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Dynamic Windowing Algorithm to Improve Ship Response Prediction in Transitory Conditions

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Abstract

The emerging trend of autonomous shipping has demanded the automation of many onboard systems and sub-systems to minimize human involvement in decision-making. Given the time- varying nature of the sea, the respective knowledge of ship response possesses a variety of applications in real-time operations and guidance, where predicting responses a few seconds ahead plays a crucial role in dynamic control. Within current literature, many long-run studies lack evaluation of the dynamics of ship response time-series in a transitory condition between sea states. To address this deficit, the present study proposes an innovative algorithm to automatically detect the substantial changes in the time series regime for ship response data and adjust the observation window for prediction accordingly. For prediction purposes, a well-known classic nonlinear regressor, Seasonal Auto-Regressive Integrating Moving Average (SARIMA) has been employed in an adaptive sense. Despite this concept being primarily developed for advancing ship maneuvering, experimental and simulation data of a moored semi-submersible vessel has been utilized, given the dynamics' simplicity. The results demonstrated the efficiency of the proposed filter in minimizing uncertainty in ship response prediction according to the prevailing sea conditions. Although the proposed algorithm shortens the prediction length in transitory signals, it essentially improves the prediction results, for the estimation models are built only on informative short-term data. The proposed workflow can not only increase the autonomy of the involved system with ship response data, but also be further used on any onboard system dealing with time-varying information.

Keywords: Autonomous ships, Intelligent systems, response prediction, time series analysis.

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1 Introduction

Short-time ship response prediction possesses a variety of applications including but not limited to launching onboard weapons, helicopter, and aircraft landing (Qu, 2016), motions compensation systems (Iola, 2011), and seaway estimation (Majidiyan, 2023). More specifically, the ship-response knowledge can be fused into any deterministic control and guidance onboard systems. In terms of onboard equipment, any system with predictive model control (PMC) and feed-forward control requires predicting a specific horizon in future. For autonomous ships and remote control, the acquisition and prediction of future events are imperative.

Fundamentally, the problem can be modelled in three forms: first principal model, grey box approach, and black box approach. For the first principal models, the attempt is toward modelling waves and ship interaction, however given a large number of associated parameters and pertinent uncertainties, this approach has not been of interest. The second and third approaches fall into the area of online system identification, where a mathematical model is constructed on the data in a buffer window of recent events (finite history algorithm). Thereby, the same model can be utilized for predicting system behavior in a few second horizons. As such, the second approach tries to model the ship with a second-order transfer function to tune the added mass and damping factor according to Equation 1 (Faltinsen, 1993). However, hydrodynamic coefficients or parameters in Equation 1 for a ship are associated with an unknown level of uncertainty and are only based on the linear assumption of ship and wave interactions. Due to this, the models cannot explain nonlinear phenomena such as viscosity-dependent phenomena. With the advancements in computational resources, the third approach has become popular, where all prior assumptions are dropped from the problem, and the data-driven model entirely relies on the available data. All models are summarized in Figure 1. In Equation (Qu, 2016), ω denotes frequency, β indicates wave relative direction, H is the transfer function (conceptually corresponding to G in figure 1), M, A, B, and C stand for hydrodynamic coefficients in brief. The real part of the H denotes Response Amplitude Operator (RAO).

$$\mathbf{H}(\omega, \beta) = \frac{\eta_a}{\zeta_a} = \left[-\omega^2 \left(\mathbf{M} + \mathbf{A}(\omega)\right) + i\omega \mathbf{B}(\omega) + \mathbf{C}\right]^{-1} \mathbf{X_j}(\omega, \beta) \text{ (Qu, 2016)}$$

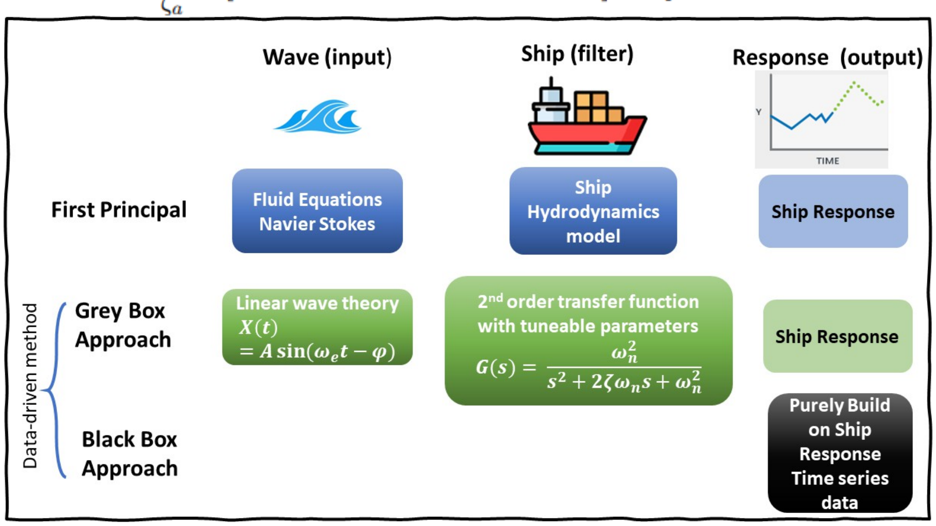

Figure 1: The existing framework of methods for ship response prediction

The available literature in this regard also has followed the same pattern, meaning that the seminal attempts endeavoured to define a first principle model such as (Kaplan, 1965). Later, the studies were directed toward a grey box approach, like defining a state-space model in (Triantafyllou, 1983) with the tremendous computational cost of deriving hydrodynamic coefficients and high noise sensitivity. Literature in the third approach is resourceful and is flourishing given the rise and emergence of intelligent learning models combined with the signal decomposition techniques such as YutuYe (2022) and Zhihong Nie (2022). In these models, the combinations of classic/intelligent regressors, comprising Auto-Regressive (AR), SVR, and long-short term memory (LSTM), applies to the sub-signals obtained from decomposition. These models have enhanced the prediction of ship response dramatically.

However, previous studies have mainly focused on predicting ship response in a fixed wave condition, and the prediction model has not been investigated in a time series with a significant regime change due to alteration of relative wave direction or ship speed. In this regard, the present study aims to highlight the issue within the transition and introduce an algorithm to dynamically change the observation window length based on the significant short-term memory in the data. The remaining is organized as follows: Section 2 illustrates the prediction models and data generation methods, which have been utilized for the current sake. Section 3 identifies the problem and proposes an innovative algorithm. The algorithm's efficacy in improving the outcomes is discussed in Section 4. Finally, Section 5 draws a conclusion and pictures the future works.

2 Materials And Methods

Rather than ship data, the data from a semi-submersible platform has been employed for simplicity. Although the present synthesized scenario might not exactly reflect the dynamics of the advancing ship, the control over the data and reduced degree of uncertainty can better assist in constructing a model for tackling the problem. The platform has been experimentally tested at Shanghai Jiao Tong University basin for a long exposure of the unidirectional waves with the JONSWAP spectrum. To further extend the response scenarios and diversify the data, a simulation has been carried out with a panel method base commercial package in ANSYS AQWA. All information regarding the platform dimension, test and simulation details can be found in Yiting (2019), YutuYe (2022) and Majidiyan (2023). Since the aim is to assess the performance of predictors for online applications, two models of Adaptive SARIMA (Box, 1994) as a linear based and SVR as an intelligent nonlinear based, which are amenable to small sample sizes have been selected. Although SARIMA is designed for nonstationary data (Tangirala, 2018), it is crucial to select an appropriate buffer to prevent high- order nonstationarity. Therefore, the observation window length is chosen as the 40s for both models. Equation 2 (Tangirala, 2018) indicated the basic form of SARIMA (1,n,1) s process, Where L is the lag operator, d denotes the AR coefficient, s is the seasonality order, n is the degree of integration, co is the constant term, c is the MA coefficient, ε_t is white noise, and y_t is the time series in t.

$$(1-d_1L)(1-L^s)(1-L)^n y_t = co + (1+c_1L)\varepsilon_t \qquad \text{(Iola, 2011)}$$

Here, a low-order SARIMA model is used, according to Equation 3. The terms in the model are set according to statistical tests of the Augmented Dickey-Fuller (ADF) test (Dickey, 1979) and Kwiatkowski– Phillips–Schmidt–Shin (KPSS) [13] given in Table 1 as the decision matrix. To estimate model parameters d in Equation 3, the Maximum Likelihood Estimate (MLE) has been employed. The term MA is entirely ignored due to intrinsic invertibility complications (Tangirala, 2018). The polynomial's order is directly and automatically determined through statistically significant lags in sample Partial Autocorrelation Function (PACF) as per (Majidiyan, 2023). Also, to reduce propagating (parameter uncertainty), reduce computational expenses, and prevent overfitting, the simplest model has been set up. Equation Majidiyan (2023) denotes the final SARIMA model that adaptively uses different orders and parameters based on the sample PACF and statistical tests.

$$(1 - d_1 L)(1 - L^s)(1 - L)^n y_t = co + \varepsilon_t \qquad \text{(Majidiyan, 2023)}$$

Table 1: Scenarios for model selection based on the statistical test outcomes

Status	ADF	KPSS	Model
Stationary	H=1 Stationary	H=0 Stationary	AR
Stationary with detrending	H=0 Nonstationary	H=0 Stationary	SARMA
Stationary with differencing	H=1 Stationary	H=1 Nonstationary	ARIMA
Nonstationary with seasonality	H=0 Nonstationary	H=1 Nonstationary	SARIMA
Non seasonal nonstationary	H=0 Nonstationary	H=0 Stationary	ARIMA with extra differencing

3 Problem Statement and Proposed Solution

For online system identification, a fixed finite buffer window slides over the data to construct a mathematical prediction model. Nevertheless, this fixed window length introduces many complications when data in a buffer window contains entirely different statistical regimes. In general, it happens when the exciting force to the process u[t] (input) changes. So, the dynamic in the response y[t] in the time series shows different behaviour. Moreover, it can occur in the sensor signal glitch or concerning ship response context when induced-wave force varies due to alterations in ship speed or relative direction to the ship, and phase lag between exciting wave force and respective induced response (Faltinsen, 1993). As a result, regardless of the type of estimation model, the mathematical model is built based on the expired piece of information. Figure 2 perfectly illustrates the problem in which the SARIMA model has been used for prediction on 1000 samples of 25 Hz sampling rate corresponding to 40s and the 20s window that is chopped up from the transition sample (501:1000). As can be observed, the 20s window length indicates a better prediction quantitively and qualitatively, although within the shorter horizon. The reason behind shortening the horizon is that the 20s data does not provide sufficient information for modelling farther horizons. Looking at the sample PACF plot for both time windows in Figure 3, it manifests that the 40s window model included statistically significant lags, which are in the first segment of the time series for modelling, or simply, the model is constructed based on the passive expired data, while for 20s, the recent lags and the short-term memory of the process has been utilized for modelling.

To address this issue, it is essential to automatically pinpoint the time stamp of substantial transition in a primary buffer window in order to adjust the observation window length for constructing an updated estimation model. To this end, the following algorithm identifies the regime change in the signal that enables adjusting the observation window accordingly.

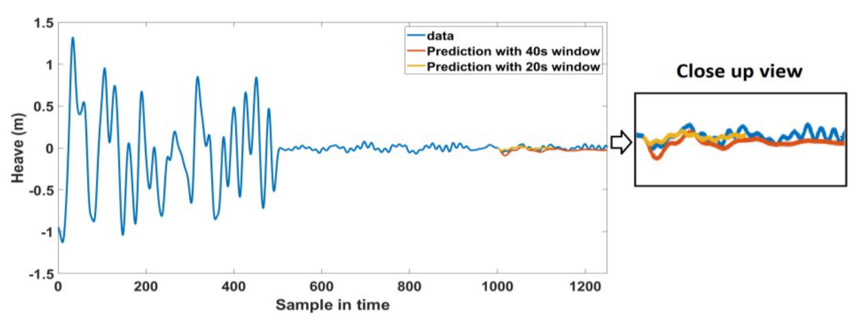

Figure 2: Transition of platform roll response to the irregular wave (JONSWAP) from wave height 5 m to 1 meter with wave direction of 270°, sampling rate 25 Hz. RMSE for 40s= 0.0323 and for 20s= 0.186

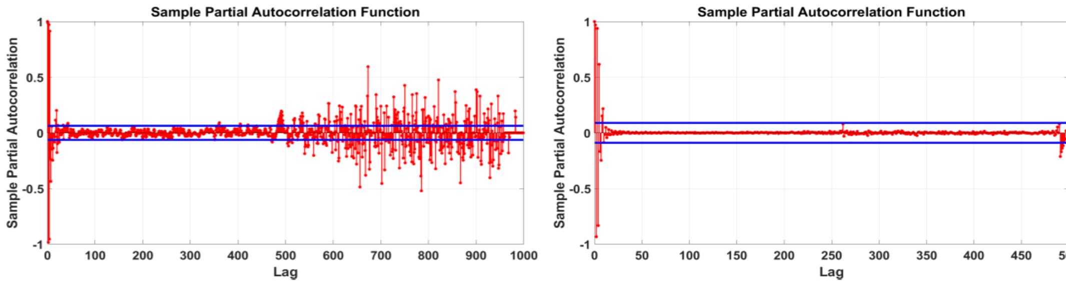

Figure 3: Comparison of sample PACF for window size 40s (left) and window size 20s (right)

Following steps define the algorithm descriptively for discrete signal of x(k) with length N:

1. The cumulative variance is done in x(k).
2. The vector of cumulative variance is split into 8 segments (5 seconds each).
3. All values are rearranged in 8 vectors.
4. Derivation of vectors in step 3 shows a maxima where the regime has changed.
5. The segment for prediction must be selected within the beginning of segment where the derivation peak is found.

Also, some constraints must be considered in the algorithm. The horizon is proportional to the observation length, and observation length should not be selected below 15s as lack of data complicates modelling and increases uncertainty. Furthermore, the peak in the first vector in stage 3 is ignored since it might only reflect local oscillations rather than regime change.

4 Results and Discussion

Many further response scenarios from synthesized data in AQWA have been employed to examine the efficacy of the proposed algorithm. After validating the RAO with experimental data, the simulation helped in extending the scenarios. Figure 4 depicts the process according to the algorithm. Figure 4(a) indicates (stage 1 in the algorithm) the vector of cumulative variance for a transition response of roll motion in wave significant height Hs=2.5 from 0° wave direction to 30°. At this point, the aim is to find the highest slope in the cumulative variance diagram. Figures 4(b) and 4(c) indicate that the highest value belongs to the difference between the variance of segments 5 and 4, and ultimately, Figure 4(d) denotes the maxima, where the buffer window must be split at that time step.

The respective prediction results for the above roll response are depicted in Figure 5. As can be visually observed, the signal has experienced a regime change at N=20, where the prediction with the second batch of data from 20s to 40s shows a better result. While it may be proposed that rather than splitting the data in a buffer window, the SARIMA model could have been constructed based on the recent statistically significant lags found in sample PACF. However, the confidence interval (CI) directly depends on the sample size statistics in the buffer window for 95% confidence level (Tangirala, 2018). The bigger is N, the tighter is the CI. Therefore, compared to the 40s window, several recent significant lags propagate in the modelling in shorter window sizes. In addition, the shorter range of data in segments 1s to 20s also influences sample mean and standard deviation. Figure 6 indicates the sample PACF for 20 lags of window length 40s and 25s (second batch of data), where CI bounds decreased and considering the addressed influences, different lags contributed to the statistically significant lags in sample PACFs. As such, the window for a new regime highly depends on different lags for modelling, while including the farther lags misleads modelling.

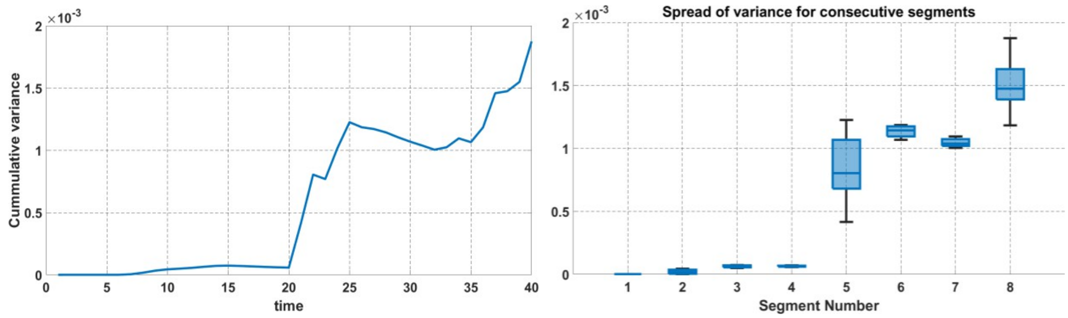

Figure 4(a): Cumulative variance for buffer window size 40s (left) and Figure **4(b)** the spread of variance from difference between consecutive segments (right)

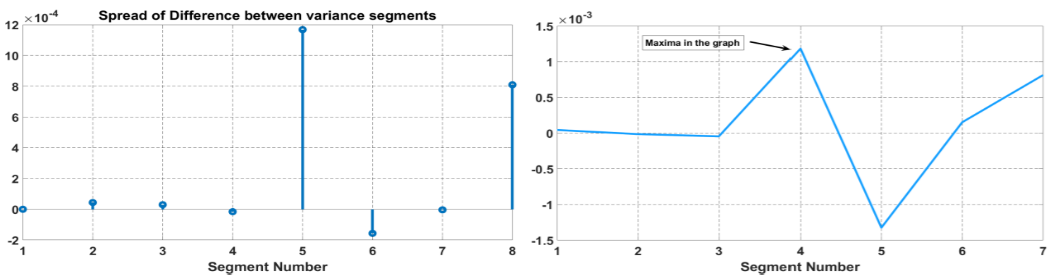

Figure 4(c): Indication of variance difference between consecutive segments (left) Figure **4(d)** and derivation of variance differences which indicates the time step for splitting the buffer window (right)

The same logic can be further generalized for all linear and nonlinear regression models too. In fact, the first batch of data has nothing statistically important to contribute in constructing the regression model, and may even play a negative role.

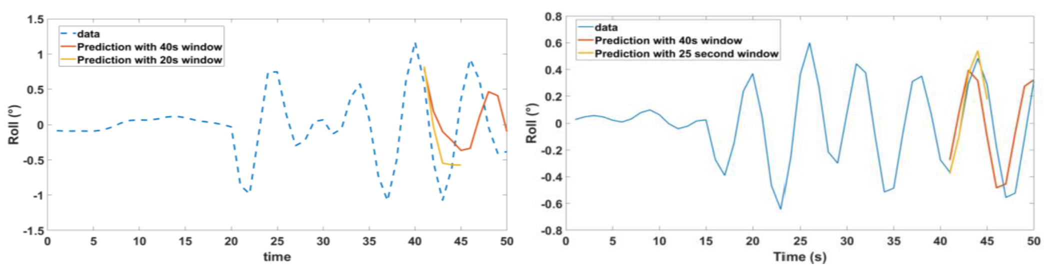

Figure 5: Prediction results for both window sizes with RMSE= 0.0662 for window size 40 and 0.0541 for window size 20 (left). Prediction results for window size 40s and 25s with RMSE=0.0215 and 0.0065 respectively (right)

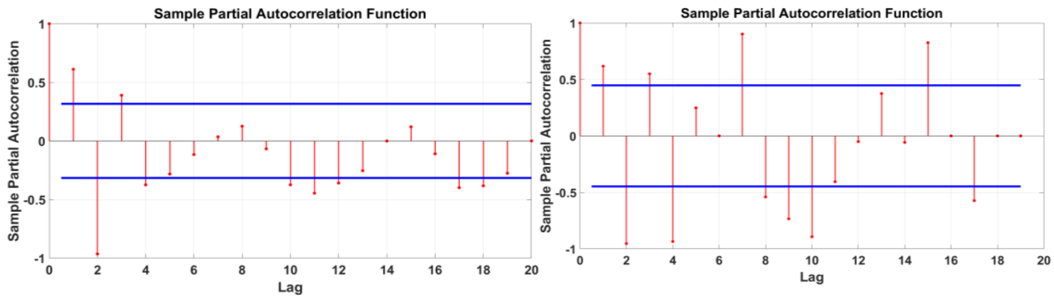

Figure 6: Sample PACF plot for window size 40s (left) and 20s (right) pertained to Figure 5 left

5 Conclusion

The current study investigated how inherent dynamics in finite history buffer windows of time series can affect estimation modelling. In this regard, the time series responses of a semisubmersible platform have been studied. The transitory scenario between wave-induced responses direction demonstrated that the latest regime of time series must only be included in modelling for prediction. An innovative algorithm has been introduced to identify significant regime change in the buffer window using a derivation of cumulative variance in a grid. Results showed that the algorithm works efficiently and improves the response prediction at the cost of receding the horizon. To test the idea, responses from stationary vessels have been employed, with application of the given mechanism to the dynamics of ship response to be the topic of future studies. The proposed workflow reduces human interference while reducing prediction errors and increases the autonomy for any areas dealing with outputs of the time series record.

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