Fifth IFSA World Congress (1993), 853-856

Chaos Simulator as a Developing Tool for Application of Chaos Engineering

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Abstract

In this paper, we describe a chaos simulator as a developing tool for applications of chaos engineering. This simulator is composed of three modules, such as generation module of chaotic signals by deterministic rules, determination module whether observed time series is chaos or not, and nonlinear system identification module by self generating Neuro Fuzzy Model.

1. Introduction

In recent years, intelligent industrial systems and consumer electronic products are widely and intensively developed. Fuzzy logic, neural network, and *neuro & fuzzy* technology which integrates these approaches are now regarded as one of the effective methods to realize such intelligent features. Furthermore, a novel paradigm as *chaos engineering* is now expected to be another key technology for various applications such as nonlinear prediction of time series, diagnosis for complex systems and comfortable home appliancees. In this paper, we describe the chaos simulator

[1] developed to provide a common tool for the research on chaos engineering

[2] and development of the products using chaos theory.

2. Chaos Simulator

Fig.1 shows the structure of chaos simulator and this simulator consists of following three modules.

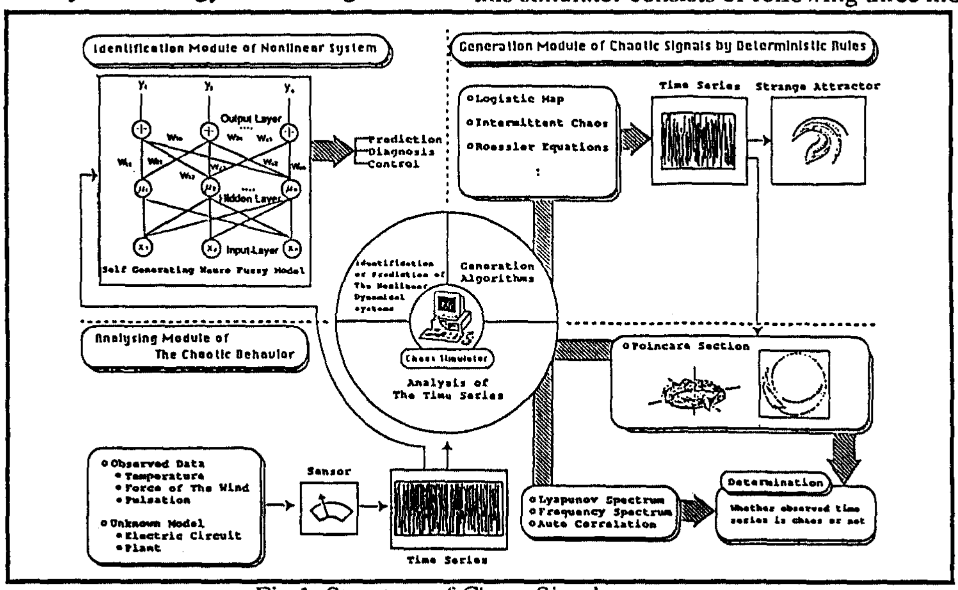


Fig.1 Structure of Chaos Simulator

2.1 Generation Module of Chaotic Signals by Deterministic Rules

This module is used for generating chaotic time series by deterministic rules such as intermittent chaos[3], logistic map, etc.

2.2 Determination Module whether observed time series is chaotic or not

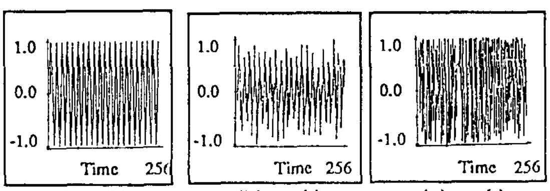
So far, many methods are proposed to determine whether observed time series is a deterministic chaos or not. We have implemented fundamental algorithms such as FFT(Fast Fourier Transform), auto correlation, Lyapunov spectrum analysis from the observed time series data, and so on. To demonstrate these functions, let us consider following time sereies as expressed by (1) ~ (3),

$$x_1(t) = \sin(0.5t) \tag{1}$$

$$x_2(t) = (\sin(0.5t) + r(t)) * 0.5 \tag{2}$$

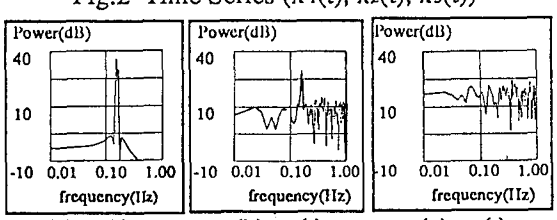
$$x_3(t) = a * x(t-1) * (1.0 - x(t-1)) \tag{3}$$

The sine wave $x_1(t)$ is periodic, therefore it's not chaotic. $r(t)$ in (2) is random noise ($r(t) \in [-1,1]$), and $x_2(t)$ is not chaotic. $x_3(t)$ is famous logistic difference equation for biological populations, and it's chaotic.These time series are shown in Fig.2, with 256 data, and frequency spectrum in Fig.3, where $a = 4.0$ and $x_3(t)$ is normalized such that $x_3(t) \in [-1,1]$.



(a) $x_1(t)$ (b) $x_2(t)$ (c) $x_3(t)$

Fig.2 Time Series ($x_1(t)$, $x_2(t)$, $x_3(t)$)



(a) $x_1(t)$ (b) $x_2(t)$ (c) $x_3(t)$

Fig.3 Frequency Spectrum ($x_1(t)$, $x_2(t)$, $x_3(t)$)

Frequency analysis

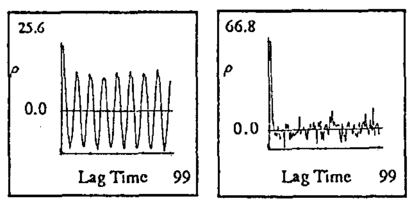
The frequency analysis of the $x1(t)$ shows dominant peak with one or more harmonics(Fig.3 (a)), and so we can find out it's not chaotic. And for $x_2(t)$ and $x_3(t)$ the frequency spectrum is broadband(Fig.3 (b),(c)), and so we can't find out whether they are chaotic or not in this stage.

Auto correlation

The auto correlation of chaotic time series drastically decreases from positive value to zero with the increase of lag time[4]. We calculated the auto correlation for $x_2(t)$ and $x_3(t)$ which can not be clarified as chaotic or not by FFT. The auto correlation is computed by (4),

$$\rho = \sum_{n=0}^{N-1-L} x(n) \cdot x(n+L) \tag{4}$$

where N is the total number of data, L is lag time. The auto correlation of $x_2(t)$ and $x_3(t)$ are shown in Fig.4 (N=256, L=0,···,99). In this case, $x_2(t)$ isn't chaotic, because the auto correlation does't converge to zero with the increase of lag time. But the ρ of $x_3(t)$ is indicates that $x_3(t)$ is chaotic.



(a) $x_2(t)$ (b) $x_3(t)$

Fig.4 Auto Correlation ($x_2(t)$, $x_3(t)$)

Lyapunov spectrum analysis

In order to evaluate the orbital instability of the observed time series, we calculated the largest Lyapunov exponent [5] by (5),

$$\lambda_{max} = \frac{1}{\tau} \frac{1}{N_k} \sum_{|X_t - X_k| < \varepsilon} \ln \left(\frac{|X_{t+\tau} - X_{k+\tau}|}{|X_t - X_k|} \right) \tag{5}$$

where Xt is a point on the reconstructed trajectory at time t, and Xk is a set of point in a small ball of radius ε centered at the point Xt. After τ time step, Xt and Xk are mapped to Xt+ τ and Xk+ τ respectively (Fig.5).

We calculated the largest Lyapunov exponent of $x_3(t)$ with 5,000 data and we obtained λ_{max} is 0.693. Furthermore this simulator provides Lyapunov spectrum analyzing method by Sano and Sawada [6].

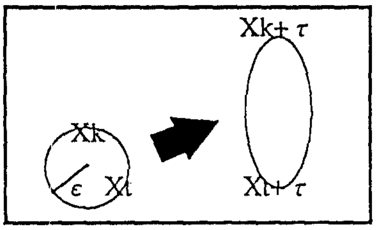


Fig.5 Orbital Instability of Chaos

2.3 Nonlinear System Identification by Self Generating Neuro Fuzzy Model

In order to identify or predict the nonlinear dynamical systems such as deterministic chaos, it is considered to be important that the model output must has smoothness which cannot be obtained by the fuzzy model with triangular or trapezoid shaped membership functions which are usually used. To obtain the smoothness of the output surface, generalized radial basis function (GRBF) [7], or fuzzy model of class C^{∞} whose membership functions are given by Gaussian [8] are proposed, which are also regarded as a layered neural network (Fig.6). The problem is that the optimization problem defined by the automatic modeling with GRBF is highly nonlinear with respect to decision parameters, and global convexity is not necessary guaranteed. To solve this problem, we have proposed self generating and tuning algorithm for GRBF [9,10] to determine the minimum number of basis functions (fuzzy rules or hidden units) automatically to realize the specified model accuracy.

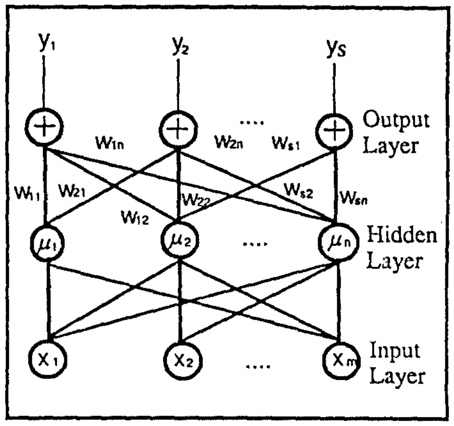


Fig.6 Neuro Fuzzy Model as Multilayer Neural Network Representation

3.Application

Now, let us explain the new kerosene fan heater we announced in June '92(Fig.7), which is the first consumer electronic product in the world using chaos theory.

It is so far believed that to keep the desired temperature stable is good for the comfortableness. On the contrary, studies by D.P.Wyon [11], where subjects were exposed to the appropriate temperature fluctuations, indicate that individuals actually prefer temperature swings about the optimum.

Based on this idea, appropriate temperature swing patterns are computed by the simple equation which produces the intermittent chaos [3].

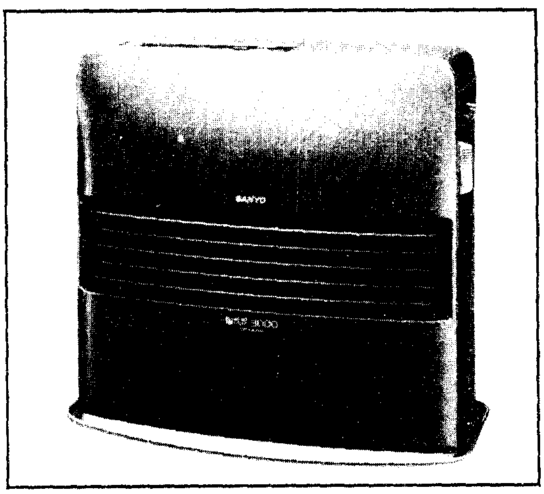


Fig.7 Kerosene Fan Heater using Chaos Theory
<CFH-A300 series>

In this kerosene fan heater, three types of *Chaotic Fluctuations* with different spectrum are selected according to the temperature variation in the environment. These kinds of *Chaotic Fluctuations* are regarded as one of the earliest industrial application of chaos theory.

Furthermore, the velocity of combustion is controled by *Fuzzy logic* in propotion of the temperature and the extent of the room, and an economical preheating of the burner for quick start is realized by *Neural Network* for learning user's life style.

4.Conclusion

We have developed chaos simulator and applied it to develop the kerosene fan heater. We expect this simulator to be applied to other home appliances to provide much more comfortableness, an equipment to diagnose mental and physical conditions, a noise canceler with adaptive mechanism, etc.

We have reviewed the fundamental technology and applications of neuro, fuzzy and chaos theory mainly concerned with consumer electronics. These novel paradigms, combined with AI technology and conventional methodlogies, will be effective to realize the intelligent products with easy operation, human friendly interface, personal features which are acquired according to the particular user's preference, learning or adaptive mechanisms in the time varying environments. We assume *Soft Information Processing* represented by these paradigms, or theories which treat the *Nonlinear Systems* as they are, will be one of promising approaches to realize such ideal products and systems.

[References]

[1]K.Kuwata,R.Katayama,Y.Kajitani,Y.Nishida: Development of Chaos Simulator, Proc. of 45th Conference of Information Processing Society of Japan, 1992. (in Japanese)

[2] Special Issue on Engineering Chaos, Trans. of IEICE, vol.E73, no.6,1990.

[3]I.Procaccia,H.Schuster:Functional renormalization group theory of universal 1/f noise in dynamical systems, Phys. Rev., A28, pp.1210-1212, 1983.

[4] E.Ott : Strange attractors and chaotic motions of dynamical systems,Rev. Modern Phy.,53-4/1, pp.655-671, 1981.

[5] S.Sato,M.Sano,Y.Sawada : Practical Methods of measuring the Generalized Dimension and the Largest Lyapunov Exponent in High Dimensional Chaotic System,Prog.Theor,Phys,77, 1/5,1987.

[6] M.Sano,Y.Sawada : Measurement of the Lyapunov Spectrum from Chaotic Time Series, Phys. Rev. Lett. 55, pp.1082-1085, 1985.

[7] T.Poggio,F.Girosi : A Theory of Networks for Approximation and Learning, A.I.Memo, No.1140, C.B.I.P. Paper, No.31, July, 1989.

[8] H.Ichihasi : Iterative Fuzzy Modeling and a Hierarchical Network, Proc. of 4th IFSA Congress, vol. Engineering,pp.49-52,1991.

[9]R.Katayama,K.Kuwata,Y.Kajitani,Y.Nishida : Self Generating Radial Basis Function as a Neuro-Fuzzy Model and its Application to Nonlinear Prediction of Chaotic Time Series, Proc. of the Second IEEE International Conference on Fuzzy Systems, San Francisco, pp.407-414, 1993.

[10]R.Katayama,Y.Kajitani,K.Kuwata,Y.Nishida : Comparative Analysis on Learning Ability of Self Generating Algorithm for Neuro Fuzzy Model with Various Radial Basis Functions, Proc. of the Fifth IFSA, Seoul, Korea, 1993.

[11] D.P.Wyon : The Role of the Environment in Building Today : Thermal Aspects (Factors Affecting the Choice of a Suitable Room Temperature), Build Intematinal, vol.6, pp.39-54, 1973.