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BIO INSPIRED OPTIMIZATION ALGORITHMS USING SOFT COMPUTING METHODS FOR MEDICAL IMAGE SEGMENTATIONS

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Abstract:

Bio-inspired optimization algorithm is a major research area in the fields of computational intelligence, soft computing, and optimization. Bio-inspired Algorithm (BIAs) has been successfully applied in many filed such as sciences, medical and engineering fields by the interest of researchers. Given the success of bio-inspired optimization algorithm methods and techniques in big data analysis applications, it is expected that they can also be successfully applied in healthcare . The evolving, dynamic and meta-heuristics nature of BIAs makes it more robust, accurate and efficient in solving image processing problems. However finding the appropriate BIAs that matches the problem at hand is a tedious and difficult task. The main idea of the proposed Exponential Particle Swarm Optimization algorithm is to prevent local solutions and find correct global optimal solutions for medical images segmentation task

Keywords: Bio-inspired, Particle Swarm Optimization, Medical image segmentation, Soft computing, Classification, Segmentation.

1. Introduction

In general the soft computing algorithms facilitate the physicians to diagnose diseases[1] at the early period. The optimization method is a type of soft computing algorithm to decrease the time consumption and to increase the accuracy in diagnosis of diseases. The manual methods are critical and consume more time. Since the optimization algorithms are closely combined with image segmentation, it is highly essential to make a comparative study of those algorithms while working with image segmentation. The combination of swarm intelligence with clustering algorithms incorporates both global search and local search abilities. The diverse optimization algorithms are discussed in detail in the subsequent sections along with the practical implementation.

2. Optimization Techniques

2.1. Particle Swarm Optimization Algorithm

Particle swarm optimization (PSO)[2] algorithm is a stochastic optimization technique based on swarm, which was proposed by Eberhart and Kennedy (1995) and Kennedy and Eberhart (1995). PSO algorithm simulates animal's social behavior, including insects, herds, birds and fishes. Optimization means finding the best possible/desirable solution by applying mathematical engineering disciplines. Optimization problems are wide ranging and numerous, hence methods for solving these problems ought to be, an active research topic. Optimization algorithms can be either deterministic or stochastic in nature. Former methods to solve optimization problems require enormous computational efforts, which tend to fail as the problem size increases. In PSO, the term ―particles refers to population members which are mass-less and volume-less (or with an arbitrarily small mass or volume) and are subject to velocities and accelerations towards a better mode of behavior. Each particle in the swarm represents a solution in a high-dimensional space with four vectors, its current position, best position found so far, the best position found by its neighborhood so far and its velocity and adjusts its position in the search space based on the best position reached by itself (pbest) and on the best position reached by its neighborhood (gbest)[3] during the search process. In each iteration, each particle updates its position and velocity as follows:

$$V_{ij}^{t+1}=\omega V^{t}_{ij}+c_1r_1^{t}(pbest_{ij}-X^{t}_{ij})+c_2r_2^{t}(gbestj-X^{t}_{ij}) \text{ and} \quad (1)$$
$$X^{t+1}_{ij}=X^{t}_{ij}+V^{t+1}_{ij} \quad (2)$$

The Steps in PSO algorithm can be briefed as below:

1).Initialize the swarm by assigning a random position in the problem space to each particle.
2).Evaluate the fitness function for each particle.
3).For each individual particle, compare the particle‘s fitness value with its pbest. If the current value is better than he pbest value, then set this value as the pbest and the current particle‘s position, xi, as pi.
4).Identify the particle that has the best fitness value. The value of its fitness function is identified as guest and its position as pg.
5).Update the velocities and positions of all the particles using (1) and (2).
6).Repeat steps 2–5 until a stopping criterion is met (e.g., maximum number of iterations or a sufficiently good fitness value).

The flowchart for the basic particle swarm optimization is shown in Figure 1.

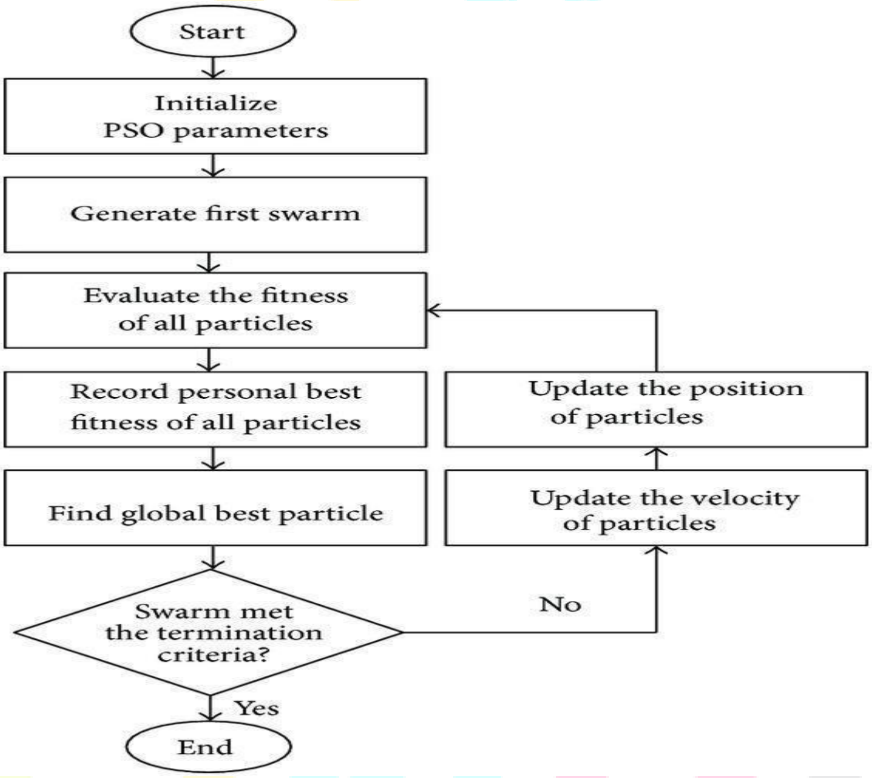

Figure 1. Flow chart for Particle swarm optimization

2.2. Guaranteed Convergence Particle Swarm OptimizationAlgorithm

The current best position in the search region is the goal of guaranteed convergence particle swarm optimization. The social part increases the search ability. The random search area around the global best position is enhanced by this[5]. The velocity update equation for the GCPSO algorithm (Patel *et al.* 2013) is depicted in Equation (2).

$$v^{ij}(t + 1) = x^{ij}(t) + pbest(t) + mv^{ij}(t) + q(t)(1 - 2r). \quad (3)$$

where, r and q(t) are the random vector and diameter of search area. The range of random vector lies between 0 and 1.

Algorithm for guaranteed convergence particle swarm optimization

1. Initialize the number of clusters and number of iterations.
2. Initialize q, SC, FC, numSuccess = 0, numFailures = 0.
3. Define the fitness function.
4. Find the fitness value for each particle.
5. Update the local best solution obtained so far.
6. Repeat steps 4 and 5 for predefined number of iterations.
7. Update velocity and position of each particle for the currentglobal best particle.
8. Execute the selection operator.
9. Repeat the steps 4 to 8, if any local best position y_i haschanged. Otherwise, end the algorithm.

2.3. Pigeon Inspired Optimization Algorithm

To overcome the limitation with respect to particle swarm optimization like convergence rate and complexity (Duan *et al.* 2014) a new swarm intelligence algorithm called Pigeon inspired optimization (PIO) was proposed by Haibin Duan and Peixin Qiao in 2014 (Zhang *et al.* 2015). The navigational ability of pigeons is unbelievable (Bingman *et al.*). It has excellent ability to correctly identify its nest even if left very far away from the nest. For the direction identification they use magnetic features and ability to remember land mark. The impact of sun also plays vital role in its navigational ability. Pigeons always try to fly towards north since they have minute magnetic elements in their beaks. Equations for velocity and position are shown in (4.20) & (4.21) (Duan *et al.* 2014).

$$v(t+1) = v(t)e^{-Rt}+C[x(gbest) - x(t)] \qquad (4)$$

$$x(t+1) = x(t)+ v(t+1) \qquad (5)$$

The Table 2.1 gives a brief overview of the parameters used inpigeon inspired optimization algorithm.

Table 2.1 Basic parameters of PIO algorithm

Parameter	Description	Symbol
Map, Compass operator	Pigeons sketch the map in their brain with the help ofearth magnetic field. Altitude of sun (compass operator) helps to adjust direction.	R
Position	Location of pigeon	$X(t)$
Velocity	Rate at which a pigeon changes its location.	$V(t)$
Global best	Current global best position	$x\ (gbest\ )$
Number of individuals	Total number of pigeons in a swarm	N_p
Iterations	Number of iterations for i^{th} operator	N_{ci}

Algorithm for Pigeon Inspired Optimization Algorithm

1. Assign random values for the pigeon's velocity and position.
2. Determine the best current position from the fitness value.
3. Evaluate map and compass operator.
4. Revise the position after velocity using Equation (4) & (5).
5. If the current iteration is greater than the maximum iterationstart land mark operation, otherwise go to step 2.
6. Arrange all the Pigeons in its increasing order of fitness value.
7. Decrease the population using $Np^{(t+1)} = \frac{N_p(t)}{2}$
8. Repeat step 2 to 7 until certain conditions are met or for predefined number p is flexible of iterations.

2.4 Gaussian Pigeon Inspired Optimization Algorithm

The land mark operator alone differs in Gaussian pigeon inspired optimization with respect to basic pigeon inspired optimization. After adapting the landmark operator, three new parameters, m, n and p should be assigned with initial values. The velocity and positions are updated using the Equations (4) and (4). Here (Zhang *et al.* 2015) m_1 and n have fixed calculating methods, but p is flexible. p is a weight factor which is responsible for the balance between uniform and Gaussian distribution (Li *et al.* 2014). In other words, m_1 and n are invariables regardless of situation, but p varies according to the situation. The algorithm for Gaussian[6] pigeon inspired optimization algorithm is illustrated below (Zhang *et al.* 2015).

Algorithm for Gaussian Pigeon Inspired Optimization Algorithm

1. Initialize the velocity and position of all the pigeons withrandom values.
2. Find the fitness value for all pigeons.
3. Search the best current position for each pigeon by comparingeach pigeon fitness value.
4. Operate the map and compass operator.
5. Update the velocity using equation (4.19).
6. Update the position using equation (4.20).
7. If NC > Nc1max Stop the map and compass operator and start the landmark operator. Otherwise go to step 4. Find $m_1 = r$, $n = 0.5 - 0.25t/(t+1)$
9. Sort all the Pigeons in its ascending order according to itsfitness value.
10. Reduce the Pigeons population using $N_P(t+1) = \frac{N_p(t)}{2}$
11. Repeat step 2 to 9 until certain conditions are met or forpredefined number of iterations.

In this research with the aid of various image segmentation algorithms and optimization techniques the solutions for the above said medical problems have been obtained and compared. In order to prove the accuracy of the various image segmentation methods basic performance measures have to be studied and they are discussed in next session.

3. Performance Measurements

The universal and well known parameters to measure[7] the segmentation accuracy are true positive, true negative, false positive, false negative and accuracy. A brief over view on the above said parameters listed here (Nagaveena *et al.* 2013; Schwenke 2007). True positive states the condition when the test result is positive and the patient has disease. True negative states the condition when the test result is negative and the patient has no disease. False positive states the condition when the test result is positive and the patient has no disease. False negative states the condition when the test result is negative and the patient has disease. The following table shows the confusion matrix to find out the accuracy[8]

Acquired Class \ True Class	T	F
Y	True Positives (TP)	False Positives (FP)
N	False Negatives (FN)	True Negatives (TN)

$$\text{True Positive Rate (TPR)} = \frac{TP}{TP+FN}$$

$$\text{False Positive Rate (FPR)} = \frac{FP}{FP+TN}$$

$$\text{Accuracy} \quad (ACC) = \frac{TP+TN}{TP+FP+TN+FN}$$

Table 3.1. Confusion Matrix.

When the true positive and true negative are high, and the false positive and false negative are low, it indicates the image is correctly segmented as foreground and background, and the accuracy will become high and almost near to 1.

4. Research Work

Image segmentation has significant applications in human health care. Thresholding, edge based and cluster based methods are generally used for image segmentation. Out of that cluster based method is powerful one because it can work on large number of variables, simple and faster than other methods. But initialization of proper cluster center is mandatory to obtain best results. In this work analysis on the accuracy of medical image segmentation[8] methods are verified by the practical verification of the Follicle detection from ultrasound ovarian image. In this research with the aid of various image segmentation algorithms and optimization techniques the solutions for the above said medical problems have been obtained and compared. In order to prove the accuracy of the various image segmentation methods basic performance measures have to be studied and they are discussed in next session.

4.1. Follicle Detection from Ultrasound OvarianImage

The formation of ovarian cysts is called polycystic ovarian syndrome[9]. Ovarian cysts are formed due to imbalance in progesterone and estrogen hormones. Women suffered by this syndrome have collection of follicles in their ovary. With the help of ultrasound the ovary image with follicle can be captured. Hence it is essential to determine the presence of follicle in the ovary to diagnose the poly cystic ovarian syndrome. This work is to suggest effective follicle detection method from an ultrasound ovarian image. In this work, a detailed comparative analysis of the performance of four different optimization algorithms has been made with practical implementation. In this research work GEO (Gene Expression Omnibus) data sets are used which contains 285 ovarian samples. Four algorithms were used in this analysis. They are, pigeon inspired optimization algorithm, Gaussian pigeon[10] inspired optimization algorithm, particle swarm optimization algorithm and chaotic particle swarm optimization[11]. The process flow diagram for ultrasound ovarian image segmentation is shown in below Figure 4.1

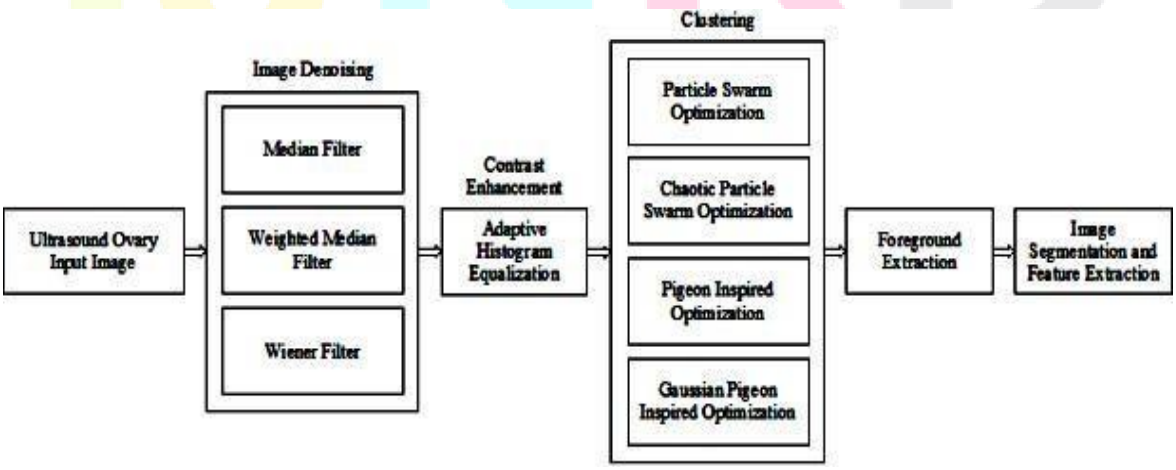

Figure 4.1 Process flow diagram for Alzheimer disease detection

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4.2. Results and Discussions

From the GEO data set 50 images have been taken for the analysis of follicle detection. The sample images have been segmented using PIO, GPIO, PSO and CPSO based segmentation methods. The input and output for two sample images are shown in the Figures 4.2, 4.3.. The variations of Jaccard and dice coefficient are shown in Tables 4.4 to 4.5. The graphical view on the above said analysis is shown in Figures 4.6 and 4.7.

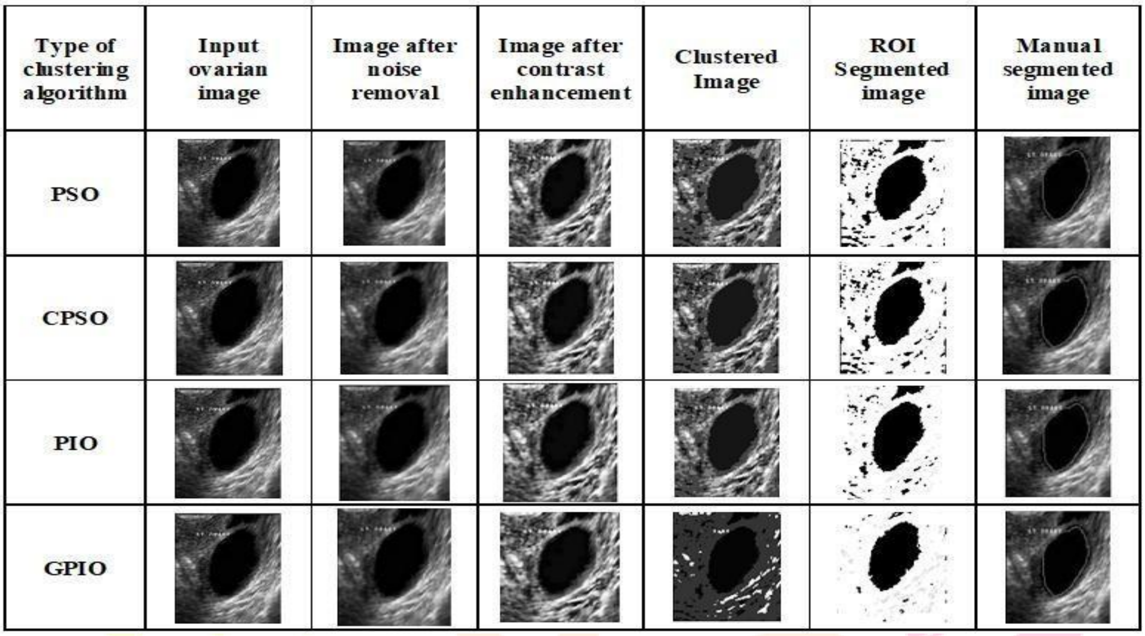

Figure 4.2 Resultant images of image 1 for cancer detection fromultrasound ovarian image

Algorithm	True Positive Rate	False Negative Rate	True Negative Rate	False Positive Rate	Accuracy	Dice Coefficient	Jaccard Coefficient
PSO	83.3135	13.6865	87.9588	12.0412	87.1881	0.8631	0.7592
CPSO	86.5560	13.4440	88.1469	11.8531	87.4008	0.8656	0.7630
PIO	88.2571	11.7429	89.4736	10.5264	88.8986	0.8826	0.7898
GPIO	89.2139	10.7861	90.2479	09.7521	89.7569	0.8921	0.8053

Table 4.1 Performance comparison for image 1 for follicle detection

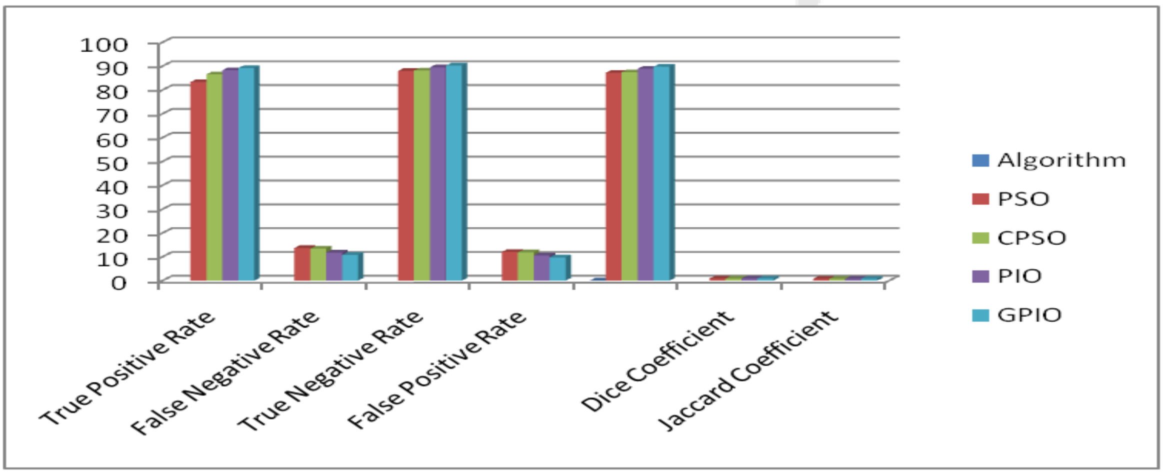

Figure 4.6 Comparative value of accuracy of image 1 for follicle detection

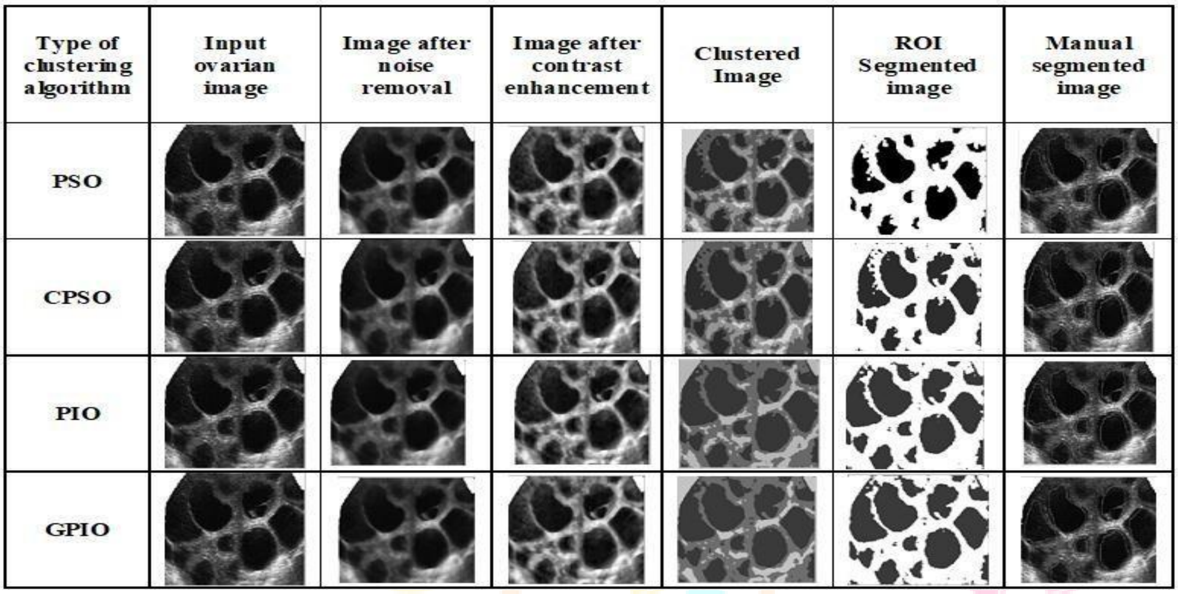

Figure 4.3 Resultant images for image 2 for cancer detection fromultrasound ovarian image

Algorithm	True Positive Rate	False Negative Rate	True Negative Rate	False Positive Rate	Accuracy	Dice Coefficient	Jaccard Coefficient
PSO	85.7147	14.2853	87.4954	12.5046	86.6629	0.8571	0.7500
CPSO	85.7429	14.2571	87.5171	12.4829	86.6875	0.8574	0.7504
PIO	88.2479	10.7524	90.2610	9.7390	89.7794	0.8925	0.8058
GPIO	90.2106	9.7900	91.0550	8.9450	90.6515	0.9021	0.8217

Table 4.2 Performance comparison for image 2 for follicle detection

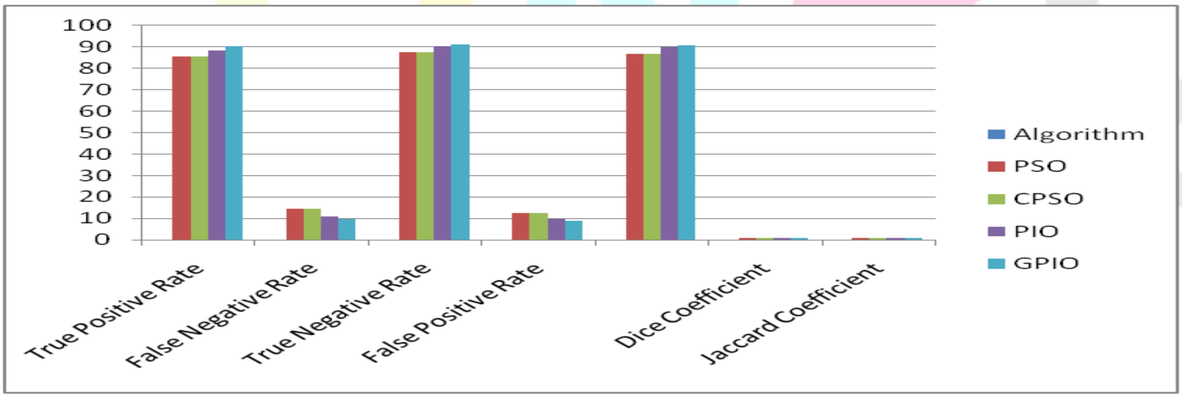

Figure 4.7 Comparative value of accuracy of image 2 for follicle detection

From the above said results it is evident that the Gaussian pigeon optimization method yields promising result for all the tested image samples. The Gaussian pigeon optimization[12] has not been applied very first time for the identification of follicle detection.

5. Conclusion

From the above experimental verification and practical study it has been clearly proved that the role of optimization algorithm in image segmentation is predominant one. Particularly when we solve problems using clustering algorithms the optimum threshold value decides the subsequent result of segmentation. The segmentation accuracy completely relies on this threshold value. Hence it is important to adopt an efficient and fast converging optimization algorithm in image segmentation process.

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