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ARTIFICIAL NEURAL NETWORKS IN ROBOT CONTROL SYSTEMS: A SURVEY PAPER

Ş. Yıldırım(*) and Ş. Sağıroğlu(**)

(*) Robotic Research Lab., Mechanical Engineering Department, Engineering Faculty, Erciyes University, 38039, Kayseri, TURKEY.
(**) Intelligent Systems Research Lab., Computer Engineering Department, Engineering Faculty, Erciyes University, 38039, Kayseri, TURKEY,
ss@erciyes.edu.tr

Abstract-This paper presents an overview on applications of artificial neural networks (ANNs) to robot control systems and outlines the contributions of ANNs. Adaptive neurocontrol architectures are introduced and compared to traditional adaptive control methods.

Key words- Artificial neural networks, control, adaptive control, robot control systems.

1. INTRODUCTION

The robotic systems are designed to behave under human authority without representing any threat [1]. The systems are highly non-linear and complex systems and their dynamic performances depending on the efficiency of computing such tasks. For instances, co-ordinate transformation between the joint-variable space and the Cartesian space, generalised forces/torques to drive the joint motors, the manipulator inertia matrix for model based control schemes, and the Jacobean matrix that relates the joint velocity in the joint-variable space to the Cartesian space. These are the basic computations for the control of robot manipulators. Some of the intensive computations occur in calculating the robot kinematics, dynamics, Jacobean and their corresponding inverses. These basic robotic computations require good modelling for robust control. Artificial neural networks (ANNs) are known to handle such computational bottlenecks.

This paper presents contributions of neural networks, some robotic applications of neural networks, traditional adaptive control systems and neural network architectures for robot control systems.

2. CONTRIBUTIONS OF NEURAL NETWORKS

ANNs have demonstrated the capabilities of modelling a large class of non-linear systems and representing input-output relationships robustly. They can be trained to generate correct control signals and hence offer a great potential for adaptive control of non-linear systems. Also, the parallel processing nature of neural networks provides the capability of processing large amounts of information in real-time once a network has been trained.

The literature describes many types of neural adaptive controllers, corresponding to the conventional adaptive controllers outlined in section 4. Several adaptive control schemes for ANN controls have been presented in [2]. Different types of neural networks have been considered [3]. The major underlying issue is how to train the network robustly and reliably when the system is rapidly time varying. The popular backpropagation (BP) algorithm has been the primary choice for ANN training.

3. NEURAL NETWORK APPLICATIONS TO ROBOT SYSTEMS

The solution of problems in robotics is difficult because even the simplest desired movement requires sophisticated mathematics, which may require more computational effort. Common problems encountered in robotics are short intensive computations with high level of data dependency and on-line calculation.

ANNs are a great deal of potentials in many disciplinarians as well as in robotics [4,5] because of the following features: generalisation through learning, fast computational capability for real-time applications, less priori information requirement and ease of implementation. ANNs have ability to provide plausible solutions for ill-posed problems in robotics such as kinematics, dynamics and control.

Most of the applications of ANNs in robot systems are in the areas of robot dynamics, control, kinematics, inverse kinematics, trajectory and path planning [4-6]. For robotic applications, the popular neural networks are multilayered perceptrons trained by backpropagation, genetic algorithms and Levenberg-Marquardt method [30-32], Hopfield network, competitive and co-operative nets, Adaptive resonance theory 1, Kohonen self-organising network [8], modified counter-propagation, functional net [9] and distributed associative memory for bin-picking, and their modified versions [10].

In the robot control systems, there is currently a growing interest in using ANN technology [5,6,11-15]. ANNs offer several potential advantages over conventional control methods. For example, calculations are in principle carried out in parallel, yielding speed advantages, and programming can be done by training, rather than defining explicit instructions. Almost all ANN applications in robot control systems involve identifying the robot dynamics or inverse dynamics and incorporating this knowledge into the robot controller [16-18]. The approaches used differ in the methods of incorporating the ANN into the controller and of training and adaptation. The basic idea is to employ a neural network to learn repeatedly characteristics of a robot and then use this knowledge to generate control inputs. A basic inverse model control scheme for a robot is shown in Figure 1. The major advantage of the neural control approach is that it can produce a learning controller for a robot that can operate in an uncertain environment.

The use of neural network for controlling of a robot has been discussed by Yildirim [19]. A new neural network was proposed to model and control of a robot. The proposed network was a modification of the original Elman network. A development of a new adaptive recurrent neural network for control of a non-linear system represented by two-link has been presented by Yildirim et al. [20]. Their proposed control system consists of an inverse neural model of robot, a neural controller which is copy of inverse neural model, a robust controller, a conventional PI controller and a second order linear filter. An investigation on the trajectory control of a robot using a new type of recurrent neural network has been presented by Yildirim et al. [21]. A three-layered recurrent neural network was used to estimate the forward dynamics model of the robot manipulator. The standard BP algorithm is employed to update the connection weights of a recurrent neural network controller with three layers using a stochastic gradient function. The use of a new recurrent neural network employing feedback error learning for control of a robot has been presented by Yildirim and Aslantaş [22]. Their control system consisted of a feedback (PID) controller and two recurrent neural-network-based joint controllers. The effectiveness of the neural network was tested using different parameters of the robot. The results have shown the significant improvement of learning time and accuracy, which practically enables the use of neural controller in robotics applications.

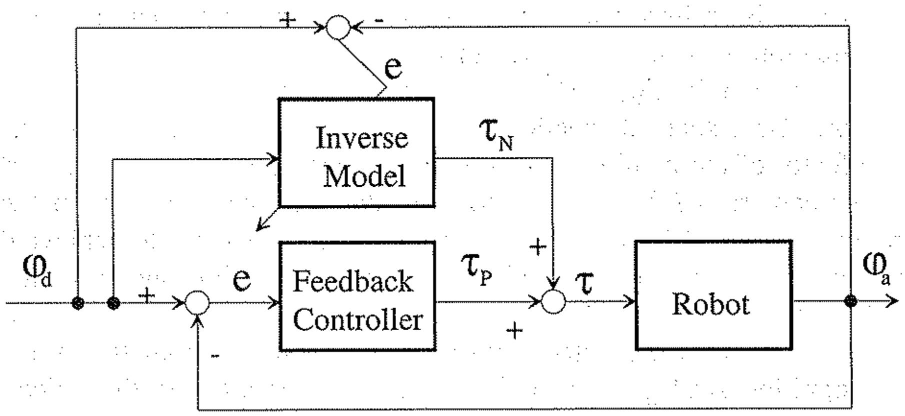

Figure 1. Inverse model control scheme

Among the five human senses; vision, hearing and touch are meaningful to robot systems. So, sensing devices are the only way of providing information to robots about their environments. The problems in sensing come from the environmental effects, temperature, noise, lack of light, fumes, humidity and components failures. Recently there has been increasing interest in upgrading robot intelligence by using multiple sensors [23-32]. Figure 2 shows how sensors are used for robotic applications.

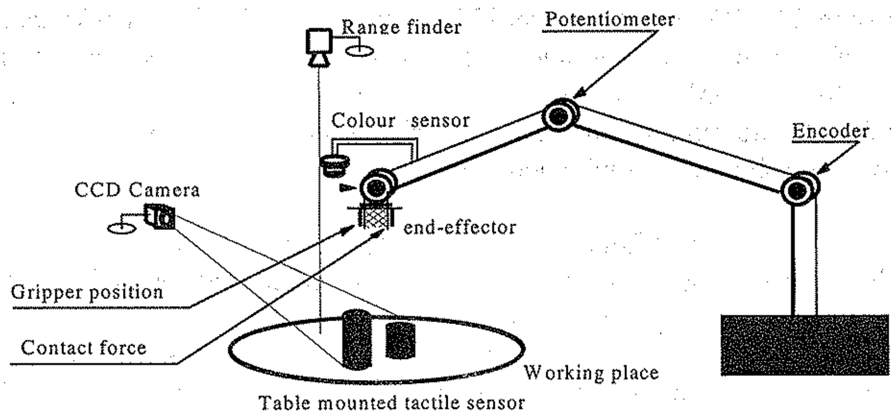

Figure 2. Multiple sensors used for robot control systems

In the figure cameras provide location information about the objects. The colour camera helps selecting a particular object depending on the object's colour. The range finder gives detail about the object shape and its range. Contact force sensor illustrates the forces on the contacts and so on so worth. Multilayered neural networks trained with different learning algorithms, BP, genetic algorithms, the Levenberg-Marquardt method, have employed to determine the location and orientation of object placed on the platform of the inertia sensor [30-32]. Their methods involve training multilayered neural networks using the backpropagation algorithm to model the operation of the sensor by mapping its natural frequency of vibration to part location information. In their paper, an approach for increasing the accuracy of the computed orientation was also investigated.

Robot vision is an important area in robotics for any movement and control. Most of the applications of neural networks in sensing can be found in robot vision systems [33-39]. As shown in Figure 2. A camera is mounted on the end-effector of a manipulator. The visual information is processed and used to position and orientate the end effector of the manipulator from image data obtained from the working place through the camera. ANNs are used to learn the non-linear mapping between image data and control signal for changes in the joint angles required to achieve the desired position and orientation using a vision system to position and orientate the end-effector [33-36].

Okamoto et al. [33] presented a vision system which automatically generates an object recognition strategy from a 3-D model, and recognises the object from this strategy. A neural network approach to machine vision systems for automated industrial inspection has been discussed by Drake and Packianather [34] for inspecting the defects of the wood veneers. The system of Hashimoto et al., [35] directly integrated the visual data into the control process without calculating an inverse kinematics of manipulator. An ultrasonic 3-D visual sensor is devised multi-layered perceptron neural networks. ANNs were used to improve acoustic images and identify objects' categories from low resolution images [37]. ANN systems can offer superior and robust solutions to the filtering problems encountered in the enhancement of sonar signals and images for mobile robot applications [38]. A neural network approach to the motion determination problem without any calibration has been presented by Wei and Hirzinger [39]. In their investigation, two kinds of sensory data, namely, camera images and laser range data, were used as the input to a multilayer feedforward neural network to associate the direct transformation from the sensory data to the required motions. This representation was used to develop a new framework for robot control with active vision.

4. ADAPTIVE CONTROL METHODS

The last decades have seen some extensive research and major breakthroughs in adaptive control [50]. The objective of adaptive control is to adjust the controller parameters in order to achieve a desired response of an unknown or time-variant system with or without an estimated model and/or reference model. If properly implemented, it can reduce the variability of parts being produced and increase productivity giving substantial economic benefits.

4.1. Traditional Adaptive Control Methods

Adaptive control has been a major topic of technical inquiry in the control community since the mid 1950s. Research in adaptive control was motivated by a desire to perform real-time control of partially or completely unknown systems. This attractive idea led to some early ingenious, but intuitive schemes. One of these initial approaches was simultaneously to estimate the unknown parameters of the system and generate control signals [40]. However, these earlier schemes did not guarantee the system's stability. As system dynamics change, such a system can become unstable or lead to an unsatisfactory performance. Recently, parametric adaptive control strategies based on rigorous stability theorems have been developed to overcome the limitations of earlier schemes.

Current adaptive control strategies can be divided into two categories: indirect and direct. The *indirect approach* is based on on-line system identification of the plant and simultaneous adjustment of control parameters. Self-tuning adaptive control strategies, which have become very popular, fall into this category. Self-tuning regulators seek to generate control laws for unknown systems, which would converge to the optimal strategies if the dynamics of the system are known.

In general, these adaptive controllers consist of three parts: a recursive parameter estimator, a design calculator and a feedback controller with adjustable parameters. Many different versions of self-tuning control are now available, mainly differing in controller design principles and on-line parameter estimation method. Some of the widely used design principles in self-tuning control entail pole-zero placement, minimum variance control and linear quadratic gaussian control. One important requirement of the self-tuning control method is that on-line identification must yield an accurate estimate of the 'locally linearized' process model, when the system is non-linear, so that the control design strategy can generate accurate control parameters.

The Direct approach does not require explicit model identification. Instead, a desired process model is specified and the controller parameters are adjusted so as to minimise the error between the model and actual system outputs. Model reference adaptive control falls into this category.

4.2. Adaptive Neural-Control Architectures

Psaltis et al. [41] proposed three different learning architectures for adaptive neural controllers: indirect learning, generalised learning and specialised learning.

The *indirect learning scheme* provides a means of generating a feedforward control law with the inverse model of the plant. A schematic of this learning architecture is shown in Figure 3. If a correct inverse model is established, the output of the overall system can track the input commands closely. The training is carried out to minimise the error between the output of the neural controller τ and the output of the inverse neural model of the plant τ_m. However, this scheme alone cannot lead to a satisfactory controller design, since the neural network model may not necessarily represent the actual system. This is because the network has the tendency of converging to a single value of τ when the input and output values of the plant are used for training.

The *generalised learning* method attempts to produce an inverse neural model for the plant by adopting a specified input space and generating corresponding output responses. This learning architecture is schematically shown in Figure 4. A major difficulty of this architecture is that one must choose an input set τ during training to generate outputs φ_a, which are sufficiently close to the desired input φ_d. This scheme, if used for adaptive control, can lead to an improperly trained network and may require persistent excitation, which can adversely affect the performance of a system.

The *specialised learning* method is an alternative method of training the network, as depicted Figure 5. Training involves using the desired responses φ_d as input to the network. The network then learns to find plant inputs τ that drive the system outputs φ_a to the desired φ_d, by using the error between desired and actual responses of the plant. This architecture addresses the main objections to the previous architectures; it can specially learn in the region of interest and it may be trained on-line by fine tuning itself, while actually performing useful work. The weakness of this architecture is that modifying the weights based on the total error must involve the plant, which normally is only approximately known.

The specialised learning scheme can be represented as an adaptive feedforward control scheme as shown in Figure 6. This type of controller, however, will have little ability to reject disturbances. If a feedback controller is used along with the feedforward controller, as shown in Figure 7, disturbance rejection will be improved. The feedback controller can be a conventional PID controller or a non-linear neural controller and the feedforward controller is a neural controller. As learning proceeds, the error signal will be reduced and the role of the feedforward controller increases.

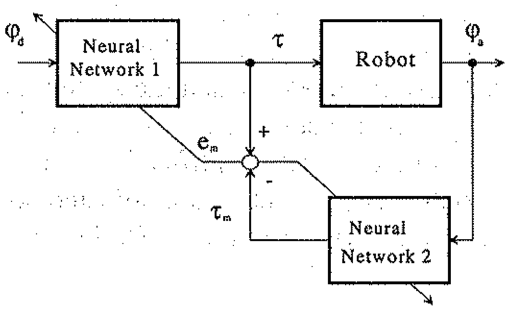

Figure 3. Indirect learning scheme

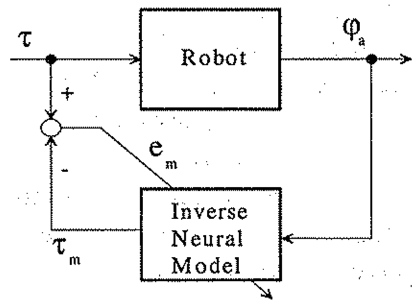

Figure 4. General learning scheme

A non-linear version of self-tuning control has been proposed that adopts a ANN as a plant identifier [41], as shown in Figure 8.

Similarly, a non-linear model reference adaptive control architecture employing a ANN in place of the linear controller has been described [4]. In this case, the non-linear ANN replaces the linear controllers. While both direct and indirect approaches have been used for the linear case, only the indirect method with a ANN has been implemented so far. The non-linear plant dynamics is first identified by an ANN and the parameters of the controller are then adjusted as shown in Figure 9.

5. DISCUSSION AND CONCLUSION

Recent studies have shown that the effectiveness in robot control systems have been concerned with the design and experimentation with new sensors, materials, technologies and methods to analyse data, process, signals and images. Artificial neural networks are the methods used successfully in many robot control systems.

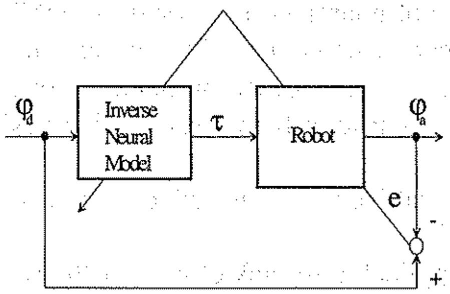

Figure 5. Specialised learning scheme

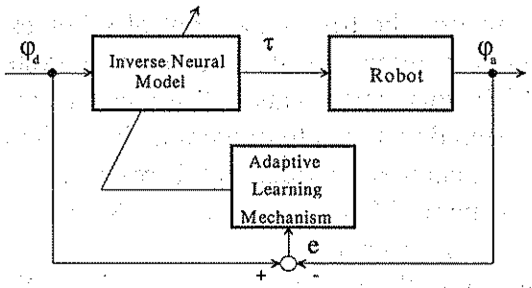

Figure 6. Open-loop feedforward neural adaptive control

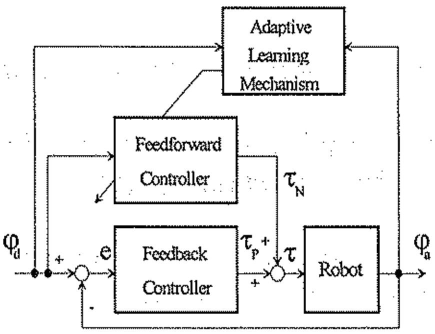

Figure 7. Feedforward adaptive control with neural network

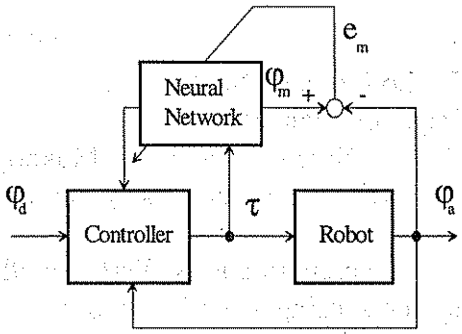

Figure 8. Self-tuning control with neural network

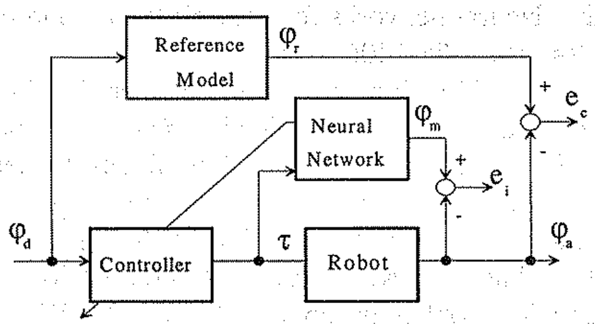

Figure 9. Indirect reference adaptive control with neural network

ANNs enable many important advantages to robotic applications. The use of ANNs in robot control system is very fascinating from both scientific and technological point of views. The following features make the ANNs more attractive for robot control system applications: adaptability and ability to learn, fast real-time operation to reduce the depebdency for massive computation on serial computers, generalise to novel conditions, tolerance to noise in the input information, less priori knowledge required, ease of integrating with other artificial intelligence techniques such as fuzzy logic, expert systems and tabu search, and using several integrated structures or/and synergy of the networks.

However, the traditional control schemes did not guarantee the system's stability. As system dynamics change, such a system can become unstable or lead to an unsatisfactory performance. But adaptive control strategies based on neural networks have been developed to overcome the limitations of earlier schemes successfully using the architectures provided in this review.

In general, MLPs, Hopfield and Recurrent Neural Networks are widely employed to robot control systems.

Although the above properties make ANNs applicable to tackle most of the robotic problems, ANNs in robot control systems have also some drawbacks that may be encountered in some applications. These drawbacks are slow convergence during training, requiring large input data set for complex systems.

REFERENCES

1. P. Coiffet and M. Chirouze, *An Introduction to Robot Technology,* Kogan Page, London, 1993.
2. K. S. Narendra and S. Mukhopadhyay, Adaptive control of nonlinear multivariable systems using neural networks, *Neural Networks*, **7**(5), 737-752, 1994.
3. K. S. Narendra and K. Parthasarathy, Identification and control of dynamical systems using neural networks, *IEEE Trans. on Neural Networks*, **1**, 4-27, 1990.
4. B. Horne, M. Jamshidi and N. Vadiee, Neural networks in robotics, *J. of Intelligent and Robotic Systems,* **3**(1), 51-66, 1990.
5. S. Sagiroglu, Artificial neural networks in robotic applications, *Mathematical and Computational Applications*, **3**(2), 67-81, 1998.
6. K.S. Narendra, Neural networks for control: theory and practice, *Proceedings of the IEEE*, **84**(10), 1385-1406, 1996.
7. S. Amari and M. Arbib, Competition and cooperation in neural nets, *Systems Neuroscience*, Metzler, J. (Ed.), Academic Press, New York, 119-165, 1977.
8. S. Kieffer, V. Morellas and M. Donath, Neural network learning of the inverse kinematic relationships for a robot arm, *Proc. IEEE Int. Conf. on Robotics and Automation*, Sacramento, California, 2418-2425, 1991.
9. L. Nguyen, R.V. Patel and K. Khorasani, Neural networks architectures for the forward kinematics problem in robotics, *IJCNN,* San Diego, California, **1**, 393-399, 1990.
10. M.T. Hagan, H.B. Demuth and M.H. Beale, *Neural Network Design*, PWS Pub Co. ISBN:0534943322. 1996.
11. S. S. Ge, C. C. Hang and L. C. Woon, Adaptive neural network control of robot manipulators in task Space, *IEEE Trans. on Industrial Electronics*, **44**, 746-752, 1997.

12. R. B. Fernandez, N. Jaramillo and N. Pandya, Neural network controllers: a literature review, *Intelligent Engineering Systems Through Artificial Neural Networks*, **6**, 533-542, 1996.
13. P. Musilek, Neural networks in navigation of mobile robots: a survey, *Neural Network World*, **5**(6), 929-943, 1995.
14. S. G. Tzafestas, Neural networks in robotics:state of the art, *IEEE International Symposium on Industrial Electronics*, **1**, 12-19, 1995.
15. M. J. Er and K. C. Liew, Control of adept one SCARA robot using neural networks, *IEEE Trans. on Industrial Electronics*, **44**, 762-768, 1997.
16. T. W. Miller III, R. S. Sutton and P. J. Werbos (Eds.), *Neural Networks for Control*, MIT, London, 1990.
17. D. T. Pham and S. J. Oh, A recurrent backpropagation neural network for dynamic system identification, *Journal of Systems Engineering*, **2**, 213-223, 1992.
18. D. T. Pham and Ş. Yıldırım, Control of the trajectory of a planar robot using recurrent hybrid networks, *Int. Journal of Machine Tools&Manufacture: Design, Research and Application*, **39**, 415-429, 1999.
19. S. Yildirim, New neural networks for adaptive control of robot manipulators', *IEEE International Conference on Neural Networks*, 1997, **3**, 1727-1731.
20. S. Yildirim, R. Demirci, M.F. Sukkar and V. Aslantas, Adaptive robust robot control using BP-SMENs, *Proceedings of the IEEE International Conference on Industrial Technology*, 522-526, 1996.
21. S. Yildirim, M.F. Sukkar, R. Demirci and V. Aslantas, Design of adaptive NNs-robust-PID controller for a robot control, *IEEE International Symposium on Intelligent Control - Proceedings*, 508-513, 1996.
22. S. Yildirim and V. Aslantas, Feedback error learning for control of a robot using SMENN' *International Workshop on Advanced Motion Control, AMC*, **2**, 518-523, 1996.
23. F. Harashima, H. Hashimoto and T. Kubota, Sensor based robot control systems, *IEEE Int. Workshop on Intelligent Motion Control,* Istanbul, Turkey, **1**, 1-10, 1990.
24. D. Vischer, Co-operating robot with visual and tactile skills, *Proc. IEEE Int. Conf. Robotics and Automation,* Nice, France, 2018-2050, 1992.
25. J. J. Helferty and S. Biswas, H. Hashimoto, T. Kubota, M. Kudou and F. Harashima, Neuromorphic control of robotic manipulators, *Proc. IEEE Int. Conf. on Robotics and Automation*, Sacramento, California, 2436-2441, 1991.
26. O. Masory and A.L. Aguirre, Sensor calibration methods-performance study, *Applications of ANNs, SPIE,* **1294**, 490-501, 1990.
27. G. Canepa, M. Morabito, D. De Rossi, A. Caiti and T. Parisini, Shape from touch by a neural net, *Proc. IEEE, Int. Conf. Robotics and Automation*, Nice, France, 2075-2080, 1992.
28. M. D. Hanes, Neural network control of force distribution for power grasp, *Proc. IEEE Int. Conf. on Robotics and Automation,* Sacramento, California, 746-751, 1991.

29. I.K. Sethi and E.K. Hajeer, Tactile object recognition using hopfield net, *Proc. Intelligent Eng. Systems Through ANNs,* St.Louis, Missouri, USA, 1991.
30. D.T. Pham and S. Sagiroglu, Three methods of training multi-layer perceptrons to model a robot sensor, *Robotica*, **13**, 531-538, 1996.
31. D.T. Pham and S. Sagiroglu, Processing signals from an inertial sensor using neural network, *Int. Journal of Machine Tools&Manucature*, **36**(11), 1291-1306, 1996.
32. D.T. Pham and S. Sagiroglu, Synergistic neural models of a robot sensor for part orientation detection, *Proc. IMECH, Part B, Journal of Engineering Manufacture*, **210**(B1), 69-76, 1996.
33. Y. Okamoto, Y. Kuno and S. Okada, Robot vision using models for recognition strategy generation and precise localisation, *IECON'90, 16th Annual Conf. Signal Processing and System Control; Factory Automation,* Pacific Grove, CA, **1**, 558-563, 1990.
34. P.R. Drake and M.S. Packianather, A decision tree of neural networks for classifying images of wood veneer, *Int. J. Advanced Manufacturing Technology*, **14**, 280-285, 1998.
35. H. Hashimoto, T. Kubota, M. Baeg and F. Harashima, A Scheme for visual tracking of robot manipulator using neural network, *IJCNN,* **2**, Singapore, 1073-1078, 1991.
36. D. J. Bozich and H. B. Mackay, Vibration cancellation using neurocontrollers, *Proc. Intelligent Eng. Systems Through ANNs,* St.Louis, Missouri, 771-775, 1991.
37. S. Watanabe and H. Watanabe, An application of neural networks to an ultrasonic 3-D visual sensor, *IJCNN,* Singapore, **2**, 1397-1402, 1991.
38. S.M. Thomas and D.R. Bull, Neural processing of airborne sonar for mobile robot applications, *IEE 2nd Int. Conf. ANNs*, Bournemouth, UK, 267-270, 1991.
39. G. Q. Wei and G. Hirzinger, Multisensory visual servoing by a neural network, *IEEE Trans. On System Man and Cybernetics, Part B-Cybernetics*, **29**(2), 276-280, 1999.
40. K.J. Astrom and B. Wittenmark, *Adaptive Control,* Reading, Mass:Addison-Wesley, 1989.
41. D. Psaltis, A. Sideris and A. Yamamura, A multilayered neural network controller, *IEEE Control Systems Magazine*, 17-21, 1989.