Model Checking Cyber-Physical Systems using Particle Swarm Optimization

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Abstract. We present a novel approach to the problem of model checking cyber-physical systems. We transform the model checking problem to an optimization one by designing an objective function that measures how close a state is to a violation of a property. We use particle swarm optimization (PSO) to effectively search for a state that minimizes the objective function. Such states, if found, are counter-examples describing safe states from which the system can reach an unsafe state in one time step. We illustrate our approach with a controller for the Quickbot ground rover. Our PSO model checker quickly found a bug in the controller that could cause the rover to collide with an obstacle.

1 Introduction

Dealing with the “state explosion problem” in model checking has been an active research area for many years. Progress has been made by using abstraction to reduce the size of search space [3], representing state space symbolically [6], bounding the number of steps when unrolling the FSM [2], or using the sheer power of parallel computing [1].

In this paper, we propose to transform the model checking problem into an optimization problem. The intuition is that if we can define an objective function that measures how close a state is to an unsafe state, then we can use available optimization techniques to optimize it. We propose an objective function such that it has a value of zero if the state is one step away from some unsafe state. Otherwise, it has some positive value depending on how far the next state is from an unsafe state. This design of objective function makes sure that when an optimizer finds an optimal state that nullify the objective function, there is a feasible transition from that state to an unsafe state.

We use Particle Swarm Optimization [5] (PSO) to optimize the objective function. PSO is a randomized approximation algorithm for finding the value of a parameter that minimizes an objective function. Using PSO is not mandatory in our approach. Other optimization techniques such that gradient descent or simulated annealing can be used in place of PSO. We chose PSO because the objective function can be nonlinear and is not required to be differentiable. PSO is also proved to be effective in our case study.
Our approach differs from statistical model checking in at least two aspects. First, the goal of statistical model checking is to provide a statistical guarantee while our goal is to find a bug. As a result, we terminate the optimizer as soon as a bug is found. Second, statistical model checking uniformly explores the state space whereas in our implementation, although PSO starts from a uniform distribution of particles, it moves the particles in strategically calculated directions so that they converge to an optimal solution.

A similar approach using genetic algorithms [4] was proposed. However, this approach is more complicated than optimizing an objective function.

We demonstrate the effectiveness of our approach with a case study of finding bugs in a controller for the Quickbot ground rover. Our PSO-based model checker was able to quickly find a bug that would cause a collision with an obstacle.

2 The Quickbot Controller Case Study

We conducted a case study of our approach using the Sim.I.am robot simulator. Sim.I.am allows one to write and test mobile robot controllers in Matlab, and then deploy these controllers on actual robots such as the Quickbot [7]. We model-checked the default Quickbot controller that comes with Sim.I.am for possible violations of collision-freedom (CF) property. The CF property ensures the rover never collides with an obstacle. We used the latest source code of Sim.I.am (https://github.com/jdelacroix/simiam/tree/cd67b5b97d67b1d32333c0a33a51cf5116640a9).

We search for states that would lead to a collision in the next time step. The state vector is \( s = (x, y, \theta, \omega, x_T, y_T) \), where \( x, y \) are initial position of the rover \( \theta, \omega \) are initial heading angle and initial rotational velocity of the rover, \( x_T, y_T \) are target location. We did not include linear velocity \( v \) in the state vector because the Quickbot controller sets \( v \) to be a constant and only controls \( \omega \). We design an objective function \( J(s) \) that measures how close a state is to a collision. For a state \( s = (x, y, \theta, \omega, x_T, y_T) \), we initialize the rover with the initial position \((x, y)\), heading angle \( \theta \) and rotational velocity \( \omega \), and then run the controller for one time step to obtain the next state \( s' = (x', y', \theta', \omega', x_T, y_T) \) (target location does not change). If the rover collides with an obstacle at the next position \( (x', y') \) then \( J(s) = 0 \). Otherwise \( J(s) = \min \text{distance from } (x', y') \) to any obstacle. Algorithm 1 describes the objective function. Clearly \( s \) is a global minimum iff \( J(s) = 0 \). We say \( s \) is a counter-example if \( s \) is a global minimum.

We used Matlab’s built-in particle swarm optimization function particleswarm to optimize \( J(s) \). If particleswarm succeeds in finding a global minimum, then we find a bug in the controller.

We ran our PSO-based model checker (PSO-MC) and caught a bug that would make the rover collide with an obstacle. Each run of the PSO-MC took about 3-4 minutes on a laptop with Core i7-7500 and 16 GB of RAM. We ran PSO multiple times and each time it found a different counter-example. Fig. 1 shows four such counter-examples. These counter-examples suggest that the Quickbot controller is susceptible to collision when turning at an obstacle.
corner. We plan to further investigate this bug in future work. Fig. 2 shows the states that PSO-MC searched. Clearly PSO-MC did not uniformly visit states but instead steer the particles to converge at an optimal solution, which is a collision state.

\[
\text{Input: } x, y, \theta, \omega, x_T, y_T, dt, \text{ controller, rover, map}
\]

\[
\text{Output: } J
\]

// Initialize the plant to initial state
Init(rover, x, y, \theta, \omega);

// Run controller for one time step
Execute(controller, rover, map, dt);

// Get the rover’s new position
\[x', y'] = \text{rover.position};

// Calculate cost at the new position
if collision(x', y', map)
    J = 0;
else
    J = MinDistanceToObstacle(x', y', map);
end if

Algorithm 1: Objective function

3 Conclusions

We have presented a novel approach based on particle swarm optimization to model check cyber-physical systems. We demonstrated how our approach was able to find a bug in a controller for the Quickbot ground rover. Currently the Quickbot case study assumes a map of obstacle locations and shapes is given. We plan to include obstacles in the search space so that PSO can also find obstacle configurations that expose bugs in the controller. We also plan to apply our method to other systems and properties.

References

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Fig. 1. Four counter-examples found from four independent runs of our PSO-based model checking algorithm. The green dots are initial positions, the black dots are targets, and the red rectangles are obstacles.

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Fig. 2. All the paths examined by PSO before it found a counter-example. As evidence here, PSO was able to effectively move the particles to converge at an optimal solution.