CONTROL NOVEL MODEL OF KNEE CPM DEVICE

Tu Diep Cong Thanh
University of Technology, VNU-HCM
(Manuscript Received on Octoberr 13th, 2008, Manuscript Revised March 10th, 2009)

ABSTRACT: *In recent years, CPM – Continuous Passive Motion has been proved to be one of the most effective therapeutic methods for patients who have problems with motion such as spinal cord injury, ankle and knee injury, parkinson and so on. Many commercial CPM devices are found in market but all of them use motors as the main actuators. The lack of human compliance of electric actuators, which are commonly used in these machines, makes them potentially harmful to patients. An interesting alternative to electric actuators for medical purposes, particularly promising for rehabilitation, is a pneumatic artificial muscle (PAM) actuator because of its high power/weight ratio and compliance properties. However, the highly nonlinear and hysteresis of PAM make it the challenging for design and control. In this study, a PID compensation using neural network control is studied to improve the control performance of the novel model of Knee CPM device*

1.INTRODUCTION

One of the most concerning fields in the world is medical and human welfare. Due to the sensibility of safeness, there were not many automatic devices and robots applying in this field. Nevertheless, the significant developments of science and technology recently have allowed high – tech equipments permeating this field, and one of the most specific area is rehabilitation. As one of the most effective therapeutic methods for patients who have problems with motion, Continuous Passive Motion has been proved. There is some commercial exercise machines designed for rehabilitation purposes in recent years. These devices are passable both in model and mechanical operations. Some commercial CPM devices are found in market but all of them use motors as the main actuators [1-3]. Although, motor is the most commonly used actuator in technology because of its advantages such as accurate position and velocity control, convenience, easy-produced characteristic...But electric actuator suffers from relatively low power/weight ratio, lack of hygiene, difficulty in preservation and especially the lack of human compliance which is the most important requirement in medical and human welfare field. Therefore, it is not an ideal actuator for human coexisting and collaborative tasks. An interesting alternative to electric actuators for medical purposes, particularly promising for rehabilitation, is a pneumatic artificial muscle (PAM) actuator. PAM possesses many muscle–like properties such as tunable stiffness, high strength to weight ratio, structure flexibility, cleanliness and especially the inherent safety and mobility assistance to humans performing tasks [4-5]. In our purpose, Knee CPM device, one set PAM-Spring is used as an actuator for a crank-slide mechanism. To guarantee the range of knee's motion a pulleys-system is used to amplify the range of PAM. All of them along with hysteresis of PAM make the device become a complex nonlinear dynamics and low-damping system. This causes many difficulties in controlling the angular position of knee. In order to realize satisfaction control performance of Knee device, some control strategies have been proposed such as an adaptive/self-tuning PID controller [6-7], self-tuning PID control structures [8-9], self-tuning predictive PID controller [10-11], and so on.. Though satisfactory performance can be obtained and the proposed controllers above provide better response, these controllers are still limited because of the limitation of capability of learning algorithm, automatically tuning control parameters and not yet handling nonlinear characteristic. To improve control performance of device, an intelligent control technique has emerged as highly potential methods [12-13]. In this study, a Hybrid Neuro-PID control algorithm using neural network for a new model knee CPM device is proposed. The experiments are carried out in practical Knee CPM device and the effectiveness of the proposed control algorithm is demonstrated through experiments with two kinds of treatment methods.

The organization of the paper is as follow: Section 2 is about the knee rehabilitation experimental setup. The proposed controller is mentioned in section 3 with structure and learning algorithm while the experiment results are taken up in section 4. Section 5 will conclude the paper.

2.EXPERIMENTAL SETUP

As proving above, PAM is an optimistic actuator for medical and human welfare field and therefore rehabilitation. Nonetheless, it is rarely applied to this field due to the difficulty in position control. Here, a device using PAM (FESTO, MAS-40-N-300-AA-MCFK) as actuator is designed specially for knee rehabilitation task. The photograph of the device is shown in Fig. 1. The system includes a personal computer which used to control the proportional valve (FESTO, MPYE-5-1/8HF-710B) through D/A board (ADVANTECH, PCI 1711). The schematic diagram of the system can easily be seen in Fig.2. A rotary encoder (METRONIX, H40-8-3600ZO) is used to measure the angular input from the device and fed back to the computer through a 32-bit digital counter board (ADVANTECH, PCI 1784). The external load conditions are considered in two cases: with and without the patient. The experiments are conducted under the pressure of 0.4 [MPa] and all control software is coded in Visual C program language

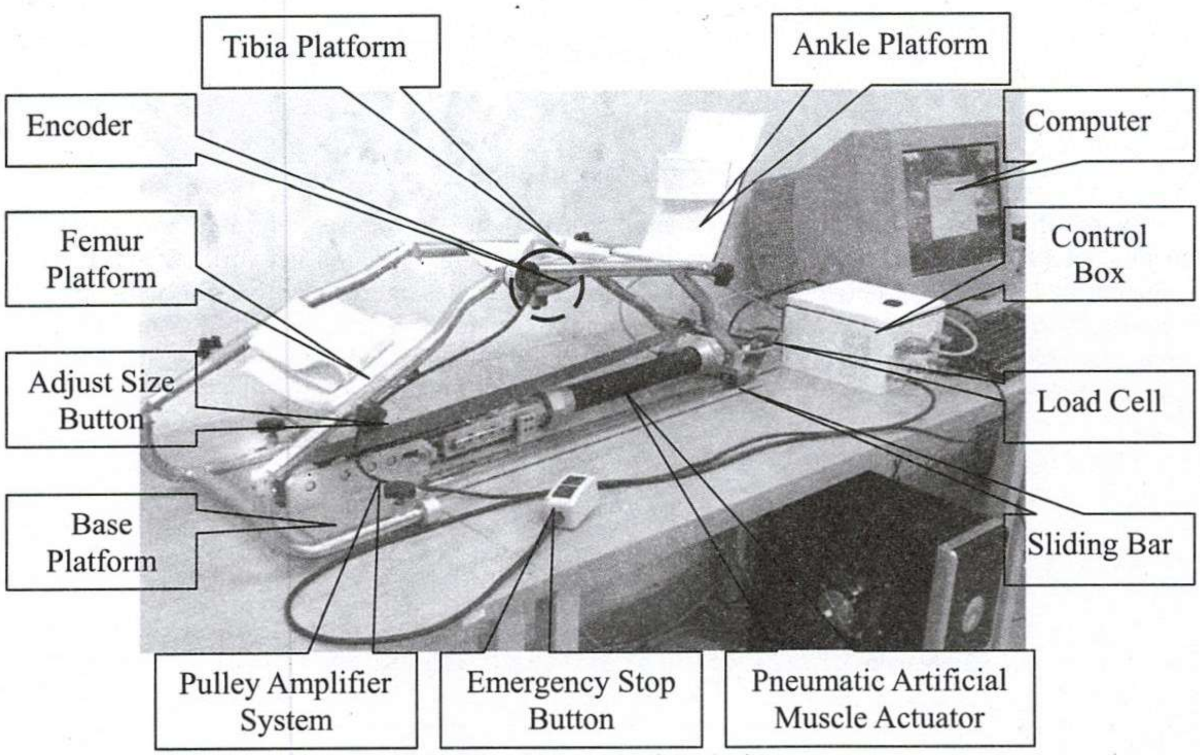

Fig 1. The photograph of the device

3.CONTROL SYSTEM

Up to now, PID is still a favorite controller because of its simplicity and effectiveness, especially in industrial domain. However, with some highly nonlinear systems, PID seems to be not a good choice. For the past decades, many modern control algorithms have been developed such as robust control, Adaptive control, Fuzzy logic control ...to solve complex control problems. Among them, Neural Network-based control algorithms have obtained much attention because of the nonlinear mapping and learning capacity. In the controller designed for knee CPM device, a combination between conventional PID and Neural Network is made to increase the performance and the adaptive ability of system. PID compensation using neural network is proposed in this case.

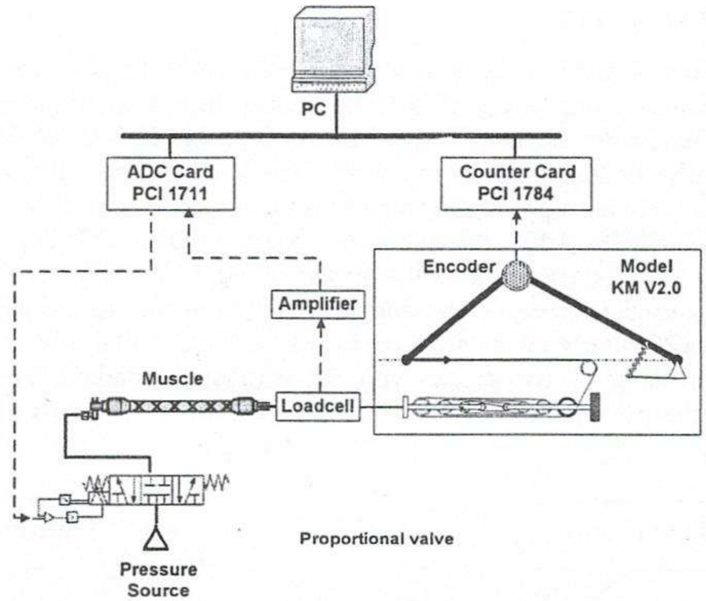

Fig 2. Schematic diagram of device

It is difficult to find suitable PID for nonlinear systems. In this section, a compensation method of PID for the nonlinear systems is proposed by using a neural network. With value compensated by neural network, the PID controller becomes more adaptive for nonlinear systems with changing external load. The control diagram is shown in Fig. 3. Here, conventional PID controller is installed in parallel with a neural network controller. A conventional PID control algorithm is applied in this paper as the basic controller.

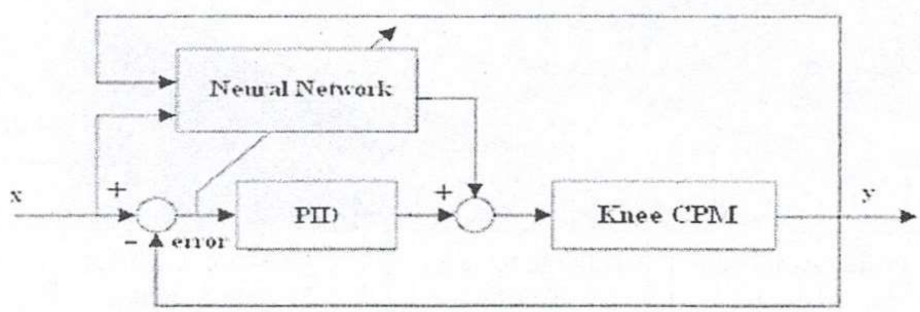

Fig 3. Diagram of PID compensation using neural network algorithm

The controller output can be expressed in the time domain as:

$$u_f(t) = K_p e(t) + \frac{K_p}{T_i}\int_0^t e(t)dt + K_p T_d \frac{de(t)}{dt} \tag{1}$$

Taking the Laplace transform of (1) yields:

$$U_f(s) = K_p E(s) + \frac{K_p}{T_i s}E(s) + K_p T_d s E(s) \tag{2}$$

The resulting PID controller transfer function of:

$$\frac{U_f(s)}{E(s)} = K_p\left(1 + \frac{1}{T_i s} + T_d s\right) \tag{3}$$

A typical real-time implementation at sampling sequence k can be expressed as:

$$u_f(k) = K_p e(k) + u(k-1) + \frac{K_p T}{T_i}e(k) + K_p T_d \frac{e(k) - e(k-1)}{T} \tag{4}$$

$$e(k) = y(k) - x(k) \tag{5}$$

where $u_f(k)$, $e(k)$, $y(k)$ and $x(k)$ are the output of conventional PID controller, the error between the desired set point and the output, the output and the desired set point, respectively.

From Fig. 3, the control input to plant can be computed as follow:

$$u(k) = u_f(k) + u_N(k) \tag{6}$$

where $u_N(k)$ is the modify-output of neural network controller.

In order to overcome the limitation of the conventional PID controller and improve its property, a neural network controller is installed in parallel with conventional PID controller as compensator. Neural network controller can represent any nonlinear function, and has self-learning and parallel processing abilities as well as strong robustness and fault-tolerance which are limitations of PID controller. Besides, its well-known steepest descent learning method allows it to fit well for online adaptive control parallel with PID controller. However, because of the risk of overtraining, non - optimizing learning rate, initial conditions and number of neurons, Neural Network alone could potentially make the system unstable. In this case, Conventional PID controller's contribution ensures the stability of the system. The PID's weak point of slow response may now appear as an important moderator which restrains the fluctuation of Neural Network Controller and tend to bring it into normal. In addition, a clear effect of conventional PID controller, which is shown in experimental results, is ensuring the stability of the system at the beginning of Neural Network's online learning process.

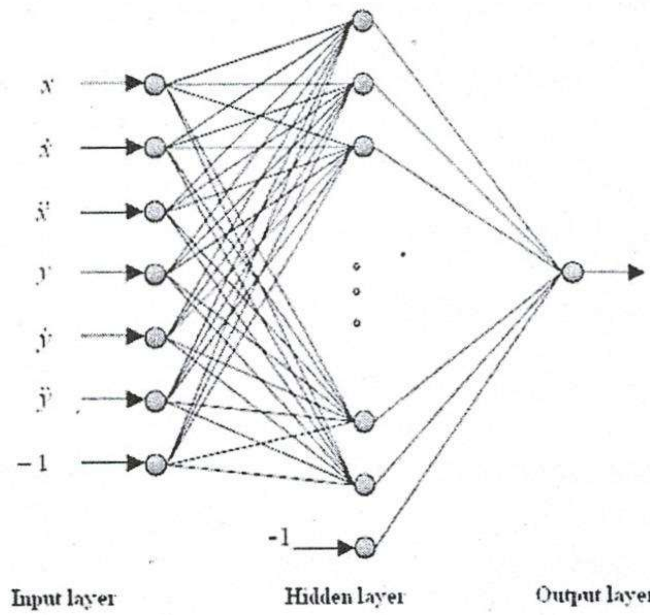

Fig 4. Structure of neural network controller

Figure 4 shows the structure of the PID compensation using neural network. The input layer has four neurons including a neuron with output of -1 to set the bias value of each neuron in hidden layer. There are seven neurons including a neuron with -1 in hidden layer. All layers are connected in only the forward direction. The input to each neuron is given as the weighted sum of outputs from the previous layer. The output of each neuron is generated by linear function in the input layer; in hidden and output layers the sigmoid function is used.

$$f_{sigmoid}(x) = \frac{1}{1+e^{-x}} \tag{7}$$

To construct learning rule, the following symbols are defined:

i_j^I : Input to the j[th] neuron in the input layer

o_j^I : Output from the j[th] neuron in the input layer

i_k^H : Input to the kth neuron in the hidden layer

o_k^H : Output of the k[th] neuron in the hidden layer

i^O : Input to the output layer

o^O : Output from the output layer

ω_{jk}^{IH} : Weight from the j[th] neuron in the input layer to the k[th] neuron in the hidden layer

ω_k^{HO} : Weight from the k[th] neuron in the hidden layer to the output layer

The modify-output of neural network controller can be expressed as following equation

$$u_N = K_n\left(o^O - 0.5\right) \tag{8}$$

K_n : Proportional gain of the output of neural network controller

The operation of each neuron is described as: $o_j^I = i_j^I$ (9)

$$o_k^H = f_{sigmoid}(i_k^H), \quad i_k^H = \sum_j \omega_{jk}^{IH} o_j^I \tag{10}$$

$$o^O = f_{sigmoid}(i^O), \quad i^O = \sum_k \omega_k^{HO} o_k^H \tag{11}$$

The leaning process is based on the back propagation algorithm, which minimizes E given by:

$$E = \frac{1}{2}\left(\theta_{ref} - \theta\right)^2 = \frac{1}{2}e^2 \tag{12}$$

The weights are updated by the following increments to minimize E:

$$\Delta\omega_{jk}^{IH} = -\eta \times \frac{\partial E}{\partial \omega_{jk}^{IH}} \tag{13}$$

$$\Delta\omega_k^{HO} = -\eta \times \frac{\partial E}{\partial \omega_k^{HO}} \tag{14}$$

where $\eta > 0$ is learning rate to determine the speed of leaning. $\frac{\partial E}{\partial \omega_k^{HO}}$ in Eq. (14) can be calculated by: $\frac{\partial E}{\partial \omega_k^{HO}} = \frac{\partial E}{\partial i^O}\frac{\partial i^O}{\partial \omega_k^{HO}}$ (15)

$$\frac{\partial i^O}{\partial \omega_k^{HO}} = \frac{\partial}{\partial \omega_k^{HO}}\left(\sum_k \omega_k^{HO} o_k^H\right) = o_k^H \tag{16}$$

$$\frac{\partial E}{\partial i^O} = -\delta^O \tag{17}$$

$$\frac{\partial E}{\partial \omega_k^{HO}} = -\delta^O \times o_k^H \tag{18}$$

δ^O is called a generalized error calculated by:

$$\delta^O = -\frac{\partial E}{\partial y}\frac{\partial y}{\partial o^O}\frac{\partial o^O}{\partial i^O} \tag{19}$$

$$\frac{\partial E}{\partial y} = \frac{\partial}{\partial y}\left(\frac{1}{2}(x-y)^2\right) = -e \tag{20}$$

$$\frac{\partial o^O}{\partial i^O} = \frac{\partial f_{sigmoid}(i^O)}{\partial i^O} = f'_{sigmoid}(i^O) \tag{21}$$

For convenience, $\frac{\partial y}{\partial o^O}$ is assumed to be constant:

$$\frac{\partial y}{\partial o^O} = C = const \tag{22}$$

The increment of weight can be written as:

$$\Delta\omega_k^{HO} = -\eta \times \frac{\partial E}{\partial \omega_k^{HO}} = \eta \times \delta^O \times o_k^H \tag{23}$$

Consequently, the weight is updated by:

$$\begin{aligned} \omega_k^{HO} &= \omega_k^{HO} + \eta \times \delta^O \times o_k^H \\ &= \omega_k^{HO} + \eta \times e \times C \times f'_{sigmoid}(i^O) \times o_k^H \end{aligned} \tag{24}$$

The update equation, Eq. (25) of the weight ω_{jk}^{IH} can be derived in the same manner.

$$\omega_{jk}^{IH} = \omega_{jk}^{IH} + \eta \times \delta_k^H \times o_j^I \tag{25}$$

where,

$$\begin{aligned} \delta_k^H &= -\frac{\partial E}{\partial y}\frac{\partial y}{\partial o^O}\frac{\partial o^O}{\partial i^O}\frac{\partial i^O}{\partial o_k^H}\frac{\partial o_k^H}{\partial i_k^H} \\ &= e \times C \times f'_{sigmoid}(i^O) \times \omega_k^{HO} \times f'_{sigmoid}(i_k^H) \end{aligned} \tag{26}$$

The structure and the learning algorithm of the network are relative simple and the physical meaning of the input and outputs is clear. The effectiveness of the proposed Hybrid Neuron - PID control strategy will be demonstrated through experiments.

4.EXPERIMENTAL RESULTS

As the suggestion from Cho Ray hospital - rehabilitation therapist, in order to give the effectiveness to the treatment method, experiments should be carried out with respect to two references input form: Sin wave form and Trapezoidal form. In the experimental results, the control parameters are chosen as follows: $K_p = 0.75$, $K_i = 0.25$, $K_d = 0.05$. Learning rate of weights in PID compensation is 0.00003. These gains are obtained by trial-and-error through experiments. Figure 5 shows the control software interface. Figure 6 shows the results of proposed controller with respect to the sine wave form of reference input with the frequency equal to 30 seconds, the amplitude is between 45 and 70 degrees. And figure 7 also shows the results of proposed controller with respect to the sine wave form of reference input with the same frequency and the amplitude is between 30 and 90 degrees. From these figures, it is understood that the system response of the proposed controller is good agreement with that of reference input and it is demonstrated that the proposed control algorithm is effective in this case and well enough for clinical testing.

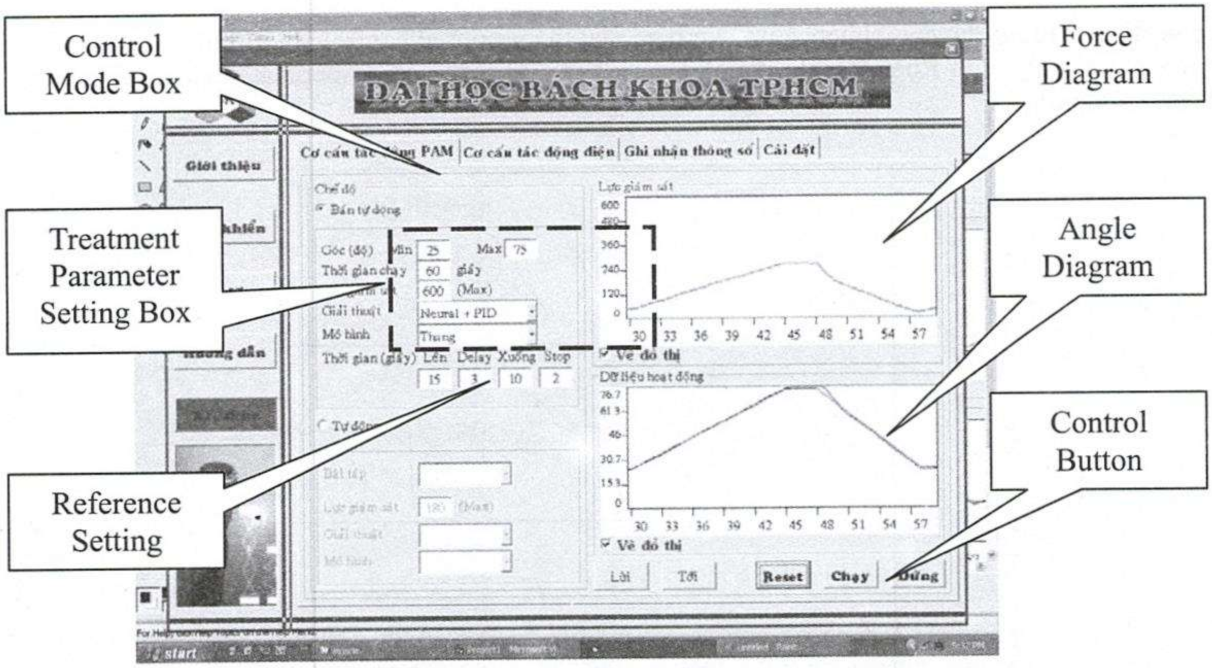

Fig 5. Control software interface

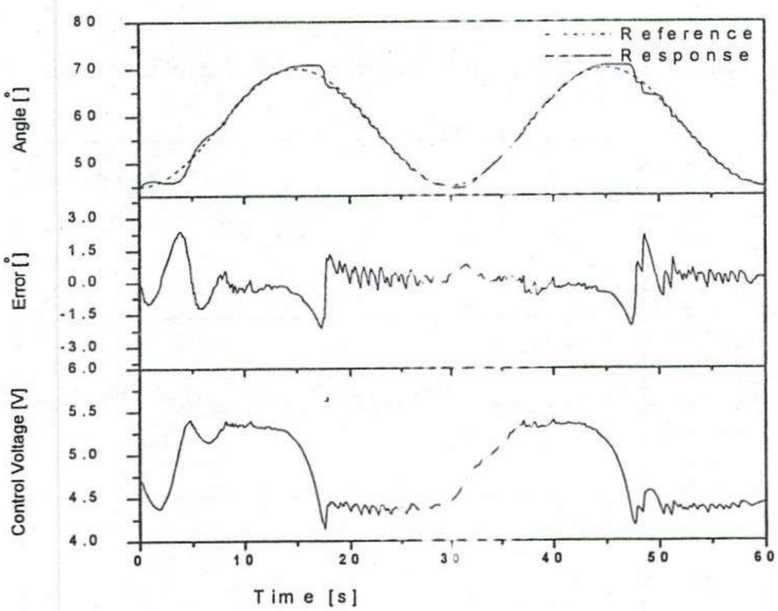

Fig 6. Experimental result of sin wave form – frequency = 30(s), amplitude is betweens 45 and 75

Next, the same controller is applied for the trapezoidal form of reference input with the frequency. Figure 8 and figure 9 show the response of system with respect to the trapezoidal form reference. The parameters of trapezoidal form are set as follows: rising time = 15(s), delay time = 3(s), decreasing time = 10(s), and stop time = 2(s) and rising time = 10(s), delay time = 3(s), decreasing time = 10(s), and stop time = 2(s) with respect to fig 8 and fig 9 respectively. From the experiments, it is verified that the proposed control algorithm is a good strategy not only with Knee Rehabilitation Device but also many other medical devices using PAM manipulator

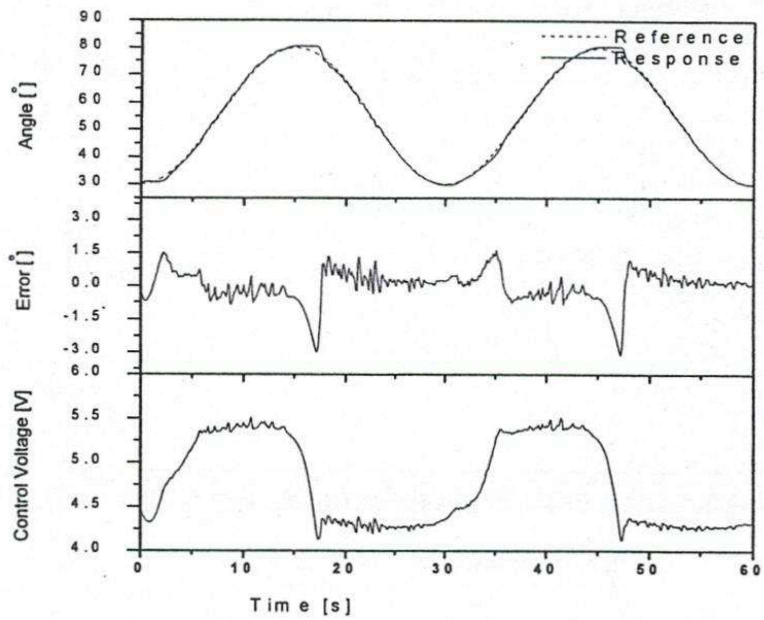

Fig 7. Experimental result of sin wave form – frequency = 30(s), amplitude is betweens 30 and 90

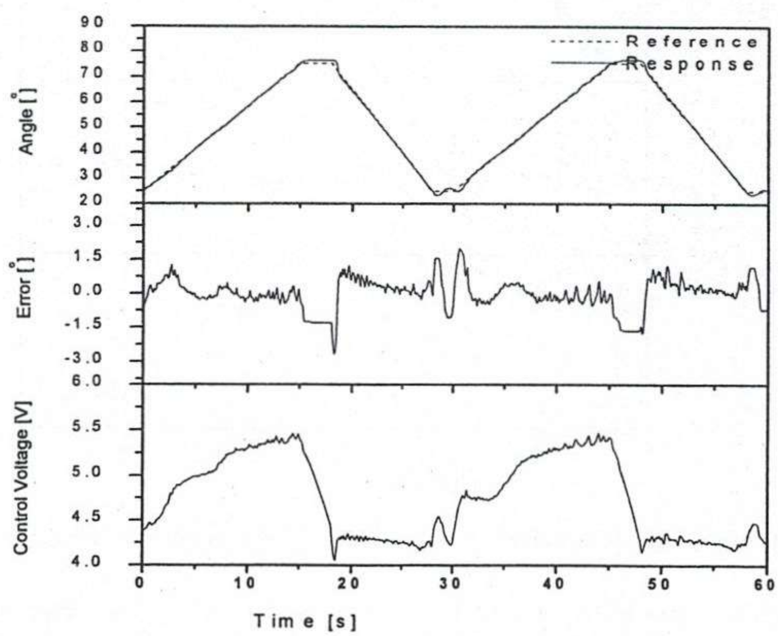

Fig 8. Experimental result of trapezoidal for:
Raising time = 15(s), delay time = 3(s), decreasing time = 10(s), and stop time = 2(s)

5.CONCLUSIONS

In this paper, a knee CPM device using pneumatic artificial muscle actuator product is introduce. It is shown that the proposed control method had a good performance for the Knee Rehabilitation Device using PAM actuator. It can be seen from experimental results that the controller had an adaptive control capability and the control parameters were optimized via the steepest descent algorithm. The controller designed by this method does not need any training procedure in advance, but it uses only the input and output of the plant for the adaptation of control parameter and can tune the parameters iteratively.

From the experiments of the position control of the PAM in this study, it was verified that the proposed control algorithm is one of effective method to develop a practically available Knee Rehabilitation Device by using PAM. The novel model of knee CPM device now is suggested to clinical test at physiotherapy department, Cho Ray Hospital in Ho Chi Minh.

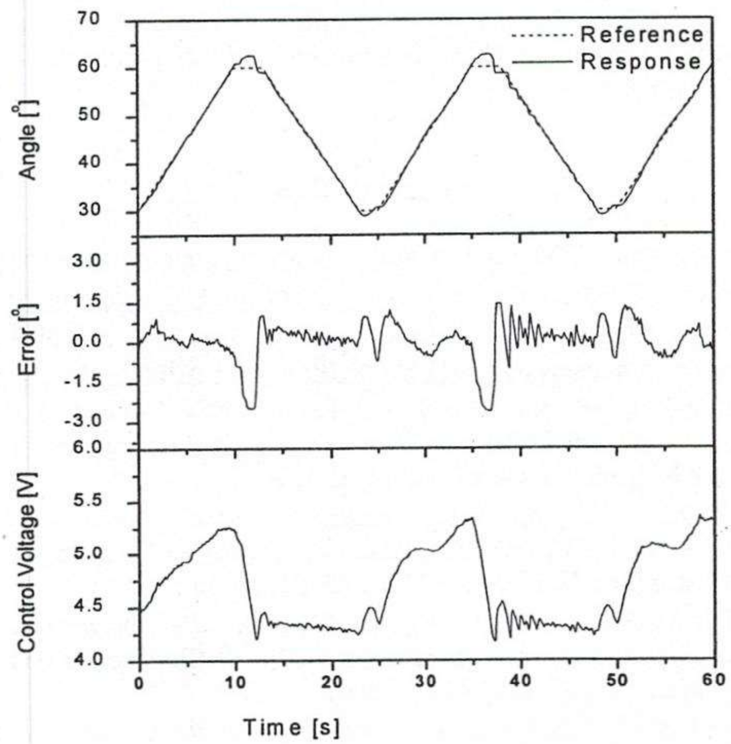

Fig 9. Experimental result of trapezoidal for:
Raising time = 10(s), delay time = 3(s), decreasing time = 10(s), and stop time = 2(s)

ĐIỀU KHIỂN THIẾT BỊ MỚI LẠ TRONG TẬP THỤ ĐỘNG KHỚP GỐI

Từ Diệp Công Thành
Trường Đại học Bách Khoa, ĐHQG-HCM

TÓM TẮT: *Trong những năm gần đây, CPM – chuyển động thụ động liên tục được xem là một trong những phương pháp trị liệu tốt nhất cho những bệnh nhân có các vấn đề về cột sống, khớp cổ chân, khớp gối, Parkinson v,v...Nhiều thiết bị đã được thương mại hóa, tuy nhiên hầu hết các thiết bị đều sử dụng động cơ làm cơ cấu truyền động chính. Sự thiếu tính chiều theo chuyển động của các động cơ điện đã tạo nên những đau đớn cho bệnh nhân. Một cơ cấu mới lạ thay thế cho các cơ cấu tác động điện trong các mục đích y học, đặc biệt trong phục hồi chức năng, là cơ cấu nhân tạo khí nén (PAM) với tỉ số công suất/ khối lượng lớn và tính chiều theo chuyển động.Tuy nhiên, độ phi tuyến và độ trễ lớn tạo nên những thách thức trong việc thiết kế và điều khiển thiết bị. Trong bài báo này, bộ điều khiển PID kết hợp với mạng thần kinh nhân tạo được giới thiệu và minh chứng cho khả năng điều khiển thiết bị mới lạ tập thụ động khớp gối này.*

REFERENCES

[1]. Artromot K1 Knee CPM Catalog, http://www.rentcpm.com/cpm.html

[2]. OptiFlex Knee CPM Catalog, http://www.metmedicalcpm.com/cpmDevices.html

[3]. Kinetec Optima Knee CPM Machine Catalog, http://www.sammonspreston.com/Supply/Product.asp?Leaf_Id=4621001601

[4]. Spherical J, Kenji Y, Norihiko S. and Toshiyuki S., *Control of Robot Arm Using Pneumatic Artificial Muscle*, International Conference on Mechatronics & Automation Niagara Falls, Canada, July (2005)

[5]. Thanh, T.D.C. and Ahn, K.K., *Intelligent Phase Plane Switching Control of Pneumatic Artificial Muscle Manipulators with Magneto-Rheological Brake*, in Int., Jour., Mechatronics, Vol. 16, No. 2, pp. 85~95, (2006.)

[6]. [6]Hamdan M, Zhiqiang Gao, *A novel PID controller for pneumatic proportional valves with hysteresis*. In: Proceedings of the IEEE International Conference on Industry Applications, 2:1198-201, (2000)

[7]. Grassi E, Tsakalis KS, Dash S, Gaikwad SV, Stein G. *Adaptive/self-tuning PID control by frequency loop-shaping*. In: Proceedings of the IEEE International Conference on Decision and Control, 2: 1099-101., (2000)

[8]. Howell MN, Gordon TJ, Best MC. *The application of continuous action reinforcement learning automata to adaptive PID tuning*. In IEEE Seminar on Learning Systems for Control, p. 2/1-4, (2000)

[9]. Gawthrop PJ. *Self-tuning PID control: algorithms and implementation*. In IEEE Trans, 31(3):201-9, (1986)

[10]. Gawthrop PJ. *Self-tuning PID control structures. In IEEE Colloquium on Getting the Best Our of PID* in Machine Control,. p. 4/1-4., (1996)

[11]. Yamamotor T, Fujii K, Kaneda M. *A self-tuning PID controller and its application for a chemical process*. In: Proceedings of the IEEE International Conference on Emerging Technologies and Factory Automation, p. 275-81, (1996)

[12]. Ahn, K.K., Thanh, T.D.C. and Ahn, Y.K., *Intelligent Switching Control of Pneumatic Artificial Muscle Manipulator*, in JSME, Int., Jour., Series C, Japan Society of Mechanical Engineering,Vol. 48, No. 4, pp. 657~667, (2005)

[13]. Thanh, T.D.C. and Ahn, K.K., *Nonlinear PID control to improve the control performance of 2 axes PAM manipulators using neural network,* in Int., Jour., Mechatronics, Vol. 16, No. 9, pp. 577~587, (2006)