Chapter 31

Moth-Flame Optimization Algorithm Based Multilevel Thresholding for Image Segmentation

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ABSTRACT

Multilevel thresholding is a popular image segmentation technique. However, computational complexity of multilevel thresholding increases very rapidly with increasing number of thresholds. Metaheuristic algorithms are applied to reduce computational complexity of multilevel thresholding. A new method of multilevel thresholding based on Moth-Flame Optimization (MFO) algorithm is proposed in this paper. The goodness of the thresholds is evaluated using Kapur's entropy or Otsu's between class variance function. The proposed method is tested on a set of benchmark test images and the performance is compared with PSO (Particle Swarm Optimization) and BFO (Bacterial Foraging Optimization) based methods. The results are analyzed objectively using the fitness function and the Peak Signal to Noise Ratio (PSNR) values. It is found that MFO based multilevel thresholding method performs better than the PSO and BFO based methods.

INTRODUCTION

Image segmentation partitions an image into some disjoint regions or extracts its boundaries. It is often considered to be the preprocessing stage of higher level processing such as, image analysis, image classification and computer vision. It is an important step in image processing as the performance of higher level processing system often depends on the accuracy of segmentation step.

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There are numerous applications of image segmentation. Some of the interesting applications such as, medical image processing (Anter, Abu, Souod, Azar, & Hassanien, 2014; Chakraborty et al., 2014), data mining application (Panda, Hassanien, Abraham, & Republic, 2016), video image processing (Aparna, 2016; Gautam Pal, Suvojit Acharjee, 2015), etc., uses image segmentation techniques. Some interesting image segmentation techniques can be found in (Bose, Mukherjee, Chakraborty, Samanta, & Dey, 2013; Hore et al., 2016).

Thresholding is simple and yet the most popular image segmentation technique. Thresholding techniques can be broadly classified into local and global thresholding. In global thresholding, a single threshold is used to subdivide an image into the object and the background. While in local thresholding, different thresholds are used to threshold different regions of the image. Kapur (Kapur, Sahoo, 1985) and Otsu (Otsu, 1979) methods are widely used image thresholding techniques. Otsu method maximizes the between class variance to find the optimum thresholds whereas, Kapur method maximizes posterior entropy of the segmented classes. Kapur and Otsu methods are easily extended to multilevel thresholding, but as the number of threshold are increased, computational complexity increases exponentially due to exhaustive search. Some of the comprehensive surveys on image segmentation techniques can be found in (Pal, 1993; Roy, Goswami, Chakraborty, Azad, 2014; Sahoo, Soltani, & Wong, 1988; Sezgin, 2004).

A modified Otsu method is proposed by Liao et al. (Liao, Chen, 2001) for multilevel thresholding. The modification is done by simplifying the between class variance function to reduce computational cost. The computational cost is further reduced by using a recursive algorithm with a look up table. Yin and Chen (Peng-Yeng Yin, 1997) proposed an iterative scheme for multilevel thresholding. This method starts with initial thresholds and then these thresholds are adjusted iteratively by improving the Kapur and Otsu's objective functions. Reddi et al. (Reddi, Rudin, & Keshavan, 1984) used a criterion function which was derived by assuming gray level histogram of an image to be a continuous probability function. Although these methods reduce the computational cost to some extent, processing time is still an issue.

Arora et al. (Arora, Acharya, Verma, & Panigrahi, 2008) proposed a statistical recursive algorithm that uses mean and variance in order to perform multilevel thresholding for image segmentation. It starts from the two extreme ends of the histogram and recursively apply the algorithm until there is no significant improvement in the segmented image. Although this method is very fast, it assumes the image histogram as a Gaussian distribution and uses only the even number of thresholds.

A number of Metaheuristic algorithms are applied in multilevel thresholding to reduce the computational complexity. Evolutionary algorithms such as, Genetic Algorithm (Yin, 1999), Differential Evolution and its modified versions (Ali, Wook, & Pant, 2014; Cuevas, Zaldivar, & Pérez-cisneros, 2010) are applied in multilevel thresholding. Swarm intelligence algorithms such as, Particle Swarm Optimization (PSO) and its improved versions (Gao, Xu, Sun, & Tang, 2010; Maitra & Chatterjee, 2008a; Wei & Kangling, 2008), Bacterial Foraging Optimization (BFO) and its modified versions (Maitra & Chatterjee, 2008b; Sathya & Kayalvizhi, 2011a, 2011b, 2011c, 2011d), Bat Algorithm (Alihodzic & Tuba, 2014), Artificial Bee Colony and its modified versions (Akay, 2013; Bhandari, Kumar, & Singh, 2015; Bouaziz, Draa, & Chikhi, 2015; Cuevas, Sención, Zaldivar, & Sossa, 2012), Cuckoo Search (Kumar, Kumar, Kumar, & Kumar, 2014; Ouadfel, Mendjeli, Meshoul, & Mendjeli, 2014; Samanta, Dey, Das, & Acharjee, 2012), modified Bees Algorithm (Hussein, Sahran, Norul, & Sheikh, 2016), Social Spiders Optimization and Flower Pollination Algorithm (Ouadfel & Taleb-ahmed, 2016), Ant Weight Lifting algorithm (Samanta, Acharjee, Mukherjee, Das, & Dey, 2013) are applied in image segmentation. A hybrid of Gravitational Search Algorithm and Genetic Algorithm (Sun, Zhang, Yao, & Wang, 2016) has also been applied in multilevel thresholding. A comparative study of six meta-heuristic algorithms- Genetic Algorithm,