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Tsallis entropy based multilevel thresholding for colored satellite image segmentation using evolutionary algorithms

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ABSTRACT

In this paper, a new technique for color image segmentation using CS algorithm supported by Tsallis entropy for multilevel thresholding has been proposed toward the effective colored segmentation of satellite images. The nonextensive entropy is a new expansion in statistical mechanics, and it is a recent formalism in which a real quantity q was introduced as parameter for physical systems that presents the long range interactions, long time memories and fractal-type structures. The feasibility of the proposed cuckoo search and Tsallis entropy based approach was tested on 10 different satellite images and benchmarked with differential evolution, wind driven optimization, particle swarm optimization and artificial bee colony algorithm for solving the multilevel colored image thresholding problems. Experiments have been conducted on a variety of satellite images. Several measurements are used to evaluate the performance of proposed method which clearly illustrates the effectiveness and robustness of the proposed algorithm. The experimental results qualitative and quantitative both demonstrate that the proposed method selects the threshold values effectively and properly.

1. Introduction

Color image thresholding is an essential process for image analysis and interpretation, and most commonly used method to differentiate the objects in a scene from the background; the image is divided into several regions on the basis of one or more threshold values. Multilevel thresholding approaches have drawn much attention during the past few years because the segmented image determined through thresholding techniques has the benefit of low storage memory, efficient processing ability as compared to a gray level image containing 256 levels. It plays a crucial role in image analysis. Multilevel thresholding based color image segmentation is a critical and challenging task, and when the level increases in multilevel thresholding problem, computation cost increases as well. This leads to significant difficulties especially when higher level threshold values are evaluated (Dey, Saha, Bhattacharyya, & Maulik, 2014). Moreover, the computational cost further increases when multilevel thresholding approach is applied to color image segmentation problem. Image segmentation algorithms can be divided into four methods: (1) histogram thresholding, (2) image feature-space clustering, (3) region-based, and (4) edge-based.

The histogram based thresholding approach is a straightforward and most widely used technique for segmenting various types of images. If the object in an image is distinguished from the background by computing a single threshold value, it is called bi-level thresholding (Kumar, Kumar, Sharma, & Pant, 2013) while, classifying the image into several different regions according to color by setting multiple threshold values is called as multilevel colored image thresholding (Kurban, Civicioglu, Kurban, & Besdok, 2014). In case of bi-level thresholding approach, image is mainly separated into two distinct classes. In this concept, pixel with gray level values higher than a certain value T are categorized as object of the image and rest gray level values, which are lesser than the threshold criteria T are categorized as background image (Arora, Acharya, Verma, & Panigrahi, 2008). However, in case of remote sensing images or real life images, bi-level thresholding does not give appropriate performance. As a result, there is strong requirement of multilevel thresholding.

Over the years, many thresholding techniques have been developed and it was found that the multilevel image thresholding using classical implementations is time consuming as they exhaustively search the best values to optimize the objective function. In favor of multilevel thresholding techniques, various studies have been reported in the literature for segmentation of images and to classify the

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significant patterns of interest (Dirami, Hammouche, Diaf, & Siarry, 2013; Ghamisi, Couceiro, Benediktsson, & Ferreira, 2012; Peng, Zhang, & Zhang, 2013; Manikandan, Ramar, Willjuice, & Srinivasagan, 2014; Sathya & Kayalvizhi, 2011a , 2011b; Xue & Titterington, 2011). In order to get better understanding or analysis of any image, the image requires to be accurately segmented into significant regions. The most leading problem in thresholding based segmentation approaches is to select the appropriate threshold value.

Therefore, to solve these problems, the evolutionary and swarm-based computing approaches stand out for their ability to search best solution from any objective function. The use of these algorithms has become widespread as they can produce high-quality solutions for difficult problems. Considering their advantages, these algorithms are preferred in finding the optimum thresholds for simple images. For example, GA and improved genetic algorithm (GA) (Zhang et al., 2014) have been used for numerous times to solve the multilevel thresholding problem. Additionally, there are efforts to solve the multilevel thresholding problem with swarm-based PSO, modified PSO (MPSO) (Liu, Mu, Kou, & Liu, 2014), and ABC techniques. Therefore, in this study, well-known nature inspired optimization algorithms are compared while solving the multilevel satellite image thresholding problem. As the objective function, Tsallis entropy is used to compare the best performance of segmented images using these optimization algorithms.

Motivation behind the exploitation of Tsallis entropy is its simple implementation. Besides the advantage of less computation cost it can be easily extended to multilevel thresholding problems as well (Akay, 2013) from bi-level thresholding (Kumar, Kumar, Sharma, & Pant, 2013). In recent years, significant amount of works have been done in this area. In 2014, Pedram et al. introduced a new multi-level thresholding method for segmentation of hyperspectral and a multispectral image which is based on fractional-order Darwinian particle swarm optimization (FODPSO) (Ghamisi, Couceiro, Martins, & Benediktsson, 2013). In 2014, Kurban et al. presented an exhaustive comparative study on multilevel color image thresholding using evolutionary and swarm based computational techniques. According to statistical analysis of objective values, swarm based algorithms are more accurate for multilevel thresholding problems (Kurban, Civicioglu, Kurban, & Besdok, 2014). Based on modified artificial Hopfield neural network, in 2014, Rachid et al. presented the agriculture satellite image segmentation, where it is reported that the satellite image segmentation is one of the most difficult problems due to factors like environmental conditions, poor resolution and poor illumination (Sammouda, Adgaba, Touir, & Al-Ghamdi, 2014). In addition, efficient multilevel image segmentation through fuzzy entropy maximization and graph cut optimization is discussed in (Yin, Zhao, Wang, & Gong, 2014). Recently, optimal multilevel image thresholding problem is addressed using Otsu guided firefly algorithms. The proposed histogram based bounded search technique helps in reducing the computation time (Sri Madhava Raja, Rajinikanth, & Latha, 2014), and takes around 100 s at 5 level of thresholding, to produce segmented image for gray level images. However, these methods still suffers from the problem of long processing time when the number of thresholds m increases.

In 1885, first time researcher Tsai (1985) has used the moment-preserving principle to select thresholds of input gray-level image called Tsallis entropy technique being widely used for image thresholding operation. After that in 2004, Portes de Albuquerque et al. presented the application of Tsallis entropy as a new method of image segmentation (Portes de Albuquerque, Esquef, & Gesualdi, 2004). However, this method is similar to maximum entropy sum method given by Kapur, Sahoo, and Wong (1985). In 2006, Sahoo and Arora (2006) introduced a thresholding technique based on two-dimensional Tsallis–Havrda–Charva't entropy. This method uses a two-dimensional histogram computed from the image. The two-dimensional histogram was constructed using the gray value and local average gray value to choose an optimal threshold value. In 2010, PSO-based Tsallis thresholding selection procedure for image segmentation has been given by Sathya and Kayalvizhi (2010). In this approach, the PSO algorithm is used to find the optimal threshold values, which maximize the Tsallis objective function. In 2011, artificial bee colony based approach has been proposed for optimal multi-level thresholding using maximum Tsallis entropy by Zhang and Wu (2011). In this approach, as a criterion, the traditional method uses the Shannon entropy, originated from information theory, considering the gray level image histogram as a probability distribution, while the Tsallis entropy is applied as general information theory entropy formalism. In this paper, it is reported that: (1) the Tsallis entropy (Tsai, 1985) is superior to traditional maximum entropy thresholding (Kapur, Sahoo, & Wong, 1985), maximum between class variance thresholding (Otsu, 1979), and minimum cross entropy thresholding (Li & Lee, 1993); (2) the artificial bee colony (Karaboga, 2005) is more rapid than genetic algorithm (Tao, Tian, & Liu, 2003) and particle swarm optimization (Kennedy & Eberhart, 1995).

Due to significant performance in multilevel thresholding areas, Tsallis entropy continuously attracts many researchers to solve segmentation related problems. In 2012, Lin and Ou (2012) presented an improved Tsallis entropy based thresholding method for segmenting the images which is presenting local long-range correlation rather than global long-range correlation. After that, in 2013, Agrawal, Panda, Bhuyan, and Panigrahi (2013) have presented an extensive study on the application of cuckoo search algorithm for multilevel thresholding for image segmentation. This paper has also reported that Tsallis entropy uses global and objective property of the image histogram which can be easily implemented for multilevel thresholding case by maximizing the Tsallis entropy. In this paper, it is noticed that the Tsallis parameter 'q' can be used as a tuning parameter for improvising image thresholding results. Recently, Bhandari, Singh, Kumar, and Singh (2014) have proposed a new approach, in which CS algorithm and WDO techniques have been used to obtain optimal threshold values for multilevel thresholding. This paper reveals that cuckoo search algorithm can be efficiently used for persevering edge information after segmentation by selection of optimized thresholds. In addition, Chang, Du, Wang, Guo, and Thouin (2006) have reported a survey and comparative study of entropy and relative entropy thresholding schemes. In 2010, a comparative study of various meta-heuristic techniques applied to multilevel thresholding problem (Hammouche, Diaf, & Siarry, 2010) was published.

The exploitation of meta-heuristic computing algorithms has been flourishing during the last decade. To achieve optimum multilevel threshold, many heuristic optimization techniques have been applied for solving multilevel image segmentation problems. Over the years, in literature, numerous works based on swarm algorithms such as genetic algorithm (GA) (Hammouche, Diaf, & Siarry, 2008; Tang, Yuan, Sun, Yang, & Gao, 2011; Zhang et al., 2014), differential evolution (DE) (Ali, Siarry, & Pant 2012; Cuevas, Zaldivar, & Pérez-Cisneros, 2010; Storn and Price, 1997), ant colony optimization (ACO) (Tao, Jin, & Liu, 2007), bacterial foraging optimization (BFO) (Bakhshali and Shamsi, 2014; Sanyal, Chatterjee, & Munshi, 2011; Sathya & Kayalvizhi, 2011a, 2011b), harmony search algorithm (HSA) (Oliva, Cuevas, Pajares, Zaldivar, & Perez-Cisneros, 2013), electromagnetism optimization (Oliva, Cuevas, Pajares, Zaldivar, & Osuna, 2014), honey bee mating optimization (HBMO) (Horng, 2010a, 2010b), firefly algorithm (Horng and Liou, 2011; Sri Madhava Raja, Rajinikanth, & Latha, 2014; Yang, 2008, 2009), artificial bee colony (ABC) (Akay, 2013; Bhandari, Soni, Kumar, & Singh, 2014a; Cuevas, Sención, Zaldivar, Pérez-Cisneros, & Sossa, 2012; Horng, 2011; Karaboga, 2005; Kumar, Kumar, Sharma, & Pant, 2013; Ma, Liang, Guo, Fan, & Yin, 2011; Soni, Bhandari, Kumar, & Singh, 2013), PSO (Gao, Xu, Sun, & Tang, 2013; Maitra and Chatterjee, 2008; Poli, Kennedy, & Blackwell 2007; Yin, 2007) and WDO (Bayraktar, Komurcu, Bossard, & Werner, 2013; Bayraktar, Turpin, & Werner, 2011; Bhandari et al., 2014)

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