Image Clustering Based on Different Length Particle Swarm Optimization (DPSO)

Somnath Mukhopadhyay[1], Pragati Mandal[2], Tandra Pal[2], and Jyotsna Kumar Mandal[3]

[1] Department of Computer Science and Engineering, Aryabhatta Institute of Engineering and Management, Durgapur, India-713148
som.cse@live.com

[2] Department of Computer Science and Engineering, National Institute of Technology, Durgapur, India-713209
{pragatimandal.bu,tandra.pal}@gmail.com

[3] Department of Computer Science and Engineering, University of Kalyani, Kalyani, India-741235
jkm.cse@gmail.com

Abstract. Partitioning image pixels into several homogeneous regions is treated as the problem of clustering the pixels in the image matrix. This paper proposes an image clustering algorithm based on different length particle swarm optimization algorithm. Three evaluation criteria are used for the computation of the fitness of the particles of PSO based clustering algorithm. A novel Euclidean distance function is proposed based on the spatial and coordinate level distances of two image pixels towards measuring the similarity/dissimilarity. Different length particles are encoded in the PSO to minimize the user interaction with the program hence the execution time. PSO with different length particles automatically finds the number of cluster centers in the intensity space.

The performance of the proposed algorithm is demonstrated by clustering different standard digital images. Results are compared with some well known existing algorithms.

Keywords: Crisp clustering, digital image, Euclidean distance, image clustering, mean square error, quantization error, different length particle swarm optimization.

1 Introduction

Clustering is a process of grouping a set of samples or data so that they are similar within each group. The groups are called clusters [3]. Clustering techniques are used in many applications, such as image processing, object recognition, data mining, machine learning, etc. The clustering algorithms try to minimize or maximize certain objective functions.

A popular partitioning clustering algorithm is K-means[15]. This algorithm clusters the samples based on *Euclidean distance* as similarity/dissimilarity measure. The algorithm is suitable for large data set and easy to implement. In any

S.C. Satapathy et al. (eds.), *Proc. of the 3rd Int. Conf. on Front. of Intell. Comput. (FICTA) 2014 – Vol. 1*, Advances in Intelligent Systems and Computing 327, DOI: 10.1007/978-3-319-11933-5_80

fixed length clustering algorithm e.g., K-means algorithm, the clustering is obtained by iteratively minimizing a fitness function that is dependent on the distance of the pixels to the cluster centers. However, the K-means algorithm, like most of the existing clustering algorithms, assume a priori knowledge of the number of clusters, K, while in many practical situations, this information cannot be determined in advance. It is also sensitive to the selection of the initial cluster centers and may converge to the local optima. Finding an optimal number of clusters is usually a challenging task and several researchers have used various combinatorial optimization methods to solve the problem. Some other fixed length image clustering algorithms [9,8,16] exist in the literature. Various approaches [6,14,13,5,7] toward the image clustering based on variable length chromosome genetic algorithm and variable length particle swarm optimization have also been proposed in the recent past years for clustering. Some cluster validity indices [12,11] are also proposed for fuzzy and crisp clustering.

In this paper, a new approach termed as *Different length Particle Swarm Optimization (DPSO)* is proposed for image clustering. In Particle Swarm Optimization [4,1], the solution parameters are encoded in the form of strings called particles. A collection of such strings are called a swarm. Initially a random population of swarm is created, which represents random different points in the search space. An objective or fitness is associated with each string that represents the degree of goodness of the solution encoded in the particles. In the proposed DPSO algorithm, a swarm of particles of different lengths, automatically determines the number of clusters and simultaneously clusters the data set with minimal user interference. By using a novel fitness function which contains three evaluation criteria such as intra cluster distance, inter cluster distance and an error minimizer function. A novel weighted *Euclidean* distance function is used as distance function between two pixels in the image matrix. The algorithm terminates when the *(gBest)* converges to optimal solution or it meets a finite number of iterations. Since the actual number of clusters is considered to be unknown, the string of different particles in the same swarm population are allowed to contain different number of clusters. As a consequence, the different particles have different lengths having different number of cluster centers.

Rest of the paper is organized as follows. The standard PSO algorithm is described in section 2. Section 3 described the proposed PSO of different length particles for image clustering. Experimental results and discussions are provided in section 4. Finally we conclude in section 5.

2 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a population based stochastic optimization technique modeled on the social behavior of bird flocks [4]. It maintains a population of particles, where each particle represents a potential solution of the optimization problem. Each particle is assigned a velocity. The particles then flow through the problem space. The aim of PSO is to find the particle position that results the best fitness value. A fitness function is associated with a given optimization problem, which gives a fitness value for each particle. Each particle keeps track of the following information in the problem space: x_i, the current position of the particle; v_i, the current velocity of the particle; and y_i, the personal best position of the particle which is the best position that it has achieved so far. This position yields the best fitness value for that particle. The fitness value of this position is called *pBest*. There is another parameter in PSO, called global best *(gBest)*. For *(gBest)*, the best particle is determined from the entire swarm. The best value obtained so far by any particle in the population is *(gBest)*. The PSO changes the velocity and position of each particle at each time step so that it moves toward its personal best and global best locations, using (1) and (2) respectively. The process is repeated for maximum iterations or sufficient good fitness value.

$$v_p(i+1) = h(i) * v_p(i) + \Psi_p * r_p * (x_{pB}(i) - x_p(i)) + \Psi_g * r_g * ((x_{gB}(i) - x_p(i)) \quad (1)$$

$$x_p(i+1) = x_p(i) + v_p(i+1) \quad (2)$$

In those equations, Ψ_p and Ψ_g are the positive learning factors (or acceleration constants). r_p and r_g are random numbers in [0, 1]. i is the generation number in [1, I_{MAX}]. I_{MAX} is the maximum number of iterations. $h(i) \in [0, 1]$ is the inertia factor. $f_{pB}(i)$ and $f_{gB}(i)$ are the *(pBest)* value and *(gBest)* values at i^{th} generation, respectively. $x_{pB}(i)$ and $x_{gB}(i)$ are respectively the personal and global best positions of p^{th} particle at i^{th} generation.

3 Different Length PSO (DPSO) Based Clustering

In this paper, a novel particle swarm optimization algorithm with different length particles is proposed. In this algorithm, a swarm of particles of different length, automatically determines the number of clusters and simultaneously clusters the data set with minimal user interference. It starts with random partitions of the image, encoded in each particle of the swarm.

The fitness function proposed by Omran and Salman [10,9] has been associated in the proposed clustering. The proposed fitness function defined in (7), contains three evaluation criteria such as intra cluster distance measure, inter cluster distance and the quantization error minimization function. These criteria are defined respectively in (4), (5) and (6). We consider the same weight of all these three criteria to the fitness of the corresponding particle. The weighted *Euclidean* distance function [9], given in (3), is used to compute the distance between two pixels in the image matrix, which is used for computing intra cluster distance measure, inter cluster distance and the quantization error. Vector containing the X-coordinate (say x), Y-coordinate (say y) and pixel intensity value (say z) are used to obtain the Euclidean distance between two pixels. The difference between two pixels termed as gray level distance as well as their spatial distance is calculated in the proposed distance function. The proposed weighted

Euclidean distance function between the i-th pixel and j-th pixel in the image matrix is given in (3).

$$d(x, y, z) = \sqrt{w_1((x_i - x_j)^2 + (y_i - y_j)^2) + w_2(z_i - z_j)^2} \quad (3)$$

In the Euclidean distance function, different weights are assigned for two different distances, the spatial and gray level distances. The spatial distance has been assigned with less weight over the gray level distance. The intensity value similarity/dissimilarity of any two pixels is given with more weight over the positional similarity/dissimilarity of the pixels. The difference in intensity values between the pixels are multiplied by a weight factor w_2=0.5, whereas coordinate level difference is multiplied by w_1=0.1.

Different length PSO (DPSO) is proposed for image clustering, where a solution gives a set of cluster centers. Let Z = (z_1, z_2, z_3, ..., z_{N_p}) be the digital image with n number of pixels. The DPSO maintains a swarm of particles, where each particle represents a potential solution to the clustering problem and each particle encodes partition of the image Z. DPSO tries to find the number of clusters, N_c. The DPSO based image clustering method has various parameters. N_p, N_c, z_p, m_j, C_j and $|C_j|$, which are respectively the number of image pixels to be clustered, N_c number of clusters, p-th pixel of the image, mean or center of cluster j, set of pixels in cluster j and the number of pixels in cluster j. Each particle can be represented by $\{m_{i1}$, ...,m_{ij}, ..., $m_{iN_c}\}$, where m_{ij} refers to the j-th cluster center vector of the i-th particle. In this algorithm, particles have different lengths since the number of clusters is unknown. The particles are initialized with random number of cluster centers in the range [K_{min}, K_{max}], where K_{min} is usually assigned to 2 and K_{max} describes the maximum particle length, which represents the maximum possible number of clusters. K_{max} depends on the size and type of image. DPSO, the proposed algorithm for image clustering using different length particle swarm optimization is presented in Algorithm 1.

The intra-cluster distances of all the clusters are measured and the maximum one among all the clusters is selected in d_{max} which is defined in (4), where Z is a partition matrix representing the assignment of pixels to clusters of particle i. A smaller value of d_{max} means that the clusters are more compact.

$$d_{max}(Z, x_i) = \max_{j=1\ to\ N_c} \{ \sum_{\forall z_p \in C_{ij}} d(z_p, m_{ij}) / \ |C_{ij}| \} \quad (4)$$

Inter-cluster separation distances for all clusters are measured and the minimum distance between any two clusters is calculated using (5). A large value of d_{min} means that the clusters are well separated.

$$d_{min}(x_i) = \min_{\forall j1, j2, j1 \neq j2} \{ d(m_{ij_1}, m_{ij_2}) \} \quad (5)$$

The quantization error function [2,9] is proposed in the clustering of image pixels which calculates the average distance of the pixels of a cluster to its cluster centers, followed by the average distances of all clusters and hence calculates new average. The problem of Esmin *et al.* [2] is that any cluster with one pixel would

Algorithm 1. DPSO Algorithm

Input: Gray Scale Image Matrix
Output: Partition Matrix

begin
Initialize the maximum number of cluster centers K_{max} and all the constant parameters
Initialize each particle with K randomly selected cluster centers
Initialize each particle x_i with the $pBest_i$ and also the *(gBest)*
while gen $< I_{max}$ **do** ▷ I_{max} is the maximum number iterations
for i=1 to NOP **do** ▷ Number of particles
  for x=1 to rows **do** ▷ Number of rows of the image matrix
    for y=1 to cols **do** ▷ Number of columns of the image matrix
      Let (x,y) be the coordinate of the p^{th} pixel
      Find Euclidean distance between p^{th} pixel and all centers of i^{th} particle
      Assign p^{th} pixel to j^{th} centers of i^{th} particle
    end for
  end for
  Compute Intra cluster distance of i^{th} particle using (4)
  Compute Inter cluster distance of i^{th} particle using (5)
  Compute Quantization error of i^{th} particle using (6)
  Compute the fitness value of i^{th} particle using (7), which uses (4), (5) and (6)
  Update *(pBest)* position $x_{pB}(i)$ and *(pBest)* value $f_{pB}(i)$ of i^{th} particle
end for
Update *(gBest)* from all the particles in the swarm
Update velocity and then position of particles using (1) and (2)
Update inertia weight
end while
end

affect the final result with another cluster containing many pixels. Suppose for i^{th} particle in a cluster which has only one pixel and very close to the center and there is another cluster that has many pixels which are not so close to the center. The problem has been resolved by assigning less weight to the cluster containing only one pixel than with cluster having many pixels. The weighted quantization error function is given in (6), where N_0 is the total number of data vectors to be clustered. The fitness function is constructed by intra-cluster distance d_{max}, inter-cluster distance d_{min} along with the quantization error Q_e function. The fitness function used to minimize $f(x_i, Z)$ [16] which is given in (7). Here z_{max} is the maximum intensity value of the digital images which is 255 for 8-bit gray scale images. In the optimization function, equal weights are assigned to the three distance functions. The fitness function is given to the PSO based optimization technique and which minimizes the value of f in each generation to make the noisy image well clustered.

$$Q_e = \{ \sum_{\forall j=1 \ to \ N_c} [(\sum_{\forall z_p \in c_{ij}} d(z_p, m_{ij}) / \ |C_{ij}|.(N_0 / \ |C_{ij}|)]\} \tag{6}$$

$$f(x_i, Z) = d_{max}(z, x_i) + (z_{max} - d_{min}(x_i)) + Q_e \tag{7}$$

4 Results and Discussion

The proposed algorithm is tested by using three standard gray scale images: *lena*, *pepper* and *airplane*. The performance of the proposed algorithm is measured by three evaluation metrics, *intra cluster distance*, *inter cluster distance* and *quantization error*. The performance of the algorithm is compared with three existing algorithm *K-means*, *Man et al.* [16] and *FPSO* [9] algorithms. For comparison purpose, the following parameter values are used for the algorithms:

- Gray scale image resolution = 512 × 512
- Number of particles (NOP) = 20
- Maximum number of clusters = 20
- Number of iterations = 50

Number of iterations for Man *et al.*, FPSO and proposed DPSO algorithms are set to 50. For K-means, the number of iterations will be 50 × number of particles, because in each iteration the fitness of 20 particles are computed in PSO based clustering algorithms. The inertia factor is set to 1 initially and decreased linearly with the number of iterations. Both the acceleration constants are set to 2. For DPSO algorithm, minimum (K_{min}) and maximum (K_{max}) number of clusters are set to 2 and 20 respectively. For K-means algorithm, only Mean Square Error (MSE) is used as fitness function. For Man *et al.*, FPSO and DPSO algorithm, the same fitness function is used for evaluation which is given in (7).

Table 1. Clustering results using Intra distance (d_{max}), Quantization Error (Q_e), Inter Distance (d_{min}) and Fitness Value

Algorithm/Image	d_{max}	Q_e	d_{min}	Fitness Value
(1.) K-Means				
Pepper	13.57	10.50	32.03	247.04
Lena	9.85	8.70	29.03	244.52
Airplane	16.30	10.12	20.57	260.85
(2.) Man et al.				
Pepper	12.11	9.87	40.20	236.78
Lena	9.35	8.49	34.72	238.12
Airplane	11.63	10.42	40.60	236.45
(3.) FPSO				
Pepper	11.82	9.50	41.60	234.72
Lena	9.11	8.23	35.70	236.64
Airplane	11.22	10.04	41.56	234.70
(4.) **DPSO**				
Pepper	10.68	9.00	42.49	232.19
Lena	8.44	7.79	36.41	234.82
Airplane	10.21	9.47	42.11	232.57

Table 1 shows the intra cluster distance, inter cluster distance, weighted quantization error and fitness value by the existing and proposed DPSO algorithms. For K-means algorithm, all the three performance metrics, intra cluster distance, inter cluster distance, weighted quantization error are worse than those of all other algorithms. FPSO is better than Man *et al.* and K-means. Proposed DPSO is best with respect to all those measures. The last column of the table shows the fitness values of the algorithms. Less the value, more is fitness. We can see from the table that the DPSO outperforms all the other algorithms in all respect.

5 Conclusion

This paper proposed a novel image clustering algorithm based on the different length particle swarm optimization (DPSO) algorithm. DPSO uses a novel fitness function with three evaluation criterion, the results show that DPSO performs better than three other existing algorithms. The weighted Euclidean function measures the similarity and/or dissimilarity among the pixels. Using the Euclidean distance and weighted quantization error functions as fitness criteria, DPSO outperforms the K-Means algorithm, Man *et al.* and FPSO algorithms with a wide margin. The algorithm can minimize the user intervention during the program run as it can find the number of cluster centers automatically in a specified range. A limitation of the proposed work is that the number of cluster centers assigned initially for a particle remains fixed. This limitation is resolved to some extent by using a large number of particles to increase the diversity regarding the number of cluster centers.

In future, cluster validity indices may be used in the fitness function of the algorithm for clustering. Another attempt may be to use *Multi-objective evolutionary algorithm (MOEA)* to get a a set of optimal solutions where three criteria used in proposed DPSO will be used as objectives. To overcome the limitations of the fixed length particles, variable length PSO based clustering may be considered the limitations of this work by merging or splitting the particles.

Acknowledgments. Authors expressed deep sense of gratitude towards the Department of Computer Science and Engineering, University of Kalyani and National Institute of Technology, Durgapur and the PURSE Project (DST, Govt. of India) of the university where the computational resources are used for the work.

References

1. Eberhart, R., Kennedy, J.: A new optimizer using particle swarm theory. In: Proceedings of the Sixth International Symposium on Micro Machine and Human Science, MHS 1995, pp. 39–43. IEEE (October 1995)

2. Esmin, A.A.A., Pereira, D.L., de Arajo, F.P.A.: Study of different approach to clustering data by using particle swarm optimization algorithm. In: Proceedings of the IEEE World Congress on Evolutionary Computation (CEC 2008), Hong Kong, China, pp. 1817–1822 (June 2008)
3. Gose, E., Johnsonbough, R., Jost, S.: Pattern recognition and image analysis. Prentice-Hall (1996)
4. Eberhart, J.K., Particle, R.C.: swarm optimization. In: IEEE International Conference on Neural Network, Perth, Australia, pp. 1942–1948 (1995)
5. López, J., Lanzarini, L., De Giusti, A.: VarMOPSO: Multi-objective particle swarm optimization with variable population size. In: Kuri-Morales, A., Simari, G.R. (eds.) IBERAMIA 2010. LNCS, vol. 6433, pp. 60–69. Springer, Heidelberg (2010)
6. Katari, V., Ch, S., Satapathy, R., Ieee, M., Murthy, J., Reddy, P.P.: Hybridized improved genetic algorithm with variable length chromosome for image clustering abstract. International Journal of Computer Science and Network Security 7(11), 1121–1131 (2007)
7. Maulik, U., Bandyopadhyay, S.: Fuzzy partitioning using a real-coded variable-length genetic algorithm for pixel classification. IEEE Transactions on Geoscience and Remote Sensing 41(5), 1075–1081 (2003)
8. Mukhopadhyay, S., Mandal, J.K.: Adaptive Median Filtering based on Unsupervised Classification of Pixels. In: Handbook of Research on Computational Intelligence for Engineering, Science and Business. IGI Global, 701 E. Chocolate Ave, Hershey, PA 17033, USA (2013)
9. Mukhopadhyay, S., Mandal, J.K.: Denoising of digital images through pso based pixel classification. Central European Journal of Computer Science 3(4), 158–172 (2013)
10. Omran, M., Enge;brecht, A., Salman, A.: Particle swarm optimization method for image clustering. International Journal of Pattern Recognition and Artificial Intelligence 19, 297–322 (2005)
11. Pakhira, M.K., Bandyopadhyay, S., Maulik, U.: Validity index for crisp and fuzzy clusters. Pattern Recognition 37(3), 487–501 (2004), `http://www.sciencedirect.com/science/article/pii/S0031320303002838`
12. Wong, M.T., He, X., Yeh, W.-C.: Image clustering using particle swarm optimization. In: 2011 IEEE Congress on Evolutionary Computation (CEC), pp. 262–268 (June 2011)
13. Qiu, M., Liu, L., Ding, H., Dong, J., Wang, W.: A new hybrid variable-length ga and pso algorithm in continuous facility location problem with capacity and service level constraints. In: IEEE/INFORMS International Conference on Service Operations, Logistics and Informatics, SOLI 2009, pp. 546–551 (July 2009)
14. Srikanth, R., George, R., Warsi, N., Prabhu, D., Petry, F., Buckles, B.: A variable-length genetic algorithm for clustering and classification. Pattern Recognition Letters 16(8), 789–800 (1995), `http://www.sciencedirect.com/science/article/pii/016786559500043G`, Genetic Algorithms
15. Tan, P., Steinbach, M., Kumar, V.: Introduction to data mining. Pearson Education (2006)
16. Wong, M.T., He, X., Yeh, W.-C.: Image clustering using particle swarm optimization. In: 2011 IEEE Congress on Evolutionary Computation (CEC), pp. 262–268 (June 2011)