

Comparing Metaheuristic Algorithms for Error Detection in Java Programs



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Motivation

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- Concurrent software is difficult to test ...
- ... and it is in the heart of a lot of critical systems



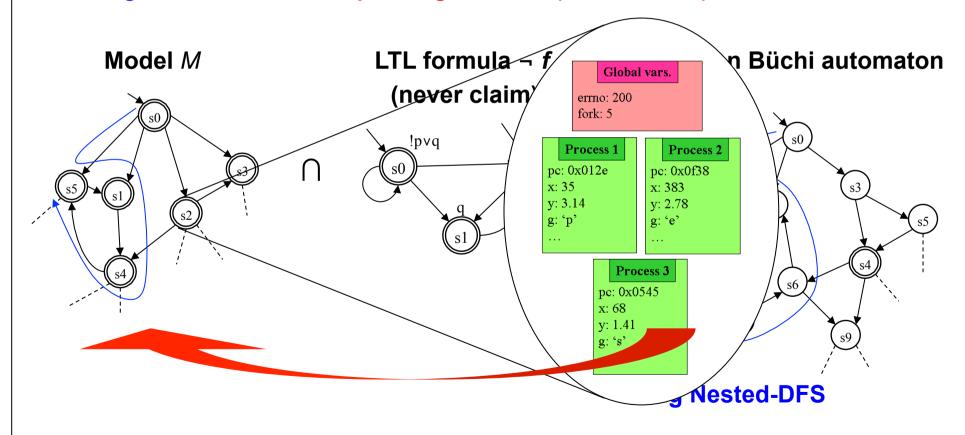


- Techniques for proving the correctness of concurrent software are required
- Model checking → fully automatic
- Traditional techniques for this purpose have problems with large models
- We compare several metaheuristics and classical algorithms for model checking



Explicit State Model Checking

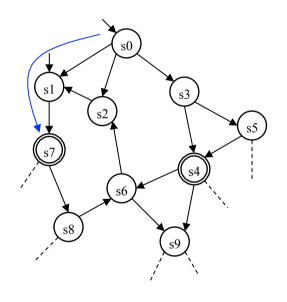
- Objective: Prove that model M satisfies the property f: $M \models f$
- In the general case, f is a temporal logic formula (LTL, CTL, etc.)





Safety properties

$$\forall \sigma \in S^{\omega} : \sigma \nvdash \mathcal{P} \Rightarrow (\exists i \geq 0 : \forall \beta \in S^{\omega} : \sigma_i \beta \nvdash \mathcal{P})$$



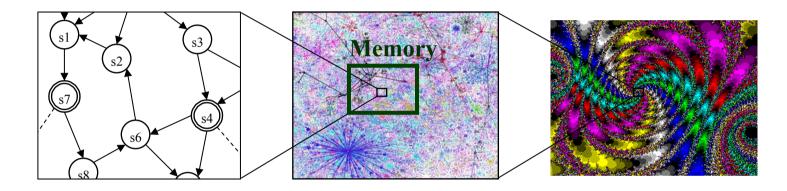
Properties in JPF

- Exceptions
- Deadlocks

- An error trail is an execution path ending in an error state
- The search for errors is transformed in a graph exploration problem (DFS, BFS)

State Explosion Problem

Number of states very large even for small models

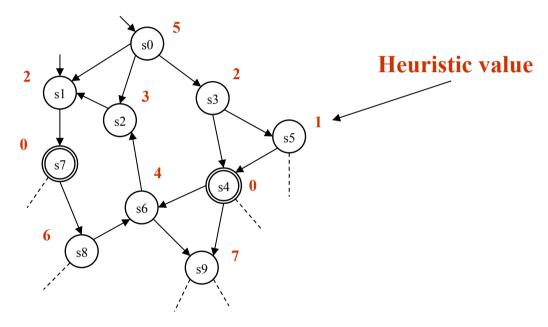


- Example: Dining philosophers with n philosophers $\rightarrow 3^n$ states
- For each state we need to store the heap and the stacks of the different threads
- Solutions: collapse compression, minimized automaton representation, bitstate hashing, partial order reduction, symmetry reduction
- Large models cannot be verified but errors can be found



Heuristic Model Checking

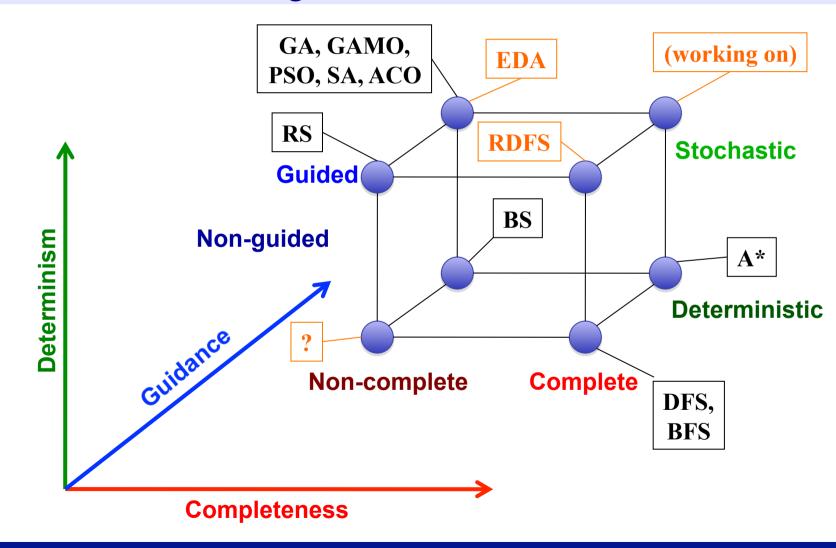
The search for errors can be directed by using heuristic information



- Different kinds of heuristic functions have been proposed in the past:
 - Formula-based heuristics
 - Structural heuristics

- Deadlock-detection heuristics
- State-dependent heuristics

Classification of Algorithms





Genetic Algorithm

```
P = \text{generateInitialPopulation}();

\text{evaluate}(P);

\text{while not stoppingCondition}() \text{ do}

P' = \text{selectParents}(P);

P' = \text{applyVariationOperators}(P');

\text{evaluate}(P');

P = \text{selectNewPopulation}(P, P');

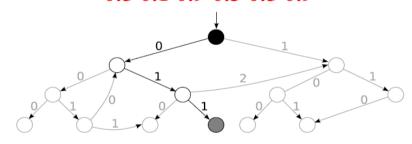
\text{end while}

\text{return} the best found solution
```

Solution encoding

(floating point values)

0.5 0.1 0.9 0.3 0.5 0.9



Crossover

```
0.5 0.1 0.9 0.3 0.5 0.9
0.2 0.6 0.1 0.7 0.8 0.4 0.2 0.0 0.6 0.2 0.6 0.1 0.7 0.8 0.4 0.9 0.3 0.5 0.9
```

Mutation

 $0.5 \ 0.1 \ 0.9 \ 0.3 \ 0.5 \ 0.9 \rightarrow 0.5 \ 0.1 \ 0.6 \ 0.3 \ 0.5 \ 0.9$



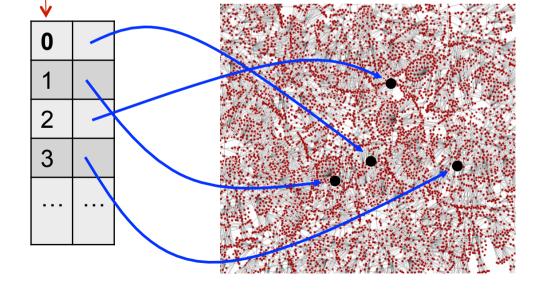
Genetic Algorithm with Memory Operator

Solution encoding

(floating point values)

0.5 0.1 0.9 0.3 0.5 0.9

Index in a table of states







Particle Swarm Optimization

P = generateInitialPopulation(); **while** not stoppingCondition() **do**evaluate(P);
calculateNewVelocityVectors(P);
move(P);

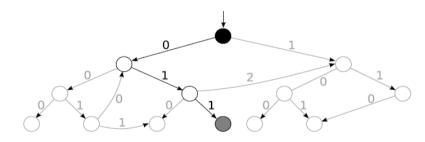
end while

return the best found solution

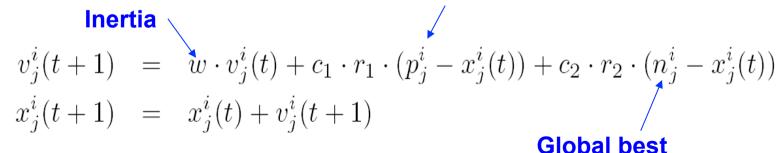
Particles

 $0.2 - 1.4 - 3.5 \rightarrow Position (solution)$

1.0 10.3 7.2 \rightarrow Velocity



Personal best

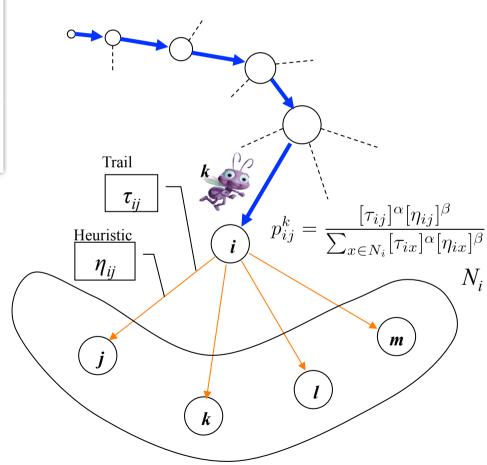




Ant Colony Optimization

procedure ACOMetaheuristic
ScheduleActivities
ConstructAntsSolutions
UpdatePheromones
DaemonActions // optional
end ScheduleActivities
end procedure

- The ant selects stochastically its next node
- The probability of selecting one node depends on the pheromone trail and the heuristic value (optional) of the edge/node
- The ant stops when a complete solution is built





Simulated Annealing

```
S = \operatorname{generateInitialSolution}();
T = \operatorname{initialTemperature};
\operatorname{while not stoppingCondition}() \text{ do}
N = \operatorname{getRandomNeighbor}(S);
\Delta E = \operatorname{energy}(N) - \operatorname{energy}(S);
\operatorname{if } \Delta E > 0 \text{ OR random}(0,1) < \operatorname{probabilityAcceptance}(\Delta E, T) \text{ then }
S = N
\operatorname{end if}
T = \operatorname{updateTemperature}(T);
\operatorname{end while}
\operatorname{return } S
```

 $probabilityAcceptance(\Delta E, T) = e^{\frac{\Delta E}{T}}$

Neighbor

 $0.5 \ 0.1 \ 0.9 \ 0.3 \ 0.5 \ 0.9 \rightarrow 0.5 \ 0.1 \ 0.6 \ 0.3 \ 0.5 \ 0.9$



Parameterization Hit Rate Length of Error Trails

Parameterization

• We used 3 scalable and 2 non-scalable models for the experiments

Program	Lo	20	Processes
dinj	j=4 to	1	j+1
phij —	j=4 to	36 3	j+1
marj	186	4	j+1
giop	74 j=2 to	10 3	7
garp	458	7	7

- Maximum number of expanded states: 200 000
- Fitness function:

$$f(x) = deadlock + numblocked + \frac{1}{1 + pathlen}$$

100 independent executions of stochastic algorithms



Parameterization Hit Rate Length of Error Trails

Hit rate

Introduction

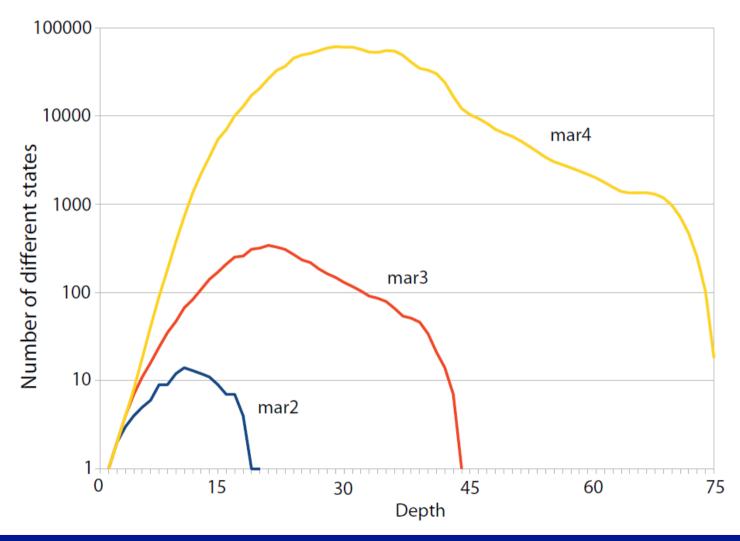
Problem	DFS	BFS	A*	GA	GAMO	PSO	SA	ACOhg	RS	BS
$\mathtt{phi}\ 4$	100	100	100	100	100	100	100	100	100	100
phi 12	0	0	0	100	100	100	100	100	100	100
$\mathtt{phi}\ 20$	0	0	0	100	100	100	100	100	100	100
$\mathtt{phi}\ 28$	0	0	0	100	100	100	100	100	100	100
$\mathtt{phi}\ 36$	0	0	0	82	100	53	79	100	100	100
$\mathtt{din}\ 4$	100	100	100	100	100	100	100	100	100	100
$\mathtt{din}\ 8$	100	0	0	100	100	100	76	100	96	100
${\tt din}\ 12$	100	0	0	100	96	85	13	68	0	100
${\tt din} \ 16$	0	0	0	91	58	20	0	2	0	100
${\tt din}\ 20$	0	0	0	52	24	0	0	0	0	100
mar 2	100	100	100	100	100	100	100	100	100	100
$\mathtt{mar}\ 4$	100	100	100	100	100	100	96	100	100	100
mar 6	100	0	0	100	100	100	100	100	100	100
mar 8	100	0	0	100	95	100	100	100	100	100
mar 10	100	0	0	100	25	100	100	100	100	100
giop	100	0	0	100	68	100	100	100	100	100
garp	0	0	0	100	2	80	87	87	100	0



Parameterization Hit Rate Length of Error Trails

Hit rate

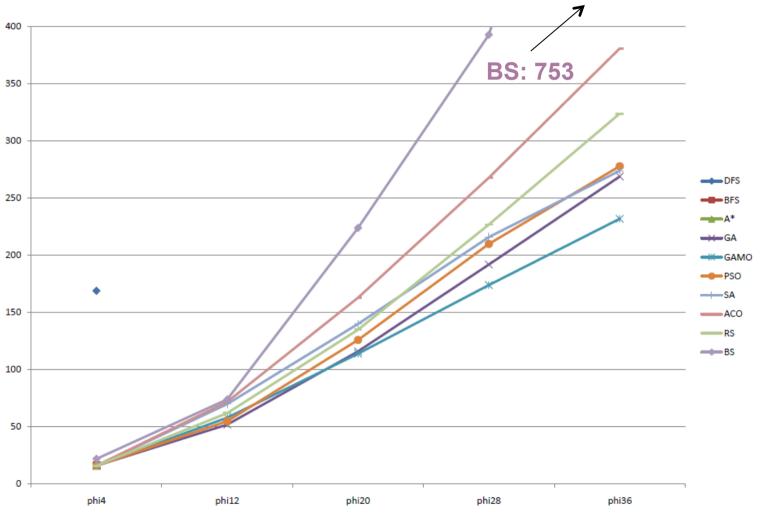
Introduction





Parameterization Hit Rate Length of Error Trails

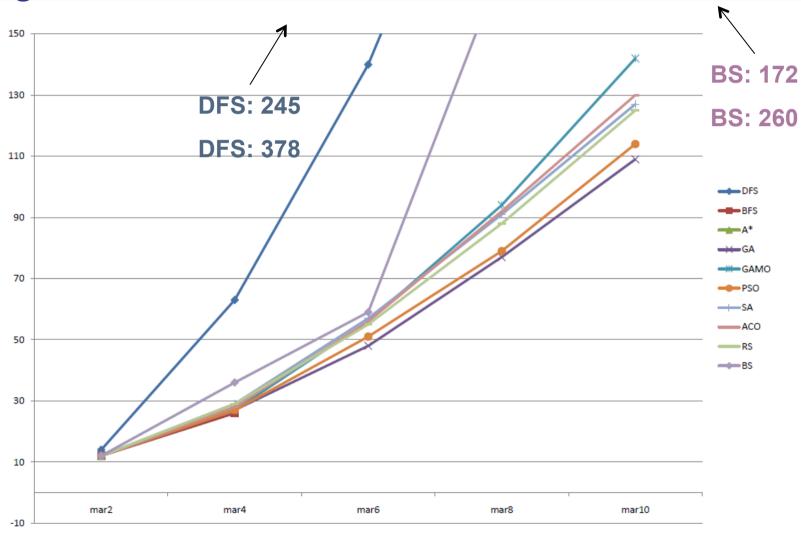
Length of Error Trails





Parameterization Hit Rate Length of Error Trails

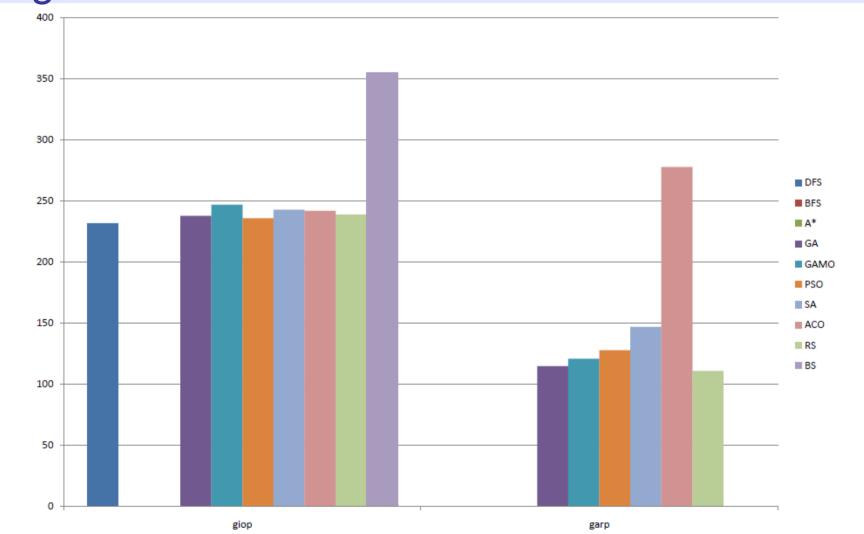
Length of Error Trails





Parameterization Hit Rate Length of Error Trails

Length of Error Trails





Conclusions & Future Work

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Conclusions

- Metaheuristics are more effective than classical algorithms in finding errors
- Beam Search has advantages over complete search algorithms
- An even distribution of the search in depth levels tends to raise hit rate
- Stochastic algorithms obtain short error trails

Future Work

- Design a stochastic complete guided algorithm to find errors and verify
- Design of hybrid algorithms to more efficiently explore the search space
- Explore the design of parallel metaheuristics for this problem

Comparing Metaheuristic Algorithms ssbse for Error Detection in Java Programs



Thanks for your attention !!!

