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A fast scheme for multilevel thresholding based on a modified bees algorithm

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ABSTRACT

Image segmentation is one of the most important tasks in image processing and pattern recognition. One of the most efficient and popular techniques for image segmentation is image thresholding. Among several thresholding methods, Kapur's (maximum entropy (ME)) and Otsu's methods have been widely adopted for their simplicity and effectiveness. Although efficient in the case of bi-level thresholding, they are very computationally expensive when extended to multilevel thresholding because they employ an exhaustive search for the optimal thresholds. In this paper, a fast scheme based on a modified Bees Algorithm (BA) called the Patch-Levy-based Bees Algorithm (PLBA) is adopted to render Kapur's (ME) and Otsu's methods more practical; this is achieved by accelerating the search for the optimal thresholds in multilevel thresholding. The experimental results demonstrate that the proposed PLBA-based thresholding algorithms are able to converge to the optimal multiple thresholds much faster than their corresponding methods based on Basic BA. The experiments also show that the thresholding algorithms based on BA algorithms outperform corresponding state-of-the-art metaheuristic-based methods that employ Bacterial Foraging Optimization (BFO) and quantum mechanism (quantum-inspired algorithms) and perform better than the non-metaheuristic-based Two-Stage Multi-threshold Otsu method (TSMO) in terms of the segmented image quality. In addition, the results show the high degree of stability of the proposed PLBA-based algorithms.

1. Introduction

Image segmentation plays a significant role in image analysis and pattern recognition. Segmentation is the process of decomposing an image into its constituent objects and regions. One of the simplest and most widely used image segmentation approaches is image thresholding [1]. Image thresholding enjoys a considerable degree of popularity in the applications of image segmentation due to its intuitive properties, high speed and simplicity of implementation. However, the accuracy of segmentation depends heavily on the image thresholding methods that are used. Image thresholding has wide applications in image processing, for example, document image analysis [7], infrared image segmentation [4,10], quality inspection of materials [36], Synthetic Aperture Radar (SAR) image segmentation [22], and medical image applications [23,33].

Thresholding can be single- or bi-level thresholding, i.e., a single threshold is required to segment the image into two classes, or multilevel thresholding, i.e., two or more thresholds are set to subdivide the image into three or more classes. A great number of thresholding approaches have been proposed in the literature over the years. Excellent and thorough surveys and studies have been conducted by [31,21], and [35]. The threshold selection techniques can be classified into global techniques and local or adaptive techniques. In global thresholding methods, for example, single- or bi-level thresholding, the threshold value is defined over the whole image. On the other hand, in local thresholding methods, the image is partitioned into sub-images, and a threshold value is assigned to each sub-image. Compared to local thresholding approaches, global approaches involve less computation and are easier to implement.

Global thresholding methods can be classified in many other ways, for example, parametric and nonparametric approaches. In parametric approaches, the distribution of the gray levels of

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each class has a probability density function that is assumed to obey a given distribution, typically a Gaussian distribution. The goal of these techniques is to estimate the distribution parameters that best fit the given histogram data in the least-squares sense. On the other hand, in nonparametric approaches, the optimal thresholds are selected based on some discriminating criteria such as the between-class variance [24], Kapur's entropy [17], cross entropy [19], maximum correlation [38], Renyi's entropy [30], the fuzzy version of the maximum entropy [6], and the Tsallis entropy [28].

Both parametric and nonparametric thresholding problems can be considered optimization problems that involve finding the optimal thresholds by minimizing or maximizing an objective function. Nonparametric methods are more computationally efficient and easier to implement than parametric methods. A common problem of both parametric and nonparametric methods is that the computational time becomes very expensive and grows exponentially when bi-level thresholding is extended to multilevel thresholding.

To overcome this problem, different techniques and schemes such as iterative [41] and recursive [20] schemes have been proposed to speed up the search process for the optimal thresholds in traditional thresholding techniques. Huang and Wang [15] presented a fast Otsu multilevel thresholding algorithm based on two stages called the Two-Stage Multi-threshold Otsu (TSMO) method. An important class of algorithms that have been employed as an alternative to fast multilevel thresholding schemes is metaheuristic algorithms, in particular swarm intelligence-based metaheuristics. Metaheuristic algorithms have the ability to move away from local optima by exploring the search space often via randomization. Meanwhile, metaheuristic algorithms are able to converge rapidly by exploiting the regions of the current good solutions and selecting the best solution by performing a fine trade-off between exploration and exploitation. Because of the exploration characteristic in metaheuristic algorithms, they are suitable for global optimization. As a result, in recent decades, they have attracted the attention of researchers attempting to solve global optimization problems by finding near-optimal solutions in reasonable running times.

Many metaheuristics have been applied to multilevel thresholding problems to accelerate the search for the optimal thresholds, e.g., Genetic Algorithm (GA) [37], Bacterial Foraging Optimization (BFO) [23,34], Particle Swarm Optimization (PSO) [2,32,39], and the Firefly Algorithm (FA) [14]. [11] proposed multilevel thresholding techniques based on Differential Evolution (DE), Ant Colony Optimization (ACO) and Tabu Search (TS) to optimize Otsu's between-class variance. In addition, they conducted a comparative study of these metaheuristics and three additional metaheuristics, namely, GA, PSO, and Simulated Annealing (SA), for the purpose of solving the multilevel Otsu's thresholding problem. Recently, Alihodzic and Tuba [3] proposed a modified version of the Bat Algorithm for multilevel thresholding based on Kapur's entropy and Otsu's between-class variance criteria. [9] proposed PSO and DE based on the quantum mechanism for the multilevel Otsu's thresholding method.

Over the last few years, bee swarm-based metaheuristic algorithms have attracted a great deal of attention from researchers seeking the optimization of thresholding problems. Horng [12,13] adopted Honey Bee Mating Optimization (HBMO) and ABC, respectively, to select multiple thresholds based on Kapur's criterion. Horng [12] compared the HBMO with PSO, the Hybrid Cooperative-Comprehensive Learning-based PSO (HCOCLPSO), and the Fast Otsu's method. The experiments indicated that the HBMO performed better than the other algorithms in terms of the quality of the thresholds obtained and the quality of the segmented images. Horng [13] conducted comparisons among the ABC, HBMO, PSO, HCOCLPSO, and the Fast Otsu's method. The experimntal results showed that the ABC outperformed PSO, HCOCLPSO, and the Fast Otsu's method, which are non-bee swarm-based algorithms, and achieved equivalent results to those obtained by the HBMO, which is a bee swarm-based algorithm. Recently, Akay [2] employed ABC to select the optimal multi-thresholds based on Otsu's and Kapur's criteria. In this work, Akay [2] conducted a comparative study between ABC and PSO, and the experiments showed that the ABC significantly outperformed PSO.

Encouraged by these promising results of the bee swarm-based metaheuristics, we apply our proposed enhanced variant of BA, i.e., PLBA, to multilevel image thresholding. The purpose of this paper is to investigate the search ability of the proposed PLBA with regard to multilevel thresholding. In this paper, our proposed PLBA is employed to find the multilevel thresholds by maximizing the between-class variance, one of the criterion proposed by Otsu [24] and Kapur's entropy [17]. The performance of the proposed multilevel thresholding algorithm based on PLBA is evaluated and compared with the metaheuristic-based methods based on Basic BA, the modified bacterial foraging optimization (MBFO) algorithm [34], the conventional bacterial foraging optimization (BFO) algorithm [34], and other state-of-the-art metaheuristic algorithms based on quantum mechanism [9]. Additionally, the performance of the proposed multilevel thresholding algorithm is compared with the non-metaheuristic-based Two-Stage Multi-threshold Otsu method (TSMO) [15].

The remainder of this paper is organized as follows. Section 2 provides a brief description of the Basic BA, BFO, MBFO algorithms, the TSMO method, and the quantum-inspired algorithms. Section 3 describes the proposed PLBA algorithm. The proposed multilevel thresholding algorithms are described in Section 4. Section 5 details the experimental results of the performance evaluations obtained by the proposed PLBA-based multilevel thresholding algorithms and compares them with the results obtained by Basic BA and other state-of-the-art metaheuristic-based and non-metaheuristic-based algorithms. Finally, Section 6 summarizes the paper.

2. Brief description of the compared algorithms

2.1. Basic BA

The Bees Algorithm (BA) is a bee swarm-based optimization algorithm proposed by Pham et al. [27] and inspired by the foraging behavior of a swarm of honeybees searching for food sources. In the BA algorithm, each bee or site in the population represents a solution for the problem being optimized. Fundamentally, the BA performs a kind of exploitative local or neighborhood search combined with an exploratory global search. Both search modes implement a uniform random search. In the global search, the scout bees are uniformly distributed at random to different areas of the search space to scout for potential solutions. In the local or neighborhood search, follower bees are recruited to exploit patches that scout bees have found to be more promising. To conduct the local search, two processes are required, namely, the selection and recruitment processes. In the selection process, the patches found to be more promising are chosen, whereas in the recruitment operation, follower bees are recruited for the promising patches, while more bees are recruited for the best patches out of those selected.

2.2. Bacterial foraging optimization (BFO)

The BFO algorithm is a population-based metaheuristic algorithm inspired by the foraging behavior of bacteria [26]. In nature, bacteria such as Escherichia coli use the chemotaxis mechanism to randomly forage for food. In the chemotaxis process, the bacteria rotate their flagella counterclockwise, causing them to swim straight toward areas with high concentrations of food.