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Iterative Learning Control Method for Improving the Effectiveness of Upper Limb Rehabilitation

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***Abstract*—In rehabilitation, passive control mode is common used at early stages of the post-stroke therapy, when the impaired limb is usually unresponsive. The simplest is the use of a proportional-integral-derivative (PID) feedback control which usually regulates the position or the interaction force along a known reference. Nonetheless PID method cannot achieve an ideal tracking performance due to dynamical uncertainties and unknown time-varying periodic disturbances from the environment. In order to minimize steady-state error with respect to uncertainties in exoskeleton passive control, Iterative Learning Control(ILC) and Neural PID control are proposed to improve the control effective of conventional linear PID. In this paper, two different control algorithms are introduced. Moreover, an experimental study on a 5-DOF upper limb exoskeleton with them is addressed for comparison.**

Keywords—upper limb exoskeleton; passive control mode; Iterative Learning Control (ILC); Neural PID Introduction

I. ITRODUCTION

According to World Health Organization (WHO), stroke is the third most common cause of death in developed countries, exceeded only by coronary heart disease and cancer [1]. Conventionally, stroke rehabilitation needs one-to-one manual interactions with therapists [7]. Treatment plans mean that it should therapy for several weeks, which makes it difficult to offer highly intensive treatment for patients [10]. In recent years, using rehabilitation robot has been received increasing attention for stroke recovery [5], which can provide repetitive, task-specific and effective treatment of the impaired upper limb [10].

In rehabilitation, it is hardy for patients to move their impaired upper limbs that are very unresponsive at the beginning [5]. Thus, passive training could be a feasible way in early period [11]. Thus, passive control has been to proposed [16], which means to control the motion of an exoskeleton rigidly along a desired reference trajectory through position feedback control with high corrective gains [6]. Actually, passive control can adopt various techniques to achieve. Proportional-integral-derivative (PID) feedback control is the most common method [3]. It is usually regulates the interaction force or the position or along a known reference (e.g. a trajectory or a force field model), and also used either at the joint or at the end-effector level. Nevertheless, there are few research regarding PID gains tuning for upper limb robots. Independently using PID tuning algorithms is not possible due to the responses being nonlinear. Therefore, intelligent control strategies have been researched and widely used [2, 26, 28]. Neural PID is a typical one. Being similar with robust adaptive control methods [24, 29], it could adjust weights in order to adjust parameters of PID by updating laws to make the closed-loop systems stable. Iterative Learning Control (ILC) has been important to provide improvement in tracking performance compared with the use of feedback controllers alone [19]. Initially, ILC algorithms were developed based on the contraction mapping theory and required priori knowledge [20]

In this paper, two different passive control methods were proposed for passive trajectory tracking of an upper limb exoskeleton robot in order to improve its effectiveness when treating stroke patients. The effectiveness of the proposed adaptation strategy is evaluated by experiments. The paper is organized as follows: Section II, iterative learning control and neural PID control are introduced, and back propagation neural network (BPNN) algorithm was presented for PID parameters adjusting. A 5 DOF upper limb exoskeleton is presented and experiments are carried out in Section III. Section IV gives conclusions of this work.

II. METHODS

A. Iterative Learning Control (ILC)

Fig 1 shows the ILC Control Structure [23]. UP represents the upper limb robot; C is the feedback of the controller, and L is the feed-forward of the controllers; MEM is the memory for the system; the control law $u = u_k + u_c$,which $k = 1,2,...,N$ is the current iteration number, where the feed-forward u_k is the input trajectory; q_k is the real output trajectory; and q_d is the desired output trajectory. u_{k+1} is next term of u_k ,which presents the feed-forward off-lined calculated iteration result The feed-forward controller is based on the update control law that improves the feed-forward control term (u_k) .For the nonlinear dynamic model, we propose the following update control law[19]:

$$u_{k+1}(t) = u_k(t) + \Gamma \dot{e}_k(t) + \Phi e_k(t) + \Psi \int_0^t e_k(\tau) d\tau \qquad (1)$$

where Γ, Φ, Ψ are learning gain matrixes; the error between real position and the desired position is $e_k(t) = q_d(t) \quad q_k(t)$;the

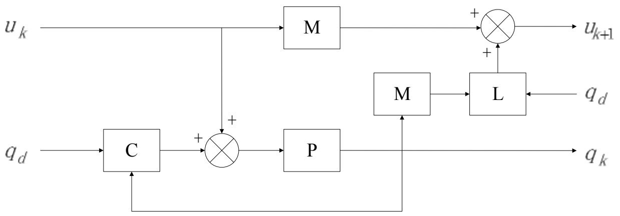

Fig. 1 ILC Control Structure

initial input of feed-forward control is $u_0(t)$; $t : t \in [0,T]$ is the tracking time, and $[0,T]$ is the robot tracking time interval.

Learning algorithm convergence analysis is very important for ILC. An adequate condition called spectral radius method is a good way to measure whether proposed update control law could guarantee robustness and convergence. It has been proved the considered dynamic model of the upper limb robot if it can be satisfied as followed [18]:

$$\left\| I - LA^{-1} \right\| \leqslant \rho < 1 \qquad (2)$$

where I is the identity matrix, A is the inertia matrix of the dynamic equations of motion, L is the learning operator that is to be specified, and $\| .. \|$ is the Euclidean matrix norm.

B. Neural PID Control

Neural PID control method is to adjust the weights of each neural network in order to achieve optimal PID parameters by training[27]. Back propagation neural network (BPNN) structure has been used. Where, $\tilde{x}_m = x_m \quad x_d$, $\dot{\tilde{x}}_m = \dot{x}_m \quad \dot{x}_d$, $\ddot{\tilde{x}}_m = \ddot{x}_m \quad \ddot{x}_d$ .There are two inputs and three outputs for the controller. First one is the l th error of positionand $e_{lp} = P_{ld} \quad P_l$ second one is the l th error of velocity $\dot{e}_{lp} = \dot{P}_{ld} - \dot{P}_l$ .Outputs are the l th desired PID parameters K_{lp} , K_{li} and K_{ld} .

This neural network included two inputs, four hidden neurons and three output neurons.

$$i_n = e(n), n = 1,2 \qquad (3)$$

$$net_{hm}(k) = \sum_{n=1}^{2} \omega_{hmn} i_n , m = 1,2...,4 \qquad (4)$$

$$O_{hm}(k) = f(net_{hm}(k)), m = 1,2...,4 \qquad (5)$$

$$O(z) = f(z) = \frac{1}{1 + e^{(-z)}} \qquad (6)$$

where i_n are inputs, which $e_{lp} = e(1)$ and $\dot{e}_{lp} = e(2)$, net_{hm} is the input of the m th hidden layer, The variable ω_{hmn} denotes the weight between neurons m and n .Then use the logistic function to squash (8) in order to get the output of . $O(z)$ is in general non-linear and differentiable so that it is commonly used as a logistic function. Correspondingly, it could be calculated both inputs and outputs of output layer.

$$net_{ov}(k) = \sum_{v=1}^{3} \omega_{ovm} o_{hm} , m = 1,2...,4 \qquad (7)$$

$$O_{ov}(k) = f(net_{ov}(k)), v = 1,2,3 \qquad (8)$$

The squared error function can be used to achieve the error for each output neuron and sum them to get the total error

$$E_{o1}(k) = \frac{1}{2}(K_{tp}(k) - K_{lp}(k))^2 \qquad (9)$$

$$E_{o2}(k) = \frac{1}{2}(K_{ti}(k) - K_{li}(k))^2 \qquad (10)$$

$$E_{o3}(k) = \frac{1}{2}(K_{td}(k) - K_{ld}(k))^2 \qquad (11)$$

$$E_{total}(k) = E_{o1}(k) + E_{o2}(k) + E_{o3}(k) \qquad (12)$$

Where $K_{tp}(k)$, $K_{ti}(k)$ and $K_{td}(k)$ are the training target PID parameters, which are compared with real outputs $K_{lp}(k)$, $K_{li}(k)$ and $K_{ld}(k)$. The goal is to update each of the weights in the network so that they cause the actual outputs to be closer the target outputs, thereby minimizing the error for each output neuron and the network as a whole.

$$\Delta\omega(k) = \eta \frac{\partial E_o(k)}{\partial \omega} + \gamma \Delta\omega(k-1) \qquad (13)$$

With gradient descent method, learning rate η and inertia coefficient γ can be used to describe weights changing.

III. Experiment and Results

In order to test these two passive control methods, a 5DOF exoskeleton has been used to track trajectory experiments. The exoskeleton consists of 5 DOF, including actuating 4 DOF (3 DOF for shoulder joint spherical motion and 1 DOF for actuating)and elbow 1 DOF(Fig.3). In addition, the exoskeleton could achieve flexion & extension, for both shoulder and elbow, medial & lateral rotation running and abduction & adduction for shoulder. By using the exoskeleton, the patients should be in a seated position in order to ensure the patients will be limited in the appropriate usage position. The exoskeleton uses five motors to operate the exoskeleton to ensure they do not interfere with the movements of the exoskeleton. A keyed shaft transmits torque between the motors and the link segments[16].

The Newton-Euler method is used to derive the equations of motion for each exoskeleton joint (14) where τ_a is the actuation torque produced by the motor-gearbox unit, τ_i is the torque due to inertia2, τ_g is the torque caused by gravitational forces, τ_f is the friction torque, τ_d is the torque caused by the disturbance user's limb movements. On a flip side, torque caused by coriolis and centrifugal effects are small since the exoskeleton operates at low velocities and are assumed to be negligible.

$$\tau_a = \tau_i + \tau_g + \tau_f + \tau_d \tag{14}$$

The inertial torque experienced by an exoskeleton joint is given by (15) where I_s is the inertia tensor of the segment at the joint coordinate system, α is the angular acceleration of the joint and N is the total number of segments acting on the joint.

$$\tau_i = \sum_{S}^{N} I_s \times \alpha \tag{15}$$

As with inertial torque, the torque caused by gravitational effects also depends on the configuration of the exoskeleton. The gravitational torque acting on an exoskeleton joint is given by (16) where p_s is the displacement vector from the joint to the center of mass of segment, m_s is the mass of the segment, R_s is the rotation transformation matrix between the global coordinate system and the joint coordinate system and g is the gravitational constant vector in the global coordinate system.

$$\tau_g = \sum_{S}^{N} p_s \times (m_s (R_s g)) \tag{16}$$

Friction is a resistance to joint motion and is present in the motor, gearbox, bearings and the Joint 4 rail. In the present work, friction is modeled using a piecewise function (17) where k_f is the positive torque constant determined experimentally. The friction torque is assumed to act in the direction opposite to joint motion and if the joint is stationary then the friction torque is considered to be acting opposite to the direction of the control output.

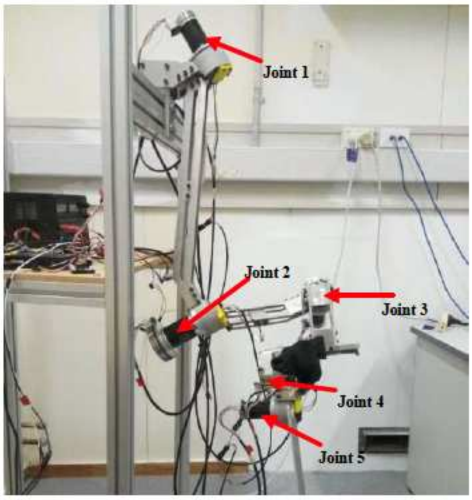

Fig. 2 The 5 DOF exoskeleton prototype

$$\tau_f \begin{cases} k_f & if(\dot{\theta} < 0 \; or \; \dot{\theta} = 0 \; \& \; \tau_m < 0) \\ 0 & if(\dot{\theta} = 0) \ldots \tau_m = 0) \\ -k_f & if(\dot{\theta} > 0 \; or \; \dot{\theta} = 0 \; \& \; \tau_m > 0) \end{cases} \tag{17}$$

The experiments consist of 2 parts. Firstly, it is designed to use elbow joint to track a $\pi/4$ arc trajectory in order to test the transient response of two methods. Secondly, a round-trip repetitive $\pi/4$ arc trajectory is used to test rapidity, accuracy and stability. For contrasting intuitively, linear PID control is implemented. It regards angle error as the result, and uses Root-Mean-Square Error (RMSE) to measure the property.

The control result of first test is shown in Fig.3, and the RMSE is shown in Table I. The performances (main transient) of both Neural PID and ILC methods are good, but linear PID one is poorer. There still exists regulation error because of mechanical vibration. Moreover, it is shown in Table I that the errors of Neural PID are smaller than ILC ones.

The control result of second test is shown in Fig.5, and the RMSE is shown in Table II, the performances of ILC method is much better than Neural PID method , According to Table II, it shows that ILC method has the smaller errors.

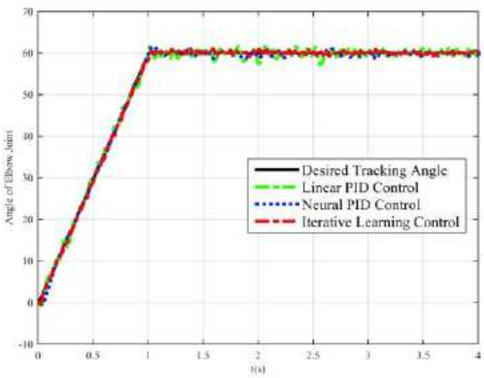

Fig. 3 Elbow Angle in first test

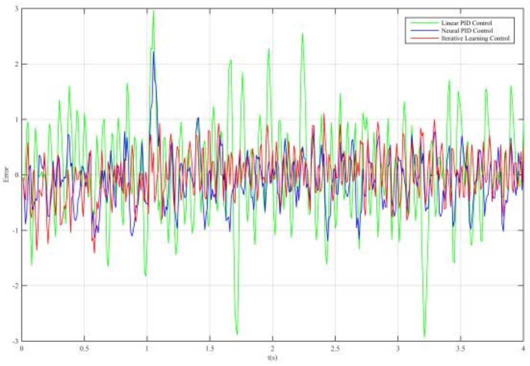

Fig. 4 Elbow Angle Errors in first test

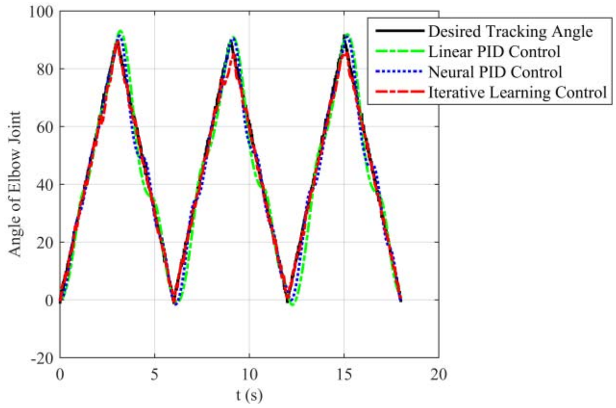

Fig. 5 Elbow Angle Errors in second test

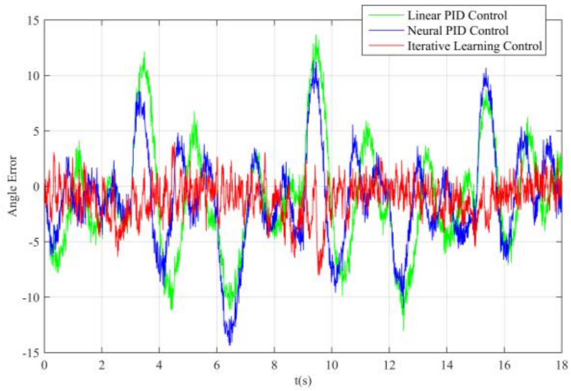

Fig. 6 Elbow Angle Errors in second test

Clearly, both Neural PID control and ILC could successfully achieve a good performance of tracking trajectory. Because they have compensator to handle the uncertainties, instead of using fixed PID parameters. Neural PID has good performance of the transient response due to its previous training parameters. However, ILC has advantage improving effectiveness by learning laws

TABLE I RMSE of first test

	ILC	**Neural PID**	**Linear PID**
	1.44	1.75	2.92
	1.75	1.81	2.76
RMSE	0.44	0.96	2.44
	0.07	0.39	2.37
	0.19	0.29	1.92

TABLE II RMSE of second test

	ILC	**Neural PID**	**Linear PID**
	5.50	9.44	10.90
	3.50	7.45	9.84
RMSE	2.41	7.43	9.88
	4.48	8.43	11.90
	1.88	6. 91	9.81

IV. Conclusion

The paper proposed a new ILC method and neural PID control method for improving the effectiveness of upper limb rehabilitation. The control methods have been developed for a passive control mode of an upper limb exoskeleton, which was developed at the Medical and Rehabilitation Robotics group at the University of Auckland. The neural PID and ILC have been developed to control the 5-DOF exoskeleton robot. Theory and experiment analysis show the different characteristics and reliable validity of control methods in the passive control mode. Neural PID method is an available control strategy displacing linear PID by achieving training parameters, the method has been compared with ILC method. Evidences showed that the ILC method is an effective technique for repetitive rehabilitation passive training because of its learning ability, which will increase tracking accuracy.

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