Acta Technica 62 No. 1B/2017, 221–232

Image segmentation algorithm based on improved fuzzy clustering[1]

Changxing Geng[2], Peng Wang[2], Pengbo Wang[2]

Abstract. Image segmentation is a key part of image processing and it plays a very important role in image analysis and information application. The principle of image segmentation based on fuzzy theory was used as the basis in this context, and the application steps of fuzzy C mean clustering in image segmentation were studied. Aiming at the problems existing in the algorithm, the objective function was improved and a new algorithm model was established. The improved fuzzy clustering image segmentation algorithm was compared with the traditional algorithm through the experiment. The improved algorithm had better image segmentation effect. The feasibility of the improved algorithm was proved, which contributed to the research of image segmentation algorithm based on improved fuzzy clustering.

Key words. Image segmentation, fuzzy theory, fuzzy C means clustering, improved algorithm
.

1. Introduction

With the rapid development of science and technology, the storage and dissemination of information become cheaper and cheaper, which leads to explosive growth in the amount of information that people are exposed to in their daily lives. Images become the main carrier of information dissemination because of their intuitive, image, easy to understand, and rich in information [1]. About 70 % come from images of all the information people acquire. However, it is very important to extract valuable information from the images obtained by various devices to meet the needs of different applications [2]. Useful information in an image is often concentrated in a particular area after researching people develop. The task of image segmentation is how to separate these regions from the image background effectively. Image segmentation can be divided into several regions according to the predefined features,

[1]This work is supported by Jiangsu Province Natural Science Foundation for Young Scholars, No. BK20140325.

[2]Robotics and Microsystems Centre, Soochow University, Suzhou 215021, China

which can be gray, color and texture [3]. With the development of image segmentation technology, it has become one of the most basic and important research contents in computer vision. It also occupies a very important position in the process of image analysis, processing and description. Image segmentation is based on the prior knowledge of the target and the background. Firstly, the target and background are marked and located in the image. And then, the targets that need to be identified are separated from the pseudo target according to these tags. Only in this way can the follow-up work of a series of information processing such as target identification and accurate positioning be realized. This result is also important because it can have a major impact on subsequent processing [4]. Image segmentation is very important for image recognition, tracking and understanding during the process of image analysis. The accuracy of image segmentation is very demanding in the process of image processing. Therefore, how to segment the required target from the background quickly and effectively has become the key to the research process [5].

2. State of the art

Zadeh proposed fuzzy set theory for the first time in 1965. Thus, fuzzy mathematics was created as a new discipline. Fuzzy set theory is extended on the basis of traditional set theory. For traditional set theory, an element belongs to a set, or does not belong to a collection. For a fuzzy set, each element belongs to a set to a certain extent, and can also belong to multiple sets at the same time [6]. Fuzzy sets theory can describe the fuzziness and randomness in human vision exactly. Fuzzy set theory has also been applied to various levels of pattern recognition. For example, the input pattern can be represented as a membership matrix for the feature layer (representing the extent of ownership of a given property). Membership values of fuzzy patterns can be used to provide information for representation and loss estimation at the classification layer [7]. Scholars have reformed some image segmentation algorithms in the course of research according to the characteristics of fuzzy sets. These algorithms can be divided into fuzzy threshold segmentation and fuzzy clustering segmentation. Among them, the fuzzy C means algorithm (FCM) is the most classical and widely used image segmentation algorithm [8]. The application of fuzzy theory to image segmentation is a classic example of the computer having some of the visual functions of human beings [9].

2.1. Methodology

Clustering is the separation and classification of things of similar nature. Clustering analysis is the classification of a given object on the basis of mathematical methods. A classical classification usually begins with a single factor or a few limited factors and uses experience or knowledge to classify things [10]. This category has a very clear line of categories and can cluster together the same thing effectively. However, with the cognition of people deeply, it is found that not everything can find a clear line of its classification, and many things are fuzzy boundaries in the image. For example, many regions is not clear enough [11]. Therefore, in order to better classify these fuzzy boundaries, fuzzy mathematics arises at the historic moment. Its generation provides a mathematical basis for this kind of soft classification, which is also called fuzzy cluster analysis. Fig. 1 shows the location of image segmentation in image engineering.

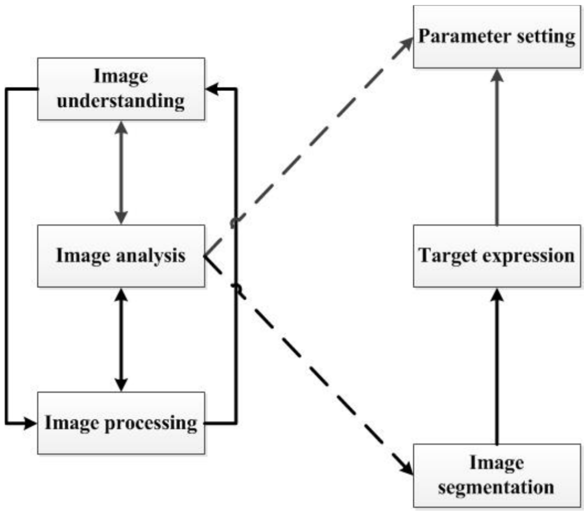


Fig. 1. Location of image segmentation in image engineering

Cluster analysis is a mathematical method of grouping similar data points into a class according to a specific criterion [12]. For the current theoretical development, the fuzzy C means clustering algorithm (Fuzzy C-Means, FCM) is one of the most famous fuzzy clustering methods. This algorithm was first proposed by Dunn. And later Bezdek improved it and gave Fuzzy C-Means Clustering an iterative optimization algorithm based on the least square method. By proving its convergence, it is proved that the algorithm can converge to an extremum [13]. Fig. 2 is the application of image processing technology.

Fig. 2. Application of image processing

The fuzzy C means clustering algorithm uses the double layer iterative method to obtain the extremum of the objective function. The inner iteration is used to correct the membership matrix and the clustering center. Inner iteration is a gradient descent method essentially. The next step of the optimization direction is determined by calculating the gradient of the current state. The outer iteration is used to test the convergence condition to determine whether the iteration meets the requirement of convergence [14]. The membership degree of each element in each class can be obtained from the membership matrix after the completion of the iteration. The division of elements can be determined according to the degree of membership.

The fuzzy C means clustering algorithm defines the following form of objective function:

$$J = \sum_{i=1}^{n} \sum_{j=1}^{c} \mu_{ij}^{m} \left\| x_i - v_j \right\|^2 \tag{1}$$

The objective function satisfies the following constraints:

$$\sum_{j=1}^{c} \mu_{ij} = 1, \ \forall i \in \{1, 2, \cdots, n\} \tag{2}$$

Here, μ_{ij} is the membership degree of the element I about class j. Symbol x_i denotes the characteristic vector of element i, v_j is the clustering center of class j, and m is the weight coefficient. According to the validity criterion, the range of m is 1.5–2.5. In general, $m = 2$.

Lagrange conditional extremum method can be applied to deduce the corresponding iterative formula [15].

$$F = \sum_{i=1}^{n} \sum_{j=1}^{c} \mu_{ij}^{m} \left\| x_i - v_j \right\|^2 + \lambda \left(1 - \sum_{j=1}^{c} \mu_{ij} \right) =$$

$$= \lambda \left(1 - \sum_{j=1}^{c} \mu_{ij} \right) + \sum_{i=1}^{n} \sum_{j=1}^{c} \mu_{ij}^{m} d_{ij}^{2} \, . \tag{3}$$

In order to maximize the function J, the first order necessary condition is as follows:

$$\frac{\partial F}{\partial \lambda} = 1 - \sum_{j=1}^{c} \mu_{ij} = 0 \, , \tag{4}$$

$$\frac{\partial F}{\partial u_{ij}} = m \left(u_{ij} \right)^{m-1} \left(d_{ij} \right)^2 - \lambda = 0 \, , \tag{5}$$

From (5), the following formula can be obtained

$$u_{ij} = \left[\frac{\lambda}{m \left(d_{ij} \right)^2} \right]^{\frac{1}{m-1}} \, . \tag{6}$$

Formula (6) is put in formula (4) to obtain that:

$$\sum_{j=1}^{c} \mu_{ij} = \sum_{j=1}^{c} \left(\frac{\lambda}{m}\right)^{\frac{1}{m-1}} \left[\frac{1}{d_{ij}^2}\right]^{\frac{1}{m-1}} = \left(\frac{\lambda}{m}\right)^{\frac{1}{m-1}} \left\{\sum_{j=1}^{c} \left[\frac{1}{d_{ij}^2}\right]^{\frac{1}{m-1}}\right\} = 1\,. \tag{7}$$

Thus, there is:

$$\left(\frac{\lambda}{m}\right)^{\frac{1}{m-1}} = \frac{1}{\sum_{j=1}^{c} \left[\frac{1}{d_{ij}^2}\right]^{\frac{1}{m-1}}}\,. \tag{8}$$

The formula (8) is fused together with (6) to get that

$$u_{ij} = \frac{1}{\sum_{i=1}^{c} \left[\frac{d_{ij}^2}{d_{il}^2}\right]^{\frac{1}{m-1}}}\,. \tag{9}$$

In view of the possibility that d_{ij} has taken as 0, the discussion is separated. For $\forall i \in \{1, 2, 3, \cdots, n\}$, the definition of T_i and its complement set T_i^c are defined as

$$T_i = \{j\,|1 \le j \le c, d_{ij} = 0\}\ , \tag{10}$$

$$T_i^c = \{1, 2, 3, \cdots c\} - T_i\,, \tag{11}$$

In order to obtain the minimum of objective function J, the value of u_{ij} should be

$$\begin{cases} \mu_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{ik}}\right)^{\frac{2}{m-1}}},\ T_i = \phi, \\ \\ \mu_{ij} = 0, \forall j \in T_i^c, \sum_{j \in T_i}^{c} \mu_{ij} = 1,\ T_i \ne \phi. \end{cases} \tag{12}$$

The iterative formula of the cluster center v_j can be obtained by using a similar iterative method:

$$v_j = \frac{\sum_{i=1}^{n} \mu_{ij}^m x_j}{\sum_{i=1}^{n} \mu_{ij}^m}\,. \tag{13}$$

The fuzzy C means clustering algorithm is to approximate the extreme value progressively from a random initial value by the constant iteration of formula (12) and formula (13). The steps of the algorithm are described below briefly:

Step 1: The cluster number c and parameter m are set.

Step 2: The cluster center v_j is initialized.

Step 3: Repeat the following operations until the value of the target function obtained by the current two rounds of iterations satisfy $|J_t - J_{t+1}| < \varepsilon$. It can be considered that better clustering results have been obtained, thus stopping updating. Among them, ε is a small positive number, which is called tolerance error.

When the algorithm converges, all kinds of clustering centers and the membership values of each object can be obtained, and then the fuzzy clustering is completed. If it is necessary, we can also blur the fuzzy clustering results. That is to say, fuzzy clustering is transformed into deterministic classification with certain criteria. The most common criterion is the maximum membership criterion. The object is partitioned into classes corresponding to the maximum of its membership.

Image segmentation using clustering analysis is a widely used and very important method in the field of image segmentation. Both color and gray scale images can be segmented by using them. Clustering is the aggregation of things of the same nature, and the differentiation of things that have significant differences in order to achieve the classification of things. Image segmentation is the process of classifying the pixels in an image according to their similarity. Naturally, people think of clustering analysis into image segmentation. The human eye has a certain degree of subjectivity and is often fuzzy to the division of the region. Therefore, it is more suitable to use fuzzy means for image segmentation. On the other hand, image segmentation often has the shortage of training samples and poor representation, and unsupervised learning methods can deal with such problems. They do not require the support of training samples during the process of processing. We can know that fuzzy clustering is a good choice from the needs of these two aspects. Fuzzy clustering is a powerful tool in the field of image segmentation.

The traditional FCM based image segmentation algorithm can get good segmentation results in more complete areas when the image has high signal-to-noise ratio and contrast ratio. Traditional FCM uses the gray value of pixels as the only feature to cluster without considering the abundant spatial location information, so there are some defects which are sensitive to noise. The objective function of FCM was improved, and the spatial location information was introduced into the calculation of the objective function so as to achieve better segmentation results in this paper.

The space constraint term is added on the basis of the traditional FCM's objective function, and the new objective function is defined as follows:

$$J = \sum_{i=1}^{n} \sum_{j=1}^{c} \left[u_{ij}^{m} \left\| x_i - v_j \right\|^2 + \sum_{\substack{k \in N_i \\ k \neq i}} \frac{\left\| x_k - v_j \right\|^2}{\left\| x_k - v_j \right\|^2 + 1} u_{ij} \left(1 - u_{ij}\right) \right], \tag{14}$$

where N_i is the collection of field points of the pixel I in the upper form, which uses a rectangular, diamond or cross range of fields generally. The space constraint term introduced is to consider the domain of the pixel in the calculation of the objective function. To some extent, this suppresses the number of pixels in a domain belonging to multiple classes. The iterative formula of the new objective function is as follows:

$$v_j = \frac{\sum_{i=1}^{n} \mu_{ij}^{m} x_i}{\sum_{i=1}^{n} \mu_{ij}^{m}}, \tag{15}$$

and

$$u_{ij} = \sum_{l=1}^{c} \left(\frac{\left\| x_k - v_j \right\|^2 + \sum_{\substack{k \in N_i \\ k \neq i}} \frac{\|x_k - v_j\|^2}{\|x_k - v_j\|^2 + 1} u_{ij} \left(1 - u_{ij}\right)}{\left\| x_k - v_l \right\|^2 + \sum_{\substack{k \in N_i \\ k \neq i}} \frac{\|x_k - v_l\|^2}{\|x_k - v_l\|^2 + 1} u_{il} \left(1 - u_{il}\right)} \right). \tag{16}$$

For the improved FCM algorithm, the space function is defined as follows:

$$h_{ij} = \sum_{k \in N_i} u_{jk} \,, \tag{17}$$

where N_i is the domain collection of pixel i in the formula. This function reflects the degree of membership of the domain pixels of the pixel i. The new membership is defined as follows:

$$u_{ij}^* = \frac{(u_{ij})^p \,(h_{ij})^q}{\sum_{k=1}^{c} (u_{ik})^p \,(h_{ik})^q} \,. \tag{18}$$

In formula (18), p and q are adjustment parameters to control the proportion of the original membership and space functions. If the pixel i and its domain pixels belong to the same class, the spatial function only increases the original membership degree. If the pixel i and its domain pixels do not belong to the same class, the spatial function will suppress the original membership degree. Thus, the pixels gathered together belong to the same class as much as possible, and the noise can be suppressed. The new clustering center functions are

$$v_j = \frac{\sum_{i=1}^{n} \left(u_{ij}^*\right)^m x_k}{\sum_{i=1}^{n} \left(u_{ij}^*\right)^m} \,. \tag{19}$$

The new target function is

$$J = \sum_{j=1}^{c} \sum_{i=1}^{n} \left(u_{ij}^*\right)^m \left\| x_i - v_j \right\|^2 \tag{20}$$

The specific algorithm steps are as follows:

Step 1: Initial parameters are set, including cluster number c, initial clustering center v_j, tolerance error e, and domain size and corresponding t values.

Step 2: The FCM is used to segment the image under the maximum membership constraint.

Step 3: The class of pixels is modified.

Step 4: The original image is chosen to smooth the noise combining the generic information of the domain pixels.

Step 5: FCM is used to segment the smoothed image for two times under the constraint of the maximum membership degree.

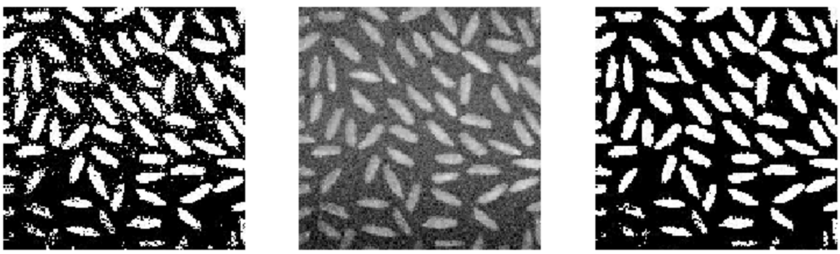
3. Result analysis and discussion

The following is the experimental image segmentation results.

The rice grain diagram was used as the experimental image. When the clustering was carried on, the clustering number was $c = 2$ and the tolerance error was $e = 0.01$. The initial clustering center was 0, 255. The weighting function took $m = 2$. Figure 3 shows the rice image from left to right. A Gauss noise figure with a mean value of 0, a variance of 400, and a grain of rice with 5 % salt and pepper noise were added. Figure 4 shows the first segmentation result of the Gauss noise map, the selective equilibrium results and the two segmentation results. Figure 5 shows a segmentation result of a salt pepper noise map, a selective smoothing result and a second segmentation result. The following table is a comparison of the indexes in the segmentation process.

(a) (b) (c)

Fig. 3. Artwork, Gauss noise map, and salt and pepper noise map



(a) (b) (c)

Fig. 4. Intermediate results and final results of the Gauss noise map

It can be seen from the previous table that selective smoothing does have an inhibitory effect on noise, especially for salt and pepper noise. Selective smoothing not only improves the signal to noise ratio of the image, but also makes the clustering center of the smoothed image closer to the cluster center of the original image, thus reducing the influence of noise effectively.

The experimental image used in this paper was a synthetic map with a resolution of 300×300. The hardware environment of the simulation experiment was AMD

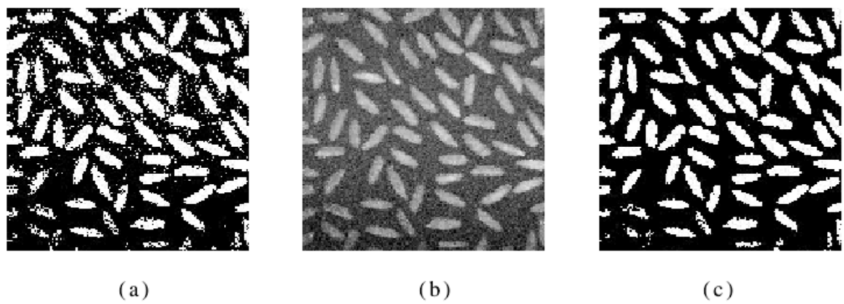


Fig. 5. Intermediate results and final results for segmentation of salt and pepper noise maps

Athlon (tm) 64 X2 Dual Core, Processor4400++. The CPU main frequency was 2.30 GHz, and the memory was 2 GB. The programming environment was Matlab7.0. Among them, the Gauss noise map was added to the original image with a mean value of 0. The variance was 400 of the Gauss noise. Salt and pepper noise map was based on the original added 5 % salt and pepper noise. The time consumed by segmentation and the correct segmentation rate are shown in Table 2. Comparison of correct segmentation rates is in Table 3.

Table 1. Comparison of the indexes in the segmentation process

	Gauss diagram	Salt pepper diagram
Artwork clustering center	{84.964,167.66}	{84.964,167.66}
Noise map clustering center	{80.281,164.8}	{81.26,175.08}
Smoothed cluster centers	{80.799,167.96}	{83.212,169.6}
Signal to noise ratio before smoothing	33.7763	15.2494
Signal-to-noise ratio after smoothing	46.0306	59.4954

Table 2. Comparison of running time

	FCM	KFCM	Paper algorithm
Gauss noise map	83.80 s	83.00 s	169.56 s
Salt and pepper noise map	85.19 s	84.25 s	179.25 s

Table 3. Comparison of correct segmentation rates

	FCM	KFCM	Paper algorithm
Gauss noise map	97.2 %	98.4 %	100 %
Salt and pepper noise map	96.3 %	98.1 %	99.8 %

It can be seen from the two objective indexes of segmentation accuracy and time consuming that FCM and KFCM were the least time-consuming and sensitive to noise. The segmentation algorithm took about 2 times as much as FCM, but the noise suppression was obvious, which improved the robustness of the algorithm greatly. This type belongs to the FCM image segmentation method of correction and spatial constraint, which can modify the class of pixels according to class dispersion. And then, the image is selectively smoothed according to the class of neighborhood pixels, and finally the two segment of the modified image is segmented. Experimental results show that the proposed algorithm has good anti-noise capability. In addition, the complexity of distance and membership calculation formula is not increased when spatial information is introduced. Therefore, the operation is the same as the traditional FCM, but the segmentation effect is better than the traditional FCM algorithm.

4. Conclusion

One of the basic problems in computer vision is image segmentation. The research of image segmentation has promoted the development of computer vision greatly, and has also promoted the development of intelligent information processing technology. There is a lot of uncertainty about the image itself. As a theory that can define fuzzy boundaries, fuzzy theory can describe the uncertainty of images effectively. Many researches have focused on the application of fuzzy clustering algorithm in image segmentation in recent years. The research status of image segmentation technology was explained and the development process of fuzzy theory was introduced in this paper. The fuzzy C means clustering algorithm was analyzed in detail. Aiming at the problem that the fuzzy C means clustering algorithm has poor noise immunity function, an improved fuzzy clustering algorithm was proposed. The algorithm presented in this paper performed FCM image segmentation by changing the objective function and based on domain pixel class constraint, which solved the problem of introducing spatial information effectively. The traditional algorithm was compared with the improved algorithm through the contrast experiment. It was proved that the algorithm can suppress the noise and improve the robustness of the algorithm without changing the time complexity by defining the objective index, including the running time and the segmentation accuracy. To some extent, the research in this paper can promote the theoretical research of image segmentation algorithm based on improved fuzzy clustering.

References

[1] K. S. Chuang, H. L. Tzeng, S. Chen, J. Wu, T. J. Chen: *Fuzzy c-means clustering with spatial information for image segmentation.* Computerized Medical Imaging and Graphics *30* (2006), No. 1, 9–15.

[2] S. Chen, D. Zhang: *Robust image segmentation using FCM with spatial constraints based on new kernel-induced distance measure.* IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics *34* (2004), No. 4, 1907–1916.

[3] Y. Han, P. Shi: *An improved ant colony algorithm for fuzzy clustering in image segmentation.* Neurocomputing *70* (2007), Nos. 4–6, 665–671.

[4] D. L. Pham, J. L. Prince: *An adaptive fuzzy C-means algorithm for image segmentation in the presence of intensity inhomogeneities.* Pattern Recognition Letters *20* (1999), No. 1, 57–68.

[5] L. O. Hall, A. M. Bensaid, L. P. Clarke, R. P. Velthuizen, M. S. Silbiger, J. C. Bezdek: *A comparison of neural network and fuzzy clustering techniques in segmenting magnetic resonance images of the brain.* IEEE Transactions on Neural Networks *3* (1992), No. 5, 672–682.

[6] S. Shen, W. Sandham, M. Granat, S. Sterr: *MRI fuzzy segmentation of brain tissue using neighborhood attraction with neural-network optimization.* IEEE Transactions on Information Technology in Biomedicine *9* (2005), No. 3, 459–467.

[7] M. Gong, Y. Liang, J. Shi, W. Ma, J. Ma: *Fuzzy c-means clustering with local information and kernel metric for image segmentation.* IEEE Transactions on Image Processing *22* (2013), No. 2, 573–584.

[8] Z. Yang, F. L. Chung, W. Shitong: *Robust fuzzy clustering-based image segmentation.* Applied Soft Computing *9* (2009), No. 1, 80–84.

[9] X. Gao, J. Li, H. Ji: *A multi-threshold image segmentation algorithm based on weighting fuzzy C-means clustering and statistical test.* Acta Electronica Sinica *32* (2004), No. 4, 661–664.

[10] M. Forouzanfar, N. Forghani, M. Teshnehlab: *Parameter optimization of improved fuzzy c-means clustering algorithm for brain MR image segmentation.* Engineering Applications of Artificial Intelligence *23*, (2010), No. 2, 160–168.

[11] Y. Chen, J. Z. Wang: *A region-based fuzzy feature matching approach to content-based image retrieval.* IEEE Transactions on Pattern Analysis and Machine Intelligence *24* (2002), No. 9, 1252–1267.

[12] P. Vasuda, S. Satheesh: *Improved fuzzy C-means algorithm for MR brain image segmentation.* International Journal on Computer Science & Engineering *2* (2010), No. 5, paper 1713.

[13] W. Cai, S. Chen, D. Zhang: *Fast and robust fuzzy c-means clustering algorithms incorporating local information for image segmentation.* Pattern Recognition *40* (2007), No. 3, 825–838.

[14] B. N. Li, C. K. Chui, S. Chang, S. H. Ong: *Integrating spatial fuzzy clustering with level set methods for automated medical image segmentation.* Computers in Biology and Medicine *41* (2011), No. 1, 1–10.

[15] S. Das, S. Sil: *Kernel-induced fuzzy clustering of image pixels with an improved differential evolution algorithm.* Information Sciences *180* (2010), No. 8, 1237–1256.

Received June 29, 2017