SELECTIVE EVOLUTION CONTROL METHOD FOR EVOLUTION STRATEGIES WITH NEURAL NETWORK METAMODELS

Pavel Afonin

Abstract. *This paper presents a new evolution control method to reduce the number of computationally expensive simulations for evolution strategies with fitness function models. A feedforward neural network is used as a fitness model and constructed with the help of some previously evaluated solutions in the search space. On-line learning is implemented during searching process. In the evolution strategy with the proposed method the number of controlled individuals is changed during optimization and the choice of parents for the next generation is always made out of controlled individuals. The results of the evolution strategy implementation with the selective evolution control method for three standard test functions in comparison with other known evolutionary strategies are presented.*

Keywords: *evolution strategy, neural network, metamodel, evolution control*

ACM Classification Keywords: *I.2 Artificial Intelligence: I.2.6 Learning: Connectionism and neural nets*

Conference topic: *Neural Networks*

Introduction

During the last several years evolutionary algorithms have found wide application for solving a great number of design optimization problems, simulation optimization problems as well as other complex problems demanding applying global optimization methods. However, in the most cases the large number of function evaluations are required for a evolutionary algorithms to converge a near-optimal solution.

One of the ways of solving the problem given is using approximate models (metamodels) instead of computationally expensive fitness function evaluations. The polynomial models [1, 8], artificial neural networks include multilayer perceptrons [4, 6], radial-basis-function networks [8] and support vector machines [9] as well as the kriging models [2, 3] can be employed as fitness function models in evolutionary algorithms (for example, evolution strategies and genetic algorithms).

In this paper a selective evolution control method for evolution strategies based on metamodels are proposed and investigated. A multilayer perceptron is used as a metamodel and on-line learning is implemented during searching process.

The remaining part of the paper is devoted to: A brief review of the methods described in the literature of approximate model incorporation into evolutionary algorithms is presented in section II. Section III introduces the selective evolution control method proposed. Section IV presents experimental results from simulations on three benchmarks. Section V summarizes paper conclusion and planning for future research.

Related works

There are two approaches to integrate metamodels into evolutionary algorithms: surrogate approach and evolution control.

In the surrogate approach at first the optimum of the metamodel is determined and after that evaluated on the real fitness function. The new evaluation is used to update the model, and the process of the metamodel improving is repeated.

In concept of evolution control propose two methods [6]: controlled individuals and controlled generations. In generation-based evolution control, all individuals in population is evaluated on either the metamodel or the fitness function. In individual-based control, part of the individuals in current population are chosen and evaluated with the real fitness function. Remaining individuals are evaluated with the approximate model. Individuals that are evaluated on the fitness function call as controlled individuals.

The main issue in the individual-based evolution control is to define which individuals in the each generation are evaluated with the real fitness function and which with the approximate model [1, 3, 6, 9].

Then describe two main individual-based evolution control methods: the best strategy and pre-selection strategy.

In the best strategy [6], $\lambda' = \lambda$ offspring are estimated with the fitness model and the λ^* best ones are evaluated with the real fitness function. After model construction the remaining $\lambda' - \lambda^*$ individuals are evaluated again with the fitness model. The μ best individuals from the λ individuals become parents of the next generation.

In the pre-selection strategy [9], $\lambda' > \lambda$ offspring are generated out of μ parents through recombination and mutation and after that estimated with the fitness model. The $\lambda^* = \lambda$ best individuals are pre-selected from the λ' offspring and re-evaluated with the real fitness function.

The important conclusion in [4] is that the stability of the evolution strategy with individual based evolution control might be improved if the parents for the next generation are selected out of controlled individuals, as it is done in the pre-selection strategy.

Hovewer, at present there remains actual one question: how many and which individuals must be controlled?

Selective evolution control method

The model fidelity can be changed from one generation to the next one due to the change of the region where population is located as well as data change for model construction. Therefore, selection quality of the model evaluated in the current generation could be invalid for predicting the number of controlled individuals in the next generation.

One of the quality criteria of the model is the rank correlation prank [7], which in turn depends on the difference between the rank of the offspring individual based on the real fitness function and on the approximate model.

It may be expected, that if at first we could evaluate the model quality in current generation and after that employ this evaluation for determining controlled individuals in the same generation than this method might prove to be effective for correct selection of parents to the next generation.

The main idea of approach is that controlled individuals should be chosen from the current generation depending on the quality of the model which should be evaluated in the same generation by means of evaluating rank difference for some individuals taken as small separate units.

For this purpose number of controlled individuals (η), which must have the best rank among all λ individuals of current generation is introduced. In this case the number of controlled individuals λ* for each generation may be from η to λ.

For more stable work of the selection operator the condition η ≥ μ is introduced, which means that the selection of μ parents for the next generation must be made out of controlled individuals.

If model quality is lower then high probability exists that the first η individuals will change their rank. In this case the number of controlled individuals is increased. If model quality is higher then low probability exists that the first η individuals will change their rank and so the number of controlled individuals is decreased.

Let us consider graphical presentation of evolution strategy with the selective evolution control (figure 1). At first, all λ offspring is generated out of μ parents of the current generation by means of recombination and mutation. After that all λ offspring estimated with the model. Further individuals are evaluated with the real fitness function. At the Step 1 the η best individuals from the λ offspring are evaluated. The first individual changing rank 1 for rank 2 remains within the η best individuals and the second one goes out of η best individuals changing rank 2 for rank 6. At the Step 2 the only one non-controlled offspring from η best individuals is evaluated, thus 1-st individual changes rank 1 for rank 4 and the 2-nd individual of rank 2 for rank 1. At the Step 3 only the 2-nd individual is evaluated and as a result it changes rank 2 for rank 1 and the 1-st individual does from rank 1 for rank 2. So all η best individuals are controlled. Further the model is updated taking into consideration the λ* controlled individuals in current generation. In conclusion the μ best individuals are selected only from the η controlled individuals.

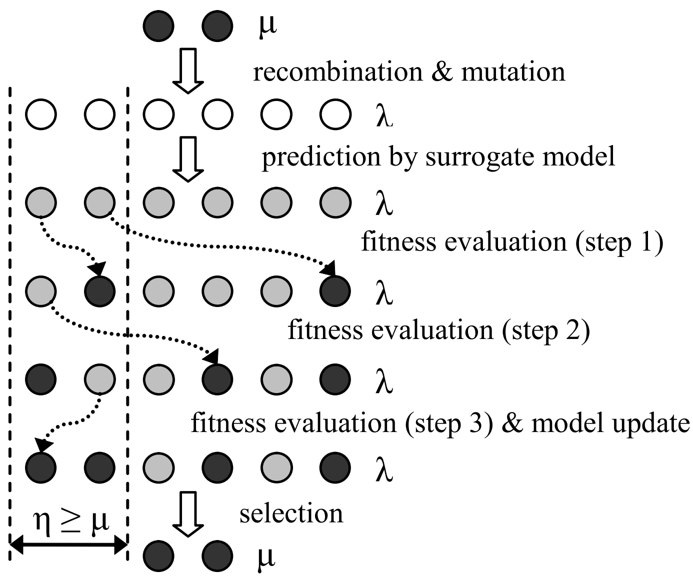

Figure 1. Evolution strategy with selective evolution control

Thus, in the evolution strategy with the proposed evolution control method the number of controlled individuals λ* for each generation depending on the quality of the model for same generation and the choice of μ parents for the next generation is always made out of controlled individuals.

Experiments on benchmarks

The (3, 12) evolution strategy with covariance matrix adaptation [5] is taken in this work. Three test functions: 12D Ackley function, 12D Rosenbrock function and 12D Schwefel function are carried out for the investigation. The evolution strategy proposed (Sel ES) is compared with the three evolution strategies: pure evolution strategy (pure ES), pre-selection strategy (PreSel ES) and best strategy (BS ES).

The values of λ' and λ are based on recommendations [4, 9] equals for pre-selection strategy: λ'=12; λ= 24 and for best strategy: λ'=6; λ= 12. The main parameter of selective evolution control method is equal 3 (η = μ). The neural network consists of 12 inputs, one hidden layer with 8 hidden neurons and one output. According to the recommendations [4, 9] for achieving good approximation in the current local region only data from 4λ to 5λ of last fitness evaluations are used for training neural network.

Program realization of the algorithms and research are made with Matlab 7.1. In Figures 2, 3, 4 (for three test functions) the median of the best fitness in each generation over 25 runs are showed against the number of fitness evaluations.

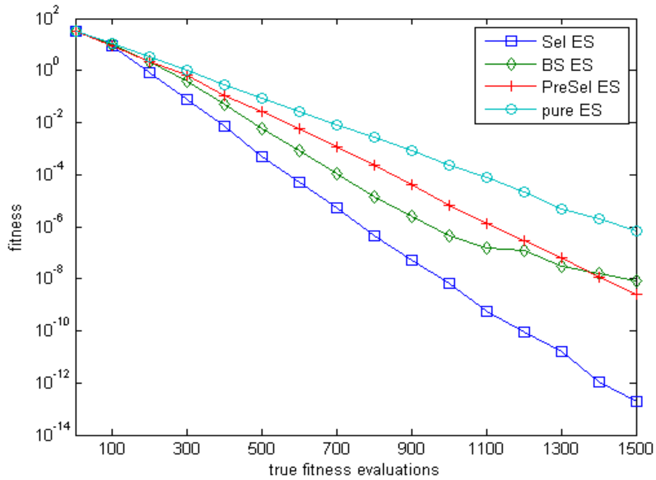

Figure 2. Results for the Sphere function

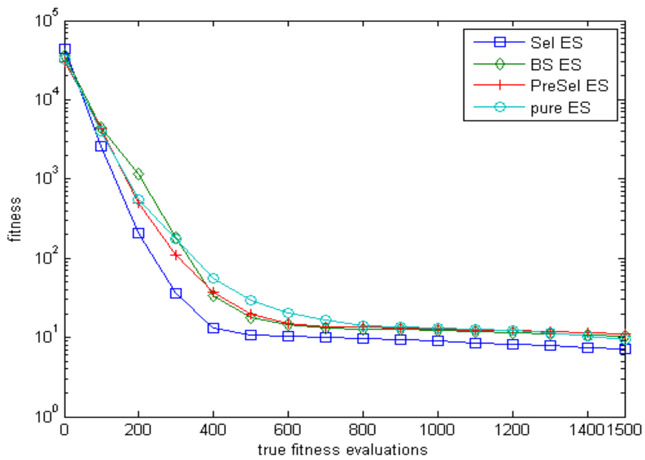

Figure 3. Results for the Rosenbrock function

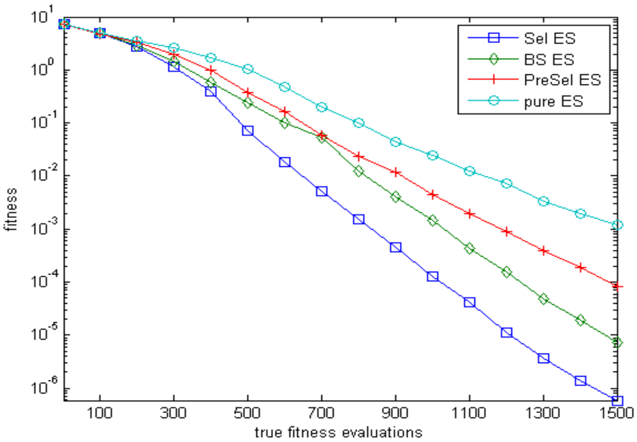

Figure 4. Results for the Ackley function

The number of generations for each number of controlled individuals from η to λ for strategy proposed is shown in Figures 5, 6 ,7 (for three functions investigated).

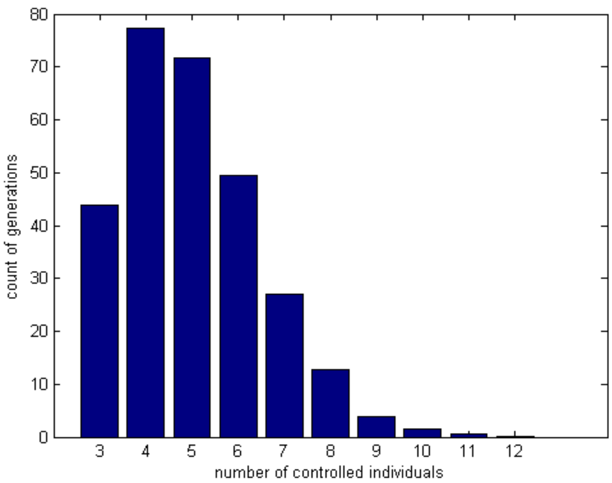

Figure 5. Results for the Sphere function

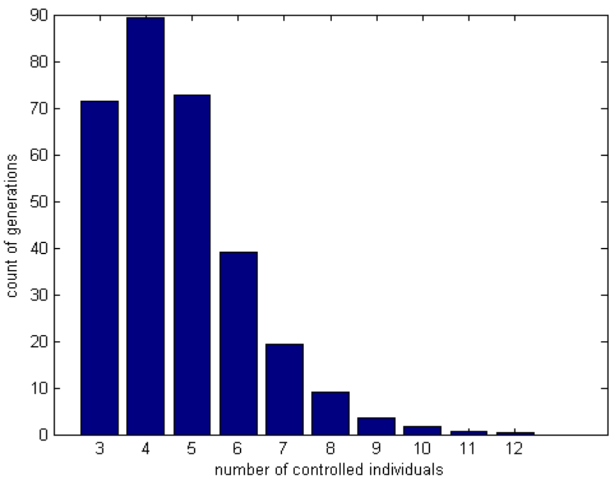

Figure 6. Results for the Rosenbrock function

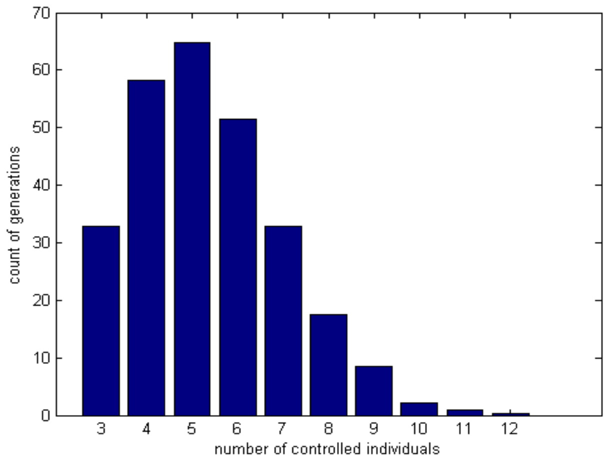

Figure 7. Results for the Ackley function

It can be seen, from the results that the evolution strategies with the selective evolution control method has better performance than the others. For Sphere and Rosenbrock functions the number of controlled individuals is less than half of the population size and this number is enough for effective algorithm convergence. The number of controlled individuals for Ackley function happened to be more than for Sphere and Rosenbrock functions. Probably, this fact may be explained that Ackley function has more complex landscape and as a consequence the model can have a greater error during the optimization process.

Conclusion

In this work a new evolution control method for evolution strategies with metamodels are proposed and investigated. This method can be used to reduce the number of computationally expensive fitness function evaluations in complex optimization problems solving. From the results, we showed that the evolution strategy with the proposed evolution control method has better performance than the others investigated strategies for common benchmarks. Future work is planed to implementation and investigation the evolution strategy with the selective evolution control method for the several real-world optimization problems.

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Bibliography

J. Branke and C. Schmidt. Fast convergence by means of fitness estimation. Soft Computing Journal, 9(1):13-20, 2005.

D. Bueche, N.N. Schraudolph, and P. Koumoutsakos. Accelerating evolutionary algorithms with Gaussian process fitness function models. IEEE Transactions on Systems, Man, and Cybernetics: Part C, 35(2), pp. 183-194, 2005.

M. Emmerich, A. Giotis, M. Özdenir, T. Bäck, and K. Giannakoglou. Metamodel-assisted evolution strategies. In Parallel Problem Solving from Nature, number 2439 of Lecture Notes in Computer Science, pp. 362-370, 2002.

L. Gräning, Y. Jin, and B. Sendhoff. Individual-based Management of Meta-models for Evolutionary Optimization with Application to Three-Dimensional Blade Optimization. Evolutionary Computation in Dynamic and Uncertain Environments, pp. 225-250, 2007.

N. Hansen and A. Ostermeier. Completely derandomized self-adaptation in evolution strategies. Evolutionary Computation, 9(2), pp. 159–196, 2001.

Y. Jin, M. Olhofer, and B. Sendhoff. A framework for evolutionary optimization with approximate fitness functions. IEEE Transactions on Evolutionary Computation, 6(5), pp. 481-494, 2002.

Y. Jin, M. Huesken, and B. Sendhoff. Quality measures for approximate models in evolutionary computation. In Alwyn M. Barry, editor, GECCO 2003: Proceedings of the Bird of a Feather Workshops, Genetic and Evolutionary Computation Conference, pp. 170–173, Chigaco, 11 July 2003. AAAI.

D. Lim, Y.S. Ong, Y. Jin, and B. Sendhoff: A study on metamodeling techniques, ensembles, and multi-surrogates in evolutionary computation. In Genetic and Evolutionary Computation Conference, pp. 1288-1295, 2007.

H. Ulmer, F. Streichert, and A. Zell. Evolution strategies with controlled model assistance. In Congress on Evolutionary Computation, pp. 1569--1576, 2004.

Authors' Information

Pavel Afonin *– ph.d.; Bauman Moscow State Technical University; 2-d Baumanskaya st..,5, Moscow, Russia; e-mail: pavlafon@yandex.ru*