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Ant Colony Optimization Based Force-Position Control for Human Lower Limb Rehabilitation Robot

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Abstract

The aim of human lower limb rehabilitation robot is to regain the ability of motion and to strengthen the weak muscles. This paper proposes the design of a force-position control for a four Degree Of Freedom (4-DOF) lower limb wearable rehabilitation robot. This robot consists of a hip, knee and ankle joints to enable the patient for motion and turn in both directions. The joints are actuated by Pneumatic Muscles Actuators (PMAs). The PMAs have very great potential in medical applications because the similarity to biological muscles. Force-Position control incorporating a Takagi-Sugeno-Kang- three- Proportional-Derivative like Fuzzy Logic (TSK-3-PD) Controllers for position control and three-Proportional (3-P) controllers for force control. They are designed and simulated to improve the desired joints position specifications such as minimum overshoot, minimum oscillation, minimum steady state error, and disturbance rejection during tracking the desired position medical trajectory. Ant Colony Optimization (ACO) is used to tune the gains of position and force parts of the Force-Position controllers to get the desired position trajectory according to the required specification. A comparison between the force-position controllers tuned manually and tuned by ACO shows an enhancement in the results of the second type as compared with the first one with an average of 39%.

Keywords: *Rehabilitation robot, Force-Position control, lower limb, Ant Colony Optimization.*

1. Introduction

Damage of the central nervous system or spinal cord injuries may result in such a loss of lower limb motor functions. The physical therapy and rehabilitation programs are applied to people with disability to increase their joint range, strength, power, flexibility, and coordination [1]. One type of rehabilitation robots is exoskeleton robot: "*Exoskeletons are, in general, structures of rigid links, mounted on the body of some living vertebrae and following the main directions and having the main joints of the living organism's endoskeleton*" [2].

In recent years, researches on rehabilitation robot have become an important topic. There are several researches deal with this field such as Ollinger. et al. [3] in 2007 that proposed 1-DOF for knee joint actuated by electric motor controlled by Proportional-Integral-Derivative (PID) controller. Also, Akdoğan and Şişman [4] in 2011 presented a robot mechanism with 3-DOF, flexion-extension movement for the knee and hip joints, and the abduction-adduction movement for the hip joint, for the rehabilitation of lower limbs. The system was designed to imply the patient's muscle signals using Force-Position feedback control method. Impedance control method was used for force control, whereas PID position control method was used for position control. Furthermore, Tu Diep and Tran [5] in 2008 introduced a 1-DOF for knee joint actuated by PMA controlled by PID with neural network. Akdo˘gan. et al. [6] in 2009 suggested an intelligent controller structure for a knee rehabilitation robot manipulator with 1-DOF. The controller of the robot manipulator works based on impedance control. Also, Aminiazar. et al. [7] in 2013 proposed a 2-DOF for knee and ankle joints controlled by PD controller.

It can be noticed from previous works that they deal with one or two joints of human lower limb through the design. This causes retraction in workspace and reduces the flexibility when interact with human motion. Furthermore, the robots were actuated by electric motors due to their simplicity of modeling control. The drawback of electric actuators that they often are expensive and heavy for high power applications [8]. Eelectric motor actuation significantly decreases power consumption during walking in comparison to pneumatic actuation. Friction in the robot joint, either in the actuators or in the joints mechanism and the effect of disturbances was not taken into consideration in most of the previous works.

In this work, Force-Position controllers are designed to overcome the nonlinearity inherent in 4-DOF lower limb wearable rehabilitation robot [9]. The detailed design and modelling of the 4-DOF lower limb wearable rehabilitation robot actuated by Pneumatic Muscles Actuators (PMAs) has been explained in details in reference [9].

The design of the Force-Position controllers for the joints of the robot incorporates three-Proportional-Derivative (TSK-3-PD) like FLC for position control and three-Proportional (3-P) controllers for force control. These types of controllers are used to deal with the forces that have an effect on the robot links by the patient limb. Force-Position controllers are designed to improve the desired position specification such as minimum overshoot, minimization of oscillation, minimum steady state error, and disturbance rejection during tracking the desired position medical trajectory. Ant Colony Optimization (ACO) is used to tune the gains of position and force parts of the Force-Position controllers to get the desired position trajectory according to the required specification.

2. Force-Position Controllers

The force-position control is the successful execution of an interaction task without jeopardizing itself or the environment. Such an interaction requires the control of both, motion and interaction forces. As presented by Karam [10], the objective of the Force-Position control is that the robot's end-effector responds to forces applied externally, according to some well-defined dynamics. More specifically, the desired dynamic relationship between the end effector position $x \in R^m$ and the vector of contact forces $F \in R^m$ are specified as follows [10]:

$$\mathrm{F_d - F = K_d(X_d - X) + B_d(\dot{X}_d - \dot{X}) + M_d(\ddot{X}_d - \ddot{X})} \quad \dots (1)$$

Where the parameter $K_d \in R^{m\times m}$ is the stiffness diagonal matrix, $B_d \in R^{m\times m}$ is the damping diagonal matrix and $M_d \in R^{m\times m}$ is the inertia diagonal matrix. F_d are the desired joint forces applying to the robot joints in (N). $x, \dot{x}, \ddot{x}$ are the position, velocity and acceleration of the robot system in the Cartesian space respectively.

The control law of the force that is applied to the dynamic model of robot is [10]:

$$U = J(q)^T\left[K_P(X_d - X) + K_V(\dot{X}_d - \dot{X}) + F_d(K_f + I) - K_f F\right] + G \quad \dots (2)$$

Where $U \in R^n$ is the control law applied to robot model, $J(q) \in R^{m\times n}$ is the Jacobean matrix and, $K_P, K_V\ and\ K_f \in R^{m\times m}$ are the position, velocity and force gain matrices respectively. $X_d = [Pd_x\ Pd_y\ Pd_z]^T$ are the desired trajectory position (in m), $F_d = [Fd_x\ Fd_y\ Fd_z]^T$ are the joint forces applied to the robot joints (in N), $\theta_i = [\theta_1\ \theta_2\ \theta_3\ \theta_4]^T$are the measured angle from each joint (in degree), $F = [F_x\ F_y\ F_z]^T$ are the generated force vector (in N), $K_f = [K_{fx}\ K_{fy}\ K_{fz}]^T$ are the joint gains and $u = [u_x\ u_y\ u_z]^T$are the outputs of fuzzy controller. In this work, tuned the gains of force-position controllers depend on the Ant Colony Optimization (ACO) algorithm [11]. However, Fig. 1 shows the block diagram for the closed loop dynamic model controlled by Force-Position controllers. The parameters of force part and position part of the controllers are tuned by ACO.

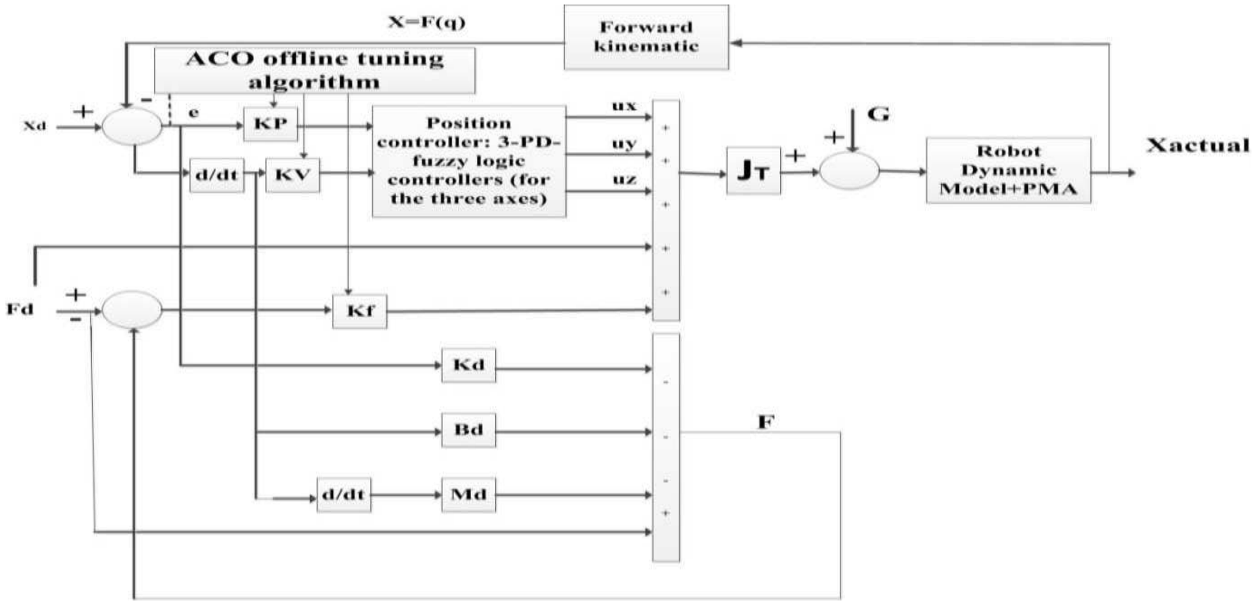


Fig. 1. Closed loop Force-Position controlled system tuned by ACO.

3. Design of Force- Position Rehabilitation Robot

Since the 4-DOF rehabilitation robot and PMA have high nonlinearity, a Force-Position controller has the ability to deal with this nonlinearity to achieve good tracking response. The front view and side view of proposed structure (the schematic diagram of the robot mechanism) are shown in Fig. 2. A TSK PD-like Fuzzy type is designed as a position controller. The inputs of the controller are the (error (e) and rate of error ($\dot{e}$)), where the control signal is:

$$u(t) = kp_i e(t) + kv_i \dot{e}(t) \qquad \dots (3)$$

The input and output scaling factors are defined as: Proportional gain, (kp), derivative gain (kv), and output gain (ko). Seven triangular shaped membership functions are selected for each input, Fig. 3. The linguistic variables of the membership functions of the FLC are; NB (Negative Big), NM (Negative Medium), NS (Negative Small), Z (Zero), PS (Positive Small), PM (Positive Medium), and PB (Positive Big). The universe of discourse for (e, $\dot{e}$) is taken within (-1, 1) since the error has positive and negative values while the output universe of discourse is within the range (0, 1) since the valve takes positive values of voltage as input. The values of output membership functions (constant type), of TSK are listed in Table 1. A typical rule in a Sugeno fuzzy model has the form:

If Input 1 = x and Input 2 = y, then Output is

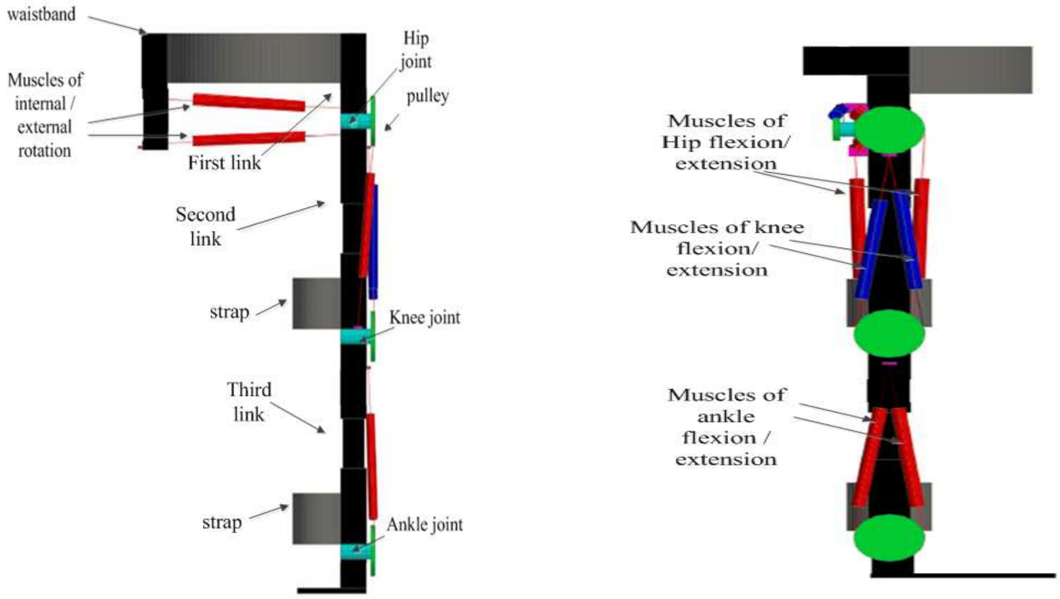
$$z = a.x + b.y + c. \qquad \dots (4)$$

For a zero-order Sugeno model, the output level z is a constant (a=b =0). However, the rules of the FLC are listed in Table 2 and selected by several trials to reach the best position response.

The parameters of the Force controller incorporating in the Force- Position control, equation (1), are selected as; K_d=3000 (N/m), B_d=200 (N·s/m) and M_d=5 (kg). These values are representing a second order reference model with damping ratio and un-damped natural frequency of ζ=0.*8164* and *wn*=24.49 (rad/sec) respectively [12]. The Simulink of the force and position controllers is shown in Fig. 4 and the Simulink of the complete Force-Position controlled system for lower limb rehabilitation robot is shown in Fig. 5. It consists of sub blocks of the dynamic model, PMA, the position controller, the force controller and the reference trajectory.

Table 1,
Constant membership functions for the output.

NB=0.3	NM=0.4	NS=0.527	Z=0.647	PS=0.7	PM=0.83	PB=0.99



(a) Front view **(b) Side view**

Fig. 2. The Proposed Structure of the Lower Limb Wearable Rehabilitation Robot.

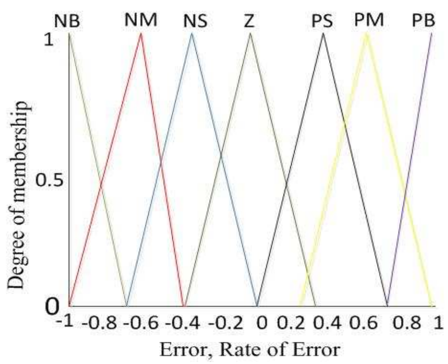


Fig. 3. Inputs Membership functions.

Table 2,
Rules of PD-like position FLC.

$e/\dot{e}$	***NB***	***NM***	***NS***	***Z***	***PS***	***PM***	***PB***
NB	NB	NB	NB	NB	NM	NS	Z
NM	NB	NB	NB	NM	NS	Z	PS
NS	NB	NB	NM	NS	Z	PS	PM
Z	NB	NM	NS	Z	PS	PM	PB
PS	NM	NS	Z	PS	PM	PB	PB
PM	NS	Z	PS	PM	PB	PB	PB
PB	Z	PS	PM	PB	PB	PB	PB

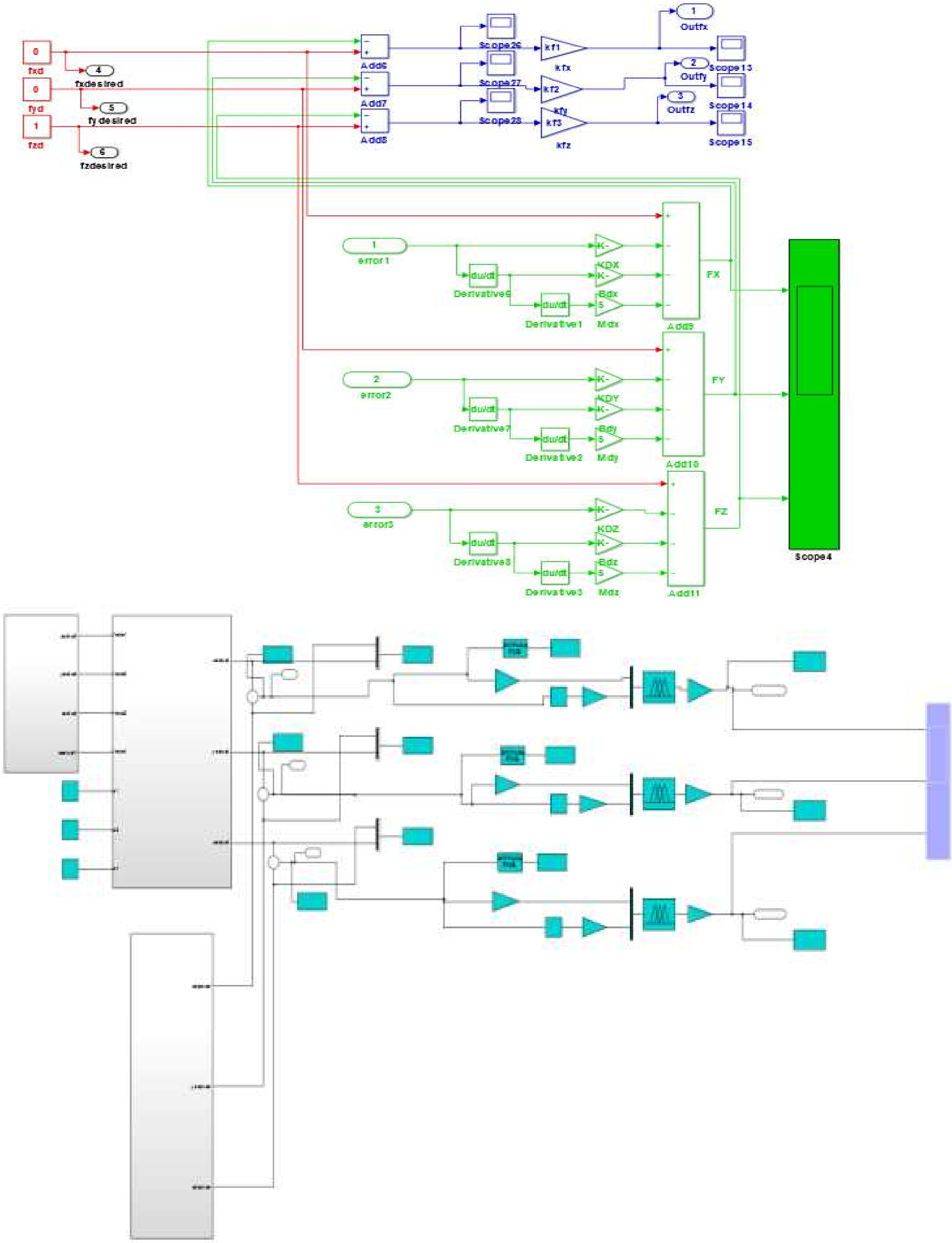


Fig. 4. The force and position controllers.

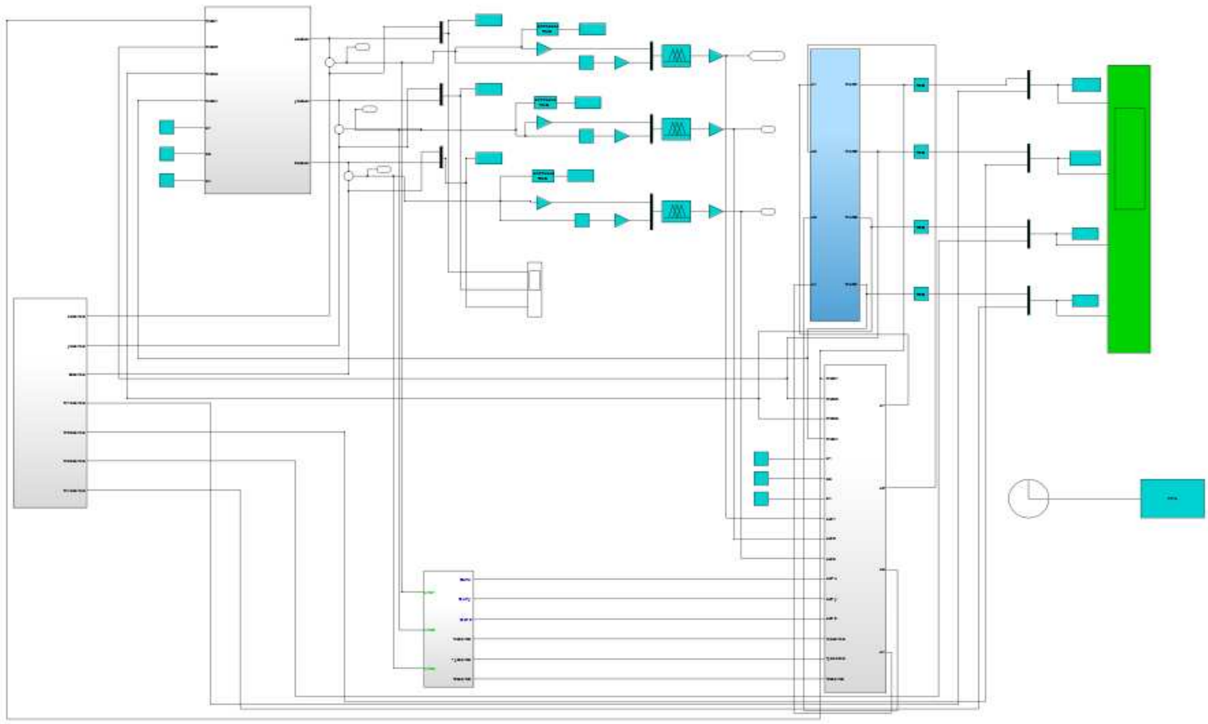


Fig. 5. The Simulink of Force-Position controlled system for the lower limb rehabilitation.

4. Simulation Results

In this work, the elliptic trajectory which enable the patient to move in x and y axes is applied. The desired trajectory is given by [13]:

$$x_d(t) = 0.614 - 0.015\,.\cos(0.2\pi\,.t - \pi) \quad \dots (5)$$

$$y_d(t) = -0.1\,.\sin(0.2\pi\,.t - 2\pi) \quad \dots (6)$$

Where $0 \le t \le 20$ seconds.

By applying the reference position trajectory, the gains of the PD- FLC and the proportional gain (K_f) of the force controller for each joint are manually tuned using several trials and error and the best values are illustrated in Table 3.

The response for each axis and the position trajectory are shown in Fig. 6 and Fig. 7 respectively. In this work, the criterion selected to measure the goodness of results as a performance index is Root Mean Square Error (RMSE) [14]:

$$RMSE = \frac{1}{N}\sum_1^N \sqrt{e_x^2(i) + e_y^2(i) + e_z^2(i)} \quad \dots (7)$$

Where $e_x^2(i)$ is the trajectory error in x-axis, $e_y^2(i)$is the trajectory error in y-axis and $e_z^2(i)$ is the trajectory error in z-axis. N is the number of samples. The performance index for first position trajectory without disturbance is calculated and equals to 0.0547.

During rehabilitation exercises, many interior factors, such as position changes and even coughing, usually cause some disturbance to the rehabilitation system. A disturbance of 4*sin (10.π.t) N.m is applied [15]. Based on the characteristics of a tremor the value of above disturbance is sufficient to describe the convulsions for human lower leg. The gains of the controller listed in Table 3 are used for the elliptic trajectory with disturbance. The response for each axis and the position trajectory are shown in Fig. 8 and Fig. 9 respectively. The performance index for position reference trajectory with disturbance is calculated and equals to 0.0652.

Table 3,
PD-like Force-Position FLC gains for the first (elliptic) trajectory.

Gain	Kp1	Kd1	Ko1	Kp2	Kd2	Ko2	Kp3	Kd3	Ko3
Value	0.23	0.54	3.6	1.5	0.7	6.8	0.04	0.008	0.4
Kf1	Kf2	Kf3							
6.4	7.85	5.27							

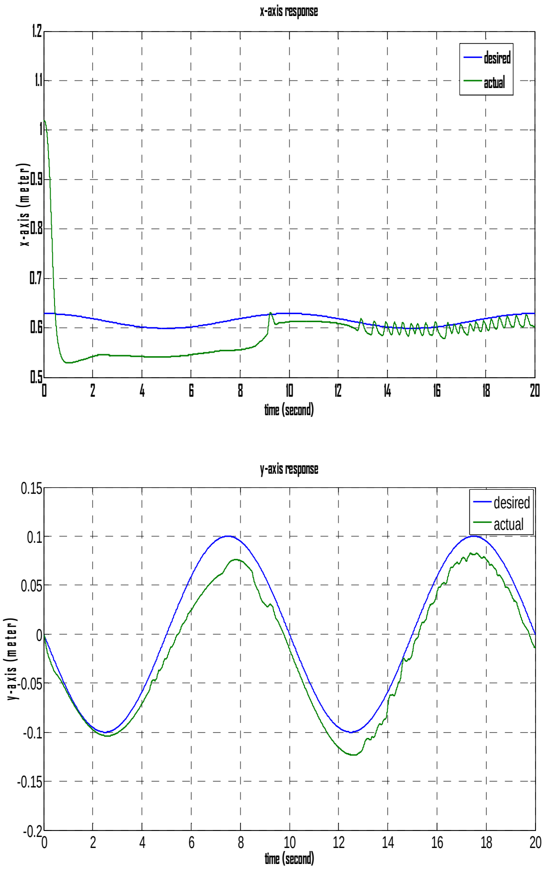


Fig. 6. Position response for the x and y axes of the elliptic reference position trajectory without disturbance.

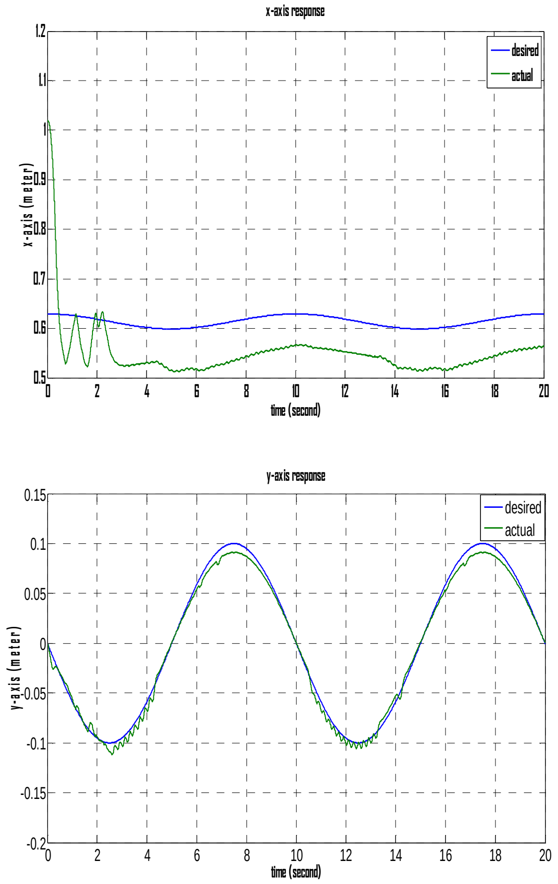


Fig. 8. Position response for the x and y axes of the elliptic reference position trajectory with disturbance.

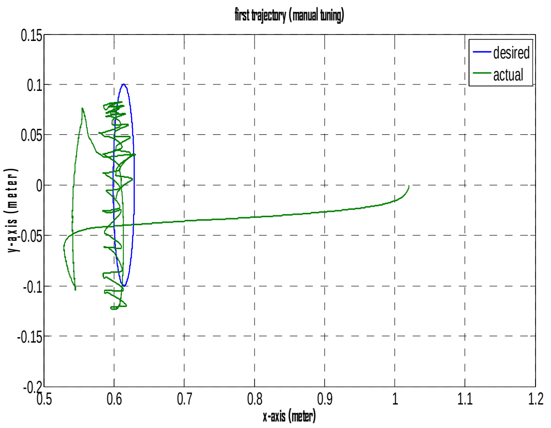


Fig. 7. Position trajectory response without disturbance in the (x-y) axes.

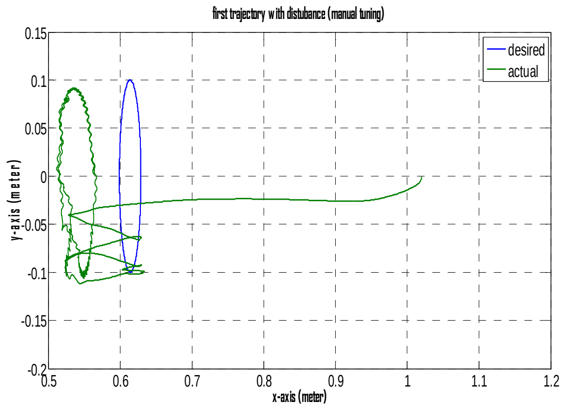


Fig. 9. Position trajectory response with disturbance in (x-y) axes

It is difficult to enhance position tracking performance using the controller tuned manually. The process of tuning the gains of the controllers consumes time and efforts. In this research, ACO algorithm is used to tune the gains of the controllers in order to reach the best position performance. To get more accurate position responses, the values of the gains (kp, kv, Ko and kf) for each controller are tuned by ACO to achieve the desired specifications. The number of iterations for position trajectory is 40 iterations. The algorithm stops iterating either when an ant found a solution or when a maximum number of iterations have been performed.

Table 4 lists the parameters of Force-Position controllers obtained by ACO tuning to follow the reference position trajectory without disturbance. The performance index for the elliptic trajectory without disturbance is calculated and equals to 0.036.

However, the response of each axis and the position tracking responses in the x, y Cartesian space are shown in Figs. 10 and 11 respectively. Moreover, Fig. 12 shows the performance index obtained by ACO.

Here the disturbance of 4*sin (10.π.t) is applied. The same parameters listed in Table 4 are used for trajectory with disturbance. The performance index for position trajectory with disturbance is calculated and equals to 0.0362.

However, the position tracking responses in the x, y Cartesian space are shown in Figs. 13 and 14 respectively.

Table 4,
PD-like Force-Position FLC gains for the elliptic trajectory tuned ACO.

Gain	Kp1	Kd1	Ko1	Kp2	Kd2	Ko2	Kp3	Kd3	Ko3
Value	0.0081	0.0029	4.6456	0.0496	0.0067	4.557	0.001	0.001	0.0065
Kf1	Kf2	Kf3							
2.381	4.6962	0.0055							

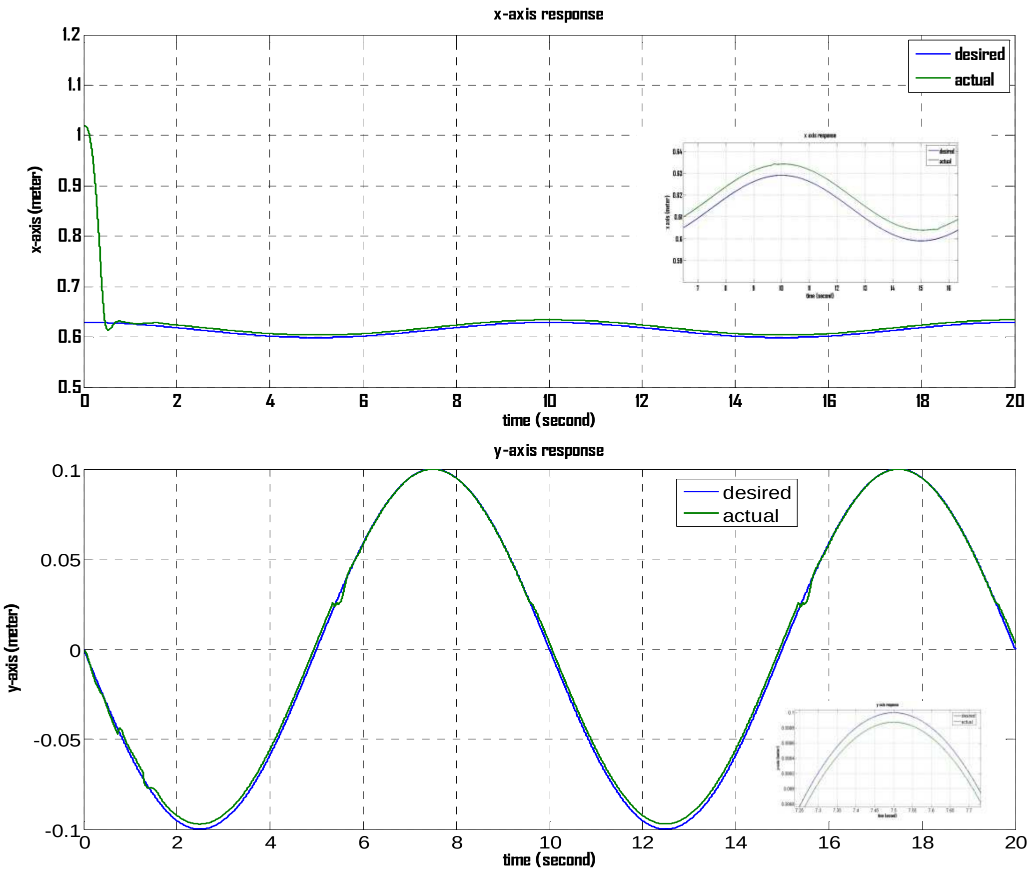


Fig. 10. Position response for the x and y axes of the elliptic reference Position trajectory tuned by ACO without disturbance.

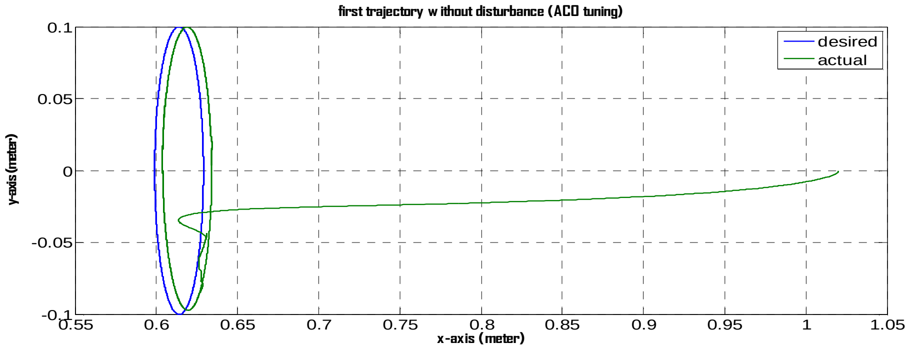


Fig. 11. Position trajectory response without disturbance.

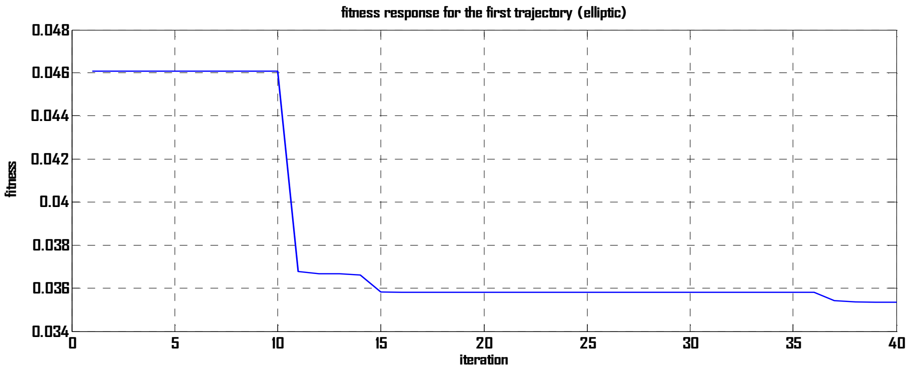


Fig. 12. ACO performance index response.

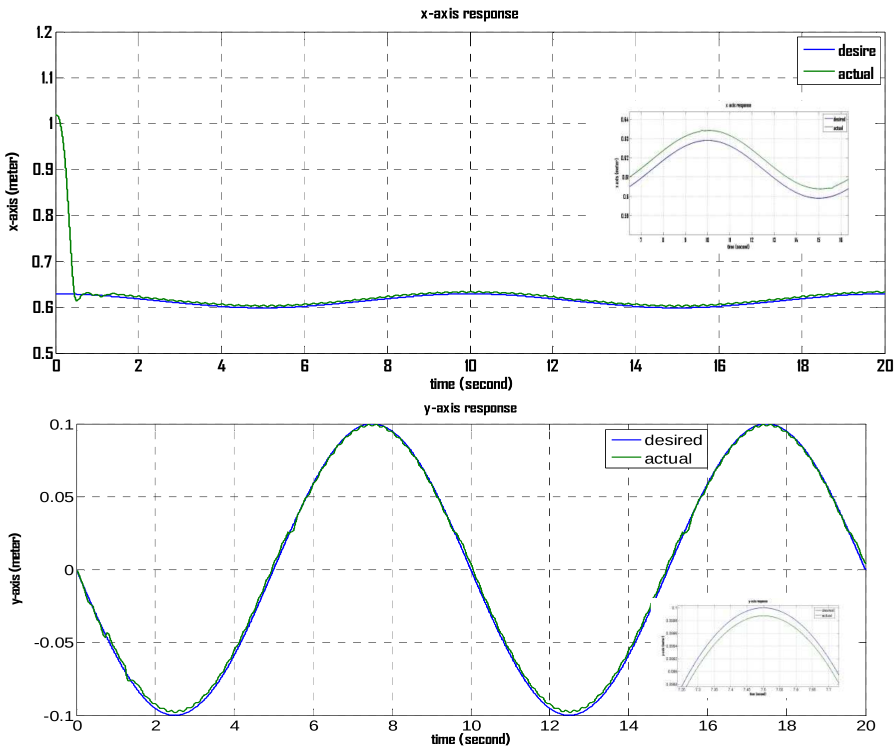


Fig. 13. Position response for the x and y axes of the elliptic reference position trajectory with disturbance.

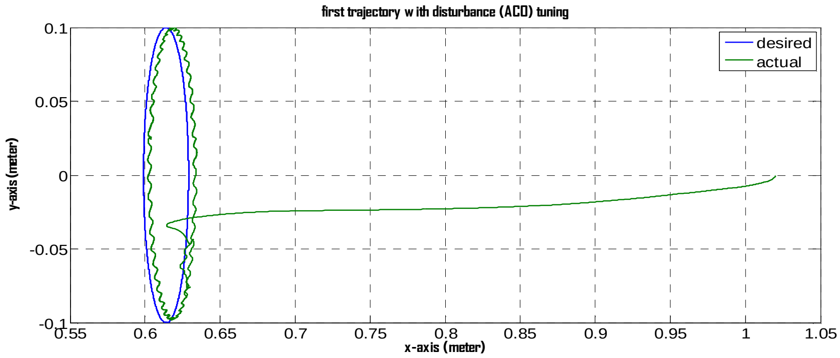


Fig. 14. Position trajectory response with disturbance.

5. Conclusions

Force-Position controllers were designed to control the proposed robot. Result showed that:

1. The proposed controller using manual tuning could not overcome the nonlinearity of dynamic model, nonlinearity of PMA, effects of frictions, and disturbances.
2. ACO algorithm was used to tune the gains of the force part and position part of force-position controllers to satisfy the desired specification. Results of applying the medical trajectory show an average enhancement in the position trajectory.
3. (Without disturbance and with disturbance) for elliptic trajectory (39 %).
4. For the proposed Force-Position controllers tuned by ACO, the results of the elliptic trajectory were compared with the results of reference 11. The percentage of enhancement for x and y axes are 50 % and 85 % respectively.
5. The proposed force-position controllers tuned by ACO had achieved the desired performance and compensated the nonlinearity of frictions, external disturbance and any other nonlinearity in the proposed model.

List of Symbols

Symbols	**Definition**	**Unit.**
B_d	Damping diagonal matrix	$N.s/m$
F	Generated force	N
F_d	The desired joint forces applying to the robot joints	N
K_d	Stiffness diagonal matrix	N/m
M_d	Inertia diagonal matrix	kg
x	The position	
$\dot{x}$	The velocity	
Kp_i	Proportional gains of ith controller	
Kv_i	Velocity gains of ith Controller	
Ko_i	Output gains of ith controller	
K_{fi}	The force gain of ith controller	
J	Jacobean matrix	
U	Voltage input	Volt
θ_i	Joint angle of link i	$degree$
ξ	Damping ratio	
W_n	Un-damped natural Frequency	rad/s
$e_x(i)$	The trajectory error in x-axis	m
$e_y(i)$	The trajectory error in y-axis	m
$e_z(i)$	The trajectory error in z-axis	m

6. References

[1] Nef, T.; Mihelj, M.; Riener, R.: ARMin: A Robot for Patient-Cooperative Arm Therapy. Medical and Biological Engineering and Computing, International Federation for Medical and Biological Engineering, 45, 887-900, 1 July (2007).

[2] Rocon, E.; Pons, J. L.: Exoskeletons in Rehabilitation Robotics, Springer-Verlag Berlin Heidelberg, 1–20, (2011).

[3] Ollinger, G. A.; Colgate, J. E.; Peshkin, M. A.; Goswami, A.: Active-Impedance Control of a Lower-Limb Assistive Exoskeleton. IEEE 10th International Conference on Rehabilitation Robotics, June 12-15, Noordwijk, Netherlands, 188-195, 12-15 June (2007).

[4] Akdoğan, E.; Şişman, Z.: A Muscular Activation Controlled Rehabilitation Robot System", Springer-Verlag Berlin Heidelberg, 271–279, 2011.

[5] Thanh, T. D. C.; Phuc, T. T.: Neural Network Control of Pneumatic Artificial Muscle Manipulator for Knee Rehabilitation. Science & Technology Development, 11, 03, 16-29, (2008).

[6] Akdo˘gan, E.; Taçgın, E.; Adli, M. A.: Knee Rehabilitation using an Intelligent Robotic System. Springer Science+Business Media, 20, 195-202, Jan. (2009).

[7] Aminiazar, W.; Najafi, F.; Nekoui, M. A.: Optimized intelligent control of a 2- Degree of Freedom Robot for Rehabilitation of Lower Limbs using Neural Network and Genetic Algorithm. Journal of Neuro Engineering and Rehabilitation, (2013).

[8] Hassan, M. Y.: A Neural Network Based Fuzzy Controller For Pneumatic Circuit, Eng. &Tech. Journal, 28, 2010.

[9] Hassan, M. Y.; Ghintab, Sh. S.: Modelling and Position Control of Human Lower Limb Rehabilitation Robot using Pneumatic Muscle Actuators. Accepted to be published in AL-MANSOUR Journal, Iraq 11/9/ (2014).

[10] Hassan, M. Y.; Karam, Z. A.: Modelling and Force-Position Controller Design of Rehabilitation Robot for Human Arm Movements, Eng. &Tech. Journal, 32, 8, 2079-2095, (2014).

[11] Chiha, I.; Liouane, N.; Borne, P.: Tuning PID Controller Using Multi objective Ant Colony Optimization. Hindawi Publishing Corporation Applied Computational Intelligence and Soft Computing Journal, 1-7, (2012).

[12] Wang, J.; Li , Y.: Hybrid Impedance Control of a 3-DOF Robotic Arm Used for Rehabilitation Treatment. 6th Annual IEEE Conference on Automation Science and Engineering Toronto, Ontario, Canada, 768-773, Aug. (2010).

[13] Chang M. K.; Liou, J. J.: T-S Fuzzy Controller Applied to Lower Limb Rehabilitation Robot Actuated by Pneumatic Muscle Actuators. CACS International Automatic Control Conference, National Taipei University of Technology, Taipei, Taiwan, November 27-29, (2009).

[14] Karam, Z. A.: Design and Implementation of Rehabilitation Robot Arm, M.Sc. thesis, University of Technology, control and system Eng. Dept., Dec. (2013).

[15] Pan, L.; Song, A.; Xu, G.; Li, H.; Xu, B.: Safety Supervisory Strategy for an Upper-Limb Rehabilitation Robot Based on Impedance Control. International Journal of Advanced Robotic Systems, 10, 127, 1-12, (2013).

مسيطر قوة- موقع لروبوتات أعادة تأهيل الاطراف السفلية بأستخدام خوارزمية مستعمرة النمل

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الخلاصة

الهدف من روبوتات أعادة التأهيل الخاصة بالأجزاء السفلية للأطراف البشرية هو أعادة القدرة على المشي وتقوية العضلات. ويقدم البحث تصميم مسيطر من نوع (قوة- موقع) لروبوت مكون من أربع درجات من الحرية، إثنتان منها في مفصل الورك، وثالثة في مفصل الركبة ورابعة في مفصل الكاحل، وهذه الدرجات من الحرية، كافية؛ لاعادة تأهيل المريض للمشي والدوران الى جهتي اليمين واليسار. إذ يتم تحريك المفاصل باستعمال مشغلات العضلة الهوائية، ويعد هذا النوع من المشغلات، الأفضل في التطبيقات الطبية؛ نظراً لخواصه المشابهة للعضلات البشرية. على الرغم من اللاخطية العالية في التصميم، إلا ان السيطرة على تتبع المسارات الطبية قد تمت عن طريق مسيطرات (قوة ـ موقع) مكون من ثلاثة مسيطرات للموقع من نوع) منطق ضبابي ذكي متناسب ـ متفاضل PD –TSK (وثلاثة مسيطرات من نوع متناسب للقوة (٣-) ، وذلك لغرض تحقيق المواصفات المطلوبة، كتقليل تجاوز المدخل، وتقليل التذبذب، وتقليل نسبة الخطأ في مواقع المسارات، فضلاً عن مقاومة الاضطرابات. اعتمد البحث خوارزمية مستعمرات النمل لكل من جزء الموقع وجزء القوة؛ لغرض تحسين المواصفات. أثبتت المقارنة بين نتائج المسيطر المنغم يدويا والمنغم بأستخدام خوارزمية مستعمرات النمل ان هناك تحسن في موقع المسار الطبي (بعدم تسليط الاضطرابات الخارجية ومع تسليطها) كمعدل بنسبة ٣٩%.