Evolutionary Algorithms for Dynamic Optimization Problems: Workshop Preface

Shengxiang Yang
Department of Computer Science
University of Leicester
University Road, Leicester LE1 7RH, U.K.
s.yang@mcs.le.ac.uk

Jürgen Branke
Institute AIFB
University of Karlsruhe
76128 Karlsruhe, Germany
branke@aifb.uni-karlsruhe.de

Categories and Subject Descriptors

I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search—*Heuristic Algorithms*

General Terms: Algorithms

Keywords

Evolutionary algorithms, dynamic optimization problems

1. INTRODUCTION

Evolutionary algorithms (EAs) have been widely applied to solve stationary optimization problems. However, many real-world optimization problems are actually dynamic. For example, new jobs are to be added to the schedule, the quality of the raw material may be changing, and new orders have to be included into the vehicle routing problem etc. In such cases, when the problem changes over the course of the optimization, the purpose of the optimization algorithm changes from finding an optimal solution to being able to continuously track the movement of the optimum over time. This seriously challenges traditional EAs since they cannot adapt well to the changing environment once converged.

However, since in a sense natural evolution is a process of continuous adaptation and evolutionary algorithms are inspired from principles of natural evolution (e.g., selection and variation), it seems straightforward to consider evolutionary algorithms with proper enhancement as appropriate candidates for dynamic optimization problems (DOPs).

In recent years, there has been a growing interest in studying EAs for dynamic problems since many real world problems are known to be dynamic [1]. And the number of papers published in this area is rising continuously (see e.g. the online repository on the topic [8]). Most of these publications can be grouped into one of the following basic categories [4]:

- Identify the occourence of a change in the environment and then deliberately increase diversity in the population, e.g. by means of increased mutation [5, 11];
- Try to avoid convergence all the time, e.g. by including new random individuals in the population in every generation [7, 15];
- Supply the EA with a memory, e.g. by using diploidy [6, 9, 10, 12] or an explicit memory [2, 13, 16], so that the EA can recall useful information from past generations;
- Using multiple populations to cover several promising areas of the search space simultaneously [3, 14].

The purpose of the workshop is to foster interest in the important subject of evolutionary algorithms for dynamic optimization problems, get together the researchers working on the topic, provide an overview on the field, and discuss recent trends and future directions in the area.

The EvoDOP-2005 workshop, held as a part of GECCO-2005, is the fourth of a successful series of bi-annual workshops on "Evolutionary Algorithms for Dynamic Optimization Problems". The past three EvoDOP workshops have been held at GECCO-1999, GECCO-2001, and GECCO-2003 respectively with 60-100 participants each.

2. EVODOP-2005 PROGRAM

For the EvoODP-2005 workshop, six papers of high quality have been accepted for presentation. Younes et al. propose a method for constructing general benchmark dynamic combinatorial optimization problems, which is an important topic for performance comparisons of EAs. Rand and Riolo describe a set of measures to examine the behaviour of genetic algorithms (GAs) in dynamic environments and use these measures to examine the GA behaviour with a dynamic test suite, called the *shaky ladder hyperplane-defined functions*. Bosman tangles the time-linkage problem (i.e., decisions taken now may influence the score in the future) and shows how such time-linkage can deceive an optimizer. A means of predicting the future by learning from the past is proposed and formalized in an algorithmic framework to address the time-linkage problem. Boumaza studies the relationship between the dynamics of the environment and the self-adaptation of the mutation steps of evolutionary strategies and shows through experimentation that the nature of the movements of the optimum is reflected in the self-adaptive mutation step. The paper by Dudy et al. presents a study on inverse robust evolutionary design in the presence of uncertainty based on the concept of multi-objective optimization. For complex real-world problems, small populations for EAs are very desirable due to computational

GECCO'05, June 25–29, 2005, Washington, DC, USA.

cost. However, small population can dramatically reduce the performance of EAs. Jin et al. suggest a method to find the optimal search accuracy for evolutionary strategies with a small population[1].

The workshop concludes with a panel discussion of relevant topics, as shown below.

3. TOPICS FOR DISCUSSIONS

The EvoODP-2005 workshop is open to all registered attendees of the GECCO-2005 conference. We are open for topics that should be discussed during the panel discussion. Some preliminary topics for discussion are listed as follows:

- What constitutes a good benchmark DOP?
- What factors contribute to the difficulty of EAs for dynamic optimization problems?
- How should one measure "adaptability"?
- What makes a DOP different from a static problem?
- What is the difference between a dynamic optimization problem and a control problem?
- What are the deficits of current approaches?
- What properties should one pursue when analysing EAs for dynamic optimization problems?
- What tools are available to analyse EAs for DOPs?

The topics discussed in EvoDOP-2005 will surely lead to interesting future directions for evolutionary algorithms for dynamic optimization problems.

4. PROGRAMME COMMITTEE

The programme committee for the EvoDOP-2005 workshop reviewed the papers and will also lead the panel discussion into interesting future directions for evolutionary algorithms for dynamic optimization problems.

- Shengxiang Yang (Co-chair, Univ. of Leicester, UK)
- Jürgen Branke (Co-chair, Univ. of Karlsruhe, Germany)
- Hussein A. Abbass (University of New South Wales, Australia)
- Tim Blackwell (University College London, UK)
- Ernesto Costa (University of Coimbra, Portugal)
- Kenneth A. De Jong (George Mason University, USA)
- Daniel Merkle (University of Karlsruhe, Germany)
- Ron Morrison (Mitretek Systems, Inc., USA)
- William Rand (University of Michigan, USA)
- Karsten Weicker (University of Stuttgart, Germany)
- Sima Uyar (Istanbul Technical University, Turkey)

We would like to thank all who have helped making the workshop a success, especially the programme committee members, and wish all participants enjoy the workshop.

[1]On the request of the authors, the work by Jin et al. will be presented at EvoDOP-2005 and included in the CD-ROM entitled "Workshop Proceedings, Tutorials, and Late-Breaking Papers at the 2005 Genetic and Evolutionary Computation Conference" as a late-breaking paper instead of in the workshop proceedings and the ACM digital library.

5. REFERENCES

[1] T. Bäck. On the behaviour of evolutionary algorithms in dynamic fitness landscape. In *Proc. of the 1998 IEEE Int. Conf. on Evolutionary Computation*, pages 446–451, 1998.

[2] J. Branke. Memory enhanced evolutionary algorithms for changing optimization problems. In *Proc. of the 1999 Congress on Evolutionary Computation*, volume 3, pages 1875–1882, 1999.

[3] J. Branke, T. Kaußler, C. Schmidth, and H. Schmeck. A multi-population approach to dynamic optimization problems. *Adaptive Computing in Design and Manufacturing*, pages 299–308, 2000.

[4] J. Branke. *Evolutionary Optimization in Dynamic Environments*. Kluwer Academic Publishers, 2002.

[5] H. G. Cobb and J. J. Grefenstette. Genetic algorithms for tracking changing environments. In *Proc. of the 5th Int. Conf. on Genetic Algorithms*, pages 523–530, 1993.

[6] D. E. Goldberg and R. E. Smith. Nonstationary function optimization using genetic algorithms with dominance and diploidy. In *Proc. of the 2nd Int. Conf. on Genetic Algorithms*, pages 59–68, 1987.

[7] J. J. Grefenstette. Genetic algorithms for changing environments. In *Proc. of the 2nd Int. Conf. on Parallel Problem Solving from Nature*, pages 137–144, 1992.

[8] Internet repository on "evolutionary algorithms for dynamic optimization problems," online, `http://www.aifb.uni-karlsruhe.de/~jbr/EvoDOP`.

[9] E. H. J. Lewis and G. Ritchie. A comparison of dominance mechanisms and simple mutation on non-stationary problems. In *Proc. of the 5th Int. Conf. on Parallel Problem Solving from Nature*, pages 139–148, 1998.

[10] N. Mori, H. Kita and Y. Nishikawa. Adaptation to changing environments by means of the memory based thermodynamical genetic algorithm. In *Proc. of the 7th Int. Conf. on Genetic Algorithms*, pages 299–306. Morgan Kaufmann Publishers, 1997.

[11] R. W. Morrison and K. A. De Jong. Triggered hypermutation revisited. In *Proc. of the 2000 Congress on Evol. Comput.*, pages 1025–1032, 2000.

[12] K. P. Ng and K. C. Wong. A new diploid scheme and dominance change mechanism for non-stationary function optimisation. In *Proc. of the 6th Int. Conf. on Genetic Algorithms*, 1997.

[13] C. L. Ramsey and J. J. Greffenstette. Case-based initializtion of genetic algorithms. In *Proc. of the 5th Int. Conf. on Genetic Algorithms*, 1993.

[14] R. K. Ursem. Multinational GAs: Multimodal optimization techniques in dynamic environments. In *Proc. of the 2000 Congress on Evolutionary Computation*, pages 19–26, 2000.

[15] S. Yang. Memory-based immigrants for genetic algorithms in dynamic environments. In *Proc. of the 2005 Congress on Evolutionary Computation*, 2005.

[16] S. Yang. Population-based incremental learning with memory scheme for changing environment. In *Proc. of the 2005 Congress on Evolutionary Computation*, 2005.