

Signal Processing for Rough Road Detection

2010-01-0673

Published
04/12/2010Tameem Assaf, David Mathews and Sanjeev Naik
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ABSTRACT

Misfire diagnostics are required to detect missed combustion events which may cause an increase in emissions and a reduction in performance and fuel economy. If the misfire detection system is based on crankshaft speed measurement, driveline torque variations due to rough road can hinder the diagnosis of misfire. A common method of rough road detection uses the ABS (Anti-Lock Braking System) module to process wheel speed sensor data. This leads to multiple integration issues including complexities in interacting with multiple suppliers, inapplicability in certain markets and lower reliability of wheel speed sensors.

This paper describes novel rough road detection concepts based on signal processing and statistical analysis without using wheel speed sensors. These include engine crankshaft and Transmission Output Speed (TOS) sensing information. Algorithms that combine adaptive signal processing and specific statistical analysis of this information are presented. Vehicle test results are shown to demonstrate the efficacy of these techniques to distinguish between rough road, smooth road, and misfire.

INTRODUCTION

On-board detection of internal combustion (IC) engine misfire is one of the requirements of Onboard Diagnostic (OBD II) regulations promulgated by the U.S. Environmental Protection Agency and the California Air Resources Board, which require the continuous on-line monitoring of key emission-related components in IC engine powered vehicles. Misfire can result from a number of causes, such as missing or improperly timed delivery of fuel, insufficient delivery of cylinder intake air, or a missing or improperly timed cylinder spark event [1].

Reduced engine performance and fuel economy or increased engine emissions may result from a misfire condition. Misfire conditions must be accurately diagnosed to avoid unnecessary application of misfire treatment procedures. Various different sensor measurements may be used to analyze engine operation and perform such diagnosis. Many of these procedures may require addition of costly hardware on the vehicle, adding to vehicle cost and adding sources of potential fault conditions. Such procedures further may be computationally intensive, adding significantly to engine or vehicle controller throughput burden.

Rough road conditions have a significant impact on misfire detection systems based upon crankshaft speed measurement. A common method of rough road detection uses the ABS module to process wheel speed sensor data. This leads to multiple integration issues:

- We require multiple ABS suppliers to implement the same rough road diagnostic specification. The increased coordination between suppliers results in redundant work and an increased likelihood of miscommunication.
- Some markets may avoid the use of ABS due to the extended costs associated with it.
- Wheel speed sensors are relatively less reliable due to their proximity to road disturbances. If a failure in wheel speed sensors takes place and the misfire diagnostic continues to operate, the likelihood of a false indication of failure would be increased.

Various techniques have been applied for misfire detection [2,3,4,5,6,7,8]. Extensive work has been done on methods for misfire detection that are based on engine crankshaft angular speed measurements [8,9,10,11,12]. A number of factors contribute to degraded misfire detection. These include tooth machining errors, run-out, cylinder-to-cylinder variation, torsionals, driveline noise, rough road disturbances, and finite

counter clock resolution. Poor performance of misfire detection systems can result from a failure to recognize and/or compensate for these disturbances.

In the next section, we look at rough road detection methods.

ROUGH ROAD DETECTION

Rough road disturbances lead to driveline torque variations that directly drive engine crankshaft speed variation that can confound misfire detection. The following will discuss various methods of rough road detection.

DETAILS OF AN ABS-BASED METHOD

Rough road is detected by monitoring changes in wheel speed acceleration. In one method, dispersion analysis is used to produce a signal which increases in magnitude as road roughness increases. Dispersion measures the spread of a data set relative to its mean. First, the absolute deviations of two wheel accelerations are computed.

Afterwards, absolute deviations are summed over a number of samples. The higher of the driven and non-driven wheel deviations will be used in the summation. After an acceptable number of samples have been collected, the average absolute deviation is computed.

OTHER ESTABLISHED METHODS

According to [16], gas tank pressure measurements exhibit a unique frequency response while a vehicle is traversing rough road. In another method illustrated by [18], air mass measurements are analyzed at a particular frequency to ascertain whether or not the vehicle is on rough road. In [19], rough road can also be detected through the use of an accelerometer.

NOVEL METHODS

We will now look at a novel virtual rough road detector that relies on a combination of signal processing and statistical analysis techniques applied to driveline speed measurements. These include engine crankshaft and transmission output speed sensing information. Next, we describe the sequence of analysis blocks covering transient removal, Adaptive Disturbance Signal Removal (ADSR) and statistical analysis.

Transient Removal

We perform transient removal prior to doing any other processing so as to compensate for the effects of speed changes (i.e. changes in reference period measurements) attributable to factors such as throttle maneuvers or gradual changes in load induced otherwise [15].

Denoting the reference period measurement sequence by $\{T(n)\}$, the running mean sequence by $\{\mu(n)\}$ and defining L_1 as the buffer length, we compute the reference period measurement sequence with running means removed, $\{x(n)\}$. Then, we can compute the first difference of the sequence $\{x(n)\}$ to get the sequence $\{y(n)\}$ from which we will adaptively estimate and remove the disturbance sequence mainly attributable to the periodic, time varying errors mentioned earlier.

$$y(n - L_1 / 2 + 1) = x(n - L_1 / 2 + 1) - x(n - L_1 / 2). \quad (1)$$

ADSR

Let $y(n)$ denote the differenced sequence of reference period measurements that have been compensated for transients as given above.

We will consider our problem as an adaptive filtering problem [13], with the objective being to remove a quasi-periodic disturbance from our signal. The disturbance is modeled as

$$d(n) = a_0 + \sum_{k=1}^{N/2} \left[a_k \cos\left(\frac{2\pi kn}{N}\right) + b_k \sin\left(\frac{2\pi kn}{N}\right) \right] = \theta^T \phi(n), \quad (2)$$

where N is the number of teeth per engine cycle. Thus, the disturbance is described through N coefficients. The coefficients are assumed to vary slowly with time. We will estimate these coefficients on-line. In order to cope with the time-varying nature of the disturbance, we will adapt our parameter estimates by basing the estimates only on the L_2 “most recent” reference period measurements.

Recursive Computational Procedure for ADSR: As shown in [15], a recursive procedure to compute the least squares parameter estimate sequence $\theta(n)$ can be derived using the fact that the basis functions (regressors) are periodic with a period that is a sub-multiple of L_2 . Upon measuring reference period $T(n)$, $y(n - L_1 / 2 + 1)$ is computed. The parameter estimate $\hat{\theta}(n - L_1 / 2)$ (based on samples $y(n - L_1 / 2 + 1 - L_2)$ through $y(n - L_1 / 2)$) is used to construct an estimate of the disturbance $\hat{d}(n - L_1 / 2 + 1)$. This disturbance estimate is removed from the differenced

reference period with mean removed, $y(n - L_1 / 2 + 1)$, to arrive at the “cleaned” signal $z(n - L_1 / 2 + 1)$.

$$z(n - L_1 / 2 + 1) = y(n - L_1 / 2 + 1) - \hat{d}(n - L_1 / 2 + 1) \quad (3)$$

Finally, $\hat{\theta}(n - L_1 / 2 + 1)$ is updated through

$$\hat{\theta}(n - L_1 / 2 + 1) = \hat{\theta}(n - L_1 / 2) + \phi(n - L_1 / 2 + 1) (y(n - L_1 / 2 + 1) - y(n - L_1 / 2 + 1 - L_2)) L_2. \quad (4)$$

The following figure shows an example of adaptive disturbance estimation and removal for some vehicle data with induced misfires.

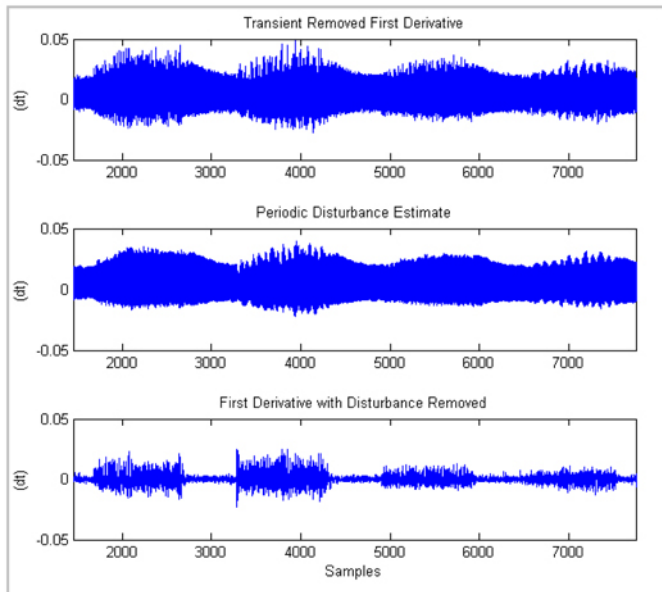


Figure 1. Illustration of Adaptive Disturbance Signal Removal

Dispersion Analysis of Alternate Sensors

In addition to the wheel speed signals, the crankshaft and Transmission Output Speed Signal (TOSS) are also impacted by rough road, and can also be analyzed through dispersion.

The core of this method is to employ a running variance calculation on the crank signal or TOSS. Other methods of statistical dispersion can be used, such as coefficient of variance, standard deviation, or inter-quartile ranges. As a minor change to the ABS based dispersion computation, variance is introduced because squaring the deviation between the current value and the mean emphasizes the dynamic range of the signal. Smaller deviations become

relatively smaller and the larger deviations become relatively larger.

$$\sigma^2(n) = \frac{1}{N} \sum_{i=1}^N (x(n) - \bar{x}(n))^2 \quad (5)$$

Crankshaft Signal Dispersion

In the case of the crankshaft speed signal, variance can be calculated by referencing an individual cylinder to itself to rule out deviations in dispersion due to tooth-to-tooth error, torsional impacts on the crankshaft, combustion variation from cylinder to cylinder and continuous misfire. By incorporating the same cylinder data over a number of engine cycles into the dispersion calculation, the sources of variation mentioned above should remain relatively constant at a given engine speed, load, and vehicle speed. This still does not take into account errors induced due to rapid fluctuations in engine speeds and random disturbances (i.e. random misfire). During stable, non-randomly misfiring conditions, crank signal dispersion provides a very concise indicator of rough road impact to the misfire detection system.

In differentiating between rough and smooth road, a calibration threshold is defined between smooth and rough road data sets. The threshold will be determined based on a number of standard deviations above the mean of a smooth road data set. This will need to be calibrated based on engine speed and air load. Air load is the percent of air mass currently being utilized in reference to the maximum capacity of the engine.

TOSS Dispersion

In reference to the aforementioned ABS detection method, the wheel speed signals will be less sensitive to engine torque fluctuations than TOSS because the transmission is more closely coupled to the engine. It is not possible to remove periodic disturbances from this signal in the angular domain because it is computed at a periodic rate. Dispersion of the transmission output will increase with the presence of high misfire (whether periodic or random). Rapid changes in output speed based on varying torque requests may also hinder the rough road computation.

There are multiple benefits to using TOSS over the crankshaft speed signal. TOSS is less sensitive to random misfire and more sensitive to rough road. In the case of random misfire, the torque fluctuation is dampened through the engine and transmission to the TOSS output. In the case of rough road, the TOSS signal is more closely coupled to the wheels which are directly impacted by rough road. Furthermore, it is more deterministic due to its periodic computation rate (relative to computing every cylinder event). Finally, it will only require a 1 dimensional