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Online prediction of ship roll motion based on a coarse and fine tuning fixed grid wavelet network

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ABSTRACT

A new coarse and fine tuning fixed grid wavelet network is proposed for online predicting ship roll motion in regular waves. This wavelet network is composed of discrete wavelet basis functions, whose structure and parameters are adjusted online based on a sliding data window. Coarse tuning refers to changing the structure of the wavelet network, and fine tuning refers to only changing the coefficients of the wavelet network. In every sliding data window, the Givens rotation method is first used to finely tune the wavelet network, then the orthogonal least squares algorithm and the error reduction ratio criterion will be used to coarsely tune the wavelet network if the fine tuning network does not satisfy the relevant conditions for model validation. This process guarantees that the method can establish not only the model of the weakly nonlinear motion but also the model of the strongly nonlinear motion. In this way, a concise prediction model of ship roll motion is obtained. This network exploits the attractive features of wavelet and the fitting capability of conventional neural network. The prediction results show that the modeling method is feasible, and it provides an effective tool for online predicting ship roll motion.

1. Introduction

Ship motion prediction is important for ship safety and efficient operation. However, ship motion at sea is a complex nonlinear and time-varying system, and it is very difficult to establish a precise mathematical model for ship motion due to the environmental disturbances such as wind, waves and current (Fossen, 2011). Of all the motion modes, the roll motion is the most crucial one since it is directly related to ship safety and operating performance. The prediction of ship roll motion is vital for the motion compensation which may prevent crash of cargo in cargo transfer, improve the landing safety of aircrafts on carrier and the fire accuracy of the ship-borne weapon systems (Khan et al., 2005, 2006).

A lot of researches on ship motion prediction have been carried out by using various methods. The classic methods using time series autoregression (AR) model, autoregressive moving average (ARMA) model and so on belong to linear analysis methods, which are not accurate enough for predicting the nonlinear ship motion. Kalman filtering method is another commonly used method; to use this method, however, the state equation of ship motion must be known, which limits its practical application in some cases. To represent the nonlinear and time-varying ship motion, neural networks have been used for the time series prediction of ship motion (Khan et al., 2004, 2005; Li et al., 2017a, 2017b). Neural network has been also implemented in ship roll stabilization control (Yin et al., 2014). Support vector machine (SVM) has also been used to identify the parameters of nonlinear ship roll motion (Hou and Zou, 2015, 2016). Neural network trained by singular value decomposition has been used for the real time prediction of ship motions (Khan et al., 2016). Theoretically, neural networks can approximate any nonlinear function with arbitrary accuracy (Kecman, 2001); for this reason, this intelligent technology is widely used in the modeling and prediction of ship motions (Lainiotis et al., 1993; Faller et al., 1997; Haddara and Xu, 1998; Haddara and Wang, 1999; Moreira and Guedes Soares, 2003; Zhang and Zou, 2013).

In this paper, a new coarse and fine tuning fixed grid wavelet network (CFT-FGWN) is proposed for online predicting ship roll motion based on a sliding data window. The idea of using wavelets in neural networks was first introduced by Zhang and Benveniste (1992). The wavelet network not only preserves most of the advantages of the conventional neural network, but also inherits the advantages of wavelet. Wavelets have the property of localization in both the time space and the frequency space. The wavelet network usually converges fast especially for modeling strongly nonlinear systems. Billings and Wei used fixed grid wavelet

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networks for nonlinear system identification in 2005 (Billings and Wei, 2005). This type of wavelet networks stems from the discrete wavelet transform, whose activation functions are some discrete wavelet functions. The other type of wavelet networks is adaptive wavelet networks, which stems from the continuous wavelet transform. Adaptive wavelet networks and wavelet decomposition have been used for short term ship motion prediction (Masi et al., 2012; Wang et al., 2012). In the fixed grid wavelet networks, the scale and translation parameters of the wavelet activation functions are determined in advance and only the outer weights are unknown. These unknown weights can be easily obtained by least squares approach. This is not the same as the conventional neural networks, which are usually trained by gradient type algorithms. Most of gradient type algorithms are sensitive to the initial conditions, and the trained network usually converges on local optimum. The fixed grid wavelet network can be viewed as a linear regression model, which avoids local optimum and converges quickly (Billings, 2013). There has been considerable interest in the implementation of wavelet networks (Cao et al., 1995; Chen et al., 2006; Wei and Billings, 2004, 2006; Wei et al., 2006). On the basis of the fixed grid wavelet network, this paper proposes a CFT-FGWN, whose structure and parameters are adjusted online as the sliding data window moves.

The modeling method based on wavelet network has the ability to represent the strongly nonlinear ship roll motion, and it is robust to noise and has high computational efficiency (Wei and Billings, 2004). The approximating method of wavelet basis functions outperforms many other fitting methods, which is shown to be asymptotically near optimal and attains excellent convergence rate (Billings, 2013). In the present study, the CFT-FGWN in conjunction with a sliding data window is used to establish the wavelet network model of ship roll motion in regular waves. First the library of wavelet candidate terms needs to be determined. This library contains a lot of discrete wavelet terms. Spectral analysis and prior knowledge are used to determine which wavelet terms should be included in this library. But the library is usually redundant; the redundant terms must be eliminated. The forward orthogonal least squares (OLS) algorithm and the error reduction ratio (ERR) criterion are efficient model term detection approaches (Chen et al., 1989, 1991). According to the ERR criterion, the most important term is selected first, and then the less important terms are added one by one until the constructed model could give a good description of the system. Therefore, the obtained model is usually concise. The simplest model of fitting the data is also the most plausible (Abu-Mostafa et al., 2012). But there is no need to find the important terms in every sliding data window. When the sliding data window moves to the next instant, the model in which only the parameters of the selected wavelet terms are adjusted may fit the data very well, which is called fine tuning. The coarse tuning is necessary to find important wavelet terms and compute the corresponding coefficients, whose computing cost is higher than the fine tuning. Initially, coarse tuning is used to obtain the wavelet network model of the system. When the sliding data window receives a new pair of data, Givens rotation method is firstly used to finely tune the wavelet network model (Ling, 1991; Luo and Billings, 1995a; Luo et al., 1996); then the coarse tuning will be implemented if the fine tuning wavelet network model does not meet the relevant conditions for model validation. As the sliding data window continues to move, the above screening process will be repeated. Because the modeling method adds a fine tuning process, and the fine tuning algorithm can establish a good dynamic model when the system changes slowly, the amount of computation will be reduced. If fine tuning is useless, coarse tuning will be triggered. Hence the online modeling method can not only change the structure of model, but also change the coefficients of model, which is different from many other online forecasting methods such as Kalman filtering method that can only modulate the coefficients. Through the above modeling process, the CFT-FGWN prediction model of ship roll motion can be obtained. The prediction results based on the simulation data and experimental data show that the CFT-FGWN modeling method is feasible.

2. A coarse and fine tuning fixed grid wavelet network

This section gives a brief introduction to the fixed grid wavelet networks, and describes how to construct a CFT-FGWN. In the following, the one dimensional function $f(x) \in L^2(R)$ is taken as an example, and two dimensional wavelets are used to illustrate the related concepts.

2.1. Wavelet networks

According to the wavelet theory, there are two schemes for decomposing a one dimensional function $f(x) \in L^2(R)$ (Zhang et al., 1995), namely:

$$f(x) = \sum_{j,k} \langle f, \psi_{j,k} \rangle \psi_{j,k}(x) \quad j, k \in Z \tag{1}$$

$$f(x) = \sum_{k} \langle f, \varphi_{j_0,k} \rangle \varphi_{j_0,\,k}(x) + \sum_{j \ge j_0,k} \langle f, \psi_{j,k} \rangle \psi_{j,k}(x) \quad j, k \in Z \tag{2}$$

where $\langle \cdot, \cdot \rangle$ represents the inner product in $L^2(R)$; j represents the resolution or scale parameter in the decomposition, and k represents the translation parameter, Z is the set of all integers; ψ and φ are the mother wavelet and father wavelet, respectively. j_0 is an arbitrary integer, representing the coarsest resolution. The above two expressions are the theoretical basis of constructing wavelet network.

In the actual function decomposition, the infinite decomposition of $f(x)$ is unnecessary and impossible. It is reasonable and feasible to represent a function using a finite decomposition of the expressions (1) or (2) at an appropriate accuracy. In the case of expression (1), a function $f(x) \in L^2(R)$ can be decomposed into the following form:

$$f(x) \approx \sum_{j=j_0}^{j_{\max}} \sum_{k \in K_j} \langle f, \psi_{j,k} \rangle \psi_{j,k}(x) \quad j, k \in Z \tag{3}$$

where $j_{\max}$ is the finest resolution, K_j $(j = j_0, j_0 + 1, \cdots, j_{max})$ are the subsets of Z, which are related to the resolution level j for all compactly supported wavelets and for most rapidly attenuating wavelets. Eq. (3) for the finite wavelet decompositions is the basis for constructing a fixed grid wavelet network, which is shown in Fig. 1. As with the conventional neural network, the wavelet function can be regarded as the activation function of neural network. Different types of wavelets can construct different wavelet network.

Although the above results are for the one-dimensional case, the relevant concept can be extended to high-dimensional case. One common approach is to treat a wavelet function as a radial basis function. For example, a d-dimensional Mexican hat wavelet $\psi^{[d]} : R^d \mapsto R$ can be constructed by

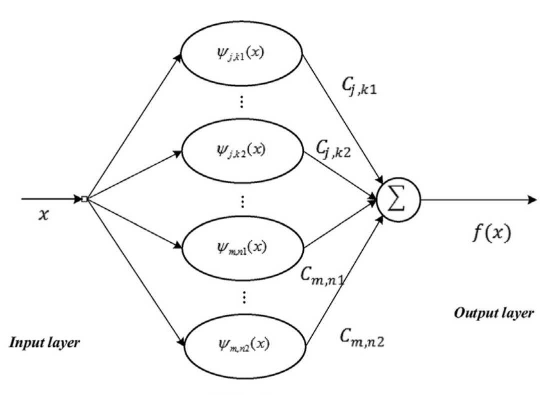

Fig. 1. The architecture of the fixed grid wavelet network.