



## A Survey on Particle Swarm Optimization Methods for Image Segmentation

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**Abstract**— Image segmentation is one of the major tasks in image processing. It is the process of subdividing a digital image into its constituent parts/regions. This paper provides an overview of image segmentation methods based on the use of Particle Swarm Optimization (PSO) based clustering techniques. PSO belongs to the unsupervised classification techniques. PSO as one of the latest and emerging image segmentation techniques inspired from the nature, was developed by Dr Kenney and Dr Eberhart in 1995, and it has been widely used as an optimization tool in different applicable areas including computer graphics, biological or medical science, tele-communications, signal processing, data mining etc. The paper surveys PSO based methods to search cluster center in the arbitrary data set automatically without any input knowledge about the number of naturally occurring regions in the data, and their applications to image segmentation.

**Keywords**— Particle Swarm Optimization (PSO), PSO Clustering, Support Vector Data Description PSO, Mixture Model Kernel PSO...

### I. INTRODUCTION

The process of partitioning a digital image into multiple segments is called as Image segmentation. It is one of the complex and essential tasks of image processing system. This process is performed to represent the image in a clear way. It is often used to partition an image into separate regions, which ideally correspond to different real-world objects. It is a critical step towards content analysis and image understanding. The outcome of image segmentation process is a collection of segments which combine to form the entire image. Real world image segmentation problems have multiple objectives such as minimize the features, minimize overall deviation, minimize the error rate of the classifier or maximize connectivity, etc. Particle swarm optimization (PSO) is an evolutionary computation technique developed by Kenney and Eberhart in 1995[1]. PSO is a population-based stochastic approach for solving continuous and discrete optimization problems. In particle swarm optimization, simple software agents, called particles, move in the search space of an optimization problem. The position of a particle represents a candidate solution to the optimization problem. Each particle searches for better positions in the search space by changing its velocity according to rules originally inspired by behavioral models of bird flocking. Particle swarm optimization belongs to the class of swarm intelligence techniques that are used to solve optimization problems. PSO simulates the behaviors of bird flocking. Means, a group of birds are randomly searching food in an area. There is only one piece of food in the area being searched. All the birds do not know where the food is. But they know how far the food is in each iteration. So the best way to find the food is to follow the bird which is nearest to the food. Flocking behavior is the behavior exhibited when a group of birds, called a flock, are foraging.

Each particle in PSO is updated by following two "best" values:

- **pbest**- Each particle keeps track of its coordinates in the solution space which are associated with the best solution (fitness) that has achieved so far by that particle. This value is called personal best, pbest.
- **gbest**- It is tracked by the PSO is the best value obtained so far by any particle in the neighborhood of that particle. This value is called Global Best, gbest.

Each particle tries to modify its position using the following information:

- the current positions,
- the current velocities,
- the distance between the current position and pbest,
- the distance between the current position and the gbest.

After finding the two best values, the particle updates its velocity and positions with following equations

$$v[] = v[] + c1 * \text{rand}() * (\text{pbest}[] - \text{ppresent}[]) + c2 * \text{rand}() * (\text{gbest}[] - \text{ppresent}[]) \quad (1)$$

$$\text{present}[] = \text{present}[] + v[] \quad (2)$$

Where;

$v[]$  is the particle velocity,  $percent[]$  is the current particle (solution).  $rand()$  is a random number between (0; 1).  $c1$ ;  $c2$  are learning factors. usually  $c1 = c2 = 2$ .

The concept of modification of a searching point by PSO algorithm is depicted in Fig 1.

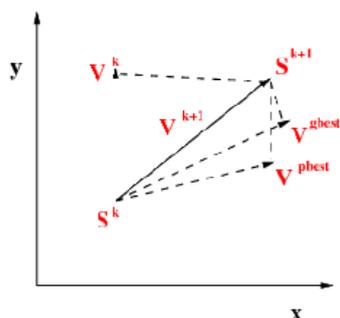


Fig 1: Concept of modification of a searching point by PSO.

## II. PSO-CLUSTERING APPROCHES IN IMAGE SEGMENTATION

Particle swarm optimization (PSO) is one of the current approaches that can be adopted in a wide variety of applications. It is an evolutionary stochastic computing method based on colony aptitude which is an important parallel searching algorithm. Image segmentation is a low level image vision task which is applicable in various applications such as object recognition, biological or medical imaging, data mining, document analysis, image and video retrieval, signal processing et . PSO itself is a very powerful and efficient technique and when merged with other computational intelligence techniques results in a truly affected and accurate approach. This paper reviewed how PSO can be combined with various other widely applied methodologies such as clustering, thresholding, neural networks, rough sets, genetic algorithm, wavelets and fuzzy systems, support data description.

Omran *et. al.* [3] developed a PSO based dynamic clustering method. Initially, the algorithm subdivides the large data set into the relatively large number of small clusters to reduce the effect of initial conditions and parameters. The binary PSO helps to select the best number of these clusters. Finally, the centers of the chosen clusters are refined by the k-means clustering technique. One of the advantages of proposed method is that user is independent to choose any validity index according to the data set. Clustering is an unsupervised method for pattern recognition and image segmentation.

Chun *et. al.* [4] proposed a method that uses fuzzy c-mean (FCM) clustering together with PSO. The main objective of FCM clustering is to search cluster centers that maximizes a similarity and/or minimizes the dissimilarity function. Here the PSO is used for the allotment of each pixel of an image to a particular cluster naturally. This hybridized FCM clustering and PSO algorithm generate better segmented images. The basic FCM algorithm is affected by the number and initial location of the centre of the predetermined clustering.

Jing *et. al.* [5] proposed a fast FCM method together with PSO for image segmentation. The PSO algorithm is an optimization process which automatically determines the number of clusters as well as the centre of the clusters. The sonar images have low signal to noise ratio. Therefore, it becomes difficult to segregate sonar images.

Liu *et. al.* [6] presented a PSO based fuzzy cluster for sonar image segmentation. This combination tends to produce strong searching and high speed convergence ability. In addition, the fuzzy measure and fuzzy integral are also calculated to compute the fitness. Since the possibilistic c-means (PCM) algorithm is very sensitive to initialization and parameters.

Jing *et. al.* [7] presented an approach to fit clusters which are close to one another. The t-Particle Swarm Optimization (t-PSO) is used to solve the complex computation as well as initial parameter sensitivity problem in order to get accurate segmentation. It is shown that the proposed algorithm is less influenced by the noise points and produce better segmentation results.

Zhang *et. al.* [8] illustrated how PCM can be integrated with PSO and provides a significant improvement on the efficiency of the segmentation. The PCM is more accurate as compared to FCM, as it overcomes the relative membership problem of FCM in image segmentation. The mahalonolis distance is used with PCM algorithm, since it enhances the performance of the clustering algorithm. The PSO is used to optimize the initial clustering centers.

In order to remove the robustness of FCM to noise, Liu *et. al.* [9] produced a new hybrid algorithm using fuzzy PSO and markov random field. The spatial information described by markov random field model is used to modify the similarity measure of FCM. The segmentation is done corresponding to the global best position of the, since it is less time consuming and also accelerate the speed of the algorithm as compared to the local best position. The underwater images have low signal to noise ratio. So, it becomes difficult to segment the image. The traditional FCM method does not provide good results and is very time consuming.

Wang *et al.* [10] presented segmentation algorithm based on histogram weighted FCM. The statistical characteristics of histogram of grey image are taken into account, which produces a fast and effective FCM algorithm for water image segmentation. Since the value of membership affects the convergence affects the convergence rate of the iterative process. The proposed improved fuzzy membership meets the requirements that increases the maximum value membership degree and reduces other memberships. FCM is very sensitive to initial value and improper selection of initial value may lead to fall into the local minimum. The PSO described by sine function has been introduced to overcome the drawback that FCM algorithm cannot reach the global optimum solution. Results indicate that the proposed method can be employed to real time applications and the processing time has also reduced.

Thresholding is the simplest method of image segmentation and separates the pixels of an image into various groups. It works efficiently for bi-modal images. Edge based detection is based on the discontinuity in an image. It is easily effected by the presence of noise and may lead to over as well as under segmentation. Region growing overcomes the drawbacks of early image segmentation techniques. Another method is clustering which groups the data into different clusters. Fuzzy set image segmentation is the rule based segmentation and takes into account the uncertainty and fuzziness in an image. PSO reveals an effect of implicit communication between particles (similar to broadcasting) by updating neighborhood and global information, which affect the velocity and consequent position of particles. Also, there is a stochastic exploration effect due to the introduction of the random multipliers ( $r_1$ ,  $r_2$  and  $r_3$ ). The PSO has been successfully used in many applications such as robotics.

Ghamisi *et al.* [11], the main goal is to increase the diversity of the population by either preventing the particles to move too close to each other and collide or to self-adapt parameters such as the constriction factor, acceleration constants, or inertia weight. The Fractional-Order Darwinian PSO (FODPSO) presented in Couceiro *et al.* (2011) is an extension of the Darwinian PSO (DPSO) in which fractional calculus is used to control the convergence rate of the algorithm. Fractional calculus (FC) has attracted the attention of several researchers Ortigueira & Tenreiro Machado, Sabatier, being applied in various scientific fields such as engineering, computational mathematics, fluid mechanics, among others. The characteristics revealed by fractional calculus make this mathematical tool well suited to describe phenomena such as irreversibility and chaos because of its inherent memory property. In this line of thought, the dynamic phenomena of particle's trajectory configure a case where fractional calculus tools fit adequately. Both FODPSO and DPSO present similar results, it is noteworthy that the fractional order algorithm is able to reach a slightly better fitness solution in less time. This should be highly appreciated as many applications require realtime segmentation methods such as the autonomous deployment of sensor nodes in a given environment or the detection of flaws in quality inspection of materials. In addition, FODPSO is slightly faster than DPSO since fractional calculus is used to control the convergence rate of the algorithm. In the DPSO, the trade-off between exploitation and exploration can only be handled by adjusting the inertia weight.

Ouadfe *et al.* [12], ACPSO (Automatic Clustering with PSO) effectively search for both the optimal cluster centers positions and the number of effective clusters, and this with minimal user interference. ACPSO has the following characteristics: (1) particles can contain different cluster number in a range defined by minimum and maximum cluster number, (2) Particles are initialized randomly to process different cluster numbers in a specified range, (3) The goal of each particle is to search the optimum number of clusters and the optimum cluster centers, (4) Three new evolving operators are introduced to evolve dynamically the partitions encoded in the particles. In this paper we have presented a new particle swarm optimization based method for automatic image clustering. ACPSO, in contrast to most of the existing clustering techniques, requires no prior knowledge of the data to be classified. ACPSO used a novel representation scheme for the search variables in order to determine the optimal number of clusters. Each particle encoded a partition of the image with a number of clusters chosen randomly from the set of the maximum number of clusters. The partition of each particle of the swarm evolves using evolving operators which aim to reduce dynamically the number of clusters centers.

### III. HIERARCHICAL SUPPORT VECTOR DATA DESCRIPTION PSO

Slimene *et al.* [13], a novel kernel clustering method is proposed. The application of the proposed clustering algorithm to the problem of unsupervised classification and image segmentation task is investigated. The proposed method provides a new scheme for classifying objects of one data set without any prior knowledge on the number of naturally occurring regions in the data or an assumption on clusters shapes. It's based on the use of Particle Swarm Optimization (PSO) algorithm and the use of core set concept which is commonly used to resolve the Minimum Enclosing Ball (MEB) problem. The performance of the proposed method has been compared with a few state of the art kernel clustering methods over a test of artificial data and the Berkeley image segmentation dataset. This method provides a new scheme for classifying objects of one data set without any prior knowledge on the number of naturally occurring regions in the data or an assumption on clusters shapes. It's based on the use of Particle Swarm Optimization (PSO) algorithm and the use of core set concept which is commonly used to resolve the Minimum Enclosing Ball (MEB) problem. The main idea underlying the proposed method was to investigate a new approach using PSO within SVDD for image segmentation. The fundamental quality of the proposed technique is that it is able to find the optimal number of clusters automatically without a prior knowledge about the number of regions is required. Moreover, it's contribute to speeding-up cluster description and labeling stages and isn't sensitive to parameter.



Fig 1: PSO Based Image Segmentation of a synthetic image.

#### IV. MULTI-ELITIST- EXPONENTIAL PARTICLE SWARM OPTIMIZATION

The enhanced PSO techniques are used to find optimal fuzzy rules and membership functions. The best fuzzy rule is selected for image segmentation. The enhanced PSO techniques give best rule set than standard PSO. In this paper both the techniques are combined to produce better result than the two individual techniques. This PSO is named as MEEPSO (Multi elitist exponential particle swarm optimization). The effectiveness of this new enhanced PSO techniques are evaluated and proved better than existing two enhanced PSO techniques EPSO and MEPSO. In Multi-Elitist Exponential particle swarm optimization PSO, we combine both the advantages of exponential particle swarm optimization and Multi – Elitist particle swarm. The linear PSO algorithm exhibited a faster, but premature convergence to a large quantization error, while the EPSO and MEPSO had a slower convergence, but to lower quantization error. MEEPSO is faster, non premature and slower convergence to very lower quantization error than other two algorithms. This paper investigated the application of the MEEPSO to Image segmentation. The MEEPSO algorithm was compared against the EPSO and MEPSO algorithms which showed that the MEPSO convergence slower to lower quantization error than other two enhanced PSOs, while the standard PSO convergence faster to a large quantization error. Also the proposed MEEPSO increases the possibility to find the optimal positions as it decrease the number of failure.[14]

#### V. MIXTURE MODEL KERNELS

Jebara *et al.* [15] introduced a new class of kernels between distributions. These induce a kernel on the input space between data points by associating to each datum a generative model  $t$  to the data point individually. The kernel is then computed by integrating the product of the two generative models corresponding to two data points. This kernel permits discriminative estimation via, for instance, support vector machines, while exploiting the properties, assumptions, and invariances inherent in the choice of generative model. It satisfies Mercer's condition and can be computed in closed form for a large class of models, including exponential family models, mixtures, hidden Markov models and Bayesian networks. For other models the kernel can be approximated by sampling methods.

Srivastava *et al.* [16] presented a new methodology for automatic knowledge driven data mining based on the theory of Mercer Kernels, which are highly nonlinear symmetric positive definite mappings from the original image space to a very high, possibly infinite dimensional feature space. Described new method is called Mixture Density Mercer Kernels and used to learn kernel function directly from data, rather than using predefined kernels. These data adaptive kernels can encode prior knowledge in the kernel using a Bayesian formulation, thus allowing for physical information to be encoded in the model. We compare the results with existing algorithms on data from the Sloan Digital Sky Survey (SDSS). The MDMK with priors was built with AutoBayes, which automatically generates code to model mixture densities with prior information. The AutoBayes system generates code to model the mixture density based on high-level specifications, automatically instantiates the associated EM algorithm schema, performs all necessary optimizations, and generates the symbolic solution along with the likelihood function. The results also indicate that the Mixture Density Mercer Kernel can be an excellent representation for classification problems using very small samples of data. In resource constrained environments, where CPU, RAM, or other computational power is constrained, this kernel may have utility. We plan to explore this avenue further to see how the MDMK behaves under constrained conditions. We also plan to generalize the MDMK to multiclass problems.

#### VI. TEXTURE BASED CLASSIFICATION USING PSO-SVM APPROACH

Zyout *et al.* Texture-based analysis of micro calcification (MC) clusters provides a robust tool for the development of a computer-aided diagnosis (CADx) in mammography. Unlike shape-based schemes, a texture approach does not require a micro calcification segmentation stage. This paper presents a new texture-based CADx that accomplishes feature selection and classification stages using a PSO-SVM framework. The proposed CADx mainly consists of texture feature extraction and heuristic parameter selection stages. The first stage characterizes MC clusters using 28 texture features from gray level co-occurrence matrices (GLCMs). The second stage involves a heuristic feature selection and performance optimization of a kernel-based support vector machine (SVM) classifier using a PSO-SVM approach. This

step uses a particle swarm optimization (PSO) algorithm to heuristically search for the most discriminative texture features and to find the optimal SVM learning model that comprises the regularization and kernel parameters. Testing the proposed parameter selection approach using MC clusters from the mini-MIAS dataset produced perfect classification accuracy and demonstrated a promising performance of parameter selection using PSO-SVM method.[17]

## VII. APPLICATIONS OF PSO

The first practical application of PSO was in the field of neural network training and was reported together with the algorithm itself. Many more areas of application have been explored ever since, including telecommunications, data mining, control, design, combinatorial optimization, power systems, signal processing, and many others. To date, there are hundreds of publications reporting applications of particle swarm optimization algorithms. Although PSO has been used mainly to solve unconstrained, single-objective optimization problems, PSO algorithms have been developed to solve constrained problems, multi-objective optimization problems, problems with dynamically changing landscapes, and to find multiple solutions. Figure 3 shows some of the important applications of PSO based clustering methods.



Fig 3: Various applications provided by PSO.

## VIII. CONCLUSION

In this paper different PSO based clustering methods for image segmentation are listed with their applications in various fields. PSO has been emerged and used in wide area of computer science and engineering. It is the natural technique of computing and provides a number of ways of solving real world problems more efficiently and quickly with accuracy. PSO has a wide range of applicability which makes it one of the important and efficient techniques for its applications. Image segmentation can be freely and amazingly done by PSO based techniques with desired results. The PSO based segmented images are generally well segmented into regions of homogeneous color and are perceptually meaningful to human's vision and can detect, automatically, very well the number of regions.

Directions for future research are briefly summarized below:

- More specific probabilistic kernels such as Mixture Model Kernel [ ] [ ] could be and investigated to develop a mechanism that learns automatically from data the parameter of kernel function.
- Applications like computer vision, medical imaging, face recognition, digital libraries and image and video retrieval could be enhanced.
- Enhancing these PSO segmentation techniques by employing the parallel PSO algorithms and extending the techniques to the 3D cases.

### Acknowledgment

The authors wish to express their heartfelt gratitude to Hon'ble Shri I.P Mishra, Chairman, Gangajali Educational Society, Bhilai; Respected Shri Abhishek Mishra, Director Systems, SSGI, Bhilai; Respected Shri P.B. Deshmukh, Director Administration, SSGI, Bhilai; Respected Dr. G.R Sinha, Associate Director, SSGI, Bhilai for providing the facilities for the research and development work and for their constant encouragement.

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