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Adaptive neural state observer for unknown non linear plants

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Abstract

A new neural state observer for non linear plants is proposed. Using a dynamical back-propagation learning algorithm, a non linear dynamical system, the neural observer, is built in order to reproduce the input/output behaviour of an unknown non linear plant and to give us an estimation by the output of the plant state. A straightforward example illustrates the proposed technique. Simulation results seem to be attractive.

1. INTRODUCTION

The problem of state observation for linear and non linear plants has been largely reported in the literature. For the linear case a method for estimating the states from the knowledge of the inputs/outputs signals has been obtained by Luenberger [1]. For the nonlinear case a general approach to the problem of state observation is extremely difficult to deal with. An interesting method to extend the Luenberger observer by a linearization technique about constant operating points of the system is presented in [2]. A different method is to apply a nonlinear transformation that converts the system into observer canonical form in order to simplify the observer design [3]. Unfortunately finding a suitable transformation is very difficult and not always possible. A drawback common to both the previous approaches is that the nonlinearities of the plant must be included into the dynamical equations of the observer. A novel technique with excellent results was proposed by Walcott [4], designing an asymptotic VSS-type observer, based on the sliding mode theory [5]. Another synthesis technique of a VSS-observer, based on the hyperstability theory [6] was given in [7]. For all these methods it is mandatory to known the analytical structure of the system in order to identify the set of unknown states.

Our approach is based on the dynamical input/output behaviour: so in order to build a state observer, there are two main steps:

1. building a system that gives the same output from the same input of the plant, i.e. performing the model identification from input/output observations

2. searching for a correlation between plant states and observer ones; this correlation gives us a satisfactory state estimation from the I/O point or view, the so called *estimation by output*.

The observer must be general and adaptive respect to many classes of plants; therefore an artificial neural model used for general purpose approximation has been chosen. In this paper we show how it is possible to obtain a non linear state observer of *unknown* nonlinear plants, limiting the heavy theoretical conditions that are typical of conventional non linear observer.

Using the recurrent multilayer perceptron model and the dynamical back-propagation learning algorithm, we build a non linear dynamical system, the neural observer, in order to reproduce the input/output behaviour of an unknown non linear plant and to give us an *estimation by the output* of the plant state, from state neurons.

2. WHY NEURAL NETWORKS

It is well known that human *parallel* recognition capabilities exceed those of machines. So an intensive research has been developed in the field of parallel neural architectures. Non linear processes with not measurable disturbances, unmodelled dynamics and component failures need a robust intelligent control strategy. The feasibility of applying recurrent networks, based on the backpropagation algorithm, in identification and control of non linear dynamical systems has been demonstrated by Narendra [8] in recent years. Even if the neural network theory is still in the initial stage in non linear control problems , generalized recurrent neural networks seem to be a very attractive tool. The neural approach would prove effective in blending the rigorous non linear control theory and the empirical studies based on computer simulations.

3. NEURAL IDENTIFICATION

Before discussing the identification problem, it is important to answer the question if an exact representation exists for continuous functions in terms of simpler functions. Kolmogorov [9-10] stated that a continuous multivariable function can be expressed in terms of sums and composition of single-variable functions. Hecht-Nielsen [11] pointed out that a Kolmogorov network is similar to a neural network consisting of summing nodes and squashing functions. The original Kolmogorov statement is the following: there exist fixed increasing continuous functions $h_{pq}(x)$ on $I=[0\ 1]$ so that each continuous function f on I^n can be written in the form:

$$f(x_1, \ldots, x_n) = \sum_{q=1}^{2n+1} g_q \left(\sum_{p=1}^{n} h_{pq}(x_p) \right) \qquad (1)$$

where g_q are properly chosen continuous functions of one variable.

Moreover Cibenko [12] and Poggio [13] proved that a network with at least one hidden layer of sigmoidal units can *approximate* arbitrary well any continuous function.

4. MODEL DESCRIPTION

The simulations have been carried out using a recurrent back-propagation network with first order units. Following the same formalism as Pineda [14], for the vector state x we obtain:

$$\frac{dx_i}{dt} = - x_i + \sigma(u_i) + I_i \tag{2}$$

where

$$u_i = \sum_j w_{ij} x_j \qquad \text{for } i = 1,2,\ldots,n \tag{3}$$

and

$$\sigma(\alpha) = \frac{1}{1+e^{-\alpha}} \tag{4}$$

The constant value I_i represents an external input bias that may be included inside or outside $\sigma(\alpha)$. X_i represents the activity of the ith neuron and w_{ij} is the connection strength from the jth to the ith neuron. The evolution of this system in the weight space is given by:

$$\frac{dw_{ij}}{dt} = -\eta \frac{\delta E}{\delta w_{ij}} \tag{5}$$

where

$$E(x) = \frac{1}{2} \sum_{i=1}^{n} J_i^2 \tag{6}$$

and

$$J_i = u_i(t) = \begin{cases} d_1 - x_i & \text{if } i \in \Omega \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

η is a numerical constant which defines the time scale on which w changes; η must be small so that x is always essentially at steady state, while d_i values belong to the set of the desired outputs.

5. NEURAL OBSERVER

Consider the non linear dynamical system given by:

$$u_i(t) = \begin{cases} x(k+1) = f(x(k),u(k)) \\ y(k+1) = h(x(k)) \end{cases} \tag{8}$$

with $x \in R^n$, $u \in R^p$, $y \in R^q$, $f : R^{n+p} \rightarrow R^n$, $h : R^n \rightarrow R^q$,
under the following hypothesis:

1) n,p,q are known
2) x(k),u(k) are bounded and measurable $\forall\ x_0$
3) f(x,u) is continuous on a compact subset $\Omega_q \in R^q$

4) h(x) is continuous and invertible on a compact subset $\Omega_n \in R^n$
Multilayer feedforward networks with hidden layers may approximate a non linear function iff 3) and 4) are true. Therefore two networks A1 and A2 are built in order to approximate the *unknown* functions f and h (Fig.1).

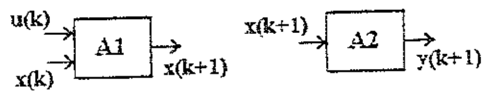

Figure 1.

It is noticeable that we cannot approximate f and h separately, because the state x is unknown and *only u and y are available*. If the two networks are connected in a cascade scheme (Fig.2) with a delay line in the feedback path, we obtain a composite network whose inputs and outputs are all available. The 'states' x(k) are now interior signal determined from the network A1.

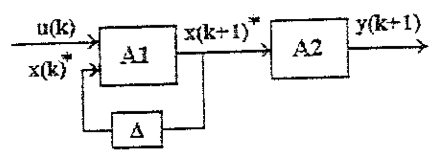

Figure 2.

The backpropagation learning algorithm is then proposed to adjust the weights of the neural network in order to identify the non linear dynamics of the system only from the knowledge of inputs and outputs.

6. SIMULATION RESULTS

Simulations of SISO systems have been performed in order to evaluate the neural observer efficiency. The topology of the neural network A1 is the following one:

inputs	outputs	hidden layers	1^{st} layer neurons	2^{nd} layer neurons	learning step
2	1	2	20	5	≥25000

The output of network A1 is linear and is set as input of network A2. As first example, consider the following non-linear system excited by sinusoidal input:

$$\begin{cases} x(k+1) = \dfrac{x(k)}{1+x(k)^2} + u \\ y(k+1) = 0.8 * x(k+1) \end{cases} \qquad (9)$$

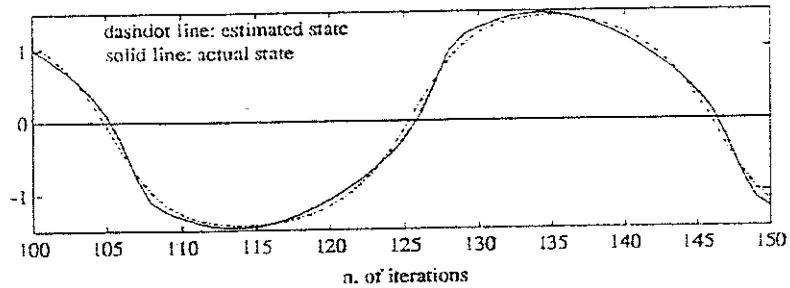

Figure 3

In this case network A2 is simply a linear neuron. Results of simulations are presented in figure 3: the observed state well-approximates the actual one, with maximum error related to the actual state amplitude of 0.58%.

In the second example network A1 is the same, while the topology of A2 is the following one:

inputs	outputs	hidden layers	1st layer neurons	2nd layer neurons	learning step
1	1	2	12	5	≥8000

The state observer has been applied to the system described by following equations:

$$\begin{cases} x(k+1) = \dfrac{\exp(x(k)^2)}{1+x(k)^2} + u \\ y(k+1) = \exp(x(k+1)) \end{cases} \tag{10}$$

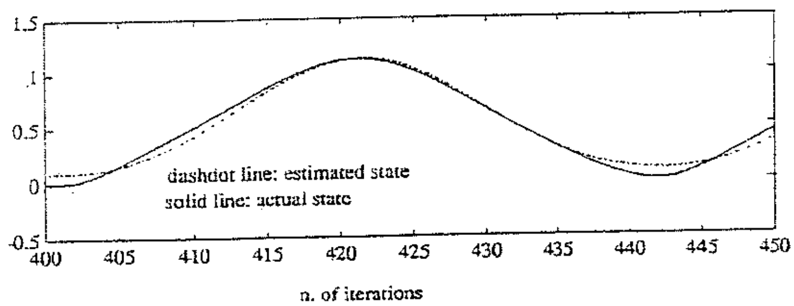

Figure 4

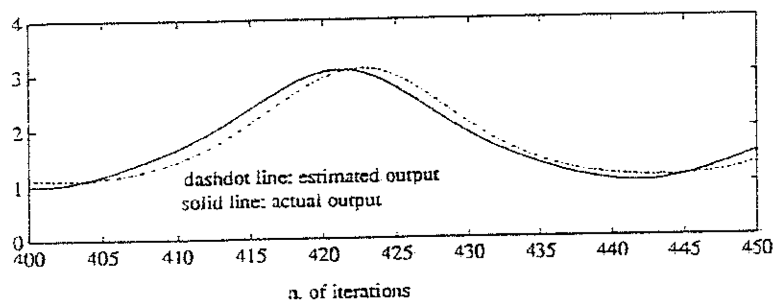

Figure 5

The process is still excited by sinusoidal input. Result of simulations are presented in figure 4 and in figure 5: the observer behaviour is still good, with maximum state error of 8.4% and maximum output error of 13%.

7. CONCLUSIONS

In this work a new neural architecture for the on-line identification is proposed. The SISO plant used for simulations is assumed to be described by non linear difference equations. The neural network adopted to identify the whole system is the recurrent multi-layer perceptron with the backpropagation learning algorithm. Only few "a priori" information concerning the class of difference equations are required. The extensive simulations carried out using the model suggested in this paper reveal that this neural architecture is effective for identification. Further investigations on high order processes and not invertible output functions are in progress.

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