Novel Image Segmentation Using Particle Swarm Optimization

Conference Paper · April 2018

DOI: 10.1145/3208955.3208962

2 authors, including:

Netra Lokhande
MIT World Peace University , Pune, Maharashtra, India

Novel Image Segmentation Using Particle Swarm Optimization

Netra M Lokhande
MIT College of Engineering, Pune
netralokhande@gmail.com

Ramachandra V. Pujeri
MIT College of Engineering, Pune
sriramu.vp@gmail.com

ABSTRACT
Data clustering and classification technique algorithms often need to possess enough and prominent number of features in the data. Repeating and dominant features are useful in clustering or segmenting the image. The image segmentation method based on k-mean clustering, hierarchical clustering, and expectation maximization derives the optimum cluster centers based on the number of features such as similar intensity region. Deriving such number optimum number of clusters and its centers is an optimization problem. The aim of this paper is to improve the image segmentation using nature inspired techniques. Image segmentation which is complex optimization problem can be solved by this simple nature inspired PSO (Particle swarm optimization) model which is formulated in this paper. PSO model is generic model which is used to solve number of scientific problems. This paper formulates simple PSO model to solve the image segmentation problem. The proposed algorithm randomly assigns the centers to swarm and best value of objective function is initialized best on the color histogram of an image. This is discussed in section 2 and 3 of paper. Section 4 and 5 discusses and results and concluding remarks on results.

CCS Concepts
• **Mathematics of computing → Network protocol design**

Keywords
Clustering; PSO (particles swarm optimization); Multi-objective optimization; Lbest; Image segmentation; K mean clustering; EM (expectation maximization); Thresholding; Local minima.

1. INTRODUCTION
Particle Swarm optimization algorithm derives its root from natural phenomenon occurring in nature is a simulation of tendency of birds to choose direction when they are in flock. It solves the problem by populating the candidate solution called as the particles and moving the particles across search space. The PSO algorithm is widely used to solve NP complete problems in machine learning, statistical methods and clustering. Various ongoing studies have applied the particle swarm optimization for cluster analysis.

1.1 Goals
The overall goal of this paper is to develop a PSO based cost function minimization using lbest strategy of PSO. The minimization of objective function would yield optimum centers. After centers are converged final image regions are classified using nearest neighborhood approach to segment the image. Selection of right PSO variant for classification of image pixel to particular cluster and formulating image segmentation problem as a clustering problem and setting an objective function in order to have the optimum clustering is targeted here.

ICBET '18, April 23–25, 2018, Bali, Indonesia

ACM ISBN 978-1-4503-6369-3/18/04…$15.00
https://doi.org/10.1145/3208955.3208962

1.2 Related Work
Vast amount of methods which uses certain parameters for segmentation have been studied and applied for preforming bi-level and multi-level thresholding. Thresholding is simplistic method of clustering image data to carry out segmentation[6] however this method has one problem. In some cases this method results into over segmentation with very detail region being segmented. In our method we have tried to eliminate the effect of local convergence since the centers will converge into global minima and maxima.

Image segmentation based on methods such as level set methods, is prominent area of research for nucleus and cytoplasm segmentation in histopathology images[7], where segmentation is used to compute nucleus to cytoplasm ratio based on which degree of cancer spread is decided. Among the most popular method chan vese model of level set method[1] is most popular and widely used. It works well in the cases background is homogeneous and the deformable contour to segment meaningful region propagate towards object. But this method has limitations when the image has multiple local regions and deformable contour is not guided so well.

Multilevel thresholding of image is one method of segmentation which carry out segmentation by dividing the image into different clusters or rather clusters are formed in image by classifying image pixel which lie between two thresholds. Generally it is difficult to decide exact places of prominent valleys in a multimodal histogram of an image that can carry out image segmentation effectively[8]. This makes the multilevel thresholding as a complex problem and this has drawn the attention of research communities. Seeded region growing is approach which does segmentation based on tessellation of points in image known as seeds. A region is grown around the seed point. Initially 3-4 number of seed points is chosen and region is grown around the seed points based on similar intensity criteria. However choosing the number of seed points, location of seed points is not clearly defined in these methods, hence the segmentation results vary depending on location of seed point.

2. PROPOSED WORK
Image segmentation and clustering are analogous problems. A good selection of centers is important for clustering algorithms. Since K-mean and other clustering algorithms are very dependent on initial Centers and has tendency of local convergence. This paper proposes an optimum clustering based on Particle swarm optimization. The proposed algorithm uses a global search method of the Particle swarm optimization to optimize the selection of the initial centers to be used for clustering The objective function is

designed in such a way that it maximize the inter class distance between the clusters and minimizes the intra class distance within the cluster. The inertia weight and correction factors are kept as fixed in the implementation. We also checked the effect of adaptively adjusting the inertia weight and other parameters of our PSO implementation to enhance the segmentation accuracy. The effect of dynamic varying inertia weight versus making the weight as fixed too is checked Also segmentation generated by PSO is compared with K-mean clustering, expectation maximization in terms of accuracy the strategy of formulating PSO for clustering is discussed as following. Here each particle of particle swarm is potential candidate for solving the problem of clustering. The clustering problem is formulated in such a way that image of M x N dimensions represents a function of X and Y. This can be formulated as

$$I = F(X, Y) \quad (1)$$

Let k be the optimum clusters in which image is to be segmented so the objective cost function which computes the distance between the center and image cluster is given by equation(2).

$$f(C_i) = \sum_{i=1}^{K} \|C(i) - M_i\|^2 \quad (2)$$

Where M_i is the i^{th} cluster for which center $C(i)$ is to be derived. The optimum centers are chosen based on the minimization of cost function expressed in equation (3).

$$C_i = \mathrm{Arg}_{\min} \sum_{i=1}^{K} \|C(i) - M_i\|^2 \quad (3)$$

To achieve the minimization of following function for C_i, we use the particle swarm optimization method. In general if M_i is the i^{th} cluster need to be derived from the algorithm and remain to be undefined during the start of the algorithm. We assumed the initial centers are fixed during the start of the algorithm. This led us to replace M_i by I from equation (3). Therefore clustering objective function is modified to

$$C_i = \mathrm{Arg}_{\min} \sum_{i=1}^{K} \sum_{j=1}^{MN} \|C(i) - I(j)\|^2 \quad (4)$$

The objective function represented in equation-4 is used to minimize using particle swarm optimization. Here the number of particles is chosen to the size of an image and three equidistant center values are chosen to assign the values to initial swarm. μ^{i} as shown in Equation(5).

$$C_i = \mu^i \sum_{m=1}^{M} I(m)\delta(m) \quad (5)$$

The particle positions are updated by following equation where V_i is the velocity of a particle

$$C_{i+1} = C_i + {}^{V_i}/_{\mathrm{Scalar}} \quad (6)$$

If the objective function values are lesser than the best value achieved so far, the particle positions are updated according to following

If $f(C_i) <$ BEST_VAL

$C_{i_{updated}} = C_{i+1}$

Where C_{i+1} is computed from equation(6)

Else

$C_{i_{updated}} = C_i$

The best value of swarm is the minimum value of an objective function obtained so far. This is used to update the velocities. This is explained in following equation in which α is the correction factor, W is the inertial weight, G_i and is the best position of particle which corresponds to the minimum value of an objective function achieved so far during iterative minimization., r are the random values generated within the interval [0,1].

$$V_{i+1} = WV_i + \alpha r_i c_{i_{updated}} - C_i + \alpha r_2 G_i - C_i \quad (7)$$

The G_i is the minimum value of an objective function [5] achieved so far and given by equation (8).

$$G_i = min\{f(C_1), f(C_2),, f(C_3), \ldots, f(C_{n=current\ iteration}),\} \quad (8)$$

3. PSO ALGORITHM

For each particle $i \in 1,...,s$ **do**

Randomly initialize C_i

Randomly initialize V_i (or just set V_i to zero)

Set $V_i = C_i$

End for

Repeat

For each particle $i \in 1,...,$ M **do**

Evaluate the fitness of particle i, $f(C_i)$

Update V_i using equation (7)

Update C_i using equation (6)

For each dimension $j \in 1,...,M$ **do**

Apply velocity update using equation (7)

endloop

Apply position update using equation (6)

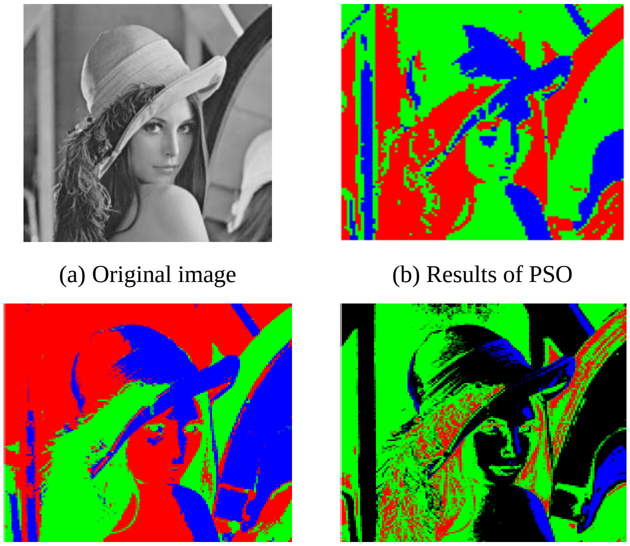
endloop

Until some convergence criteria is satisfied.

4. RESULTS

As shown below in Figure 1. to Figure 7. comparison results of various methods are shown. For comparison of PSO segmentation is done with respect to K-mean and expectation maximization. For all the algorithms, the number of centers were kept 3 and iterations are 20.

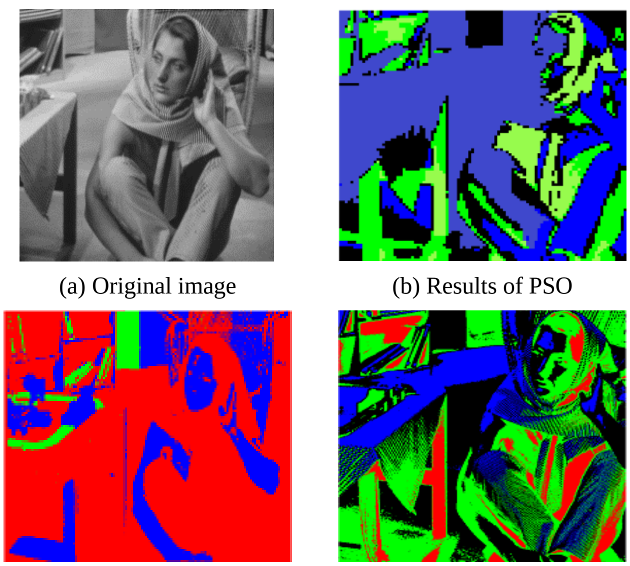
It can be seen from the results that over segmentation is minimum with PSO based method. Compared to EM and k mean methods over clustering is minimum in case of PSO based method. PSO method overcomes local maxima and minima in some cases. This can be seen in the results shown on camera image, elephant image.



(a) Original image (b) Results of PSO

(c) Results of K-mean (d) Results of expectation maximization

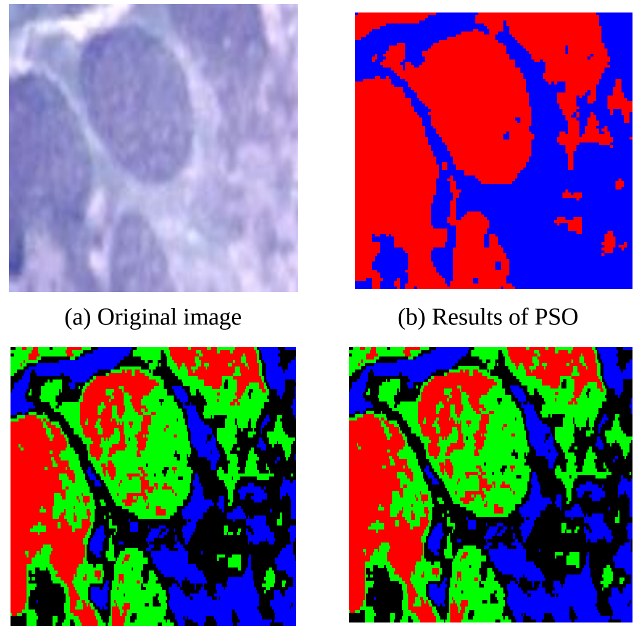
Figure 1. Segmentation results comparison on Lena image.(Original, PSO, K-mean, EM, no of centers = 3, iterations=20).



(a) Original image (b) Results of PSO

(c) Results of K-mean (d) Results of expectation maximization

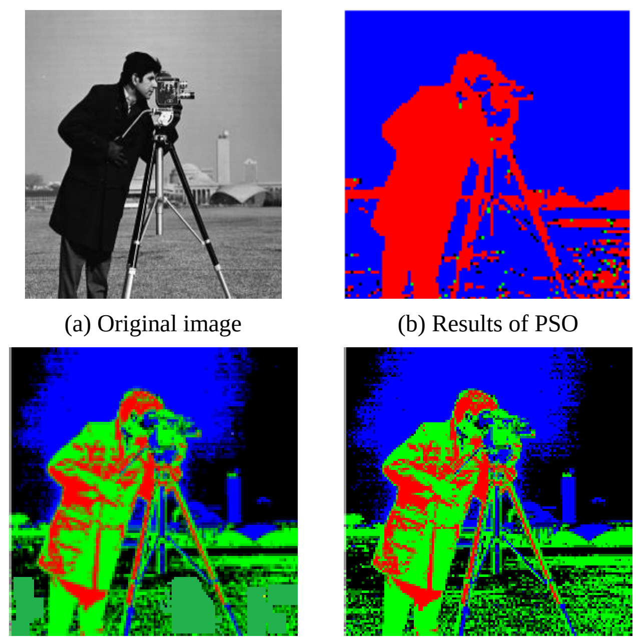
Figure 2. Segmentation results comparison on Barbara image.(Original, PSO, K-mean, EM, no of centers = 3, iterations=20).



(a) Original image (b) Results of PSO

(c) Results of K-mean (d) Results of expectation maximization

Figure 3. Segmentation results comparison on cervical cancer pap smear.(Original, PSO, K-mean, EM, no of centers = 3, iterations=20).



(a) Original image (b) Results of PSO

(c) Results of K-mean (d) Results of expectation maximization

Figure 4. Segmentation results comparison on Cameraman image.(Original, PSO, K-mean, EM, no of centers = 3, iterations=20).

(a) Original image

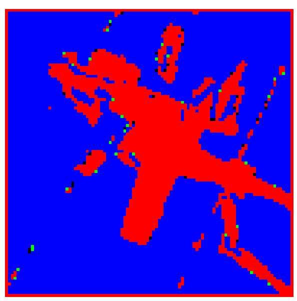
(b) Results of PSO

(c) Results of K-mean

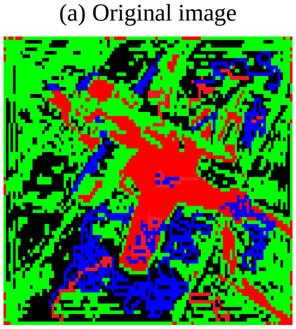
(d) Results of expectation maximization

Figure 5. Segmentation results comparison on Elephant image.(Original, PSO, K-mean, EM, no of centers = 3, iterations=20).

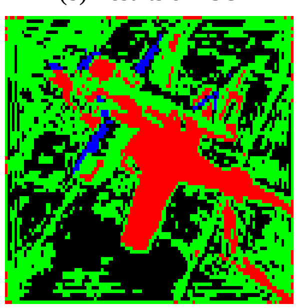
(a) Original image



(b) Results of PSO



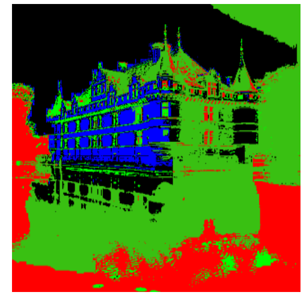
(c) Results of K-mean



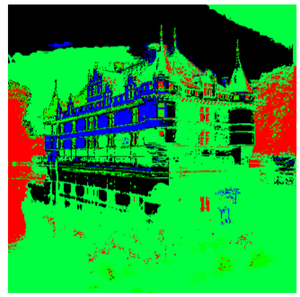
(d) Results of expectation maximization

Figure 6. Segmentation results comparison on aeroplane image.(Original, PSO, K-mean, EM, no of centers = 3, iterations=20).

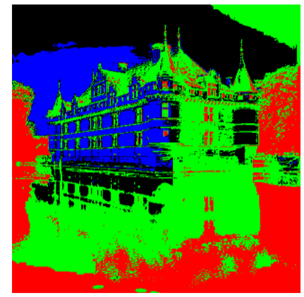
(a) Original image



(b) Results of PSO



(c) Results of K-mean



(d) Results of expectation minimization

Figure 7. Segmentation results comparison on church image.(Original, PSO, K-mean, EM, no of centers = 3, iterations=20).

5. CONCLUSION

We have successfully formulated lbest model of PSO for deriving optimum clusters for image segmentation. It can be seen from the results in some cases PSO method based segmentation avoids the problem of local minima. This is seen in the segmentation of elephant, cameraman and plane image. The results are far better in case of elephant and pap smear image. We can also investigate the application of current clustering algorithm mentioned in the paper for other areas such as unsupervised clustering, unsupervised image segmentation. An adaptive clustering algorithm which would detect the number of centers dynamically can also be explored with some modifications with existing PSO algorithm.

6. FUTURE SCOPE

PSO method based segmentation can be further extended where over convergence can be avoided. This can be done by enhancing the cost function in Equation (3). The cost function would be designed in such a way that enough distance between the centers can be kept at the time of convergence.

7. ACKNOWLEDGMENTS

Our thanks to MIT College of Engineering, Pune management for their support and motivation. We would also like to thank our colleagues as they have helped us as and when required. We would also like to thank our family members for their kind support. Last but not the least thanks to ACM SIGCHI for providing us platform to showcase our research.

8. REFERENCES

[1] Bing Xue, Mengjie Zhang, Will N. Browne, 2012 Particle Swarm Optimization for Feature Selection in Classification:

A Multi-Objective Approach ,IEEE Trans. Cybern., 2168-2267

[2] Long Tan, A Clustering K-means Algorithm Based on Improved PSO Algorithm,2015 Fifth International Conference on Communication Systems and Network Technologies

[3] Richard O. Duda, Peter E. Hart and David G. Stork, 2008.Pattern classification, Wiley

[4] Tom M. Mitchell, Machine learning, 2010, McGraw Hill.

[5] Fahd Mohsen, Mohiy Hadhoud, Kamel Mosta, Sep 2012, A new Image Segmentation Method Based On Particle Swarm Optimization, The International Arab Journal of Information Tech.,Vol 9,No 5.

[6] Molka DHIEB, A Multilevel Thresholding Algorithm for Image Segmentation Based on Particle Swarm Optimization.

[7] H Irshad et al., "Methods for nuclei detection, segmentation and classification in digital histopathology: A review. Current status and future potential," IEEE review in biomedical engineering, vol. 7, pp. 97–114, 2014.

[8] Aleksandar Lanzinica, Particle swarm optimization, 2009, In Tech, Austria