Image Segmentation Based on Neural Network and Differential Evolution Algorithm

Wenjuan Zeng, Haibo Gao

College of Information Science and Engineering,
Hunan International Economics University,
Changsha 410205, Hunan, China

Abstract
Image segmentation is the technical process of partitioning the image into multiple specific and unique regions and extracting the interested objects. This paper improves the artificial neural network with relatively ideal image segmentation effect and takes the gray-scale image with specific objects as the image to be segmented. Because the differential evolution (DE) algorithm can compute the non-linear multi-dimensional data space in a quick and effective manner, it cannot only get the global optimum, but it also greatly reduces the computation time, therefore, to study the sample with DE algorithm and BP algorithm can get the training network. Then, with the pixel matrix of the image as the input vector, classify it in the well-trained network and realize the segmentation finally. The simulation experiment proves that with excellent segmentation effect, the image segmentation method based on neural network and differential evolution algorithm is a feasible image segmentation method.
Key words: IMAGE SEGMENTATION, NEURAL NETWORK, DIFFERENTIAL EVOLUTION ALGORITHM

1. Introduction

Image segmentation is a key step to transit from image processing to image analysis and it occupies an important position in the image engineering. Image segmentation is the technique and process to partition the regions with unique features and extract the interested objects [1]. The features here can refer to the grayscale, color and texture of the pixels and the pre-defined object can correspond to single region or multiple regions. On one hand, image segmentation is the foundation of object expression and it greatly affects the feature measurement, on the other hand, the original image has become more abstract and compact due to the object expression, feature extraction and parameter measurement, making the higher-level image analysis and understanding possible [2]. From image analysis to image processing, image segmentation is of indispensable importance, additionally, as a significant image technology, image segmentation has played an important role in pattern recognition and image processing and it has also been developed rapidly in practical applications [3].

The development of image segmentation technique is closely related to many other displaces and fields such as biology, artificial intelligence and computer science. The researchers have come up with many methods in the development of image segmentation technique, including threshold segmentation, region segmentation, edge segmentation and the segmentation method combined with specific theories [4]. The threshold, region and edge segmentation methods have been developed maturely, however, due to object diversity and object imaging uncertainty, it is difficult for single feature extraction method to obtain satisfactory extraction result on the images with complicated objects and the existing algorithms still have the following problems: the segmentation result is easy to distort, the accuracy of segmentation is low, the algorithms costs much time and they are not suitable for large-scale data processing[5]. The latest research hotspot is the segmentation methods integrating specific theories, which include artificial neural network, intelligence algorithm, cluster analysis and fuzzy set theory. The continuous emergence of new methods have broadened the application scope of the image segmentation and improved its accuracy [6,7].

Based on the above analysis, the current research of the image segmentation requires the combination of multiple methods to make full use of and avoid the disadvantages of every method. This paper first analyzes the basic principles and characteristics of BP neural network and differential evolution algorithm as well as the problems of the existing image segmentation techniques in practical applications. Then it proposes an image segmentation method based on BP neural network and differential evolution algorithm to better combine them together in the application of image segmentation. Finally, it is the experiment simulation and analysis.

2. Basic Principles of DE Algorithm

DE algorithm has become an effective and robust method to solve non-linear, indifferentiable, multiextremum and high-dimensional complicated functions. Starting from a certain random initial population, DE algorithm produces new individuals through the summation of the weighted vector difference of any two individuals and the third individual. Then, it compares the new individual with the pre-defined individual in the current population: if the fitness of the new individual is superior to that of the old one, the new individual will supersede the old one in the next generation, otherwise, the old one will be reserved. Through continuous iteration, the excellent individuals are reserved while the inferior are eliminated, thus, leading the search process to be close to the optimum solution[8]. The main evolution operators in DE algorithm include: mutation, crossover and selection operators.

(1) Initialization

DE uses NP real-value parameter vectors with D dimensions as the population of every generation and every individual is referred as:

$$X_{i,G}(i=1,2,\ldots,\ NP) \qquad (1)$$

In this formula, is the sequence of the individual in the population, G is the number of evolutional generations and NP is the population scale. In the minimization, NP remains the unchanged [9].

In order to build the initial point of optimization search, the population must be initialized. Generally, a method to search the initial population is to randomly select from the given boundary constraints. In the research of DE, it is generally assumed that all the randomly initialized population conforms to the uniform probability distribution. Assume that the boundary of the parameter variable is $X_j^{(L)} < X_j < X_j^{(U)}$, then:

$$X_{ji,0} = rand(0,1)\cdot(X_j^{(U)} - X_j^{(L)}) + X_j^{(L)} \quad (i=1,2,\ldots,NP;\ j=1,3,\ldots,D) \qquad (2)$$

In this formula, rand[0,1] is the uniform random number generated between [0,1].

(2) Mutation Operation

$$v_i = x_i + F\cdot(x_{i_2} - x_{i_3}) \qquad (3)$$

$$v_i = x_{i_1} + F\cdot(x_{i_1} - x_{best}) + F\cdot(x_{i_2} - x_{i_3}) \qquad (4)$$

Here, $F > 0$ is the real constant to control differential mutation, i_1, i_2, i_3 are the individuals randomly selected from the population and x_{best} is the optimum solution to be found [10].

In the computation of differential evolution, the change value of gene-bit is determined by the difference between other individuals. It fully utilizes the information of other individuals in the population for the purpose of expanding the population diversity and avoids the randomness and blindness resulting from the pure mutation operation within the individuals. In the random-vector differential evolution, the mutation of every individual depends on the vector difference of any two random individuals[11].

(3) Crossover Operation

$$v_{ij} = \begin{cases} v_{i,j}, & if\ (U < CR) \\ x_{i,j}, & otherwise \end{cases} \quad (5)$$

In this formula, CR is the crossover probability and U is a variable randomly generated between 0 and 1.

In the computation of differential evolution, the subjects to perform crossover operation are the parent individuals and the new individual produced from the parent individuals after the mutation operation. Although it seems that no information exchange is conducted between the individuals, since the new individuals come from mutation and they carry the information of other individuals in the population, the crossover operator also has the mechanism of information exchange among the individuals [12].

(4) Selection Operation

In order to decide whether the test vector $u_{i,G+1}$ will become a member of the next generation, DE will compare the test vector with the object vector of the current population in accordance with the greedy criterion. If the object function is to be minimized, the vector with smaller object function value will win a place in the next-generation population. All the individuals in the next generation are at least as good as if no better than the corresponding individuals of the current population. Please note that in DE selection, the test vector is only to be compared with only one individual instead of all the individuals, as indicated in Formula (6).

$$x_i = \begin{cases} v_i, & if\,(f(v_i) < f(x_i)) \\ x_i, & otherwise \end{cases} \quad (6)$$

In this formula, f is the fitness and DE uses the greedy selection method to guarantee the population of the next generation contains the vector with better fitness [13].

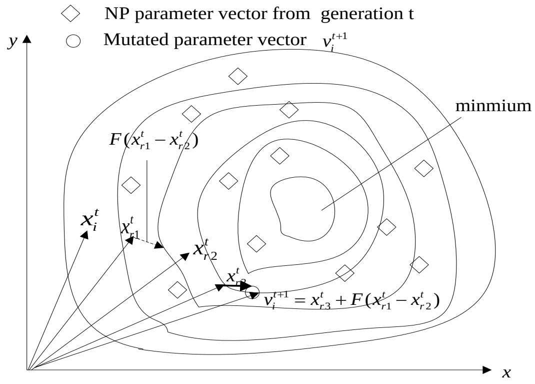

Figure 1. Generation process of vectors in DE algorithm

According to the above analysis, DE algorithm has the following characteristics: this algorithm is universal so that it won't rely on the problem information, it can operate on the structure objects directly without restricting the object functions, its cooperative search has inherent parallelism and it has local information of the individuals and global information of the population to instruct the further searching ability of the algorithm. The generation process of the vector in DE algorithm is indicated in Figure 1.

3. BP Neural Network Model and Its Basic Principles

Short for back-propagation neural network, BP neural network is constituted by one input layer, one or multiple hidden layers and one output layer and is comprised of certain neurons. Just like human nerve cells, these neurons are inter-related[14]. The basic idea of BP algorithm is that the learning process includes the signal forward propagation and the error back propagation. In the forward propagation, the input sample passes from the input layer through the processing of the hidden layer(s) and to the output layer. If the actual output of the output layer is inconsistent with the expected output (teacher signal), then turn to the phase of back propagation of error. The error back propagation propagates the output error through the hidden layer to the input layer in some form and allocates the error to all the units in every layer so as to get their error signals as the basis to correct the weights of every unit [15]. This signal forward propagation and the weight adjustment of the error back propagation go in cycles. The continuous adjustment of the weights is the training process of network and it goes on until its output error is acceptable or until it reaches the pre-set learning times[16]. The propagation of BP neural network is as follows:

(1) Signal Forward Propagation

The input net_i in the ith node in the hidden layer:

$$net_i = \sum_{j=1}^{M} w_{ij} x_j + \theta_i \tag{7}$$

The output y_i in the ith node in the hidden layer:

$$y_i = \phi(met_i) = \phi\left(\sum_{j=1}^{M} w_{ij} x_j + \theta_i\right) \tag{8}$$

The input net_k in the kth node in the output layer:

$$net_k = \sum_{i=1}^{q} w_{ki} y_i + a_k = \sum_{i=1}^{q} w_{ki} \phi\left(\sum_{j=1}^{M} w_{ij} x_j + \theta_i\right) + a_k \tag{9}$$

The input o_k in the kth node in the output layer:

$$o_k = \psi(net_k) = \psi\left(\sum_{i=1}^{q} w_{ki} y_i + a_k\right) = \psi\left(\sum_{i=1}^{q} w_{ki} \phi\left(\sum_{j=1}^{M} w_{ij} x_j + \theta_i\right) + a_k\right) \tag{10}$$

(2) Error Back Propagation

The error back propagation is to compute the output error of the neurons in different layers layer by layer from the output layer and then adjust the weight and threshold of various layers according to the error gradient descent method to make the corrected final output be close to the expected value[17].

The quadratic error criterion function of every sample p is E_p:

$$E_p = \frac{1}{2} \sum_{k=1}^{L} (T_k - o_k)^2 \tag{11}$$

The system's overall error criterions function on p training samples:

$$E = \frac{1}{2} \sum_{p=1}^{p} \sum_{k=1}^{L} (T_k^p - o_k^p)^2 \tag{12}$$

Correct the correction Δw_{ki} of the weight and the correction Δa_k of the threshold in the output layer as well as the correction Δw_{ij} of the weight and the correction $\Delta \theta_i$ of the threshold in the hidden layer according to the error gradient descent method [18].

Plenty of processing units interconnect into a non-linear and self-adaptive information processing system. It is raised on the basis of the research achievements of modern neuroscience, trying to process the information by simulating the form the brain neural network processes and memorizes information [19].

Generally, BP network is a two-layer or more neural network and every neurons in different layers in the right and left to realize full connection, namely every neuron in the first layer in the left connects every neuron in the first layer in the right while there is no connection between the neurons in the upper and lower layers[20].

4. The Application of DE Neural Network in Image Segmentation

Read the image, get its pixel matrix and get the input vector through dimension reduction operation on the matrix. Train the input vector with the well-trained differential evolution neural network and the final output vector is the classification result of the image. Restore the classification result from one-dimensional vector array into the image matrix form and display the segmentation result. Every sample to be classified is one corresponding pixel point T_{ij} in the image T and put this sample into the DE neural network $Denn$ for classification. Get an output value O_{ij} and classify the pixel points of the image according to the output value [21, 22].

$$O_{ij} = Denn(T_{ij}) \tag{13}$$

$$T_{ij} = \begin{cases} F, & O_{ij} \ge 0.5 \\ B, & O_{ij} < 0.5 \end{cases} \tag{14}$$

Here, F is the object region, B is the background region and T is the segmented image. Restore the classification result from one-dimensional vector array to the image matrix form and indicate the segmentation result [23]. The application procedure of DE neural network in image segment as shown in Figure 2.

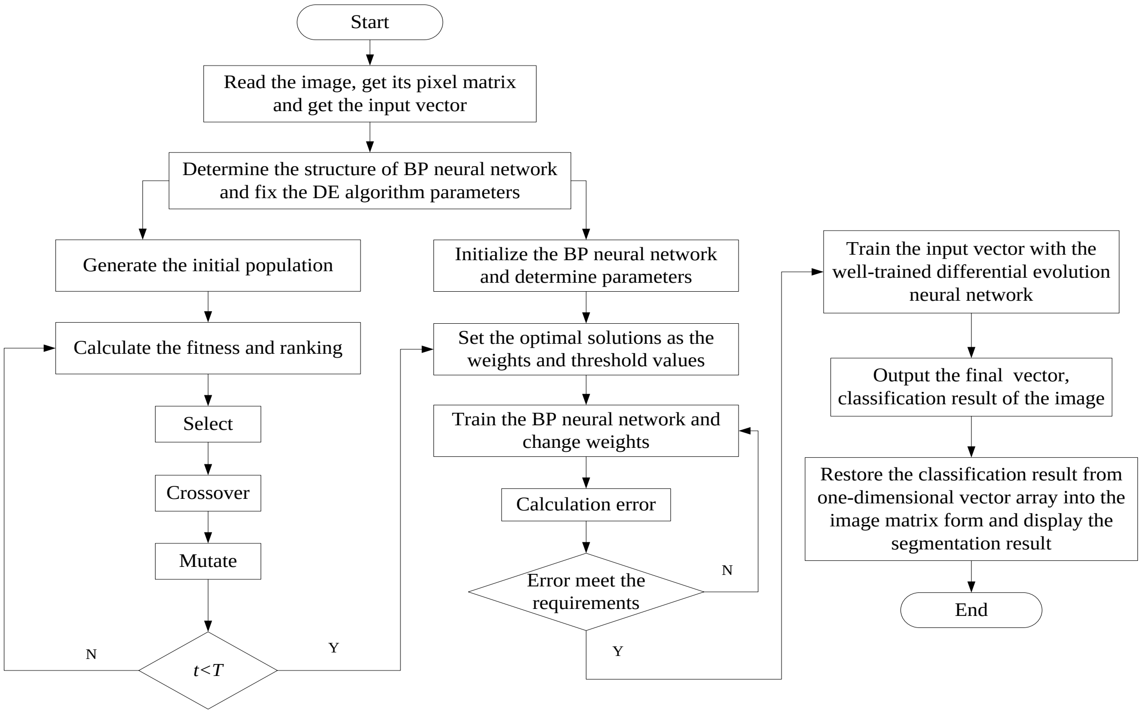

Figure 2. Operation flowchart of DE algorithm to optimize BP neural network

5. Simulation Experiment and Analysis

In order to prove the feasibility and validity of the method of this paper in the image segmentation, train the BP neural network by selecting 300 images from the image segmentation library. Select and test the gray-scale images with certain specific features and give the comparison results of the image segmentation based on DE neural network and BP neural network. All the simulation experiments in this paper take Matlab R2012a with the platform and the storage and computation of the image are conducted in the form of matrix and vector. The experimental results are as follows Figure 3.

(a) Original image (b) DE neural network (c) Neural network

Figure 3. Simulation experiment analysis

From the image to be segmented, the original test image has more object regions and the contrasts in some regions are weak. The above analysis of the experimental result proves that the image segmentation result by the algorithm of this paper has high definition, obvious edge, sufficient extraction of object region, excellent stability and segmentation accuracy. Therefore, it can be seen that the image segmentation method based on BP neural network is an effective algorithm.

6. Conclusion

This paper has studied the basic principles of differential evolution algorithm and BP neural network systematically and proposed the image segmentation method based on differential evolution algorithm and BP neural network. It improves the BP neural network by using the strong global searching ability of differential evolution algorithm so as to make up for the shortcomings of BP neural network such as slow training speed, easy trap in local minimum and weak global searching ability. In the end, it has given the basic procedures of the algorithm in this paper and the steps of image segmentation and simulated the BP neural network before and after the improvement with MATLAB, proving the validity of the algorithm in this paper.

Acknowledgements

This work was supported by IPIS2012.(Scientific research projects funded 2015 hunan province department of education, and Hunan Provincial Education Science five-year plan funded project (XJK014BGD046)).

References

1. Chathurika Dharmagunawardhana, Sasan Mahmoodi, Michael Bennett, Mahesan Niranjan (2014) Gaussian Markov Random Field Based Improved Texture Descriptor for Image Segmentation. *Image and Vision Computing*, 32(11), p.p.884-895.
2. Kazim Hanbay, M. Fatih Talu (2014) Segmentation of SAR Images Using Improved Artificial Bee Colony Algorithm and Neutrosophic Set. *Applied Soft Computing*, 21(8), p.p.433-443.
3. H. E. Suryavanshi, Amit Mishra, Shiv Kumar (2013) Digital Image Watermarking in Wavelet Domain. *International Journal of Electrical and Computer Engineering*, 3(1), p.p.1-6.
4. Chengzhi Deng, Saifeng Hu, Wei Tian, et al. (2013) Total Variation based Multivariate Shearlet Shrinkage for Image Reconstruction. *TELKOMNIKA Indonesian Journal of Electrical Engineering*, 11(1), p.p. 40-47.
5. Ali R. Yildiz (2013) Hybrid Taguchi-differential Evolution Algorithm for Optimization of Multi-Pass Turning Operations. *Applied Soft Computing*, 13(3), p.p.1433-1439.
6. E. Hamzeloo, M. Massinaei, N. Mehrshad (2013) Estimation of Particle Size Distribution on an Industrial Conveyor Belt Using Image Analysis and Neural Networks. *Powder Technology*, 261(7), p.p.185-190.
7. Sung-Kwun Oh, Sung-Hoon Yoo, Witold Pedrycz (2013) Design of Face Recognition Algorithm Using PCA -LDA Combined for Hybrid Data Pre-Processing and Polynomial-based RBF Neural Networks: Design and Its Application. *Expert Systems with Applications*, 40(5), p.p.1451-1466.
8. Umesh Kumar Rout, Rabindra Kumar Sahu, Sidhartha Panda (2013) Design and Analysis of Differential Evolution Algorithm Based Automatic Generation Control for Interconnected Power System. *Ain Shams Engineering Journal*, 4(3), p.p.409-421.
9. Banaja Mohanty, Sidhartha Panda, P.K. Hota (2013) Controller Parameters Tuning of Differential Evolution Algorithm and Its Application to Load Frequency Control of Multi-Source Power System. *International Journal of Electrical Power & Energy Systems*, 54(1), p.p.77-85.
10. Fábio Fabris, Renato A. Krohling (2013) A Co-evolutionary Differential Evolution Algorithm for Solving Min–Max Optimization Problems Implemented on GPU Using C-CUDA. *Expert Systems with Applications*, 39(12), p.p.10324-10333.
11. Jinn-Tsong Tsai, Jia-Cen Fang, Jyh-Horng Chou (2013) Optimized Task Scheduling and Resource Allocation on Cloud Computing Environment Using Improved Differential Evolution Algorithm. *Computers & Operations Research*, 40(12), p.p.3045-3055.
12. M. Fatih Tasgetiren, Quan-Ke Pan, P.N. Suganthan, Ozge Buyukdagli (2013) A Variable Iterated Greedy Algorithm with Differential Evolution for The No-idle Permutation Flowshop Scheduling Problem. *Computers & Operations Research*, 40(7), p.p.1729-1743.
13. Ismaila Idris, Ali Selamat, Sigeru Omatu (2014) Hybrid Email Spam Detection Model with Negative Selection Algorithm and Differential Evolution. *Engineering Applications of Artificial Intelligence*, 28(2), p.p.97-110.
14. Kunihiko Fukushima (2013) Artificial Vision by Multi-Layered Neural Networks: Neocognitron and Its Advances. *Neural Networks*, 37(1), p.p.103-119.
15. Diego Viejo, Jose Garcia-Rodriguez, Miguel Cazorla (2014) Combining Visual Features and Growing Neural Gas Networks For Robotic 3D SLAM. *Information Sciences*, 276(20), p.p.174-185.

16. A.V. Savchenko (2013) Probabilistic Neural Network with Homogeneity Testing in Recognition of Discrete Patterns Set. *Neural Networks*, 46(10), p.p.227-241.
17. K. Seetharaman, S. Sathiamoorthy (2013) Color Image Retrieval Using Statistical Model and Radial Basis Function Neural Network. *Egyptian Informatics Journal*, 15(1), p.p.59-68.
18. Mohamad Awad (2014) Sea Water Chlorophyll-A Estimation Using Hyperspectral Images and Supervised Artificial Neural Network. *Ecological Informatics*, vol.24, p.p.60-68.
19. Poonam Sharma, K.V. Arya, R.N. Yadav (2013) Efficient Face Recognition Using Wavelet-based Generalized Neural Network. *Signal Processing*, 93(6), p.p.1557-1565.
20. P.V. Arun, S.K. Katiyar (2013) An Evolutionary Computing Frame Work toward Object Extraction from Satellite Images. *The Egyptian Journal of Remote Sensing and Space Science*, 16(2), p.p.163-169.
21. O. Zahran, H. Kasban, M. El-Kordy, F.E. Abd El-Samie (2013) Automatic Weld Defect Identification from Radiographic Images. *NDT & E International*, 57(7), p.p.26-35.
22. Sudha Radhika, Yukio Tamura, Masahiro Matsui (2013) Cyclone Damage Detection on Building Structures from Pre- and Post-Satellite Images Using Wavelet Based Pattern Recognition. *Journal of Wind Engineering and Industrial Aerodynamics*, 136(1), p.p.23-33.
23. P. Boniecki, K. Koszela, H. Piekarska-Boniecka, J. Weres, M. Zaborowicz, S. Kujawa, A. Majewski, B. Raba (2013) Neural Identification of Selected Apple Pests. *Computers and Electronics in Agriculture*, 110(1), p.p. 9-16.