and the extracted follicular size. PSO algorithms which preceded and not preceded by contrast enhancement are applied on same PCO image using PSO parameter mentioned on above section.

The region of interest (ROI) generated by both methods are compared to the actual ROI which manually segmented by doctor. DICE coefficient will be used as evaluation criteria. The PSO segmented image which has closer ROI to the reference image will be identified by higher DICE coefficient.

$$DICE = \frac{2\cdot|(\alpha\cap\gamma)|}{|\alpha|+|\gamma|} \tag{20}$$

The DICE coefficient is defined as twice the ratio of intersection of the automatically segmented region and the expertly segmented region to the total area of the automatically and expertly segmented region [12]. This metric calculate the amount of overlap between the two regions, it is 0 if the region are disjoint and 1 if they are identical

IV. Experiment Results

A. Experiment 1

Based on the experimental set-up describe on the section III.A, we get the average and standard deviation of intra-cluster distance, quantization error and inter-cluster distance which shown in the Table 1 and Table II.

TABLE I. PSO Image Clustering with Previous Fitness Function (equation-11)

Images	F1 (previous fitness function)					
	intra-cluster distance ($\bar{d}_{max}$)		quantization error (J_e)		inter-cluster distance (d_{min})	
	mean	stdev	mean	stdev	mean	stdev
PCO Image 1	7.90	0.19	6.68	0.14	30.52	0.71
PCO Image 2	7.37	0.74	4.91	0.20	27.52	1.66
Lenna	6.25	0.05	5.08	0.03	23.00	0.00
Pepper	7.40	0.09	5.70	0.07	26.92	0.40
Airplane	7.20	0.02	5.54	0.02	27.00	0.00

TABLE II. PSO Image Clustering with Our Proposed Fitness Function (equation-16)

Images	F2 (the proposed fitness function)					
	Intra-cluster distance ($\bar{d}_{max}$)		quantization error (J_e)		inter-cluster distance (d_{min})	
	mean	Stdev	mean	stdev	mean	stdev
PCO Image 1	7.62	0.00	6.61	0.002	22.84	0.37
PCO Image 2	7.04	0.00	5.08	0.00	20.00	0.00
Lenna	6.42	0.04	4.65	0.09	17.00	0.00
Pepper	7.03	0.05	5.29	0.04	23.00	0.00
Airplane	8.46	0.00	4.91	0.00	19.00	0.00

Table 1 shows the result of PSO image clustering using previous non parametric fitness function proposed by Omran given in equation (11). Table II shows the results of PSO image clustering using the proposed non parametric fitness function given in equation (16). From both tables above, the standard deviation of intra-cluster distance, inter-cluster distance and quantization error generated by the proposed fitness function are less than standard deviation generated by previous fitness function. In addition, the standard deviation of intra-cluster distance and inter-cluster distance also close to zero in several images. It means the proposed non parametric fitness function produced more convergence solution for PSO image clustering than previous non parametric fitness function especially when applied on ultrasound images.

B. Experiment II

Based on the experimental set-up describe on the section III.B, we get the result as follow:

TABLE III. PSO IMAGE CLUSTERING WITHOUT CONTRAST ENHANCEMENT

	Intra-cluster distance ($\bar{d}_{max}$)		Quantization error (J_e)		Inter-cluster distance (d_{min})	
s	mean	stdev	mean	stdev	mean	stdev
10	7.88	0.166	6.59	0.112	21.56	1.15
20	7.83	0.062	6.56	0.026	21.12	0.33
30	7.84	0.064	6.56	0.028	21.04	0.2
40	7.84	0.044	6.56	0.023	21	0
50	7.84	0.047	6.55	0.012	21	0
60	7.84	0.044	6.55	0.012	21	0
70	7.84	0.0473	6.55	0.012	21	0
80	7.83	0.036	6.56	0.009	21	0
90	7.82	0.0217	6.56	0.004	21	0
100	7.83	0.036	6.56	0.009	21	0

TABLE IV. PSO IMAGE CLUSTERING WITH CONTRAST ENHANCEMENT

	Intra-cluster distance ($\bar{d}_{max}$)		quantization error (J_e)		Inter-cluster distance (d_{min})	
s	mean	stdev	mean	stdev	mean	stdev
10	13.58	0.351	12.72	0.028	48.16	0.85
20	13.63	0.379	12.71	0.020	48.48	0.77
30	13.63	0.377	12.72	0.020	48.4	0.707
40	13.66	0.381	12.72	0.019	48.6	0.64
50	13.56	0.373	12.72	0.019	48.6	0.57
60	13.60	0.378	12.72	0.018	48.6	0.64
70	13.68	0.392	12.71	0.017	48.44	0.58
80	13.65	0.392	12.72	0.016	48.48	0.58
90	13.65	0.394	12.72	0.019	48.52	0.51
100	13.41	0.286	12.73	0.015	48.88	0.44

Table III and IV shows the result of PSO image clustering with and without contrast enhancement. PSO image clustering which preceded by contrast enhancement produces larger intra-cluster distance, inter-cluster distance and quantization error for all swarm size (s).

The larger intra-cluster and inter-cluster distance have an advantage when follicles size extracted. On the same number of cluster and swarm size, PSO with contrast enhancement produces closer ROI toward to reference ROI. The figures below shows the ROI of PSO with contrast enhancement has higher DICE coefficient than ROI of PSO without contrast enhancement. It means contrast enhancement can improve the the extracted follicular size to be closer to the actual follicular size.

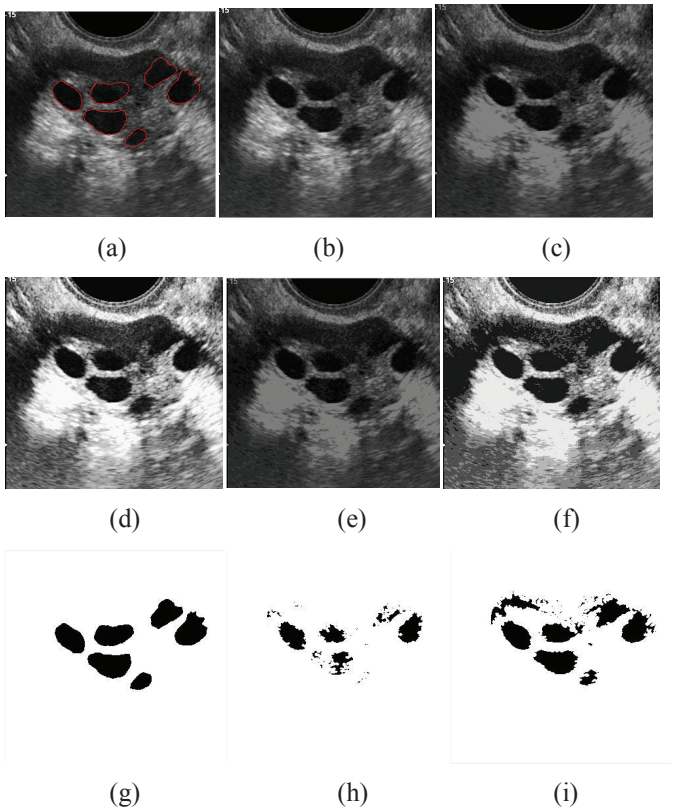

Fig. 3. (a) Reference image, (b) Original PCO image, (c) Denoised PCO image, (d) contrast enhanced PCO image, (e) PSO image clustering without contrast enhancement, (f) PSO image clustering with contrast enhancement, (g) ROI of reference image, (h) ROI of PSO without contrast enhancement-DICE coefficient =0.5988, (i) ROI of PSOwith contrast enhancement –DICE coefficient =0.8107

V. CONCLUSION

This paper proposed a non-parametric fitness function which can improve the convergence solution of PSO image clustering. The proposed fitness function has some objectives: to minimize error in term of pixel values and to maximize the similarity in term of human eye perception. The experimental results show that the standard deviation of intra-cluster distance, inter-cluster distance and quantization error generated by the proposed fitness function are less than standard deviations generated by previous fitness function.

PSO image clustering which preceded by contrast enhancement step will produce larger inter-cluster distance, intra-cluster distance and quantization error than PSO image clustering which not preceded by contrast enhancement. By comparing the DICE coefficient of ROI generated by both PSO methods, we can conclude that contrast enhancement can improve the the extracted follicular size to be closer toward to the actual follicular size.

VI. Future Work

We would like to use machine learning approach by adding classification step for all extracted follicles feature using Logistic Regression classifier. So, the follicles can be identified automatically by system.

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