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Identification of slow drift motions of a truss spar platform using parametric Volterra model

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ABSTRACT

Identification of the first and second-order surge motion transfer functions of a truss spar platform from model test data is presented in this paper. The identification is carried out by estimating the time-varying kernels coefficients of a second-order Volterra model. The coefficients are estimated using proposed method, named particle swarm optimization based Kalman smoother (PSO-KS). System input–output data for identification process are wave height and surge motion from a scaled 1:100 model of a prototype truss spar. The applicability of proposed method is assessed numerically and experimentally under unidirectional long-crested random waves. The results show that the linear and quadratic frequency response functions (LFRF and QFRF) as well as the wave and low frequency responses of a truss spar platform can be well identified either in time or frequency domains. The LFRF and QFRF have high resolution so that evolution of the nonlinear wave interactions can be revealed.

1. Introduction

When a moored floating structure is subjected to random waves, there will be interaction effects between the waves and the structure (Faltinsen, 1990). The nonlinear effects are known to be important in the analysis and design of floating structures and usually approximated to the second-order. Those effects appear in the surge motion of moored or tethered offshore structures and are of great importance in the case of mooring and riser systems. The surge motion of floating structures can be split into a mean excursion, wave frequency response (WFR) and low frequency response (LFR). The WFR is linear response which is linearly proportional to the wave height and corresponds to the frequency of random waves as excitation. The LFR is nonlinear response, known as slow-drift motion and qudratically proportional to the wave height. The LFR lies within the resonant bandwidth of the floating structures results in large response since it forces the structure at its resonant frequencies. The existence of LFR is a typical nonlinearity in floating structures and well documented in literatures, such as Newman (1974) and Pinkster (1980). To compute the LFR, numerical models are usually developed by generating the equation of motion of the structures and solved by numerical methods. This effort has been carried out by many researchers such as Spanos et al. (2005) and Naess et al. (2007). Furthermore, recent numerical modeling of LFR has been carried out by Montasir and Kurian (2011) by investigating the structural displacement, axial divergence, free-surface fluctuation, convective acceleration and temporal acceleration due to the second-order velocity potential as the causes for the existence of the LFR.

Numerical approach, however, requires rigorous mathematical formulations. It is less practical for applications that require fast calculations, unless simplifications are imposed on the physical modeling as proposed by Low and Langley (2008) as an example. Also, experimental verifications are rarely conducted. Due to these constraints, empirical models might be considered as alternative. This approach involves system identification methods. Several applications of system identification in offshore structures can be found in references such as Stansberg (1994, 1997a, 1997b), Kwon et al. (2005), Paik and Roesset (1996), Bunnik et al. (2006), Birkelund et al. (2002), Kim (2004), Liu et al. (2004), Liu and Su (2005), Torrest et al. (2014) and Taylor et al. (2005). Some identification models have been used to model the nonlinear dynamic of offshore structures such as Volterra model in Kwon et al. (2005), Paik and Roesset (1996), Bunnik et al. (2006), Birkelund et al. (2002) and Kim (2004), NARMAX model in Liu et al. (2004) and Liu and Su (2005) and Lienard model for a marine riser in Torrest et al. (2014). Particularly, identification of the WFR and LFR from the measured system input–output can be found in Kim (2004). Frequency domain Volterra model based on higher-order spectral analysis (HOSA) method had been used for the purpose. The finding result is extraction of the LFR from model test data is more difficult than the WFR in sea state below than rough sea state. That

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is because the quality of extraction depends on the quality of transfer functions estimates. A disadvantage of using HOSA is that this method introduces bias and high variance in the estimates because of the higher-order spectral moments property. Also, the optimal sample length in calculating transfer functions from discrete experimental data must be determined according to Taylor et al. (2005) since it affects the accuracy of estimation. The limitations above suggest that there is a need for the improvement of the Volterra model in the context of identification of the WFR and LFR from model test data.

For these reasons, an alternative method that avoids the use of HOSA method is proposed. Firstly, the kernel coefficients are identified by minimizing the surge motion response differences between measurements and simulations by using proposed estimation method, named particle swarm optimization based on Kalman smoother (PSO-KS). Kalman smoother is combination between Kalman filter and smoothing equations which will be discussed in the next section. Applications of Kalman filter in offshore engineering can be found in Mizumura (1984), Wilde and Kozakiewicz (1993), Altunkaynak and Ozger (2004), Fossen and Perez (2009) and Banazadeh and Ghorbani (2013). The proposed method is completely carried out in time domain Volterra model which is in sharp contrast with the previous reports (Birkelund et al., 2002; Kim, 2004). Link from time to frequency domain is provided by the kernel coefficients by converting the coefficients to time-varying generalized frequency response function via harmonic probing method. Since the transfer functions are represented by the kernel coefficients, a robust and accurate estimation technique is needed to estimate these coefficients. Hence, becomes the objective of this study. Proposed method is applied to the measured wave height and surge motion response of a truss spar model to test its applicability. The identification process will, therefore, run in wave-to-motion transfer function (Taghipour et al., 2008).

This paper is organized as follows: Section 1 gives research background. Section 2 explains the conversion of the time domain Volterra model into a single state-space model. By assuming the kernel coefficients following a Gauss–Markov process, the first and second-order kernels are represented in the form of adaptive filters. KS method is introduced to estimate the kernel coefficients. Section 3 discusses the implementation of PSO algorithm for optimization. Section 4 describes the modification of regressor vector of Volterra model in terms of forward, backward, combined forward–backward estimator. Section 5 describes the coherence functions. Section 6 presents the extraction results obtained from numerical simulation and experimental data. Finally, Section 7 provides the concluding remarks.

2. Representation of Volterra model in a state-space model

2.1. First and second-order Volterra kernels in the form of adaptive filters

Nonlinear relationship between system input u and system output y is often expressed by a functional power series of system input u and known as the Volterra model. In discrete time index n and data length N, Volterra model is written as,

$$\hat{y}_q(n) = \sum_{k_1,\ k_q=1}^{K} c_{0,q}(k_1,\cdots,k_q,n) \prod_{i=1}^{q} u(n-k_i)\ , \tag{1}$$

where q is the nonlinearity degree and K is the memory length. Eq. (1) shows that the current output is a multidimensional convolution between system inputs $u(n-k_i)$ and impulse response functions $c_{0,q}(k_1,\cdots,k_q,n)$ up to q-order with $\prod_{i=1}^{q} u(n-k_i)$ called q-th – order-lag-product operator. Decomposition of Eq. (1) into linear and quadratic responses can be illustrated as,

1. Setting the lag of system input $q=1$, Eq. (1) results Eq. (2),

$$\hat{y}_1(n) = \sum_{k_1=1}^{K} c_{0,1}(k_1,n)\, u(n-k_1)\ . \tag{2}$$

2. Setting the lag of system input $q=2$, Eq. (1) results Eq. (3),

$$\hat{y}_2(n) = \sum_{k_1,\ k_2=1}^{K} c_{0,2}(k_1,k_2,n)\, u(n-k_1)\, u(n-k_2)\ . \tag{3}$$

Since this study focuses in the first-order and second-order responses, Eqs. (2) and (3) are combined to form Eq. (4),

$$\hat{y}(n) = \sum_{k_1=1}^{K} c_{0,1}(k_1,n)\, u(n-k_1) + \sum_{k_1,\ k_2=1}^{K} c_{0,2}(k_1,k_2,n)\, u(n-k_1)\, u(n-k_2)\ . \tag{4}$$

Eq. (4) is known as second-order Volterra model (Azpicueta-Ruiz et al., 2011; Luigi and Ahsan, 2010), where $c_{0,1}$, $c_{0,2}$ are the first-order and second-order Volterra kernel coefficients, respectively and suggest that the coefficients are time-variant so that it can be utilized for identification linear time-varying (LTV) and nonlinear time-varying (NLTV) systems. For easy interpretation of Eq. (4), it can be reformulated into matrix form and expressed in Eq. (5),

$$\hat{y}(n) = \begin{Bmatrix} u(n) \\ u(n-1) \\ \vdots \\ u(n-K+1) \end{Bmatrix}^T \begin{Bmatrix} c_{0,1}(0,n) \\ c_{0,1}(1,n) \\ \vdots \\ c_{0,1}(K-1,n) \end{Bmatrix} + \begin{bmatrix} u^2(n) & u(n)u(n-1) & \cdots & u(n)u(n-K+1) \\ u(n)u(n-1) & u^2(n-1) & \cdots & u(n-1)u(n-K+1) \\ \vdots & \vdots & \vdots & \vdots \\ u(n-K+1)u(n) & u(n-K+1)u(n-1) & \cdots & u^2(n-K+1) \end{bmatrix}^T \begin{bmatrix} c_{0,2}(0,0,n) & c_{0,2}(0,1,n) & \cdots & c_{0,2}(0,K-1,n) \\ c_{0,2}(1,0,n) & c_{0,2}(1,1,n) & \cdots & c_{0,2}(1,K-1,n) \\ \vdots & \vdots & \vdots & \vdots \\ c_{0,2}(K-1,0,n) & c_{0,2}(K-1,1,n) & \cdots & c_{0,2}(K-1,K-1,n) \end{bmatrix}. \tag{5}$$

Due to symmetrical property in the nonlinear part of Eq. (5), only the upper of the triangular matrix is taken for the estimation