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Complex Nonlinear Control by Simple Neural Decision Networks

Shaohua Tan, Bart De Moor, Jianbin Hao and Joos Vandewalle
ESAT Lab., Dept. Electrical Engineering, K.U.Leuven
Kardinaal Mercierlaan 94, B-3030 Heverlee - Belgium

(Summary)

Majority of control problems can often be phrased as choosing right inputs to bring the state of system to some desired position in the state space. A typical example is *stabilization*, by which the desired control action is to bring the state of a system to zero by designing appropriate control inputs. Another example is the shift of set-point. In this case, a control input is sought in order to bring the state of a system from a previous set-point to the intended one. Control problems as such can be extremely involved even for relatively simple nonlinear systems, no general methodology is available for actually carrying out such a design.

There exist, however, certain classes of nonlinear control problems for which the allowable control inputs are restricted to a few fixed functional types. Problems of this kind can usually be translated into finite decision problems which can in turn be solved using simple neural nets. Originated by Widrow, this idea turns out to be powerful in handling difficult control problems.

Early works in this direction have not fully demonstrated the potential of this decision approach as it was only applied to simple linear control problems. These linear control problems can in fact be solved more elegantly by using techniques developed in linear control theory.

We demonstrate this decision approach by designing a neural controller for a truly nonlinear control problem: Shifting the set-point of the well-known car-pole system. The system consists of an inverted pendulum mounted in a cart which can move freely in a track. The control task here is to swing up the pendulum from its stable position (vertically down) to the zero state (up right) and keep it there. The constrained control inputs are the two forces of identical magnitude (with opposite direction) applied to the mass center of the cart. This is a highly nonlinear control problem, and can obviously not be solved by a linear controller.

To translate such a control problem into a decision problem, the state-space of the system is divided into a finite number of areas within which the positive or negative force should be applied. For this example, such a division is easily obtained through computer simulation. Fig.1 illustrates one possibility of such a division which is the basis for the design of our neuron controller.

The actual construction of the controller follows a simple geometrical method which results in a 4-neuron time-delay multilayer perceptron neural network (See Fig.2). The simulation

result of our neural control system is shown in Fig.3. One feature of this neural controller is that the weight change leads to the change in the decision boundary, which can be utilized to adjust the set-point transition time. Another feature is that our neural controller can be easily adapted to swing and stabilize the pendulum at any desired position (not just the up right).

The decision boundaries as such do not always follow from the analysis of system dynamics. This is especially true for complex and/or higher dimensional nonlinear systems. In this case, a modified version of the reinforcement learning will be used to locate the desired decision boundaries based on the trail input and output. The net structure is superimposed, the learning procedure determines the weights. We are currently working on this approach, and will be able to explain the detailed mechanism in the full paper.

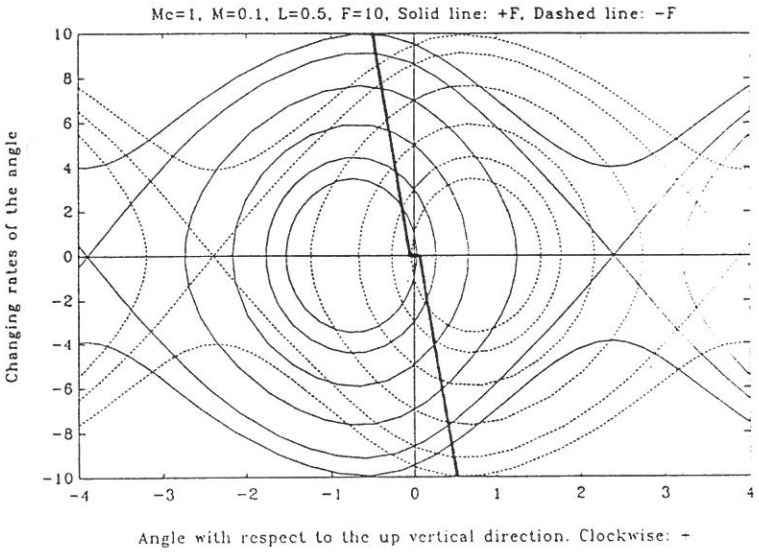


Fig. 1

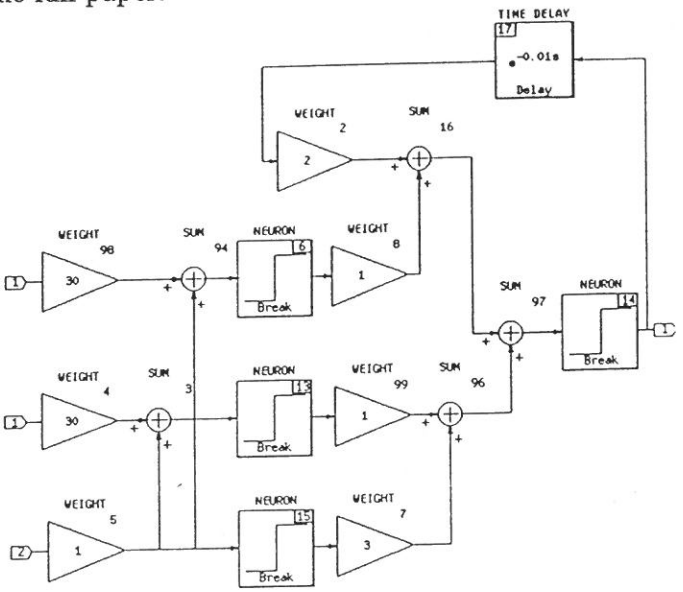


Fig. 2

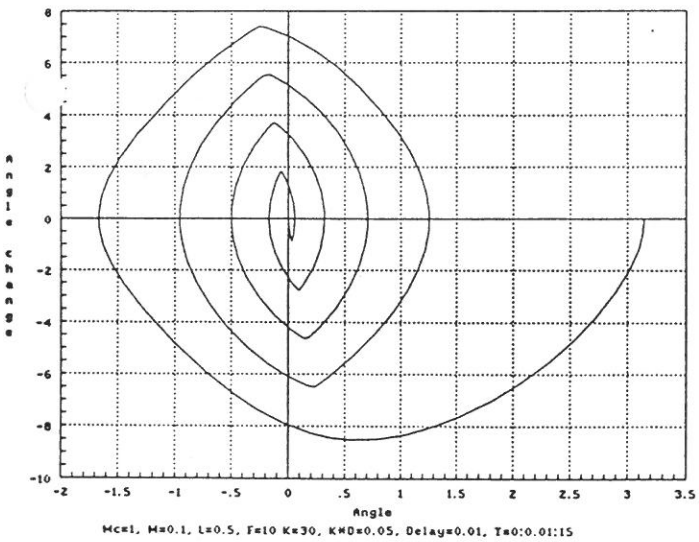


Fig. 3a

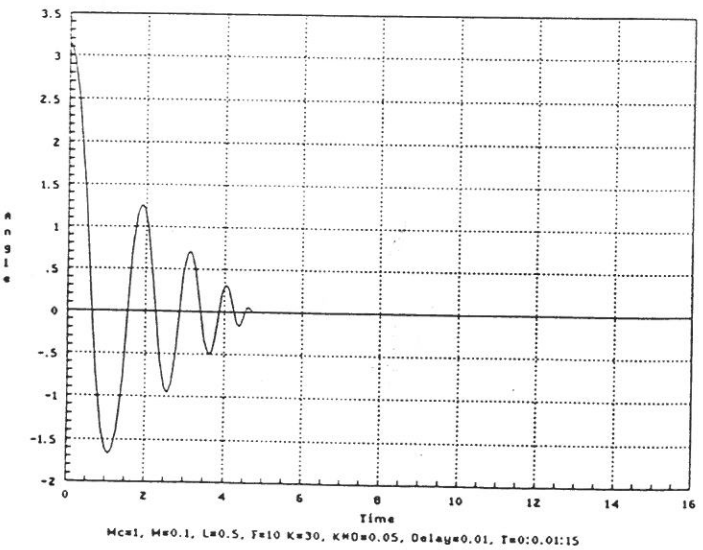


Fig. 3b