ADVANCED SIGNAL PROCESSING FOR MISFIRE DETECTION IN AUTOMOTIVE ENGINES

William B. Ribbens and Steven Bieser

Department of Electrical Engineering and Computer Science
The University of Michigan
Ann Arbor, Michigan 48109-2122 USA

ABSTRACT

This paper presents an application of artificial neural networks to the reliable detection of misfires in automotive engines. By government regulations, automobiles are required to be equipped with instrumentation to detect engine misfires and to alert the driver whenever the misfire rate has the potential to affect the health of emission control systems. A relevant model for the powertrain dynamics is developed in this paper as well as an explanation of the instrumentation. The basis for using a neural network to detect these misfires is explained and experimental system performance data (including error rates) are given. It is shown in this paper that the present method has the potential to meet the government mandated requirements.

INTRODUCTION

This paper presents a method having the potential to meet one of the more challenging new governmental regulations facing the automotive industry. The California Air Resources Board (CARB), an agency of the state government, has invoked new rules for passenger cars sold in the state that are known as On-Board Diagnostics II (OBDII). These rules are generally intended to monitor (in real time) the performance of the exhaust emission control system. Included in the OBDII rules is the requirement to detect engine misfires due, e.g., to improper fueling or ignition failure. Misfire is a condition in which there is no combustion of the fuel/air mixture during the power stroke of the engine (in which combustion normally occurs). Whenever the rate of misfire exceeds a mandated threshold (such that emissions are adversely affected), the driver is to be alerted such that corrective repairs can be undertaken.

The present paper presents a novel method for detecting each single misfire based upon an application of digital signal processing techniques to signals coming from a sensor that is part of the normal electronic engine control system. This work is an outgrowth of research conducted at the Vehicular Electronics Lab (VEL) at the University of Michigan (UM) on dynamic modeling of engine/drivetrain (power train) dynamics. This paper briefly explains the problem in terms of power train dynamics, summarizes the theory of the method and presents results of actual experimental road test measurements.

POWER TRAIN CONFIGURATION AND MODEL

The present method of detecting misfires is based upon the influence of misfire on the torque and power generated by the engine. Furthermore, this method involves the dynamic response of the powertrain to misfire related torque generation. The power train for the present method consists of a multicylinder gasoline fueled, reciprocating engine coupled to a transmission and associated driveline or transaxle and tire dynamics. Modern automotive engines are of the 4-stroke/cycle variety requiring two complete revolutions of the crankshaft for each cylinder to contribute a power stroke.

The torque produced by combustion of fuel and air is pulsating owing to the reciprocating nature of the engine (as opposed to continuous in a gas turbine). For an ideal engine at steady state, the torque pulsations of each cylinder would be identical. A misfire would correspond to a missing torque pulse for the affected cylinder. A measurement or estimate of torque would reveal the misfire rather simply. Furthermore, torque generation, even at steady state, is not uniform. Rather, the torque waveform is a random process (superposed upon the mean steady-state torque) owing to variability of fueling and the combustion process itself.

On the other hand, the random torque fluctuations in a well tuned engine are small compared to misfire. Consequently, the misfire condition can be identified through suitable statistical processing as explained later in this paper.

Furthermore, although direct measurement of torque is not feasible, misfires can be detected through noncontacting measurements of crankshaft angular speed. The relationship between the torque misfire signature and crankshaft angular speed can be explained with the linear, approximate equivalent circuit as developed and explained in [1] to [3] shown in Fig. 1. This model, though simplified, is sufficiently robust to explain the present method and to yield a practical functioning misfire detection.

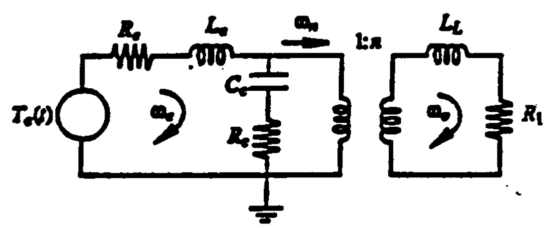

Fig. 1. Equivalent Circuit Model for IC Engine.

Within the validity of the equivalent circuit of Fig. 1, it is evident that angular speeds ω_e and ω_o can be represented as the response of a linear dynamic system to an input τ_e consisting of the torque applied at the crankshaft. This relationship can, of course, be expressed in the frequency domain

$$\omega_e(j2\pi f) = \tau_e(j2\pi f)\, H(j2\pi f)$$

where H is the appropriate frequency response for the system.

Torque fluctuations due to misfire result in corresponding fluctuations in angular speed. Noncontacting measurements of crankshaft angular speed, which are straightforward, provide the basis of our method of detecting misfires.

It has been shown in [4] that the dynamic equations for the system of Fig. 1 can also be written with crankshaft angle θ as the independent variable. Furthermore the discrete time representation in crankshaft angle is given by

$$\tau_k = \tau_e(\theta_k)$$
$$\omega_k = \omega_e(\theta_k) \qquad k = 1, 2, \ldots, K$$

where $\qquad \theta_k = \frac{4\pi}{K}.$

The corresponding frequency domain representation is given by the DFT or some equivalent transformation [5]

$$A_p = \sum_{k=1}^{K} \omega_k \left(W_K\right)^{pk} \qquad p = 1, 2, \ldots, K$$

where K is the number of uniformly spaced samples in two revolutions of the crankshaft and where

$$W_K = \exp\left(j\frac{2\pi}{K}\right).$$

For convenience, we denote the magnitude and phase of A_p, M_p and ϕ_p, respectively.

For misfire detection in an N cylinder engine, only the fundamental and Nth harmonic (i.e., $p = 1$ and $p = N$) are required as explained in [5] and as demonstrated in our experimental road tests.

For misfire detection, it is advantageous to compute the spectral components recursively over successive intervals of length K. We term this recursive computation a sliding window (of length K) algorithm. We denote the shift in the window position by index j ($j = 1, 2, \ldots$). The jth computation of A_p is denoted $A_p(j)$

$$A_p(j) = \sum_{k=1}^{K} \omega_{k+j-1} \; W_K^{pk} \qquad j = 1, 2, \ldots,$$

The recursive algorithm is given by

$$A_p(j+1) = A_p(j)\, W_K^{-p} - \omega_j + \omega_{j+K} \; W_K^{pk}.$$

As each new data sample comes in, a new spectral component is computed with only two complex products. There are K such complex products for each engine cycle (i.e., two crankshaft revolutions).

Typically in any practical application, K is determined by the sensor configuration used in the measurement of crankshaft angular position. However, it is desirable for $6N \leq K \leq 12N$ for an N cylinder engine to have adequate sampling and yet avoid having excessively high computational burden.

It is perhaps instructive to examine samples of the crankshaft angular speed variation signal such as are depicted in Fig. 2. This figure depicts the instantaneous crankshaft angular speed signal for a pair of complete engine cycles of a 5-cylinder inline engine. Figure 2(top) gives $\omega(t)$ for a normal combustion cycle and Fig. 2(bottom) gives $\omega(t)$ for a cycle in which cylinder No. 2 has misfired.

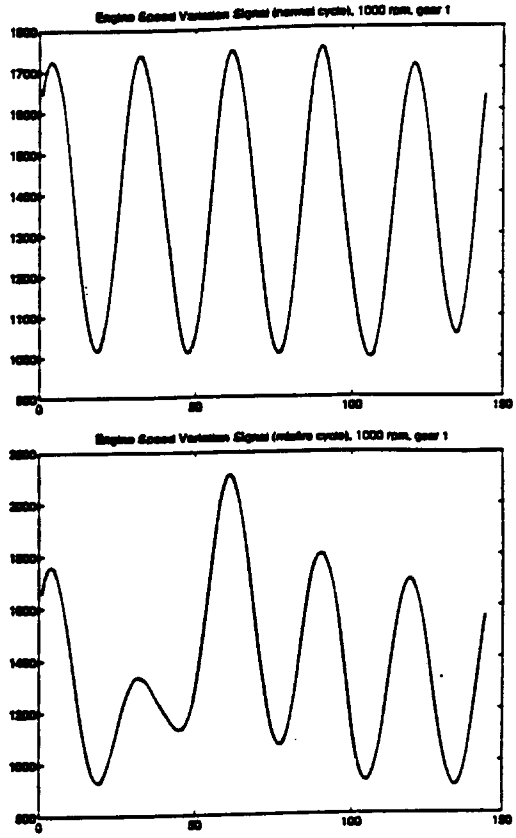

Fig. 2

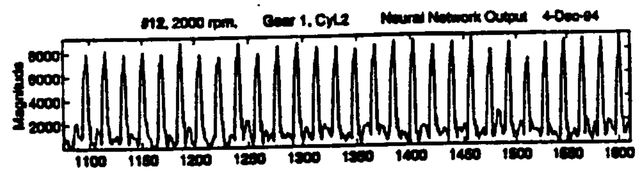

Fig. 3

This influence of misfire on the spectrum A_p is illustrated in Fig. 3 for a specific example operating condition and vehicle configuration. This figure shows the magnitude $M_1(j)$ of $A_1(j)$ (i.e., $M_1 = |A_1|$). In this sample, misfire events are indicated by amplitudes of the order of 7000 to 8000. The corresponding magnitude for engine cycles is a random process having amplitude less than about 2000. The samples in Fig. 3 happen to be taken with the car on the road driving in first gear at 2000 RPM but these details are unimportant to the present illustration.

The random fluctuations in $M_1(j)$ are a characteristic of normal combustion in automotive engines. These fluctuations constitute the 'noise' environment in which the misfire 'signal' is to be detected. Although the signal/noise for the sample of Fig. 3 appears to be relatively high, there are other operating conditions having a lower signal/noise.

The final step in detecting misfire is the application of a decision algorithm. In principle, a simple threshold decision algorithm could be applied to the data $M_1(j)$ to detect misfires.

In practice, the relationship between $M_1(j)$ and torque varies significantly with operating conditions. Moreover, the signal/noise for many operating conditions is lower than that for the sample of Fig. 3.

Our studies ([2] and [5]) have shown that misfire detection system performance is enhanced if the decision algorithm adapts to operating conditions. One of the methods of adapting the decision algorithm to operating condition has been through the use of a neural network. The steps involved in this misfire detection system are depicted in Fig. 4.

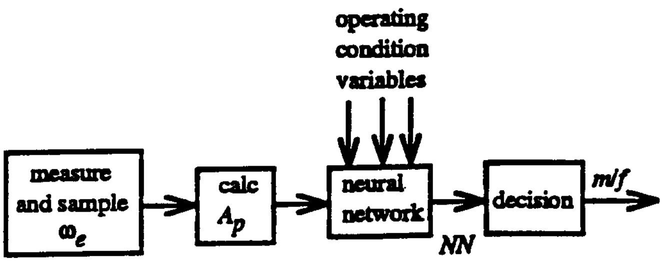

Fig. 4.

The inputs to the neural network, in general, should include certain spectral components as well as variables that are indicative of operating conditions. Of course, in the interest of operating the decision algorithm in real time, the number of inputs should be kept as small as possible.

The final component in the system of Fig. 4 is a threshold decision block. This decision algorithm is a threshold algorithm applied to the neural network output $NN(j)$

$$NN(j) < N_T \quad \Rightarrow \text{normal}$$
$$NN(j) > N_T \quad \Rightarrow \text{misfire.}$$

The performance of any threshold decision algorithm is expressed in terms of its error rates. There are, of course, two types of error: 1) missed detection (*md*) and 2) false alarm (*fa*). We evaluate the performance of our misfire detection by the error rates p_{md} and p_{ms}, respectively, in this paper.

Our studies ([2] and [5]) have shown that the important spectral components are $M_1(j)$ and $M_N(j)$ (where N = number of cylinders). The operating condition is, perhaps, best represented by the engine RPM, and load and by the transmission gear ratio. Engine load is represented by either the mass flow rate of air into the engine (MAF) or the intake manifold absolute pressure (MAP) (although other choices are available in certain car models).

It should be emphasized that the inclusion of gear ratio is merely an option that may prove to be cost effective on cars equipped with automatic transmissions. Our experience to date has shown that it is not required as a neural network on the cars we have studied to date.

For the work reported in this paper, the neural network consisted of three layers. The input layer has three input nodes for $M_1(j)$, RPM(j) and MAF(j). The hidden layer has six nodes and the output layer has one node. The neural networks that we have evaluated are relatively simple in that they are trained using back propagation with Sigmoid functions from layer one to layer two and linear functions from layer two to the output. The neural network software was developed at the University of Michigan and is resident on a Sun Sparcstation 20/50 workstation with about 160M of memory.

An experimental evaluation of the UM misfire detection system has been conducted by instrumenting various production cars and operating the system in actual road tests. The performance of the system in a variety of implementations and in a variety of different car makes and models have been reported ([1], [2] and [5]). In this paper, we report the performance of the system as described above for a passenger car equipped with a 5-cylinder in-line engine and a manual transmission.

The instrumentation that was installed in the test car has a block diagram as depicted in Fig. 5.

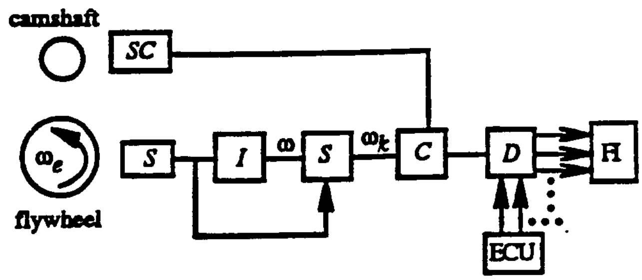

Fig. 5

In this figure, a variable reluctance sensor S is placed close to the starter ring gear. Each of the approximately uniformly spaced starter ring gear teeth generates one cycle of output voltage as that tooth passes the sensor axis. It has been shown [1] that this sensor generates an output having a frequency that is proportional to the instantaneous crankshaft angular speed. Another magnetic sensor S_c couples magnetically to the camshaft and generates a timing reference for each complete engine cycle. Interface electronics consisting of a frequency to voltage converter and a tunable band pass filter generates an analog of crankshaft speed variation. Sampling electronics that are triggered by pulses coming from sensor S generates the sequence ω_k as described above.

This sequence, along with the once per engine cycle signal, are received by a portable computer C. The computer also generates an output signal for inducing misfire. This signal is received by interface electronics D that is responsible for interrupting the driver current to one of the fuel injectors. This circuitry interrupts the current from the car engine control unit (ECU) that normally drives the fuel injectors. In this way, a misfire is induced under program control by preventing fuel delivery to the appropriate cylinder. The program has the capability of inducing a misfire in any given cylinder during any given engine cycle. During development and testing, different misfire sequences are required including random sequences. The program has the capability to meet these requirements.

During experimental evaluation of the University of Michigan misfire detection system, the computer creates data files containing the data sequence ω_k, the operating conditions RPM(k) and MAF(k) and a binary signal indicating misfire/normal combustion.

A 3-layer neural network having inputs $A_1(j)$, RPM(j) and MAF(j), a 6-node hidden layer and a single output was trained. The neural network was trained with data from normal engine operation as well as data from a continuously misfiring cylinder. Similar training data was collected for operation spanning the envelope of normal driving.

Once the neural network was trained, it was tested with the training set to evaluate its performance under training conditions. The error rates for this evaluation were $\leq 10^{-5}$ for all operating conditions.

The performance of the neural network was next evaluated in actual road tests. These tests included continuous misfire for conditions other than those for which the neural network was trained. A more significant test than this, however, is the evaluation of its performance under randomly induced, intermittent misfires. This test is effectively accomplished by inducing a misfire in each M cylinder firing events where M is an integer that is not an integral multiple of N (i.e., the number of cylinders). By proper choice of M, it is possible to induce a misfire in a different cylinder for each misfire and to have a number of normal combustion cycles between successive misfire events.

Experimental evaluation of the present misfire detection system has been conducted with several combinations of intermittent misfire and for various steady operating conditions. These tests were conducted by driving the car on the road, inducing misfires and collecting data and then evaluating misfires off-line.

When tested under these conditions, the neural network has essentially perfect performance. Similar tests of continuous misfire and normal combustion at speed-load points that are different from the training set provide combined error rates (i.e., $p_{fa} + p_{md}$) less about 10^{-3}.

On the other hand, a more challenging test than continuous misfire at constant speed load is for transient driving conditions with intermittent misfire. Such conditions represent a large departure from training conditions and are representative of practical driving conditions. Perhaps the most interesting test involves driving from a stop and increasing speed, shifting at suitable points as is normally done. It should be noted that misfires are not induced during shifting transients since the throttle is closed during this time and the fuel control strategy shuts off fuel delivery.

A sample of the performance of the present misfire detection system under the above driving conditions is illustrated in Fig. 6. This figure shows the three inputs to the neural network at the top, the neural output at the bottom and the decision output in the next to the bottom. This test was conducted under normal driving conditions including a startup transient. A transmission shift can clearly be seen for ($250 \leq j \leq 350$). The induced misfires are identified in this figure by the binary valued variable indicated by a dark line that is displaced downward from 0 and 1 for clarity. The neural network has correctly identified all of the induced misfires during this sample.

Similar samples have been taken for a wide range of steady driving conditions on a wide variety of roads. The error rates for these tests vary somewhat with operating condition. However, for these cases as well as the steady operating conditions, error rates $< 10^{-3}$ have been measured.

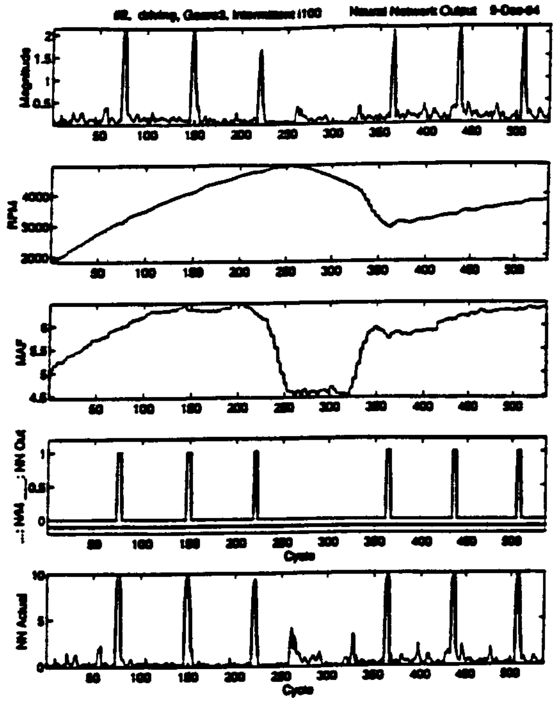

Fig. 6

SUMMARY AND CONCLUSIONS

This paper has presented a method of detecting misfiring in automotive engines. The method utilizes noncontacting measurements of crankshaft angular speed. Samples of this speed that are uniformly spaced in crankshaft angular position from which various spectral components are computed. A design algorithm based upon a neural network identifies individual misfires with error rates $\leq 10^{-3}$. This method has the potential to meet regulatory requirements for on-board misfire detection.

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