Neural Networks Controler of a Lower Limbs Robotic Rehabilitation Chair

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Abstract: In this paper, we propose a new control law using a kinematic model based on a Feed forward neural network (FFNN). This controller is designed for the control of a robotic rehabilitation chair of the lower limbs designed and created in the LRPE laboratory, with high accuracy. The results of the validation tests, show that the lower limb joints trajectories of the proposed control law are similar to the physiological joints trajectories of a patient. This demonstrates that the proposed control law provides a high performance and a fast convergence with extremely low error.

1 INTRODUCTION

Robotic devices find a growing interest in their use to assist in providing therapy rehabilitation following neurological injuries such as spinal cord injury, stroke and after a joint and / or muscle traumas (Reinkensmeyer, 2004; Riener, 2005). Many rehabilitation devices of human limbs and joints are the subject of study by researchers to assist therapists and patients. In this context, we developed in the LRPE laboratory a rehabilitation prototype of lower limbs. The device is a robotic chair for neuromatrix rehabilitation of lower limb with two motorized orthotics (right and left leg), with 3DOF for each of them (hip, knee and ankle). Position sensors are mounted on each link to manage the flow of a predetermined motion in real time.

We find in literature different strategies to control the path to follow for robotic rehabilitation. For the upper limbs, (Lo, 2012) reviews the control strategies, among the control structures, devices using PID (Moughamir, 05), others use either fuzzy or neuro-fuzzy logic (Zeinali, 2010; Rahman, 2006). However, for lower limb, there are not many works addressing control strategy to control desired trajectories. Schmitt & Métrailler used to control Motion Maker in (Schmitt, 2004) an intelligent central unit "Control unit", called Industrial PC, composed of different modules; (Seddiki, 2006) proposed three control laws for a SOKINETICS's good trajectory tracking, two with a PI and a third fuzzy H-infinite hybrid control. Fuzzy logic has been used in (Akdogan, 2011). The control in, (Anama, 2012) is done with a PID. Meanwhile, they used a hierarchical control with PD, even modified genetic algorithms have been used (Jamwal, 2009). Therefore, we conclude that the use of neural networks for system control of the lower limbs is not common.

Our work consists of controlling the trajectory of a rehabilitation system of lower limbs (robotic rehabilitation chair, and the originality lies in the fact that we us the kinematic model of the robotic rehabilitation chair based on neural networks {Feed forward neural network (FFNN)}. In this approach a PID controller is used offline to train the FFNN. This results in better online results than when using traditional PID controllers.

The outline of this paper is as follows: First, we present the rehabilitation system developed in the LRPE laboratory for which we establish the geometric and kinematic model before proposing its control law. Then, we present the control system used for parameters identification based on a conventional PID and the new scheme using a neural controller (feed forward neural network (FFNN)). After that, we present the implementation of the controller on the system. Finally, a discussion of the results and conclusions are presented.

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2 SYSTEM DESCRIPTION

The prototype dedicated to the rehabilitation of lower limbs for patients with motor deficiencies developed in our laboratory is shown in (figure-1). The main use of this prototype is to provide functional rehabilitation of the lower limbs using functional orthotics. The implemented system allows the reproduction of physiological joints trajectories and take back segmental loads of body movements, especially walking.

Figure 1: Lower limbs rehabilitation chair robot.

The robotic rehabilitation chair is made up of two orthosis and a seat mounted on a frame. Both mechanical orthotics, are placed on either side of the seat. Each orthotic, which can operate around three degrees of freedom, consists of three joints: hip, knee and ankle and three segments: thigh, leg and foot. Joints ensure transmission of movement between the different segments taking into account the factor of safety, the patient's weight and waist using a mechanism consisting of rods, gears and DC motors (Merrouche, 2011; Saadia, 2009).

3 SYSTEM MODEL

In order to create the geometric model of the system, we usual introduce a fixed coordinate system (frame) in which all objects is referenced. In our approach, we establish the basic coordinate system with chair's frame, represented by Ox_1y_1, as shown in Figure 2. The coordinates of the point are given according to the plan Ox_2y_2 which Ox_2 superimposed on l_1. In the same way, the coordinates of the last point are given on the plan Ox_3y_3 where Ox_3 is superimposed on l_2.The tool's coordinates are expressed in this coordinate system (Spong, 2005; Fu, 1987). l_1, l_2 and l_3 represent the length of each segment, θ_i is the angle between Ox_i and l_i.

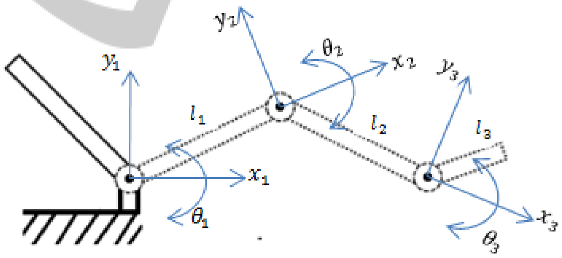

Figure 2: Three link Coordinate system of the chair's frame.

The direct geometric model (DGM) of the system is represented by the relation

$$x = f(\theta) \qquad (1)$$

Where θ is the vector of joint coordinates such as :

$$\theta = [\theta_1\ \theta_2\ \theta_3]^T \qquad (2)$$

The vector x is defined by the elements of the homogeneous transformation matrix ${}^{\alpha}A_{\beta}$ (Khalil, 2010; Dombre, 2007). This matrix (${}^{\alpha}A_{\beta}$) gives the coordinate frame R_{β} from those of frame R_{α} :

$$^{0}A_1 = \begin{bmatrix} C_1 & -S_1 & 0 & l_1C_1 \\ S_1 & C_1 & 0 & l_1S_1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (3)$$

$$^{1}A_2 = \begin{bmatrix} C_2 & -S_2 & 0 & l_2C_2 \\ S_2 & C_2 & 0 & l_2S_2 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (4)$$

$$^{2}A_3 = \begin{bmatrix} C_3 & -S_3 & 0 & l_3C_3 \\ S_3 & C_3 & 0 & l_3S_3 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (5)$$

l_1, l_2 and l_3 are the lengths corresponding to the thigh, leg and foot. They can be manually adjusted. In our test, we choose respectively the values 50, 60 and 25 cm.

We calculate the $^{0}A_3$ matrix which leads to the coordinate frame R_3 from those of frame R_0

$$^{0}A_3 = {}^{0}A_1 * {}^{1}A_2 * {}^{2}A_3$$

$$^{0}A_3 = \begin{bmatrix} C_{123} & -S_{123} & 0 & l_1C_1 + l_2C_{12} + l_3C_{123} \\ S_{123} & C_{123} & 0 & l_1S_1 + l_2S_{12} + l_3S_{123} \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (6)$$

Where:

$C_i = \cos(\theta_i)$; $S_i = sin(\theta_i)$; $C_{il} = \cos(\theta_i + \theta_l)$; $S_{il} = sin(\theta_i + \theta_l)$; $C_{ilk} = \cos(\theta_i + \theta_l + \theta_k)$; $S_{ilk} = (\theta_i + \theta_l + \theta_k)$;

3.1 Kinematic Model

The direct kinematic model (DKM) is given by (Jazar, 2010; Khalil, 2004):

$$\dot{x}(t) = J(\theta) * \dot{\theta}(t) \quad (7)$$

Where J(θ) denotes the (i x j) Jacobian matrix. The élément «J_ij (θ) » is given by equation (8):

$$J_{ij}(\theta) = \frac{\delta f_i(\theta)}{\theta_j} \quad (8)$$

The inverse kinematic model (IKM) is calculated from the inverse matrix J^{-1} according to the mathematical formulas, the model equation is:

$$\dot{\theta}(t) = J^{-1}(\theta) * \dot{x}(t) \quad (9)$$

The workspace and manipulability are based on kinematics criteria often used for robot architecture selection (Bhangale, 2004). The workspace for one orthesis of the lower limbs robotic rehabilitation chair is illustrated in figure-3. This figure shows all the possible position configurations during the movement of the joint depending on the previous one; they are represented by discontinuous lines. As an example we took a configuration that we have shown with continuous lines.

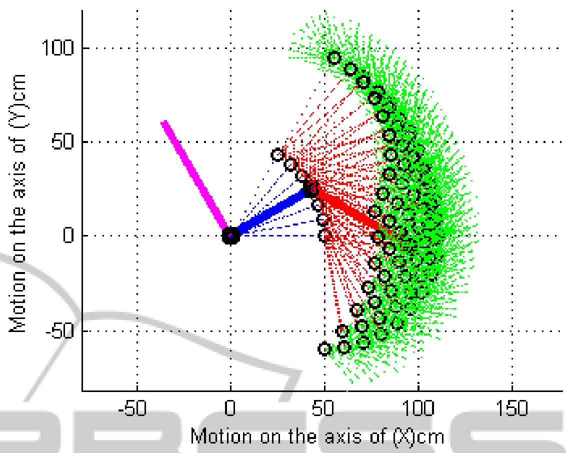

Figure 3: One orthesis Workspace.

4 THE CONTROL STRATEGY

In order to control this system, we propose a control structure using a kinematic model of the robotic rehabilitation chair based on neural networks (Feed Forward Neural Network (FFNN)). The control law is implemented in two steps, the first one is an offline phase and consists of training the FFNN and the second law is performed online in order to adjust the parameters of the FFNN to get the best parameters of the control structure connected to the learning.

Given that the two orthesis are identical, they are represented with the same model equations. For simplicity reasons, we will command only the right orthotic. In addition, we use a decoupled architecture where each joint is controlled separately. Therefore, we will have three identical control schemes for each orthotic. The control schemes are illustrated in (figure 4 -5).

- In the first step, to perform the learning process, we choose to use a PID controller. The FFNN controller is trained off-line through a classical control (PID) law (Figure-4). The PID is used to identify and provide the required training data. To train the FFNN we use the backpropagation algorithms.

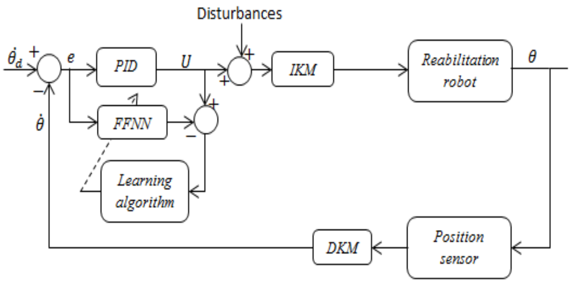

Figure 4: Parameters identification of the control law structure.

- In the second step an online adaptation of the neural controller to regulate its parameters according to the task performed is used (Figure-5).

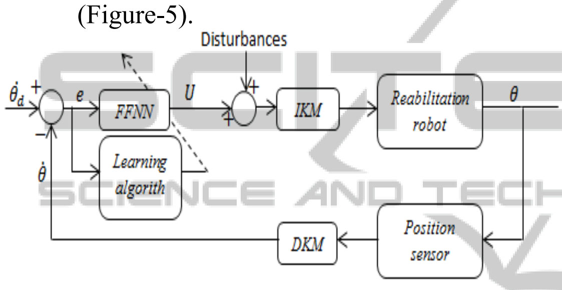

Figure 5: Real time control law Structure.

The figure below represents the architecture used in the FFNN. It is composed of three layers. The input layer consists of three neurons, the hidden layer of four neurons, and the output layer of one neuron.

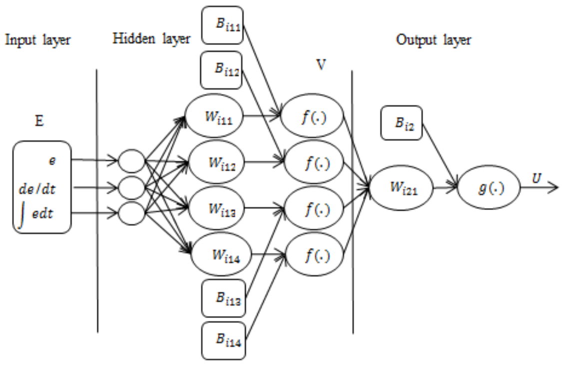

Figure 6: Neural network Structure.

The input "E" and output "U" represent the error and the control vectors respectively. The matrix output « V » of the hidden layer and the output « U » of the network are given by:

$$V = f(W_{i1}E + B_{i1}) \quad (10)$$

$$U = f(W_{i2}V + B_{i2}) \quad (11)$$

Where (W_{i1}, W_{i2}) and (B_{i1}, B_{i2}) are the weights and bias matrices of respectively to adjust. And $i = 0, \dots, 3$ number of joints. $f(.)$ and $g(.)$ are the activation function of the neurons in hidden and output layer. These functions are choose as sinusoidal for the hidden layer, and as linear for the neurons of the output layer.

The proposed control law, according to the equations (12) (Khalil, 2004; Corke, 2011), allows the matching of error values (Δθ) and the signal control given by:

$$U = C(\dot{\theta}_d - \dot{\theta}) \quad (12)$$

Where:

- $\dot{\theta}_d$ and $\dot{\theta}$ are the desired and measured values.
- C is the control law.
- U is the signal control

Implementation of this control law requires steps mentioned above and illustrated in (Figure-4 & 5).

5 IMPLEMENTATION AND TESTS

To validate the command structure that we have established, we must make the implementation of the lower limbs robotic rehabilitation chair by generating a specified path of the rehabilitation. This trajectory is a challenge that is the subject of discussion within the scientific community. Marchal has made a detailed study that includes several works on this subject (Marchal-Crespo, 2009). In this article, we simulate joints trajectory by generating sinusoidal signals because they are similar to physiological movements (flexion – extension). Indeed, it is important to test the controller with a signal that is as natural as possible for even of the system behavior. The signal is within the operating range of the rehabilitation robot.

The architecture of the neural networks used is made of three layers. The input layer has three neurons; the hidden layer has four neurons and the output layer has one neurons.

For the learning function algorithm of the FFNN, we use the « trainlm » function from the MATLAB toolbox. Indeed, the network learning function updates weight and bias values according to the Levenberg-Marquardt optimization scheme. « trainlm » is often the fastest backpropagation algorithm in the toolbox, and is highly recommended as a first-choice supervised algorithm, although it requires more memory than other algorithms (Mathworks). The Neural network's parameters (weights and biases) obtained after the learning process are given below:

The controller's parameters of the first joint

$$W_{11} = \begin{bmatrix} 3.3668 & -11.6782 & 1.8655 \\ -7.3454 & 11.4598 & -3.7226 \\ -3.2088 & 9.5054 & -1.7756 \\ 10.4749 & 0.0577 & 208.5848 \end{bmatrix};$$

$$B_{11} = \begin{bmatrix} -18.2953 \\ -18.7634 \\ 20.3442 \\ 1.4435 \end{bmatrix};$$

$$W_{12} = 10^3 * [0.0094 \quad -0.0161 \quad -0.6235 \quad 1.5369];$$

$$B_{12} = [-619.8668];$$

- The controller's parameters of second joint

$$W_{21} = \begin{bmatrix} 3.3668 & -11.6779 & 1.8655 \\ -7.3454 & 11.4584 & -3.7226 \\ -3.2088 & 9.5039 & -1.7756 \\ 18.8783 & 0.1021 & 376.9088 \end{bmatrix};$$

$$B_{21} = \begin{bmatrix} -18.2971 \\ -18.7659 \\ 20.3515 \\ -0.4344 \end{bmatrix};$$

$$W_{22} = 10^3 * [0.0094 \quad -0.0161 \quad -0.3429 \quad 1.7353];$$

- The controller's parameters of third joint

$$W_{31} = \begin{bmatrix} 6.9021 & -2.2635 & 1.7780 \\ 10.1509 & 0.6958 & -246.7756 \\ 24.8331 & 0.7387 & -66.6627 \\ 10.4108 & 0.3036 & 25.4001 \end{bmatrix};$$

$$B_{31} = \begin{bmatrix} -16.6639 \\ -0.1546 \\ 3.1295 \\ 1.1637 \end{bmatrix};$$

$$W_{32} = 10^3 * [-0.0286 \quad -0.3671 \quad -0.5476 \quad 1.5733];$$

$$B_{32} = [-504.9972];$$

We present in figure (7) the behavior of the controller and in figure (8) the evolution of the error for the three joints (hip, knee and ankle). The variation of the rehabilitation chair first joint (hip) in its trajectory is shown in (Figure-7). Figure 8 illustrates the error between the desired and measured value.

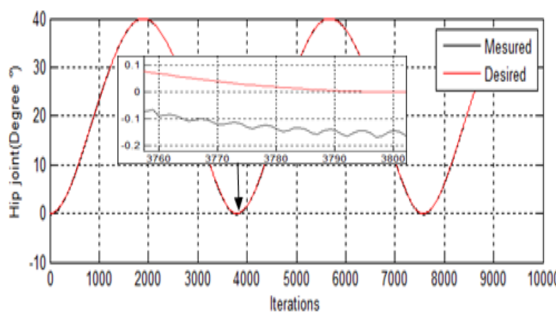

Figure 7: Varying the path of the first joint (hip joint).

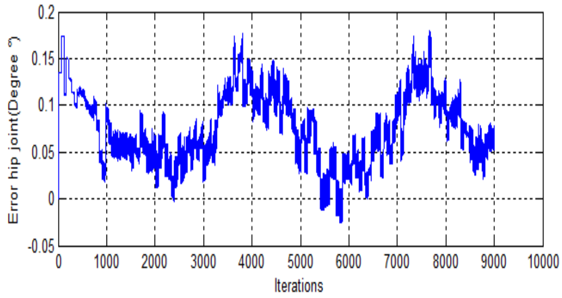

Figure 8: The error in the desired trajectory of the first joint (hip joint).

We generate desired positions joint in the operating range of the hip joint of the rehabilitation device, the signal varies between 0° and 40° and as a starting point 0°. The output obtained (real position joint) are identical with the signal desired, which gave an error not exceeding 0.17°.

Figures (9, 10) represent respectively the variation of the second joint (knee) and its error.

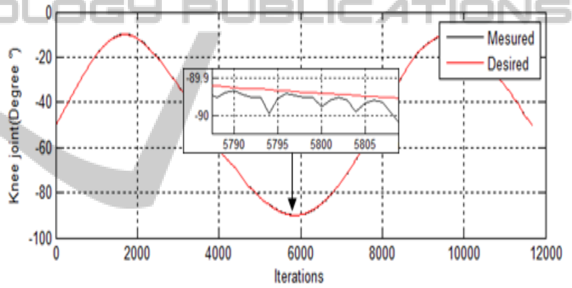

Figure 9: Varying the path of the second joint (Knee joint).

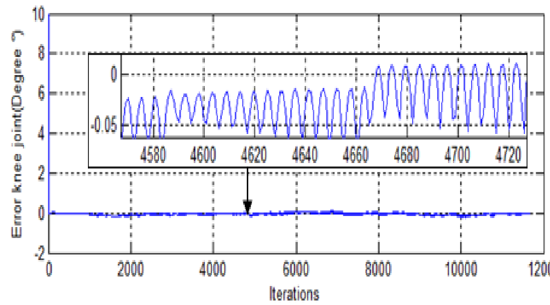

Figure-10: The error in the desired trajectory of the second joint (Knee joint).

For the knee joint, the signal is also sinusoidal shape varying between -30° and -90°, as a starting point -50°, this range was chosen based on the operating range of rehabilitation device. The output signal is obtained similar to the desired signal, the highest value of the error obtained is 0.1°. The starting point we got an error of 10°, this is due to the initial position of the joint.

At the end, the variation of the ankle joint and it's error are illustrated in (Figures 11 and 12).

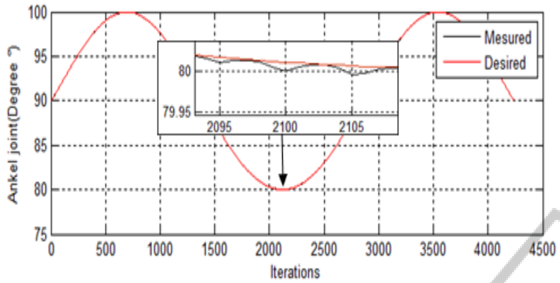

Figure 11: Varying the path of the third joint (Ankel joint).

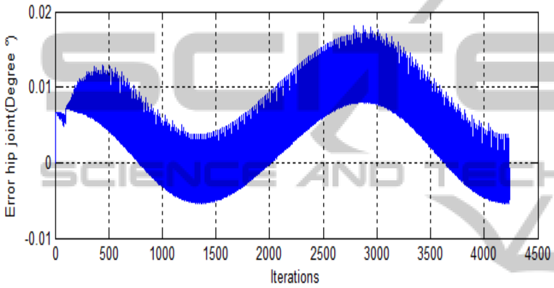

Figure 12: The error in the desired trajectory of the third joint (Ankel joint).

For the ankle joint, the signal that we generated varies between 80° and 100°, with 90° initial value. The output signal is virtually identical to the desired signal; as a result we had a very weak error, less than 0.02°.

The plots show that the obtained results are very good, as the measured values are very close to the desired ones. In fact, the error's values does not exceed (0.2°) most. Nevertheless, the error signals present considerable oscillation cycle.

Corresponding control signal of the three joints are shown in Figures (13, 14 and 15)

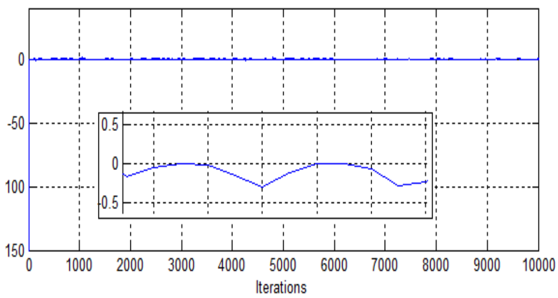

Figure 13: Control signal (U) of the first joint (hip joint).

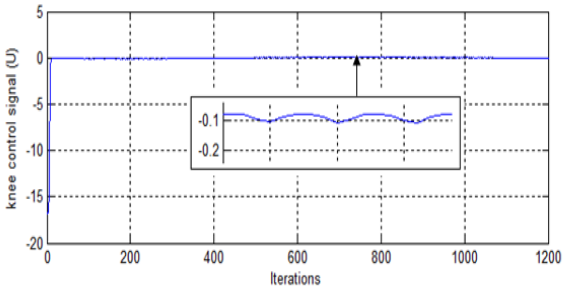

Figure 14: Control signal (U) of the second joint (Knee joint).

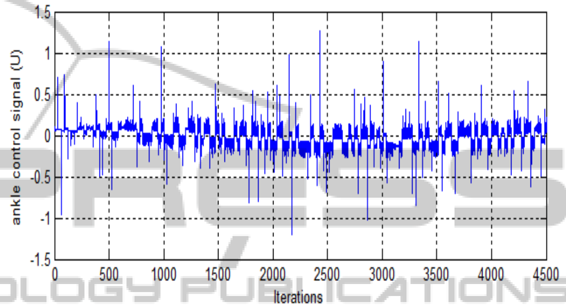

Figure 15: Control signal (U) of the third joint (Ankel joint).

The variation of the amplitude of the control signal of the three joints is not very intense, we believe that it is optimal signals, which gave good performance in the trajectory tracking with very low error.

6 DISCUSSION AND CONCLUSIONS

The objective of this work is to establish an intelligent control law using neural networks for the kinematic model of the robotic rehabilitation chair of the lower limbs. This is latter consists of two orthesis operating in three degrees of freedom. The implementation of the control law is performed by generating a similar signal (closer) to the physiological joint trajectories. To obtain the smallest possible error and try to get a signal error with the least possible oscillations, we performed several learning attempts, with a more or-less long time. A high frequency of oscillation of the error signal involves a large variation in the control signal, which is harmful for the electronic components, such as motors. However, once this step is done, the controller performs very well. The implemented control law gives very good performance. Indeed the error of each joint is very small; it does not exceed (0.2 °). The results are satisfying. However, the error form of each joint signal has thousands of oscillations. These oscillations are due to variations in the successive orders. By varying the desired signal very quickly, the controller will not be able to follow; it will give a very big order which leaves the workspace of the chair. Perspectives, The patient's weight which varies from one individual to another, can be regarded as a parameter. Than considered as an extrinsic disturbance. We propose to improve the monitoring of the path by using a dynamic model of the robot in order to take into account all the parameters and to achieve high accuracy and minimized oscillations on the output signal.

REFERENCES

Akdogan, E., Adli, M, A., 2011. The disgn and control of a therapeutic exercise robot for lower limb rehabilitation: physioterabot. In MECHATRONIC, 21: 509-522.

Anama, K., Al-Jumailyb, A, A., 2012. Active exoskeleton control systems: State of the art. In *Procedia Engineering*, 41: 988-994.

Bhangale, PP., Saha, SK., Agrawal, VP., 2004. A Dynamic Model Based Robot Arm Selection Criterion. In *Multibody System Dynamics*, 12: 95-115.

Corke, P., 2011. Robotics, Vision and Control Fundamental Algorithms in MATLAB. In *Springer*. ISBN: 978-3-642-20143-1.

Dombre, E., Khalil, W., 2007. Robot manipulators, modeling performance and analysis and control. In *ISTE,* ISBN 10: 1-905209-10-X.

Fu, K, S., 1987. Robotics: Control, Sensing, Vision, And Intelligence. The book,McGraw-Hill Book Company. 1987. ISBN: 0-07-022625-3.

Jamwal, P, K., Xie, S., Aw, K, C., 2009.Kinematic design optimization of a parallel ankele rehabilitation robot using modified geneticalgorithm. In *Robotics and Autonomous Systems*. 57: 1018–1027.

Jazar, R, N., 2010. Theory of Applied Robotics Kinematics, Dynamics and Control. In *Springer*. ISBN: 978-1-4419-1749-2.

Khalil, W., Dombre, E., 2004.Modeling, identification and control of robots. In *Kogan page science*. ISBN: 1-9039-9666-X.

Khalil, W., 2010. Dynamic modeling of robots using recursive newton-euler techniques. In *ICINCO2010*, Portugal,7: 19-31.

Lo, H, S., Xie, S, Q,. 2012. Exoskeleton robots for upper-limb rehabilitation: State of the art and future prospects. In *Medical Engineering & Physics*, 34:261-268.

Marchal-Crespo, L., Reinkensmeyer1, D, J., 2009. Review of control strategies for robotic movement training after neurologic injury. In *Journal of Neuro Engineering and Rehabilitation*, 6: 20,

http://www.mathworks.com/help/nnet/ref/trainlm.html.

Merrouche, l, M., 2011. Conception d'orthèses fonctionnelles pour les paraplégiques. Mémoire, USTHB, Alger mars 2011.

Moughamir, S., Deneve, A., Zaytoon, J., Afilal, L., 2005. Hybrid force/impedance control for the robotized rehabilitation of the upper limbs. In *IFAC World Congress*, 16: 2169-2169.

Rahman, M. H., Kiguchi, K., Rahman, M, M., Sasaki, M., 2006. Robotic exoskeleton for rehabilitation and motion assist. In *International conference on industrial and information systems*, 2: 241-6.

Reinkensmeyer, D. J., Emken, J. L., Cramer, SC., 2004. Robotics, motor learning, and neurologic recovery. In *Annual Review of Biomedical Engineering*, 6:497-525.

Riener, R., Nef, T., Colombo, G., 2005. Robot-aided neurorehabilitation of the upper extremities. In *Med Biol Eng Comput*, 43(1):2-10.

Saadia, N., Djezzar, K, B., Abdenbi, M., Ziri , N., Merrouche , L., Ababou , A., Ababou, N., 2009. Dispositif Automatique de Rééducation Fonctionnelle des membres inférieurs. In *CGE*, Alger,6.

Schmitt, C., Métrailler, P., Al-Khodairy, A., Brodard, R., Fournier, J., Bouri, M., Clavel, R., 2004. The motion maker ™: a rehabilitation system combining an orthosis with closed-loop electrical muscle stimulation». In 8^{th} *Vienna International Workshop on Functional Electrical Stimulation.*

Seddiki, L., Guelton, K., Mansouri, B., Zaytoon, J., 2006. H-infinity Takagi-Sugeno fuzzy control of a lower limbs rehabilitation device. In *International Conference on Control Applications*. 06: 927-932.

Spong, M, W., Hutchinson, S., 2005. Robot modeling and control. In *JOHN WILEY & SONS*, ISBN-10: 0471649902.

Zeinali, M., Notash, L., 2010. Fuzzy logic based hybrid impedance/force control for upper limbs robotized rehabilitation. In *Transactions of the Canadian Society for Mechanical Engineering*. 34: 137-150.