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Neuro Sliding Mode Control for Exoskeletons with 7 DoF

Haci Mehmet GUZEY*[1]

Abstract.

In this work, a novel neuro-sliding mode controller (NSMC) is developed for a 7 degree of freedom (DoF) upper limb exoskeleton. Even though the regular sliding mode controller (SMC) is very sufficient tool when the unknown dynamics of the system is time invariant, variation in the unknown dynamics cannot be handled by regular SMC. Therefore, two-layer neural network (NN) is used to approximate the exoskeleton dynamics in the structure of the SMC. Stability of the NSMC is developed by using Lyapunov stability criteria. To validate our theoretical claims and to compare NSMC with regular SMC, simulation results are provided at the end of the paper. In the simulation section, advantage of the NSMC over regular SMC is presented in the presence of time-varying unknown exoskeleton dynamics.

Keywords: Exoskeleton, sliding mode control, neural networks.

1. INTRODUCTION

Stroke or cerebrovascular accidents are one of the main chronical diseases that seriously affect patient's daily live [1]. Stroke cases are expected to increase rapidly in the future in the world. One of the biggest reasons for this can be given as the aging of the population. In this process, motor function or upper limb injuries are expected to continue increasingly. Current researches show that therapeutic treatments consisting of intensive repeated movements of the defective limbs are some of known adequate approaches to partially rehabilitate the motor ability [2]. Nonetheless, therapeutic treatments are labor-intensive and expensive, posing a potentially undesirable difficulty to patient's families' and national healthcare services while consuming a lot of time and energy. Therefore, it is obvious that there is a significant demand for rehabilitation tools, such as exoskeletons, can be used to enhance the motor ability of upper/lower limbs and streamline the rehabilitation process [7].

In [3], the proposed control method comprises three major layers: an operating impedance control that estimates the users' arm's motion aims and guarantees an spontaneous response of the dress to the wearers' motions; a mid-level controller that compensates the transmission backlash and calculates desired position of the actuator from the reference arm motion ; a nonlinear low-level controller which drives the actuators by compensating the nonlinear dynamics to produce the desired assistive torques at the joints.

In [4], human-machine interaction is dealt. Intentional reaching direction (IRD) is estimated.

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Motion intentions of the wearers' upper limb is estimated by designing a human-robot interface which contains force-sensing resistors in real time.

The exoskeletons developed in [3], [4] controls only arm, excludes the hand and fingers. However, in [5], authors focused on the design and control of (CAREX-7), a 7-degreeof-freedom cable-driven arm exoskeleton used for active motion (inclusive of Rotation and translation) assistance or training of the whole-arm, including hand and fingers.

In all aforementioned works [3]-[5], nonlinear system Dynamics are assumed to be known. However, the dynamics model of the exoskeletons may not be accurate and changes for each patient. Therefore, uncertain exoskeleton dynamics should be approximated through neural network algorithms. Recently, an adaptive control algorithm was developed for the upper-limb exoskeleton in [6] by using NN.

In the meanwhile, one of nonlinear control schemes which does not require system's dynamic model is the SMC scheme. SMC can be considered as a simple and capable controller since it has been utilized in variety of motion control operations. One of the power of SMC is that closed loop stability of the controlled system is guaranteed through Lyapunov's stability theorem for either non model based or model based designs [6]-[12]. The performance of non-model based SMC lean on the properly selection of nonlinear gains, that is time consuming. Nonlinear gains have to handle the entire exoskeleton dynamics that is usually uncertain and time-varying/ patient-varying. To deal with the uncertainty problem, neural network is used [11]-[13], and fuzzy logic based controller is utilized in the structure of the SMC [14].

In this work, a two-layer neural network control is utilized to estimate the exoskeleton dynamics in the structure of the SMC. Combination of the SMC and NN forms the NSMC structure. Stability of the NSMC is developed by using Lyapunov stability theorem.

Figure 1 Myomo mPower100

Next, the dynamics of the exoskeleton shown in Figure 1 and saturated controller scheme is provided.

2. EXOSKELETON DYNAMICS AND SATURATED CONTROLLER DESIGN

The general exoskeleton dynamics with saturated control is considered similar as [6]

$$M(q)\ddot{q}+C(q,\dot{q})\dot{q}+G(q)=S(\tau)-f_{dis} \tag{1}$$

with $q \in \Re^n$ being the joint variables vector, $S(\tau)$ is the function of saturation on control torque τ . $C(q,\dot{q}) \in \Re^{n\times n}$, $M(q) \in \Re^{n\times n}$ and $G(q) \in \Re^n$ are the dynamics functions of $q,\dot{q}$. The matrix $C(q,\dot{q})$ which is defined as $\dot{M}(q)-2C(q,\dot{q})$ is skew-symmetric. $f_{dis} \in \Re^n$ represents the time varying disturbance, and there exists a nonnegative constant f_M^* such that $\|f_{dis}\| \le f_M^*$.

According to (1), define the state variables as $x_1 = q, x_2 = \dot{q}$, then the exoskeleton Dynamics can be re-written as

$$\dot{x}_1 = x_2 \tag{2}$$

$$\dot{x}_2 = M(q)^{-1}\left(S(\tau)-f_{dis}-C(x_1,x_2)x_2+G(x_1)\right) \tag{3}$$

Define the error signals as

$$\begin{aligned} z_1 &= x_1 - x_d \\ z_2 &= x_2 - \alpha_1 \end{aligned} \tag{4}$$

with x_d is the reference angles of each joints of exoskeleton, α_1 is the virtual controller being $\alpha_1 = \dot{x}_d - K_1 z_1$, $K_1 = K_1^T > 0$. In order to cancel the saturation nonlinearity effect, the auxilary design system is provided similar to [6] as

$$\dot{\beta} = \begin{cases} -K_\beta \beta - \dfrac{\left|z_2^T \Delta\tau\right| + 0.5\Delta\tau^T \Delta\tau}{\|\beta\|^2}\beta + \Delta\tau, & \|\beta\| \ge \chi \\ 0, & \|\beta\| < \chi \end{cases} \tag{5}$$

where; $\Delta\tau = S(\tau) - \tau, K_\beta = K_\beta^T > 0, \chi > 0$ is a small positive real number, and $\beta \in \Re^n$ is the state of the auxiliary design system. Later, the controller signal is provided in [6] as

$$\begin{aligned} \tau = &-z_1 - K_2\left(z_2 + \beta\right) + f_{dis} \\ &+ C\left(x_1, x_2\right)\alpha_1 + G\left(x_1\right) + M\left(x_1\right)\dot{\alpha}_1 \end{aligned} \tag{6}$$

with $K_2 = K_2^T > 0$.

Realize that the control torque in (6) requires all the exoskeleton dynamics, accurately. In this work, NSMC in the presence of unknown exoskeleton dynamics is investigated.

Assumption 1: In this work, the saturation function $S(\tau)$ is assumed to be zero and the control torque in the dynamics (1) is denoted as τ

3. NEURO SLIDING MODE CONTROLLER DESIGN

In this part, the NSMC of an exoskeleton (1) with 7 DoF is proposed. The main contribution of this paper is taking second order SMC structure and upgrade it by using two-layer NN to approximate uncertain exoskeleton dynamics and develop a robust controller against time-varying uncertain exoskeleton dynamics.

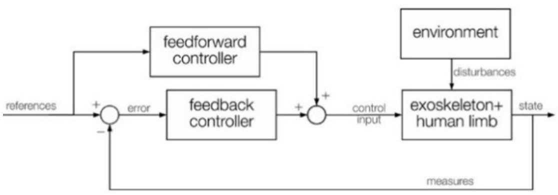

Figure 2 Exoskeleton controller scheme [15]

First, define the sliding surface as

$$s = k_1 z_1 + k_2 \dot{z}_1 \tag{7}$$

where $k_1 > 0, k_2 > 0$ are positive design parameters.

Define the Lyapunov function based on the sliding surface (7) as

$$L = \frac{1}{2} s^T s\ . \tag{8}$$

Take derivative of (8) and get

$$\begin{aligned} L &= s^T \dot{s} \\ &= s^T\left(k_1 \dot{z}_1 + k_2 \ddot{z}_1\right) \\ &= s^T\left(k_1\left(x_2 - \dot{x}_d\right) + k_2\left(\dot{x}_2 - \ddot{x}_d\right)\right) \\ &= s^T \begin{pmatrix} k_1\left(x_2 - \dot{x}_d\right) \\ +k_2 \begin{pmatrix} M(q)^{-1} \begin{pmatrix} \tau - f_{dis} - C\left(x_1, x_2\right)x_2 \\ +G\left(x_1\right) \end{pmatrix} \\ -\ddot{x}_d \end{pmatrix} \end{pmatrix}. \end{aligned} \tag{9}$$

Define the control torque in (9) as

$$\tau = \frac{1}{k_2}\begin{pmatrix} M(q)\left(f_{dis} + C\left(x_1, x_2\right)x_2 - G\left(x_1\right)\right) \\ +\ddot{x}_d - k_1\left(x_2 - \dot{x}_d\right) - k_s s \end{pmatrix} \tag{10}$$

with $k_s > 0$ is a design parameter, then (9) becomes

$$L = -k_s \|s\|^2\ . \tag{11}$$

From (11), it can be concluded that the system exoskeleton (1) tracks its desired trajectory, x_d asymptotically.

However, when the dynamics equation used in controller (11) has uncertainties, the controller (10) is not feasible. To compensate the uncertain dynamics, SMC is provided in the literature by using sign function as

$$\tau = \frac{1}{k_2}\left(\ddot{x}_d - k_1\left(x_2 - \dot{x}_d\right) - k_s \operatorname{sgn}(s)\right). \tag{12}$$

Realize that the controller in (12) does not require system dynamics and stability of the SMC (12) is proven in the literature [7],[10]. However, the chattering effect of the SMC and more importantly, time varying nature of the uncertain dynamics motivated the scientists to develop NN based adaptive SMC. In order to develop the NSMC, combine the dynamics equations and define

$$f_{unc} = \left(f_{dis} + C\left(x_1, x_2\right)x_2 - G\left(x_1\right)\right). \tag{13}$$

The uncertain nonlinear dynamics (13) are given as

$$f_{unc}(\bar{z}) = \Theta^T \psi\left(H^T \bar{z}\right) + \varepsilon \tag{14}$$

where $\Theta \in \Re^{2\times h}$ is the ideal NN weights with h is the number of hidden layer neurons, $\psi\left(H^T \bar{z}\right)$ is the basis function with $H^T \in \Re^{h\times n}$ is the mapping from the inputs to the hidden-layer neurons , n is the number of NN inputs, ε is the NN reconstruction error that is bounded and satisfying $\|\varepsilon\| \le \varepsilon_M$, with a positive constant ε_M , $\bar{z}$ is the NN inputs to estimate the exoskeleton dynamics. The unknown NN weights are estimated as $\hat{\Theta}$ and estimated uncertain dynamics can be given by

$$\hat{f}_{unc}(\bar{z}) = \hat{\Theta}^T \psi\left(\bar{z}\right). \tag{15}$$

Now, the NN weight estimation errors are described as $\tilde{\Theta} = \Theta - \hat{\Theta}$ and the estimation error dynamics are reached as $\dot{\tilde{\Theta}} = -\dot{\hat{\Theta}}$. The control torque, using (15), is obtained as

$$\tau = \frac{1}{k_2}\left(\hat{f}_{unc} + \ddot{x}_d - k_1\left(x_2 - \dot{x}_d\right) - k_s s\right) . \tag{16}$$

Assumption 2. The ideal NN weights are bounded such that $\|\Theta\| \le \Theta_M$ with Θ_M being a positive bounded real number.

Theorem. Consider the exoskeleton system (1) along with the control torque (16) using the NN estimate (15) of the uncertain dynamics by using the following NN weight update rule

$$\dot{\hat{\Theta}} = \psi\left(z\right)s - k_\Theta \hat{\Theta} \tag{17}$$

where $k_\Theta > 0$ is the small positive learning rate. Consider Assumption 1 and assumption 2 holds. Then, the tracking errors and the NN weight estimation errors are semi globally uniformly ultimately bounded (SGUUB).

Proof. Define the NN estimation error on the uncertain dynamics as

$$\tilde{f}_{unc}\left(\bar{z}\right) = \tilde{\Theta}^T \psi\left(z\right) + \varepsilon \tag{18}$$

and the Lyapunov function based on the sliding surface as well as the NN estimation error as

$$L_u = \frac{1}{2}s^T s + \frac{1}{2}tr\left\{\tilde{\Theta}^T \tilde{\Theta}\right\} . \tag{19}$$

Take derivative of (19) and get

$$\begin{aligned}
\dot{L}_u &= s^T \dot{s} + tr\left\{\tilde{\Theta}^T \dot{\tilde{\Theta}}\right\} \\
&= s^T\left(k_1 \dot{z}_1 + k_2 \ddot{z}_1\right) + tr\left\{\tilde{\Theta}^T \dot{\tilde{\Theta}}\right\} \\
&= s^T\left(k_1\left(x_2 - \dot{x}_d\right) + k_2\left(\dot{x}_2 - \ddot{x}_d\right)\right) + tr\left\{\tilde{\Theta}^T \dot{\tilde{\Theta}}\right\} \\
&= s^T\left(k_1\left(x_2 - \dot{x}_d\right) + k_2\left(M\left(q\right)^{-1}\left(\tau - f_{unc}\right) - \ddot{x}_d\right)\right) \\
&\quad + tr\left\{\tilde{\Theta}^T \dot{\tilde{\Theta}}\right\}.
\end{aligned} \tag{20}$$

Use the controller (16) in (20) and obtain

$$\begin{aligned}
\dot{L}_u &= s^T\left(\tilde{f}_{unc} - k_s s\right) + tr\left\{\tilde{\Theta}^T \dot{\tilde{\Theta}}\right\} \\
&= -k_s\|s\|^2 + s^T \tilde{\Theta}^T \psi\left(z\right) + s^T \varepsilon - tr\left\{\tilde{\Theta}^T \dot{\hat{\Theta}}\right\}
\end{aligned} \tag{21}$$

By using adaptation law (17) in (21) yields

$$\begin{aligned}
\dot{L}_u &= -k_s\|s\|^2 + s^T \varepsilon + k_\Theta tr\left\{\tilde{\Theta}^T \hat{\Theta}\right\} \\
&= -k_s\|s\|^2 + s^T \varepsilon + k_\Theta tr\left\{\tilde{\Theta}^T\left(\Theta - \tilde{\Theta}\right)\right\} \\
&= -k_s\|s\|^2 + s^T \varepsilon - k_\Theta\left\|\tilde{\Theta}\right\|^2 + k_\Theta tr\left\{\tilde{\Theta}^T \Theta\right\}.
\end{aligned} \tag{22}$$

Using upper bounds on NN approximation error and NN weight estimation error, ε_M, Θ_M respectively in (22) yields

$$\dot{L}_u \le -k_s\|s\|^2 + s^T \varepsilon_M - k_\Theta\left\|\tilde{\Theta}\right\|^2 + k_\Theta\left\|\tilde{\Theta}\right\|\Theta_M .$$

Now, use the Young's inequality to get

$$\begin{aligned}
\dot{L}_u &\le -k_s\|s\|^2 + \frac{1}{2}\|s\|^2 + \frac{1}{2}\varepsilon_M^2 - k_\Theta\left\|\tilde{\Theta}\right\|^2 \\
&\quad + \frac{k_\Theta}{2}\left\|\tilde{\Theta}\right\|^2 + \frac{k_\Theta}{2}\Theta_M^2
\end{aligned} . \tag{23}$$

Combine the similar terms in (23) and obtain

$$\dot{L}_u \leq -\left(k_s - \frac{1}{2}\right)\|s\|^2 - \frac{k_\Theta}{2}\|\tilde{\Theta}\|^2 + \frac{1}{2}\varepsilon_M^2 + \frac{k_\Theta}{2}\Theta_M^2 \quad (24)$$

Assume that we choose $k_s > \frac{1}{2}$ and define sum of the positive terms in (24) as $Pt = \frac{1}{2}\varepsilon_M^2 + \frac{k_\Theta}{2}\Theta_M^2$, the bounds on NN estimation error and sliding surface can be calculated as

$$0 \geq -\left(k_s - \frac{1}{2}\right)\|s\|^2 + Pt$$

$$\left(k_s - \frac{1}{2}\right)\|s\|^2 \geq Pt$$

$$\|s\| \geq \sqrt{\frac{Pt}{\left(k_s - \frac{1}{2}\right)}} \quad (25)$$

The exoskeleton system becomes asymptotically stable when it moves away from the sliding surface with the altitude of (25). The bound can be reduced by choosing k_s as large as possible. Or, second bound can be found as

$$0 \geq -\frac{k_\Theta}{2}\|\tilde{\Theta}\|^2 + Pt$$

$$\frac{k_\Theta}{2}\|\tilde{\Theta}\|^2 \geq Pt$$

$$\|\tilde{\Theta}\| \geq \sqrt{\frac{2Pt}{k_\Theta}} \quad (26)$$

Finally, if one of the bounds (25) or (26) satisfies, the system becomes asymptotically stable. Therefore, the system is SGUUB.

Next, simulation results are provided to validate our theoretical claims.

4. SIMULATION RESULTS

In this part, an exoskeleton system with seven degree of freedom is controlled through NSMC. Each link is forced to track a sinusoidal trajectory given as

$$x_d = \begin{bmatrix} \sin(t)+1, \cos(t), 2\sin(t)+1, 2\cos(t)+2, \\ \cos(t)+3, \sin(t)+3, 3\cos(t) \end{bmatrix}.$$

The controller gains are selected as $k_1 = 10.2$, $k_2 = 10.1$, $K_1 = 1.3$, $k_s = 120.3$ while the initial conditions are chosen as

$$q(0) = \begin{bmatrix} 15 & 14 & 13 & 12 & 11 & 10 & 9 \end{bmatrix}$$
$$\dot{q}(0) = \begin{bmatrix} -1 & -1 & -1 & -1 & -1 & -1 & -1 \end{bmatrix}.$$

Case1: Time invariant Uncertain Dynamics.

In the first case, the uncertain dynamics of the exoskeleton system are assumed to be time invariant. For this scenario, two different controllers are applied: Regular SMC (12) and the NSMC (16).

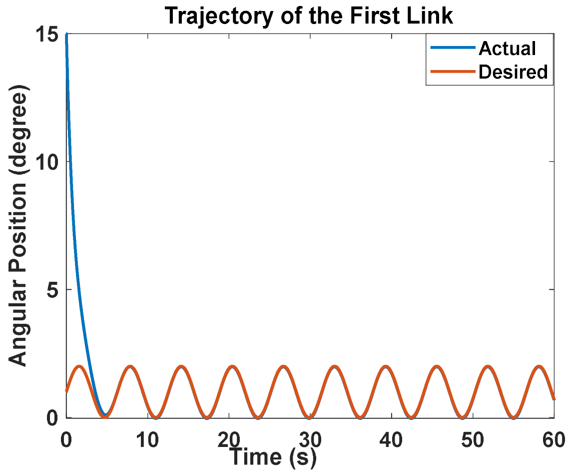

Figure 3 Desired vs actual trajectories of the first link of the Exoskeleton with NSMC

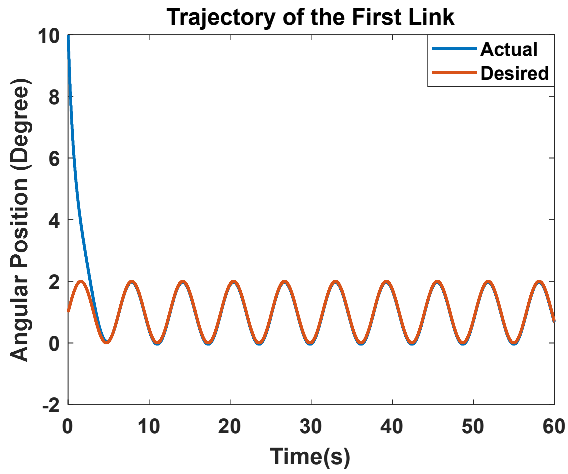

Figure 4 Desired vs actual trajectories of the first link of the Exoskeleton with SMC

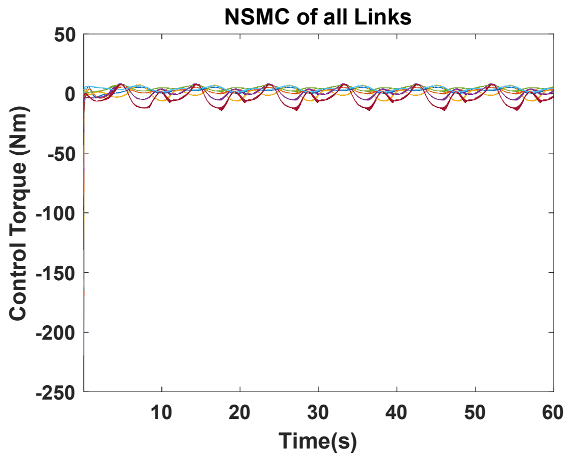

Figure 5 NSMC signal of the first Link

As shown in Fig.3 and Fig. 4, both SMC (12) and the NSMC (16) is able to stabilize the exoskeleton system in the presence of time invariant uncertain system dynamics.

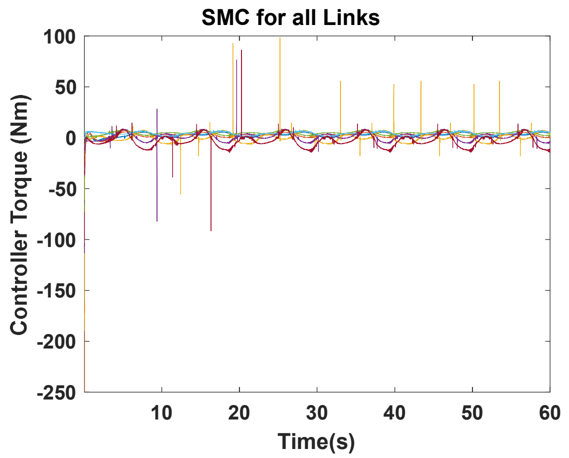

Figure 6 SMC signal of the first Link

Fig. 5 and Fig.6 illustrates the control signal of the NSMC and the regular SMC control of the first link of the exoskeleton. When compare two controller signals, it can be seen that the NSMC is smoother than the SMC. There are spikes, which is not desirable, on SMC as can be realized on Fig.6.

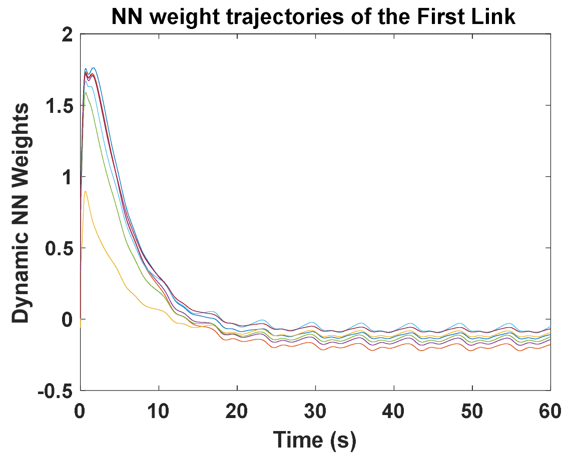

Figure 7 Trajectories of the dynamic NN weights of the first link of Exoskeleton

Fig. 7 depicts the NN weights trajectories of the first link. It is obvious that the NN weights converge after some time which means the dynamics of the exoskeleton estimated through our two layer NN design.

Fig.8 illustrates the trajectories of the other links of the exoskeleton. As can be seen, all of them converge to the desired trajectories in 4-5 seconds. The actual trajectories remain same with the desired trajectories as time evolves.

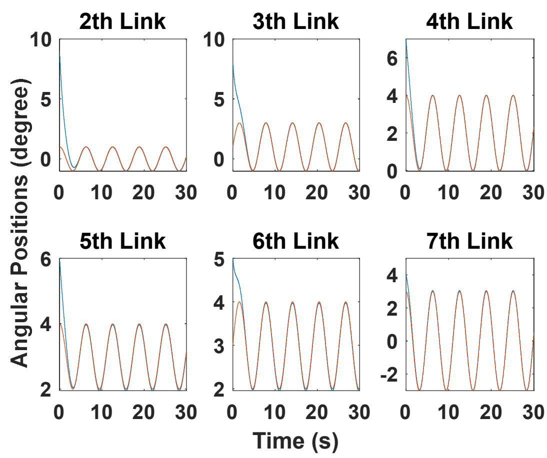

Figure 8 Desired vs actual trajectories of the other links of the Exoskeleton with NSMC

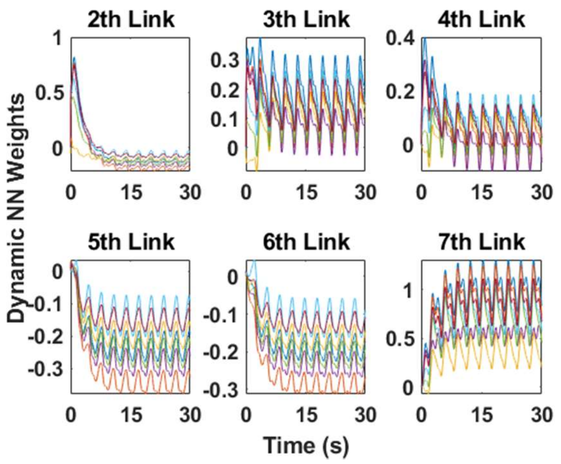

Figure 9 Trajectories of the dynamic NN weights of the other links of Exoskeleton

Dynamics weights of the NN of each link is depicted in Fig.9. Similar to the first link dynamical NN weights on Fig. 7, other links' NN weights converge after some time.

Remark: In this case, performance of the NSMC is shown and it is compared with regular SMC. Even though chattering affect is compensated for the SMC in the literature, time varying uncertain dynamics' effect cannot be compensated by using regular SMC. In the next case, performances of both SMC and NSMC compared in the presence of time varying uncertain dynamics.

Case2: Time Varying Uncertain Dynamics.

In the previous case (case 1), the dynamics of the exoskeleton is assumed to be uncertain and time invariant. In this case, the uncertain dynamics are changed on 20^{th} second. This scenario can be applicable for most of the electro-mechanical systems.

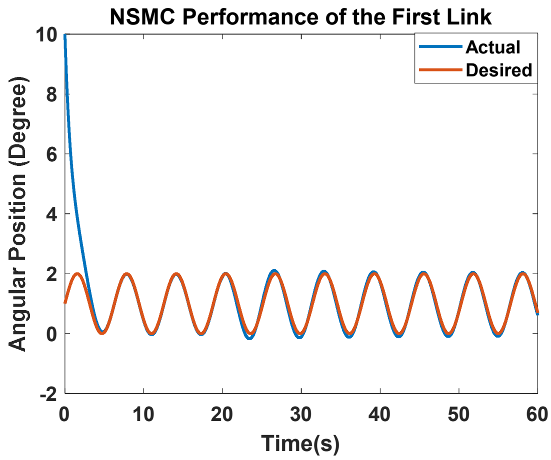

Figure 10 Desired and actual trajectory of the first link of the Exoskeleton with NSMC in the presence of time-varying uncertain dynamics

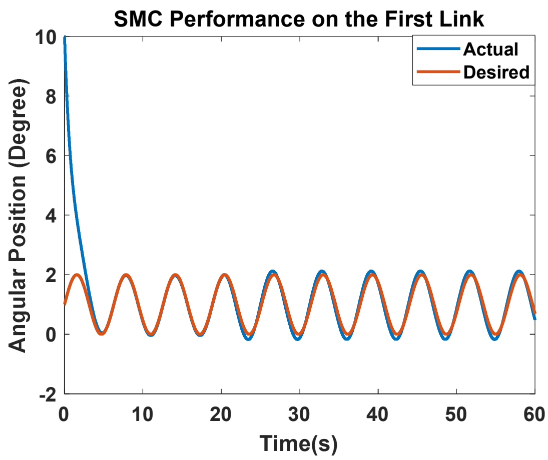

Figure 11 Desired and actual trajectory of the first link of the Exoskeleton with SMC in the presence of time-varying uncertain dynamics

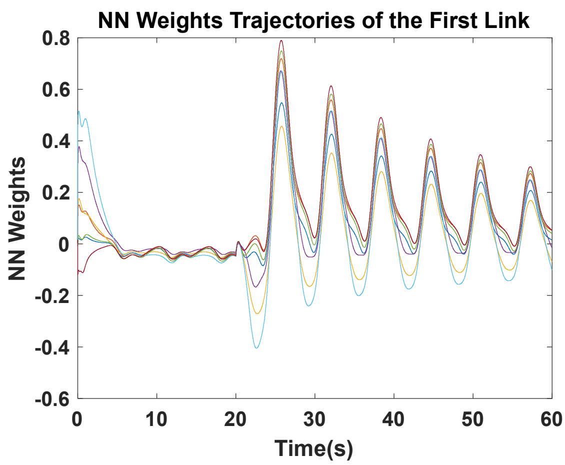

Figure 12 Trajectories of the dynamic NN weights of the first link of Exoskeleton in the presence of time-varying uncertain dynamics

Fig. 10 and Fig.11 illustrates the tracking performance of NSMC and SMC of exoskeleton in the presence of time varying uncertain dynamics. In both controllers, the dynamics are changed significantly after 20^{th} second. Tracking performance of NSMC is effected due to significant change on system dynamics initially but it fixes the tracking error eventually as shown in Fig.10. However, the same performance cannot be seen from regular SMC on Fig. 11. The tracking error remains same after 20^{th} second.

Dynamic NN weights trajectories of the first link can be viewed on Fig. 12. The weights converge before the dynamics change which means learns the dynamics. After the 20^{th} second, the weights start searching again to adapt the new dynamics. It takes longer to learn the dynamics after 20^{th} second when compare to the initial learning time. This is probably because the system angular velocities were zero at the beginning while it is nonzero on 20^{th} second.

In the next section, some concluding remarks are given.

5. CONCLUSIONS AND FUTURE WORK

In this work, a NSMC was designed for an exoskeleton with 7 DoF in the presence of time-varying uncertain system dynamics through Lyapunov stability theorem. Both sliding surface errors and NN weight estimation errors were shown to be SGUUB with controllable bounds those are controlled through control gains and the NN weights' learning rate. Simulation results were utilized to validate that our proposed NSMC provides significantly adequate outcomes when compared to regular SMC in the presence of time-varying uncertain dynamics. For the future work, the authors can consider saturation on the control torque.

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No conflict of interest or common interest has been declared by the author.

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