Preface

Many problems in engineering nowadays concern with the goal of an "optimal" solution. Several optimization methods have therefore emerged, being researched and applied extensively to different optimization problems.

Typically, optimization methods arising in engineering are computationally complex because they require evaluation of a quite complicated objective function which is often multimodal, non-smooth or even discontinuous. The difficulties associated with using mathematical optimization on complex engineering problems have contributed to the development of alternative solutions. Evolutionary computation (EC) techniques are stochastic optimization methods that have been developed to obtain near-optimum solutions in complex optimization problems, for which traditional mathematical techniques normally fail.

EC methods use as inspiration our scientific understanding of biological, natural or social systems, which at some level of abstraction can be represented as optimization processes. In their operation, searcher agents emulate a group of biological or social entities which interact with each other based on specialized operators that model a determined biological or social behavior. These operators are applied to a population (or several sub-populations) of candidate solutions (individuals) that are evaluated with respect to their fitness. Thus in the evolutionary process, individual positions are successively approximated to the optimal solution of the system to be solved.

Due to their robustness, EC techniques are well-suited options for industrial and real-world tasks. They do not need gradient information and they can operate on each kind of parameter space (continuous, discrete, combinatorial, or even mixed variants). Essentially, the credibility of evolutionary algorithms relies on their ability to solve difficult real-world problems with the minimal amount of human effort.

There exist some common features clearly appear in most of the EC approaches, such as the use of diversification to force the exploration of regions of the search space, rarely visited until now, and the use of intensification or exploitation, to investigate thoroughly some promising regions. Another common feature is the use of memory to archive the best solutions encountered.

EC techniques are used to estimate the solutions to complex optimization problems. They are often designed to meet the requirements of particular problems because no single optimization algorithm can solve all problems competitively. Therefore, in order to select an appropriate EC technique, its relative efficacy must be appropriately evaluated.

Several comparisons among ECT have been reported in the literature. Nevertheless, they suffer from one limitation: their conclusions are based on the performance of popular evolutionary approaches over a set of synthetic functions with exact solutions and well-known behaviors, without considering the application context or including recent developments.

Numerous books have been published taking in account many of the most widely known methods, namely simulated annealing, tabu search, evolutionary algorithms, ant colony algorithms, particle swarm optimization or differential evolution, but attempts to consider the discussion of alternative approaches are scarce. The excessive publication of developments based on the simple modification of popular EC methods present an important disadvantage, in that it distracts attention away from other innovative ideas in the field of EC. There exist several alternative EC methods which consider very interesting concepts; however, they seem to have been completely overlooked in favor of the idea of modifying, hybridizing or restructuring traditional EC approaches.

The goal of this book is to present the comparison of various EC techniques when they face complex optimization problems extracted from different engineering domains. In the comparisons, special attention is paid to recently developed algorithms. This book has been structured so that each chapter can be read first independently from the others. In each chapter, a complex engineering optimization problem is posed. Then, a particular EC technique is presented as the best choice, according to its search characteristics. Finally, a set of experiments are conducted in order to compare its performance to other popular EC methods.

Chapter 1 describes evolutionary computation (EC). This chapter concentrates on elementary concepts of evolutionary algorithms. Readers that are familiar with EC could skip this chapter.

In Chap. 2, the problem of multilevel segmentation in images is presented. In the approach, the Electromagnetism-Like algorithm (EMO) algorithm is proposed as the best option to find the optimal threshold values by maximizing the Tsallis entropy. In the approach, the algorithm uses as particles the encoding of a set of candidate threshold points. An objective function evaluates the segmentation quality of the candidate threshold points. Guided by the values of this objective function, the set of encoded candidate solutions are modified by using the EMO operators so that they can improve their segmentation quality as the optimization process evolves. The approach is compared to the cuckoo search algorithm (CSA) and the particle swarm optimization (PSO).

In Chap. 3, the problem of detecting circular shapes from complicated and noisy images is considered. The detection process is approached as a multimodal optimization problem. The artificial bee colony (ABC) algorithm is presented as the best possibility to solve the recognition problem. In the method, the ABC algorithm searches the entire edge-map looking for circular shapes by using the combination of three non-collinear edge points that represent candidate circles (food source locations) in the edge-only image of the scene. An objective function is used to measure the existence of a candidate circle over the edge map. Guided by the values of such objective function, the set of encoded candidate circles are evolved through the ABC algorithm so that the best candidate can be fitted into the most circular shape within the edge-only image. A subsequent analysis of the incorporated exhausted-source memory is then executed in order to identify potential useful local optima (other circles). The approach generates a fast sub-pixel detector which can effectively identify multiple circles in real images despite circular objects exhibiting significant occluded sections. Experimental evidence shows the effectiveness of the method for detecting circles under various conditions. A comparison to one state-of-the-art genetic algorithm-based method and the bacterial foraging optimization algorithm (BFOA) on different images has been included to demonstrate the performance of the proposed approach. Conclusions of the experimental comparison are validated through statistical tests that properly support the discussion.

In Chap. 4, the application of template matching (TM) is considered. TM plays an important role in several image processing applications. In a TM approach, it is sought the point in which it is presented the best possible resemblance between a sub-image known as template and its coincident region within a source image. TM involves two critical aspects: similarity measurement and search strategy. The simplest available TM method finds the best possible coincidence between the images through an exhaustive computation of the normalized cross-correlation (NCC) values (similarity measurement) for all elements of the source image (search strategy). In the chapter, the social spider optimization (SSO) algorithm is proposed to reduce the number of search locations in the TM process. The SSO algorithm is based on the simulation of cooperative behavior of social spiders. The algorithm considers two different search individuals (spiders): males and females. Depending on gender, each individual is conducted by a set of different evolutionary operators which mimic different cooperative behaviors that are typically found in the colony. In the proposed approach, spiders represent search locations which move throughout the positions of the source image. The NCC coefficient, used as a fitness value, evaluates the matching quality presented between the template image and the coincident region of the source image, for a determined search position (spider). The number of NCC evaluations is reduced by considering a memory which stores the NCC values previously visited in order to avoid the re-evaluation of the same search locations. Guided by the fitness values (NCC coefficients), the set of encoded candidate positions are evolved using the SSO operators until the best possible resemblance has been found. The approach is compared to imperialist competitive algorithm (ICA) and the particle swarm optimization (PSO).

In Chap. 5, the problem of motion estimation is presented. Motion estimation is a major problem for video-coding applications. Among several other motion estimation approaches, block matching (BM) algorithms are the most popular methods due to their effectiveness and simplicity at their software and hardware implementation. The BM approach assumes that the pixel movement inside a given region of the current frame (Macro-Block, MB) can be modeled as a pixel translation from its corresponding region in the previous frame. In this procedure, the motion vector is obtained by minimizing the sum of absolute differences (SAD) from the current frame's MB over a determined search window from the previous frame. Unfortunately, the SAD evaluation is computationally expensive and represents the most time-consuming operation in the BM process. The simplest available BM method is the full search algorithm (FSA) which finds the most accurate motion vector through an exhaustive computation of SAD values for all elements of the search window. However, several fast BM algorithms have been lately proposed to reduce the number of SAD operations by calculating only a fixed subset of search locations at the price of poor accuracy. In this chapter, the differential evolution (DE) method is proposed to reduce the number of search locations in the BM process. In order to avoid the computing of several search locations, the algorithm estimates the SAD (fitness) values for some locations by considering SAD values from previously calculated neighboring positions. The approach is compared to the popular particle swarm optimization (PSO).

In Chap. 6, the application of modeling solar cells is presented. In order to improve the performance of solar energy systems, accurate modeling of current versus voltage (I–V) characteristics of solar cells has attracted the attention of various researches. The main drawback in accurate modeling is the lack of information about the precise parameter values which indeed characterize the solar cell. Since such parameters cannot be extracted from the datasheet specifications, an optimization technique is necessary to adjust experimental data to the solar cell model. Considering the I–V characteristics of solar cells, the optimization task involves the solution of complex nonlinear and multimodal objective functions. Several optimization approaches have been proposed to identify the parameters of solar cells. However, most of them obtain suboptimal solutions due to their premature convergence and their difficulty to overcome local minima in multimodal problems. This chapter proposes the use of the artificial bee colony (ABC) algorithm to accurately identify the solar cells' parameters. In comparison with other evolutionary algorithms, ABC exhibits a better search capacity to face multimodal objective functions. In order to illustrate the proficiency of the proposed approach, it is compared to other well-known optimization methods. Experimental results demonstrate the high performance of the proposed method in terms of robustness and accuracy.

Chapter 7 presents the problem of parameter identification in induction motors. Induction motors represent the main component in most of the industries. They consume the highest energy percentages in industrial facilities. This energy consumption depends on the operation conditions of the induction motor imposed by its internal parameters. Since the internal parameters of an induction motor are not directly measurable, an identification process must be conducted to obtain them. In the identification process, the parameter estimation is transformed into a multidimensional optimization problem where the internal parameters of the induction motor are considered as decision variables. Under this approach, the complexity of the optimization problem tends to produce multimodal error surfaces for which their cost functions are significantly difficult to minimize. This chapter presents an algorithm for the optimal parameter identification of induction motors. To determine the parameters, the proposed method uses a recent evolutionary method called the gravitational search algorithm (GSA). Different from most of existent evolutionary algorithms, GSA presents a better performance in multimodal problems, avoiding critical flaws such as the premature convergence to suboptimal solutions. The approach is compared to the popular particle swarm optimization (PSO), differential evolution (DE) and artificial bee colony (ABC).

In Chap. 8, the application of white blood cells (WBC) detection in images is presented. The automatic detection of WBC still remains an unsolved issue in medical imaging. The analysis of WBC images has engaged researchers from fields of medicine and computer vision alike. Since WBC can be approximated by an ellipsoid form, an ellipse detector algorithm may be successfully applied in order to recognize them. In this chapter, the differential evolution (DE) algorithm is used for the automatic detection of WBC embedded into complicated and cluttered smear images. The approach transforms the detection task into an optimization problem where individuals emulate candidate ellipses. An objective function evaluates if such candidate ellipses are really present in the edge image of the smear. Guided by the values of such function, the set of encoded candidate ellipses (individuals) are evolved using the DE algorithm so that they can fit into the WBC enclosed within the edge-only map of the image. Experimental results from white blood cell images with a varying range of complexity are included to validate the efficiency of the proposed technique in terms of accuracy and robustness.

Chapter 9 presents the problem of estimating view transformations from image correspondences. Many computer vision algorithms include a robust estimation step where model parameters are computed from a dataset containing a significant proportion of outliers. Based on different criteria, several robust techniques have been suggested to solve such a problem, being the random sampling consensus (RANSAC) algorithm the most well-known. In this chapter, a method for robustly estimating multiple view relations from point correspondences is posed. The approach combines the RANSAC method and the harmony search (HS) algorithm. With the combination, the proposed method adopts a different sampling strategy than RANSAC to generate putative solutions. Under the new mechanism, at each iteration, new candidate solutions are built taking into account the quality of the models generated by previous candidate solutions, rather than purely random as is the case of RANSAC. The rules for the generation of candidate solutions (samples) are motivated by the improvisation process that occurs when a musician searches for a better state of harmony. As a result, the proposed approach can substantially reduce the number of iterations still preserving the robust capabilities of RANSAC. The method is generic and its use is illustrated by the estimation of homographies, considering synthetic and real images. The approach is compared to the popular particle swarm optimization (PSO).

Finally, in Chap. 10, the problem of identification of infinite impulse response (IIR) models is posed. System identification is a complex optimization problem which has recently attracted the attention in the field of science and engineering.

In particular, the use of infinite impulse response (IIR) models for identification is preferred over their equivalent finite impulse response (FIR) models since the former yield more accurate models of physical plants for real-world applications. However, IIR structures tend to produce multimodal error surfaces for which their cost functions are significantly difficult to minimize. This chapter presents the comparison of various evolutionary computation optimization techniques applied to IIR model identification. In the comparison, special attention is paid to recently developed algorithms such as cuckoo search and flower pollination algorithm, also including popular approaches. Results over several models are presented and statistically validated.

The material has been compiled from a teaching perspective. For this reason, the book is primarily intended for undergraduate and postgraduate students of science, engineering, or computational mathematics. It can be appropriate for courses such as Artificial Intelligence, Evolutionary Computation, Computational Intelligence, etc. Likewise, the material can be useful for researches from the evolutionary computation and artificial intelligence communities. The important purpose of this book is to bridge the gap between evolutionary optimization techniques and complex engineering applications. Therefore, researchers, who are familiar with popular evolutionary computation approaches, will appreciate that the techniques discussed are beyond simple optimization tools since they have been adapted to solve significant problems that commonly arise on several engineering domains. On the other hand, students of the evolutionary computation community can prospect new research niches for their future work as master or Ph.D. thesis.

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