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An optimum multi-level image thresholding segmentation using non-local means 2D histogram and exponential *Kbest* gravitational search algorithm

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A R T I C L E I N F O

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A B S T R A C T

Multi-level image thresholding segmentation divides an image into multiple non-overlapping regions. This paper presents a novel two-dimensional (2D) histogram-based segmentation method to improve the efficiency of multi-level image thresholding segmentation. In the proposed method, a new non-local means 2D histogram and a novel variant of gravitational search algorithm (exponential *Kbest* gravitational search algorithm) have been used to find the optimal thresholds. Further, for the optimization, a 2D Rényi entropy has been redefined for multi-level thresholding. The proposed method has been tested on the Berkeley Segmentation Dataset and Benchmark (BSDS300) in terms of both subjective and objective assessments. The experimental results affirm that the proposed method outperforms the other 2D histogram-based image thresholding segmentation methods on majority of performance parameters.

1. Introduction

Image segmentation, the foremost process of image analysis, divides an image into non-overlapping and similar sub-regions. The outcomes of different application areas of computer vision, such as object recognition; object detection; and content-based retrieval, are highly dependent on the efficacy of image segmentation. However, segmenting an object from a complex and coarse image is still a complicated process. Over the last three decades, prevalent segmentation methods have been proposed such as graph-based (Shi and Malik, 2000; Felzenszwalb and Huttenlocher, 2004; Tian et al., 2015), histogram-based (Cheng et al., 2002; Tan and Isa, 2011), thresholding-based (Dirami et al., 2013; Zhang et al., 2015), fuzzy rule-based (Sezgin and others, 2004; Zhang et al., 2008), contour detection-based (Arbelaez et al., 2011), markov random field-based (Mignotte, 2010), texture-based (Krinidis and Pitas, 2009), pixel clustering-based (Yu et al., 2010), and principal component analysis-based (Han et al., 2013). Out of these methods, histogram-based image thresholding segmentation methods are simple and successfully implemented in various application areas.

Image thresholding segmentation can be categorized into bi-level and multi-level segmentation methods based on the number of regions of interest (ROI) in the image. Generally, images contain more than two ROI and hence require multi-level thresholds for segmentation. Further, image thresholding segmentation has also been categorized into six groups by Sezgin and others (2004) on the basis of the information that is used by the methods: histogram-based methods, clustering-based methods, entropy-based methods, object attribute-based methods, spatial methods, and local methods.

The histogram-based methods analyze the one dimensional (1D) histogram information such as peaks, valleys, and curvatures. However, the performances of 1D histogram-based methods are unsatisfactory as they consider the gray level information of an image only and do not deal with spatial correlation among the pixels, an important parameter for segmentation. Therefore, Abutaleb (1989) proposed a 2D histogram-based image thresholding segmentation method where the original gray-level histogram is integrated with local averaging of pixels to form the gray-local 2D histogram. The experimental results of this method are promising in comparison to 1D histogram-based methods. Recently, many researchers used the concept of the 2D histogram for efficient image thresholding segmentation methods (Brink, 1992; Zhao et al., 2016; Sarkar and Das, 2013; Nakib et al., 2007; Ishak, 2017).

Normally, gray-local 2D histogram of an image maps the gray values of the pixels with corresponding local mean values (Abutaleb, 1989; Brink, 1992) to represent the spatial correlation among the pixels. Furthermore, its diagonal plane contains information about the objects and background while the off-diagonal planes carry edge and noise information. Gray-local 2D histogram takes the mean value of a group of pixels surrounding a target pixel to smooth the image due to which the fine details such as points, lines, and edges are blurred (Buades

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et al., 2005). As an attempt to consider the edge information, Xue-guang and Shu-hong (2012) proposed a gray-gradient 2D histogram. However, this approach often generates inferior results than gray-local 2D histogram (Sha et al., 2016). Therefore, to include greater post-filtering clarity, this paper proposes a novel 2D histogram based on the non-local means filter. Non-local means filter (Buades et al., 2005; Goossens et al., 2008) calculates the mean of all pixels in the image and is further weighted by the similarity of the pixels with the target pixel.

Moreover, the 2D histogram-based multi-level image thresholding segmentation methods have high computational cost due to the exhaustive search for the optimal thresholds (Otsu, 1979; Kapur et al., 1985). To overcome this problem, meta-heuristic algorithms have widely been employed by the researchers in place of existing derivative-based numerical methods (Zhao et al., 2016; Sarkar and Das, 2013). Meta-heuristic algorithms use the natural phenomena to solve complex optimization problems (Yang, 2014) and are widely used for the image thresholding segmentation (Zhao et al., 2016; Sarkar and Das, 2013; Nakib et al., 2007; Ishak, 2017; Nakib et al., 2010). Differential evolution (DE) (Sarkar and Das, 2013), particle swarm optimization (PSO) (Qi, 2014; Tang et al., 2007; Lei and Fu, 2008), genetic algorithm (GA) (Cheng et al., 2000), simulated annealing (SA) (Fengjie et al., 2009), ant colony optimization (ACO) (Shen et al., 2009), artificial bee colony (ABC) (Kumar et al., 2012), swallow swarm optimization (SSO) (Panda et al., 2017), and artificial fish-swarm algorithm (AFS) (Xiao-Feng et al., 2016) are the meta-heuristic algorithms, used for bi-level and multi-level 2D histogram image thresholding segmentation. According to No Free Lunch theorem (Wolpert and Macready, 1997), no ideal meta-heuristic algorithm exists for all optimization problems and new or existing algorithms can outperform the other for the specific set of optimization problems. This paper focuses on finding an efficacious multi-level image thresholding segmentation method by leveraging the strength of gravitational search algorithm (GSA) proposed by Rashedi et al. (2009).

Gravitational search algorithm (GSA) (Rashedi et al., 2009) is a recently proposed meta-heuristic algorithm based on the concept of Newtonian gravity. In comparison with traditional meta-heuristic algorithms, GSA has performed better in searching the solutions for non-linear functions in multi-dimensional space (Rashedi et al., 2009). GSA uses the collective behavior of objects for finding the optimal solution. Initially, it explores the search space and then exploits it gradually according to Newton's law of gravity and law of motion. Although GSA has the merits of fast convergence rate and low computational cost (Kumar and Sahoo, 2014), it sometimes traps into local optimum and produces poor solution precision (Mittal et al., 2016; Zhang et al., 2012). Therefore, different variants of GSA have been presented in the literature by modifying its parameters like; position (Chatterjee et al., 2012), velocity (Han and Chang, 2012), gravitational constant (Li et al., 2014), and $Kbest$ (Pal et al., 2013). $Kbest$ is one of the important function that maintains the balance between exploration and exploitation in GSA. Generally, it is a linearly decreasing function and defines the number of objects, applying gravitational force at a particular iteration. Hence, it is responsible for the linear transition of GSA from exploration to exploitation (Tsai et al., 2013). Pal et al. (2013) modified $Kbest$ function to enhance the exploitation gradually over exploration after some iterations and solved dynamic constrained optimization problems (DCOP). However, the modified $Kbest$ is also a linearly decreasing function. Recently, chaotic $Kbest$ GSA (cKGSA) (Mittal et al., 2016) has been proposed in which the linear decreasing behavior of $Kbest$ is modified to the chaotic behavior. Although cKGSA shows preferable precision, quick convergence rate, and better global search ability, however, the dependency of chaotic behavior on initial conditions may affect the results (Boccaletti et al., 2000). Therefore, this paper proposes a novel variant of GSA termed as exponential $Kbest$ gravitational search algorithm (eKGSA) in which an exponentially decreasing $Kbest$ has been introduced to intensify the vicinity of search space. Further, the proposed eKGSA has been used to find the optimal thresholds in non-local means 2D histogram-based multi-level image segmentation method.

Moreover, the solution of a meta-heuristic algorithm is dependent on the selection of the optimization (or cost) function (Sarkar et al., 2015). Entropy is a popular cost function, used by meta-heuristic algorithms in multi-level image thresholding segmentation (Akay, 2013; Marciniak et al., 2014). It represents a measure of disorder or randomness in system (Bekenstein, 1973). In an image, homogeneous regions correspond to minimum entropy while non-homogeneous regions define maximum entropy. Therefore, the high entropy of a segmented image represents better separation among regions, thus may serves as an objective function for finding the optimal thresholds. Shannon entropy (Shannon, 2001), Kapur entropy (Kapur et al., 1985), Tsallis entropy (Albuquerque et al., 2004), Cross entropy (Li and Tam, 1998), and Rényi entropy (Renyi, 1961) are widely used entropies in image thresholding segmentation (Sarkar et al., 2015; Albuquerque et al., 2004; Sahoo and Arora, 2004). Abutaleb (1989) compared the use of entropy on 1D and 2D gray-local histograms and observed that the segmentation results using 2D histogram were more accurate than the 1D histogram. Qi (2014) used adaptive PSO and 2D Shannon exponential entropy for performing bi-level image segmentation. Sahoo and Arora (2006) introduced a 2D Tsallis–Havrda–Charvt entropy for image thresholding segmentation. Moreover, Sarkar and Das (2013) used 2D Tsallis entropy and DE algorithm for an automatic multilevel image thresholding scheme. Further, Nie (2015) determined the optimal thresholds for bi-level image segmentation by using a 2D Tsallis cross-entropy. Zhao et al. (2016) proposed an approach that calculates the 2D K–L divergence between an image and its segmented regions by adopting 2D histogram as the distribution function. An image segmentation technique based on 2D Rényi's entropy has been introduced by Sahoo and Arora (2004) in which the work of Sahoo et al. (1997) has been extended. Xiao-Feng et al. (2016) presented a 2D Rényi's entropy using the adaptive artificial fish-swarm algorithm for segmentation of infrared images. Further, due to the complexity of 2D Rényi entropy, Cheng et al. (2014) introduced another image thresholding segmentation method based on 2D Rényi gray entropy and fuzzy clustering where two 1D Rényi entropies were computed for forming 2D Rényi entropy. It has been observed from the literature that Rényi entropy on 2D histogram shows better performance (Xiao-Feng et al., 2016; Cheng et al., 2014), however, it has only been used for bi-level thresholding. Therefore, this paper introduces the multi-level version of Rényi entropy for the 2D histogram.

The overall contribution of this paper has been divided into four folds, (i) a novel 2D histogram has been introduced based on non-local means, (ii) a novel variant of GSA, exponential $Kbest$ gravitational search algorithm (eKGSA), has been presented and used to find the optimal thresholds in 2D histogram, (iii) the Rényi entropy has been redefined for multilevel thresholding on 2D histogram and used as a fitness function for eKGSA, (iv) a two-dimensional non-local means exponential $Kbest$ gravitational search algorithm (2DNLMeKGSA) for multi-level image thresholding segmentation has been introduced. To validate the efficiency of 2DNLMeKGSA, extensive experimental analysis has been done on 300 images from the Berkeley Segmentation Dataset and Benchmark (BSDS300) (The Berkeley Segmentation Dataset and Benchmark, 2017). The results are illustrated for 3-level and 5-level image thresholding segmentations and analyzed in terms of both subjective and objective assessments. The result evaluations are based on human-made image segmentations (Ground Truth) and twelve performance parameters of segmentation namely; boundary displacement error (BDE), probability rand index (PRI), variation of information (VoI), global consistency error (GCE), structural similarity index (SSIM), feature similarity index (FSIM), root mean squared error (RMSE), peak signal to noise ratio (PSNR), normalized cross-correlation (NCC), average difference (AD), maximum difference (MD), and normalized absolute error (NAE).

The rest of the paper is organized as follows: Section 2 briefly introduces non-local means; gravitational search algorithm; and Rényi