Expert Systems with Applications 40 (2013) 1213–1219

Contents lists available at SciVerse ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

A comparison of nature inspired algorithms for multi-threshold image segmentation

Valentín Osuna-Enciso [a,*], Erik Cuevas [b], Humberto Sossa [a]

[a] Centro de Investigación en Computación-IPN, Av. Juan de Dios Batiz S/N, Col. Nueva Industrial Vallejo, Mexico, D.F., Mexico
[b] Departamento de Ciencias Computacionales, Universidad de Guadalajara, CUCEI, Av. Revolución 1500, Guadalajara, Jal., Mexico

ARTICLE INFO

Keywords:
Image segmentation
Differential Evolution
Particle Swarm Optimization
Artificial Bee Colony Optimization
Automatic thresholding
Intelligent image processing
Gaussian function sum

ABSTRACT

In the field of image analysis, segmentation is one of the most important preprocessing steps. One way to achieve segmentation is by mean of threshold selection, where each pixel that belongs to a determined class is labeled according to the selected threshold, giving as a result pixel groups that share visual characteristics in the image. Several methods have been proposed in order to solve threshold selection problems; in this work, it is used the method based on the mixture of Gaussian functions to approximate the 1D histogram of a gray level image and whose parameters are calculated using three nature inspired algorithms (Particle Swarm Optimization, Artificial Bee Colony Optimization and Differential Evolution). Each Gaussian function approximates the histogram, representing a pixel class and therefore a threshold point. Experimental results are shown, comparing in quantitative and qualitative fashion as well as the main advantages and drawbacks of each algorithm, applied to multi-threshold problem.

1. Introduction

Nature has been a great source of inspiration for creating metaheuristic algorithms, as can be seen of important proposals in such areas since first evolutive programs were created almost three decades ago Yang (2011), leaving clear that even today, this trend is still valid, by the development and use of concepts such as artificial neural networks, evolutionary algorithms, swarming algorithms and so on, not to mention new developments in the computational paradigms mentioned. Particularly, three of those algorithms are Differential Evolution (DE), Particle Swarm Optimization (PSO) and Artificial Bee Colony Optimization (ABC) that have been used to solve difficult optimization problems. DE, originally proposed by Storn and Price (1995), is a population-based algorithm in which the population is evolved from one generation to the next using special defined operators such as mutation, crossover, and selection. The PSO algorithm, introduced in 1995 (Kennedy & Eberhart, 1995), is based on swarm behavior of birds and fish where the solutions, called particles, 'fly' through the search space using simple mapping equations; this algorithm has been used to solve distinct optimization problems, being the main vision and video processing (Poli, 2007). More recently in 2005, the ABC algorithm has been introduced by Karaboga (2005). Such algorithm, inspired by the intelligent behavior of honey-bees, consists of three essential components: food source positions, nectar-amount and honey-bee classes. Each food source position represents a feasible solution for the problem under consideration. The nectar-amount for a food source represents the quality of such solution (represented by fitness value). Each bee-class symbolizes one particular operation for generating new candidate food source positions. The aforementioned algorithms have been used to deal with several optimization problems in the area of image analysis, giving good results in terms of performance (Chih-Chih, 2006; Cuevas, Zaldıvar, & Pérez-Cisneros, 2010; Karaboga, 2005; Wei & Kangling, 2008; Zhiwei, Zhengbing, Huamin, & Hongwei, 2011).

Image segmentation has been the subject of intensive research and a wide variety of segmentation techniques has been reported in the last two decades. In general terms, image segmentation divides an image into related sections or regions, consisting of image pixels having related data feature values. It is an essential issue since it is the first step for image understanding and any other, such as feature extraction and recognition, heavily depends on its results. Segmentation algorithms are based on two significant criteria: the homogeneity of a region (thresholding) and the discontinuity between adjacent disjoint regions (finding edges). Since the segmented image obtained from the homogeneity criterion has the advantage of smaller storage space, fast processing speed and ease in manipulation, thresholding techniques are considered the most popular (Arora, Acharya, Verma, & Panigrahi, 2008).

Thresholding techniques can be classified into two categories: bi-level and multi-level. In the former, one limit value is chosen to segment an image into two classes: one representing the object

* Corresponding author.
E-mail addresses: valentin.osuna@cucei.udg.mx (V. Osuna-Enciso), erik.cuevas@cucei.udg.mx (E. Cuevas), hsossa@cic.ipn.mx (H. Sossa).

0957-4174/$ - see front matter © 2012 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.eswa.2012.08.017

and the other one segmenting the background. When distinct objects are depicted within a given scene, multiple threshold values have to be selected for proper segmentation, which is commonly called multi-level thresholding. A variety of thresholding approaches have been proposed for image segmentation, including conventional methods (Guo & Pandit, 1998; Pal & Pal, 1993; Shaoo, Soltani, Wong, & Chen, 1988; Snyder, Bilbro, Logenthiran, & Rajala, 1990) and intelligent techniques (Chen & Wang, 2005; Chih-Chih, 2006; Wei & Kangling, 2008; Cuevas et al., 2010; Cuevas, Osuna-Enciso, Zaldívar, & Pérez-Cisneros, 2009; Yang, 2011). Extending the segmentation algorithms to a multilevel approach may cause some inconveniences: (i) they may have no systematic or analytic solution when the number of classes to be detected increases and (ii) they may also show a slow convergence and/or high computational cost (Pujol, Pujol, Rizo, & Pujol, 2011).

In this work, the segmentation approach is based on a parametric model composed by a group of Gaussian functions (Gaussian mixture). Gaussian mixture (GM) represents a flexible method of statistical modelling with a wide variety of scientific applications (Janev, Pekar, Jakovljevic, & Delic, 2010; Kocsor & Tóth, 2004). In general, GM involves the model selection, i.e., to determine the number of components in the mixture (also called model order), and the estimation of the parameters of each component in the mixture that better adjust the statistical model. Computing the parameters of Gaussian mixtures is considered a difficult optimization task, sensitive to the initialization (Park, Amari, & Fukumizu, 2000) and full of possible singularities (Park & Ozeki, 2009). As an optimization problem, the presented here requires an objective function, which makes use of Hellinger distance to compare the GM candidate and the original histogram. This distance measure works with probability density functions, making it appropriate to the problem presented in this work, and was shown that this distance is the most suitable to construct a minimum distance estimator (Donoho & Liu, 1988). The Hellinger distance has been used in on-line recognition of handwritten text (Mezghani, Mitiche, & Cheriet, 2004), in signal modulation (Umebayashi, Lehtomaki, & Ruotsalainen, 2006) and classification and localization of underwater acoustic signals (Bissinger, Culver, & Bose, 2009), only to mention some uses.

This paper presents the use of evolutionary algorithms to compute threshold selection for image segmentation. In this approach, the segmentation process is considered as an optimization problem approximating the 1-D histogram of a given image by means of a Gaussian mixture model whose parameters are calculated through the DE, the PSO and the ABC algorithm. In the model, each Gaussian function approximating the histogram represents a pixel class and therefore a threshold point in the segmentation scheme. Those algorithms are experimentally compared by solving the multi-threshold problem, obtaining in such a way the main advantages and drawbacks of each one.

Previous studies performed to assess the performance of DE, PSO and ABC algorithms included the work in Karaboga and Akay (2009) showing that ABC performs better than PSO, and DE on a suite of classical benchmark functions. It was shown that the performance of ABC is better or at least similar than DE and PSO while having a smaller number of parameters to tune. In Mezura-Montes et al. (2006) several DE variants were empirically compared over a benchmark of 13 functions, finding that the version *best/1/bin* has the best behavior regardless quality and robustness. A study comparing variations of PSO over power systems is made in Vlachogiannis and Lee (2006), finding that the enhanced general passive congregation PSO shown the best performance, but also has a high computational cost. The performance of DE, PSO and real valued Genetic Algorithm over a benchmark of functions was made in Vesterstrom and Thomsen (2004), and the best results were obtained in general by DE. The aforementioned studies suffer from one limitation: the comparisons are based on a set of synthetic functions with exact and well-known solutions and none of them were applied to image processing. The proposed study overcomes such drawbacks by assessing the performance of the set of evolutionary algorithms when they are applied to the image processing problem of segmentation, particularly multi-threshold segmentation (the GM estimation), where an exact solution does not exist. The comparison is carried out based on two different statistics namely: the solution reached and the histogram approximation according to a quality measure based on Hausdorff distance among ground-truth images and segmentation results, considering that such a distance measure has been used in order to test the performance of thresholding algorithms (Abak, Baris, and Sankur (1997)). The versions of algorithms studied in this work are DE (best/1/bin), PSO (attractive/repulsive PSO) and normal ABC.

The remainder of this work is organized as follows: in section 2 we present the method following Gaussian approximation of the histogram, whereas in Sections 3–5 we show a brief overview of Differential Evolution, Particle Swarm Optimization and Artificial Bee Colony Optimization, respectively, as well as some of their implementation details. Experimental results are shown up in Section 6, followed by conclusions in Section 7.

2. Gaussian approximation

In what follows histogram $h(g)$ represents a gray level distribution of an image with L gray levels $[0,1,\ldots,L-1]$; it is also assumed that $h(g)$ is normalized, considered as a probability distribution function:

$$h(g) = \frac{n_g}{N}, \quad h(g) \geqslant 0, \\ N = \sum_{g=0}^{L-1} n_g, \quad \text{and} \quad \sum_{g=0}^{L-1} h(g) = 1, \tag{1}$$

where n_g denotes the number of pixels with gray level g, whereas N represents the total number of pixels contained in the image. The mix of Gaussian probability functions:

$$p(x) = \sum_{i=1}^{K} P_i \cdot p_i(x) = \sum_{i=1}^{K} \frac{P_i}{\sqrt{2\pi}\sigma_i} \exp\left[\frac{-(x-\mu_i)^2}{2\sigma_i^2}\right] \tag{2}$$

can approximate the original image histogram, dealing with P_i as the a priori probability of class i, $p_i(x)$ as the probability distribution function of gray-level random variable x in class i, μ_i and σ_i as the mean and standard deviation of the i-th probability distribution function and K as the number of classes contained in the image. In addition, the constraint $\sum_{i=1}^{K} P_i = 1$ must be made certain.

The Hellinger distance is used to estimate the 3 K (P_i, μ_i and σ_i, $i = 1,\ldots,K$) parameters, comparing in such way the mixture of Gaussian functions (or candidate histogram) and the original histogram:

$$E = \sqrt{\sum_{j=1}^{n} \left[\sqrt{p(x_j)} - \sqrt{h(x_j)}\right]^2} \tag{3}$$

where $p(x_j)$ is the histogram formed with the candidate Gaussian mixture and $h(x_j)$ is the experimental histogram that corresponds to the gray level image. Such a formula represents the fitness function used by the three nature inspired algorithms reported in this work and it does not need extra parameters.

The next step is to determine the optimal threshold values. Considering that the data classes are organized such that $\mu_1 < \mu_2 < \ldots < \mu_K$, the threshold values can thus be calculated by estimating the overall probability error for two adjacent Gaussian functions, as follows:

$$E(T_i) = P_{i+1} \cdot E_1(T_i) + P_i \cdot E_2(T_i), \\ i = 1,2,\ldots,K-1 \tag{4}$$