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A Maple package for improved global mapping forecast☆

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ABSTRACT

We present a Maple implementation of the well known global approach to time series analysis and some further developments designed to improve the computational efficiency of the forecasting capabilities of the approach. This global approach can be summarized as being a reconstruction of the phase space, based on a time ordered series of data obtained from the system. After that, using the reconstructed vectors, a portion of this space is used to produce a mapping, a polynomial fitting, through a minimization procedure, that represents the system and can be employed to forecast further entries for the series. In the present implementation, we introduce a set of commands, tools, in order to perform all these tasks. For example, the command **VecTS** deals mainly with the reconstruction of the vector in the phase space. The command **GfiTS** deals with producing the minimization and the fitting. **ForecasTS** uses all these and produces the prediction of the next entries. For the non-standard algorithms, we here present two commands: **IforecasTS** and **NiforecasTS** that, respectively deal with the one-step and the N-step forecasting. Finally, we introduce two further tools to aid the forecasting. The commands **GfiTS** and **AnalysTS**, basically, perform an analysis of the behavior of each portion of a series regarding the settings used on the commands just mentioned above.

Program summary

Program title: TimeS

Catalogue identifier: AERW_v1_0

Program summary URL: http://cpc.cs.qub.ac.uk/summaries/AERW_v1_0.html

Program obtainable from: CPC Program Library, Queen's University, Belfast, N. Ireland

Licensing provisions: Standard CPC licence, http://cpc.cs.qub.ac.uk/licence/licence.html

No. of lines in distributed program, including test data, etc.: 3001

No. of bytes in distributed program, including test data, etc.: 95018

Distribution format: tar.gz

Programming language: Maple 14.

Computer: Any capable of running Maple

Operating system: Any capable of running Maple. Tested on Windows ME, Windows XP, Windows 7.

RAM: 128 MB

Classification: 4.3, 4.9, 5

Nature of problem:
Time series analysis and improving forecast capability.

Solution method:
The method of solution is partially based on a result published in [1].

Restrictions:
If the time series that is being analyzed presents a great amount of noise or if the dynamical system behind the time series is of high dimensionality (Dim $\gg$ 3), then the method may not work well.

☆ This paper and its associated computer program are available via the Computer Physics Communication homepage on ScienceDirect (http://www.sciencedirect.com/science/journal/00104655).

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Unusual features:
Our implementation can, in the cases where the dynamics behind the time series is given by a system of low dimensionality, greatly improve the forecast.

Running time:
This depends strongly on the command that is being used.

References:
[1] Barbosa, L.M.C.R., Duarte, L.G.S., Linhares, C.A. and da Mota, L.A.C.P., Improving the global fitting method on nonlinear time series analysis, Phys. Rev. E 74, 026702 (2006).

1. Introduction

For any observed system, physical or otherwise, one generally wishes to make predictions on its future evolution. Sometimes, very little is known about the system. Possibly, the dynamics behind the phenomenon being studied is unknown, and one is given just a time series of one (or a few) of its parameters. Therefore, performing a time-series analysis is the best one can do in order to learn the properties of the phenomenon. Its relevance may be gauged by the existence of extensive studies in a great diversity of branches of knowledge, in physics as well as in economics and the stock exchange, meteorology, oceanography, medicine, etc.

A time series is normally taken as a set of numbers that are the possible outcomes of measurements of a given quantity, taken at regular intervals. In reality, however, the assumption that the time series reflects in some way the underlying dynamics of the systems is worsened by the fact that the measured data usually contain irregularities. These may be due to a random external influence on a linear system, a noise (induced possibly by the measuring apparatus or other sources of contamination) which gets mixed with the desired information, thereby hiding it. But it may well be that they appear as a manifestation of low-dimensional deterministic chaos resulting from an intrinsic nonlinear dynamics governing the quantity under study (over which a random noise may also be superimposed), with the characteristic sensitivity to initial conditions.

If the time series is the only source of information on the system, prediction of the future values of the series requires a modeling of the system's (perhaps nonlinear) dynamical law through a set of differential equations or through discrete maps. However, it is even possible that we do not know whether the measured quantity is the only relevant degree of freedom (frequently it is not) of the dynamical problem, nor how many of them there are.

Both noise-contaminated linear and nonlinear systems have nevertheless been studied, with a reasonable degree of success, employing statistical tools, chaos-theory concepts, together with time-series analyses [1–4]. Given a time series, one should ask first whether it represents a causal process or whether it is stochastic. Tools have been developed to decide upon this fundamental question (see [5,6]). In the case of a series originated from a low-dimensionality chaotic dynamics, traditional linear methods of analysis are not adequate, but an analysis apparatus was devised for applications to such nonlinear systems [5,6] and we will not be concerned with stochastic processes in this paper.

Methods for dealing with nonlinear time series fall mainly into two categories: local or global methods. Local methods are based on the assumption that, while in the long run nearby trajectories on the phase space diverge considerably, they stay within the same neighborhood for a while. One may conjecture that to predict the next step in a time series, a good indication should come from the previous visits the system had made to the phase space neighborhood containing the "last point" of the series. An average of the behavior of the system for neighboring points, with a minimization of the distance in the phase space between them, gives good results for the next-step forecasting.

Global methods, on the other hand, postulate a functional form for the dynamics to be valid for any time. Usually one considers polynomials of a suitable degree and one should devise a convenient way to estimate its coefficients.

Nonlinear analysis of time series does not rely on the original maps of the system, but on its *time-delay reconstruction*. All discussions on the nonlinear treatment of time series make use of this reconstruction scheme. Some classic references dealing with the subject are [1,7]. This method allows one to reconstruct the phase space of the system with reasonable accuracy, using the information contained in the series only.

Lorenz [8] has shown that dynamical systems of low dimensionality could present strange attractors in their phase spaces. Takens [9] has proposed a method to reconstruct such phase spaces from the knowledge of a time series obtained from the system. He demonstrated that the original attractor and the reconstructed one are characterized by the same asymptotic properties and topological characteristics [10,11]. Based on this result, if one is given a time series, we have to reconstruct the attractor in the phase space of the system in order to analyze its properties.

This paper certainly does not intend to cover, in any sense, the complete analysis which would be needed for an experimentally obtained nonlinear time series. Before beginning the reconstruction proper, a real-life time series should be cleaned from any random noise and regularized if the measurements were taken at uneven times; also, one should estimate the adjustable parameters the method introduces: the dimension of the delay coordinate space and the delay time. Our intention here is to concentrate only on the forecasting algorithm, for which we have developed a program for the Maple user. Therefore, we first test it not on a "real" time series, but on a mathematically defined one, namely, the series provided by the well-known Lorenz system. In this way, we avoid having to deal with noise and we know already the dimension of the vector space (it is the number of degrees of freedom of the system). Besides, as we know the dynamical law behind the time series, we may check the results of our predictions by comparing them with the sequence generated by the law itself and estimate how much the predictions (for one, two, or more steps in the future) deviate from the sequence. However, we also apply the algorithm to time series obtained from actual measurements, on which an elimination of the noise was performed, although we will not describe this point here.

Forecasting obtained with the algorithm proposed in this paper is compared with results from both the local and global methods computed in the traditional way. We achieve, for the mathematical series we have studied so far, an impressive error reduction with our method.