Physics-data cooperative ship motion prediction with onboard wave radar for safe operations

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Abstract*—The advancement of sensing technologies brings digitalization into the field of offshore operations. Especially, practitioners have paid attention to ensuring operational safety by predicting ship motion with motion sensors and onboard wave radars. This study proposes a novel physics-data cooperative approach for on-site ship motion prediction with wave radars. First, the proposed approach makes a stochastic ship motion prediction by using a physics-based ship model. Such a physics-based approach is widely popular, however, it requires extensive effort in calibrating a whole system to achieve good performance. To improve its performance, this study employs a linear regression model to map physics-based prediction into true ship motion. The coefficients of the regression model are determined in a data-driven manner. A primary challenge of such a cooperative approach is the imbalance of datasets dominated by samples with small motions. To improve the performance for samples with large motions, undersampling is a key element in the proposed approach. A large-scale validation study was performed by employing a 33.9m research vessel with a commercial virtual wave-radar system on a navigational X-band radar. 104 samples were collected for developing and testing the cooperative approach. Data-driven support notably improved the performance of physics-based prediction. Undersampling was found to be effective when roll motion is large. Thus, this study firstly reports such a physics-data cooperative approach with a large-scale validation study.

***Index Terms*—wave radar, ship motion prediction, hybrid model**

I. Introduction

THE development of sensing technologies has brought benefits of digitalization and informatization to a broad range of industries. Ships in the offshore industry are no exception to this trend. They could be viewed as a large body of a collection of sensors and electronics providing real-time data, such as ship motions, navigation, and sea states. For researchers both in electronics and maritime, this perspective has gained much attention [1]. Ships have played a key role in diverse offshore operations such as installing offshore wind turbines [2] and offshore helicopter landing [3]. To avoid fatal consequences that marine accidents lead to, the industry has devoted much effort to ensuring the safety of such onboard operations by using sensors for decision makings [4].

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Fig. 1: A snapshot of an example operation. Excessive ship motion leads to damaging onboard equipment and compromising the safety of personnel.

In particular, ship's wave-frequency motions in pitch, roll, and heave directions pose a big challenge to safe onboard operations. When ships are doing construction and loading works, they activate Dynamic Positioning (DP) system to keep their horizontal position and heading by using thrusters. However, ships easily move in the heave, roll, and pitch directions during DP operations. Fig. 1 shows a snapshot of an example crane operation, conducted by the research vessel Gunnerus, where ship motion prediction is of great importance for ensuring safety. Operations must be stopped when excessive motions are expected in the future. Otherwise, onboard personnel and equipment could be damaged. However, operations also need to keep being conducted as much as possible for minimizing the operation schedule. Such decision making needs to be made on-site during operations. Hence, to further deliver benefits of advanced sensing and electronics into safe offshore operations, it has been a primary agenda for the offshore industry to develop a ship motion predictor, which works accurately on-site, using onboard sensors.

Predicting a future ship motion based on a time history of ship motions has been an economically-feasible approach only with traditional ship motion sensors. State-of-the-art machine learning algorithms were employed to extract time-history features [4], however, it does not make an accurate prediction if sea states change. To obtain more information about sea states in a more explicit way, Schirmann et al. [5] developed a data-driven ship motion predictor based on the weather forecast. It would be practical for planning sea routes avoiding excessive ship motions, however, their approach does not provide an on-site prediction since the spatio-temporal resolution of the weather forecast is highly limited.

To overcome these challenges, onboard wave radars seem to be a promising on-site data source. They directly provide onsite measurements of sea states surrounding a ship by taking clutter images of the sea surface and processing them. Due to the fact that they are expensive facilities that require calibration frequently, their applications have been rather limited. However, recently, it is becoming more feasible thanks to virtual wave radars that can be virtually installed on existing X-band radars for navigation purposes without physically installing new radars. Moreover, the automatic calibration [6] using external reference data makes wave radars a more attractive and feasible solution to the industry. Nevertheless, to the authors' best knowledge, only limited research and validation work have been conducted for predicting ship motion based on on-site wave-radar measurements so far. Next Ocean [7] and Futurewaves [8] are companies providing a commercial ship motion predictor based on wave-data measurements. Some research projects have been also reported [9]–[14]. They made deterministic motion predictions up to a-few-minute future by using physics ship dynamic models. They reported a great performance, however, extensive effort has been paid to designing dedicated models and experiments. Physics-based approaches offer more reliable and explainable ship motion prediction than black-box models. However, some researchers reported that it was challenging to achieve a good performance only by relying on such open-loop estimation when transferring between wave information and ship motion [5], [15] due to uncertainties in measurements and physics-based models. To overcome this challenge, this study proposes a novel physics-data cooperative approach for ship motion prediction with a large-scale validation study. In this study, we conducted a large-scale experiment to investigate the necessity and possibility of making a synergy of physics knowledge and data. The proposed approach makes a stochastic ship motion prediction from two-dimensional wave spectrum observed by a commercial virtual wave-radar system, which is installed on a conventional navigation X-band radar. A physics-based ship response model delivers a foundation for prediction. Data-driven linear regression models map such physics-based prediction into true values. Hence, this study employs a physics knowledge as a foundation while calibrating its performance in a data-driven manner. Moreover, we focus on a practical challenge in data-driven calibration is the imbalance of datasets where large ship motion is rarely observed. This study introduces the undersampling technique which remedies such imbalance of a dataset for enhancing prediction performance for cases with large ship motions.

In a validation study of this work, a 33.9m Research Vessel (R/V) Gunnerus was employed for one year. She was equipped with the Miros *Wavex* [16] that is a commercial virtual wave radar on the conventional X-band radar for navigation purposes. Along the west coast of Norway, during DP operations, 104 samples were collected with two-dimensional wave spectrum measured by *Wavex* and five-minute time histories of pitch, roll, and heave motions right after the wave-radar measurement. In the case study, the data-driven calibration notably improved prediction performance of the physics-based open-loop estimation. The present undersampling was effective in enhancing prediction performance for samples with large responses when predicting roll motions. Contributions of this article are summarised as follows:

- Proposing a novel physics-data cooperative approach of on-site stochastic prediction of ship motion, composed of a commercial virtual wave radar, physics-based model, data resampling, and data-driven calibration.
- Conducting a large-scale validation study of such an on-site ship motion prediction for the first time.

II. Related works

For ensuring operational safety, ship motion prediction has gathered significant attention for years. In this section, previous works will be briefly revisited to clarify the contribution of this work. They are grouped into two categories: approaches without/with using onboard wave radars.

A. Approaches without using wave radars

This category has been a majority since it offers the most economically-feasible solution without installing onboard wave radars. They predict a short-term ship motion by analyzing time series of past ship motion. Traditionally, physics-based [17] and statistical approaches [18] are known. Thanks to the recent advancement of machine-learning (ML) technologies, ML models opened a new era of data-driven models in this category. In particular, the Long Short-Term Memory (LSTM) [4], [19] is becoming the gold standard, which is powerful in recognizing time-series features. On the other hand, researchers are also aware of the fact that wave data are important for ship motion prediction. [20] built LSTM models for predicting motions of a semi-submersible in an experiment tank where wave probes were installed. They reported that the prediction performance was 10-15% better with wave data than that without wave data. In addition, this category relying on past ship motion can not deal with a change of sea states. To be more informed of wave data, [5] employed wave forecast to predict ship motion. Their approach would be helpful for planning sea routes, however, it would not be applied to onboard decision makings since wave forecast has a low spatiotemporal resolution.

B. Approaches using wave radars

Wave radars provide on-site observation of waves surrounding ships. It is believed that it plays a key role in a future framework of onboard decision support [21]. Real-world case studies have been performed in several research projects such as CASH [9], ESMF [10], [11], and OWME [12], [13] projects. In these projects, physics-based transfer functions map wave-radar observations into ship motions. It requires extensive effort in developing accurate physics-based ship response models. However, in real-life applications, as reported in [5], it is known that it is time/effort-consuming

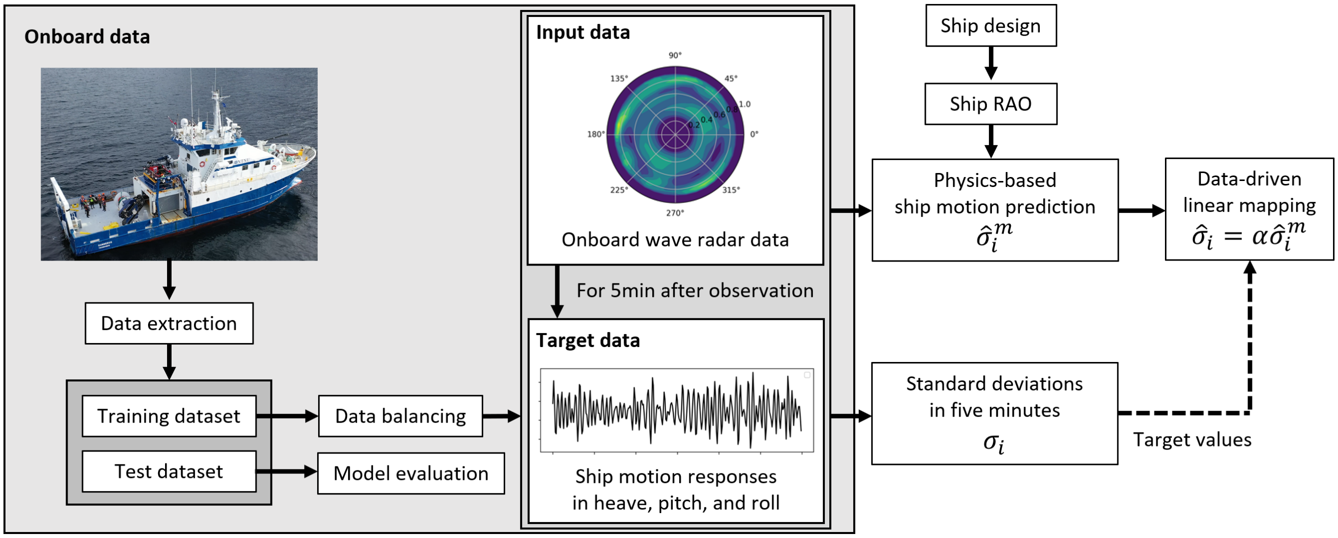


Fig. 2: A schematic overview of the proposed approach.

to achieve a good performance solely relying on the physics-based model. On the contrary, in [22], neural networks were built such that they map a wave-radar observation into ship motion in a data-driven manner instead of building physics-based models. They validated their work with simulation experiments, however, it is expected that we face challenges in real-life applications. A primary challenge would be the fact that real-life datasets are highly imbalanced. Thereby, pure black-box models fully relying on data would be hardly accepted due to hurdles in training efficiency, reliability, and interpretability. Hence, both physics-based and data-driven models would face practical challenges. In this study, we present data-driven support for the performance of the physics-based mapping from wave-radar observation into ship motion.

III. Methodology

A. Overview

A schematic overview of the proposed approach is shown in Fig. 2. A dataset is constructed by collecting measurements from the onboard wave radar and ship motion sensors. Taking clutter images of the sea surface, the wave radar outputs a two-dimensional wave spectrum, which is a matrix of wave energy for different wave frequencies and directions. Given that this study employs a commercial virtual wave-radar system [16], this section does not explain their technology in detail. In this study, a target of prediction is a standard deviation of ship motions σ_i, which has been used for representing how harsh ship motion is [5]. This study assumes wind and current forces have marginal impacts on this value. First, raw data are pre-processed. In this step, from long-history data, we extract samples composed of two-dimensional wave spectrum and ship motion, which satisfy criteria for data extraction. Extracted samples are grouped into training and test datasets. The test dataset is used not for model development but only for model evaluation. Subsequently, data balancing is performed to remedy a negative impact of having a poorly-balanced training dataset on the prediction performance. However, it would be the scope of our future work since this study is a preliminary work for validating a physics-data cooperative approach with a large-scale experiment. By using a physics-based ship linear response model, standard deviations of heave, pitch, and roll motions $\hat{\sigma}_i^m$ are predicted. A suffix i in variables represents the variable is defined for the ith Degree of Freedom (DoF) of the ship motion; namely, $i = 3$, 4, and 5 are for the heave, pitch, and roll motions, respectively. In this study, such physics-based predictions provide a baseline estimation. In the case study, true values and physics-based predictions showed a qualitative agreement, however, they had room to be calibrated. Physics-based prediction is an open-loop estimation, thereby, it accumulates errors coming from measurements, a physics model, and nonlinear ship dynamics. It takes much effort to identify multiple sources of errors and calibrate all the components properly. Moreover, it seems difficult to interfere with a data-processing system of commercial wave radars with upcoming data. Thereby, in this study, we develop a simple linear-mapping function of physics-based prediction into true values to calibrate such errors since it was found to be effective in the training dataset in the case study. Target values σ_i are given by history ship motion in the collected dataset. Once the linear function is estimated, it makes physics-data cooperative prediction for a new sample in the test dataset.

B. Data extraction

A raw onboard dataset gives a long time history of ship motion and two-dimensional wave spectrum taken by a virtual wave radar. The radar was not always used for the purpose of monitoring waves but for navigation, thereby, we firstly make combinations of the wave-radar observation and five-minute time series of ship motions right after the observation. Hereinafter, we call these combination samples. We remove samples of which time series have an overlap with that of the previous sample. As we focus on making ship motion prediction during DP operations, samples are further removed if the ship maneuver is not stationary. Samples with a warning of poor accuracy of wave-radar observation are also removed in this step. The remaining samples are eligible for being involved in modeling. Samples are grouped into the training and test datasets. The training dataset is used for model development. The test dataset is used only for model evaluation. When dividing samples into two datasets, they are not shuffled.

C. Data balancing

There exist different approaches to deal with the imbalance in a dataset. In particular, undersampling has been offering a great performance only by removing some samples from the original dataset [23]. Undersampling technique draws a line to group samples in the original dataset into rare and nominal groups. In this study, the 90% percentile of target values in the training dataset is the line dividing two groups. To balance the number of samples in two groups, undersampling technique randomly picks out samples from samples in the nominal group such that the size of the selected samples is equal to that of the rare group. Thus, undersampling improves prediction performance for samples in the rare group. It was implemented in the *resreg* package [24] in Python in this study.

D. Ship motion

The target of the proposed ship motion predictor is the standard deviation of the heave, pitch, and roll motions. This prediction provides stochastic insights of future ship motions for us so that we can make a decision if offshore operations can be conducted with such a sea state during DP operations. In the model training phase, these target values are given as:

$$\sigma_i = \sqrt{\frac{1}{N_t}\sum_{t=1}^{N_t}(\eta_i^t - \overline{\boldsymbol{\eta}}_i)} \tag{1}$$

where $\boldsymbol{\eta}_i = [\eta_i^1, ..., \eta_i^{N_t}]$ is the time history of the ship motion in five minutes after the wave-radar observation, $\overline{\boldsymbol{\eta}}^i$ is its average, and N_t is the length of the time history.

E. Physics-based prediction

Based on the measured two-directional wave spectrum, $\hat{\sigma}_i^m$ is predicted based on the understanding of ship dynamics. Assuming the linear relationship between waves and ship motions, the wave buoy analogy method is popular [15] to relate the energy spectrum of ship motion $S_i(\omega)$ and two-directional wave spectrum as:

$$S_i(\omega) = \int_{-\pi}^{\pi} |\mathrm{RAO}_i(\omega,\theta)|^2 S_w(\omega,\theta)d\theta \tag{2}$$

where ω is the angular frequency, θ is the relative direction of waves with respect to ship's heading, $\mathrm{RAO}_i(\omega,\theta)$ is the Response Amplitude Operator (RAO) of the ship for the i-th direction, and $S_w(\omega,\theta)$ is the directional wave spectrum. Note that the encounter wave frequency is assumed to be identical to the wave frequency since we focus on DP operations. In this study, $S_w(\omega,\theta)$ measured by the wave radar is a discretized 36×32 matrix where it has 36 different wave directions with 10° interval and $N_\omega = 32$ different wave frequencies with 0.01Hz interval from 0Hz to 0.32Hz. Corresponding discretized RAO_i is calculated through a hydrodynamic workbench *ShipX* [25] based on the ship's specifications and geometries. It yields a vector of energy spectrum of ship motion $S_i(\omega)$ in the discretized form. Its zeroth-order moment of m_i is:

$$m_i = \sum_{k=1}^{N_\omega} S_i(\omega) \tag{3}$$

Then, $\hat{\sigma}_i^m = \sqrt{m_i}$ is derived for the heave, pitch, and roll motions.

TABLE I: Specifications of the R/V Gunnerus

Specification	Value
Mass	584t
Breadth middle	9.6m
Length between perpendiculars	33.9m

F. Linear mapping of physics-based prediction

$\hat{\sigma}_i^m = \sqrt{m_i}$ are mapped into the physics-data cooperative prediction by using a linear regression function:

$$\hat{\sigma}_i = \alpha\hat{\sigma}_i^m \tag{4}$$

α is a coefficient of this linear-mapping function. $\hat{\sigma}_i^m$ becomes zero if the wave energy observed by the wave radar is zero. Thereby, the zero intercept of the linear mapping is estimated. It is estimated such that it minimizes Mean Squared Error (MSE) between predicted and true vectors in the training dataset as:

$$\alpha = (\boldsymbol{x}^T\boldsymbol{x})^{-1}\boldsymbol{x}^T\boldsymbol{y} \tag{5}$$

where $\boldsymbol{x} = [\hat{\sigma}_{i,1}^m, ..., \hat{\sigma}_{i,j}^m, ..., \hat{\sigma}_{i,N}^m]$ is the input vector, $\hat{\sigma}_{i,j}^m$ is $\hat{\sigma}_i^m$ for the j-th sample in the training dataset, N is the number of samples in the training dataset, $\boldsymbol{y} = [\sigma_{i,1}, ..., \sigma_{i,j}, ..., \sigma_{i,N}]^T$ is the target vector, and $\sigma_{i,j}$ is σ_i for the j-th sample in the training dataset.

IV. Case Study

To validate the proposed approach in the real-life application, a large-scale case study was performed.

A. Data

1) Data collection: Data collections were carried out from January 2021 to May 2022 by 33.9m-length RV Gunnerus. Her specifications are listed in Tab. I. During DP operation, she employs two azimuth thrusters and one tunnel thruster to maintain her horizontal positions and heading actively under environmental disturbances. During data collection, we sampled ship motion in 1Hz including the following measurements:

- Positions: Latitude and longitude of the ship's position were provided by GPS. Heading in the global coordinate was also measured.

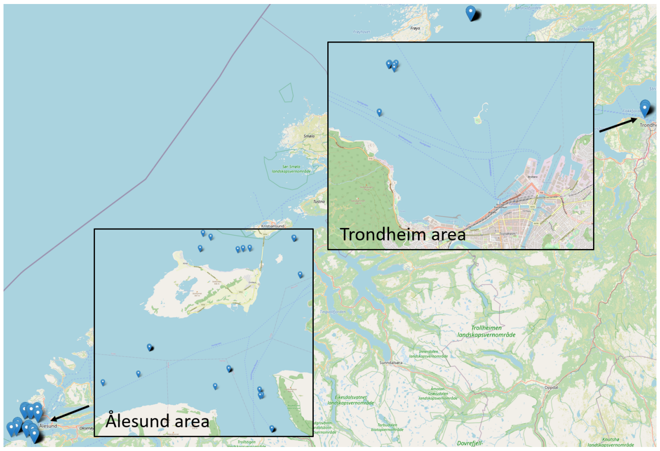


Fig. 3: Locations of 104 samples in the case study. All samples were taken along the west coast of Norway.

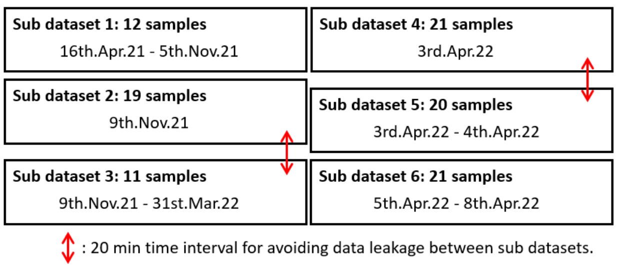


Fig. 4: Sub datasets for the case study.

- Velocities: surge, sway, and yaw velocities were measured.
- Wave-frequency motion: displacements in heave, pitch, and roll were measured.

In addition, onboard measurement of two-dimensional wave spectrum was provided by miros *Wavex* radar system [16]. *Wavex* is a commercial wave radar system virtually installed on the conventional X-band navigation radar. In the case study, it was installed on a Furuno 2xx7 series X-band navigation radar. It enables present work to be easily applied to ships with smaller costs without physically installing a new radar. *Wavex* provides two-directional spectrum based on sea clutter images taken by an X-band radar. It is connected to ship motion sensors and the impact of ship motions on sea clutter images is automatically compensated for.

2) Data extraction: In the collected dataset, only samples that satisfy the following criteria were extracted for the case study.

- **Data quality**: The quality of wave-radar measurements can be degraded due to factors such as wind drops and heavy precipitations. *Wavex* is equipped with automatic data quality control. Samples with unacceptable quality were removed.
- **Surge speed limit**: Samples with surge speed $>$ 2.0 knots were removed since maneuvering operations are not the scope of this case study.
- **Steady heading**: If the heading changes over 15° within five minutes after the wave-radar observation, the samples were removed.
- **Heave motion**: The scope of the case study is the ship motion under wave excitation. If the standard deviation of the five-minute time history of the heave displacement was smaller than 0.025m, the samples were removed.

These criteria yielded 104 samples without overlaps. These samples were taken in the diverse locations as shown in Fig. 3. They were taken from diverse locations mainly off the coast of Trondheim and Ålesund. As shown in Fig. 4, 104 samples were grouped into six sub datasets for the case study. To avoid data leakage between sub datasets, samples in different subsets were taken on different dates or 20-min time intervals were taken between subsets.

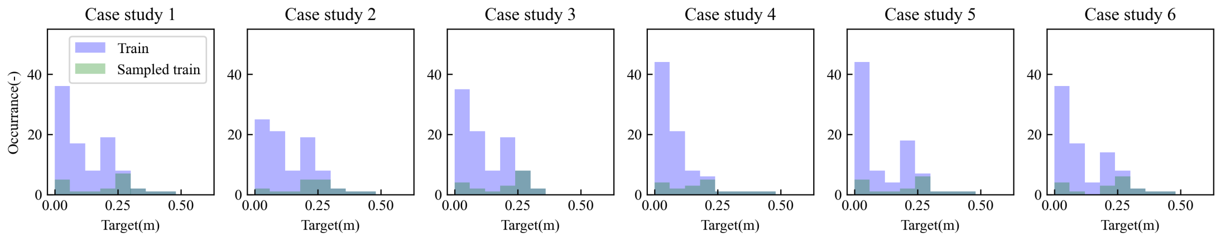
In this section, six case studies from Case Study (CS) 1 to CS6 were conducted. For the CSk, the sub dataset k was employed as a test dataset used only for the model evaluation. The other five sub datasets were used for developing linear mapping functions.

B. Performance evaluation

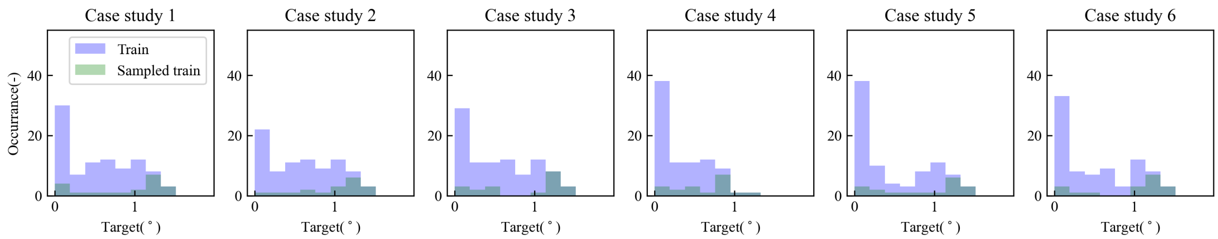
Fig. 5 shows distributions of target values σ_{3-5} in training and under-sampled datasets in six case studies. It is clearly seen that the original training datasets are highly imbalanced in terms of three-direction motions. Ships for offshore operations need a motion prediction over a wide range of motions, however, as shown, it is a challenge that real-life datasets are dominated by small-motion samples since ships mostly operate under the mild sea states for safety reasons. By applying undersampling, as shown in green bars in Fig. 5, such imbalance was notably remedied by removing small-motion samples from the training datasets.

In Fig. 6, scatter plots of true and predicted ship motions in the test dataset in heave, pitch, and roll directions for six case studies are shown. Green, red, and blue dots represent results made by the physics-based response model, its linear mapping with original training datasets, and its linear mapping with under-sampled datasets. The diagonal lines in the figures show true lines where predicted values are equal to true values. If a dot is above the line, prediction is larger than the true value, and vice versa.

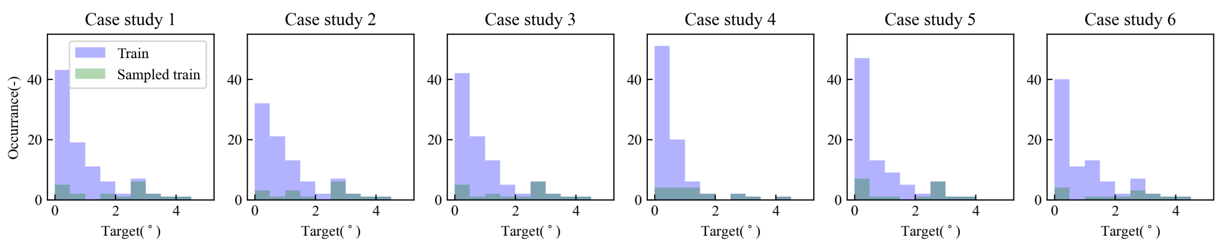
In the heave direction, the physics-based model showed a qualitative agreement with true values in all case studies, however, it was found to be mostly larger than true values. Prediction by the physics-based model is open-loop, thereby, a quantitative agreement was hardly accomplished. On the other hand, with a linear mapping trained with a corresponding training dataset, such error was notably reduced for most samples. In the CS3, the linear mapping worsened the prediction performance of the physics-based model for two samples with motion $\sigma_3 > 0.3$. It is seemingly because the training dataset of the CS3 did not have samples with such large motions. In the pitch direction, the same trend as shown for the heave direction is seen. For both heave and pitch motions, a positive impact of undersampling the training datasets was found to



(a) Heave



(b) Pitch



(c) Roll

Fig. 5: Distributions of target values, which are standard deviations σ_i in the (a) heave, (b) pitch, and (c) roll motions. Blue histograms show distributions in the original training dataset for each case study. Green histograms show that after undersampling was performed.

be marginal. By removing samples with small motions from the training datasets, prediction performance for large motions was slightly improved in return for having a slightly worse performance for small motions.

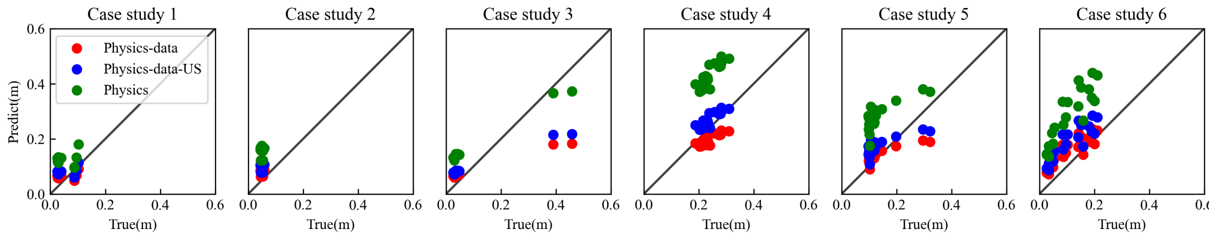
For the roll motion, it seems that the prediction performance of the physics-based model was rather limited although it captured a rough trend of true values. Linear mappings with the original training datasets notably reduced such error only for small motions. For large motion, with the original training datasets, linear mappings of the physics-based predictions underestimated the motion. It is because the original datasets are dominated by small motions, thereby, linear mapping did not efficiently learn the trend for large motions. By undersampling the training dataset, the prediction performance of linear mappings were found to be significantly improved for large motions as shown in the CS3, 4, and 5.

C. Discussion

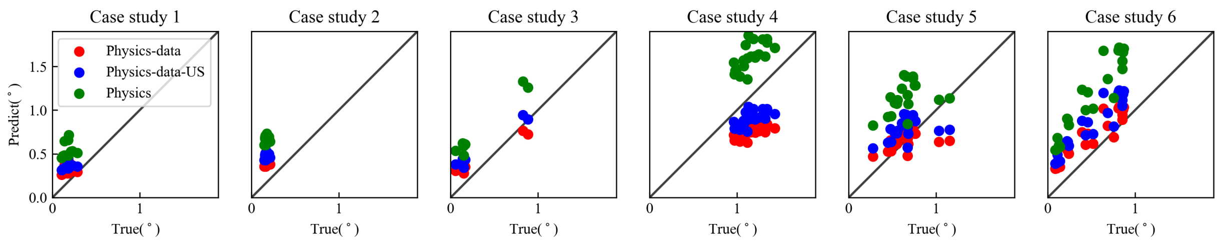
In the case studies, the physics-based prediction mostly overestimated true motions while it captured a qualitative trend of true motions. Performance of the physics-based prediction could be improved by devoting more effort and expertise to carefully conducting measurements and modeling, however, it can be difficult in real-life applications. The present calibration in performance of the physics-based prediction with a simple linear-mapping function was validated to offer one solution to this challenge while data-driven tuning of the whole system requires more effort with directly intervening commercial systems. The linear function is interpretable, thereby, designers could also utilize its estimated coefficient to improve their models and measurement systems.

As discussed, a huge obstacle for pure data-driven models is the fact that real-life datasets have limited samples for large motions. It is hard to ensure reliability of pure data-driven models trained with such imbalanced datasets. Since it is also hard to achieve a good performance with a physics-based model, we need to focus on making a physics-data synergy for developing accurate and reliable models. With a large-scale experiment, this study becomes the first milestone in presenting the idea of such a cooperative approach for on-site ship motion prediction with using virtual wave radars.

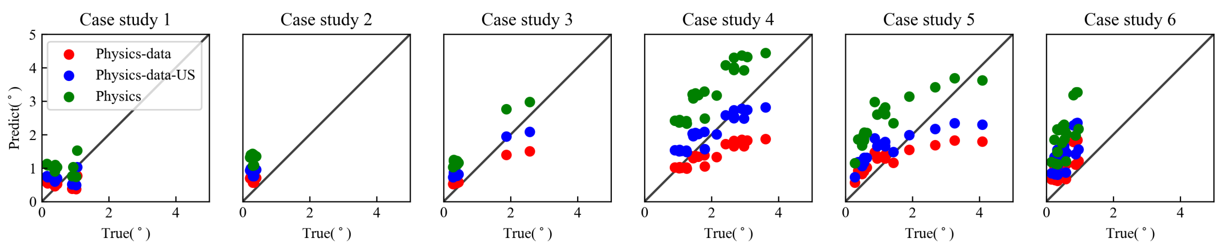
This study proposed a whole package of on-site ship motion



(a) Heave



(b) Pitch



(c) Roll

Fig. 6: True versus predicted values in the (a) heave, (b) pitch, and (c) roll directions in the test datasets for all case studies. (green: Physics) predictions only with the physics-based model. (red: Physics-data) predictions with the physics-based model and its data-driven mapping by using the original training datasets. (blue: Physics-data-US) predictions with the physics-based model and its data-driven mapping by using the UnderSampled (US) training datasets.

prediction, which is composed of virtual wave radar, motion sensors, under sampling, and linear-mapping function. It is a great contribution that this study performed a large-scale validation study for such a package for the first time. However, it is still a preliminary study and the authors plan to act toward further improving each component of the package. In particular, imbalance of real-world datasets needs more attention. In the future work, we might be able to develop an unsupervised-learning model for detecting large motions given that we have limited samples for large motions.

V. Conclusion

For ensuring safe offshore operations during dynamic positioning, this article proposed a novel physics-data cooperative approach of on-site ship motion prediction composed of a virtual wave radar, motion sensors, a physics-based ship motion model, undersampling, and data-driven performance calibration. It predicted a standard deviation of heave, pitch, and roll motions based on two-dimensional wave spectrum observed by an onboard virtual wave radar. To validate the proposed method, we conducted a large-scale experiment by the 33.9m-length research vessel along the west coast of Norway. Such a large-scale case study was conducted for wave-radar-based ship motion prediction for the first time. In the case study, physics-based prediction showed qualitative agreement with true ship motions, however, its simple linear mapping showed a better quantitative agreement. With undersampling technique, samples with small and large motions were well balanced. It contributed to having a better prediction performance for samples with large motions especially for predicting the heave motion. The presented work becomes the first milestone of physics-data cooperative approaches which seem to be a promising direction for dealing with system uncertainties and imbalance of real-life datasets. Although this study presented a validity of on-site ship motion prediction with a virtual wave radar in a physics-data cooperative way, some works remain for our future research. Our primary agenda for future work is to further investigate how to make use of data-driven models while having a physics-based prediction as a prediction foundation.

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