Control Engineering Practice 47 (2016) 37–47

Contents lists available at ScienceDirect

Control Engineering Practice

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

A flywheel error compensation algorithm for engine misfire detection ☆

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ARTICLE INFO

Article history:
Received 18 February 2015
Received in revised form
10 December 2015
Accepted 11 December 2015
Available online 24 December 2015

Keywords:
Flywheel error estimation
Flywheel error adaptation
Engine misfire detection
Extended Kalman Filter
Constant Gain Extended Kalman Filter

ABSTRACT

The crankshaft angular velocity measured at the flywheel is a commonly used signal for engine misfire detection. However, flywheel manufacturing errors result in vehicle-to-vehicle variations in the measurements and have a negative impact on the misfire detection performance. A misfire detection algorithm must be able to compensate for this type of vehicle-to-vehicle variations if it is to be used in production cars to assure that legislations are fulfilled. It is shown that flywheel angular variations between vehicles in the magnitude of 0.05° have a significant impact on the measured angular velocity and must be compensated for to make the misfire detection algorithm robust. A misfire detection algorithm is proposed with flywheel error adaptation in order to increase robustness and reduce the number of mis-classifications. Evaluations using measurements from a number of vehicles on the road are used to quantify the negative impact of the flywheel errors and show that the number of mis-classifications is significantly reduced when performing on-line flywheel error adaptation.

1. Introduction

Engine misfire detection is an important part of the On Board Diagnostics (OBD) system in personal cars with the purpose of reducing emissions and avoid damage to the catalytic converter (Mohammadpour, Franchek, & Grigoriadis, 2012). A common approach to detect misfires is to use the crankshaft angular velocity signal measured at the flywheel (Jung, Eriksson, Frisk, & Krysander, 2015). The flywheel signal measures elapsed time between given angular intervals defined by teeth, or punched holes, on the flywheel. A misfire is detected by identifying the resulting crankshaft speed drop caused by the failed combustion, see Fig. 1.

The available resolution of the angular velocity measurements is typically 6° (Kiencke, 1999) but lower resolutions are also used (Naik, 2004; Osburn, Kostek, & Franchek, 2006). Here, a lower resolution signal with 30° resolution is used and the main reason is reduction in data-flow, and thereby also in computational effort, by a factor of 5 which is significant in the control system. To use the lower resolution signal while keeping the detection performance at desired levels and significantly reduce the computational effort compared to a high-resolution approach is a main research effort demonstrated here. This is possible by extending the work in Jung et al. (2015) which uses the 30° resolution signal and a low complexity detection algorithm. Utilizing high-resolution data has the potential for increased misfire detection performance, but at the same time requires more detailed models, are more sensitive to quantification errors in the timing measurements for higher engine speeds, and may consume significantly more computational power. The above discussion highlights main reasons why our industrial partner have chosen the lower resolution signal for misfire detection.

The misfire detection problem is complicated by variations in the signal behavior since the engine works in a wide operating range, which affects the measurements. Two examples of differences in the measured angular velocity at different operating points with misfire are shown in Figs. 1 and 2. A misfire is visible as a speed drop in both examples but each oscillation corresponding to a firing cylinder is quite different. Therefore, the flywheel angular velocity signal is often processed before it is used for misfire detection, for example by using frequency analysis (Rizzoni & Zhang, 1994) or estimating cylinder torque (Jung et al., 2015; Kiencke, 1999). Several model based approaches are relying on different types of filters to estimate cylinder torque, for example, the Kalman Filter (Kiencke, 1999), the Parametric Kalman Filter (Helm, Kozek, & Jakubek, 2012), the Extended Kalman Filter (Kallenberger, Hamedovic, & Zoubir, 2007), and the Unscented Kalman Filter (Itoh, Higashi, & Iwase, 2012; Kallenberger et al., 2007). Other measurements proposed for misfire detection are, for example, ion-current (Auzins, Johansson, & Nytomt, 1995; Fan, Bian, Lu, Tong, & Li, 2014) and engine vibration (Abhishek,

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

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http://dx.doi.org/10.1016/j.conengprac.2015.12.009
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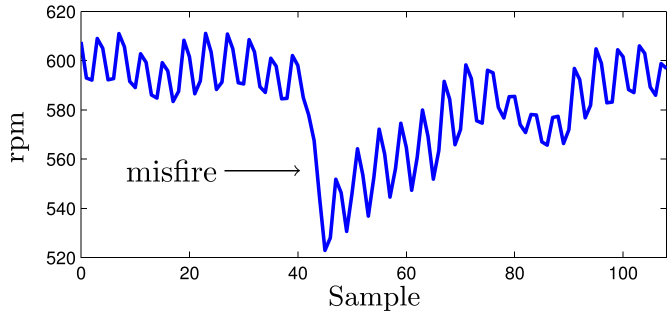

Fig. 1. Example of angular velocity measured at the flywheel at low speed and load. A misfire occurs at sample 40 (Jung et al., 2015).

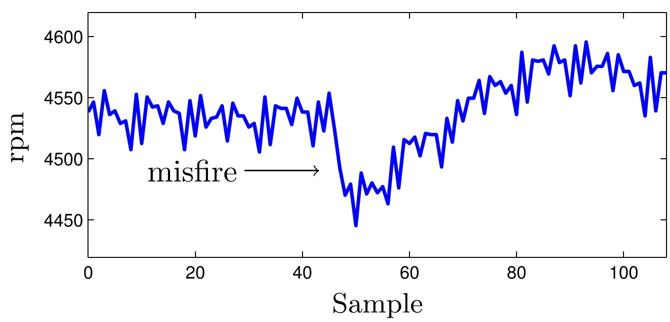

Fig. 2. Example of angular velocity measured at the flywheel at high speed and load. A misfire occurs at sample 45 (Jung et al., 2015).

Sugumaran, & Babu Devasenapati, 2014).

A main complicating factor when using the flywheel signal for misfire detection is flywheel manufacturing errors, such as tooth angle errors or eccentric mounting (Kiencke, 1999). For example, observations discussed in Section 7 show that tooth angle errors in the magnitude of 0.06° can increase the amount of mis-classifications from 0.01% to more than 6%. These manufacturing errors cause vehicle-to-vehicle variations in the measurements and by compensating for the manufacturing errors, better misfire detection performance and robustness of the misfire detection algorithm can be achieved. This is important if the misfire detection algorithm is implemented in production vehicles to assure that no vehicle exceeds the emission requirements due to production variations. The main contribution of this work is a detection algorithm that automatically compensates for flywheel manufacturing errors.

Another complicating factor is crankshaft oscillations (Jung et al., 2015), usually visible after a misfire has occurred causing additional false alarms. In Kiencke (1999), a Kalman filter approach is used to estimate the engine torque and the eccentric mounting is estimated using least squares and the flywheel tooth angle errors are considered random noise. With respect to previous work, a computationally cheap algorithm is proposed in this work which compensates for both tooth angle errors and eccentric mounting.

2. Problem motivation

The main objective is to develop a method that adapts for the effects of flywheel tooth angle errors and eccentric mounting of the flywheel to improve the detection performance of the engine misfire detection algorithm in Jung et al. (2015). Thus, the main contribution is extensions to Jung et al. (2015) for increased robustness to vehicle-to-vehicle variations in the flywheel signal.

The flywheel error compensation here is considered both on-line and off-line. An on-line algorithm is attractive since the compensation would still work without any explicit re-calibration if engine parts were to be replaced, e.g., the ECU or the flywheel itself, and automatic compensation for maintenance actions that could affect flywheel operation. If feasible, the algorithm can also be used for off-line calibration at manufacturing time, with no specific calibration cycles.

The misfire detection algorithm proposed in Jung et al. (2015) uses a low-resolution (30°) flywheel signal to estimate the engine torque. Misfires are detected using a linear classifier based on support vector machines (Bishop, 2006). All calibration of the misfire detection algorithm is made off-line using training data to minimize the computational cost on-line when implemented in a vehicle. Validation on data from vehicles on the road shows that a low mis-classification rate is achieved, even for known complicated situations such as cold starts. The misfire detection algorithm is calibrated using training data from several vehicles in order to take the vehicle-to-vehicle variations, and crankshaft oscillations, into consideration. However, this requires that measurements are available from a set of vehicles that represents the whole range of vehicle-to-vehicle variations and this would be time-consuming to achieve. If the vehicle-to-vehicle variations are significant, tuning the algorithm to a wide range of vehicles will make the detection algorithm robust. The downside is that the tuning will not be optimal for an individual vehicle, i.e., robustness can be improved at the cost of reduced detection performance. Therefore, a flywheel error compensation algorithm that is applied to each vehicle individually has the potential to improve both robustness and performance of the misfire detection algorithm. Also, it is necessary that the misfire detection algorithm is robust to vehicle-to-vehicle variations if it is to be used in personal cars.

The solution proposed is to model and estimate tooth angle errors on the flywheel using the flywheel angular velocity signal. Results in Therén (2014) indicate that the vehicle-to-vehicle variations in the flywheel signal between vehicles could be modeled as constant flywheel tooth angle errors. By estimating and adapting for the flywheel errors, the misfire detection performance can be significantly improved. Thus, the misfire detection algorithm can be calibrated off-line using one vehicle and the vehicle-to-vehicle variations can then be compensated for on-line. The flywheel tooth angle error model used in this work is the same as in Therén (2014) and Weißenborn, Bossmeyer, and Bertram (2011). The flywheel error compensation in Weißenborn et al. (2011) uses both the engine speed and cylinder pressure signals. However, the proposed method cannot be used here since the cylinder pressure signal is not available. One important contribution here is an approach to estimate and compensate for the flywheel errors without any model describing the nominal flywheel signal behavior.

The outline is as follows. First, a description of the available data is presented in Section 3 and a summary of the misfire detection algorithm in Section 4. Modeling the flywheel tooth angle errors is described in Section 5 and the estimation problem is analyzed, both off-line and on-line, in Section 6. The performances of the proposed flywheel tooth angle error compensation algorithms are evaluated in Section 7 and finally some conclusions are presented in Section 8.

3. Available data from vehicles on the road

Measurements from three vehicles on the road are used in this work. The data has also been used in Jung et al. (2015) and the same vehicle and data set identification numbers are used here to make comparisons easier. The vehicles have a six-cylinder inline engine where 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. The firing order of the engine is 1–5–3–6–