CI/CC and Evolutionary Computation

My part of the Podium Discussion at the 9th IEEE International Conference on Cognitive Informatics (ICCI 2010) and my part of Article "Perspectives on the Field of Cognitive Informatics and Its Future Development."
– see last page for reference and details –

Thomas Weise

Nature Inspired Computation & Applications Laboratory, University of Science and Technology of China

I. INTRODUCTION

Evolutionary Computation (EC, [1]) comprises all Monte Carlo metaheuristics which iteratively refine sets (populations) of multiple candidate solutions. Most EC approaches are either Swarm Intelligence (SI) methods or Evolutionary Algorithms (EAs). SI is inspired by fact that natural systems of many independent, simple agents (such as ants or birds) are often able to find pieces of food or shortest-distance routes very efficiently. EAs, on the other hand, copy the behavior of natural evolution and treat candidate solutions as individuals which compete and reproduce in a virtual environment defined by the user-provided objective function(s). Generation after generation, these individuals adapt to the environment and thus, tend to become suitable solutions for the problem at hand.

II. PAST

The roots of EC go back to the mid-1950s, where the biologist Barricelli [2] began to apply computer-aided simulations in order to gain more insight into the natural evolution. Bremermann [3] and Bledsoe [4] were the first ones to use evolutionary approaches for solving optimization problems. In the early 1980s Genetic Programming emerged as the youngest member of the EA family [5]. The most common SI methods followed in the 1990s [6, 7].

III. PRESENT

Evolutionary Computation now exists for almost 50 years. When taking a look on the current situation of this area, I get the impression that **(1)** countless algorithm variants and analyses have been published and EC became widely accepted *in the research community*. **(2)** Most of the evidence of the efficiency of EAs is based on experiments and empirical studies. Due to the many configuration parameters of EAs and the wide range of existing optimization problems, it is very hard to define meaningful boundaries for performance or required runtime. **(3)** A tendency towards hybridizing optimization techniques can be observed, resulting from this lack of knowledge about which algorithm is "good" for which problem. This trend began in the 1970s [8], lead to the development of Memetic Algorithms [9], and now culminates in the emergence of portfolio methods [10], which choose the best methods from an algorithm portfolio *during* the actual process of solving a given problem. **(4)** Despite the available evidence for the high utility of EAs, practitioners who solve real-world optimization problems appear to often prefer traditional, exact methods. Large-scale problems, which these approaches cannot handle anymore due to their computational complexity, are often approached manually instead of using metaheuristics which could have provided much better solutions in shorter time [11]. **(5)** The communication between researchers working on metaheuristic optimization and those working on traditional, exact methods is low, both communities appear to be separated.

IV. FUTURE

My humble opinion about the future development in the EC area is that **(1)** in the next ten to twenty years, metaheuristic optimization should undergo a slow *transition from a research area to a service*. Virtually every decision or design task in engineering and business is an optimization problem. Yet currently, only the fewest of them are recognized as such and even fewer are actually solved using a suitable technique. More *joint projects* between research and economy targeting real-world applications are necessary to improve the awareness and trust of practitioners in EC. **(2)** EA research should thus focus on tasks which are interesting for practitioners, such as large-scale real-world problems [11], in order to become more attractive for them. **(3)** Up to date, in my opinion, there exists no framework for analyzing EAs theoretically which provides results that are actually useful in practice. The development of a robust and simple analysis approach would be highly desirable since it would further increase the acceptance of EC. **(4)** A closer cooperation between the EC community and traditional operations researchers should be pursued, since an exchange of ideas would be beneficial for both sides.

REFERENCES

[1] Thomas Weise. *Global Optimization Algorithms – Theory and Application*. it-weise.de (self-published): Germany, 2009. URL http://www.it-weise.de/projects/book.pdf.

[2] Nils Aaall Barricelli. Esempi Numerici di Processi di Evoluzione. *Methodos*, 6(21–22):45–68, 1954.

[3] Hans J. Bremermann. Optimization Through Evolution and Recombination. In Marshall C. Yovits, George T. Jacobi, and Gordon D. Goldstein, editors, *Self-Organizing Systems (Proceedings of the conference sponsored by the Information Systems Branch of the Office of Naval Research and the Armour Research Foundation of the Illinois Institute of Technology.)*, pages 93–103. Spartan Books: Washington, DC, USA, 1962. URL http://holtz.org/Library/Natural%20Science/Physics/.

[4] Woodrow "Woody" Wilson Bledsoe. Lethally Dependent Genes Using Instant Selection. Technical Report PRI 1, Panoramic Research, Inc.: Palo Alto, CA, USA, 1961.

[5] Stephen Frederick Smith. *A Learning System based on Genetic Adaptive Algorithms*. PhD thesis, University of Pittsburgh: Pittsburgh, PA, USA, 1980.

[6] Marco Dorigo, Vittorio Maniezzo, and Alberto Colorni. The Ant System: Optimization by a Colony of Cooperating Agents. *IEEE Transactions on Systems, Man, and Cybernetics – Part B: Cybernetics*, 26(1):29–41, February 1996. doi: 10.1109/3477.484436. URL ftp://iridia.ulb.ac.be/pub/mdorigo/journals/IJ.10-SMC96.pdf.

[7] Russel C. Eberhart and James Kennedy. A New Optimizer Using Particle Swarm Theory. In *Proceedings of the Sixth International Symposium on Micro Machine and Human Science (MHS'95)*, pages 39–43. IEEE Computer Society: Piscataway, NJ, USA, 1995. doi: 10.1109/MHS.1995.494215. URL http://webmining.spd.louisville.edu/Websites/COMB-OPT/FINAL-PAPERS/SwarmsPaper.pdf.

[8] Jack Bosworth, Norman Foo, and Bernard P. Zeigler. Comparison of Genetic Algorithms with Conjugate Gradient Methods. Technical Report 00312-1-T, University of Michigan: Ann Arbor, MI, USA, February 1972. URL http://hdl.handle.net/2027.42/3761. Other Identifiers: UMR0554.

[9] Pablo Moscato. On Evolution, Search, Optimization, Genetic Algorithms and Martial Arts: Towards Memetic Algorithms. Caltech Concurrent Computation Program C3P 826, California Institute of Technology (Caltech), Caltech Concurrent Computation Program (C3P): Pasadena, CA, USA, 1989. URL http://www.each.usp.br/sarajane/SubPaginas/arquivos_aulas_IA/memetic.pdf.

[10] Fei Peng, Kē Táng, Guóliáng Chén, and Xīn Yáo. Population-based Algorithm Portfolios for Numerical Optimization. *IEEE Transactions on Evolutionary Computation (IEEE-EC)*, 14(5):782–800, March 29, 2010. doi: 10.1109/TEVC.2010.2040183.

[11] Thomas Weise, Alexander Podlich, Kai Reinhard, Christian Gorldt, and Kurt Geihs. Evolutionary Freight Transportation Planning. In Mario Giacobini, Penousal Machado, Anthony Brabazon, Jon McCormack, Stefano Cagnoni, Michael O'Neill, Gianni A. Di Caro, Ferrante Neri, Anikó Ekárt, Mike Preuß, Anna Isabel Esparcia-Alcázar, Franz Rothlauf, Muddassar Farooq, Ernesto Tarantino, Andreas Fink, and Shengxiang Yang, editors, *Applications of Evolutionary Computing – Proceedings of EvoWorkshops 2009: EvoCOMNET, EvoENVIRONMENT, EvoFIN, EvoGAMES, EvoHOT, EvoIASP, EvoINTERACTION, EvoMUSART, EvoNUM, EvoSTOC, EvoTRANSLOG (EvoWorkshops'09)*, volume 5484/2009 of *Theoretical Computer Science and General Issues (SL 1), Lecture Notes in Computer Science (LNCS)*, pages 768–777. Springer-Verlag GmbH: Berlin, Germany, 2009. doi: 10.1007/978-3-642-01129-0_87.

[12] Thomas Weise. CI/CC and Evolutionary Computation, July 9, 2010. Position Paper.

[13] Fuchun Sun, Yingxu Wang, Jianhua Lu, Bo Zhang, Witold Kinsner, and Lotfi A. Zadeh, editors. *Proceedings of the 9th IEEE International Conference on Cognitive Informatics (ICCI'10)*, July 7–9, 2010. IEEE Computer Society Press: Los Alamitos, CA, USA.

[14] Yingxu Wang, Bernard Widrow, Bo Zhang, Witold Kinsner, Kenji Sugawara, Fuchun Sun, Jianhua Lu, Thomas Weise, and Du Zhang. Perspectives on the Field of Cognitive Informatics and Its Future Development. *The International Journal of Cognitive Informatics and Natural Intelligence (IJCINI)*, 5(1):1–17, January–March 2011. doi: 10.4018/jcini.2011010101.

This was my (Thomas Weise) contribution [12] to the
podium discussion at ICCI 2010 [13]. It became a part of
the journal article [14].

```
@inproceedings{W2010CCAEC,
  title       = {CI/CC and Evolutionary Computation},
  author      = {Thomas Weise},
  booktitle   = {Podium Discussion at the 9th IEEE International
                  Conference on Cognitive Informatics (ICCI 2010)},
  month       = jul # {~7--9,},
  year        = {2010},
  location    = {Tsinghua University, Beijing, China},
  publisher   = {IEEE Computer Society Press, Los Alamitos, CA, USA},
  isbn        = {978-1-4244-8040-1},
}

@article{WWZKSSLWZ2011POTFOCIAIFD,
  author      = {Yingxu Wang and Bernard Widrow and Bo Zhang and
                  Witold Kinsner and Kenji Sugawara and Fuchun Sun
                  and Jianhua Lu and Thomas Weise and Du Zhang},
  title       = {{Perspectives on the Field of Cognitive Informatics
                   and Its Future Development}},
  publisher   = {New York, NY, USA: Idea Group Publishing
                  (Idea Group Inc., IGI Global)},
  journal     = {The International Journal of Cognitive Informatics
                  and Natural Intelligence (IJCINI)},
  number      = {1},
  volume      = {5},
  pages       = {1--17},
  year        = {2011},
  month       = jan # {--} # mar # {, },
  doi         = {10.4018/jcini.2011010101},
  eiid        = {20114014384631},
  inspec      = {12451742},
},
```