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A novel hybrid algorithm of gravitational search algorithm with genetic algorithm for multi-level thresholding

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ABSTRACT

The multi-level thresholding is a popular method for image segmentation. However, the method is computationally expensive and suffers from premature convergence when level increases. To solve the two problems, this paper presents an advanced version of gravitational search algorithm (GSA), namely hybrid algorithm of GSA with genetic algorithm (GA) (GSA-GA) for multi-level thresholding. In GSA-GA, when premature convergence occurred, the roulette selection and discrete mutation operators of GA are introduced to diversify the population and escape from premature convergence. The introduction of these operators therefore promotes GSA-GA to perform faster and more accurate multi-level image thresholding. In this paper, two common criteria (1) entropy and (2) between-class variance were utilized as fitness functions. Experiments have been performed on six test images using various numbers of thresholds. The experimental results were compared with standard GSA and three state-of-art GSA variants. Comparison results showed that the GSA-GA produced superior or comparative segmentation accuracy in both entropy and between-class variance criteria. Moreover, the statistical significance test demonstrated that GSA-GA significantly reduce the computational complexity for all of the tested images.
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1. Introduction

Image segmentation is an important technology for image processing and is a fundamental process in many image, video, and computer vision applications [1]. It is useful for separating objects from backgrounds or discriminating objects from objects with distinct gray-levels. Image thresholding is often used in image segmentation. The main purpose of image segmentation is to determine an efficient threshold (for bi-level thresholding) or several thresholds (for multi-level thresholding) according to some criteria [2]. Bi-level thresholding classifies pixels into two groups: one group includes pixels with gray-levels above a certain threshold, and the other group includes the rest. This is the simplest thresholding problem, as only one gray value need to be found. However, for real-world image processing, multi-level thresholding is more often utilized. The multi-level thresholding method divides pixels into several groups by assigning a single intensity value to pixels that belong to a group. In each group, pixels have intensity values within a specific range.

Multi-level thresholding techniques can be classified into two types: optimal thresholding methods and property-based thresholding methods [3]. Optimal thresholding methods search for the optimal thresholds by optimizing an objective function based on image gray-level histogram. Researchers have proposed several algorithms to determine objective functions, where thresholds are determined by jointly maximizing class uncertainty and region homogeneity. The algorithms include maximizing entropy to measure the homogeneity of segmented classes (e.g. Kapur's entropy) [4,5], maximizing the separability measure based on between-class variance (e.g. Otsu method) [6,7], thresholding based on the fuzzy similarity measure [8], and minimizing of Bayesian error [9], etc. Among them, the Otsu method [6] and the Kapur's entropy method [4] are the most preferred methods and they are relatively easy to use [10]. Therefore, they are selected as the objective functions in this study. However, with the thresholds increase, all these methods encounter two common problems: (1) the computational complexity increases as exponentially and (2) prone to premature convergence [7,11,12].

Over the past decades, researchers have developed several algorithms to solve these types of optimization problems, including branch-and-bound [13], meta-heuristics [14], and gradient-based methods [15]. Among them, meta-heuristics based methods have been extensively employed for performing fast search of optimal thresholds because of their significantly advantages in escaping from local optima. The popular meta-heuristic algorithms include genetic algorithm (GA) [6], simulated annealing (SA) [16], ant colony optimization (ACO) [17], artificial bee colony optimization (ABC) [18], differential evolution (DE) [19], biogeography-based optimization (BBO) [20], differential search algorithm (DS) [21], particle swarm optimization (PSO) [22], and so on. Moreover, to further improve the convergence accuracy and speed, a number of hybrid meta-heuristic algorithms have been proposed, such as GAPSO (hybrid GA with PSO) [23,24], ACO/PSO (hybrid ACO with PSO) [25], SA/PSO (hybrid SA with PSO) [26], BBO-DE (hybrid DE with BBO) [20], etc. Recently, many of these algorithms and their variants have been applied to multi-level thresholding as illustrated in Table 1.

Generally speaking, all these pure meta-algorithms have achieved certain successes and have showed different advantages. For example, the DE is the most efficient with respect to the quality of the optimal thresholds compared with GA, PSO, ACO, and SA whereas PSO converges the most quickly when comparing with ACO, GA, DE, and SA [29]. Besides, the DS consumes the shortest running time for multi-level color image thresholding when comparing with DE, GA, PSO, ABC, etc. [10].

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Table 1
Meta-heuristic algorithms for multi-level thresholding.

Meta-heuristic algorithms	Author	Year	Ref.
GA	Yin	1999	[27]
	Tao, Tian, and Liu	2003	[28]
	Hammouche, Diaf, and Siarry	2008	[29]
PSO	Clerc and Kennedy	2002	[30]
	Yin	2007	[31]
	Nabizadeh, Faez, and Tavassoli et al.	2010	[32]
	Akay	2013	[7]
DE	Ali, Ahn, and Pant	2014	[12]
	Ayala, dos Santos, and Mariani et al.	2015	[33]
	Sarkar, Das, and Chaudhuri	2015	[5]
ACO	Yin	2007	[31]
ABC	Akay	2013	[7]
SA	Kurban, Civicioglu, and Kurban et al.	2014	[10]
DS	Kurban, Civicioglu, and Kurban et al.	2014	[10]
GAPSO	Juang	2004	[24]
	Baniani and Chalechale	2013	[23]
SA/PSO	Zhang and Yu	2012	[26]
BBO-DE	Boussaï d, Chatterjee, and Siarry et al.	2013	[20]

Nevertheless, the deficiencies of the algorithms themselves still weaken their application in multi-level thresholding. For example, in PSO, a particle i can only learn from the experience of its neighbors (donated by ***gbest***) and the experience of itself (donated by $\boldsymbol{pbest}_i$), if the ***gbest*** is trapped, the convergence process will suffer from premature convergence [34,35]. The success of DE in solving a specific problem crucially depends on appropriately choosing trial vector generation strategies and their associated control parameter values [36]. Therefore, a number of hybrid meta-heuristic algorithms have been presented for multi-level thresholding, in which the GAPSO [23] and BBO-DE [20] have been proved to be preferable algorithms. However, GAPSO cannot obtain high-quality optimal thresholding sometimes for its performance heavily depends on the settings of three parameters and the topology structure of the neighbors [37]. Similarly, BBO-DE performs better than the pure DE, but its optimization capability still crucially depends on the selecting of trial vector generation strategies and their associated control parameter values.

In short, the unavoidable disadvantages of the meta-heuristic algorithms make it still a challenge task to obtain the optimal thresholds rapidly while maintaining high quality capabilities [12]. Consequently, many researches have been focusing on improving the existing algorithms as well as exploiting new meta-heuristic algorithms.

As one of the newest meat-heuristic algorithms, the gravitational search algorithm (GSA), which is inspired by the law of gravity and mass interactions, has proven its promising efficiency for solving complex problems [38]. Compared to the aforementioned meta-heuristic algorithms, GSA possesses simpler concept, higher computational efficiency, and fewer parameters [39]. A number of researches have reported the superiority of GSA in terms of the convergence precision, convergence speed, and stable convergence characteristics over many other meta-heuristic algorithms, such as PSO, GA, Central Force Optimization (CFO), and ACO [38,40–43], etc. These advantages of GSA make it a potential choice for solving multi-level thresholding. However, due to the gravitational force absorbs masses into each other, no recovery for GSA if premature convergence occurs [44]. In this situation, GSA loses its ability of explore and the convergence speed in the last iterations is slow. New operators should thus be added to GSA to prevent premature convergence and to increase its flexibility in solving more complicated problems [44].

In the past few years, many researches have paid close attention to the improvement of GSA and presented some GSA variants, such as [39–42,45–47]. Most of the GSA variants were presented to prevent the premature convergence problem or decrease the computational complexity of GSA by designing new learning strategies or hybrid with other algorithms/operators. However, very few of the algorithms have focused on the application on multi-level thresholding. When applying GSA into multi-level thresholding, especially when the number of thresholds is increased, the two problems, premature convergence and high computational complexity, become more serious.

Actually, the lack of diversity is one important reason for the premature convergence [48]. As basic operators to provide the necessary diversity within a population, mutations have been utilized in many meta-heuristic optimization algorithms [49,50]. GA, as an adaptive meta-heuristic search algorithm premised on the evolutionary ideas of natural selection and genetics, is famous for its mutation operator [51]. Keeping this in view, the population diversity in GSA can be greatly enhanced by the hybrid of GSA with GA. However, due to the rotatory hybrid may cause high computational complexity, taking the evolutionary stages into consideration to guide the hybrid of GSA and GA is necessary.

Based on the above analysis, in this paper, we developed a novel hybrid algorithm of GSA with GA (GSA-GA) for multi-level thresholding. In GSA-GA, the discrete mutation operator of GA was introduced to promote the population diversity when premature convergence occurred. To identify whether the population suffers from premature convergence, we calculated the standard deviation of objective functions first. If the standard deviation is smaller than a random number $rand \in [0, 1]$ or the $rand$ is bigger than the ratio of the current iteration t to the maximum iterations $Iter_{\max}$, the mutation operator is carried out. This makes the GSA-GSA is provided with adaptive characteristics along with the evolutionary stages. Moreover, for selecting the particles for mutation, the roulette selection of GSA was also introduced. The introduction of these operators therefore could promote GSA-GA to perform faster and more accurate multi-level image thresholding. The entropy and between-class variance were respectively considered as evaluation criteria for GSA-GA.

The remainder of this paper is organized as follows. Section 2 first briefly describes the frameworks of GA and GSA, and then reviews the entropy and between-class variance criteria. In Section 3, details of the proposed GSA-GA are given followed by the implement of GSA-GA for multi-level thresholding. The experimental set up and results are included in Section 4. Finally, the paper is concluded in Section 5.

2. Background

2.1. GA

GA is a stochastic search algorithm based on the mechanics of natural evolution which can be used to solve optimization problems [51,52]. It starts optimization with a randomly initialized population $\boldsymbol{x} = [\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_N]$ where N is the size of the population. In the population, each individual $\boldsymbol{x}_i$ represents a point in the search space and thus a candidate solution to the problem. Each candidate solution for a specific problem is called a chromosome and contains a linear list of genes. GA then uses three basic operators (selection, crossover, and mutation) to manipulate the genetic composition of a population. Selection is a process in which individuals with the highest fitness values in the current generation are reproduced in the new generation. The crossover operator produces two offspring (new candidate solutions) by recombining the information from two parents. Mutation is a random alteration of some gene values in an individual. The allele of each gene is a candidate for mutation, and the mutation probability determines its function [24]. In the new generation, the population is more adapted to the environment than the previous generation, and the evolution continues until meeting an optimization criterion. After decoding the last individual, an optimal solution can be gained.

2.2. GSA

In GSA, a particle $\boldsymbol{x}_i = [x_{i1}, x_{i2}, \ldots, x_{iS}]$ moves through the S-dimensional search space with the velocity $\boldsymbol{v}_i = [v_{i1}, v_{i2}, \ldots, v_{iS}]$

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