Muscle Tone Level Classification Based on Upper-Limb Impedance Model

Zaw Lay Htoon, Shahrul Naim Sidek, and Sado Fatai
Mechatronics Engineering Department, International Islamic University Malaysia,
Email: mohdyahyazlh@gmail.com, snaim@iium.edu.my, abdfsado1@gmail.com

***Abstract*—Many tools have been developed for the assessment of muscle tone of impaired limbs. Despite, having the appropriate knowledge, therapists still face with challenge in the assessment due to the subjective evaluation of muscle tone during training sessions. Moreover, the training has become more-costly and time consuming since the subjects have to face the therapists over a long period of time. By deploying robot-assisted system, some of these problems could have been addressed but the aspect of proper assessment of subjects' muscle tone levels still remain. Assessment of subjects' muscle tones allows proper prescription of task during training session. Recent studies have established links between muscle tone and upper-limb mechanical impedance. However the development of adequate estimation algorithm for subjects' upper-limb impedance parameters and the prediction of muscle tone level in a more objective manner is still a subject of many research works. This study proposes an appropriate strategy for the estimation of upper-limb mechanical impedance parameters as a mean for the assessment of subjects' muscle tone levels. Both simulation and experimental results show that the upper-limb impedance parameters can be estimated to a good accuracy level, while the subjects' muscle tone level can be consistently predicted.**

***Index Terms*—robot-assisted system; muscle tone; upper-limb impedance parameter; recursive least square estimator; ANN**

I. Introduction

People with muscle impairment due to traumatic accident for example, demand early intervention and constant physical therapy of the affected extremities for fast recovery due to neurological disorder which deteriorates over time [1]. In the last two decades, robot assisted systems have been introduced to complement the work of human therapists and have shown positive outcome to help subjects recover to healthy muscle tone level and enable them to regain their activities of daily living (ADL). In particular, robot-assisted systems have been used in stroke rehabilitation for recovery [1] and have shown great potential to counteract the risk of stroke rather than conventional therapy. Subject with muscle tone impairment requires detailed attention and assistance from therapist during training sessions to recover and the process is usually time and energy consuming. Researchers have developed robotic systems to assist therapist in training session to move the subjects' limbs without helping aid of the therapist. Such systems offer numerous advantages namely cost optimization, decrease in subject recovery time, satisfaction in treatment or training session and the possibility for the training to be conducted at home as compared to conventional approach which is conducted at training centers [2].

Upper-limb paralysis due to neurological injury is a serious problem affecting the ADL such as reaching, grasping, twisting and so on [3]. On another notes, [4, 5], reported that the property of impedance parameters of the affected limb changes during training for recovery. Therefore, precise knowledge and measurement of impedance parameters could be significant factors in developing optimized neurological training regime [6]. A proper assessment and estimation of the subject mechanical impedance parameters can be developed and conducted as a set of scales to categorize the different levels of muscle tone conditions [7].

Estimation of upper-limb impedance parameters has remained a challenge since majority of the assessments made during the experiments are limited with validity and reliability [8]. Exhaustive estimation and understanding of basic symptom and extent of neurological injuries are crucial for the suitable training in numerous ways [9] so the therapist can deploy the most effective training regime he deemed appropriate. Amongst the most common methods or tools to assess the quality or level of muscle tones are by using the Fugl-Meyer Assessment (FMA) scale [10] and Wolf Motor Function Test (WMFT) scale [11]. The assessment is generally subjective though guided with complete description. As such, they are not the preferred method for a more objective studies of muscle impedance parameters [12]. Since robotic systems do not experience fatigue and, proneness to perception due to external environment and can work precisely, it seems the better option to exhaustively estimate and access the muscle level [13]. In [14], the author proposed the impedance control method to monitor the robot's performance which presently used by [15] in which they measured the dynamic relation between the robot and the environment (subject) to govern the control system. The estimation of subject's impedance parameters is used to determine specific task during the training session. For example, [8, 12, 16] proposed method to measure the impedance parameters by using electromechanical simultaneous sensor cum actuator.

Manuscript received May 7, 2018; revised July 9, 2019.

Majority of well-known robot-assisted training systems are complex and expensive, and can only be found in dedicated rehab centers. [17, 18] reported that the most important element in the training of impaired muscle tone was to monitor the upper-limb impedance parameters during recovery state. Considering the impedance parameters to be the key parameters to be monitored during recovery state [19, 20], reacting towards the parameters during the interaction of force and position of the end effector during training could provide improvement in the effectiveness of the training.

For the past decades, researchers have developed robot-assisted based-training for subjects with muscle tone impairments which goal is to complement the conventional manual training approach. In manual based training, therapist used to estimate the instantaneous muscle tone level before deploying a specific training task. The estimation is based on numerous assessment tools which subjectively describe the upper limb impedance parameters and movement ability during training. The description of the assessment is usually qualitative in nature. In this paper, we propose to unearth assessment strategy that can measure subjects' upper limb impedance parameters in a quantitative and objective manners.

The strategy can provide continuous estimation of impedance parameters of the subject's impaired upper-limb muscle during training. It targets to reduce the extent of dysfunction and increase the individual functional range of motion (ROM) when proper training task is deployed based on the estimation. The estimation method is based on online Recursive Least Squares (RLS) algorithm and the prediction of subject's upper-limb muscle tone level is based on Artificial Neural Network (ANN) framework.

In the subsequent sections, the following key issues will be discussed as follows: The methodology of the work is presented in section 2. The results from the current work are presented and discussed in section 3, and the conclusion is presented in section 4.

II. Methodology

A. Auto Regressive Exogenous (ARX) Model

In this paper, the Auto Regressive eXogenous (ARX) model structure is used to represent human hand dynamic equation. The ARX model can be described using a transfer function in (1).

$$\frac{F(q)}{Z(q)} = q^{-nk}\frac{D(q)}{A(q)} + e(t) \tag{1}$$

where, $F(q)$ and $Z(q)$ denote the output and the input signals respectively. $A(q)$ and $D(q)$ represent the coefficients which are described by the polynomials as follows,

$$A(q) = 1 + a_1 q^{-1} + \ldots + a_{na} q^{-na} \tag{2}$$

$$D(q) = d_1 + d_2 q^{-1} + \ldots + d_{nb} q^{-nb+1} \tag{3}$$

where, the parameters na is the order of polynomial $A(q)$ and nb is the order of polynomial $D(q)$ respectively, while nk is the input-output delay expressed as fixed leading zeros of the $D(q)$ polynomial. Substituting (2) and (3) into (1) and re-arranging the terms yields,

$$A(q)F(t) = D(q)z(t-nk) + e(t) \tag{4}$$

The input-output data can be represented in a linear difference equation form by substituting (2) and (3) into (4) to get,

$$\begin{aligned} &F(t) + a_1 F(t-1) + \ldots + a_{na} F(t-na) = \\ &d_1 z(t-nk) + \ldots + d_{nb} z(t-nb-nk-1) + \\ &e(t) \end{aligned} \tag{5}$$

where, the number of present output $F(t)$ relates to a finite number of earlier outputs $F(t-k)$ and inputs. Eq. (5) is a common form of the ARX equation/model which is used in this work.

B. Recursive Least Square (RSL) Estimator

Recursive Least Squares (RLS) is an estimation block in *Matlab* software used in order to estimate the unknown variable(s) in a system. RLS estimate the linear parameters of the system. Eq. (6) depicts the linear parameters form of the system.

$$F(t) = z(t)D(t) \tag{6}$$

where, the known parameters $F(t)$ and $z(t)$ correspond to the output and regressor inports of the Recursive Least Squares Estimator block for a given time step, t, respectively. The unknown parameter $D(t)$ corresponds to the parameters outport. $z(t)$ and $D(t)$ are real-valued vectors of length N, where N is the number of parameters to be estimated and $F(t)$ must be real-valued scalar. The known parameters $F(t)$ and $z(t)$ are provided to the function block to estimate the unknown parameter $D(t)$, where the estimation model used is forgetting factor method.

C. Human Hand Impedance Model

The estimation of mechanical impedance parameters of the upper limp muscle is essential to be monitored so to suggest and improve the efficacy of the muscle training session. Generally, subjects with high stiffness at the upper limb muscle due severe tremor of the muscles can cause the condition to deteriorate if not treated early. Hence, the knowledge of the change of the impedance parameters is critical to chart the path of the efficient training session.

The upper limb can be modeled mechanically (as shown in Fig. 1 analogous to a second-order equation and can be represented by a dynamic model in (7).

$$F(t) = M(t)\ddot{z}(t) + C(t)\dot{z}(t) + K(t)z(t) \tag{7}$$

where, $M(t)$, $C(t)$, and $K(t)$ are the mechanical impedances which symbolizing mass, damping and stiffness factors respectively while $F(t)$ represents the interaction force with the manipulator.

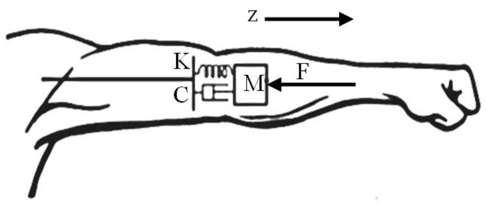


Figure 1. Upper-limb impedance model

In this paper, we use position, $z(t)$ as the input and force, $F(t)$ as the output. Eq. (7) can be presented as a first and second order derivative of position, $z(t)$, which also can be presented in the finite difference equation form as,

$$\dot{z}(t) = \frac{z(t) - z(t-1)}{T} \quad \text{and} \quad \ddot{z}(t) = \frac{\ddot{z}(t) - \ddot{z}(t-1)}{T}$$

where, T is the sampling time. By arranging the $\dot{z}(t)$ and $\ddot{z}(t)$ in (7) then we obtained the ARX equation/model structure as (8).

$$F(t) = d_1 z(t) + d_2 z(t-1) + d_3 z(t-2) \tag{8}$$

where

$$d_1 = \frac{(M + CT + KT^2)}{T^2}, d_2 = \frac{-(2M + CT)}{T^2} \text{and} \quad d_3 = \frac{M}{T^2} \tag{9}$$

Eq. (8) represents the ARX equation/model of the upper-limb with input $z(t)$ and output $F(t)$. In real time, the Recursive Least Square (RLS) Estimator MATLAB/Simulink Block was used to compute the coefficients d_1, d_2 and d_3. The upper-limb impedance parameters as mass, damping and stiffness factors are determined by using a derived sample linear expression like (9).

D. *Experimental Setup and the Procedure*

The robot-assisted training system has been developed to contain two parts; the mechanical and electrical parts and has been extensively described in [21]. As shown in Fig. 2, the device has a revolute-revolute-prismatic (R-R-P) configuration and is composed of one DC motor to drive the linear guide, two brushless DC motors for tilting and panning the platform and 3-axis force sensor attached at the robot end-effector for force measurement. There are three encoders fixed to the system to measure the information on speed of the system.

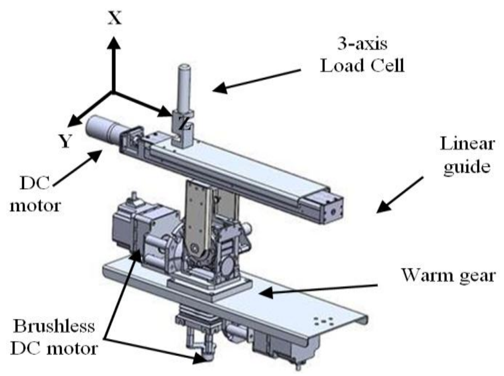


Figure 2. Mechanical design of 3-DOF end-effector training robot [26]

In the experiment, five healthy subjects, aged 27±2 years old were recruited and they were asked to sit on a chair in the upright position while holding the handle (as shown in Fig. 3) and resisting the longitudinal motion of the end effector of the robot starting at 0N force which is defined as no resistance force, then 5N, 10N, 15N, 20N and finally 25N resistance forces respectively. In this work the focused motion is the extension and flexion of the arm. Force sensor is attached at the robot end-effector for resistive force measurement. The robot uses the feedback system to achieve the desired position at constant speed during the experiment. The impedance is sensitive to the subject's position and the speed change, as such during experiment this two factors is maintained as much possible for a consistent constant resistance force during experiment.

Figure 3. Experimental setup and subject's posture

E. *Neural Network Architecture*

In the recent decades, Artificial Neural Network (ANN) has been commonly applied as artificial intelligence model option in the field of pattern recognition. In this paper, the ANN uses a given set of input/output data for learning and classifying/predicting the subsequent output class.

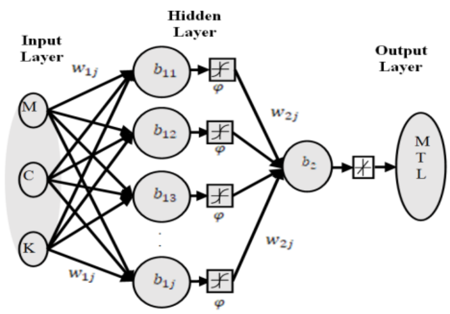


Figure 4. The neural network structure [23]

The training and classification of the subjects' muscle tone levels adopts feed-forward, back-propagation ANN structure. The ANN consists of three layers including one hidden layer. The sigmoid activation function is used in the hidden layer whereas the pure linear activation is adopted in the output layer which is most appropriate for function fitting problems. The subjects' mass, damping, and stiffness parameters that are the required impedance parameters serve as three set of input data to the network and the subject's muscle tone level serves as the output. A total of 6006 data points obtained from each subject is used for training the neural network. For the best performance, the data were divided into 90% training datasets, 5% testing, and 5% validation datasets. A Levenberg-Marquardt (LM) algorithm is used to adjust the weights of the network. The input datasets are scaled between 0 and 1 by means of a Max-Min Normalization function given in (10) at the pre-processing stage.

$$X_{norm} = a + \frac{(X - X_{min})(b-a)}{X_{max} - X_{min}} \quad (10)$$

where, $X(norm)$ is the normalized data, X is the data to be normalize, $Xmin$ is the minimum value in a set of data, $Xmax$ is the maximum value in a set of data, a and b are 0 and 1 respectively, which represent the scaled range.

Eq. (11) represents the mathematical representation of the structure for the approximation of the muscle tone level (MTL) using the impedance parameters.

$$MTL = w_{2j}^T \varphi\left(w_{1j}^T z_i^T + b_{1j}^T\right) + b_2 \quad (11)$$

where z_i is the impedance values (input) as mass, damping and stiffness, w_{2j} is the weight of the output layer; w_{1j} is the weight of the hidden layer, b_{1j} is the j^{th} bias value of the hidden layer, b_2 is the bias of the output layer and φ is the activation function of the hidden layer. b_{1j} is the j^{th} bias value of the hidden layer, b_2 is the bias of the output layer and φ is the activation function of the hidden layer. In this study, $i = 1, 2$ and 3 and $j = 1$ to n (where n is the number of neurons which is decided after rigorous training). The activation function φ (e.g. sigmoid) is given by the Eq. (12),

$$\varphi = \frac{1}{1+e^{-z}} \quad (12)$$

III. Result and Discussion

A. Estimation of Upper-Limb Impedance

The experimental setup for the estimation of the subjects' impedance parameters consists of a single degree of freedom (DOF) horizontal motion using the device described in [22]. The training involves a simple extension motion of the upper limb and the impedance parameters are estimated using the proposed estimation algorithm under varying degree of resistive/interactive forces online. The resulting data is tabulated in Table 1 as averaged impedance parameter values from a series of four trials.

TABLE I. Impedance Parameters from a Single Degree Motion

Interactive Force	Impedance Parameters		
	***M(kg)* Avg.**	***C(Ns/m)* Avg.**	***K(N/m)* Avg.**
0N	0.0018	-0.4514	65.7588
5*N*	-0.0086	2.1282	-264.0264
10*N*	-0.0164	4.1059	-524.2925
15*N*	-0.0251	6.2945	-802.3924
20*N*	-0.0374	9.2143	-1.1246e+03
25N	-0.0479	10.7359	-1.4148e+03

Fig. 5, 6 and 7 show the subjects' upper-limb impedance parameter dynamics for the different interactive forces (0*N*, 5*N*, 10*N*, 15*N*, 20*N* and 25*N*). It can be seen from the plots that the value of the impedances vary with the different amount of resistive force and position.

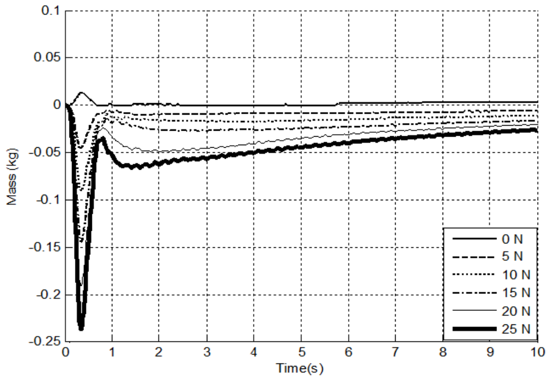


Figure 5. Subject's upper-limb mass factor

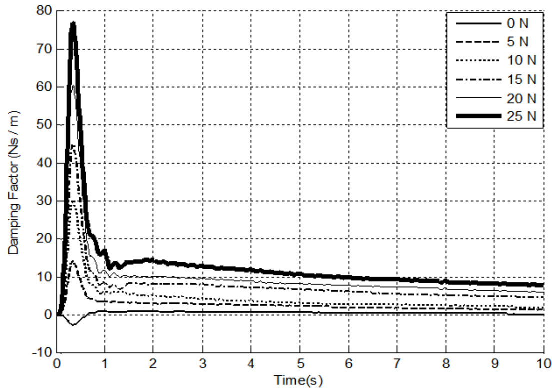


Figure 6. Subject's upper-limb damping factor

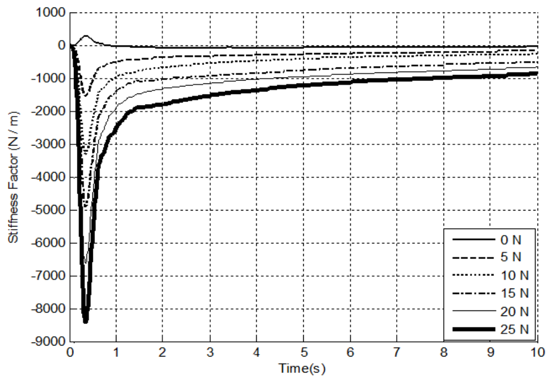


Figure 7. Subject's upper-limb stiffness factor

Table 2 and Table 3 give the average impedance parameters and subjects' impedance estimation error for the experiment and simulation study over the six (6) different resistance force levels. The average impedance parameters for all subjects taken for the different resistance force level is compared with the simulation results as shown in Fig. 8, 9, and 10. It can be seen from the plot that the human upper-limb impedances parameters varies with the degree of resistance force. Higher damping parameters are noticed for all the subjects as the degree of resistance force increases, whereas for mass and stiffness parameters, higher negative values are recorded since the direction of the resistance force is opposite the direction of motion. The transients show on the plots as shown in Figs. 8, 9, and 10, during the 4s, are due to the response time taken by the force sensor to give stable output reading.

TABLE II. EXPERIMENTAL RESULTS: AVERAGE IMPEDANCE PARAMETERS AND AVERAGE ESTIMATION ERROR FOR THE DIFFERENT FORCE LEVEL

Resistance Force	Impedance			Error Estimation
	M (kg) *Average for five subjects*	*C (Ns/m)* *Average for five subjects*	*K (N/m)* *Average for five subjects*	
0N	-2.8284e-04	0.0173	13.3781	-0.0465
5N	-0.0111	2.6979	-322.5111	-0.3024
10N	-0.0245	5.8521	-671.0463	-0.2901
15N	-0.0296	7.2343	-876.2959	-0.2993
20N	-0.0397	9.7316	-1.1705e+03	-0.3018
25N	-0.0425	10.6272	-1.3406e+03	-0.3108

TABLE III. SIMULATION RESULTS: AVERAGE IMPEDANCE PARAMETERS AND AVERAGE ESTIMATION ERROR FOR THE DIFFERENT FORCE LEVEL

Resistance Force	Impedance			Error Estimation
	M (Kg) *Avg*	*C (Ns/m)* *Avg*	*K (N/m)* *Avg*	
0N	1.5296e-06	-4.3813e-04	0.0324	0.0135
5N	-0.0070	2.0072	-150.1244	0.0168
10N	-0.0140	4.0311	-301.4855	0.0192
15N	-0.0211	6.0717	-454.0715	0.0218
20N	-0.0282	8.1291	-607.9031	0.0244
25N	-0.0354	10.2037	-763.0017	0.0270

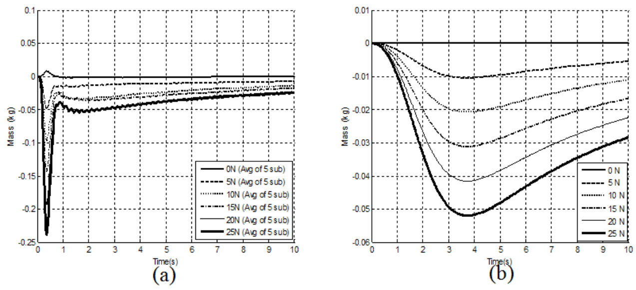


Figure 8. (a) Experimental results of average for five subjects' mass and (b) Simulation results of mass for the different resistance force level

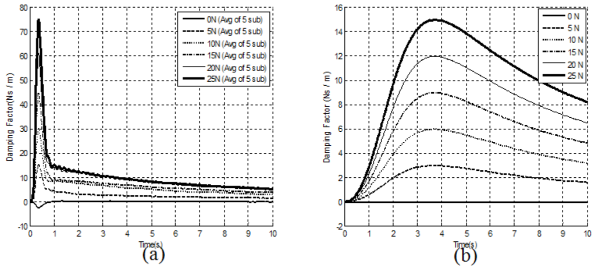


Figure 9. (a) Experimental results of average for five subjects' damping factors and (b) Simulation results of damping factors for the different resistance force level

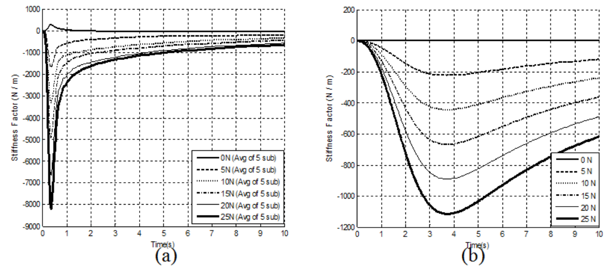


Figure 10. (a) Experimental results of average for five subjects' stiffness and (b) Simulation results of stiffness for the different resistance force level

In Figs. 11, 12 and 13, notice that the plots of the impedance parameters are made to start at 4s. This is due to the fact that the system exhibits a high transient behavior which is largely due to the sensitivity of the force sensor. An appropriate signal conditioning circuit can be used however to improve this condition in the future work [22, 23].

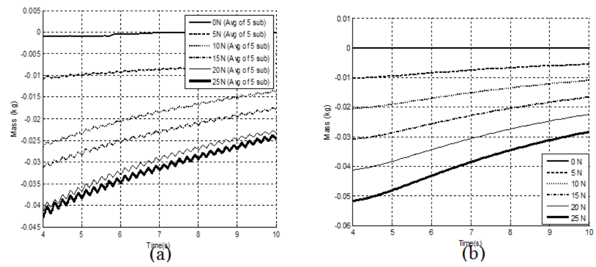


Figure 11. (a) Experimental results of average for five subjects' mass and (b) simulation results of mass for the different resistance force level (from 4s)

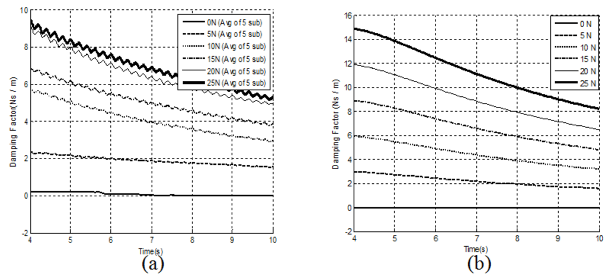
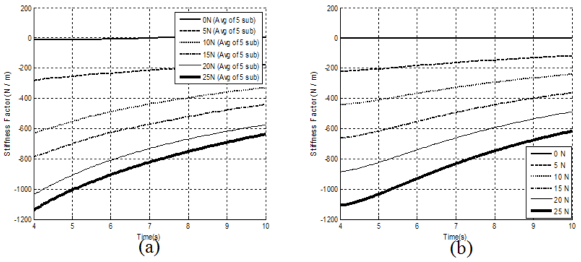


Figure 12. (a) Experimental results of average for five subjects' damping factors and (b) simulation results of damping factors for the different resistance force level (from 4s)



(a) (b)

Figure 13. (a) Experimental results of average for five subjects' stiffness factors and (b) simulation results of stiffness factors for the different resistance force level (from 4s)

B. Classification of Muscle Tone Levels

The upper-limb muscle tone characterization of the subject is given in *Table 4*. The characterization is achieved based on the subjects' impedance dynamic data measured during the experiments. The muscle tone is considered as the degree of muscle-fibre tension or resistance during rest or response to stretch. Thus, in this paper, the upper-limb impedances are used as a measure of the muscle tone. A high muscle tone level corresponds to a high estimated impedance parameter, and vice versa.

TABLE IV. LIST OF MUSCLE LEVELS

Level	Resistance Force(N)	Muscle Tone Level (MTL)	Modified Ashworth Scale
0	0	Normal tone	0 (0)
1	0-5	Slight increase in tone	1 (1)
2	5-10	Increase in tone	1+ (2)
3	10-15	More marked increase in tone	2 (3)
4	15-20	Considerable increase in tone	3 (4)
5	20-25	Limb rigid in flexion or extension	4 (5)

Prediction and classification of the subjects' muscle tone level is achieved by means of the trained artificial neural network using the setup given in Fig. 4. Five subjects were recruited to participate in the muscle tone prediction experiment. The experiment involved a simple extension exercise in which the subjects were asked to resist the motion of the end-effector starting randomly with any resistance force between 15N and 25N, and then decrease the resistance to zero over the exercise period of 10 seconds. Simulation studies was also carried out with the real data to validate the experimental results. The classification of muscle tone levels is as described in Table 5 and also compare with Modified Ashworth Scale.

TABLE V. CLASSIFICATION OF MUSCLE TONE LEVELS

Muscle Tone Level	Impedance Range		
	Mass, *M* (kg) (Min-Max)	Damping factor, *C* (Ns/m) (Min-Max)	Stiffness factor, *K* (N/m) (Min-Max)
0	(-0.0017, 0.0082)	(-2.5655, 0.2984)	(-10.3618, 280.2173)
1	(-0.0486, 4.0421e-05)	(-0.0107, 15.2576)	(-1.6671e+03, 0.7883)
2	(-0.0960, 3.6690e-05)	(-0.0094, 30.1705)	(-3.3023e+03, 0.6684)
3	(-0.1428, 3.5168e-05)	(-0.0085, 44.8385)	(-4.9044e+03, 0.5618)
4	(-0.1936, 3.3422e-05)	(-0.0083, 60.7918)	(-6.6503e+03, 0.5342)
5	(-0.2382, 3.1900e-05)	(-0.0082, 74.8031)	(-8.1833e+03, 0.5190)

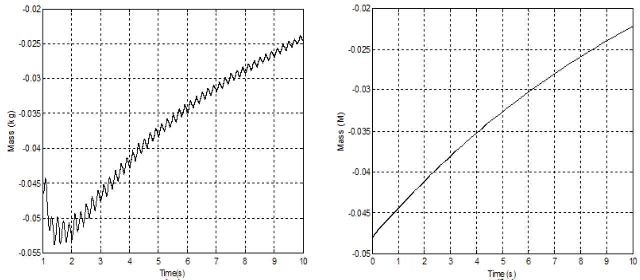
Preliminary simulation studies to test the system ability to predict the upper-limb muscle tone level is achieved using approximated impedance (mass (M), damping factor (C) and stiffness factor (K) variability functions given in (12), (13), and (14) and shown in Fig. 14 through Fig. 16. Fig. 17 gives the simulation result over a simulation time of 10s for the prediction of subject's muscle tone level using the proposed neural network algorithm. The results show that the predicted subject's muscle tone level increase with a corresponding negative increase in the mass and stiffness parameters (as seen in Fig. 14 and 16) since the direction of the resistance force is opposite in the direction of motion. Whereas the trend is reversed for the damping parameter, as seen in Fig. 15. As recorded from experimental estimation studies, the estimated damping parameter increases positively while the mass and stiffness factors increases negatively during passive training for rising level of muscle tone. Notice that, a rounding function has been used to extract each muscle tone level shown in Fig. 17. The function approximates the predicted output of the neural network to its nearest neighbourhood is using the rounding mathematical function.

$$M = (((-0.048 * e\hat{}((-0.3t))) + (0.7 * (-0.11 * t))) \tag{13}$$

$$C = (((14.7) * e\hat{}((-0.3t))) + (0.99 * (-0115 * t))) \tag{14}$$

$$K = (((-2300) * e\hat{}((-0.3t))) + (0.1 * (-0.11 * t))) \tag{15}$$

The experimental result summary for the muscle tone level prediction also described which also can be seen in Fig. 14 to Fig. 17. The subjects show variability in their muscle tone level during the controlled experiment in which they are asked to mimic a physical recovery process. Overall, as expected, the predicted subjects' muscle tone level is seen decrease when the subjects' resistance decreases. Aforementioned, force sensor need the time to response the stable output reading, therefore, it plotted from 1s to compare the simulation plot. Although, to train the data in neural network which is started from 0s.



(a) (b)

Figure 14. Simulated subject's upper-limb mass: (a) Experimental and (b) Simulation results

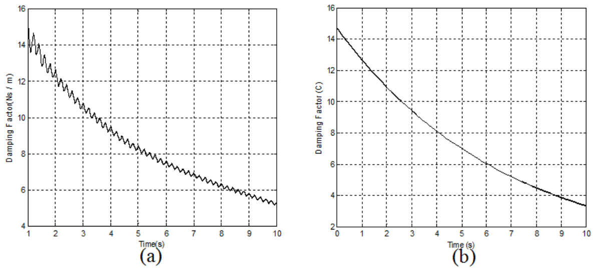


Figure 15. Simulated subject's upper-limb damping: (a) Experimental and (b) Simulation results

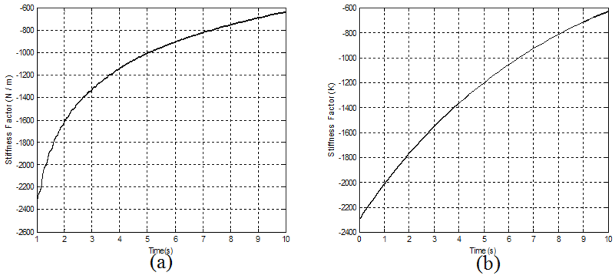


Figure 16. Simulated subject's upper-limb stiffness factor: (a) Experimental and (b) Simulation results

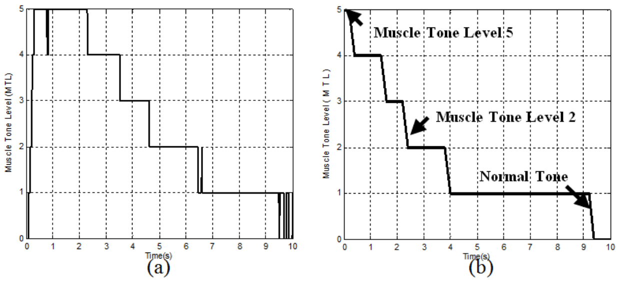


Figure 17. Prediction of subject's upper-limb muscle tone level: (a) Experimental and (b) Simulation results

IV. Conclusion

In this work, upper-limb impedance parameter estimation system for predicting the muscle tone level of subjects with muscle impairment has been developed. The system has the ability to estimate the upper-limb mechanical impedance parameters by means of online Recursive Least Squares (RLS) estimator. It can predict subject's upper-limb muscle tone level and recovery state using an Artificial Neural Network (ANN). Both simulation and experimental results show that the upper-limb impedance parameters can be estimated to an accuracy level of 83%, while the subjects' muscle tone level can be reliably predicted with 95% accuracy level. Therefore, these acquired outcomes could be useful in robot-patients interaction while undergoing dedicated training regimen.

Acknowledgment

The experiment was conducted in Biomechatronic Research Lab at International Islamic University Malaysia. The authors would like to acknowledge the Ministry of Science, Technology and Innovation (MoSTI) and Ministry of Higher Education (MoHE) for partly funding the research work using grant number SF15-015-0065 and FRGS17-029-0595 respectively.

References

[1] P. Maciejasz, et al., "A survey on robotic devices for upper limb rehabilitation," *Journal of Neuroengineering and Rehabilitation*, vol. 11, no. 1, 2014.

[2] M. Trlep, M. Mihelj, U. Puh, and M. Munih, "Rehabilitation robot with patient-cooperative control for bimanual training of hemiparetic subjects," *Advanced Robotics*, vol. 25, no. 15, pp. 1949-1968, 2011.

[3] W. H. Chang and Y. H. Kim, "Robot-assisted therapy in stroke rehabilitation," *Journal of Stroke*, vol. 15, no. 3, pp. 174-181, 2013.

[4] E. J. Dijkstra, "Upper limb project: Modeling of the upper limb," *MSc. Thesis Biomechanical Engineering Department of Engineering Technology University of Twente*, 2010.

[5] N. Hogan, "Adaptive control of mechanical impedance by coactivation of antagonist muscles," *IEEE Transactions on Automatic Control*, vol. 29, no. 8, pp. 681-690, 1984.

[6] H. M. Hondori, L. Shih-Fu, and R. Khosrowabaldi, "Muscles' Co-activation in a stationary limb alteres according to the movement of other limb," *BIODEVICES*, pp. 163-165, 2010.

[7] Dyck, M. and M. Tavakoli. "Measuring the dynamic impedance of the human arm without a force sensor", *in Rehabilitation Robotics (ICORR), 2013 IEEE International Conference on.*, 2013.

[8] O. Lambercy, et al., "Robots for measurement/clinical assessment," *Neurorehabilitation Technology*, Springer. pp. 443-456, 2012.

[9] A. C. Lo, P. D. Guarino, L. G. Richards, J. K. Haselkorn, G. F. Wittenberg, D. G. Federman, B. T. Volpe,"Robot-assisted therapy for long-term upper-limb impairment after stroke," *New England Journal of Medicine,* vol. 362, no. 19, pp. 1772-1783, 2010.

[10] K. J. Sullivan, J. K. Tilson, S. Y. Cen, D. K. Rose, J. Hershberg, A. Correa, et al., "Fugl-meyer assessment of sensorimotor function after stroke standardized training procedure for clinical practice and clinical trials," *Stroke*, vol. 42, pp. 427-432, 2011.

[11] M. Woodbury, C. A. Velozo, P. A. Thompson, K. Light, G. Uswatte, E. Taub, "Measurement structure of the Wolf Motor Function Test: implications for motor control theory," *Neurorehabilitation and Neural Repair,* vol. 24, pp. 791-801, 2010.

[12] H. M. Hondori and L. Shih-Fu, "A novel device for measuring mechanical impedance during dynamic tasks", *Biodevices*, pp. 64-68, 2010,

[13] H. M. Hondori and A. W. Tech, "Smart mug to measure hand's geometrical mechanical impedance," *Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE*, 2011, pp. 4053-4056.

[14] G. Xu, A. Song, and H. Li, "Adaptive impedance control for upper-limb rehabilitation robot using evolutionary dynamic recurrent fuzzy neural network," *Journal of Intelligent & Robotic Systems*, vol. 62, pp. 501-525, 2011.

[15] C. Ott, R. Mukherjee, and Y. Nakamura, "Unified impedance and admittance control," *2010 IEEE International Conference on Robotics and Automation (ICRA),* 2010, pp. 554-561.

[16] H. M. Hondori and L. S. Fu, "A simultaneous sensing cum actuating method for measuring human arm's mechanical impedance," *BIODEVICES*, pp. 64-68, 2010.

[17] N. Hogan, Impedance control: "An approach to manipulation: Part II—Implementation," *Journal of dynamic systems, measurement, and control,* Vol. 107, pp. 8-16, 1985.

[18] H. M. Hondori and L. Shih-Fu, "Perturbation-based measurement of real and imaginary parts of human arm's mechanical impedance," *Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE,* 2010, pp. 5911-5914.

[19] D. Piovensan, P. DiZio, and J. R. Lackner, "A new time-frequency approach to estimate single joint upper limb impedance," *Annual International Conference of the IEEE on Engineering in Medicine and Biology Society*, 2009, pp. 1282-1285.

[20] G. u, A. Song, and H. Li, "Adaptive impedance control for upper-limb rehabilitation robot using evolutionary dynamic recurrent

fuzzy neural network," *Journal of Intelligent & Robotic Systems*, vol. 62, no. (3-4), pp. 501-525, 2011.

[21] S. Fatai, S. N. Sidek, M. Y. Hazlina, L. M. Hafiz, and A. Y. Babawuro, "Development and control of a 3dof upper-limb robotic device for patients with paretic limb impairment," *ARPN Journal of Engineering and Applied Sciences*, vol. 10, no. 23, pp. 17356-17362, 2015.

[22] L. H. Zaw, S. N. Sidek, S. Fatai, and M. R. Muhammad, "Estimation of upper limb impedance parameters using recursive least squares estimator," *International Conference on Computer and Communication Engineering 2016 (ICCCE 2016)*, 25-27 July. 2016, pp. 144 – 148.

[23] L. H. Zaw, S. N. Sidek, & S. Fatai, "Assessment of upper limb muscle tone level based on estimated impedance parameters," *IEEE Conference on Biomedical Engineering and Sciences 2016 (IECBES 2016)*, 4-8 Dec. 2016, pp. 742 – 747.

Zay Lay Htoon received the B. Eng. degree from Yangon Technological University, Myanmar in 2012 and M.Sc. degree in Mechatronics Engineering from the International Islamic University Malaysia, Kuala Lumpur Malaysia, in 2017.

He is currently working in Accenture as system analyst. His research interests include analysis of bio-signals, prostheses design and robot-assisted rehabilitation.

Shahrul Naim Sidek was born and obtained early education in Malaysia. He did his undergraduate study and obtained Bachelor in Electrical Engineering from Vanderbilt University, USA in 1998. He later pursued and obtained PhD degree from Vanderbilt in 2008 in Engineering.

He then joined the International Islamic University Malaysia and is currently designated as Associate Professor at the Department of Mechatronics Engineering. He is actively engaged in research related to human robot interaction especially in affective computing, stroke modalities and rehabilitation.

Dr. Naim is a senior member in IEEE and currently holds 3 patents related to stroke rehabilitation machine.

Fatai Sado received the B.Sc. degree (with honors) in Electronics and Electrical Engineering from the Obafemi Awolowo University, Ile-Ife, Nigeria, in 2007 and the M.Sc. degree in Mechatronics engineering from The International Islamic University Malaysia, Kuala Lumpur Malaysia, in 2014.

He is currently working towards the Ph.D. degree in Automation, Control and Robotics in the Department of Mechanical Engineering, University of Malaya, Kuala Lumpur, Malaysia. His research interests include automation and control of exoskeleton robots, human–robot interaction, robot-assisted rehabilitation, and nonlinear control of dynamic systems.