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Improving segmentation velocity using an evolutionary method

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ABSTRACT

Image segmentation plays an important role in image processing and computer vision. It is often used to classify an image into separate regions, which ideally correspond to different real-world objects. Several segmentation methods have been proposed in the literature, being thresholding techniques the most popular. In such techniques, it is selected a set of proper threshold values that optimize a determined functional criterion, so that each pixel is assigned to a determined class according to its corresponding threshold points. One interesting functional criterion is the Tsallis entropy, which gives excellent results in bi-level thresholding. However, when it is applied to multilevel thresholding, its evaluation becomes computationally expensive, since each threshold point adds restrictions, multimodality and complexity to its functional formulation. Therefore, in the process of finding the appropriate threshold values, it is desired to limit the number of evaluations of the objective function (Tsallis entropy). Under such circumstances, most of the optimization algorithms do not seem to be suited to face such problems as they usually require many evaluations before delivering an acceptable result. On the other hand, the Electromagnetism-Like algorithm is an evolutionary optimization approach which emulates the attraction–repulsion mechanism among charges for evolving the individuals of a population. This technique exhibits interesting search capabilities whereas maintains a low number of function evaluations. In this paper, a new algorithm for multilevel segmentation based on the Electromagnetism-Like algorithm is proposed. In the approach, the optimization algorithm based on the electromagnetism theory is used to find the optimal threshold values by maximizing the Tsallis entropy. Experimental results over several images demonstrate that the proposed approach is able to improve the convergence velocity, compared with similar methods such as Cuckoo search, and Particle Swarm Optimization.

1. Introduction

Segmentation is one of the basic steps of an image analysis system, and consists in separating objects from each other, by considering characteristics contained in a digital image. It has been applied to feature extraction (Kong, Deng, & Dai, 2015), object identification and classification (Cao, Li, Du, Zhang, & Zheng, 2014), surveillance (Bhandari, Singh, Kumar, & Singh, 2014), among other areas. In order to obtain homogeneous regions of pixels, a common method is using the histogram's information with a thresholding approach (Sarkar & Das, 2013).This method is considered the easiest one in segmentation, and it works taking threshold values which separate adequately the distinct regions of pixels in the image being processed. In general, there are two thresholding approaches, namely bi-level and multilevel. In bi-level thresholding (BT), it is only needed a threshold value to separate the two objects of an image (e.g. foreground and background). For real life images, BT does not provide appropriate results. On the other hand, multilevel thresholding (MT) divides the pixels in more than two homogeneous classes and it needs several threshold values (Akay, 2012; Maitra & Chatterjee, 2008). Threshold methods are divided in parametric and nonparametric (Akay, 2012; Xia, Song, & He, 2015). In parametric approaches, it is necessary estimating the parameters of a probability density function capable of modeling each class. Such an approach is time consuming and computationally expensive. A nonparametric technique employs a given criteria (between-class variance, entropy and error rate

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(Kapur, Sahoo, & Wong, 1985; Moser, Serpico, & Member, 2006; Otsu, 1979)) which must be optimized to determine the optimal threshold values. These approaches result an attractive option due their robustness and accuracy (Sezgin & Sankur, 2004).

For bi-level thresholding there exist two classical methods: the first one, proposed by Otsu (1979), maximizes the variance between classes, whereas the second one, proposed by Kapur in (Kapur et al., 1985), uses the entropy maximization to measure the homogeneity among classes. Their efficiency and accuracy have been already proved by segmenting pixels into two classes (Sathya & Kayalvizhi, 2011). Both methods, Otsu and Kapur, can be expanded for multilevel thresholding; however, their computational complexity is increased, and also its accuracy decreases with each new threshold added into the searching process (Agrawal, Panda, Bhuyan, & Panigrahi, 2013; Sathya & Kayalvizhi, 2011).

The Tsallis entropy (TE), proposed in Tsallis (1988), is known as the non-extensive entropy, and can be considered as an extension of Shannon's entropy. Recently, there exist several studies that report similarities among the Tsallis, the Shannon and the Boltzmann–Gibbs entropies (Agrawal et al., 2013; Tang, Suganthan, & Yao, 2006; Tsallis, 2002, 2009; Zhang & Wu, 2011). Different to the Otsu and Kapur methods, the Tsallis entropy produces a functional formulation whose accuracy does not depend on the number of threshold points (Zhang & Wu, 2011). In the process of image segmentation, under the TE perspective, it is selected a set of threshold values that maximize the TE functional formulation, so that each pixel is assigned to a determined class according to its corresponding threshold points. TE gives excellent results in bi-level thresholding. However, when it is applied to multilevel thresholding (MT), its evaluation becomes computationally expensive, since each threshold point adds restrictions, multimodality and complexity to its functional formulation. Therefore, in the process of finding the appropriate threshold values, it is desired to limit the number of evaluations of the TE objective function. Under such circumstances, most of the optimization algorithms do not seem to be suited to face such problems as they usually require many evaluations before delivering an acceptable result.

Recently, evolutionary optimization approaches have been reported in the literature to find the appropriate threshold values by maximizing the complex objective function produced by Tsallis entropy. Such approaches have produced several interesting segmentation algorithms using different optimization methods such as Differential evolution (DE) (Sarkar & Das, 2013), Particle Swarm Optimization algorithm (PSO) (Sri, Raja, Kavitha, & Ramakrishnan, 2012), Artificial Bee Colony (ABC) (Zhang & Wu, 2011), Cuckoo Search algorithm (CSA) (Agrawal et al., 2013) and Bacterial Foraging Optimization (BFOA) (Sathya & Kayalvizhi, 2011). All these approaches permit with different results to optimize the TE fitness function in despite of its high multimodality characteristics. However, one particular difficulty in their performance is the demand for a large number of fitness evaluations before delivering a satisfying result.

This paper presents a multilevel thresholding method that uses the Electromagnetism-Like algorithm (EMO) to find the best threshold values. EMO is a population-based evolutionary method which was firstly introduced by Birbil and Fang (2003) to solve unconstrained optimization problems. The algorithm emulates the attraction–repulsion mechanism between charged particles within an electromagnetism field. Each particle represents a solution and carries a certain amount of charge which is proportional to its fitness value. In turn, solutions are defined by position vectors which give real positions for particles within a multi-dimensional space. Moreover, objective function values of particles are calculated considering such position vectors. Each particle exerts repulsion or attraction forces over other members in the population; the resultant force acting over a particle is used to update its position. Clearly, the idea behind the EMO methodology is to move particles towards the optimum solution by exerting attraction or repulsion forces among them. Different to other evolutionary methods, EMO exhibits interesting search capabilities such as fast convergence still keeping its ability to avoid local minima in high modality environments (De Castro & Von Zuben, 2002; De Jong, 1988; Dorigo, Maniezzo, & Colorni, 1996). Recent studies (Birbil, Fang, & Sheu, 2004; Rocha & Fernandes, 2009a, 2009b; Wu, Yang, & Wei, 2004) demonstrate that the EMO algorithm presents the best balance between optimization results and demand of function evaluations. Such characteristics have attracted the attention of the evolutionary computation community, so that it has been effectively applied to solve a wide range of engineering problems such as flow-shop scheduling (Naderi, Tavakkoli-Moghaddam, & Khalili, 2010) communications (Hung & Huang, 2011), vehicle routing (Yurtkuran & Emel, 2010), array pattern optimization in circuits (Jhang & Lee, 2009), neural network training (Lee & Chang, 2010), image processing and control systems (Ghamisi, Couceiro, Benediktsson, & Ferreira, 2012).

In this paper, a new algorithm for multilevel segmentation based on the Electromagnetism-Like algorithm (EMO) is proposed. In the approach, the EMO algorithm is used to find the optimal threshold values by maximizing the Tsallis entropy. As a result, the proposed algorithm can substantially reduce the number of function evaluations preserving the good search capabilities of an evolutionary method. In our approach, the algorithm uses as particles the encoding of a set of candidate threshold points. The TE objective function evaluates the segmentation quality of the candidate threshold points. Guided by the values of this objective function, the set of encoded candidate solutions are modified by using the EMO operators so that they can improve their segmentation quality as the optimization process evolves. In comparison to other similar algorithms, the proposed method deploys better segmentation results yet consuming less TE function evaluations.

The rest of the paper is organized as follows. In Section 2, the standard EMO algorithm is introduced. Section 3 gives a simple description of the Tsallis entropy method. Section 4 explains the implementation of the proposed algorithm. Section 5 discusses experimental results and comparisons after testing the proposal over a set of benchmark images. Finally, in Section 6 the conclusions are discussed.

2. Electromagnetism – Like optimization algorithm (EMO)

EMO is a population-based evolutionary method which was firstly introduced by Birbil and Fang (2003) to solve unconstrained optimization problems. Different to other evolutionary methods, EMO exhibits interesting search capabilities such as fast convergence still keeping its ability to avoid local minima in high modality environments (De Castro & Von Zuben, 2002; De Jong, 1988; Dorigo et al., 1996). Recent studies (Birbil et al., 2004; Rocha & Fernandes, 2009a, 2009b; Wu et al., 2004) demonstrate that the EMO algorithm presents the best balance between optimization results and demand of function evaluations. From the implementation point of view, EMO utilizes N different n-dimensional points $x_{i,t},\ i = 1, 2, \ldots, n$, as a population for searching the feasible set $\mathbf{X} = \{x \in \Re^n | l_i \leqslant x \leqslant u_i\}$, where t denotes the number of iteration (or generation) of the algorithm. The initial population $\mathbf{Sp}_t = \{x_{1,t}, x_{2,t}, \ldots, x_{N,t}\}$ (being $t = 1$), is taken of uniformly distributed samples of the search region, $\mathbf{X}$. We denote the population set at the tth iteration by $\mathbf{Sp}_t$, and the members of $\mathbf{Sp}_t$ changes with t. After the initialization of $\mathbf{Sp}_t$, EMO continues its iterative process until a stopping condition (e.g. the maximum number of iterations)