Intelligent Phase Plane Switching Control of Pneumatic Artificial Muscle Manipulators with Magneto-Rheological Brake

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Abstract: Industrial robots are powerful, extremely accurate multi-jointed systems, but they are heavy and highly rigid because of their mechanical structure and motorization. Therefore, sharing the robot working space with its environment is problematic. A novel pneumatic artificial muscle actuator (PAM actuator) has been regarded during the recent decades as an interesting alternative to hydraulic and electric actuators. Its main advantages are high strength and high power/weight ratio, low cost, compactness, ease of maintenance, cleanliness, readily available and cheap power source, inherent safety and mobility assistance to humans performing tasks. The PAM is undoubtedly the most promising artificial muscle for the actuation of new types of industrial robots such as Rubber Actuator and PAM manipulators. However, some limitations still exist, such as the air compressibility and the lack of damping ability of the actuator bring the dynamic delay of the pressure response and cause the oscillatory motion. In addition, the nonlinearities in the PAM manipulator still limit the controllability. Therefore, it is not easy to realize motion with high accuracy and high speed and with respect to various external inertia loads in order to realize a human-friendly therapy robot

To overcome these problems a novel controller, which harmonizes a phase plane switching control method with conventional PID controller and the adaptabilities of neural network, is newly proposed. In order to realize satisfactory control performance a variable damper – Magneto-Rheological Brake (MRB) is equipped to the joint of the manipulator. Superb mixture of conventional PID controller and a phase plane switching control using neural network brings us a novel controller. This proposed controller is appropriate for a kind of plants with nonlinearity uncertainties and disturbances. The experiments were carried out in practical PAM manipulator and the effectiveness of the proposed control algorithm was demonstrated through experiments, which had proved that the stability of the manipulator can be improved greatly in a high gain control by using MRB with phase plane switching control using neural network and without regard for the changes of external inertia loads.

Keywords: Pneumatic artificial muscle, Magneto-Rheological brake, Phase plane switching control, Manipulator, Neural network.

1. INTRODUCTION

For most robotic applications, the common actuator technology is electric system with very limited use of hydraulics or pneumatics. But electrical systems suffer from relatively low power/weight ratio and especially in the case of human friendly robot, or human coexisting and collaborative systems such as a medical and welfare fields. Therefore, sharing the robot working space with its environment is problematic. Conversely, the human arm is not very accurate, but its lightness and joint flexibility due to the human musculature give it a natural capability for working in contact. The orientation of industrial robotics toward applications needing greater proximity between the robot and the human operator has recently led researchers to develop novel actuator sharing some analogies with natural skeletal muscle. A novel pneumatic artificial muscle actuator has been regarded during the recent decades as an interesting alternative to hydraulic and electric actuators. The pneumatic artificial muscle is undoubtedly the most promising artificial muscle for the actuation of new types of industrial robots such as Rubber Actuator and PAM manipulators. Thus, the PAM manipulator has been applied to construct a therapy robot in the case of having high level of safety for humans required. However, the air compressibility and the lack of damping ability of the pneumatic muscle actuator bring the dynamic delay of the pressure response and cause the oscillatory motion. Therefore, it is not easy to realize the performance of transient response with high speed and with respect to various external inertia loads in order to realize a human-friendly therapy robot.

The limitations of the PAM manipulators have promoted research into a number of control strategies, such as a Kohonen-type neural network for the position control of robot end-effector within 1 cm after learning [1]. Recently, the authors have developed a feed forward neural network controller and accurate trajectory was obtained, with an error of 1^o [2]. After applying a feed forward + PID-type controller approach [3], the authors are turning to an adaptive controller [4-6]. Recently, the authors have announced that the position regulation of the joints of their arm prototype is better than $\pm 0.5^o$ [7]. In addition, PID control [8], sliding mode control [9-10], fuzzy PD+I learning control [11], fuzzy + PID control [12], robust control [10, 13-14], feedback linearization control [15], feed forward control + fuzzy logic [16], variable structure control algorithm [17], H infinity control [18-19] and so on, have been applied to control the PAM manipulator. Though these systems were successful in addressing smooth actuator motion in response to step inputs, the manipulator must be controlled slowly in order to get stable, accurate position control and the external inertia load was also assumed to be constant or slowly varying. Assuming that PAM manipulator is utilized in therapy robot in the future, which is the final goal of our research, it is necessary to realize fast response, even if the external inertia load changes severely. But fast response cannot be obtained in most pneumatic control system. At the same time, the external inertia loads cannot always be known exactly. Therefore, it is necessary to propose a new control algorithm, which is applicable to a very compressible pneumatic muscle system with various loads.

Intelligent control techniques have emerged to overcome some deficiencies in conventional control methods in dealing with complex real-world systems such as PAM manipulator. Many new control algorithms based on a neural network have been proposed. An intelligent control using a neuro-fuzzy network was proposed by Iskarous and Kawamura [20]. A hybrid network that combines fuzzy and neural network was used to model and control complex dynamic systems, such as the PAM system. An adaptive controller based on the neural network was applied to the artificial hand, which is composed of the PAM [21]. Here, the neural network was used as a controller, which had the form of compensator or inverse of the model and it was not easy to apply these control algorithms to the quickly-changing inertia load systems. In addition, these control algorithms were not yet to reconcile both damping and response speed in high gain control.

To over come these problems, a new technology, Electro-Rheological Fluid Damper (ER Damper), has been applied to the PAM manipulator. Noritsugu and his team have used ER damper to improve the control performance of the PAM manipulator with PI controller and pulse code modulated on-off valves [22-23]. The results show that the ER damper is one of effective methods to develop a practically available human friendly robot by using the PAM manipulator and also the performance of position control is improved without the decrease of response speed. However, some limitations still exist, such as ER Fluid (ERF) requires extremely high control voltage (kV) which is problematical and potentially dangerous, only operates in a narrow range of temperature which can not be applied for PAM manipulator, and has also the characteristics of nonlinearity. Because ERF has many unacceptable disadvantages, Magneto-Rheological Fluid (MRF) attracts people's attention with these advantages in Table 1, in recent years. MR fluid is similar to ER fluid but is 20~50 times stronger in the yield stress. It can also be operated directly from low-voltage power supplies and is far less sensitive to contaminants and temperature.

Thus, the goal of this paper is to implement a MRB to develop a fast accurate pneumatic control system by phase plane switching control using neural network and without regard for the changes of external inertia loads. Superb mixture of conventional PID controller and a phase plane switching control using neural network brings us a novel controller. This proposed controller is appropriate for a kind of plants with nonlinearity uncertainties and disturbances. The experiments were carried out in practical PAM manipulator and the effectiveness of the proposed control algorithm was demonstrated through experiments, which had proved that the stability of the manipulator can be well improved in a high gain control by using MRB with phase plane switching control using neural network and without decreasing the response speed and low stiffness of manipulator.

2. EXPERIMENTAL SETUP

2.1 Experimental apparatus

The schematic diagram of the PAM manipulator is shown in Fig. 1. The hardware includes an IBM compatible personal computer (Pentium 1 GHz) which calculates the control input and controls the proportional valve (FESTO, MPYE-5-1/8HF-710 B) and Magneto-Rheological Brake (LORD, MRB-2107-3 Rotary Brake), through D/A board (Advantech, PCI 1720), and two pneumatic artificial muscles (FESTO, MAS-10-N-220-AA-MCFK). The braking torque of MRB is controlled by D/A broad through voltage to current converter, Wonder Box Device Controller Kit (LORD, RD-3002-03). The structure of PAM is shown in Fig. 2. The rotating torque is generated by the pressure difference between the antagonistic artificial muscles and the external load is rotated as a result (Fig. 3). A joint angle, θ, is detected by rotary encoder (METRONIX, H40-8-3600ZO) and the air pressure into each chamber is also measured by the pressure sensors (FESTO, SDE-10-10) and fed back to the computer through 24-bit digital counter board (Advantech, PCL 833) and A/D board (Advantech, PCI 1711), respectively. The external inertia load could be changed from 20[kg·cm^2] to 200[kg·cm^2], which is a 1,000[%] change with respect to the minimum inertia load condition. The experiments are conducted under the pressure of 0.4[MPa] and all control software is coded in C program language. A photograph of the experimental apparatus is shown in Fig. 4.

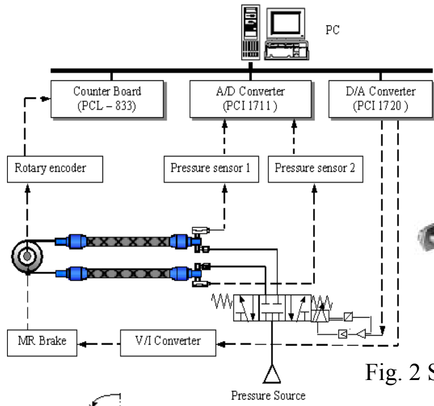


Fig. 1 Schematic diagram of PAM manipulator.

Fig. 2 Structure of PAM.

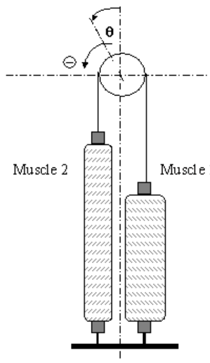


Fig. 3 Working principle of PAM manipulator.

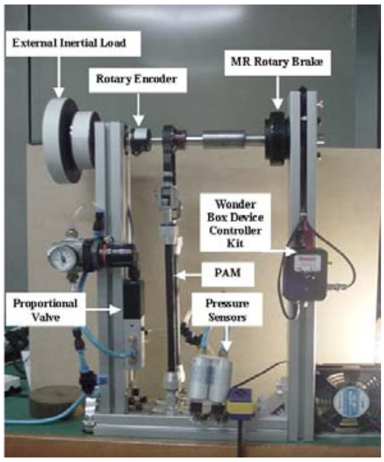


Fig. 4 Photograph of the experimental apparatus.

2.2 Characteristics of MRB

Construction of MRB was shown in Fig. 5. The rotor in Fig. 5 is fixed to the shaft, which can rotate in relation to housing. Between rotor and housing there is a gap filled with MR fluid. Braking torque of MRB can be controlled by the electric current in its coil. An apparent viscosity of MR fluid is changed at few milliseconds after the application of a magnetic field, and goes back to the normal viscosity with no magnetic field.

The following experiments are performed to investigate the characteristics of MRB, which measurement data is shown in Fig. 6 and Table 2. MRB is connected with a torque transducer and a servomotor in series. In the experiments, the rotational speed is changed from 100[rpm] to 1000[rpm] and the current applied for MRB is changed from 0[A] to 1[A]. The reason for choosing this range of rotational speed and current is that the response of system does not reach to 1000[rpm] and the maximum current applied for MRB is 1[A]. Figure 6 shows the damping torque with respect to the change of the input current (a) and rotational speed (b) of MRB. From Fig. 6, it is clear that the damping torque of MRB is independent of rotational speed and almost proportional to input current. Thus an equation (1) holds between the inputs current I and damping torque T_b

$$T_b = f(I) = a + bI \tag{1}$$

Here, a and b are constant.

3. CONTROL SYSTEM

3.1 Positioning control system

The strategy of PID control has been one of the sophisticated methods and most frequently used in the industry. This is because that the PID controller has a simple form and strong robustness in broad operating area. To control this PAM manipulator a conventional PID control algorithm is applied in this paper as the basic controller. The controller output can be expressed in the time domain as:

$$u(t) = K_p e(t) + \frac{K_p}{T_i}\int_0^t e(t)dt + K_p T_d \frac{de(t)}{dt} \qquad (2)$$

Taking the Laplace transform of (2) yields

$$U(s) = K_p E(s) + \frac{K_p}{T_i s}E(s) + K_p T_d s E(s) \qquad (3)$$

and the resulting PID controller transfer function is

$$\frac{U(s)}{E(s)} = K_p\left(1 + \frac{1}{T_i s} + T_d s\right) \qquad (4)$$

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

$$u(k) = K_p e(k) + u(k-1) + \frac{K_p T}{T_i}e(k) + K_p T_d \frac{e(k) - e(k-1)}{T} \qquad (5)$$

where u(k) and e(k) are the control input to the control valve and the error between the desired set point and the output of joint, respectively.

In addition, MRB is one of effective methods to improve the control performance of the PAM manipulator by reconciling both the damping and response speed because it works in only the regions where the acceleration or deceleration is too high. Here, s is Laplace operator, T_a is torque produced by manipulator, T_c is constant torque and K_{ED} determines a gain for the torque proportional to the angular speed $\dot{\theta}$, V_c is a control voltage of source calculated from Eq. (1) to produce T_c. A direction of a damping torque is every time opposite to the rotary direction of the arm. So Eq. (6) below indicates that the damper produces a torque T_b.

$$T_b = \left(K_{ED}\dot{\theta} + T_c\right)sign(\dot{\theta}) \qquad (6)$$

The structure of the proposed phase plane switching control method is shown in Fig. 7.

3.2 Phase plane switching control method

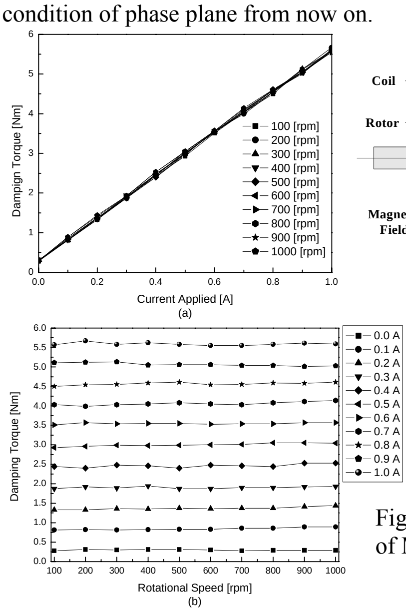
The damping torque T_b improves the damping performance of the manipulator. Since the damping torque every time acts in the direction against the rotational direction of manipulator, its acceleration performance is degraded. In the region that the joint angle of the arm approaches to the desired angle, a~b, c~d in Fig. 8(a), the current is not applied not to interfere the movement of the arm, since the high response speed is required. In the region the arm passes the desired angle, i.e. the diagonally shaded areas of b~c, d~e in Fig. 8(a), a current is applied to improve the damping performance to converge to the desired angle quickly. To determine whether the magnetic field should be applied or not, the phase plane shown in Fig. 8(b) is used. The horizontal axis in the phase plane corresponds to joint angle deviation e between the desired angle θ_r and the joint angle θ, and the vertical axis corresponds to the derivation of the deviation $\dot{e} = \frac{de}{dt} = -\dot{\theta}$. Each point a~e on the phase plane corresponds to each point a~e in Fig. 8(a). Here, the region with the application of current are controlled by h[s^{-1}], the gradient of the line shown in Fig. 8(b). The region under the application of the damping torque expands as $|h|$ decrease.

3.3 Experimental results of PID and phase plane switching controller

Experiments were carried out with 3 cases of external inertia loads (20, 60, 200 kg.cm^2). The comparison between the conventional PID controller and the phase plane switching controller was shown from Fig. 9 to Fig. 12.

Figure 9 shows the experimental results of the conventional PID controller where the minimum external inertia load is 20kg.cm^2 and control parameters are $K_p = 200\times10^{-6}$ $K_i = 1\times10^{-6}, K_d = 70\times10^{-6}$ (PID controller 1) and $K_p = 1000\times10^{-6}, K_i = 10\times10^{-6}, K_d = 130\times10^{-6}$ (PID controller 2). It is obvious that it is difficult to satisfy both the damping and response speed. The manipulator must be controlled slowly in order to have a good stability. On the contrast, the overshoot and oscillation are always included if one wants fast response. In addition, experimental results with PID controller 2 were shown in Fig. 10 where the external inertia loads change from 20kg.cm^2 to 200kg.cm^2. From these results, it was understood that the system response became more oscillatory according to the increase of the external inertia load and became unstable with ten times bigger external inertia load with respect to the minimum inertia load condition.

Next, the experiments were carried out in practical PAM manipulator and the control parameters of the proposed controller, which was mentioned in Eq. (6), were set to be T_c=0.4, h=-20 with various K_{ED} (K_{ED} = 0.010,0.015, 0.020) in experiment condition 1 and K_{ED} = 0.015, T_c=0.4 with various h ($h=-10, h=-20, h=-50$) in experiment condition 2. These parameters were obtained by trial-and-error through experiments. The experimental results with respect to the experimental condition 1 and 2 were shown in Fig.11 and 12, respectively. In Fig. 11 and 12, the control parameters of phase plane switching controller were set to be $K_{ED} = 0.015, T_c = 0.4$ *and* $h = -20$. From these experimental results, it is understood that the settling time becomes very big in some value of design parameters of switching controller. To guarantee the control performance, the control parameters must be tuned adaptively and we proposed phase plane switching control with neural network newly, which is explained in detail in next section. All experiments with phase plane switching control method were carried out by this condition of phase plane from now on.



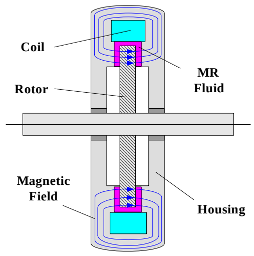


Fig. 5 Construction of MRB.

Fig. 6 Characteristics of MRB.

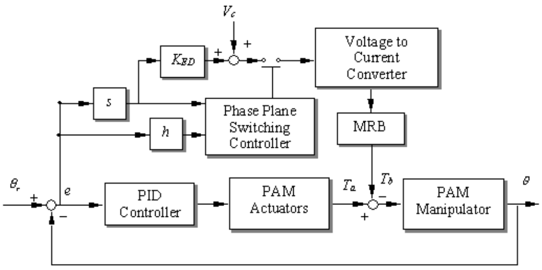


Fig. 7 Block diagram of phase plane switching control.

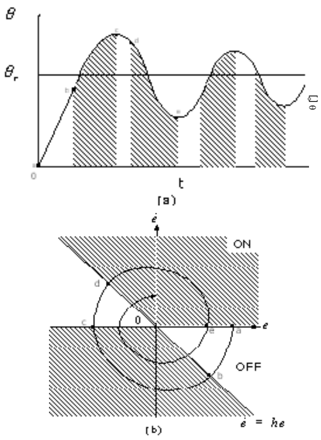


Fig. 8 Concept of phase plane switching control.

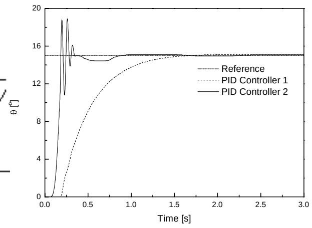


Fig. 9 Comparison between PID controller 1 and PID controller 2.

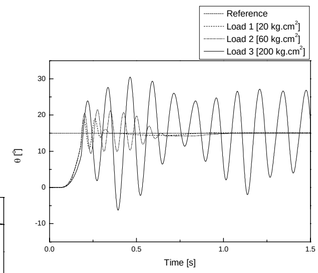


Fig. 10 Experimental results of PID controller 2 with various loads.

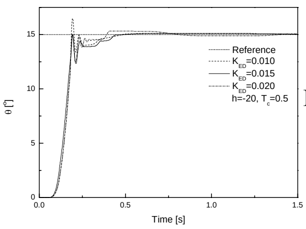


Fig. 11 Experimental results of proposed controller with various parameter of K_{ED}

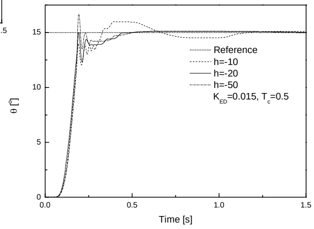


Fig. 12 Experimental results of proposed controller with various parameter of h

4. PROPOSED PHASE PLANE SWITCHING CONTROL USING NEURAL NETWORK

4.1 Structure of phase plane switching control using neural network

From the experimental results, modification of control parameters of phase plane switching control must be adjusted to realize more accurate control. It is obvious that the phase plane switching control method is limited because the K_{ED} parameter is constant. This means that the damping torque is not adaptable and optimal in any case. Here, we propose an intelligent phase plane switching control, which has the adaptability of control parameter to minimize the position error. With the capacity of learning and adaptability of neural network, the proposed controller can solve these problems. The damping torque will be tuned adaptively and optimally in order to minimize the position error without respect to the variation of external inertia loads.

Figure 13 shows the structure of phase plane switching control using neural network. In Fig.13, the proportional gain K_{ED} in Fig. 7 was modified by neural network. The block diagram of neural network is shown in Fig. 14. Here $K_E(k)$, $K_{ED}(k)$, $e(k)$, $e_D(k)$, $x(k)$ and $f(x)$ are the proportional gain, the derivative gain, the system error between desired angle output and output of joint of the PAM manipulator, the difference of the system error, control input of MRB and sigmoid function of neural network, respectively. The sigmoid function, $f(x)$, which has a nonlinear relation is presented in the following equation:

$$f(x) = \frac{2(1-e^{-x \cdot Yg})}{Y_g(1+e^{-x \cdot Yg})} \tag{7}$$

where x is the input of sigmoid function and Y_g is the parameter determining its shape. Figure 15 shows the shapes of sigmoid function with various Y_g. As shown in Eq. (7), the sigmoid function $f(x)$ becomes linear when Y_g approaches zero.

We have two-layered nonlinear neurons. Neural networks are trained by the conventional back propagation algorithm to minimize the system error between the output of joint of the PAM manipulator and desired angle.

In Fig. 14, the input signal of the sigmoid function in the output layer, x(k), becomes:

$$x(k) = K_E(k)e(k) + K_{ED}(k)e_D(k) \tag{8}$$

where,

$$e(k) = \theta_r(k) - \theta(k),\ e_D(k) = \frac{e(k)(1-z^{-1})}{\Delta T}$$
$$\Delta T : sampling\ time,\quad z : operator\ of\ Z - transform,$$
$$k : discrete\ sequence \tag{9}$$

$\theta_r(k)$ and $\theta(k)$ are desired angle and output of joint of the PAM manipulator, respectively.

The damping torque of phase plane switching control using neural network can be obtained as the following equation:

$$T_b(k) = \left(f\left(x(k)\right) + T_c\right)sign(\dot{\theta}) \tag{10}$$

4.2 Learning algorithm of neural network

From Eq. (10), in order to get the optimal value of damping torque, the control parameters K_E and K_{ED} must be adjusted automatically in order to minimize the position error.

To tune K_E and K_{ED}, the steepest descent method using the following equation was applied.

$$K_E(k+1) = K_E(k) - \eta_E \frac{\partial E(k)}{\partial K_E}$$
$$K_{ED}(k+1) = K_{ED}(k) - \eta_{ED} \frac{\partial E(k)}{\partial K_{ED}} \tag{11}$$

where η_E and η_{ED} are learning rates determining convergence speed, and E(k) is the error defined by the following equation:

$$E(k) = \frac{1}{2}\left(\theta_r(k) - \theta(k)\right)^2 \tag{12}$$

From Eq. (12), using the chain rule, we get the following equations:

$$\frac{\partial E(k)}{\partial K_E} = \frac{\partial E(k)}{\partial \theta}\frac{\partial \theta(k)}{\partial u}\frac{\partial u(k)}{\partial x}\frac{\partial x(k)}{\partial K_E}$$
$$\frac{\partial E(k)}{\partial K_{ED}} = \frac{\partial E(k)}{\partial \theta}\frac{\partial \theta(k)}{\partial u}\frac{\partial u(k)}{\partial x}\frac{\partial x(k)}{\partial K_{ED}} \tag{13}$$

These following equations are derived by using Eqs. (8), (12):

$$\frac{\partial E(k)}{\partial \theta} = -\left(\theta_r(k) - \theta(k)\right) = -e(k) \tag{14}$$

$$\frac{\partial u(k)}{\partial x} = f'\left(x(k)\right); \quad \frac{\partial x(k)}{\partial K_E} = e(k); \quad \frac{\partial x(k)}{\partial K_{ED}} = e_D(k)$$

The following expression can be derived from Eqs. (13), (14):

$$\begin{aligned}\frac{\partial E(k)}{\partial K_E} &= \frac{\partial E(k)}{\partial \theta}\frac{\partial \theta(k)}{\partial u}\frac{\partial u(k)}{\partial x}\frac{\partial x(k)}{\partial K_E} \\ &= -e(k)\frac{\partial \theta(k)}{\partial u} f'\left(x(k)\right)e(k) = -\frac{\partial \theta(k)}{\partial u} f'\left(x(k)\right)e^2(k) \\ \frac{\partial E(k)}{\partial K_{ED}} &= \frac{\partial E(k)}{\partial \theta}\frac{\partial \theta(k)}{\partial u}\frac{\partial u(k)}{\partial x}\frac{\partial x(k)}{\partial K_{ED}} \\ &= -e(k)\frac{\partial \theta(k)}{\partial u} f'\left(x(k)\right)e_D(k) = -\frac{\partial \theta(k)}{\partial u} f'\left(x(k)\right)e(k)e_D(k)\end{aligned} \tag{15}$$

and $$f'(x) = 4\frac{e^{-x \cdot Yg}}{(1+e^{-x \cdot Yg})^2} \tag{16}$$

As done by Yamada and Yabuta [24], for convenience, $\frac{\partial \theta(k)}{\partial u} = 1$ is assumed. Then the Eq. (11) is expressed as:

$$\begin{aligned} K_E(k+1) &= K_E(k) + \eta_E e(k)e(k)\frac{4e^{-x \cdot Yg}}{(1+e^{-x \cdot Yg})^2} \\ K_{ED}(k+1) &= K_{ED}(k) + \eta_{ED} e(k)e_D(k)\frac{4e^{-x \cdot Yg}}{(1+e^{-x \cdot Yg})^2}\end{aligned} \tag{17}$$

The effectiveness of the proposed phase plane switching control using neural network with tuning algorithm of damping torque will be demonstrated through experimental results with various external inertia loads.

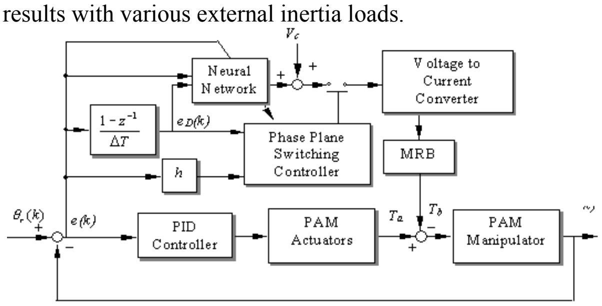


Fig. 13 The structure of phase plane switching control using neural network.

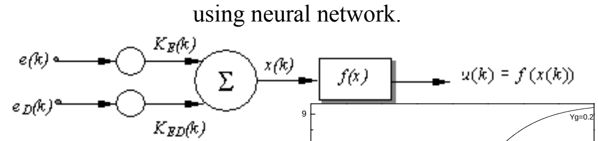


Fig. 14. The block diagram of neural network.

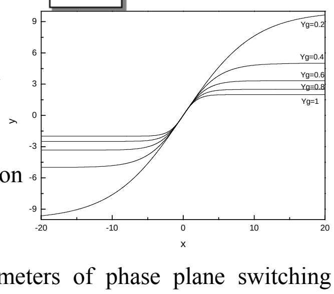


Fig. 15 The sigmoid function shapes.

4.3 Experimental results

The initial control parameters of phase plane switching control using neural network were set to be $T_c = 0.5, h = -1$, $Y_g = 0.3$, $K_E = 0.010, K_{ED} = 0.010$, $\eta_E = 170 \times 10^{-8}$ and $\eta_{ED} = 1 \times 10^{-8}$. These control parameters were obtained by trial-and-error through experiments. Thus, from now on, these control parameters were applied for the phase plane switching control using neural network in all case of experiments.

In Fig. 16, comparisons were made between the conventional PID controller 2, the proposed phase plane switching controller with and without using neural network with respect to load condition 1. In the experiments, the joint angle of PAM manipulator was in good agreement with that of reference by using phase plane switching controller without neural network. However it has too large settling time because of fixed parameters of switching controller. We have a very good performance of the PAM manipulator in the case of using switching controller with neural network. It is clear that the newly proposed controller using neural network was very effective in this experimental condition. The effectiveness of the proposed control algorithm with neural network was also shown in detail in Fig. 17. The damping torque was not applied for fast response when the manipulator starts to move and the damping torque was generated by MRB to the rotational axis of PAM manipulator in order to reduce the overshoot and oscillation when the manipulator reaches the desired angle. In addition, during the experiment of the PAM manipulator, the control parameters K_E and K_{ED} was tuned adaptively by neural network to minimize the position error.

Next, experiments were executed to investigate the control performance with various external inertia loads. Figure 18 shows the comparison between the conventional PID controller 2 and the proposed controller with and without neural network in the case of the load condition 2. From the experimental results, it was found that a good control performance and strong robustness were obtained without respect to the variation of external inertia load by using phase plane switching control method. In Fig. 19, the experimental result of phase plane switching control using neural network with external inertia load condition 2 was shown in detail. From these experimental results, the damping torque was applied and released very frequently according to the approach to the desired angle. It was demonstrated that the proposed algorithm was effective in the case of various external inertia loads.

In order to demonstrate the proposed phase plane switching control using neural network, the external inertia load with ten times larger with respect to the minimum inertia load condition was applied to the PAM manipulator. Experiments were conducted to compare the system response of PID controller 2 and proposed phase plane switching controller with and without neural network under the external load condition 3 in Fig. 20. With up to ten times bigger external inertia load with respect to the minimum external inertia load, a good control performance was also obtained in the case of without neural network but it has too large settling time due to the fixed control parameter of phase plane switching control. With newly proposed controller using neural network, the overshoot was almost reduced and the steady state error was reduced within $\pm 0.025^0$. Figure 21 shows the experimental results of phase plane switching control using neural network in detail with respect to the external inertia load condition 3. It was concluded that the proposed controller was very effective in the high gain control, good control performance, fast response, and strong robust stability with ten times changes of external inertia load.

From these results, we can conclude that newly proposed phase plane switching control using neural network is one of the most effective methods to develop a practically available human friendly robot by using PAM manipulator with MRB, which made a challenging and appealing system for modeling and control design.

In the near future, these develop control algorithms are anticipated applying to the pneumatic artificial muscle actuator for human-friendly therapy robot.

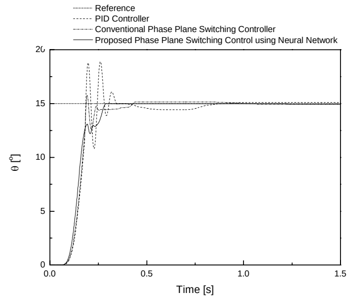


Fig. 16 Comparison between PID controller 2 and phase plane switching control with and without using neural network (Load 1).

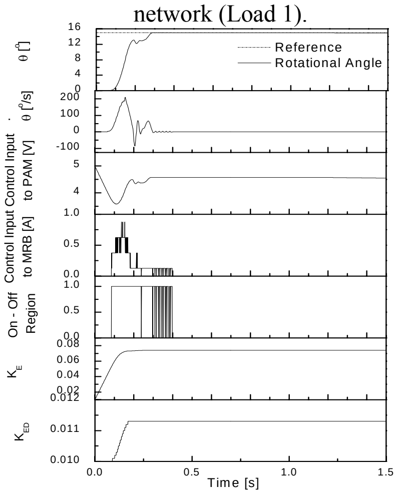


Fig. 17 Experimental results of phase plane switching control using neural network (Load 1).

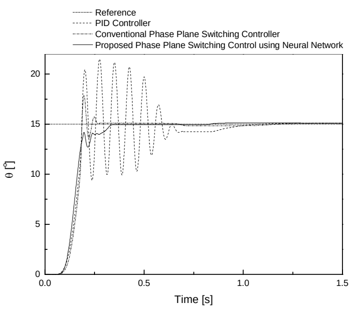


Fig. 18 Comparison between PID controller 2 and phase plane switching control with and without using neural network (Load 2).

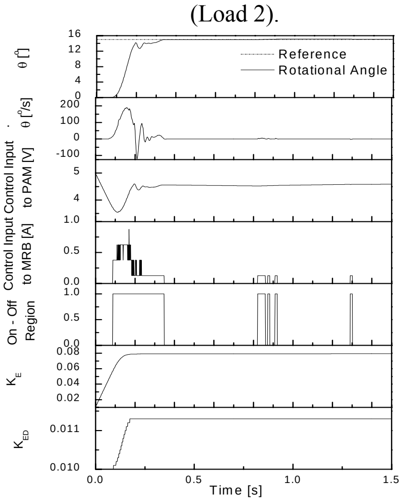


Fig. 19 Experimental results of phase plane switching control using neural network (Load 2).

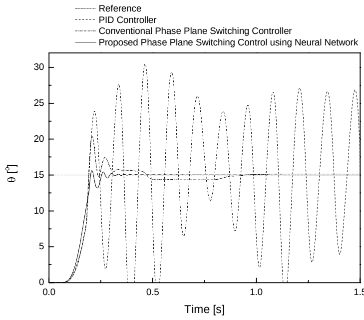


Fig. 20 Comparison between PID controller 2 and phase plane switching control with and without using neural network (Load 3).

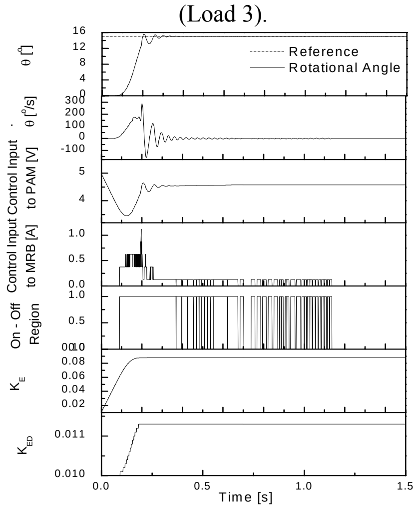


Fig. 21 Experimental results of phase plane switching control using neural network (Load 3).

Table 1 Comparison of Rheological fluids

	MRF	ERF
Max. Yield Stress	50 –100 kPa	2 – 5 kPa
Viscosity	0.1 – 1.0 Pa-s	0.1 – 1.0 Pa-s
Operable Temp.	-40 to + 150 oC	+10 to + 90 oC
Stability	Unaffected by most impurities	Cannot tolerate impurities
Response Time	< milliseconds	< milliseconds
Density	3 – 4 g/cm3	1 – 2 g/cm3
Max. Density	0.1 Joule/cm3	0.001 Joule/cm3
Power Supply	2 – 25 V, 1 – 2A	2–25 kV, 1–10 mA

Table 2 Measurement Data of MRB

W/A	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
100	0.28	0.81	1.33	1.87	2.44	2.93	3.51	4.03	4.5	5.11	5.57
200	0.31	0.82	1.33	1.92	2.4	2.96	3.57	3.99	4.54	5.12	5.67
300	0.3	0.81	1.36	1.89	2.48	2.99	3.54	4.03	4.55	5.13	5.58
400	0.31	0.82	1.35	1.94	2.46	2.98	3.55	4.05	4.59	5.05	5.62
500	0.31	0.83	1.37	1.87	2.4	2.99	3.55	4.08	4.61	5.06	5.58
600	0.3	0.83	1.36	1.87	2.48	3	3.53	4.05	4.54	5.06	5.55
700	0.28	0.86	1.37	1.9	2.46	3.01	3.54	4.03	4.55	5.04	5.55
800	0.29	0.86	1.37	1.9	2.44	3.05	3.54	4.08	4.59	5.04	5.58
900	0.29	0.89	1.41	1.92	2.53	3.05	3.57	4.11	4.58	5.01	5.61
1000	0.29	0.89	1.44	1.93	2.53	3.04	3.57	4.14	4.61	5.03	5.59

W: Rotational Speed [rpm]   A: Current Applied [A]

5. CONCLUSION

In this paper, a newly proposed phase plane switching control using neural network was applied to the pneumatic artificial muscle manipulators with MRB in order to improve the control performance with various external inertia loads.

From the experimental results, the damping torque of MRB was controlled by the applying magnetic field strength and the position control performance was improved without the decrease of response speed by separating the region where the damper produces an damping torque by phase plane switching control method.

In addition, to have optimal control parameters for the proposed phase plane switching control method, the neural network was used. The structure and leaning algorithm of neural network controller were very simple and applicable to any control system in order to minimize the position error.

From the experimental results, the newly proposed phase plane switching control using neural network was very effectively in high gain control with respect to the 1,000 [%] external inertia load variation. And the steady state error with respect to various loads was reduced within $\pm 0.025^{0}$.

The results show that the phase plane switching control using neural network is one of effective methods to develop a practically available human friendly robot by using the PAM manipulator.

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