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SVR-based identification of nonlinear roll motion equation for FPSOs in regular waves

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ABSTRACT

A novel system identification method, Support Vector Regression (SVR), is proposed for identifying the nonlinear roll motion equation of a FPSO vessel in regular waves. Firstly, the roll motion of a vessel is simulated, and the simulated data are used to identify the parameters in the roll motion equation. Then the roll motion is predicted by using the identified parameters, and the prediction results are compared with the simulated data to verify the identification method. Secondly, model test data of a FPSO vessel are used to identify the parameters in the roll motion equation. The roll motion is predicted by using the identified parameters and compared with the model test data. In addition, by using the model test data, the time histories of the nonlinear damping and restoring moments in the non-parametric roll motion equation are identified and the identified results are used to predict roll motion. Comparison of the prediction results with the model test data shows the validity of the identification method in identifying the non-parametric roll motion equation. It is shown that the SVR-based identification method can be effectively applied to parametric and non-parametric identification of the nonlinear roll motion equation.

1. Introduction

An accurate prediction of the motion experienced by a vessel is crucial for the design as well as safe and efficient operations. Generally, the determination of the motion of a floating structure in six degrees of freedom can be accomplished by commercial software based on potential theory. However, because of the strong nonlinear nature of the roll damping, the correct prediction of the roll motion may be challenging. To predict the roll motion accurately, it is necessary to estimate the characteristics of the nonlinear roll damping correctly. Although the roll motion of ships and floating structures has been investigated by many researchers for a long time since William Froude in the 19th century, a universal method to predict the damping moment which is a function of motion parameters is still absent. Traditionally, there are three kinds of methods available for predicting the roll motion, i.e., model test (Faltinsen, 1990), semi-empirical method (Ikeda, 1978; Chakrabarti, 2001; Ikeda, 2004) and direct numerical calculation (Wanderley et al., 2007; Yang et al., 2013). During the last decade, system identification techniques, aiming at finding the best mathematical model that relates the output to the input of a system, have been used to analyze the roll motion of ships and floating structures.

System identification techniques include parametric identification and non-parametric identification. Parametric identification can be applied to estimate unknown parameters in the equation describing the roll motion of a vessel. Non-parametric identification can be applied to model the roll motion of a vessel by means of appropriate and sufficient input and output.

In the aspect of parametric identification, a number of methods have been proposed and applied to identify the unknown linear and nonlinear parameters in the roll motion equation. Based on a combination of the random decrement technique, a multiple linear regression algorithm and neural network technique, Mahfouz (2004) and Haddara (2006) identified the ship roll motion equation by using the measured stationary roll response. Unar (2007) applied MLP and RBF neural network to identify the roll damping coefficients of a ship. Xing and McCue (2009) applied artificial neural network (ANN) to identify the unknown hydrodynamic parameters of two nonlinear models for describing ship roll motion by using experimental data.

In the aspect of non-parametric identification, Jang et al. (2009) proposed a method based on inverse formulism to recover the functional form of the nonlinear roll damping and nonlinear restoring forces in nonlinear oscillation systems by using the measured transient data. Owing to the application of a regularization method in the identification process to overcome the numerical instability, the proposed method can be applied to analyze the contaminated data. On

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the basis of the proposed method, Jang et al. (2010a, 2010b) identified the functional form of the nonlinear roll damping for a particular ship using the measured experimental data, and Jang (2011, 2013, 2014) identified the nonlinear damping, nonlinear restoring forces and external harmonic excitation of nonlinear systems by using contaminated data. One of the main merits of the proposed method is that it can deal with contaminated data effectively, which is particularly advantageous, since the real data are usually contaminated. Besides, Xing and McCue (2010) applied ANN to model the roll motion of ships at sea. Han and Kinoshita (2012a) presented an application of a stochastic inverse non-parametric identification method for the nonlinear damping in the general mechanical system; Han and Kinoshita (2012b, 2012c) applied this method to identify the nonlinear roll damping moment of a ship at zero forward speed and non-zero forward speed, respectively.

Support Vector Machine (SVM), a new generation of machine learning method, was first proposed by Vapnik (1999) in 1990s. Due to its unique performance, SVM has been extensively applied in various branches of science and engineering. Compared with ANN, SVM has several merits and demerits. Firstly, SVM is based on the criteria of structural risk minimization, while ANN is based on the criteria of empirical risk minimization, so SVM can avoid the over-fitting problem of data and achieve better generalization performance than ANN, especially in the case of learning with small samples. Secondly, by taking advantage of convex quadratic programming, SVM can obtain the global optimal solution, while ANN is apt to fall into local optimization. Thirdly, SVM's solution is sparse and only depends on support vectors which consist of limited training samples. Fourthly, by introducing kernel function, SVM can easily avoid the curse of dimensionality, which is often encountered by ANN. Finally, owing to its worse on-line workability, SVM is suitable for off-line machine learning. According to its application, SVM can be divided into two categories: one is Support Vector Classifier (SVC) which is often used to solve classification problems, and the other is Support Vector Regression (SVR) which is used to solve regressive problems. As to the application of SVR in ship and ocean engineering, Luo and Zou (2009) used Least Square-SVR to identify the hydrodynamic coefficients in ship maneuvering motion equations. Zhang and Zou (2011, 2013) applied SVR to identify the Abkowitz model for ship maneuvering motion and the maneuvering hydrodynamic coefficients from captive model test results. Xu et al. (2012, 2013) applied SVR to identify the nonlinear coefficients in the dynamic model of underwater vehicles. In these studies, parameteric identification was dealt with and the validity of the identification method was verified.

In the present study, SVR with linear function as the kernel function is applied to identify the unknown parameters in the nonlinear roll motion equation of a FPSO vessel in regular waves. To improve the efficiency of SVR, Sequential Minimal Optimization (SMO) algorithm is applied to solve SVR. In order to validate the applicability of SVR in the parametric identification of the roll motion, case studies based on numerically simulated data and model test data are designed. After that, SVR with Gauss radial basis function as the kernel function is applied to identify the time histories of the nonlinear damping and restoring moment in the non-parametric roll motion equation by using model test data. Then the roll motion is predicted using the identified nonlinear damping and restoring moment, and the prediction results are compared with the model test data to demonstrate the validity of the identified non-parametric equation in the prediction of the roll motion.

2. Equation of roll motion

The roll motion of a vessel in regular waves can be described by a second-order nonlinear ordinary differential equation in the form (Bhattacharyya, 1978; Malta et al., 2010):

$$(I_{xx}+J_{xx})\ddot{\phi}+D\left(\dot{\phi}\right)+R(\phi)=M \tag{1}$$

where ϕ is the roll angle (rad); I_{xx} is the mass moment of inertia (kg m^2); J_{xx} is the added mass moment of inertia (kg m^2); $D\left(\dot{\phi}\right)$ is the damping moment (N m); $R(\phi)$ is the restoring moment (N m); and M is the wave exciting moment (N m).

The roll damping term $D\left(\dot{\phi}\right)$ can often be represented by a linear term plus a quadratic term in the form

$$D\left(\dot{\phi}\right)=D_1\dot{\phi}+D_2\dot{\phi}\left|\dot{\phi}\right| \tag{2}$$

where D_1 and D_2 are the linear and nonlinear damping coefficients, respectively. Assuming that the restoring force is linear, Eq. (1) can be rewritten as

$$(I_{xx}+J_{xx})\ddot{\phi}+D_1\dot{\phi}+D_2\dot{\phi}\left|\dot{\phi}\right|+C_0\phi=M \tag{3}$$

where C_0 is the linear restoring coefficient. Dividing Eq. (3) by the total moment of inertia $(I_{xx}+J_{xx})$, the following equation is obtained

$$\ddot{\phi}+p_1\dot{\phi}+p_2\dot{\phi}\left|\dot{\phi}\right|+c\phi=f \tag{4}$$

where $p_1=D_1/(I_{xx}+J_{xx})$; $p_2=D_2/(I_{xx}+J_{xx})$; $c=C_0/(I_{xx}+J_{xx})$ and $f=M/(I_{xx}+J_{xx})$. Considering that the incident waves are regular, the wave exciting moment per unit virtual mass moment of inertia f can be expressed as (Bhattacharyya, 1978)

$$\begin{aligned} f &= f_a \cos(\omega t+\theta) \\ &= f_r \cos \omega t + f_i \sin \omega t \end{aligned} \tag{5}$$

where f_a and θ are the amplitude and phase shift of f, respectively; $f_r=f_a \cos \theta$ and $f_i=-f_a \sin \theta$. Substituting Eq. (5) into Eq. (4), the parametric nonlinear roll motion equation can be rewritten as

$$\ddot{\phi}+p_1\dot{\phi}+p_2\dot{\phi}\left|\dot{\phi}\right|+c\phi=f_r \cos \omega t+f_i \sin \omega t \tag{6}$$

3. Support Vector Regression

SVR is applied in this paper to identify the roll motion equation of a FPSO vessel in regular waves. In the following, SVR is briefly introduced, and more details can be found in Smola and Schölkopf (2004).

The training data is given as

$$T=\left\{(x_i,y_i), i=1,2,\cdots,l\right\}\in\left(\mathfrak{R}^n\times\mathfrak{R}\right)^l \tag{7}$$

where $x_i\in\mathfrak{R}^n$ is the ith n-dimension training input vector and $y_i\in\mathfrak{R}$ is the corresponding training output value; l is the number of training sample; $\mathfrak{R}^n$ is the n-dimension Euclidean space and $\mathfrak{R}$ is the set of real numbers.

The goal is to find a feature function $g(x)$ that has at most ε deviation from the actually obtained targets y_i for all the training data and at the same time is as flat as possible. The feature function $g(x)$ of SVR is often described as

$$g(x)=w^T\Phi(x)+b\ \left(x\in\mathfrak{R}^n\right) \tag{8}$$

where $\Phi(x)$ is a transformation function which transforms the input vector x in Euclidean space into $\mathrm{X}=\Phi(x)$ in feature space; $w\in\mathfrak{R}^n$ is a weight matrix; $b\in\mathfrak{R}$ is the bias.

The optimization problem is

$$\begin{aligned} &\min_{w,\,b,\,\xi^{(*)}} J(w,\xi^{(*)})=\frac{1}{2}w^Tw+C\sum_{i=1}^{l}\left(\xi_i+\xi_i^*\right) \\ &s.t.\left[\langle w,\Phi(x_i)\rangle+b\right]-y_i\le\varepsilon+\xi_i; \\ &y_i-\left[\langle w,\Phi(x_i)\rangle+b\right]\le\varepsilon+\xi_i^*; \\ &\xi_i,\xi_i^*\ge 0; \\ &i=1,2,\cdots,l \end{aligned} \tag{9}$$