Comparing Performance of the

Learnable Evolution Model and Genetic Algorithms

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Abstract

This paper describes an application of the Learnable Evolution Model (LEM) to a digital signal filter parameter identification problem and compares its performance to genetic algorithm solutions.

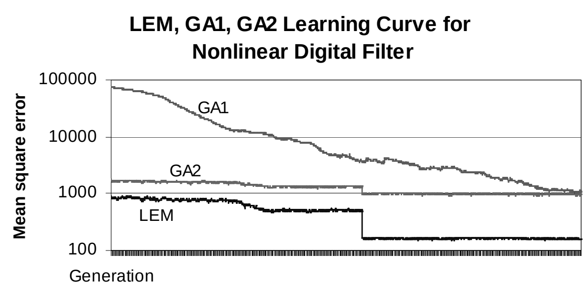
1 METHODOLOGY

LEM augments a genetic algorithm by adding a symbolic learning operator. This operator learns what differentiates the most fit individuals in a population from the least. The symbolic learning operator then generates a new population based on this knowledge. LEM toggles between using the symbolic learning operator and typical genetic algorithm operators (i.e., selection, mutation, and crossover). LEM's learning mode changes when the current operator or operators makes no significant improvement for the best fitness measure in a generation, or after a certain number of generations are produced.

LEM had previously performed well when compared with two other genetic algorithms on the De Jong test suite (Michalski, 1998). In this experiment, we wanted to compare the LEM method to two genetic algorithm based solutions when applied to solving for the coefficients of a digital filter.

2 EXPERIMENTS

The symbolic learning program AQ18 was used to implement the symbolic learning operator. The genetic algorithms GA1 and GA2 were used; the former employed only mutation, while the latter used both mutation and uniform crossover. We used GA2 for LEM's genetic algorithm implementation. The following figure shows the experimental results.



3 CONCLUSIONS

A genetic algorithm augmented by the use of a symbolic learning mechanism has significant speedup over more traditional genetic algorithm for this continuous parameter optimization problem. See LEM GMU MLIL Publications for a complete discussion.

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References

Michalski, R.S., Learnable Evolution: Combining Symbolic and Evolutionary Learning Proceedings of the Fourth International Workshop on Multistratey Learning, (MSL98), Desenzana del Garda, Italy, pp. 14-20, June 11-13, GMU MLI publication P98-9, 1998.

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