Retrofittable Fuel Usage Monitor and Economizer for Diesel Ground Vehicles

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ABSTRACT

A retrofittable intelligent vehicle performance and fuel economy maximization system would have widespread application to military tactical and non-tactical ground vehicles as well as commercial vehicles. Barron Associates, Inc. and Southwest Research Institute (SwRI) recently conducted a research effort in collaboration with the U.S. Army RDECOM to demonstrate the feasibility of a Fuel Usage Monitor and Economizer (FUME) – an open architecture vehicle monitoring and fuel efficiency optimization system. FUME features two primary components: (1) vehicle and engine health monitoring and (2) real-time operational guidance to maximize fuel efficiency and extend equipment life given the current operating conditions. Key underlying FUME technologies include mathematical modeling of dynamic systems, real-time adaptive parameter estimation, model-based diagnostics, and intelligent usage monitoring. The research included demonstration of the underlying FUME technologies applied to a vehicle simulation constructed using SwRI's RAPTOR™ software toolkit and to LMTV and MRAP vehicle data sets collected under the AMSAA Sample Data Collection (SDC) effort.

1 Introduction

Barron Associates, Inc. and Southwest Research Institute (SwRI) recently conducted a research effort in collaboration with the U.S. Army RDECOM to demonstrate the feasibility of a Fuel Usage Monitor and Economizer (FUME) – an open architecture vehicle monitoring and fuel efficiency optimization system. The initial phase of the research culminated in demonstration of the underlying FUME technologies applied to a vehicle simulation using SwRI's RAPTOR™ software toolkit and to LMTV and MRAP vehicle data sets collected under the AMSAA Sample Data Collection (SDC) effort. The U.S. Army RDECOM provided data sets collected in the field on board 2.5 Ton Light Medium Tactical Vehicles (LMTVs) and Mine Resistant Ambush Protected (MRAP) vehicles via the AMSAA SDC effort. Application of FUME algorithms to real vehicle data afforded the opportunity to address many of the complexities encountered in the field, such as sensor noise and ambiguity, discernment of vehicle state in a complex environment, and sensor validation and calibration issues. Application of FUME algorithms to a validated FMTV RAPTOR simulation afforded the opportunity to conduct realistic, controlled experiments for the purposes of algorithm development and demonstration.

This paper is organized as follows. Section 2 highlights the analysis of the LMTV and MRAP data sets, including how these data could be exploited by FUME to achieve the research objectives. Section 3 describes the derivation of models from the data. Section 4 briefly discusses the RAPTOR™ model outputs. Section 5 presents the conclusions from the first phase of the research effort and looks ahead to the next phase.

2 AMSAA Data Processing

As aforementioned, it is highly valuable to analyze MRAP and LMTV data collected in the field under the AMSAA SDC in order to unequivocally demonstrate the feasibility of the envisioned FUME. Importantly, FUME application to vehicle data provided the opportunity to address many real-world issues not typically encountered in a simulation-based feasibility study. Real-world data collection limitations, such as sensor noise, sampling rates, and signal quantization can, if not comprehensively and systematically addressed, render promising modeling and diagnostic approaches useless. Any practical monitoring system must also accommodate the wide range of vehicle loads and configurations while maintaining acceptable rates of false alarms and missed detections. FUME will accomplish this goal using, for example, online calculations of vehicle resistance, road grade, and accelerations. Accurate estimation of these quantities depends on signal processing methods to overcome the potential pitfalls associated with noisy, quantized data and miscalibrated sensors.

2.1 Total Variation Regularization

The AMSAA data channels, by their nature, contain data that are noisy or quantized or both. For offline data analysis, however, it is sometimes necessary to find the derivatives of these signals (i.e., vehicle acceleration) as well as analyze signals where noise has been eliminated. Furthermore, the derivatives of the data are often jump discontinuous. As a result, standard finite difference techniques only serve to magnify the noise or round-off error present in the data. Although data filtering may provide good results for a denoised signal, the sensitivity of finite difference methods will still exaggerate any variation present in the filtered signal. As such, a more innovative approach is necessary.

In the framework of inverse problems [1], a source of data, *d* is often considered to be the result of some source *f* and a process *K*, *viz.*

$$Kf = d \qquad (1)$$

However, the inverse of *K* may be

ill-conditioned or K may be singular. In such a case, then, it is possible to approximate the source by regularizing the process. A common method, known as Tikhonov Regularization, is to minimize a functional

$$T(g)= \alpha R(f)+ \rho(K(f),g) \qquad (2)$$

where α is a regularization parameter, R is a penalty term, and ρ is a data fidelity term. A technique recently developed by Chartrand [2] proffers a framework for numerical differentiation of nonsmooth data in the presence of noise, the formulation of which is briefly summarized herein. Given a signal f supported on $[0,L]$ with derivative u, (1) becomes

$$F(u)= \alpha R(u)+\rho(Au-f) \qquad (3)$$

where A represents the antidifferentiation operator, $A=\int_0^x u$. In the context of numerical differentiation, we seek to use the total variation of u as a measure of the penalty term. The data fidelity term follows logically as a least squares measure. The functional then becomes

$$F(u)=\alpha\int_0^L |u'|+\frac{1}{2}\int_0^L |Au-f|^2 . \qquad (4)$$

This approach eliminates noise in the derivative, u, without eliminating jump discontinuities. Applying the Euler-Lagrange equations to (3), we arrive at a differential equation for the unique solution u:

$$0=\alpha\frac{d}{dx}\frac{u'}{|u'|}-A^*(Au-f) \qquad (5)$$

where A^* represents the L^2-adjoint of A, $A^*v=\int_x^L v$. Solution of this equation over the interval $[0,L]$ is not as straightforward, however. Instead, we cast $u(x)=u(x,t)$ along a dummy variable t, and consider (5) to be the partial derivative of u with respect to t, *viz.*

$$u_t=\alpha\frac{d}{dx}\frac{u'}{|u'|}-A^*(Au-f). \qquad (6)$$

We then evolve the solution of this to stationarity, which presents us with the solution of (5).

Discretizing u_t about some fixed Δt permits an iterative approach to solving the PDE to stationarity. Replacing $\frac{d}{dx}\frac{u'}{|u'|}$ with $\frac{d}{dx}\frac{u'}{|u_n'|}$, where u_n is the n^{th} iteration of u enables us to use the lagged diffusivity method presented in [1]. On a uniform grid $\{x_i\}_0^L$ representing the points at which data acquisition takes place, u is computed at the halfway points using centered difference approximations. Similarly, the antiderivative is computed using the standard midpoint quadrature. Given m points in the data set, we construct a finite difference matrix D and an antidifferentiation matrix K each dimensioned $m-1\times m$, *viz.*

$$D = \begin{bmatrix} \frac{-1}{\Delta x} & \frac{1}{\Delta x} & 0 & \cdots & 0 \\ 0 & \frac{-1}{\Delta x} & \frac{1}{\Delta x} & \cdots & 0 \\ \vdots & & \ddots & \ddots & \\ 0 & \cdots & & \frac{-1}{\Delta x} & \frac{1}{\Delta x} \end{bmatrix} \qquad (7)$$

$$K = \begin{bmatrix} \frac{\Delta x}{2} & \frac{\Delta x}{2} & 0 & \cdots & 0 \\ \frac{\Delta x}{2} & \Delta x & \frac{\Delta x}{2} & \cdots & 0 \\ \vdots & & & \ddots & \vdots \\ \frac{\Delta x}{2} & \Delta x & \cdots & \Delta x & \frac{\Delta x}{2} \end{bmatrix} \qquad (8)$$

Then, for a small ε let E_n be a diagonal matrix such that

$$E_{n_i} = \left((u_n(x_i) - u_n(x_{i-1}))^2 + \varepsilon \right)^{-1/2}. \qquad (9)$$

Then,

$$L_n = \Delta x D^T E_n D \qquad (10)$$

$$H_n = K^T K + \alpha L_n \qquad (11)$$

$$g_n = K^T (K u_n - f) + \alpha L_n u_n. \qquad (12)$$

H_n is an approximation to the Hessian of the functional $F(u_n)$. The lagged diffusivity method is a gradient search method, and the update step s_n is the solution to

$$H_n s_n = -g_n \qquad (13)$$

and

$$u_{n+1} = u_n + s_n. \qquad (14)$$

A solution is found when $(u_{n+1} - u_n)/\Delta t$ is sufficiently small that u_t can be considered to be in stationarity. The solution u can then be integrated by the matrix K to find a reconstructed source $\hat{f}$.

Applying the algorithm to the accelerometer data yields some encouraging results. Since the accelerometers are not filtered and are subject to structural vibration as well as sensor noise, using the data in offline analysis will prove difficult unless the signal can be denoised effectively. Figure 1 shows the results of using the TVR method to recompute a noiseless accelerometer signal from noisy data.

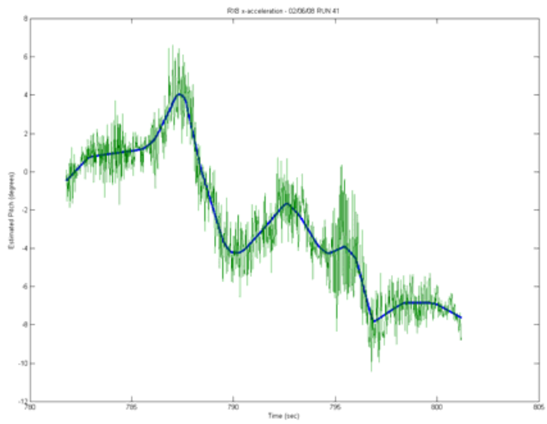

Figure 1: Estimated Vehicle Pitch Using TVR

A further benefit of the TVR method is that it offers a means by which accurate qualitative data can be obtained. Increasing the regularity parameter α penalizes the total variation of the derivative signal u more severely. As a result, the method will be less sensitive to quantization or noise. This is useful in ignoring spots where the quantized speed rapidly changes by a jump discontinuity. Because of discretization error in the sensor, such a drop in the measured data will not correspond to a similarly large variation in the actual behavior of the vehicle. The TVR method seeks to ignore such variational errors. Figure 2 shows the road speed and acceleration of a vehicle where the TVR data are made less sensitive to the quantized data. The effect of the small spikes is ignored. This allows us to identify times where the vehicle's acceleration is approximately zero, or equivalently, where the road speed is roughly constant, which will be useful in engine and transmission models. Finite difference methods, on the other hand, are not able to capture this behavior.

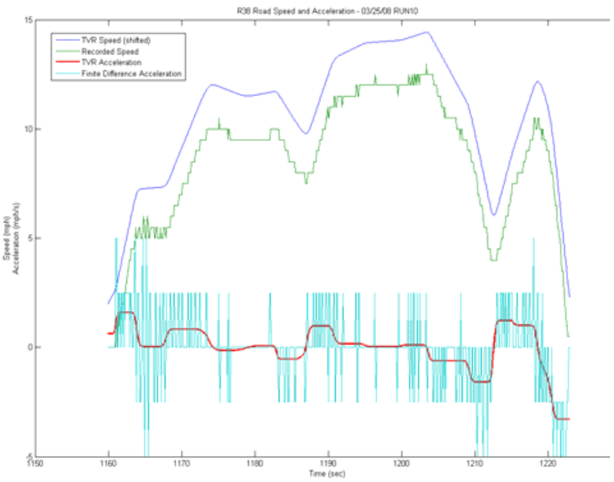

Figure 2: Vehicle Speed and Acceleration

3 Vehicle, Engine, and Environmental Models

The FUME architecture will be comprised of several model-based diagnostic components, including: (1) vehicle fuel efficiency model (2) powertrain (engine and transmission) efficiency model and (3) comprehensive dynamic models. Given the widely-varying vehicle configurations and loads, the vehicle fuel efficiency model can only be meaningful given explicit estimation of road grade, vehicle mass, and resistance parameters. The comprehensive dynamic model will represent dynamic state dependencies between many data channels of interest, such as oil pressure and coolant temperature, which can be analyzed to infer vehicle and engine health.

3.1 Vehicle Road Grade and Resistance Modeling

The vehicle road grade estimation and resistance modeling are crucial to reliable, accurate assessment of vehicle and engine health and early detection of incipient faults. Total vehicle propulsion resistance can be modeled using the following form:

$$R = C_1 + C_2 v + C_3 v^2 + Mg\alpha \qquad (15)$$

where C_i, i=1…3 are unknown constants, v is vehicle speed, M is vehicle mass, g is acceleration due to gravity, and α is the road grade. This representation includes: (1) friction force losses that are not a function of speed (including the primary effect of tire rolling loss force), (2) resistance effects that are linearly proportional to speed (often negligible on smooth, paved highways), (3) losses that are proportional to the square of the vehicle speed (aerodynamic losses), and (4) resistance due to road grade [3]. Given the known model structure of (15), we can design an adaptive scheme to estimate the unknown parameters C_1, C_2, C_3, and M, which are uncertain due to variations in vehicle configuration and loading and are needed for accurate vehicle modeling.

As aforementioned, the construction of robust models is important in model-based fault detection and isolation (FDI) schemes because differences in the model predictions and observed data that cannot be attributed to noise will be considered to be fault events. Barron Associates has recently developed a new adaptive estimation technique that is a computationally-efficient method for identifying the parameters of physics-based models. The technique can be applied effectively to any dynamic system having a known model structure, but unknown and/or time-varying parameters.

In the present application to vehicle resistance modeling, it is straightforward to implement the new methodology with the vector of unknown parameters defined as

$$\theta = [C_1\ C_2\ C_3\ M]^T \tag{16}$$

and the regressor vector of measured quantities (all of which may be extracted from the existing AMSAA vehicle instrumentation) defined as

$$\phi = [1\ v\ v^2\ \alpha]^T. \tag{17}$$

The unknown parameters can be estimated online directly from the measured data.

3.2 Vehicle Mass Estimation

The acquired data are sufficiently well-defined to allow for offline analysis of our adaptive algorithms. Several methods of estimating various aspects of the parametric vehicle model are found in the literature. Some of these models ignore the individual contributions of aerodynamic drag and rolling resistance [4,5]. Others use least-squares techniques with existing sensor data to account for the lack of other sensors that may provide more useful or accurate information [6,7]. We seek to improve upon some of the previous methods by making use of the ample sensor data to obtain estimates of the relevant vehicle parameters using our adaptive parameter estimation techniques.

Using Newton's law, we can write the balance of forces on the vehicle in the longitudinal axis as a sum of components [6]:

$$\Sigma F = F_{wheel} - R. \tag{18}$$

We assume the propulsive force of the vehicle to be proportional to engine torque:

$$F_{wheel} = k\frac{pT_{max}}{r_w} \tag{19}$$

where p is the percent of maximum engine torque for the given engine speed, T_{max}, r_w is the radius of the wheels and k represents efficiency and transmission effects. It is well known that the aerodynamic drag is proportional to the velocity squared and that friction losses due to engine speed, as well as the effects of sway or bumps in the road are linearly proportional to the velocity. However, because the frictional forces on the foundation brakes are not well-known, F_{brake} can at best be assumed to be invariant with velocity. In practice, online estimation of resistance parameters is suspended when the foundation brakes of the vehicle are enabled [8]. Because we assume the contribution of the brakes to be negligible while the vehicle is not experiencing any significant deceleration events, and because the rolling resistance can be considered constant and simply subtracted from the accelerometer signal, for the purposes of our analysis we assume this component to be zero.

The net sum of the forces on the vehicle given by (18) can be written in terms of its acceleration *a*. As such, we can rewrite (18) as a balance of acceleration terms:

$$a = \frac{1}{m} k \frac{pT_{max}}{r_w} - \frac{k_r}{m} v - \frac{k_d}{m} v^2 - g\sin(\alpha). \quad (20)$$

This allows us to isolate parameters and create a parameter vector $\theta = \left[\frac{1}{m} \ \frac{k_r}{m} \ \frac{k_d}{m} \ g^T \right]^T$ and a regressor vector $\phi = \left[k\frac{pT_{max}}{r_w} \ -v \ -v^2 \ -sin\alpha \right]^T$. Doing so allows us to easily fuse the algorithm with available online sensor data. The model is then

$$a = \theta^T \phi. \quad (21)$$

To identify the parameter vector θ, we use ou adaptive parameter estimation algorithms using the corrected longitudinal accelerometer signal, a_s, in our error model

$$\varepsilon = a_s - a = a_s - \theta^T \phi. \quad (22)$$

Though at first it may seem counterintuitive to identify the gravitational constant, doing so provides useful analytic data. If the gravitational constant does not remain constant, it suggests that the choice of gain may be inappropriate. Furthermore, if the constant converges but is identified as something other than the known value of *g*, then it may indicate a problem in orientation of the accelerometer, potentially a roll offset that is not identified using other techniques.

Using a rough estimate of the mass to create an initial parameter vector θ(0), we applied the iterative online algorithm to the AMSSA data to estimate the vehicle mass and resistance parameters. The road speed and road grade values were obtained and corrected via the methods described previously. Figure 3 shows convergence of the resistance parameters. The model error is shown in Figure 4.

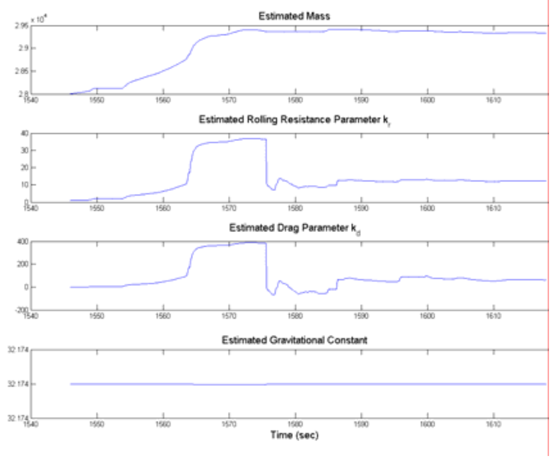

Figure 3: Estimated Vehicle Parameters

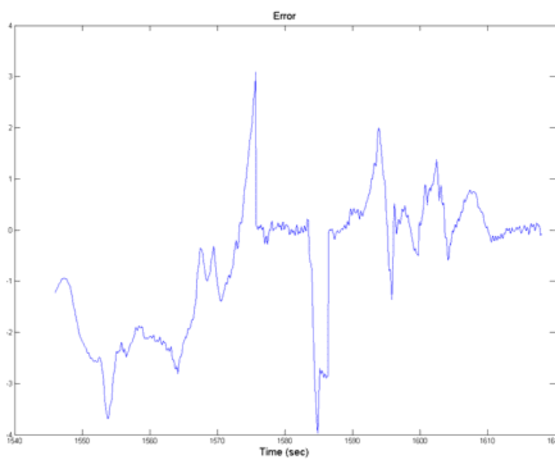

Figure 4: Model Error from Est. Parameters

4 RAPTOR Vehicle Model

SwRI's latest generation of vehicle modeling software, which was used as the simulation platform, is the Rapid Automotive Performance Testing and Optimization Resource (RAPTOR™) - A Virtual Vehicle Test and Development Environment. RAPTOR is a modular modeling and development simulation tool for vehicle fuel economy, performance, and emissions in both virtual and hardware-in-the-loop environments. RAPTOR™ allows the user to configure a virtual vehicle from component and sub-component models. RAPTOR™ is an application program written in MATLAB and Simulink to ensure modularity and flexibility for many vehicle configurations. RAPTOR™ is composed of system and subsystem libraries that can be configured and stored as complete vehicles. In addition to the vehicle library, primary standard subsystem libraries include the Engine Library (engine mechanical, fuel rate, turbo, heat rejection, fuel shut off control, emissions, warmup), Engine Accessories Library (air conditioning, power steering, alternator system, cooling fan, generic mechanical, generic electrical), Launch Device Library (torque converter, clutch), Manual or Automatic Transmission Library (transmission gearbox, shift logic), Continuously Variable Transmission (transmission ratio mechanism, ratio scheduling), Transfer Case Library (differential/axles), and the Tire Library (rolling resistance, traction coefficient, dynamic radius).

SwRI has previously created and validated a RAPTOR™ model of a 2.5 ton LMTV. Although the LMTV model may not be identical to the configuration of any of the LMTVs for which AMSAA data were collected, it is a validated, realistic LMTV model suitable for demonstration and evaluation of underlying FUME technologies and algorithms.

We use the RAPTOR™ model to inject abrupt faults and dynamic chances as well as simulated accelerated long-term efficiency losses due to component wear. Figure 5 shows the vehicle speed and drivetrain torque output during a simulated accelerated increase load. Figure 6 shows the fuel consumption during the same event. This simulation could correspond to increased engine friction forces due to accessory component wear or potentially to wear in the wheel bearings or hub assembly.

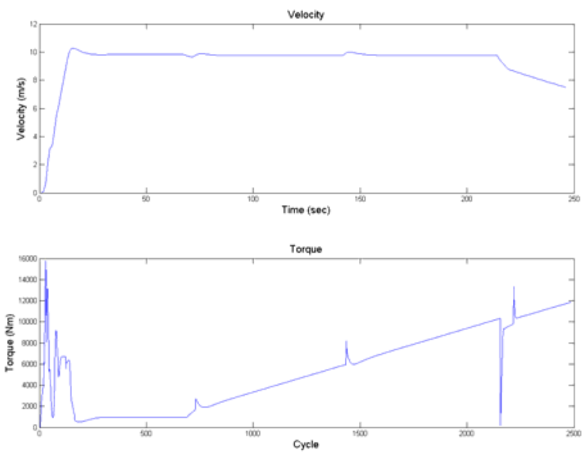

Figure 5: Accelerated Friction Buildup

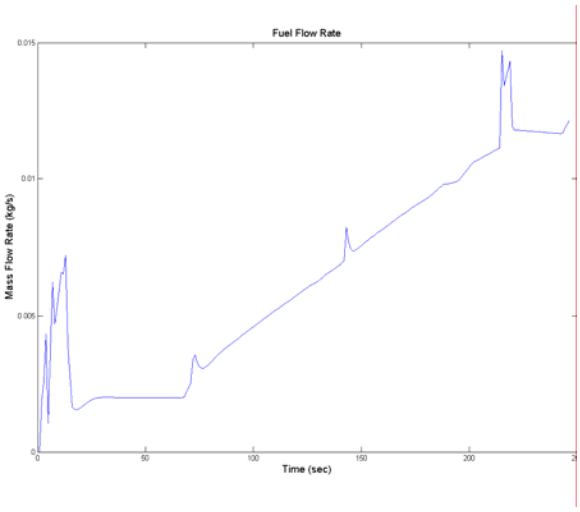

Figure 6: Fuel Flow during Friction Buildup

5 Conclusions

An affordable, retrofittable intelligent vehicle performance and fuel economy maximization system would have widespread application to military tactical and non-tactical ground vehicles as well as commercial vehicles. Barron Associates, Inc. and SwRI conducted a successful research effort in collaboration with the U.S. Army RDECOM to demonstrate the feasibility of the Fuel Usage Monitor and Economizer (FUME) — an intelligent, open architecture vehicle monitoring and fuel efficiency optimization system. FUME will feature vehicle and engine health monitoring and real-time operational guidance to maximize fuel efficiency and extend equipment life given the current operating conditions. Key underlying FUME technologies include mathematical modeling of dynamic systems, real-time adaptive parameter estimation, model-based diagnostics, and intelligent usage monitoring.

The first phase of the research included application to both real and simulated vehicle data. Application of FUME algorithms to real vehicle data afforded the opportunity to address many of the complexities encountered in the field, such as sensor noise and ambiguity, discernment of vehicle state in a complex environment, and sensor validation and calibration issues. Importantly, algorithms for the accurate estimation of vehicle acceleration, road grade, and vehicle mass — all of which are crucial to reliable vehicle and powertrain models needed for diagnostics — were developed and applied to real vehicle data. Application of FUME algorithms to a validated FMTV RAPTOR™ simulation afforded the opportunity to conduct controlled experiments for the purposes of algorithm development and demonstration.

The next phase of the research effort will include implementation of a FUME prototype using COTS hardware components as well as design and implementation of a RAPTOR™-based vehicle emulator that will enable realistic engine-in-the-loop tests prior to in-vehicle deployment.

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