Center for
Experimental Software Engineering

Requirements Extraction from Models of Automotive Software

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The Model Checking Problem

$$M \overset{?}{\models} \varphi$$

system / model

satisfies / possesses

property / requirement

The Synthesis Problem

$$? \models \varphi$$

The Requirements-Extraction Problem

$M \models ?$

Motivation for Requirements Extraction

- System comprehension
- Specification reconstruction
  - Missing / incomplete / out-of-date documentation
  - “Implicit requirements” (introduced by developers)

Requirements Extraction for Automotive Software

- Joint project: UMD, Fraunhofer, Bosch
- Outline
  - Automotive software development
  - Reqts-extraction via machine learning
  - Pilot study
  - Conclusion

Automotive Software

- Driver of innovation

  90% of new feature content based on sw [GM]
  50M+ lines of code [GM]

- Rising cost

  20% of 2006 vehicle cost due to software [Conti]

- Warranty, liability, quality

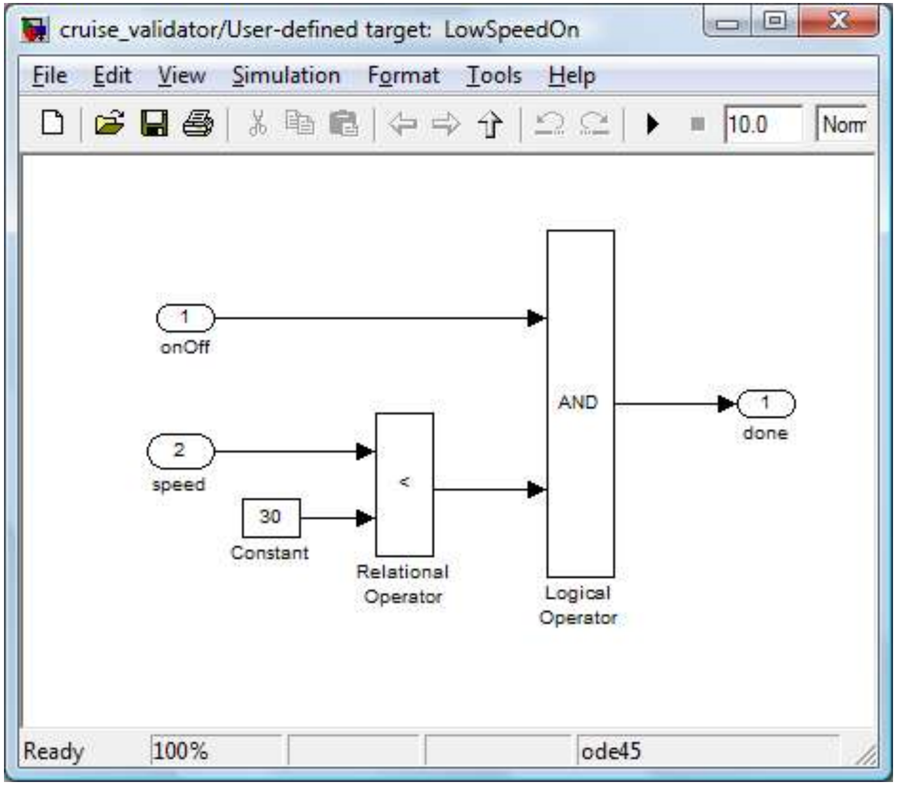
  High-profile recalls in Germany, Japan, US

Automotive Software Development

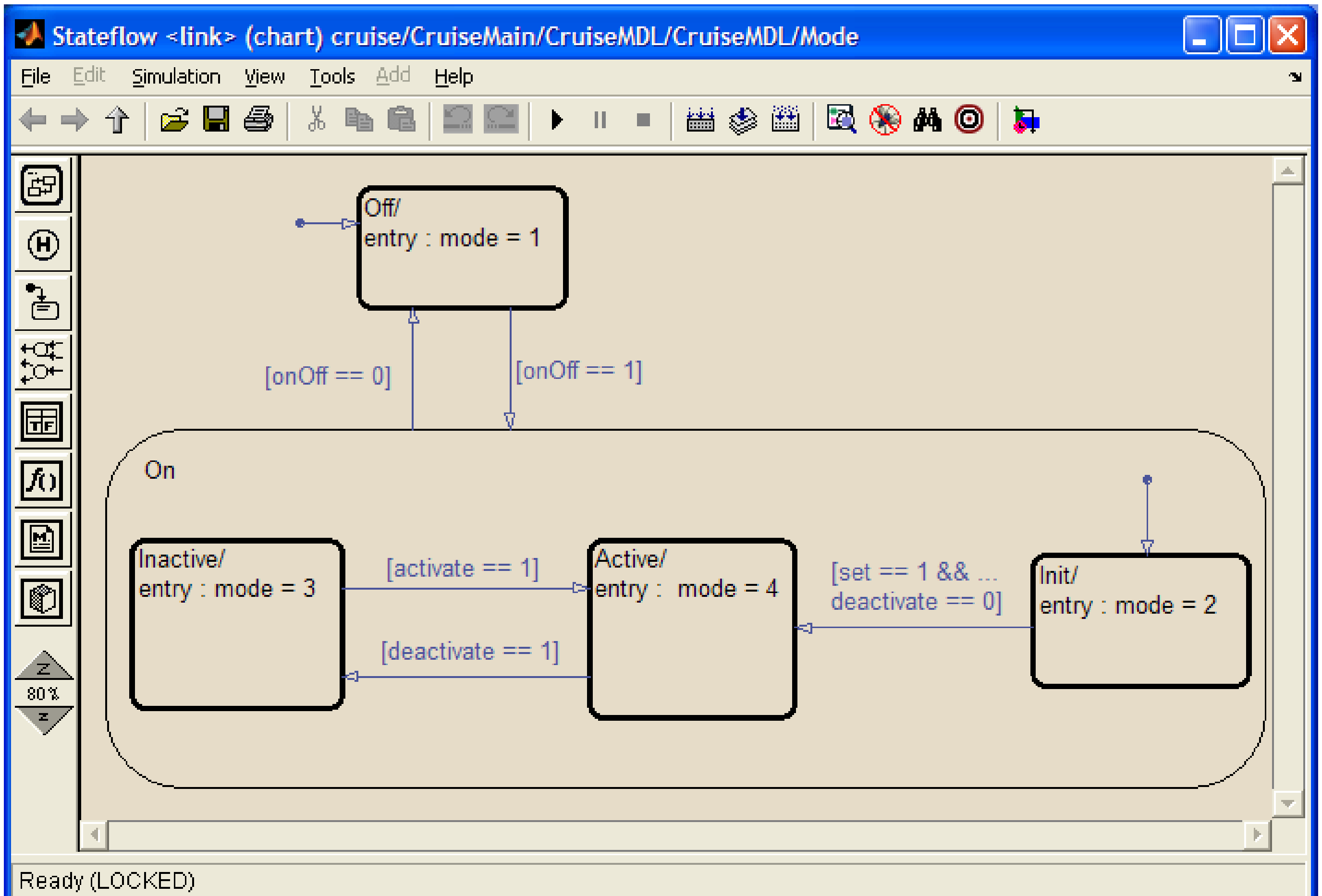
- Ensure high quality of automotive software
  - ... while preserving time to market
  - … at reasonable cost
- How?
  - Model-based development (MBD)
    Efficiencies in production
  - Automated testing
    Efficiencies in verification and validation (V&V)

Models: Simulink®

- Block-diagram modeling language of The MathWorks, Inc.
- Hierarchical modeling
- Simulation
- Continuous, discrete semantics



Models: Stateflow®

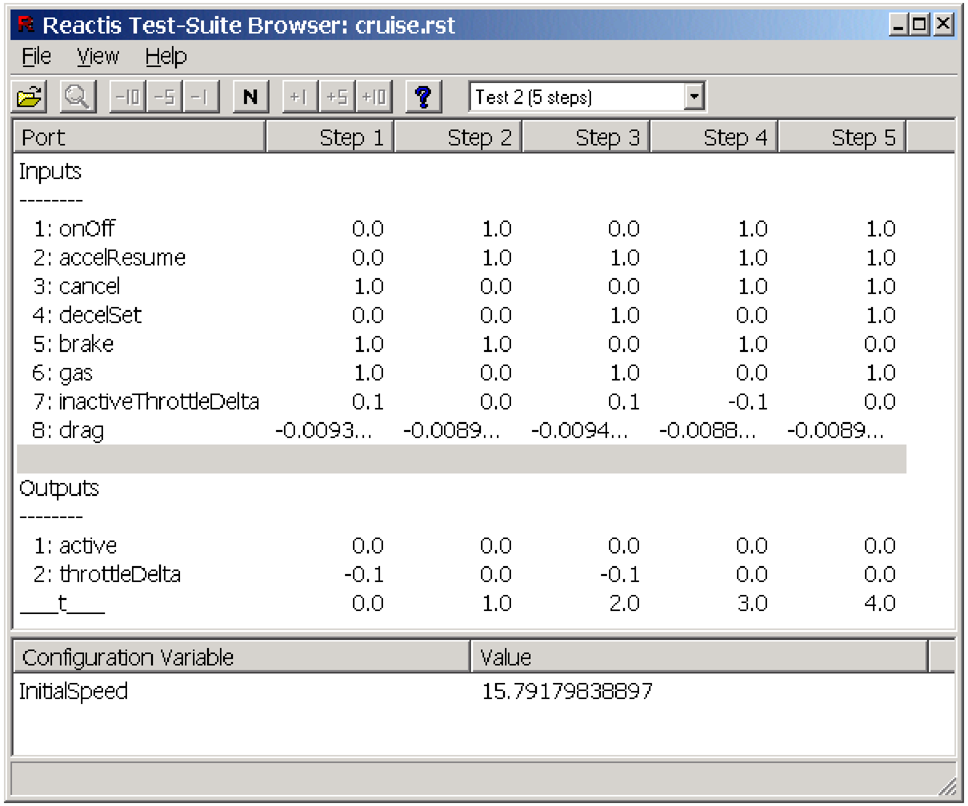


Semantics

- Simulink has different “solvers” (= semantics)
  - Continuous: inputs / outputs are signals
  - Discrete: inputs / outputs are data values
- Analog modeling: continuous solvers
- Digital-controller modeling: discrete solvers
  - Synchronous
  - Run-to-completion
  - Time-driven

Automated Testing: Reactis®

- Automatic test suites from Simulink / Stateflow
  - Maximize coverage
  - Capture outputs
- Uses
  - Compare models, systems
  - Model validation via *Instrumentation-Based Verification*



Port	Step 1	Step 2	Step 3	Step 4	Step 5
Inputs					

1: onOff	0.0	1.0	0.0	1.0	1.0
2: accelResume	0.0	1.0	1.0	1.0	1.0
3: cancel	1.0	0.0	0.0	1.0	1.0
4: decelSet	0.0	0.0	1.0	0.0	1.0
5: brake	1.0	1.0	0.0	1.0	0.0
6: gas	1.0	0.0	1.0	0.0	1.0
7: inactiveThrottleDelta	0.1	0.0	0.1	-0.1	0.0
8: drag	-0.0093...	-0.0089...	-0.0094...	-0.0088...	-0.0089...
Outputs					

1: active	0.0	0.0	0.0	0.0	0.0
2: throttleDelta	-0.1	0.0	-0.1	0.0	0.0
___t___	0.0	1.0	2.0	3.0	4.0

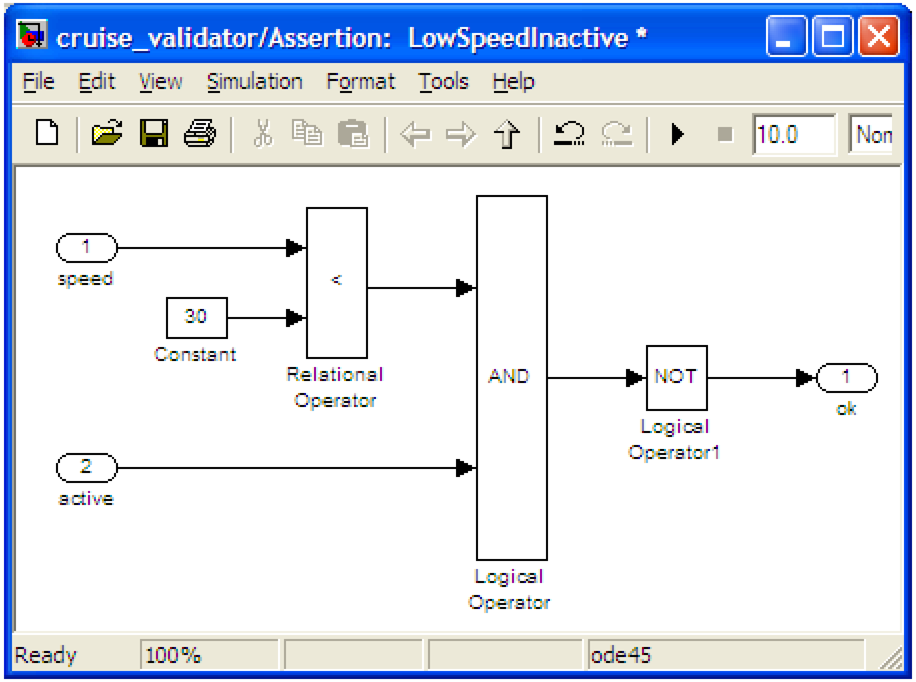
Configuration Variable	Value
InitialSpeed	15.79179838897

Coverage Testing via Guided Simulation

- Test = simulation run = *sequence* of I/O vectors
- Goal: maximize *model coverage*
  e.g. branch, state, transition, MC/DC, etc.
- Method: *guided simulation*
  - Simulate model, BUT
  - Choose input data to guide simulation to uncovered parts
  - Turn simulation runs into test data
- Input selection by Monte Carlo, constraint solving
- Implemented in Reactis®

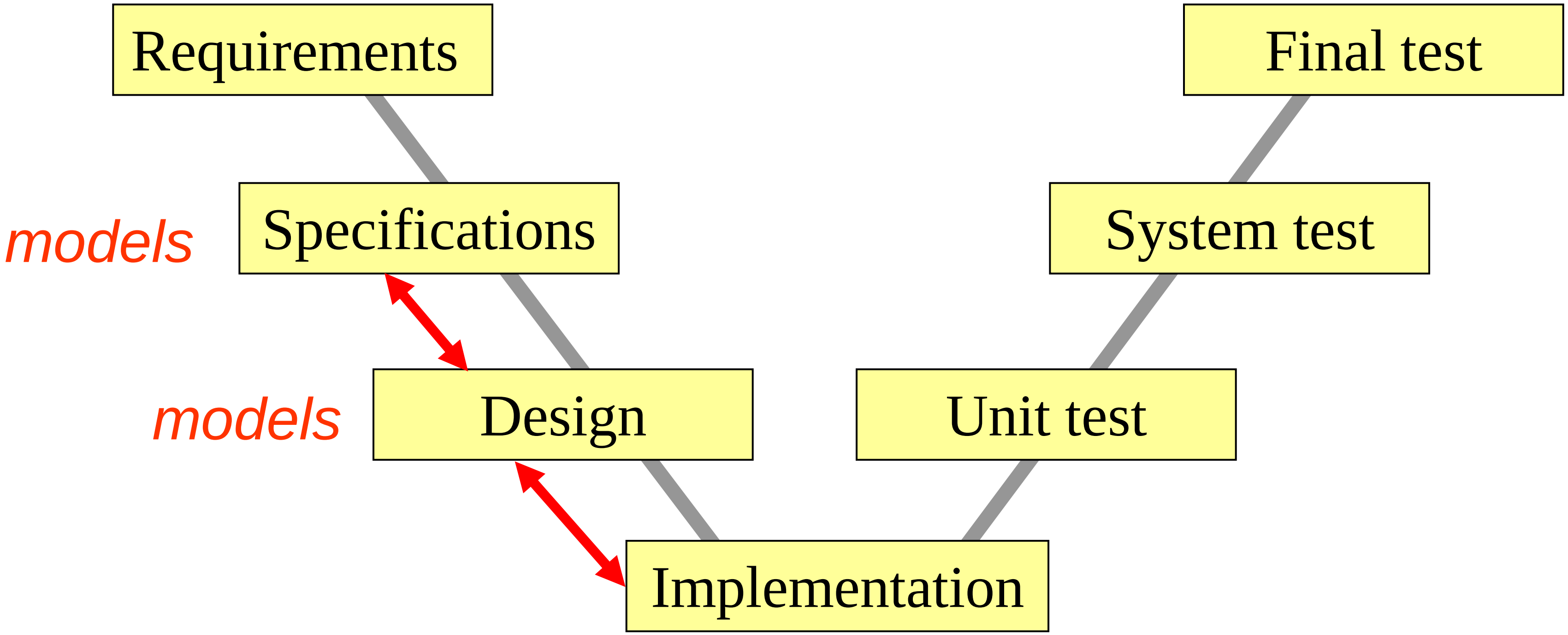
Instrumentation-Based Verification

- Formulate requirements as *monitor models*
  - Inputs: signals in model
  - Outputs: boolean flags
    - Flag = true: no violation
    - Flag = false: violation
- Instrument main model with monitors
- Test instrumented model to search for violations



"If speed is < 30, cruise control must remain inactive"

(Model-Based) Development



- Models formalize specifications, design
- Models support V&V, testing, code generation
- Models facilitate communication among teams

Requirements Extraction

- The extraction problem
  - Given: system (M)
  - Produce: requirements (φ)
- Approach
  - Generate test data satisfying *coverage criteria*
  - Use *machine learning* to propose invariants
  - Check invariants using *instrumentation-based verification*

Machine Learning

- Tools for inferring relationships among variables based on time-series data
  - Input: table

Time	*x*	*y*
0	1	0
1	-1	-1
2	2	1
…	…	…

  - Output: relationships ("association rules")
    e.g. $0 \leq x \leq 3 \;\; -> \;\; y \geq 0$

Machine Learning and Requirements Extraction

- General dea
  - Treat tests (I/O sequences) as experimental data
  - Use machine learning to infer relationships between inputs, outputs
- Our insight
  - Ensure test cases satisfy coverage criteria (e.g. branch coverage) to ensure "thoroughness"
  - Use IBV to double-check proposed relationships

Pilot Study: Production Body-Electronic Application

- Artifacts
  – Simulink model (ca. 75 blocks)
  – Requirements formulated as state machine
  – Requirements correspond to 42 invariants defining transition relation
- Goal: Compare our approach, random testing [Raz]
  – Completeness (% of 42 detected?)
  – Accuracy (% false positives?)

Pilot Study: Tool Chain

- Automated test-generation tool: Reactis
- Machine-learning tool: Magnum Opus
- Additional tooling
  - – Test-format conversions
  - – Automated generation of monitor models, instrumentation

Experimental Design

- Repeat five times
  1. Generate coverage tests (Reactis)
  2. Create invariants (Magnum Opus)
  3. Use IBV to double-check invariants (Reactis)
  4. Combine original, IBV tests, rerun 2, 3
- Repeat five times
  1. Generate random tests (Reactis)
  2. Create invariants (Magnum Opus)
  3. Use IBV to double-check invariants (Reactis)
  4. Create second set of random tests, combine with first
  5. Repeat 3

Experimental Results

- Hypothesis: coverage-testing yields better invariants than random testing
- Coverage results:

  95% of inferred invariants true
  97% of requirements inferred
  Two missing requirements detected
- Random results:

  55% of inferred invariants true
  40% of requirements inferred
- Hypothesis confirmed

Conclusions

- Coverage-testing yields better requirements
- IBV double-checks generated invariants effectively
- Future directions
  - Extraction of temporally complex requirements
  - Visualization of generated requirements
  - Analysis of “near-invariants”

Related Work

- Specification mining [Larus et al. / Biermann et al. / Su et al. / Necula et al. / …]
- DAIKON [Ernst et al.]
- IODINE [Hangal et al.]
- Invariants + BMC [Cheng et al.]

CMACS Collaboration: Computational Genomics

- Single-nucleotide polymorphisms (SNPs)
  - Locations in genetic code whose variations induce genetic traits
- Goal: develop model for predicting which SNPs cause which traits
  - Models are linear
  - Model development means discovering linear coefficients
- Problem: 100,000s of SNPs!
- Approach:
  - Use latest machine-learning techniques to speed up learning of coefficients
  - Combine with statistical tests to detect, eliminate “non-contributive” SNPs
- Collaborators: Tongtong Wu (UMD SPH), Sam Huang (UMD CS)

CMACS Collaboration: Stochastic Hybrid Control

- Hybrid-system modeling used in traditional control
  - Deterministic plant models (continuous)
  - Discrete controllers
- In real-world, plant behavior not fully predictable
- Goal: theory for modeling, analyzing stochastic hybrid systems
  - Basic modeling
  - Compositionality
  - Simulation
  - Reachability
- Collaborators: Steve Marcus, Rance Cleaveland

Thank You!

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