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Journal of Terramechanics 71 (2017) 45–56

Journal of Terramechanics

www.elsevier.com/locate/jterra

Bayesian calibration of Vehicle-Terrain Interface algorithms for wheeled vehicles on loose sands

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Received 12 May 2016; received in revised form 31 January 2017; accepted 14 February 2017

Abstract

The Vehicle-Terrain Interface (VTI) model is commonly used to predict off-road mobility to support virtual prototyping. The Database Records for Off-road Vehicle Environments (DROVE), a recently developed database of tests conducted with wheeled vehicles operating on loose, dry sand, is used to calibrate three equations used within the VTI model: drawbar pull, traction, and motion resistance. A two-stage Bayesian calibration process using the Metropolis algorithm is implemented to improve the performance of the three equations through updating of their coefficients. Convergence of the Bayesian calibration process to a calibrated model is established through evaluation of two indicators of convergence. Improvements in root-mean square error (RMSE) are shown for all three equations: 17.7% for drawbar pull, 5.5% for traction, and 23.1% for motion resistance. Improvements are also seen in the coefficient of determination (R^2) performance of the equations for drawbar pull, 2.8%, and motion resistance, 2.5%. Improvements are also demonstrated in the coefficient of determination for drawbar pull, 2.8%, and motion resistance, 2.5%, equations, while the calibrated traction equation performs similar to the VTI equation. A randomly selected test dataset of about 10% of the relevant observations from DROVE is used to validate the performance of each calibrated equation.

Keywords: Off-road mobility; Vehicle Terrain Interface (*VTI*) model; Bayesian calibration; Metropolis algorithm; Sand; Drawbar pull (*DP*); Traction; Motion resistance; Database Records for Off-road Vehicle Environments (DROVE)

1. Introduction

Off-road vehicles serve a crucial role for both civilian and military transportations. Effective modeling of off-road vehicle mobility at diverse fidelities and on various terrains is an important task for many vehicle design applications. Two popular off-road vehicle performance models are the NATO Reference Mobility Model (NRMM) (Ahlvin and Haley, 1992; Vong et al., 1999) and the Virtual Autonomous Navigation Environment (VANE) (Jones et al., 2007), although other models have also been used (Lee, 2015; Taheri et al., 2015). These models relate vehicle performance, environmental conditions, and the terrain.

The Vehicle Terrain Interface (VTI) model is a high-resolution empirical model that addresses the interactions at the traction-terrain element interface and was developed as part of the NRMM and VANE models. The VTI serves

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http://dx.doi.org/10.1016/j.jterra.2017.02.003
0022-4898/

Nomenclature

VTI	Vehicle Terrain Interface
DROVE	Database Records for Off-road Vehicle Environments
DP	drawbar pull
NRMM	NATO Reference Mobility Model
VANE	Virtual Autonomous Navigation Environment
F_t	net tractive effort
R	total motion resistance
ISTVS	International Society for Terrain-Vehicle Systems
DBP	coefficient of drawbar pull
T	coefficient of traction
MR	coefficient of motion resistance
s	slip
r_R	rolling radius
ω	angular velocity of the wheel
V_v	forward velocity of the vehicle
W	vehicle or wheel load
α	steering angle
N_s	sand numeric
G	penetration gradient
b	tire width
h	section height
δ	difference between loaded and unloaded section heights
x_i	general coefficients for calibration
$N_{s,u}$	unpowered sand numeric
CI_{0-15}	average soil cone index from 0 to 15 cm
BC	Bayesian calibration
θ	calibration parameters
ϕ	variable parameters
η	model output
ϵ	observation error
$L(D\|\theta)$	likelihood function
$P(\theta)$	prior distribution
$P(\theta\|D)$	posterior distribution
D	data for calibration
PDF	probability density function
v	variance of an observation
y	property being modeled
θ_{can}	candidate vector of calibration parameters
θ_0	previous vector of calibration parameters
V	variance-covariance matrix
P_{can}	prior distribution of candidate vector
L_{can}	likelihood function of candidate vector
P_0	prior distribution of previous vector
L_0	likelihood function of previous vector
γ	Metropolis ratio
n	Length of the Markov chain
θ^n	final set of accepted calibration parameters from Markov Chain
Min_{ref}	minimum for reflection
Max_{ref}	maximum for reflection
σ	standard deviation
a	term to adjust step size in the Metropolis algorithm
μ	mean
c	second term to adjust step size of the Metropolis algorithm
UB	upper bound
LB	lower bound
RMSE	root-mean square error
R^2	coefficient of determination
CAVS	Center for Advanced Vehicular Systems

as a practical tool to support virtual prototyping of off-road vehicles without the computational cost of the larger models, a valuable part of the computer-aided design process (MacLeod, 2001). One advantage of the VTI model is its flexibility, being able account for both tracked and wheeled vehicles, steering conditions, and whether or not the vehicle is operating on ridged or fixed materials (Rohde et al., 2009). Steering is supported in the VTI model by equations for turning of the wheel on a deformable media developed by Melzer (1976), reorganized by Durham (1976) and implemented in the VTI (Jones et al., 2007).

The empirical nature of the VTI model allows for, or even necessitates, updating of the VTI equations as new data become available through either laboratory or field-testing. A recent effort to evaluate the performance of vehicle mobility models resulted in the Database Records for Off-road Vehicle Environments (DROVE) (Vahedifard et al., 2016, 2017), and suggested the performance of the VTI model could be improved for loose, dry sands.

In the current study, a two-stage Bayesian calibration technique was employed to improve the performance of the drawbar pull, traction, and motion resistance equations within the VTI model. The following sections of this paper include a brief discussion of the VTI model and the equations considered, an overview of Bayesian calibration, and results including the calibrated algorithms and their performance.

2. Vehicle performance parameters

Three vehicle performance parameters described in the VTI model are considered in this effort: drawbar pull force (DP), gross traction force (F_p), and total motion resistance (R) defined according to the ISTVS standards (Meyer et al., 1977; Priddy, 1999). Each parameter is normalized by weight to give the coefficient of drawbar pull (DBP), coefficient of traction (T), and coefficient of motion resistance (MR) illustrated for non-steered tires in Fig. 1.