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NEW GEOMETRIC ATTRACTOR AND NEURAL NETWORKS APPROACH TO STUDYING CHAOTIC PROCESSES IN PHOTOELECTRONICS SYSTEMS

Nonlinear modelling of chaotic processes in systems and devices, including quantum electronics and photo may be based on the concept of compact geometric attractors. We present a new approach to analyze and predict the nonlinear dynamics of chaotic systems based on the concept of geometric attractors, chaos theory methods and algorithms for neural network simulation. Using information on the phase space evolution of the physical process in time and AI simulation of neural network modelling techniques can be considered as one of the fundamentally new approaches in the construction of global nonlinear models of the most effective and accurate description of the structure of the corresponding attractor.

1. Introduction

It is very well known now that multiple quantum-and photoelectronics systems and devices could demonstrate the typical chaotic behaviour [1-2]. One could remind here laser and different quantum generators, radio-technical devices, multi-element semiconductors etc. To date, the obvious is the fact that the overwhelming number of physical and technical systems are formally very complex, and this feature is manifested at different spatial and temporal scale levels [1-11]. Naturally, the task list for studying the dynamics of complex systems is not limited to the above examples. It is not difficult to understand that examples of such systems are the chemical systems, biological populations, and finally, cybernetical (neurocybernetical) and communication system and its subsystems.

Most important, the fundamental issue in the description of the dynamics of the system is its ability to forecast its future evolution, i.e. predictability of behavior. Recently, the theory of dynamical systems is intensively developed, and, in particular, speech is about the application of methods of the theory to the analysis of complex systems that provide description of their evolutionary dynamics by means solving system of differential equations. If the studied system is more complicated then the greater the equations is necessary for its adequate description. Meanwhile, examples of the systems described by a small amount of equations, are known nevertheless, theses systems exhibit a complicated behavior. Probably the best-known examples of such systems are the Lorenz system, the Sinai billiard, etc. They are described, for example, three equations (i.e., in consideration included three independent variables), but the dynamics of their behavior over time shows elements of chaos (so-called "deterministic chaos"). In particular, Lorentz was able to identify the cause of the chaotic behavior of the system associated with a difference in the initial conditions. Even microscopic deviation between the two systems at the beginning of the process of evolution leads to an exponential accumulation of errors and, accordingly, their stochastic divergence. During the analysis of the observed dynamics of some characteristic parameters of the systems over time it is difficult to say to what class belongs to the system and what will be its evolution in the future. Many interesting examples can be reminded in the modern sstatistical physics, physics of non-ordered semiconductors etc.

In recent years for the analysis of time series of fundamental dynamic parameters there are with varying degrees of success developed and implemented a variety of methods, in particular, the nonlinear spectral and trend analysis , the study of Markov chains, wavelet and multifractal analysis, the formalism of the matrix memory and the method of evolution propagators etc. Most of the cited approaches are defined as the methods of a chaos theory. In the theory of dynamical systems methods have been developed that allow for the recording of time series of one of the parameters to recover some dynamic characteristics of the system. In recent years a considerable number of works, including an analysis from the perspective of the theory of dynamical systems and chaos, fractal sets, is devoted to time series analysis of dynamical characteristics of physics and other systems [1-11]. In a series of papers [12-15] the authors have attempted to apply some of these methods in a variety of the physical, geophysical, hydrodynamic problems. In connection with this, there is an extremely important task on development of new, more effective approaches to the nonlinear modelling and prediction of chaotic processes in physical, (in particular, quantum- and photo-electronics) systems. In this work we present an advanced approach to analysis and forecasting nonlinear dynamics of chaotic systems, based on conceptions of a geometric attractor and neural networks modelling [11,16].

2. New approach to analysis of chaotic processes

The basic idea of the construction of our approach to prediction of chaotic properties of complex systems is in the use of the traditional concept of a compact geometric attractor in which evolves the measurement data, plus the implementation of neural network algorithms. The existing so far in the theory of chaos prediction models are based on the concept of an attractor, and are described in a number of papers (e.g. [1-10]). The meaning of the concept is in fact a study of the evolution of the attractor in the phase space of the system and, in a sense, modelling ("guessing") time-variable evolution..

From a mathematical point of view, it is a fact that in the phase space of the system an orbit continuously rolled on itself due to the action of dissipative forces and the nonlinear part of the dynamics, so it is possible to stay in the neighborhood of any point of the orbit $y(n)$ other points of the orbit $y^r(n)$, $r = 1, 2, \ldots, N_B$, which come in the neighborhood $y(n)$ in a completely different times than n. Of course, then one could try to build different types of interpolation functions that take into account all the neighborhoods of the phase space and at the same time explain how the neighborhood evolve from $y(n)$ to a whole family of points about $y(n+1)$. Use of the information about the phase space in the simulation of the evolution of some physical (geophysical etc.) process in time can be regarded as a fundamental element in the simulation of random processes.

In terms of the modern theory of neural systems, and neuro-informatics (e.g. [11]), the process of modelling the evolution of the system can be generalized to describe some evolutionary dynamic neuro-equations (miemo-dynamic equations). Imitating the further evolution of a complex system as the evolution of a neural network with the corresponding elements of the self-study, self- adaptation, etc., it becomes possible to significantly improve the prediction of evolutionary dynamics of a chaotic system. Considering the neural network (in this case, the appropriate term "geophysical" neural network) with a certain number of neurons, as usual, we can introduce the operators S_{ij} synaptic neuron to neuron u_i u_j, while the corresponding synaptic matrix is reduced to a numerical matrix strength of synaptic connections: $W = || w_{ij} ||$. The operator is described by the standard activation neuro-equation determining the evolution of a neural network in time:

$$s_i' = sign(\sum_{j=1}^{N} w_{ij} s_j - \theta_i), \qquad (1)$$

where $1<i<N$.

Of course, there can be more complicated versions of the equations of evolution of a neural network. Here it is important for us another proven fact related to information behavior neuro-dynamical system. From the point of view of the theory of chaotic dynamical systems, the state of the neuron (the chaos-geometric interpretation of the forces of synaptic interactions, etc.) can be represented by currents in the phase space of the system and its the topological structure is obviously determined by the number and position of attractors. To determine the asymptotic behavior of the system it becomes crucial information aspect of the problem, namely, the fact of being the initial state to the basin of attraction of a particular attractor.

Modelling each physical attractor by a record in memory, the process of the evolution of neural network, transition from the initial state to the (following) the final state is a model for the reconstruction of the full record of distorted information, or an associative model of pattern recognition is implemented. The domain of attraction of attractors are separated by separatrices or certain surfaces in the phase space. Their structure, of course, is quite complex, but mimics the chaotic properties of the studied object. Then, as usual, the next step is a natural construction parameterized nonlinear function $\boldsymbol{F}(x, \boldsymbol{a})$, which transforms:

$$\mathbf{y}(n) \rightarrow \mathbf{y}(n+1) = \mathbf{F}(\mathbf{y}(n), \mathbf{a}),$$

and then to use the different (including neural network) criteria for determining the parameters a (see below). The easiest way to implement this program is in considering the original local neighborhood, enter the model(s) of the process occurring in the neighborhood, at the neighborhood and by combining together these local models, designing on a global nonlinear model. The latter describes most of the structure of the attractor.

Although, according to a classical theorem by Kolmogorov-Arnold -Moser, the dynamics evolves in a multidimensional space, the size and the structure of which is predetermined by the initial conditions, this, however, does not indicate a functional choice of model elements in full compliance with the source of random data. One of the most common forms of the local model is the model of the Schreiber type [3] (see also [10]).

3. Construction of the model prediction

Nonlinear modelling of chaotic processes is based on the concept of a compact geometric attractor, which evolve with measurements. Since the orbit is continually folded back on itself by the dissipative forces and the non-linear part of the dynamics, some orbit points $\mathbf{y}^r(k)$, $r = 1, 2, \ldots, N_B$ can be found in the neighbourhood of any orbit point $\mathbf{y}(k)$, at that the points $\mathbf{y}^r(k)$ arrive in the neighbourhood of $\mathbf{y}(k)$ at quite different times than k. Then one could build the different types of interpolation functions that take into account all the neighborhoods of the phase space, and explain how these neighborhoods evolve from y (n) to a whole family of points about y (n + 1). Use of the information about the phase space in modelling the evolution of the physical process in time can be regarded as a major innovation in the modelling of chaotic processes.

This concept can be achieved by constructing a parameterized nonlinear function F(x, a), which transform y(n) to y(n+1)=F(y(n), a), and then using different criteria for determining the parameters a. Further, since there is the notion of local neighborhoods, one could create a model of the process occurring in the neighborhood, at the neighborhood and by combining together these local models to construct a global nonlinear model that describes most of the structure of the attractor.

Indeed, in some ways the most important deviation from the linear model is to realize that the dynamics evolve in a multidimensional space, the size and the structure of which is dictated by the data. However, the data do not provide “hints” as to which model to select the source to match the random data. And the most simple polynomial models, and a very complex integrated models can lead to the asymptotic time orbits of strange attractors, so for part of the simulation is connected with physics. Therefore, physics is “reduced” to fit the algorithmic data without any interpretation of the data. There is an opinion that there is no algorithmic solutions on how to choose a model for a mere data.

As shown Schreiber [3], the most common form of the local model is very simple :

$$s(n+\Delta n)=a_0^{(n)}+\sum_{j=1}^{d_A}a_j^{(n)}s(n-(j-1)\tau) \qquad (2)$$

where Δ n - the time period for which a forecast.

The coefficients $a_j^{(k)}$, may be determined by a least-squares procedure, involving only points $s(k)$ within a small neighbourhood around the reference point. Thus, the coefficients will vary throughout phase space. The fit procedure amounts to solving (d_A + 1) linear equations for the (d_A + 1) unknowns.

When fitting the parameters *a*, several problems are encountered that seem purely technical in the first place but are related to the nonlinear properties of the system. If the system is low-dimensional, the data that can be used for fitting will locally not span all the available dimensions but only a subspace, typically. Therefore, the linear system of equations to be solved for the fit will be ill conditioned. However, in the presence of noise the equations are not formally ill-conditioned but still the part of the solution that relates the noise directions to the future point is meaningless . Note that the method presented here is not only because, as noted above, the choice of fitting requires no knowledge of physics of the process itself. Other modelling techniques are described, for example, in [3,10].

Assume the functional form of the display is selected, wherein the polynomials used or other basic functions. Now, we define a characteristic which is a measure of the quality of the curve fit to the data and determines how accurately match y (k + 1) with F (y (k), a), calling it by a local deterministic error:

$$\varepsilon_D(k)=\mathbf{y}(k+1)-\mathbf{F}(\mathbf{y}(k),\mathbf{a}). \qquad (3)$$

The cost function for this error is called W (ε). If the mapping F (y, a), constructed by us, is local, then one has for each adjacent to y (k) point, $y^{(r)}(k)$ (r = 1, 2, ..., N_B),

$$\varepsilon_D^{(r)}(k)=\mathbf{y}(r,k+1)-\mathbf{F}(\mathbf{y}^{(r)}(k),\mathbf{a}), \qquad (4)$$

where y (r, k + 1) - a point in the phase space which evolves y (r, k). To measure the quality of the curve fit to the data, the local cost function is given by

$$W(\varepsilon,k)=\frac{\sum_{r=1}^{N_B}\left|\varepsilon_D^{(r)}(k)\right|^2}{\sum_{r=1}^{N_B}\left[\mathbf{y}(k)-\langle\mathbf{y}(r,k)\rangle\right]^2} \qquad (5)$$

and the parameters identified by minimizing W (ε, k), will depend on a.

Furthermore, formally the neural network algorithm is launched, in particular, in order to make training the neural network system equivalent to the reconstruction and interim forecast the state of the neural network (respectively, adjusting the values of the coefficients). The starting point is a formal knowledge of the time series of the main dynamic parameters of a chaotic system, and then to identify the state vector of the matrix of the synaptic interactions $\|w_{ij}\|$ etc. Of course, the main difficulty here lies in the implementation of the process of learning neural network to simulate the complete process of change in the topological structure of the phase space of the system and use the output results of the neural network to adjust the coefficients of the function display. The complexity of the local task, but obviously much less than the complexity of predicting the original chaotic processes in physical or other dynamic systems.

4. Conclusions

Here we have considered an new approach to nonlinear modelling and prediction of chaotic processes in physical and other systems which is based on two key functional elements. Besides using other elements of starting chaos theory method the proposed approach includes the application of the concept of a compact geometric attractor, and one of the neural network algorithms, or, in a more general definition of a model of artificial intelligence. The meaning of the latter is precisely the application of neural network to simulate the evolution of the attractor in phase space, and training most neural network to predict (or rather, correct) the necessary coefficients of the parametric form of functional display.

References

1. Lichtenberg A., Liebermann A., Regular and chaotic dynamics.-N.-Y.: Springer.-1992.
2. Abarbanel H., Analysis of observed chaotic data.- N.-Y.: Springer.-1996.
3. Schreiber T., Interdisciplinary application of nonlinear time series methods// Phys. Rep. 1999.-Vol.308(1).-P.1-64.
4. Sivakumar B., Chaos theory in geophysics: past, present and future // Chaos, Solitons & Fractals.-2004.-Vol.19.-P.441-462.
5. Kennel M. B., Brown R., Abarbanel H., Determining embedding dimension for phase-space reconstruction using a geometrical construction // Physical Review A.-1992.-Vol.45.- P.3403-3411.
6. Turcotte D. L., Fractals and chaos in geology and geophysics.-Cambridge: Cambridge University Press, 1997.
7. Hastings A. M., Hom C., Ellner S, Turchin P., Godfray Y., Chaos in ecology: is Mother Nature a strange attractor?// Ann. Rev. Ecol. Syst.-1993.-Vol.24.-P.1-33.
8. May R. M., Necessity and chance: deterministic chaos in ecology and evolution // Bull. Amer. Math. Soc.-1995.-Vol.32.-P.291-308.
9. Grassberger P., Procaccia I., Measuring the strangeness of strange attractors// Physica D.-1983.-Vol.9.-P.189–208.
10. Glushkov A. V., Methods of a chaos theory.- Odessa: OSENU, 2012.
11. Glushkov A. V., Svinarenko A. A., Loboda A. V., Theory of neural networks on basis of photon echo and its program realization.-Odessa: TEC.- 2004.
12. Glushkov A. V., Loboda N. S., Khokhlov V. N., Using meteorological data for reconstruction of annual runoff series: Orthogonal functions approach// Atmospheric Research (Elsevier).-2005.-Vol.77.-P.100-113.
13. Glushkov A. V., Khokhlov V. N., Tsenenko I. A.: Atmospheric teleconnection patterns: wavelet analysis //Nonlinear Processes in Geophysics.-2004.-Vol.11(3).-P.285-293.
14. Khokhlov V. N., Glushkov A. V., Loboda N. S, Bunyakova Yu. Ya., Short-range forecast of atmospheric pollutants using non-linear prediction method// Atmospheric Environment (Elsevier).-2008.-Vol.42.-P.1213-1220.
15. Glushkov A. V., Kuzakon' V. M., Khetselius O. Yu., Prepelitsa G. P., Svinarenko A. A., Zaichko P. A.: Geometry of Chaos: Theoretical basis's of a consistent combined approach to treating chaotic dynamical systems and their parameters determination // Proceedings of International Geometry Center.-2013.-Vol.6(1).-P.43-48.
16. Khetselius O. Yu., Forecasting evolutionary dynamics of chaotic systems using advanced non-linear prediction method // Dynamical Systems - Theory and Applications.-2013.-Vol.1.-P. LIF142 (11p.).

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Abstract

Nonlinear modelling of chaotic processes in systems and devices, including quantum electronics and photo may be based on the concept of compact geometric attractors. We present a new approach to analyze and predict the nonlinear dynamics of chaotic systems based on the concept of geometric attractors, chaos theory methods and algorithms for neural network simulation. Using information on the phase space evolution of the physical process in time and simulation of neural network modelling techniques can be considered as one of the fundamentally new approaches in the construction of global nonlinear models of the most effective and accurate description of the structure of the corresponding attractor.

Key words: electronics systems, chaotic processes, the geometric attractor neural network approach

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НОВЫЙ ПОДХОД К ИЗУЧЕНИЮ ХАОТИЧЕСКИХ ПРОЦЕССОВ В СИСТЕМАХ ФОТОЭЛЕКТРОНИКИ НА ОСНОВЕ КОНЦЕПЦИИ ГЕОМЕТРИЧЕСКИХ АТТРАКТОРОВ И НЕЙРОННО-СЕТЕВОГО МОДЕЛИРОВАНИЯ

Резюме

Нелинейное моделирование хаотических процессов в системах и устройствах, в частности, квантовой- и фотоэлектроники, может быть основано на концепции компактных геометрических аттракторов. Мы представляем новый подход к анализу и прогнозированию нелинейной динамики хаотических систем, основанный на концепции геометрических аттракторов, методах теории хаоса и алгоритмах нейросетевого моделирования. Использование информации о фазовом пространстве эволюции физического процесса во времени и ее имитация методами нейросетевого моделирования может рассматриваться в качестве одной из принципиально новых идей при построении глобальной нелинейной модели наиболее эффективного и точного описания структуры соответствующего аттрактора физического процесса.

Ключевые слова: системы электроники, хаотические процессы, геометрический аттрактор, нейросетевой подход

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НОВИЙ ПІДХІД ДО ВИВЧЕННЯ ХАОТИЧНИХ ПРОЦЕСІВ В СИСТЕМАХ ФОТО-ЕЛЕКТРОНІКИ НА ОСНОВІ КОНЦЕПЦІЇ ГЕОМЕТРИЧНИХ АТРАКТОРІВ І НЕЙРОННО- МЕРЕЖЕВОГО МОДЕЛЮВАННЯ

Резюме

Нелінійне моделювання хаотичних процесів в системах та приладах, зокрема, квантової- та фото електроніки, може бути засновано на концепції компактних геометричних атракторів. Ми представляємо новий підхід до аналізу та прогнозування нелінійної динаміки хаотичних систем, заснованих на концепції геометричних атракторів, методах теорії хаосу та алгоритмах нейромережевого моделювання. Використання інформації про фазовий простір еволюції фізичного процесу у часі та її імітація методами нейромережевого моделювання може розглядатися в якості однієї з принципово нових ідей при побудові глобальної нелінійної моделі найбільш ефективного та точного опису структури відповідного аттрактора.

Ключові слова: системи електроніки, хаотичні процеси, геометричний атрактор, нейромережевий підхід