Incorporation of Ship Motion Prediction into Active Heave Compensation for Offshore Crane Operation

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***Abstract*—Ship motion has significant effects on certain maritime applications like offshore crane operation. In particular, the vertical heave motion is undesired for safe transferring, accurate positioning and subsea installation. In recent years, there have been growing tasks in utilizing ship motion data for online operation improvement based on the development of virtual simulation environment, digital twin and automatic remote-control systems. How to effectively utilize ship motion data is fundamental to these tasks. This paper presents a neural-network-based method to predict ship motion and use the prediction to improve active heave compensation (AHC) of offshore crane operation. A virtual prototype of the lifting system is developed including implementation of the proposed AHC algorithms. A multilayer perceptron model is trained to predict ship motion. By feeding the future motion of the ship into the controller, the lifting performance can be tested in the virtual environment and the result can be applied to its counterpart. Through simulation with measured sensor data, the proposed method is verified efficient in improving crane operation performance.**

***Index Terms*—hybrid simulation, neural network, active heave compensation**

I. Introduction

In the last few decades, physics-based modelling has been extensively used for simulation and analysis of dynamic engineering systems. On one hand, such model-based approaches require comprehensive knowledge of the physical system of interest. Moreover, it's often necessary to estimate the model parameters through observations and measurements in physical experiments. This class of problems is referred to inverse modelling and inverse problems in the literature. On the other hand, efficient simulation of complex multi-domain systems is one of the major challenges with respects to computational cost and model interface across various domains. Recently, significant efforts have been made to develop tool-independent interface standard for complex cyber-physical systems through model exchange and co-simulation [1]. It has been proved in many industrial applications that increments of simulation efficiency can be obtained with small degrees of accuracy loss.

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Compared with physics-based modeling, data-driven approaches rely solely on measured data to tackle the aforementioned problems. Data-driven simulation is particularly effective for analyzing complex non-linear systems whose behaviour and structure are difficult to represent mathematically. For applications within maritime domain like offshore crane operation, the random ship motion is extremely important, but efficient modelling and simulation of the ship response in the time domain is challenging. The performances of pure data-driven approaches, however, are highly dependent on the size and quality of the available data. Such data in the maritime applications are often inadequate and rarely used for such purposes. Therefore, hybrid simulation is needed to bridge the gap between the two modeling approaches [2].

The Mechatronics Lab at Norwegian University of Science and Technology in Aalesund has been investigating intelligent control and virtual prototyping development for demanding maritime operations for many years [3] [4]. One of their ongoing projects aims to develop digital twins of maritime systems. It will be not only an open virtual simulator as the next generation of marine industrial infrastructure for overall system design, allowing configuration of systems and verification of operational performance, but also integrated tools for early warning, life cycle service support, and system behaviour prediction.

In this paper, we present an application of such a digital twin system to offshore crane operation, specifically, for active heave compensation (AHC). In order to eliminate environmental perturbations, we propose to feed the measured ship motion into the the digital twin system to verify the effects of active compensation. As far as the performance is in the acceptable range, the control command could be further fed into the real counterpart. The contributions of the paper include: (1) decoupling and devitalizing crane operation system with the ship dynamics; and (2) applying future ship motion to improve the control performances of compensation.

The rest of the paper is organized as follows. In Section II, a neural network (NN) model is employed to produce the predicted motion of the ship with high accuracy as well as high efficiency using motion reference unit (MRU) sensor data. In Section III, an AHC approach with the estimated ship motion as input is briefly described. Section IV presents the modeling of the physical system with implementation of the proposed AHC algorithms. Section V presents the simulation results and discussions. And finally, Section VI concludes the paper.

II. Coupling of Ship Motions for Active Heave Compensation

How to obtain the motions of the ship dynamically is of great importance for safe and effective maritime operations. The majority of past work has been focusing on formulations in the frequency domain. In [5], Cibicik et. al. presented the derivation of combined equations of motion for a ship and a deck crane using screw theory. The ship motion is modeled by the well-established method where force response amplitude operators (RAOs) are used to calculate the wave forces on the ship and the waves are described with the JONSWAP wave spectrum. The method considers the reaction forces of the crane to the ship and is used to study the effect of the roll and pitch compensation platform in numerical simulations. Model-based simulation is great, however, ship behavior in waves is complex and nonlinear, and requires extensive model test for tuning the model coefficients.

Furthermore, using processed measured sensor data in control always introduces a signal delay with respect to the true wave motions. The dynamic behaviors of the ship, the lifting equipment and the suspended load are subject to random disturbances from the external environment, which might result in propagation of control errors. Therefore, we see the motivations for research as first, to propose a hybrid simulation structure for demanding maritime operations with consideration of real-time ship motion; second, to reduce the consequential effects of sensor signal latency and external disturbances by using prediction in the control loop; third, to identify the amplitude peaks of relative heave motion where the AHC system might fail, so that warning and adaptions can be provided to the controller. The structure of the hybrid simulation system is shown in Fig. 1.

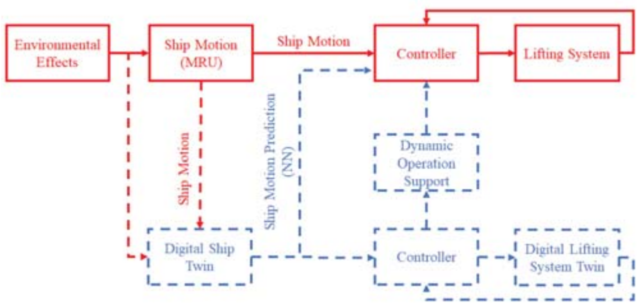

Fig. 1. Model structure diagram of hybrid simulation of offshore operation using ship motion prediction.

AHC aims to stabilize the suspended payload during operation to minimize the effects of ship movements. A flexible approach for heave compensation in offshore crane operation is proposed and presented in [4]. It relies on solving the kinematic structure of the manipulator, for example, the crane. To keep the suspended load in position, the crane joints move inversely to compensate the motion of the ship, therefore stabilize the crane tip position. In the case study, the Palfinger crane consists of four joints as shown in Fig. 2. The joint velocity for the crane tip to remain stabilized can be calculated by (1). Accordingly, the velocities of the joint actuators can be derived. This approach is able to compensate the tip motions in three degree of freedoms depending on the kinematic structure of the manipulator. Considering only the vertical heave motion, compensation for the load position can be done by actively spooling in and out the wire through the winch drum. Limitations with heave compensated using winch include the response characteristics of the actuation system and wire related issues.

Fig. 2. The Palfinger crane in lifting operation.

$$\dot{\theta} = J^{-1}\dot{q} \tag{1}$$

where J is the velocity Jacobian, $\dot{\theta}$ denotes the joint velocity and $\dot{q}$ denotes the crane tip velocity.

For the suspended payload, a spring-damper system is assumed for the relative motion between the crane tip and the load. Since the load position cannot be measured directly, the load speed is estimated from the winch speed. The estimation is suitable as the oscillations of the wire are expected to be small. Using classic PID-controller, the reference speed for the crane and the winch controller to compensate the heave motion is given by the inversion of the heave speed. In Section V, the simulation results of using delay sensor data and predicted heave motion based on the aforementioned two AHC approaches are presented.

III. Ship Motion Prediction

Several prediction techniques have been proposed for ship motion predictions [6]–[10]. A comparison of these prediction methods are summarized in [11]. The main weighting factor for selecting a prediction method for such applications is its ability of producing real-time predictions beyond 5 seconds up to 60 seconds ahead of measurements. Vessel response predictions more than 30 seconds ahead usually cannot be improved

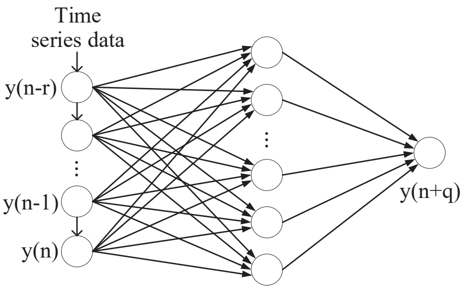

Fig. 3. Multilayer perceptron model for time series prediction.

by conditioning the prediction on measured data alone [12]. In general, statistical algorithms tends to be more computational expensive compare to NN algorithms. Online, offline and hybrid learning procedures are the most often used strategies in conjunction with NN structures. Different strategies affect the ability of generalization as well as prediction accuracy. Since the learning strategies of different NN algorithms produce similar results, evaluation of the performance of different prediction algorithms is not the focal point of this paper. In the case study, we used multilayer perceptron (MLP) network to predict the future motion the ship.

Fig. 3 depicts the structure of the predictive model for time series ship motion prediction. It consists of an input layer with r neurons, several hidden layers and an output layer with a sole output neuron. This implies the inputs are from the r steps of time series data from sensors, whereas the output is the predicted motion output in q time ahead. By using the backpropagation technology, the weight of the MLP NN is adjusted to minimize the error between the sensor data and the MLP NN output. In general, 80% of data will be used for training and the rest can be used for testing.

IV. Case Study: Kinematics and Dynamics of the Crane Lifting System

The kinematics analysis of the Palfinger crane is derived using the Denavit-Hartenberg method [13] which is commonly used in robotics. A good alternative for kinematics and dynamics derivation is based on the screw theory [14]. The line sketch of the reference frames and the link dimensions for the Palfinger crane are shown in Fig. 4. The last telescope link which consists of 8 parts is consider as one prismatic joint. The velocity Jacobian matrix for the crane tip frame to the base frame is given by (2). The variables s_1, c_1, s_{23}, c_{23} denote $sin(\theta 1)$, $cos(\theta 1)$, $sin(\theta 2 + \theta 3)$, $sin(\theta 2 + \theta 3)$ respectively.

Dynamics of the crane is derived using the Lagrange's equations by analysing the energy properties of the system. Lagrange's equations provide an elegant formulation of the dynamics of a robot-like multi-body system, because it reduces the equations needed to describe the motion of such systems using generalized coordinates instead of every single body with mass and inertia. These equations are particularly convenient for implementation using energy-based modeling methods such as bond graphs. The equation of motion of the multi-body system can be formulated by (3). For the controllers, we use classic PID-control for the actuator's output of the crane and winch. The coefficient to the maximum output force or torque, depending on the actuators.

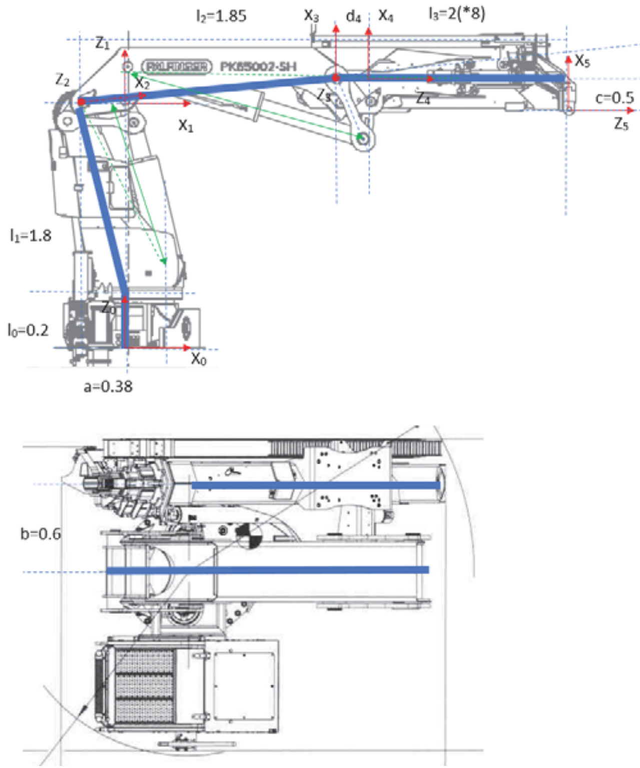

Fig. 4. The kinematics structure of the Palfinger crane.

$$M(\theta)\ddot{\theta} + C(\theta, \dot{\theta})\dot{\theta} + N(\theta, \dot{\theta}) = \tau \tag{3}$$

where $M(\theta)$ is the generalized inertia matrix, $C(\theta, \dot{\theta})$ denotes the Coriolis matrix which gives the Coriolis and centrifugal force terms in the equations of motion, $N(\theta, \dot{\theta})$ is the gravity terms and τ is the vector of actuator torques.

V. Simulation Results

We obtained data measured by MRU mounted at the crane tip for prediction. The sampling rate of the sensor data is recorded at every 0.03 second. An MLP NN was built with

$$J = \begin{bmatrix} -s_1(-a - cc_{23} + l_2c_2 + s_{23}(l_3 + d_4)) - bc_1 & c_1(-l_2s_2 + (l_3 + d_4)c_{23} + cs_{23}) & c_1((l_3 + d_4)s_{23} + cs_{23}) & c_1s_{23} \\ c_1(-a - cc_{23} + l_2c_2 + s_{23}(l_3 + d_4)) - bs_1 & s_1(-l_2s_2 + (l_3 + d_4)c_{23} + cs_{23}) & s_1((l_3 + d_4)s_{23} + cs_{23}) & s_1s_{23} \\ 0 & l_2c_2 + (l_3 + d_4)s_{23} - cc_{23}) & (l_3 + d_4)s_{23} - cs_{23} & -c_{23} \end{bmatrix} \tag{2}$$

TABLE I
RMSEs OF PREDICTED SHIP MOTION IN DIFFERENT TIME STEPS

Prediction Time [s]	RMSE [m/s]
1	0.042
2	0.094
3	0.105
5	0.149
8	0.176
10	0.217

$r = 20$ and trained for a variety of horizon $p \in [1, 350]$. The prediction of the heave velocity with 35 steps (approximate 1 second) ahead of measurement is shown in Fig. 5. More results show that the performance of the prediction algorithms beyond 5 seconds is not good enough and the result cannot be used as control input. The root-mean-square-errors (RMSEs) of the predictions with different time steps are shown in Table I. Since the overall delays in such systems are usually below 2 seconds, this is not a problem. The prediction of the heave velocity with 350 steps (i.e., 10 seconds) ahead of measurement is shown in Fig. 6. As can be seen, the prediction performed poorly between 10 second to 30 second and 110 second to 120 second. In these time periods the amplitude of the ship motion is small. As the purpose for longer time prediction is to detect the extreme motion amplitudes where the system operation failure is likely to happen, this is not a major concern.

Typical MRU signal latency is about 9 milliseconds plus the transmission delay. Simulation of the crane operation is implemented in the digital twin ship simulator as shown in Fig. 7. The simulation scenario is defined as: simulation starts with the crane at a fixed position at the starboard side, AHC using the crane joints activated from 20 seconds to 60 seconds, and AHC using the winch activated from 60 seconds to 120 seconds. The initial crane tip position in the vertical direction is 7.37 meters above the center of gravity of the ship. The default wire length is 5 meters from the crane tip. Accordingly, the initial load position is set at 2.37 meters above the center of gravity of the ship.

Fig. 8 shows the simulated crane tip position in vertical direction compared with the MRU sensor data. As can be seen the simulation result matches with the measurement. The overall delay between the measured signal and the control input is set to 0.5 second [8]. The load position using MRU sensor data with 0.5 second delay and using predictions with 1 second ahead of measurement is shown in Fig. 9. The result clearly shows that without AHC the peak value of the relative load motion is about 2.1 meters. AHC using the MRU sensor data with 0.5 second delay to the controller reduces the peak value to 0.8 meter. AHC using predictions overcome the delays and the peak value of the relative load motion is about 0.13 meter.

As mentioned, the results with longer time predictions cannot be used as control input. The simulation results of the load position using predictions with 5 and 10 seconds ahead of measurement are shown in Fig. 10. The variations of the load displacement are up to 0.27 and 0.38 meter respectively. However, simulation with longer time predictions is useful to detect the extreme values of variation.

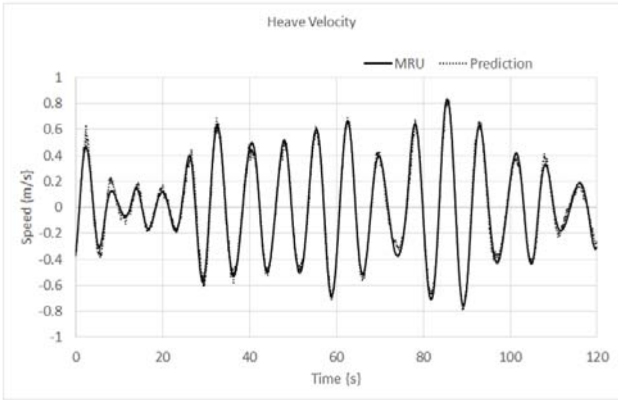

Fig. 5. Predictions of the heave velocity with 1s time ahead of measured data.

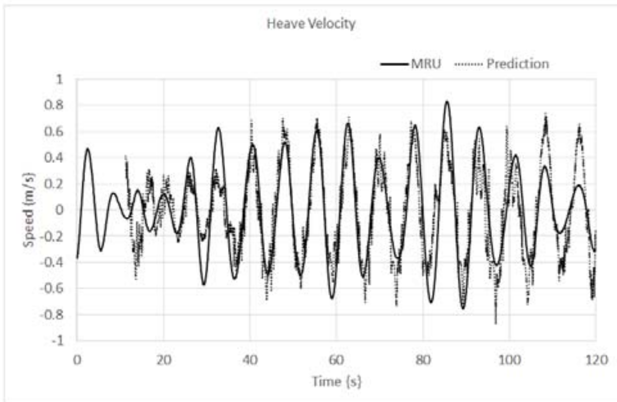

Fig. 6. Predictions of the heave velocity with 10s time ahead of measured data.

VI. CONCLUSIONS AND FUTURE WORK

In this paper, we presented an application of utilizing the prediction of ship heave motion to offshore crane operation. The approach successfully decoupled the ship dynamics in simulation using only measured MRU sensor data to predict the ship motion for crane AHC control. Using the predicted data for control helps to overcome the signal delay of the measured sensor data. An MLP NN model is utilized in this paper for motion prediction. We take the MRU data as the input for the MLP model to predict the heave velocity ahead of the measured data from 1 second up to 10 seconds. The results show increased RMSE with the growth of prediction time.

In the case study, the dynamic model of the operation system is developed, which consists of a four-joints crane, a winch and a suspended payload. AHC using the crane and the winch to compensate the crane tip and load motion is

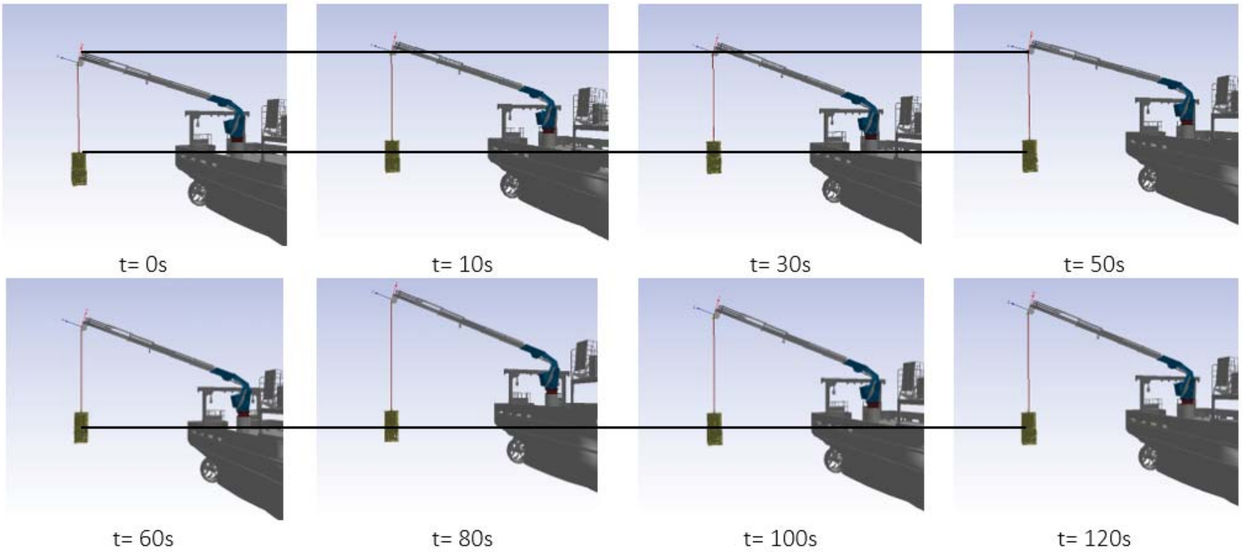

Fig. 7. 3D visualization of the Palfinger crane operation. Time $0 \sim 60s$: AHC using crane; $60s \sim 120s$: AHC using winch.

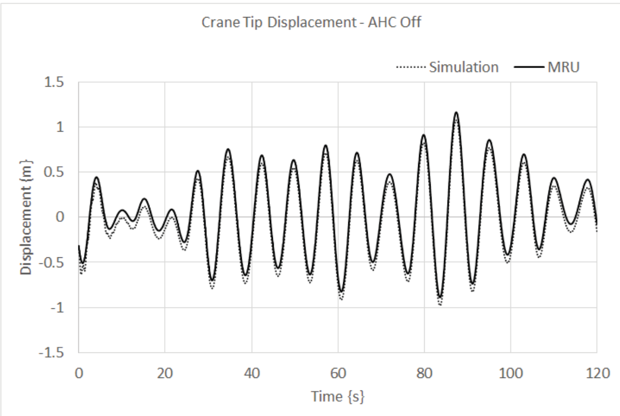

Fig. 8. Crane tip position when AHC is off.

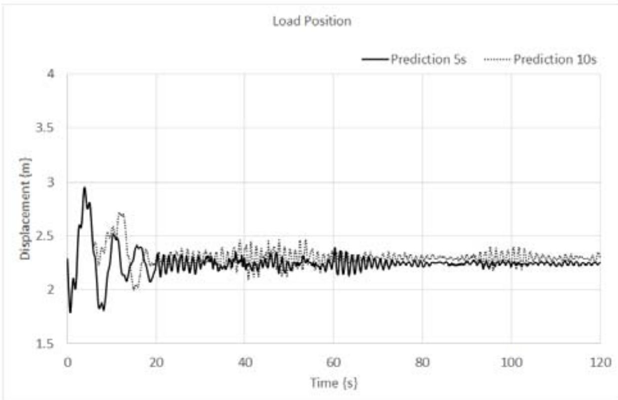

Fig. 10. Load position using longer time predictions of ship heave motion in AHC operation.

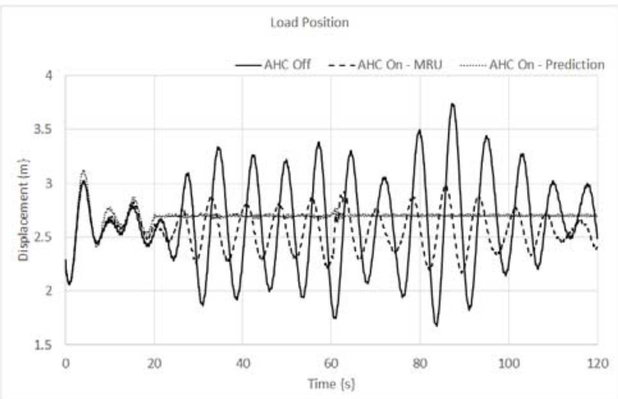

Fig. 9. Load position using delayed and predicted ship heave motion in AHC operation.

implemented based on the analysis of the system's kinematic structure. The effectiveness and performance are evaluated by simulation and measurement. It is shown that using ship motion prediction in the control algorithm improves the AHC performance. Longer time predictions can also provide on-board support and early warning to prevent system failure. In order to do this, predictions using combination of sensor data and real-time dynamic models of wave and ship response is needed. As part of the future work regarding ship motion prediction, more sensor data can be utilized such as weather forecast, radar and wind sensors that are already available on ships. These can be used to generate time series of wave spectrum and combined with a ship response model.

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