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Trajectory control of electro-hydraulic excavator using fuzzy self tuning algorithm with neural network †

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Abstract

This paper presents the trajectory control of a 2DOF mini electro-hydraulic excavator by using fuzzy self tuning with neural network algorithm. First, the mathematical model is derived for the 2DOF mini electro-hydraulic excavator. The fuzzy PID and fuzzy self tuning with neural network are designed for circle trajectory following. Its two links are driven by an electric motor controlled pump system. The experimental results demonstrated that the proposed controllers have better control performance than the conventional controller.

Keywords: Intelligent control; Trajectory following control; Fuzzy self tuning control; Fuzzy PID control

1. Introduction

Nowadays, excavators play an important industrial role, especially in construction, forestry and mining. These machines are used for a variety of tasks: lifting, carrying, digging and ground leveling. Most of them are now operated by humans, which leads to low efficiency, low operation speed and inability to operate in area that humans cannot access. The automatic control of excavation tasks is an important step that will make feasible the future automation of construction work even in a hostile environment. Automation promises to improve productivity by enabling machines to drive at a higher average speed, improve safety by separating the human from the machine and minimizing the risk of accident, and reduce operational costs by minimizing the labor and maintenance needed for each machine. Also, it can be used in lunar and planetary construction sites or in situations where the direct physical presence of human operators is hazardous.

Various authors have studied issues related to the automatic robotic excavator operation in recent years [1, 2] to reduce human interaction with the vehicle. The main long-term goal of this work is to move a tracked vehicle from a starting point to a target point in an unstructured outdoor environment. The kinematics and dynamics of an excavator in both Newton-Euler and Euler-Lagrange formulation were derived in [1, 2]. However, the operation of the conventional excavator is controlled by a hydraulic system (valve controlled system), thus a great deal of energy is wasted to heat due to throttle losses at the control valves. These models are very difficult to apply for mobile machines because of complicated components. Moreover, in recent years, hydraulic technology has been developing rapidly to enhance their performance parameters such as accurate speed control, high power weight ratios, physical size, controllability, reliability, cost and so on. To overcome these weak points and to satisfy new requirements, a new concept of hydraulic actuator, which is called a hybrid actuator, has been proposed. In this paper we present the difference technique for control hydraulic system by

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Table 1. MMP Specification.

1	Rated Output	250W
2	Rated Voltage	DC12V
3	Rated Flow	0.9LPM
4	Rated Pressure	6.4MPa
5	Cylinder rod diameter	20mm
6	Cylinder stroke	300mm

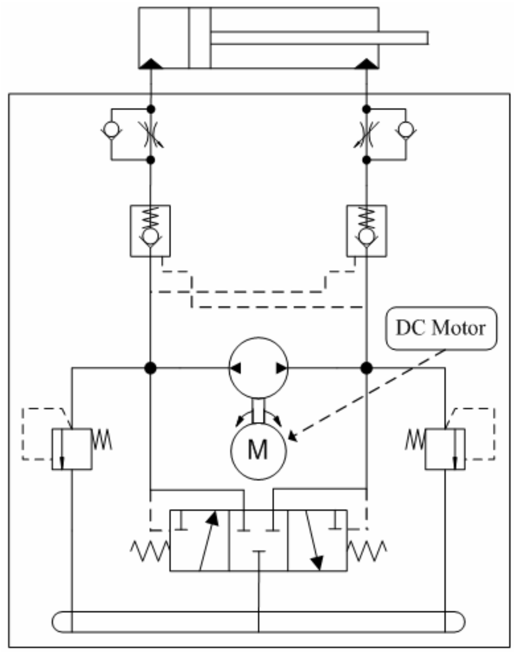


Fig. 1. The structure of mini motion package (MMP).

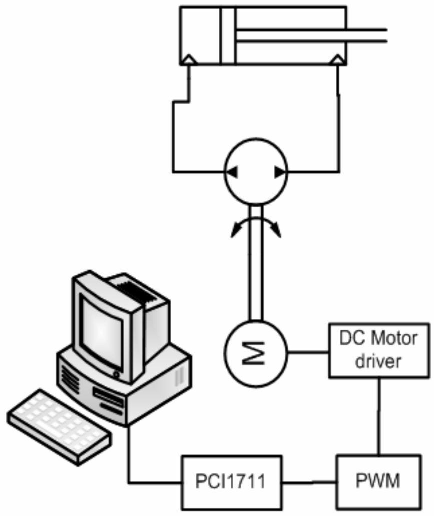


Fig. 2. The operation principles of the MMP system.

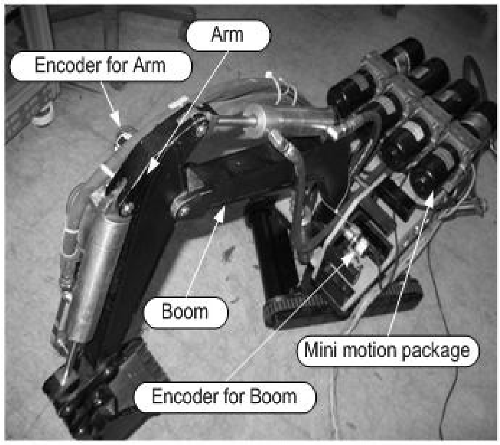


Fig. 3. Photograph of experimental apparatus.

using the mini motion package (MMP). The structure and the specification of the MMP are shown in the following Fig. 1 and Table 1, respectively.

From Fig. 1, it can be seen that the MMP consists of one DC servo motor, one variable bidirectional rotational pump, one hydraulic tank, and one cylinder. The position of the cylinder can be controlled by the DC servo motor which will adjust and supply the pressure and flow rate to the hydraulic pump. Because the hydraulic pump here is a bidirectional rotational pump it is very convenient to change the direction of the actuator by changing the direction of the DC motor. The MMP system has not only energy saving and low noise features but also a competitive price with other drives due to the use of a DC motor as the power supply. In addition, it can be installed easily by flexible suction pipe and used without any lubrication. The operation principles of the MMP system are shown in Fig. 2. For measuring the axis position, each controlled axe of the excavator is attached one rotary encoder. It is connected directly to the computer by PCI-QUAD04 card. This MMP and rotary encoder are equipped for boom, arm, and bucket of the mini electro hydraulic excavator as shown in Fig. 3. Conventional control theories have proven to be very effective for systems that can be modeled relatively precisely by mathematical equations. However, they have been found to be inefficient in handling systems that are either too complex or too vague to be described by accurate mathematical models. The control of a robotic excavator is difficult from the standpoint of the following problems: parameter variations in mechanical structures, various nonlinearities in hydraulic actuators, and disturbances due to the contact with the ground. In mechanical structures, the inertial and gravitational forces vary largely with joint motions. To overcome these difficulties, this paper presents the fuzzy self tuning control with neural network (FN) algorithm, which does not require a precise system model in the control design for the trajectory control of the mini excavator. Experiments have been implemented to test the performance of the proposed control algorithm.

2. Mathematical model

Since the immediate concern is control of path following motion, which does not excavate the soil, the end-effector and the swing angle are held constant. It follows that the movements of the excavator mechanism during digging occur in a vertical plane, and the object now is concentrated to control the position of the boom and arm. For the control task, the forward kinematics and inverse kinematics of excavator are derived. Both forward and inverse kinematics equations are derived from the fundamental theory for a robotic manipulator. These equations have been developed to describe the experimental excavator as a robotic manipulator with 2 degree of freedom.

2.1 Forward kinematics equation

Kinematics is described as motion of the system. In kinematics, direction and position play an important role. Robot kinematics is necessary for calculating the position of the robot. In other words, robot excavator kinematics observes all of the arm motions of the robot without force and moment [3]. The 2DOF mini excavator is shown in the following diagram:

Forward kinematics will give the coordinates of link 2 as a function of the joint angles and arm lengths. The lengths of two links excavator are l_1, l_2 and the rotation angle are θ_1, θ_2 respectively

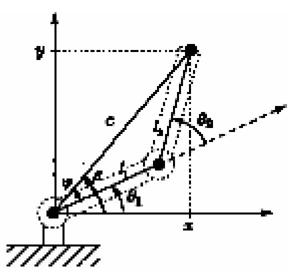


Fig. 4. Diagram of 2DOF mini electro-hydraulic excavator.

The homogeneous matrix

$$H = R_z(\theta_1) \times T_{x1}(l_1) \times R_z(\theta_2) \times T_{x2}(l_2) \quad (1)$$

where the rotation matrix around z axis and translation matrix of link 1 and link 2 are, respectively, as follows:

$$R_z(\theta_1) = \begin{bmatrix} \cos(\theta_1) & -\sin(\theta_1) & 0 \\ \sin(\theta_1) & \cos(\theta_1) & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (2)$$

$$R_z(\theta_2) = \begin{bmatrix} \cos(\theta_2) & -\sin(\theta_2) & 0 \\ \sin(\theta_2) & \cos(\theta_2) & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (3)$$

$$T_{x1}(l_1) = \begin{bmatrix} l_1 \\ 0 \\ 0 \end{bmatrix}, T_{x2}(l_2) = \begin{bmatrix} l_2 \\ 0 \\ 0 \end{bmatrix} \quad (4)$$

Then the x, y coordinate of the end-effector of link 2 is

$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} l_1 \times \cos(\theta_1) + l_2 \times \cos(\theta_1 + \theta_2) \\ l_1 \times \sin(\theta_1) + l_2 \times \sin(\theta_1 + \theta_2) \\ 1 \end{bmatrix} \quad (5)$$

2.2 Inverse kinematics

The inverse kinematics equation will give a set of joint angles that will achieve a desired Cartesian position. From Fig. 4 the joint angles θ_2 and θ_1 are derived as follows:

$$\cos(\theta_2) = \frac{c^2 - l1^2 - l2^2}{2 \times l1 \times l2} \quad (6)$$

Then $\sin(\theta_2) = \sqrt{1 - \left(\frac{c^2 - l1^2 - l2^2}{2 \times l1 \times l2}\right)^2}$ (7)

$$\tan(\theta_2) = \frac{\sin(\theta_2)}{\cos(\theta_2)} = \frac{\sqrt{1 - \left(\frac{c^2 - l1^2 - l2^2}{2 \times l1 \times l2}\right)^2}}{\frac{c^2 - l1^2 - l2^2}{2 \times l1 \times l2}} \quad (8)$$

Therefore

$$\Rightarrow \theta_2 = \tan^{-1}\left(\frac{\sqrt{1 - \left(\frac{c^2 - l1^2 - l2^2}{2 \times l1 \times l2}\right)^2}}{\frac{c^2 - l1^2 - l2^2}{2 \times l1 \times l2}}\right) \quad (9)$$

The angle θ_1 is calculated as follows:

$$\theta_1 = \beta - \psi \tag{10}$$

$$\theta_1 = A\sin\left(\frac{y}{c}\right) - A\sin\left(\frac{l_2 \sin\theta_2}{c}\right) \tag{11}$$

$$\theta_1 = A\sin\left(\frac{y}{\sqrt{x^2+y^2}}\right) - A\sin\left(\frac{l_2 \sin\theta_2}{\sqrt{x^2+y^2}}\right) \tag{12}$$

3. Conventional PID controller

The PID controller has been widely used because of its simple structure. It assures acceptable performance for the majority of industrial projects. It is a kind of linear controller which forms a control variable by linearly combining the proportional, integral, and derivative of the error e (t). The expression of the conventional PID controller is as follows:

$$u(t) = K_p e(t) + \frac{K_p}{T_i}\int_0^t e(t)dt + K_p T_d \frac{de(t)}{dt} \tag{13}$$

The Laplace transform of (13) is:

$$U(s) = K_p E(s) + \frac{K_p}{T_i s}E(s) + K_p T_d E(s) \tag{14}$$

And the resulting PID transfer function is:

$$\frac{U(s)}{E(s)} = K_p\left(1 + \frac{1}{T_i s} + T_d s\right) \tag{15}$$

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

$$u(k) = u(k-1) + K_p e(k) + \ldots$$
$$+\frac{K_p T}{T_i}e(k) + K_p T_d \frac{e(k) - e(k-1)}{T} \tag{16}$$

Where u (k), e (k) are control input to the DC servo motor and error between reference and output signal, respectively.

4. Fuzzy PID and fuzzy self tuning controller

It is generally known that the conventional PID controller does not work very well for nonlinear systems, higher order and time-delayed linear systems, and particularly complex and vague systems that have no precise mathematical models. To overcome these difficulties, various types of modified conventional PID controllers have been developed such as fuzzy PID, fuzzy self tuning controllers and so on.

4.1 Fuzzy controller

Fuzzy logic consists of three parts: fuzzification, fuzzy inference and defuzzification. The fuzzification is an interface that produces a fuzzy subset from measurement. The fuzzy inference is an interface that produces a new fuzzy subset from the result of the fuzzification. The defuzzification is an interface that produces a crisp output from the results of the fuzzy inference.

In this paper the fuzzy logic controller has two inputs, the position error (e), change of the error ($\dot{e}$) and one output (u). The input ($\mu(e)$, $\mu(\dot{e})$) and output ($\mu(u)$) fuzzy membership functions were selected symmetrically as shown in Fig. 5. Triangle membership functions were used in this work. The position error, change rate of position error and the output signal were partitioned in to seven fuzzy sets: negative large (NL), negative medium (NM), negative small (NS), zero (ZR), positive small (PS), positive medium (PM), positive large (PL).

The important part of the fuzzy logic controller is to design a rule table. In this work, the rule table consists of the rules that connect the error and the change in error with the control input. It contains linguistic

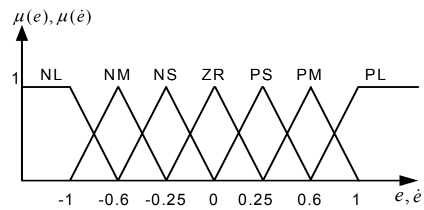


Fig. 5. The membership function of position error and the change rate of error.

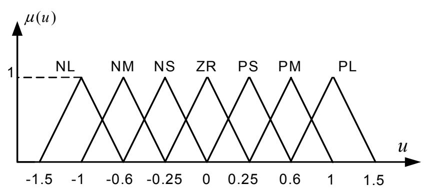


Fig. 6. The membership functions of output signal.

Table 2. Rule table of fuzzy controller.

$\dot{e}$ \ e	NL	NM	NS	ZR	PS	PM	PL
PL	ZR	PS	PM	PL	PL	PL	PL
PM	NS	ZR	PS	PM	PL	PL	PL
PS	NM	NS	ZR	PS	PM	PL	PL
ZR	NL	NM	NS	ZR	PS	PM	PL
NS	NL	NL	NM	NS	ZR	PS	PM
NM	NL	NL	NL	NM	NS	ZR	PS
NL	NL	NL	NL	NL	NM	NS	ZR

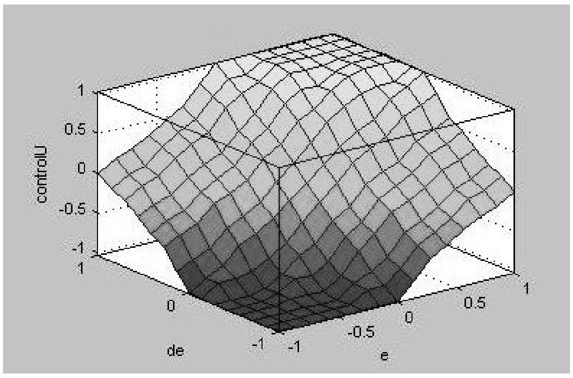


Fig. 7. Surface of fuzzy rule.

rules of the form:

If e is e_k and $\dot{e}$ is $\dot{e}_k$ then u is u_k

where e_k, $\dot{e}_k$, u_k are the fuzzy subsets of e, $\dot{e}$, u_k, respectively. According to seven fuzzy subsets of e and $\dot{e}$, we have 49 rules, and therefore the rule base is represented in a 7x7 matrix in Table 2.

4.2 Fuzzy PID controller

For complex nonlinear systems like the excavator, it is not easy to design a good fuzzy controller so the fuzzy PID control algorithm is applied because its heuristic nature is associated with simplicity and effectiveness. Its nonlinear property of control gains can improve and achieve better system performance than a conventional PID controller.

The fuzzy PID controller consists of two main blocks: fuzzy controller block and PI block. The fuzzy controller block has two inputs, signal error e and error change $\dot{e}$, and one control signal output as introduced in chapter 4.1. The PI block, which consists of a conventional integral block and proportional

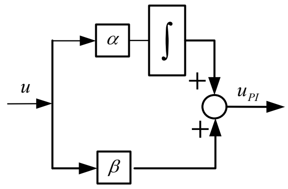


Fig. 8. PI controller.

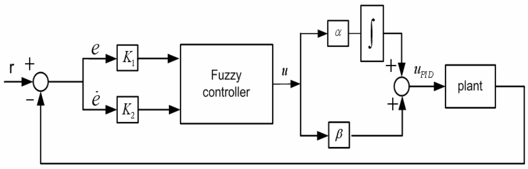


Fig. 9. Fuzzy PID controller.

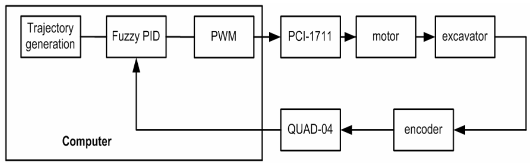


Fig. 10. Overall structure of control system by using the fuzzy PID controller.

block, is introduced in Fig. 8.

The proposed fuzzy PID controller is shown in Fig. 9, and Fig. 10 shows the overall structure of the control system by using the fuzzy PID controller of the mini excavator.

From Fig. 9, the control signal u_{PID} is

$$\begin{aligned} u_{PID} &= \alpha\int udt + \beta u \\ &= (\beta A + \alpha At) + (\beta K_1 P + \alpha K_2 D)e + \\ &\quad \alpha K_1 P\int edt + \beta K_2 D\dot{e} \end{aligned} \tag{17}$$

where K_1, K_2, α, β, A, P and D are scaling factors for e and $\dot{e}$, integral gain, proportional gain, fuzzy set of error, $P = \dfrac{u_{i+1} - u_i}{e_{i+1} - e_i}$ and $D = \dfrac{u_{i+1} - u_i}{\dot{e}_{i+1} - \dot{e}_i}$, respectively. Hence the fuzzy controller becomes a PID controller with varying parameter [4], where its equivalent proportional control, integral control and derivative control components are $\beta K_1 P + \alpha K_2 D$, $\alpha K_1 P$ and $\beta K_2 D$, respectively.

4.3 Fuzzy self tuning with neural network (FN) controller

Clearly, the advantage of the proposed fuzzy PID algorithm is in simplifying the control rule base significantly and thus greatly increasing the inference efficiency. On the other hand, the disadvantage of this approach is that the controller parameters are coupled with each other and have to be regulated in combination. This problem can be resolved by introducing parameter learning and optimization algorithms, such as neural-network-based algorithms.

Nowadays, the fuzzy self tuning controller has been widely used for industrial processes because of its heuristic nature associated with simplicity and effectiveness for both linear and nonlinear systems. The on-line parameter adjustment of the fuzzy self tuning controller has practicability in real-time process control. The fuzzy self tuning controller proposed in this paper has three blocks: fuzzy block, neural network block and the conventional PD tuning block.

4.3.1 Fuzzy block

In order to compare the performance result between fuzzy PID and fuzzy self tuning with neural network which are applied to the mini excavator, the fuzzy block has the same membership functions and the same control rule table as introduced in section 4.1. The output of this block is divided into three parts, then each part is fed into the neural block. A diagram of this process is presented in Fig. 11. The control output signal is tuned online by the update process of the weight coefficient weight of the neural network w_1, w_2, w_3.

$$u_{nn} = (w_1 + w_2 + w_3) \times u_F \tag{18}$$

Where u_F is the output signal from the fuzzy and u_{nn} is the signal output from the neural network block.

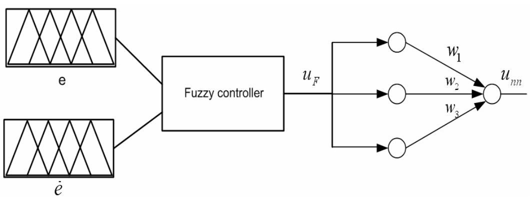


Fig. 11. Structure of proposed fuzzy self tuning with neural network algorithm.

4.3.2 Neural block

Artificial neural network (ANN) is a class of nonlinear regression and discrimination models. It offers great advantages in learning, adaptation, fault tolerance, parallelism, and generalization. Because of the complexity of the excavator system, the output of the fuzzy controller is fed back to the input of the neural network, which is presented in Fig. 12. With its ability to learn, this hybrid technique can be used to improve the performance of the control system.

The proposed neural block is designed with a single node neural structure and consists of one input layer and output layer where the input layer receives the signal output from fuzzy block. The output layer contains a set of adjustable parameter w_i, only one neural node with input function.

$$f = \sum_{i=1}^{m} w_i \times u_{F_i} \quad with\ m = 3 \tag{19}$$

where u_{F_i} is the input signal of this node

The activation function of the neural output is given by equation:

$$a = u_{nn} \frac{f}{\sum_{i=1}^{m} u_{F_i}} \tag{20}$$

The learning algorithm of the neural block is based on the minimization of the cost function which is defined as

$$E = \frac{\varepsilon^2}{2} \tag{21}$$

where ε is calculated as the following equation:

$$\varepsilon = u_{control} - u_{nn} = u_{PD} \tag{22}$$

This means that the energy of the control effort is

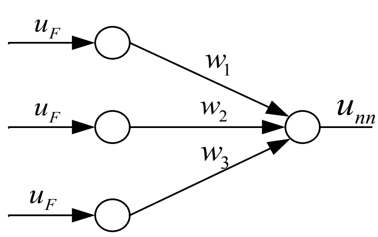


Fig. 12. Neural output node.

minimized.

The update process of the synaptic weights or adjustable parameters w_i is computed as follows

$$w_i(t+1) = w_i(t) + \eta \times u_{PD} \times \frac{u_{F_i}}{\sum_{i=1}^{m} u_{F_i}} \tag{23}$$

where η is the learning rate [5]. This equation is implemented on each step of the learning algorithm for the parameters which correspond to the outputs of the fuzzy controller.

4.3.3 Tuning block

It has been known that the fuzzy algorithm has some limitation in being directly applied to robot control problems. First, the fuzzy subsets are defined on the discrete universe of discourse and the fuzzy inference is performed over such fuzzy sets; the control input is also determined by a quantized value. Therefore, the effect is insensitive to noise, so smooth motion cannot be expected. Second, the procedure of the fuzzy inference which calculates the overall relationship matrix requires much computational time in proportion to the number of rules. Finally, a dedicated electronic device for high speed fuzzy reasoning is needed. To avoid these restrictions the fuzzy with neural is modified by an additional conventional feedback controller (CFC) PD tuning block. This CFC was proposed by Gomi and Kawato to apply for a nonlinear feedback controller (Hiroaki GOMI., 1990). This PD tuning block is added in parallel with the neural block, as shown in the block diagram of fuzzy self tuning controller in Fig. 13. Therefore, the control input to the excavator is

$$u_{control} = u_{nn} + u_{PD} \tag{24}$$

From the block diagram in Fig. 13, the overall structure of the control system by using FN can be constructed in the following figure. In Fig. 14, the reference trajectory is generated by PC and the control input is calculated by using the fuzzy self tuning algorithm. The calculated control input is sent to the PWM block and is converted to an on/off digital signal by using DIO (PCI-1711). This signal then controls the electric DC motor.

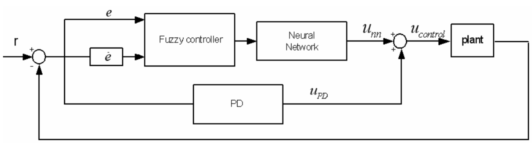


Fig. 13. Block diagram of fuzzy self tuning controller.

5. Experimental results

In the experiment, the mini excavator was controlled by using three algorithms: conventional PID, fuzzy PID and fuzzy self tuning with neural network control. The sampling time was set at T=0.001s in all experiments. The length and mass of the boom and arm are l1=0.61m, m1=2.836kg, l2=0.295m, m2= 1.348kg, respectively. The feedback signal is read to the computer by the rotary encoder. The system hardware consists of an IBM compatible personal computer (Pentium 1 GHz), which is used to get the feedback signal through the encoder board (Advantech, PCI-QUAD 04) and give the control input signal through the I/O board (Advantech, PCI-1711). The DC motor is controlled by the PWM algorithm. The system hardware is presented in Fig. 15 and Fig. 16.

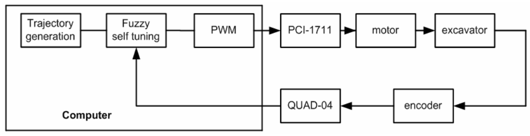


Fig. 14. Overall structure of control system by using FN.

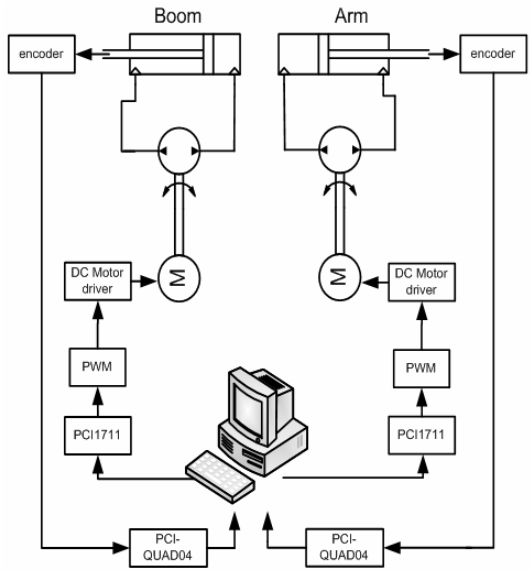


Fig. 15. Schematic diagram of the experimental equipment.

Table 3. Reference Trajectory for Case 1.

Time (s)	1st joint angle (boom)	2nd joint angle (arm)
0-15	12	16
15-30	21	30
30-45	30	45
45-60	45	60
60-75	30	36
75-100	15	24
100-120	0	0

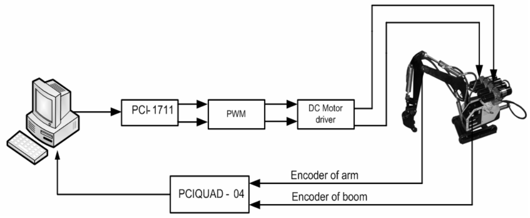
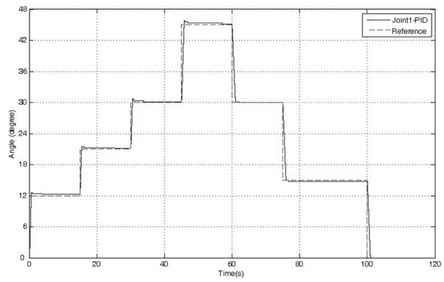
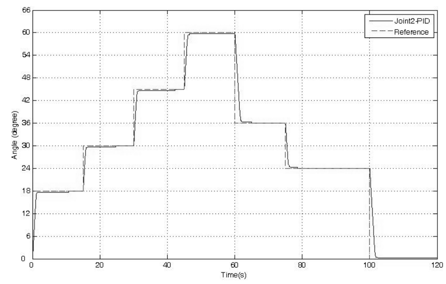


Fig. 16. Experimental apparatus.



(a) Boom

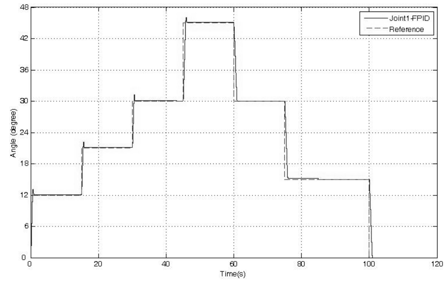


(b) Arm

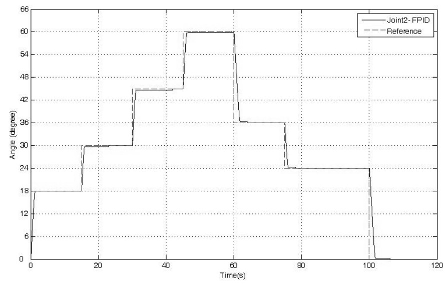
Fig. 17. PID control results of two links of the excavator .

Based on the reference trajectory, the angle of each link is calculated and converted to the number of pulses for generating a control signal PWM output. For doing the experiments, two cases of trajectory were investigated as follows:

Case1:

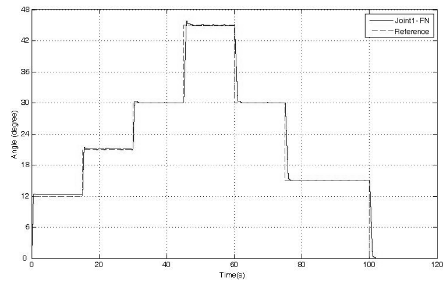


(a) Boom

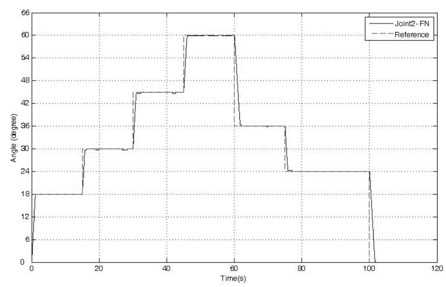


(b) Arm

Fig. 18. FPID control results of two links of the excavator.



(a) Boom



(b) Arm

Fig. 19. FN control results of two links of the excavator.

The setting trajectory of the boom and arm of mini excavator is presented in Table 3. The trajectory is given to check the step response of the proposed control algorithm.

The multiple step responses of the conventional

PID, fuzzy PID and fuzzy self tuning controllers with neural network are shown in Figs. 17, 18 and 19, respectively. It was verified from these figures that fuzzy self tuning with neural network (FN) and fuzzy PID algorithm has a better control performance than the conventional PID algorithm with faster response and smaller error.

Case 2: In this case, the trajectory of the boom and arm of the mini excavator is selected as a circle with a diameter of 70 [mm]. From Fig. 20, it is understood that the maximum error of the angle between the reference trajectory and measured angle of joint 1 and joint 2 is 1.6 [°] and 3 [°], respectively, by using the PID algorithm. The error is still large and the amplitude of error is also large. It is about 2.2 [°] for joint 1 and 5 [°] for joint 2 and it will be reduced by using the fuzzy PID and the FN control algorithm.

From Fig. 21, it can be realized that with the fuzzy PID algorithm, the accuracy is better than the conventional PID algorithm with the maximum error of the

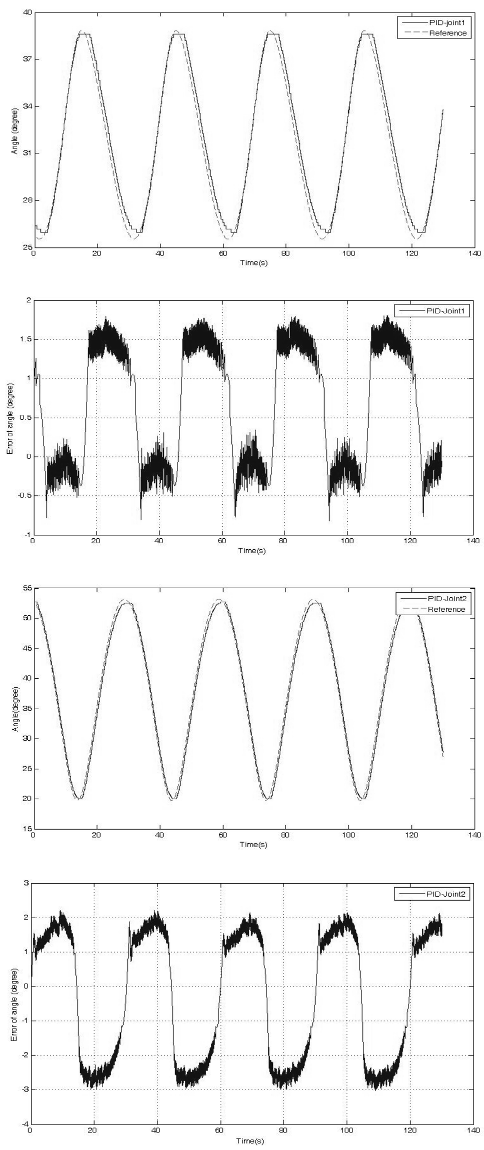


Fig. 20. PID control results and the error of angle between reference and real signal of the boom and arm of the excavator.

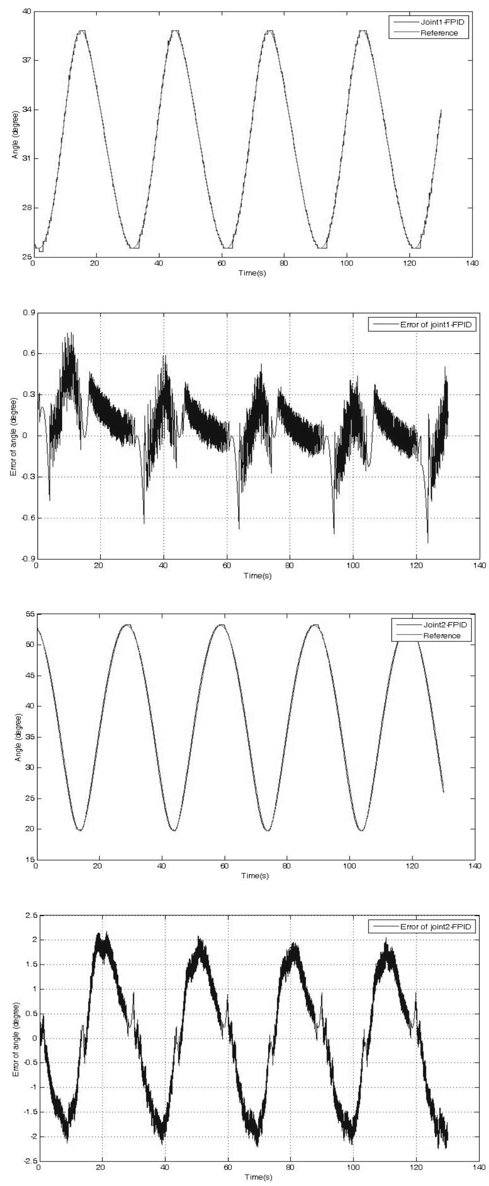


Fig. 21. Fuzzy PID control results and the error of angle between reference and real signal of the boom and arm of the excavator.

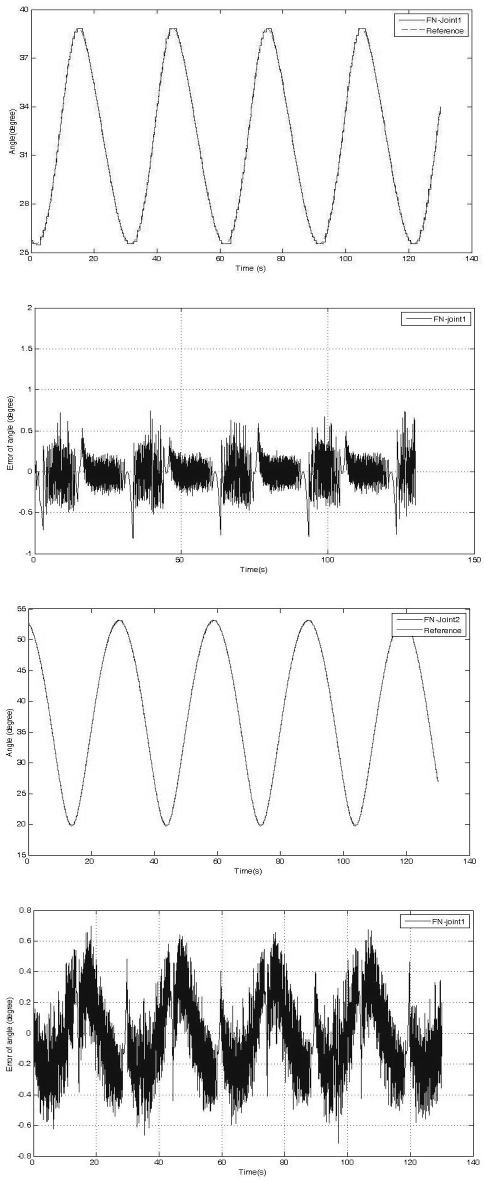


Fig. 22. Fuzzy self tuning control results and the error of angle between reference and real signal of boom and arm of the mini electro hydraulic excavator.

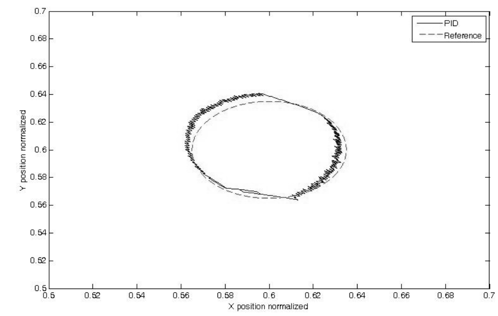


Fig. 23. Circle path following the mini electro hydraulic excavator by using PID controller.

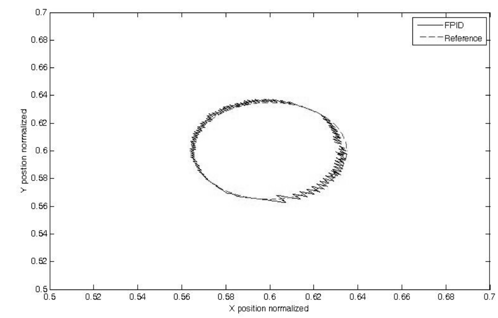


Fig. 24. Circle path following the mini electro hydraulic excavator by using Fuzzy PID controller.

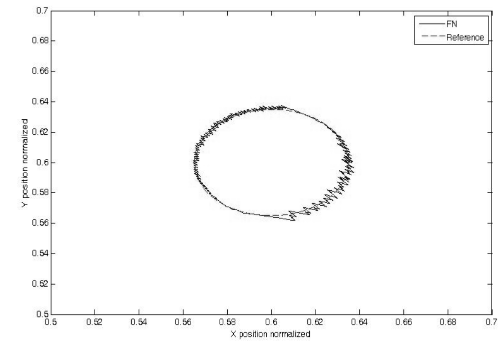


Fig. 25. Circle path following the mini electro hydraulic excavator by using FN controller.

angle between the reference trajectory and measured angle of joint 1 and joint 2 of just 0.7 [°] and 2 [°], respectively. Compared with the PID algorithm, the error is reduced 50% for joint 1 and about 30% for joint 2. But the amplitude of the error is still quite large: about 1.4 [°] for joint 1 and about 4 [°] for joint 2. From Fig. 22, with ability of learning and using the optimization algorithm, the error is now the smallest compared with PID and fuzzy PID algorithm with the maximum error of the angle between the reference trajectory and measured angle of joint 1 and joint 2 of just 0.6 [°] and 0.6 [°], respectively. The error is reduced 65% for joint 1 and about 80% for joint 2 compared with PID algorithm and the amplitude of error is small. It is about 1.2 [°] for joint 1 and about 1.2 [°] for joint 2. It can be seen from Figs. 23, 24, 25 that the fabricated electro hydraulic excavator follows the desired trajectory with good agreement in the case of the intelligent fuzzy PID and FN controller.

6. Conclusion

Due to the disadvantages of the traditional PID controller in the mini excavator system, two controllers based on fuzzy logic, including the fuzzy PID controller and fuzzy self tuning with neural network, were developed to control the electro hydraulic mini excavator. The experimental results show that the fuzzy PID controller and FN obviously have better control performance than the conventional PID. The fuzzy self tuning with neural network is more flexible because the control output signal is tuned online by the update process of the neural network. The tracking performance was improved by applying the fuzzy self tuning controller with neural network because of its better adaptability to disturbances and nonlinear systems.

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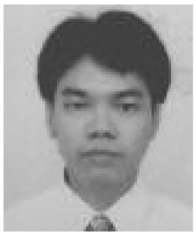

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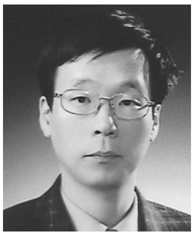

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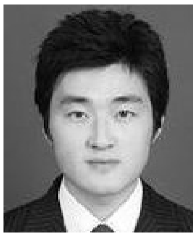

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