Research Article

Adaptive Fault-Tolerant Tracking Control of Nonaffine Nonlinear Systems with Actuator Failure

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1. Introduction

The increasing demands on the performance of many modern systems will correspondingly increase the possibility of system failures. Faults may occur in any locations and dramatically change the system behaviour resulting in degradation or even instability. To improve system reliability and stability, fault-tolerant control (FTC) for dynamic systems has become an attractive topic and has received considerable attention during the past two decades. The FTC can be mainly classified into two types: passive and active [1]. In the passive approach, the same controller is used throughout the normal case as well as the fault case [2–5]. An active FTC system compensates for the effect of fault by synthesizing a new control strategy based on online accommodation [6–8]. Generally speaking, the active approach is less conservative than the passive one, which has increasingly been the main methodology in designing FTC systems [9].

On the other hand, tracking control plays an important role in the field of industrial production, aeronautics, and astronautics, such as a flexible robotic, aerospace vehicle, and so forth. Therefore, it has been a hot research topic for scientists and engineers over the past few years [10–12]. The tracking controller design of complex nonlinear systems is not easy work, particularly for nonaffine nonlinear systems. One nonlinear approach is the inverse system method. Although the existence of an inverse function can be guaranteed by the implicit function theorem [13], it is generally difficult to prescribe a technique to actually obtain such an inverse. In another approach, an integrator, that is, $u = \int_0^t \dot{u} \, dt$, is introduced to a new control input $\dot{u}$. However, the relative degree of the augmented system is higher than that of the original system [14, 15].

As an important research direction of active FTC, fault accommodation (FA) is paid attention by many researchers. Recently, some results for fault estimation and accommodation have been obtained [16–18]. Compared with fault detection and isolation (FDI) only, fault estimation and accommodation of nonaffine nonlinear systems are not an easy task. About two parts of FA must be developed, such as a reconfigurable nonlinear tracking controller and a fault estimation (state unmeasured) module. As far as we know, most
articles of fault-tolerant tracking control are mainly focused on affine systems and how to design tracking controller of nonaffine nonlinear systems, which is the main obstacle for fault-tolerant tracking control of nonaffine systems.

This paper addresses the fault-tolerant tracking control problem for nonaffine nonlinear systems in the presence of actuator faults. A novel dynamic model approximation method is first proposed to approximate the nonaffine nonlinear dynamics, which is a solution that bridges the gap between affine and nonaffine control systems. Then, the unscented Kalman filter (UKF) algorithm is employed to estimate plant states and faults from the measurable output. Recent studies on nonlinear systems [19] have shown to estimate plant states and faults from the measurable output. Here, the plant dynamics and measurements are described by the discrete nonlinear model

\[
\begin{bmatrix}
x(k+1) \\
\mu(k+1)
\end{bmatrix} = \begin{bmatrix}
F(x(k), u(k), \mu(k)) \\
\mu(k)
\end{bmatrix} + \begin{bmatrix}
v(k) \\
\omega(k)
\end{bmatrix},
\]

(3)

where \(\mu(t)\) describe fault signal and can be constant or time varying. The existence of failure can lead to steady state offsets. A significant concern in the formulation of the fault accommodation algorithm is the requisite tracking action in the closed-loop. A proper fault and state model must be designed such that they can be estimated from the measurable output. Here, the plant dynamics and measurements are described by the discrete nonlinear model

\[
\begin{align*}
\dot{x} &= F(x, u, \mu) + \frac{\partial F(x, u, \mu)}{\partial u} |_{u=u_n} (u - u_n) + O(\cdot), \\
y &= h(x) + \xi(k),
\end{align*}
\]

(4)

where

\[
O(\cdot) = \sum_{i=2}^{\infty} \frac{\partial^i F(x, u, \mu)}{\partial u^i} |_{u=u_n} (u - u_n)^i.
\]

(5)

If we let \(g(x, u_n, \mu) = (\partial F(x, u, \mu) / \partial u)|_{u=u_n} f(x, u_n, d, \mu) = F(x, u_n, \mu) - g(x, u_n, \mu)u_n + \mathcal{E}(x)d\), so we can rewrite (2) as

\[
\begin{align*}
\dot{x} &= f(x, u_n, \mu) + g(x, u_n, \mu)u + O(\cdot), \\
y &= h(x).
\end{align*}
\]

(6)

Assumption 2. There exists a known constant \(g_M\) such that \(\|g(x, u_n, \mu)\| \leq g_M\) for all \((x, u_n, \mu) \in \Omega_x \times R\).

Lemma 3. If \(\partial F(\omega) / \partial \omega\) exists and is continuous on \(U\), that is, \(F\) is \(C^1\), then \(F\) is locally Lipschitz on \(U\).

Proof. See [20].

Proposition 4. There exists a constant \(L_2\) which satisfies the inequality \(\|O(\cdot)\| \leq L_2\|u - u_n\|\) for all \(x \in \Omega_x\).

[19]
Proof. Rearranging (4) with respect to $O(\cdot)$, we obtain

$$O(\cdot) = F(x, u, \mu) - F(x, u_n, \mu) - g(x, u_n, \mu) (u - u_n).$$  

(7)

From Assumptions 1 and 2 and Lemma 3, there exist $L_1$ and $g_M$ such that

$$\|F(x, u, \mu) - F(x, u_n, \mu)\| \leq L_1 \|u - u_n\|,$$

$$\|g(x, u_n, \mu)\| \|u - u_n\| \leq g_M \|u - u_n\|.$$  

(8)

Taking the absolute value on both sides of (7) and using (8), we can easily induce

$$\|O(\cdot)\| \leq \|F(x, u, \mu) - F(x, u_n, \mu)\| + \|g(x, u_n, \mu)\| \|u - u_n\|$$

$$\leq L_1 \|u - u_n\| + g_M \|u - u_n\|$$

$$= L_2 \|u - u_n\|,$$

where $L_2 = L_1 + g_M$. \qed

From (9), it can be seen that if we let $\lim \|u - u_n\| = 0$, then $\lim \|O(\cdot)\| = 0$. In many actual process control systems and flight control systems, $\|u(t) - u(t - \tau)\| \in [0, \delta]$ is a physical restriction of many practical systems because their actuators cannot change too fast due to system "inertia." So in [21, 22], the $u(t - \tau)$ is used to replace $u_n$. However, if the time-delay $\tau$ is selected too large, the precision of approximation of simplified model will be reduced. So the selection of $\tau$ often requires experience. Theoretically, the smaller $\tau$ can provide the better precision of global approximation. If $\tau = 0$, the best precision of global approximation can be achieved. But $u$ is control law to be solved, so it is unable to be realized. In order to obtain exact time-varying trim point $u_n$, here, further improvement of above proposed method is given as follows. Consider lag property of the filtering as

$$u_n = -\xi u_n + \zeta u.$$  

(10)

Then $\lim_{\tau \to \infty} u_n = u$. So use filter (10); it can be ensured that $\lim_{\tau \to \infty} \|O(\cdot)\| = 0$.

Remark 5. Here, $\zeta \to \infty$ is only a rigorous expression for mathematics meanings; in general, $\zeta \in [5, 50]$. Filter (10) is not unique. The filtering $u_n$ can be completely replaced by other filtering equation, such as higher-order differentiator [23].

From above analysis, system (2) can be described as an affine system with time-varying parameters by the following:

$$\dot{u}_n = -\xi u_n + \zeta u,$$

$$\dot{x} = f(x, u_n, \mu) + g(x, u_n, \mu) u,$$

$$y = h(x).$$  

(11)

3.2. Ideal Fault-Tolerant Controller. Let $r_i$, the linearizability index, be the minimum order of the derivative of $y_j$ ($i = 1, \ldots, n$) for which the coefficient of at least one $u_k$ ($k = 1, \ldots, m$) is not zero. When the Lie derivative notation is used, this derivative can be expressed as

$$y_j^{(r_i)} = L_j^r h_j + \sum_{k=1}^m L_{g_k} L_j^{r-1} h_j u_k,$$  

(12)

where the Lie derivatives are defined as

$$L_j^r h_j (x) \equiv h_j (x),$$

$$L_j^s h_j (x) = \frac{\partial L_j^{s-1} h_j (x)}{\partial x} f(x, u_n, \mu),$$

$$L_{g_k} L_j^{r-1} h_j (x) = \frac{\partial L_j^{r-1} h_j (x)}{\partial x} g_k (x, u_n, \mu),$$  

(13)

$i = 1, 2, \ldots, n, k = 1, 2, \ldots, m$.

Given that the nonlinear system is input-output (I/O) linearizable, for each output $y_j$ there exists a linearizability index $r_i$.

Assumption 6. The drift term, $L_j^r h_j$, and the control gain, $L_{g_k} L_j^{r-1} h_j$, of the I/O dynamics (12) are globally bounded and Lipschitz.

Define

$$\mathscr{F}(x) = \left[ L_j^r h_1, \ldots, L_j^r h_n \right],$$

$$\mathscr{G}(x) = \left[ \mathscr{G}_1 (x), \ldots, \mathscr{G}_m (x) \right],$$

with $\mathscr{G}_i (x) = \left[ L_{g_k} L_j^{r-1} h_1, \ldots, L_{g_k} L_j^{r-1} h_j \right]$, $i = 1, 2, \ldots, n$, $k = 1, 2, \ldots, m$.

Define $A_i = \text{diag} [A_1, \ldots, A_n]$, $B_i = \text{diag} [B_1, \ldots, B_m]$, $C_i = \text{diag} [C_1, \ldots, C_m]$, $\mathcal{A} = \text{diag} [A_1, \ldots, A_n]$, $\mathcal{B} = \text{diag} [B_1, \ldots, B_m]$, $\mathcal{C} = \text{diag} [C_1, \ldots, C_m]$.

$$A_i = \begin{bmatrix} 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 \end{bmatrix}_{r \times r},$$

$$B_i = \begin{bmatrix} 0 \\ \vdots \\ 1 \\ 0 \end{bmatrix}_{r \times 1},$$

$$C_i = \begin{bmatrix} 1 \\ \vdots \\ 0 \\ 0 \end{bmatrix}_{1 \times r}.$$  

(14)

Define $x = [y_1, \ldots, y_j^{(r-1)}, \ldots, y_n, \ldots, y_j^{(r-1)}]^T$; then (12) can be rewritten as

$$\dot{x} = \mathcal{A} x + \mathcal{B} \left[ \mathscr{F}(x) + \mathscr{G}(x) u \right],$$

$$y = \mathcal{C} x.$$  

(15)
For the given references $y_{1m}, \ldots, y_{rm}$, define the tracking errors as
\begin{equation}
    e_1 = y_1 - y_{1m},
    \vdots
    e_n = y_n - y_{rm}
\end{equation}
and $Y_m = [y_{1m}, \ldots, y_{1m}^{(r-1)}, \ldots, y_{nm}, \ldots, y_{nm}^{(r-1)}]^T$; then $e = [e_1, \ldots, e_1^{(r-1)}, \ldots, e_n, e_n^{(r-1)}]^T$.

So the control law can be chosen with (10) as
\begin{equation}
    u = -\zeta u_n + \xi u,
\end{equation}
\begin{equation}
    u = \mathcal{G}^{-1}(x, u_n, \mu) - \mathcal{H}^T \mathcal{F}(x, u_n, \mu) + y_m^T + \mathcal{H}_{\zeta}^T \xi,
\end{equation}
where $y_m^{(r)} = [y_{1m}, \ldots, y_{1m}^{(r-1)}]^T$. Substituting (17) into (15) yields
\begin{equation}
    \dot{\xi} = \left(\mathcal{A} - \mathcal{B} \mathcal{H}_{\zeta}^T\right) \xi.
\end{equation}

It can be seen that we can design the gain matrix $\mathcal{H}_{\zeta}$ by following Riccati equation:
\begin{equation}
    \left(\mathcal{A} - \mathcal{B} \mathcal{H}_{\zeta}^T\right)^T \mathcal{H} + \mathcal{H} \left(\mathcal{A} - \mathcal{B} \mathcal{H}_{\zeta}^T\right) = -\mathcal{Q},
\end{equation}
where $\mathcal{Q} = \mathcal{Q}_{\xi}^T > 0$. Hence, if $x$, $d$, and $\mu$ are known, the above controller achieves the control objective. However, since states and fault information are generally unknown, the adaptive fault-tolerant controller is implemented by replacing the failure-related parameters and their estimates, as discussed below.

4. Adaptive Fault-Tolerant Controller Design

4.1. Unscented Kalman Filter Based Fault-Tolerant Controller.

Define the variables $x = [x^T, \mu^T]^T$; the adaptive fault-tolerant controller is now chosen in the form
\begin{equation}
    u = \mathcal{G}^{-1}(\hat{x}, u_n) - \mathcal{H}^T \mathcal{F}(\hat{x}, u_n) + y_m^T + \mathcal{H}_{\zeta}^T \xi.
\end{equation}

Next, we recapitulate the UKF state estimation algorithm utilized in this study. The model (3) can be expressed equivalently by the discrete-time model
\begin{equation}
    x(k+1) = f(x(k), u(k)) + v(k),
    y(k) = h(x(k)) + \xi(k),
\end{equation}
where $v = [v^T, \omega^T]^T$. An $n^a$-dimensional vector $x^a(k-1 | k-1)$ is then defined by augmenting the state vector with the process and measurement noise vectors following in
\begin{equation}
    x^a(k-1 | k-1) = [x^T(k-1 | k-1), v^T(k-1), \xi^T(k-1)]^T.
\end{equation}

Since the process and measurement noise are supposed to be zero-mean, the mean $\bar{x}^a(k-1 | k-1)$ of the augmented state vector is presented by
\begin{equation}
    \bar{x}^a(k-1 | k-1) = \left[\bar{x}^T(k-1 | k-1), 0^{1\times(n^a+2m)}, 0^{1\times n}\right]^T.
\end{equation}

Thus, the discrete-time nonlinear model (21) can be rephrased in terms of the augmented vector yielding
\begin{equation}
    x^a(k+1 | k) = f^a(x^a(k | k), u(k)),
    y(k) = h^a(x^a(k | k)).
\end{equation}

The covariance matrix $P^a(k | k)$ of the augmented system can be calculated from
\begin{equation}
    P^a(k | k) = \begin{bmatrix} P(k | k) & 0 & 0 \\ 0 & Q(k) & P^{a\xi}(k) \\ 0 & P^{\xi a}(k) & R(k) \end{bmatrix},
\end{equation}
where $P(k | k)$ is the estimation error covariance of the state $x(k)$, $Q(k)$ is the covariance of the process noise $v(k)$, and $R(k)$ is the covariance of the measurement noise $\xi(k)$. The prediction step of the UKF algorithm includes the propagation of a given set of sigma points within the nonlinear system to produce a consistent set of changed points which are then used to make predictions of the state estimates. Now, the set of $(2n^a+1)$ sigma points $\chi_i(k-1 | k-1)$ is computed according to the algorithm
\begin{equation}
    \chi^a_0(k-1 | k-1) = \bar{x}^a(k-1 | k-1),
    \chi^a_i(k-1 | k-1) = \bar{x}^a(k-1 | k-1) + [(n^a + \kappa) P^a(k-1 | k-1)]_{i}^{1/2},
    \chi^a_{i+n^a}(k-1 | k-1) = \bar{x}^a(k-1 | k-1) - [(n^a + \kappa) P^a(k-1 | k-1)]_{i}^{1/2}
\end{equation}
for all integers $i \in [0, 2n^a]$. Here, $\kappa$ is a scalar parameter used to “fine tune” higher order moments of the supply in order to reduce global prediction errors. Julier et al. [24] recommend that it be chosen such that $n^a + \kappa = 3$. In the monitoring, we represent the total sigma point set by $\chi^a(k-1 | k-1)$.

Each sigma point in the set $\chi^a(k-1 | k-1)$ is propagated via the nonlinear process model over the sampling interval $[t-1, t]$, in order to produce a set of changed points $\chi_i(k-1 | k-1)$ given by
\begin{equation}
    \chi_i(k-1 | k-1) = f^a(\chi^a_i(k-1 | k-1), u(k-1)).
\end{equation}

The predicted state estimate $\bar{x}(k | k-1)$ is computed as a weighted average of the changed points given by
\begin{equation}
    \bar{x}(k | k-1) = \sum_{i=0}^{2n^a} W_i \chi_i(k | k-1),
\end{equation}
where $W_i$ are the weights assigned to each sigma point. The updated state estimate $\hat{x}(k | k)$ is then obtained by incorporating the measurement $y(k)$ into the state estimate $\bar{x}(k | k-1)$ using the measurement update step of the UKF algorithm.

The state estimation error covariance $P^a(k | k)$ is then updated using the measurement update step of the UKF algorithm, as given by
\begin{equation}
    P^a(k | k) = \begin{bmatrix} P(k | k) & 0 & 0 \\ 0 & Q(k) & P^{a\xi}(k) \\ 0 & P^{\xi a}(k) & R(k) \end{bmatrix}.
\end{equation}

The adaptive fault-tolerant controller is then used to replace the failure-related parameters and their estimates, as discussed above.
where the weighting factors $W_i$ are selected corresponding to the algorithm

$$W_i = \begin{cases} \frac{k}{(r^2 + k)}, & \text{if } i = 0, \\ \frac{1}{2(r^2 + k)}, & \text{if } i \neq 0. \end{cases} \quad (29)$$

The predicted estimation error covariance $P(k | k - 1)$ is computed from the weighted outer result of the changed points given by

$$P(k | k - 1) = \sum_{i=0}^{2n'} W_i \left[ x_i(k | k - 1) - \hat{x}(k | k - 1) \right] \times \left[ x_i(k | k - 1) - \hat{x}(k | k - 1) \right]^T. \quad (30)$$

The propagated set of sigma points $x_i(k | k - 1)$ are then represented within the nonlinear measurement function $h^r(.)$, generating a set of outputs $Y_i(k)$ communicated by

$$y_i(k) = h^r(x_i(k | k - 1)). \quad (31)$$

In a fashion analogous to the predicted state estimate, the predicted output $\hat{y}(k)$ is computed as a weighted average of the represented outputs (31) given by

$$\hat{y}(k) = \sum_{i=0}^{2n'} W_i Y_i(k). \quad (32)$$

The novelty covariance $P_{yy}$ and the cross relationship $P_{xy}$ are calculated, respectively, from the following illustration:

$$P_{yy} = \sum_{i=0}^{2n'} W_i \left[ Y_i(k) - \hat{y}(k) \right] \left[ Y_i(k) - \hat{y}(k) \right]^T,$$

$$P_{xy} = \sum_{i=0}^{2n'} W_i \left[ x_i(k | k - 1) - \hat{x}(k | k - 1) \right] \left[ Y_i(k) - \hat{y}(k) \right]^T. \quad (33)$$

The measurement improvement terms for the unscented filter are presented by

$$\hat{x}(k | k) = \hat{x}(k | k - 1) + K(k) (y(k) - \hat{y}(k)),$$

$$P(k | k) = P(k | k - 1) - K(k) P_{yy} K(k)^T, \quad (34)$$

where the Kalman gain $K(k)$ is computed from $K(k) = P_{xy} P_{yy}^{-1}$.

4.2. Stability Analysis. Define estimation error $\bar{x} = \hat{x} - x$. Equation (15) can be equivalent as follows:

$$\dot{x} = Ax + B \left[ F(\bar{x}, u) + T(\bar{x}, u) \right] u + B \bar{P} \bar{x},$$

$$y = Cx, \quad \text{with } \phi \in [x, \bar{x}]. \quad (35)$$

Substituting (20) into (35), the dynamics of close-loop can be obtained as

$$\dot{e} = (A - B \bar{H}_{c}) e + B \bar{F} \bar{x}. \quad (36)$$

Choose the following Lyapunov function:

$$V = e^T \bar{H} e. \quad (37)$$

The time derivative of $V$ is given by

$$\dot{V} = -e^T \bar{H} e + 2e^T \bar{F} \bar{P} \bar{x} \quad (38)$$

Under Young’s inequality $2a^T b \leq a^T a + e^{-1}b^T b$, we have

$$\dot{V} \leq -\lambda_{\text{min}}(\bar{\mathcal{H}}) e^T \bar{H} e + 2e^T \bar{F} \bar{P} \bar{x} \quad (39)$$

where $\lambda_{\text{min}}(\bar{\mathcal{H}}) = \lambda_{\text{min}}(\bar{\mathcal{H}})$, $\lambda_{\text{max}}(\bar{\mathcal{H}})$, and $\mu_{1}$ are the largest and smallest eigenvalues of a matrix. Hence, using global uniform ultimate boundedness (GUUB) stability [20], $V$ is exponential convergence, and the tracking error $e$ can converge to a closed ball domain

$$\Omega_\epsilon = \left\{ \epsilon \ | \ \epsilon \leq \frac{q(t)}{\lambda \cdot \lambda_{\text{min}}(\bar{\mathcal{H}})} \right\}. \quad (40)$$

5. Simulation Results

In this section the intention is to evaluate the performance of the novel adaptive FTC. The evaluation is carried out on the 3-DOF model of UAV dynamics that can be found in [14]. The differential equations governing the point-mass UAV dynamics are given by

$$\dot{V} = g \left( \frac{T - D}{W} - \sin \gamma \right),$$

$$\dot{\gamma} = g \frac{V}{(n \cos \mu - \cos \gamma)}, \quad (41)$$

where $\gamma = \sin \mu \cos \gamma$. Hence, using global uniform ultimate boundedness (GUUB) stability [20], $V$ is exponential convergence, and the tracking error $e$ can converge to a closed ball domain

$$\Omega_\epsilon = \left\{ \epsilon \ | \ \epsilon \leq \frac{q(t)}{\lambda \cdot \lambda_{\text{min}}(\bar{\mathcal{H}})} \right\}. \quad (40)$$
Table 1: UAV model parameters.

<table>
<thead>
<tr>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Density, $\rho$</td>
<td>1.2251 kg/m$^3$</td>
</tr>
<tr>
<td>Weight, $W$</td>
<td>14,515 kg</td>
</tr>
<tr>
<td>Reference area, $S$</td>
<td>37.16 m$^2$</td>
</tr>
<tr>
<td>Maximum thrust, $T_{\text{max}}$</td>
<td>113,868 N</td>
</tr>
<tr>
<td>Maximum lift coefficient, $C_{L_{\text{max}}}$</td>
<td>2.0</td>
</tr>
<tr>
<td>Maximum load factor, $n_{\text{max}}$</td>
<td>7</td>
</tr>
<tr>
<td>Induced drag coefficient, $k$</td>
<td>0.1</td>
</tr>
<tr>
<td>Parasite drag coefficient, $C_{D_{p}}$</td>
<td>0.02</td>
</tr>
</tbody>
</table>

thrust $T$, load factor $n$, and bank angle $\mu$. UAV position variables $x$, $y$, and $z$ are represented in the inertial frame. The drag force $D$ is represented by a simple drag polar model as

$$D = 0.5\rho V^2 S C_{D_h} + \frac{2kn^2 W^2}{\rho V^2 S}.$$  \hspace{1cm} (43)

Detailed UAV model parameters are summarized in Table 1.

Let $x = [V, y, \chi]^T$, $u_c = [T, n, \mu]^T$, and $y = x = h(x)$. The initial flight condition is a level flight with $V = 300$ m/s at $z = 3048$ m. To generate a differentiable command signal, reference command is transferred to the controller through the command filter $F = \omega_n^2 n / (s^2 + 2\omega_n s + \omega_n^2)$, where $\omega_n = 3$ rad/s and $\zeta = 1$. In all simulations, it is assumed that the design objective is to assure that the forward velocity $V$ is regulated around the desired value 300 m/s, while the heading angle $\chi$ and flight path angle $\gamma$ follow 30 deg heading and 5 deg path angle commands as follows:

$$\chi_d = \left\{ \begin{array}{ll}
0, & t < 5, \\
6(t - 5), & 5 < t \leq 10,
30, & 10 < t \leq 20,
30(5-0.2t), & 20 < t \leq 30,
-30, & 30 < t \leq 40,
-30(9-0.2t), & 40 < t \leq 45,
0, & t > 45,
\end{array} \right. \hspace{1cm} (44)$$

$$\gamma_d = \left\{ \begin{array}{ll}
0, & t \leq 15,
0.5(t - 15), & 15 < t \leq 25,
5, & 25 < t \leq 35,
0.5(45-t), & 35 < t \leq 45,
0, & t > 45.
\end{array} \right. \hspace{1cm} (44)$$

It is assumed that the desired thrust $T$ and the applied thrust factor $T_c$ are related as $T_c = k_n T$, where $k_n$ denotes the thrust effectiveness coefficient such that $0 < \sigma \leq k_n \leq 1$. In the nominal case $k_n = 1$. The controller parameter is selected as $\mathcal{H}_c = \text{diag}(1, 1, 1)$. The covariance of process and measurement is selected as $Q = \text{diag}(10^{-10}, 10^{-10}, 10^{-3}, 10^{-10})$, $R = \text{diag}(10^{-10}, 10^{-10}, 10^{-3})$. The parameter of filter (10) is chosen as $\xi = 50$.

The state responses of the UAV with the adaptive FTC and without FTC are shown in Figure 1. It is seen that the response is substantially improved compared to the case of without FTC. The control input can be seen in Figure 2. Figure 3 shows the 3D trajectories with FTC and without FTC, respectively. From Figure 4, it is seen that the estimate of thrust LOE factor $k_n$ converges to the true value.

6. Conclusions

This study deals with the fault-tolerant tracking control problem for nonaffine nonlinear systems. And a stability analysis was performed on the adaptive FTC law based on UKF. The proposed model approximation method is a solution that bridges the gap between affine and nonaffine control systems. The designed adaptive FTC strategy is applied to 3-DOF simulation of a typical fighter aircraft, and simulation results are provided to demonstrate the effectiveness of the theoretic results obtained. Based upon the results presented in the paper, it is concluded that the fault-tolerant control
scheme successfully handles failures if actuators fail. The UKF-based controller was also able to track the kinematic states successfully during and after failures. After proposed nonaffine nonlinear tracking control, based on UKF, we further promote its conclusions to the fault-tolerant tracking control.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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