

---

# Comparing Performance of the Learnable Evolution Model and Genetic Algorithms

---

|  |   |   |   |   |
|--|---|---|---|---|
| <b>Mark Coletti</b><br>Computer Science Dept.<br>George Mason<br>University<br>Fairfax, VA 22030<br>mcoletti@clark.net | <b>Thomas D. Lash</b><br>Electrical Engineering<br>Dept.<br>George Mason<br>University<br>Fairfax, VA 22030<br>tlash@rocketmail.com | <b>Ryszard Michalski</b><br>Machine Learning<br>and Inference<br>Laboratory<br>George Mason<br>University<br>Fairfax, VA 22030<br>michalski@gmu.edu | <b>Craig Mandsager</b><br>Computer Science<br>Dept.<br>George Mason<br>University<br>Fairfax, VA 22030<br>craig@thegame.com | <b>Rida Moustafa</b><br>Computer Science<br>Dept.<br>George Mason<br>University<br>Fairfax, VA 22030<br>rmoustafa@gmu.edu |
|--|---|---|---|---|

## 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

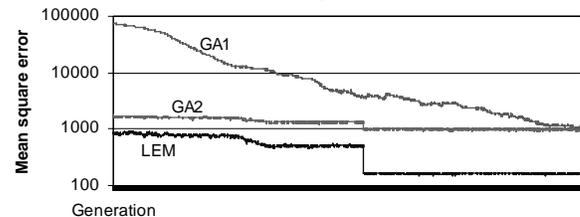
LEM augments a genetic algorithm by adding a symbolic learning operator. This operator learns what differentiates the most fit individuals in a population from the least. The symbolic learning operator then generates a new population based on this knowledge. LEM toggles between using the symbolic learning 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.

LEM, GA1, GA2 Learning Curve for  
Nonlinear Digital Filter



## 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.

### Acknowledgments

Dr. Kenneth DeJong for GA1 and GA2 source code. Guido Cervone provided administrative assistance. Dr. Ken Kaufman provided original LEM source code.

### References

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

Coletti M., Lash, T., Mandsager, C., Michalski, R.S. and Moustafa, R., Comparing Performance of the Learnable Evolution Model and Genetic Algorithms Applied to Digital Signal Filters, GMU MLIL publication (to be published 1999)