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Bioinspired metaheuristics for image segmentation

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1 Abstract

In general, the purpose of Global Optimization (GO) is finding the global optimum of an objective function defined inside a search space. The GO has applications in many areas of science, engineering, economics, among other, where mathematical models are utilized. Those algorithms are divided into two groups: deterministic, and evolutionary. Since deterministic methods only provide a theoretical guarantee of locating local minimums of the objective function, they face great difficulties in solving GO problems. On the other hand, evolutionary methods are faster in locating a global optimum than deterministic ones, because they operate over a population of candidate solutions, therefore they have a bigger likelihood of finding the global optimum, and a better adaptation to black box formulations or complicated function forms.

Despite that during the last decade the field of metaheuristics applied to optimization has had an important increase, the quest of such methods still considered as an open problem in research, due to the most part that they yet present difficulties; for instance, the premature convergence, and the difficulty to overcome local optimum values in multimodal functions. For that reason, in this work it is proposed a bio-inspired algorithm, which utilizes the allostatic mechanism as a base model.

Allostasis means 'to maintain stability through change (of several set points -SP)'. That medical model considers the existence of several set points of mechanisms, their non-linear relationships with mediators, other mechanisms, and the brain. Moreover, in this model the brain 'predicts' the new set points, allowing faster responses concerning to the instability. In general terms, once the brain detects some external or internal change (stress, pollution, changes in social status, disease, etc), it determines if the stability (of a single organ, organ system, condition, health, etc) is compromised. Supposing that the instability is confirmed, then the body activates the communication-coordination scheme and starts sending chemical-electrical signals (mediators) to specific mechanisms (viz., target cells, tissues, organs, or even other OS). Those mechanisms should modify

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their behavior (as a result of adjusting their functioning SP), and send back a feedback signal to the brain, which evaluates whether the changes are good enough to bring back the stability, in whose case, the modified SP will replace the previous, and these will kept in memory.

By using the allostatic mechanisms as a metaphor, it is proposed a metaheuristic algorithm, which we called Allostatic Optimization (AO). The AO algorithm provides a searching procedure that is population-based, in which all the individuals, seen as SP, are defined in a multidimensional search space; aforementioned agents are either generated or modified by mean of several evolutionary operators that emulate different operations used by the allostatic process, whereas an objective function evaluates the individual stability of each SP.

We made a comparison of AO against DE, ABC and PSO and, we found that the proposed algorithm favors the exploration process, and eliminates some flaws related with the premature convergence, this is because AO is capable to maintain the population diversity; in fact, in the 57% of the functions, the diversity maintained by AO relieves the convergence, by introducing operators which avoid particle concentration on some search space regions, and so helping the exploration. Neverheless, it was also found that maintaining a high population diversity does not guarantee a proper convergence of AO in all the benchmark functions (43%), thus a potential investigation work could be to perform a more complete study of the relations among the function properties, the diversity, and an adequate algorithm convergence.

With the idea of demonstrating the utility of the algorithm in a particular family of problems, AO was utilized in image segmentation by means of a mixture of functions. One way to achieve segmentation is by utilizing thresholding selection, where each pixel that belongs to a class is labeled according to a selected threshold, giving as a result pixel groups which share visual characteristics in the image. In this work it was utilized a method based on a mixture of Cauchy functions, to approximate gray level histograms of images taken from known benchmarks, and it was found that AO improves the segmentation quality in about 14%, compared with Otsu's method.

Moreover, the metaheuristic algorithms DE, ABC and PSO were examined in contrast they are applied to image segmentation by using a method that uses a mixture of Gaussian functions to approximate 1D histograms, since an analysis of that type was not found in the literature; in the empirical results, DE gave best results related with convergence speed, as well as the segmentation quality, when they are compared with ground-truth images.

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