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Handling Subject Arm Uncertainties for Upper Limb Rehabilitation Robot using Robust Sliding Mode Control

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Upper Limb Rehabilitation Robots (ULRR) for the patient having shoulder and elbow joint movement disorders, requires further study for development. One aspect that must be fulfilled by such robots, is the need to handle uncertainties due to biomechanical variation of different patients, without significantly degrading performance. Currently, rehabilitation robots require re-tuning of controller gain for each individual. This is time consuming process and requires expert training. To overcome this problem, we propose robust sliding mode control algorithm, which uses very basic information of subject like weight, height, age and gender to handle these model uncertainties. For analysis, we have compared our proposed algorithm with Robust Computed Torque Control (RCTC) and Boundary Augmented Sliding Mode Control (BASMC) algorithms with diverse subjects. Results describe the superiority of the proposed algorithm in handling uncertain parameters human arm and robot without degrading the performance.

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NOMENCLATURE

RCTC = Robust Computed Torque Control
BASMC = Boundary Augmented Sliding Mode Control
RSMC = Robust Sliding Mode Control
ULRR = Upper Limb Rehabilitation Robot

1. Introduction

There are 795,000 new stroke patients every year in the US[1]. About 85% of these patients suffer from hemiparesis which causes impairment of the upper limb.[1] Fortunately, 50% of these patients are recoverable. However, recovery process requires intensive health care. Physicians use robot-aided rehabilitation for this purpose.[2-11] Using robot-aided rehabilitation, patients receive more effective and stable rehabilitation process, while permitting therapists to reduce their workload. These robots can also offer reliable information regarding functional assessment of patient recovery by measuring physical parameters, such as speed and strength of patient's residual voluntary activity.[6,12,13] Much progress has been made for rehabilitation robots in different spheres including design, bio-mechatronics, and control system engineering.[13] However, we are still far from the desired goals as existing devices have not been fully able to restore body mobility.[14,15]

Upper Limb Rehabilitation Robots (ULRR) are not like most industrial robots, which can be modeled and controlled by linear control techniques. These robots are designed to provide minimum and maximum compliant assistance for rehabilitation. In the minimum compliance, subjects are completely passive and their limbs are 100% guided by the robot on reference physiological trajectories. Whereas in the maximum compliance, subjects have more freedom to drive the robot. A key requirement to provide passive rehabilitation and/or passive arm movement for minimum compliance is consistent, high dynamic tracking performance to move the robot with human subject in an effective manner.

In literature, many researchers have proposed different approaches, such as Proportional and Derivative (PD[16,17]), and Proportional, Integral and Derivative (PID[16,18]) and nonlinear control techniques such as Computed Torque Control[16,17] and impedance control.[16,19] Linear control approaches are unable to fulfill the requirement even if we consider nonlinearities as disturbances.[20,21] Simple computed torque control techniques which includes robust computed torque control or passivity based robust control technique, are also not successful because of degraded performance under uncertain dynamics. To handle such problems several other control techniques have been proposed including factious gain,[22] fuzzy adaptation[23] and adaptive control.[19,21] Main problem with these techniques is that they are good for industrial robots but not for ULRR where the uncertainties change from subject to subject.[22] Due to diverse biomechanical variations, mathematical model of wearable ULRR changes completely which means controller needs to be re-adjusted for each patient every time. Moreover, adaptive control technique always depends on switching frequency for the adaptation law to update the control gain, which may diverge if the system has a malfunction. This phenomenon is particularly not safe for rehabilitation robots.[24]

Some researchers have used Sliding Mode Control (SMC) technique for upper limb rehabilitation robot.[8] However, this method only handles matched/structured uncertainties. These uncertainties act as additive noise with input (control torque) channel.[25] Moreover, chattering phenomenon in sliding mode control makes this technique unsafe for the clinical equipment. Rehman et al. has made a detailed discussion about it and proposed exponentially reaching sliding mode for rehabilitation robot[8] but it has two main drawbacks. 1) Exponentially reaching sliding mode control law only handles matched uncertainty. 2) Control needs to be retuned for each individual. Re-tuning controller gain for each individual is a difficult problem and it requires expert training. Moreover, overestimated gain not only raises safety issued for the patient but also makes robotic systems less efficient for rehabilitation. In order to overcome these problems, we propose robust sliding mode control algorithm.

We have developed chattering free Robust Sliding Mode Control (RSMC) law to handle subject's arm and robot model uncertainties. RSMC is designed to overcome matched and unmatched uncertainties for upper limb rehabilitation. It uses simple information like weight, height, age and gender, and does not require expert training to tune controller. Robust convergence is ensured without chattering making it perfectly suitable for rehabilitation robot. Proposed RSMC law is evaluated on seven degree of freedom (DOF) upper limb rehabilitation robot and the results are compared with Robust Computed Torque Control (RCTC) and Boundary Augmented Sliding Mode Control (BASMC) laws.

Rest of the paper is organized as follows. In Section 2, we have described the experimental setup. In Section 3, we have described development of chattering free robust sliding mode control for the robot. Section 4 describes experimental evaluation for the developed control to handle uncertainties. Section 5 concludes the results and findings.

2. Problem Formulation

2.1 Dynamic modeling human-robot system

In this section, we describe the mathematical modeling of an upper limb rehabilitation robot with human subject, which is referred as Human-Robot System. We consider the robot and human arm as a single rigid body for modeling simplicity. The system dynamics can be formulated using the Newton-Euler method as[10]

$$M(\bar{q})\ddot{\bar{q}} + C(\bar{q},\dot{\bar{q}})\dot{\bar{q}} + G(\bar{q}) + F(\dot{\bar{q}}) = \bar{\tau} - \bar{\tau}_h \tag{1}$$

where $\bar{q} \in \mathbb{R}^n$ and $\dot{\bar{q}} \in \mathbb{R}^n$ represents the joint angles and velocities in the radians and radian/sec, respectively. Furthermore, $M(\bar{q}) \in \mathbb{R}^{n\times n}$, $C(\bar{q},\dot{\bar{q}}) \in \mathbb{R}^{n\times n}$, $G(\bar{q}) \in \mathbb{R}^n$, $F(\dot{\bar{q}}) \in \mathbb{R}^n$ are Inertial, Coriolis, Gravitational and Friction matrices for the Human-Robot system for n degrees of freedom; whereas $\bar{\tau}$ represents the actuator torque of robot while $\bar{\tau}_h$ represents human applied torque.

Eq. (1) can also be rewritten in simple form as

$$\ddot{\bar{q}} = M^{-1}\left(\bar{\tau} - \bar{\eta}(\bar{q},\dot{\bar{q}}) - \bar{\tau}_h\right) \tag{2}$$

where

$$\bar{\eta}(\bar{q},\dot{\bar{q}}) = C(\dot{\bar{q}},\bar{q})\dot{\bar{q}} + G(\bar{q}) + F(\bar{q},\dot{\bar{q}}) \tag{3}$$

where inertial matrix $M(\bar{q})$ is written as M for simplicity. As modeling errors in robot and subject's arm models are inevitable, therefore controller must be designed considering uncertainties. Uncertain dynamics of human-robot system can be represented as

$$\hat{\ddot{\bar{q}}} = \hat{M}^{-1}(\bar{\tau} - \hat{\bar{\eta}}(\bar{q},\dot{\bar{q}}) - \bar{\tau}_h) \tag{4}$$

where $\hat{\ddot{\bar{q}}}, \hat{\bar{\eta}}(\bar{q},\dot{\bar{q}})$ and $\hat{M}$ represents estimated information of the concerned parameter and This system has matched and unmatched uncertainties,[25] so the parameters M^{-1} and $M^{-1}(\bar{\eta}(\bar{q},\dot{\bar{q}}))$ are not precise. However, this imprecision is bounded by the following functions:

$$\begin{gathered} M^{-1} = (1-\Delta(q))\hat{M}^{-1} \\ |\Delta(q)_{ii}| \le D(q)_{ii} < 1 \end{gathered} \tag{5}$$

where $D(q) = [D(q)_{i,j}] \in \mathbb{R}^{n\times n}$ is the upper bound of inertial matrix which also resembles to matched uncertainty. This upper bound is calculated based on maximum expected variation from the measured or calculated concerned parameter. Similarly, unmatched uncertainties are bounded as

$$|M^{-1}\,\hat{\bar{\eta}}(\bar{q},\dot{\bar{q}}) - M^{-1}\bar{\eta}(\bar{q},\dot{\bar{q}})| \le \bar{h}(\bar{q},\dot{\bar{q}}) \tag{6}$$

It is important to note that the bounded limit $\bar{h}(\bar{q},\dot{\bar{q}})$ and $D(\bar{q})$ are a function of the joint angles $\bar{q}$ and velocity $\dot{\bar{q}}$. Such time varying changes for robotic systems are also not considered in the literature.

2.2 Problem statement

Based on the above discussion about the modeling of human robot system and it bounded properties of matched and unmatched uncertainties, the problem is described. Main objective of the problem is to find the joint torque $\bar{\tau}$ so that the robot is able to track the desired trajectory for minimum compliance without degrading the performance due the robot and subject's arm modeling uncertainties. In the minimum compliance case, the subject is completely passive and the robot is run under 100% force to guide the subject's limb on reference physiological trajectories.

3. Design of Robust Sliding Mode Control

To meet the desired objective, we have designed Robust Sliding Mode Control (RSMC) algorithm. For this purpose, sliding surface is defined as

$$\bar{s} = \dot{\tilde{q}} + C_g\,\lambda\,\tilde{q} \tag{7}$$

where $\tilde{q} = \bar{q} - \bar{q}_d$ and $\dot{\tilde{q}} = \dot{q} - \dot{q}_d$ Moreover, C_g and λ are positive scalars. The proposed control law for the aforementioned Human-Robot system is

$$\bar{\tau} = \hat{M}(\ddot{\bar{q}}_d + \hat{M}(\hat{\eta} + \bar{\tau}_h) - C_g\lambda\,\dot{\tilde{q}} - K\bar{s} \tag{8}$$

where $\hat{\eta}(\bar{q}, \dot{q})$ is written $\hat{\eta}$ as simplicity and $K \in \mathbb{R}^{n\times n}$ is the continuous feedback controller gain. This gain can be calculated as

$$\bar{h}(\bar{q}, \dot{q}) + D\left|\ddot{\bar{q}}_d + \hat{M}^{-1}(\hat{\eta} + \bar{\tau}_h) - C_g\lambda\dot{\tilde{q}}\right| + \mu\bar{s} = K\bar{s} - D\left|K\bar{s}\right| \tag{9}$$

where $\mu \in \mathbb{R}^{n\times n}$ is the positive definite matrix and defines the convergence rate. Furthermore, we can find K by solving the following equation, which satisfies the Laypunov stability condition, as

$$\begin{aligned} &h_i + D_{ii}\left|q_{d_i} + \hat{M}^{-1}(\hat{\eta} + \bar{\tau}_h)_i - C_{g_i}\lambda_i\dot{\tilde{q}}_i\right| + \mu_{ii}s_i = K_{ii}s_i - D_{ii}\left|K_{ii}s_i\right| \text{ if } s_i > 0 \\ &K_{ii} = 0 \text{ if } s_i = 0 \\ &h_i + D_{ii}\left|q_{d_i} + \hat{M}^{-1}(\hat{\eta} + \bar{\tau}_h)_i - C_{g_i}\lambda_i\dot{\tilde{q}}_i\right| - \mu_{ii}s_i = -K_{ii}s_i - D_{ii}\left|K_{ii}s_i\right| \text{ if } s_i < 0 \end{aligned} \tag{10}$$

Proof:

To prove the closed loop convergence, we define Lyapunov function as

$$V = \bar{s}^T\bar{s} \tag{11}$$

Further, from Eq. (7), $\dot{\bar{s}}$ can be written as

$$\dot{\bar{s}} = \ddot{\bar{q}} - \ddot{q} + C_g\,\lambda\,\dot{\tilde{q}} \tag{12}$$

Using Eq. (2), we can rewrite Eq. (12) as

$$\dot{\bar{s}} = M^{-1}(\bar{\tau} - \bar{\eta} - \bar{\tau}_h) - \ddot{\bar{q}} + C_g\lambda\dot{\tilde{q}} \tag{13}$$

Now, using $\bar{\tau}$ from Eq. (8), we obtain

$$\dot{\bar{s}} = M^{-1}\left(\left(\hat{M}(\ddot{\bar{q}}_d + \hat{M}(\hat{\eta} + \bar{\tau}_h) - C_g\lambda\,\dot{\tilde{q}} - K\bar{s}\right) - \bar{\eta} - \bar{\tau}_h\right) - \ddot{\bar{q}} + C_g\lambda\dot{\tilde{q}} \tag{14}$$

From Eq. (5), we can have

$$M^{-1}\hat{M} = (I + \Delta) \tag{15}$$

Using above condition, we can simplify Eq. (14) as

$$\dot{\bar{s}} = \Delta\ddot{\bar{q}} + \bar{f} - \hat{\bar{f}} - \Delta\hat{\bar{f}} - \Delta C_g\,\lambda\dot{\tilde{q}}(I + \Delta)K\bar{s} \tag{16}$$

where

$$\begin{aligned} \bar{f} &= -\bar{\eta} - \bar{\tau}_h \\ \hat{\bar{f}} &= -\hat{\bar{\eta}} - \bar{\tau}_h \end{aligned} \tag{17}$$

Moreover, we can define as $\dot{V} = \dot{\bar{s}}\bar{s}$; and express it as

$$\dot{V} = \left(\Delta\ddot{\bar{q}}_d + \bar{f} - \hat{\bar{f}} - \Delta\hat{\bar{f}} - \Delta C_g\lambda\dot{\tilde{q}}(I + \Delta)K\bar{s}\right)\bar{s} \tag{18}$$

Now, applying upper bounds for $[s_1, s_2, \ldots, s_n]^T > [0_1, 0_2, \ldots, 0_n]^T$, as described in Eqs. (5) and (6), we have

$$\dot{V} \le \left(\bar{h} + D\left|\ddot{\bar{q}}_d - \hat{\bar{f}} - C_g\lambda\dot{\tilde{q}}\right| - K\bar{s} + D|K\bar{s}|\right)\bar{s} \tag{19}$$

If we prove that Eq. (19) is negative definite, our control law will always converge to stable equilibrium point.[15] It can be proved negative definite if we define K such as

$$-K\bar{s}^T\bar{s} + \left(-\bar{h} - D\left|\ddot{\bar{q}} - \hat{\bar{f}} - C_g\lambda\dot{\tilde{q}}\right| + D|K\bar{s}|\right)\bar{s} = -\mu\bar{s}^T\bar{s} < 0 \tag{20}$$

where $\mu \in \mathbb{R}^{n\times n}$ is the positive definite matrix which defines the convergence rate and robustness of the overall system. To choose K for Eq. (19) to be negative definite for $[s_1, s_2, \ldots, s_n]^T > [0_1, 0_2, \ldots, 0_n]^T$, we solve

$$\bar{h} + D\left|\ddot{\bar{q}}_d - \hat{\bar{f}} - C_g\lambda\dot{\tilde{q}}\right| + \mu\bar{s} = K\bar{s} - D|K\bar{s}| \tag{21}$$

Eq. (21) is equally valid for individual n[th] order sliding surfaces satisfying the condition $s_n > 0$ as well.

In a very similarly way, we can rearrange Eq. (19) for $[s_1, s_2, \ldots, s_n]^T > [0_1, 0_2, \ldots, 0_n]^T$ as follows

$$-K\bar{s}^T\bar{s} + \left(-\bar{h} - D\left|\ddot{\bar{q}} - \hat{\bar{f}} - C_g\lambda\dot{\tilde{q}}\right| - D|K\bar{s}|\right)\bar{s} = -\mu\bar{s}^T\bar{s} < 0 \tag{22}$$

and control gain can be calculated by solving the following equation:

$$\bar{h} + D\left|\ddot{\bar{q}}_d - \hat{\bar{f}} - C_g\lambda\dot{\tilde{q}}\right| + \mu\bar{s} = K\bar{s} + D|K\bar{s}| \tag{23}$$

Remarks:

Proposed robust sliding mode control law has no discontinuity as shown in Eq. (8). Hence, controller effort is smooth and chattering free.

Proposed Control law has no time varying adaptive update law which makes rehabilitation robot unsafe for subjects. Control effort $\bar{\tau}$ is systematically calculated for the desired response based on simple information about modeling and hence it does not need to be re-tuned for each subject. This makes proposed control scheme widely applicable especially for wearable ULRR.

4. Experimental Evaluation

4.1 Upper limb rehabilitation robot system

Proposed control algorithm is experimentally evaluated using Upper Limb Rehabilitation Robot (ULRR). General structure of the experimental setup is shown in Fig. 1. It is a unilateral device and only attachment to the right arm is studied. The maximum joint range of motion for shoulder and forearm flexion/extension were -30~135^o and 0~150^o, respectively. All other DOFs were kept free. Shoulder abduction/adduction motion was kept passive and revolute joint was used for this purpose. This frame was connected to human with two braces: one at shoulder section and other at forearm section as shown in Fig. 1. Brushless DC motors were incorporated with harmonic

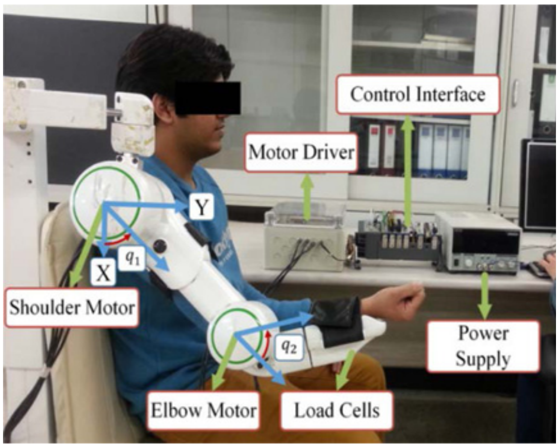

Fig. 1 Schematic diagram of exoskeleton with a human subject; q_1 and q_2 refers to shoulder and elbow joint angles, respectively

derives (with gear ratio 100:1 for shoulder and 160:1 for elbow). These actuators can provide the peak torques of 45 Nm (shoulder motor) and 25 Nm (elbow motor). EPOS2 70/10 and EPOS2 25/5 Maxon DC drives are employed for motors. System implementation is carried out on National Instrument card NI cRIO9024. Hardware was programmed using LabVIEW 2012.

Several safety features were installed in the robotic arm and control hardware. Mechanical stops were placed on shoulder and elbow joints to avoid the robot to go beyond the physiological motion range. Moreover, in case of fast and uncontrolled movement whole plant shut down feature is programmed. Independent safety circuit is also incorporated that can power down the system in case of any danger or if the subject's feels discomfort.

4.2 Upper limb rehabilitation robot parameters

Robot parameters for Upper Limb Rehabilitation Robot (ULRR) are shown in Table 1. Human upper limb parameters like segment mass, center of mass and lengths are calculated by subject's gender, body weight, height and age as described in the literature.[26,27]

For the experiments, ten healthy neurologically intact male subjects (age 25-35 years) were selected. Details of the participants are given in Table 2. We have considered 20% variations in their biomechanical properties.

4.3 Evaluation of RSMC law

We have compared RSMC algorithm with Robust Compute Torque Control[10] (RCTC) and Boundary Augmented Sliding Mode Control[15] (BASMC).

The RCTC equation is listed below.

$$\bar{\tau} = \hat{M}\left(\ddot{\bar{q}}_d - K_p\tilde{\bar{q}} - K_d\dot{\tilde{\bar{q}}} + \bar{\tau}_h + \delta a\right) + \hat{C}(\bar{q},\dot{\bar{q}})\dot{\bar{q}} + \hat{\bar{G}} + \bar{\tau} \tag{24}$$

where K_p and K_d are the proportional and differential gains, while $\delta\alpha$ is obtained as per rules given in the literature.[10] It is important to note that RCTC requires to tune 6^n (where n represents DOF) parameters. This is quite complicated to use and demands high expertise.

The BASMC equation can be written as

Table 1 Robot parameters

Parameter	Shoulder Link	Elbow Link
Length (m)	0.32	0.30
Mass (kg)	0.3	0.2
Center of mass (m)	0.16	0.15

Table 2 Subject participants data

Age (Years)	25 to 35
Gender	Male
Body Weight (kg)	65-82
Height (m)	1.7 to 1.82

$$\bar{\tau} = \hat{M}\left(\ddot{\bar{q}}_d - \hat{M}^{-1}(\hat{\bar{\eta}} + \bar{\tau}_h) - \lambda\dot{\tilde{\bar{q}}} - K\cdot\mathrm{sat}(\bar{s})\right) \tag{25}$$

where $sat(\bar{s})$ is the saturation function and K is the control gain. This gain can be obtained by solving the following equation as

$$\bar{h} + D\left|\ddot{\bar{q}}_d + \left(\hat{M}^{-1}(\hat{\bar{\eta}} + \bar{\tau}_h)\right) - \lambda\dot{\tilde{\bar{q}}}\right| + \mu\bar{s} = (I - D)K \tag{26}$$

Proposed RSMC equation can be represented as

$$\bar{\tau} = \hat{M}\left(\ddot{\bar{q}}_d + \hat{M}^{-1}(\hat{\bar{\eta}} + \bar{\tau}_h) - C_g\lambda\dot{\tilde{\bar{q}}} - K\bar{s}\right) \tag{27}$$

where the controller gain is obtained by solving Eqs. (21) and (23). Once the controllers are tuned, no changes are made between the tests in terms of gains in control strategy which is the key advantage of RSMC. Good performance can also be achieved with RCTC and BASMC but it needs to be retuned for each individual. However, RSMC does not need to be re-tuned. A block diagram of the experimental setup is shown in Fig. 2. The output of the controllers are the desired torque for shoulder and elbow joints. We converted torque command to desired motor current. To ensure the system to follow desired current command, we have implemented local closed loop system using simple proportional integral (PI) controller followed by saturation function to limit the desired current. Output current is filtered using Kalman Filter.[15] Experimental setup is developed using LabVIEW 2012 FPGA module. Sampling rate for controllers is 500 μs while the current loop controller sampling time was 50 μs.

4.4 Experimental results

All the controllers were evaluated experimentally with ten different subjects. We found errors and variations in trajectories. These experiments were carried out for minimum compliance which means that controllers are run under 100% force to guide the subject's limb on reference trajectories. During this mode, the maximum angular deviation from the desired trajectory must be less than 5°.

In Fig. 3, trajectory tracking results for RCTC is represented, while Figs. 4 and 5 represents the response with BASMC and RSMC, respectively. It is evident from the Fig. 3 that RCTC is mostly affected by biomechanical variations. BASMC also suffers from unacceptable deviations from the desired trajectory (as shown in Fig. 5) and hence not suitable for ULRR. On the other hand, RSMC (as shown in Fig. 5) tracks the desired trajectory with minimum variations. It is found that tracking error due to these uncertain variation is as high as 20° for

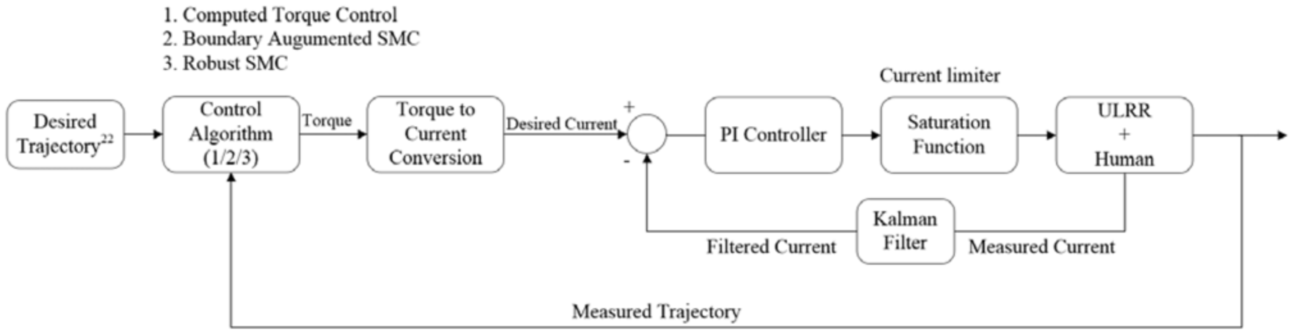

Fig. 2 Control architecture of Upper Limb Rehabilitation Robot (ULRR)

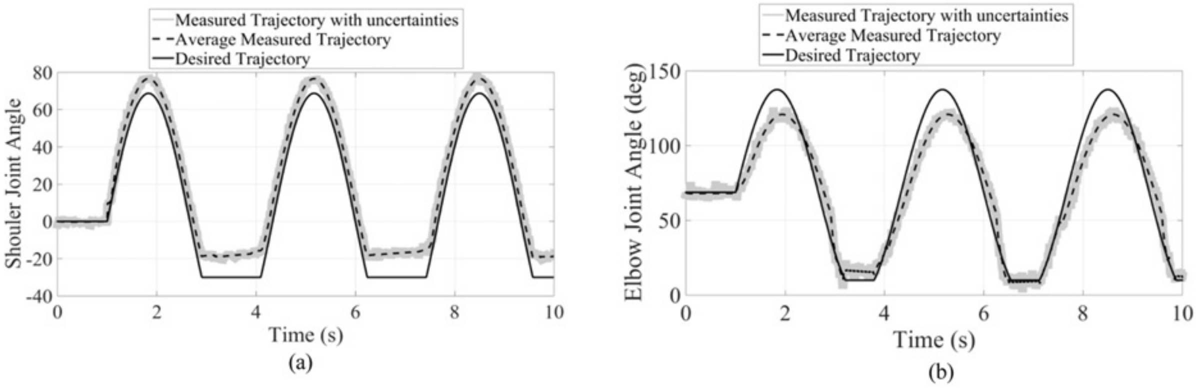

Fig. 3 ULRR trajectory tracking results using RCTC; (a) for shoulder joint, (b) for elbow joint

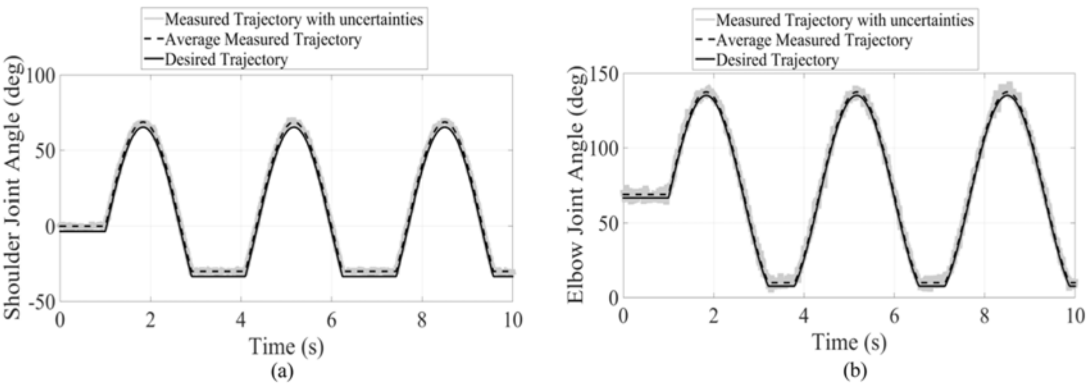

Fig. 4 ULRR trajectory tracking results using BASMC; (a) for shoulder joint, (b) for elbow joint

RCTC whereas for BASMC, it is up to 12^{o}, but with RSMC it only varies from 1^{o} to 4^{o}. We have highlighted this error comparison in Fig. 6. It is clear from Fig. 6 that RSMC is least affected by subject's arm uncertainties as trajectory tracking error using RSMC is 10 times less than RCTC and three times less than BASMC. Overall, the least performance is obtained by RCTC. This performance was mainly because of control algorithm's inability to handle subject and robot model uncertainties which makes RCTC impractical to use for Upper Limb Rehabilitation Robot (ULRR). BASMC handles uncertain system parameters better than RCTC, but it lacks in handling time varying un-matched uncertainties. Un-matched uncertainties are part of unmolded dynamics which acts through the non-control input channel e.g., ($\bar{\tau}$).[15] Therefore, BASMC is also not suitable for ULRR. So, the best performance is achieved using RSMC. Main reason for this performance is the ability of RMSC to cater matched & unmatched uncertainty, smoothly. For better understanding, we have presented statistical analysis in Fig. 7.

We repeated experiments 20 times and plotted average RMS error for each control law. Fig. 7 represents the performance variation for RCTC, BASMC and RSMC over repeated experiment. Statistical

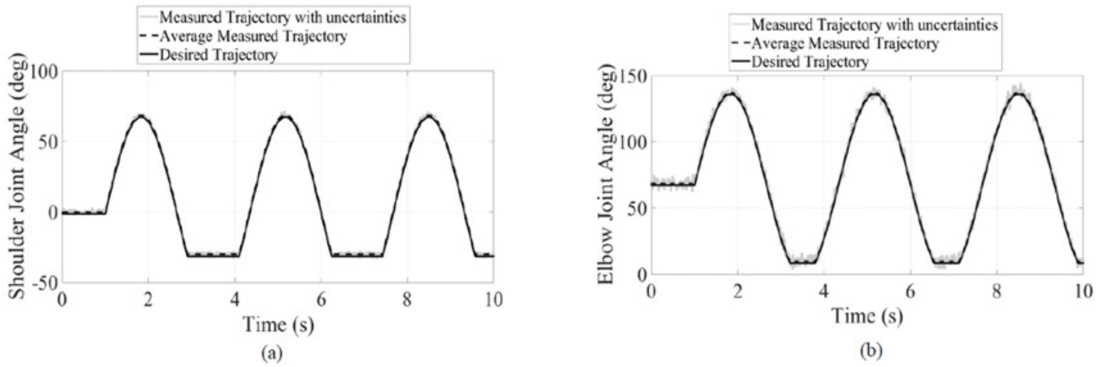

Fig. 5 ULRR response using RSMC; (a) for shoulder joint, (b) for elbow joint

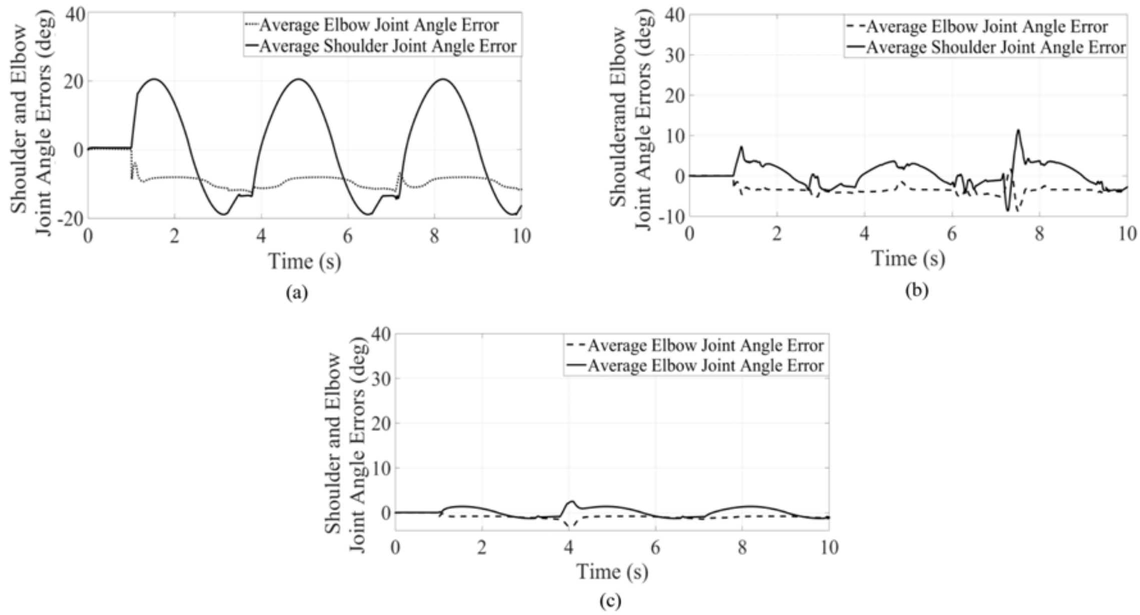

Fig. 6 ULLR trajectory tracking error; (a) using RCTC, (b) using BASMC, (c) using RSMC

analysis is summarized in Table 3. Fifth column of table elaborates standard deviation normalized to RSMC for comparison. It can be seen that standard deviation σ, for RCTC is more than four times of RSMC while σ for BASMC, it is almost two times.

5. Discussion

RCTC and BASMC controllers can be tuned in an attempt to achieve better performance. However, tuning process needs to be repeated for each individual. Moreover, RCTC requires 6^n parameters to be tuned while BASMC requires 2^n parameters whereas RSMC requires 3^n parameters for the controller tuning. Although, BASMC requires lesser parameters than RSMC but it has two major disadvantages as follows: 1) BASMC cannot handle unmatched uncertainties. These unmatched uncertainties acts through non-input channel and causes chattering. RSMC law not only overcomes this problem but is also chattering free. 2) BASMC needs to be retuned for each individual every time whereas RSMC does not need this retuning, it can handle matched and unmatched uncertainties very well. Once, bounds and desired response time is defined, controller does not need to be retuned for parametric variations due to different subjects. With just basic information of human subject parameters like weight, height, age and gender,[26,27] controller is simply re-adjusted for these parameters. So, once the controller is tuned, no further tuning is required for different subjects. Results in Sections 4.4 presents comparative analysis of the proposed methodology.

6. Conclusions

In this paper, we have discussed issues and control challenges for upper limb rehabilitation robot particularly concerned with changing subject's arm parameters. We have proposed chattering free robust sliding mode control for upper limb rehabilitation robot (ULRR). Proposed methodology is evaluated on seven degree of freedom robot

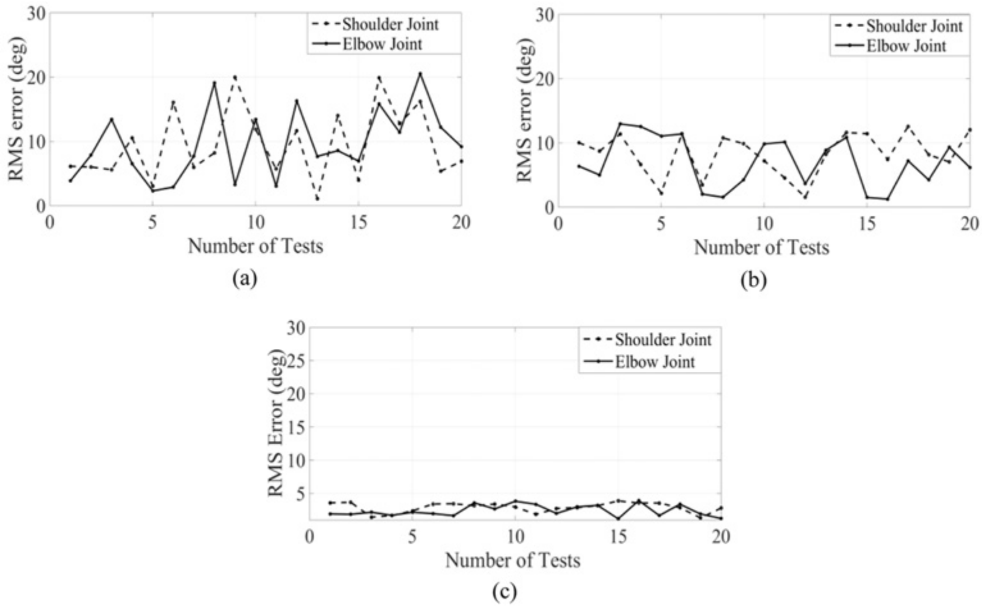

Fig. 7 Root Mean Square Error plot of 20 tests; (a) for RCTC, (b) for BASMC, (c) for RSMC

Table 3 Statistical comparison of the controller with 10 subjects. Standard deviation σ of RSMC is the lowest compared to BASMC and RCTC Laws

Controller	σ of RMS Error for Shoulder Joint	σ of RMS Error for Elbow Joint	σ of Average RMS Error	Normalized to RSMC, σ of RMS Error
RSMC	1.85	1.67	1.76	1
BASMC	3.42	3.53	3.475	1.97
RCTC	7.305	7.91	7.61	4.32

with two active and five passive joints. These active joints make the robot able to move in sagittal plane only. We have successfully demonstrated the RSMC performance against RCTC and BASMC. Tracking performance is compared while varying the subject's physical characteristics. Results indicate that RSMC achieves better performance in handling diverse subject's arm uncertainties as compared to RCTC and BASMC. Thus, we conclude RSMC can be more effective for Upper Limb Rehabilitation Robot.

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