Applied Soft Computing 17 (2014) 1–11

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

Multi-level image thresholding by synergetic differential evolution

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ARTICLE INFO

Article history:
Received 15 January 2013
Received in revised form 8 September 2013
Accepted 29 November 2013
Available online 31 December 2013

Keywords:
Image segmentation
Optimization
Entropy
Gaussian curve fitting

ABSTRACT

The multi-level image thresholding is often treated as a problem of optimization. Typically, finding the parameters of these problems leads to a nonlinear optimization problem, for which obtaining the solution is computationally expensive and time-consuming. In this paper a new multi-level image thresholding technique using synergetic differential evolution (SDE), an advanced version of differential evolution (DE), is proposed. SDE is a fusion of three algorithmic concepts proposed in modified versions of DE. It utilizes two criteria (1) entropy and (2) approximation of normalized histogram of an image by a mixture of Gaussian distribution to find the optimal thresholds. The experimental results show that SDE can make optimal thresholding applicable in case of multi-level thresholding and the performance is better than some other multi-level thresholding methods.

1. Introduction

Image segmentation is a very common image processing operation, since all image processing schemes need some sort of operation of the pixels into different classes. In order to determine thresholds for segmentation, most methods analyze the histogram of the image. The optimal thresholds are those values of intensity that can separate different objects from each other or from the background to such an extent that a decision can be made without further processing [1,2] and these are often found by either minimizing or maximizing an objective function with respect to the values of the thresholds. It is typically simple and computationally efficient and based on the assumption that the objects can be distinguished by their gray levels. The automatic fitting of these thresholds is one of the main challenges in image segmentation. There are a lot of approaches classifying thresholding methods. Sezgin and Sankur [3] presented a survey of a variety of thresholding techniques. They classified the thresholding techniques in terms of parametric and non parametric approaches.

Parametric thresholding methods exploit the first-order statistical characterization of the image to be segmented. An attempt to find an estimate of the parameters of the distribution that best fit the given histogram data is made by using the least-squares estimation method. Over the years, many researchers have proposed several algorithms to solve the problem of Gaussian curve fitting for multi-level thresholding. Some instances of parametric thresholding methods available in literature as follows: Snyder et al. [4] presented a method for fitting curves based on a heuristic method called tree annealing. Nakib et al. [5] proposed a fast scheme for optimal thresholding using a simulated annealing algorithm. Zahara et al. [6] proposed a hybrid Nelder–Mead Particle Swarm Optimization (NM-PSO) method, while a hybrid method based on Expectation Maximization (EM) and Particle Swarm Optimization (PSO + EM) is proposed by Fan and Lin [7] for dealing with image segmentation. Application of basic differential evolution (DE) for solving image segmentation problem is given in [8].

Non-parametric approaches, on the other hand, find the thresholds that separate the gray-level regions of an image based on some discriminating criteria such as the between class variance, entropy and cross entropy. Otsu's [2] proposed a method in which optimal thresholds are selected by maximizing the *between class* variance. However, inefficient formulation of between class variance makes the method very time-consuming for multi-level threshold selection. To overcome this problem, Liao et al. [9] proposed a fast recursive algorithm called Fast Otsu method, along with a look-up-table and implemented it for multi-level thresholding. Ye et al. [10] applied PSO algorithm to optimize the Otsu's criterion. Kapur et al. [11] have given a method for gray-level picture thresholding by using the entropy of the histogram. Dirami et al. [12] adopted a fast multilevel thresholding image segmentation scheme through a multiphase level set method. Madhubanti and Amitava [13] presented a hybrid cooperative–comprehensive learning based PSO algorithm based on maximum entropy criterion. Yin [14] developed a recursive programming technique to reduce the order of magnitude of computing the multi-level thresholds and further

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http://dx.doi.org/10.1016/j.asoc.2013.11.018

used the PSO algorithm to minimize the cross entropy. Horng [15] proposed honey bee mating optimization based multi-level thresholding using maximum entropy. Recently, Kwedlo [16] presented a clustering method combining differential evolution with the *K-means* algorithm.

Despite the availability of large amounts of algorithms/methods for dealing with image thresholding using conventional parametric and non parametric approaches, it is worth noting that the computational time using these techniques grows exponentially with the increase in the number of required thresholds. To overcome this deficiency, several algorithms have so far been proposed in literatures [4–16] which aims at reducing the computational time for searching thresholds with quality effectiveness taking the advantage of intelligent techniques, such as neural networks (NN) and evolutionary algorithms (EAs). Over the last few decades, Neural Networks have shown a good potency in dealing with the problems in complicated systems [17–20]. In the past, some researchers tried various neural network methods to solve the problem of image segmentation [21,22]. All works on neural networks illustrated that the methods of neural networks were capable in handling image segmentation problems. Taking into account the advantages of the evolutionary algorithms (EAs), the deployment of thresholding techniques based on it have flourished in recent years [4–8,10,12–16]. It has been shown that these techniques offer better performances than the classical approaches due to their domain independent nature and the capability of finding optimal or near optimal solutions in a large search space. Although these methods have shown to be efficient in solving the multi-level thresholding problem and provide better effectiveness than other traditional methods, finding of threshold in multi-level thresholding is still time taking process which indicates that further improvement is needed to enhance the efficiency of existing methods while maintaining quality.

Differential evolution (DE) is one of the most prominent evolutionary algorithms, proposed by Storn and Price [23,24]. It is well known for its ability to efficiently and adaptively explore large search spaces. It has two main advantages: faster convergence over other evolutionary algorithms on some problems [25], and it has very few control parameters to adjust. The advantages of DE over other evolutionary algorithms, make it a potential choice for solving real life application problems [16,26–30]. Keeping this in view, an improvement on Gaussian curve fitting and the entropy method could be greatly enhanced in the case of multi-level thresholding.

In the present study we have chosen an advanced DE version called synergetic differential evolution (SDE) which has been successfully applied by the authors for dealing with benchmark and real life problems [31]. Motivated by the results of our SDE algorithm [31] on benchmark and real life problems in this paper SDE is used for multi-level image thresholding. Gaussian curve fitting and the entropy functions respectively are considered as evaluation criteria for SDE and has been named as SDE_Gaus and SDE_Entropy respectively. SDE is a fusion of three modifications (1) opposition based learning (OBL) for population initialization [32]. The basic idea behind OBL is the simultaneous consideration of an estimate and its corresponding opposite estimate to achieve a better approximation for the current candidate solution. Mathematically, it has been proven that the opposite numbers are more likely to be closer to the optimal solution than purely random ones. (2) Best of random individuals as base individual in mutation step [33]. The rationale of using tournament best process is to prevent the search from becoming a purely random search or a purely greedy search. (3) Dynamic population update (i.e. Single population) [34], the population is updated immediately if the newly found solution is better than the target solution. While in original DE the population update step is performed after the completion of the generation. The newly found better solutions can take part in mutation and crossover operation in the current generation itself as opposed to DE where these better solutions take part in mutation and crossover operations in next generation. Although these modifications are very simple and naive, the respective studies have shown that the effects of these changes are considerable. Our objective in this study is to observe the combined effect of some of these variations that showed distinct advantages in the empirical study concerning convergence rate and solution quality. Experimental results on four synthetic and three real test images demonstrate the algorithm's ability to perform threshold selection while preserving main features of the original image.

The remainder of the paper is structured as follows. Section 2 describes the SDE algorithm. Image thresholding techniques are given in Section 3. Section 4 gives the details of test images, parameter settings and performance metric. Results are analyzed and discussed in Section 5 and finally, the paper is concluded in Section 6.

2. Synergetic differential evolution (SDE)

This section briefly introduces the Synergetic Differential Evolution (SDE) [31]. The working of SDE is given in Algorithm 1 with the help of a pseudo-code. Like all other population based search algorithms, SDE starts with a population S of NP candidate solutions: $X_i = (x_{i,1}, x_{i,2}, \ldots, x_{i,D})$, $i = 1, 2, \ldots, NP$, where the index i denotes the ith individual of the population and D denotes the dimension of the problem. The main operations of SDE are as follows:

Population initialization: Generate a population P of NP individuals randomly between lower and upper bounds $X_{\min} = (x_{\min,1}, x_{\min,2}, \ldots, x_{\min,D}), X_{\max} = (x_{\max,1}, x_{\max,2}, \ldots, x_{\max,D})$ using Eq. (1) and generate it's corresponding opposite population OP, also of size NP using Eq. (2)

$$P_{i,j} = x_{\min,j} + r_{i,j} \times (x_{\max,j} - x_{\min,j}) \tag{1}$$

$$OP_{i,j} = x_{\min,j} + x_{\max,j} - P_{i,j}, \quad i = 1, 2, \ldots, NP; \ j = 1, 2, \ldots, D \tag{2}$$

where $P_{i,j}$ and $OP_{i,j}$ denote the jth variable of the ith individual of the population and its opposite population, respectively and $r_{i,j}$ is a uniform random number between 0 and 1. Select NP best individuals as initial population S from $\{P \cup OP\}$.

Mutation: Mutation operator used in SDE follows the rule of selecting the best individual from the three distinct individuals X_{tb}, X_{r2} and X_{r3} randomly from the population corresponding to target point X_i (distinct from X_i). After that the best individual (say) X_{tb} is taken as the base individual while the other individuals act as donors for vector differences. Mathematically it is given by

$$V_i = X_{tb} + F \times (X_{r2} - X_{r3}) \tag{3}$$

the scaling factor F is a positive control parameter and is used for scaling the difference of vectors.

Crossover: The crossover operation of SDE is same as of DE. Here, the mutant vector $V_i = (v_{i,1}, v_{i,2}, \ldots, v_{i,D})$ exchanges its components with the target vector $X_i = (x_{i,1}, x_{i,2}, \ldots, x_{i,D})$ to form a *trial* vector $U_i = (u_{i,1}, u_{i,2}, \ldots, u_{i,D})$ using the equation

$$u_{i,j} = \begin{cases} v_{i,j} & \text{if } r_{i,j} \le C_r \vee j = j_{rand} \\ x_{i,j} & \text{otherwise} \end{cases} \tag{4}$$

where $j = 1,\ldots,D$ and $j_{rand} \in \{1, \ldots, D\}$ is a random parameter's index and C_r is crossover probability.

Selection: Selection operation determines whether the target or the trial individuals will survive for further generation. Inspired by the advantage of Gauss–Seidel method against Jacobi method for linear equations, the dynamic strategy is used in population update. There is only one population in which individuals are continuously