Information Sciences 294 (2015) 408–422

Contents lists available at ScienceDirect

Information Sciences

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

Dynamic-context cooperative quantum-behaved particle swarm optimization based on multilevel thresholding applied to medical image segmentation

Yangyang Li [a,*], Licheng Jiao [a], Ronghua Shang [a], Rustam Stolkin [b]

[a] Key Laboratory of Intelligent Perception and Image Understanding of Ministry of Education of China, International Research Center for Intelligent Perception and Computation, Xidian University, Xi'an 710071, China
[b] School of Mechanical Engineering, University of Birmingham, Birmingham B15 2TT, UK

ARTICLE INFO

Article history:
Received 14 May 2012
Received in revised form 29 June 2014
Accepted 5 October 2014
Available online 12 October 2014

Keywords:
Quantum-behaved particle swarm optimization
Cooperative method
Context vector
Image segmentation

ABSTRACT

This paper proposes a dynamic-context cooperative quantum-behaved particle swarm optimization algorithm. The proposed algorithm incorporates a new method for dynamically updating the context vector each time it completes a cooperation operation with other particles. We first explain how this leads to enhanced search ability and improved optimization over previous methods, and demonstrate this empirically with comparative experiments using benchmark test functions. We then demonstrate a practical application of the proposed method, by showing how it can be applied to optimize the parameters for Otsu image segmentation for processing medical images. Comparative experimental results show that the proposed method outperforms other state-of-the-art methods from the literature.

1. Introduction

1.1. Background

Medical imaging, in the form of X-ray radiography, transformed medicine with its introduction more than a century ago. The availability of powerful computing resources, as well as advances in physics and other technologies, saw the rapid proliferation of additional methods over the past few decades, including CT, MRI and ultrasound imaging. This in turn has led to a rapidly increasing demand for powerful and computationally efficient numerical methods for processing ever increasing numbers of such images to improve their clarity and automatically extract salient information to assist medical professionals.

Effective medical image processing methods are needed to help the doctor to gain more useful information, with greater accuracy, in shorter amounts of time. A particularly important capability is image segmentation, [43]. Segmentation is the process of partitioning an image into a set of non-intersecting regions, such that each region is homogeneous, but the union of no two adjacent regions is homogeneous. This is a fundamental problem in Computer Vision, and a number of methods have been proposed for solving it, [42,37]. In medical imaging, the goal of segmentation is to simplify and/or change the representation of an image, to make it more meaningful and easier to analyze.

* Corresponding author.
E-mail address: yyli@xidian.edu.cn (Y. Li).

http://dx.doi.org/10.1016/j.ins.2014.10.005
0020-0255/

To define a dissimilarity measure between neighboring regions, we must first define an appropriate feature space. Features like grayscale [6], color [14], texture [58], local statistical characteristics [8], and spectrum characteristics [36] are useful for segmentation purposes and can be extracted from an image region. Popular medical image segmentation methods can broadly be divided into region growing algorithms, [44], and edge or boundary detection methods, [51].

Thresholding is the simplest and most commonly used parallel detecting method for segmentation [48]. Thresholding is often used as a preprocessing step, followed by other post-processing methods (e.g., [22,3,18]). It is also commonly used for skin or bone segmentation in CT images, [5].

Single threshold segmentation can separate an object from the background, whereas multi-threshold methods, e.g. [16], are often needed to distinguish multiple salient objects. For binary segmentation of grayscale images, a common approach is to represent objects or salient regions as distributions of pixel gray-levels (Gaussian distributions or histograms are commonly employed) and use the minimum value of the intersection between the two distribution peaks to set the threshold, [6]. Alternatively, a variety of objects can be distinguished by setting multiple thresholds at each local minimum over a distribution curve of all image pixels, [16].

A shortcoming of these simple approaches is that they may not be suitable for multichannel images or images with similar characteristic values. Additionally, they may fail when the distribution of pixels for a salient object or image region is multi-modal. In addition, such methods fail to exploit spatial information contained in images, [4,17], which can be combined with other kinds of imaging parameters [24,62], and a priori knowledge, [52]. Thresholding is also sensitive to uneven noise and grayscale distribution; for example, different thresholds might be necessary at different locations in the same image. To overcome these difficulties, many scholars have proposed improvement methods, such as transition region determination, [61], variable thresholding with pixel spatial location information, [39], and unsupervised connectivity-based thresholding segmentation, [30].

Selecting the appropriate threshold is a difficult problem for images containing multiple objects or segmentation categories and has received considerable attention from researchers in recent years. Pun [45] proposed threshold selection based on a maximum entropy principle which is now recognized as one of the most important automatic threshold selection methods. This approach attempts to divide an image's grayscale histogram into multiple classes, in a way which maximizes the expected information. Kapur et al. further developed this method [25]. Sahoo et al. proposed replacing the general entropy with Renyi entropy [47]. Yen et al. proposed an alternative threshold selection method, based on the max-relativity principle [59], to replace the general maximum entropy principle.

The Otsu method [41] is a nonparametric and unsupervised method of automatic threshold selection for image segmentation. In Otsu, an optimal threshold is selected according to a discriminant criterion. The procedure is very simple; however, the computation time grows exponentially with the number of thresholds due to its exhaustive searching strategy, which would limit the multiple thresholding applications [16]. To overcome this problem, researchers have attempted to replace the exhaustive search strategy of the original Otsu method with more advanced numerical optimization methods, [20,60], and there is an emerging interest in the use of particle swarm optimization (PSO) methods to tackle this problem, [55].

1.2. Particle swarm optimization

The past 20 years have seen a growing interest in the use of particle swarm optimization (PSO) methods, for solving difficult numerical optimization problems, especially those involving large search spaces, discontinuous, or un-differentiable surfaces, and other problems. PSO is useful because it is simple to understand and program, it does not rely on any assumptions about the underlying problem space, and it uses only a small number of parameters. Since 2003, many improved swarm intelligence algorithms have been proposed, [63,9]. However, like other intelligent heuristic-based methods, PSO cannot guarantee globally optimal convergence and can easily become distracted by local optima. In [31], we proposed a cooperative quantum-behaved particle swarm optimization algorithm for numerical optimization (CQPSO), which addresses these problems by making use of quantum uncertainty and cooperation mechanisms. In this paper, we improve the performance of our previous work, [31], by proposing a new method for dynamically updating the context vector at each iteration, and we also show how to combine this approach with the Otsu segmentation method to deliver high performance processing of medical images.

The PSO literature can roughly be divided into work which addresses the improvement of the algorithm, algorithm analysis, and applications of PSO algorithms. Many attempts have been made to improve the performance of PSO. The use of binary system particle swarm optimization, for optimizing the structure of neural networks, was proposed by Kennedy and Eberhart in 1997, [28]. Shi and Eberhart introduced an inertia factor, w, into PSO and improved the convergence property, [49]. An extension of this work employed fuzzy systems to nonlinearly change the inertia weight during optimization, [50]. Clerc [9] introduced the Contraction–Expansion factor into evolution algorithms to guarantee the convergence of the algorithm, [32], while relaxing the speed limit. In 1998 and 1999, [1,2], the concept of selection and crossover was introduced into PSO by Angeline. This process involves comparing fitness values to eliminate less fit particles while a new population is formed by selecting the more fit particles from the parent population and the offspring population. Lovbjerg et al. made a further study of PSO with selection and crossover, proposing a successful form of crossover operation, [34].

Population diversity is particularly important for improving the global convergence of PSO algorithms. The concept of "special scope" was introduced into the standard PSO algorithm by Suganthan, [53]. In order to enhance the population diversity, Kennedy, [26], introduced neighborhood topology to PSO and also introduced "social beliefs" to enhance