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# Identification Method for Evolution of Time Series with Poor Information Using Grey System Theory

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**Abstract**

Based on the grey system theory, a new method is presented to identify evolution of time series with poor information. Via definition of the original state sequence and the evolution state sequence, the information element function along with the grey confidence level is introduced into the criterion for identification of the stability of time series. The simulation test of initial worn stages of a mechanical device shows that without any prior information of trends and functions, the method can effectively recognize and evaluate the state of evolution of time series. It follows that corresponding measures in a timely manner can be taken and serious accidents can be avoided.

**Keywords:** time series, evolution, stability, identification, grey system theory, poor information

## 1. Introduction

Process identification of time series is used widely in many fields, such as, natural world, environment, society, economy, national defense, industry, agriculture, geology, public health, and information (Eleni, 2008; Paulin, 2005; Li, 2012). Timely and scientifically recognizing the stability of evolution of events with characteristics of time series can contribute to effective precautions of serious accidents by taking appropriate measures, producing tremendous economic and social profits.

There are many methods to study time series at present (Eleni, 2008; Paulin & Connely, 2005; Li & Hu, 2012; Sheng, Zhao, Liu, & Wang, 2012; Castro & Azevedo, 2012; Chen, Hong, & Tseng, 2012; Çoban, Büyüklü, & Das, 2012; Ailliot & Monbet, 2012; Khvorostovsky, 2012; Das & Maitra, 2012). The models structured by available findings manly include wavelet neural network and catastrophe theory model, self-organization theory model, regression model, autoregressive regression model, piecewise linearization model, adaptive segmentation linearization model, predicted network model, interval number model, empirical mode decomposition and phase space reconstruction model, and similarity model. With the help of information that time series present, these models are effective under the condition of known trends and functions, such as, potential functions, wavelet basis functions, kernel functions, probability distribution functions, and piecewise linear functions.

With the rapid development of economy and science, information that time series displays is characterized by diversity and complexity and the feature of some information is unknown in advance. For example, trends and functions of many events have uncertainty, diversity, mutability, and nonmonotonicity (Eleni, 2008; Paulin et al., 2005; Sheng et al., 2012; Coban et al., 2012). The problem studied, in fact, belongs to the category of the information-poor system (Deng, 1989, 2002; Xia, Chen, Zhang, & Yang, 2007; Xia & Li, 2011; Xia & Chen, 2011a). Poor information means incomplete information, such as, in system analysis, unknown trends and functions. This generates that statistical methods for time series analysis are faced with the flinty challenge. For this reason, the paper proposes a new method for identification of the stability of evolution of time series with poor information by means of the grey system theory (Deng, 1989, 2002; Xia et al., 2007, 2011, 2011a). The simulation test of initial worn stages of a mechanical device is conducted to verify effectiveness of the method proposed in the paper.

## 2. Introduction to Grey System Theory

In 1989, Prof. Deng Julong proposed the grey system theory (Deng, 1989) to research mainly the uncertainty systems with poor information. The systems can be divided into three types: the black system, the white system,

and the grey system. The black system is not perceived one, the white system is perceived one, and the grey system is a partly perceived and unascertained system between the black and white systems (Xia, 2012).

The grey relational grade as a very important concept in the grey system theory is widely used in many fields of science and technology (Xia et al., 2007, 2011, 2011a; Jiang & He, 2012; Wen, You, & Lee, 2010; Sridhar, Narasimha Murthy, Pattar, Vishnu Mahesh, & Krishna, 2012; Palanikumar, Latha, Senthilkumar, & Davim, 2012). For example, it can be employed to evaluate the difference of the attributes of systems acoording to the geometry shape of data series outputted by these systems. The bigger the value the grey relational grade takes, the smaller the difference of the attributes of systems; or else, the bigger the difference.

Assume $t$ stands for time and $X_i$ for the $i$th curve where $i$=1, 2, 3 is the sequence number. Figure 1 shows three time series expressed as the curves $X_1$, $X_2$, and $X_3$, respectively. According to the grey system theory, the grey relational grade of $X_2$ to $X_1$ is greater than that of $X_3$ to $X_1$ because the geometry shape of $X_2$ and $X_1$ is more similar than that of $X_3$ and $X_1$. This means that the difference between the attributes of $X_1$ and $X_2$ is smaller than that between the attributes of $X_1$ and $X_3$. Based on this, evolution of time series can be evaluates.

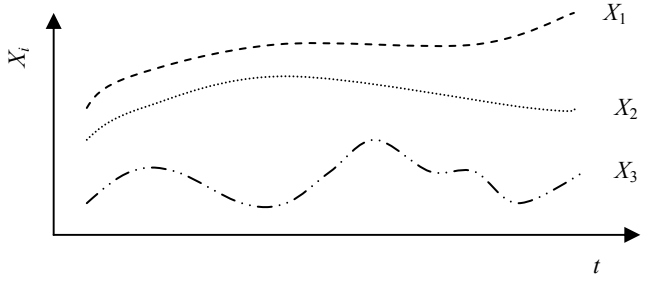


Figure 1. Similarity of curves

### 3. Information Element Function Along with Grey Confidence Level

In the process of evolution of an event studied, $n$ data are collected and then the time series $X$ can be obtained as

$$X = (x(1), x(2), ..., x(i), ..., x(n)) \tag{1}$$

where $x(i)$ is the $i$th datum in $X$ and $n$ is the number of the data in $X$.

The time series $X$ is divided into $m$ subseries, which are given by

$$X_w = (x_w(1), x_w(2), ..., x_w(k), ..., x_w(K)); w = 0,1,2,..., m-1; k = 1,2,..., K; K = n/m \tag{2}$$

where $x_w(k)$ is the kth datum in $X_w$ and $K$ is the number of the data in $X_w$.

In equation (2), the first subseries is defined as the original state sequence $X_0$ and the others are defined as the evolution state sequence. The original state sequence $X_0$ is given by

$$X_0 = (x_0(1), x_0(2), ..., x_0(k), ..., x_0(K)) \tag{3}$$

and the evolution state sequence $X_j$ is given by

$$X_j = (x_j(1), x_j(2), ..., x_j(k), ..., x_j(K)); j = 1,2,..., m-1 \tag{4}$$

The reference sequence $X_C$ is defined as

$$X_C = (x_C(1), x_C(2), ...x_C(k), ..., x_C(K)) = (x_0(1), x_0(1), ..., x_0(1), ..., x_0(1)) \tag{5}$$

According to the grey system theory (Deng, 1989, 2002; Xia et al., 2007, 2011, 2011a), the grey relational grade of the original state sequence $X_0$ to the reference sequence $X_C$ is given by

$$\gamma_{0C}(\xi) = \frac{1}{K}\sum_{k=1}^{K}\frac{\min\limits_{k}|x_C(k)-x_0(k)| + \xi \max\limits_{k}|x_C(k)-x_0(k)|}{|x_C(k)-x_0(k)| + \xi \max\limits_{k}|x_C(k)-x_0(k)|} \tag{6}$$

and the grey relational grade of the evolution state sequence $X_j$ to the reference sequence $X_C$ is given by

$$\gamma_{jC}(\xi)=\frac{1}{K}\sum_{k=1}^{K}\frac{\min\limits_{k}|x_C(k)-x_j(k)|+\xi\max\limits_{k}|x_C(k)-x_j(k)|}{|x_C(k)-x_j(k)|+\xi\max\limits_{k}|x_C(k)-x_j(k)|} \tag{7}$$

According to the grey system theory (Xia et al., 2007, 2011, 2011a), the information element function is defined as

$$r_{0j}=\begin{cases}1-\dfrac{1}{\eta}\max\limits_{\xi\to\xi^*}|\gamma_{0C}(\xi)-\gamma_{jC}(\xi)|; \max\limits_{\xi\to\xi^*}|\gamma_{0C}(\xi)-\gamma_{jC}(\xi)|\in[0,\eta] \\ 0 \qquad\qquad\qquad\qquad\qquad\quad ; \max\limits_{\xi\to\xi^*}|\gamma_{0C}(\xi)-\gamma_{jC}(\xi)|\in[\eta,1]\end{cases} \tag{8}$$

where $r_{0j}$ stands for the information element function of evolution of the time series, $\eta$ for the weight, $\xi$ for the distinguishing coefficient, and $\xi^*$ for the optimal distinguishing coefficient.

According to the grey system theory (Xia et al., 2007, 2011, 2011a), the grey confidence level is given by

$$P_{0j}=(1-0.5\eta)\times 100\% \tag{9}$$

where $P_{0j}$ is the grey confidence level.

Equation (8) is called the information element function along with the grey confidence level (viz., equation (9)), which can be used for identifying the stability of the time series.

## 4. Criterion for Identifying Stability of Time Series

Letting the information element function $r_{0j}$=0.5, the criterion of the stability of time series is defined and shown in Table 1 by means of the least information principle (Deng, 2002) in the grey system theory and the little probability event principle (Xia et al, 2007) in the statistical theory and the information-poor theory.

Table 1. Criterion for identification of stability of time series

| Code of grade | Condition of grey confidence level | Grade and stability of time series | Possibility of potential safety problem |
|---|---|---|---|
| G1 | $P_{0j}\in[99\%,100\%]$ | Grade 1 and best stability | Smallest |
| G2 | $P_{0j}\in[95\%,99\%)$ | Grade 2 and better stability | Smaller |
| G3 | $P_{0j}\in[90\%,95\%)$ | Grade 3 and good stability | Small |
| G4 | $P_{0j}\in[85\%,90\%)$ | Grade 4 and bad stability | Large |
| G5 | $P_{0j}\in[75\%,85\%)$ | Grade 5 and worse stability | Larger |
| G6 | $P_{0j}\in[0\%,75\%)$ | Grade 6 and worst stability | Largest |

## 5. Simulation Test

This is a simulative case of time series. In the process of monitoring of running state of a simulated mechanical device, an operating parameter is taken into account with the help of simulation of a time series that is in motion from initial worn stages to normal worn stages. Suppose the theoretical value of the operating parameter is zero.

The data of the operating parameter are collected seven times, one time every five days, and 400 data are obtained one time, thus the time series $X$ of size $n$=2800 is formed in the simulation test, as shown in Figure 2.

Let $K$=400 and $m$=7, then seven subseries are structured. In Figure 1, the first interval of values the abscissa $k$ takes, viz., [1,400], corresponds to the original state sequence $X_0$ and the other intervals of values the abscissa $k$ takes, viz., [401,800], [801,1200], [1201,1600], [1601,2000], [2001,2400], and [2401,2800], correspond to the evolution state sequences $X_1$, $X_2$,…, $X_5$, and $X_6$, respectively.

Let the information element function $r_{0j}$=0.5, then the grey confidence level $P_{0j}$ can be calculated from equations (8) and (9) and the process of evolution of the operating parameter of the mechanical device can therefore be distinguished. The results are presented in Table 2.

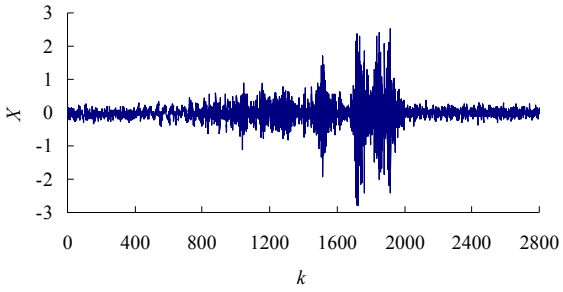


Figure 2. Time series of operating parameter of simulated mechanical device

It can be seen from Table 2 that the running state of the mechanical device is very stable for the evolution state sequences $X_1$, $X_2$, $X_3$, $X_5$, and $X_6$, because the grey confidence level $P_{0j}$ takes values in the range from 94.05% to 96.77%, which result from the stationary initial worn stage and normal worn stage; and the running state of the mechanical device is unstable for the evolution state sequences $X_4$, because the grey confidence level $P_{0j}$ takes value 89.65%, which results from the nonstationary initial worn stage.

Table 2. Identification result of running state of simulated mechanical device

| Evolution state sequence, $X_j$ | Grey confidence level, $P_{0j}$ | Grade | Stability | Running state of simulated mechanical device |
|---|---|---|---|---|
| $X_1$ | 95.96 | G2 | Better | Start of initial worn |
| $X_2$ | 94.05 | G3 | Good | Fluctuation of initial worn |
| $X_3$ | 96.77 | G2 | Better | Progress of initial worn |
| $X_4$ | 89.65 | G4 | Bad | Acme of initial worn |
| $X_5$ | 95.98 | G2 | Better | End of initial worn |
| $X_6$ | 96.65 | G2 | Better | Start of normal worn |

As a result, without any prior information of trends and functions, the method proposed in the paper can effectively recognize and evaluate the state of evolution of time series. Therefore, the method is a new method for time series analysis and can be considered as one of complements for the existing time series theory in use.

## 6. Conclusions

The identification method for evolution of time series with poor information is proposed by means of the grey system theory. Without any prior information of trends and functions, the method can effectively recognize and evaluate the state of evolution of time series, so that corresponding measures in a timely manner can be taken and serious accidents can be avoided.

The method is a new method for time series analysis and can be considered as one of complements for the existing time series theory in use.

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