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A hybrid real-time tidal prediction mechanism based on harmonic method and variable structure neural network

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ABSTRACT

Accurate real time tidal prediction is essential for human activities in coastal and marine fields. Tidal changes are influenced not only by periodic revolutions of celestial bodies but also by time-varying meteorological factors. For accurate real-time tidal prediction, a hybrid prediction mechanism is constructed by taking both advantages of harmonic analysis and neural network. In the proposed mechanism, conventional harmonic analysis is employed for representing the influences of celestial factors; and neural network is used for representing the nonlinear influences of meteorological factors. Furthermore, to represent time-varying tidal dynamics influenced by meteorological factors, a variable neural network is real-time constructed with the neurons and the connecting parameters are adaptively adjusted based on a sliding data window (SDW). The hybrid prediction method uses only the latest short-period data to generate predictions sequentially. Hourly tidal data measured at four American tidal stations are used to validate the effectiveness of the hybrid sequential tidal prediction model. Simulation results of tidal prediction demonstrate that the proposed model can generate accurate short-term prediction of tidal levels at very low computational cost.

1. Introduction

Tidal prediction is an important issue in areas of coastal construction design, tidal energy utilization, ocean natural calamities prevention and military affairs (Fang et al., 1986). Accurate real-time tidal prediction is also vital for marine safety, such as stipulating ship operation schedule of navigating over shallow waters or through an overhead bridge. Harmonic analysis, where the tide is expressed as superposition of several sinusoidal constituents (Pugh, 1987), is the most commonly used tidal prediction method and still the basis for long-term tidal prediction (Lee, 2004). Apart from relative motion of celestial bodies and costal topography, tidal level is also influenced by meteorological factors such as atmospheric pressure, wind, rainfall, ice etc. However, the harmonic analysis is made for average meteorological conditions by neglecting the real-time hydro-meteorological effects. Variation in sea level is a complex outcome of many environmental forces, and the neglect of influences of meteorological factors may cause the prediction values diverge from the actual ones (Ghorbani et al., 2010). These differences can be very large under extreme weather conditions such as storm surges or strong winds. Furthermore, meteorological factors' influences on tide are complex and are hard to be accurately represented by strictly founded mathematical model, which presents challenges for accurate tidal prediction.

In recent years, artificial neural network (ANN) became increasingly popular in areas of prediction attributes to its merits such as nonlinearity, adaptivity, arbitrary approximation capability and parallel information processing mechanism (Haykin, 1999). As a kind of data-driven technique, neural network can represent complex nonlinear and non-periodic relationships based on the learning of data samples, which is superior to the harmonic method and suitable for tidal predictions.

A fundamental principle in data modeling is to incorporate useful a priori information regarding the underlying data generating mechanism into the modeling process (Benhammadi et al., 2011; Chen et al., 2011). The topology of neural prediction model is of great importance for the predictive efficiency (Günaydın, 2008). Inclusion of more useful information which makes contribution to the system mapping is helpful to improve the model's prediction accuracy. Therefore, a reliable prediction of the sea levels can be performed using more sophisticated models by incorporating relevant information. Various research works have been carried out to make best use of useful information. Rajasekaran et al. (2006) construct functional networks and sequential learning neural networks based on history tidal observations; Pashova and Popova (2011) utilized statistical parameters of tidal level for

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daily mean sea level prediction. Huang et al. (2003) proposed regional neural network for water level (RNN-WL) prediction method by taking use of tidal level data of stations distributed in regional scale; Lee (2004) employed tidal constituents for generating long-term predictions; Chang and Lin (2006) incorporated the factors related to tide-generating forces in the neural network; Lee and Jeng (2002) considered the residual fluctuation in the network's input layer for prediction purposes; Altunkaynak (2012) employed current wind speed and the previous significant wave height as inputs to give predictions of current significant wave height; Liang et al. (2008) incorporated wind information in the neural tidal prediction model, such as wind speed, wind direction, and day-averaged wind speed. Herman et al. (2007) utilized the principle components of tide, together with the wind components and historical tidal data, for predictions of tidal level and currents. Sufficient information is more crucial for predictions of abnormal tidal changes under violent meteorological conditions, such as strong winds and sudden changes in atmospheric pressure (Lee, 2008). Tseng et al. (2007) used typhoon's characteristics, local meteorological conditions and typhoon surges at a considered tidal station as inputs for typhoon surges forecast; Lee (2006, 2008) incorporated wind information and atmospheric pressure in the model for storm surge prediction.

All above-mentioned factors related to tide are time-varying and many of them (especially meteorological factors) vary rapidly with time. However, most of the neural networks employed for application are static with fixed structure and parameters, which cannot represent the fast variation of tide dynamics. Therefore, there is a practical need to establish a variable neural network whose structure and parameters can both be adaptively tuned in real-time to represent the time-varying changes of tide dynamics caused by meteorological factors. Furthermore, the theory of neural network also indicates that excessive learning usually leads to the phenomenon of over-fitting which will damage the generalization capability of network. The expansion of network dimension will also cause the "curse of dimension" and slower the computational speed consequently (Haykin, 1999). Therefore, there should be a mechanism to adjust the dimension of network.

In this paper, a hybrid model is established to for real-time tidal prediction. The harmonic analysis method is employed to give harmonic tidal level predictions; the residual influenced by meteorological factors is predicted by a variable neural network. The final prediction is the summation of prediction results of the two approaches. The efficiency of hybrid model is verified by tidal prediction simulations which are conducted based on the actual measurement of tidal stations at the port of Tampa and other three tidal stations in America.

2. Hybrid tidal prediction mechanism

2.1. Harmonic analysis method

The most conventionally used method for tidal level prediction is harmonic analysis. The principal long period cyclicities of tide are related to the astronomical factors like relative positions of the sun, moon, and earth. In harmonic analysis, the astronomical component is expressed as superposition of many sinusoidal constituents with amplitudes and frequencies determined by a local analysis of the measured tide waves. Thus, daily sea level $y(t)$ for certain time t can be represented by a time-dependent function:

$$y(t) = a_0 + \sum_{i=1}^{n} h_i \cos(w_i t - \phi_i) + r(t) \tag{1}$$

where a_0 is a long-term mean sea level; n is the number of constituents; h_i, ω_i, and ϕ_i are the amplitude, temporal frequency (speed) and phase offset of the ith constituent, respectively. The residual $r(t)$ is the unmodelled random fluctuations representing the effects of meteorological factors, random noises and other unmodelled effects.

2.2. Variable RBF neural network

As the metrological factors (such as atmospheric pressure P, wind force F, wind direction θ, water temperature T) vary fast with time, their influences should be represented by variable model whose structure and parameters can be both adjustable. As meteorological and other unmodelled factors' effects on tidal level, the residual term $r(t)$ in Eq. (1) can be expressed as the functions of such factors:

$$r(t) = f(P, F, \theta, T, r) + \varepsilon(t) \tag{2}$$

where $f(\cdot)$ is the mapping from meteorological factors to the residual, and $\varepsilon(t)$ is the noises. Static neural network with fixed structure cannot represent time-varying dynamics efficiently, so there is a practical need of variable network whose structure and parameters are both adjusted in real time.

Construction of variable-structure neural network by sequential learning is a research focus in recent years (Suresh et al., 2010). Sequential learning algorithm is a popular method for representing time-varying system dynamics by variable neural network (Platt, 1991; Liang et al., 2006). It processes samples sequentially, and tunes the network's structure and parameters adaptively. By adjusting the network dimension, it can also avoid the phenomenon of over-fitting and under-fitting, thus guarantee generalization capability as well as accelerate processing speed. Among various types of network, radial basis function network (RBFN) is the most conventionally used network in sequential learning attributing its merits such as locally response character, simple topology, fast convergence speed and no phenomenon of local minima (Haykin, 1999).

In this study, to represent the time-varying dynamics of tide caused by various meteorological factors, the $f(\cdot)$ is modeled by a variable neural network constructed by a kind of sequential learning algorithm, which is described as follows.

In the algorithm, the adjustment of network structure includes network growing and network pruning. In the growing process, the newest sample is added to a new hidden neuron directly; in the pruning process, each neuron's contribution is evaluated individually and neurons which consecutively contribute less to the output will be pruned from the network. Once the neurons are determined, the connecting weight between the hidden layer and output layer is adjusted accordingly.

In a sequential learning scheme, the samples are presented sequentially but, if algorithm only learns the latest received single sample at one step, the resulted network would rely too much on the particular sample and may result in instability of network; while if the algorithm processes all the received samples at one time, the resulted network could not reflect the current changes in system dynamics, and the computational burden would also be increased. To make a compromise, a sliding data window (SDW) is employed and algorithm learns samples in the window (Yin et al., 2012). The SDW is a first-in-first-out (FIFO) sequence:

$$W_{SD} = [(x_t, y_t), (x_{t-1}, y_{t-1}), \ldots, (x_{t-N+1}, y_{t-N+1})], \tag{3}$$

where N denotes the width of sliding window, x and y denote the input vector and output vector at the corresponding time (t, $t-1$, …,$t-N+1$), respectively. That is, the window is a combination of input matrix $X = [x_t, \ldots, x_{t-N+1}] \in R^{n \times N}$ and the output matrix $Y = [y_t, \ldots, y_{t-N+1}]^T \in R^{m \times N}$, with n and m being the dimensions of input and output, respectively. Therefore, the window is updated in real-time and can be employed to represent current dynamics