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NEURAL NETWORKS FOR NONLINEAR PREDICTION OF TURBULENT SIGNALS FROM DATA MEASURED ABOVE AMAZON FOREST AND PASTURE

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Abstract: Feed-forward networks were implemented for nonlinear prediction and map approximation of turbulent signals measured above Amazon Forest and Pasture. The data analyzed were collected during RBLE3 experiment in Western Amazon. The initial results indicate that neural networks may be used to predict points in turbulent signals with considerable increase in accuracy over conventional methods. The nonlinear map obtained from the neural networks will be interesting for further investigating the characteristics of Amazon Forest turbulent signals.

Keywords: Amazon Forest, neural networks, nonlinear prediction, signal processing, turbulence

I. INTRODUCTION

Prediction and determination of the nonlinear map for time series (specially for chaotic dynamics) are an exciting recent application of neural networks. The approximation of time series can be put to a variety of uses: detection of chaos, prediction of x_{t+k} given x_t , and determination of the largest Lyapunov exponent via Jacobian-based methods etc. (Gallent and White, 1992). There are a number of approximation methods available for these kind of problems (Casdagli, 1989). Neural networks were found to be competitive with the best recent approximation methods (Lapdes and Farber, 1987, Gallent and White, 1992).

In this paper, feed-forward networks were implemented for nonlinear prediction and map approximation of turbulent signals measured above Amazon Forest and Pasture. The data analyzed were collected during RBLE3 experiment in Western Amazon (Sá et al., 1995). The initial results indicate that neural networks may be used to predict points in turbulent signals with considerable increase in accuracy over conventional methods. The nonlinear map obtained from the neural networks will be interesting for further investigating the characteristics of Amazon Forest turbulent signals (Sá et al., 1995, Li and Sá, 1995).

II. THE THEORY AND ALGORITHM

For a measured time series $x(t)$, $t=1,2,\dots,T$, where $x(t)$ is taken at time $T\Delta t$ and Δt is the time interval between measurements, an attractor may be reconstructed from (Packard et al., 1980):

$$x(t) = f(x(t-m), x(t-2m), \dots, x(t-(d_e-1)m)) \quad \text{for } t=1,2,\dots,T \quad (1)$$

where, d_e is the embedding dimension and $m\Delta t$ is the time delay, d_e with $m > 0$. If the dimension of the attractor is defined to be d_a , then $d_e \leq 2d_a+1$. In the case $d=d_e-1$ and $m=1$, the equation (1) will be:

$$x(t) = f(x(t-1), x(t-2), \dots, x(t-d)) \quad \text{for } t=1,2,\dots,T \quad (2)$$

For approximating the function $f(\cdot)$, one type of network -- feed-forward single hidden layer networks (Rumelhart et al., 1986) will be used in this work. The input values $x(t-1)$, $x(t-2)$, ..., $x(t-d)$ are received through d input units, which simply pass the input forwards to the hidden units u_j , $j=1,2,\dots,q$. Each connection performs a linear transformation determined by the connection strength w_{ij} , so the total input for hidden unit u_j is $\sum_{i=1}^d w_{ij} x(t-i)$. Each unit performs a nonlinear transformation on its total input, producing output:

$$o_j = \Phi(w_{0j} + \sum_{i=1}^d w_{ij} x(t-i)) \quad (3)$$

The activation function Φ is the same for all units. Here, Φ is a sigmoid function with limiting value 0 and 1 as $o_j \rightarrow -\infty$ and $o_j \rightarrow +\infty$ respectively:

$$\Phi(o_j) = 1/(1+\exp(-o_j)) \quad (4)$$

The hidden layer outputs o_j are passed along to the single output unit with connection strength β_j , which performs an affine transformation on its total input. Then, the network's output $x(t)$ can be represented as:

$$x(t) = \beta_0 + \sum_{j=1}^q \beta_j \Phi(w_{0j} + \sum_{i=1}^d w_{ij} x(t-i)) \quad (5)$$

for d inputs and q units in the hidden layer.

One way to make predictions at various next step t , $t-1$, $t-2$, ..., $t-k\Delta t$ to place previously predicted values on the input lines to bootstrap one's way to higher i values (Lapedes and Farber, 1987). After training a network to predict at t , the predicted values can be fed back to the inputs to predict at $t+1$, $t+2$, ... etc. In this way, unacceptable prediction errors should not occur until k is quite large.

III. PREDICTION AND MAP

III.1 The data

The turbulent signals measured above Amazon Forest and Pasture were collected during the RBLE3 experiment (Rondonia Boundary Layer Experiment), in Rondonia, Western Amazonia, in August 1994 (Sá et al., 1995). The main goal of this experiment was to obtain meteorological data of the boundary layer above the Amazon Forest and Pasture (grassland). The Forest experiment data (S2321300, 20/08/94) were measured from a tower at 15 m above the Jaru river biological reserve, a huge intact forest site (268,000 ha) $10^\circ 05' S$, $61^\circ 55' W$ and 120m above the sea level. The Pasture experiment data (S2291200, 17/08/94) were obtained from a mast at 3.5m above the ground in Nossa Senhora de Aparecida farm, a deforested area, 10 km far from the town of Ouro Preto do Oeste. There are four data series in every group (S2291200 and S2321300): wind speed in 3 dimensions (u , w , v) which were collected with a "three-dimensional ultrasonic anemometer-thermometer Gill" (Gill instruments, Solen House)

and the temperature (t). The available data are in the range of 25,000 with sampling frequency 21 Hz.

III.2 Signals prediction

In the prediction of the signals of the wind velocity in x direction and temperature of S2291200 and S2321300, the signals were reconstructed with $d = 4$. Then, 4 inputs and 20 hidden units are used in a single layer feed-forward network. The training of the network was based on 2000 observations. 20 points from 2001 to 2020 were predicted. Fig. 1 gives the prediction relative error (ϵ) along these points. For S2291200, the data observed over pasture on midday, the ϵ of wind velocity in u direction was less than 10% and the ϵ of temperature was less than 2%. For S2321300, the data observed over Forest near midday, the ϵ of the first six points of wind velocity in u direction was lesser than 30%. After that point the ϵ was larger than 30%. The ϵ of temperature were almost zero. The good prediction results of the temperature is due to the stable temperature values during this second (20 observations). The problem of turbulence's predictability has already intensively discussed. Ruelle (1989) stressed his scepticism concerning the possibility of prediction of the time series' future thru methods of dynamical systems. However, the above results encourage this subject and show that neural networks may be a suitable method for turbulence's prediction.

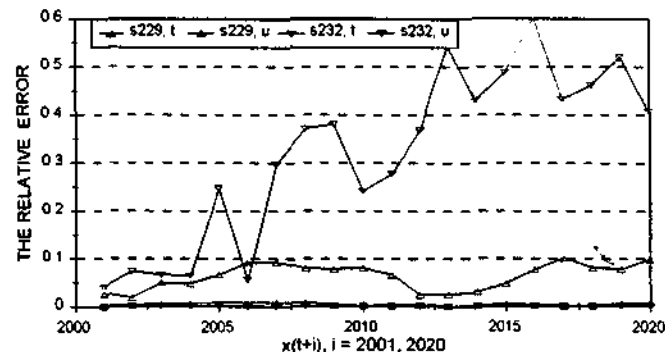


Fig. 1 The prediction relative error (ϵ) of S2291200 and S2321300

III.3. The nonlinear map

After training the networks, a group of weights ($\beta_0, \beta_1, \dots, \beta_q$, and w_{ij} , $i = 0, 1, \dots, d$, $j = 1, 2, \dots, q$) is obtained. The map defined by equation (5) of observed signals is available. In case of a single hidden layer feed-forward network with 4 inputs, 20 hidden units and 2000 observations of signals S2291200, the maps were approximated after 4200 training cycles. The RMSE (Root Mean Square Error) of the wind velocity (u) map is 0.02026 and the RMSE of the temperature map is 0.01826. These results suggest more studies concerning an eventual different nature for each kind of turbulence, but using sufficient data and several physical situations. Comparisons of observed data and its estimate by map of wind velocity in u direction and temperature are shown in Fig. 2 and 3 respectively.

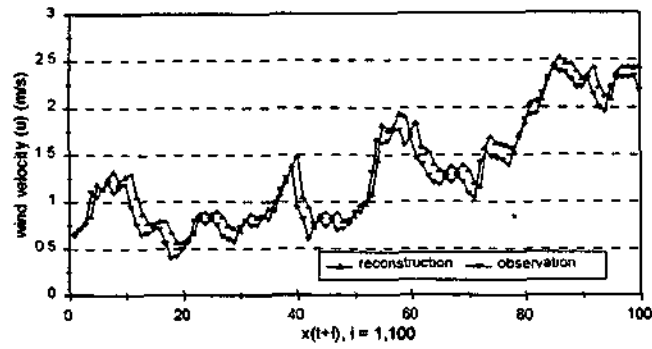


Fig. 2 Wind velocity (u) of S2291200 reconstructed by its map

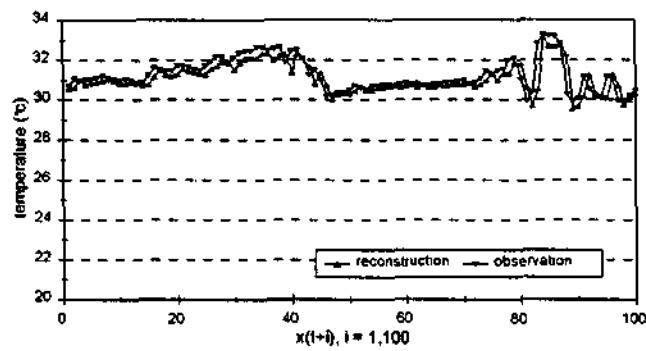


Fig. 3 Temperature of S2291200 reconstructed by its map

To analyze the precision of the map, four cases of temperature map of signals S23213000 were studied (Table 1). According to the criterion of RMSE, there is almost no difference between case 1 and case 2. This means that the number of inputs does not affect map approximation. Remembering the number of inputs of the networks d equals $(d_e - 1)$ and that d_e is the embedding dimension of the map, to correctly choose d is difficult for the nonlinear mapping problem. Nychka and others (Nychka, et al., 1992) suggested using the 'Bayesian

Table 1 Map precision analysis for temperature of S2321300

CASE	INPUTS	HIDDEN UNITS	DATA	RMSE (500 cycles)
1	20	20	2000	0.006386
2	4	20	2000	0.006138
3	4	4	2000	0.007213
4	4	4	500	0.012412

information criterion' to get a possible combination of d , q and other parameters. Comparing case 2 with case 3, the number of hidden units influences the RMSE. When increasing the quantity of training data, the RMSE reduced significantly. For the 2000 observations of case 3, the RMSE is 0.007213. For 500 observations of case 4, the RMSE increased to 0.012412.

IV. CONCLUSIONS

Feed-forward neural networks were robust for prediction and approximating these turbulent signals. For these typical turbulent signals wind velocity, the network can predict at least 5 points with the accepted precision (less than 30% error). The approximating nonlinear map can also reconstruct the signals with 0.022 RMSE or less. Future work will analyze other RBLE3 experiment data and study more suitable prediction and approximation techniques including neural networks (Li and Sá, 1995).

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