Prediction and Control of Complex Systems via Neural Networks

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In order to control systems as complex as tokamaks and accelerators, methods employing neural networks appear to be promising candidates. In this paper we describe three systems where we have attempted to use a neural network to predict their behavior. We examine two quantities which can determine feasibility for control of complex systems: dimension and entropy.

1. Introduction

Biological systems seemly with ease are able to predict and control complex systems without having an underlying knowledge of the physics of the system. For example, a seal is able to balance a stick on its nose for an extended period of time without any knowledge of Newtonian mechanics. Artificial neural network models were constructed to mimic in some ways the characteristics of the brain. As a result, in recent years neural networks have been used extensively in a variety of areas such as high energy physics, nuclear fusion, and accelerator physics. Most recently, research fields in neural network applications have expanded to solution of dynamic problems such as time series prediction.

In this paper we concentrate on the aspect of prediction and control of complex systems by neural networks. We first begin by describing the basic properties of a neural network. We then present three systems where we attempt prediction by a neural network. From a time series of some variable of the system we then show two characteristics which can be extracted which determine predictability and controllability: dimension and entropy.

2. Neural Network

Formally speaking a neural network is a system composed of many simple processors (units) and interconnections among the units. As there are a lot of excellent textbooks of introduction of neural networks [1] we present here only a minimum description. Figure 1 shows the structure of a simple feed-forward neural network composed of 3 layers. Data flows from the input layer on the left hand side to the output layer on the right hand side. Between the input and output layers there is a hidden layer. A weight is assigned to each connection between two units belonging to adjacent layers. The weighted data are summed up at each unit (neurons) and the result is subject to a nonlinear transformation assigned to the unit, usually something like a smooth step function to mimic the behavior of actual neurons. The weights are usually determined using the error-back propagation algorithm [1] which makes the deviations of the network values from the desired values as small as possible for a given set of training data. This type of network has achieved great success in spite of the large number of training data sets and iterations required to achieve good convergence

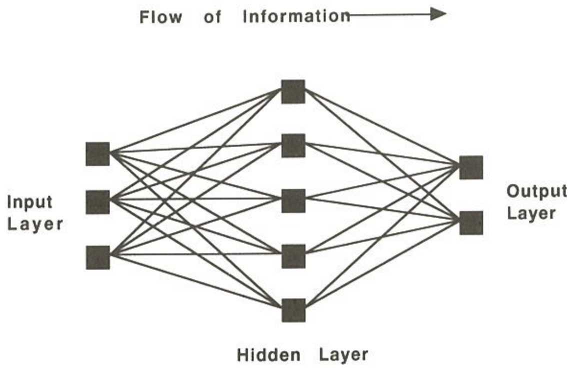

Figure 1 Simple picture of a multi-layer neural network

properties. This is mainly due to the fact that neural networks can learn any nonlinear mapping function given enough nodes in the hidden layer and training sets.

3. Examples of Prediction

In this section we show three examples where we have attempted to predict the behavior of each system with a neural network.

First we look at the Lorenz map. This system has been thoroughly studied so we refer the reader to other references for a more detailed treatment [2]. In Figure 2 we show the time series of the X component of the Lorenz attractor which was run for 10^4 interations with the parameters given in the figure. A neural network fit to the next time step from the input previous three time steps is also shown in the figure which overlaps the original data showing that the network has learned the system and can predict forward in time.

Next we show results from application of tokamak control. In a tokamak error in determination of the vertical position of the plasma-current-center (Z_J) by standard linear regression sensor algorithms result in Vertical Displacement Events (VDE) which can cause severe damage in tokamak fusion reactors like ITER. In this problem we constructed a neural network consisting of input magnetic field probe data and one output node with the Z_J position. The original data and the neural network prediction are shown in Figure 3. With this network we were able to obtain very high accuracy in the determination of the plasma position

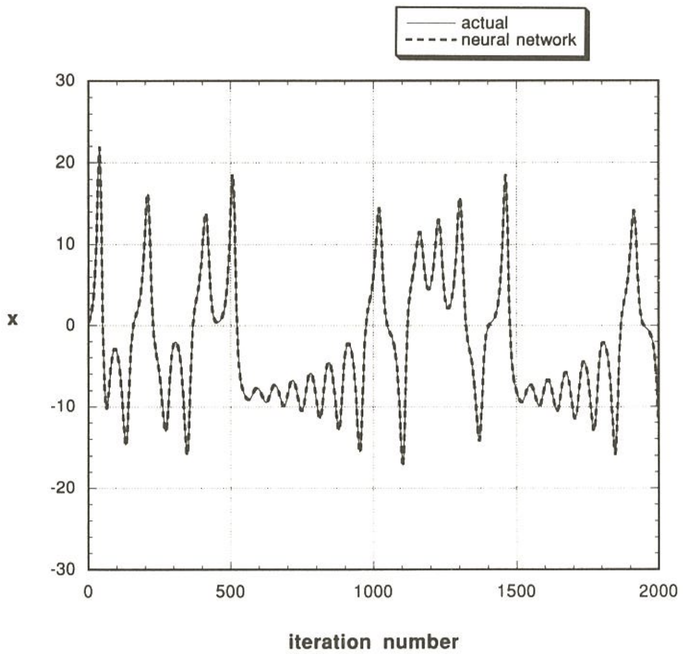

Figure 2 Time series of the X component of the Lorenz attractor system with σ=10, b=8/3, and γ=28 with initial values of (X,Y,Z) = (0, 1, 0) showing 2000 of 10^4 iterations (see cited references for description of parameters).

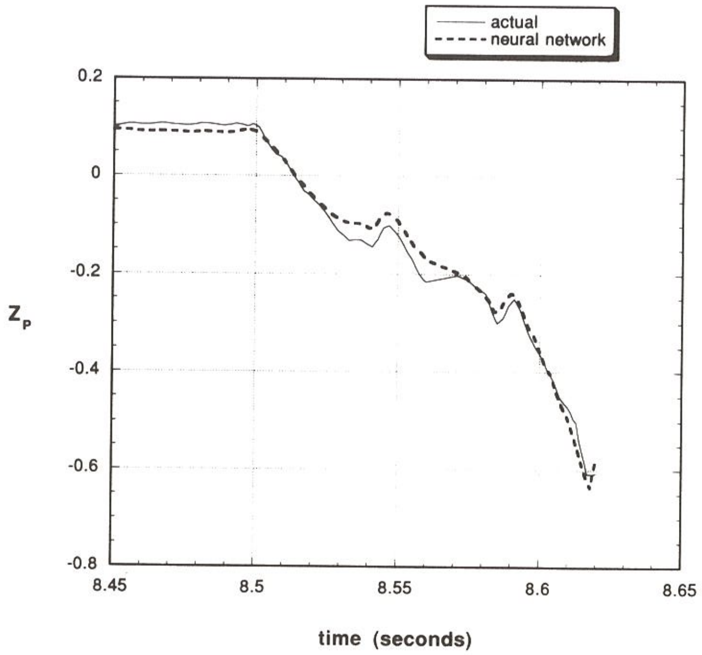

Figure 3 Time series of the vertical position ZJ of the plasma during a single shot in JT-60 U

enough to eliminate VDE [3].

In the third system we examine the predictability for charged particle beam cooling methods. In the beat wave cooling method a finite set of laser modes is adjusted to kick a charged particle beam to cool it. For details of this method see reference [4]. Using data from a computer simulation we input the laser light previously scattered by the beam to predict the next laser amplitude (A) used to cool a charged particle beam. It can be seen in Figure 4 that the fit by the network is not good even though network used in this case was large (~100 input values).

4. Dimension and Entropy

In the previous section we showed that the neural network prediction in two cases was very good and in one case the prediction was not good. The reason for this can be determined by two quantities which can be extracted from time series of the system.

It has been shown that one can predict the evolution of a system with knowledge of previous measurement of some physical variable of the system. The number of previous measurements needed is referred to as the dimension or the degrees of freedom of the system. This dimension can be extracted from the time series of the system by techniques which can be found in various references [2].

The degrees of freedom gives us a handle on the amount of data that is needed for prediction; however, another parameter is needed to indicate the time ahead over which the calculation can predict the behavior of the system. A good quantity for this is known as the Kolmogorov entropy which is a measure of the average rate of loss of information in a system [5].

The need for both the dimension and entropy can be seen from the following. If we calculate a high dimension for a system, then by simply inputting a large number of previous values of the system into a neural network it would seem that we could predict the next step. However, the Kolmogorov entropy gives us an idea of the limit on the number of useful previous values. If this number is large, then inputting a large number of previous values will not improve predictability.

We calculated these two quantities for all three systems and summarize the results in Table 1. The dimension and entropy of the Lorenz map and the tokamak control problem are low, indicating that a good fit is possible. In the case of beat wave cooling both the dimension and entropy are large indicating that predictability is difficult using a single variable. However, the use of a large number of variables at the same time may increase predictability.

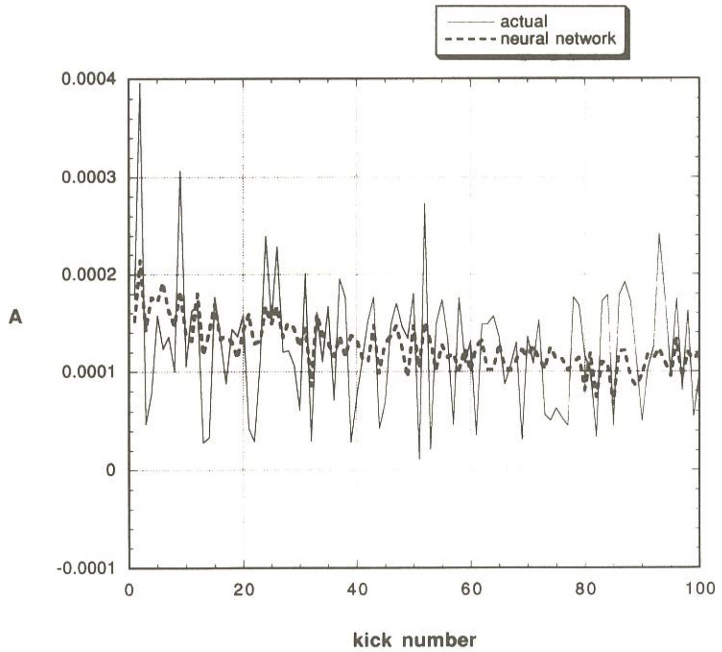

Figure 4 Time series of the laser field amplitude (A) used to cool a charged paticle beam.

Table 1 Characteristics of the Three Systems

System	Dimension	Entropy
Lorenz Map	2	~0.06
Tokamak Control	4-5	~0.05
Beat Wave Cooling	30-40	~0.1-0.2

5. Discussion

We have shown in this paper that various systems can be predicted by a neural network. In some systems predictability is easy and others difficult. We have shown that two quantities are helpful in determining the predictability and possible control of systems from the time series of some relevant parameter describing the system. These tools are useful in constructing a neural network to control the system. We have found that prediction is fairly easy for low dimensional systems where the entropy of the time series is low. However, in high dimensional systems with high entropy such as cooling, the control of the system is difficult by a neural network due to the size of the network that is necessary and the time over which prediction is possible.

In this paper we examined only the feasibility of control of complex systems by looking at the predictability. We are curently attempting actual control in a tokamak system. The dimensionality calculations which we have discussed only can measure the degrees of freedom described by the time series. If there are underlying degrees of freedom, they are not detected. We speculate that when control is applied to a system, the feedback may expose more of the underlying degrees of freedom of the system, thus requiring a larger neural network to describe the problem.

Finally, however, with the proper use of neural networks machines such as neural tokamaks and neural accelerators represent tantalizing future possibilities. Our group is currently examining these possibilities.

References

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