Control Engineering Practice 34 (2015) 49–60

Contents lists available at ScienceDirect

Control Engineering Practice

journal homepage: www.elsevier.com/locate/conengprac

Development of misfire detection algorithm using quantitative FDI performance analysis ☆

Daniel Jung *, Lars Eriksson, Erik Frisk, Mattias Krysander

Department of Electrical Engineering, Linköping University, SE-581 83 Linköping, Sweden

ARTICLE INFO

Article history:
Received 22 October 2013
Accepted 3 October 2014
Available online 5 November 2014

Keywords:
Misfire detection
Fault diagnosis
Fault detection and isolation
Kullback–Leibler divergence
Pattern recognition

ABSTRACT

A model-based misfire detection algorithm is proposed. The algorithm is able to detect misfires and identify the failing cylinder during different conditions, such as cylinder-to-cylinder variations, cold starts, and different engine behavior in different operating points. Also, a method is proposed for automatic tuning of the algorithm based on training data. The misfire detection algorithm is evaluated using data from several vehicles on the road and the results show that a low misclassification rate is achieved even during difficult conditions.

1. Introduction

Engine misfire detection is an important part of the On-Board Diagnostics II (OBD-II) legislations to reduce exhaust emissions and avoid damage to the catalytic converter. Designing a misfire detection algorithm able to detect misfires during different conditions such as different operating points and cold starts requires tuning of many algorithm parameters. Manual tuning of these parameters in order to achieve satisfactory performance is often time-consuming.

The importance of having an accurate misfire detection algorithm requires a significant part of the available computational capacity. However, in order for the algorithm to be implementable in a vehicle the computational complexity of the algorithm must also be kept low. Thus, it is desirable to both reduce complexity of the algorithm and maintain sufficient detectability performance. In this work, the misfire detectability problem is analyzed and an automatically tuned misfire detection algorithm with low complexity is proposed.

An overview of misfire detection research can be found in Mohammadpour, Franchek, and Grigoriadis (2012) and the most common used signal for misfire detection is the angular velocity measured at the flywheel. Signal analysis approaches used in, e.g., Naik (2004) and Osburn, Kostek, and Franchek (2006) utilize the oscillations in the angular velocity signal, related to the cylinder combustions, to detect when one or several cylinders fail to fire. In Rizvi, Bhatti, and Butt (2011), a Markov chain-based algorithm is proposed to detect misfires. Compared to previous works, the angular velocity signal is used in this work to compute estimated torque which is used to detect misfires.

Beside the angular velocity signal, there are other measurements proposed for misfire detection, such as engine vibration (Chang, Kim, & Min, 2002; Sharma, Sugumaran, & Babu Devasenapati, 2014; Sugumaran, Ramachandran, & Babu Devasenapati, 2010) and ion current (Auzins, John, Johansson, Hasse, & Nytomt, 1995; Fan, Bian, Lu, Tong, & Li, 2014; Lundström & Schagerberg, 2012). With respect to previous works which might require additional sensors, the angular velocity signal is used in this work since it is already available in modern vehicles.

A common model-based approach for misfire detection is to estimate the indicated torque to detect torque drops related to misfire (Connolly & Rizzoni, 1994; Kiencke, 1999; Wang & Chu, 2005). In Connolly and Rizzoni (1994), indicated torque is estimated in the frequency domain and a metric of torque imbalance is used as a test quantity to detect misfires. However, in Connolly and Rizzoni (1994) only detection is considered and not identification of the misfiring cylinder. Other approaches consider estimating the cylinder pressures (Molinar-Monterrubio & Castro-Linares, 2007) or the relative changes in kinetic energy during compression and expansion stroke (Tinaut, Melgar, Laget, & Domínguez, 2007). A contribution here with respect to previous works is a model-based misfire detection algorithm and an automatic off-line tuning strategy using training data of the misfire detection algorithm in order to handle different complicating conditions, such as cold starts.

☆The work is partially supported by Volvo Car Corporation and the Swedish Research Council within the Linnaeus Center CADICS.

* Corresponding author. Tel.: +46 13 28 5743; fax: +46 13 139 282.
E-mail addresses: daner@isy.liu.se (D. Jung), larer@isy.liu.se (L. Eriksson), frisk@isy.liu.se (E. Frisk), matkr@isy.liu.se (M. Krysander).

http://dx.doi.org/10.1016/j.conengprac.2014.10.001
0967-0661/

The use of Kalman filters to estimate the indicated torque for misfire detection is proposed in Helm, Kozek, and Jakubek (2012) and Kiencke (1999), and sliding mode observers in Rizvi, Zaidi, Sajjad Syed Haider, Akram, and Bhatti (2012), Wang and Chu (2005), and Wang, Krishnaswami, and Rizzoni (1997). The use of observer-based solutions increases the computational complexity and limits the applicability in an on-line OBD system. Compared to these works, a contribution in this work is a model-based test quantity for misfire detection without the use of an observer to reduce computational complexity. The algorithm can handle different complicating conditions, such as cold starts. It is also able to identify the misfiring cylinder and can be automatically tuned off-line given training data.

The available maximum sampling resolution of the flywheel angular velocity signal is commonly 6° which is used in Kiencke (1999), but also lower resolutions are used (e.g., 30°, Osburn et al., 2006 and 90°, Naik, 2004). High resolution data gives more information about each combustion but requires more computational power and is also more sensitive to measurement errors caused by flywheel manufacturing errors and signal sampling resolution (Naik, 2004). In this work, measurements with an angular resolution of 30° are used.

The misfire detection performance varies with different operating points, such as load and speed, and is also affected by disturbances such as cycle-to-cycle and cylinder-to-cylinder variations, driveline oscillations, and flywheel manufacturing errors, see Naik (2004). A contribution in this work is an analysis of measurement data, from different vehicles with the same type of engine, to see how misfire detection performance varies for different loads and speeds but also, in contrast to previous works, other complicating circumstances such as cold starts. The analysis is applied during the development process of the misfire detection algorithm to evaluate achieved performance for different designs of the algorithm.

The outline is as follows. First, the problem formulation is presented in Section 2. A model of the crankshaft is described in Section 3 and an analysis of misfire detectability performance in Section 4. Then, the misfire detection algorithm is presented in Section 5 which is evaluated in Section 6. Finally, some conclusions are presented in Section 7.

2. Problem formulation

Misfire detection is a difficult problem which is complicated by that the vehicle is operated in different conditions, such as different loads, speeds, cold starts, and climate variations. The purpose of this work is to perform a quantitative analysis of the misfire detection performance, by analyzing measurement data, in order to develop a model-based misfire detection algorithm. The algorithm should be automatically tunable using training data and should be able to handle variations in load and speed but also other conditions such as cold starts.

In this analysis, data from four cars with six-cylinder inline engines is used. The cylinders are numbered $1, 2, \ldots, 6$ such that cylinder 1 is closest to the flywheel and driveline and cylinder 6 is located furthest away. A list of signals from the vehicle control system used in this work is shown in Table 1. The flywheel angular velocity ω is converted to rpm from the original signal which measures elapsed time between given angular intervals (Eriksson et al., 2013). The air mass induced per revolution m_a [g/rev] is used to represent the engine load (Kiencke, 1999).

Table 1
A list of available signals.

Signal	Variable	Unit
Flywheel angular velocity	ω	rpm
Air mass induced per revolution	m_a	g/rev
Crank angle counter	–	–
Catalyst warming flag	–	–

The crank angle counter keeps track of the flywheel angle which is used to identify the firing cylinders during each revolution. With 30° resolution, each cycle contains $2 \cdot 360°/30° = 24$ samples, i.e., 4 samples for each combustion in a six cylinder engine. The value of the crank angle counter identifies when during a cycle a sample is measured using the indexes $1, 2, \ldots, 24$. The firing order of the engine is 1–5–3–6–2–4 and an example of samples related to each cylinder is shown in Fig. 1.

Misfire detection is considered based on the flywheel angular velocity signal with an angular sample resolution of 30°. Measurement data is available with intermittent misfires injected in all cylinders from four Volvo cars on road with the same type of six cylinder engine.

Two examples of the angular velocity signal with angular resolution of 30° for two different operating points are shown in Figs. 2 and 3. In Fig. 2 data from low speed and low load is shown

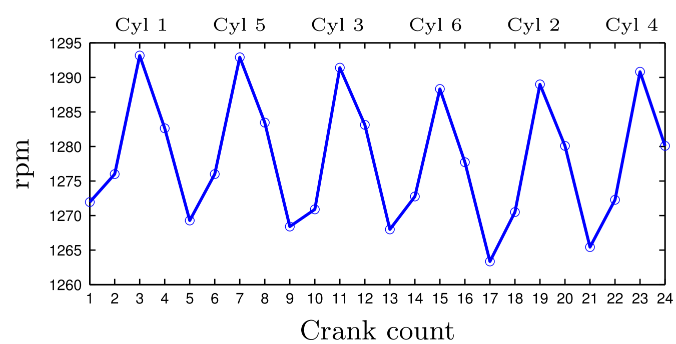

Fig. 1. Flywheel angular velocity where the crank counts associated to the combustion of each cylinder are shown.

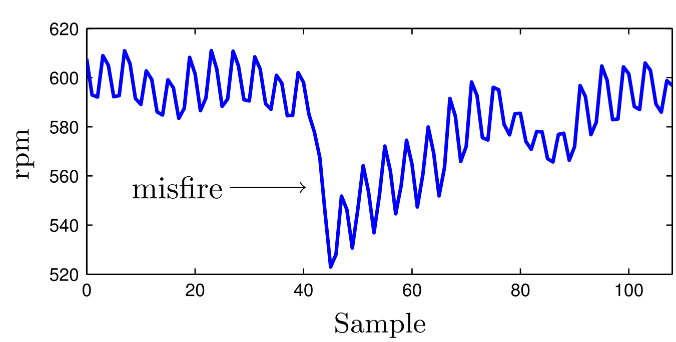

Fig. 2. Flywheel angular velocity measurements around speed 600 rpm and load 0.33 g/rev.

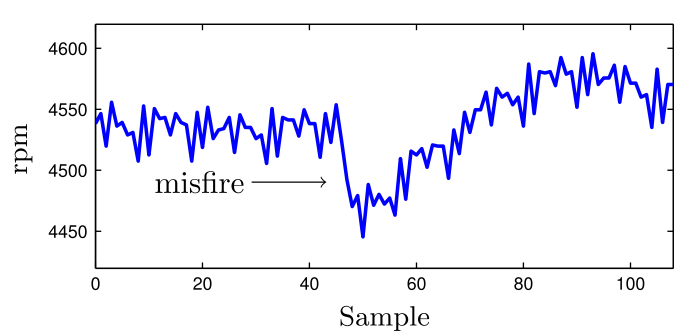

Fig. 3. Flywheel angular velocity measurements around speed 4500 rpm and load 2.87 g/rev.