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Research Article

Model Reference Adaptive Control of Linear System Despite Sensor Bias

Ebadollah Amouzad Mahdiraji*

Department of Engineering, Sari Branch, Islamic Azad University, Sari, Iran

Keywords

Model Reference Adaptive Control,
Sensor Bias,
Kalman Filter,
Fault Estimation.

Abstract

Based on the simulation results, steady-state tracking errors are improved. Control of indeterminate systems, despite the actuator and sensor bias, has been and remains a major challenge. Sensor error can cause process error. Among the cases where sensor bias is common, air velocity measurements and gyroscope rates can be mentioned. Although considerable research efforts have previously focused on adapting the error, the bias correction of the sensor appears to be relatively limited. However, the cause of several crashes was the sensor error (due to radio altimeter error, angle of attack sensor error, airspeed speed sensor error). Also, finding a way to fix the sensor bias problem is of the utmost importance. The direct model reference adaptive control (MRAC) method is used to control uncertain systems using controllers that are adapted to achieve a performance close to a reference model. However, these controllers maintain system stability and provide close tracking of the reference model response. In this paper, we intend to address the problem of unknown sensor bias matching by adjusting the direct reference model adaptive control for state-feedback for state-tracking (SFST). Also, to obtain an asymptotic stable bias sensor estimator, we use the Kalman filter to estimate the bias sensor error. Based on the simulation results, steady-state tracking errors are improved.

1. Introduction

Sensor bias matching schemes are usually investigated by the SFST-MRAC method and the problem of bias matching of unknown sensors in controlling uncertain systems is considered. Such errors may cause serious damage to the stability and performance of the closed loop. Therefore, the MRAC control law is modified to estimate sensor bias with gain matching and to form asymptotic tracking and signal limiting [1]. Also, the discussion [2–7] of the adaptive control discussion, despite the driving error and sensor error in the process, is aimed at the simultaneous matching of the sensor and bias sensor errors with the help of MRAC control law. Therefore, the reference model adaptive control method is proposed, which is a promising method for maintaining stability and controllability in the event of driver error (without the need for error detection, identification and reconfiguration). Although the results presented are for cases with a single reference input, they can be extended to systems with multiple stimuli and multiple reference inputs. In [8] the FTFC scheme is proposed which includes both the outer ring controller and the inner ring. By first introducing a leader-follower control mechanism by integrating a collision avoidance mechanism as an outer ring control (designed to guarantee the UAV to prevent collisions with impediments), then an FTC strategy, as a controller The inner ring is designed to counteract stimulus errors as well as to prevent saturation of healthy stimuli. Although they are practically applicable and especially attractive in terms of elegance and simplicity, there are drawbacks to the method of avoiding collision. Therefore, the research path can be directed towards updating the mechanism of avoidance of dealing with smart and adaptive capabilities. Bias estimations for multi-sensor systems are discussed in [9–11], which are important in some practical areas, such as target tracking, integrated navigation, transmission network, fault

* Corresponding Author: Ebadollah Amouzad Mahdiraji
E-mail address: ebad.amouzad@gmail.com

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tolerance, and so on. In fact, studies on the state matching problem for a type of dynamic system with multiple asynchronous sensors, where observations from different sensors are accidentally missing. Here, optimum state matching is achieved by using the multipurpose system theory and the modified Kalman filter. In addition, the problem of point-setting tracking is discussed by sensor bias and actuator offset in [12-15]. For example, we consider a process that may be the trigger input of an unmodulated offset, while sensor measurements may also be corrupted by an unmodulated bias. (Which is probably due to incomplete calibration.) So the question arises whether it is possible to achieve a constant zero-state error in the presence of both unknown states (stimulus offset and unknown sensor bias)? In SISO systems, while there are both offset and bias sensor offsets, a servo-loop architecture with forward and reverse controllers cannot be used to track the position of the set point. Although the results in these papers are limited to SISO transfer functions, generalizations about MIMO based on state space models are also being investigated. (For the case of both operator and sensor disturbances, both of which are measured, set point tracking using feed control is provided. MRAC schemes by output feedback for output tracking in sensor error display, in [16-19]. And [20], have been expanded, and in fact the sensor uncertainty compensation problem has been addressed for the adaptive control of the multi-system reference model, two output feedback-based MRAC schemes for dynamically recognized MIMO systems. Sensor uncertainty as an indefinite function is a parameter adjustable and a compensator designed to be able to adapt Therefore, for unknown dynamical systems, a new feedback control structure is created so that (by matching) it will be able to detect uncertainties in both types of measurements. Effectively offsets (system and sensor) the simulation results show that the proposed MRAC scheme for unknown dynamic systems can significantly improve tracking performance despite sensor uncertainty [21].

2. Modify MRAC by Estimating Sensor Bias

In this section, we use a bias estimator that is part of the adaptive control law and uses measurable values that can limit state tracking error while guaranteeing signal constraint [1]. Let's first define $\hat{\beta}$, which is an estimate of the unknown sensor bias β. Using this $\hat{\beta}$, we define a modified state such that $\bar{x}(t) \in R^n$:

$$\bar{x} = y - \hat{\beta} \tag{1}$$

$$\bar{x} = x + \beta - \hat{\beta} = x + \tilde{\beta} \tag{2}$$

Given $\tilde{\beta} = \beta - \hat{\beta}$ (which is defined as a bias estimation error), the structure of the adaptive control law is as follows:

$$u = \hat{K}_1^T y + \hat{K}_2 r + \hat{k}_3 \tag{3}$$

Here $\hat{K}_1(t) \in \mathrm{R}^{n\times m}$, $\hat{\boldsymbol{K}}_2(t) \in \mathrm{R}^{m\times m_r}$,and $\hat{k}_3(t) \in \mathrm{R}^m$ are comparative benefits, ($\hat{k}_3$ The auxiliary input is for better performance which helps us in the simulation.) So the closed-loop modified state equation is:

$$\begin{aligned}\dot{\bar{x}} &= Ax + B\left(\hat{K}_1^T y + \hat{K}_2 r + \hat{k}_3\right) + \dot{\hat{\beta}} \\ &= Ax + B(K_1^T y + K_2 r + k_3) + B\left(\tilde{K}_1^T y + \tilde{K}_2 r + \tilde{k}_3\right) + \dot{\hat{\beta}} \\ &= (A + BK_1^T)x + B\left(\tilde{K}_1^T y + \tilde{K}_2 r + \tilde{k}_3\right) + BK_2 r + Bk_1^T\beta + Bk_3 + \dot{\hat{\beta}}\end{aligned} \tag{4}$$

Here are $\tilde{K}_1 = \hat{K}_1 - K_1$, $\tilde{K}_2 = \hat{K}_2 - K_2$ and $\tilde{k}_3 = \hat{k}_3 - k_3$

Assume the matching conditions for the ideal interests of K_1, K_2 and k_3:

$$A_m = A + BK_1^T \qquad B_m = BK_2 \qquad Bk_1^T\beta = -Bk_3 \tag{5}$$

Given (5) and pasting (2) into (3), we will have:

$$\dot{\bar{x}} = A_m\bar{x} + B_m r + B\left(\tilde{K}_1^T y + \tilde{K}_2 r + \tilde{k}_3\right) - A_m\tilde{\beta} + \dot{\hat{\beta}} \tag{6}$$

The measurable auxiliary error signal $\hat{e}(t) \in R^n$using $\bar{x}$ is defined as:

$$\hat{e} = \bar{x} - x_m \tag{7}$$

$$\hat{e} = \bar{x} - x_m + \tilde{\beta} = e + \tilde{\beta} \tag{8}$$

$$\dot{\hat{e}} = \dot{\bar{x}} - \dot{x}_m \tag{9}$$

$$\dot{\hat{e}} = A_m\hat{e} + B\left(\tilde{K}_1^T y + \tilde{K}_2 r + \tilde{k}_3\right) - A_m\tilde{\beta} + \dot{\hat{\beta}} \tag{10}$$

The following theory updates the obtained comparative gain and bias estimation rules that guarantee the closed-loop signal limitation as well as the tracking error limitation.

$$\begin{aligned}\dot{\hat{K}}_1 &= -\Gamma_1 y\hat{e}^T PB \\ \dot{\hat{K}}_2 &= -\Gamma_2 B^T P\hat{e}r^T \\ \dot{\hat{k}}_3 &= -\Gamma_3 B^T P\hat{e}\end{aligned} \tag{11}$$

While $\Gamma_3 \in R^{m\times m}$ and $\Gamma_2 \in R^{m\times m}$ and $\Gamma_1 \in R^{n\times n}$, the positive definite matrices are symmetrically stable and the bias estimation law is:

$$\dot{\hat{\beta}} = -\eta P^{-1}A_m^T P\hat{e} \tag{12}$$

Here $\eta \in R$ is an adjustable positive constant gain, which guarantees the constraint of all closed-loop signals, including adaptive gain and bias estimation with $e(t)$ tracking error.

$$V = \hat{e}^T P\hat{e} + \sum_i^n \tilde{K}_{1i}^T \Gamma_1^{-1}\tilde{K}_{1i} + \sum_i^{m_r} \tilde{K}_{2i}^T \Gamma_2^{-1}\tilde{K}_{2i} + \tilde{k}_3^T\Gamma_3^{-1}\tilde{k}_3 + \frac{1}{\eta}\tilde{\beta}^T P\tilde{\beta} \tag{13}$$

Here index *i* shows columns $\widetilde{K}_1$ and $\widetilde{K}_2$. By deriving time from (13), in (1) and (11) and the properties of the trace matrix and the resulting interest rate laws in (11), we obtain the following equation.

$$\dot{V} < -\hat{e}^T Q\hat{e} - 2\hat{e}^T PA_m\tilde{\beta} - 2\hat{e}^T P\dot{\hat{\beta}} - \frac{2}{\eta}\tilde{\beta}^T P\dot{\hat{\beta}} \tag{14}$$

Using the equation of the bias estimation law (11) in (13) we have:

$$\dot{V} < -\hat{e}^T Q\hat{e} - 2\hat{e}^T PA_m\tilde{\beta} + 2\eta\hat{e}^T A_m^T P\hat{e} + 2\tilde{\beta}^T A_m^T P\hat{e}$$

$$= -\hat{e}^T Q\hat{e} - \eta\hat{e}^T Q\hat{e} = -(1+\eta)\hat{e}^T Q\hat{e} \tag{15}$$

Adaptive control law in theory 1 guarantees stability (signal limiting) and limiting error tracking and boundary states, but since it is a direct comparative control method, our parameters do not converge to the main parameters in the system. Therefore it would be more desirable to obtain asymptotic tracking. In the next section, to achieve asymptotic tracking, we will deal with an asymptotic stable bias estimator that is achievable separately.

3. MRAC with Asymptotic Stable Bias Estimator

Suppose an asymptotic stable bias estimator is available. Asymptotic stable means that the estimation error is zero and $\hat{\beta}$ will converge to β. So with these conditions in mind, we want to design an asymptotically stable system.
This section shows how an asymptotic bias estimator can be used in MRAC law to allow for asymptotic state tracking [1]. In fact, given these conditions, we want to design an asymptotically stable system. To do this, we first need to consider a bias estimator whose estimation error becomes zero. So we assume a bias estimator with matching error dynamics as follows:

$$\dot{\tilde{\beta}} = A_\beta\tilde{\beta} \tag{16}$$

In this respect, $\hat{\beta}$ is an estimate of β and $\tilde{\beta}(t) = \beta - \hat{\beta}(t)$ is an error estimate.

$$\dot{\hat{K}}_1 = -\Gamma_1 y\hat{e}^T PB \tag{17}$$

$$\dot{\hat{K}}_2 = -\Gamma_2 B^T P\hat{e}r^T$$

$$\dot{\hat{k}}_3 = -\Gamma_3 B^T P\hat{e}$$

Whereas $\Gamma_3 \in R^{m\times m}$ and $\Gamma_2 \in R^{m\times m}$ and $\Gamma_1 \in R^{n\times n}$ are fixed positive symmetric matrices and guarantee that all closed-loop signals include the matching benefits are finite and the tracking error $e(t)$will tend to zero. (While $t \rightarrow \infty$)

$$V = \hat{e}^T P\hat{e} + \sum_i^n \widetilde{K}_{1i}^T \Gamma_1^{-1}\widetilde{K}_{1i} + \sum_i^{m_r} \widetilde{K}_{2i}^T \Gamma_2^{-1}\widetilde{K}_{2i} + \tilde{k}_3^T\Gamma_3^{-1}\tilde{k}_3 + \tilde{\beta}^T P_\beta\tilde{\beta} \tag{18}$$

Here, the index *i* represents the columns $\widetilde{K}_1$ and $\widetilde{K}_2$, and $P_\beta = P_\beta^T \in R^{n\times n}$ is a positive definite matrix for Lyapunov inequality.

$$A_\beta^T P_\beta + P_\beta A_\beta < -Q_\beta \tag{19}$$

For certain positive matrices,

$$Q_\beta - Q_\beta^T \in R^{n\times n} \tag{20}$$

By deriving the relation of (18) to time using equations (1), (10), (16) and (19) and matrix tracking properties, the following statement is easily obtained.

$$\dot{V} \le -\hat{e}^T Q\hat{e} - 2\hat{e}^T P(A_m - A_\beta)\tilde{\beta} - \tilde{\beta}^T Q_\beta\tilde{\beta} + 2\tilde{k}_3^T\{B^T P\hat{e} + \Gamma_3^{-1}\dot{\hat{k}}_3\} \tag{21}$$

$$+2Tr\left[\widetilde{K}_1^T\left\{y\hat{e}^T PB + \Gamma_1^{-1}\dot{\hat{K}}_1\right\}\right] + 2Tr\left[\widetilde{K}_2^T\left\{B^T P\hat{e}r^T + \Gamma_2^{-1}\dot{\hat{K}}_2\right\}\right]$$

Given the updated rules of interest (17) and the equation (21) we have:

$$\dot{V} \le -\hat{e}^T Q\hat{e} - 2\hat{e}^T P(A_m - A_\beta)\tilde{\beta} - \tilde{\beta}^T Q_\beta\tilde{\beta} = -z^T\bar{Q}_z \tag{22}$$

Given $z \in R^{2n}$, we define z as:

$$z = [\hat{e} \quad \tilde{\beta}]^T \tag{23}$$

And the matrix $\bar{Q} \in R^{2n\times 2n}$ is thus defined:

$$\bar{Q} = \begin{bmatrix} Q & P(A_m - A_\beta) \\ (A_m - A_\beta)^T p & Q_\beta \end{bmatrix} \tag{24}$$

Since Q is a positive definite, the Q matrix is also positive if:

$$Q_\beta - (A_m - A_\beta)^T PQ^{-1}P(A_m - A_\beta) > 0 \tag{25}$$

Q_β can be chosen to fulfill (25).

$\dot{V} < 0$ and $V(T)$ is restricted to all T. Also $\hat{e}(t)$, $\hat{\beta}(t)$, $y(t)$, $\widehat{K}_1$, $\widehat{K}_2$,and $\hat{k}_3$ are all constrained $\tilde{\beta}(t)$and $\hat{e}(t) \in L^2$.

We have (16) and (10) and unlimited closed-loop signals:

$$\dot{\hat{e}}(t), \dot{\tilde{\beta}} \in L^\infty$$

$$\lim_{t\to\infty} \hat{e}(\mathrm{t}) = 0$$

$$\lim_{t\to\infty} \tilde{\beta}(t) = 0$$

$$\lim_{t\to\infty} e(\mathrm{t}) = 0$$

$$\dot{\hat{K}}_{1i}, \dot{\hat{K}}_{2i}, \dot{\hat{k}}_3 \in L^2 \cap L^\infty$$

So we can conclude:

$$\ddot{\hat{K}}_{1i}, \ddot{\hat{K}}_{2i}, \ddot{\hat{k}}_3 \in L^\infty$$

$$\lim_{t\to\infty} \dot{\hat{K}}_{1i} = 0$$

$$\lim_{t\to\infty} \dot{\hat{K}}_{2i} = 0$$

$$\lim_{t\to\infty} \dot{\hat{k}}_3 = 0$$

As stated at the beginning of this section, to have an asymptotically stable bias estimator, we need to set the estimation error to zero assuming $\hat{\beta}$ to β and:

$$\lim_{t\to\infty} \tilde{\beta}(t) = 0$$

Therefore, we will use the Kalman filter to achieve a non-bias estimation to achieve this goal. (The bias-free estimate is that $\hat{x}$ tends to x, thus $\hat{y}$ t to y, accurately detects β.)

3.1. Kalman Filter

The Kalman filter is an efficient recursive filter that estimates the state variables of a dynamic system utilizing a set of indirect and distorted noise measurements. The original Kalman filter format is based on a white noise linear system, which is why it is guaranteed only under the assumptions of linearity of the system as well as white and system noise independent and Kalman filter optimality. Therefore, to use the Kalman filter, accurate information on the nature of the noise, including mean, variance, and standard deviation, must be available, which is sometimes difficult or impossible. The purpose of the Kalman filter is to estimate system state variables based on measurements with noise and random variables. The Kalman filter is a powerful and general tool for combining information in uncertain and dynamic environments. In most cases, the information extracted by this filter is very accurate. Before we get into the Kalman filter discussion, let's first briefly discuss random processes.

4. Performance Testing of the Control Rules Provided

To test the efficiency of the different control rules presented in this paper, in the presence of unknown sensor bias, the following two simulations are performed. (In each of these cases an unknown bias is assumed to occur at t = 0.)

4.1. Theory 1 (MRAC Feedback Bias Estimation)

The state variables for the longitudinal dynamic model are the four state variables: Actual velocity (s/m), angle of attack α (Degree), ground angle θ (Degree) and ground velocity q (Degree/second). Elevator and throttle inlet are the control inputs, denoted by u_e (in degrees) and u_t, respectively. Input u_e shows the elevator position (in degrees) and the input The u_t valve shows the coefficient of strength by a fixed operating scale, so no unit is used for u_t [1] The units of measurement of the β components that represent biases in (v, α, θ, q)Are, respectively, m/s, degrees, degrees, degrees per second By measuring bias values, implement the standard MRAC control law, which applies, by conventionally or optionally, $\hat{K}_1(t)$ and $\hat{K}_2(t)$ at half their actual value. (Initializes) and matching interests are selected on a contractual or optional basis.

$$A = \begin{bmatrix} -0.0062 & -0.0815 & -0.1709 & -0.0026 \\ -0.0344 & -0.5717 & 0 & 1.0050 \\ 0 & 0 & 0 & 1.0000 \\ 0.0115 & -1.0490 & 0 & -0.6803 \end{bmatrix} \quad (26)$$

$$B = \begin{bmatrix} 0 & 1.3287 \\ -11.4027 & -0.0401 \\ 0 & 0 \\ -44.5192 & 0.8824 \end{bmatrix} \quad (27)$$

$$x(t) = [v \quad \alpha \quad \theta \quad q]^T \quad (28)$$

$$u(t) = [u_e \quad u_t]^T \quad (29)$$

$$A_m = A + Bk_1^T \quad (30)$$

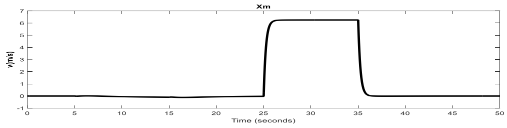
$$B_m = BK_2 \quad (31)$$

Here K_1 is the LQR gain designed for optimal closed-loop performance. Interest $K_2 = L_2$, such that $B_{\boldsymbol{m}} = B$. In the simulation, K_2 is chosen to provide the appropriate scale $r(t)$ (reference input). The unknown constant bias, in the case measurement, is either optionally or optionally selected as follows:

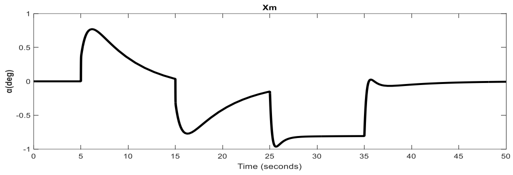
$$\beta = [5 \quad 2 \quad -1 \quad 10] \quad (32)$$

$$\begin{aligned} \hat{K}_1(t) &= 0.5K_1 \\ \hat{K}_2(t) &= 0.5K_2 \\ \Gamma_1 &= 0.005I_4 \\ \Gamma_2 &= 0.005I_2 \end{aligned} \quad (33)$$

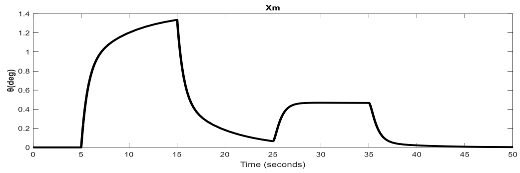
Figure 1 and Figure 2 show that by examining the simulation results, we conclude that the law of comparative control in Theory 1, the stability (limited signal) and the limitation of the tracking error (which is zero). It ensures that the states are slow, but by comparing $\mathrm{x_m}$ and $\bar{\mathrm{x}}$, we find that our parameters do not converge with the main parameters in the system. Therefore, the limitation of the closed-loop signal or the limitation of the tracking error cannot be proved. However, in this example, the tracking error appears to be close to some constant non-zero values. So we need to have a correct estimate of β.



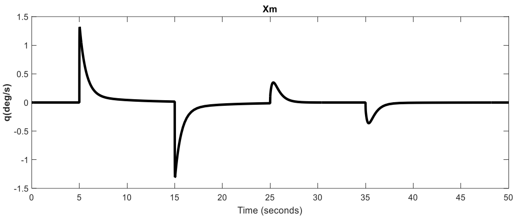
A.Parameter v



B. Parameter α

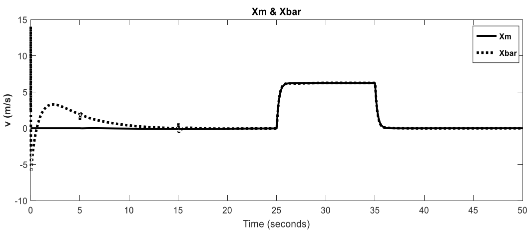


C.Parameter θ

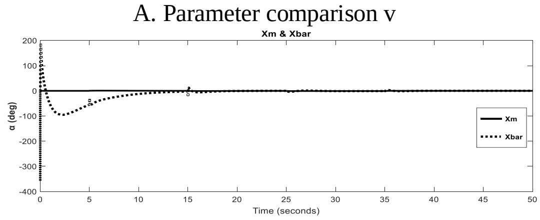


D. Parameter q

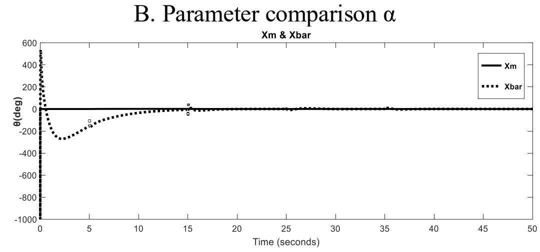
Figure 1. Show model reference modes (x_m) of theory 1



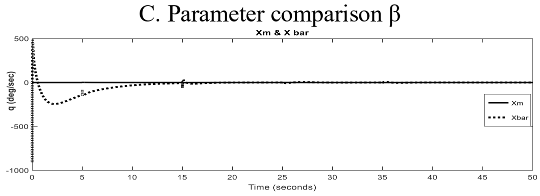
A. Parameter comparison v



B. Parameter comparison α



C. Parameter comparison β

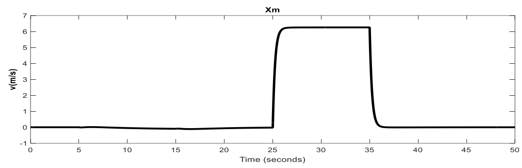


D. Parameter Comparison q

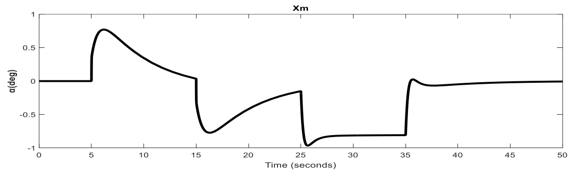
Figure 2. Comparison of the parameter (x_m) and ($\bar{x}$) of Theory 1

4.2. Theory 2 (Using Asymptotic Bias Estimator by MRAC)

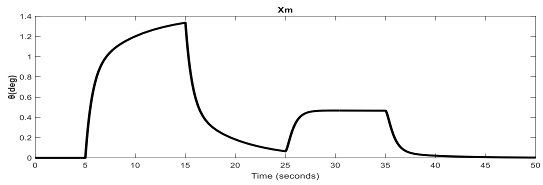
In theory 2 (asymptotic bias estimator) almost all the parameters are fully corrected and their values are closely converged to the reference model. Therefore, the more accurate the $\hat{\beta}$ estimate is, the better x can be measured and the closer to $\bar{x}$. The figures below show the accuracy of the material. Figures (3) and (4) show the correctness of the use of the Kalman filter to accurately estimate β. In Theory 1, by adding the feedback bias estimation based on the MRAC control law, the actual velocity parameters are v(s/m), angle of attack α (degrees), ground angle θ (degrees) and ground velocity q (degrees/seconds), to some extent. It is modified, but because it is a direct adaptive method, the device's parameters do not converge with the main parameters in the system. In theory 2 (Asymptotic Bias Estimator), almost all parameters are completely corrected and their values are close and convergent to the reference model. So the more accurate the estimate (β), the more accurate the ($\hat{\beta}$). As a result, the measurable $\bar{x}$ will get better and closer to x_m.



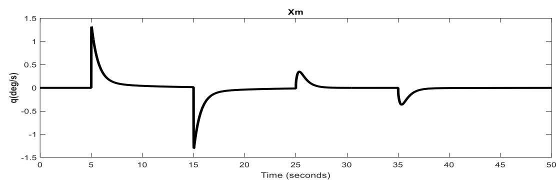
A. Parameter v



B. Parameter α

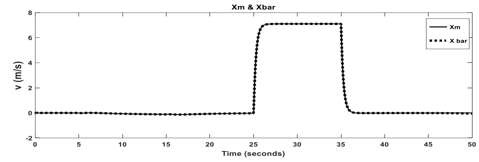


C. Parameter θ

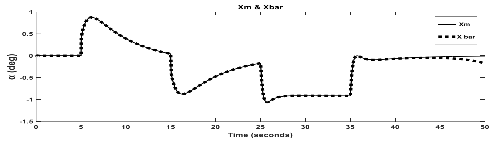


D. Parameter q

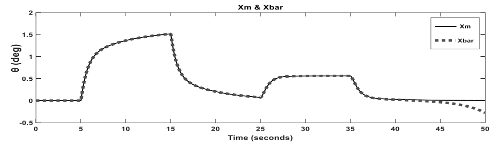
Figure 3. Representation of model reference states (x_m) of Theory 2



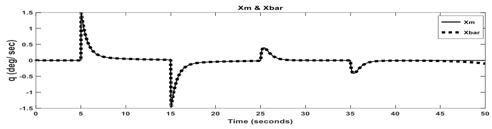
A. Parameter comparison v



B. Parameter comparison α



C. Parameter comparison β



D. Parameter Comparison q

Figure 4. Comparison of the parameters ($\bar{x}$) and (x_m) of theory 2

5. Conclusion

This paper shows that bias can be estimated and used by MRAC to guarantee asymptotic state tracking and closed loop stability. For accurate estimation of β (bias), we used Kalman filter. The purpose of the Kalman filter is to estimate system state variables based on measurements with noise and random variables. Based on the simulation results, steady-state tracking errors are improved. In fact, the tracking error tends to zero. In Theory 1, by adding the feedback bias based on the MRAC control law, the actual velocity parameters are v(m/s), angle of attack α (degree), ground angle θ (degree) and ground velocity q (degree/second), partly. It is modified, but since it is a straightforward comparative method, the parameters of the device do not converge to the main parameters in the system. In Theory 2 (Asymptotic Bias Estimator), we obtain an accurate estimate of the bias using the Kalman filter, As a result, almost all parameters are fully corrected and their values are closely converged to the reference model.

Conflict of Interest Statement

The authors declare no conflict of interest.

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