# Training of Neural Networks for Inverse Kinematics Computation of a Flexible Robot by Employing an ADAMS–Model.

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## ABSTRACT

In robot position control, mapping from Cartesian space to joint space is a fundamental problem. This inverse kinematics problem is nonlinear and the solution is not easy to find or does not even always exist in closed form. If flexibility of structure is included, the problem becomes even more complicated. Neural networks can be used to solve the inverse kinematics problem. Multiple–layer networks are capable of approximating any function with a finite number of discontinuities. For learning the inverse kinematics neural network needs information about coordinates, joint angles and actuator positions. The information needed for the training of the neural network is slow and difficult to get by measuring the real structure. By creating flexible ADAMS–model of the robot and equipping it with virtual instruments it is possible to simulate the data needed for the training of the neural network. The correct function of the neural network can be checked by creating a neural network subprogram to ADAMS. The desired Cartesian coordinates are given as input to the neural network that returns actuator positions as output. The robot position is simulated using these actuator positions as reference values for each actuator.

## 1. INTRODUCTION

The inverse kinematics problem has been studied in several papers (/1/,/2/ and /3/), but in all these cases the mathematical side of the problem is emphasized. The studied mechanisms, figure 1. have been simple, rigid two link manipulators. In these cases getting the training information for neural networks is quite simple. The kinematics of a simple, rigid two link manipulator can be easily modelled analytically and the desired information, such as actuator positions and Cartesian coordinates, can be quickly calculated with computer analysis. When the number of manipulator degrees of freedom increases, and structural flexibility is included, analytical modelling becomes almost impossible. On the other hand, when the number of manipulator degrees of freedom increases, and structural flexibility is included, the amount of information needed for training the neural networks increases.

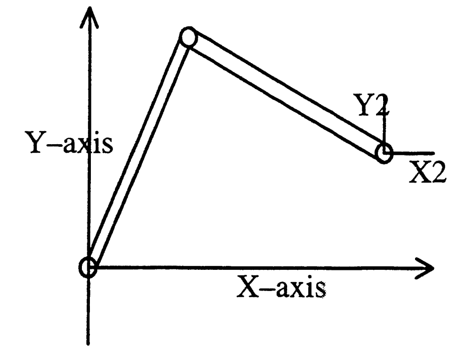


*Figure 1.* A simple two link manipulator.

In this study the number of training vectors was 1750, and another 350 separate vectors were used for testing the neural network . Measuring this amount of actuator positions and Cartesian coordinates accurately enough is difficult and time consuming. Furthermore, the position error due to the flexibility of the structure is difficult to measure. Using both a flexible and a rigid ADAMS– model it is possible to easily, quickly and accurately obtain position errors, actuator positions and coordinates needed for training the neural networks.

## 2. FLEXIBLE ROBOT MODEL

The examined structure, figure 2., was a log crane manufactured by KESLA OY. The boom structure of the crane was very elastic so the deflection came out clearly. The flexibility of the boom structure was modelled using the ANSYS finite element program. Mass– and stiffness matrices were transferred to ADAMS.

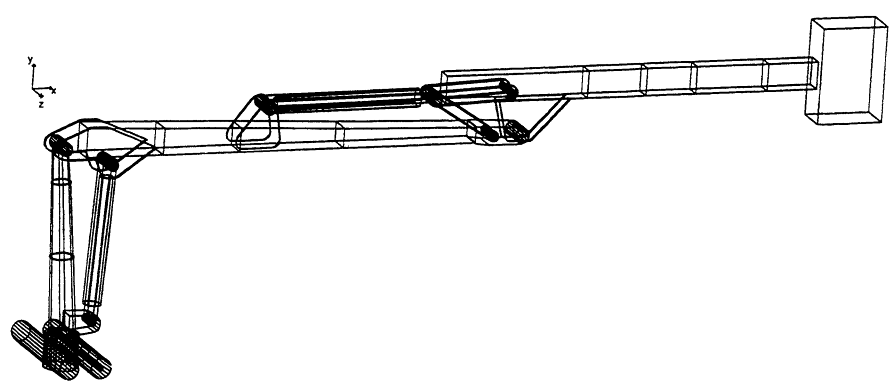

*Figure 2.* Flexible robot model.

The reliability of the model was tested measuring the existing structure and comparing the results to the simulated ones /5/.

## 3. TRAINING THE NEURAL NETWORK

The neural network is trained to recognize the actuator positions of the flexible robot structure as function of mass load and desired Cartesian coordinates, figure 3. The training method used was the backpropagation method /4/.

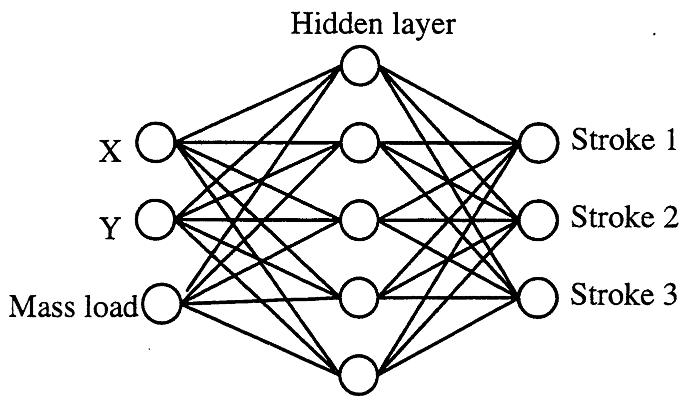


*Figure 3.* Architecture of the neural network used.

The correct size for the neural network is identified by training several neural networks with different number of neurons in hidden layer. The error between results calculated by neural network and training vectors becomes smaller when the number of neurons increases. In the training phase the functionality of the neural network must be checked with a separate set of vectors. The error between the results calculated by the neural network and the separate set of vectors decreases when the number of neurons increases to certain limit, figure 4, and then starts growing. The optimum size for the neural network is in the point where the error between the neural network results and the separate vector set is minimum.

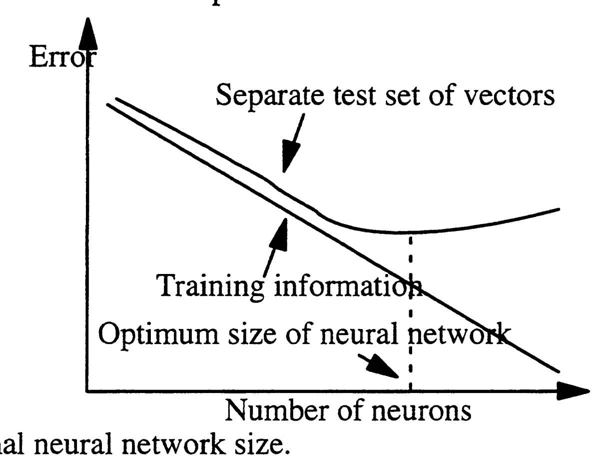


*Figure 4.* The optimal neural network size.

The optimum size for neural network used in this study was 10 sigmoid neurons in the hidden layer.

## 4. RESULTS

Figure 5 presents errors between the test vector set and the results calculated using the trained neural network and flexible ADAMS model. The average error in the x–coordinate is 0.0063 m and in the y–coordinate 0.0067 m. This is accurate enough for compensating the deflection. But the maximum error especially in the y–coordinate is too big.

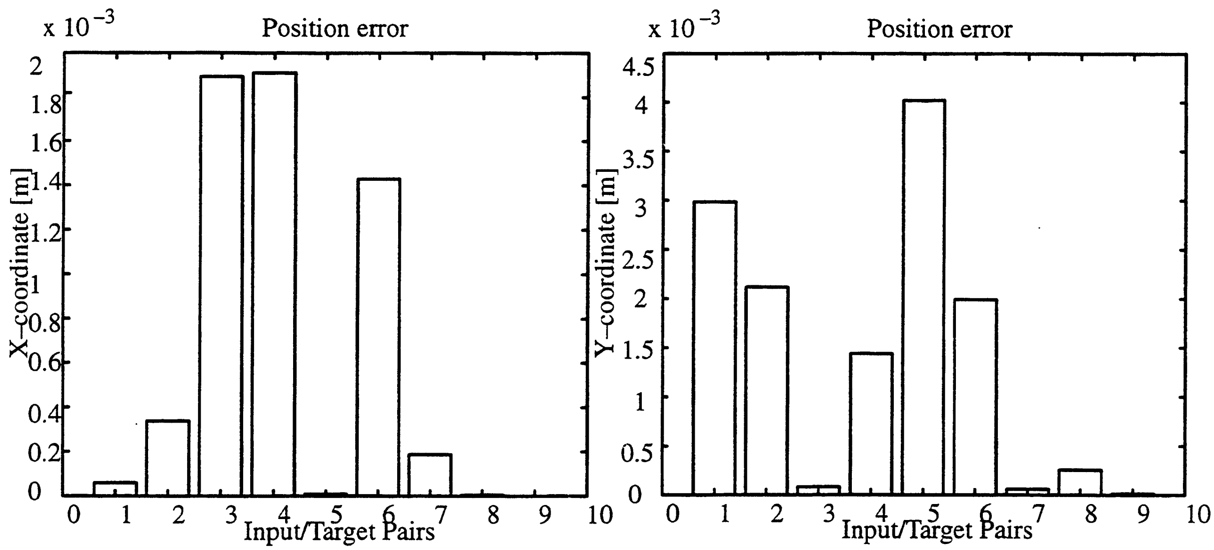


*Figure 5.* Simulated results compared to test vector set.

## 5. CONCLUSIONS

This paper presents the use of a simulation model in training a neural network for the inverse kinematics computation of a flexible robot. The training information for the neural network is obtained by employing a flexible ADAMS simulation model. Positioning results are calculated using the trained neural network and flexible ADAMS model. The results show that the positioning of a flexible robot using an inverse neural network model is possible but the accuracy is not yet good enough. The accuracy is increased by increasing the number of training vectors and training the neural network again.

## References


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