Wavelet neural network sliding mode control of two rigid joint robot manipulator

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Abstract
To solve the problems of low accuracy and poor stability due to uncertainties, external disturbances and unknown load, which exist in the position control of rigid joint robot manipulator; this article is to propose Non-Singular Fast Terminal Sliding Mode Control strategy with Wavelet neural networks observer (NSFTSMCW). The wavelet observer is designed using the online approximation capability of the neural network, which is used to online estimate the modeling error, external disturbances and uncertainties generated by the dynamic surface control of the joint robot online. Combining the above strategies, the robot manipulators position controller is designed. The stability of this control strategy is demonstrated by stability analysis using the Lyapunov criterion. Simulations on the 2-Link Rigid Joint (2LRJ) robot show that the control strategy can overcome the chattering phenomena ensures the accuracy and stability of the joint robot position control.

Keywords
Robot manipulator, non-singular fast terminal sliding mode control, wavelet neural networks, stability

Introduction
Nowadays, robotic manipulators are presenting in different fields, such as space exploration, surgical robot, industrial application. In order to meet the requirements of control performance, various advanced control technologies could be applied to the controllers of robotic manipulators. Racking control of robot manipulators, which is required to provide high accuracy, stability and safety, in the presence of huge uncertainties, disturbance has been a critical issue in both academic and industrial applications. How to improve the tracking performance and transient response for robot manipulators, particularly in the presence of external disturbance and possible actuation failures is still a challenge research community.

In the literature, several methodologies have been developed in order to increase the tracking performance, and reliability of robot manipulators. In the initial approaches, PID controller, optimal control, learning control, robust control, adaptive control, backstepping control, fuzzy control, sliding mode control, and neural network control have been developed. Among these controllers, the Sliding Mode Control (SMC) has proven to be very robust against uncertainties and disturbances for non-linear systems. As a result, (SMC) has been widely taking into account for application in real systems. However, traditional
(SMC) has drawbacks that limit its performance. It does not provide a finite time convergence, it is worst to tackle the rapid variations effects of disturbances. It is still suffers from chattering behavior, and the design procedure requires a prior knowledge of the upper bound value of the uncertainties, and disturbance.\textsuperscript{14}

Beside the references cited above, many several other approaches have been developed to preserve the benefits and reduce or eliminate the drawbacks of the conventional (SMC). For example, to mimic the property of the integral component in the (PID) controller to enhance the transient response of the conventional (SMC), Integral Sliding Mode Control (ISMC) or PID-based SMC (PID-SMC) has been developed. In order to obtain both fast transient response and finite time convergence, Integral Terminal Sliding Mode Control (ITSMC), has been worked out.\textsuperscript{15}

To eliminate the chattering, several approaches have been improved by using either boundary method or disturbance observer or High-Order Sliding Mode Control (HOSMC).\textsuperscript{16} In addition, Fast Terminal Sliding Mode Control (FTSMC) and Nonsingular Terminal Sliding Mode Control (NTSMC), have been realized separately.\textsuperscript{14,17} Unfortunately, the individual approaches based on (FTSMC) or (NTSMC) have just only solved one aspect and ignored the other problems of the conventional SMC. In order to obtain both fast finite time convergence and singular elimination, Nonsingular Fast Terminal Sliding Mode Control (NFTSMC) has been proposed.\textsuperscript{18–21}

However, chattering is not suppressed by applying a high frequency reaching control term to the control input of the above systems. One of the key issues when designing a (NFTSM) controller is to know the bounded value of dynamic perturbations and uncertainties.\textsuperscript{22–27} In order to tackle this dependence, several attempts have been introduced as observers, neural networks.\textsuperscript{28,29} Recently, researchers have developed a considerable interest in using the Wavelet Neural Network (WNN) to approximate the bound value of uncertainties.\textsuperscript{30,31} In summary, each drawback of the conventional (SMC) has been tackled by a corresponding approach that considers all the drawbacks of (SMC) together and solve them simultaneously.

Motivated by the above issues, this paper presents a new approach allowing a finite time convergence without singular problem, fast transient response, high tracking precision and less chattering. Therefore the proposed approach is based on a Non-Singular Fast Terminal Sliding Mode Control with compensation term based on Wavelet neural network observer (NSFTSMCW), As wavelet has the capability to approximate unknown functions faster and with fewer nodes than conventional neural networks, it is capable of working out the target threat evaluation contrasted with the other traditional approaches.

The main contributions of this paper are as follows:

- Unlike the existing robust approaches which are formulated under the assumption that the bound of the system uncertainty and disturbances are usually required to be known in advance, an adaptive parameter-tuning procedure is proposed here to estimate the unknown upper bounds. Therefore, the bound of the lumped uncertainty is unnecessary.

- The nonsingular fast terminal sliding manifold is proposed in the same way as other research work on the same topic, but the method used to approximate the bound value of uncertainties is dealt with differently.

- Based on the good performance of using Neural Network (NN) to estimate the upper bound of uncertainty, and due to the superiority of Wavelet Neural Network (WNN) over (NN), we admit in this paper the (WNN) as the approximation tool instead of adaptive laws. Owing to (WNN) estimation properties, the chattering phenomenon is remarkably reduced.

- In addition, a robust term is proposed in this paper to elevate the effect of approximation errors. The proposed controller (NFTSMCW) inherits the benefits of NFTSMC, WNN, adaptive rules, and the robust term, as a consequence, the tracking performance is enhanced considerably despite the presence of uncertainties and external disturbances.

The remainder of this paper is organized as follows. Section II outlines the problem formulation. Section III details the design of the Non-Singular Fast Terminal Sliding Mode Control with compensation term based on Wavelet neural network observer (NFTSMCW), then the globally asymptotic stability proof is discussed using the Lyapunov criterion. Section IV describes the simulation model and results. Finally, in section V some observations, conclusions and prospects for the future research are given.

**Problem formulation**

Figure 1 exhibits the chosen architecture of the robot. The dynamic model of the (2LRJ) manipulator, is described by the following equation (1):

$$M(q)\ddot{q} + C(q, \dot{q}) + G(q) = \tau(t) + \tau_d(t) \quad (1)$$

Where \(q(t), \dot{q}(t), \ddot{q}(t)\) denote the position, velocity, and acceleration of the link, \(M(q)\) represents the positive-definite inertia matrix, \(C(q, \dot{q})\) represents the centripetal-Coriolis matrix, and \(G(q)\) denotes the gravitational...
and frictional effects of the link dynamics, \( \tau(t) \) denotes the input joint matrix, and \( \tau_d(t) \) denotes the load disturbance matrix.

The 2LRJ robotic manipulator dynamics can be examined as the following matrix equation (2).

\[
\begin{pmatrix}
M_{11}(q) & M_{12}(q) \\
M_{21}(q) & M_{22}(q)
\end{pmatrix}
\begin{pmatrix}
\ddot{q}_1 \\
\ddot{q}_2
\end{pmatrix}
+
\begin{pmatrix}
C_{11}(q, \dot{q}) & C_{12}(q, \dot{q}) \\
C_{21}(q, \dot{q}) & C_{22}(q, \dot{q})
\end{pmatrix}
\begin{pmatrix}
\dot{q}_1 \\
\dot{q}_2
\end{pmatrix}
+
\begin{pmatrix}
G_1(q) \\
G_2(q)
\end{pmatrix}
= \begin{pmatrix}
\tau_1 \\
\tau_2
\end{pmatrix}
\tag{2}
\]

Where \( L_1, L_2 \) denote the length of the link, \( m_1, m_2 \) denote the mass of the link, \( I_1, I_2 \) denote the inertia of the link and \( g \) denotes the gravity acceleration. The different notations used in the matrix equation (2) are explained in the following equations (3).

\[
M_{11}(q) = (m_1 + m_2)L_2^2 + m_2L_1^2 + 2m_1L_1L_2 \cos(q_2) + I_1
\]
\[
M_{12}(q) = M_{21}(q) = m_2L_2^2 + 2m_1L_1L_2 \cos(q_2)
\]
\[
M_{22}(q) = m_2L_2^2 + I_2
\]
\[
C_{11}(q, \dot{q}) = -2m_2L_1L_2 \sin(q_2)\dot{q}_2
\]
\[
C_{12}(q, \dot{q}) = -m_2L_1L_2 \sin(q_2)\dot{q}_2
\]
\[
C_{21}(q, \dot{q}) = m_2L_1L_2 \sin(q_2)\dot{q}_1
\]
\[
C_{22}(q, \dot{q}) = 0
\]
\[
G_1(q) = (m_1 + m_2)gL_1 \cos(q_1) + m_2gL_2 \cos(q_1 + q_2)
\]
\[
G_2(q) = m_2gL_2 \cos(q_1 + q_2)
\tag{3}
\]

**Controller design**

**NSFTSMC**

In order to use a simple form of equation (1), we introduce the notation \( F, \Delta, \) and \( B, \) which leads to the equation (4):

\[
\ddot{q} = F(q, \dot{q}) + B(q)\tau(t) + \Delta_r(q, \dot{q}, t)
\tag{4}
\]

Where:

\[
F(q, \dot{q}) = -M^{-1}(q, \dot{q})\dot{q} + G(q);
\]

the nominal dynamic model of the robot manipulator without perturbations and uncertainties.

\[
\Delta_r(q, \dot{q}, t) = M^{-1}(q)[\tau_d - \Delta M(q)\dot{q} - \Delta C(q, \dot{q})\dot{q} - \Delta G(q)];
\]

stands for the lumped unknown component including perturbations and uncertainties, and \( B(q) = M^{-1}(q) \)

**Assumption A1.** The inertia matrix \( M(q) \) is an invertible, positive definite, and symmetric that adheres to the bounded condition:

\[
\lambda_m \leq M(q) \leq \lambda_M : \lambda_m > 0, \lambda_M > 0
\tag{5}
\]

**Assumption A2.** The lumped unknown disturbance acting on the system denoted by \( \Delta_r \) satisfies (6) with \( \Omega \) indicates the upper bound of lumped uncertainties.

\[
|\Delta_r(q, \dot{q}, t)| \leq \Omega
\tag{6}
\]

Assuming, that the control input does not involve the acceleration signal, the upper bound of the lumped uncertainty is a function consisting only of position and velocity measurements, therefore \( \Omega \) can be described by equation (7):

\[
\Omega = b_0 + b_1|e| + b_2|\dot{e}| : b_i > 0, i = 1, 2, 3
\tag{7}
\]

with \( b_0, b_1, \) and \( b_2 \) are all positive numbers, \( e = q - q_d \) and \( \dot{e} \) denote the error and its derivative between the actual position \( q \) and the desired \( q_d \) one respectively. In order to specify the sliding surface, we need the following notations:

for a variable vector \( x = [x_1, x_2, ..., x_n]^T \in R^n \) for all \( \alpha > 1 \) as follows:

\[
\begin{aligned}
\text{sign}(x)^\alpha &= |x|^\alpha \text{sign}(x) \\
\frac{d}{dt}(\text{sign}(x)^\alpha) &= \alpha|x|^{\alpha-1}\dot{x}
\end{aligned}
\]

The sliding surface can be chosen as the following equation (8):

\[
x(t) = e + k_1\text{sign}(e)^\gamma_1 + k_2|\dot{e}|^\gamma_2
\tag{8}
\]

Then time derivative of the sliding surface is expressed by the equation (9):

\[
\dot{x}(t) = \dot{e} + \gamma_1k_1|e|^{\gamma_1-1}\dot{e} + \gamma_2k_2|\dot{e}|^{\gamma_2-1}\dot{e}
\tag{9}
\]

Where, the terminal sliding manifold is defined as:

\[
(k_1, k_2) > 0, \quad (\gamma_1, \gamma_2) > 0 \quad \text{and} \quad \gamma_2 < \gamma_1, \quad 1 < \gamma_2 < 2
\]

When the state of the system is far from the equilibrium state, the sub-element \( k_1\text{sign}(e)^\gamma_1 \) dominates \( k_2|\dot{e}|^{\gamma_2} \), which guarantees a high convergence rate.
Additionally, when the system state is close to the equilibrium state, the sub-element $k_2\text{sign}(\dot{e})^{\gamma_2}$ guarantees system convergence in a finite-time. Then, we design the equivalent control term $\tau_{eq}$, by replacing the expression (4) into the derivative sliding surface $\dot{s}(t)$ and recognizing that $\dot{s} = 0$, we obtain:

$$\tau_{eq} = B^{-1}(q)\left\{ \hat{q}_d - F(q, \dot{q}) - \frac{1}{\gamma_2 k_2} |\dot{e}|^{\gamma_2} (1 + \gamma_1 k_1 |e|^{\gamma_1}) \text{sign}(\dot{e}) \right\}$$

(10)

The switching control law $\tau_{sw}$ is given by:

$$\tau_{sw} = -B^{-1}(q)(\Omega + Y)\text{sign}(s)$$

(11)

Where: $\Omega > 0$ and $\Omega$ the uncertainties upper bound. The overall control law is depicted in the following equation (12):

$$\tau = \tau_{eq} + \tau_{sw} + \tau_c$$

$$\tau = B^{-1}(q)\left\{ \hat{q}_d - F(q, \dot{q}) + (\Omega + Y)\text{sign}(s) - Ks \right\}$$

(12)

Where: $\tau_c = -B^{-1}Ks$, $K \geq 0$. $\tau_c$ used as a compensation term to suppress the effects of uncertainties of the system. Substituting the proposed global term (12) into (9) provides:

$$\dot{s}(t) = \dot{e} + \gamma_1 k_1 |e|^{\gamma_1} \dot{e} + \gamma_2 k_2 \ddot{e}$$

$$= \dot{e} + \gamma_1 k_1 |e|^{\gamma_1} \dot{e} + \gamma_2 k_2 |e|^{\gamma_2} (\ddot{q} - \ddot{q}_d)$$

$$= \dot{e} + \gamma_1 k_1 |e|^{\gamma_1} \dot{e} + \gamma_2 k_2 |e|^{\gamma_2} - [F(q, \dot{q}) + B(q)\tau(t) + \Delta_s(q, \dot{q}, t) - \ddot{q}_d]$$

$$\dot{s}(t) = \dot{e} + \gamma_1 k_1 |e|^{\gamma_1} \dot{e} + \gamma_2 k_2 |e|^{\gamma_2} - [F(q, \dot{q}) + B(q)\tau_{eq} + \tau_{sw} + \tau_c + \Delta_s(q, \dot{q}, t) - \ddot{q}_d]$$

(13a)

We get the final equation (13b):

$$\dot{s} = \gamma_2 k_2 |e|^{\gamma_2} [\Delta_s(q, \dot{q}, t) - (\Omega + Y)\text{sign}(s) - Ks]$$

(13b)

Wavelet estimator design

Wavelets Neuron Network (WNN), a family of functions from signal and image processing, which have recently been shown to possess the property of universal approximation. Combined with efficient learning algorithms, they constitute a powerful modeling tool for nonlinear processes. Therefore, the output $\hat{\Omega}$ of (WNN), can be used as estimator which precisely approximates the unknown upper bound of uncertainty.

$$\hat{\Omega} = \hat{W}^T \Psi(x, m, d)$$

(14)

Where:

$x \in R^{N \times 1}$: input vector of the network, 
$\hat{W}$: stands for the weighting variables, 
$m$: translation parameter, 
$d$: dilation parameter, 
$\Psi$: multidimensional wavelet.

$$\Psi_j = \prod_{i=1}^{N} \Psi\left( \frac{x_i - m_{ij}}{d_{ij}} \right) = \prod_{i=1}^{N} \Psi(z_i)$$

(15)

$N_i$: number of neurons in the input layer, 
$N_H$: number of the neurons in the hidden layer, 
$m_{ij}$: translation parameter, 
$d_{ij}$: dilation parameter.

Mexican hat function is chosen as the mother wavelet as given in the following equation (19):

$$\Psi(z_i) = (1 - z_i^2)e^{z_i^2}$$

(16)

Assumption A3. For any small positive constant $\chi$, there is always an optimal wavelet neuron network architecture $\hat{\Omega}^*$ with its optimal parameters $W^*$ that satisfy the following form:

$$\hat{\Omega}^* = W^* + \chi$$

(17)

$$\left\{ \begin{array}{l} \hat{\Omega}^* = W^* \Psi(x, m, d) \\ \hat{\Omega} = \hat{\Omega} - \hat{\Omega} \end{array} \right.$$  

(18)

$\hat{\Omega}^*$ is defined as the optimal output of the wavelet neural network. 
$\chi$: is the approximation error and is assumed to bounded by $|\chi| \leq \chi_N$, $\chi_N \leq Y$.

In the new sliding mode control, firstly, uncertainties are approximated with wavelet network. Next, we combine the outputs of (WNN) with (NSFTSMC). Through this combination, the overall control law can be shown in the following equation (19):

$$\tau = \tau_{eq} + \tau_{aw} + \tau_{ac}$$

(19)

Where $\tau_{aw}$ and $\tau_{ac}$ are respectively expressed by:

$$\tau_{aw} = -B^{-1}(q)[\hat{\Omega} + Y] \text{sign}(s)$$

(20)

$$\tau_{ac} = -B^{-1}(q)\hat{K}s$$

(21)

$\hat{\Omega}$ is defined as an estimation of the upper bound of the uncertainties and external disturbances defined as $\Omega$. 

The proposed control approach is summarized in Figure 2. Substituting the overall control law (19) into \( \dot{s}(t) \) in (9) yields:

\[
\dot{s} = \gamma_2 k_2 |\dot{e}|^{\gamma_2 - 1} \left[ \Delta_r(q, \dot{q}, t) - (\Omega + \Psi) |s| \right] - \dot{\tilde{K}} s
\]

(22)

The parameters of the proposed controller are adjusted on-line as following:

\[
\begin{cases}
\dot{W} = \omega_w \gamma_2 k_2 |\dot{e}|^{\gamma_2 - 1} |s| \Psi(x, m, d) \\
\dot{\tilde{K}} = \omega_K \gamma_2 k_2 |\dot{e}|^{\gamma_2 - 1} s^2
\end{cases}
\]

(23)

Where \( \omega_w \) and \( \omega_K \) are positive constants.

If the (NSFTSMCW) is defined by (8), assumptions A1, A2, A3, and A4 are satisfied and the control approach is elaborated as (19). With its online adaptation method described in (23), the proposed controller ensures the convergence of the tracking error to zero in a finite time.

**NSFTSMCW stability**

The Lyapunov function \( V_2 \) is described as the following form (26):

\[
V_1 = \frac{1}{2} \dot{s}^2 + \frac{1}{2 \omega_w} \dot{W}^T \dot{W} + \frac{1}{2 \omega_K} \tilde{K}^T \tilde{K}
\]

(24)

Where: \( \dot{W} = W^* - \dot{W} \) and \( \tilde{K} = \tilde{K} - K \), we get the derivative of (24) as:

\[
\dot{V}_1 = s \ddot{s} - \frac{1}{\omega_w} \dot{W}^T \dot{W} + \frac{1}{\omega_K} \tilde{K}^T \tilde{K}
\]

(25)

According to (23), in terms of assumption A2 and A4, we get:

\[
\dot{V}_1 = \gamma_2 k_2 |\dot{e}|^{\gamma_2 - 1} \left[ \Delta_r(q, \dot{q}, t) s - (\Omega + \Psi) |s| - \dot{\tilde{K}} s^2 \right] - \frac{1}{\omega_w} \dot{W}^T \dot{W} + \frac{1}{\omega_K} \tilde{K}^T \tilde{K}
\]

\[
\leq \gamma_2 k_2 |\dot{e}|^{\gamma_2 - 1} \left[ \left| \Delta_r(q, \dot{q}, t) \right| |s| - (\Omega + \Psi) |s| - \dot{\tilde{K}} s^2 \right] - \frac{1}{\omega_w} \dot{W}^T \dot{W} + \frac{1}{\omega_K} \tilde{K}^T \tilde{K}
\]

\[
\leq \gamma_2 k_2 |\dot{e}|^{\gamma_2 - 1} \left[ \left| \Omega + \Psi \right| s + \lambda |s| - \dot{\tilde{K}} s^2 \right] - \frac{1}{\omega_w} \dot{W}^T \dot{W} + \frac{1}{\omega_K} \tilde{K}^T \tilde{K}
\]

\[
\leq \gamma_2 k_2 |\dot{e}|^{\gamma_2 - 1} \left[ \Omega^T \Psi s + (\lambda - \dot{\tilde{K}}) |s| \right] - \frac{1}{\omega_w} \dot{W}^T \dot{W} + \frac{1}{\omega_K} \tilde{K}^T \tilde{K}
\]

\[
\leq \gamma_2 k_2 |\dot{e}|^{\gamma_2 - 1} \left[ \Omega^T \Psi s + (\lambda - \dot{\tilde{K}}) |s| \right] - \frac{1}{\omega_w} \dot{W}^T \dot{W} + \frac{1}{\omega_K} \tilde{K}^T \tilde{K}
\]

(26)
The WNN architecture used for the synthesis of the estimator is based on 10 nodes in the hidden layer, initial parameters were set randomly, and the (WNN) input was selected as: \( x = (e \hspace{0.1cm} \dot{e} \hspace{0.1cm} s)^T \). The parameters values corresponding to this controller are defined in Table 1.

To ascertain the robustness of the proposed strategy, we evaluate the system performance while introducing parameter variation and external disturbances into the system which are modeled as follows:

\[
\tau_d(t) = \begin{pmatrix} \tau_{1d}(t) \\ \tau_{2d}(t) \end{pmatrix} = \begin{pmatrix} 2 \sin(t) + 0.5 \sin(200\pi t) \\ \cos(2t) + 0.5 \sin(200\pi t) \end{pmatrix}
\]

For dynamic parameters, an additive variance of 20% of their nominal values is considered. Two typical cases are considered. Firstly, the performance of the established proposal (NSFTSMCW) is checked in the presence of uncertainties and external disturbances. Secondly, a variation of the payload is considered to further test the efficiency of the proposed adaptive approach. The position and velocity tracking performances under uncertainties and time-varying external disturbances are illustrated in Figures 3 and 4, respectively. Figures 3 and 4 show that in the absence of the term of compensation, a degradation in the performance of the controller is clearly observed. It comes in the form of a decrease in speed which directly influences the tracking performance.

Figure 5 verifies, that the control input is smooth which demonstrates the insensitivity of the suggested (NSFTSMCW) to unknown parameter variations and external disturbances. Furthermore, a small control effort at the beginning is noticed, which helps to avoid the harmful saturation of the control inputs. The effectiveness of the (NSFTSMCW) is also demonstrated in Figure 6, where the sliding manifold is chattering free. The tracking performance is enhanced due to the capability of the (NSFTSMCW) to cancel estimation errors and disturbances.

In the presence of the uncertainty and time varying external disturbances, the position and velocity tracking are illustrated in Figures 7 and 8. For testing, a load is picked by the robotic manipulator at \( t = 10s \), and the mass of link 2 is increased from 1.5 to 2.5 kg. Figures 7 and 8, present a smooth control input, a small control effort at the beginning is also noticed, which makes it possible to avoid the harmful saturation of the control inputs. The Figure 8 confirms, that the finite time

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**Discussion and results**

In this section, the proposed strategy was applied to a pathway tracking control for the (2LRJ) robot manipulator shown in Figure 1. For numerical simulation the desired trajectories for the position tracking is defined as the following form (29):

\[
q_d = \begin{pmatrix} q_{1d} \\ q_{2d} \end{pmatrix} = \begin{pmatrix} 1.25 - \frac{7}{4}e^{-t} + \frac{7}{4}e^{-4t} \\ 1.25 + e^{-t} + \frac{7}{4}e^{-4t} \end{pmatrix}
\]

The initial values of the system are selected as:

\( q_1(0) = 1, \hspace{0.1cm} q_2(0) = 1.5, \hspace{0.1cm} q_1(0) = 0, \hspace{0.1cm} q_2(0) = 0 \)

The following nominal parameters are considered for the robot manipulator model:

\[
\begin{align*}
L^0_1 &= 1 m, & L^0_2 &= 0.8 m, & m^0_1 &= 0.5 kg, \\
m^0_2 &= 1.5 kg, & l^0_1 &= l^0_2 &= 5 kgm^2
\end{align*}
\]
Figure 3. Position tracking: (a) joint 1 - and (b) joint 2.

Figure 4. Velocity tracking: (a) joint 1 - and (b) joint 2.

Figure 5. Control torque: (a) joint 1 - and (b) joint 2.

Figure 6. Sliding surface: (a) joint 1 - and (b) joint 2.
tracking performance of the robotic arm is always achieved as the load on link 2 varies.

Figure 9 illustrates the control input torques, while Figure 10 depicts the sliding surfaces of both joints. The simulation result confirms that the engineered (NFTSMCW) is insensitive to variations in unknown parameters and external disturbances. This observation is validated by the smooth shape of the curve recorded in Figure 9(j), indicates the presence of an additional control effort which can overcome the undesirable saturation of the control inputs.
Conclusion

In this paper, we have developed a new robust control approach. The proposed strategy (NFTSMCW) is a combination of (NFTSMC) and (WNN) acting as estimator of uncertainties and external disturbances. The validation of the developed controller is tested for trajectory tracking of a two-link rigid robot manipulator arm. In terms of robustness, the proposed controller is adopted in order to reduce the stresses at start-up while maintaining fast convergence toward zero. The numerical simulations illustrate improvements made by the proposed approaches. Future work will involve the use of the recurrent wavelet network instead of the conventional wavelet network. The effects of the measurement noises and sensor faults to the system control performance will be studied. Tuning mechanisms will also be developed to obtain the optimal values for the major parameters of the proposed controller.

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