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Self-adaptive dragonfly based optimal thresholding for multilevel segmentation of digital images

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Abstract Dragonfly optimization (DFO) is a population based meta-heuristic optimization algorithm that simulates the static and dynamic swarming behaviors of dragonflies. The static swarm comprising less number of dragonflies in a small area for hunting preys, while the dynamic swarm with a large number of dragonflies migrates over long distances; and they represent the exploration and exploitation phases of the DFO. This paper introduces a self adaptive scheme for tuning the DFO parameters and suggests a methodology involving self-adaptive DFO (SADFO) for performing multilevel segmentation of digital images. The multilevel segmentation problem is formulated as an optimization problem and solved using the SADFO. The method optimizes the threshold values through effectively exploring the solution space in obtaining the global best solution. The results of real life and medical images illustrate the performance of the suggested method.

1. Introduction

Image segmentation, a task of dividing an image into several non-overlapping meaningful regions with homogeneous characteristics in respect of texture, gray value, position, etc, has been one of the most difficult and challenging tasks and extensively investigated since 1960s. In other words, it is a process of assigning a label to each pixel in an image, where the pixels with the same label share certain visual characteristics. The segmented regions provide more information than individual pixels since the interpretation of images based on objects is more meaningful than the interpretation based on individual pixels. Image segmentation is considered as an important task in the analysis, interpretation and understanding of images, and widely applied for classification and object recognition in many applications such as fault diagnosis, tracking, monitoring, crack detection, etc. (Skarbek and Koschan, 1994).

In recent years, image segmentation plays a vital role in numerous medical imaging applications such as quantification of tissue volumes, diagnosis, localization of pathology, study of anatomical structure, treatment planning, partial volume correction of functional imaging data and computer integrated surgery. The segmentation methods vary widely depending on the specific application, imaging modality and other factors. For example, the segmentation of brain tissue has different requirements from liver image segmentation. There is thus no single segmentation method that provides acceptable results for all kinds of medical images, thereby making the selection of

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an appropriate segmentation method a dilemma. But the radiologists demand a generalized segmentation tool for delineation of anatomical structures and other regions of interest in medical images (Tarabalka et al., 2010; Fauvel et al., 2013).

Numerous segmentation methods have been suggested in the recent decades. These methods can be classified into three categories; threshold-based, deformation-based and clustering-based. The threshold-based methods determine the threshold values using the image histogram and then classify the image pixels based on these values (Otsu, 1979; Kapur et al., 1985; Bonnet et al., 2002; Baradez et al., 2004; Natarajan et al., 2012). Deformation-based methods, employing region growing (Shih and Cheng, 2005; Hojjatoleslami and Kittler, 1998) and level set (Xie et al., 2005; Li et al., 2011) approaches, have been proposed for identification of the cancer boundary. Most of the deformation-based segmentation methods are semiautomatic since the generation of initial points is difficult to automate. The region growing methods group the pixels into homogeneous regions and segment the image into some major areas, while the level set methods utilize dynamic variational boundaries for segmentation; The clustering-based methods segment the feature space of image into several clusters and derive a sketch of the original image, such as K-means (Papamichail and Papamichail, 2007; Clausi, 2002; Juang and Wu, 2010), Fuzzy C-means (FCM) (Carvalho, 2007; Chen and Zhang, 2004; Chuang et al., 2006; Chaira, 2011) and mean-shift (Comaniciu and Meer, 2002) algorithms.

Among the available techniques, thresholding is a simple and effective tool for image segmentation and popular due to lower storage requirement and fast computations. The number of threshold values used for segmentation varies depending on the nature of the application and the type of image. The best threshold number and values are chosen by a trial and error approach. The segmented result should be appropriate, otherwise it may affect the subsequent processes such as feature extraction and classification. The thresholding methods can be partitioned into bi-level and multilevel thresholding depending on the number of thresholds required to be detected (Sezgin and Sankur, 2004). Bi-level thresholding involves one threshold value and creates two classes: one below the threshold and the other above the threshold, while the multi-level thresholding creates nc classes with $nc-1$ threshold levels. These methods employ parametric approach involving gray distribution of the pixels or nonparametric approach requiring an objective function for optimizing the threshold levels. It has been reported (Sezgin and Sankur, 2004) that Kapur's entropy based thresholding offers better performance than any other thresholding approaches.

Nature inspired optimization techniques have been applied for image segmentation in recent years. A dynamic clustering approach based on particle swarm optimization (PSO) that determines optimum number of centroids for image segmentation has been suggested (Omran et al., 2005). A fast image segmentation method based on artificial bee colony (ABC) optimization to estimate the appropriate threshold values in a continuous gray scale interval has been outlined (Ma et al., 2011). A hybrid approach using matched filter and ant colony optimization for extraction of blood vessels in ophthalmoscope images has been presented (Cinsdikici and Aydın, 2009). A color clustering method based on ant colony optimization for the detection of flower boundaries has been notified (Aydın and Ugur, 2011). The search abilities of PSO and ABC have been exploited in multi-level thresholding (Akay, 2013). A multilevel thresholding based on harmony search optimization (HSO) has been presented (Oliva et al., 2013). A gray-level histogram based multilevel thresholding of digital images using bat optimization (BO) has been explained (Rajinikanth et al., 2014). A multi-level image thresholding using Otsu technique and firefly based optimization (FFO) has been notified (SriMadhava Raja et al., 2014). A modified PSO based multilevel threshold has been outlined (Yi et al., 2015). Although these methods offer reasonably good results for image segmentation problems, the improper choice of certain parameters, such as attractiveness and random movement factor in FFO, harmony memory considering rate and pitch adjusting rate in HSO, affects the convergence and leads to suboptimal solution.

More recently, a Dragonfly optimization (DFO), a swarm intelligence based stochastic optimization technique inspired from the static and dynamic swarming behaviors of dragonflies, has been suggested for solving combinatorial optimization problems in (Mirjalili, 2015). Since its introduction, it has been applied to several real world optimization problems (Hamdy et al., 2016; Tiwari et al., 2016) and found to yield satisfactory results. The robustness of the DFO algorithm can be further improved by adaptively adjusting its parameters that have influence on the convergence and the final solution.

The focus of this paper is to develop a self-adaptive scheme for DFO and then use it in developing a robust multilevel segmentation method for processing digital images with a view of obtaining the global best solution and studying its performances on real life and medical images.

2. Dragonfly optimization

The static and dynamic swarming behaviors of dragonflies are the main inspiration of the DFO algorithm, representing the exploration and exploitation phases of meta-heuristic optimization. DFO initially produces a swarm of dragonflies located randomly in the search space. The position of each dragonfly in the solution space represents a potential solution of the optimization problem. Each ith dragonfly is denoted by a vector df_i as (Mirjalili, 2015).

$$df_i = [df_i^1,\ df_i^2,\ \ldots,\ df_i^{nv}] \tag{1}$$

where df_i^j indicates jth position parameter of ith dragonfly and nv represents the number of problem variables.

The search space is limited by the following inequality

$$df^k(min) \leqslant df^k \leqslant df^k(max): \quad k = 1,\ 2, \ldots,\ nv \tag{2}$$

Initially, the positions of the dragonflies are generated from a uniform distribution using the following equation

$$df_i^k = df_i^k(min) + (df_i^k(max) - df_i^k(min)) \times rand \tag{3}$$

Here, $rand$ is a random number in between 0 and 1. A fitness function receives the position of a dragonfly as input and returns a single numerical output value denoting how good the potential solution is. The behavior of swarms are represented through separation, alignment and cohesion with an objective of survival through attraction and distraction, which are mathematically modeled as:

The separation of ith dragonfly, S_i, from its neighbors is computed by