Transactions on Information and Communications Technologies vol 19, © 1997 WIT Press, www.witpress.com, ISSN 1743-3517

# Control of a Wall Climbing Robot Named Rostam

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## Abstract

To automate nondestructive inspections of aircraft structures, a robot has been built equipped with jointed legs and suction cup feet that allow it to maneuver over the skinned surface of an aircraft exterior. ROSTAM (Robotic System for Total Aircraft Maintenance) has two prismatic degrees of freedom, two revolute degrees of freedom, and sensors for leg (suction cup) contact with the climbing surface. ROSTAM was designed with a sequential controller that runs on a computer attached via an umbilical cord. The sequential controller manipulates each joint separately in a distinct sequence of operations which moves the robot across the surface while maintaining adequate suction attachment during the process. To enhance the motion of the robot, a feed-forward neural network controller is trained to copy the control provided by the current sequential controller. The neural network takes as inputs, the same state and sensor information and outputs the same sequence of control actions as the sequential controller. This network controller is the first step in a plan to design a neural controller that can learn a viable walking procedure without copying an existing controller.

### 1 Introduction

Study of neural networks and robots have historical parallels. Both are biologically inspired in their origin. In the recent years, a number of investigators have attempted to create robot controllers which are modeled on known processes in the brain and musculo-skeletal systems. ROSTAM designed by Bahr[1,2] is made up of a central body and two legs as shown in Fig. 1. Each leg has two joints, namely one revolute and one prismatic joint as shown in Fig 2. There are two suction cups on each leg which are connected at the end of the prismatic joints. The linear joints are driven by the air cylinders. The revolute joint is constructed using a worm gear system that allows relative rotation between the legs and the body. It is important to point out that the pneumatic elements (cylinders, suction cups, vacuum generator, solenoid valves), worm gear system (worm, worm gear, DC motor) and some control elements comprise most of the robot, and that these parts can be selected from

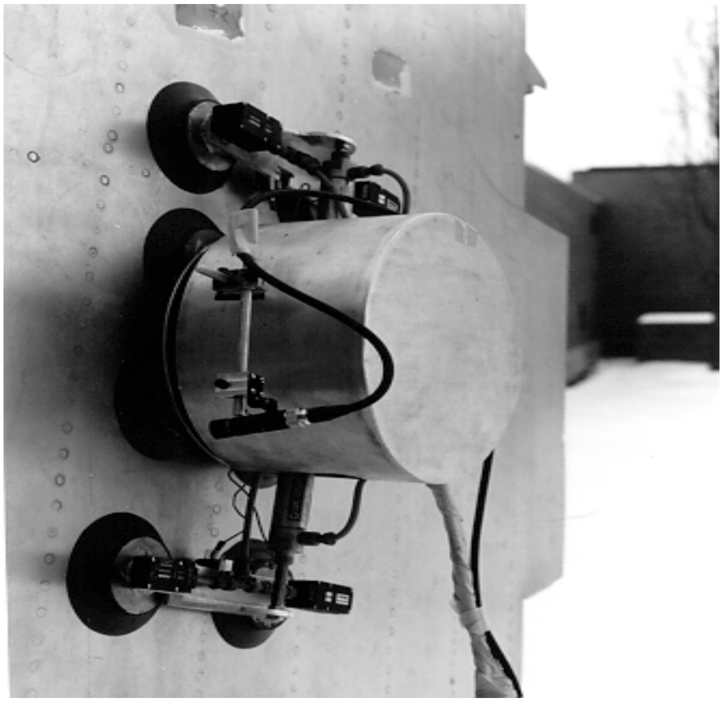

Figure 1 The picture of the robot on a vertical surface.

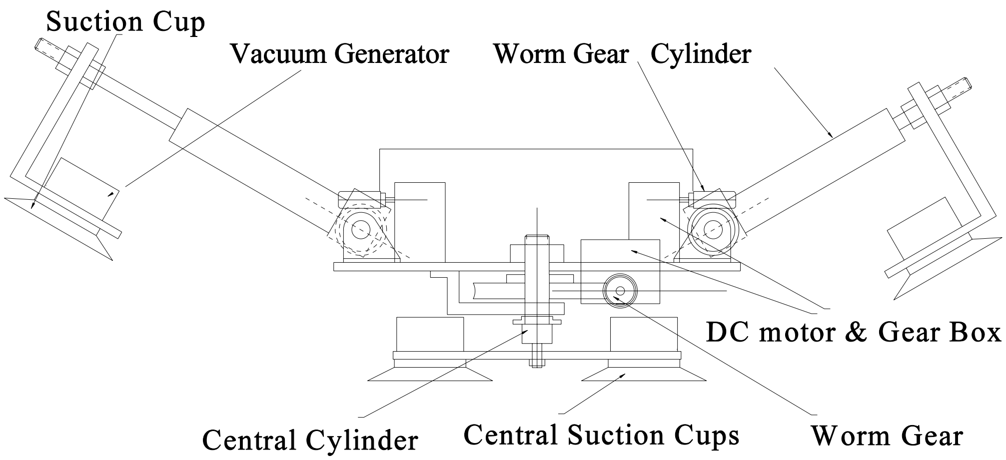


Figure 1. Schematic diagram of the robot

commercially available products. The robot uses 24 volt DC electrical power and pressured air at 0.0116 Pa (80 psi). The criterion for picking the cylinder is to ensure that it will generate enough force move the robot. A worm gear system was chosen such that it would have enough torque to rotate the robot and the legs.

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The central body is composed of two parts, a non-rotational section, and a rotational section. The non-rotational section has four suction cups on a plate that is connected to a non-rotational rod of a cylinder. The rotational part is composed of the cylinder with a worm gear. The corresponding worm gear and the DC motor are fixed on the central body that can rotate about the cylinder. Therefore, when the DC motor drives the worm, it will generate relative rotation between the robot body and the bottom suction cups so that the robot can change its direction to any desired angle. The central cylinder can lift the central suction cups up and down with respect to the central body.

### 1.1 Neural Network Controller for Robots

A structured neural network for behavior control of mobile robots has been developed by several researchers such as Sekiguchi, et al.[1,2], Nagata, et al.[4,5], Holland et al.[6], Gita et al.[7], and Beer et al[8]. In this paper ROSTAM was used it has can move freely on the surface in any desired direction with three motors. Twelve sensors are used to monitor internal conditions and environ mental changes. These sensor signals are presented to the input layer of the network, and the output is used as motor control signals. The network model is divided into two sub-networks connected to each other by short-term memory units. A new learning algorithm called pseudo-impedance control method has been used to train the network. The behaviors of small mobile robots were controlled, and the usefulness of the structured hierarchical network model was verified.

A three layered neural network has been developed by Josin[9] for the problem of a two-dimensional transformation in manipulator control. Two input-layer neurons represent the desired x-y coordinates of the end effector in the two-dimensional plane, 32 neurons in a single hidden layer, and two output-layer neurons for the corresponding joint angle pair $\theta_1$ and $\theta_2$. The three-layered network operates using the backpropagation algorithm. It was trained on sets of examples of x-y coordinates and corresponding joint angles. The network successfully learned the two-dimensional coordinate transformation from examples to within the preset tolerance of 0.025.

A Cerebellar Model Articulation Controller (CMAC) neural network has been applied to coordinate and control the leg movements of a walking machine by Lin and Song.[10] In particular a CMAC network learns the non-linear relationships of the leg kinematics. A preliminary example is provided to evaluate the effectiveness of the CMAC network for the walking control of a four legged walking machine in straight line motion.

## 2. Design of the Neural Network Controller

The final goal of this project is to design a neural control system for the wall climbing robot that can learn from scratch an optimal sequence of limb movements to move the robot across the skin of an aircraft while not losing suction contact with the skin. As the first step, a feedforward neural network is trained with backpropagation to produce the sequence of motions detailed above which will safely move the robot up a smooth vertical surface. This walking sequence has been demonstrated through microprocessor based control of the robot.

The microprocessor based sequential controller is designed to step through the sequence of actions. Each action requires a wait time for that action to be completed, implemented by a delay loop of sufficient duration in the program or a sensor signal indicating completion. Essential to designing a workable neural controller to perform the same sequence of actions, was the placement of enough sensors on the robot to define a unique state at each point during the actions. The network would then be able to be trained to map the robot's current state and the desired global motion variables (move forward, backward turn) to produce as outputs the appropriate signals to the various joints and suction cup that would cause the robot to take the next sequential motion action. The network would then operate in an 'intelligent' fashion by examining the state of its own body via the sensors, considering the desired global motion and decide what the next appropriate limb action should be. Two neural controllers were designed and trained for the robot. The first allowed only forward and backward motion, while the second extended the first to add rotating the body to turn the robot as shown in Fig 3.

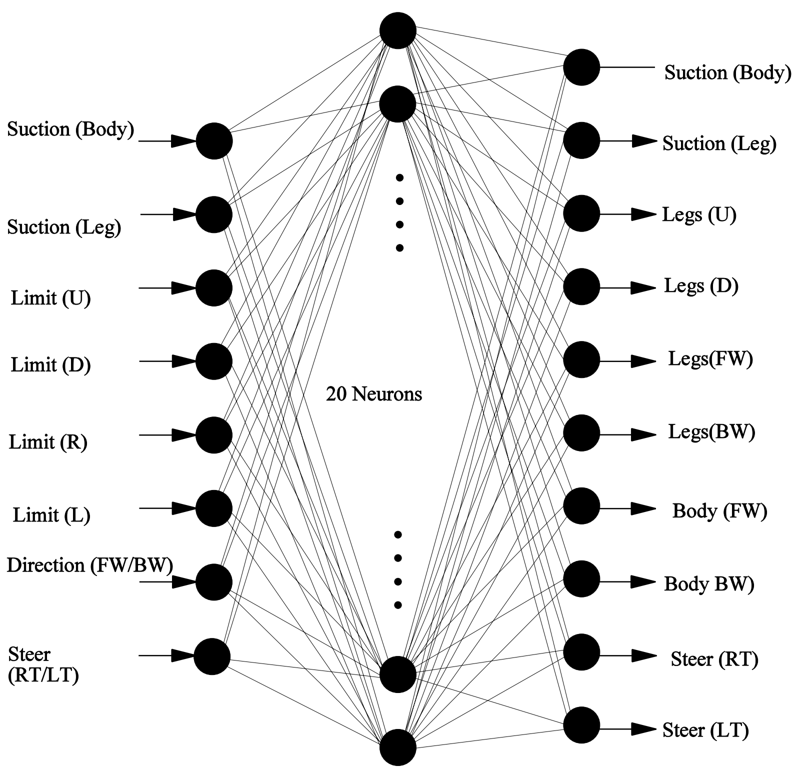


Figure 3 Neural Network Architecture for Forward, Backward, Right turn and Left turn.

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Training data for both networks were composed of; inputs which were a complete set of all possible combinations of sensor states and the global motion control inputs, and outputs which were the appropriate signals to the suction cups and the leg and body actuators and motors. Each network had 1 hidden layer composed of 20 hidden neurons with tanh activation functions. An example of the input training data is shown in Table 1. The inputs are: suction sensors at the body and leg suction cups, the position of the legs up or down, and limit switch signals indicating if the legs are extended or retracted. Also input are the command directions of forward (FW) or backward (BW) motion as well as the steering commands of right or left turn. The directions are indicated with a "1" for "forward", "0" for "stand still" and "-1" for "backward". Steering is indicated as a "1" for "right turn", "0" for "no turning" and "-1" for "left turn".

The output training data is shown in Table 2. The outputs are suction on “1" or off “0" at the body and legs, actuator signals for the legs, up (U) or down (D) and forward (FW) or backward (BW), actuator signals for the body forward (FW) or backward (BW). Also output are the steering actuator signals right turn (RT) and left turn (LT).

Standard backpropagation was used for training of the networks using a 'C' code. A learning rate of 0.1 was used for both networks. The first network converged in 2000 epochs, the second in 4000 epochs. Network training results are shown in figures 4 through 13. All these figures show the comparison between the correct and neural network output. Both neural controllers produced accurate robot responses when commanded to move forward, backward and turn.

## 3. CONCLUSIONS

It has been shown that a small feedforward network trained with backpropagation can easily perform the sequential control required to more the wall climbing robot along a vertical surface. Further work is planned to allow the network to learn to make the robot walk using a performance evaluation critic in place of a predefined sequence of actions, and to use the trained networks to control the actual robot, and to implement the networks in neural hardware chips.

**Training Patterns for Wall Climbing Robot**

| Pattern | Input (8) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Suction (Body) | Suction (Legs) | Limit (U) | Limit (D) | Limit (R) | Limit (L) | Direction (FW/BW) | Steer (RT/LT) |
| 1 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 1 |
| 2 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 1 |
| 3 | 1 | 0 | 1 | 0 | 0 | 1 | 1 | 1 |
| 4 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 1 |
| 5 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 1 |
| 6 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 1 |
| 7 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 |
| 8 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 1 |
| 9 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | -1 |
| 10 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | -1 |
| 11 | 1 | 0 | 1 | 0 | 0 | 1 | 1 | -1 |
| 12 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | -1 |
| 13 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | -1 |
| 14 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | -1 |
| 15 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | -1 |
| 16 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | -1 |
| 17 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 0 |
| 18 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 0 |
| 19 | 1 | 0 | 1 | 0 | 0 | 1 | 1 | 0 |
| 20 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 |
| 21 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 0 |
| 22 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 0 |
| 23 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 0 |
| 24 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 0 |
| 25 | 1 | 1 | 0 | 1 | 1 | 0 | -1 | 1 |
| 26 | 1 | 0 | 0 | 1 | 1 | 0 | -1 | 1 |
| 27 | 1 | 0 | 1 | 0 | 1 | 0 | -1 | 1 |
| 28 | 1 | 0 | 1 | 0 | 0 | 1 | -1 | 1 |
| 29 | 1 | 1 | 1 | 0 | 0 | 1 | -1 | 1 |
| 30 | 1 | 1 | 0 | 1 | 0 | 1 | -1 | 1 |
| 31 | 0 | 1 | 0 | 1 | 0 | 1 | -1 | 1 |
| 32 | 0 | 1 | 0 | 1 | 1 | 0 | -1 | 1 |
| 33 | 1 | 1 | 0 | 1 | 1 | 0 | -1 | -1 |
| 34 | 1 | 0 | 0 | 1 | 1 | 0 | -1 | -1 |
| 35 | 1 | 0 | 1 | 0 | 1 | 0 | -1 | -1 |
| 36 | 1 | 0 | 1 | 0 | 0 | 1 | -1 | -1 |
| 37 | 1 | 1 | 1 | 0 | 0 | 1 | -1 | -1 |
| 38 | 1 | 1 | 0 | 1 | 0 | 1 | -1 | -1 |
| 39 | 0 | 1 | 0 | 1 | 0 | 1 | -1 | -1 |
| 40 | 0 | 1 | 0 | 1 | 1 | 0 | -1 | -1 |
| 41 | 1 | 1 | 0 | 1 | 1 | 0 | -1 | 0 |
| 42 | 1 | 0 | 0 | 1 | 1 | 0 | -1 | 0 |
| 43 | 1 | 0 | 1 | 0 | 1 | 0 | -1 | 0 |
| 44 | 1 | 0 | 1 | 0 | 0 | 1 | -1 | 0 |
| 45 | 1 | 1 | 1 | 0 | 0 | 1 | -1 | 0 |
| 46 | 1 | 1 | 0 | 1 | 0 | 1 | -1 | 0 |
| 47 | 0 | 1 | 0 | 1 | 0 | 1 | -1 | 0 |
| 48 | 0 | 1 | 0 | 1 | 1 | 0 | -1 | 0 |
| 49 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 0 |
| 50 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 0 |
| 51 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 0 |
| 52 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 |
| 53 | 1 | 1 | 1 | 0 | 1 | 0 | 0 | 0 |
| 54 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 |
| 55 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 0 |
| 56 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 0 |
| 57 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 |
| 58 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 0 |

Table 1 Training pattern for forward, backward, right turn and left turn motion of ROSTAM.

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| Output (10) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Suction (Body) | Suction (Legs) | Legs (U) | Legs (D) | Legs (FW) | Legs (BW) | Body (FW) | Body (BW) | Steer (RT) | Steer (LT) |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |

Table 2 The output of the Neural Network Controller.

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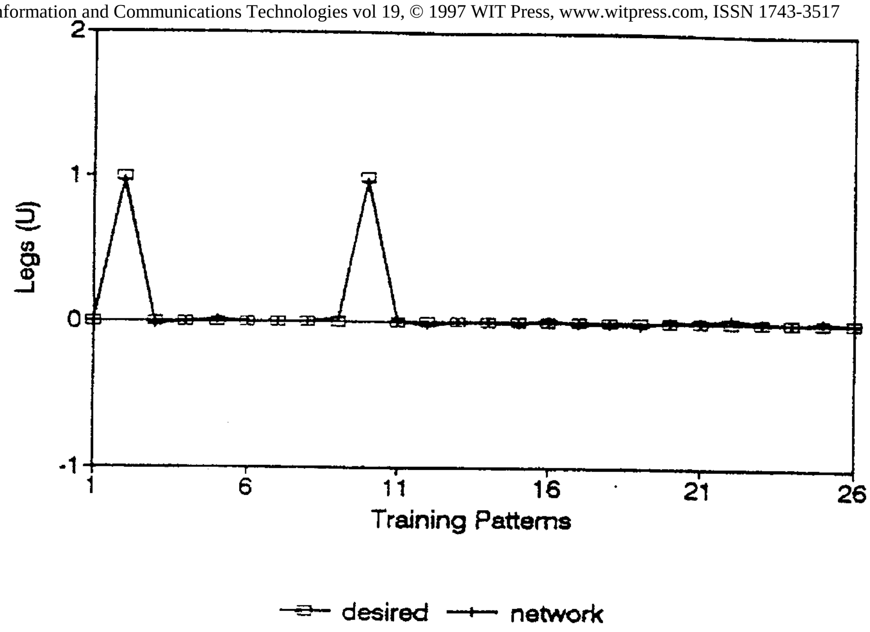


Figure 4 Training Results for legs upward motion.

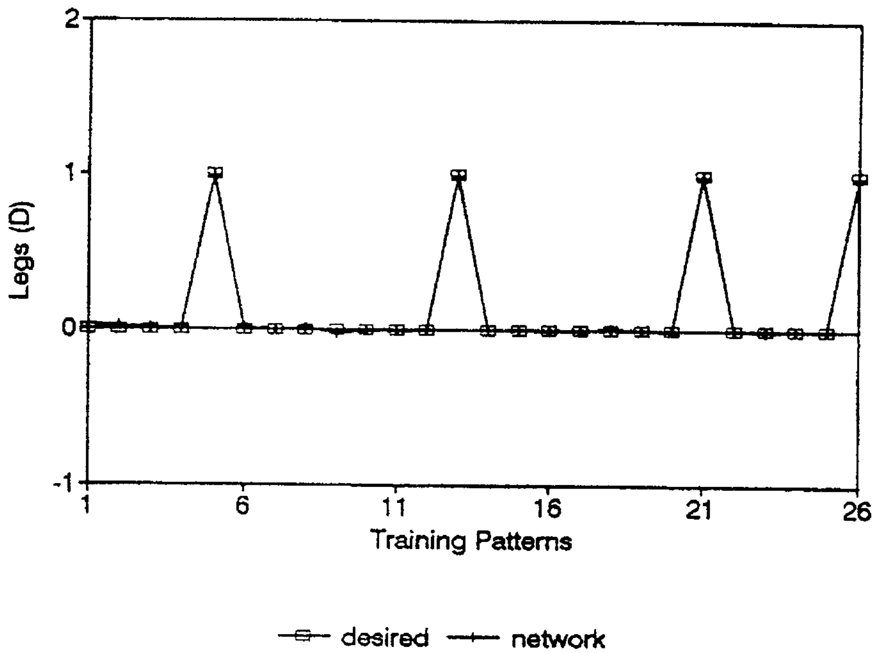


Figure 5 Training results for leg moving downward.

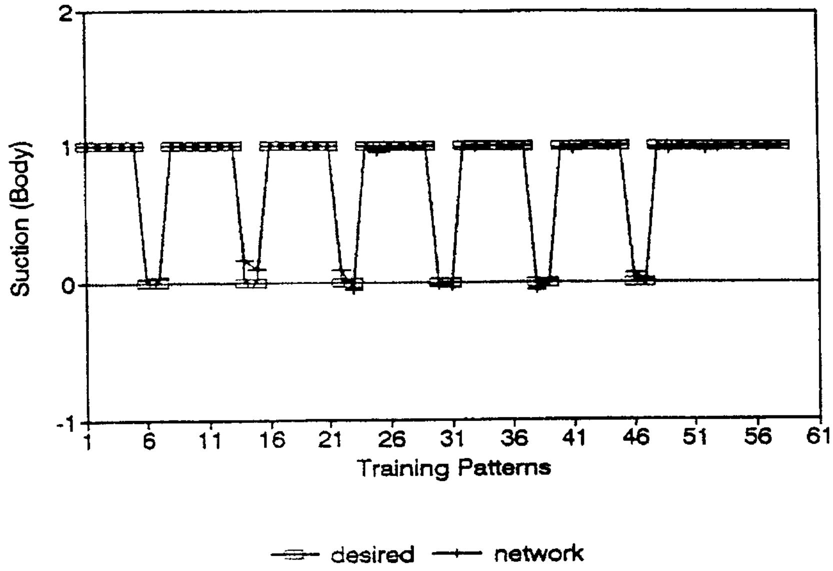


Figure 6 Training results for suction cups for the body.

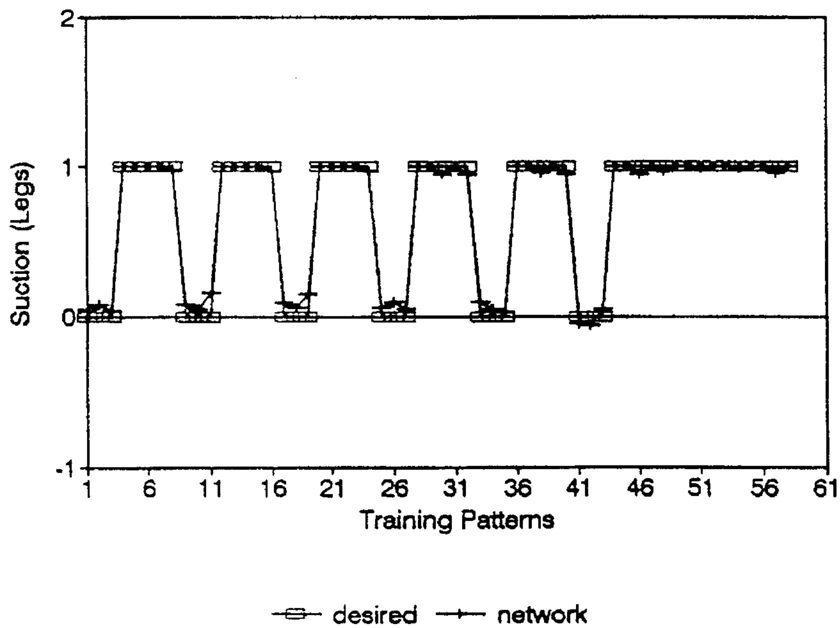


Figure 7 Training results for the suction cups of the legs.

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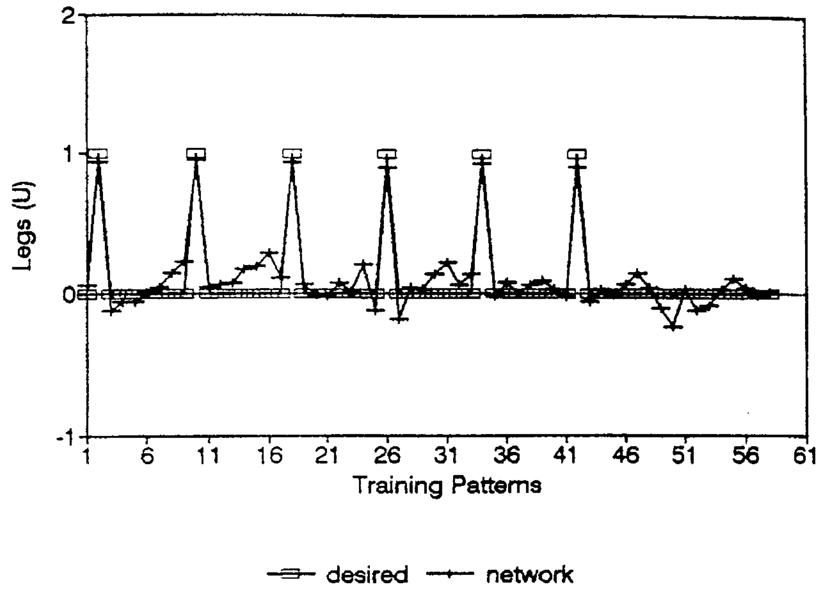


Figure 8 Training results for the legs moving upward.

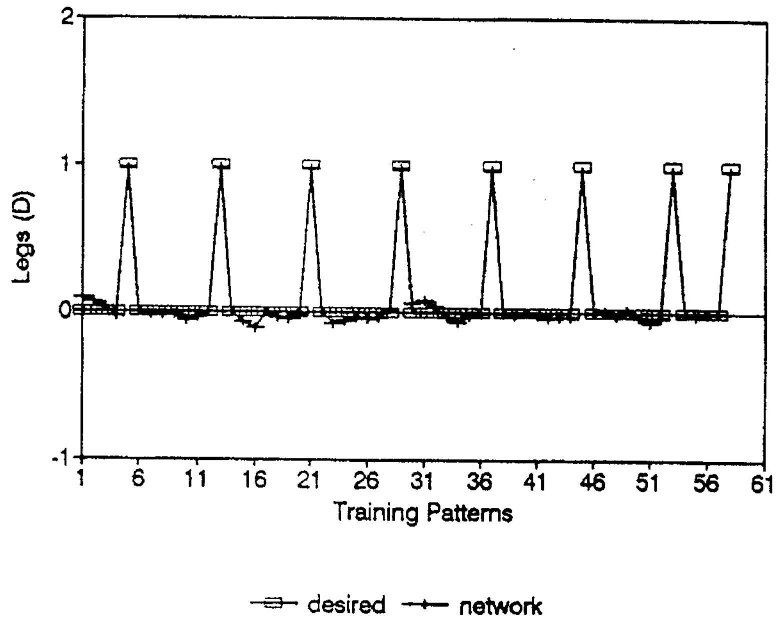


Figure 9 Training results for the legs moving downwards.

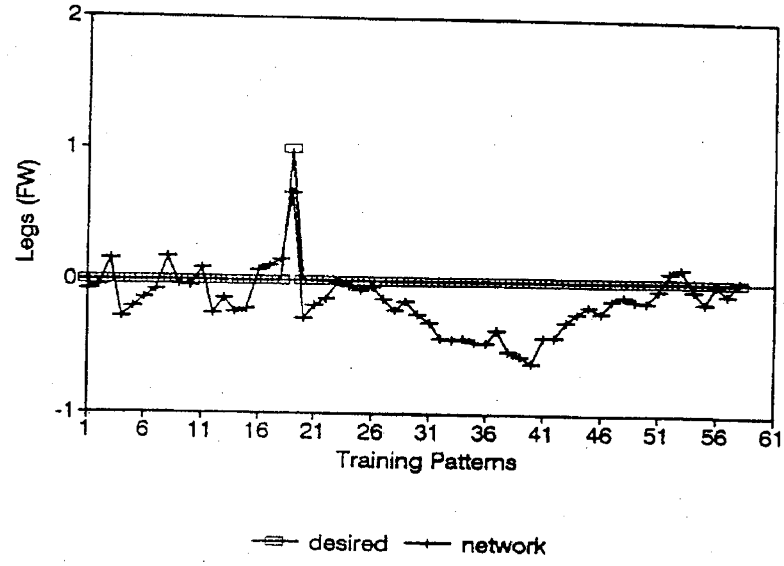


Figure 10 Training results for the legs moving forward.

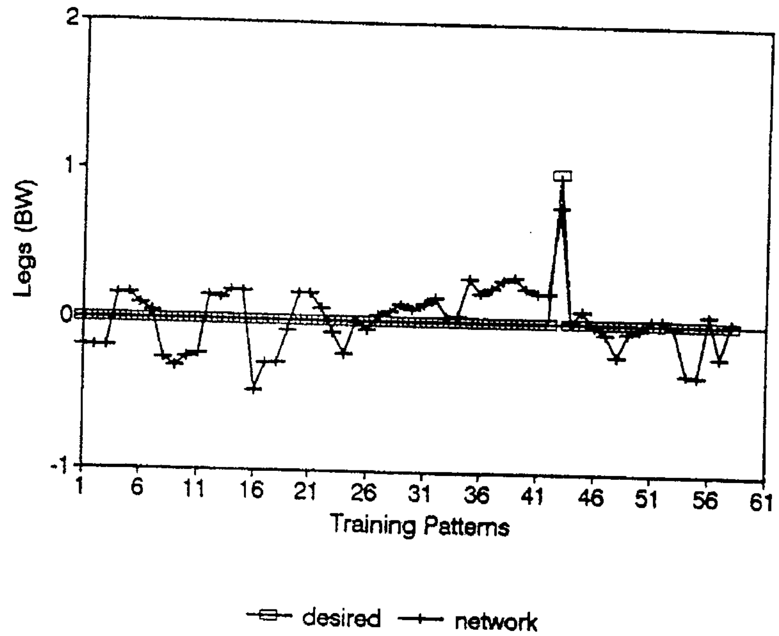


Figure 11 Training results for the legs moving backward.

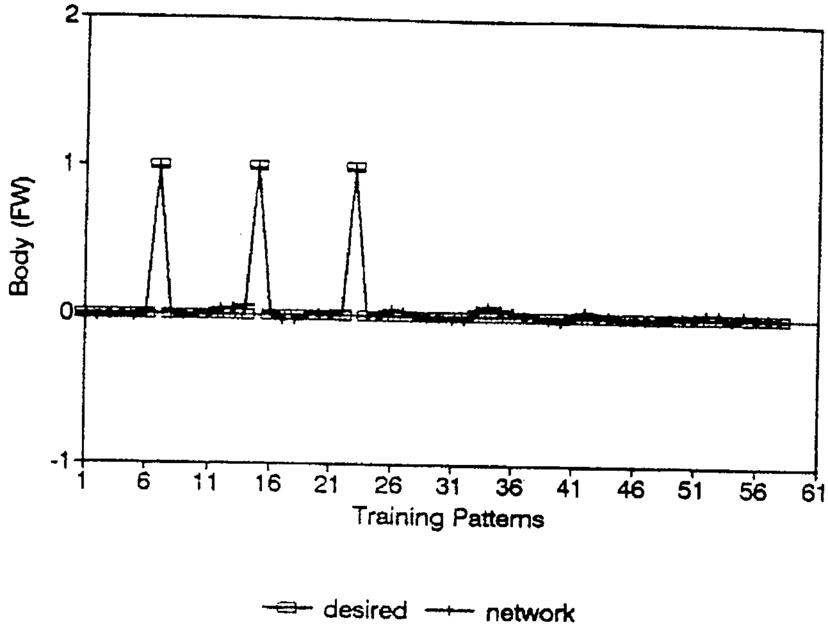


Figure 12 Training results for body moving forward.

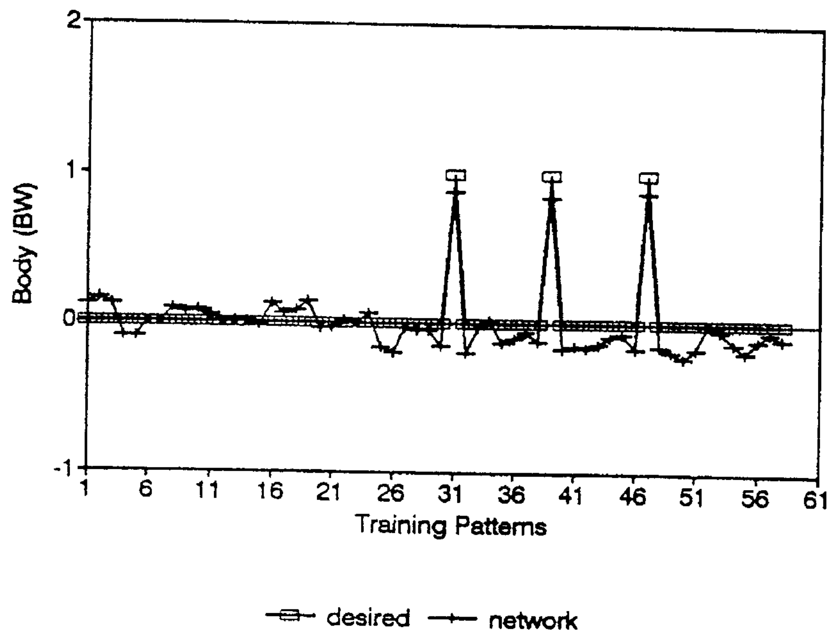


Figure 13 Training results for the body moving backward.

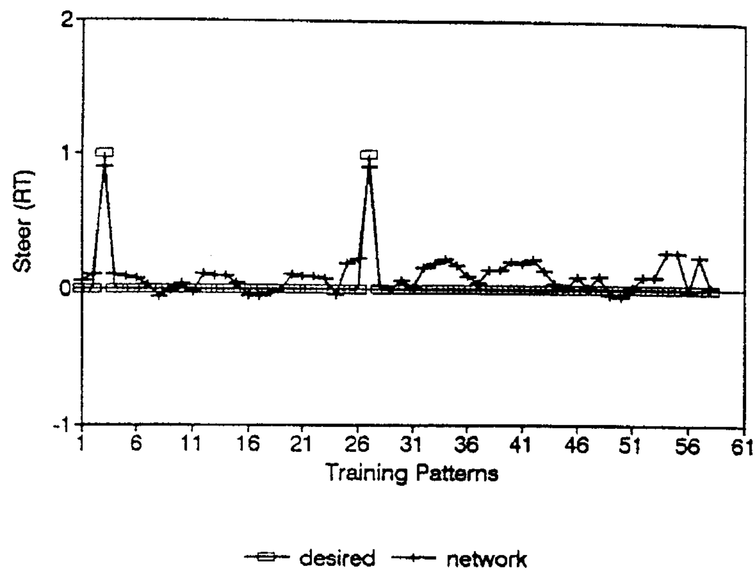


Figure 14 training results for the steer (right turn).

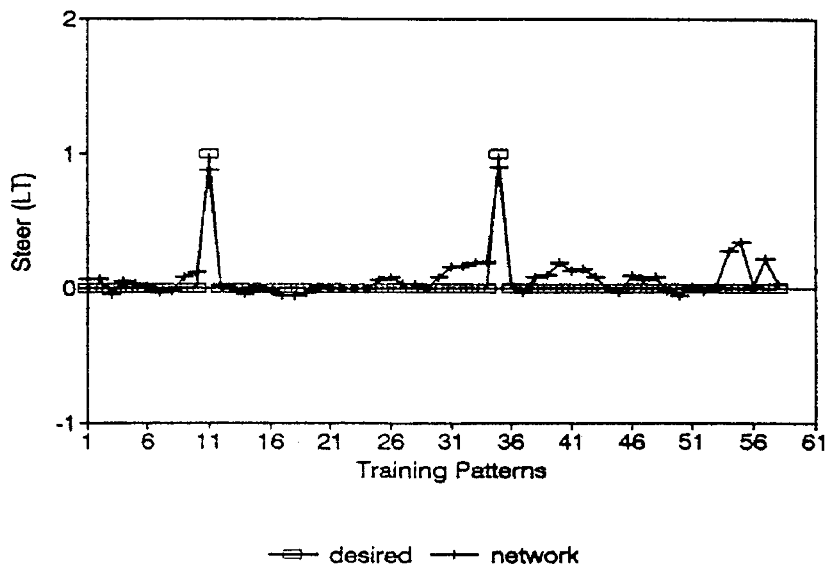


Figure 15 Training results for the steer (left turn).

Wall-Climbing, Robot, Neural Network

## 5 REFERENCES


1. Bahr, B. & Wu, F. Design and Safety Analysis of the Portable Wall-Climbing Robot, *International Journal of Robotics and Control.* Vol. 9, No. 4, 1994, pp. 160-166.

2. Bahr, B., Li, Y. & Najafi, M., "Design and Suction Cup Analysis of a Climbing Robot," *Journal of Computers and Electrical Engineering,* Vol. 22, No. 3 pp. 193-209, 1996.

3. Sekiguchi, M., Nagata, S. & Asakawa, *K. Behavior Control for a Mobile Robot Multi-Hierarchical Neural Networks*, Pro. IEEE ICRA, pp. 578-1583, 1989.

4. Nagata, S., Kimoto, T. & Asakawa, K. *Control of Mobile Robots with Neural Networks*, INNS, sup. 1, p. 349, 1988.

5. Nagata, S., Selkguchi, M. & Asakawa, K. *Mobile Robot Control by a Structured Hierarchical Neural Network,* IEEE Control System Magazine, pp. 69-76, April 1990.

6. Holland, M.O. & Snaith M. Neural Control of Locomotion in a Quadrupedal Robot, *2nd International Conference on Artificial Neural Networks, IEE Conference Publication*, Nfichael Faraday House, Stevenage, England, pp 333-335, 1991.

7. Gita, K., Ang M.H., & Gerry A.B. Structured Neural Network approach to Robot Motion Control, *IEEE International Joint Conference on Neural Networks -UCNN'91, Singapore, Nov 18-21, 1991, IEEE Service Center, Piscataway, USA*, pp 1059-1066, 1991.

8. Beer, R.D., Chiel, H.J., Quinn, R.D., Espenschied, K.S. & Larsson, P. A Distributed Neural Network Architecture for Hexapod Robot Locomotion, *Neural Computation*, Vol. 4, pp. 356-365, 1992.

9. Josin, G. Integrating Neural Networks with Robotics, *AI Expert*, pp. 50-58, August, 1988.

10. Lin, Y., & Song, S.M. A CMAC Neural Network for the kinematic control of Walking Machine, *Neural Networks in Robotics, edited by George A. Bekey and Kenneth Y. Goldberg*, pp 29-43, Kluwer Academic Publishers, Massachusetts, October 1993.