Simulation of Online Human Arm Inertia Estimation for Robot-aided Rehabilitation

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***Abstract*—Most of the studies on rehabilitation robots consider the human arm inertia and the gravity torque as system disturbances. Individual anthropometry varies from patient to patient, and therefore human limbs are not modelled. Some studies used the Disturbance Observer (DOB) as a method of disturbance rejection. However, if the inertia and gravity torque parameters of the human arm could be estimated, they could be effectively used in the controller loop to achieve precise motion control. This paper proposes a novel Reaction Torque Observer (RTOB) based estimation technique which updates parameters using learning and recursive algorithms in real-time. The proposed method is applicable to many robot systems where the load inertia or the load is not known. A simulation was carried out with realistic parameters to compare the performance of two competing methods proposed namely, Adaptive Linear Neuron (ADALINE) and Recursive Least Squares (RLS). Results show that the RLS method outperforms the ADALINE method based on the performance criteria of accuracy, precision and convergence speed for estimating the inertia.**

Keywords*—Inertia Estimation, Reaction Torque Observer, AI-based, Rehabilitation, ADALINE, Recursive Least Squares

I. Introduction

Recovery from reduced range of motion is an important part in rehabilitation of sensorimotor functions after a stroke or a spinal cord injury. There are several rehabilitation techniques used to recover from reduced Range of Motion (ROM) caused by stroke or bone fracture. These are passive ROM, active assisted ROM, active ROM exercises to recover from the reduced ROM and resistance exercises to build up the strength. In passive exercises, the therapist will move the impaired limb along with muscles and joints through full range of motion while the patient does not exert any effort. It has a positive effect on repairing joints [1]. Patients with the opportunity to undergo passive ROM exercises early in the recovery process, benefits from reduced hospital stay and are able to return to daily activities sooner. In active assisted ROM exercises, if the patient's muscles cannot accomplish the complete movement, the therapist will assist as needed. Active assisted ROM exercises are used to improve the elbow motion. Active ROM exercises relies on the muscles of the patient. The patient performs the exercise by himself moving as far as possible in each direction. In resistance training the therapist will hold the patient's arm and apply resistance force against the patient's arm movement. This is used to strengthen the muscles.

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Rehabilitation robotics provides efficient therapy for patients by incorporating robotic devices to the traditional rehabilitation process. It is advantageous for both the patient and the therapist where the patient benefits from intensive training while the therapist can be released from exhaustive manual therapy. The accurate measurements provided by the robotic devices involved help extensively to keep a track of the improvement of the patient health. This in turn increases the therapist's capacity to handle more patients and also to concentrate more on the treatment plan [2]. Studies on animals suggest that performing 400-600 repetitions can help make structural neurological changes[3]. However manual therapy without the assistance of rehabilitation robotics limits the number of repetitions to 40-60 per session. Where human attention span and reflexes are subjective from therapist to therapist, a robot can detect sudden changes of the joint resistance consistently making it a better solution. Comparison of Fugl-Meyer assessment of sensorimotor recovery also shows that the robot aided therapy has larger improvements compared to the conventional manual therapy [4]. Therefore, rehabilitation robotics is becoming increasingly popular.

A number of rehabilitation robots have been developed to provide all kinds of ROM exercises. These robots are often subjected to unknown disturbances from the environment as well as the disturbances invoked by the rehabilitee. Therefore the controller performance may deteriorate. The disturbances caused by the gravity, inertia and friction forces are usually dominant. In a recent work by Urgulu *et al*. a rehabilitation robot with gravity compensation was designed with the gravity effect of the patient's arm modelled as a disturbance [5]. Compensation of the disturbance caused by the gravity increases the overall system robustness. However, the weight and the inertia of the patient arm were not estimated. The inertia of a human arm was identified in advance, assuming it is a constant [6]. However, this is not the case in rehabilitation systems as it may change with time. In this study, the movement of the exoskeleton robot was limited to the horizontal plane such that the gravity does not have an effect the robot. Nevertheless, a method for estimating the inertia while the robot is moving in the vertical plane could be useful for other joints such as the knee joint since moving in the horizontal plane would be uncomfortable. Calculating the precise values for inertia and the weight parameters of a human limb is not practical as the

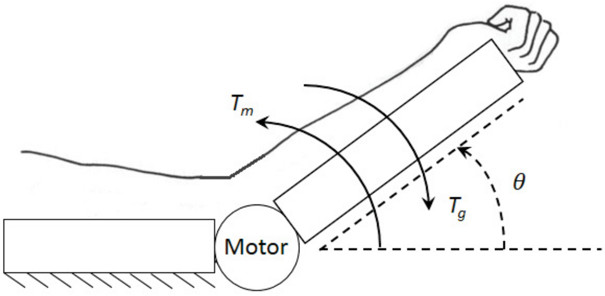

Fig. 1: Proposed rehabilitation robot model

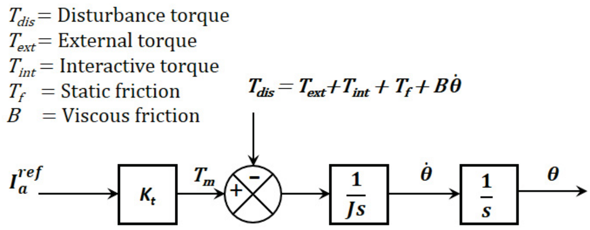

Fig. 2: DC motor model

TABLE I: Nomenclature

Parameter	Description
J_T	Total inertia of the system
J_M	Nominal inertia of the motor
J_R	Nominal inertia of the exoskeleton
J_H	Inertia of the human forearm
J_n	Nominal inertia of the robot system
J	Actual inertia of the robot system
k_{tn}	Nominal torque constant
k_t	Actual torque constant
I_a^{ref}	Current reference
B	Viscous friction coefficient of the robot
F_S	Static friction of the robot
$\widehat{t}_{rec}$	Estimated reaction torque
g_{rec}	Reaction torque observer gain
m_H	Mass of the human forearm
m_R	Mass of the forearm exoskeleton
g	Gravitational acceleration
r_H	Distance from motor axis to COG of human forearm
r_R	Distance from motor axis to COG of forearm exoskeleton
y_k	Modified RTOB output
$\widehat{y}_k$	Estimated y_k
W	Weight vector
x	Input vector
a	ADALINE output
d	Desired output
e	Error
α_i	Initial learning rate
α_f	Final learning rate
T	Current training time
T_{max}	Total training time
λ	Forgetting factor

forearm and the upper arm are connected. The parameters also change from patient to patient or even for the same patient with respect to time or the angle of the joint.

Stroke patients are often unable to lift their affected limb by themselves since their muscles are weakened and lack the necessary strength. In this case, estimation of gravity effect of the human arm is useful since the exoskeleton systems can compensate for the estimated gravity effect of the patient's arm. The patient can then engage in the rehabilitation exercises even at an early stage which would ultimately provide an early recovery. Knowing the inertia of the patient arm is advantageous for designing the robust control systems for rehabilitation robots.

Therefore, in this paper, a novel method for iteratively estimating the inertia and the gravity effect of the human arm is presented. The aim is to estimate the inertia and the gravity effect during the passive rehabilitation exercises. In this case, it is assumed that the patient does not apply any external force while the robot is moving the patient's arm. At this moment the system will automatically estimate the parameters. While the system is proposed for the rehabilitation of the elbow, the same principles can be extended for any limb of the body. Automatic identification and compensation of the inertial and gravity torque disturbances leads to the overall system robustness.

This research uses a sensorless force sensing method using the Reaction Torque Observer (RTOB) [7]. Conventional force sensors add weight to the system and have a narrower bandwidth. Compared to force sensor based systems, sensorless force sensing is less noisy. The RTOB can be used with a higher bandwidth since the bandwidth can be made high as the sampling frequency.

II. Modelling

A. Reaction Torque Observer

The proposed elbow rehabilitation device is a single Degree of Freedom (DoF) device with a DC motor actuator as shown in Figure 1. The motor is torque controlled. The Figure 2 shows the classic DC motor model. The generated motor torque is denoted by (1). Table I shows the nomenclature.

$$T_m = k_t I_a^{ref} \tag{1}$$

The total disturbance acting on the system is denoted by T_{dis}. Since the proposed system has only one degree of freedom, the interactive torque is zero [8]. A reaction torque observer can be used to estimate the reaction torque without using any force sensors as shown in Figure 3. It estimates the reaction torque based on the torque constant and inertia. Here k_t and J are the actual parameters in the system while k_{tn} and J_n are the nominal parameters. The friction forces are also compensated to estimate the pure reaction torque. A reliable estimation of the parameters must be obtained by conducting several experiments [9]. Once the parameters are known, the reaction torque can be estimated. The total inertia of the robot with and without the patient's arm is denoted by (2) and (3) respectively.

$$J_T = J_M + J_R + J_H \tag{2}$$

$$J_n = J_M + J_R \tag{3}$$

The total gravity effect is composed by the patient's arm weight and the robot weight as shown in (4). The gravitational

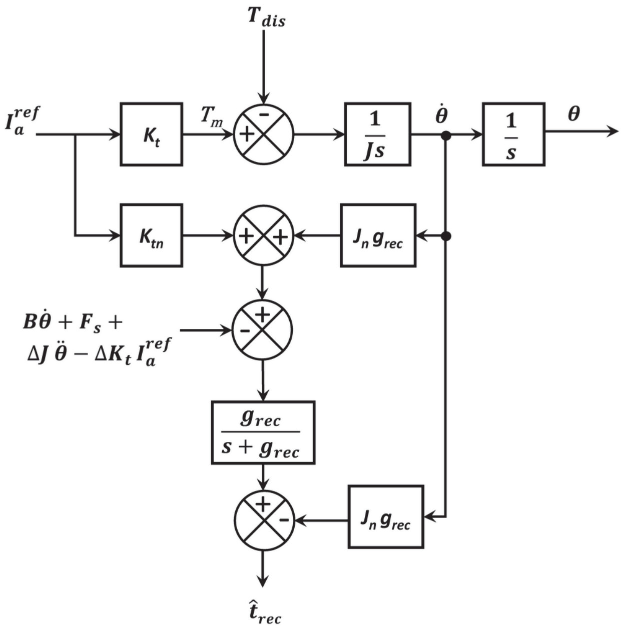

Fig. 3: Reaction Torque Observer

acceleration $g = 9.81ms^{-2}$.

$$T_g = m_H g \cos(\theta) r_H + m_R g \cos(\theta) r_R \tag{4}$$

The total disturbance torque for the exoskeleton system without the patient's arm is depicted in (5). The friction forces of the robot can be found by the experiments as detailed by Chinthaka *et al*. [10]. Then the RTOB output can be derived as in (6).

$$T_{dis} = (J_M + J_R)\ddot{\theta} + m_R g \cos(\theta) r_R + B\dot{\theta} + F_S \tag{5}$$

$$\widehat{t}_{rec} = m_R g \cos(\theta) r_R + \Delta J\ddot{\theta} - \Delta k_t I_a^{ref} \tag{6}$$

Assuming the human arm elbow joint friction is small and negligible, and the patient does not provide any external force to the robot during the passive ROM exercises, the reaction torque can be modelled as in (7),

$$\widehat{t}_{rec} = J_H\ddot{\theta}_k + m_H g \cos(\theta_k) r_H + m_R g \cos(\theta) r_R + \Delta J\ddot{\theta} - \Delta k_t I_a^{ref} \tag{7}$$

The inaccuracies in the nominal inertia and the torque constant causes the RTOB output to contain $\Delta J\ddot{\theta}$ and $\Delta k_t I_a^{ref}$ variations from the actual reaction torque. These variations can be reduced to near zero with experiments of finding the inertia and the torque constant [9]. Therefore by neglecting these variations, the RTOB output can be depicted as in (8).

$$\widehat{t}_{rec} = J_H\ddot{\theta}_k + m_H g \cos(\theta_k) r_H + m_R g \cos(\theta) r_R \tag{8}$$

The gravity effect of the robot mechanism could be identified in advance using a CAD model [11]. A modified output of the RTOB at k^{th} iteration is obtained by removing the gravity torque of the robot mechanism as shown in (9).

$$y_k = J_H\ddot{\theta}_k + m_H g \cos(\theta_k) r_H \tag{9}$$

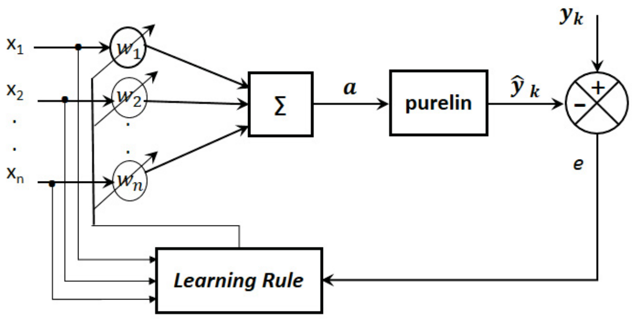

Fig. 4: ADALINE block diagram

It is identical to equation (10) where the parameters of interest are denoted by w_1 and w_2.

$$y_k = w_1\ddot{\theta}_k + w_2 \cos(\theta_k) \tag{10}$$

The measured data is received in an iterative manner and therefore a complete dataset is not available at once. Although storing the previous data and using an offline parameter estimation method is possible, in a robot system it might occupy the microprocessor memory rather quickly. Since it is preferred for the parameters to be estimated online, an iterative method which updates the model based on the newly measured data is essential. Therefore, a learning algorithm such as ADALINE (ADAptive LInear NEuron) with LMS (Least Mean Square) learning rule [12] or an adaptive filter such as Recursive Least Squares (RLS) filter [13] can be convenient. When the angle of the robot is changing arbitrarily, the RTOB output will change accordingly. With each newly measured dataset, the parameters will be updated. Both algorithms were implemented and simulated.

B. ADALINE

A single ADALINE is represented in Figure 4. The output of the neuron of the network is shown in (11).

$$a = purelin(W^T X) \tag{11}$$

ADALINE uses a linear activation function and therefore $\widehat{y_k} = purelin(a) = a$. To find the parameters, a single ADALINE with 2 inputs is used. Here $\ddot{\theta}_k$ and $\cos(\theta_k)$ is modelled as the input vector as shown in (12).

$$x(k) = [\ddot{\theta}_k \;\; \cos(\theta_k)]^T \tag{12}$$

The parameters that needed to be found are then contained in the weight vector and it is represented as shown in (13).

$$W = [w_1 \;\; w_2]^T \tag{13}$$

The weight vector of the ADALINE neuron is corrected in every iteration using the Least Mean Square (LMS) algorithm. The LMS algorithm is shown in (14) and (15) where $d(k)$ is the target which is the modified output of the RTOB ($y(k)$).

$$W(k) = W(k-1) + 2\alpha e(k)x(k) \tag{14}$$

$$e(k) = d(k) - a(k) \tag{15}$$

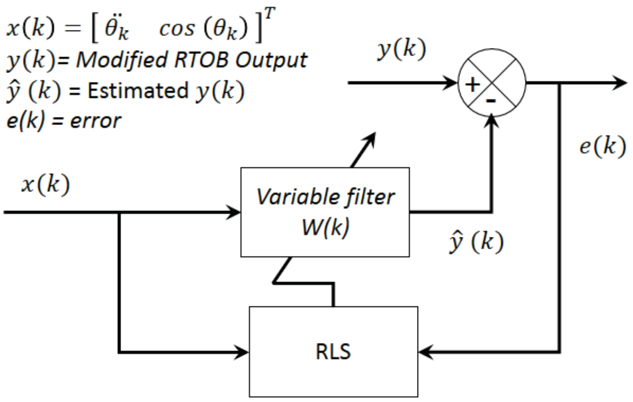

Fig. 5: RLS block diagram

The stability and the speed of the algorithm's convergence depends on the learning rate α. To attain both stability and speed, a variable learning rate is used as shown in (16).

$$\alpha = \alpha_i \left(\frac{\alpha_f}{\alpha_i}\right)^{\frac{T}{T_{max}}} \tag{16}$$

The initial and final learning rates are selected experimentally.

C. Recursive Least Squares

Recursive least squares is an algorithm used for finding the required coefficients of an input signal $x(k)$ which would provide the desired signal, in this case it is the modified RTOB output y_k. The block diagram of RLS is shown in Figure 5. The input $x(k)$ and the weights $W(k)$ are modelled similarly to the ADALINE method. The forgetting factor λ determines the effect of the old samples to the estimation process and it is set experimentally. The recursive algorithm is depicted in equations (17)-(20).

$$W(k) = W(k-1) + L(k)e(k) \tag{17}$$

$$e(k) = d(k) - x^T(k)W(k-1) \tag{18}$$

$$L(k) = \frac{\lambda^{-1}P(k-1)x(k)}{1+\lambda^{-1}x^T(k)P(k-1)x(k)} \tag{19}$$

$$P(k) = \lambda^{-1}P(k-1) - \lambda^{-1}L(k)x^T(k)P(k-1) \tag{20}$$

The initial value of the parameter covariance matrix $P(k)$ is given as $P(0) = \delta I$. The δ value is set to a very high number since the real parameters are not known.

III. Results

A simulation of the proposed methods was done using MATLAB. The system was modelled with robot parameters. The load was modelled with an arbitrary weight and COG corresponding to a forearm of a new patient. A PID (Proportional, Integral, Derivative) position controller was engaged to move the load (forearm) in a sinusoidal angular displacement throughout a 6s time interval. With the output of the PID controller (acceleration), the required motor current can be calculated as shown in Figure 6. A random noise with a magnitude of $\pm 5\%$ was added to both the input angle and the

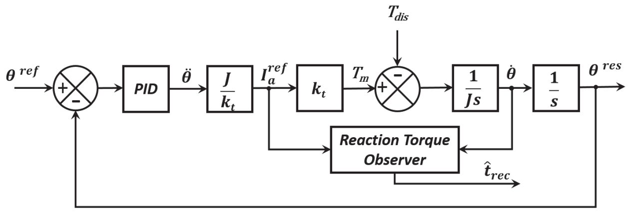

Fig. 6: Control block diagram

motor current to mimic the real world scenario. The resultant data is shown in Figure 7.

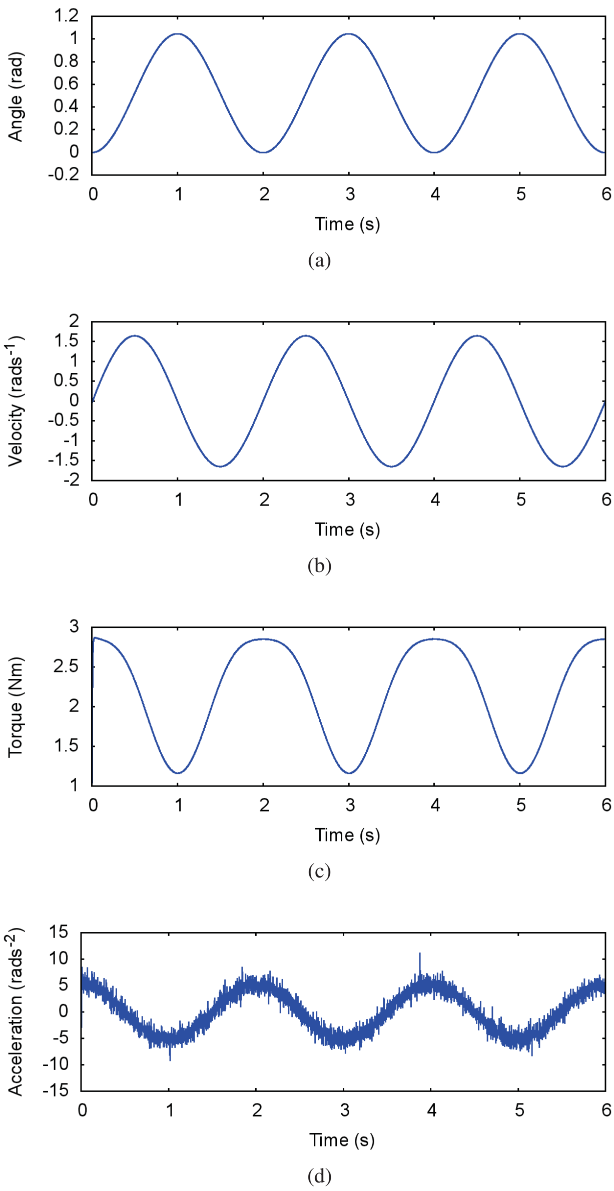

Fig. 7: Simulation data of the system model. (a) Angle. (b) Angular velocity. (c) Reaction torque. (d) Angular acceleration.

Parameters were estimated for the simulated data using ADALINE and RLS algorithms as shown in Figure 8 and

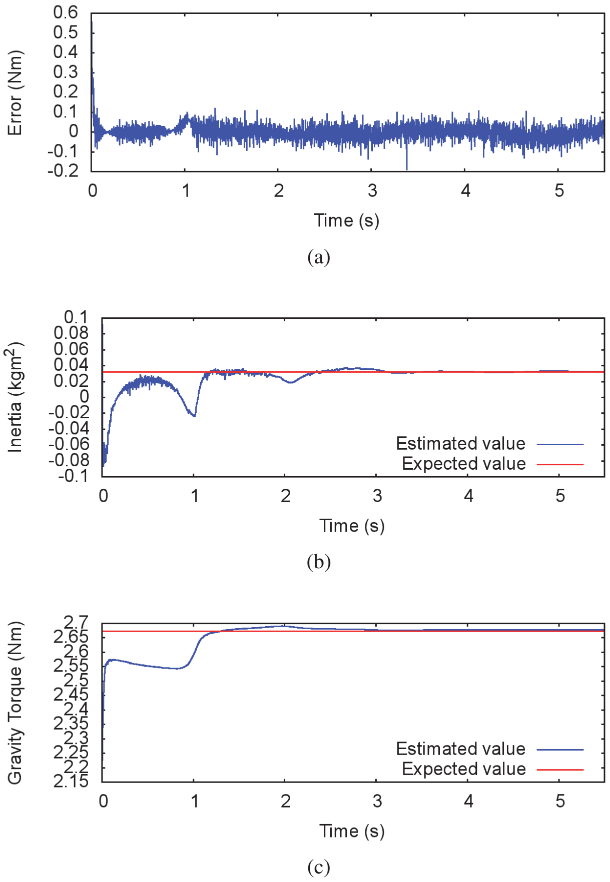

Fig. 8: Estimation of the parameters using ADALINE. (a) Error. (b) Estimated inertia. (c) Estimated gravity torque.

TABLE II: Simulation Parameters

Parameter	Value
P	11200.0
I	0.0
D	630.0
dt	0.001 s
J_n	0.1 Nms^2rad^{-1}
k_{tn}	1.4 NmA^{-1}
B	0.3925 $Nmsrad^{-1}$
F_S	0.2966 Nm
g_{rec}	200.0
α_i	0.03
α_f	0.00001
λ	0.9998
δ	100000

Figure 9 respectively. Initially, the weight vector was set to a random value corresponding to anthropometric data [14]. The simulation parameters are shown in Table II. For ADALINE, the maximum error of the estimated parameters reduced to 8.31% in 3.003 seconds. The error of estimate gravity torque. RLS reduced the maximum error of estimated parameters to 6.96% in 1.222 seconds. A comparison of the results are shown in Table III.

Boxplots representing minimum, maximum and median for the estimated inertia and gravity torque are shown in Figure 10. The sample size n = 10. For the estimated inertia using the

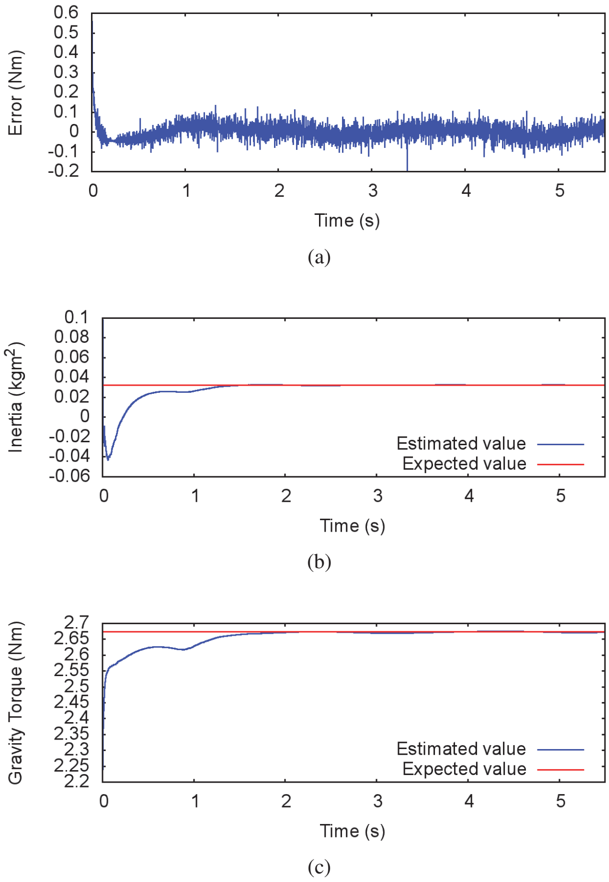

Fig. 9: Estimation of the parameters using RLS. (a) Error. (b) Estimated inertia. (c) Estimated gravity torque.

ADALINE and RLS algorithms, the interquartile range was 0.0004 and 0.0000125 respectively. For the estimated gravity torque the interquartile range for ADALINE was 0.0015 whereas for RLS it was 0.0000675. The algorithms converge at different points. However in both cases, ADALINE is less precise and less accurate than RLS.

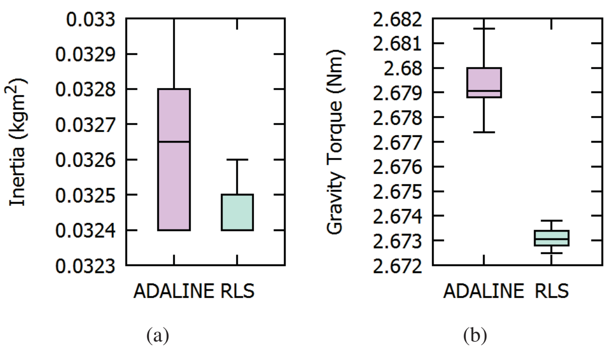

Fig. 10: Boxplots for the estimated parameters (n=10). (a) Estimated inertia. (b) Estimated gravity torque.

TABLE III: Comparison of different estimation methods

Method	Estimated inertia (kgm^2)	%Error	Estimated gravity torque (Nm)	%Error	Average settling time (s)
ADALINE	0.03625	1.08	2.6791	0.20	3.186
RLS	0.03250	0.01	2.6731	0.02	1.827

IV. Conclusion

In this paper a novel method of estimating the human arm inertia and the gravity effect using the RTOB was proposed, modelled, and simulated considering real world scenarios. Both ADALINE and RLS algorithms estimated the inertia and the gravity torque of the patient's arm in few seconds with an error smaller than 8.31%. At convergence the errors are less than 2%. In this experiment the RLS algorithm outperformed ADALINE with faster convergence, higher accuracy and higher precision with the expense of high computational complexity. As the errors are very small, both algorithms are suggested for estimating the inertia. The proposed method is very useful since the patient does not have to perform any special movement other than the passive ROM exercise. Parameters were estimated online and almost in real-time. The methods discussed in this paper can be applied in rehabilitation robot design and power assist systems (exoskeletons) design. Rather than treating the inertia of the human limb as a disturbance, it could be estimated as proposed. That makes the control systems robust. Furthermore, estimation and compensation of the gravity torque allow the patients to access the full range of motion even if they do not have the required strength to lift their arm.

References

[1] C.-N. Tseng, C. C.-H. Chen, S.-C. Wu, and L.-C. Lin, "Effects of a range-of-motion exercise programme," *Journal of Advanced Nursing*, vol. 57, no. 2, pp. 181–191, 2007.

[2] R. Riener, T. Nef, and G. Colombo, "Robot-aided neurorehabilitation of the upper extremities," *Medical and Biological Engineering and Computing*, vol. 43, no. 1, pp. 2–10, 2005.

[3] E. J. Plautz, G. W. Milliken, and R. J. Nudo, "Effects of repetitive motor training on movement representations in adult squirrel monkeys: role of use versus learning," *Neurobiology of learning and memory*, vol. 74, no. 1, pp. 27–55, 2000.

[4] P. S. Lum, C. G. Burgar, P. C. Shor, M. Majmundar, and M. Van der Loos, "Robot-assisted movement training compared with conventional therapy techniques for the rehabilitation of upper-limb motor function after stroke," *Archives of physical medicine and rehabilitation*, vol. 83, no. 7, pp. 952–959, 2002.

[5] B. Ugurlu, M. Nishimura, K. Hyodo, M. Kawanishi, and T. Narikiyo, "Proof of concept for robot-aided upper limb rehabilitation using disturbance observers," *IEEE Transactions on Human-Machine Systems*, vol. 45, no. 1, pp. 110–118, 2015.

[6] F. Mobasser and K. Hashtrudi-Zaad, "A method for online estimation of human arm dynamics," in *Engineering in Medicine and Biology Society, 2006. EMBS'06. 28th Annual International Conference of the IEEE*. IEEE, 2006, pp. 2412–2416.

[7] A. H. S. Abeykoon and K. Ohnishi, "Improvement of tactile sensation of a bilateral forceps robot by a switching virtual model," *Advanced Robotics*, vol. 22, no. 8, pp. 789–806, 2008.

[8] M. Mizuochi, T. Tsuji, and K. Ohnishi, "Improvement of disturbance suppression based on disturbance observer," in *9th IEEE International Workshop on Advanced Motion Control, 2006.* IEEE, 2006, pp. 229–234.

[9] G. A. Perera, M. B. Pillai, A. Harsha, and S. Abeykoon, "Dc motor inertia estimation for robust bilateral control," in *7th International Conference on Information and Automation for Sustainability*. IEEE, 2014, pp. 1–7.

[10] M. D. Chinthaka and A. H. S. Abeykoon, "Friction compensation of dc motors for precise motion control using disturbance observer," *ECTI Transactions on Computer and Information Technology (ECTI-CIT)*, vol. 9, no. 1, pp. 74–82, 2015.

[11] F. Just, K. Baur, R. Riener, V. Klamroth-Marganska, and G. Rauter, "Online adaptive compensation of the armin rehabilitation robot," in *Biomedical Robotics and Biomechatronics (BioRob), 2016 6th IEEE International Conference on*. IEEE, 2016, pp. 747–752.

[12] M. T. Hagan, H. B. Demuth, M. H. Beale, and O. De Jesús, *Neural network design*. PWS publishing company Boston, 1996, vol. 20.

[13] J. Jiang and Y. Zhang, "A revisit to block and recursive least squares for parameter estimation," *Computers & Electrical Engineering*, vol. 30, no. 5, pp. 403–416, 2004.

[14] D. A. Winter, *Biomechanics and motor control of human movement*. John Wiley & Sons, 2009.