Cold Regions Science and Technology 111 (2015) 13–26

Contents lists available at ScienceDirect

Cold Regions Science and Technology

journal homepage: www.elsevier.com/locate/coldregions

Model-based force and state estimation in experimental ice-induced vibrations by means of Kalman filtering

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ARTICLE INFO

Article history:
Received 18 March 2014
Received in revised form 1 October 2014
Accepted 4 December 2014
Available online 11 December 2014

Keywords:
Dynamic ice-structure interaction
Inverse problems
Kalman filtering
Force identification
State estimation

ABSTRACT

Bottom-founded structures deployed in ice-choked waters may experience severe ice-induced vibrations. A direct monitoring of the level-ice forces requires installation and use of load panels. This is often cumbersome and costly. Indirect measurements interpreted by inverse techniques are therefore favourable since sensors for response measurements are easier to install, less expensive and provide information as to the structural motion. In this paper, the level-ice forces exerted on a scale model of a compliant bottom-founded structure are identified from non-collocated strain and acceleration measurements by means of a joint input-state estimation algorithm. The algorithm allows for uncertainty in the model equations, can be applied to full-scale structures and reconstructs forces without any prior assumptions on their dynamic evolution. The identification is performed employing two different finite element models. One is entirely based on the blueprints of the structure. The other is tuned to reproduce the measured first natural frequency more accurately. Results are presented for two different excitation scenarios characterized by the ice failure process and ice velocity. These scenarios are known as the intermittent crushing and the continuous brittle crushing regimes. The accuracy of the identified forces is assessed by comparing them with those obtained by a frequency domain deconvolution, on the basis of experimentally obtained frequency response functions. The results show successful identification of the level-ice forces for both the intermittent and continuous brittle crushing regimes even when significant modelling errors are present. The response (displacements) identified in conjunction with the forces is also compared to those measured during the experiment. Here the estimated response is found to be sensitive to the modelling errors in the blueprint model. Simple tuning of the model, however, enables high accuracy response estimation.

1. Introduction

Level-ice forces have been measured on bottom-founded structures since the very first oil platforms in the Cook Inlet, Alaska (Peyton, 1966). Bjerkås (2006) summarized the variety of methods used in field measurements to obtain the ice forces acting on fixed structures. Direct measurements of force–time histories (Interfacial methods (Bjerkås, 2006)) are often executed by means of load panels mounted on the structure. The Molikpaq platform was deployed at different sites in the Canadian Beaufort Sea in the 1980s. The platform was equipped with data acquisition systems for measuring ice forces and deformations of the structure. The measured ice forces from the so-called MEDOF panels have been widely used since then, but also questioned for their operational accuracy and reliability, reviewed by Frederking et al. (2002), Jefferies et al. (2011) and Spencer (2013).

Force identification by means of frequency domain deconvolution was performed by Montgomery and Lipsett (1981) to study the river-ice forces on the bridge crossing the Athabaska River in Alberta, Canada. They identified the forces from a single-degree-of-freedom model and the measured structural response using a frequency response function (FRF). Määttänen (1982) applied the same method to identify the ice forces on a lighthouse in the Gulf of Bothnia. An icebreaker, connected with a wire to the lighthouse, was used to perform a step relaxation test (Ewins, 2000) in order to obtain the FRF from the measured excitation and response. Unfortunately, a poor coherence function was found, such that the ice forces had to be identified using an FRF from modal decomposition instead. Määttänen (1983) identified the ice forces using the experimentally obtained FRF in a later report. Frederking et al. (1986) used the same approach to identify the dynamic ice forces on a lightpier in the St. Lawrence River, Canada, while the static force component was measured by load panels.

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http://dx.doi.org/10.1016/j.coldregions.2014.12.003
0165-232X/

The accuracy of the frequency domain deconvolution approach has been questioned by Timco et al. (1989) and Singh et al. (1990). They drew attention to the fact that the identified ice forces were overestimated, compared to the directly measured forces in regimes where the response was close to the natural frequency of the structure. In order to resolve the difference between the identified and measured forces, they suggested increasing the damping in the dynamic model. Fabumni (1986) studied the number of forces that can be identified at an individual frequency dependent on the number of participating modes at that frequency. It was demonstrated that in the presence of measurement noise only one force could be reconstructed with acceptable accuracy when only one mode is contributing to the response signal, as is the case around one of the natural frequencies.

The harsh environment affects the ability to deploy sensors on Arctic offshore structures. Unless the inner surface of the structure can be accessed, the ice-action point may be a challenging location to install a sensor since the ice is crushing against the outer surface. This implies that non-collocated sensors may be the only realistic option. Hollandsworth and Busby (1989) demonstrated the significance of sensor collocation, and found that if the sensors were deployed far from the excitation point, the forces were likely to be underestimated. Water level fluctuations or rafting of the ice causes variations in the location of the ice-action point on bottom-founded structures. This implies that perfect collocation of the sensors is in practice difficult to achieve.

Identification accuracy does not rely only on the sensor locations or modelling errors, but also on the structural design of the experiment, calibration procedures and noise levels. When using direct ice-force measurements, the internal damping and natural frequencies of the load panels or load cells may interfere with the ice failure. On occasions when the directly measured force signals include inertia from the measurement setup itself, subtraction of the undesired inertia is required to obtain the ice force (Barker et al.(2005)).

Another instrument that can be used to obtain the ice forces is tactile sensors (e.g., Sodhi (2001), Määttänen et al. (2011)). These sensors have the advantage of being able to measure pressure with high spatial resolution, and they can be tailored to fit any indenter and enable extraction of both contact area and pressure. However, tactile sensors can only measure stresses normal to the surface of the indenter, such that any shear stresses have to be derived through assumed static and dynamic friction coefficients. So far the application of the tactile sensor has been limited to small and medium-scale experiments.

Ice forces have traditionally been obtained by either direct force measurements or deterministic force identification in the frequency domain. A disadvantage of the latter method is that it is often problematic to accurately determine the FRFs of large structures. Since the offshore structures deployed in the Arctic are not an exception, in situ ice forces are difficult to obtain from frequency domain deconvolution and output only measurements. Direct measurement, on the other hand, implies heavy costs related to the load panels, installation and maintenance. Response measurements are therefore still a favourable means to obtain the forces. Furthermore, they provide additional important information about the structural motion.

In this contribution, we demonstrate a methodology to overcome the aforementioned difficulties. A recently developed deterministic–stochastic approach is used to jointly identify the ice forces and the states. The original algorithm, proposed by Gillijns and De Moor (2007), was intended for use in the field of optimal control. Lourens et al. (2012a) extended the algorithm for use with reduced-order systems, which are often encountered in structural dynamics. Niu et al. (2011) used the original algorithm to identify forces on a laboratory-scale structure. The deterministic–stochastic nature of the algorithm allows for improved results when the model equations are inexact. Since the algorithm requires no regularization, it can be applied online.

In what follows, the ice forces are identified in conjunction with the states, using the original algorithm (Gillijns and De Moor, 2007) and a limited number of response measurements on a laboratory test setup designed for studying ice-induced vibrations. The results are assessed by comparison with the forces obtained with frequency domain deconvolution, and the estimated displacements are compared with the ones measured.

2. Fundamentals

2.1. System equations

The governing equations of motion for a linear system discretized in space and excited by an external force can be written as follows:

$$\mathbf{M}\ddot{\mathbf{u}}(t)+\mathbf{C}\,\dot{\mathbf{u}}\,(t)+\mathbf{K}\mathbf{u}(t)=\mathbf{f}(t)=\mathbf{S}_{\mathrm{p}}\mathbf{p}(t) \tag{1}$$

where $\mathbf{u}\in\mathbb{R}^{n_{\mathrm{DOF}}}$ is the displacement vector, and the matrices $\mathbf{M}$,$\mathbf{C}$, $\mathbf{K}\in\mathbb{R}^{n_{\mathrm{DOF}}\times n_{\mathrm{DOF}}}$ denote the structural mass, damping and stiffness matrix, respectively. The excitation vector $\mathbf{p}(t)\in\mathbb{R}^{n_{\mathrm{p}}}$ is specified to act on the desired locations through the force influence matrix $\mathbf{S}_{\mathrm{p}}\in\mathbb{R}^{n_{\mathrm{DOF}}\times n_{\mathrm{p}}}$, where n_{p} is the number of force time histories. A step action table is provided below to communicate the governing elements to perform the force and state identification presented in this paper:

1. Model assembly and tuning; extract mass, damping and stiffness matrices ($\mathbf{M}$,$\mathbf{C}$,$\mathbf{K}\in\mathbb{R}^{n_{\mathrm{DOF}}\times n_{\mathrm{DOF}}}$).
2. Define force influence locations ($\mathbf{S}_{\mathrm{p}}\in\mathbb{R}^{n_{\mathrm{DOF}}\times n_{\mathrm{p}}}$).
3. Define sensor locations and assemble the data vector (Section 2.2).
4. State-space transform (Section 2.2).
5. Perform joint state and input estimation (Section 2.3).

2.2. State-space description

The continuous-time state vector $\mathbf{x}(t)\in\mathbb{R}^{n_{\mathrm{s}}}$, $n_{\mathrm{s}}=2n_{\mathrm{DOF}}$ is defined as:

$$\mathbf{x}(t)=\begin{pmatrix}\mathbf{u}(t)\\ \dot{\mathbf{u}}(t)\end{pmatrix} \tag{2}$$

whereby the equation of motion of second order in (1) can be organized as a first-order continuous-time state equation

$$\dot{\mathbf{x}}\,(t)=\mathbf{A}_{\mathrm{c}}\mathbf{x}(t)+\mathbf{B}_{\mathrm{c}}\mathbf{p}(t) \tag{3}$$

where the system matrices $\mathbf{A}_{\mathrm{c}}\in\mathbb{R}^{n_{\mathrm{s}}\times n_{\mathrm{s}}}$ and $\mathbf{B}_{\mathrm{c}}\in\mathbb{R}^{n_{\mathrm{s}}\times n_{\mathrm{p}}}$ are defined as

$$\mathbf{A}_{\mathrm{c}}=\begin{bmatrix}\mathbf{0} & \mathbf{I}\\ -\mathbf{M}^{-1}\mathbf{K} & -\mathbf{M}^{-1}\mathbf{C}\end{bmatrix},\mathbf{B}_{\mathrm{c}}=\begin{bmatrix}\mathbf{0}\\ \mathbf{M}^{-1}\mathbf{S}_{\mathrm{p}}\end{bmatrix} \tag{4}$$

The measurements are arranged in a data vector $\mathbf{d}(t)\in\mathbb{R}^{n_{\mathrm{d}}}$, in which the observations can be a linear combination of displacement, velocity and acceleration, with n_{d} the number of data measurements. The data vector is constructed as follows:

$$\mathbf{d}(t)=\mathbf{S}_{\mathrm{a}}\ddot{\mathbf{u}}(t)+\mathbf{S}_{\mathrm{v}}\,\dot{\mathbf{u}}\,(t)+\mathbf{S}_{\mathrm{d}}\mathbf{u}(t) \tag{5}$$

where the selection matrices $\mathbf{S}_{\mathrm{a}}$, $\mathbf{S}_{\mathrm{v}}$ and $\mathbf{S}_{\mathrm{d}}\in\mathbb{R}^{n_{\mathrm{d}}\times n_{\mathrm{DOF}}}$ are populated according to the spatial location where acceleration, velocity and/or displacement are measured. By premultiplying Eq. (1) with $\mathbf{M}^{-1}$, inserting the resulting expression into Eq. (5), and further utilizing the definition of the state vector, Eq. (5) can be transformed into the state-space form:

$$\mathbf{d}(t)=\mathbf{G}_{\mathrm{c}}\mathbf{x}(t)+\mathbf{J}_{\mathrm{c}}\mathbf{p}(t) \tag{6}$$