International Journal of Power Electronics and Drive System (IJPEDS)
Vol. 13, No. 3, September 2022, pp. 1854∼1869
ISSN: 2088-8694, DOI: 10.11591/ijpeds.v13.i3.pp1854-1869 ❒ 1854

Fault-tolerant control with high-order sliding mode for manipulator robot

Khaoula Oulidi Omali, Mohammed Nabil Kabbaj, Mohammed Benbrahim
Laboratory of Engineering, Modeling, and Systems Analysis (LIMAS), Sidi Mohamed Ben Abdellah University, Fez, Morocco

Article Info

Article history:

Received Feb 5, 2022
Revised Jun 21, 2022
Accepted Jul 4, 2022

Keywords:

Fault detection
Fault-tolerant control
Higher order sliding mode
Robotic

ABSTRACT

The safety of manipulators systems is receiving a lot of attention these days. Faults have the ability to carry out harmful activities that harm equipment, the environment, or persons. As a result, it is critical to detect and diagnose problems as soon as possible, as well as to incorporate fault tolerance to avoid performance deterioration and harmful circumstances. Robust sensor fault detection and isolation (FDI) as well as fault-tolerant control (FTC) for a robotic system are discussed in this work. The goal of this research is to create an FDI method that uses a super-twisting third-order sliding mode (STW-TOSM) observer to estimate residual signals. A suggested system based on a higher-order sliding mode (HOSM) observer/controller approaches is used to accomplish this. In comparison to an active FTC technique, the test results demonstrate high level of performance. Finally, simulation results illustrate the efficacy of the presented techniques.

Corresponding Author:

Khaoula Oulidi Omali
Laboratory of Engineering, Modeling, and Systems Analysis, Sidi Mohamed Ben Abdellah University
Fez, Morocco
Email: khaoula.oulidiomali@usmba.ac.ma

1. INTRODUCTION

In processing, modern industries, and diverse operational situations such as automobile production, space missions, medical services, and packaging, robot manipulators have been widely used. The robot has the capability of treating complex tasks in hard environments and they are used in our life to decrease the charge of work. Various observer-based approaches have already been utilized for fault detection and isolation (FDI), and they are widely divided into two groups: Linear and nonlinear based observers [1]. Among the non-linear observers we find the fuzzy logic observer which has works in uncertain conditions and have an acceptable state estimation, but the reliability is the main drawback of this method. Feedback linearization observers are stable. They are, however, insufficiently robust [2], [3] the neural network learning approach has also been proposed. However, the observer's utility does not ensure finite-time convergence. As a result, the NN-based technique's performance is rather low, and this strategy is not resilient and steady in the face of system uncertainties and external disruptions [4]. As a result, the SM observer based has been used to overcome this problem [5]. However, the conventional sliding mode control (SMC) has a common disadvantage which is the chattering phenomenon. Various techniques were already presented to remove the dangerous chattering of SMC and get higher convergence accuracy. The higher-order sliding mode (HOSM) techniques were refined and used to real-world scenarios. HOSM works with discontinuity control that operates on the HO time derivative by shifting the control's transitioning to higher derivatives, unlike regular SMC. As a result, the control signal gets continuous, and the chattering is gone.

Some HOSM algorithms, such as the quasi-continuous [6], the suboptimal algorithm [7], or the super-twisting (STW) algorithm [8], have a basic issue in that they require utilizing the first time derivative of the sliding variable. This method is useful for reconstructing velocities from location data since it doesn't require the time derivative of the sliding variable [9]. The super-twisting HOSM observer has two major benefits. First, it doesn't require filtration to obtain accurate velocity estimates. Second, it allows for the use of comparable control characteristics to detect unknown inputs. For fault diagnostics in mechanical systems, the super-twisting second-order sliding mode observer (STW-SOSMO) were being employed [10]. Nevertheless, requires the employment of a low-pass filter since the unknown input is rebuilt from a discontinuous function. Utilizing the STW-SOSM observer necessitates the inclusion of a low-pass filter. In [10] we require a time delay and error for the deployment of the filter to reduce the problem of diagnostic achievement. To skill this issue, a STW-TOSM observer be used to provide an uncertain input estimation without filtration as well as precise theoretical velocity estimates for the system [11].

Even if there is a mistake, a modern robot manipulator should be able to finish the task. The system is therefore defined to be fault tolerant with regard to that defect, when it is able to automatically self-correct and effectively accomplish the given job, in order to increase system dependability and ensure control performance even if the system is afflicted by one or more errors. FTC is the term for this job. Overall, FTC technique can be classified into two types: active and passive methods [12]. To begin with, in passive FTC systems, a single controller is utilized for both the regular and fault cases, eliminating the requirement to identify and isolate the existence of a problem [13]. However, because this approach requires only a partial understanding of the system issue, its applicability in real-world applications is restricted. The active FTC system, which is based on fault information [13], is the second category.

Various techniques for improving the FTC of robot manipulators in the face of defects, uncertainties, and disruption have been proposed in the literature. Intelligent learning methods have been proposed among them, however they may create a large number of weighted learning parameters, posing implementation challenges [14]. SMC is one of the most reliable methods that has gained a lot of attention from researchers because of its robustness against uncertainty, disturbance, and quick transient response [15]. This strategy has been frequently used to correct for the uncertainty component in nonlinear systems in real-world situations [3]. This excellent feature of SMC was also used in the construction of the FTC system [16]. Traditional SMC, on the other hand, has a number of flaws that limit its use in FTC, such as the fact that it does not give finite-time convergence. Because it use a nonlinear sliding surface rather than a linear one, an SMC advancement renowned as terminal SMC (TSMC) was proposed as an effective technique to address this difficulty [17]. However, the aforementioned SMC or TSMC-based FTC is robust against uncertainties and faults when the system states are kept at a distance from the sliding surface; however, when the system states are kept at a distance from the sliding surface, the uncertainties and faults may damage the system dynamics. Integral SMC (ISMC) has been designed to solve the problem [18]. This technique, however, has disadvantages, such as a sluggish transient reaction, a high steady state inaccuracy, and chattering. A novel proportional integral derivative (PID)-based SMC, or its modified variant, dubbed SOSM area [19], has been researched and compared to the classic SMC to address these issues. The proportional-integral-derivative (PID)-based SMC has been proven to have numerous advantages, including lower inaccuracy in the steady-state, quicker transient response, and lower tracking error. For the purpose of removing chattering, a variety of methods have been studied. The first is to employ a boundary layer technique, in which the sign function is replaced with a saturation or sigmoid function. However, due to the saturation function's limit, this approach causes significant steady-state errors. Second, the size of the switching gain influences the amplitude of chattering; hence, employing a disturbance observer to estimate the disturbances is the best approach (DO). After using DO to compensate for the disturbance, The consequences of the system's disruption have been greatly reduced. Therefore a decreased switching gain may be used to maintain the sliding mode's current state. Only a tiny amount of chattering will result from this gain. The HOMS techniques are a third option. The benefit of this strategy is that it can minimize chattering while maintaining the SMC's resilience [20].

A novel FDI and FTC method for a robot manipulator is given in this work, which uses a STW-HOSM controller and observer to adjust for both uncertainty and faults, resulting in quick convergence, high precision, and minimal chattering. For sensor defect detection and isolation, a super-twisting third order sliding mode observer (STW-TOSMO) is employed. The FTC system is designed using SMC after the first portion. An active FTC based on the STW-SOSMC was designed to provide good performance for the control effort outcomes, minimize chattering, and increase accuracy. The Lyapunov theory demonstrates the FTC system's stability and convergence. To prove the effectiveness of the proposed FDI and FTC methodologies, simulation results are then compared to results from other methods under sensor malfunctions. The suggested method outperforms existing methods under uncertainties, unknown external load disturbances, and sensor faults.

The rest of this paper is laid out as follows. The problem statements are detailed in section 2. In section 3, we discuss sensor failure detection strategy and residual generation. The STW-TOSM observer is used to develop fault diagnostic methods (see section 4). In section 5, the proposed active FTC based on the STW-SOSM controller and the STW-TOSM observer is considred. To validate the efficacy of the suggested approach, the computer simulation results for a robot are presented in section refresults. Finally, in section 7, the conclusions are provided.

2. PROBLEM STATEMENTS

The equation indicates the robot:

$$\ddot{q} = M(q)^{-1}(\tau - C(q, \dot{q}\dot{q}) - F(\dot{q}) - G(q)) - \tau_d) + \beta(t - T_f)\phi(q, \dot{q}, \tau) \tag{1}$$

where $q, \dot{q}, \ddot{q} \in \mathbf{R}^n$ represent the joint position, velocity and acceleration vectors, respectively, $M(q) \in \mathbf{R}^{(n\times n)}$ is the inertia matrix (symmetrical definite positive, thus, $M(q)^{-1}$ always exists), $C(q, \dot{q}) \in \mathbf{R}^{(n\times n)}$ is the centrifugal and Coriolis matrix, $G(q) \in \mathbf{R}^n$ is the gravitational vector, $F(\dot{q}) \in \mathbf{R}^n$ is the vector of viscous friction torque at the joint,$\phi(q, \dot{q}, \tau) \in \mathbf{R}^n$is a vector of sensors, $\beta(t-T_f) \in \mathbf{R}^n$ is the faults time profile where T_f represents the faults occurrence time, and is expressed as (2).

$$\beta_i(t - T_f) = \begin{cases} 0 & if \quad t < T_f \\ 1 - e^{-\varphi}(t - T_f) & if \quad t \geq T_f \end{cases} \tag{2}$$

Where $\varphi_i > 0$ represents the unknown fault evolution rate.A slow-developing fault, also known as an incipient fault, has a modest value of $varphii$. The profile of β_i approximates a a step function that simulates sudden faults. When $\varphi_i \to \infty$, β_i turns into a fully step function, and the incipient fault becomes an abrupt fault. In (1) can be recast as follows to make further design and analysis easier:

$$\ddot{q} = M(q)^{-1}(\tau - H(q, \dot{q})) - \Delta(q, \dot{q}, t) + \beta(t - T_f)\phi(q, \dot{q}, \tau) \tag{3}$$

with $H(q, \dot{q}) = C(q, \dot{q}) + G(q)$, and $\Delta(q, \dot{q}, t) = M^{-1}(q)(F(\dot{q})\tau_d)$ demonstrates the modeling uncertainty in the robot manipulator's dynamic model.

A STW-TOSM observer is investigated in this study for estimating system states and collecting residual generation in order to acquire fault information for use with an active FTC method, specifically a STW-SOSMC to handle the impactsof ambiguities and defects. Figure 1 illustrates the design's main concept. Next, the following hypotheses are made:

- Hypothesis 1. Uncertainty in modeling is constrained in the following way:

$$||M^{-1}(q)(F(\dot{q}) + \tau_d)|| = \Delta(q, \dot{q}, t) \leq \bar{\Delta}, \tag{4}$$

- Hypothesis 2. The unknown fault function has the following bounds:

$$||\phi(q, \dot{q}, \tau)|| < \bar{\phi}, \tag{5}$$

with $\bar{\phi}$ and $\bar{\Delta}$ are a well-established stable.

3. GOS SCHEME WITH SLIDING MODE OBSERVERS AND RESIDUAL GENERATION FOR SENSOR FAULT DETECTION

3.1. Sensors fault detection strategy

A total of n observers are employed to identify sensor faults, one per of sensor. generalized observer scheme (GOS) is the name of this method. Apart from the measurement from the i_{th} sensor, the input law of the i_{th} GOS observer is computed using each and every sensor output (Figure 1). That is, the i_{th} GOS observer's input law has the i_{th} component equal to zero [21].

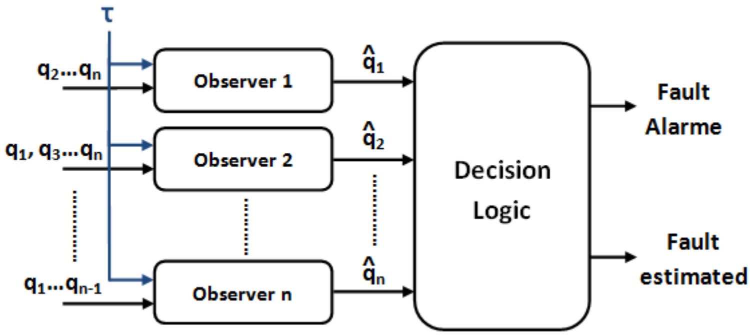

Figure 1. GOS observer structure for a sensors

3.2. Residual generation

The state estimation error $r(t)$ (Figure 2) can be calculated as [22]:

$$r(t) = y(t) - \hat{y}(t) \tag{6}$$

when there are faults on the sensors, the residuals are expected to differ from zero ($r(t) = 0$) when there are no problems on the sensors, and to be zero when there are no abnormalities on the sensors ($r(t) \neq 0$). As a result, the residuals for $i = 1, ..., 5$ are as (7). The residual fault signatures is shown in Table I. The residuals aren't the same.

$$r_i = |q_i - \hat{q}_i| \tag{7}$$

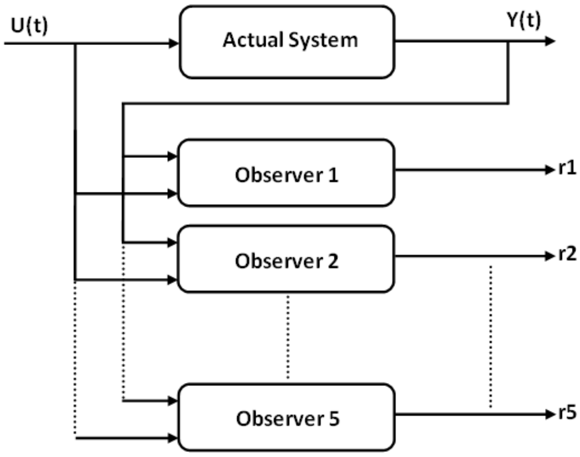

Figure 2. Observer based residual generation

Table 1. Sensor fault detection and isolation signature table

d_i/r_i	r_1	r_2	r_3	r_4	r_5
d_1	0	1	1	1	1
d_2	1	0	1	1	1
d_3	1	1	0	1	1
d_4	1	1	1	0	1
d_5	1	1	1	1	0

4. FDI TECHNIQUE WITH STW-TOSM OBSERVER

The state observer and fault diagnostics use the same observer based on STW-TOSM observer is presented in this section.

4.1. FDI methodology

With $x_1 = q \in \mathbf{R}^n$ and $x_2 = \dot{q} \in \mathbf{R}^n$, the dynamics of the robot in (1) can be written in state-space form as (8).

$$\begin{aligned}&\dot{x}_1 = x_2,\\&\dot{x}_2 = f(x_1, x_2, \tau) + \Delta(x_1, x_2, t) + \beta(t - T_f)\phi(x_1, x_2, \tau),\\&y = x_1,\end{aligned} \tag{8}$$

Where $f(x_1, x_2, \tau) = M^{-1}(q)[\tau - C(q, \dot{q})\dot{q} - G(q)]$. An STW-TOSMO which from the aforementioned form is considered [23]:

$$\begin{aligned}&\dot{\hat{x}}_1 = \hat{x}_2 + \alpha_2||x_1 - \hat{x}_1||^{2/3} sign(x_1 - \hat{x}_1)\\&\dot{\hat{x}}_2 = f(x_1, \hat{x_2}, \tau) + \alpha_1||\dot{\hat{x}}_1 - \hat{x}_2||^{1/2} sign(\dot{\hat{x}}_1 - \hat{x}_2) + \hat{z}_{eq}\\&\dot{\hat{z}}_{eq} = \alpha_0 sign(\dot{\hat{x}}_1 - \hat{x}_2),\end{aligned} \tag{9}$$

where α_i to be created is the SM gain. The state estimate error is defined by substituting (8) for (9).

$$\begin{aligned}&\dot{\tilde{x}}_1 = \tilde{x}_2 - \alpha_2||x_1 - \hat{x}_1||^{2/3} sign(x_1 - \hat{x}_1)\\&\dot{\tilde{x}}_2 = d(x_1, \hat{x}_2, \tilde{x_2}) + \Delta(x_1, x_2, t) + \phi(x_1, x_2, \tau)\\&- \alpha_1||\dot{\hat{x}}_1 - \hat{x}_2||^{1/2} sign(\dot{\hat{x}}_1 - \hat{x}_2) - \hat{z}_{eq}\\&\dot{\hat{z}}_{eq} = \alpha_0 sign(\dot{\hat{x}}_1 - \hat{x}_2),\end{aligned} \tag{10}$$

where $\tilde{x_i} = x_i - \hat{x}_i (i = 1, 2)$ and $d(x_1, \hat{x_2}, \tilde{x_2}) = f(x_1, x_2, \tau) - f(x_1, \hat{x}_2, \tau)$. If we defined $F(x_1, x_2, \hat{x}_2, \tau) = d(x_1, \hat{x_2}, \tilde{x_2}) + \Delta(x_1, x_2, t) + \phi(x_1, x_2, \tau)$, based on hypotesis 1 and 2, there exists a constant f^+ such that.

$$F(x_1, x_2, \hat{x}_2, \tau) < f^+ \tag{11}$$

According to the study in [23], the sliding gains should be set to $alpha0 = 1.1f+, alpha1 = 1.5(f+)1/2$, and $alpha2 = 1.9(f+)1/3$ to ensure convergent and equilibrium. The estimating states $(hatx1, hatx2)$ converge to the true state $(x1, x2)$ once the differentiator converges, Assuming the necessary equality conditions are met:

$$\Delta(x_1, x_2, t) + \phi(x_1, x_2, \tau) - \alpha_1||\dot{\hat{x_1}} - \hat{x}_2||^{1/2} sign(\dot{\hat{x_1}} - \hat{x}_2) - \hat{z}_{eq} = 0. \tag{12}$$

the third term of (12) is equal to zero when the differentiator converges to zero. After that, the uncertainties and defects may be rebuilt as follows:

$$\hat{z}_{eq} = \Delta(x_1, x_2, t) + \phi(x_1, x_2, \tau) \tag{13}$$

4.2. FDI decision

The STW-TOSM EOI calculated in (9) was used as a residual to discover and isolate faults in this study. When $t < T_f$, the system is in normal functioning, according to (2), $\phi(q, \dot{q}, \tau) = 0$. Then we have $\hat{z}eq = \Delta(q, \dot{q}, t)$ and Assumption 2 from (9).

$$\hat{z}_{eq} = \Delta(x_1, x_2, t) \leq \bar{\Delta} = z_{th}. \tag{14}$$

The threshold is set such that the remnant can tell the difference between normal and abnormal operation. In normal operation, the residual $\hat{z_e}q$ is always lower than z_th, therefore z_th is selected as the threshold [24]. When a fault occurs, the residual $\hat{z}_{eq} = \Delta(x_1, x_2, t) + \phi(q, \dot{q}, \tau) > z_{th}$, and the fault has been proclaimed. As a result, anytime the residual is present, the problem is recognized and isolated. $(\hat{z}_{eq})$ exceeds the associated threshold (z_{th}).

5. SM-FTC

The proposed robust AFTC scheme by using SMC and STW-SOSM are created based on the FDI by using STW-TOSMO. The goal of the FDI is to obtained fault information and utilized for compensating the fault effect of robot manipulator system. Then, the SMC technique is replacing by STW-SOSM scheme to achieve and ensure the stability of the framwork, to compensate the error, to ensure finite time convergence, to obtain higher accuracy and reduce the chattering.

5.1. Fault estimation and SMC are being used active FTC

Based on this method, the exposed active FTC is:

$$u = u_{eq} + u_c + u_s \tag{15}$$

where ueq is utilized to manage the nominal system and is designed as in (18). uc is the corrected uncertainty and fault using the STW-TOSM observer's derived EOI. To correct for the STW-TOSM compensation error, us is utilized. The following are the parameters:

$$u_c = -M(x_1)\hat{z}_{eq} \tag{16}$$

u_s is designed such that.

$$u_s = -M(x_1)\upsilon sign(s) \tag{17}$$

$$u_{eq} = M(x_1)(\ddot{x}_d - \lambda(\hat{x}_2 - \dot{x}_d) - g(x_1, \hat{x}_2)) \tag{18}$$

The sliding mode gain is υ. The sliding surface's derivative is now calculated using the control input (15) as [25]:

$$\begin{aligned}
\dot{s} &= \ddot{e} + \lambda\dot{e} \\
&= M^{-1}(x_1)(u_eq + u_c + u_s) + g(x_1, x_2) + \Delta(x_1, x_2, t) \\
&+ \phi(x_1, x_2, u) - \ddot{x_d} + \lambda(x_2 - \dot{x_d}) \\
&= M^{-1}(x_1)(u_s) - \hat{z}_{eq} + \Delta(x_1, x_2, t) + \phi(x_1, x_2, u) \\
&= M^{-1}(x_1)(u_s) - (\hat{\Delta}(x_1, x_2, t) + \hat{\phi}(x_1, x_2, u)) \\
&+ \Delta(x_1, x_2, t) + \phi(x_1, x_2, u) \\
&= -\upsilon sign(s) + \epsilon_1 + \epsilon_2
\end{aligned} \tag{19}$$

where $\hat{\Delta}(x_1, x_2, t)$ and $\hat{\phi}(x_1, x_2, u)$ are the predictions of inaccuracy and faults supplied by the STW-TOSMO EOI, respectively, $\epsilon_1 = \Delta(x_1, x_2, t) - \hat{\Delta}(x_1, x_2, t)$ is the uncertainty estimation error, and $\epsilon_2 = \phi(x_1, x_2, \tau) - \hat{\phi}(x_1, x_2, \tau)$ the estimation errors are limited, with $\epsilon 1 \leq \bar{\epsilon 1}$ and $\epsilon 2 \leq \bar{\epsilon 2}$, thanks to the STW-TOSM observer's capacity to be resilient to uncertainties and defects. The sliding mode gain in (17) is selected so that $\upsilon \geq ||\bar{\epsilon 1} + \bar{\epsilon 2}||$ [26]. In order for the sliding surface s to converge to zero. The SM gains $upsilon$ in the active FTC scheme (17) might be set to be considerably less since $\bar{\epsilon_1} \ll \bar{\Delta}$ and $\bar{\epsilon_2} \ll \bar{\phi}$. As a result, the chattering caused by (17) is considerably reduced. This indicates that when the fault diagnostic observer's fault information is valid, the active FTC's performance is good.

5.2. Active FTC based on a STW SOSMC

Even though the active FTC technique in (15) can minimize chattering by decreasing the switching period sliding gain, the classic SMC's discontinuous sign function still produces chattering. An STW-SOSM controller is meant put back the traditional SMC in order to eliminate chattering and improve precision. The chattering is not abolished, but it is significantly reduced, because the STW method under the integral, there lies a discontinuous function.

Starting from (19) with u_{eq} and u_c presented in (18) and (16), similarly, the sliding surface's derivative $dots$ may be expressed as (20).

$$\dot{s} = M^{-1}(x_1)u_s + \rho(t, x_1, x_2), \tag{20}$$

Where u_s, the control input, is designed based on the STW-SOSM controller and $\rho(t, x_1, x_2) = \epsilon_1 + \epsilon_2 \leq \bar{\epsilon_1} + \bar{\epsilon_2} = \bar{\epsilon}$ is supposed to be a perturbation bounded term that is unknown. At this stage, the STW-SOSM controller's stability might be proposed as (21).

$$\begin{aligned}
&u_s = -M(x_1)u_{stw-sosm}, \\
&u_{stw-sosm} = k_1||s||^{1/2}sign(s) - z_2, \\
&\dot{z_2} = -k_2 sign(s)
\end{aligned} \tag{21}$$

From (20) and (21), the closed loop error dynamics are given by (22).

$$\dot{s} = -k_1||s||^{1/2}sign(s) + z_2 + \rho(t, x_1, x_2), \dot{z}_2 = -k_2 sign(s). \tag{22}$$

To ensure stability and convergence, the sliding gains are chosen as follows [8]:

$$\begin{aligned} &k_1 > 2\bar{\epsilon}, \\ &k_2 > k_1 \frac{5k_1 + 4\bar{\epsilon}}{(2k_1 - 4\bar{\epsilon})}\bar{\epsilon}, \end{aligned} \tag{23}$$

the sliding surface s also becomes stable and in a finite length of time merges to zero.

6. SIMULATIONS AND RESULTS

To confirm the prospective FDI's capabilities, after the injection of an abrupt fault in the process, the fault is appeared in the sensors at T=15 s and the simulation of the system during the time of T=40 s. Figures 3, 4, 5, 6, 7 show the residuals under the influence of the provided fault. As can be seen, the figures change from one another Each time, the residuals react in accordance with the fault characteristic matrix. Figures 8, 9, 10, 11, 12 illustrate the true and estimated states of the STW-TOSM observer in the situation of sensor failures. As a result, we may infer that the issue has been properly identified and isolated. As a result, the STW-TOSM observer offers an accurate velocity estimation that is free of filtering. As a result, it is utilized as a residual for detecting and isolating defects. Finally, the suggested FDI techniques may produce good results when compared to the original state and the state predicted; as a consequence, the state estimate converges to the real state quickly, and the residuals are found to be zero. As a result, in a robot manipulator, these approaches discover and isolate sensor problems.

In the second portion of the simulation, the performance of the recommended active FTC is displayed. The goal of the control system is to keep the trajectory on track $x_d = [x_{1d}, x_{2d}, x_{3d}, x_{4d}, x_{5d}]$. When a failure occurs under the active STW-SOSM-FTC, the intended trajectories and joint angles for each joint of the robot manipulator are indicated in the Figures 13, 14, 15, 16, 17. We evaluated the suggested active FTC based on STW-SOSM (ASTW-SOSM-FTC) to the standard SM to demonstrate its superior performance. The active STW-SOSM-FTC outperforms the traditional SM-FTC in terms of performance. Figures 18, 19, 20, 21, 22 show that chattering is decreased more with ASTW-SOSM-FTC than with traditional SM. As a result, the ASTW-SOSM-FTC offers excellent In the face of external disruptions and system uncertainty, fault tolerance and robustness are essential.

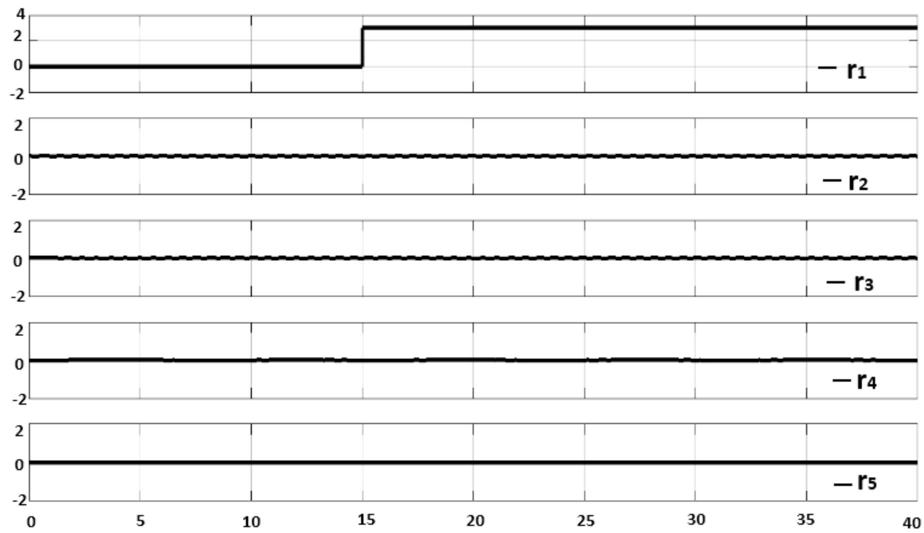

Figure 3. Residuals along with fault for the articulation 1

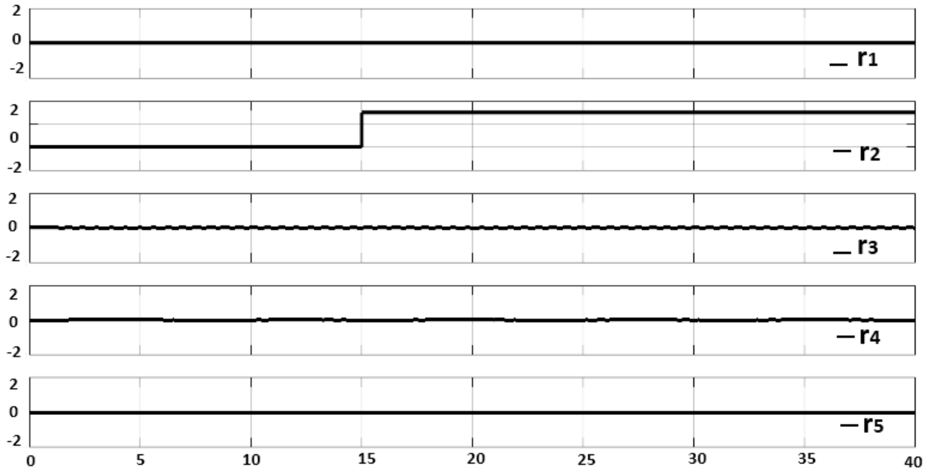

Figure 4. Residuals along with fault for the articulation 2

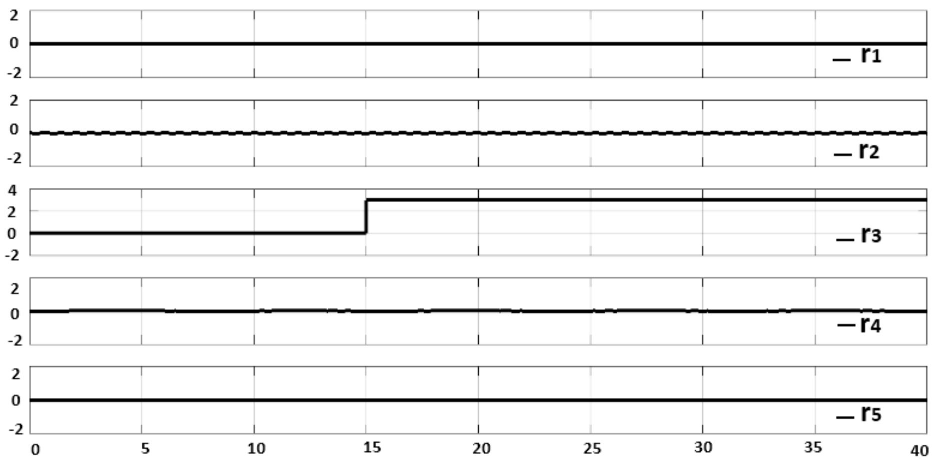

Figure 5. Residuals along with fault for the articulation 3

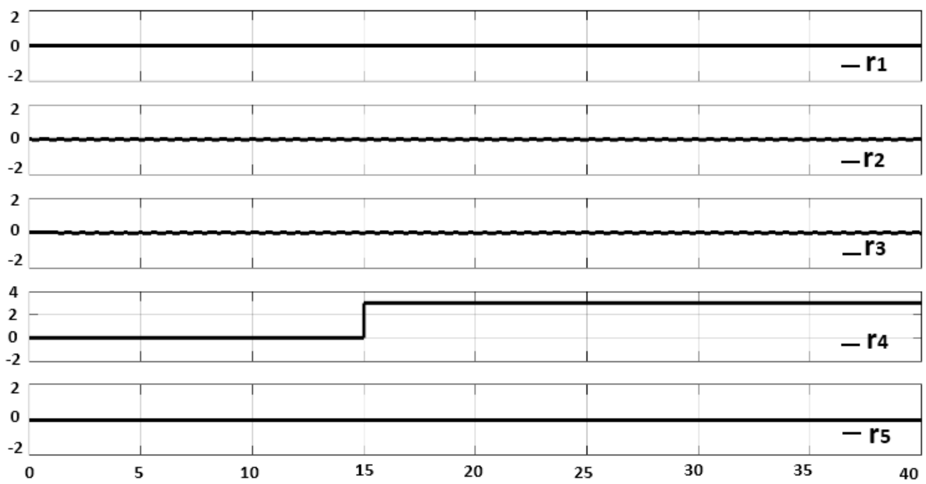

Figure 6. Residuals along with fault for the articulation 4

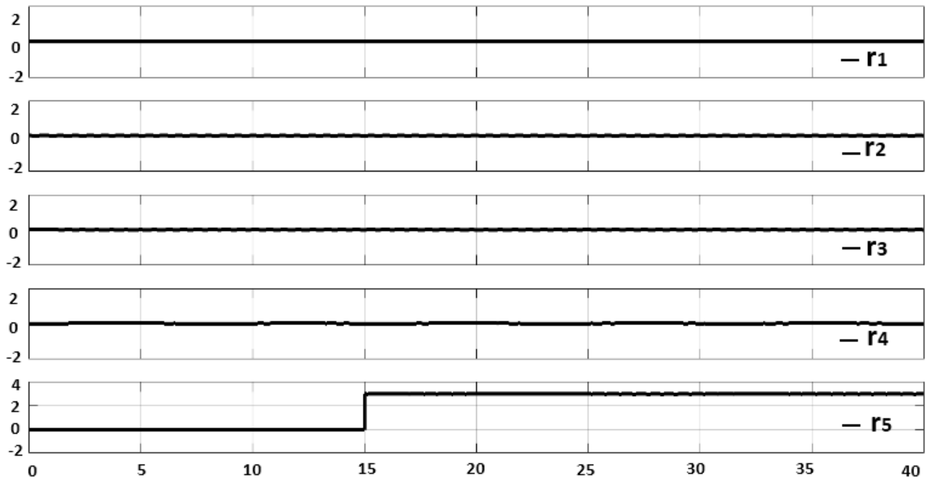

Figure 7. Residuals along with fault for the articulation 5

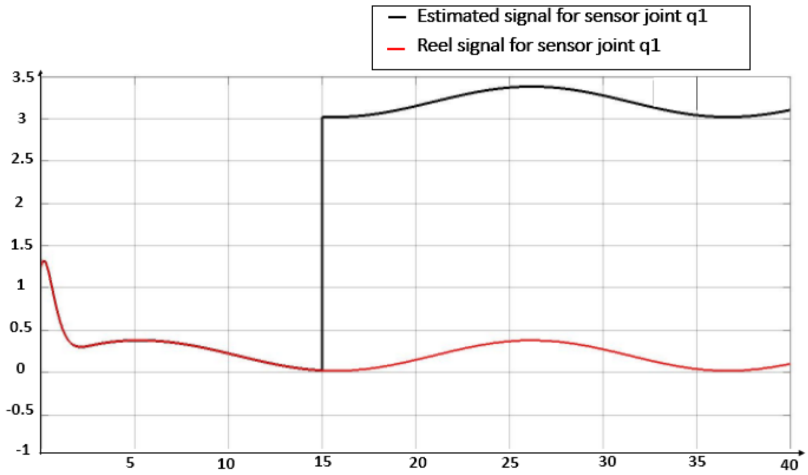

Figure 8. FDI on the first sensor. FDI with STW-TOSMO

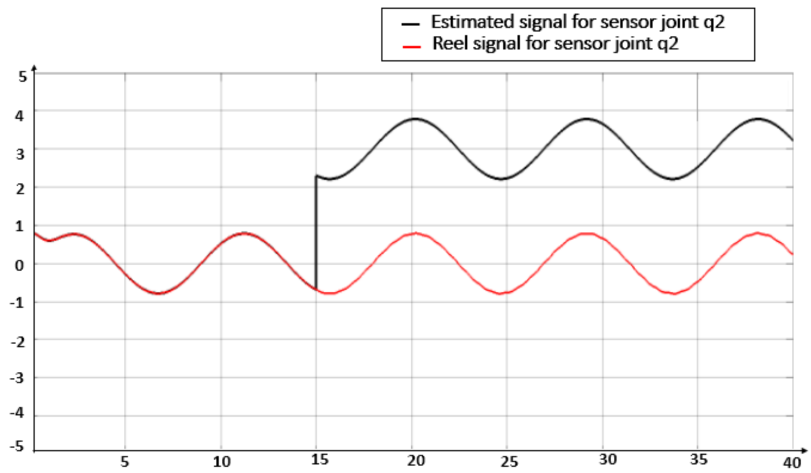

Figure 9. FDI on the second sensor. FDI with STW-TOSMO

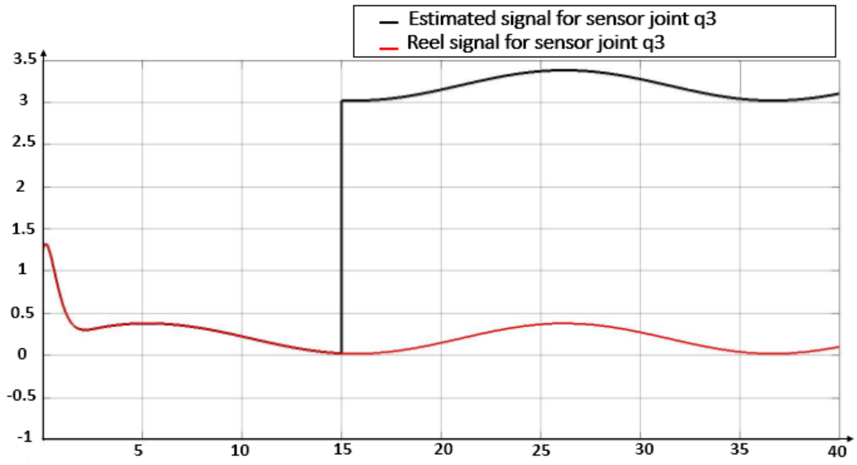

Figure 10. FDI on the third sensor. FDI with STW-TOSMO

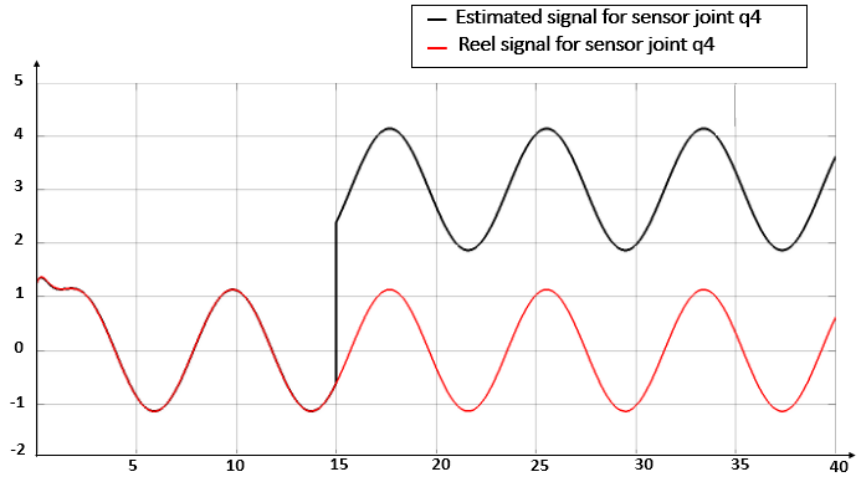

Figure 11. FDI on the fourth sensor. FDI with STW-TOSMO

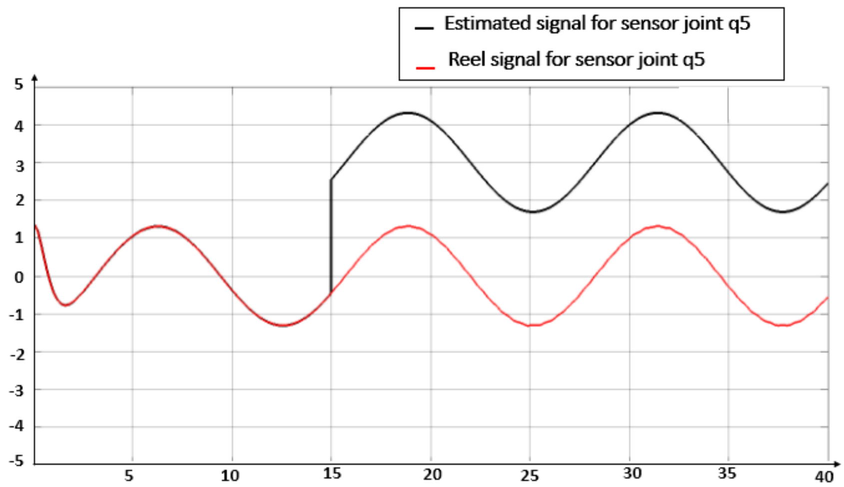

Figure 12. FDI on the five sensor. FDI with STW-TOSMO

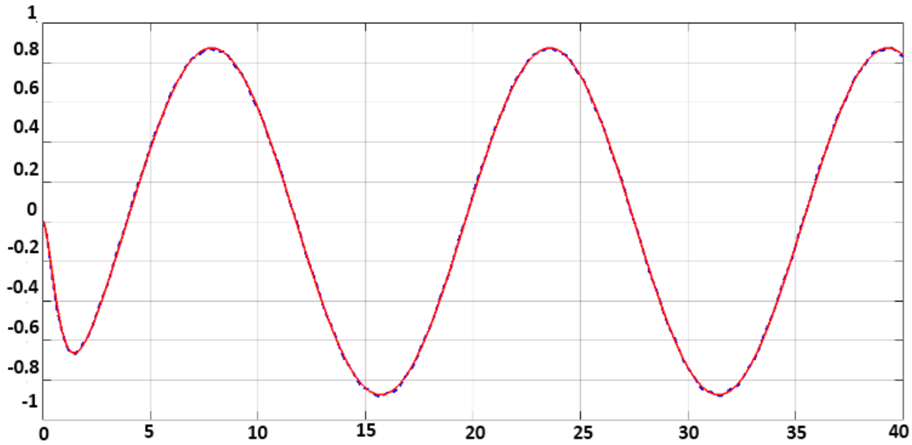

Figure 13. The desired trajectories and the angle of the joint '1' for robot when a fault appears in the active STW-SOSM-FTC

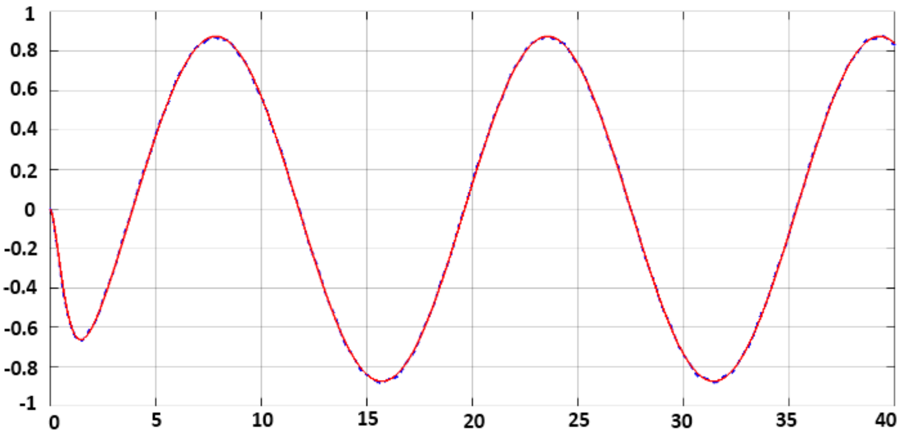

Figure 14. The desired trajectories and the angle of the joint '2' for robot when a fault appears in the active STW-SOSM-FTC

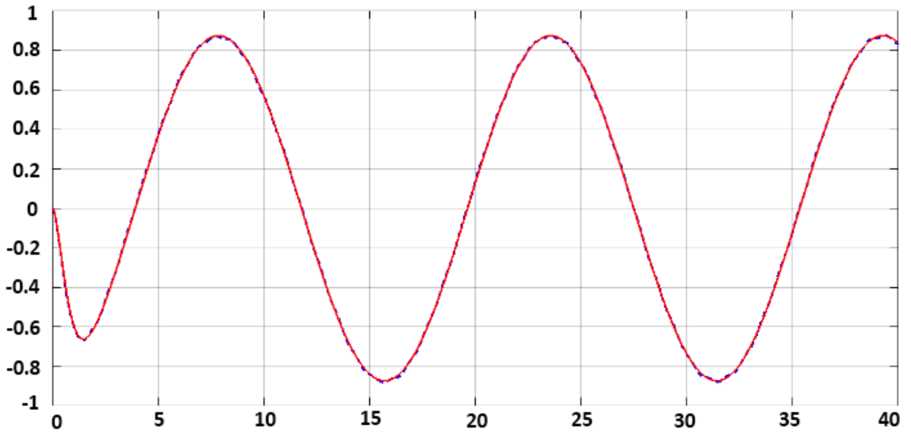

Figure 15. The desired trajectories and the angle of the joint '3' for robot when a fault appears in the active STW-SOSM-FTC

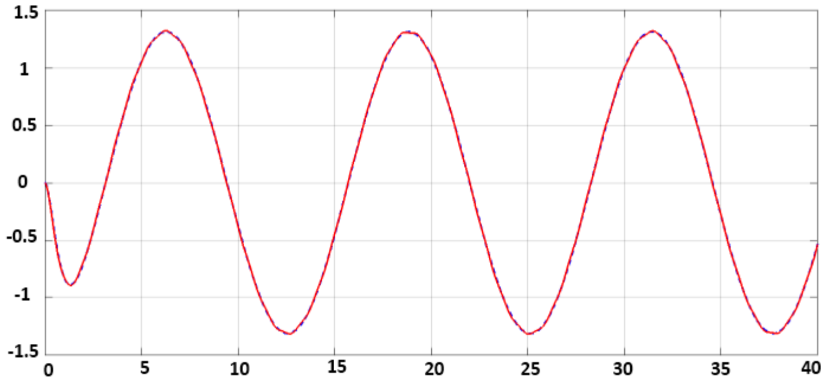

Figure 16. The desired trajectories and the angle of the joint '4' for robot when a fault appears in the active STW-SOSM-FTC

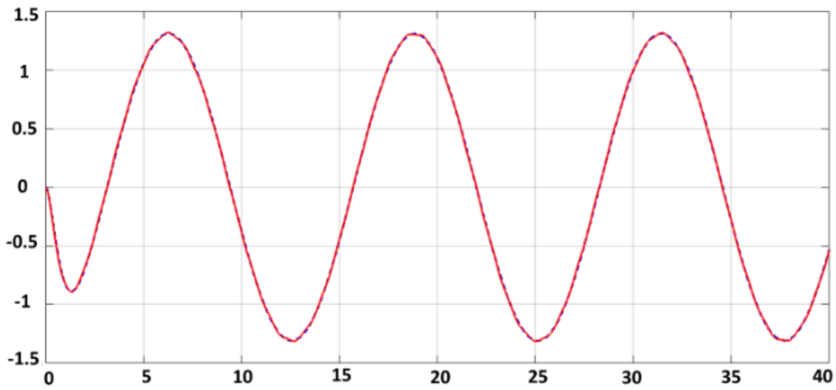

Figure 17. The desired trajectories and the angle of the joint '5' for robot when a fault appears in the active STW-SOSM-FTC

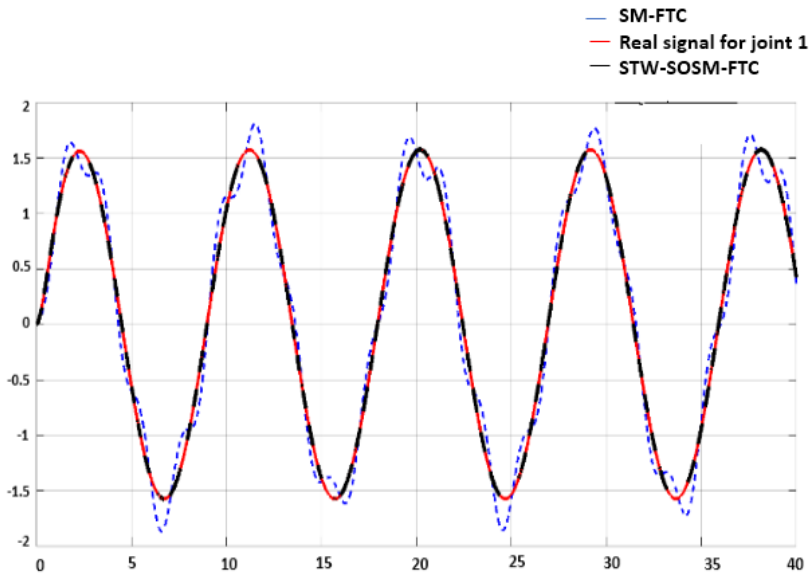

Figure 18. Comparaison between the active FTC by SMC and STW-SOSM for articulation 1

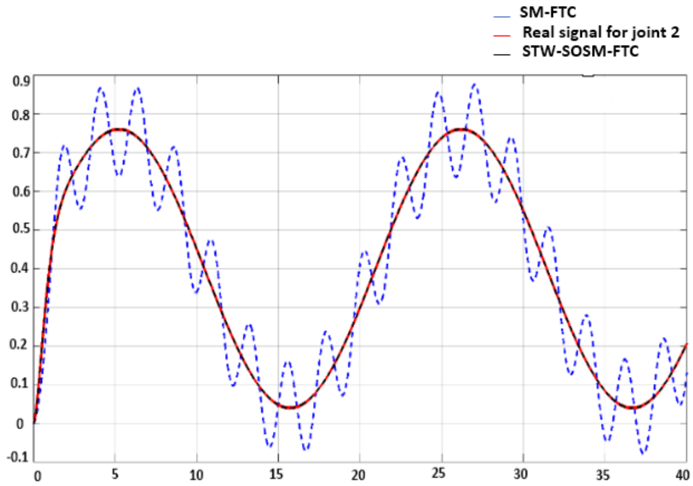

Figure 19. Comparaison between the active FTC by SMC and STW-SOSM for articulation 2

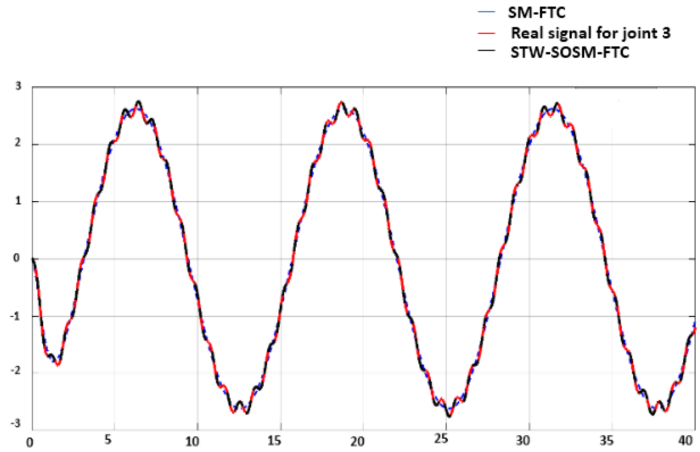

Figure 20. Comparaison between the active FTC by SMC and STW-SOSM for articulation 3

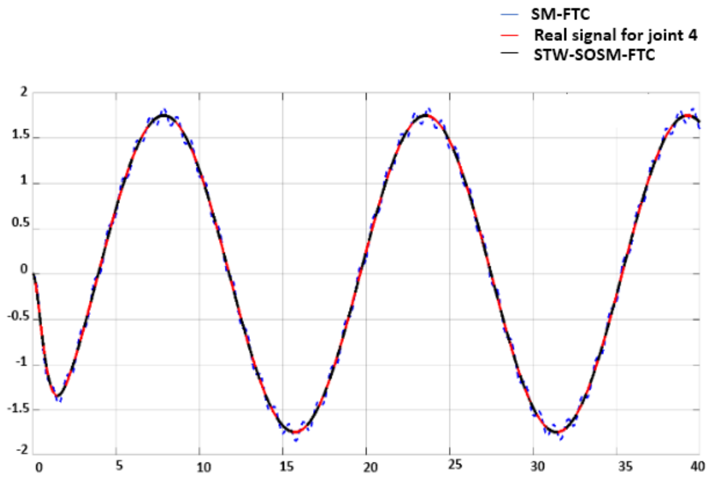

Figure 21. Comparaison between the active FTC by SMC and STW-SOSM for articulation 4

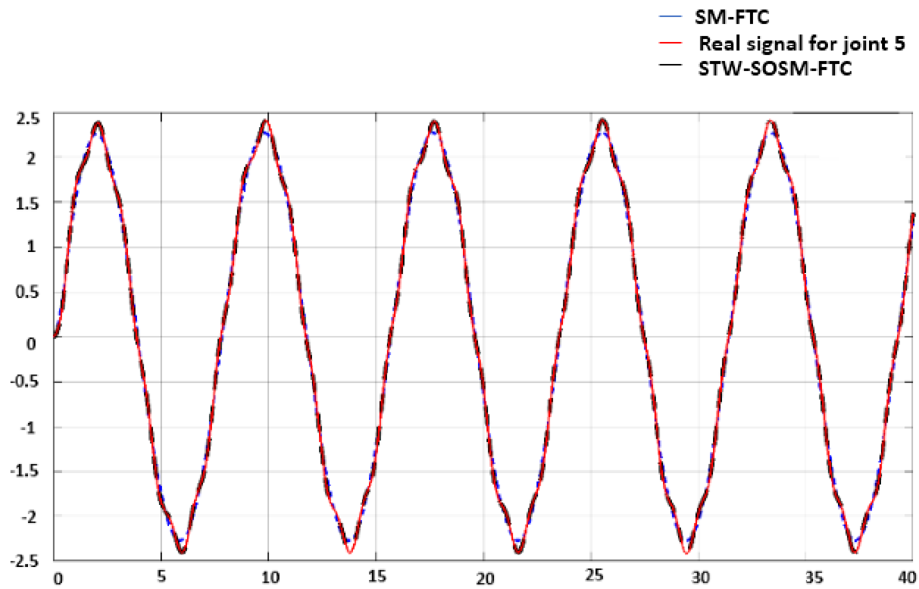

Figure 22. Comparaison between the active FTC by SMC and STW-SOSM for articulation 5

Finally, for both a healthy and a defective system, active FTC systems based on STW-SOSM have adequate performance and stability. As a result, ASTW-SOSM-FTC provides better accuracy, faster convergence, and no chattering. Advanced control methods for systems under the impact of parametric uncertainties owing to external perturbations, nonlinearities, and modeling inaccuracy have been well established in recent control development. SMC has attracted the attention of control engineers due to its benefits among the several robust control systems. Because of its unique features, such as insensitivity to matched uncertainties, lower order SM equations, zero error closed loop system convergence, and nonlinear control, it is used in a variety of applications. SMC has expanded fast as a control in contrast to additional effective control methods. The STW-SMC outperforms the SMC and the disturbance observer plus neural-fuzzy network in terms of robustness. Figures 18, 19, 20, 21, 22 most conventional nonlinear model reference controllers are less reliable than SMC, such as the feedback linearization approach, despite chattering in the face of uncertainty. As a result, STW-SOSM outperforms SMC in terms of robustness.

7. CONCLUSION

In this article, a two-step strategy for the robot manipulator system was suggested in order to avoid performance deterioration and harmful circumstances. The following are the main findings of this preliminary study: The STW-TOSM observer is used to build and describe a fault diagnosis technique in this article. The STW-TOSM observer uses comparable output injection to acquire the unknown input without filters. In order to estimate the residual signals, these characteristics were utilized as the residual for FDI. Furthermore, anytime the residual exceeds its associated threshold, a defect is recognized and isolated. Second, using a combination of the STW-TOSMO and the STWSOSMC, the researchers suggested an active FTC system. This FTC method could handle both the fault and the uncertainty, and it didn't require any velocity measurements. Based on these findings and previous research, the Active STW-SOSM-FTC appears to be a potential option for reducing disturbances and system uncertainty. This technique can give a high level of fault tolerance and resilience. Based on the data provided in this work, the suggested fault tolerant control techniquehas better results in terms of quick reaction speed, lower tracking error, and better sensor fault compensation performance.

REFERENCES

[1] A. T. Vemuri and M. M. Polycarpou, "Neural-network-based robust fault diagnosis in robotic systems," *in IEEE Transactions on Neural Networks*, vol. 8, no. 6, pp. 1410-1420, Nov. 1997, doi: 10.1109/72.641464.

[2] Q. Song, W. J. Hu, L. Yin, and Y. C. Soh, "Robust adaptive dead zone technology for fault-tolerant control of robot manipulators using neural networks," *Journal of Intelligent and Robotic Systems*, vol. 33, no. 2, pp. 113–137, 2002, doi: 10.1023/A:1014603028024.

[3] V. I. Utkin, *Sliding modes in control and optimization.* Berlin, Germany: Springer, 1992.

[4] Yi Xiong and M. Saif, "Sliding mode observer for nonlinear uncertain systems," in *IEEE Transactions on Automatic Control*, vol. 46, no. 12, pp. 2012-2017, Dec. 2001, doi: 10.1109/9.975511.

[5] X. -G. Yan and C. Edwards, "Adaptive sliding-mode-observer-based fault reconstruction for nonlinear systems with parametric uncertainties," in *IEEE Transactions on Industrial Electronics*, vol. 55, no. 11, pp. 4029-4036, Nov. 2008, doi: 10.1109/TIE.2008.2003367.

[6] A. Ferrara and M. Rubagotti, "A sub-optimal second order sliding mode controller for systems with saturating actuators," in *IEEE Transactions on Automatic Control*, vol. 54, no. 5, pp. 1082-1087, May 2009, doi: 10.1109/TAC.2008.2010992.

[7] G. Bartolini, A. Pisano, E. Punta, and E. Usai, "A survey of applications of second-order sliding mode control to mechanical systems," *International Journal of Control*, vol. 76, no. 9-10, pp. 875–892, 2003, doi: 10.1080/0020717031000099010.

[8] M. Van, H.-J. Kang, and K.-S. Shin, "Backstepping quasicontinuous high-order sliding mode control for a Takagi-Sugeno fuzzy system with an application for a two-link robot control," *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, 2014, vol. 228, no.9, pp. 1488–1500, doi: 10.1177/0954406213508936.

[9] M. Van, H.-J. Kang, and Y.-S. Suh, "Second order sliding mode based output feedback tracking control for uncertain robot manipulators," *International Journal of Advanced Robotic System*, vol. 10, p. 16, 2013, doi: 10.5772/55060.

[10] L. Yang and J. Yang, "Nonsingular fast terminal sliding-mode control for nonlinear dynamical systems," *International Journal of Robust and Nonlinear Control*, vol. 21, no. 16, pp. 1865–1879, 2011, doi: 10.1002/rnc.1666.

[11] M. Van and H.-J. Kang, "Robust fault-tolerant control for uncertain robot manipulators based on adaptive quasi-continuous high-order sliding mode and neural network," *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, 2015, vol. 229, no. 8, pp. 1425–1446, doi: 10.1177/0954406214544311.

[12] V. Mien, H.-J. Kang, and K.-S. Shin, "Adaptive fuzzy quasicontinuous high-order sliding mode controller for output feedback tracking control of robot manipulators," *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, 2014, vol. 228, no. 1, pp. 90–107, doi: 10.1177/0954406213490465.

[13] M. Benosman and K. -Y. Lum, "Passive actuators' fault-tolerant control for affine nonlinear systems," in *IEEE Transactions on Control Systems Technology*, vol. 18, no. 1, pp. 152-163, Jan. 2010, doi: 10.1109/TCST.2008.2009641.

[14] A. Šabanovic, "Variable structure systems with sliding modes in motion control—a survey," in *IEEE Transactions on Industrial Informatics*, vol. 7, no. 2, pp. 212-223, May 2011, doi: 10.1109/TII.2011.2123907.

[15] Q. Hu and B. Xiao, "Fault-tolerant sliding mode attitude control for flexible spacecraft under loss of actuator effectiveness," *Nonlinear Dynamics*, vol. 64, no. 1, pp. 13–23, 2011, doi: 10.1007/s11071-010-9842-z.

[16] J. Li and K. D. Kumar, "Decentralized fault-tolerant control for satellite attitude synchronization," in *IEEE Transactions on Fuzzy Systems*, vol. 20, no. 3, pp. 572-586, Jun. 2012, doi: 10.1109/TFUZZ.2011.2180391.

[17] S. S. -D. Xu, C. -C Chen, and Z. -L. Wu, "Study of nonsingular fast terminal sliding-mode fault-tolerant control," in *IEEE Transactions on Industrial Electronics*, vol. 62, no. 6, pp. 3906-3913, Jun. 2015, doi: 10.1109/TIE.2015.2399397.

[18] F. -J. Lin, Y. -C. Hung, and K. -C. Ruan, "An intelligent second-order sliding-mode control for an electric power steering system using a wavelet fuzzy neural network," in *IEEE Transactions on Fuzzy Systems*, vol. 22, no. 6, pp. 1598-1611, Dec. 2014, doi: 10.1109/TFUZZ.2014.2300168.

[19] Y. Cao and X. B. Chen, "Disturbance-observer-based sliding-mode control for a 3-DOF nanopositioning stage," in *IEEE/ASME Transactions on Mechatronics*, vol. 19, no. 3, pp. 924-931, Jun. 2014, doi: 10.1109/TMECH.2013.2262802.

[20] J. Zhang, X. Liu, Y. Xia, Z. Zuo, and Y. Wang, "Disturbance observer-based integral sliding-mode control for systems with mismatched disturbances," in *IEEE Transactions on Industrial Electronics*, vol. 63, no. 11, pp. 7040-7048, Nov. 2016, doi: 10.1109/TIE.2016.2583999.

[21] K. O. Omali, M. N. Kabbaj, and M. Benbrahim, "Nonlinear observer-based fault detection and isolation for a manipulator robot," In *New Developments and Advances in Robot Control*, Singapore: Springer, vol 175, pp. 163-185, 2019, doi: 10.1007/978-981-13-2212-9_7.

[22] K. O. Omali, M. N. Kabbaj, and M. Benbrahim, "Sensor fault detection and isolation for a robot manipulator based on high-gain observers," In *Lecture Notes in Real-Time Intelligent Systems*, Cham, Switzerland: Springer, vol. 756, pp. 426-435, 2019, doi: 10.1007/978-3-319-91337-7_38.

[23] M. Jin, J. Lee, and K. K. Ahn, "Continuous nonsingular terminal sliding-mode control of shape memory alloy actuators using time delay estimation," in *IEEE/ASME Transactions on Mechatronics*, vol. 20, no. 2, pp. 899-909, Apr. 2015, doi: 10.1109/TMECH.2014.2323897.

[24] M. Van, H.-J. Kang, Y.-S. Suh, and K.-S. Shin, "Output feedback tracking control of uncertain robot manipulators via higherorder sliding-mode observer and fuzzy compensator," *Journal of Mechanical Science and Technology*, vol. 27, no. 8, pp. 2487–2496, 2013, doi: 10.1007/s12206-013-0636-3.

[25] K. O. Omali, M. N. Kabbaj, and M. Benbrahim, "Sensor fault detection and isolation for robot manipulator," *AIP Conference Proceedings*, 2019, vol. 2074, no. 1, 2019, doi: 10.1063/1.5090640.

[26] J. Davila, L. Fridman, and A. Levant, "Second-order sliding-mode observer for mechanical systems," in *IEEE Transactions on Automatic Control*, vol. 50, no. 11, pp. 1785-1789, Nov. 2005, doi: 10.1109/TAC.2005.858636.

BIOGRAPHIES OF AUTHORS

Khaoula Oulidi Omali received the M.S degree in Engineering of Industrial Automated Systems, and Ph.D. in electrical engineering from the University of Sidi Mohamed Ben Abdellah, Fez, Morocco, in 2016 and 2021, respectively. She is currently a Professor at National School of Computer Science and Systems Analysis in Rabat, Mohamed 5 University. Her main research interests are in engineering sciences, robotics, and automatic control. She can be contacted at email: khaoula.oulidiomali@usmba.ac.ma.

Mohammed Nabil Kabbaj obtained two M.Sc. from UCL Belgium in 1999 and from UPS France in 2000 and his Ph.D. from the University of Perpignan in 2004. He is a Professor at the Faculty of Sciences of Fez. His research interests include control and engineering applications. He can be contacted at email: n.kabbaj@usmba.ac.ma.

Mohammed Benbrahim received the B.Eng. degree in electromechanical engineering from the Higher National School of Mines, in 1997 and the M.Sc. and Ph.D. degrees in automatic and industrial informatics from Mohammadia School of Engineers, in 2000 and 2007, respectively. Currently, he is a Professor at the Department of Physics and the program coordinator for the Master Smart Industry at the Faculty of Sciences, Sidi Mohamed Ben Abdellah University. His research interests include robotics, automatic control, intelligent systems, predictive maintenance, modeling, and optimization. He can be contacted at email: mohammed.benbrahim@usmba.ac.ma.