

Progress on Powertrain Verification Challenge with C2E2*

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Abstract. In this paper, we present the progress we have made in verifying the benchmark powertrain control systems introduced in the last ARCH workshop. We implemented the algorithm reported in [8] in the hybrid system verification tool C2E2 for automatically computing local discrepancy (rate of convergence or divergence of trajectories). We created Stateflow translations of the original models to aid the processing using C2E2 tool. We also had to encode the different driver behaviors in the form of state machines. With these customizations, we have been successful in verifying one of the easier (but still challenging) benchmarks from the powertrain suite. In this paper, we present some of the engineering challenges and describe the artifacts we created in the process.

1 The Powertrain Benchmarks

The benchmark suite of powertrain control systems were published in [10,9] as challenge problems for hybrid system verification. The suite has a set of Simulink™ models with increasing levels of sophistication and fidelity. At a high-level, all the models take inputs from a driver (throttle angle) and the environment (sensor failures), and define the dynamics of the engine. The key controlled quantity is the air to fuel ratio which in turn influences the emissions, the fuel efficiency, and torque generated.

The first model (model 1) is the most complex. It has look-up tables, delayed differential equations, and switches. Models 2 and 3 are simpler but still complicated enough for most hybrid verification tools. Model 3 is a hybrid automaton with polynomial differential equations and continuously computed control inputs, and Model 2 is similar but with nonlinear differential equations and both continuous and discretely sampled variables. The requirements for the system are stated in signal temporal logic (STL). A typical property, for example, $\diamond_t(x \in [x_{eq} - \epsilon, x_{eq} + \epsilon])$, states that after t units of time, the continuous variable x is within the range $x_{eq} \pm \epsilon$.

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Breach [2] and STaliro [1] have been used for finding counterexamples (or falsifying) models in [12,10,11,3]. In this paper we discuss of the progress we have made in verifying models 2 and 3 using our verification tool C2E2 [5,4] and present the artifacts we have created in the process.

2 Background on C2E2

C2E2 implements a generic, simulation-based, algorithm for bounded time verification of invariant and temporal precedence properties of nonlinear hybrid models (see [4,5,6] for details). The algorithm iteratively computes more and more precise over-approximations of the reachable states of the system until it either proves the property (the requirement) or finds a counter-example.

Our current implementation does not use hybrid simulations, instead, it generates over-approximations for each location, finds the intersection of the reachtube with the out-going guards from that location, and continues with these intersections as the initial sets in the next location. The key step in the algorithm is to compute and refine reach set over-approximations for ODEs for a given location. This step uses validated simulations and discrepancy functions that give a bound on the convergence (divergence) of trajectories starting from neighboring states [4].

Finding discrepancy functions for nonlinear models can be challenging. One of the main developments that enabled this verification, is the implementation of a new algorithm in C2E2 (presented in detail in [8]) for automatic computation of local discrepancy along trajectories of the system. Using this improved C2E2, we were not only able to find counterexamples, but also verify the key STL requirements of the powertrain benchmark in the order of minutes.

In this paper, we use the algorithm presented in [8] for computing local discrepancy functions on-the-fly along validated simulations. This algorithm uses the Jacobian J_f and a Lipschitz constant L_f of the ODE. First it computes a coarse over-approximation $S(x_i)$ of the reach set from a simulation point for a short duration. Then it computes an exponential (possibly negative) bound on the divergence rate of trajectories over $S(x_0)$ by finding a bound on the maximum eigenvalue of the symmetric part of the Jacobian J_f over the region $S(x_0)$. We refer the reader to the technical report [8] for the details of this algorithm.

For verifying the powertrain system, we implemented the local discrepancy algorithm in C2E2¹. This modified implementation only requires the user to supply the Jacobian matrix of the system. The eigenvalues of the symmetric parts of the Jacobian are computed using Eigen library [7]. For maximizing the norm of error matrices our implementation uses interval arithmetic.

¹The modified tool and related files are available from <http://publish.illinois.edu/c2e2-tool/powertrain-challenge/>

3 Model Transformation

We transform the SimulinkTM diagram of the benchmarks with switching blocks, to Stateflow models which essentially capture hybrid automata. Models 2 and 3 of [10] translate to hybrid automata with 4 locations and 5 continuous variables. The locations are *startup*, *normal*, *power*, and *sensor_fail*. The continuous variables are: (a) intake manifold pressure (p), (b) intake manifold pressure estimate (p_e), (c) air-fuel ratio (λ), (d) integrator state (i), (e) throttle angle (θ_{in}). These translated Stateflow models are made available as part of this paper.

This transformation is relatively straightforward and has been described in [13]. The Simulink model uses several function blocks connected by feedback lines. While the Stateflow model uses differential equations and transitions. The transitions are decided by the boolean operation of several user inputs like throttle angle and sensor failure. Keeping these input signals constant, we rewrite the differential equations of the four discrete modes in Stateflow blocks, and then replace the function block *Switch* in Simulink with *Transitions*.

Model 2 (the second model in [10]) differs in two aspects: (1) the right-hand side of the system equations are general nonlinear functions instead of polynomial functions; (2) only two of the four variables are continuous, other two are discrete variables updated periodically. Only the differential equations of the two continuous variables would appear in the Stateflow modes. We introduce the third variable t with the dynamic $\dot{t} = 1$. Initially $t = 0$, whenever $t =$ discrete sample time, there will be a transition to the mode itself with transition action $t = 0$ and the update of the two discrete variables.

C2E2 currently handles only closed automaton models. Therefore, for every driver behavior of interest, we explicitly construct a family of switching signals that determine the timing of the mode switches. The initial set of the automaton is a ball in the state space which corresponds to the measurement uncertainty in state components.

The goal of the powertrain control system is to maintain the air-fuel ratio at a desired value for optimal functioning of internal combustion engine under different driving behaviors and conditions. These control objectives or requirements are stated in [10] using STL formulas. An example requirement for the *normal* mode of operation is the following:

$$rise \Rightarrow \square_{(\eta, \zeta)}(0.98\lambda_{ref} \leq \lambda \leq 1.02\lambda_{ref}), \quad (1)$$

which can be read as “If the throttle angle θ_{in} changes from 0 to 60, denoted by the event *rise*, then the air-fuel ratio λ should be in the range $[0.98\lambda_{ref}, 1.02\lambda_{ref}]$ after η time units and stay in that region until ζ time units. Here λ_{ref} is the desired value of air-fuel ratio and η and ζ are parameters of the property. We note that this type of requirements can also be expressed as bounded time invariants—the class of properties currently handled by C2E2. We simply need to introduce a *timer* variable that keeps track of time elapsed since the last occurrence of the relevant events like *rise* in the above example.

Coordinate Transformation. An important technical detail that makes the implementation scale is the coordinate transformation proposed in [8]. For Jacobian matrices with complex eigenvalues the local discrepancy computed directly using the above algorithm can be a positive exponential even though the actual trajectories are not diverging. This problem can be avoided by first computing a local coordinate transformation and then applying the algorithm. Coordinate transformation provides better convergence, but comes with a multiplicative cost in given by the condition number of the matrix. This trade-off between the exponential divergence rate and the multiplicative error has been tuned by choosing the time horizon over which the coordinate transformation is computed.

In our experiments, we have observed that the condition number for *startup* mode is 20 and for all other modes are of the order of 200. Thus, one cannot perform this coordinate transformation over small periods as this would lead to large errors in the overapproximations. Thus, the number of steps for which coordinate transformation should be applied is an engineering decision based on the condition number and the exponential rate of convergence. For verifying the powertrain control system, we have analyzed different possibilities and observed that coordinate transformation after every 3000 steps (i.e. 3 time units) provides overapproximation that is adequate for verification.

Results. Table 1 provides the results of verifying different STL properties. The first six properties provided in Table 1 are invariant properties. These invariant properties can be global (i.e. correspond to all modes) or could be restricted to a certain mode of operation provided in the *Mode* column. The invariants assert that the air-fuel ratio should not go out of the specified bounds. Observe that C2E2 could not only prove that the given specification is satisfied, but also that a stricter version of invariants for *startup* and *power* modes is violated. The next four properties are about the settling time requirements. These requirements enforce that in a given mode, whenever an action is triggered, the fuel air ratio should be in the given range provided after η (or η^{pwr} for power mode) time units. Similar to the invariant properties, C2E2 could also find counterexample for a stricter version of the settling time requirement (η^s settling time instead of η) in *power* mode. When C2E2 finds an overapproximation that violates a given property, it immediately terminates and hence C2E2 takes less time when it finds counterexamples. The parameters used for verification are $\eta = \eta^{pwr} = 1$, $\eta^s = 0.5$, $T_s = 9$, $T = 20$, $\lambda_{ref} = 14.7$, $\lambda_{ref}^{pwr} = 12.5$, and $\zeta = 4$.

5 Conclusion

In this paper, we have successfully applied the simulation based verification technique with local discrepancy functions to find counterexamples and verify the polynomial hybrid automata model of powertrain benchmark challenge.

The simulation based verification approach with on-the-fly discrepancy function shows a promising approach for verifying the polynomial hybrid model of the powertrain control system provided in model 3. One of the main challenges

Property	Mode	Sat.	Sim.	Time
$\square_{T_s, T} \lambda \in [0.8\lambda_{ref}, 1.2\lambda_{ref}]$	<i>all modes</i>	yes	53	11m58s
$\square_{[0, T_s]} \lambda \in [0.8\lambda_{ref}, 1.2\lambda_{ref}]$	<i>startup</i>	yes	50	10m21s
$\square_{[T_s, T]} \lambda \in [0.95\lambda_{ref}, 1.05\lambda_{ref}]$	<i>normal</i>	yes	50	10m28s
$\square_{[T_s, T]} \lambda \in [0.8\lambda_{ref}^{pwr}, 1.2\lambda_{ref}^{pwr}]$	<i>power</i>	yes	53	11m12s
$\square_{[0, T_s]} \lambda \in [0.98\lambda_{ref}, 1.02\lambda_{ref}]$	<i>startup</i>	no	2	0m24s
$\square_{[T_s, T]} \lambda \in [0.9\lambda_{ref}^{pwr}, 1.1\lambda_{ref}^{pwr}]$	<i>power</i>	no	4	0m43s
$rise \Rightarrow \square_{(\eta, \zeta)} \lambda \in [0.9\lambda_{ref}, 1.1\lambda_{ref}]$	<i>startup</i>	yes	50	10m40s
$rise \Rightarrow \square_{(\eta, \zeta)} \lambda \in [0.98\lambda_{ref}, 1.02\lambda_{ref}]$	<i>normal</i>	yes	50	10m15s
$(\ell = power) \Rightarrow \square_{(\eta^{pwr}, \zeta)} \lambda \in [0.95\lambda_{ref}^{pwr}, 1.05\lambda_{ref}^{pwr}]$	<i>power</i>	yes	53	11m35s
$(\ell = power) \Rightarrow \square_{(\eta^s, \zeta)} \lambda \in [0.95\lambda_{ref}^{pwr}, 1.05\lambda_{ref}^{pwr}]$	<i>power</i>	no	4	0m45s

Table 1: Table showing the result and the time taken for verifying STL specification of the powertrain control system. Sat: Satisfied, Sim: Number of simulations performed. All the experiments are performed on Intel Quad-Core i7 processor, with 8 GB ram, on Ubuntu 11.10.

in extending this approach to Model 2 is the periodic inputs provided by the controller. In Model 2, the discretely updated controller updates the values of variable p_e and i at discrete time intervals using a control law that stabilizes the Fuel/Air to the required value. As the values of p_e and i are updated discretely, the discrepancy function using the technique provided in this paper would provide a coarse overapproximation. The nonlinearities in the control law make this task even more challenging. Hence new developments in computing the input-to-state discrepancy functions are required to extend the analysis to Model 2. In future, we wish to extend these techniques to handle higher fidelity models in the powertrain verification challenge.

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