Neurocomputing 129 (2014) 168–174

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Online ship roll motion prediction based on grey sequential extreme learning machine

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ARTICLE INFO

Article history:
Received 2 July 2013
Received in revised form
5 September 2013
Accepted 7 September 2013
Communicated by G.-B. Huang
Available online 23 October 2013

Keywords:
Extreme learning machine
Grey prediction
Grey relational analysis
Sequential learning
Radial basis function network
Ship roll prediction

ABSTRACT

For the online prediction of nonlinear systems with characteristics of time-varying dynamics and uncertainty, a sequential grey prediction approach is proposed based on the online sequential extreme learning machine (OS-ELM). The grey processing of time series alleviates the unfavorable effects of uncertainty in measurement data; the extremely fast learning speed and high generalization accuracy of OS-ELM enable online application of the sequential grey prediction approach. Ship's roll motion at sea is a complex nonlinear process with time-varying dynamics. Its dynamics also involves uncertainty caused by wind, random waves and rudder actions. In this paper, the proposed OS-ELM-based grey prediction approach is implemented for online ship roll prediction. The simulation of prediction is based on measurement data obtained from sea trials of the scientific research and training ship *Yu Kun*. Simulation results of ship roll prediction demonstrate the effectiveness and efficiency of the proposed grey neural prediction approach in dealing with time-varying nonlinear system with uncertainty.

1. Introduction

Neural network theories show that single hidden layer feedforward networks (SLFNs) with additive or radial basis function (RBF) hidden nodes can work as universal approximators when all parameters of networks are allowed adjustable [1]. However, the tuning of network parameters is usually time-consuming as it may involve many iterations. Unlike conventional neural network theories, Huang et al. proposed a new theory to show that SLFNs with randomly generated additive or RBF hidden nodes can work as universal approximators [2,3]. Huang et al. further proposed a new learning algorithm for the feedforward neural network referred to as extreme learning machine (ELM). In ELM, parameters of hidden nodes are randomly selected and the output weights are analytically determined. ELM has been shown to generate good generalization performance at extremely high learning speed in dealing with benchmark problems [2,4–6] as well as in real-world applications [7–10]. Based on ELM, Liang et al. proposed online sequential ELM (OS-ELM), improved ELM from batch learning to sequential learning. OS-ELM is able to handle data which arrives sequentially or chunk-by-chunk with varying chunk size [11]. Simulation results indicate that OS-ELM produces better generalization performance with faster processing speed, compared with other sequential learning algorithms such as resource allocation network (RAN) [12] and its extensions [13–17].

Grey system theory is a generic theory in processing system whose information involves uncertain or incomplete meanings [18]. Nowadays, it has been improved by combining with intelligent computational techniques such as genetic algorithms [19,20], fuzzy systems [22,21] and neural networks. In implementing conventional grey prediction (GP) method, prediction result is achieved by solving differential equation with linear least square (LS) method. However, system dynamics underlying practical time series is usually nonlinear in its nature. As neural network has been proved to be an efficient intelligent computation technique in representing complex nonlinear mappings, the combination of grey prediction and neural network technique can better represent system dynamics characterized by uncertainty and nonlinearity. In recent years, many contributions concentrate on introducing the neural network techniques in implementing grey system [23,24]. In this study, OS-ELM is online applied for prediction within a grey prediction framework, and the RBFs are selected as hidden nodes. The coherent nonlinear nature of RBFN enables the nonlinear

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http://dx.doi.org/10.1016/j.neucom.2013.09.043

representing capability; the local response characteristic enables its fast convergence speed [25,26].

Furthermore, system dynamics is hard to be represented by static neural network as their dynamics is usually time-varying under practical circumstances. Therefore, there is a practical need to build a kind of dynamic model which can capture and represent the time-varying dynamics [11,27,28]. In this study, we implement the OS-ELM to capture and represent the time-varying dynamics underlying grey time series.

Online prediction of ship roll motion is an important issue concerning marine safety and navigational economics; it is also vital for the landing and taking off of air vehicles on ship's deck. However, it is hard to establish mathematical model of ship's rolling movement at sea because of its underlying natures such as nonlinearity and time-varying dynamics. Its movement dynamics also inevitably involves uncertainty caused by rudder actions and environmental disturbances such as random waves, wind, and current [29]. To better represent the nonlinearity in ship motion, neural networks have been implemented in ship roll motion prediction [30] and ship roll stabilization control [31]. In this study, we employ online ship roll motion prediction as our case study to validate the reliability and accuracy of the proposed OS-ELM-based grey predictive model, the results are compared with those achieved by conventional prediction methods.

This paper is organized as follows. Sections 2 and 3 give brief reviews of the online sequential extreme learning machine (OS-ELM) and grey system theory, respectively. The structure and principle of the OS-ELM-based grey prediction system are presented in Section 4. Further, experimental results and discussions to support the proposed prediction method can be seen in Section 5. Conclusions are derived in Section 6.

2. Online sequential extreme learning machine (OS-ELM)

The main idea of ELM is that for N arbitrary distinct samples $(\mathbf{x}_k, t_k)$, in order to obtain arbitrarily small non-zero training error, one may randomly generate $\tilde{N}(\leq N)$ hidden nodes (with random parameters). The connecting weights $\boldsymbol{\omega}$ are estimated by

$$\hat{\boldsymbol{\omega}} = \mathbf{H}^{\dagger}\mathbf{T} = (\mathbf{H}^{\mathrm{T}}\mathbf{H})^{-1}\mathbf{H}^{\mathrm{T}}\mathbf{T}, \tag{1}$$

where $\mathbf{H}^{\dagger}$ is the Moore–Penrose generalized inverse of the hidden layer response matrix $\mathbf{H}$. Calculation of the connecting weights is done in one single step here. This avoids lengthy training procedure to choose parameters (learning rate and learning epochs, etc.), thus enables its extreme processing speed. Universal approximation capability of ELM has been analyzed [2]. It is indicated that SLFNs with randomly generated additive or RBF nodes can universally approximate any continuous target function on any compact subspace of $\mathbf{R}^n$. Besides, in the implementation of ELM, the activation functions for additive nodes can be any bounded nonconstant piecewise continuous functions.

As training data may be presented one-by-one or chunk-by-chunk, the ELM is modified so as to make it suitable for online sequential computation [11]. Suppose a new chunk of data is given, it results in a problem of minimizing

$$\left\| \begin{bmatrix} \mathbf{H}_0 \\ \mathbf{H}_1 \end{bmatrix} \omega - \begin{bmatrix} \mathbf{T}_0 \\ \mathbf{T}_1 \end{bmatrix} \right\|. \tag{2}$$

When a new sample arrives or a chunk of samples arrive, the connecting weight ω becomes

$$\omega^{(1)} = \mathbf{K}_1^{-1} \begin{bmatrix} \mathbf{H}_0 \\ \mathbf{H}_1 \end{bmatrix}^{\mathrm{T}} \begin{bmatrix} \mathbf{T}_0 \\ \mathbf{T}_1 \end{bmatrix}, \tag{3}$$

where

$$\mathbf{K}_1 = \begin{bmatrix} \mathbf{H}_0 \\ \mathbf{H}_1 \end{bmatrix}^{\mathrm{T}} \begin{bmatrix} \mathbf{H}_0 \\ \mathbf{H}_1 \end{bmatrix} = \mathbf{K}_0 + \mathbf{H}_1^{\mathrm{T}}\mathbf{H}_1.$$

For the efficiency of sequential learning, it is reasonable to express $\omega^{(1)}$ as a function of $\omega^{(0)}$, $\mathbf{K}_1$, $\mathbf{H}_1$ and $\mathbf{T}_1$, which is independent of the original data set,

$$\begin{aligned} \begin{bmatrix} \mathbf{H}_0 \\ \mathbf{H}_1 \end{bmatrix}^{\mathrm{T}} \begin{bmatrix} \mathbf{T}_0 \\ \mathbf{T}_1 \end{bmatrix} &= \mathbf{H}_0^{\mathrm{T}}\mathbf{T}_0 + \mathbf{H}_1^{\mathrm{T}}\mathbf{T}_1 \\ &= \mathbf{K}_1\omega^{(0)} - \mathbf{H}_1^{\mathrm{T}}\mathbf{H}_1\omega^{(0)} + \mathbf{H}_1^{\mathrm{T}}\mathbf{T}_1 \end{aligned} \tag{4}$$

$\omega^{(1)}$ can be expressed as follows by combining (3) and (4):

$$\omega^{(1)} = \mathbf{K}_1^{-1} \begin{bmatrix} \mathbf{H}_0 \\ \mathbf{H}_1 \end{bmatrix}^{\mathrm{T}} \begin{bmatrix} \mathbf{T}_0 \\ \mathbf{T}_1 \end{bmatrix} = \omega^{(0)} + \mathbf{K}_1^{-1}\mathbf{H}_1^{\mathrm{T}}(\mathbf{T}_1 - \mathbf{H}_1\omega^{(0)}). \tag{5}$$

Iteratively, when the $(k+1)$th new chunk of data arrives, the recursive method is implemented for acquiring the updated solution. $\omega^{(k+1)}$ can be updated by

$$\omega^{(k+1)} = \omega^{(k)} + \mathbf{K}_{k+1}^{-1}\mathbf{K}_{k+1}^{\mathrm{T}}(\mathbf{T}_{k+1} - \mathbf{H}_{k+1}\omega^{(k)}) \tag{6}$$

with

$$\mathbf{K}_{k+1}^{-1} = \mathbf{K}_k^{-1} - \mathbf{K}_k^{-1}\mathbf{H}_{k+1}^{\mathrm{T}}(\mathrm{I} + \mathbf{H}_{k+1}\mathbf{K}_k^{-1}\mathbf{H}_{k+1}^{\mathrm{T}})^{-1} \times \mathbf{H}_{k+1}\mathbf{K}_k^{-1}. \tag{7}$$

3. Grey system

3.1. Grey relational analysis (GRA)

Grey relational analysis (GRA) and grey prediction (GP) are two basic mathematical operations in grey system theory [18]. The GRA is implemented for determining the relationship between two stochastic time series in grey system. The reference series and the comparison series are noted as x_0 and x_i $(i=1, \ldots, m)$, respectively, with m being the number of time series for comparison. The degree of grey relation between the series at a particular time step k is represented by the grey relational coefficient $r(x_0(k), x_i(k))$:

$$r(x_0(k), x_i(k)) = \frac{\min_i \min_k |x_0(k) - x_i(k)| + \xi \max_i \max_k |x_0(k) - x_i(k)|}{|x_0(k) - x_i(k)| + \xi \max_i \max_k |x_0(k) - x_i(k)|} \tag{8}$$

where $k = 1, 2, \ldots, n$, with n being the number of samples in time series, and ξ being a resolution scale coefficient whose value is usually assigned as 0.5.

The grey relational degree of each comparison time series x_i corresponding to the reference series x_0 at full time scale can be achieved by

$$r(x_0(k), x_i(k)) = \frac{1}{n}\sum_{k=1}^{n} r(x_0(k), x_i(k)), \quad i = 1, 2, \ldots, m. \tag{9}$$

The GRA approach is implemented to calculate the grey relational coefficient between comparison series x_i and reference series x_0, using (8) and (9). The series x_i would be in closer relation with x_0 than that x_j with x_0 if we have $r(x_0, x_i) > r(x_0, x_j)$.

3.2. Grey prediction (GP)

In conventional time series prediction approaches, a large amount of data is usually needed to derive a predicted value. Whereas, grey prediction (GP) model has been proved to be effective in processing incomplete information with limited number of elements. GP model can hold effective provided that the series is in a consecutive time order at equal intervals as well as the sample number is larger than four [32]. There are three