

Exponential Particle Swarm Optimization Algorithm for Complexly Structured Images Segmentation [†]

Samer El-Khatib ¹, Yuri Skobtsov ^{2,*} and Sergey Rodzin ¹

¹ ICTIS Department, Southern Federal University, 105/42 B. Sadovaya, Rostov-on-Don 344006, Russia; samer_elkhatib@mail.ru (S.E.-K.); srodzin@yandex.ru (S.R.)

² Institute of Information Technologies and Programming, Saint Petersburg State University of Aerospace Instrumentation, 67 B. Morskaya Str., Saint-Petersburg 190000, Russia

* Correspondence: ya_skobtsov@list.ru; Tel.: +7-931-580-5059

† Presented at the 15th International Conference “Intelligent Systems” (INTELS’22), Moscow, Russia, 14–16 December 2022.

Abstract: Image segmentation is the process of dividing an image into homogeneous regions according to certain features and is widely used in image processing. Complexly structured images usually contain complex and essential objects. These images are non-linear structural images and they contain a large number of elements with required specifications. The main goal of the proposed EPSO (Exponential Particle Swarm Optimization) algorithm is to prevent local solutions and find the exact global optimal solutions for the task of segmenting medical images. The execution time is compared with well-known segmentation algorithms. The EPSO method is superior to the segmentation methods studied, including the graph algorithm. Comparisons were made with existing segmentation algorithms (Grow cut, Random Walker, DPSO, K-means PSO, and hybrid-K-means ant colony optimization algorithm) in tabular form.

Keywords: complexly structured image segmentation; swarm intelligence; particle swarm optimization algorithm



Citation: El-Khatib, S.; Skobtsov, Y.; Rodzin, S. EPSO Algorithm for Complexly Structured Images Segmentation. *Eng. Proc.* **2023**, *33*, 47. <https://doi.org/10.3390/engproc2023033047>

Academic Editors: Askhat Diveev, Ivan Zelinka, Arutun Avetisyan and Alexander Ilin

Published: 13 July 2023



Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

The development of image recognition methods is one of the difficult and involved tasks in AI. The development of image recognition methods is well studied in theory; however, there is no general method to solve it and the practical solution seems to be very difficult [1,2].

Complexly structured images often contain difficult and essential objects. These images are images with a difficult structure and they contain a large number of elements with required specifications. Images have a complex structure that contains many different semantics. These images contain the following attributes:

- Contains a lot of dissimilar objects;
- Objects on images are different;
- Each object has different properties that must be considered;
- Morphologically complex structures;
- Object and background usually have almost the same color distribution.

Examples of such images include geographic or topographical maps, remote sensing images of the earth, etc. Examples of such images are also medical images, including magnetic resonance imaging called MRI images or computed tomography images.

Recent research findings have demonstrated the potential for using techniques inspired by nature, such as ant, particle swarm (PSO), and bee colony optimizations. The application of biologically inspired techniques, including PSO, is still under-studied and more research is needed. In the article, it is proposed to modify the PSO algorithm to a Modified Exponential Particle Swarm Optimization algorithm (EPSO).

2. Particle Swarm Optimization

The PSO approach employs a collection of particles, each of which has a unique local solution [3,4]. According to its own habits and those of its neighbors, the particle's behavior varies every time it enters the search zone. Each particle keeps track of its own position coordinates with the best objective function and best neighbor, from which the best overall solution is derived.

Each particle stores the best fitness value and coordinates. This fitness value can be expressed as y_i and named as a cognitive component. Similar to this, let us indicate the best global optimum obtained by all particles as $\hat{y}(t)$ and call it the social component.

Each i -th particle has properties such as velocity $v_i(t)$ and position $x_i(t)$ a time t . Particle location changes based on

$$x_i(t + 1) = x_i(t) + v_i(t + 1), \tag{1}$$

where $x_i(0) \sim U(x_{min}, x_{max})$.

$$v_{ij}(t + 1) = v_{ij}(t) + c_1 r_{1j}(t)[y_{ij}(t) - x_{ij}(t)] + c_2 r_{2j}(t)[\hat{y}_j(t) - x_{ij}(t)]. \tag{2}$$

The best position (gbest) at a time $(t + 1)$ can be obtained as follows

$$y_i(t + 1) = \begin{cases} y_i(t) & \text{if } f(x_i(t + 1)) \geq f(y_i(t)) \\ x_i(t + 1) & \text{if } f(x_i(t + 1)) < f(y_i(t)), \end{cases} \tag{3}$$

where $f : R^{n_\infty} \rightarrow R$ is target function, that says if current position is optimal. $\hat{y}_j(t)$ (pbest) at a time t can be calculated as follows

$$\hat{y}(t) \in \{y_0(t) \dots y_{n_s}(t)\} | f(\hat{y}(t)) = \min\{f(y_0(t)) \dots f(y_{n_s}(t))\} \tag{4}$$

where n_s is the sum of all swarm particles.

3. EPSO Algorithm for Complexly Structured Images Segmentation

To obtain better segmentation results, a combined method has been proposed which utilizes all the advantages of K-means and PSO algorithms.

The EPSO algorithm is basically similar to the mixed ACO K-means algorithm [5].

Each swarm particle x_i represents N areas (clusters) such as $x_i = (m_{i1}, \dots, m_{ij}, \dots, m_{iN})$ where m_{ij} is center for area j for swarm particle i . Target function can be represented as follows

$$f(x_i, Z_i) = \omega_1 \bar{d}_{max}(Z_i, x_i) + \omega_2 (z_{max} - d_{min}(x_{min})), \tag{5}$$

where $z_{max} = 2^s - 1$ for image with s -bits; Z is representative table for connectivity between pixel and center of the area for particle i .

The table indicates if point z_p is in area c_{ij} for swarm particle i . Constant values ω_1 and ω_2 are user-defined, \bar{d}_{max} —max average Euclidian distance from swarm particles to linked areas. It can be measured as follows:

$$\bar{d}_{max}(Z_i, x_i) = \max_{j=1, \dots, N} \left\{ \sum_{\forall z_p \in c_{ij}} d(Z_p m_{ij} / |c_{ij}|) \right\}, \tag{6}$$

$$d_{min}(x_i) = \min_{j_1, j_2, j_1 \neq j_2} \{d(m_{ij_1}, m_{ij_2})\} \tag{7}$$

Formula (7) contains minimal Euclidian distance among each pair of the area centers.

In the next task, the swarm is used to achieve good clustering using the passed parameters. It was achieved through self-study. Each particle in the PSO algorithm represents a pixel. The pixel intensity is used as an input parameter for the PSO algorithm.

The Algorithm 1 includes the following steps:

Algorithm 1 Exponential PSO segmentation algorithm

1. Presented swarm m . Set the number of swarm particles, personal and global acceleration rates c_1 and c_2 , max allowed number of iterations N_{max} , parameters for target function $f(5)$.
2. For $i = 1, \dots, m$ (for each particle)
 - 2.1 Initialize starting position of the particle using vector x_i .
 - 2.2 Starting position of the particle is currently known best position $y_i = x_i$.
 - 2.3 If $f(y_i) < f(\hat{y})$, then update best swarm's value replacing \hat{y} to y_i .
 - 2.4 Randomly initialize velocities of the particles v_i .
3. Current number of iterations $N = 1$.
4. For $i = 1, \dots, m$ (for each particle)
5. For $j = 1 \dots, n$ (fitness function parameters)
 - 5.1 Update particle's velocity v_{ij} and position according to $x_{ij} = x_{ij} + v_{ij}$.
6. If $f(x_i) < f(y_i)$, then replace best local solution for particle $y_i = x_i$, otherwise return to Section 4.
7. If $f(x_i) < f(\hat{y})$, update best global swarm's solution $\hat{y} = x_i$, otherwise return to Section 4.
8. Increase Number of iterations on 1: $N = N + 1$.
9. If $N \leq N_{max}$, then return to Section 4, otherwise \hat{y} contains best found solution.
10. Initialize K centers of the clusters using best particles positions.
11. Calculate pixel's belonging to cluster (according to distance to the center).
12. Using (5) recalculate clusters centers. If they are not equal to previous, then repeat Section 11.
13. Save best individual solution for each particle (pbest (3)).
14. Save best common solution for m particles (gbest (4)).
15. Update clusters centers.
16. If centers have changed, then return to Section 12.

Thanks to the particle optimization algorithm, all particles tend to fly directly to the best location found by the best particle. This approach enables the rapid discovery of potential solutions. Using this mechanism, particles often accumulate in a local minimum instead of a global minimum, resulting in suboptimal solutions. To avoid this effect, El-Desouky [6] suggested making ω linear, for example

$$\omega = (\omega - \omega_1) \frac{(n_{max} - n)}{n_{max}} + \omega_{min}, \quad (8)$$

where n_{max} is maximum number of iterations, n is the number of the current iteration. Recommended values are $\omega_{max} = 0.9$; $\omega_{min} = 0.4$. ω can be decreased down to ω_{min} over 1500 iterations. In this article, we propose to change ω exponentially. In the presented algorithm, we propose to change ω in the following way:

$$\omega = (\omega - \omega_1) e^{\frac{(n_{max} - n)}{n_{max}}} + \omega_{min} \quad (9)$$

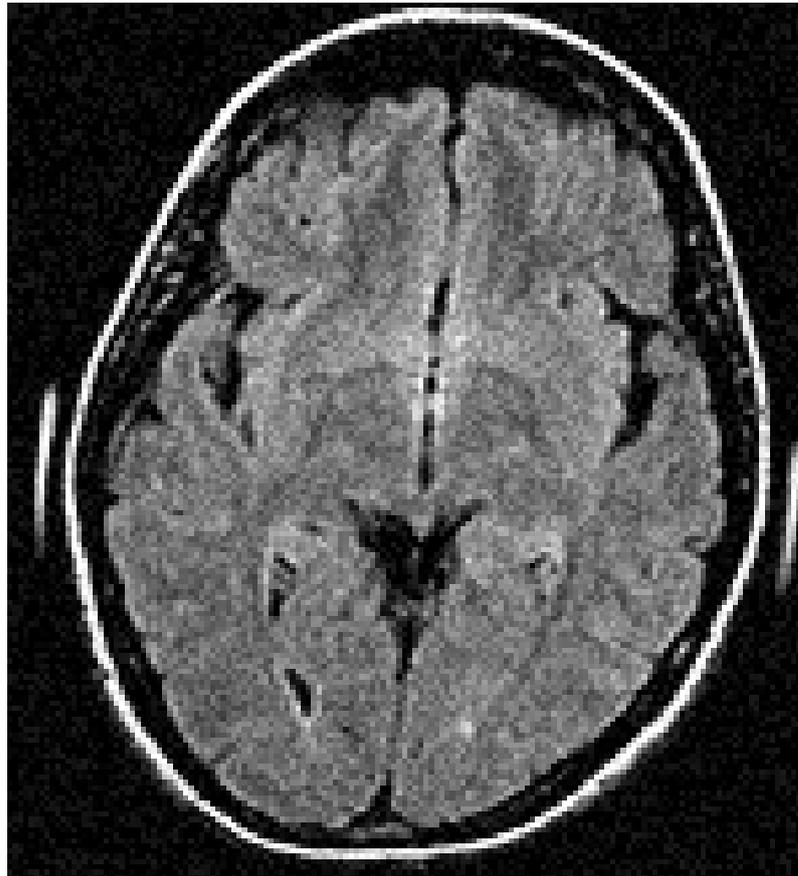
4. Testing EPSO Segmentation Method

To evaluate the efficiency of the algorithm, numerical experiments were provided. Six segmentation methods were considered. Among them are FC-Means [7], Darwinian PSO [8], PSO modification—K-means PSO [8], Grow cut [9], Modified HACO-K-means algorithm—K-means ACO [10,11], and Random Walker [12].

Table 1 represents the running time for three images from well-known image dataset [11] (Figures 1–3).

Table 1. Time taken for each image tested using different algorithms.

Image	K-Means-PSO	EPSO	ACO-K-Means	FC-Means	Grow Cut	Random Walker	Darwinian PSO
1	7.48	7.34	12.14	9.49	14.78	5.01	11.85
2	0.19	0.18	0.93	0.87	1.35	2.2	16.34
3	17.5	17.5	24.04	12.14	45.30	14.2	15.95

**Figure 1.** MRI image of the Brain. Params— 421×392 , 8 bits per pixel.**Figure 2.** Noised brain image. Parameters: 151×166 , 8 bits per pixel.

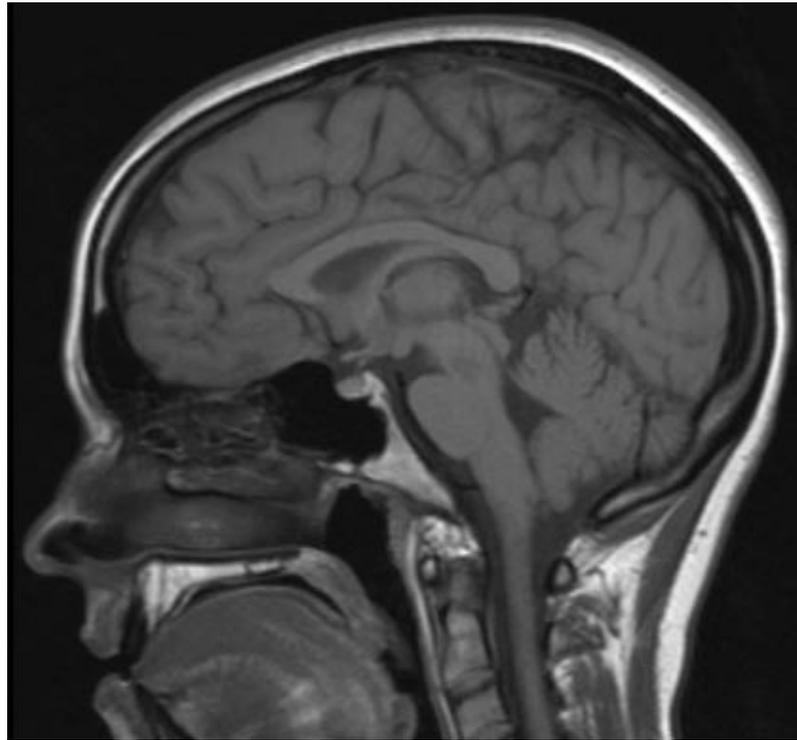


Figure 3. Sagittal MRI image of the knee. Parameters 802×450 , 8 bits.

From Table 1 it can be observed that the proposed method outperforms all existing modifications of ACO and PSO and graph-based methods, except for Random Walker (in this case, the execution time affects the segmentation quality—EPSO- segment quality exceeded Random Walker by 15%).

5. Conclusions

In the presented paper, the modified EPSO algorithm for segmenting complexly structured images was introduced. A comparison of the results of the algorithm with other methods has been presented. In all cases, the algorithm produces a better final sharding time than the studied techniques (with the exception of the Random Walker algorithm, which has over 15% lower segmentation quality). All test results were obtained using the Ossirix MRI image dataset and own software products. The obtained results show that the transform EPSO algorithm can be used in digital image processing for images with complex structures.

Author Contributions: Co-authors: S.E.-K., Y.S., S.R. Description of the contribution of co-authors: Conceptualization, Y.S.; software, S.E.-K.; methodology, S.R.; validation, Y.S., S.R.; writing—original draft, Y.S.; investigation, S.E.-K.; writing—review and editing, S.E.-K.; formal analysis, S.E.-K.; methodology, S.R. All authors have read and agreed to the published version of the manuscript.

Funding: Presented research was supported by Russian Foundation for Basic Research according to the research project № 19-07-00570 “Bio-inspired models of problem-oriented systems and methods of their application for clustering, classification, filtering and optimization problems, including big data”.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Gonzalez, R.C.; Woods, R.E. *Digital Image Processing*, 3rd ed.; Prentice-Hall: Hoboken, NJ, USA, 2008.
2. Kennedy, J.; Eberhart, R.C. Particle swarm intelligence. In Proceedings of the IEEE International Joint Conference on Neural Networks, Perth, WA, Australia, 27 November–1 December 1995; pp. 1942–1948.
3. El-Khatib, S.; Rodzin, S.; Skobtsov, Y. Investigation of Optimal Heuristical Parameters for Mixed ACO-k-means Segmentation Algorithm for MRI Images. In *Proceedings of the III International Scientific Conference on Information Technologies in Science, Management, Social Sphere and Medicine (ITSMSSM 2016)*; Part of Series Advances in Computer Science Research; Atlantis Press: Amsterdam, The Netherlands, 2016; Volume 51, pp. 216–221; ISBN 978-94-6252-196-4. [\[CrossRef\]](#)
4. Saatchi, S.; Hung, C.C. Swarm intelligence and image segmentation swarm intelligence. *ARS J.* **2007**. [\[CrossRef\]](#)
5. Das, S.; Abraham, A.; Konar, A. Automatic kernel clustering with a Multi-Elitist Particle Swarm Optimization Algorithm. In *Pattern Recognition Letters*; Elsevier B.V.: Amsterdam, The Netherlands, 2008; Volume 29, pp. 688–699.
6. Ossirix Image Dataset. Available online: <http://www.osirix-viewer.com/> (accessed on 10 May 2023).
7. Skobtsov, Y.A. *Speransky DV Evolutionary Computation: Hand Book.-Moscow*; The National Open University “INTUIT”: Moscow, Russia, 2015; 331p. (In Russian)
8. El-Khatib, S.; Skobtsov, Y.; Rodzin, S.; Potryasaev, S. Theoretical and Experimental Evaluation of PSO-K-Means Algorithm for MRI Images Segmentation Using Drift Theorem. In *Artificial Intelligence Methods in Intelligent Algorithms. CSOC 2019. Advances in Intelligent Systems and Computing*; Silhavy, R., Ed.; Springer: Cham, Switzerland, 2019; Volume 985.
9. El-Khatib, S.; Skobtsov, Y.; Rodzin, S. Improved Particle Swarm Medical Image Segmentation Algorithm for Decision Making. In *Intelligent Distributed Computing XIII. IDC 2019. Studies in Computational Intelligence*; Kottenko, I., Badica, C., Desnitsky, V., El Baz, D., Ivanovic, M., Eds.; Springer: Cham, Switzerland, 2020; Volume 868.
10. Bozhenyuk, A.; El-Khatib, S.; Kacprzyk, J.; Knyazeva, M.; Rodzin, S.I. Hybrid Ant Fuzzy Algorithm for MRI Images Segmentation. In *Lecture Notes in Computer Science; Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics*; Springer: Cham, Switzerland, 2019; Volume 11509, pp. 127–137. [\[CrossRef\]](#)
11. Rother, C.; Kolmogorov, V.; Blake, A. GrabCut: Interactive foreground extraction using iterated graph cuts. *ACM Trans. Graph.* **2004**, *23*, 309–314.
12. El-Khatib, S.A.; Skobtsov, Y.A.; Rodzin, S.I. Theoretical and Experimental Evaluation of Hybrid ACO-k-means Image Segmentation Algorithm for MRI Images Using Drift-analysis. *Procedia Comput. Sci.* **2019**, *150*, 324. [\[CrossRef\]](#)

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.