Solving Five Instances of the Artificial Ant Problem with Ant Colony Optimization

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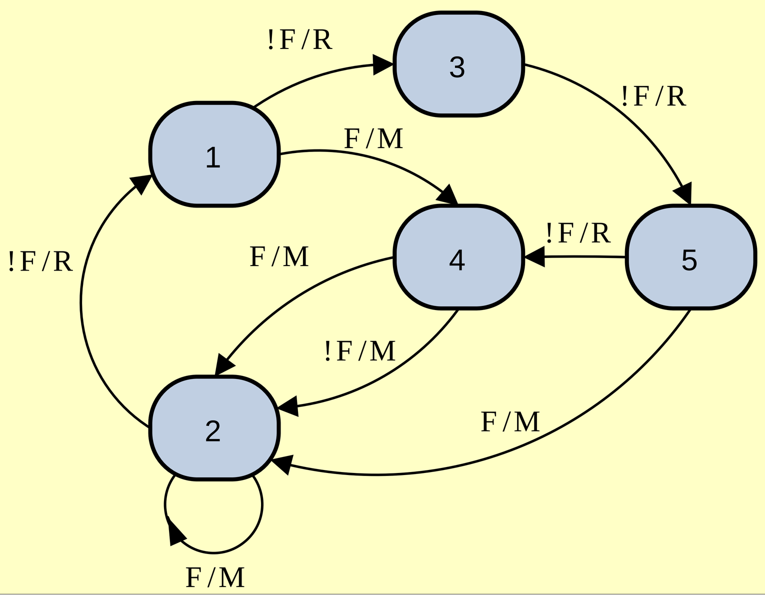
Finite-State Machine

- S – set of states
- Σ – set of input events
- Δ – set of output actions
- $\delta : S \times \Sigma \to S$ – transition function
- $\lambda : S \times \Sigma \to \Delta$ – action function
- $s_0 \in S$ – initial state

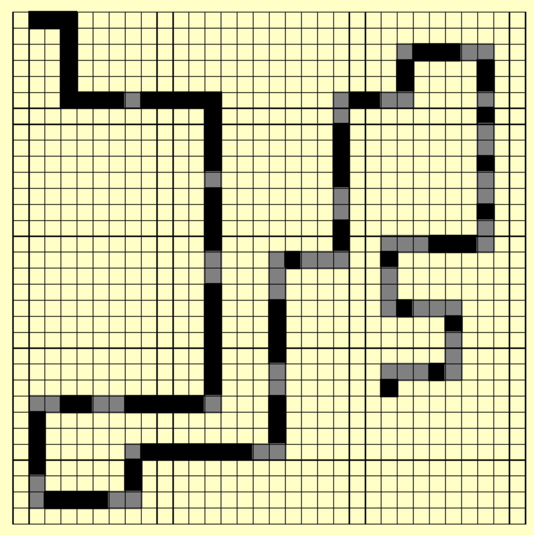


Artificial Ant Problem

- Two events: *F* (food ahead) and *!F* (no food ahead)
- Three actions: *L* (turn left), *R* (turn right), *M* (move forward)
- A maximum of s_{max} time steps
- Maximize fitness function:

$$f = n_{food} + \frac{s_{max} - s_{last} - 1}{s_{max}}$$

- n_{food} – eaten food count
- s_{last} – last step

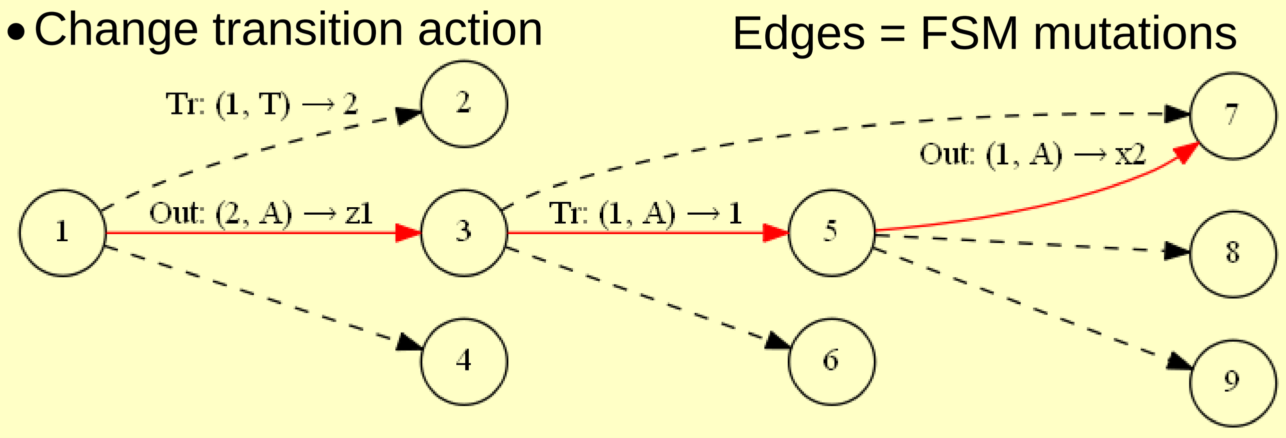


Santa Fe food trail field

Mutation-Based Ant Colony Optimization for Learning Finite-State Machines

FSM mutations:
- Change transition end state
- Change transition action

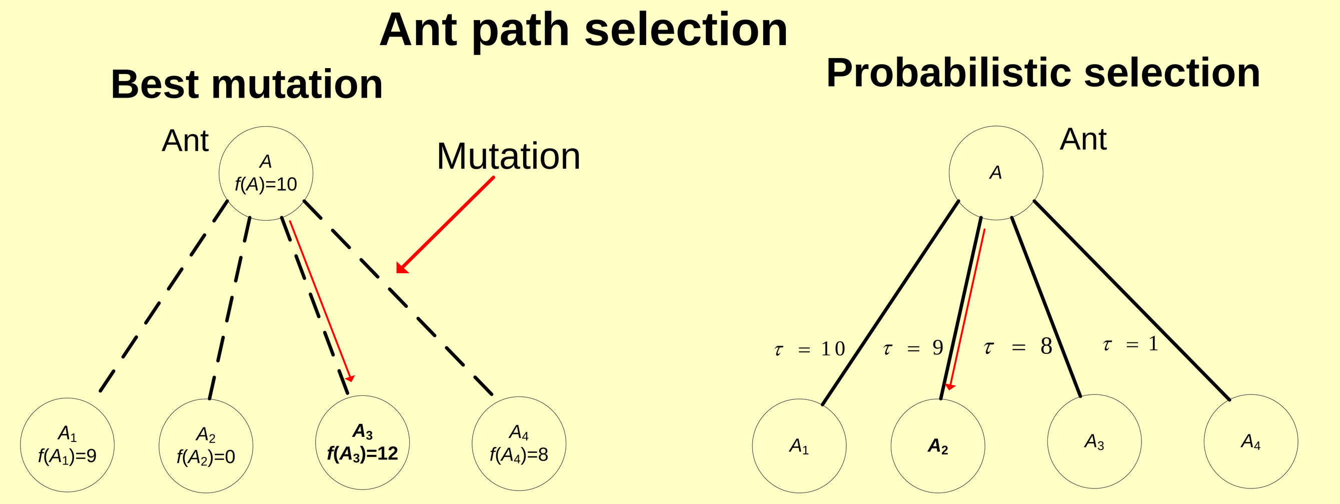
Construction graph:
Nodes = Finite-State Machines
Edges = FSM mutations



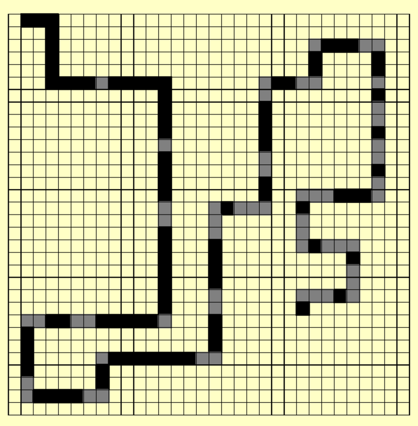
Algorithm

while (true)
  Build solutions with ant colony
  Update pheromone
  Check stop criteria

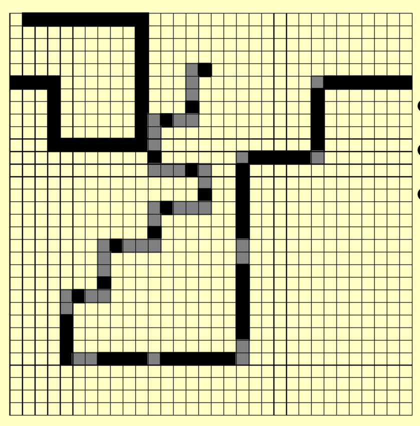
Ant path selection



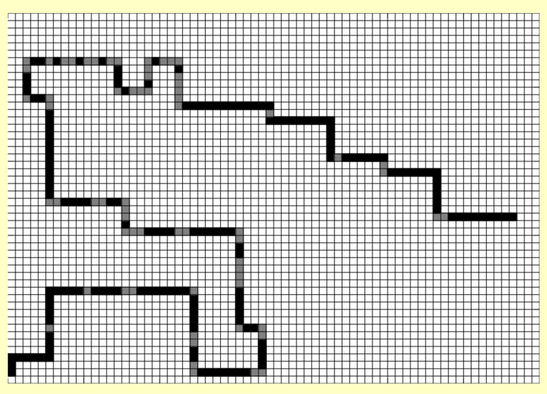
Experimental Results: Artificial Ant Problem



Santa Fe Trail
- s_{max} = 400, 500, 600
- Compare with Christensen et al. (2004)
- Measure mean fitness evaluations

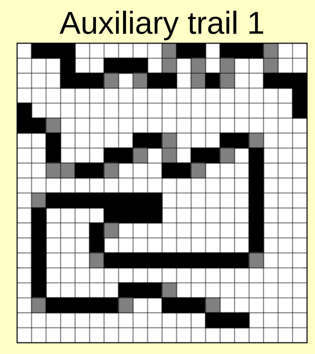


John Muir Trail
- s_{max} = 200
- Compare with Tsarev et al. (2007)
- Measure mean fitness evaluations



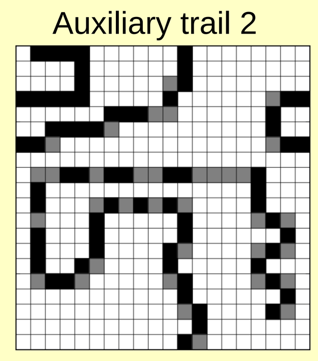
Los Altos Hills Trail
- s_{max} = 800
- Compare with Mesot et al. (2002)
- Measure mean number of ant steps

Auxiliary trail 1

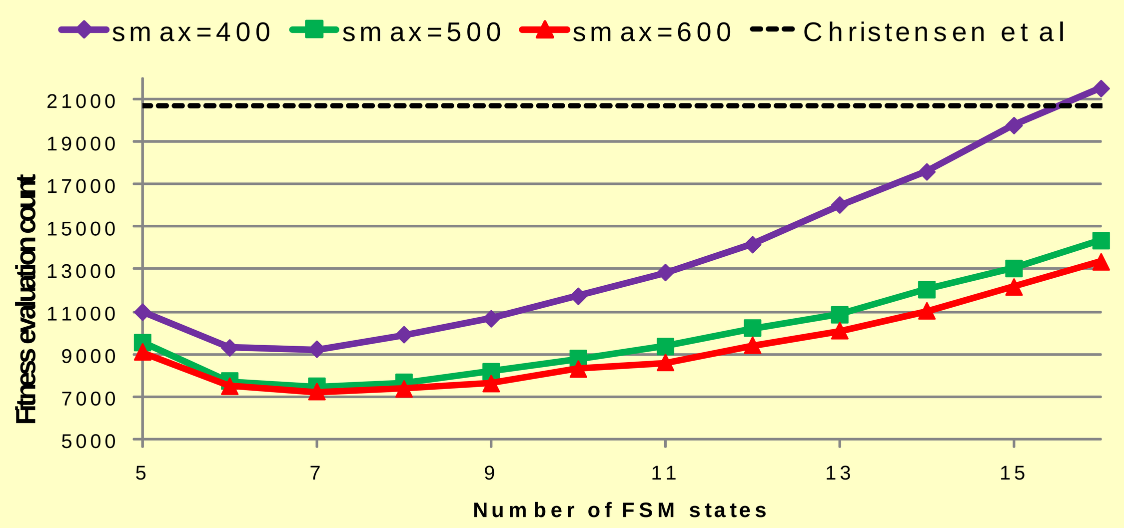


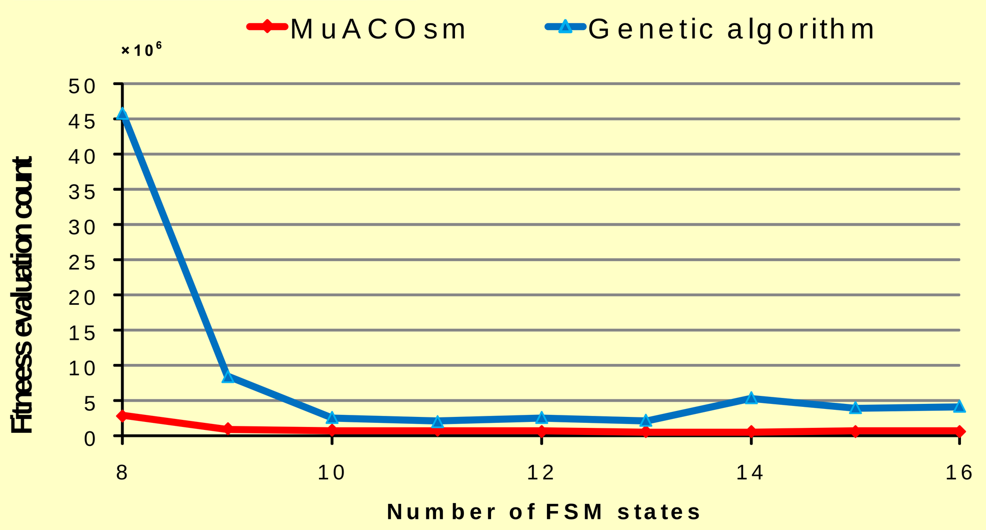
- MuACOsm is five times faster than evolution strategy

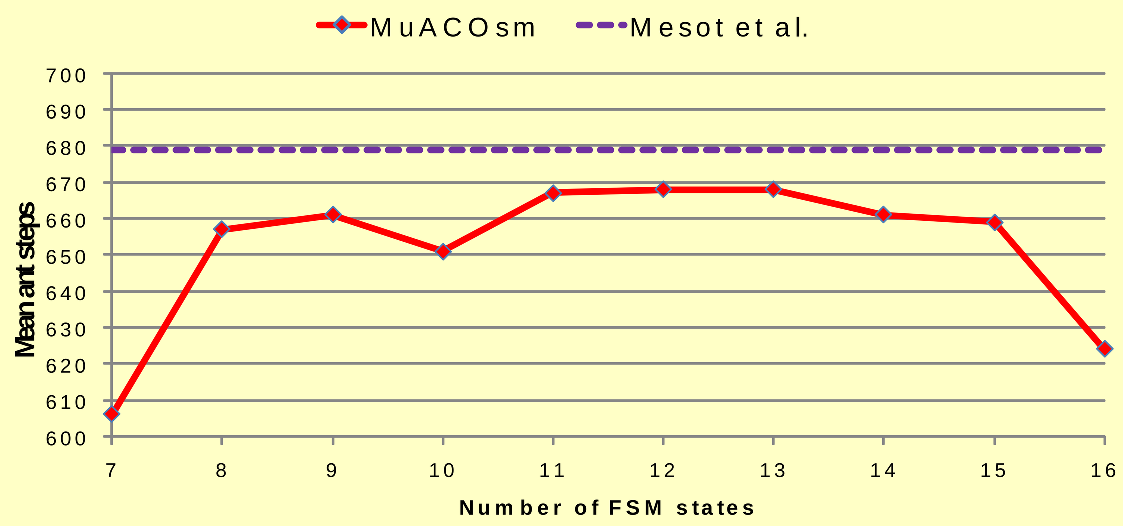
Auxiliary trail 2



- MuACOsm is six times faster than evolution strategy

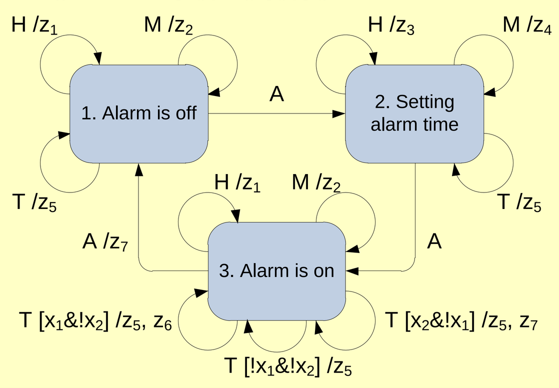






Experimental Results: Inducing EFSMs from test examples

Extended FSM:
- S – set of states
- Σ – set of input events
- Δ – set of output actions
- X – set of Boolean input variables
- $\delta : \Sigma$□E□$2^X \to S$ – transition function
- $\lambda : \Sigma$□E□$2^X \to Z^*$ – action function
- $s_0 \in S$ – initial state



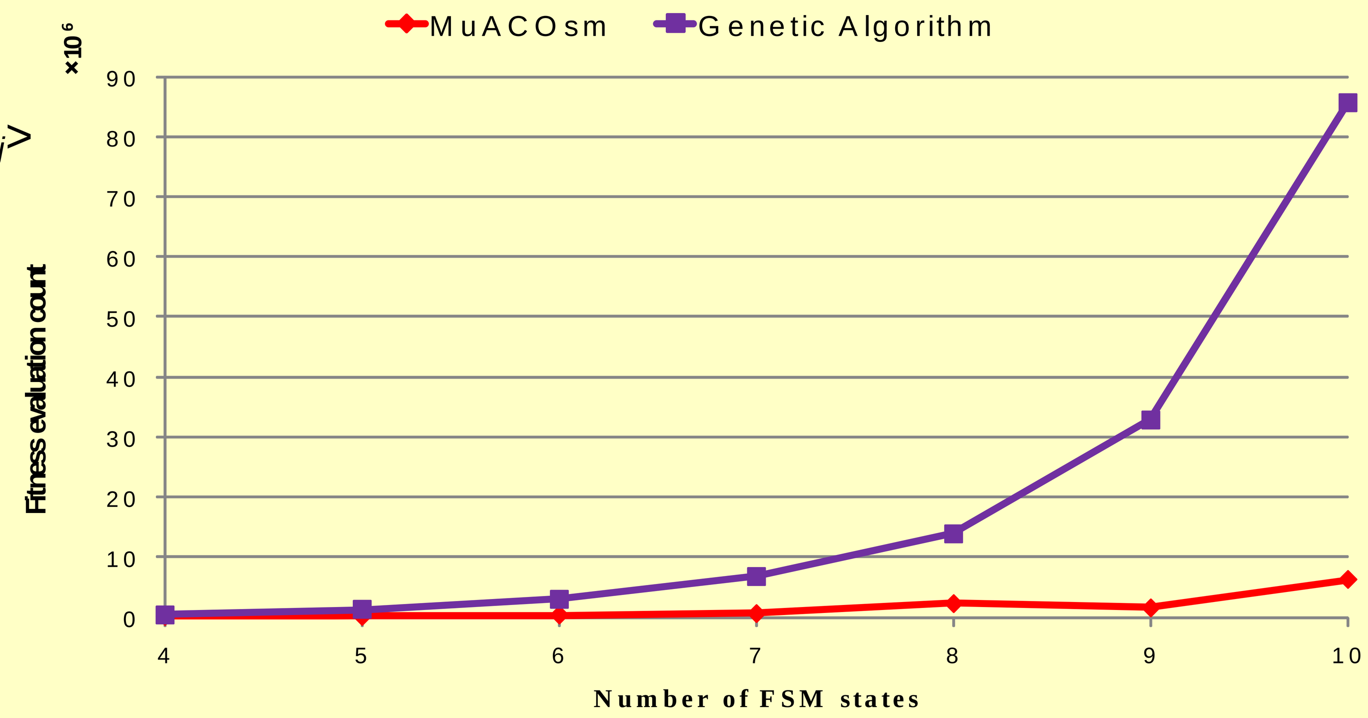
Input data:
- Number of states N and sets Σ and Δ
- Set of test examples T
- T_i=<events sequence I_j, output sequence O_j>

Set of tests → Induction Algorithm → EFSM

Fitness function:

$$f' = \frac{1}{|T|}\sum_{j=1}^{|T|}\left(1 - \frac{ED(O_j, A_j)}{\max\left(len(O_j), len(A_j)\right)}\right)$$

$$f = 100 \cdot f' + \frac{1}{100} \cdot (100 - n_{trans})$$



Experimental setup:
- 2 input events
- 2 output actions
- Max output actions = 2
- One input variable
- 100 experiments
- Tests size = $150 \cdot N_{states}$

Publications

- Chivilikhin D., Ulyantsev V. Learning Finite-State Machines with Ant Colony Optimization // Lecture Notes in Computer Science, 2012, Volume 7461/2012, pp. 68-275
- Chivilikhin D., Ulyantsev V., Tsarev F. Test-Based Extended Finite-State Machines Induction with Evolutionary Algorithms and Ant Colony Optimization / Proceedings of the 2012 GECCO Conference Companion on Genetic and Evolutionary Computation. NY.: ACM. 2012, pp. 603 – 606.
- Ulyantsev V., Tsarev F. Extended Finite-State Machine Induction using SAT-Solver / Proceedings of the Tenth International Conference on Machine Learning and Applications, ICMLA 2011, Honolulu, HI, USA, 18-21 December 2011. IEEE Computer Society, 2011. Vol. 2. P. 346–349.

Summary

- MuACOsm outperforms all published algorithms on inducing FSMs for Artificial Ant Problem
- MuACOsm significantly outperforms GA on inducing EFSMs from test examples

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