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A multilevel image thresholding segmentation algorithm based on two-dimensional K–L divergence and modified particle swarm optimization

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ABSTRACT

Multilevel image segmentation is a technique that divides images into multiple homogeneous regions. In order to improve the effectiveness and efficiency of multilevel image thresholding segmentation, we propose a segmentation algorithm based on two-dimensional (2D) Kullback–Leibler(K–L) divergence and modified Particle Swarm Optimization (MPSO). This approach calculates the 2D K–L divergence between an image and its segmented result by adopting 2D histogram as the distribution function, then employs the sum of divergences of different regions as the fitness function of MPSO to seek the optimal thresholds. The proposed 2D K–L divergence improves the accuracy of image segmentation; the MPSO overcomes the drawback of premature convergence of PSO by improving the location update formulation and the global best position of particles, and reduces drastically the time complexity of multilevel thresholding segmentation. Experiments were conducted extensively on the Berkeley Segmentation Dataset and Benchmark (BSDS300), and four performance indices of image segmentation – BDE, PRI, GCE and VOI – were tested. The results show the robustness and effectiveness of the proposed algorithm.

1. Introduction

Image segmentation is the process of partitioning an image into non-overlapping, homogeneous regions containing similar objects, which is widely used in computer vision applications such as object recognition, content-based retrieval, and object-based video coding. Though numerous algorithms have been proposed in recent years, image segmentation is still far from being an easy problem to solve.

At present, commonly used segmentation algorithms include graph cut [1,2], contour detection [3], and thresholding segmentation [4,5]. Thresholding segmentation has been widely adopted due to its simplicity, which consists of bi-level and multilevel segmentation. Bi-level segmentation splits an image into object and background. However, with the advent of multi-object technology such as multi-object optimization and multi-object tracking, dividing an image into just two regions cannot meet the requirements of most pattern recognition and machine vision applications. To overcome the limitations of bi-level segmentation, multilevel segmentation approaches that split an image into multiple objects and background have been developed. However, conventional multilevel image thresholding segmentation methods [6,7] are costly in time since they search exhaustively for the optimal multiple threshold values of the image. Moreover, the time complexity grows exponentially with the number of thresholds.

Metaheuristics provide a very popular way to yield near optimal solutions for a wide variety of complex optimization problems [8]. They combine rules and randomness to imitate some natural phenomena, and have grown significantly in usage in the past few decades. If we treat multiple threshold values as space dimensions of metaheuristics, their parallelism provides an efficient means to address the problem of computational cost of multilevel image thresholding segmentation. The PSO algorithm [9], introduced by Eberhart and Kennedy in 1995, is a swarm-based metaheuristic technique that models the social behavior of bird flocking. It is well adapted to the optimization of nonlinear functions in multidimensional space. PSO is easy to implement

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and may outperform other evolutionary algorithms [10,11]; However, it is liable to trap local optimization and cause premature convergence.

The fitness function of metaheuristics is a criterion for selecting the optimal solution, and in recent years, using entropy as a fitness function has drawn the attention of researchers [8,12]. Many entropy-based segmentation algorithms adopt one-dimensional (1D) entropy to calculate the summation of regional entropy as an objective function of image segmentation [13,14]. However, 1D entropy only takes account of gray values of the image with no spatial correlation between pixels, and thus the performance is usually unsatisfactory. Abutaleb [15] extended 1D entropy to 2D, regarding the 2D histogram as a distribution function to calculate entropy and achieving more accurate segmentation results than those based on 1D entropy. We also utilize the idea of 2D entropy in our segmentation algorithm proposed in this paper.

Kullback–Leibler(K–L) divergence was proposed by Kullback [16] under the name of directed divergence, which is a relative entropy to measure the information theoretical distance between two distributions P and Q. It was also studied by *Rényi* [17], who pointed out that the K–L divergence can be interpreted as the expectation of the change in the information content when substituting Q for P. The less the information changes, the smaller the divergence is, and the divergence will be zero if two distributions are the same. According to these characteristics of K–L divergence, when we regard image region and its corresponding segmentation result as P and Q respectively, minimizing the sum of K–L divergence of different regions in an image is to search for the optimal image segmentation. Because the searching process is time-consuming, PSO is introduced to reduce computational cost by using its parallelism in our work.

In this paper, we propose an unsupervised algorithm for multilevel image thresholding segmentation which combines 2D K–L divergence and modified PSO (2DKLMPSO). 2D histogram of an image is denoted as the distribution function to calculate the proposed 2D K–L divergence, which is then considered as the fitness function of MPSO to improve the accuracy of multilevel image segmentation. To reduce the time complexity of seeking the optimal threshold values of multilevel thresholding segmentation, we propose MPSO to manage the convergence and diversity of particles to conquer the drawback of premature convergence of PSO. Extensive experiments conducted on the BSDS300 illustrate that the proposed algorithm not only achieves better segmentation results, but also has lower time complexity.

The main contributions of this paper are as follows:

(1) We propose the 2D K–L divergence to be applied to multilevel image segmentation, and derive the formulation of 2D K–L divergence as an objective function of multilevel image segmentation to improve the accuracy of segmentation;
(2) We propose MPSO that modifies the location update formula and the global best position of particles to overcome the defect of premature convergence of PSO;
(3) We propose a scheme for multilevel image thresholding segmentation that denotes 2D K–L divergence as the fitness function of MPSO, which improves the effectiveness of the segmentation and reduces the time complexity.

The rest of this paper is organized as follows. We summarize the development of multilevel image thresholding segmentation in Section 2, followed by a brief introduction of K–L divergence, 2D histogram concept and PSO in Section 3. Section 4 describes the proposed algorithm. Section 5 illustrates our experimental results. Conclusions are drawn in Section 6.

2. Related works

Roughly speaking, the development of multilevel image thresholding segmentation algorithm has gone through two stages. Early stage approaches, such as between-class variance [6] and entropy [7], which are unsupervised and nonparametric, explore exhaustively the optimal threshold values to optimize the objective function. Although those segmentation approaches can produce accurate results, they are extremely time-consuming. To reduce the computational complexity, iterative schemes [18,19] and dichotomization techniques [20] were developed, which significantly reduced the computing time while producing results of comparable quality.

In recent years, many researchers have focused on metaheuristics in multilevel image thresholding segmentation domain to reduce computational cost. The commonly used metaheuristic algorithms include Genetic Algorithm (GA) [21,22], Particle Swarm Optimization (PSO) [23,24] and Differential Evolution (DE) [25]. PSO is characterized as simple in concept, easy to implement, and computationally efficient when compared with other heuristic techniques, so PSO has been widely discussed in many domains in recent years [23,26]. However, since the traditional PSO method tends to get stuck in local optima, many subsequent approaches based on PSO have been proposed. Wu et al. [27] developed guidelines for parameter settings both for PSO and discrete PSO to produce better results. Quantum inspired PSO [28] was proposed to reduce computational complexity for multilevel image segmentation. Hu et al. [29] studied an intelligent selection mechanism to trigger appropriate search methods. Liu et al. [11] adopted adaptive inertia and adaptive population to improve the performance of PSO.

Bhandari et al. [30] studied Cukoo search algorithm and wind driven optimization. Tuba et al. [31] compared evolutionary and swarm-based computational techniques. In order to consider spatial contextual information of the image, energy function combined GA [32] has been used. Yin et al. [33] employed the fuzzy c-partition entropy and ABC to select thresholding, and used graph cut instead of thresholing for each pixel to oversegment the image into small regions. Akay [12] used Kapur's entropy and Otsu as fitness function of PSO and artificial bee colony (ABC) to compare segmentation results, and pointed out Kapur's entropy was better than Otsu for multilevel image thresholding segmentation. Cross entropy combined DE algorithm was studied in color image by Sarkar et al. [8]. These methods use evolution algorithms or swarm-based algorithms to seek the optimal multilevel thresholding. Different objective functions, such as an energy function, Otsu and entropy, are adopted as the fitness function of metaheuristic algorithm. Entropy-based approaches, have drawn the attention of many researchers [34] because they have a solid foundation in information theory. The above-mentioned entropy approaches all employed 1D entropy as the objective function of image segmentation.

To involve spatial correlation between pixels in image segmentation, some researchers adopted 2D entropy to achieve better segmentation performance. Qi [35] combined adaptive PSO and 2D Shannon exponential entropy to pursue the optimal threshold values of image segmentation. However, he only divided the image into object and background, and did not implement multilevel thresholding segmentation. Sarkar et al. [36] proposed an automatic multilevel image thresholding scheme based on 2D Tsallis entropy and DE algorithm. They analyzed the Tsallia entropy and focused on how to calculate the maximum entropy of multilevel images. Nie [37] introduced 2D Tsallis cross-entropy to determine the optimal threshold value, which shows it as a new criterion of image thresholding, but it belongs to bi-level, not multilevel, segmentation.