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# Development of Adaptive Learning Control Algorithm for a two-degree-of-freedom Serial Ball And Socket Actuator

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## 1. Introduction

For any newly developed mechanism the most challenging task is the controller. The controller is an algorithm that organizes the mechanism input energy to perform a specified task. Robot control usually requires the directing of signals or fluid paths of power elements to indicate robot end-effector dynamic behaviour. Furthermore, robot control can be divided into two main areas: kinematic control (the coordination of the links of the kinematic chain to produce desired motions of the robot) and dynamic control (driving the actuators of the mechanism to follow the commanded position velocities). These control strategies are widely used in most robots involving position coordination in Cartesian space by a direct kinematic method (Karlik and Aydin, 2000).

In this chapter, an artificial neural network (ANN) adaptive learning algorithm has been implemented for dynamic behaviour control of a new two-degree- of-freedom (2DOF) serial ball-and-socket actuator. The ANN provides computer simulation of human brain activity that gives computers the ability to learn and predict a decision for a specific task. The ANN requires a specific network design followed by a training process. A variety of modifications could be carried out for the network design during the training process.

For a robot control scheme there are many uncertainties in the parameters of both the actuators (hydraulic, pneumatic, and electric drivers) and the mechanical parts of the manipulators (Cheah et al., 2003, Tso & Law, 1993, Mills, 1994, Yang & Chu, 1993, Tsao & Tomizuka, 1994, Park & Cho, 1992, Ambrosino et al., 1998). Therefore, to cover the overall complexity of the robot control problem and the quest for a truly autonomous robot system, the application of an ANN to the robot control scheme has been considered (Ananthraman, 1991, Cruse & Bruwer, 1990, Kuperstein & Wang, 1990, Miller et al., 1990, Hasan et al., 2007, Abdelhameed, 1999, Sharkey & Noel, 1997, Brun-Picard et al., 1999). In addition, the proposed hydraulic power system is one with highly non-linear behaviour. Variations in parameters affect the hydraulic system operation and performance, e.g. the laminar and turbulent flows, channel geometry, friction results in the system equation, the relation between flow velocity and pressure, and oil viscosity (Knohl & Unbehauen, 2000). Hence, to

cope with situations of this kind, the hydraulic system required a non-linear controller such situation such as an ANN, which has been the focus of work by various researchers (Mills et al., 1994, Chen & Billings, 1992).

In robotics, the revolute joint has one-degree-of-freedom and, because of its simplicity, is by far the most used joint. In order to imitate the shoulder or hip joint, two revolute actuators are required to provide the necessary 2DOF motion. In the biomedical literature, the representation of the human arm as three rigid segments connected by frictionless joints with a total of seven degrees of freedom is the generally accepted model (Desmurget & Prablanc, 1997, Lemay & Cragi, 1996, Raikova, 1992). In the 7DOF arm models the shoulder joint is usually considered as a ball-and-socket joint and the axes in the elbow and wrist joints are assumed to be orthogonal and intersecting (Perokopenko et al., 2001).

Consequently, a new 2DOF serial ball-and-socket actuator has been fabricated to replace the two revolute actuators in the serial robot manipulator. The fabricating process has been done by combining actuator elements such as the actuator mechanism, the electrohydraulic powering system, the communication interface board, and the adaptive learning algorithm.

The ball-and-socket joint, used in engineering as a mechanical connection between parts that must be allowed some relative angular motion in nearly all directions, represents articulation with two rotational degrees of freedom. Ball-and-socket joints are successfully used for parallel robots and simulators powered by pneumatic or hydraulic cylinders. The available basic methods to transmit the power are electrical, mechanical, and fluid drivers. Most applications are a combination of these three methods. Each of these methods has advantages and disadvantages, so the use of a particular method depends on the application and environment (McKerrow, 1991). Among the power transmission systems, the hydraulic system will be recommended for use in the developed actuator on account of its ability to store energy when no power supply is offered by keeping the pressurized fluid inside the cylinder. This is a necessary step to stabilize the ball-and-socket actuator. Therefore, two electrohydraulic cylinders have been developed; each will perform one degree of freedom with the other supporting, and vice versa.

An ANN model has been developed and trained to build control knowledge that covers all the control parameters for the ball-and-socket actuator. This control knowledge will function from digital signals, extracted by computer, to the target end-effector dynamic behaviour, without any involvement of actuator mechanism behaviour, with the flexibility to cover any modification without changing the control scheme. The ANN model has been simulated using C++ programming language. The completed system has been run and tested successfully in the laboratory. The remainder of this chapter will demonstrate the basic elements of the ball-and-socket actuator, and will examine the control approach and the process of development and training of the ANN model.

## 2. Actuator Design Specifications

The proposed ball-and-socket actuator comprised an actuator mechanism, a power system, and a communication interface board. The actuator mechanism represents the mechanical elements and comprises the base, ball-and-socket joints, two double-acting electrohydraulic cylinders, and the end-effector rod. A diagram of the ball-and-socket actuator is shown in Fig. 1, while Fig. 2 shows the fabricated actuator mechanism built to represent the developed ball-and-socket actuator.

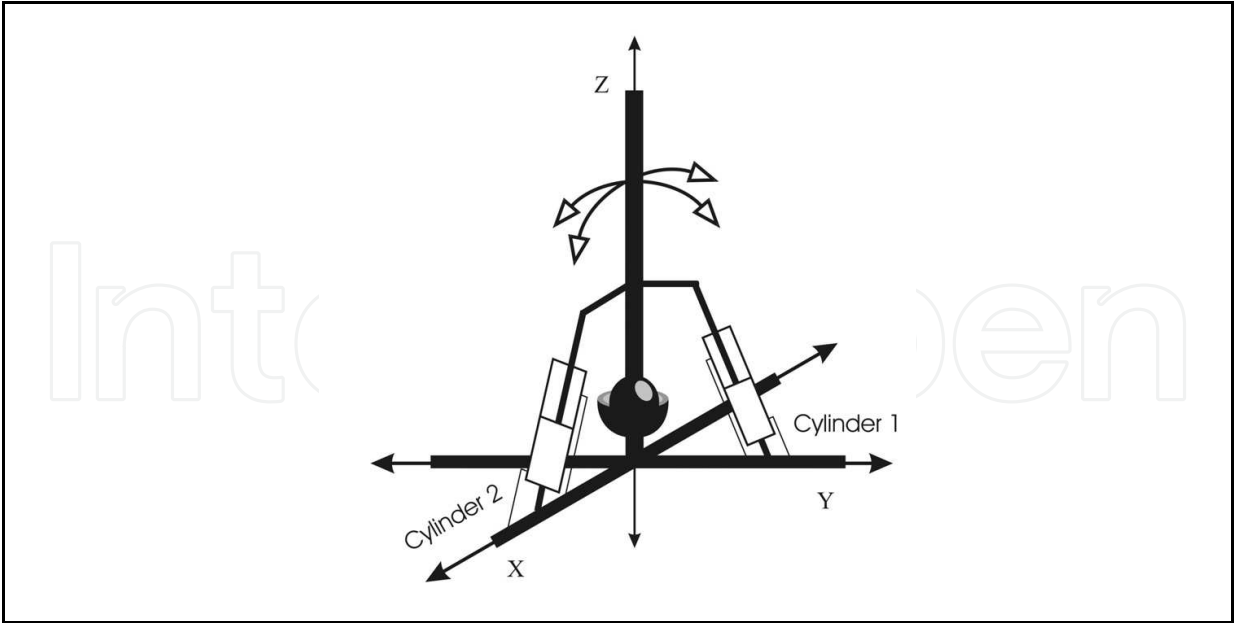


Fig. 1. Positioning of the support cylinder for the actuator



Fig. 2. Fabricated Ball and socket actuator

The power transmission system is complicated by the characteristics of the joints which must be free to rotate in all directions and need a dual-tasking power system. Therefore, an electrohydraulic cylinder powered by a 1 hp pump was used. The system consists of two double-acting electrohydraulic cylinders that are capable of maintaining their position when the pressurized fluid is kept inside them. This is a very necessary step to ensure sufficient actuator stability for the other cylinder when operating to the desired direction and is an advantage of the ball-and-socket actuator. The double-acting electrohydraulic cylinders have a two-direction movement scheme that provides an inward and outward motion for

the end-effector rod. Moreover, the deployment of double-acting electrohydraulic cylinders reduces the number of supporting points that are necessary to run and stabilize the actuator mechanism to 2 instead of 4 as in the case of single-acting cylinders.

A communication interface board has been designed and fabricated to establish the necessary signals to operate the actuator. Basically it is a transistor relay driver circuit converting a 5 V digital signal from the computer mother board operating the learning algorithm (ANN) to the necessary 24 d.c. signals required to operate the electrohydraulic cylinders.

### 3. Actuator Controlling Approach

To plan a controller it is necessary to understand the system behaviour and characteristics. The equations

$$(x) \quad 2r_1 \sin \theta_1 \cos \phi_1 = r_2 \sin \theta_2 \cos \phi_2 + r_3 \sin \theta_3 \cos \phi_3 \quad (1)$$

$$(y) \quad 2r_1 \sin \theta_1 \sin \phi_1 = r_2 \sin \theta_2 \sin \phi_2 + r_3 \sin \theta_3 \sin \phi_3 \quad (2)$$

$$(z) \quad 2r_1 \cos \theta_1 = r_2 \cos \theta_2 + r_3 \cos \theta_3 \quad (3)$$

illustrate the relationship between angles  $\theta_1$  and  $\phi_1$ , representing the angular displacement of the end effector, and  $\theta_2, \theta_3, \phi_2, \phi_3, r_2$ , and  $r_3$  for kinematic analysis on the  $x$ ,  $y$ , and  $z$  axes, where  $\theta_2, \theta_3, \phi_2, \phi_3$  are the angular displacements of cylinders 1 and 2, and  $r_2$  and  $r_3$  are the lengths of cylinders 1 and 2 respectively.

The equations

$$\theta_1 = \sin^{-1} \left( \frac{r_2 \sin \theta_2 \cos \phi_2 + r_3 \sin \theta_3 \cos \phi_3}{2r_1 \cos \phi_1} \right) \quad (4)$$

$$\phi_1 = \cos^{-1} \left( \frac{r_2 \sin \theta_2 \cos \phi_2 + r_3 \sin \theta_3 \cos \phi_3}{2r_1 \sin \theta_1} \right) \quad (5)$$

$$\theta_1 = \cos^{-1} \left( \frac{r_2 \sin \theta_2 \cos \phi_2 + r_3 \sin \theta_3 \cos \phi_3}{2r_1 \sin \theta_1} \right) \quad (6)$$

$$\phi_1 = \sin^{-1} \left( \frac{r_2 \sin \theta_2 \sin \phi_2 + r_3 \sin \theta_3 \sin \phi_3}{2r_1 \sin \theta_1} \right) \quad (7)$$

$$\theta_1 = \cos^{-1} \left( \frac{r_2 \cos \theta_2 + r_3 \cos \theta_3}{2r_1} \right) \quad (8)$$

represent the solutions for finding the angles  $\theta_1$  and  $\phi_1$  from equations (1) to (3).

Finding the solution for  $\theta_1$  and  $\phi_1$  as illustrated in the above equations will depend on  $(\sin^{-1})$  and  $(\cos^{-1})$  which are not single-value functions. Furthermore, equations (4), (6), and (8) can be used to find  $\theta_1$  values that are not unique.

In this chapter, an ANN adaptive learning algorithm has been proposed for controlling a 2DOF serial actuator. In this approach, the adaptive learning algorithm finds an alternative



solution of the kinematic relation for the ball-and-socket actuator. Therefore, all parameters operating the actuator will be considered as target learning input data for the ANN model, while the output target data will be the angular displacement, angular velocity, and angular acceleration of the actuator end-effector.

The shape of the actuator mechanism, as shown in Fig. 1, can be controlled by varying the length of the electrohydraulic cylinders. The hydraulic cylinders operate as a result of allowing pressurized fluid to run them. All the parameters affecting this operation, such as the valve order, time, flow-rate, pump pressure, and the fluid head losses, will have been incorporated as inputs for the ANN model. After running the cylinder length, the output for the ANN will be the dynamic behaviour of the actuator end-effector.

The workspace, the region that can be reached by the end-effector, is considered to be an important performance indicator. Therefore, the control approach is to drive the actuator to reach a point from any point within the desired workspace area. Experimental operation shows a square workspace for the fabricated actuator mechanism, as illustrated in Fig. 3. As can be seen from Fig. 3, the workspace is divided into nine points within the  $x$ - $y$  plane. Therefore, experimental operation has been carried out to estimate and collect the control parameters that drive the actuator from one specific point to another individual point. These collected control data have been arranged as datasets. Each set represents input control data to drive the actuator mechanism and outputs as angular displacement, angular velocity, and angular acceleration of the end-effector. All the datasets were used as target learning data by the ANN to build the control knowledge required to operate the ball-and-socket actuator.

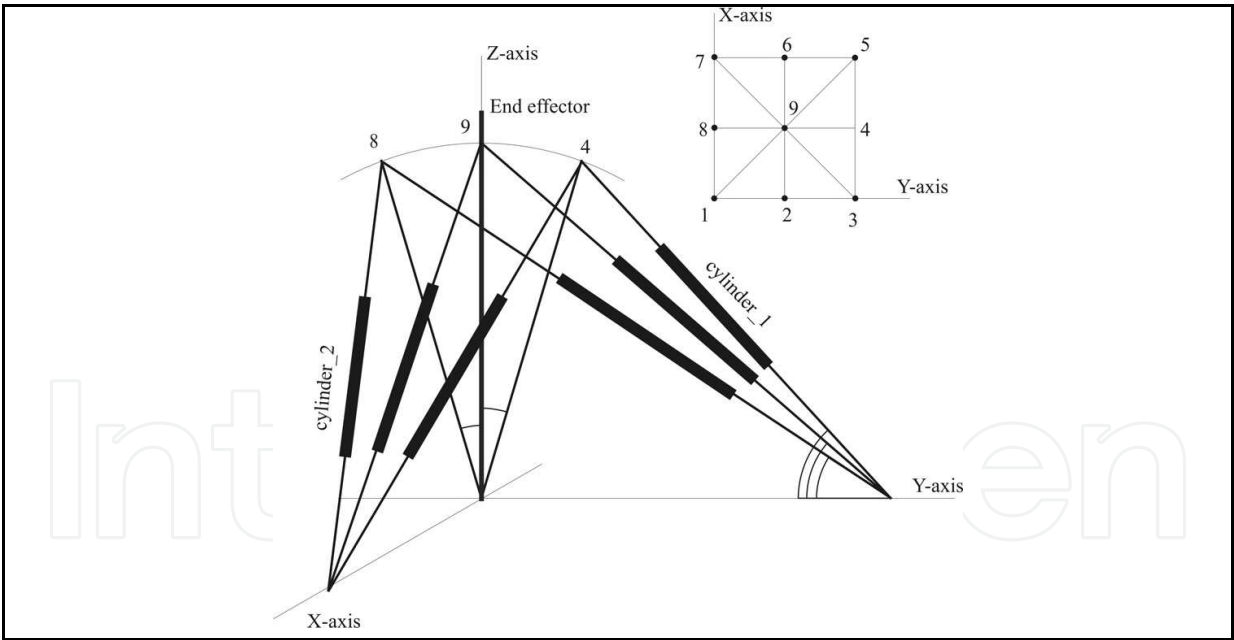


Fig. 3. Motion analyses of the ball-and-socket actuator

#### 4. Adaptive Learning Algorithm

ANN adaptive learning algorithm computer software was proposed to learn and adopt the control parameters to provide the necessary digital signal from the computer main board to operate the actuator mechanism. These digital signals could be extracted through various

computer outputs such as serial, parallel, and USB ports. In this chapter, the parallel port (printer port) has been chosen to extract +5 V digital signals from the computer.

Although the ANN method is being implemented to learn a set of information, a specific network design is required to cover each individual dataset and application. Consequently, a special network has been designed to adopt the control parameters for the ball-and-socket actuator that consists of an input layer (valve order, time, pump power, flow-rate, output pressure, and head losses for the system), one hidden layer, and an output layer (angular displacement 1, angular displacement 2, angular velocity 1, angular velocity 2, angular acceleration 1, and angular acceleration 2), as shown in Fig. 4.

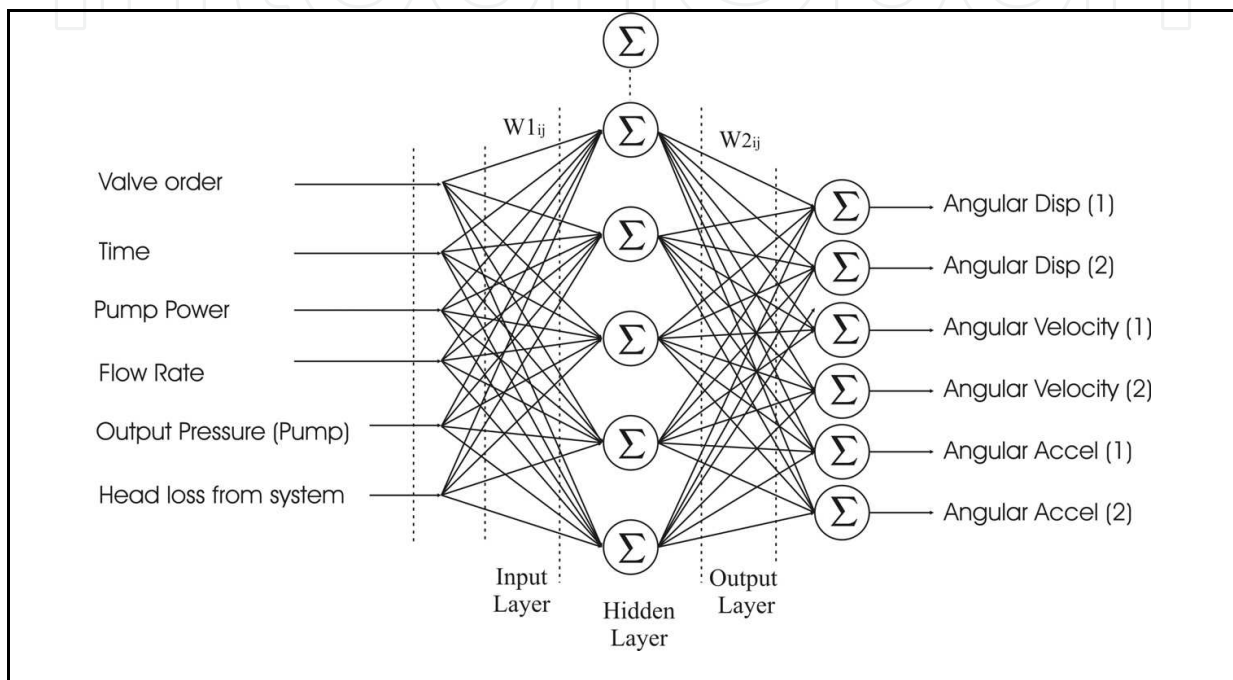


Fig. 4. ANN for controlling the ball-and-socket actuator

After designing the network, a training process had to be accomplished to build control knowledge, which is considered to be the most important step in designing ANN algorithms. A neural network was trained by presenting several target data that the network had to learn according to a learning rule. The training rule indicated transfer of a function such as the binary sigmoid transfer function (equation (9)), forward learning for the input layer (equation (10)), forward learning for the hidden layer (equation (11)), backward learning for the output layer (equation (12)), and backward learning for the hidden layer (equation (13))

$$y_q = f(u_q) = \frac{1}{1 + \exp(-u_q)} \quad (9)$$

$$h = f^{(1)}[W^{(1)}x] = \frac{1}{1 + \exp(-W^{(1)}x)} \quad (10)$$

$$o = f^{(2)}[W^{(2)}h] = \frac{1}{1 + \exp(-W^{(2)}h)} \quad (11)$$

$$\delta_2 = o(1 - o)(y - o) \quad (12)$$

$$\delta_1 = h(1-h) \sum \delta_2 W^{(2)} \quad (13)$$

The training process also indicates weight adjustments for each node of the network with adjustment of the hidden neuron numbers and learning factor. In this chapter, ten hidden neurons were assigned. This type of training process formally was known as the back-propagation learning algorithm or delta learning rule. The back-propagation for the output layer is represented by the equation

$$W^{(2)}(t+i) = W^{(2)}(t) + \mu \delta_2 h \quad (14)$$

and for the hidden layer by the equation

$$W^{(1)}(t+i) = w^{(1)} + \mu \delta_1 x \quad (15)$$

In addition, a learning factor  $\mu$  of 0.7 was assigned to adjust the training process. The effectiveness and convergence of the error back-propagation learning algorithm depends significantly on the value of the learning factor. In general, the optimum value of  $\mu$  depends on the problem being solved, and there is no signal learning factor value suitable for different training cases. This leads to the conclusion that  $\mu$  should indeed be chosen experimentally for each problem (Zurada, 1992). The training process will be continued until the network is able to learn all the target data. The accuracy of the learning process depends on the type of data to be learned and the application of the network.

## 5. Results and Discussion

The ANN was trained with predefined target control datasets. C++ programming language was developed to simulate the ANN control algorithm with the necessary arrangement of output signals operating the electrohydraulic power system. All control datasets values had been scaled individually so that the overall difference in the dataset was maximized; this was due to the sigmoid transfer function employed with a learning range from 0 to 1. Training sets were taken by manually driving the actuator to follow a desired path.

The training control data were broken up into 64 input-output sets, which covered the entire motion range of the ball-and-socket actuator. Each set represented the valve order with the time needed to move the actuator from a desired point to another with the incorporated parameters. These control data were used to drive the actuator to follow a desired path and to move the actuator through all intermediate points. The neural network was trained repeatedly for 300 000 iterations with the predefined datasets. To validate the design of the network, predicted output sets for angular displacement 1, angular displacement 2, angular velocity 1, angular velocity 2, angular acceleration 1, and angular acceleration 2 were compared with values from experimental data collected.

The average absolute errors are summarized in Table 1. Figure 5 illustrates the deviation between predicted outputs and the data obtained from the ANN. The results show that the design network is capable of learning and predicting the control parameters as shown in Figures 6, 7, and 8.



Parametrs	Percenatge of Error
Angular Disp_1	3.86
Angular Disp_2	5.23
Angular Velocity_1	6.35
Angular Velocity _2	4.36
Angular Accel_1	3.98
Angular Accel_2	2.77

Table 1. Mean absolute percentage error

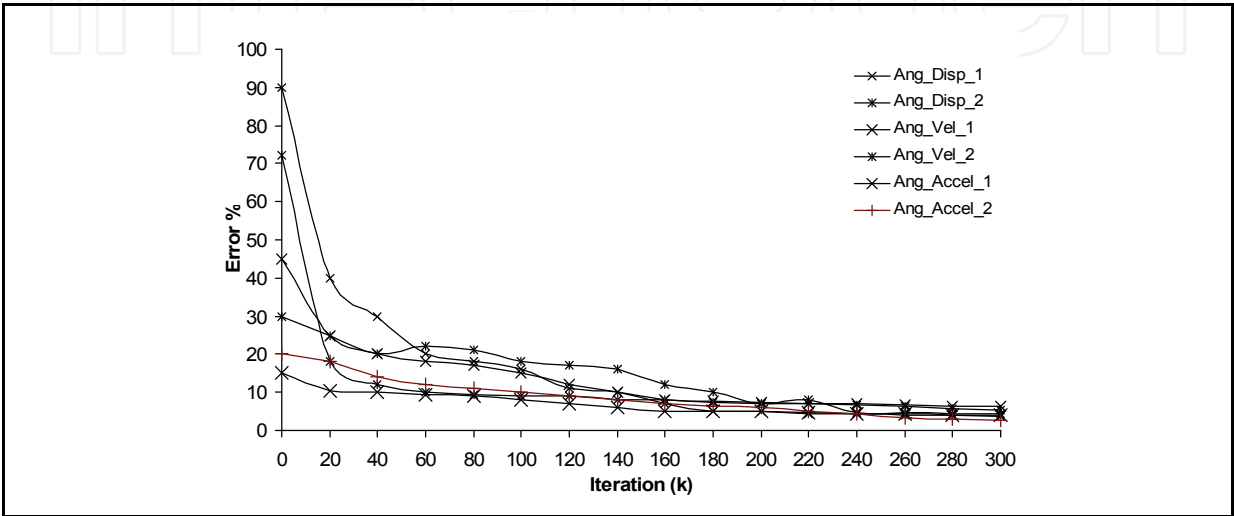


Fig. 5. Process of building knowledge for the learning Algorithm

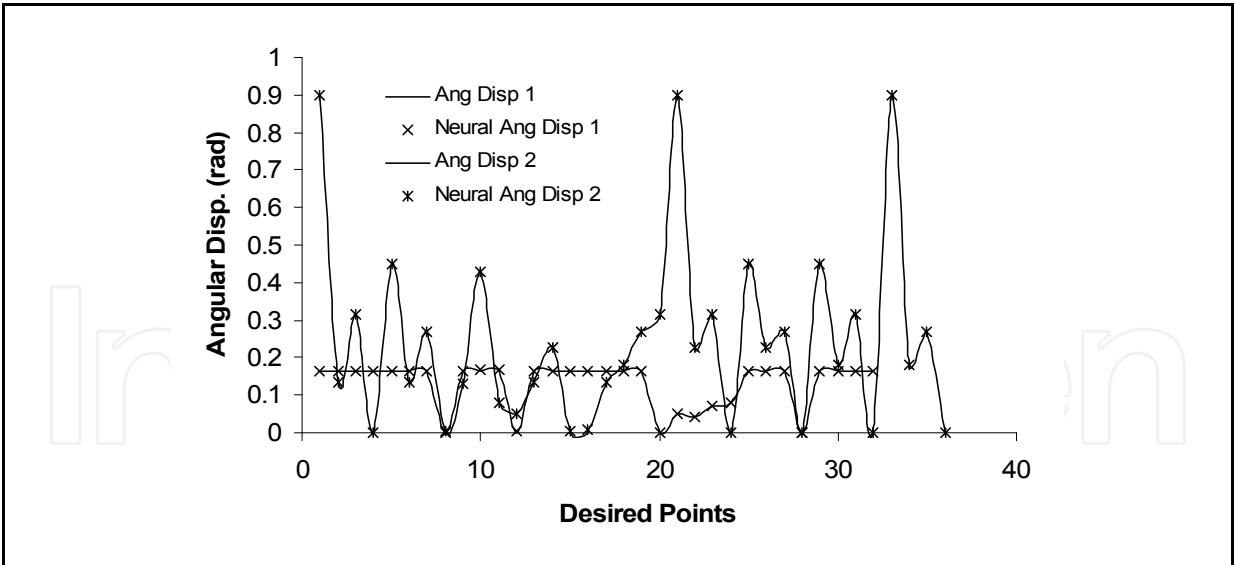


Fig. 6. Predicted angular displacements

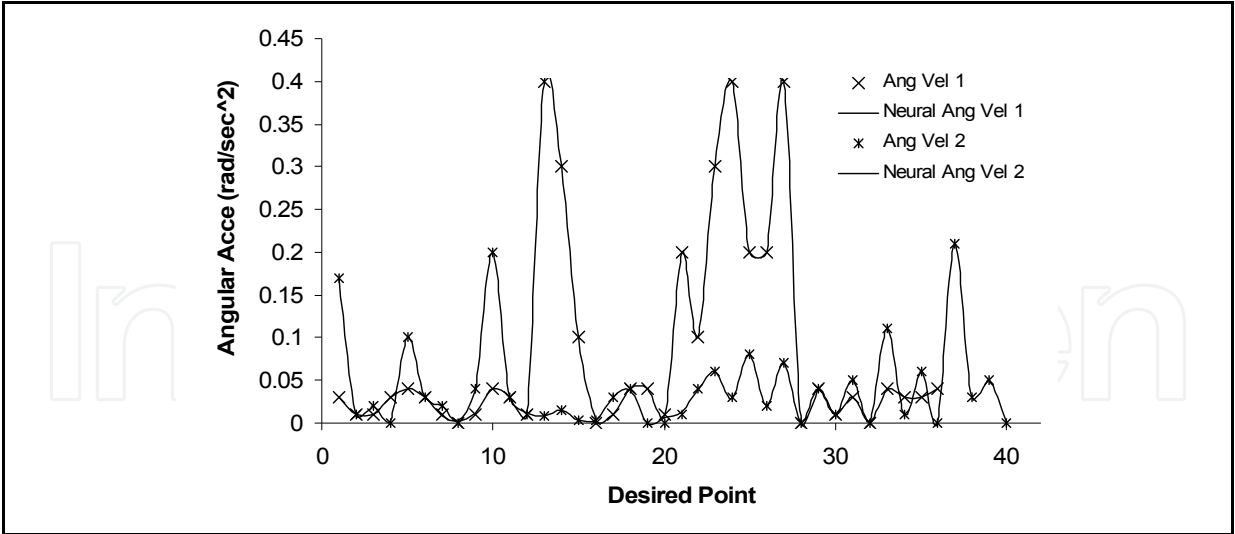


Fig. 7. Predicted angular velocities

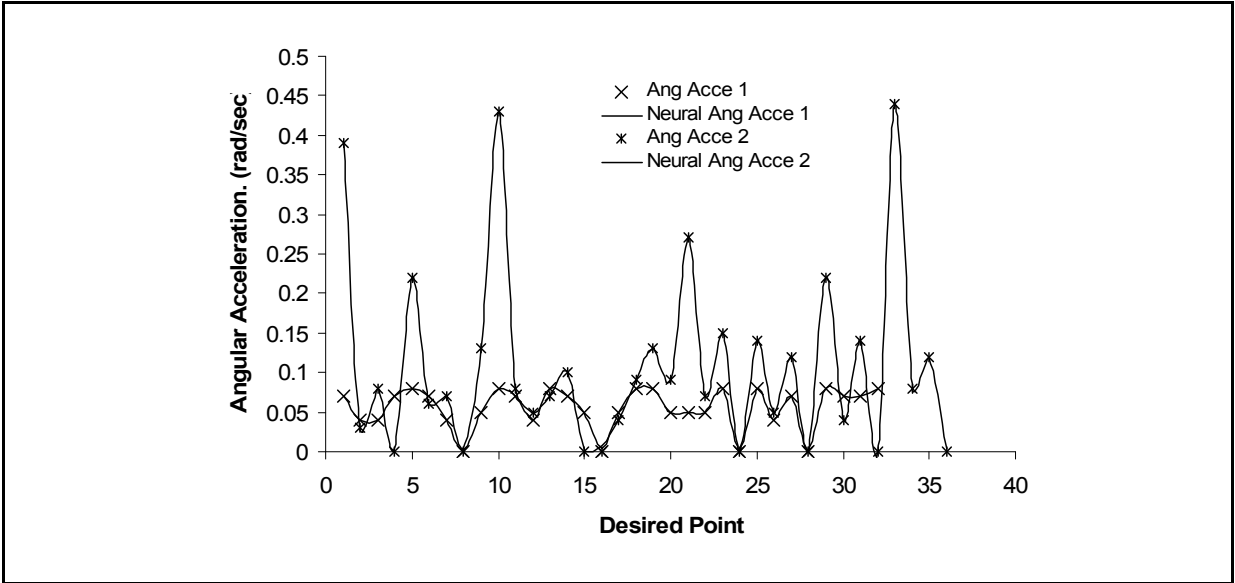


Fig. 8. Predicted angular acceleration

6. Conclusion

The ANN adaptive learning algorithm developed has been implemented successfully on a new 2DOF ball-and-socket actuator. The algorithm has the capability of getting round the drawback of some control schemes that depend on modelling the system being controlled. An actuator has been fabricated to replace the two revolute actuators in serial robot manipulators. The trained ANN showed the ability to operate the ball-and-socket actuator properly in real time by achieving angular displacement, angular network velocity, and angular acceleration.

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Robot manipulators are developing more in the direction of industrial robots than of human workers. Recently, the applications of robot manipulators are spreading their focus, for example Da Vinci as a medical robot, ASIMO as a humanoid robot and so on. There are many research topics within the field of robot manipulators, e.g. motion planning, cooperation with a human, and fusion with external sensors like vision, haptic and force, etc. Moreover, these include both technical problems in the industry and theoretical problems in the academic fields. This book is a collection of papers presenting the latest research issues from around the world.

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