Book Review

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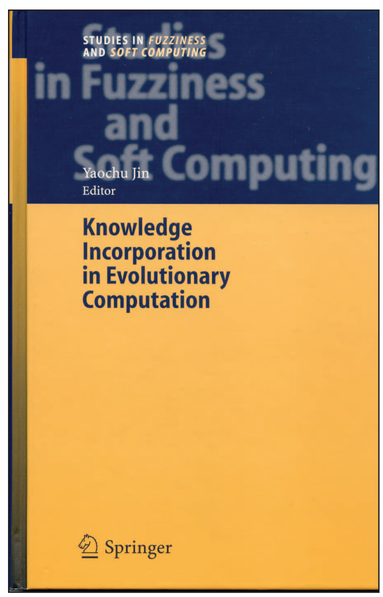
Knowledge Incorporation in Evolutionary Computation

Knowledge Incorporation in Evolutionary Computation by Yaochu Jin (ed), Springer, Berlin Heidelberg, 2005, pp. 548, hardcover, ISBN: 3-540-22902-7.

In recent years, we have witnessed a rapidly growing research activity that incorporates learning techniques, human preferences, and domain knowledge into evolutionary algorithms for solving complex search and optimization problems. It reflects a basic principle that is theoretically supported by the No Free Lunch Theorem: an efficient and effective algorithm should be able to adapt itself to the problem structure and thus problem-specific. Although numerous research papers on incorporation of knowledge into evolutionary computation can be found in a range of academic journals and conferences, there is a lack of suitable reference books in this area for researchers and practitioners. This edited book aims at addressing this challenge. It carefully classifies the various research topics and presents the state-of-the-art of both techniques and applications in a systematic way.

The book is divided into six parts. Part I of the book contains a single chapter written by Xin Yao that provides a concise yet insightful introduction to evolutionary computation. Apart from a generic framework for evolutionary algorithms, theoretical and practical aspects concerning the benefit of using a population, search step-size adaptation, and constraint handling are discussed.

Six chapters are collected in Part II describing various approaches to the embedding of *a priori* knowledge and domain knowledge acquired from the previous search into population initialization, recombination, and mutation. Chapter 2 shows how knowledge stored in the form of memory can be helpful in genetic programming-based symbol regression and robotic control. The application of cultural algorithms, a class of evolutionary methods that extract and reuse domain knowledge, to a job shop scheduling problem is presented in Chapter 3. Knowledge extraction and incorporation using case-based reasoning techniques is described in Chapter 4. A chained cultural genetic programming algorithm in which two populations communicate by means of a shared belief space is presented in Chapter 5. The effectiveness of this algorithm is demonstrated in solving nonlinear program problems and simulating consumer markets. The reduction of randomness in mutation and crossover is advocated in Chapter 6, where polynomials and neural networks, which are two of the most widely-used surrogate models that are able to exploit domain knowledge hidden in the previous search data and thus speed up evolution, are employed to access the quality of candidate solutions. Consequently, those fitter solutions according to the surrogates are chosen as the final offspring. Part II concludes with a chapter that presents a method for extracting knowledge in the form of fuzzy rules that can be used to adapt the crossover and mutation rate in a genetic algorithm for the design of electronic circuits.



Part III contains six papers dealing with knowledge incorporation in offspring generation and selection, among which the first two papers (Chapters 8 and 9) are on estimation of distribution algorithms (EDAs) that generate offspring solutions from probabilistic models learning from the previous search history. Chapter 8 gives an in-depth survey of existing EDAs based on a clearly defined taxonomy of probabilistic model-building evolutionary algorithms, while Chapter 9 supplies an interesting application example of an

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EDA to forest management. The other four papers in this part investigate the use of external memory, case-based reasoning, domain knowledge, and a tabu list in reproduction and selection. In Chapter 10, previous individuals of near-average quality (i.e., they have failed to survive in the previous selection) are stored in a library, which is updated according to the lifetimes of the individuals. These individuals are combined with those in the current generation in reproduction. Chapter 11 presents another example on case-based reasoning techniques for population initialization and reproduction with application to job shop scheduling. A knowledge-based problem-specific selection strategy for inductive concept learning is suggested in Chapter 12. The final chapter of Part III considers the use of tabu restrictions and heuristic reasoning to promote population diversity and local minimum avoidance in evolutionary multi-objective optimization [3].

Part IV addresses knowledge incorporation on evolutionary computation by using approximate models (surrogates) for fitness evaluations, which can be treated as a general approach for knowledge incorporation in fitness evaluation. Chapter 14 deals with fitness approximation using feed-forward neural networks where an approximate fitness function is used with the original fitness function under two different model management frameworks. Chapter 15 reviews several frameworks that employ radial-basis-function networks and Gaussian processes for local modelling of fitness functions using history data. In these frameworks, surrogates are used to replace or supplement the original fitness function in hybrid evolutionary search, where a sequential quadratic programming solver is used for local search in the light of Lamarckian evolution, and in co-evolutionary search. A surrogate-assisted evolution strategy is given in Chapter 16, where the preselection method is discussed. The preselection strategy is, in essence, equivalent to a combination of the informed crossover and mutation described in Chapter 6. I believe that the work along the line of fitness approximation should be very helpful for bridging between evolutionary computation and traditional optimization methods.

Knowledge incorporation into evolutionary algorithm through lifetime learning and human-computer interactions are the topics of Part V. The first chapter in this part, Chapter 17, studies the Baldwin effect and Lamarckian evolution in a cellular genetic algorithm for optimization of recurrent neural networks. It is concluded that the Lamarckian evolution is more efficient in the optimization of recurrent neural networks. Chapter 18 investigates the use of local search in multi-objective evolutionary algorithms, which is nontrivial because an optimal local search direction is not easy to obtain. Two replacement rules in multi-objective memetic algorithm are first compared and then generalized based on the dominance relation. The remaining two chapters in Part V discuss the most straightforward knowledge embedding scheme in evolutionary computation, namely interactive evolutionary algorithms. Chapter 19 employs an interactive genetic algorithm for fashion design, whereas Chapter 20 describes an interactive evolutionary algorithm in a complex, multi-objective design environment in which data mining and visualization techniques are also considered in addition to human preferences.

A detailed treatment of articulating human preferences in evolutionary multi-objective optimization is presented in the final part of the book. The first chapter, Chapter 21, of this part compares two methods integrating vague human preferences, the guided dominance approach and the biased crowding distance approach. The pros and cons of the two methods are discussed. Chapter 22 addresses the human preferences in terms of utility functions and outranking based preferences. A method for converting fuzzy preferences into weights for different objectives is described. Preference articulation in co-evolution is also discussed. While the previous two chapters belong to *a posterior* approaches, Chapter 23 focuses on an interactive approach where an interactive fuzzy satisfying method is applied to multi-objective integer programming problems. In the final chapter of Part VI, an approach that takes advantage of different roles of computer and human users in an interactive engineering design environment is suggested. The approach combines learning-oriented and search-oriented methods for preference articulation by which the design trade-off strategy can be adapted and refined when more preference information is learned during the evolutionary search process.

The most remarkable feature of this book is its unique and comprehensive treatment of the area of knowledge incorporation into evolutionary computation. By reading the book, the reader is able to bring home the most representative and well-studied techniques for incorporating knowledge into evolutionary algorithms. The book is a must for researchers, particularly research students seeking research topics in this area. For practitioners, the book is an excellent reference for finding ways out after recognizing that evolutionary algorithms may not be ready-to-use for solving complex engineering problems. On the other hand, this is also true for the various knowledge incorporation algorithms presented in the book in that these algorithms might not always be ready-to-use and need to be adapted to their problem at hand.