PSO-2S Optimization Algorithm for Brain MRI Segmentation

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Abstract. In image processing, finding the optimal threshold(s) for an image with a multimodal histogram can be done by solving a Gaussian curve fitting problem, *i.e.* fitting a sum of Gaussian probability density functions to the image histogram. This problem can be expressed as a continuous nonlinear optimization problem. The goal of this paper is to show the relevance of using a recently proposed variant of the Particle Swarm Optimization (PSO) algorithm, called PSO-2S, to solve this image thresholding problem. PSO-2S is a multi-swarm PSO algorithm using charged particles in a partitioned search space for continuous optimization problems. The performances of PSO-2S are compared with those of SPSO-07 (*Standard Particle Swarm Optimization in its 2007 version*), using reference images, *i.e.* using test images commonly used in the literature on image segmentation, and test images generated from brain MRI simulations. The experimental results show that PSO-2S produces better results than SPSO-07 and improves significantly the stability of the segmentation method.

1 Introduction

Digital image processing has attracted a growing interest, due to its practical relevance in many fields of research and in industrial and medical applications. Image segmentation is typically used to locate objects and boundaries in images. It is one of the main components of several image analysis systems, thus it received a great deal of attention. Several surveys and comparative papers are available in the literature [13,10,14,7]. Image thresholding is one of the most popular segmentation approaches. It makes use of the image histogram to partition the images into several meaningful groups of pixels. In automatic image thresholding methods, the segmentation problem can be formulated as a continuous nonlinear optimization problem. Hence, the use of a metaheuristic is a relevant choice to solve it efficiently.

In this paper, we propose to use a recently proposed algorithm [5], called PSO-2S, which is a new variant of particle swarm optimization (PSO) [8]. PSO is inspired by social behavior simulations of bird flocking. It has already been

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applied successfully to image processing problems [6,9]. This algorithm optimizes a problem by iteratively improving a candidate solution with regard to a given measure of quality. PSO-2S is a multi-swarm PSO algorithm based on several initializations in different zones of the search space, using charged particles. This algorithm uses two kinds of swarms, one main and several auxiliary swarms. The best particles of the auxiliary ones generate the main swarm. More precisely, the auxiliary swarms are initialized several times in different zones. An electrostatic repulsion heuristic is then applied in each zone to increase the diversity of the particles. Each auxiliary swarm performs several generations based on standard PSO algorithm to provide the best solution in its related zone. The provided solutions are then used as the main swarm.

This paper is structured as follows: Section 2 presents an overview of the standard particle swarm optimization and its new variant PSO-2S. Section 3 is dedicated to the presentation of the image thresholding method. The image segmentation criterion is given in Section 4. Experimental protocol and parameter setting are presented in Section 5. Experimental results are discussed in Section 6. The work in this paper is concluded in section 7.

2 Presentation of the PSO-2S Algorithm

2.1 Review of the Standard PSO

The particle swarm optimization (PSO) [8] is inspired originally by the social and cognitive behavior existing in the bird flocking. The algorithm is initialized with a population of particles randomly distributed in the search space, and each particle is assigned a randomized velocity. Each particle represents a potential solution to the problem.

In this paper, the swarm size is denoted by s, and the search space is n-dimensional. In general, the particles have three attributes: the current position $X_i = (x_{i,1}, x_{i,2}, ..., x_{i,n})$, the current velocity vector $V_i = (v_{i,1}, v_{i,2}, ..., v_{i,n})$ and the past best position $Pbest_i = (p_{i,1}, p_{i,2}, ..., p_{i,n})$. The best position found in the neighborhood of the particle i is denoted by $Gbest_i = (g_1, g_2, ..., g_n)$. These attributes are used to update iteratively the state of each particle in the swarm. The objective function to be minimized is denoted by f. The velocity vector V_i of each particle is updated using the best position it visited so far and the overall best position visited by its neighbors. Then, the position of each particle is updated using its updated velocity per iteration. At each step, the velocity of each particle and its new position are updated as follows:

$$v_{i,j}(t+1) = wv_{i,j}(t)+c_1 r_{1_{i,j}}(t)\,[pbest_{i,j}(t)-x_{i,j}(t)]+c_2 r_{2_{i,j}}(t)\,[gbest_{i,j}(t)-x_{i,j}(t)] \quad (1)$$

$$x_{i,j}(t+1) = x_{i,j}(t) + v_{i,j}(t+1) \quad (2)$$

where w is called inertia weight, c_1, c_2 are the learning factors and r_1, r_2 are two random numbers selected uniformly in the range $[0, 1]$.

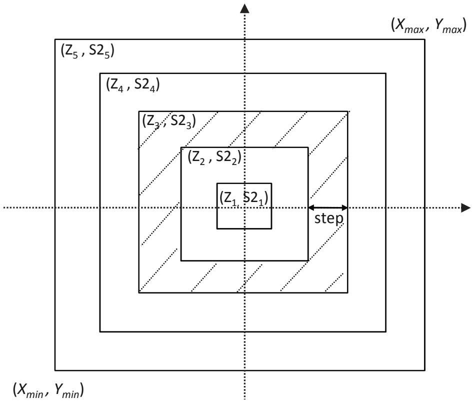


Fig. 1. Partitioning of the search space

2.2 PSO Improved Variant: PSO-2S

An improved variant of the original PSO algorithm, called PSO-2S, was proposed by El Dor et al. [5]. This variant consists of using three main ideas: the first is to use two kinds of swarms: a main swarm, denoted by S1, and s auxiliary ones, denoted by $S2_i$, where $1 \leq i \leq s$. The second idea is to partition the search space into several zones in which the auxiliary swarms are initialized (the number of zones is equal to the number of auxiliary swarms s). The last idea is to use the concept of the electrostatic repulsion heuristic to diversify the particles for each auxiliary swarm in each zone.

To construct S1, the auxiliary swarms $S2_i$ evolve several times in different areas, and then each best particle for each $S2_i$ is saved and considered as a new particle of S1. To do so, the population of each auxiliary swarm is initialized randomly in different zones (each $S2_i$ is initialized in its corresponding zone i). After each of these initializations, $nb_{generation}$ displacements of particles, for each $S2_i$, are performed in the same way as standard PSO. Then the best solution found by each auxiliary swarm, named $gbest_i$, is added to S1. The number of initializations of $S2_i$ is equal to the number of particles in S1.

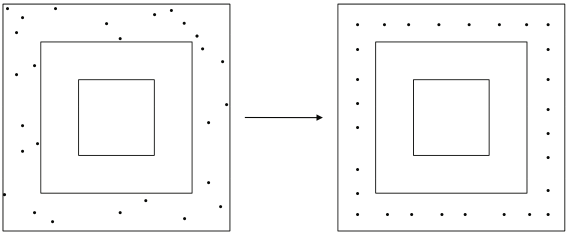
As mentioned above, the second idea is to partition the search space $[min_d, max_d]^D$ into several zones (max_{zone} zones). Then, one calculates the $center_d$ and the $step_d$ of each dimension separately, according to (3) and (4). In the case of using an uniform (square) search space, the $step_d$ are similar for all dimensions.

$$center_d = (max_d + min_d)/2 \tag{3}$$

$$step_d = (max_d - min_d)/2 \times max_{zone} \tag{4}$$

where max_{zone} is a fixed value, and d is the current dimension ($1 \leq d \leq D$).

This process is illustrated in Figure 1, where the i^{th} swarm $S2_i$ and its attributed zone Z_i are denoted by (Z_i, $S2_i$).



(a) (b)

Fig. 2. Repulsion process: (a) $(Z_3,\ S2_3)$ before repulsion, (b) $(Z_3,\ S2_3)$ after repulsion

The sizes of the zones of the partitioned search space are different $(Z_1 < Z_2 < \ldots < Z_{max_{zone}})$. Therefore, the number of particles in $\mathrm{S2_i}$, denoted by $S2_{isize}$, depends on its corresponding zone size. Indeed, a small zone takes less particles and the number of particles increases when the zone becomes larger. The size of each auxiliary swarm is calculated as follows:

$$S2_{isize} = num_{zone} \times nb_{particle} \tag{5}$$

where $num_{zone} = 1, 2, ..., max_{zone}$ is the current zone number and $nb_{particle}$ is a fixed value.

After the initializations of the auxiliary swarms in different zones $(Z_i, \mathrm{S2_i})$, an electrostatic repulsion heuristic is applied to diversify the particles and to widely cover the search space [4]. This technique is used in an agent-based optimization algorithm for dynamic environments [11]. Therefore, this procedure is applied in each zone separately, hence each particle is considered as an electron. Then a force of $1/r^2$ is applied, on the particles of each zone, until the maximum displacement of a particle during an iteration becomes lower than a given threshold ϵ (where r is the distance between two particles, ϵ is typically equal to 10^{-4}). At each iteration of this procedure, the particles are projected in the middle of the current zone, before a new application of the repulsion heuristic. Figure 2 presents an example of the repulsion applied to $(Z_3,\ S2_3)$.

3 The Problem at Hand

The segmentation problem has received a great deal of attention, thus any attempt to survey the literature would be too space-consuming. The most popular segmentation methods may be found in [15]. In this work, image segmentation is performed using the thresholding approach. Image thresholding is a supervised segmentation method, *i.e.* the number of regions (classes of pixels) and their properties are known in advance by the user. The segmentation is done by determining, for each pixel, the class whose properties are the closest to those observed for that pixel. The thresholding technique is based on the assumption that different regions of the image can be distinguished by their gray levels.

It makes use of the histogram $h(j)$ of the processed image, *i.e.* the observed probability of gray level j. It can be defined as follows:

$$h(j) = \frac{g\left(j\right)}{\sum_{i=0}^{L-1} g\left(i\right)} \tag{6}$$

where $g(j)$ denotes the occurrence of gray-level $j \in \{0, 1, \ldots, L-1\}$ in the image.

Thresholding the image into N classes is to find the $N-1$ thresholds that will partition the histogram into N zones.

The main contribution of the work we present here is to show the significance of using PSO-2S for MR image segmentation. The performances of PSO-2S are first compared with those of SPSO-07 (*Standard Particle Swarm Optimization* in its 2007 version) [2], using reference images, commonly used in the literature on image segmentation. Then, the performances of both algorithms are compared using images from a database generated by brain MRI simulation [1,3]. This database, called *BrainWeb*, provides images for which an "optimal" segmentation is known. Indeed, the BrainWeb MRI simulations are based on a predefined anatomical model of the brain. The images generated by these simulations can then be used to validate a segmentation method, or to compare the performance of different methods.

4 Image Segmentation Criterion

Before using this criterion we must fit the histogram of the image to be segmented to a sum of Gaussian probability density functions (pdf's). This procedure is named Gaussian curve fitting, more details about it are given below. The pdf model must be fitted to the image histogram, typically by using the maximum likelihood or mean-squared error approach, in order to find the optimal threshold(s). For the multimodal histogram $h(i)$ of an image, where i is the gray level, we fit $h(i)$ to a sum of d probability density functions [12]. The case where the Gaussian pdf's are used is defined by:

$$p\left(x\right) = \sum_{i=1}^{d} P_i \exp\left[-\frac{\left(x-\mu_i\right)^2}{\sigma_i^2}\right] \tag{7}$$

where P_i is the amplitude of Gaussian pdf on μ_i, μ_i is the mean and σ_i^2 is the variance of mode i, and d is the number of Gaussians used to approximate the original histogram and corresponds to the number of segmentation classes.

Our goal is to find a vector of parameters, Θ, that minimizes the fitting error J, given by the following expression:

$$J(\Theta) = \sum_{i=0}^{L-1} \left|h(i) - p(\Theta, i)\right|^2 \tag{8}$$

where $h(i)$ is the measured histogram. Here, J is the objective function to be minimized with respect to Θ, a set of parameters defining the Gaussian pdf's and the probabilities, given by $\Theta = \{P_i,\quad \mu_i,\quad \sigma_i;\quad i = 1,\ 2, \cdots,\ d\}$. After fitting the multimodal histogram, the optimal threshold could be determined by minimizing the overall probability of error, for two adjacent Gaussian pdf's, given by:

$$e(T_i) = P_i \int_{-\infty}^{T_i} p_i\,(x)\,dx + P_{i+1} \int_{T_i+1}^{\infty} p_{i+1}\,(x)\,dx \tag{9}$$

with respect to the threshold T_i, where $p_i(x)$ is the i^{th} pdf and $i = 1, \ldots, d-1$. Then the overall probability to minimize is:

$$E(T) = \sum_{i=1}^{d-1} e(T_i) \tag{10}$$

where T is the vector of thresholds: $0 < T_1 < T_2 < ... < T_{(d-1)} < L - 1$. In our case L is equal to 256.

5 Experimental Protocol and Parameter Setting

To compare the performance of PSO-2S and SPSO-07, the criterion (8) is minimized for each test image in Figure 3 (a). The stagnation criterion used is satisfied if no significant improvement (greater than 1E−10) in the current best solution is observed during 1E+4 successive evaluations of the objective function. In addition, the maximum number of evaluations allowed is set to 300000.

In this figure, LENA and BRIDGE are reference images used for the validation of segmentation methods in the literature. The images MRITS and MRICS are obtained from BrainWeb [1] and correspond to transverse and coronal sections of a brain, respectively. The parameters used for the MRI simulation are a T1-weighted sequence, a slice thickness of 1mm, a Gaussian noise of 3% calculated relative to the brightest tissue, and a 20% level of intensity non-uniformity (radio frequency bias).

The values of the PSO and SPSO-07 parameters used for the segmentation problem are defined below:

- PSO-2S using 30 zones and $\frac{p^4}{7000} + 10$ particles in each zone, where p is the zone number. The parameter K used to generate the neighborhood of the particles is set to $K = 3$. The parameter $Nb_{generation}$ is set to 15 ;
- SPSO-07 (*Standard Particle Swarm Optimization* in its 2007 version) [2] using $10+2\sqrt{D}$ particles (the formula recommended by the authors of SPSO-07), where D is the dimension of the problem. The parameter K is set to $K = 3$.

6 Experimental Results and Discussion

In this section, the experimental results obtained with PSO-2S and SPSO-07 are presented. The segmentation results are shown in Figure 3. In this figure, the

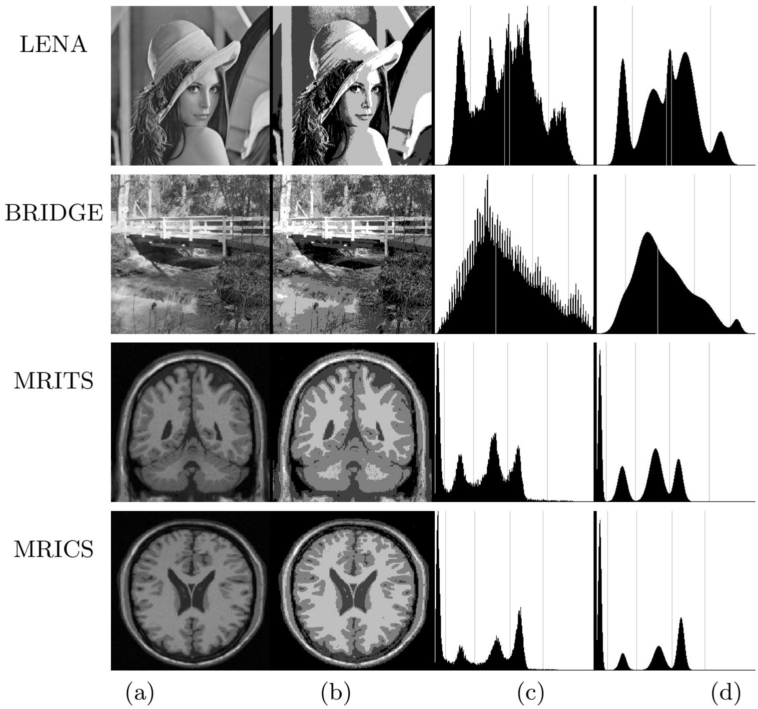
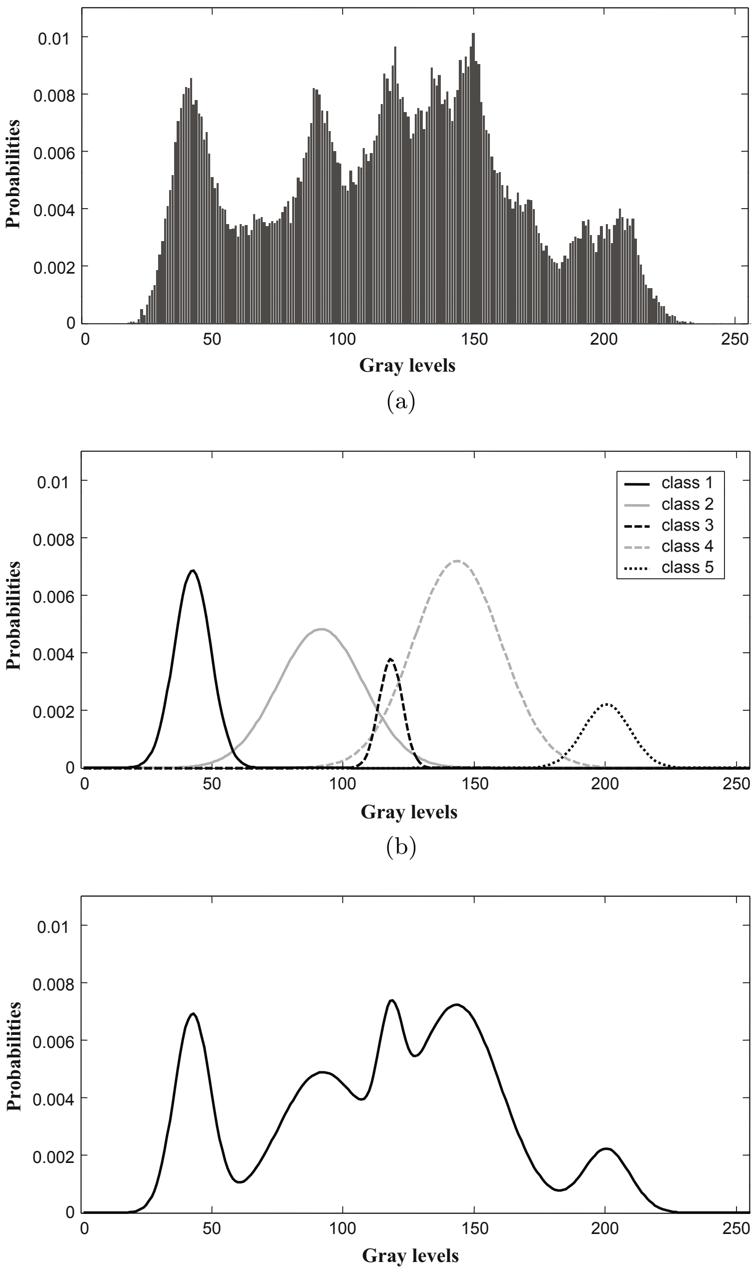


Fig. 3. Illustration of the segmentation process. (a) Original images. (b) Segmented images using thresholds in Table II. (c) Original histograms. (d) Approximated histograms.

original images and their histograms are illustrated in (a) and (c), respectively. Approximated histograms are presented in (d), and segmented images (using 5 classes) are shown in (b). For each test image, one can see that the approximation of its histogram, illustrated in detail for LENA in Figure 4, leads to a good image segmentation.

The histogram approximation results, for each test image, are presented in Table 1. In this table, the parameters of each of the five Gaussian pdf's used to approximate the histogram of each image are given. The parameters of the i^{th} pdf of an image are denoted by P_i, μ_i and σ_i. Threshold values between the different classes of pixels, calculated for each image using its approximated histogram, are given in Table 2.

For each test image, the number of evaluations performed by each algorithm, averaged over 100 runs, is given in Table 3. The success rate (the percentage of acceptable solutions found among the ones of the 100 runs, *i.e.* the percentage of solutions with an objective function value lower or equal to 5.14E−4, 5.09E−4, 7.51E−4, 7.99E−4 for LENA, BRIDGE, MRITS, MRICS, respectively), and the average approximation error (the average value of the objective function for the



(c)

Fig. 4. Illustration of the histogram approximation process for LENA. (a) Original histogram. (b) Gaussian pdf's for each class of pixels. (c) Sum of the Gaussian pdf's (approximated histogram).

Table 1. Parameters of the Gaussian pdf's used to approximate the histogram of each test image

Image	μ_1	P_1	σ_1	μ_2	P_2	σ_2	μ_3	P_3	σ_3	μ_4	P_4	σ_4	μ_5	P_5	σ_5
LENA	41.62	0.17	9.87	90.57	0.28	23.14	117.21	0.06	6.33	142.54	0.43	23.82	199.56	0.07	12.64
BRIDGE	41.13	0.06	15.36	76.75	0.39	25.97	119.25	0.38	34.73	173.38	0.14	28.43	225.53	0.02	9.09
MRITS	4.71	0.28	3.78	40.79	0.17	10.05	94.50	0.36	14.26	131.55	0.19	9.17	225.60	0.00	252.92
MRICS	4.66	0.41	3.66	41.76	0.09	7.64	99.57	0.21	11.92	135.53	0.29	7.46	192.73	0.00	239.82

Table 2. Threshold values for each test image

Image	Thresholds
LENA	57 112 120 183
BRIDGE	46 98 156 215
MRITS	15 62 117 184
MRICS	17 64 121 177

Table 3. Average number of evaluations for the segmentation of an image, approximation error and success rate obtained for each algorithm, for each test image

Image	Algorithm	Evaluations	Approximation error	Success rate
LENA	PSO2S	119721.7 ± 64844.3	5.44E−4 ± 3.06E−5	41 %
	SPSO-07	67057.1 ± 64316.9	5.52E−4 ± 3.08E−5	25 %
BRIDGE	PSO2S	241537.8 ± 70707.8	5.27E−4 ± 9.54E−5	48 %
	SPSO-07	125524.4 ± 63277.9	5.16E−4 ± 6.01E−6	24 %
MRITS	PSO2S	81080.9 ± 66569.8	7.69E−4 ± 1.26E−4	95 %
	SPSO-07	44212.0 ± 57321.5	8.79E−4 ± 2.73E−4	77 %
MRICS	PSO2S	72922.5 ± 35894.4	8.68E−4 ± 1.18E−4	70 %
	SPSO-07	28185.4 ± 16188.4	9.46E−4 ± 2.71E−4	54 %

best solution found) of an image histogram are also given in this table, for 100 runs of an algorithm.

In this table, we see that PSO-2S requires more evaluations than SPSO-07 to converge to an acceptable solution. However, its success rate is significantly higher than the one of SPSO-07 for all images, according to the Fisher's exact test with a 95% confidence level. Indeed, PSO-2S is designed to prevent premature convergence of PSO algorithm. Hence, it significantly improves the stability of the segmentation method. It shows the significance of using PSO-2S for this class of problems.

7 Conclusion

In this paper, we present an image segmentation method using the thresholding approach to identify several classes of pixels in standard and medical images. This method includes an optimization step in which we integrated our PSO-2S algorithm. We also tested the method using the algorithm SPSO-07.

Segmentation results obtained on several test images, commonly used in the literature in image processing and on synthetic images obtained from simulations of brain MRI, are satisfactory. We show that using PSO-2S provides greater stability for this segmentation method, compared with SPSO-07. It shows the relevance of using PSO-2S for this type of problems. Our work in progress consists in the improvement of the segmentation criterion in order to enhance the segmentation quality and accelerate the optimization process.

References

1. BrainWeb: Simulated Brain Database, `http://brainweb.bic.mni.mcgill.ca/brainweb` (2012)
2. Clerc, M., et al.: The Particle Swarm Central website (2012), `http://www.particleswarm.info`
3. Collins, D.L., Zijdenbos, A.P., Kollokian, V., Sled, J.G., Kabani, N.J., Holmes, C.J., Evans, A.C.: Design and construction of a realistic digital brain phantom. IEEE Transactions on Medical Imaging 17(3), 463–468 (1998)
4. Conway, J., Sloane, N.: Sphere Packings, Lattices and Groups. Springer (1999)
5. El Dor, A., Clerc, M., Siarry, P.: A multi-swarm PSO using charged particles in a partitioned search space for continuous optimization. Computational Optimization and Applications 53(1), 271–295 (2012)
6. Feng, H.-M., Horng, J.-H., Jou, S.-M.: Bacterial Foraging Particle Swarm Optimization Algorithm Based Fuzzy-VQ Compression Systems. Journal of Information Hiding and Multimedia Signal Processing 3(3), 227–239 (2012)
7. Gonzalez, R.C., Woods, R.E.: Digital Image Processing, 3rd edn. Prentice-Hall, Inc., Upper Saddle River (2006)
8. Kennedy, J., Eberhart, R.C.: Particle swarm optimization. In: The IEEE International Conference on Neural Networks IV, Perth, Australia, November 27-December 1, pp. 1942–1948 (1995)
9. Kwok, N.M., Wang, D., Ha, Q.P., Fang, G., Chen, S.Y.: Locally-Equalized Image Contrast Enhancement Using PSO-Tuned Sectorized Equalization. In: Chatterjee, A., Siarry, P. (eds.) Computational Intelligence in Image Processing, pp. 21–36. Springer (2013)
10. Lee, S.U., Chung, S.Y., Park, R.H.: A comparative performance study of several global thresholding techniques for segmentation. Computer Vision, Graphics, and Image Processing 52(2), 171–190 (1990)
11. Lepagnot, J., Nakib, A., Oulhadj, H., Siarry, P.: A new multiagent algorithm for dynamic continuous optimization. International Journal of Applied Metaheuristic Computing 1(1), 16–38 (2010)
12. Nakib, A., Oulhadj, H., Siarry, P.: Non-supervised image segmentation based on multiobjective optimization. Pattern Recognition Letters 29(2), 161–172 (2008)
13. Pitas, I.: Digital Image Processing Algorithms and Applications. John Wiley & Sons (2000)
14. Sahoo, P.K., Soltani, S., Wong, A.K.C., Chen, Y.C.: A survey of thresholding techniques. Comput. Vision Graph. Image Process. 41(2), 233–260 (1988)
15. Sezgin, M., Sankur, B.: Survey over image thresholding techniques and quantitative performance evaluation. Journal of Electronic Imaging 13, 146–165 (2004)