2009 American Control Conference
Hyatt Regency Riverfront, St. Louis, MO, USA
June 10-12, 2009

Unknown Input Estimation for a Class of Nonlinear Systems and Its Application to Automotive Engine Controls

Chia-Shang Liu and Pingan He

Abstract— **System unmodeled dynamics and uncertainties are common issues in the design of model based controllers and observers. One way to deal with this is to design an unknown input observer to estimate those unknown variables. However it is not feasible, if measurement noises corrupt the estimator significantly. This paper proposes a new approach in the design of an unknown input estimator with proportional and integral terms. Unlike existing high gain or sliding mode based unknown input observers where the high gain is applied at the proportional error term, the proposed one applies the high gain at the integral term, which will render of less sensitivity to measurement noises without sacrificing estimation accuracy. The reduction of measurement noises effect is due to the property of the integrator that can significantly diminish measurement noises. The presented techniques can also be applied to a class of uncertain systems to estimate both the unknown states and disturbances with less sensitivity to measurement noises and less restrictive conditions than those of the previous approaches. Two case studies will be presented for the application of the proposed estimator to automotive engines: The first one is a feedback linearization controller synthesized with the unknown input observer for airpath controls of turbocharged diesel engines and the second one is to reconstruct the signal of the thermal sensor which has a slow response.**

I. INTRODUCTION

Design and implementation of unknown input or disturbance observers have received considerable attention in the past two decades [1]-[2]. The motivation of estimating unknown inputs is due to the fact that their information can be beneficial for control robustness, fault detection and diagnostics [3]. Its applications to automotive engines also showed significant improvement of the engine system performance and the reduction of emission [4]-[5].

There are several classes of disturbance observer problems discussed in [3]. This paper focuses mainly on the problem of the system subject to unknown inputs or disturbances with full state measurement. The objective is to estimate the unknown disturbance inputs by using the measured states and known signals. Various techniques to solve this kind of problems have been proposed. References [2], [5] and [6] assumed the structure of disturbance is known and can be included in the augmented plant. The most common assumption is a piece-wise constant disturbance [5]. A sliding mode observer was proposed in [7] and [8] to estimate the unknown inputs, which is used to obtain the differentiation of relevant states. In [4] a high gain observer was introduced, where the observer applies auxiliary variables to estimate unknown inputs. A method called dirty differentiation observer is also discussed in [4] to estimate the disturbances by the derivative of measured output. As described in [4], the techniques mentioned above can achieve satisfactory estimation accuracy by choosing large observer gains. However, these approaches will amplify the measurement noise significantly.

In this paper, a novel design of the disturbance estimator is proposed by applying the state observer and the system outputs, as well as their integration to estimate unknown inputs. Since the integrator will significantly diminish the noise effect, the proposed approach used this property to choose the observer gains and is thus less sensitive to measurement noises. The developed observer can be further applied to a class of uncertain systems [9]-[11] to simultaneously estimate unknown states and inputs. The amplification of measurement noises due to the need of the derivate of output measurement [9] or the proportional high gain approach [10]-[11] are avoided in this paper. The proposed schemes show less restrictive conditions than those of the previous work that bounded unknown inputs is not required and it can work for certain nonminimum phase systems. On the basis of the developed observers, a new approach of airpath controls of turbocharged diesel engines is presented. This approach will demonstrate better robustness of airpath control design due to system uncertainties. Another example of the application of the unknown input estimator is to rebuild the signal of thermal coupler which has a slow response.

II. PROBLEM STATEMENT AND FORMULATION

Two nonlinear systems will be defined in this section. To begin with, a system subject to unknown inputs with full state measurement is considered and the second one is a class of nonlinear uncertain systems similar to those in [9]-[11]. The one with full measurement is used as the basis for the design of the disturbance input observer and the second one is used to estimate both the unknown states and inputs by applying the developed estimator.

A. System with Full State Measurement

Considering the following nonlinear equation

$$\dot{x} = g(y,u) + Gd_0 \tag{1a}$$

C. S. Liu is with IAV Automotive Engineering Inc., Northville, MI, USA. (e-mail: chia-shang.liu@iav-usa.com).

P. He was with IAV Automotive Engineering Inc and is currently with General Motors, Milford, MI, USA. (e-mail: pingan.he@gm.com).

978-1-4244-4524-0/09/$25.00 ©2009 AACC

$$y = x \quad (1b)$$

where $x \in \mathbf{R}^n$ is the system state, $g \in \mathbf{R}^n$ is a known nonlinear function, $u \in \mathbf{R}^r$ the known input, $y \in \mathbf{R}^n$ is the output measurement, $d_0 \in \mathbf{R}^m$ is the unknown disturbance inputs, which include system uncertainties, unknown nonlinear functions and unmodeled dynamics, $\dot{x} \in \mathbf{R}^n$ is unknown and $G \in \mathbf{R}^{n\times m}$ is a known constant matrix which is used to describe the distribution of unknown inputs. The objective here is to construct an estimator to estimate the input d_0 using only the available signals y and u. To achieve this goal, the following assumptions are introduced.

***Assumption* 1.** Matrix G has full column rank. If G has rank deficiency, there will be a nontrivial subspace that any disturbance in this subspace will not be able to distinguish from zero.

***Assumption* 2.** $\|\ddot{d}_0\| \le \varepsilon_0$, where $\|(\cdot)\|$ denotes the norm operator, and $\varepsilon_0 > 0$ is a scalar.

Since G has full column rank, (1) can be rewritten as

$$\dot{x} = g(y,u) + d \quad (2a)$$

$$y = x \quad (2b)$$

$$d_0 = G^{+} d \quad (2c)$$

where $d \in \mathbf{R}^n$ and G^{+} is the left inverse of G. From *Assumption* 2, we will have $\|\ddot{d}\| \le \varepsilon$, $\varepsilon > 0$.

Equation (2) will later be used to design the unknown input observer in this paper.

B. A class of uncertain systems

Considering the following system

$$\dot{\mathcal{X}} = \mathcal{A}\mathcal{X} + f(\mathcal{Y},u) + \mathcal{G}d_o \quad (3a)$$

$$\mathcal{Y} = \mathcal{C}\mathcal{X} \quad (3b)$$

where $\mathcal{X} \in \mathbf{R}^{\bar{p}}$ is the system state, $f \in \mathbf{R}^{\bar{p}}$ is a known nonlinear function, $\mathcal{Y} \in \mathbf{R}^q$ is the output measurement, and $\mathcal{A} \in \mathbf{R}^{\bar{p}\times\bar{p}}$, $\mathcal{C} \in \mathbf{R}^{q\times\bar{p}}$ and $\mathcal{G} \in \mathbf{R}^{\bar{p}\times m}$ are known constant real matrices.

According to [12], if the rank of observability matrix $(\mathcal{A},\mathcal{C}) \le \bar{p}$, there exists a similarity transformation matrix T such that (3) becomes

$$\dot{\mathcal{X}}_{no} = \mathcal{A}_{no}\mathcal{X}_{no} + \bar{\mathcal{A}}_{12}\mathcal{X}_o + f_{no}(\mathcal{Y},u) + \mathcal{G}_{no}d_o \quad (4a)$$

$$\dot{\mathcal{X}}_o = \mathcal{A}_o\mathcal{X}_o + f_o(\mathcal{Y},u) + \mathcal{G}_o d_o \quad (4b)$$

$$\mathcal{Y} = \mathcal{C}\mathcal{X} = \mathcal{C}_o\mathcal{X}_o \quad (4c)$$

where $\mathcal{X}_{no} \in \mathbf{R}^{\bar{p}-p}$ is the unobservable state, $\mathcal{X}_o \in \mathbf{R}^p$ is the state which is observable, $T\mathcal{A}T^T = \begin{bmatrix} \mathcal{A}_{no} & \bar{\mathcal{A}}_{12} \\ \mathbf{0} & \mathcal{A}_o \end{bmatrix}$, $T\mathcal{X} = [\mathcal{X}_{no} \quad \mathcal{X}_o]^T$, $Tf = [f_{no} \quad f_o]^T$, $T\mathcal{G} = [\mathcal{G}_{no} \quad \mathcal{G}_o]^T$, $\mathcal{C}T^T = [\mathbf{0} \quad \mathcal{C}_o]$, $(\mathcal{A}_o,\mathcal{C}_o)$ is an observable pair, $\mathcal{A}_o \in \mathbf{R}^{p\times p}$, $\mathcal{C}_o \in \mathbf{R}^{q\times p}$ and $\mathcal{G}_o \in \mathbf{R}^{p\times m}$.

Equations (4a)-(4c) will be used to construct the unknown state and input estimator. To transform (4) into a desirable structure, the following assumptions [9]-[11] are given.

***Assumption* 3.** rank ($\mathcal{G}_o$) = m, which means that both $\mathcal{G}_o$ and $\mathcal{G}$ have full column rank.

***Assumption* 4.** rank ($\mathcal{C}_o\mathcal{G}_o$) = rank ($\mathcal{G}_o$). This implies that $q \ge m$, which means the number of scalar measurement is greater or equal to the number of scalar inputs.

***Assumption* 5.** For every complex number λ with nonnegative part, $rank\begin{bmatrix} \mathcal{A}_o - \lambda I & \mathcal{G}_o \\ \mathcal{C}_o & 0 \end{bmatrix} = n + m$. This means the system $[\mathcal{A}_o,\mathcal{G}_o,\mathcal{C}_o]$ is minimum phase.

III. DESIGN OF UNKNOWN INPUT ESTIMATOR

A. A Disturbance Estimator for Systems Described in (2)

On the basis of system described in (2), the following estimator is proposed to estimate the unknown disturbance input d,

$$\dot{\hat{x}} = g(y,u) + \hat{d} \quad (5)$$

$$\hat{d} = -K_0(\hat{x} - x) - K_1\int_0^t (\hat{x} - x)d\tau \quad (6)$$

where K_0 and K_1 are observer gain matrices, $\hat{x}$ and $\hat{d}$ are estimates of x and d, respectively.

Without loss of generality, we assume K_0 and K_1 are diagonal matrices in the following forms,

$$K_0 = \begin{bmatrix} k_{01} & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & k_{0n} \end{bmatrix} \quad (7)$$

$$K_1 = \begin{bmatrix} k_{11} & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & k_{1n} \end{bmatrix} \quad (8)$$

Subtracting (2a) from (5), gives the error dynamics as

$$\dot{e}_x = e_d \quad (9)$$

where $e_x = \hat{x} - x$ and $e_d = \hat{d} - d$.

Lemma 1. Supposing that *Assumption* 1 and 2 hold and the observer gains k_{0i} and k_{1i} are chosen to satisfy the equation

$$s^2 + k_{0i}s + k_{1i} = s^2 + 2\xi_i\omega_i s + \omega_i^2 \quad (10)$$

where $1 > \xi_i > 0$, ω_i is a positive scalar, i = 1, 2, …, n.

(i) The estimation error e_d will asymptotically approach to zero if $k_{1i} \to \infty$.

(ii) If $\dot{d} = c$, where c is a constant vector, e_d will exponentially decay to zero.

Proof. (i) Substituting (6) into (9), we have

$$\dot{e}_x = -K_0 e_x - K_1 \int_0^t e_x d\tau - d \tag{11}$$

Taking the derivate of (11)

$$\ddot{e}_x = -K_0 \dot{e}_x - K_1 e_x - \dot{d} \tag{12}$$

Taking Laplace transform of (12), and from (7), (8) and (10) one can obtain

$$\dot{E}_{xi}(s) = -\frac{\ddot{D}_i(s) + \dot{d}_i(0) - s\dot{e}_i(0)}{(s^2 + 2\xi_i \omega_i s + \omega_i^2)} \tag{13}$$

where $\dot{E}_x(s)$ and $\ddot{D}(s)$ denote the Laplace transform of $\dot{e}_x(t)$ and $\ddot{d}(t)$, respectively and the subscript i indicates the *i*th element of the relevant vector.

The initial condition in (13) can be ignored, if the poles of (13) are stable. Taking inverse Laplace transform of (13),

$$\dot{e}_{xi}(t) = \frac{-\int_0^t e^{-\xi_i \omega_i \tau} \cdot \sin(\omega_i \sqrt{1-\xi_i^2}\,\tau) \cdot \ddot{d}_i(t-\tau) d\tau}{\omega_i \sqrt{1-\xi_i^2}} \tag{14}$$

From (9), (10) and $\|\ddot{d}\| \le \varepsilon$, we have (14) as

$$\|e_{di}(t)\| = \|\dot{e}_{xi}(t)\| \le \frac{2\varepsilon \left|(1-e^{-k_{0i}t/2})\right|}{|k_{0i}| \sqrt{k_{1i}} \sqrt{1-(k_{0i}^2/4k_{1i})}} \tag{15}$$

From (15) we have $e_{di} \to 0$ if $k_{0i} > 0$ and $k_{1i} \to \infty$.

(ii) If $\dot{d} = c$, then $\ddot{d} = 0$. From (13) one can easily show that $e_d(t) \propto e^{-k_{0i}t/2}$. □

B. Disturbance and State Estimator for (4)

Lemma 2. Supposing that *Assumption* 3, 4 and 5 hold, there exist transformations $x_o = \mathcal{T}\begin{bmatrix}\varsigma_1\\ \varsigma_2\end{bmatrix}$ and $\mathcal{Y} = \mathcal{S}\begin{bmatrix}\eta_1\\ \eta_2\end{bmatrix}$ such that (4b) and (4c) can be transformed into

$$\begin{bmatrix}\dot{\varsigma}_1\\ \dot{\varsigma}_2\end{bmatrix} = \begin{bmatrix}\mathcal{A}_{11} & \mathcal{A}_{12}\\ \mathcal{A}_{21} & \mathcal{A}_{22}\end{bmatrix}\begin{bmatrix}\varsigma_1\\ \varsigma_2\end{bmatrix} + \begin{bmatrix}\mathcal{G}_1\\ 0\end{bmatrix} d_0 + \begin{bmatrix}f_1(\mathcal{Y},u)\\ f_2(\mathcal{Y},u)\end{bmatrix}$$

$$\eta_1 = \mathcal{C}_{11}\varsigma_1 \tag{16}$$

$$\eta_2 = \mathcal{C}_{22}\varsigma_2$$

where $\mathcal{T}$, $\mathcal{S}$, $\mathcal{C}_{11}$ and $\mathcal{G}_1$ are nonsingular matrices,

$$\mathcal{T}^{-1}\mathcal{A}_o\mathcal{T} = \begin{bmatrix}\mathcal{A}_{11} & \mathcal{A}_{12}\\ \mathcal{A}_{21} & \mathcal{A}_{22}\end{bmatrix},\ \mathcal{T}^{-1}\mathcal{G}_o = \begin{bmatrix}\mathcal{G}_1\\ 0\end{bmatrix},$$

$$\mathcal{S}^{-1}\mathcal{C}_o\mathcal{T} = \begin{bmatrix}\mathcal{C}_{11} & 0\\ 0 & \mathcal{C}_{22}\end{bmatrix},\ \mathcal{T}^{-1} f_o(\mathcal{Y},u) = \begin{bmatrix}f_1(\mathcal{Y},u)\\ f_2(\mathcal{Y},u)\end{bmatrix},$$

$\varsigma_1 = \mathcal{C}_{11}^{-1}\tilde{\mathcal{S}}_1\mathcal{Y}$, $\eta_2 = \tilde{\mathcal{S}}_2\mathcal{Y}$, the pair $(\mathcal{A}_{22}, \mathcal{C}_{22})$ is detectable, $\mathcal{S}^{-1} = [\tilde{\mathcal{S}}_1 \quad \tilde{\mathcal{S}}_2]^T$, ς_1 and η_2 are available signals that can be obtained from the measured output $\mathcal{Y}$.

Proof. Please refer to [9] and [10]. □

Lemma 3. Supposing (4) can be transformed into (16) and *Assumption* 2 holds. If the state and unknown input observers are chosen as

$$\dot{\hat{\varsigma}}_1 = \mathcal{A}_{11}\varsigma_1 + \mathcal{A}_{12}\hat{\varsigma}_2 + f_1(\mathcal{Y},u) + \mathcal{G}_1\hat{d}_0 \tag{17a}$$

$$\dot{\hat{\varsigma}}_2 = \mathcal{A}_{22}\hat{\varsigma}_2 + \mathcal{A}_{21}\varsigma_1 + f_2(\mathcal{Y},u) + \mathcal{k}(\eta_2 - \mathcal{C}_{22}\hat{\varsigma}_2) \tag{17b}$$

$$\mathcal{G}_1\hat{d}_0 = -\mathcal{K}_0 e_{\varsigma_1} - \mathcal{K}_1\int_0^t e_{\varsigma_1} d\tau \tag{17c}$$

where observer gains $\mathcal{k}$, $\mathcal{K}_0$ and $\mathcal{K}_1$ are selected such that $\mathcal{A}_{22} - \mathcal{k}\mathcal{C}_{22}$ is a Hurwitz matrix, select $\mathcal{K}_0 > 0$, $\mathcal{K}_1 \to \infty$, and $e_{\varsigma_1} = \hat{\varsigma}_1 - \varsigma_1$, then we will have

(i) $\hat{\varsigma}_2 - \varsigma_2 = e_{\varsigma_2} \to 0$

(ii) $\hat{d}_0 - d_0 = e_{d_0} \to 0$

(iii) Furthermore, if $\mathcal{A}_{no}$ in (4) is Hurwitz, then by applying the observer

$$\dot{\hat{x}}_{no} = \mathcal{A}_{no}\hat{x}_{no} + \overline{\mathcal{A}}_{12}\hat{x}_o + f_{no}(\mathcal{Y},u) + \mathcal{G}_{no}\hat{d}_0 \tag{17d}$$

makes $e_{x_{no}} = \hat{x}_{no} - x_{no} \to 0$.

Proof. (i) From (17b) and (16), one can obtain the error dynamics as $\dot{e}_{\varsigma_2} = (\mathcal{A}_{22} - \mathcal{k}\mathcal{C}_{22})e_{\varsigma_2}$. Since from Lemma 2 $(\mathcal{A}_{22}, \mathcal{C}_{22})$ is a detectable pair, one can have $\mathcal{A}_{22} - \mathcal{k}\mathcal{C}_{22}$ be Hurwitz such that $e_{\varsigma_2} \to 0$ exponentially.

(ii) From (17a) and (16), we have the error dynamics of e_{ς_1} as $\dot{e}_{\varsigma_1} = \mathcal{A}_{12}e_{\varsigma_2} + \mathcal{G}_1 e_{d_0}$. Take the derivate of $\dot{e}_{\varsigma_1}$ and from (17c), the error dynamics of e_{ς_1} will be described by $\ddot{e}_{\varsigma_1} = -\mathcal{K}_0\dot{e}_{\varsigma_1} - \mathcal{K}_1 e_{\varsigma_1} - \mathcal{G}_1\dot{d}_0 + \mathcal{A}_{12}\dot{e}_{\varsigma_2}$ which is similar to (12). Since e_{ς_2} exponentially decays to zero, $\dot{e}_{\varsigma_2}$ and $\ddot{e}_{\varsigma_2}$ will approach to zero exponentially. Because *Assumption* 2 holds and according to Lemma 2 $\mathcal{G}_1$ is nonsingular, then from Lemma 1, we can choose $\mathcal{K}_0 > 0$ and $\mathcal{K}_1 \to \infty$ such that $\mathcal{A}_{12}e_{\varsigma_2} + \mathcal{G}_1 e_{d_0} \to 0$, which implies $e_{d_0} \to 0$.

(iii) From (4a) and (17d), we have the error dynamics described as $\dot{e}_{x_{no}} = \mathcal{A}_{no}e_{x_{no}} + \overline{\mathcal{A}}_{12}e_{x_o} + \mathcal{G}_{no}e_{d_0}$, where $e_{x_o} = \hat{x}_o - x_o$, $\hat{x}_o = \mathcal{T}[\varsigma_1 \quad \hat{\varsigma}_2]^T$. Since $\mathcal{A}_{no}$ is Hurwitz, $e_{d_0} \to 0$ and $e_{x_o} = \mathcal{T}[0 \quad e_{\varsigma_2}]^T \to 0$, we can conclude that $e_{x_{no}} = \hat{x}_{no} - x_{no} \to 0$. □

IV. Comparison with the Approach in [4]

In this section, the proposed approach is compared to the high gain approach used by Stotsky and Kolmanovsky [4] with the following system

$$\begin{bmatrix}\dot{x}_1\\ \dot{x}_2\end{bmatrix} = \begin{bmatrix}-2 & 4\\ -3 & -2\end{bmatrix}\begin{bmatrix}x_1\\ x_2\end{bmatrix} + \begin{bmatrix}2\\ 0\end{bmatrix} d \tag{18a}$$

$$\mathcal{Y} = [1 \quad 0][x_1 \quad x_2]^T \tag{18b}$$

$$d = 4\sin(2\pi t) + (3\sin(x_1) + x_1)x_2 \tag{18c}$$

where y denotes the measured output, d is the unknown input, and $[x_1(0) \quad x_2(0)]^T = [0.2 \quad 1]^T$. The objective is to estimate d and unknown state x_2. One can verify that (18) satisfies *Assumption* 2-5 and is in the form of (16).

For comparison, the method adopted in [4] is used and is described in the following. For system (18), a high gain observer is defined in terms of auxiliary h such that

$$\dot{h} = -\gamma_g h + 0.5\gamma_g^2 y_e$$

$$\hat{d}_h = 0.5\gamma_g y_e - h \tag{19}$$

where γ_g is a positive observer gain, $y_e = \hat{x}_{1h} - x_1$, $\dot{\hat{x}}_{1h} = -2x_1 + 4\hat{x}_{2h}$, $\dot{\hat{x}}_{2h} = -3x_1 - 2\hat{x}_{2h}$ and $\hat{d}_h$ is the estimate of d with high gain approach.

From (17), the proposed PI observer will be

$$\dot{\hat{x}}_1 = -2x_1 + 4\hat{x}_2 + 2\hat{d}$$

$$\dot{\hat{x}}_2 = -3x_1 - 2\hat{x}_2$$

$$\hat{d} = -K_0(\hat{x}_1 - x_1) - K_1\int_0^t(\hat{x}_1 - x_1)dt \tag{20}$$

The observer gains are chosen for (19) such that the comparison between (19) and (20) will have the same level of estimation accuracy. Given the observer gains as γ_g=300, and K_0=15, K_1=2500, the two observers will have similar amount of steady-state estimation error, which is shown at Fig. 1 where $e_d = \hat{d} - d$ are plotted without measurement noise effects.

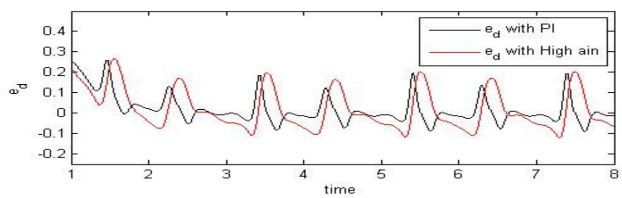

Fig. 1. Estimation Error e_d without Measurement Noises

Assuming that the measurement is corrupted with ±0.02 uniformly distributed random signals and sampling time is 10 ms. The simulation results by applying (19) and (20) are plotted at the top and the bottom of Fig. 2, respectively, where (20) shows less sensitive to measurement noise than that of (19) under the same level of estimation accuracy.

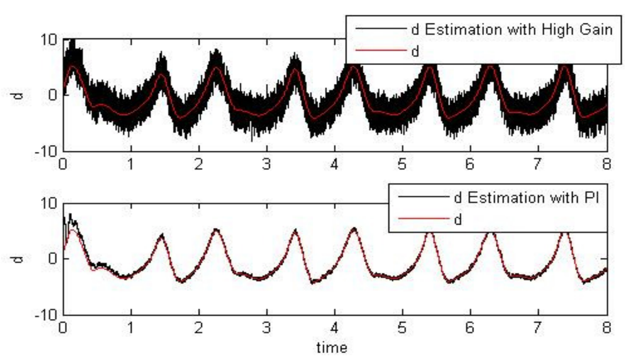

Fig. 2. Estimation of d by (19) and (20)

V. Application to Automotive Engines

A: Application to Turbocharged Diesel Engines

A turbocharged diesel engine is shown in Fig. 3, which is equipped with variable geometry turbine (VGT) and exhaust gas recirculation (EGR) to control the airpath flow rate to reduce engine emissions and to improve engine performance, where T_{im}, p_{im}, T_{em} and p_{em} denote temperature and pressure of intake manifold and those of exhaust manifold, respectively.

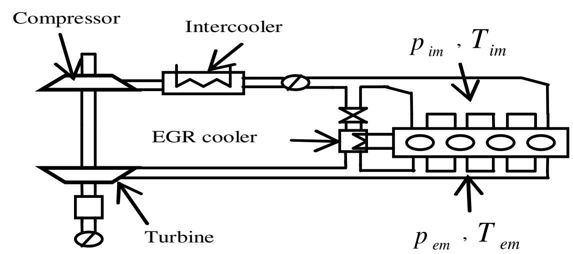

Fig. 3. Schematics of Turbocharged Diesel Engine

The highly nonlinear airpath dynamics and the cross coupling of the VGT and EGR effects pose a challenge in the design of airpath controls. To cope with these problems, a disturbance rejection approach based on the observer schemes (6) is proposed. According to [13] and [14] a simplified third-order nonlinear airpath model is described by the following dynamic equations

$$\dot{W}_c = \phi_1(W_c, p_{em}, e_{im}) - \alpha u_{egr} + \beta u_t + d_1$$

$$\dot{p}_{em} = \phi_2(W_c, p_{em}, e_{im}) - k_{em}u_{egr} - k_{em}u_t + d_2$$

$$\dot{p}_{im} = \phi_3(W_c, p_{em}, e_{im}) + k_{im}u_{egr} + d_3 \tag{21}$$

where

$\phi_1 = -\alpha(W_c - k_e p_{im}) - W_c / \tau_c$;

$\phi_2 = k_{em}(k_e p_{im} + W_f)$;

$\phi_3 = k_{im}(W_c - k_e p_{im})$;

$\alpha = k_{im}\gamma_c \tilde{p}_{im}^{(\gamma_c - 1)} W_c / (\tilde{p}_{im}^{\gamma_c} - 1)$;

$\beta = \dfrac{\eta_c \eta_t \eta_m}{\tau_c} \dfrac{T_{em}}{T_a} \dfrac{1 - \tilde{p}_{em}^{-\gamma_c}}{\tilde{p}_{im}^{\gamma_c} - 1}$;

d_i, i=1, 2, 3, are added in (21) to account for the system uncertainty, un-modeled dynamics and external disturbances; $k_{im} = RT_{im}/V_{im}$; $k_{em} = RT_{em}/V_{em}$; W_c, u_{egr}, u_t, and W_f denote compressor flow, EGR flow, turbine flow, and fuel rate, respectively; V_{im} and V_{em} are the volumes of the intake manifold and exhaust manifold; $k_e = \eta_v V_d N_e / (120 T_{im} R)$, R is the air gas constant; η_v is the volumetric efficiency; V_d is the engine displacement volume; N_e (rpm) is the engine speed; η_m is the turbocharger mechanical efficiency; τ_c is the compressor time constant; $\gamma_c = (\gamma - 1)/\gamma$; γ is the specific heat ratio; η_c denotes the compressor isentropic efficiency; $\tilde{p}_{im} = p_{im}/p_a$; $\tilde{p}_{em} = p_{em}/p_a$; T_a and p_a are the temperature and pressure of ambient air, respectively and η_t is the turbine isentropic efficiency.

To simplify the controller design, the EGR flow u_{egr} and turbine flow u_t are used as the control inputs. The corresponding actuator positions can then be determined by EGR and Turbine flow maps. Due to the unstable zero dynamics of (21) and in order to apply the input-output linearization techniques [13], the following outputs are chosen, $e_1 = W_c - \overline{W}_c$ and $e_2 = p_{em} - \overline{p}_{em}$, where $\overline{p}_{em}$ is the exhaust manifold pressure set point, $\overline{W}_c$ is the compressor flow set point. It can be shown that there is a unique set point of $\overline{p}_{im}$ with respect to set points $\overline{p}_{em}$ and $\overline{W}_c$. From the chosen outputs and the defined variable $e_z = p_{im} - \overline{p}_{im}$ for zero dynamics subsystem.

Since it has been shown in [13]-[14] the determinant of the matrix $G_d = \begin{bmatrix} -\alpha & \beta \\ -k_{em} & -k_{em} \end{bmatrix}$ will not vanish, and the relevant zero dynamics e_z can be shown to be asymptotically stable [13], the techniques of output feedback linearization can be applied. From (21) the output dynamics of e_1 and e_2 can then be rewritten as

$$\begin{bmatrix} \dot{e}_1 \\ \dot{e}_2 \end{bmatrix} = \begin{bmatrix} \phi_1 \\ \phi_2 \end{bmatrix} + G_d \begin{bmatrix} u_{egr} \\ u_t \end{bmatrix} + \begin{bmatrix} d_1 \\ d_2 \end{bmatrix} \tag{22}$$

Assuming that signals of p_{im}, p_{em}, W_c and the variables in ϕ and G_d are either measured or available. However, the values of the variables in ϕ and G_d need not to be accurate since these uncertainties can be attributed to d.

From (22) and (6), an observer to estimate d can be described by

$$\begin{bmatrix} \dot{\hat{e}}_1 \\ \dot{\hat{e}}_2 \end{bmatrix} = \begin{bmatrix} \phi_1 \\ \phi_2 \end{bmatrix} + G_d \begin{bmatrix} u_{egr} \\ u_t \end{bmatrix} + \begin{bmatrix} \hat{d}_1 \\ \hat{d}_2 \end{bmatrix} \tag{23a}$$

$$\begin{aligned} \hat{d}_1 &= k_{01}(\hat{e}_1 - e_1) + k_{11}\int(\hat{e}_1 - e_1)dt \\ \hat{d}_2 &= k_{02}(\hat{e}_2 - e_2) + k_{12}\int(\hat{e}_2 - e_2)dt \end{aligned} \tag{23b}$$

An input-output linearization scheme can be established from (22) and (23) as

$$u = -G_d^{-1}\left(\begin{bmatrix} \phi_1 + \hat{d}_1 \\ \phi_2 + \hat{d}_2 \end{bmatrix} - \begin{bmatrix} v_1 \\ v_2 \end{bmatrix}\right) \tag{24}$$

Substituting (24) into (23) gives

$$\begin{bmatrix} \dot{e}_1 \\ \dot{e}_2 \end{bmatrix} = \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} + \begin{bmatrix} d_1 - \hat{d}_1 \\ d_2 - \hat{d}_2 \end{bmatrix} \tag{25}$$

where v_1 and v_2 are new inputs. If $d - \hat{d}$ is made sufficiently small by choosing appropriate observer gains, (25) will be passive. Asymptotical stabilization of (25) can then be accomplished by choosing $v_1 = -\gamma_1 e_1$ and $v_2 = -\gamma_2 e_2$, where γ_1 and γ_2 are positive constants. Since the zero dynamics e_z is asymptotically stable, the linear exponentially stable e-subsystem will render a cascade of a stable nonlinear e_z-subsystem.

To evaluate the performance of the controller (24), a full order of mean value turbo-charged diesel engine model equipped with EGR and VGT was used [15].

During simulation, the variables k_{im}, k_{em}, α and β of the controller are held as constants. Some of the parameters for example η_v, τ_c are set to be half of their true values in the controller design. It is expected that the model mismatch will be accounted for by $\hat{d}$. Simulation results of intake manifold pressure p_{im} and compressor air flow W_c shown in Fig. 4 have perfect regulation which is in contrast to the robust controller in [13] whose regulation performance is affected by the system mismatch. This demonstrates that the proposed controller's performance will not be compromised under system uncertainties, which implies that accurate model information is not required.

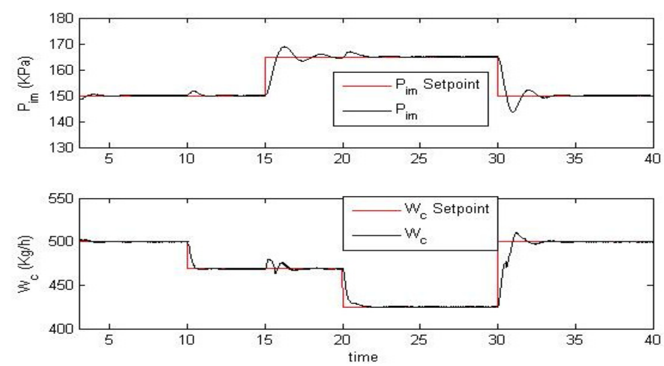

Fig. 4. Tracking of p_{im} and W_c by (24)

B: Correction of Thermal Sensor Signals

The production thermocouple sensor used in automotive engines normally has slow time responses with the order of a few seconds, e.g., with time constant of 4 - 9 seconds. The slow response of temperature sensor may have impact on the performance of model based estimation and control schemes. In such cases fast thermocouple sensors are desirable but they have much shorter life expectation than the slow ones do. The problem of slow response of the thermocouple sensor can be compensated by the proposed unknown input observer. The dynamics of a thermocouple sensor can be represented by a first order lag model [16] as

$$T_m(s) = T_t(s)/(\tau_T s + 1) \tag{26}$$

where T_m is the measured temperature, T_t is the actual temperature, τ_T is the time constant of temperature sensor and s is the Laplace operator.

In (26) we can treat T_t as an unknown input. On the basis of the observer scheme in (5) and (6), the estimator of the actual temperature can be described as

$$\dot{\hat{T}}_m(t) = \left(-T_m(t) + \hat{T}_t(t)\right)/\tau_T \tag{27}$$

$$\hat{T}_t(t) = -\tau_T \left(k_0 e_T(t) + k_1 \int_0^t e_T(t) dt \right) \quad (28)$$

where $e_T(t) = \hat{T}_m(t) - T_m(t)$.

$\hat{T}_t$ can then be used to replace T_m to compensate the measured temperature of the sensor with slow response time. The following example is used to demonstrate the observer shown in (27) and (28).

Assuming that the time constant of the thermal sensor is τ_T = 4.5 sec but the time constant used in the observer design is 4 sec to assume a deviation from actual time constant. The temperature sensor is contaminated with ± 10 ^{o}K random noises. The temperature sensor is to measure the exhaust manifold gas temperature of a diesel engine which is obtained from a high fidelity diesel engine model built on the basis of the model library from THEMOS [15]. The observer gains used in (28) are k_0 = -8 and k_1 = -100. A third order Butterworth low pass filter is used to filter out the high frequency measurement noise. The sampling time is 10 ms. A Federal Test Procedure cycle is used as the simulation operating conditions of the diesel engine model. The result of the observer to correct the low response time temperature sensor is shown in the following figure where the dotted line is the sensor measured temperature, the solid line is the corrected temperature derived by the observer and the dash-dot line is the actual exhaust manifold gas temperature.

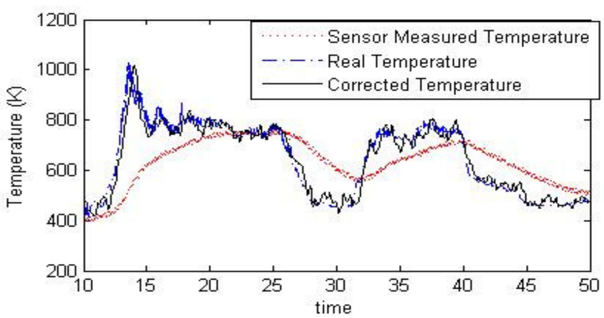

Fig. 5. Corrected Temperature by the Observer (27) & (28)

From Fig. 5, we can see that the unknown input observer can track the actual temperature well. This proves that the observer based temperature correct scheme is a good substitute of the slow temperature sensor.

VI. Conclusion

In this paper an unknown input observer scheme was proposed. The presented approach can be applied to a class of nonlinear systems to simultaneously estimate unknown states and inputs. Due to the integrator's ability to significantly diminish the measurement noises and the choices of observer gains, less sensitive to measurement noises than that of existing approaches was achieved and was demonstrated by numerical simulation. The proposed estimation scheme also has less restrictive conditions than those of previous works.

Based on the proposed observer, a disturbance rejection airpath control of turbocharged diesel engine was developed, which showed the properties of robustness to system uncertainties and less dependency on modeling accuracy. Another example is to apply the proposed observer to correct the measured temperature with a slow response sensor. The case studies demonstrated the proposed estimator's potential usage in automotive engine controls.

Acknowledgment

The authors would like to thank Mr. Jason McConnell and Mr. Wilfried Brunssen at IAV Automotive Engineering Inc. for supporting this work.

References

[1] Y. Dote, H. Kobayashi, J. Fujikawa, A. Syitno, and M. Strefezza "Disturbance observer-based robust and fast speed controller for induction motors," in *Conf. Rec. IEEE Industry Applications Society Annual Meeting*, vol. 1, pp. 653–662, Seattle, WA, Oct. 1990.

[2] E. Schrijver and J. Van Dijk, "Disturbance observers for rigid mechanical systems: equivalence, stability, and design," *ASME Journal of Dynamic Systems, Measurement, and Control*, vol.124, pp. 539-548, Dec. 2002.

[3] A. Radke and Z. Gao, "A survey of state and disturbance observers for practitioners," in *American Control Conference*, Minneapolis MN, pp. 5183-5188, June 2006.

[4] A. Stotsky and I. Kolmanovsky, "Application of input estimation techniques to charge estimation and control in automotive engines," *IFAC Journal of Control Engineering Practice*, vol. 10, no. 12, pp. 1371-1383, Dec. 2002.

[5] A. Gibson, I. Kolmanovsky, and D. Hrovat, "Application of disturbance observers to automotive engine idle speed control for fuel economy improvement," in *American Control Conference*, Minneapolis, MN, pp. 1197-1202, June 2006.

[6] C. Wang and M. Tomizuka, "Design of robustly stable disturbance observers based on closed loop consideration using H_∞ optimization and its applications to motion control systems," in *American Control Conference*, Boston MA, pp. 3764-3769, June 2004.

[7] A. Levant, "Robust exact differentiation via sliding mode technique," *Automatica,* vol. 34, no. 3, pp. 379-384, 1998.

[8] A. Stotsky, J. K. Hedrick, and P. P. Yip, "The use of sliding modes to simplify the backstepping control method," in *American Control Conference*, Albuquerque, New Mexico, pp. 1703-1708, June 1997.

[9] Y. Park and J. L. Stein, "Closed-loop, state and input observer for system with unknown inputs" *Int. J. Control*, vol. 48, no. 3, pp. 1121–1136, 1988.

[10] M. Corless and J. Tu, "State and input estimation for a class of uncertain systems," *Automatica*, vol. 34, no. 6, pp. 757-764, 1998.

[11] Y. Xiong and M. Saif, "Unknown disturbance inputs estimation based on a state functional observer design," *Automatica*, vol. 39, no. 8, pp. 1389-1398, 2003.

[12] M. M. Rosenbrock, *Linear State-Space and Multivariable Theory.* John Wiley, New York, 1970.

[13] M. Jankovic, M. Jankvoic, and I. Kolmanovsky, "Constructive Lyapunov control design for turbocharged diesel engines," *IEEE Transactions on Control System Technology*, vol. 8, no. 2, pp. 288-299, March 2000.

[14] M. Jung and K. Glover, "Calibratable linear parameter-varying control of a turbocharged diesel engine," *IEEE Transactions on Control System Technology*, vol. 14, no. 1, pp. 45-62, January 2006.

[15] I. Friedrich, H. Pucher and T. Offer , "Automatic model calibration for engine-process simulation with heat-release prediction," in 2006 SAE World Congress, Detroit, MI, paper 2006-01-0655.

[16] K. Kar, A. K. Swan and R. Raine, "Identification of time-varying time constants of thermocouple sensors and its application to temperature measurement," *ASME Journal of Dynamic Systems, Measurement, and Control*, vol. 131, Jan. 2009.