Estimating Waves Through Measured Ship Responses

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1 INTRODUCTION

Proper assessments of safety and energy efficiency of marine operations require detailed information about the acting wave system in the given situation. This is particularly true for floating structures, such as ships, wind turbines, fish cages, etc., and applies to real-time, in-situ assessments as well as post-operation analyses. It is possible - with an analogy to classical wave buoys - to obtain information about the acting wave system by processing sensor measurements of wave-induced responses (e.g., motions and structural responses) from the given floating structure. Although research in this direction has been carried out during the past 3-4 decades, there is still relatively little awareness in the community about the relevant possibilities considering different applications. This note highlights the status and ongoing developments made at DTU Construct with selected partners for *estimating waves through measured ship responses*. Onward, we refer to wave-estimation methods of this type under the umbrella term the Wave Buoy Analogy (WBA). In the presentation, we also discuss associated limitations, problems, and future applications of the WBA.

2 THEORETICAL CONCEPTS AND METHODOLOGIES

Fundamentally, the WBA relies on measuring of wave-induced ship responses; say, heave (z), roll (ϕ), and pitch (θ). Introducing the linear time-invariant (LTI) assumption, facilitates the use of transfer functions, leading to what will be referred to as physics-based methods with formulations in both the frequency domain and the time domain. In contrast thereto, purely data-driven approaches exist, relying on machine learning, and referred to as ML-based methods. Common to all WBA methods is the characteristic of a ship as a wave filter, and the relative dimensions, notably the ratio of length to wavelength, indicate how well the measured responses can be used for wave inference.

2.1 Physics-based methods

From a measured set of responses, corresponding response spectra $S_{i,j}(\omega_{e,l})$, $i,j = \{z,\phi,\theta\}$, can be computed under the assumption of stationary and ergodic processes. Here, $\omega_{e,l}$ defines the encounter frequency discretised by $l = 1, 2, ..., L$ components. Formally, the directional wave spectrum $E(\omega,\mu)$ can be determined from the spectral equation,

$$\min \sum_{i,j} \sum_{l=1}^{L} \left| S_{i,j}(\omega_{e,l}) - \int_0^{2\pi} \left\langle \Phi_i(\omega,\beta)\overline{\Phi_j(\omega,\beta)} E(\omega,\mu) \frac{d\omega}{d\omega_e} \right\rangle_{\omega_{e,l}} d\mu \right|^2 \tag{1}$$

where the transfer function is $\Phi_i(\omega,\beta)$, and the overline denotes the complex conjugate. The intrinsic frequency is ω [rad/s], and $\beta = (180 + \chi - \mu)$ [deg] is the wave encounter angle with waves propagating *from* the compass direction μ while the compass heading of the ship is χ. The straight-line brackets $\langle\cdots\rangle_{\omega_{e,l}}$, with $\omega_{e,l}$ as index, is used to emphasise that evaluation happens for a given frequency of encounter. Frequency-domain solutions build on different assumptions and, typically, a distinction is made between non-parametric methods and parametric methods. Non-parametric methods solve for the unknown wave spectrum $E(\omega, \mu)$ at all discrete pairs of (ω, μ), necessitating regularization techniques and/or iterative schemes for dealing with the highly under-determined equation system. In the parametric methods, the directional wave spectrum is formed by an idealized wave spectrum, e.g., Bretschneider, JONSWAP or summations of such, overlaid with a spreading function. Thus, the minimization of Eq. (1) leads to an optimized set of wave parameters governing the idealized wave spectrum. In the spectral equation, it is an inherent complexity that the Doppler shift, for ships with forward speed, introduces a 1-to-3 relationship between the encounter frequency and the intrinsic frequency for all wave encounter angles between followings waves and beam waves. Although mathematically elementary, the Doppler shift is a practical complication and care must be taken when it is implemented in the WBA. As indicated by Eq. (1), several responses are used simultaneously, and the cross spectra reveal the necessary information about the phase relationships needed to infer the (relative) direction of the waves.

Transfer functions have also been used for developing methods in the time domain, and resulting solutions can produce the real and imaginary parts of the amplitudes of the component waves forming the wave system. Specifically, a solution has been derived in terms of Prolate Spheroidal Wave Functions (PSWF) for a ship without forward speed.

2.2 Machine learning-based methods

Modelling the ship motion dynamics via the governing physics necessitates several assumptions that can be relaxed if the relation between waves and motions instead is explored and determined entirely through data. In ML-based methods, the general relationship between waves and induced responses of a particular ship is learned by comprehensive training with large datasets of measured responses against available sea state information. The main advantage of ML-based methods is that transfer functions are not needed, and all associated uncertainties are thus removed. On the other hand, the need for high-quality sensor measurements is emphasized and so is the importance of having accurate (”external”) sea state information at the exact spatio-temporal position of the ship. Generally, sea state information can be obtained, for instance, through dedicated wave radar systems or via third-generation spectral wave models, such as WaveWatch III or WAM, often assimilated with data in re-analyses.

Many ML architectures allow, with relatively little effort through supervised regression, estimation of integral wave parameters, e.g., the significant wave height, the peak period, the mean relative wave direction, and attempts to estimate the actual (directional) wave spectrum have also been made. As with the physics-based approaches, ML methods can be formulated in both the time domain and in the frequency domain; stressing the importance in having the phase relationships between responses, like with the physics-based methods, for obtaining reliable estimates of the (relative) wave direction.

3 CASE STUDIES

3.1 Wave spectrum estimation

The non-parametric and parametric physics-based frequency-domain methods have the directional wave spectrum as their output. An example is seen in Figure 1. The spectrum has been obtained by analysis of full-scale motion data from R/V Gunnerus [1]. In this particular case, the final output is produced by combining the non-parametric estimate [2] with the parametric estimate [3]. It can be seen that the agreement with corresponding estimates by a wave buoy (Datawell BV) is good. In some applications, for instance related to dynamic positioning, it may be enough to have just wave parameters (e.g., H_s and T_p) to ensure efficient working capabilities of the DP control system, and specific developments of the WBA have been made in this direction [4, 5].

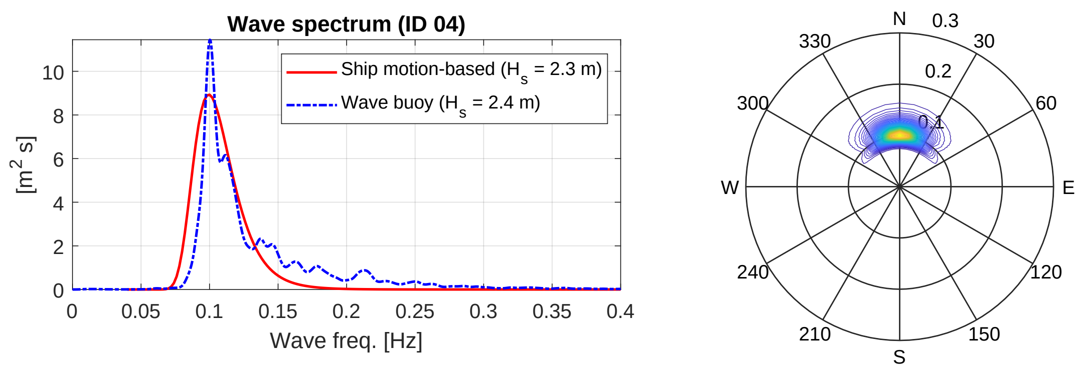

Figure 1: Wave spectrum estimation. Left: Comparison between the WBA and a Datawell BV wave buoy. Right: The corresponding directional spectrum produced by the WBA.

3.2 Determination of the incident wave profile

In the study of nonlinear wave-ship interaction problems, the incident wave (i.e., the surface elevation) must be available. The time-domain method by [6] offers estimates of the encountered wave elevation based on short-time sequences of response measurements. An example is presented in Figure 2, which is produced by analysis of seakeeping experiments from the model tank of the National Maritime Research Institute in Tokyo. The plot shows estimates of the incident wave, based on different models (”uni-modal” and ”tri-modal”), together with the true incident wave resulting from a short-crested sea state.

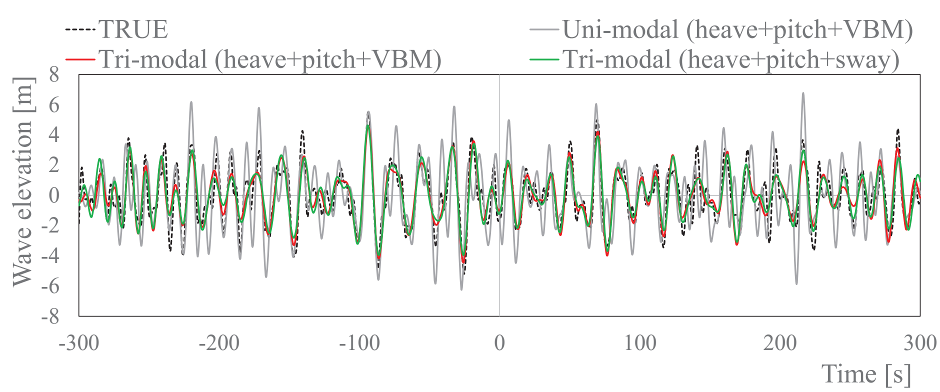

Figure 2: Determination of the encountered incident wave. From [6].

3.3 Sea state identification using machine learning

Based on an extensive dataset of wave-induced responses from an in-service container ship, multiple deep neural networks have been trained, and the sensitivity to sensor recordings, sample length, and frequency discretization on estimation accuracy has been studied [7]. A selection of the main results, in terms of estimation capabilities, is shown in Figure 3, where estimates are compared against the "ground truth", here taken from a wave radar system (WaVex). The plots present validation results obtained from an Inception (frequency-domain) model making use of response spectra and applied in a multi-task learning setting for estimation of significant wave height (H_s), peak period (T_p), and relative wave direction (β). In the plots, the estimates are shown on the vertical axis.

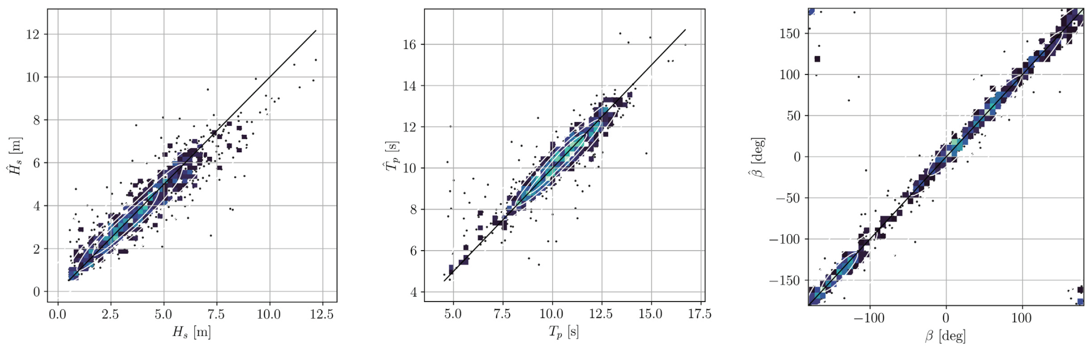

Figure 3: Each point represents the result corresponding to 25-minutes of data.. From [7].

4 PERSPECTIVES

In-situ estimates of waves can directly benefit assessments of safety and energy efficiency of the ship encountering these waves. The WBA is a useful tool in this connection, emphasising that, instrumentation-wise, only a few relatively inexpensive sensors are needed. It is believed that applications of the WBA goes beyond the assessment of the operations of a single ship. A future, more general, application could be related to met-ocean forecasting networks [8].

ML-based methods have wide and large potential but the complexity of the system (*a ship in a confused sea*) being considered, makes the use of ML delicate, and generalization of results (operational profile, different ships) must be made with extreme care. As part of the problem, the quality of ship telemetry data is notoriously low, and a fallback framework (physics-informed ML) seems necessary.

REFERENCES

[1] Nielsen, U. D., Brodtkorb, A., and Sørensen, A. 2018. *A brute-force spectral approach for wave estimation using measured vessel motions.* Marine Structures **60**, 101–121.

[2] Nielsen, U. D. 2008. *Introducing two hyperparameters in Bayesian estimation of wave spectra.* Probabilistic Engineering Mechanics **23**, 84–94.

[3] Nielsen, U., and Stredulinksy, D. 2012. *Sea state estimation from an advancing ship - A comparative study using sea trial data.* Applied Ocean Research **34**, 33–44.

[4] Brodtkorb, A. H., Nielsen, U. D., and Sørensen, A. J. 2018. *Sea state estimation using vessel response in dynamic positioning.* Applied Ocean Research **70**, 76–86.

[5] Brodtkorb, A. H., and Nielsen, U. D. 2022. *Automatic sea state estimation with online trust measure based on ship response measurements.* Control Engineering Practice **130**, 105375.

[6] Takami, T., Nielsen, U. D., Jensen, J., and Xi, C. 2023. *Estimation of Encountered Wave Elevation Sequences Based on Response Measurements in Multi-directional Seas.* Applied Ocean Research (under review).

[7] Mittendorf, M., Nielsen, U. D., Bingham, H. B., and Storhaug, G. 2022. *Sea state identification using machine learning: A comparative study based on in-service data from a container vessel.* Marine Structures **85**, 103274.

[8] Mounet, R. E. G., Chen, J., Nielsen, U. D., Brodtkorb, A. H., Pillai, and Ashton, I. G. C. 2023. *Deriving spatial wave data from a network of buoys and ships.* Environmental Modelling Software (under review).