An Intelligent Control for Lower Limb Exoskeleton for Rehabilitation

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Abstract

This paper proposes an intelligent lower extremity rehabilitation training system controlled by adaptive fuzzy controllers. The structure of the robotic leg exoskeleton can be divided into three parts including hip joint, knee joint, and ankle joint, which is driven by DC motors. Inverse kinematics with geometric strategy is applied to calculate joint angles from Clinical Gait Analysis (CGA) data. Then, the measured data is filtered before being sent to the controllers to improve control quality. Finally, workability of the proposed system is verified by simulation results with sufficient performances and effectiveness.

Keywords — *Adaptive fuzzy control, exoskeleton rehabilitation, inverse kinematics, filtering signal, Sim Mechanics simulation.*

I. INTRODUCTION

Researches on exoskeletons have started more than a half of century, but only has recently been applied to rehabilitation and functional substitution in patients suffering from motor disorder. After brief and unsuccessful attempts in these years, advances in sensing, actuation and computing technologies have renewed the confidence in the viability of developing an autonomous exoskeleton system for human performance augmentation. Not only do these advances permit the realization of more compact, lightweight and robust robotic hardware design, but they also permit the development of increasingly sophisticated control laws in terms of both real-time processing capability and design and analysis computer aided tools. Generally, the device is to be designed and controlled in such a way that the human can conduct a wide spectrum of activities without feeling the device.The future possible applications of exoskeletons are endless and include construction workers, earthquake rescue personnel, space exploration, and physical rehabilitation. Currently, the demand of health care is the strongest need in the modern society [1-5].A method of lower-limb exoskeleton control aimed at improving the agility of leg-swing motion by emulating inertia compensation or producing a virtual modification of the mechanical impedance of the human limbs is proposed in [6].Besides, adaptive fuzzy control has been a potential and active research area in the past decades. Fundamental issues such as stability, robustness, and performance analysis have been solved. An adaptive fuzzy controller is synthesized from a collection of fuzzy IF-THEN rules. The parameters of the membership functions characterizing the linguistic terms in the fuzzy IF-THEN rules change according to some adaptive law for the purpose of controlling a plant to track a reference trajectory. These fuzzy IF-THEN rules are either collected from experienced human operators or generated automatically during the adaptation procedure as shown in [7-8].

This paper proposes a flexible robotic lower limb exoskeleton for rehabilitation providing a variety of exercises for users. The exoskeleton is comprised of two 3-DOF legs modeled by mathematical equations and SimMechanics in MATLAB Simulink.In order to make the exoskeleton work, an indirect adaptive fuzzy controller is determined according to the mathematical model then applied to the SimMechanics model for workability verification.

The paper is organized into several sections. Section II introduces specifically the structure, mathematical model and inverse kinematics calculations of the proposed exoskeleton. Control method is presented in Section III. Section IV illustrates input signal processing, SimMechanics model and simulation results of the system. Conclusions and future work are discussed in Section V.

II. EXOSKELETON SYSTEM

A. Structure of the proposed exoskeleton system

The proposed exoskeleton system consists of two legs, one treadmill, and one suspension bar as shown in Fig. 1. Legs of the exoskeleton are designed with ability to adjust the length of thigh and shin to fit every patient.The hip joint angle, the knee joint angle and the ankle joint angle will be driven by DC motors. Angulardisplacements and velocities of joints are obtained by encoders.

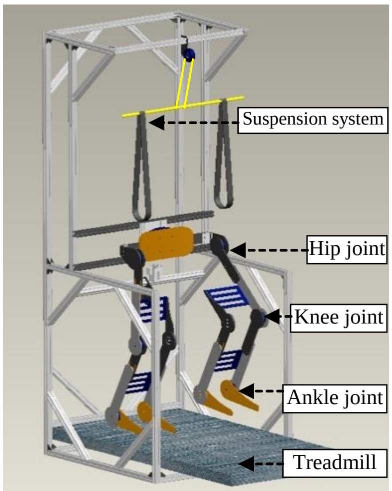


Fig.1. Structure of the exoskeleton

B. Mathematical model of the system

The mathematical model of the ankle joint has been proposed in [9]. It is assumed that the only forces putting on the links are the joint torques ($T_2$for hip joint, T_3 for knee joint and $T_4$for ankle joint) and the gravitational force (g_a). Therefore, the desired torques for each joint are in term of joint angles ($q_2$for hip joint, $q_3$for knee joint and q_4 for ankle joint), joint velocities ($\dot{q}_2, \dot{q}_3, \dot{q}_4$), joint accelerations ($\ddot{q}_2,\ddot{q}_3, \ddot{q}_4$) and constant dimensions and mass parameters of the exoskeleton links. In order to design the control system, a simplified model of each joint is applied to determine controller parameters. Equations (1-4) present the mathematical model of the ankle joint in which the velocities and accelerations of other joints ($\dot{q}_2, \ddot{q}_2, \dot{q}_3, \ddot{q}_3$) are nullified.

$$\ddot{x}_2 = f(x_1) + g(x_1)u \tag{1}$$

$$f(x_1) = \frac{g_a(m_f h_{Gf} \sin(x_1) - m_f L_{Gf} \cos(x_1))}{I_f + m_f(h_{Gf}^2 + L_{Gf}^2)} \tag{2}$$

$$g(x_1) = \frac{1}{I_f + m_f(h_{Gf}^2 + L_{Gf}^2)} \tag{3}$$

$$x_1 = q_4; x_2 = \dot{q}_4; u = T_4;\ y = x_1 \tag{4}$$

where q_2, q_3, $q_4$are angular angles of the hip joint, knee joint and ankle joint respectively as shown in Fig. 2;T_4 is the torque need to be exerted on the ankle joint;x_1 ,$x_2$are state variables of the ankle joint;h_{Gf} is the distance from the foot (pedal) to the center of gravity of foot (COG) while$L_{Gf}$is the distance from the ankle joint to COG along the pedal;m_f and $I_f$are the mass and the inertia torque of the foot respectively.

The models for hip and knee joints are acquired by the same way as that of ankle joint.In fact, physical coupling of these joints exists in the real system andSimMechanics model (will be discussed in Section IV-B). However, the simplification of the mathematical model in this section aims at facilitating the design of an adaptive controller with ability to adjust its own parameters according to changes in the system model. Therefore, it helps to minimize serious impacts of disturbances on control quality.

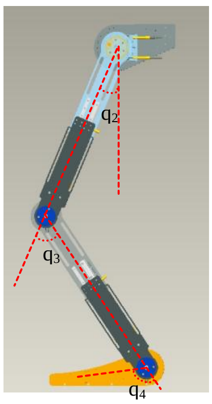


Fig.2. Design of one leg of the exoskeleton system

C. Inverse kinematics

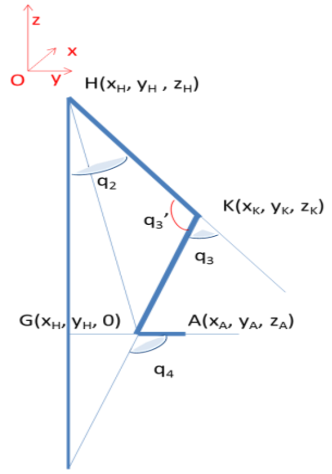


Fig.3. Geometric method for inverse kinematics calculations

In this research, the collected datacontains information about positions of joints provided by an experimental measurement from human walking (Clinical Gait Analysis CGA). The author proposes the geometric method to solve inverse kinematics problemas illustrated in Fig. 3. H(x_H,y_H,z_H), K(x_K,y_K,z_K) and A(x_A,y_A,z_A) are three marked points of hip, knee and ankle joints with coordinate data.It is assumed that G is the point that makesthe line from H to G vertical to the ground then$G=(x_H,y_H,0)$and the pedal is always parallel to the ground. Solutions of joints angles (q_2,q_3,q_4) are determined in equations (5-8).

$$q_3^{'} = \cos^{-1}((HK^2 + KA^2 - HA^2)/(2HK.KA)) \tag{5}$$

$$q_3 = \pi - q_3^{'} \tag{6}$$

$$q_2 = \cos^{-1}\left(\frac{\overrightarrow{HK}.\overrightarrow{HG}}{HK.HG}\right) \tag{7}$$

$$q_4 = 2\pi - q_2 - q_3^{'} \tag{8}$$

III. CONTROLMETHOD

The rehabilitation exoskeleton system involves plenty of uncertainties and the lack of information. Accordingly, this paper proposes adaptive fuzzy controllers enabling the system to be able to walk autonomously as a human regardless of the existence of unknown parameters.If the plant parameters change, estimates of these changes will be provided by the identifierthen the controller designer will subsequently tune the controller. It is inherently assumed that the estimated plant parameters are equivalent to the actual ones at all times (this is called the "certainty equivalence principle"). Then if the controller designer can specify a controller for each set of plant parameter estimates, it will succeed in controlling the plant. The mentioned approach is called "indirect adaptive control" since we tune the controller indirectly by first estimating the plant parameters (as opposed to direct adaptive control, where the controller parameters are estimated directly without first identifying the plant parameters).The controllers can be applied to control the hip, knee, and ankle joint angles independently.

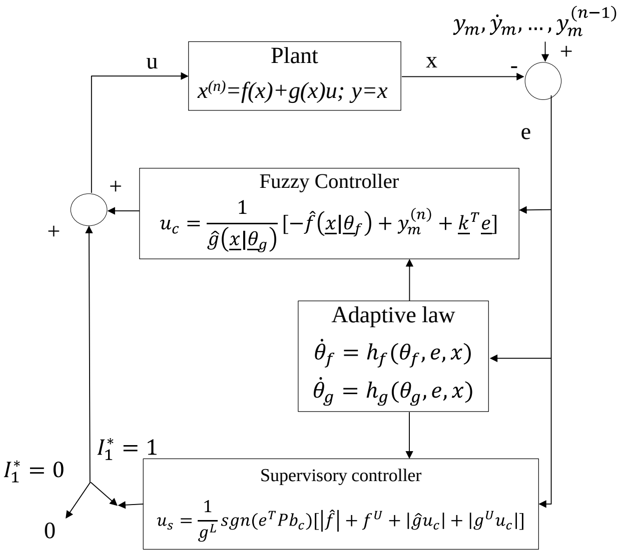


Fig.4. Block Diagram of an Adaptive Fuzzy Controller

Calculations of the ankle joint controller depend on mathematical equations (1-4) in associated with the control scheme as shown in Fig. 4. Actually, *f(x)* and *g(x)* are unknown so designers need to estimate values of them. These valuesdenoted by $\hat{f}(\underline{x}|\underline{\theta}_f)$ and $\hat{g}(\underline{x}|\underline{\theta}_g)$ will be obtained by adaptive law and the fuzzy basic function [10]. There are 3 steps to design the controller as listed as follows:

A. *Step 1: Off-line preprocessing*

Specify $k_1=2$; $k_2=1$then substitute into the equation (9) to obtain the solution $s_1 = s_2 = -1$ in the open left-half plane.

$$s^2 + k_1 s + k_2 = 0 \quad (9)$$

$$Q = \begin{bmatrix} 10 & 0 \\ 0 & 10 \end{bmatrix} \quad (10)$$

A positive definite 2x2 matrix Q is chosen as shown in equations (10). After that, by solving the Lyapunov equation (11)enables toestimate a symmetric matrix P (13).

$$\Lambda_C^T P + P \Lambda_C = -Q \quad (11)$$

$$\Lambda_C = \begin{bmatrix} 0 & 1 \\ -k_2 & -k_1 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -1 & -2 \end{bmatrix} \quad (12)$$

$$P = \begin{bmatrix} 15 & 5 \\ 5 & 5 \end{bmatrix} > 0 \quad (13)$$

Choose $M_f=16$; $M_g=1.6$ and$\bar{V} = 0.01$ are constant values for adaptive laws in Step 3.

B. *Step 2: Initial controller construction*

Definitions of 5 fuzzy sets $F_1^1, F_1^2, F_1^3, F_1^4, F_1^5$ for $x_1$and 5 fuzzy sets $F_2^1, F_2^2, F_2^3, F_2^4, F_2^5$ for x_2 areshown in Figs. 5-6.

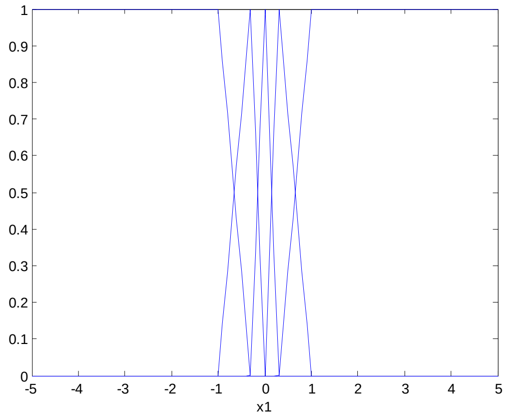


Fig.5. Membership functions of state variable x_1

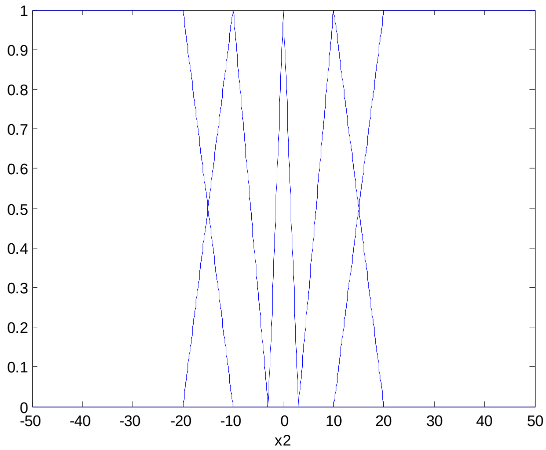


Fig.6. Membership functions of state variable x_2

Those membership functions are fixed and designed by the author. The ranges of $x_1$and x_2 are chosen depending on the maximum values of angle and angular velocity of joints. Hence, 25 fuzzy rules are used to implement the inference engine to estimate the fuzzy logic system $\hat{f}(\underline{x}|\underline{\theta}_f)$ and $\hat{g}(\underline{x}|\underline{\theta}_g)$(14-16).

The fuzzy basis functions of the first-type controller:

$$\xi^{(l_1,\ l_2)}(\underline{x}) = \frac{\prod_{i=1}^{2} \mu_{F_i^{l_i}}(x_i)}{\sum_{l_1=1}^{5}\sum_{l_2=1}^{5}(\prod_{i=1}^{2} \mu_{F_i^{l_i}}(x_i))} \quad (14)$$

$$\hat{f}(\underline{x}|\underline{\theta}_f) = \underline{\theta}_f^T \underline{\xi}(\underline{x}) \quad (15)$$

$$\hat{g}(\underline{x}|\underline{\theta}_g) = \underline{\theta}_g^T \underline{\xi}(\underline{x}) \quad (16)$$

where$\xi(\underline{x})$ is a 25 dimensional vector that collect $\xi^{(l_1,\ l_2)}(\underline{x})$ from the fuzzy basis functions with $l_1 = \overline{1,5}$ and $l_2 = \overline{1,5}$.

C. *Step 3: On-line Adaptation*

The feedback control can be calculated according to equations (17-19).

$$u = u_c + u_s \tag{17}$$

$$u_c = \frac{1}{\hat{g}(\underline{x}|\underline{\theta}_g)}\left[-\hat{f}(\underline{x}|\underline{\theta}_f) + y_m^{(2)} + \underline{k}^T\underline{e}\right] \tag{18}$$

$$u_s = \begin{cases} I_1^* sgn(\underline{e}^T P \underline{b}_c)\frac{1}{g_L(\underline{x})}[|\hat{f}(\underline{x}|\underline{\theta}_f)| + f^U(\underline{x}) + \\ \qquad +|\hat{g}(\underline{x}|\underline{\theta}_g)| + |g^U(\underline{x})u_c|] \end{cases} \tag{19}$$

where $I_1^* = 1$ if $V_e = \frac{1}{2}\underline{e}^T P \underline{e} > \bar{V} = 0.01$ (obtained constant specified in Step 1), else $I_1^* = 0$;*sgn(y)=1*if $y \geq 0$ and *sgn(y)=-1* if $y < 0$; and$\underline{e} = (e, \dot{e}, \dots, e^{(n-1)})^T$ is the error vector between reference input y_m and system output y (Fig. 4).

Parameter vectors $\underline{\theta}_f$ and $\underline{\theta}_g$ are adjusted by the following adaptive laws:

• If $(|\underline{\theta}_f| < M_f)$ *or* $(|\underline{\theta}_f| = M_f$ and$\underline{e}^T P \underline{b}_c \underline{\theta}_f^T \underline{\xi}(\underline{x}) \geq 0)$ then $\dot{\underline{\theta}}_f = -\gamma_1 \underline{e}^T P \underline{b}_c \underline{\xi}(\underline{x})$

• If $(|\underline{\theta}_f| = M_f$ and$\underline{e}^T P \underline{b}_c \underline{\theta}_f^T \underline{\xi}(\underline{x}) < 0)$ then

$$\dot{\underline{\theta}}_f = \begin{cases} P\left\{-\gamma_1 \underline{e}^T P \underline{b}_c \underline{\xi}(\underline{x})\right\} = \\ = -\gamma_1 \underline{e}^T P \underline{b}_c \underline{\xi}(\underline{x}) + \gamma_1 \underline{e}^T P \underline{b}_c \frac{\underline{\theta}_f {\underline{\theta}_f}^T \underline{\xi}(\underline{x})}{|\underline{\theta}_f|^2} \end{cases}$$

• If $(\underline{e}^T P \underline{b}_c \xi_i(\underline{x}) u_c < 0)$ then $\dot{\theta}_{gi} = -\gamma_2 \underline{e}^T P \underline{b}_c \xi_i(\underline{x}) u_c$

• If $(\underline{e}^T P \underline{b}_c \xi_i(\underline{x}) u_c \geq 0)$ then $\dot{\theta}_{gi} = 0$

where$\xi_i(\underline{x})$ is the *ith* component of $\underline{\xi}(\underline{x})$ and P{*} is the projection operator.

Otherwise, the adaptive rules for $\dot{\underline{\theta}}_g$ as follows:

• If $(|\underline{\theta}_g| < M_g)$*or* $(|\underline{\theta}_g| = M_g$ and$\underline{e}^T P \underline{b}_c \underline{\theta}_g^T \underline{\xi}(\underline{x}) u_c \geq 0)$ then $\dot{\underline{\theta}}_g = -\gamma_2 \underline{e}^T P \underline{b}_c \underline{\xi}(\underline{x}) u_c$

• If $(|\underline{\theta}_g| = M_g$ and$\underline{e}^T P \underline{b}_c \underline{\theta}_g^T \underline{\xi}(\underline{x}) u_c < 0)$ then

• $\dot{\underline{\theta}}_g =$

$$\begin{cases} P\left\{-\gamma_2 \underline{e}^T P \underline{b}_c \underline{\xi}(\underline{x}) u_c\right\} = \\ = -\gamma_2 \underline{e}^T P \underline{b}_c \underline{\xi}(\underline{x}) u_c + +\gamma_2 \underline{e}^T P \underline{b}_c \frac{\underline{\theta}_g {\underline{\theta}_g}^T \underline{\xi}(\underline{x}) u_c}{|\underline{\theta}_g|^2} \end{cases}$$

IV. SIMULATION

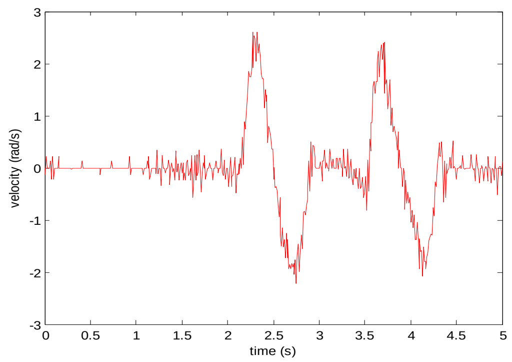
A. *Clinical Gait Analysissignal processing*

The system is designed to assist patients to rehabilitate their walking ability by using the sample data measured from Clinical Gait Analysis (CGA). Markerspinned to specific parts (joints and links) on a human body are recognized by a system of cameras. These recorded images will be analyzed by CGA software to generate the positions of joints. The partial data is shown in Table 1.However, if the data is sent directly to the controller, disturbances of the measured data will probably decrease the quality of input data such as position and velocity. It leads to an inaccuracy of control behaviors. Therefore, a method to smooth signals is necessary. The function *smooth* in MATLAB will be undertaken tofilters the data to eliminate noises. The moving average filter smooths data by replacing each data point with the average of the neighboring data points defined within the span.

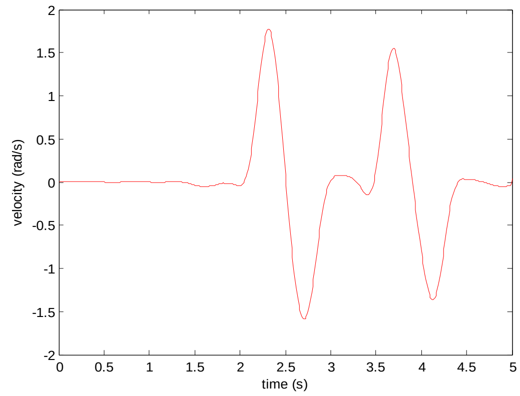
Table I . Measured Joint Positions from Clinical Gait Analysis

No.	a_x	a_y	a_z	k_x	k_y	k_z	h_x	h_y	h_z
1	528	-119	93	542	-25	456	566	-10	845
2	528	-119	93	542	-25	456	566	-10	845
3	527	-119	93	542	-24	456	566	-10	845
4	528	-119	93	541	-24	456	566	-10	845
5	528	-119	93	541	-24	456	566	-10	845
6	527	-119	93	541	-24	456	566	-10	845
7	527	-119	93	541	-24	456	566	-10	845
…	…	…	…	…	…	…	…	…	…

This process is equivalent to low-pass filtering with the response of the smoothing given by the difference equation. Hence, velocity reference input is improvedfrom noisy signal (Fig. 7a) to a smooth wave (Fig. 7b). It is thanks to the filter that the control signal turns from a nosy waveform (Fig. 8a) intoa smoother one (Fig. 8b).The control signalu is an input of DC motor drive system. After that, the drive system needs to generate equivalent PWM pulses to make DC motor rotate with expected angles and velocities.

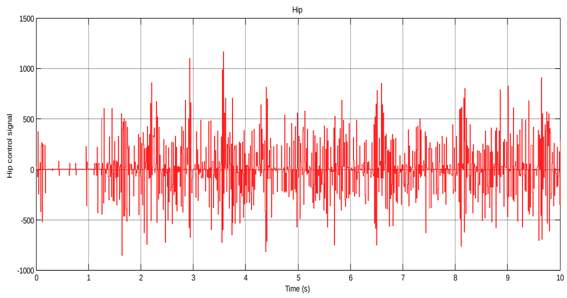


(a)

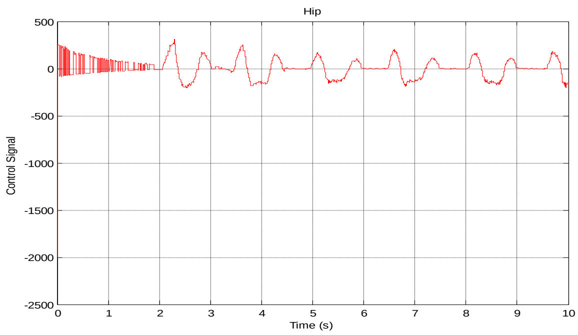


(b)

Fig.7. Velocity reference signal (a) without filter (b) filtered signal



(a)



(b)

Fig.8. Control signal (a) without filter (b) when inputs are filtered

B. Simulations with different models

MATLABis applied to design and validate workability ofthe system. The mathematical model as mentioned in Section II-B and Simmechanics modelare consideredto demonstrate the performance ofadaptive fuzzy controllers in the proposed exoskeleton system. Besides, two waveforms of the input signal applied to the system are sinusoidal and human trajectory. The perfect sinusoidal signal enables to test the performance of the system with an easy case while the human trajectoryformed from normal human walking experiments in the laboratory (CGA data)intends to check the adaptation ability of the controller. After being collected, the raw data is filtered to remove noise in order to have a smooth shape as mentioned in Section IV-A.Therefore, the system using the target trajectory enablesparalyzed patients to walk naturally.

1) Simulation with mathematical model

The mathematical model of the ankle joint in equations (1-4) is used to simulate the system with the performance as demonstrated in Fig. 9and Fig. 10. It can be seen that the controlledjoint angle follows the desired one with tinny errors (approximately zero)and no overshoot in two cases of input. Results for other joints are the same as that of ankle joint.

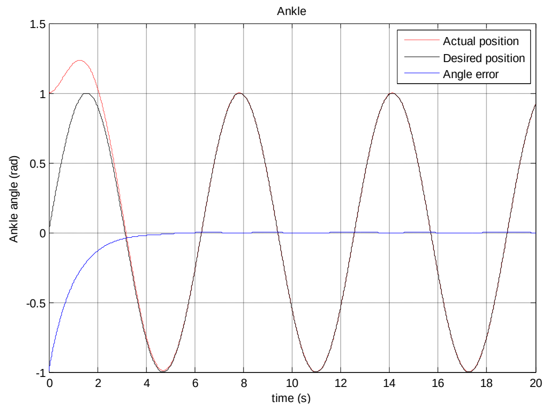


Fig.9. Ankle angle with the sinusoidal input

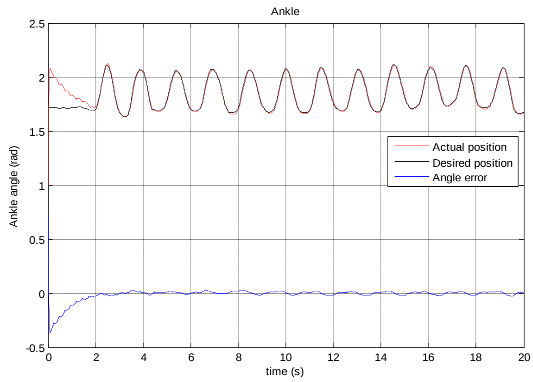


Fig.10. Ankle angle with the human trajectory

2) Simulation with SimMechanics model

The 3-DOF model of the system is designed by MATLAB Simulink and SimMechanicsas shown in Fig.11. SimMechanics software is a block diagram modeling environment for the engineering design and simulation of rigid multi-body machines and their motions, using the standard Newtonian dynamics of forces and torques.The right leg of the exoskeleton comprises 3 joints and 3 links. Three joints including hip, knee and ankleare designed as revolute joints by using Joint Actuator blocks. Three links are thigh, shank and foot builtby Body blocks. Parameters of three links are obtained according to the dimensions of the proposed exoskeleton as shown in Table 2.

Table II. Dimensions of the Exoskeleton

Segments	Length	Mass
Hip connection		254 g
Thigh (l_1)	$41 \pm 4.5\ cm$	465 g
Shank (l_2)	$41 \pm 4.5\ cm$	462 g
Foot		273 g
Human load		80 kg

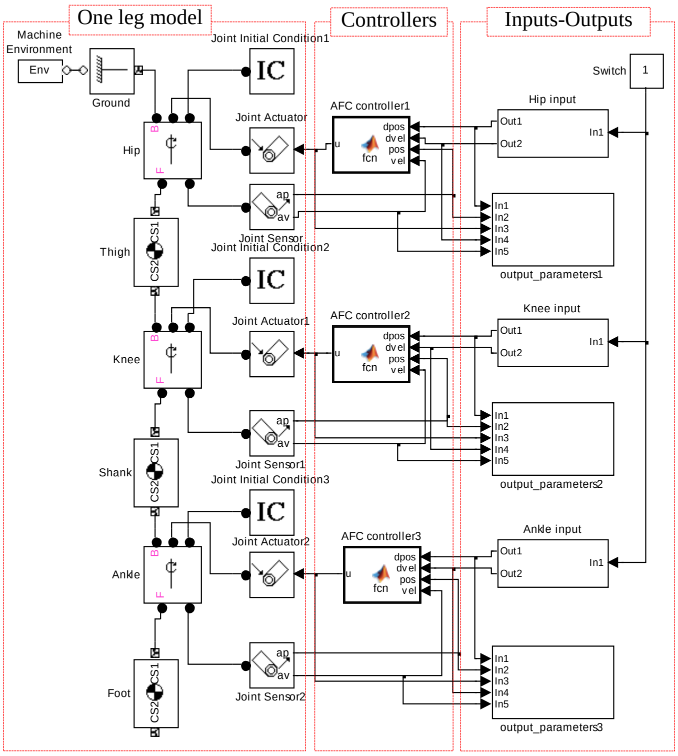


Fig.11. Simulation model of 3 DOF exoskeleton system

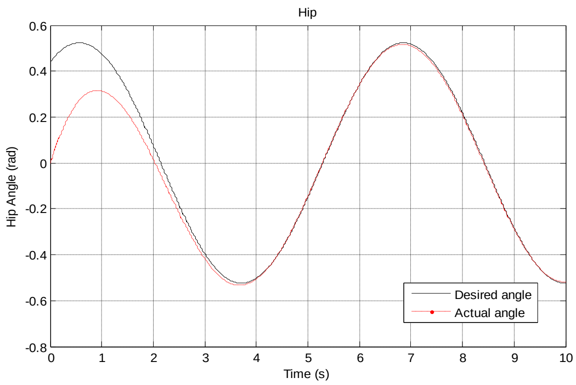


Fig.12. Hip angle with sinusoidal input

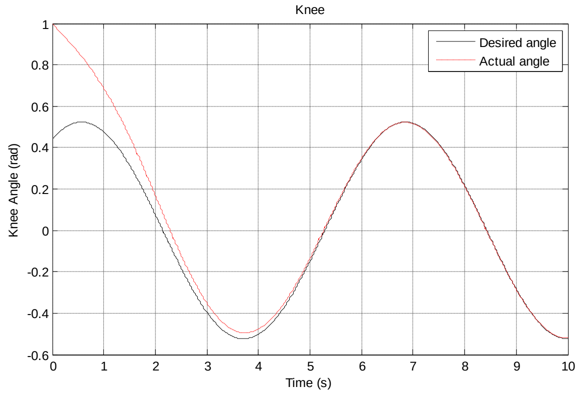


Fig.13. Knee angle with sinusoidal input

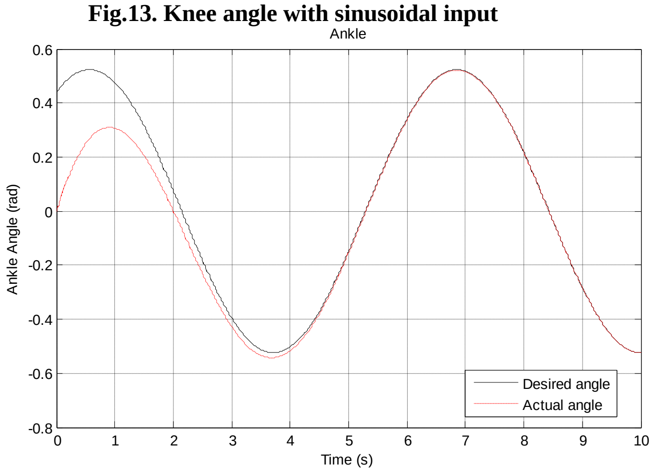


Fig.14. Ankle angle with sinusoidal input

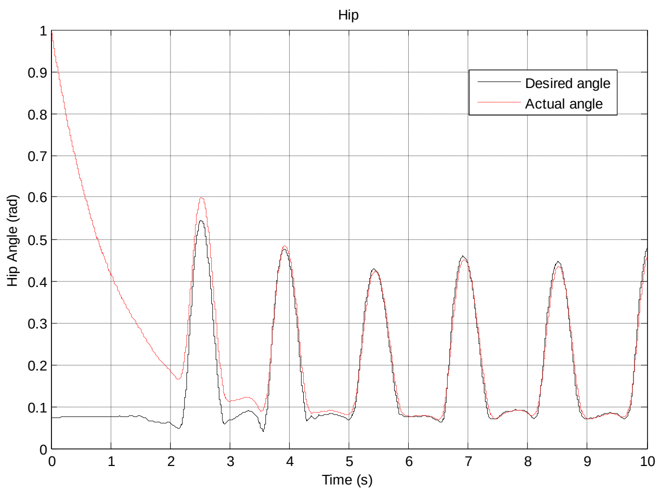


Fig.15. Hip angle with the target trajectory

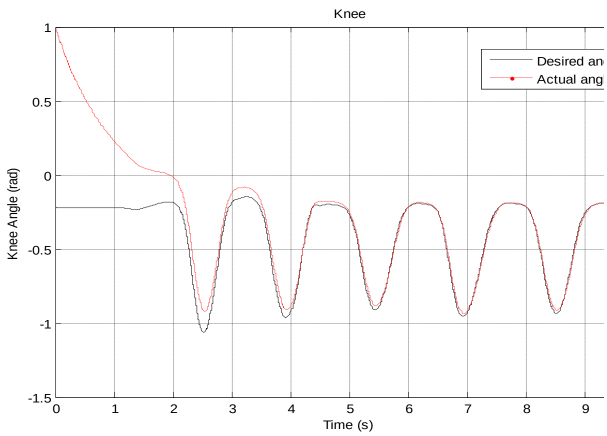


Fig.16. Knee angle with the target trajectory

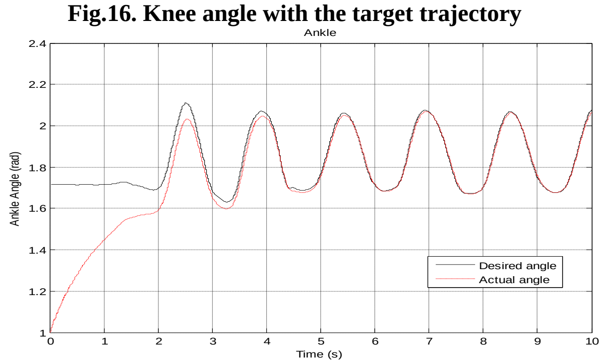


Fig.17. Ankle angle with the target trajectory

Sinusoidal input performance is illustrated in Figs. 12-14. We can see from the data that actual hip, knee and ankle angles converge to the desired sinusoidal signal with negligible errors. Figs. 15-17 reveal angle performance of three joints with the human trajectories. Especially, these responses of the exoskeleton system do not consist of overshoots in all cases of input signals. It leads to guaranteeing safety of patients when using the rehabilitation system. Angular trajectory of every joint follows CGA data with very minor error.

V. CONCLUSION

In this paper, a novel intelligent lower extremity rehabilitation training systemis proposed for robotic leg exoskeleton. Design and models of the system are built to obtain parameters of the controller. Then, the data from CGA is filtered to improve quality of the control system.The adaptive fuzzy controller used to drive each joint in robotic leg exoskeleton shows its significant performance with two types of input signals.In the future, this system wouldbe implemented in the real system. Moreover, an interaction between the assisted exoskeleton and the central nerve system of patients will be considered to improve flexibility of the rehabilitating system.

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