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USING BACKPROPAGATION WITH TEMPORAL WINDOWS TO LEARN THE DYNAMICS OF THE CMU DIRECT-DRIVE ARM II

K. Y. Goldberg and B. A. Pearlmutter
School of Computer Science
Carnegie Mellon University
Pittsburgh, PA 15213

ABSTRACT

Computing the inverse dynamics of a robot arm is an active area of research in the control literature. We hope to learn the inverse dynamics by training a neural network on the measured response of a physical arm. The input to the network is a *temporal window* of measured positions; output is a vector of torques. We train the network on data measured from the first two joints of the CMU Direct-Drive Arm II as it moves through a randomly-generated sample of "pick-and-place" trajectories. We then test generalization with a new trajectory and compare its output with the torque measured at the physical arm. The network is shown to generalize with a root mean square error/standard deviation (RMSS) of 0.10. We interpreted the weights of the network in terms of the velocity and acceleration filters used in conventional control theory.

INTRODUCTION

Dynamics is the study of forces. The dynamic response of a robot arm relates joint torques to the position, velocity, and acceleration of its links. In order to control an arm at high speed, it is important to model this interaction. In practice however, the dynamic response is extremely difficult to predict.

A dynamic controller for a robot arm is shown in Figure 1. Feedforward torques for a desired trajectory are computed off-line using a model of arm dynamics and applied to the joints at every cycle in an effort to linearize the resulting system. An independent feedback loop at each joint is used to correct remaining errors and compensate for external disturbances. See ([3]) for an introduction to dynamic control of robot arms.

Conventional control theory has difficulty addressing physical effects such as friction [1], backlash [2], torque non-linearity (especially dead zone and saturation) [2], high-frequency dynamics [2], sampling effects [7], and sensor noise [7].

We propose to use a three-layer backpropagation network [4] with sigmoid thresholds to fill the box marked "inverse arm" in Figure 1. We will treat the arm as an unknown non-linear transfer function to be represented by weights of the network.