An Improved Unsupervised Image Segmentation Method Based on Multi-Objective Particle Swarm Optimization Clustering Algorithm

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Abstract: Most image segmentation methods based on clustering algorithms use single-objective function to implement image segmentation. To avoid the defect, this paper proposes a new image segmentation method based on a multi-objective particle swarm optimization (PSO) clustering algorithm. This unsupervised algorithm not only offers a new similarity computing approach based on electromagnetic forces, but also obtains the proper number of clusters which is determined by scale-space theory. It is experimentally demonstrated that the applicability and effectiveness of the proposed multi-objective PSO clustering algorithm

Keywords: Multi-objective optimization, particle swarm optimization, electromagnetic forces, scale-space theory.

1 Introduction

Image segmentation is the division of an image into several non-overlapping areas containing pixels with identical or similar attributes [Ponttuset, Arbelaez, Barron et al (2017)]. Image segmentation is an important aspect of image processing and determines the final results and quality of image analysis. Clustering-based image segmentation methods have been widely used [Choy, Shu, Yu et al (2017); Chen, Li, Bo (2017); Yang, Chung, Wang (2009)]. A clustering method uses the feature information of the image pixels to segment the image by merging pixels with identical or similar features into one group based on the similarity measure.

Merwe et al. [Merwe and Engelbrecht (2004)] first proposed PSO for data clustering. Xiao et al. [Xiao (2003)] hybridized PSO with Self-Organizing Maps (SOM) to use SOM to cluster the data and PSO to optimize weights of the SOM. Lin et al. [Lin, Tong, Shi et al. (2014)] used the results of K-means in combination with PSO and multiclass merging to perform data clustering. Omran et al. [Omran, Salman and Engelbrecht (2006)] suggested a dynamic clustering algorithm based on PSO and K-means for image segmentation. Fornarelli [Fornarelli (2017)] used an unsupervised multi-particle

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clustering method for image segmentation; this method conducts a spatial search based on the minimum distance criterion and then uses the same group structure to improve the results for image segmentation. Benaichouche et al. [Benaichouche, Oulhadj and Siarry (2013)] proposed an improved method of fuzzy C-means (FCM) clustering that introduces the heuristic PSO algorithm in the initial stage to overcome local minima; the local information and Mahalanobis distance are taken into account in the classification criteria, and a greedy algorithm is used to optimize the local standard and detect potential pixel misclassification. Nanda et al. [Nanda and Panda (2013)] presented a multi-objective immune PSO algorithm according to the Pareto archive of unsupervised problems based on the recently proposed hybrid evolutionary immune PSO algorithm; this multi-objective immune PSO algorithm can perform clustering automatically and optimize two objective functions simultaneously.

This paper proposes a new two objective functions calculation methods based on different evaluations of the effectiveness of PSO clustering performance which includes the particle trajectory and speed in the global optimization. Two objective functions are used to avoid the defects of single objective function evaluation criterion in the traditional clustering algorithm. Furthermore, the optimal clustering number is determined by space-scale theory. An unsupervised image segmentation based on a multi-objective PSO clustering algorithm (UISMOPC) is proposed in this paper, and experimental data from University of California, Berkeley are applied to evaluate the algorithm.

2 Unsupervised image segmentation based on a multi-objective PSO clustering algorithm (UISMOPC)

2.1 Determination of the clustering number based on scale-space theory

UISMOPC is an unsupervised clustering algorithm, so it is of great significance that the clustering number needs to be determined in advance. So the scale-space theory [Babaud, Witkin, Baudin et al. (1986)] is applied to obtain the proper clustering number.

We define that the scale space image of a continuous signal $I(x)$ as follows:

$$F(x,\sigma) = I * G \tag{1}$$

where * represents convolution. We take the Gaussian function G as:

$$G(x,\sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}} \tag{2}$$

Then

$$F(x,\sigma) = \int I(\zeta) \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\zeta)^2}{2\sigma^2}} d\zeta \tag{3}$$

We define $E(x,\sigma)$ as:

$$E(x,\sigma) = \frac{d^2}{dx^2} F = \frac{d^2}{dx^2} \int I(\zeta) \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\zeta)^2}{2\sigma^2}} d\zeta \tag{4}$$

The relationship of x, σ determined by $E(x, \sigma) = 0$ is called the fingerprint of $I(x)$. Bahaud et al. [Babaud, Witkin, Baudin et al. (1986)] proved that scale space filtering theory can determine the signal $I(x)$ and obtain all information which can reconstruct the signal. We obtain the number of the one-dimensional Gaussian function that constitutes the signal by the theory, which is the clustering number. The original signal can be interpreted by analyzing the fingerprints. Fig. 1 is the fingerprint of a normal probability density function $I(x)$ which follows $N(\mu, \delta)$, zero-crossings in the second derivative of E are the positions where curvature of E changes sign. Sections of the signal over which $E < 0$ are convex, while sections over $E > 0$ are concave, zero-crossing where changes from $E > 0$ to $E < 0$ is labeled a lower turning point, while zero-crossing where changes from $E < 0$ to $E > 0$ is labeled an upper turning point. It is proved that a funnel between a lower turning point and an upper turning point could determine a normal distribution, and the intersection points in the fingerprints when $\sigma = 0$ could reconstruct the original signal, its width is approximately equal to 2δ, and the fingerprint is centered at $x = \mu$. That is, $\sigma \approx 0$ intersects the figures at $(\mu - \delta, \sigma)$ and $(\mu + \delta, \sigma)$.
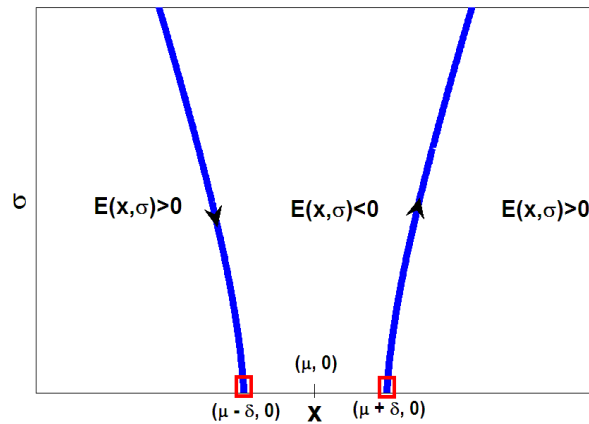

Figure 1: Fingerprints of a normal probability density function

$x - \sigma$ image can also be applied for analyzing the original signal when there is a superposition of several normal distributions, we go through all the funnels in the image successively so that information including the number of clusters, component centers, standard deviation values can be shown as the same method.

2.2 Similarity measure and multi-objective function

The similarity criterion $D(\cdot)$ is one of the most important aspects of clustering algorithms. We usually use the Euclidean distance between the sample and the cluster center as the criterion; this criterion does not consider the impact of cluster size on the clustering results. In fact, the larger cluster attracts more data points because each data point tends to join the cluster with more points. We present the similarity measurement, inspired by the

magnetic attraction calculation formula $F = k'\dfrac{N_1 N_2}{r^2}$ in physics between clusters and data as follows, For clusters $\{C_1, C_2, ..., C_k\}$, the similarity of subclass C_i of the data points x_j can be represented as $S(v_i, x_j) = k\dfrac{\| v_i - x_j \|}{m + count(i) / N}$, where $\| v_i - x_j \|$ is the Euclidean distance between the cluster center V_j and the sample X_j. The value $Count(i)$ denotes the data number of the $i-th$ cluster. K is a constant, m is the adjustment coefficient, and N is the total number of data points. Smaller values of $\| v_i - x_j \|$ and greater values of $Count(i)$ indicate greater potential for incorporation of X_j into class C_i.

Considering the similarity measures discussed above, we present two different objective functions based on the criteria of minimizing the within-class similarity and maximizing the similarity between clusters. The first objective function $f_1(x)$ concerning the intra-class precision and the second objective function $f_2(x)$ concerning the inter-class incoherence is defined as follows,

$$f_1(x) = \sum_{i=1}^{c} (\sum_{j=1}^{count(i)} S(v_i, x_j)) \ \ x_j \in c_i. \tag{5}$$

$$f_2(x) = 1 / (\sum_{i=1}^{c} (\sum_{j=1}^{n - count(i)} S(v_i, x_j))) \ \ x_j \notin c_i \tag{6}$$

$f_1(x)$ is the sum of the similarity between x_j and the cluster to which it belongs. A smaller value of $f_1(x)$ indicates superior clustering results. $1/f_2(x)$ is sum of the similarity between x_j and other clusters, excluding the one to which it belongs. A smaller value of $f_2(x)$ indicates better clustering results. It is obvious that we need to minimize $f_1(x)$ and $f_2(x)$ simultaneously. It is apparent that the sum of $f_1(x)$ and $f_2(x)$ equals the sum of the similarity of each x_j to all clusters, and thus the equation $J_1 + J_2 = \sum_{i=1}^{c} \sum_{j=1}^{n} s(v_i, x_j)$ is true. Then, the clustering problem is transformed to a multi-objective optimization of calculating $\min(f_1(x), f_2(x))$.

2.3 Multi-objective optimization based on Pareto optimal

The multi-objective clustering method is the unsupervised division of the dataset based on the constraints of multiple objective functions simultaneously. The multi-objective particle swarm guides the particles' velocity and position by multiple objective functions, and thus the best particles eventually fall within the scope of the Pareto set. This method uses the idea of external archive of Pareto Optimal introduced in the MOPSO algorithm [Coello, Pulido, Lechuga et al. (2004)]. A multi-objective optimization problem optimizes two or more target objects simultaneously and can be illustrated as follows:

$$\begin{cases} y = \min f(x) = \min(f_1(x), f_2(x)..., f_n(x)) \\ \quad x = (x_1, x_2, ..., x_n)^T, x \in R \\ \quad s.t. g_i(x) \geq 0 \end{cases} \tag{7}$$

where $f_i (1 \leq i \leq k)$ is the target function, so that the best particles can be obtained within

a scope to make the algorithm much more robust; the algorithm also proposes new fitness functions which illustrates the similarities between each cluster. The description of UISMOPC algorithm is displayed as follows:

Table 1: Flowchart of UISMOPC

Input: original image, the scale of the particle swam N, constants *rnd1(), rnd2(),* maximum iterations *iiter,* particle length L

Output: the segmented image

1. Determine the number of clusters of the image by the scale-space theory, defined as n
2. Initialize the particle swarm c, set v_m and x_m of cluster centers as the initial value of the particle
3. **While** it is not termination condition
4.   **If** particle $x_i \in$ The external archive **Then**
5.   fpbest1(i) = f₁(x)
6.   fpbest2(i) = f₂(x)
7.   **Update** the leaders Pareto Optimal in the external archive
8.   **for** j=1 to L **do**
9.   pbest1(i,j) =C(min(fpbest1(i), j)
10.   pbest2(i,j)=C(min(fpbest2(i),j)
11.   gbest1(j) =C(min(fpbest1(i),j)
12.   gbest2(j)=C(min(fpbest2(i),j)
13.   ppbest(i, j) = (pbest1(i, j) + pbest2(i, j)) / 2
14.   ggbest(j) = (gbest1(j) + gbest2(j)) / 2
15.   i++, j++, iter++
16.   **end for**
17. **end if**
18. v(i, j) = (0.8 - iiter * (0.8 - 0.4) / iter) *v(i, j) + 2 * Rnd * (ppbest(i, j) - c(i, j)) + 2 * Rnd * (ggbest(j) - c(i, j))
19. **if** v(i, j) > v$_{max}$ **then** v(i, j) = v$_{max}$
20. **if** v(i, j) < v$_{min}$ **then** v(i, j) = v$_{min}$
21. c(i, j) = v(i, j) + c(i, j)
22. **end**

In the UISMOPC algorithm, *f1* and *f2* are the itness functions of Multi-objective PSO algorithm, and they can be calculated by formula (5) and (6), *ggbest* is a global search variable that ensures information exchange between each particle and the other particles in the swarm. *ggbest* drives the particle to the best position in the whole swarm based on social knowledge and overcomes the traditional drawbacks of the clustering algorithm, which is sensitive to the initial values and can easily fall into local optima. The linear

transformation of w along with the change in the iteration adjusts the overall ability of the algorithm and avoids its premature convergence.

3 Experimental results and analysis

To evaluate the unsupervised image segmentation algorithm based on multi-objective PSO (UISMOPC), a comparison analysis using *K*-means [Niknam (2010)], FCM [Kannan, Ramathilagam and Chung (2012)], PSO-*K*-means [Niknam and Amiri (2010)] and PSO-FCM [Liu, Pei, Zhou et al. (2008)] methods was performed. We used a graphic dedicated workstation by Dell with an Intel Core i5 processor CPU, 1.6 GHz speed, 4 Gb memory, 500 Gb hard disk, and matlab2010 as the experimental software. The performance of the proposed algorithm was evaluated using 300 images from the Berkeley Segmentation Dataset and Benchmark (BSDB) [Fowlkes, Martin, and Malik (2013)]. The clustering numbers are obtained based on scale-space theory. Some selected results are presented here.

3.1 Evaluation method

Both supervised and unsupervised objective evaluation methods can be used to describe the results of image segmentation quantitatively. The supervised evaluation method requires the standard image as a precondition; this image is not easy to obtain, and thus the unsupervised evaluation method is accepted [Zhang, Jason, Fritts et al. (2008)]. The unsupervised evaluation method is the measure of the segmentation results by a set of parameter measurements and does not require a standard image in the evaluation process. We used intra-region uniformity metrics and inter-region disparity metrics to demonstrate the effectiveness and rationality of the method proposed in this paper.

Intra-region uniformity metrics are an intuitive and effective way to evaluate segmentation performance by measuring intra-region uniformity. The image segmentation quality evaluation criterion [Zhang, Jason, Fritts et al. (2008)] is as follows:

$$F(I) = \frac{1}{1000(M \times N)} \sqrt{R} \sum_{i=1}^{R} \frac{e_i^2}{\sqrt{A_i}} \tag{8}$$

where I is the segmentation results of the image; $M \times N$ is the size of the image; R is the number of categories in the image segmentation; A_i is the area of the i-th region, that is, the total number of pixels; and e_i is the average color error number of the i-th region, A smaller F value indicates improved segmentation.

The evaluation method F_{RC} uses $\bar{D}(I)$ as its measure of global inter-region disparity. In the version of F_{RC} designed for non-textured images, $\bar{D}(I)$ is computed as the average of the weighted sum of $\bar{D}(R_i)$ over all regions. For each region, $\bar{D}(R_i)$ is computed by dividing the difference in the average gray-level between region R_i and other regions in the image by the number of gray levels in the image. $\bar{D}$ is defined as the weighted sum of the difference between two regions $D(R_i, R_j)$:

$$\bar{D} = \frac{1}{N} * \sum_{R} D(R_i, R_j) \tag{9}$$

where N is the clustering number, R represents all regions, and $D(R_i, R_j)$ is the difference between two regions, defined as:

$$D(R_i, R_j) = \frac{\left| \hat{C}_x(R_i) - \hat{C}_x(R_j) \right|}{NG}$$

(10)

where NG is the gray-level of the image. We set $NG = 256$ in this paper. $\hat{C}_x(R_i)$ is the average value of all gray-levels in the i-th region, S_i is the sum of pixels of the i-th region, $\hat{C}_x(R_i)$ can be calculated as:

$$\hat{C}_x(R_i) = \left(\sum_{p \in R_i} C_x(p) \right) / S_i$$

(11)

3.2 Experimental results using real data

The experimental data were obtained from the University of California, Berkeley, BSDB standard test image database. We compare the K-means, FCM, PSO-K-means, PSO-FCM and UISMOPC image segmentation in this paper. The clustering numbers of the original images shown in Fig. 2 are obtained by scale-space theory discussed in Chapter 2.1, the clustering number can be obtained, it can be shown that the number is 3,3,4,4,6,5,4,4 respectively. The 8 original test images are shown in the first line of Fig. 3, the results using the K-means, FCM, PSO-K-means, PSO-FCM-means and the proposed UISMOPC method are shown in the 2-6 line respectively.

To quantitatively evaluate the segmentation results of the algorithms, we used the F value and F_{RC} as the evaluating indicators to compare the segmentation results of several classic clustering methods and the proposed segmentation method. Tab. 2 presents the F_{RC} values of eight different images using five segmentation methods. The abscissa represents the images, and the ordinate represents the evaluation criteria of the segmentation quality.
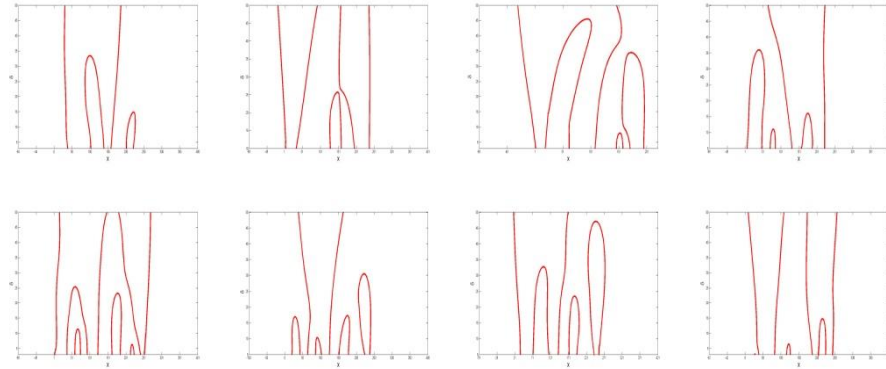

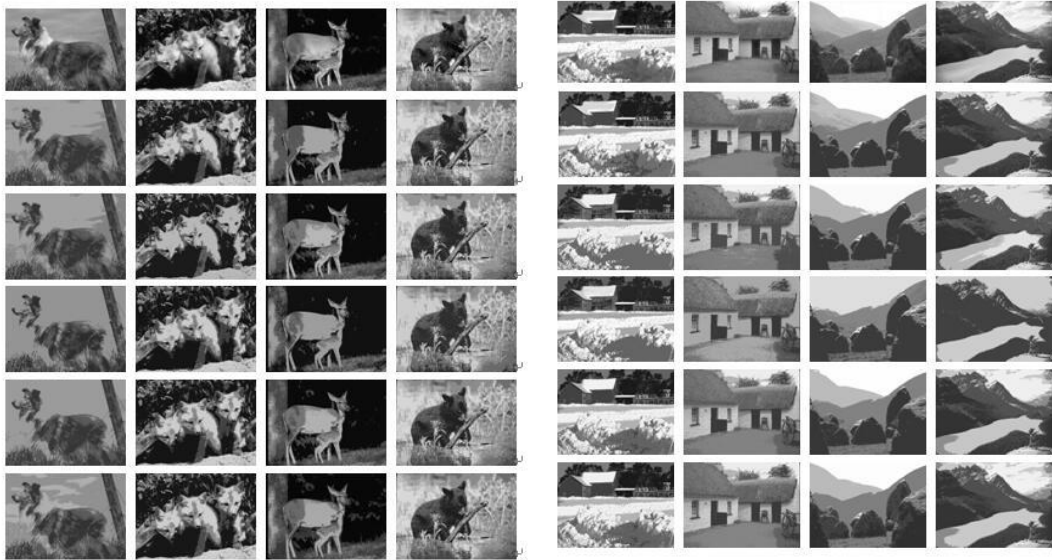**Figure 2:** Fingerprints of gray level density

Figure 3: Segmentation results of 8 test images

The results in Tab. 2 indicate that the image segmentation results of the PSO-*K*-means and PSO-FCM methods are superior to those of the *K*-means and FCM methods. The F_{RC} value is higher for the proposed UISMOPC algorithm than the other four segmentation methods. The segmentation result of the proposed method is superior to those of the other image segmentation methods from the perspective of regional coherence.

Table 2: F_{RC} values of the segmentation results

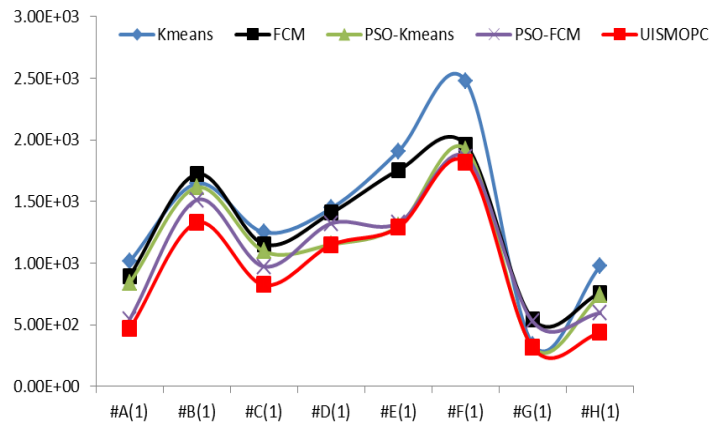|	#A(0)	#B(0)	#C(0)	#D(0)	#E(0)	#F(0)	#G(0)	#H(0)
K-means	0.7071	1.193	1.1176	1.8623	2.0787	1.3647	1.4584	1.5371
FCM	0.6008	1.1396	0.9219	1.7785	2.0964	1.1684	1.6282	1.0197
PSO-*K*-means	0.8196	1.2161	1.101	2.2772	2.3625	1.8108	1.9622	1.8412
PSO-FCM	0.7283	1.2144	1.0595	2.2255	2.0889	1.3836	1.6484	1.546
UISMOPC	0.8913	1.2756	1.2319	2.3104	2.5387	1.8975	2.1223	1.9174

Figure 4: Comparison of the *F* values of our UISMOPC method and the other four algorithms

Fig. 4 presents the different *F* values of the different segmentation methods. We selected formula (9) as the indicator to evaluate image segmentation results. Fig. 4 presents the *F* values of several images using the five segmentation methods. The abscissa represents different images, and the ordinate represents the *F* value evaluation criterion. As shown in Fig. 4, the *F* values of the PSO-*K*-means algorithm and PSO-FCM segmentation methods are smaller than those of the *K*-means and FCM methods; the latter two methods are over-dependent on the initial value in the image segmentation. The PSO-*K*-means and PSO-FCM methods incorporate the PSO algorithm to obtain more accurate clustering centers and, consequently, superior segmentation quality compared to the traditional division of the *K*-means and FCM methods. The *F* value of the proposed UISMOPC algorithm is smaller than those of the other methods because the PSO-*K*-means and PSO-FCM segmentation methods divide the image data using one objective function, whereas the UISMOPC image segmentation method is based on multiple objective functions and consequently produces superior segmentation quality

Using the two evaluation indexes, we appraised the results in terms of intra-class precision and inter-class incoherence. The proposed image segmentation method based on the UISMOPC algorithm is superior to the traditional *K*-means, FCM segmentation and clustering algorithms based on single objective functions.

4 Conclusions

In this paper, we proposed an unsupervised image segmentation method based on a multi-objective PSO clustering algorithm by defining two different objective functions. The experimental results demonstrated that the clustering effectiveness was further improved by multi-objective optimization compared to other methods. As an unsupervised algorithm, UISMOPC not only proposes new fitness functions which illustrates the similarities between each cluster but also uses the idea of external archive of Pareto Optimal, so that the best particles can be obtained within a scope to make the algorithm much more robust. Furthermore, the determination of clustering number proposed by

scale-space theory can help us to obtain more accurate number for those clustering-based methods. We will focus on transforming the clustering problem and multi-objective optimization more reasonably in the future.

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