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Short-term wave force prediction for wave energy converter control

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ABSTRACT

Given the importance of wave excitation force prediction in most advanced control schemes for wave energy converters, where every new wave force estimation becomes available every fraction of second, the main objective of this paper is to perform a short-term wave prediction that can meet a trade-off between low computational complexity, limited memory usage and accuracy. To this aim, two prediction algorithms are proposed using Kalman filtering theory. The proposed prediction methods are evaluated by using real measurements.

1. Introduction

Wave energy converters (WECs) are devices used to produce electrical energy from wave movements. A schematic example of a WEC is given in Fig. 1: an oscillating body (the captor or primary converter) moves under the action of waves and is connected to a Power-Take-Off (PTO) system; the PTO, by exercising an appropriate force on the captor, converts its mechanical energy into electrical energy. The PTO can be a linear electric generator, or a multistage device, such as a hydraulic motor connected to a rotary electric generator.

The PTO can be used as an actuator to adjust the natural response of the captor to waves, in order to maximize the extracted energy. The ideal conditions for optimal energy absorption have been studied in Falnes (2002), showing that an energy maximizing controller requires future knowledge of the wave excitation force F_{ex}, that is, the force exerted by the incoming wave on the captor. Among the many different approaches to hydrodynamic control of WECs, see Korde and Ringwood (2016) for a thorough review, latching control (Babarit & Clément, 2006; Saupe, Gilloteaux, Bozonnet, Creff, & Tona, 2014), declutching control (Babarit, Guglielmi, & Clément, 2009), and model predictive control (MPC) (Li & Belmont, 2014) are examples of strategies relying, directly or indirectly, on this knowledge. In the MPC context, for instance, the complete control scheme must include an online algorithm to compute future values of the wave excitation force over the prediction horizon, as shown in Fig. 2.

Notice that, while it is relatively straightforward to measure excitation force using a dedicated experiment and a well-positioned force sensor (Nguyen & Tona, 2017), only indirect measurements or estimations are possible during normal WEC operation. Two experimentally-validated methods for wave force estimation from available measurements are described in Nguyen and Tona (2017). Assuming that local wave elevation measurements are possible during WEC operation, another, less direct, approach could consist of computing future values of the wave excitation force from wave elevation predictions, though this would require an inconvenient increase of the prediction horizon, to cope with the non-causal nature of the impulse function relating wave elevation to wave excitation force. Indeed, for its important role in the optimization of WEC energy yield, short-term wave forecasting, with a particular focus on wave elevation, has drawn a lot of attention in the hydrodynamic control community.

A first possible approach to perform short-term wave forecasting is spatial prediction, using up-wave measurements from sensors installed around the location of a WEC (Paparella et al., 2015; Serafino, Lugni, & Soldovieri, 2010; Tedd & Frigaard, 2007). The method is reported to forecast quite long prediction horizons with a good performance (Belmont, Horwood, Thurley, & Baker, 2006). However the forecasting model can become very complex, since the wave propagation nonlinearities or/and the possible multi-directionality of waves have to be taken into account (Frigaard & Brorsen, 1995).

A second approach, that has become popular in the last years because of its simplicity, is to use past time series of local measurements or estimates, at the float position. In Fusco and Ringwood (2010), using real wave elevation data, Fusco and Ringwood show that a relatively simple linear auto-regressive (AR) model can perform quite well, provided that the high-frequency content is filtered out from the time series data. To avoid introducing a phase lag, the use of a non-causal zero-phase filter is advocated. The solution is based on a *batch-processing* approach, which also includes a computationally-expensive nonlinear least squares problem to be solved and a spectral analysis to be performed in order to compute an optimal sampling period for all the computations. It

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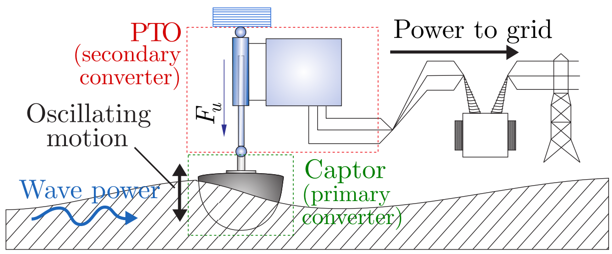

Fig. 1. Schematic diagram of a wave energy converter of the point-absorber type.

is worth noticing that considering a more complex model structure in this context, namely an auto regressive moving average (ARMA) model instead of an AR model, does not seem to bring any particular benefit (Yerai & John, 2017). In Fischer, Kracht, and Perez-Becker (2012), an iterative, more easily implementable approach is proposed, based on a bank of least squares estimators. However, as it will be shown later, it is implicitly assumed that the sea state is constant. Furthermore, as noticed in Fischer et al. (2012), the prediction performance degrades as quickly as the prediction horizon increases.

Two novel solutions for short-term wave forecasting are proposed in this paper. They are also based on past time series of local WEC measurements or estimates. Implementation aspects such as computational complexity and accuracy are investigated. Their performance is assessed using wave excitation force time series, obtained from data collected in the wave basin of Aalborg University, on a lab-scale wave energy converter prototype.

Three main features of the proposed solutions, built around AR-model estimation, are:

- It is shown that, for the first method, the multi-step ahead error criterion adopted in Fusco and Ringwood (2010) is a particular case of our criterion.
- The first method is based on the extended Kalman filter. Hence the algorithm is recursive and easy to implement.
- To improve the performance, overcoming the error accumulation problem that comes with the first method, an alternative approach is proposed. It builds an independent model for each horizon, using an adaptive Kalman filter. It is also shown that the approach in Fischer et al. (2012) is a limiting case of ours, when the sea state is assumed to be constant.

The paper is organized as follows. The problem is formulated in Section 2 together with a review from the literature. Then the multi-step error minimization approach with extended Kalman filter is proposed in Section 3, while in Section 4, an adaptive Kalman filtering approach is considered. In Section 5, the available data as well as the prediction results are presented. In Section 6 the computation of a forecasting interval is considered. Some conclusions are drawn in Section 7.

2. Problem formulation

Given available estimates $\{\hat{F}_{ex}(l)\}$ of the wave excitation force taken at discrete time instants $l = 0, 1, \ldots, k$, where k is the current time, our objective is to predict the wave excitation force at time $k+1$, $k+2$, $\ldots$, $k+N_p$, where N_p is the prediction horizon. For this purpose, some prediction methods in the literature are first reviewed. These methods will be compared to the new approaches developed in the paper. In the following, for simplicity denote $y(k) = \hat{F}_{ex}(k)$.

2.1. Decomposition based approach

This approach is based on the assumption that $y(k)$ may be regarded as the sum of several sinusoidal waves of different frequencies, amplitudes and phases,

$$y(k) = \sum_{j=1}^{m} A_j \sin(\omega_j k + \phi_j) \tag{1}$$

where m is the total number of components, A_j, ω_j and ϕ_j are the amplitude, the angular wave frequency and the phase angle of the jth component, respectively (Hals, Falnes, & Moan, 2011). Note that in the model (1) the frequencies ω_j are known and fixed, while A_j and ϕ_j are unknown. The parameters A_j and ϕ_j can be estimated through least squares or Kalman filter procedures and can be used to forecast the future wave excitation force (Fusco & Ringwood, 2010).

The main advantage of the model (1) is its direct physical meaning. However the constant frequencies assumption is rather restrictive and unrealistic, since it is well known that the wave excitation force spectrum is time-varying (Jonkman, 2007). Consequently, it is not reliable to use the model (1) to predict the future wave excitation force.

2.2. Sinusoidal extrapolation based approach

The idea is to model $y(k)$ as a single sinusoidal signal with a time-varying frequency, amplitude and phase,

$$y(k) = A(k)\sin\left(\omega(k)k + \phi(k)\right) \tag{2}$$

where $A(k)$, $\omega(k)$ and $\phi(k)$ are unknown.

Evidently, the model (2) is nonlinear in $A(k)$, $\omega(k)$ and $\phi(k)$. As a consequence, a linear recursive estimator cannot be directly applied. It is possible, however, to use a truncated Taylor expansion of (2), and then an extended Kalman filter (EKF) to estimate the values of $A(k)$, $\omega(k)$ and $\phi(k)$ (Fusco & Ringwood, 2010).

A direct physical meaning is also an advantage of model (2). However, it is clear that using one sinusoid to describe a wave is only effective for very narrow-banded wave systems. In addition, the extension to a model with multiple time-varying frequencies is not as straightforward as it may seem.

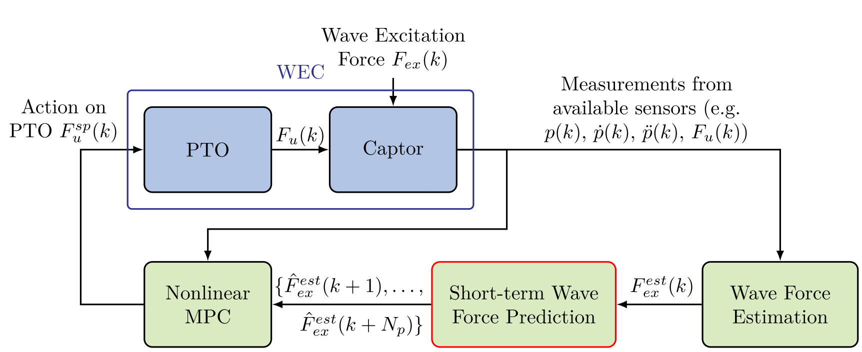

Fig. 2. Wave excitation force prediction in the context of MPC.