

Non-Intrusive Diagnostics of Oxygen Sensors

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ABSTRACT

The usage of the universal exhaust gas oxygen (UEGO) sensor to control the air-fuel ratio (AFR) in gasoline engines allowed to significantly improve the efficiency of the combustion process and reduce tailpipe emissions. The diagnostics of this sensor is very important to ensure proper operation and indicate the need for service when the sensor fails to accurately determine the AFR upstream of the catalyst. California air resources board (CARB) has imposed several legislations around the operation of the UEGO sensor and particularly when specific faults would cause tailpipe emissions to exceed certain limits. In this paper, the possible sensor faults are reviewed, and a non-intrusive diagnostics monitor is proposed to detect, identify and estimate the magnitude of the fault present. This paper extends the approach in [4] where technical details are emphasized and algorithm improvements are discussed. Results from online vehicle implementation of the algorithm in different experimental vehicles are shown and discussed.

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INTRODUCTION

Powertrain systems of gasoline engines operating in the United States are, among others, subject to increasingly stringent requirements under regulations being legislated and implemented by CARB. These regulations require the automotive companies to design and implement engineering solutions (whether software or hardware) in the vehicle to monitor the operation of certain components and processes against certain failure modes that could potentially cause vehicle emissions to exceed certain allowable limits. In gasoline engines, the combustion process requires stoichiometric mixing of oxygen and fuel to improve the efficiency of operation as well as to achieve lower tailpipe emissions. The introduction of the UEGO sensor in automotive industry to measure the AFR has greatly impacted the efficiency of controls thanks to the accurate information it provides of the AFR upstream of the catalyst and allows more precise AFR controls and tighter operation around stoichiometry [5]. The response of the UEGO sensor around stoichiometry is fairly linear and the frequency response function is usually modeled using a first order plant with a delay [6]. Numerous methods were proposed for the AFR controller design, mainly based on linear control theory [7], sliding mode control [8] and delay compensation theory [9, 10]. Most of the available methods in the literature are model-based that require some accurate model of the combined combustion process and sensor dynamics in order to provide accurate controls actions necessary for tracking performance and disturbance rejections. Uncertainties of the measurements, effects of aging of the sensor and disturbances rejection issues remain hot topics for research in order to improve and refine the control strategy of the AFR regulation system.

Apart from the control related issues, the diagnostics of the UEGO sensor is becoming a very challenging problem and is among the priorities of research as it is closely related to the overall performance and robustness of the AFR control system. In fact, several types of oxygen sensor faults may severely effect the performance of the fuel system and could potentially cause an increase in the emissions and a decrease in the fuel economy. In addition, a properly functioning UEGO sensor is also required to diagnose a three-way catalyst [11]. These faults are typically characterized by a change in the sensor dynamics or in its operational characteristics. Several methods have been proposed to diagnose the operation of the UEGO sensor such as data-driven, model-based and statistics-based approaches [12, 13, 14, 15]. According to CARB, the UEGO sensor faults may be due to an additional lag or delay in the transition of the response from lean ($AFR < 1$) to rich ($AFR > 1$) or rich to lean. In [16] it has been reported that "asymmetrical faults may result in emission failures at much lower thresholds than symmetrical faults. Therefore, the logic to determine fault vs. no fault conditions should determine the type of fault present (symmetrical vs. asymmetrical)". Based on this statement, it has been interpreted that six possible modes of sensor failures may occur and that need to be diagnosed. A statistics based approach combined with a system identification process are presented in this paper to address the diagnostics of the UEGO faults (referred to as six-pattern faults) where the fault type is isolated, the direction of the fault is determined and the magnitude of the fault is estimated.

BACKGROUND INFORMATION

Review of the UEGO Six-Pattern Faults

CARB regulations [16] required the presence of an OBD monitor to diagnose the operation of the primary fueling sensor (in this case it is a UEGO sensor) for any possible malfunction effecting the transition from lean to rich or rich to lean. These faults may cause instability of the closed-loop operation and could lead to degradation of the performance of the AFR regulation loop, and result in the vehicle tailpipe emissions to exceed the target thresholds. It has been interpreted that the monitor must detect any of the six discrete faults as illustrated in Fig. (1, 2, 3), where λ indicates the normalized AFR as defined in Eq.(1). The data shown in these graphs was collected from a V6-3.7L engine in a Ford Mustang. Fig. (1) shows both lean to rich and rich to lean filter faults. These faults are due to asymmetry in the time constant T_c between lean and rich modes; the time delay T_d in both transitions is the same. Fig. (2) shows both lean to rich and rich to lean delay faults. These faults are due to asymmetry in the time delay; the time constants are the same in both transitions. Fig. (3) shows both symmetric filter faults and symmetric delay faults.

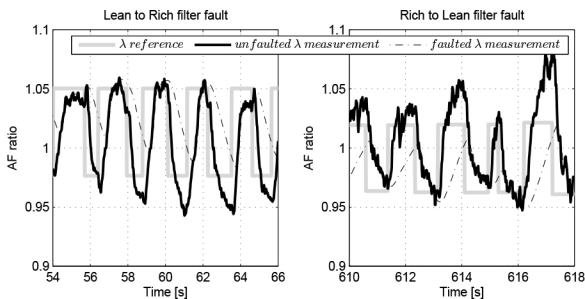


Figure 1. Faulted/unfaulted λ measurements due to asymmetric filter faults in the UEGO sensor

For testing and validation purposes, these faults were artificially induced in the system using a “Fault injection and scan tool (FIST)”. This dedicated software in the loop (SIL) reads the type of fault as well as the associated time constant and time delay to simulate the faulted sensor measurement with the appropriate fault magnitude and direction.

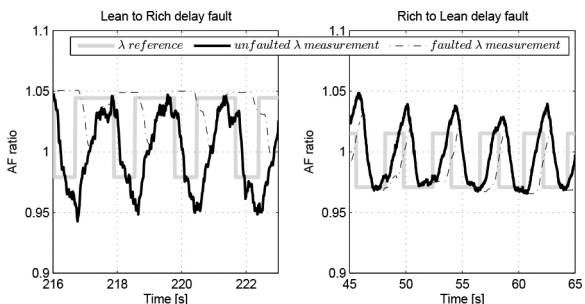


Figure 2. Faulted/unfaulted λ measurements due to asymmetric delay faults in the UEGO sensor

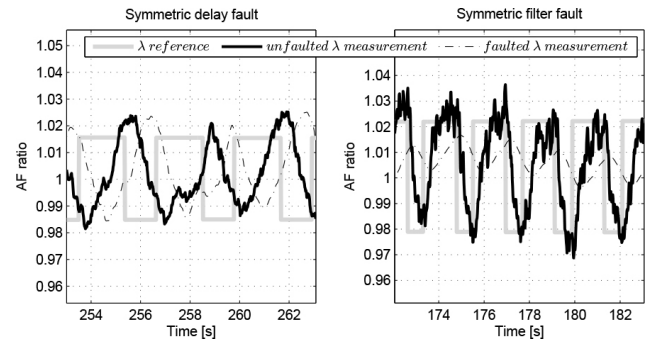


Figure 3. Faulted/unfaulted λ measurements due to symmetric filter and delay faults in the UEGO sensor

AFR Control System

To maintain the AFR as close to stoichiometric operation as possible, the current fuel control strategy employs a feed-forward system together with a closed loop system that consists of a Proportional-Integral (PI) controller and a Smith predictor (SP) for delay compensation [17]. The inner-loop control diagram is shown in Fig. (4). The Smith Predictor controller is tuned to compensate for the delay part in the feedback signal from the UEGO sensor and the PI controller is set to track the commanded AFR and to reject disturbances mainly caused by purging the fuel vapor from the carbon canister [18]. The normalized AFR is defined as

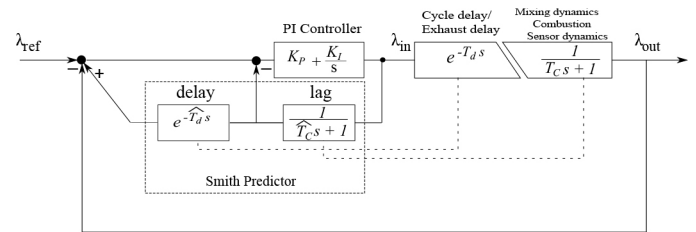


Figure 4. Simplified structure of the AFR control system

$$\lambda = \frac{1}{K_{stoi}} \frac{\dot{m}_{O_2}}{\dot{m}_{fuel}} \quad (1)$$

where $\dot{m}_{O_2}$ denotes the inlet oxygen mass flow rate to the engine, $\dot{m}_{fuel}$ denotes fuel mass flow rate and K_{stoi} is the stoichiometric AFR.

The overall open-loop dynamic process will be approximated by a first order transfer function with delay as follows [15]

$$G(s) = \frac{\lambda_{out}(s)}{\lambda_{in}(s)} \approx \frac{e^{-T_d s}}{T_c s + 1} \quad (2)$$

where T_c denotes the nominal time constant and T_d denotes the nominal time delay. The equivalent discrete time domain transfer function of (2) is given by

$$G(q^{-1}) = \frac{\frac{1}{T_c} q^{-1}}{1 - e^{-\frac{T_s}{T_c}} q^{-1}} q^{-\frac{T_d}{T_s}} = \frac{a_1 q^{-1}}{1 + b_1 q^{-1}} q^{-m} \quad (3)$$

where T_s is the sampling time. Hereafter, the nominal time constant and time delay of the plant system will be denoted as T_c and T_d respectively.

STATISTICS BASED DETECTION AND ISOLATION OF UEGO SENSOR FAULTS

Fault Classification

In [15], a diagnostics method was proposed that consisted of splitting the operation of the system into separate lean to rich and rich to lean transitions and identifying the time constant and time delay associated with each transition. By comparing the estimated parameters to the nominal parameters of a healthy operation, a decision can be made about the type of operation. This method works efficiently well with many faults but fails in some cases due to the way these faults are being induced in the system. In fact, it has been observed that for asymmetrical faults, the inducing mechanism is scheduled to work based on the local variations of the UEGO signal and not based on the commanded AFR reference signal, which becomes very challenging in the presence of noise and disturbances. The method presented in this paper uses only the measurement from the UEGO sensor to make the decision on the type of operation. For asymmetric filter faults, the sensor response is slower in the faulted direction. For asymmetric delay faults, the sensor response will have a deadtime before the sensor reacts in the faulted direction. By observing the distribution of $\Delta\lambda(k)$ (defined as $\Delta\lambda(k) = \lambda(k) - \lambda(k-1)$) for each type of fault, we obtain three different types of histograms as illustrated in Fig. (5). The first type is characterized by a symmetrical shape which is specific to the symmetrical operations. The second type is characterized by a noticeable high and sharp central peak. This peak is due to the presence of the asymmetric dead time in the UEGO response (lean to rich delay (L2RD) or rich to lean delay (R2LD)). The third type is characterized by an asymmetric distribution either skewed to the left or to the right depending on the direction of the fault. If an additional lag is induced in the transition from rich to lean, this transition will have smaller slope compared to the the other transition which consequently causes the distribution to displace to the positive side of the vertical axis. In the opposite case, an additional lag is induced in the transition from lean to rich causing the shift of the distribution to the left side from the vertical axis (L2RF). As a synthesis of these observations, it can be concluded that using two characteristic parameters of the distribution function (**central peak** and **shape**) it is possible to detect the type of operation of the UEGO sensor (either symmetric or asymmetric), and if asymmetric, the type the fault can be isolated and the direction can be determined. The 2D plot in Fig. (6) classifies each fault according to the these characteristic parameters. It can be seen that there are four

different zones. The central zone (in black) corresponds to distributions with a low magnitude central peak and non skewed shape which indicates a symmetrical operation. The zone on the right -when the shape parameter is relatively higher- indicates the presence of a L2RF fault and the zone on the left -when the shape is relatively lower- indicates the presence of a R2LF fault. The upper zone is marked by a relatively high central peak which indicates the presence of an asymmetrical delay fault (L2RD or R2LD).

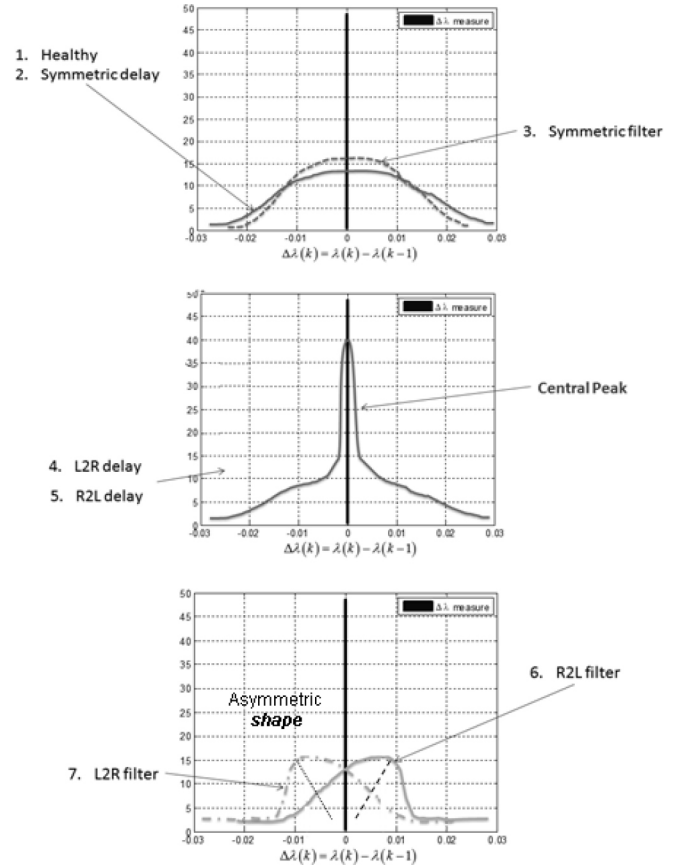


Figure 5. The main shapes of $\Delta\lambda$ distribution functions obtained with all different types of operation. (a) symmetric fault or no fault, (b): asymmetric delay, (c): asymmetric filter.

Statistical Modeling

In order to characterize the distribution of $\Delta\lambda$ for a given operation of the UEGO sensor, it is necessary to consider a density function that fits the data distribution ($\Delta\lambda(k)$) regardless of the type of operation (symmetrical/asymmetrical). In addition to the scale and the location, the density function should have a parameter for the shape to better fit the distribution in case of an asymmetrical filter fault. One good candidate is the generalized extreme value distribution function (GEV). The probability density function (PDF) of this distribution is given by [19, 20]