Incremental Learning Method for Impedance Controller Used for Human Assist System

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Abstract—**Impedance control for robot manipulators is a widely used and widely accepted control method, but in most of the cases it is used in fixed and/or predefined environments. The environment humans live in is way more complex and constantly changing. To be able to use such systems as a man-machine power assist system in a human environment, it has to be able to adjust to that environment. In this paper a lifelong learning impedance controller is proposed for a man-machine power assist system. The first simulations show that the impedance controller should be able to stably control multiple environments.**

Index Terms—**Learning control systems, robotic manipulator, man-machine systems, lifelong learning.**

I. Introduction

EVER since the work of Hogan [1], impedance control is a widely used and intensively researched control method for robot manipulators and many successful applications in industry resulted from it. In industry, however, the environment where these manipulators work in is fixed and well defined, which makes the appropriated choice of impedance feasible.

This is different from the environment where humans live in, this one is highly complex, unknown and constantly changing. This is why neural network (NN) controllers are successfully applied and widely used in the field of man-machine systems. NN controllers are able to adjust to uncertainties in (environment) model parameters and disturbances from the environment. A NN based on backpropagation is able to learn the impedance model of its environment, but only of one environment. Learning a new environment will mean that it will 'forget' the previous one.

In this paper a *lifelong* learning impedance controller is proposed for a man-machine power assist system. The experimental setup is a one-link manipulator and in this paper simulations for this setup will be shown.

The controller consists of a neural network with the cascade-correlation architecture that will represent the environment model. This type of neural network is capable of representing multiple environments. In section II the scheme of the impedance controller that is used will be described, section III gives an explanation of the cascade correlation architecture and how it is used in this case. Section IV tells about the simulations and V gives the results of these simulations.

II. Control Scheme

The control scheme used for this application is a resolved acceleration position controller combined with an NN. This NN will approximate a model for the environment and this environment model is used to compensate the forces between the environment and the manipulator at the input of the position controller.

III. Cascade Correlation Architecture

Cascade correlation learning [3] is a supervised learning method for artificial neural networks.

A. Learning method

A cascade correlation neural network (CCNN) starts with zero hidden layers and every time it has to learn a new task, the learning algorithm will add layers (with each one neuron in it) to the network, one at a time, until the error is low enough. Each new neuron is connected to the inputs of the CCNN and all previous neurons in the network. The input weights of the new neuron are trained by maximizing the correlation between the output of the new neuron and the output error of the CCNN. After training the input weights of the new neuron, the incoming weights of the neuron are fixed, so it will not loose previously learned knowledge. Only the output weights are trained repeatedly. To prevent the forgetting of knowledge the CCNN has to be re-trained after learning each new task.

In this case, first a neural network based on back-propagation (backprop NN) is used to become an expert at the new task and then this neural network is used to train the CCNN. The input-output data obtained with the backprop NN's is stored and used for the re-training of the CCNN.

B. *Advantages of cascade correlation*

As mentioned before CCNNs provide a way to store the information of previous tasks to some extend and still learn new tasks. But caution has to be taken when the CCNN is not properly re-trained, it can still lead to 'catastrophic forgetting' of information.

Because the incoming weights to the hidden neurons are fixed every learning procedure (both when maximizing correlation and when training the output weights) will be performed over a single layer, so there is no need to back-propagate the error through the whole network, like with multi layer back-propagation learning, which will increase the learning speed.

CCNNs are able to recognize features of old tasks and use them to represent new tasks, which also can speed up the learning process.

IV. SIMULATION

Figure 1 shows the flow scheme of the learning algorithm. The training set acquired by the backprop NN is run through then CCNN. When the error is too big, it will first try to train the output weights. At some time a learning asymptote will be reached and the training set is run through the CCNN again. If the error is still too big then the algorithm will add a neuron in a new layer. The input weights of the new neuron will be trained by maximizing the correlation between the output of the new neuron and the error of the CCNN. If the correlation is maximized the inputs to the new neuron are fixed and the

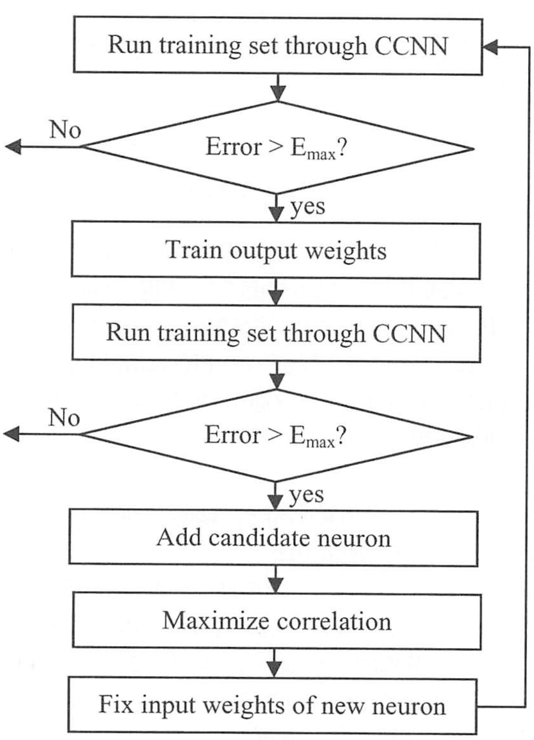

Fig. 1. Flow scheme of the cascade correlation algorithm.

process will be start over again until the error will be small enough.

The first phase of the simulation is to train several backprop NNs to represent different environments. This is done using simple backprop NN's and delta-rule learning, adjusting learning rate and momentum for each different environment.

The second phase is to use the backprop NN's to train the CCNN to be able to represent the multiple training sets, according to the flow scheme in figure 1.

V. RESULTS

First simulation results show that a CCNN should be able to represent multiple environments. Figure 2 shows the position error of the manipulator when interacting with three different environments when following a sine position trajectory.

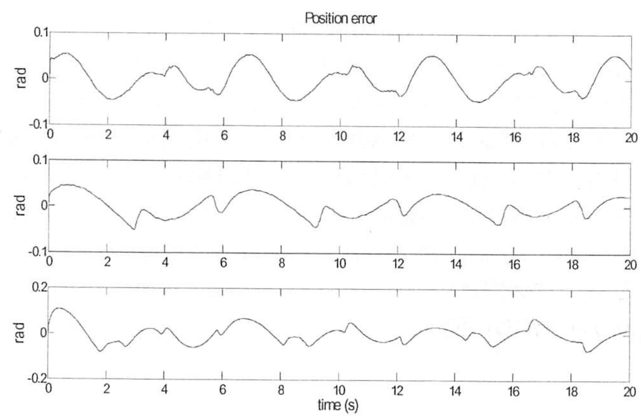

Fig. 2. Position error of manipulator interacting with three different environments.

VI. CONCLUSION

In this paper an incremental learning method for a robot manipulator is proposed, which is able to adjust robot control to different environments. First simulation results show that the controller should be able to control multiple environments.

However, experimental tests will have to show the validity of the simulation results.

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