Maintaining Diversity through Adaptive Selection, Crossover and Mutation

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ABSTRACT

This paper presents an Adaptive Genetic Algorithm (AGA) where selection pressure, crossover and mutation probabilities are adapted according to population diversity statistics. The creation and maintenance of a diverse population of healthy individuals is a central goal of this research. To realise this objective, population diversity measures are utilised by the parameter adaptation process to both explore (through diversity promotion) and exploit (by local search and maintenance of a presence in known good regions of the fitness landscape). The performance of the proposed AGA is evaluated using a multi-modal, multi-dimensional function optimisation benchmark. Results presented indicate that the AGA achieves better fitness scores faster compared to a traditional GA.

TRACK NAME: Genetic Algorithms.

Categories and Subject Descriptors

I.2.8 [**Artificial Intelligence**]: Problem Solving and Search

General Terms

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Keywords

Adaptive Genetic Algorithm (AGA), adaptive selection, weighted population diversity, parameter adaptation

1. INTRODUCTION

Eiben [1] demonstrates that the choice of GA parameters strongly influences GA performance and that optimal parameter settings vary during the evolutionary process.

The AGA presented in this paper counters premature convergence through intelligent adaptation of selection pressure and crossover to maintain sustainable convergence properties (i.e. promoting survival of the fittest), while employing an adaptive mutation rate to introduce new genetic diversity for exploration.

The proposed AGA employs a measure of population diversity to control mutation and crossover rates [2, 7, 8], while a novel selection operator regulates selection pressure by adapting tournament size, according to a new weighted measure of population diversity. Weighted Population Diversity (WPD) refers to how diverse a population is from a fitness perspective (i.e. a measure of the diversity of healthy individuals).

2. POPULATION DIVERSITY MEASURES

2.1 Calculating Population Diversity (PD)

PD is calculated by finding the position of the average individual within the problem's search space and summing the Euclidean distances from this average point to the location of every other individual. This measure provides the standard deviation of the population's individuals. The standard deviation is expressed relative to the mean as a coefficient of variation.

2.2 Calculating Weighted Population Diversity (WPD)

While the PD measure of diversity outlined provides a good indication of population spread, it does not indicate the diversity of healthy individuals.

To deal with the challenge of describing the diversity of a population's healthy individuals, a WPD measure is introduced. This is achieved through weighting each individual's influence on the average individual position, according to its probability of selection (fitness).

Next, each individual's Euclidean distance to the weighted average is weighted according to its probability of selection, to calculate a weighted standard deviation.

The weighted coefficient of variation is calculated to relate the weighted standard deviation measure to the mean.

3. AGA IMPLEMENTATION

3.1 Adaptive Crossover

With the proposed AGA, individuals that do not undergo crossover are instead subjected to an adaptive rate of mutation. This technique essentially corresponds to splitting the population into two sub-sections: an exploitation (crossover) division and an exploration (adaptive mutation) division. The sizes of these divisions are determined by the population diversity (PD) measure.

Equation 1 details the proposed crossover probability (P_c) equation. In this work P_c varies from 0.4 (K1) to 0.8 (K2) based on population diversity ($0 < PD <= 100$).

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$$P_c = \left[\left(\frac{PD}{100} * (K_2 - K_1)\right) + K_1\right] \quad (1)$$

3.2 Adaptive Mutation

The AGA mutation rate employed is an average of two measures: population diversity mutation ($P_m^{Diversity}$) [2, 7, 8] and parent fitness mutation ($P_m^{Fitness}$) [4, 5, 6, 7]. Single parent selection (no recombination) and random re-initialisation mutation are employed.

Equation 2 is used to determine the proposed mutation rate according to population diversity mutation ($P_m^{Diversity}$). K=0.2 corresponds to the maximum possible rate of mutation.

$$P_m^{Diversity} = \frac{-(PD - 100)}{100} * K \quad (2)$$

Equation 3 defines the proposed method for calculating parent fitness mutation.

$$P_m^{Fitness} = -\left[\left(\frac{f - f_{\min}}{f_{\max} - f_{\min}} * K\right) - K\right] \quad (3)$$

Here, f corresponds to parent fitness; f_{max} and f_{min} correspond to the best and worst fitness individuals in the population respectively. Again, the selected value of K is 0.2.

Equation 4 defines the proposed method for calculating the overall net adaptive mutation rate (P_m).

$$P_m = \frac{P_m^{Fitness} + P_m^{Diversity}}{2} \quad (4)$$

3.3 Adaptive Selection

The measure of WPD is used to vary tournament size. Equation 5 details the proposed adaptive selection implementation. Tsize refers to the tournament size used by the operator. $Tsize_{max}$ refers to the maximum possible tournament size

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$$Tsize = \left[\frac{WPD}{WPD_{\max}} * Tsize_{\max}\right] \quad (5)$$

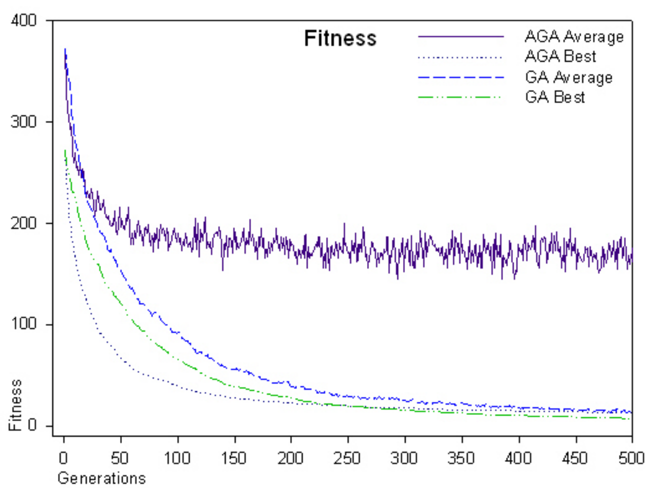

Figure 1. Rastrigin 20d Fitness.

4. EXPERIMENTAL ANALYSIS

A 20-dimensional multi-modal Rastrigin function [3] is employed to test the performance of the proposed AGA. The average and best fitness results of the AGA and GA over 15 evolutionary runs are compared (Figure 1).

5. CONCLUSION

A novel adaptive AGA has been proposed. The performance of the proposed AGA is evaluated using a multi-modal, multi-dimensional function optimisation benchmark and compared to a traditional GA implementation. Benchmark test results indicate that the AGA outperforms the GA in the early stages of search through more efficient and effective exploration. However, once the GA locates the region of the global optimum, its tendency to converge and search locally becomes more effective in 'hill climbing' to the optimal solution. However, this converging local search eliminates much of the useful genetic diversity in the population.

The AGA locates fitter solutions faster than the traditional GA especially for multi-modal (typically real world) problems where no information on the shape of the fitness landscape exists. The diversity, creation and maintenance properties of the AGA can be applied to real-world adaptive and fault tolerant applications.

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7. REFERENCES

[1] AE Eiben, R. Hinterding, and Z. Michalewicz. Parameter control in evolutionary algorithms. Evolutionary Computation, IEEE Transactions on, 3(2):124–141, 1999.

[2] H. Hagras, A. Pounds-Cornish, M. Colley, V. Callaghan, and G. Clarke. Evolving spiking neural network controllers for autonomous robots. Robotics and Automation, 2004. Proceedings. ICRA'04. 2004 IEEE International Conference on, 5.

[3] H.S. Kim and S.B. Cho. An efficient genetic algorithm with less fitness evaluation byclustering. Evolutionary Computation, 2001. Proceedings of the 2001 Congress on, 2, 2001.

[4] R. Krohling, Y. Zhou, and A.M. Tyrrell. Evolving FPGA-based robot controllers using an evolutionary algorithm. 1st International Conference on Artificial Immune Systems, Canterbury, September, 2002.

[5] D.P. Liu and S.T. Feng. A novel adaptive genetic algorithms. Machine Learning and Cybernetics, 2004. Proceedings of 2004 International Conference on, 1, 2004.

[6] PP Palmes, T. Hayasaka, and S. Usui. Mutation-based genetic neural network. Neural Networks, IEEE Transactions on, 16(3):587–600, 2005.

[7] M. Srinivas and LM Patnaik. Adaptive probabilities of crossover and mutation in genetic algorithms. Systems, Man and Cybernetics, IEEE Transactions on, 24(4):656–667, 1994.

[8] KQ Zhu. A diversity-controlling adaptive genetic algorithm for the vehicle routing problem with time windows. Tools with Artificial Intelligence, 2003. Proceedings. 15th IEEE International Conference on, pages 176–183, 2003.