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Sequential learning radial basis function network for real-time tidal level predictions

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ABSTRACT

Real time tidal level prediction is essential for management of human activities in coastal and marine areas. However, prediction model with static structure cannot represent the variations caused by time-varying factors such as weather condition and river discharge. This paper presents the application of a sequential learning radial basis function (RBF) network for accurate real-time prediction of tidal level. The proposed prediction model employs a sliding data window as dynamical observer, and tunes the structure and parameters of RBF network to adapt to the dynamical changes of tide. The algorithm uses only short-period data as training data and generates predictions sequentially. Hourly tidal data measured at seven tidal stations on west coast of Canada are used to test the effectiveness of the sequential prediction model. Tidal level prediction performance shows that the proposed model can give accurate short-term prediction of tidal levels with very low computational cost.

1. Introduction

Prediction of tidal level is an important activity for design of costal constructions such as jetties and harbors. Real time tidal level prediction is also involved in various decision-making processes of ships or platforms in offshore areas. Precise tidal level prediction a few hours ahead is especially required in operation planning, such as making ship schedule of navigating through shallow waters. Under such a condition, decision regarding the water depth under keel or clearance under bridge can be taken based on the hourly prediction of tidal level. Therefore, the accurate real-time prediction of tides remains as a concern in coastal and ocean engineering.

Nowadays, the harmonic analysis is the most popular technique in the study on tide, in which the tide can be expressed as the superposition of several sinusoidal constituents determined by harmonic analysis. It is still the basis for long-term tidal prediction (Lee, 2004). However, there are some drawbacks of the harmonic analysis method in applications. Firstly, it requires a considerably long period of tidal level record (usually hourly data of 369 days) to determine necessary harmonic constituents, whereas long-term tidal level records may be not available due to the high cost of field data monitoring; Secondly, the model considers only the factors concerning astronomical effects and coastal topography like coastline shape and sea floor profile. It cannot represent the complex time-varying meteorological effects on tide which are produced by weather conditions like wind, atmospheric pressure, ice, rainfall, etc. In addition, other time-varying factors like river discharge also affect tidal level at estuary sites. Therefore, an adaptive model is needed, whose structure and parameters can adapt to the time-varying environmental changes.

The emerging artificial intelligence (AI) techniques have shown their power in computational efficiency, and have been widely applied in coastal and ocean engineering (Malekmohamadi et al., 2011). For example, genetic algorithm (Remya et al., 2012), Bayesian networks (Randon et al., 2008), support vector machines (Rajasekaran et al., 2008) and artificial neural network (ANN) (Lee, 2008) have been successfully applied in this field. ANN learns the knowledge from measured data directly, and stores the knowledge within computational neurons and connecting weights (Haykin, 1999). ANN has been proved to be capable of learning and representing complicated relationship from data, attributing to its natures such as inherent nonlinearity and parallel information processing mechanism. It has been implemented successfully in prediction of different type of tides (Lee and Jeng, 2002). To improve prediction accuracy, various information relating the tidal level are incorporated in the prediction model as inputs, e.g., previous tidal data (Rajasekaran et al., 2006), tidal data at regional stations (Huang et al., 2003), tidal constituents (Lee, 2004), astronomical position parameters (Chang and Lin, 2006), meteorological conditions

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(Liang et al., 2008) and unexpected residual fluctuation (Lee and Jeng, 2002). Sufficient information appears more important for tidal predictions under violent meteorological conditions (Tseng et al., 2007; Lee, 2006, 2008).

However, the structures of the commonly implemented neural networks (most of them are BP network) are static, while the dynamics of tide varies with the time due to environmental changes mentioned above. The static neural network cannot represent the changes of system dynamics. Furthermore, with the changes of tide dynamics, the network with static dimension will result in the unfavorable phenomenon of over-fitting or under-fitting, which would deteriorate the generalization capability of network.

Sequential learning algorithms are designed for neural network to identify systems with time-varying dynamics in real time (Platt, 1991). The algorithms online generate variable structure neural network, whose hidden neurons are added or pruned at each step upon sequential learning of the samples presented, and the parameters are tuned simultaneously (Liang et al., 2006; Yin et al., 2010). As tides tend to be affected by various environmental changes, the variable structure neural network is suitable to represent the tidal level changes.

It is worth noting that there are usually no sufficient coastal topographical data and accurate real-time meteorological record, hence there is a practical demand for a convenient tidal prediction strategy based on short-term data. The present study implements a sequential learning radial basis function (RBF) network to establish a tidal prediction model based on time series forecasting technique (Chang et al., 2009). The model employs a sliding data window as dynamic observer, online constructs variable structure RBF network by learning samples in the sliding window, and makes predictions simultaneously. The proposed neural prediction model is applied to real-time tidal level prediction at seven tidal stations along the west coast of Canada, to validate its feasibility and effectiveness.

2. Sequential learning algorithm for RBF network

Real-time construction of variable-structure neural network by sequential learning is a research focus in recent years (Suresh et al., 2010). Among various neural network types, RBF network is the prevailing network style in sequential learning, attributing to its merits such as local response nature, simple topology, fast convergence and no phenomenon of local minima. In order to express the time-varying dynamics of actual tide, a sequential learning algorithm is employed to construct variable-structure RBF network. In this study, the RBF network with single hidden layers is employed, and the Gaussian function is selected as the activation function of the hidden neurons.

In the present sequential learning scheme, samples are presented to the algorithm sequentially. The hidden neurons are adjusted by adding the latest received sample into the hidden layer directly and simultaneously pruning neurons which contribute less to the output. Once the neurons are determined, the connecting weight between the hidden layer and output layer is adjusted accordingly. The most important feature of the resulting network is that the number and locations of hidden neurons are adjusted at each learning step according to the learning of data in the sliding window, thus the variable structure network can capture the real-time changes in system dynamics.

In a sequential learning scheme, if algorithm learns only the latest received single sample at one step, the resulted network would be highly affected by the particular sample and may result in instability of network; while if there are too much samples to be learned at one step, the resulted network cannot reflect the real-time changes in system dynamics, and the computational burden will be increased. To make a compromise, a sliding data window is employed in the present study to represent the input–output mapping of prediction model, and the algorithm learns samples in the window (Yin et al., 2010, 2012). The window is a first-in-first-out (FIFO) sequence: when the newly received sample slides in the window, the foremost one will be removed simultaneously.

The sliding data window is described as:

$$W_{SD}=[(x_{t-N+1},y_{t-N+1}),\ldots,(x_t,y_t)] \tag{1}$$

where N denotes the width of the sliding window, x and y denote the input vector and output vector, respectively.

The current system dynamics is represented by the input matrix $X=[x_{t-N+1},\ldots,\ x_t]\in R^{n\times N}$ and the output matrix $Y=[y_{t-N+1},\ldots,\ y_t]^{T}\in R^{m\times N}$, with n and m being the dimensions of input and output, respectively.

The contribution of each hidden neuron is measured by an index referred to as normalized error reduction ratio (*nerr*) (Yin et al., 2010):

$$nerr_k=\frac{err_k}{\sum_{k=1}^{M}err_k} \tag{2}$$

where M is the number of currently existing hidden neurons, and err_k denotes error reduction ratio (*err*) (Chen et al., 1991) of the k-th neuron which is calculated according to:

$$err_k=\frac{(w_k^{T}y)}{(w_k^{T}w_k)(y^{T}y)} \tag{3}$$

where w_k is the k-th vector of the orthogonalized response matrix W of input matrix with regard to the hidden neurons matrix $C\in R^{n\times M}$, by calculating the Gaussian functions of the Euclidean distance between the input sliding window X and hidden neurons matrix C. In this study, the orthogonalization is performed by the Gram–Schmidt decomposition method: $\Phi=WA$, where A is an upper triangle matrix.

For multi-in multi-output (MIMO) process (Chen et al., 1992), the values of *err* are calculated by:

$$err_{k,i}=\frac{\sum_{i=1}^{m}(w_k^{T}y_i)^2}{(w_k^{T}w_k)\mathrm{trace}(Y^{T}Y)} \tag{4}$$

where i denotes the index of outputs.

As can be noticed the index of *nerr* is a generalized application of the concept of *err*. The generalization is performed to enable the direct implementation of the index, because the summation of the $nerr_k$ ($k=1, 2,\ldots, M$) is 1.

At each step, the *nerr* of each hidden neuron is calculated and the neurons with small *nerr* are selected in ascending order. The selection is terminated once the summation of *nerr* reaches the preset accuracy threshold ρ:

$$\sum_{j=1}^{p}nerr\geq\rho \tag{5}$$

where p is the number of selected hidden neurons which are considered to be contributing little to the output at the particular step. If certain neurons have been selected for l consecutive steps, they will be regarded as obsolete and pruned from network. After the hidden neurons are adjusted at each step, the connecting weights Θ of the network will be updated using the pseudo-inverse method:

$$\Theta=\Phi^{+}Y=(\Phi^{T}\Phi)^{-1}\Phi^{T}Y \tag{6}$$

Therefore, the structure and connecting parameters are determined by learning the data in the sliding window which is updated in real time. The resulted network can be consequently implemented for identification and prediction purposes. The algorithm is also featured by its small number of tuning