Uncertainty quantification in ground vehicle dynamics through high fidelity co-simulation

Master’s Thesis

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Explanation of the Title

Uncertainty quantification in ground vehicle dynamics through high fidelity co-simulation

Two parts

First: Develop a high fidelity simulation environment thorough the idea of “co-simulation”

Second: quantify uncertainties pertaining to model definition and model inputs
Part 1

A framework for high fidelity virtual prototyping of ground vehicles through co-simulation
What is co-simulation?

- Leverage 3 specialty software by combining their individual capabilities in a single simulation

  - ADAMS/Car
    - Vehicle Simulation
  - Powertrain Systems Analysis Toolkit
    - Powertrain Simulation
  - FTire
    - Tire Simulation
ADAMS/Car
ADAMS/Car

- A simulation tool for vehicle dynamics
  - Commercially available: Distributed by MSC software
  - Subsystems combined together to form a full vehicle assembly (details to follow)
  - State of art in the area of vehicle simulation
  - Well validated
  - Wide range of post-processing abilities: forces, displacements, accelerations and so on.
Vehicle model under consideration

- US Army’s High Mobility Multi-Wheeled Vehicle (HMMWV)
  - Not identical but fairly similar
HMMWV simulation over an uneven terrain
Motivation for co-simulation
Drawbacks of the ACAR model

- Powertrain System
  - Not sophisticated
  - Predefined in by property files: torque vs throttle vs engine rpm
  - Only conventional powertrain system
  - Can not predict fuel efficiency
Drawbacks of the ACAR model

- Tire models
  - Very basic tire models
  - Slow simulation speeds for “non-flat” roads
  - Inaccurate for simulations on roads with high frequency undulations (typically smaller than the tire circumference)
How to overcome these drawbacks?

- Use co-simulation to
  - Simulate the powertrain system in “Powertrain Systems Analysis Toolkit” (PSAT)
  - Simulate tire-terrain interactions in “FTire”
  - But at the same time, maintain the rest of the vehicle model in ADAMS Car
PSAT
Powertrain Systems Analysis Toolkit

- More sophisticated powertrain systems
  - conventional
  - electric
  - fuel cell
  - several varieties of hybrid (parallel, series, power split, series-parallel) powertrains
- Able to predict fuel economy
- Validated within 2% fuel economy for conventional and mild hybrid vehicles (Honda Insight, Ford P2000) and up to 5% for full hybrid vehicles (Toyota Prius)
- Modeled using MATLAB, Simulink
FTire
FTire

- Designed for even or uneven roadways
- Simulations on road irregularities even with extremely short wavelengths
- Fast (cycle time only 5 to 20 times real-time) and numerically robust
Co-simulation
Overview

- Matlab-Simulink is the preferred platform
  - Simulink model of ADAMS/Car vehicle is generated
    - FTire is invoked internally by ADAMS solver
  - Simulink model of the PSAT powertrain is generated
  - The two models are connected to run a combined simulation
Simulink Model of ACAR Vehicle
Simulink Model of PSAT powertrain
Data Transfer between the two models

- The vehicle + wheels + road blocks in PSAT model were replaced by ADAMS/Car model

![Diagram showing data transfer between ADAMS and PSAT]

- Driveline speed, longitudinal velocity
- Driveline torque, brake demand
Co-simulation ADAMS-PSAT

PSAT vehicle block is removed

ADAMS vehicle block is inserted in Simulink to work with PSAT

FTire used in ADAMS vehicle
Combined model
Co-simulation Results
Straight line Acceleration

1000 kg

1500 kg

2000 kg

2500 kg

3000 kg

3500 kg
Fuel Economy
CO$_2$ Emission

CO$_2$ emission vs Vehicle Mass for acceleration from 10m/s to 18m/s (attempted) in 60 seconds
Part 1: Wrap up

cosimulation documented in detail
Part 2

Uncertainty Quantification
The Uncertainty Side of the Problem

- Complex multibody systems are modeled and analyzed often times with incomplete information
  - External Force sometimes unknown
  - Terrain description is vague
  - Parameters associated with model change in time and from vehicle to vehicle
The Uncertainty Side of the Problem

- **Fundamental question:**
  - Given input uncertainties and model uncertainties, what can one say about the response of the system?

- **Specifically,**
  - I need statistical estimates (average response, confidence intervals, etc.) to be able to gauge the range of possible outcomes

- **Approach taken:**
  - Produce a statistical representation of the uncertainty in the inputs and propagate this uncertainty through the dynamics of the system
    - Rely on Gaussian Processes (GP) and Bayesian inference
Capturing Uncertainty

- Rely on Gaussian Processes (GP)
  - Collection of random variables, any finite number of them having a joint normal distribution
  - Completely defined by an average function $m(x)$ and a correlation function $k(x, x')$:

$$f(x) \sim \mathcal{GP}(m(x), k(x, x'))$$
Why/Where is This Relevant?

- Understanding the response (time evolution) of system
  - Virtual Prototyping
    - Simulate before you build
  - Real-Time predictive control
    - Is this vehicle going to roll over or not?
    - Am I going to start sliding and spin out of control?

- Condition-Based Maintenance (CBM)
  - Producing load histories with confidence intervals
    - Essential input in predicting the durability of a vehicle
UQ in MBS
~Proposed Framework~

- Summarized in image below
- Fleshed out over next slides
- General, but discussion placed in the context of vehicle simulation

1. Gather Data
2. Select Correlation Function
3. Run Parameter Identification (Maximum Likelihood Estimation)
4. Get Mean Vector and Covariance Matrix for Fine-Grid Distribution
5. Sample Posterior to Produce Data on Fine Grid
6. Run COTS Software (ADAMS) for Multibody Dynamics Analysis
Before Getting Too Abstract… (Typical Example)
Typical Example:

- Road information available on a sparse grid and/or with noise in it

Questions:
- How can you generate road information on a fine grid?
- How can you generate compatible road profiles on the same grid?
Gathering Data

● Why?
  ● Needed later in characterizing the underlying statistics of the uncertain information

● How?
  ● For our example, measure the road profile (height $y$ at each location $(x_{i,1}, x_{i,2})$)
  ● The more data, the better (at least in theory)
  ● Design of Experiments pertinent and relevant
Select Correlation Function

- Problem approached in a Bayesian framework
- Start with uniform prior on weights $\mathbf{w}$ for the regression function $f(x)$

\[
y = f(x) = \Phi^T(x)\mathbf{w} \quad \mathbf{w} \sim \mathcal{N}(0, \Sigma_p)
\]

\[
E[f(x)] = E[\Phi^T(x)\mathbf{w}] = \Phi^T(x) \cdot E[\mathbf{w}] = 0
\]

\[
cov(f(x), f(x')) = E[f(x)f(x')] = \Phi^T(x)E[\mathbf{w}\mathbf{w}^T]\Phi(x') = \Phi^T(x)\Sigma_p\Phi(x') \equiv k(x, x')
\]

\[
f(x) \sim \mathcal{GP}(0, k(x, x'))
\]
Select Correlation Function

- Many choices available for correlation function $k(x, x')$:
  - Stationary vs. nonstationary
  - Compact support vs. infinite support
  - Leading to smooth or nonsmooth random functions
  - Etc.

$$k(x, x'; \theta_1, \theta_2) = \exp \left( - \left[ \frac{(x_1 - x'_1)}{\theta_1} \right]^{2/\gamma} - \left[ \frac{(x_2 - x'_2)}{\theta_2} \right]^{2/\gamma} \right)$$

$$k(r; \nu, l) = \frac{2^{1-\nu}}{\Gamma(\nu)} \left( \frac{\sqrt{2\nu r}}{l} \right)^\nu K_\nu \left( \frac{\sqrt{2\nu r}}{l} \right)$$

$$k(x, x'; \Sigma) = \frac{2}{\pi} \sin^{-1} \left( \frac{2\tilde{x}^T\Sigma\tilde{x}'}{\sqrt{(1 + 2\tilde{x}^T\Sigma\tilde{x}) (1 + 2\tilde{x}'^T\Sigma\tilde{x})}} \right)$$
Learning from Data

- Suppose the correlation function is (SE, OU):

\[
k(x, x'; \theta_1, \theta_2) = \exp \left( - \left[ \frac{(x_1 - x'_1)}{\theta_1} \right]^{2/\gamma} - \left[ \frac{(x_2 - x'_2)}{\theta_2} \right]^{2/\gamma} \right)
\]

- Fundamental Question: How do I choose the model parameters that support the observed data?

- Answer: rely on Maximum Likelihood Estimation (MLE)
  - Get the likelihood of the data conditioned on a set of arbitrary parameters
  - Select that set of parameters that maximizes the likelihood
Learning from Data (cntd.)

- Log Likelihood can be computed as

\[
\log p(y|\theta) = -\frac{1}{2} y^T K(\theta)^{-1} y - \frac{1}{2} \log |K(\theta)| - \frac{M}{2} \log 2\pi
\]

- Notation:

\[
y(X) = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_M \end{pmatrix} \sim N(0, K(\theta))
\]

\[
K(\theta) = \begin{pmatrix} k(x_1, x_1; \theta) & \cdots & k(x_1, x_M; \theta) \\
k(x_2, x_1; \theta) & \cdots & k(x_2, x_M; \theta) \\
\vdots & \vdots & \vdots \\
k(x_M, x_1; \theta) & \cdots & k(x_M, x_M; \theta) \\
\end{pmatrix}
\]

- First Order Optimality Conditions (for maximizing the likelihood):

\[
\frac{\partial \log p(y|\theta)}{\partial \theta_j} = \frac{1}{2} \text{tr} \left[ K^{-1} y (K^{-1} y)^T - K^{-1} \right] \frac{\partial K}{\partial \theta_j} = 0 \quad j = 1, 2
\]
Generating the Posterior Distribution

- Choosing a family of Gaussian processes; i.e. a correlation function, leads to infinitely many candidate functions

- I need to select the ones compatible with the measured data

---

(a), prior

(b), posterior
Generating the Posterior Distribution

- Recall Bayesian linear model leads to Gaussian Process:

\[
\begin{bmatrix}
  y \\
  y'
\end{bmatrix}
\sim \mathcal{N}
\left(
\begin{bmatrix}
  0 \\
  0
\end{bmatrix},
\begin{bmatrix}
  K(X, X) & K(X, X') \\
  K(X', X) & K(X', X')
\end{bmatrix}
\right)
\]

Condition the joint Gaussian prior distribution on the observations \( y \) taken at \( X \)

\[
y' | y, X, X' \sim \mathcal{N}(m, \Sigma)
\]

\[
m \equiv K(X', X)K(X, X)^{-1}y
\]

\[
\Sigma \equiv K(X', X') - K(X', X)K(X, X)^{-1}K(X, X')
\]
Sampling Posterior

- Rely on MATLAB to generate sample out of posterior normal distribution
Quantify Uncertainty through Monte Carlo Analysis

- Rely on COTS (ADAMS) for vehicle model:

  Gather Data
  Select Correlation Function
  Run Parameter Identification (Maximum Likelihood Estimation)
  Get Mean Vector and Covariance Matrix for Fine-Grid Distribution
  Sample Posterior to Produce Data on Fine Grid
  Run COTS Software (ADAMS) for Multibody Dynamics Analysis

Points of interest
Quantify Uncertainty through Monte Carlo Analysis

- Produce average behavior, compute confidence intervals

![Graphs showing force over time and confidence intervals](image)

- Gather Data
- Select Correlation Function
- Run Parameter Identification (Maximum Likelihood Estimation)
- Get Mean Vector and Covariance Matrix for Fine-Grid Distribution
- Sample Posterior to Produce Data on Fine Grid
- Run COTS Software (ADAMS) for Multibody Dynamics Analysis
Effect of grid size on CI bounds

- \( \Delta x = 2 \)
- \( \Delta y = 8 \)
- \( \Delta x = 0.5 \)
- \( \Delta y = 2 \)

Force in front upper control arm
Conclusions

- High fidelity vehicle analysis achieved through co-simulation
  - All major vehicle components taken into consideration
  - Leverage COTS software packages

- A framework for handling uncertainty in the response of nonlinear multibody systems investigated
  - General
  - Nonintrusive (can be used in conjunction with COTS)
  - Posed in Bayesian framework and relies on Gaussian Processes
Open Issues

- Co-simulation
  - The process is manual to a large extent
  - Not easily modifiable

- Uncertainty Quantification
  - Handling large sets of data sometimes problematic
  - The process can require a vast amount of computational effort
    - Factorization of the covariance matrix
    - ADAMS simulations can take a long time to complete
  - Robustness an issue for large problems