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An Overview of PSO- Based Approaches in Image Segmentation

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ABSTRACT

Particle swarm optimization (PSO) is recent approach that can be employed in a wide range of applications. It is an evolutionary computing method based on colony aptitude which is a better parallel searching algorithm. Image segmentation is a low level vision task which is applicable in various applications such as object recognition, medical imaging, document analysis, just to name a few. PSO itself is a very powerful technique and when combined with other computational intelligence technique results in a truly affected approach. In this paper we have reviewed how PSO can be combined with various other methodologies such as neural networks, rough sets, clustering, thresholding, genetic algorithm, wavelets and fuzzy systems.

Keywords- *Particle swarm optimization, Image segmentation, Thresholding, Fuzzy system, Genetic algorithm, Wavelets, Clustering, Rough set, Neural network*

I. INTRODUCTION

Image segmentation has received a lot of attention by the research people. It subdivides an image into its constituents regions which are more meaningful and easier to analyse. The level of detail to which subdivision is carried depends on the problem being solved. That is, segmentation should stop when objects or region of interest in an application has been detected. The partitioned regions can have same color or texture. All the pixels in the region share certain visual characteristics. The result of image segmentation is a set of regions which cover the entire image. Each of the pixels in a region are similar with respect to some characteristics such as color, intensity or texture. Adjacent regions are dissimilar with respect to same characteristics. Applications of image segmentation are locating tumours [1], face recognition [2], [3] and image retrieval [4].

Particle swarm optimization (PSO) is an evolutionary computation technique proposed by Kennedy and Eberhart [5]. The basic idea of PSO is inspired by social behaviour of bird flocking, fish schooling and swarm theory. One of the advantages of PSO is that it is easier to implement and there are very few parameters to adjust. PSO shares many similarities with other computation techniques such as genetic algorithm. PSO has been employed to solve a range of optimization problems, including neural network training [6], [7] and function minimization [8], [9].

Image segmentation methods are a) thresholding, b) edge based segmentation, c) region growing, d) clustering, e) region splitting, f) fuzzy set image thresholding and so on. Thresolding 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.

II. PARTICLE SWARM OPTIMIZATION (PSO)

The Particle swarm optimization (PSO), first introduced by Kennedy and Eberhart [1], is a stochastic optimization technique that is similar to the behaviour of a flock of birds or the sociological behaviour of a group of people. Consider a scenario in which a flock of birds are searching for a piece of food in an area. All the birds do not exactly know where the food is, but with each iteration they come to know how far the food is. The best strategy will be to follow the bird which is near to food and also from its own previous best position. This is the basic idea on which PSO works. In PSO algorithm the five essential parameters that are considered [10] are as tabulated in table 1.

Table 1 - Particle Swarm Optimization

Parameters	Description
particle	candidate solution to a problem
velocity	rate of position change
fitness	the best solution achieved
p_{best}	best value obtained in previous particle
g_{best}	best value obtained so far by any particle in the population

The detailed operation of particle swarm optimisation [11] is given below:

Step 1: Initialisation. The velocity and position of all particles are randomly set to within pre-defined ranges.

Step 2: Velocity Updating. In each iteration, the velocities of all particles are updated according to:

$$\vec{v_i} = w\vec{v_i} + c_1R_1(\vec{p}_{i,best}-\vec{p_i})+c_2R_2(\vec{g}_{i,best}-\vec{p_i})$$

Where $\vec{v_i}$ and $\vec{p_i}$ are the velocity and position of particle I, respectively. $\vec{p}_{i,best}$ and $\vec{g}_{i,best}$ are the position with the 'best' objective value found so far by particle *i* and the entire population respectively; *w* is used to control the convergence behaviour of PSO; R_1 and R_2 are random variables in the range [0, 1]; c_1 and c_2 control how far a particle move in single iteration. After updating, velocity should be checked and secured within a pre-specified range to avoid violent random walking.

Step 3: Position Updating. Assuming a unit time interval between successive iterations, the positions of all particles are updated according to:

$$\vec{p_1} = \vec{p_i} + \vec{v_i}$$

After updating, p_i should be checked and limited to the allowed range.

Step 4: Memory Updating: Update $\vec{p}_{i,best}$ and $\vec{g}_{i,best}$ when condition is met

$$\vec{p}_{i,best}=\vec{p}_i \quad \text{if } f(\vec{p}_i) > f(\vec{p}_{i,best})$$
$$\vec{g}_{i,best}=\vec{g}_i \quad \text{if } f(\vec{g}_i) > f(\vec{g}_{i,best})$$

Step 5: Termination Checking. The algorithm repeats Steps 2 to 4 until certain termination conditions are met, such as a pre-defined number of iterations or a failure to make progress for a certain number of iterations. Once terminated, the algorithm reports the values of $\vec{g}_{best}$ and f ($\vec{g}_{best}$) as its solution.

III. PSO- HYBRID TECHNIQUES

PSO itself is a very powerful technique and when combined with other computational intelligence technique results in a truly affected approach.

A. PSO-Thresholding Approaches in Image Segmentation

Minimum cross entropy thresholding method is very time consuming in multilevel thresholding as compared to bi-level thresholding for complex image segmentation. Yin *et. al.* [12] proposed a method which uses PSO together with minimum cross entropy to obtain a threshold for image segmentation. This method overcomes the problem of time consumption. The results of the proposed method are compared with exhaustic search method. It has been concluded that although thresholds of the proposed method with PSO are equivalent to that of exhaustic search method but in latter case computational time increases exponentially with the number thresholds whereas the computational time of former case is negligible.

Nakib *et. al.* [13] proposed two-dimensional survival exponential entropy with PSO for segmentation of magnetic resonance imaging (MRI) images. Initially, the two dimensional histogram is obtained in order to avoid the problem of spatial distribution. The PSO is used for optimization of two-dimensional survival exponential entropy to solve the segmentation problem. Result show that the proposed method produced better results on comparison with two-dimensional Shannon entropy.

A successful application was introduced by Djerou *et. al.* [14] using a combination of thresholding and binary PSO. This approach determines the number of thresholds optimal. The objective function depends on the user's data set. In this paper, mainly two thresholding methods are optimized using proposed algorithm namely, Kapur's method [15] and Otsu's method [16]. The uniformity measure is used to evaluate the quality of threshold images. Experimental results show that computation time of Otsu's method is better than Kapur's method. Therefore the proposed algorithm using Otsu's method is more efficient.

Another approach that uses PSO with entropy has been proposed by Hongmei *et. al.* [17]. The author applied improved PSO to predict the multi-level thresholding for image segmentation. The proposed improved PSO overcomes the problem of premature convergence of PSO. One of the problems with standard PSO is parameter selection. This can be improved by making random numbers instead of acceleration coefficients in PSO and referring the coevolution model. The uniformity measure is used which qualitatively measure the performance of image segmentation method. Results show that on increasing the number of thresholds, the running time of proposed method does not significantly increased and the efficiency as well as the convergence rate of the basic PSO can also be improved.

The multimodal images are more complex to segment as compared to bimodal images. De *et. al.* [18] presented a region growing technique along-with thresholding and PSO for the segmentation of multimodal MRI images. The basic idea was that the diseased portion will have different intensity value as compared to non-diseased portion. Initially, the normalised histogram of the diseased MRI image is calculated and then entropy maximization is used to obtain the range of grey level of diseased portion. This range of grey level of diseased portion is optimized using PSO. At last the concept of variable mask is applied over the region of interest to obtain the final segmented image.

Yu *et. al.* [19] proposed an image segmentation technique based on maximum entropy thresholding and quantum behaviour of PSO. This method overcomes the problem of earlier convergence of the PSO and the shortcomings of large calculation of multi thresholding segmentation.

B. PSO-Fuzzy System Approaches in Image Segmentation

Masooleh *et. al.* [20] proposed a fuzzy system in conjunction with PSO for image segmentation. A sugeno fuzzy system is used in the proposed method. By applying a set of fuzzy rules, each pixel is assigned a colour class. For fuzzy colour classification, HSL colour space is used. The main problem with fuzzy system is the large number of fuzzy rules. Therefore, PSO is used which automatically produces the least number of optimum fuzzy rules and generate the optimized membership function.

Puranik *et. al.* [21] presented a colour image segmentation using comprehensive learning PSO based fuzzy system. Comprehensive learning PSO is an improved version of PSO, in which all particle's p_{best} are used to update the velocity of other particles. A fitness function is used which rates the optimality of each particle. Comprehensive learning PSO is an optimization process which finds the optimal fuzzy rules as well as the membership function. Each particle is assigned a set of fuzzy rules. During this process, each particle tries to maximize the fitness function. Also Comprehensive learning PSO discourages the premature convergence of original PSO. Furthermore, HSL colour space is used in the proposed method as the colour can be presented in three-dimensional for fuzzy colour classification.

Gopal *et. al.* [22] presented two phase of MRI segmentation. The first phase includes pre-processing and enhancement. In order to remove labels and x-ray marks from MRI images, a tracking algorithm has been proposed. Along with this, a median filter is used to remove high frequency components from MRI images. The fuzzy c-means (FCM) calculates the adaptive threshold, after PSO which automatically determines the optimal threshold value of the given image to select initial cluster seed point.

Murugesan *et. al.* [23] illustrated multi elistic exponential PSO hybridized with fuzzy system in order to perform segmentation of coloured images. Multi elistic exponential PSO is a combination of multi elistic PSO and exponential PSO. Multi elistic PSO employs a kernel induced similarity measure for searching global best of PSO. The standard PSO converges too early in the search space. The multi elistic PSO helps to prevent this convergence behaviour of PSO. On the other hand, exponential PSO avoids the particles from stagnation of local optima by varying the inertia weight exponentially. This hybridized PSO is used to find the optimal fuzzy rules and membership function. Each particle tries to maximize the fitness function. The best fuzzy rule is selected for image segmentation.

C. PSO-Genetic Algorithm Approaches in Image Segmentation

The traditional FCM clustering algorithm is sensitive to noise. One of the simplest methods is low pass filtering of an image and then applying the FCM clustering algorithm. The drawback this approach was that it may lead to loss of the important details present in an image. To overcome this drawback, an important FCM clustering algorithm has been proposed by Shen *et. al.* [24]. An important parameter that can affect the performance of FCM clustering method is the parameter optimization. Forouzanfer *et. al.* [25] proposed a breeding warm algorithm that helps to find optimum attraction parameters. The breeding swarm algorithm combines the strength of both PSO and genetic algorithm. The algorithm is so designed so that PSO facilitates local search and genetic algorithm performs global search. Experimental results indicate that the proposed breeding swarm with FCM clustering algorithm is a good technique for the segmentation of MRI images.

Kole *et. al.* [26] described an approach for image segmentation using hybrid technique based on PSO and genetic algorithm. The PSO based dynamic clustering has been used to find the optimal number of clusters. This information is further used by genetic algorithm to improve the final result of the PSO based method. At last, the best result is obtained by comparing their respective validity indices [27] and the data is partitioned accordingly.

D. PSO-Wavelet Approaches in Image Segmentation

In the standard PSO, the particles are prematurely attracted to the local attractor. Wei *et. al.* [28] proposed an inertia adaptive PSO and wavelet mutation algorithm which helps the particles to escape from local minima and increases the speed of the segmentation process. The fitness function of the particles in the swarm is calculated by using fuzzy entropy. The motion of the particles is governed by two dynamical regimes. In the first case, if there is an improvement in the fitness function of the particles from iteration to iteration, in such a case inertia adaptive PSO has been used to sample the particles. In the second case, if there is no improvement, it results in stagnation. In such a case, the wavelet mutation has been proposed. One of the advantages of wavelet mutation is that it exhibits a fine tuning ability.

De *et. al.* [29] illustrated how PSO can be successfully integrated with wavelet mutation and provides a more effective approach to resolve the stagnation problems. Initially, the normalized histogram of the MRI images is obtained. Then entropy maximization is employed to get the expert knowledge of the probable threshold grey level range for segmentation of MRI images. The hybrid PSO together with wavelet mutation is used to optimize the initial value of the threshold. Using this threshold value, the region of interest is obtained. Finally, a variable mask is employed on region of interest to get the segmented MRI images with lesions.

E. PSO-Clustering Approaches in Image Segmentation

Omran *et. al.* [30] presented a dynamic clustering based on PSO. Initially, the algorithm partitions the data set into the relatively large number of clusters in order to reduce the effect of initial conditions. The binary PSO helps to select the best number of clusters. At last, the centres of the chosen clusters are refined by k-means clustering. One of the advantage of proposed method is that user can choose any validity index according to the given data.

Clustering is an unsupervised technique for image segmentation. Chun *et. al.* [31] proposed a method that uses FCM clustering together with PSO. The main objective of FCM clustering is to find cluster centres that maximizes a similarity function or minimizes the dissimilarity function. The PSO is used for assigning each pixel to a cluster. This hybridized FCM clustering and PSO algorithm produce better segmentation results.

The basic FCM algorithm is affected by the number and initial location of the centre of the predetermined clustering.

Jing *et. al.* [32] 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.* [33] 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.* [34] 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.* [35] 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 centres.

In order to remove the robustness of FCM to noise, Liu *et. al.* [36] 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.* [37] 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.

F. PSO-Rough Set Approaches in Image Segmentation

An approach that uses rough set entropy with PSO has been proposed by Feng *et. al.* [38]. The author applies rough set entropy to segment a grey-scale image. The algorithm obtains the optimal threshold by using PSO and rough set entropy which is based on boundary conditions. Experimental results show that the proposed algorithm is time efficient and the system becomes more stable. Also, the sensibility of the algorithm to partition size image sub-piece is low.

Behera *et. al.* [39] presented a hybrid rough set PSO for partitioning an image into different meaningful segments. In rough c-means, each cluster is treated as an interval or rough set. The k-means clustering algorithm has been used to classify image pixels, which calculates the initial means and their positions in clusters. After obtaining the cluster centres, the upper and lower bounds of the clusters are calculated. The rough set is used to upgrade the cluster centres. PSO is used to tune the parameters of rough c-means. In this approach, a statistical mathematical function called Davies Bouldin [40] index is used for the purpose of the fitness function in PSO. The performance evaluation of PSO shows that this method reduces noisy spots and is less sensitive to noise.

G. PSO-Neural Networks Approaches in Image Segmentation

Yi *et. al.* [41] illustrated white blood cell image segmentation incorporating an online trained neural network. Initially, a mean shift algorithm [42] has been employed to search the cluster centre. After this, uniform sampling is performed so as to reduce the size of the training set. By using uniform sampling, the statistical data has revealed that subset can represent the entire data set approximately. Furthermore, the PSO algorithm has been employed which helps in faster convergence as well as helps to escape from local optimum.

Lian *et. al.* [43] proposed a new approach for segmenting magnetic resonance imaging (MRI) images based on modified adaptive probabilistic Neural Networks (MAPNN). The MAPNN incorporates self-organizing map (SOM), modified particle swarm optimization (MPSO) and Probabilistic Neural Network (PNN) for segmentation. In this approach, SOM [44] neural network is trained with training feature set, so as to yield a SOM map for PNN. Then, according to this SOM map, MPSO [45] provides the smoothing factor to PNN. The feature extraction is also performed in order to improve training quality of neural network.

Image enhancement and pre-processing is required for ultrasound images, since they have low contrast and speckle noise. Alamelumangai *et. al.* [45] presented a neuro-fuzzy filter [46] for image enhancement in the proposed algorithm. After pre-processing, an artificial neuro-fuzzy networks (ANFN) and eliminating particle swarm optimization (EPSO) had been employed for image segmentation. The proposed ANFN algorithm is basically a 5-layer network and the inputs are fuzzy values. The EPSO eliminates the weakest particle and searches for optimal solution. The proposed algorithm helps to reduce the computational time without affecting the accuracy of the solution.

Table 2 - PSO – Hybrid Techniques

PSO- Hybrid techniques	Reference	Year	Optimization using PSO	Advantages	Images	Quality measurement
Thresholding	Yin [12]	2007	Minimum cross entropy	1.Efficient 2.Computation time is less 3.Suited for more complex image analysis 3.Used in real time applications	1.Standard	1.Computation time
	Nakib [13]	2007	2-Dimensional survival exponential entropy	1.Low computational cost 2.Good speed gain factor	1.Synthetic 2.MRI	1.Misclassification error 2.Uniformity 3.Speed gain factor
	Djerou [14]	2009	Gray level thresholds	1.Easy to implement 2.Self adaptive thresholding	1.Synthetic 2.Natural	1.Uniformity factor
	Hongmei [17]	2010	Maximum entropy	1.Less computational cost 2.Good search ability 3.Fast convergence	1.Standard	1.Uniformity factor
	De [18]	2010	Range of gray levels of diseased cells of MRI image	1.Segmentation of multimodal images 2.Useful for diagnosis of diseased MRI images	1.Diseased MRI	
	Yu [19]	2011	Maximum entropy thresholding	1.Easy to implement 2.Overcomes the shortcomings of large calculation of multi-threshold segmentation	1.Standard 2.Gray 3.HD Grayscale	1.Mean threshold 2.Mean time 3.False astringent
Fuzzy based	Masooleh [20]	2008	Appropriate individual for fuzzy classification system	1.Fewer number of rules 2.Response time is less 3.Minimum error rate	1.Colored images of middle sized RoboCup Soccer field	1.Number of rules 2.Efficiency
	Puranik [21]	2009	1.High classification rate 2.Lower number of rules	1.Minimum error rate 2.High computational speed 3.Better accuracy 4.More efficient in terms of computational complexity	Standard data base images of: 1.Natural outdoor scenes 2.Terrestial and aerial views 3.Satellite	1.Number of rules 2.Execution time
	Gopal [22]	2010	Optimal threshold value of given image to select initial cluster seed point	1.Better accuracy 2.Reliable 3.More efficient 3.Simple to implement	1.MRI	1.Overall accuracy 2.Pixel Error rate 3.Position error rate
	Murugesan [23]	2010	1.Lower number of fuzzy rules 2.Adjust fuzzy membership function	1.Faster 2.Increases the possibility to find optimal solutions 3. Non premature convergence	1.Coloured images of middle sized RoboCup Soccer field	1.Number of iterations 2.Fitness function
Genetic algorithm	Forouzanfar [25]	2010	Parameter optimization of IFCM algorithm	1.Able to locate the optimal solution significantly faster than either PSO&GA 2.Combines the strength of PSO & Gas simultaneously	1.MRI 2.Synthetic	1.Under segmentation 2.Over segmentation 3.Incorrect segmentation 4.Similarity index
	Kole [26]	2010	Calculate the optimal number of clusters	1.Determines the optimum clustering of an image dataset with minimum used intervention 2.Gives satisfactory results when applied to natural image	1.Natural 2.Satellite	1.Number of clusters

Wavelet based	Wei [28]	2010	Best fuzzy parameter	1.Good segmentation 2.Self adaptive 3.Robust algorithm	1.Standard	1.Uniformity
	De [29]	2011	Initial value of threshold	1.Overcome the deficiencies of PSO algorithm 2.Diagnosis of MRI images with lesions	1.MRI	
Clustering based	Omran [30]	2005	Best number of clusters	1.Can work with any validity index 2.Can be used with PSO/or GA 3.Optimum number of clusters are selected	1.Synthetic 2.Natural 3MRI 4.Satellite	1.Mean 2.Standard deviation
	Chun [31]	2008	Assigns each pixel to a cluster	1.Accurate clustering can be obtained 2.Potential method to accelerate the threshold selection in real time application	1.Standard	1.Image
	Jing [32]	2010	Centres and number of clusters	1.Avoid coincident cluster problem 2.Less initialization sensitivity 3.Higher segmentation accuracy	1.Standard	1.Accuracy
	Hongpo [33]	2010	Cluster centre	1.Better performance 2.Robust algorithm 3.Improves anti-noise ability 4.Improves accuracy 5.Can handle low SNR sonar segmentation problem	1.Sonar	1.Image
	Jing [34]	2010	Centre and number of clusters	1.Easy to compute 2.Better segmentation 3,Better robustness 4.Reduces the production of false disease spot to a certain extent	1.Standard	1.Image
	Zhang [35]		Initial cluster centre	1.Significant improvement in the efficiency of segmentation 2.More effective	1.Standard	1.Image
	Liu [36]		Membership function and local conditional probability	1.Superior to FCM and PSO 2.Fast convergence of algorithm	1.Synthetic	1.Accuracy
	Wang [37]		Local optimal solution for FCM algorithm	1.Processing time of image is reduced 2.More efficiency 3.Improves quality of segmentation	1.Underwat er	1.Time consumption
Rough set based	Feng [38]	2009	Threshold value	1.Quality and stability of image segmentation is high 2.Less time consumption	1.Grayscale	1.Time consumption
	Behera [39]	2011	Threshold parameters, upper and lower approximations of rough set.	1.Easier to analyse 2.Optimal solution with smallest Davies-Bouldin index	1.Noisy	1.Low Davies-Bouldin index
Neural network based	Yi [41]	2005	Training neural network	1.Running time is reduced 2.Computational cost is reduced 3.Training set is reduced	1.Blood cell	1.Training time 2.Accuracy
	Lian [43]	2010	Smoothing parameter of the kernel function in the neural network	1.Effective algorithm 2.Robust 3.Reduces the training set	1.MRI	1.Error rate

	Alamelumangai [45]	2010	Optimum cluster	1.Low computational time and complexity 2.Handle entire image automatically and accurately instead of focussing exclusively on ROIs 3.Less sensitive to noise	1.Ultrasound	1.Match rate

IV. CONCLUSION

In this paper we provided an overview of different PSO approaches applied in various image segmentation domains. Since PSO itself is a very powerful technique, but when combined with other computational intelligence techniques results in a more effective approach. We have illustrated that PSO have been successfully combined with fuzzy sets, neural networks, clustering, wavelets, genetic algorithm, thresholding and rough sets for image segmentation.

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