

Model-Based Control-Oriented Combustion Phasing Feedback for Fast CA50 Estimation

Qilun Zhu
Clemson Univ.

Shu Wang
ICAR-Clemson Univ.

Robert Prucka
Clemson Univ.

Michael Prucka and Hussein Dourra
FCA US LLC

ABSTRACT

The highly transient operational nature of passenger car engines makes cylinder pressure based feedback control of combustion phasing difficult. The problem is further complicated by cycle-to-cycle combustion variation. A method for fast and accurate differentiation of normal combustion variations and true changes in combustion phasing is addressed in this research. The proposed method combines the results of a feed forward combustion phasing prediction model and “noisy” measurements from cylinder pressure using an iterative estimation technique. A modified version of an Extended Kalman Filter (EKF) is applied to calculate optimal estimation gain according to the stochastic properties of the combustion phasing measurement at the corresponding engine operating condition. Methods to improve steady state CA50 estimation performance and adaptation to errors are further discussed in this research. Finally, the proposed CA50 observer was applied to a SI engine and validated with simulation and dynamometer tests using a prototype engine controller. The new method provides more responsive and accurate CA50 estimation performance than discrete low pass filter techniques.

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INTRODUCTION

Control of combustion phasing with cylinder pressure feedback is difficult due to cycle-by-cycle variations and the highly transient operational nature of passenger car engines. The phasing of combustion, generally defined by crank angle location at which certain portion of the fuel energy is released (e.g. CA10, CA50 and CA90), has a significant impact on the engine performance [1][2]. Real-time calculation of these combustion phasing variables is possible using the Rassweiler and Withrow method [1][3] on measured cylinder pressure. However, cycle-by-cycle combustion variations make it difficult to determine if a shift in mean combustion phasing occurs in a very small sample set of engine cycles. To demonstrate the effectiveness of the proposed methodology, this paper uses the example of CA50 estimation. Although the proposed approach can be used with different types of IC engines with a corresponding combustion phasing model, its application with SI engines is primarily discussed in this document.

Applying a moving average, or discrete low pass filter (treating each engine cycle as an event k), is the most intuitive and common solution to the CA50 estimation problem. With this approach, filter design inevitably involves a tradeoff between accuracy and responsiveness. For most applications, the moving average filter order n is from 10 to 20 engine cycles to generate a reasonably accurate estimation of CA50. This response time is considered very slow for most real world driving situations, where there are not many steady-state events that last more than a few engine cycles.

$$CA50_{est}(k) = \frac{1}{n} \sum_{i=0}^{n-1} CA50(k-i), k = 1, 2, \dots \quad (1)$$

Although most simplified models developed for feed-forward CA50 control suffer from accuracy issues, these models can be implemented as a “virtual CA50 sensor”. This additional prediction can be combined with the cylinder pressure based CA50 feedback, generating a fast and

accurate estimation of the combustion phasing. Previous researchers [4], [5], [6], [7], [8], [9], [10], [11] presented models that can be used to predict CA50 for a SI engine. Most of these models are physics based and control oriented, so they can be run online within each engine cycle. These models ignore cycle-by-cycle dynamics since they are difficult to predict for most operating conditions.

A Kalman Filter (KF) method was developed to estimate linear system states under the influence of measurement noise and actuation disturbance [14]. If the noise\disturbance is Gaussian distributed and the system dynamics are Linear Time Invariant (LTI), the KF has proven to provide the optimal estimation of system states [15]. The KF based estimation approach is especially favorable for systems whose states are affected by their time history. These dynamics help to converge steady state estimation error. Ghazimirsaid et al. [12] and Ravi et al. [13] identified that the CA50 of Homogeneous Charge Compression Ignition (HCCI) engines is strongly affected by the engine states of previous engine cycles. These dynamics were exploited by [16], [17], [18], [19], who applied EKF based techniques on nonlinear CA50 dynamics models for HCCI engine control. Most of these methods calculate their estimation gain using the stationary solution of the algebraic Riccati equation. The proposed method considers the dynamics of estimation variance. This approach improves the steady state estimation accuracy and transient state responsiveness. Previous combustion research has shown that the variation of combustion phasing can be very different according to IC engine operating conditions [24]. Therefore, the estimation gain should be calculated according to the combustion stochastic characteristics of current engine operation conditions. To achieve this goal with stationary KF, one can either solve the Riccati equation online or store pre-calibrated values in a look up table. Both approaches cost either additional computation power or memory demand and calibration time. As for the proposed approach, the variance of combustion can be conveniently included with recursive calculation of estimation gain. Applying a KF to the CA50 estimation of SI engines is rarely discussed due to the lack of cyclic dynamics that helps converge the estimation error. This paper demonstrates that applying a KF to SI engine CA50 estimation can also significantly reduce the impact of measurement noise and modeling errors. The proposed approach utilizes steady and transient state switching operation modes to reduce steady state error without sacrificing transient response. The KF based combustion phasing estimator was augmented with a forgetting factor to guarantee observability for situations with significant modeling errors.

This paper presents a generalized KF based CA50 estimation method which can be used for applications with and without consideration of cyclic dynamics. Methods to improve steady state estimation performance and response to un-modeled dynamics are also discussed. It is shown by this research work that the optimal estimation gain of a KF should be calculated considering the stochastic properties of combustion variation. After a brief description of the experimental setup the basic model assist filter algorithm is described. This section is followed by a discussion of methods to improve KF performance with an adaptive switching mode structure, forgetting-factor, and determination of weighting based on combustion variation analysis. Finally, simulation and test results are presented and conclusions are drawn.

EXPERIMENTAL SETUP

The data in this research was recorded using a port fuel injected 3.6L spark-ignition V-6 engine connected to an AC dynamometer. The test engine was controlled using an ETAS ES910 system overriding the stock ECU. AVL Concerto software was used to process the data that were acquired during each experiment. Each cylinder of one engine bank was instrumented with passage-mounted AVL GH12D piezoelectric cylinder pressure sensors. The sensors were located in the cylinder head to maximize accuracy according to Patterson and Davis [20], and were equipped with flame guards to minimize thermal shock errors. The cylinder pressure measurement was sent to a Cylinder Pressure Development Controller (CPDC) unit to compute CA50 and IMEP [21]. The communication between the CPDC and ES910 was established via a CAN communications link. A summary of engine geometry is given in Table 1.

Table 1. Engine Parameters

Fuel	Gasoline (97 Pump Octane)
Compression Ratio	10.2
Bore	96 mm
Stroke	83 mm
Connecting Rod Length	156.5 mm
Intake Valve Diameter	39 mm
Exhaust Valve Diameter	30 mm

MODEL ASSIST FILTERING

Most explicit models of CA50 consist of exogenous terms relating combustion phasing to current engine operation conditions and n^{th} order homogeneous or auto-regression terms reflecting the cyclic dynamics of CA50 [16], [17], [18], [19]. The generalized canonical form of the CA50 model presented in this research is expressed as the following:

$$CA50_{est}^{(n)}(k) = f \left[CA50_{est}^{(n)}(k-1) \right] + \begin{bmatrix} 1 \\ 0 \\ \vdots \end{bmatrix} [g(RPM, MAP, SPKT \dots) + w(k)]$$

$$CA50_{est}(k) = [1 \quad 0 \quad \dots] CA50_{est}^{(n)}(k) + w(k) \sim N[0, Q(k)] \quad (2)$$

The existence of $w(k)$ is due to the modeling error and measurement noise of engine operating conditions. While the homogeneous term f is often constructed linearly or it can be approximated with a 1st order Taylor series expansion and linearized at any specific operating point. Therefore, equation (2) can be transformed into:

$$CA50_{est}^{(n)}(k) = A(k) CA50_{est}^{(n)}(k-1) + H^T [g(RPM, MAP, SPKT \dots) + w(k)]$$

$$CA50_{est}(k) = H CA50_{est}^{(n)}(k)$$

Where:

$$H = [1, 0, \dots, 0]$$

The CA50 measurement at the k^{th} cycle can be considered as the “true” CA50 corrupted with white noise v :

$$CA50_m(k) = HCA50_t^{(n)}(k) + v(k)$$

$$v(k) \sim N[0, R(k)]$$

(4)

The recursive estimation of CA50 can be formulized as the following:

$$CA50_{est}^{(n)}(k)^+ = CA50_{est}^{(n)}(k)^- + L(k) [CA50_m(k) - H CA50_{est}^{(n)}(k)^-]$$

$$CA50_{est}^{(n)}(k)^- \text{ Prior state estimate at step } k$$

(5)

Where $L(k)$ is estimation gain

The determination of estimation gain $L(k)$ is to minimize the covariance of estimation error $P(k)$. With the information of disturbance and noise variance [$Q(k)$ and $R(k)$, will be discussed in a later section], the estimation gain can be optimally obtained by the KF method. Prior and post estimate errors and corresponding covariance are defined as:

$$CA50_e^{(n)}(k)^+ = CA50_{est}^{(n)}(k)^+ - CA50_t^{(n)}(k)$$

$$CA50_e^{(n)}(k)^- = CA50_{est}^{(n)}(k)^- - CA50_t^{(n)}(k)$$

$$P(k)^{\pm} = E \left[\left(CA50_e^{(n)}(k)^{\pm} \right) \left(CA50_e^{(n)}(k)^{\pm} \right)^T \right]$$

(6)

Then, substitute equations (4) and (6) into (5) and rearrange:

$$CA50_e^{(n)}(k)^+ = [I - L(k)H]CA50_e^{(n)}(k)^- + L(k)v(k)$$

(7)

The post estimation error covariance can be updated from prior error covariance by substituting equation (7) into (6):

$$P(k)^+ = [I - L(k)H]P(k)^-[I - L(k)H]^T + L(k)R(k)L^T(k)$$

(8)

The prior error covariance is calculated from the post covariance of the previous engine cycle according to the linear system errors propagation theorem:

$$P(k)^- = A(k-1)P(k-1)^+A^T(k-1) + Q(k-1)$$

(9)

The optimal estimation gain $L^*(k)$ is used to minimize the post estimation error covariance $P(k)^+$ in equation (8). This can be achieved by finding the $L(k)$ that minimizes $J(k) = \text{trace}[P(k)^+]$:

$$\frac{\partial J(k)}{\partial L(k)} = 0$$

(10)

The solution of equation (10) is:

$$L(k) = P(k)^-H^T[HP(k)^-H^T + R(k)]^{-1}$$

(11)

The update between prior and post error covariance can be simplified by substituting equation (11) into (8):

$$P(k)^+ = [I - L(k)H]P(k)^-$$

(12)

In the cases that cycle-by-cycle dynamics are neglected (e.g. SI engines), the KF can be greatly simplified as $A(k) = 0$ and $H = 1$. Equation (3) is transformed into a stationary model:

$$CA50(k) = g(RPM, MAP, SPKT \dots) + w(k)$$

(13)

It can be inferred from equation (9) that the prior estimation error covariance is constant:

$$P(k)^- = Q(k-1)$$

(14)

From equation (11), the optimal estimation gain can be calculated from the variance of noise $R(k)$ and disturbance $Q(k)$, which is the same as the least square estimation gain for a stationary system.

$$L(k) = \frac{Q(k-1)}{Q(k-1) + R(k)}$$

(15)

ADAPTIVE FILTERING

As a general concept, adaptive filtering represents a class of estimation techniques whose algorithm or involved models evolve with real time measurement. The application of adaptive filtering can reduce accuracy demands of modeling, improve robustness of the control algorithm and generate better steady state results. The exogenous function $g(RPM, MAP, SPKT \dots)$ can be extremely complex and highly nonlinear due to the dynamics of charge motion and flame propagation. Since adaptive filtering can update the system model through identification techniques, it is possible to use a fast yet less accurate model in the observer without sacrificing too much performance. A single layer Artificial Neural Network (ANN) with 10 neurons is used in this research to relate CA50 to RPM, intake manifold absolute pressure (MAP), intake camshaft centerline (ICL), exhaust camshaft centerline (ECL) and spark timing (SPKT). Test results indicate that the computational time for the proposed EKF approach with an ANN model is negligible for the prototype controller. Figure 1 shows the steady state performance of the ANN model. Though the model captures most of the tendencies, non-trivial steady state errors are present in some cases, which can be corrected by online ANN identification.