Chapter 43
Digital Images Segmentation Using a Physical-Inspired Algorithm

Diego Oliva
Tecnológico de Monterrey, Mexico & Universidad de Guadajalara, Mexico & Tomsk Polytechnic University, Russia & Scientific Research Group in Egypt (SRGE), Egypt

Aboul Ella Hassanien
Cairo University, Egypt & Scientific Research Group in Egypt (SRGE), Egypt

ABSTRACT

Segmentation is one of the most important tasks in image processing. It classifies the pixels into two or more groups depending on their intensity levels and a threshold value. The classical methods exhaustively search the best thresholds for a spec image. This process requires a high computational effort, to avoid this situation has been incremented the use of evolutionary algorithms. The Electro-magnetism-Like algorithm (EMO) is an evolutionary method which mimics the attraction-repulsion mechanism among charges to evolve the members of a population. Different to other algorithms, EMO exhibits interesting search capabilities whereas maintains a low computational overhead. This chapter introduces a multi-level thresholding (MT) algorithm based on the EMO and the Otsu's method as objective function. The combination of those techniques generates a multilevel segmentation algorithm which can effectively identify the threshold values of a digital image reducing the number of iterations.

INTRODUCTION

The success of an image processing system depends directly on the quality of the input images. Considering that the image acquisition process there exist different situations that a affects features of the scene, there is necessary to apply methods that permits the analysis of the elements contained in the image. Almost all methods of image processing require a first step called segmentation. This task permits the classification of pixels in the image depending on its gray (or RGB in each component) level intensity. Several techniques had been studied (Akay, 2012; Ghamisi, Couceiro, Benediktsson, & Ferreira, 2012;

DOI: 10.4018/978-1-5225-2229-4.ch043

Copyright © 2017, IGI Global. Copying or distributing in print or electronic forms without written permission of IGI Global is prohibited.

Hammouche, Diaf, & Siarry, 2010; Kapur, Sahoo, & Wong, 1985; Kittler & Illingworth, 1986; Liao, Chen, & Chung, 2001; Otsu, 1979; Sezgin & Sankur, 2004, Ali et al., 2015, Ibrahim et al., 2015). Thresholding is the easiest method for segmentation, it works taking a threshold (*th*) value and the pixels which intensity value is higher than are labelled as the first class and the rest of the pixels correspond to the second class. When the image is segmented in two classes it is called bi-level thresholding (BT) and it is necessary only one value. On the other hand, when pixels are separated in more than two classes it is called multilevel thresholding (MT) and there are required more than one values (Akay, 2012; Hammouche et al., 2010; J. N. Kapur, P. K. Sahoo, A. K. C. Wong, 1985; Kittler & Illingworth, 1986; Liao et al., 2001; Otsu, 1979; Sathya & Kayalvizhi, 2011; Sezgin & Sankur, 2004). Threshold based methods are divided in parametric and nonparametric (Akay, 2012; Hammouche, Diaf, & Siarry, 2008; Liao et al., 2001). The nonparametric employs a given criteria between-class variance, entropy and error rate (J. N. Kapur, P. K. Sahoo, A. K. C. Wong, 1985; Kittler & Illingworth, 1986; Otsu, 1979) that must be optimized to determine the optimal threshold values. These approaches result an attractive option due their robustness and accuracy (Sezgin & Sankur, 2004).

One of the classical method used for bi-level thresholding is the between classes variance and was proposed by Otsu (Otsu, 1979). The efficiency and accuracy have been already proved for two segmentation classes (Sathya & Kayalvizhi, 2011). Although Otsu's can be expanded for multilevel thresholding, its computational complexity increases exponentially with each new threshold (Sathya & Kayalvizhi, 2011). This chapter introduces a multilevel threshold method based on the Electromagnetism-like Algorithm (EMO). EMO is a global optimization algorithm that mimics the electromagnetism law of physics. It is a population based and physical inspired method which has an attraction-repulsion mechanism to evolve the members of the population guided by their objective function values (Birbil & Fang, 2003).

The main idea of EMO is move a particle through the space following the force exerted by the rest of the population. The force is calculated using the charge of each particle based on its objective function value. In comparison with other methods as Genetic Algorithms (GA) (Goldberg, 1989) or Differential Evolution (DE) (Storn & Price, 1997) each particle is influenced by all other particles within its population. This process is similar to Particle Swarm Optimization (PSO) (Kennedy & Eberhart, 1995) or Ant Colony Optimization (ACO) (Dorigo, Maniezzo, & Colorni, 1996). However recent works have exhibited its better accuracy regarding optimal parameters (A. M. a. C. Rocha & Fernandes, 2009; A. M. A. C. Rocha & Fernandes, 2009; Tsou & Kao, 2008; Wu, Yang, & Wei, 2004), yet showing convergence (Birbil, Fang, & Sheu, 2004). In recent works, EMO has been used to solve different sorts of engineering problems such as ow-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 (Cuevas, Oliva, Zaldivar, Pérez-Cisneros, & Sossa, 2012) and control systems (Guan, Dai, Qiu, & Li, 2012).

The approach presented in this chapter generates a multilevel segmentation algorithm which can effectively identify the threshold values of a digital image in a reduced number of iterations and decreasing the computational complexity of the original proposals. In the segmentation process the optimization of the best thresholds is performed by EMO considering as objective function the Otsu´s method. Experimental results show performance evidence of the implementation of EMO for digital image segmentation. An example of the implementation of MTEMO is presented in Figure 1, it shows the original image in gray scale, the best threshold values and the evolution of the objective function values for a predefined number of iterations.

20 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage:
www.igi-global.com/chapter/digital-images-segmentation-using-a-physical-inspired-algorithm/180981

Related Content

Experience-Based Approach for Cognitive Vehicle Research
Hironori Hiraishi (2020). *International Journal of Software Science and Computational Intelligence (pp. 60-70).*
www.irma-international.org/article/experience-based-approach-for-cognitive-vehicle-research/262588

Fuzzy-DSS Human Health Risk Assessment Under Uncertain Environment
Palash Dutta (2018). *Handbook of Research on Investigations in Artificial Life Research and Development (pp. 316-347).*
www.irma-international.org/chapter/fuzzy-dss-human-health-risk-assessment-under-uncertain-environment/207210

Digitalization in Software Engineering and IT Business
Denis Pashchenko (2020). *International Journal of Software Science and Computational Intelligence (pp. 1-14).*
www.irma-international.org/article/digitalization-in-software-engineering-and-it-business/252212

Looking for Reverse Transformations between NP-Complete Problems
Rodolfo A.Pazos R., Ernesto Ong C., Héctor Fraire H., Laura Cruz R.and José A.Martínez F. (2012). *Logistics Management and Optimization through Hybrid Artificial Intelligence Systems (pp. 181-206).*
www.irma-international.org/chapter/looking-reverse-transformations-between-complete/64922

Protoforms of Linguistic Database Summaries as a Human Consistent Tool for Using Natural Language in Data Mining
Janusz Kacprzykand Slawomir Zadrozny (2009). *International Journal of Software Science and Computational Intelligence (pp. 100-111).*
www.irma-international.org/article/protoforms-linguistic-database-summaries-human/2788