Automatic Histogram Thresholds using Multi-objective Bacterial Foraging Optimization

B.Khomri[1], L. Djerou[2], M.C.Babahenini[3], N. Khelil[4]

1. LESIA Laboratory, University of Biskra, Algeria
khomri-bilal@hotmail.fr
2. LESIA Laboratory, University of Biskra, Algeria
ldjerou@yahoo.fr
3. LESIA Laboratory, University of Biskra, Algeria
Chaouki.babahenini@gmail.com
4. AM Laboratory, University of Biskra, Algeria
khelilna@yahoo.fr

Keywords : Bacterial foraging optimization, Image thresholding, Multi-objective optimization, Health sorting approach.

1 Introduction

Bacterial Foraging Optimization (BFO) is a recently developed nature-inspired optimization algorithm, which is based on the foraging behavior of E. coli bacteria. Generally the foraging strategy governed by four distinct processes, namely, chemotaxis, swarming, reproduction, and elimination and dispersal [3].

Although a large number of articles have been published on analysis of the foraging behavior and self adaptability properties of BFO as a single objective optimizer, till date, to the best of our knowledge, little such analysis exists for the multi-objective BFO. Niu et al. [2] exposed the potential of implementing bacterial foraging as a multi-objective optimization process and proposed a Multi-objective Bacterial Foraging Optimization Algorithm (MBFOA). In this algorithm, a fitness survive mechanism by Health sorting approach and Pareto dominance mechanism are integrated together to find a much better spread of solutions and faster convergence to the true Pareto-optimal front. The diversity is preserved by keeping a certain unfeasible border solutions, the choice rely on a given probability.

Image thresholding is an important technique for image segmentation. Recently, it is treated as multi-objective problem. The use of the algorithm NSGA-II to optimize several thresholding criteria simultaneously gave satisfactory results [1].

This work represents the first adaptation of MBFOA in image thresholding problem resolution, that can be summarized as follows: suppose that an image I having N pixels with $L+1$ gray levels $L = \{0, 1, ..., L\}$ is to be classified into $k+1$ classes $(C_0, C_2, ..., C_k)$ with the set of k thresholds $T=\{t_1, t_2, ..., t_k\}$. To optimize M segmentation criteria simultaneously and to obtain the Pareto front and then the optimal Pareto solution (optimal threshold values for image segmentation), we adapt the bacterial foraging optimization algorithm [2] that consists in using a colony of S bacteria $Bac=(X_j^1, ..., X_j^i, ..., X_j^S)$ that are located initially at random positions on this parameter space. $X_j^i = (x_{j,1}^i, ..., x_{j,p}^i, ..., x_{j,k}^i)$ is the i^{th} bacterium in j^{th} chemotactical step and $x_{j,p}^i$ is the p parameter of the X_j^i bacterium, such that $x_{j,p}^i \in [0, L-1]$. As for MBFOA which has M objectives to solve (in this work M=2), needs to compute the values of each function $J_l(X_j^i)$; l= 1… M:

$$J_l(X_j^i) = f(X_j^i) + J_{cc}(X_j^i) \tag{1}$$

and

$$J_{cc}(X_j^i) = \sum_{i=1}^{S}\left[-d_{attract}\exp\left(-\omega_{attract}\sum_{m=1}^{k}(X_{m_{gm}} - X_m^i)^2\right)\right] + \sum_{i=1}^{S}\left[h_{repellant}\exp\left(-\omega_{repellant}\sum_{m=1}^{k}(X_{m_{gm}} - X_m^i)^2\right)\right] \tag{2}$$

Where: $f(X_j^i)$ is the value of objective function (thresholding criterion) and $J_{cc}(X_j^i)$ represents an attractant-repellant profile which provides the cost value. $d_{attract}$, $\omega_{attract}$, $h_{repelent}$, and $\omega_{repelent}$ are different coefficients that are to be chosen judiciously, $X_{m_{gm}}$ is the m^{th} parameter of the global optimum bacterium X_{gm} .

The health of bacterium X_j^i (J_{health}^i) is the sum of the function values accepted in the process of chemotaxis (in NC steps), it is a measure of how many nutrients the i^{th} bacterium got over its lifetime and how successful it was at avoiding noxious substances. The higher cost of J_{health}^i means the lower health. Sort the health values J_{health}^i of each bacterium from small to big to prepare for pareto-optimal step. The bacteria with highest J_{health}^i values are given the high chance to die and the ones with the best values are probably kept to reproduce. Based on J_{health}^i order, if the j^{th} bacterium is dominated by i^{th} bacterium, the j^{th} bacterium is to die.

$$J_{health}^i = \sum_{j}^{NC} J_l(X_j^i) \tag{3}$$

The proposed method is validated by illustrative examples; the following figure shows the segmentation of a synthetic image with noise, the optimal thresholds of two criteria: Between-Class Variance 2D and Entropy 2D, and the Pareto front.

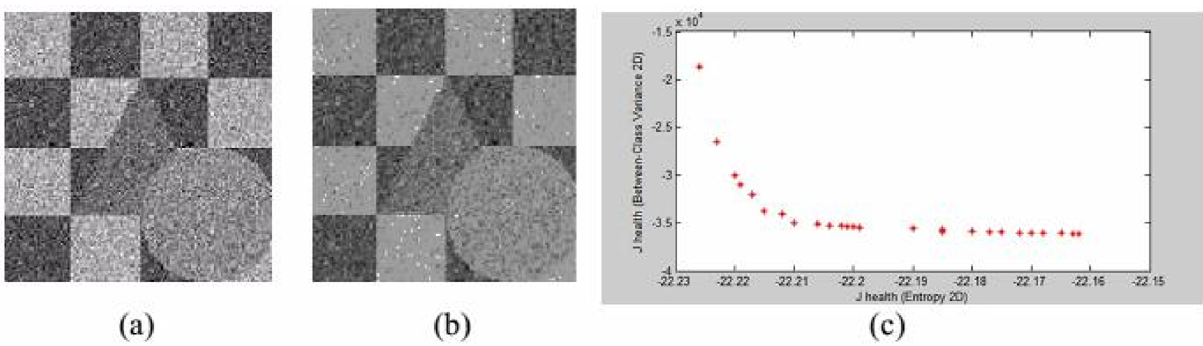

FIG1. Thresholding results of synthetic image with noise: (a) Original, (b) Segmentation into 3 classes, the optimal thresholds of two criteria: Between-Class Variance 2D and Entropy 2D (157,219) (c) Pareto front.

References

[1] A., Nakib et al. (2010), Image thresholding based on Pareto multiobjective optimization, Engineering Applications of Artificial Intelligence, 23, 313-320.

[2] B. Niu et al. (2013), Multi-objective bacterial foraging optimization, Neurocomputing 116, 336–345.

[3] K.M.Passino (2002), Biomimicry of bacterial foraging for distributed optimization and control, *IEEE Control Systems Magazine*, vol. 22 (3), 52–67.