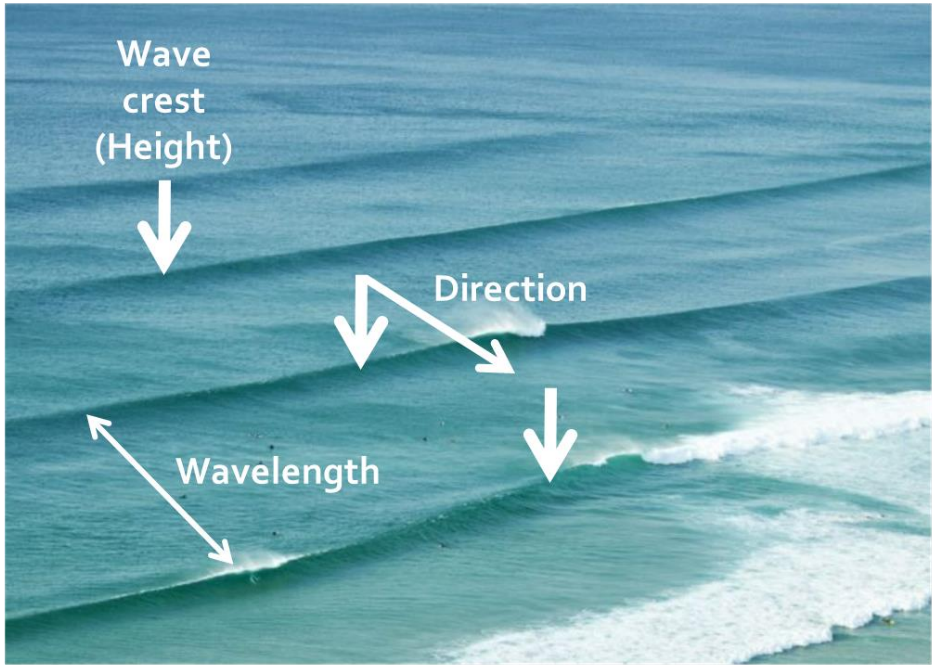
Estimation of wave direction using IMU data from a surface drone

- Manele Ait Habouche
- Jean-Philippe Babau
- Mickaël Kerboeuf
- Goulven Guillou

Context

- USV (Unmanned Surface Vehicle) applications
  - Marine exploration
  - Environmental monitoring
- Wave characteristics
  - Significant wave **height**
  - **Period** between two crests
  - **Direction**
- Objective
  - Navigation
  - Operational safety



Sea state estimation using machine learning

- Traditional methods (wave buoys, wave radars, satellites)
  - High costs [1]
  - Limited spatial resolution [1]
- Data-driven approaches
  - Recent papers (2019 => 2024) [1 – 2, 11 – 12]
  - Wave buoy analogy

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ORIGINAL ARTICLE

Sea state estimation using monitoring data by convolutional neural network (CNN)

Toshiki Kawai[1] · Yasumi Kawamura[2] · Tetsuo Okada[2] · Taiga Mitsuyuki[2] · Xi Chen[2]

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Abstract
In recent years, the size of container ships has become larger, thus requiring a more evident assurance of the hull structural safety. In order to evaluate the structural safety in operation, it is necessary to grasp the encountered sea state. The aim of this study is to estimate the encountered sea state using machine learning from measurement data of ocean-going 14,000TEU container ships. In this paper, as a first step in the study, considerable amounts of virtual sea state data and corresponding ship motion and structural response data are prepared. A convolutional neural network (CNN) is developed using these data to estimate the directional wave spectrum of encountered sea based on the hull responses. The input parameters of the formulated CNN include the spectral values of ship motion and structural response spectrum. The output of the CNN includes the sea state parameters of the Ochi-Hubble spectrum, specifically, significant wave height, modal wave frequency, mean wave direction, kurtosis, and concentration of wave energy directional distribution. It is found from the performance examination that the developed CNN is capable of accurately estimating the sea state parameters, although the level of accuracy decreases when the hull response is low. However, the decrease in accuracy when the hull response is low has a weak influence on the evaluation of the structural response to the estimated sea state.

Keywords Container ship · Convolutional neural network · Ochi-Hubble spectrum · Machine learning · Health monitoring

1 Introduction

In recent years, the sizes of container ships have continued to increase, requiring a more evident assurance of the structural safety of these vessels. Accordingly, it is essential to grasp actual stress history experienced by ship structures to facilitate efficient design and maintenance as well as use it to achieve optimal ship operation. In order to evaluate the structural safety in operation, it is important to accurately estimate the responses of all parts of the structure. Recently, as part of the structural health monitoring system, in which ship motion and structural responses (stresses) are measured by some sensors, has been developed and installed into many ships. However, in the current monitoring system, although it is possible to evaluate the stress responses of representative parts where the sensors are installed, the evaluation of responses from all parts of the ship including non-instrumented locations is not possible. Moreover, it is unrealistic to install sensors on all parts of the hull. To construct a structural safety evaluation system, it is necessary to develop a method that can estimate the structural response of any structural member based on the measurements of representative sensors.

Okada [1] proposed a concept to grasp the directional wave spectrum from the measurement of motion and structural response of the hull structure, and use it for estimate the stress history of any part of the hull structure using corresponding stress response functions. Recently, this concept gained considerable attention because it can be

Toshiki Kawai
kawai-toshiki-vm@ynu.jp
Yasumi Kawamura
kawamura-yasumi-zx@ynu.ac.jp
Tetsuo Okada
okada-t@ynu.ac.jp
Taiga Mitsuyuki
mitsuyuki-taiga-my@ynu.ac.jp
Xi Chen
chin-xi-vr@ynu.ac.jp

1 Graduate School of Engineering, Yokohama National University, Yokohama, Kanagawa 240-8501, Japan
2 Faculty of Engineering, Yokohama National University, Yokohama, Kanagawa 240-8501, Japan

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Wave direction estimation

- All current approaches consider ships
  - Slower response time
  - Large turning radius
  - Drones are more agile => Quick directional changes
- Classification
  - Discrete categories of angles (intervals)
  - Not precise enough
  - More classes are not the solution
- Direction estimation for drones using machine learning
  - Need to collect data to form a dataset
  - Adequate ML model

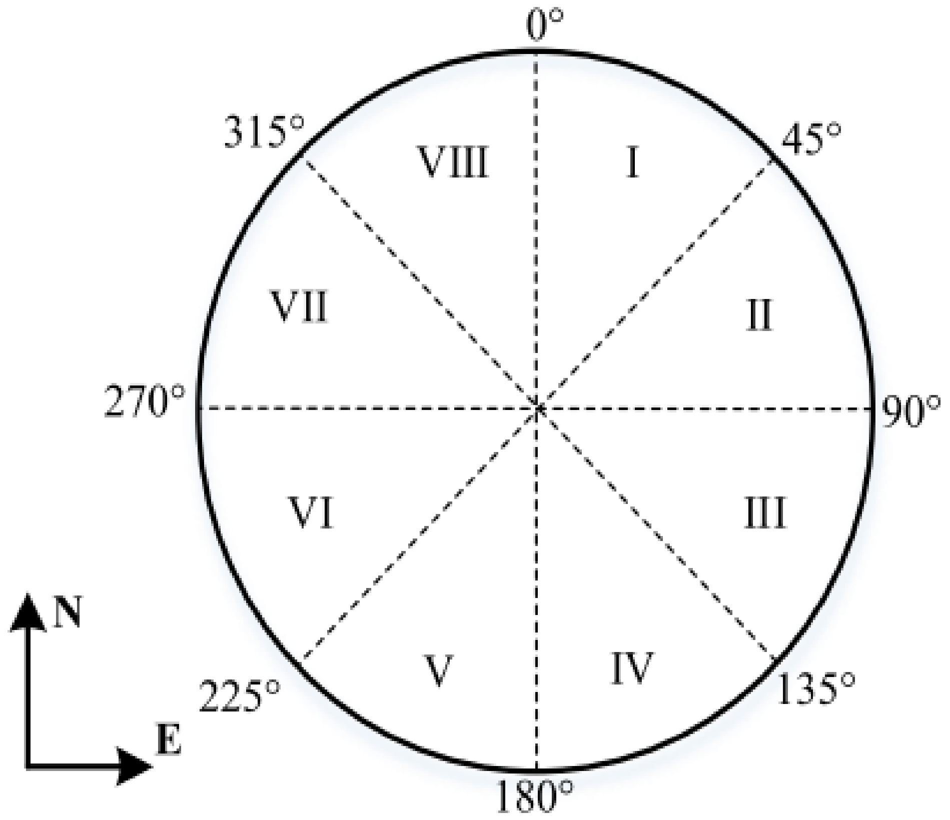
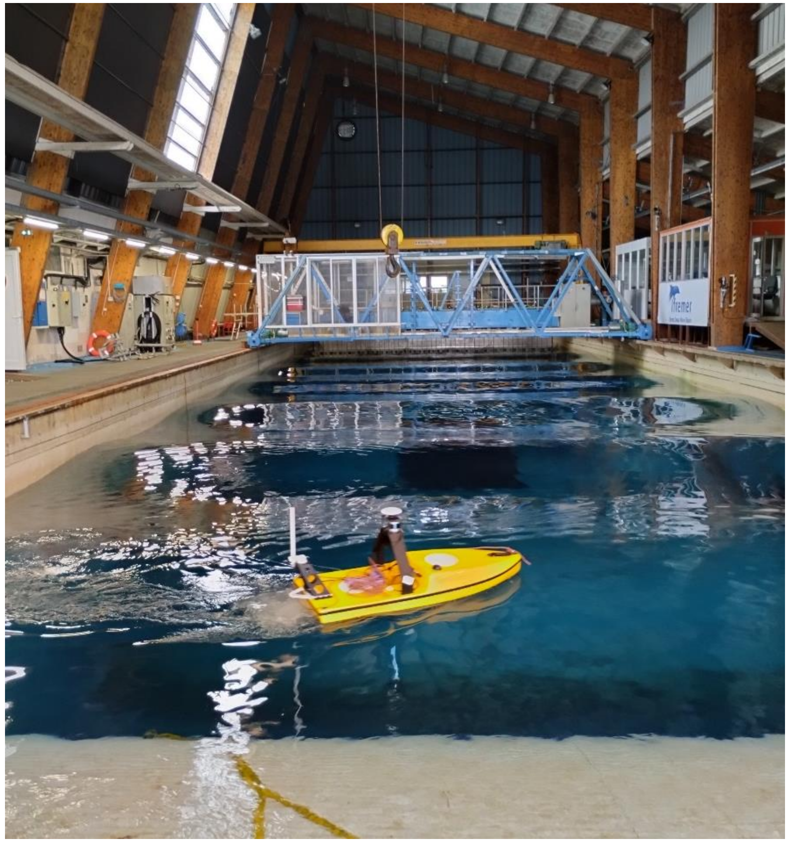


Image taken from [2]

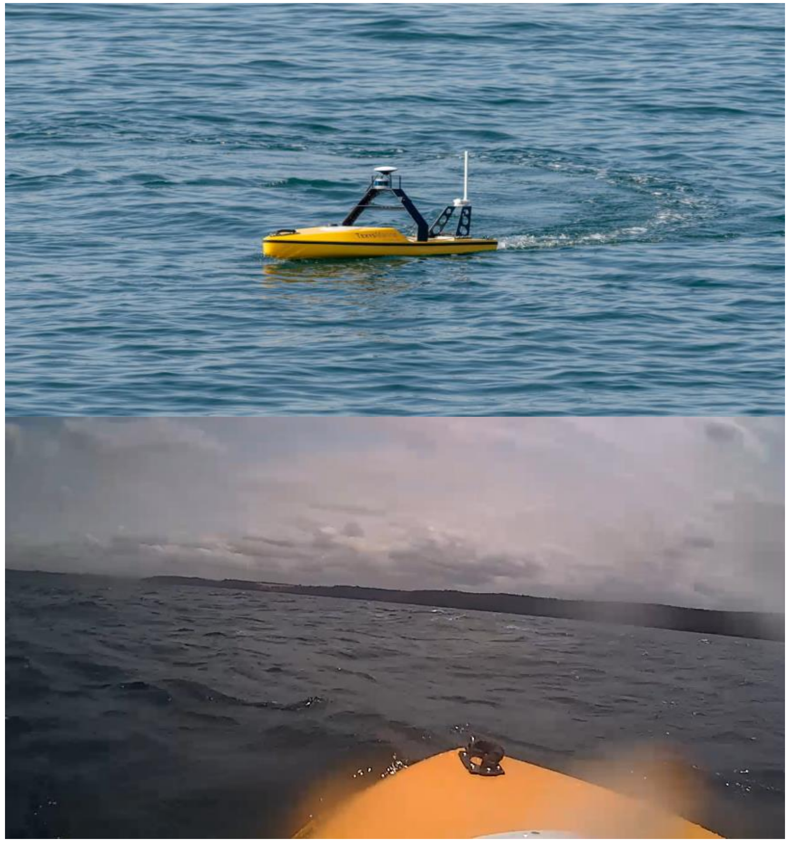
Outline

- Wave direction estimation
- Data collection
- Machine learning model
- Results
- Future challenges

Experimental settings



Experimental pool



Open sea

Experimental pool data

- IMU and navigation data from a surface drone
- 10 trajectories
- Tests under various conditions
  - Wave height
  - Wave period
  - Steering rate PID
  - Speed/throttle PID
- Controlled wave direction

Open sea data

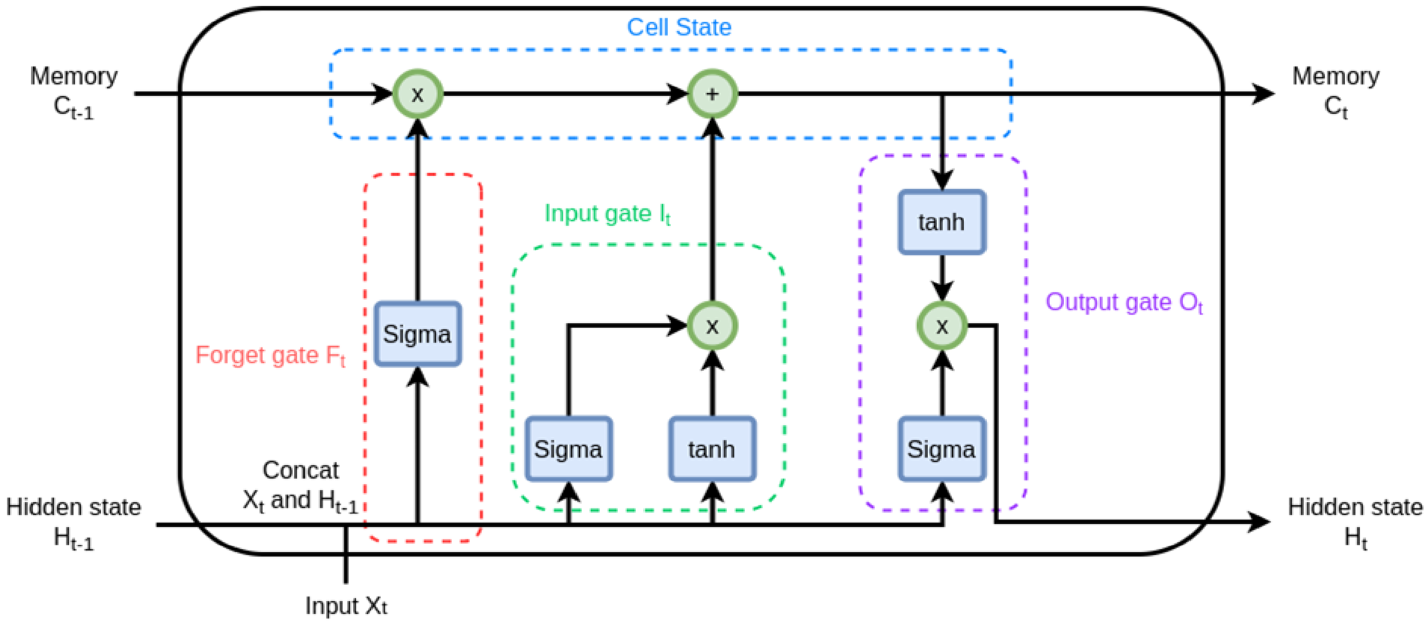
- IMU and navigation data from a surface drone
- 6 trajectories
- Tests under various conditions
  - Steering rate PID
  - Speed/throttle PID

Outline

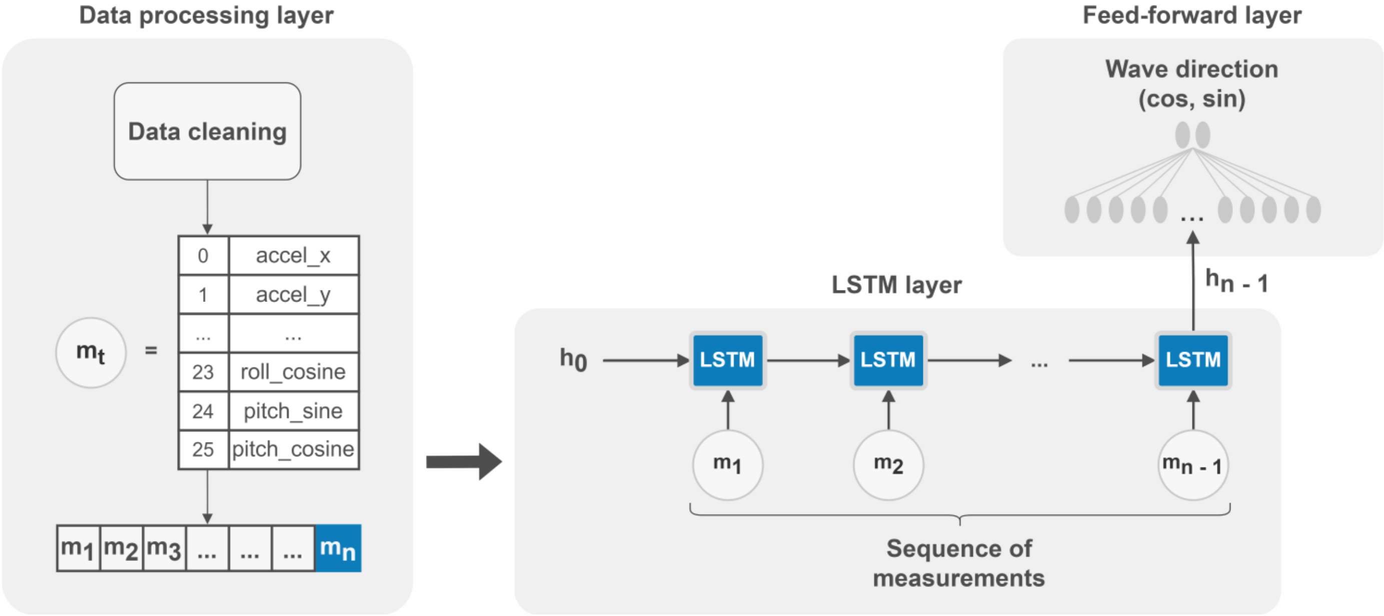
- Wave direction estimation
- Data collection
- Machine learning model
- Results
- Future challenges

Long-Short Term Memory (a spatial view)

- Designed for **sequential** data
- Components
  - Memory: Store information over “long” periods
  - Hidden state: Output of the current cell
- Gates to control the flow of information
  - Input gate
  - Forget gate
  - Output gate



Our model (a temporal view)



- Features: IMU data (acceleration, angular velocity, Euler angles, etc.)
- Target: Wave angle relative to the drone's current orientation
- Sequence generation (*n* steps)
- Prediction of the *n*th element based on the (n – 1) previous steps

Ait Habouche, M., Kerboeuf, M., Guillou, G., & Babau, J.-P. (2024). *Machine Learning-Based Estimation Of Wave Direction For Unmanned Surface Vehicles*. arXiv. https://doi.org/10.48550/arXiv.2412.16205

Training and validation

- Experimental pool data divided into training, validation and test datasets
- Training loss: MSE (Mean Squared Error)
- Evaluation metrics
  - MAPE (Mean Absolute Percentage Error)

$$MAPE = \frac{1}{p} \times \sum_{i=1}^{p} \frac{|predicted_i - actual_i|}{actual_i}$$

  - Angular score

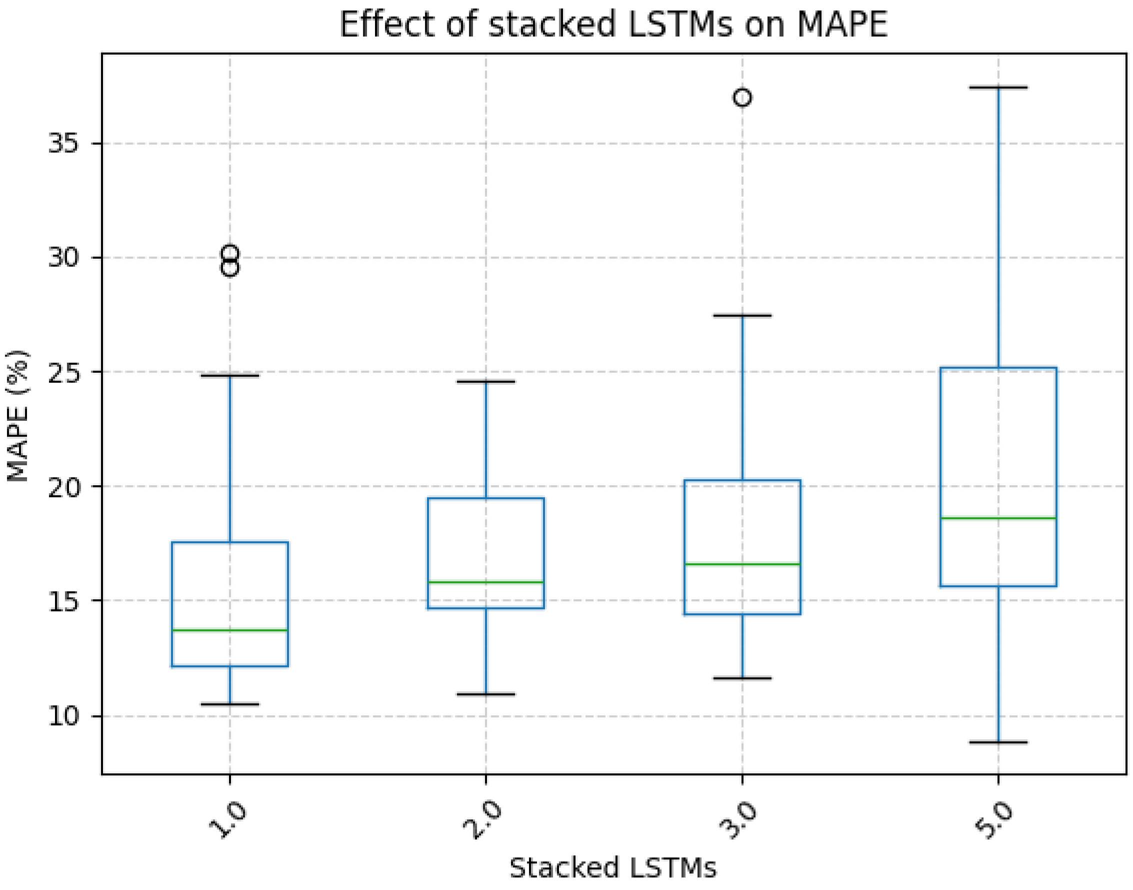
$$Angular\ \ score = \sqrt{\frac{1}{p} \times \sum_{i=1}^{p} normalized\_diff_i{}^2}$$

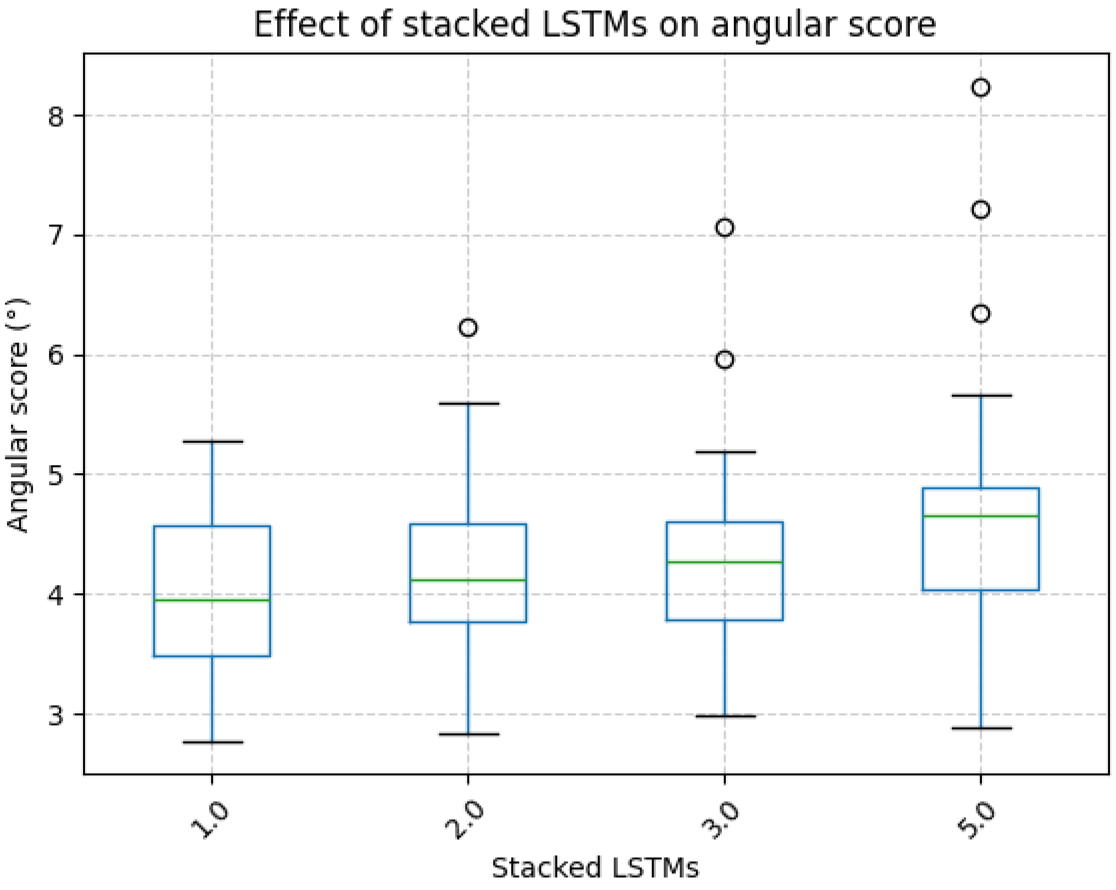
Hyperparameters tuning

- Hyperparameters
  - Sequence size
  - Hidden size (hidden state dimension)
  - Stacked LSTMs
  - Learning rate

Sequence size	Hidden state dimension	Stacked LSTMs	Learning rate	MAPE (%)	Angular score (°)
10	10	1	0.001	11.10	2.81
10	10	1	0.0001	29.51	3.41
20	10	1	0.001	17.70	4.57
20	10	1	0.0001	30.20	5.27
30	10	1	0.001	11.67	3.70
30	10	1	0.0001	19.10	4.31
10	20	1	0.001	10.52	**2.77**
10	20	1	0.0001	17.07	3.04
⋮					
20	20	5	0.0001	26.64	6.35
30	20	5	0.001	**8.83**	3.94
30	20	5	0.0001	20.87	4.90
10	100	5	0.001	21.10	4.00
10	100	5	0.0001	15.96	2.88
20	100	5	0.001	18.71	4.87
20	100	5	0.0001	15.33	4.79
30	100	5	0.001	12.07	4.04
30	100	5	0.0001	17.48	4.10

Hyperparameters tuning





Hyperparameters tuning

- Hyperparameters
  - Sequence size
  - Hidden size (hidden state dimension)
  - Stacked LSTMs
  - Learning rate
- Chosen configuration
  - Sequence size = 10
  - Hidden size = 20
  - Stacked LSTMs = 1
  - Learning rate = 0.001

Sequence size	Hidden state dimension	Stacked LSTMs	Learning rate	MAPE (%)	Angular score (°)
10	10	1	0.001	11.10	2.81
10	10	1	0.0001	29.51	3.41
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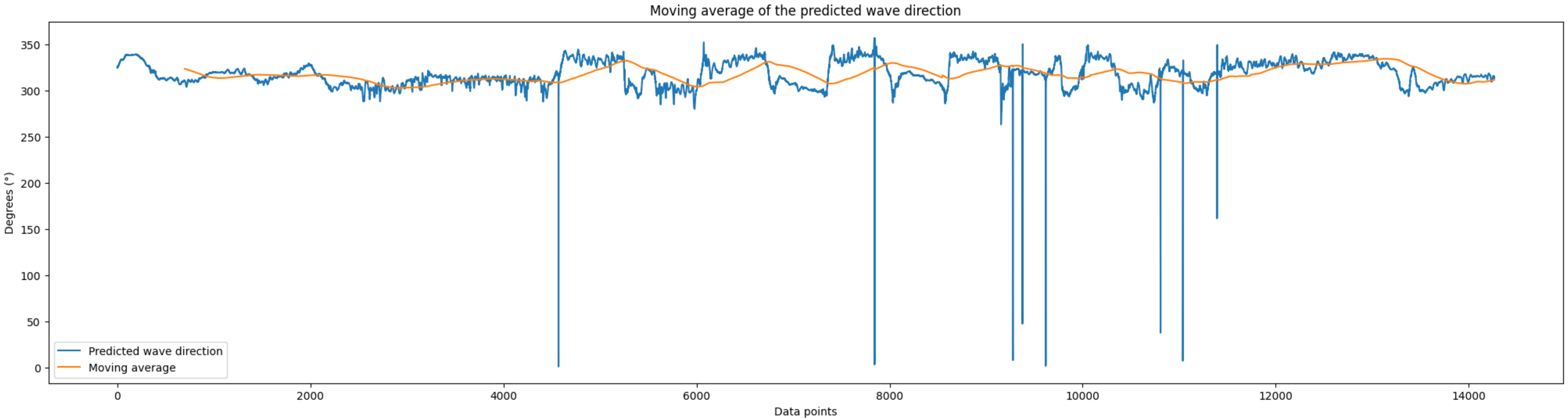
Evaluation on unseen data



- Prediction error: 40°
- Moving average on sequences of 28 seconds
  - Mean: 317°
  - Standard deviation: 7°
  - Error: 37°

Future challenges

- Representative dataset
  - Conduct more experiments in different sea conditions to capture a broader range of data
- Other sea characteristics to enhance the model
  - Wind
  - Current
- Real-time estimation
  - Short inference time
  - Energy constraints
- Navigation adaptation

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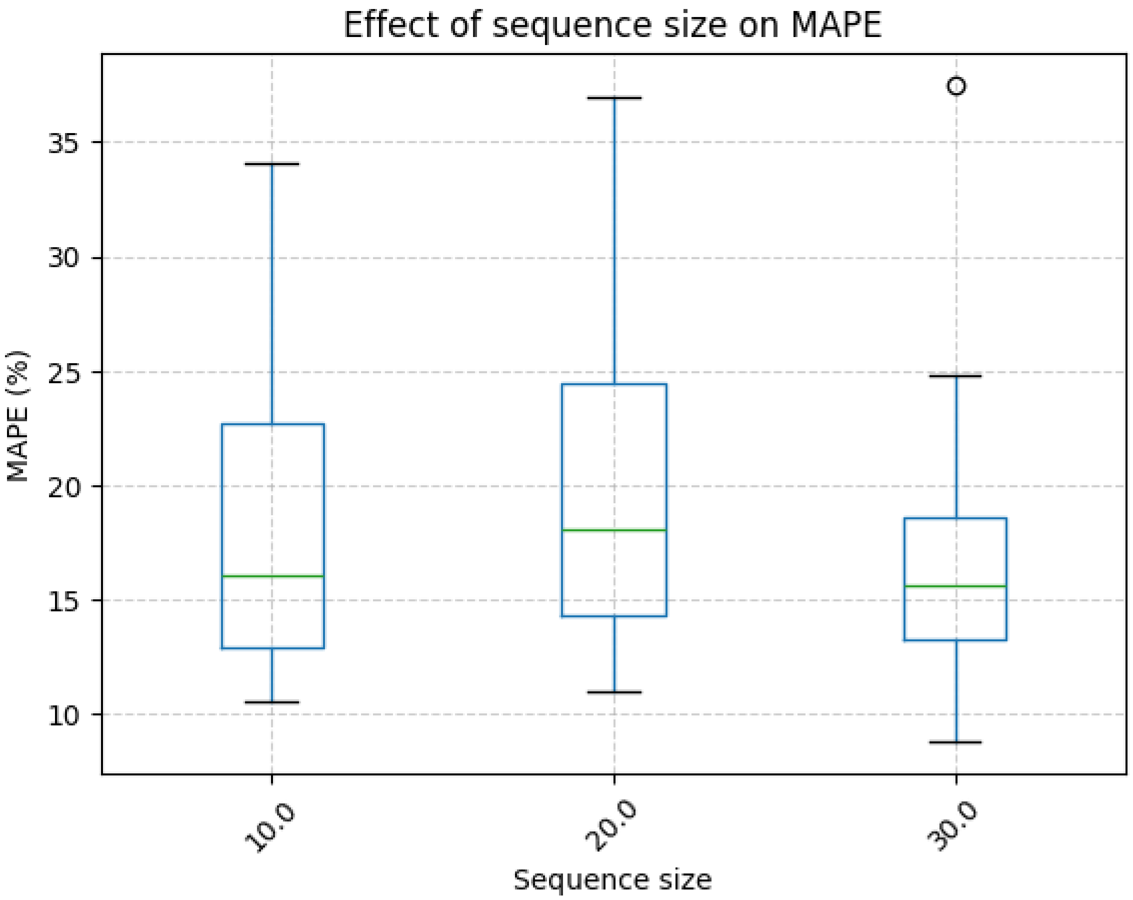
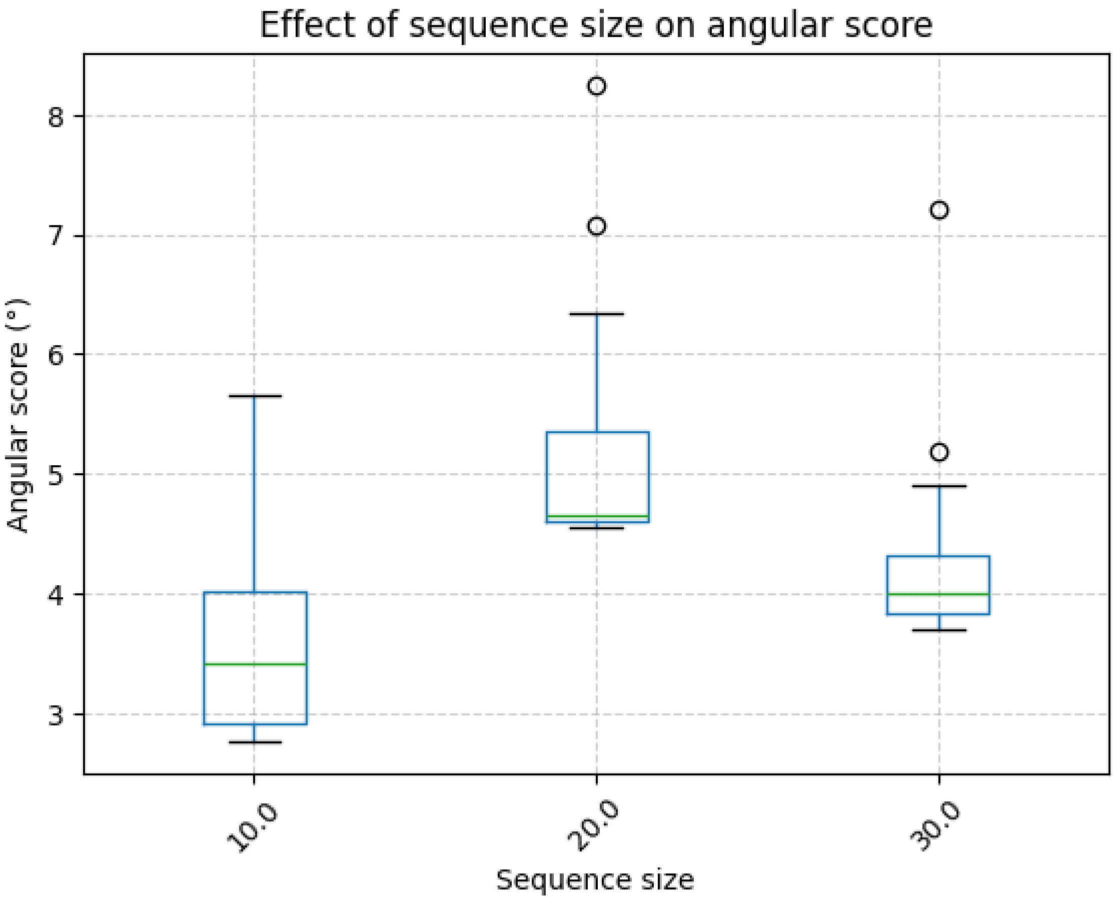
Thank you for your attention

Comparison with baseline predictors

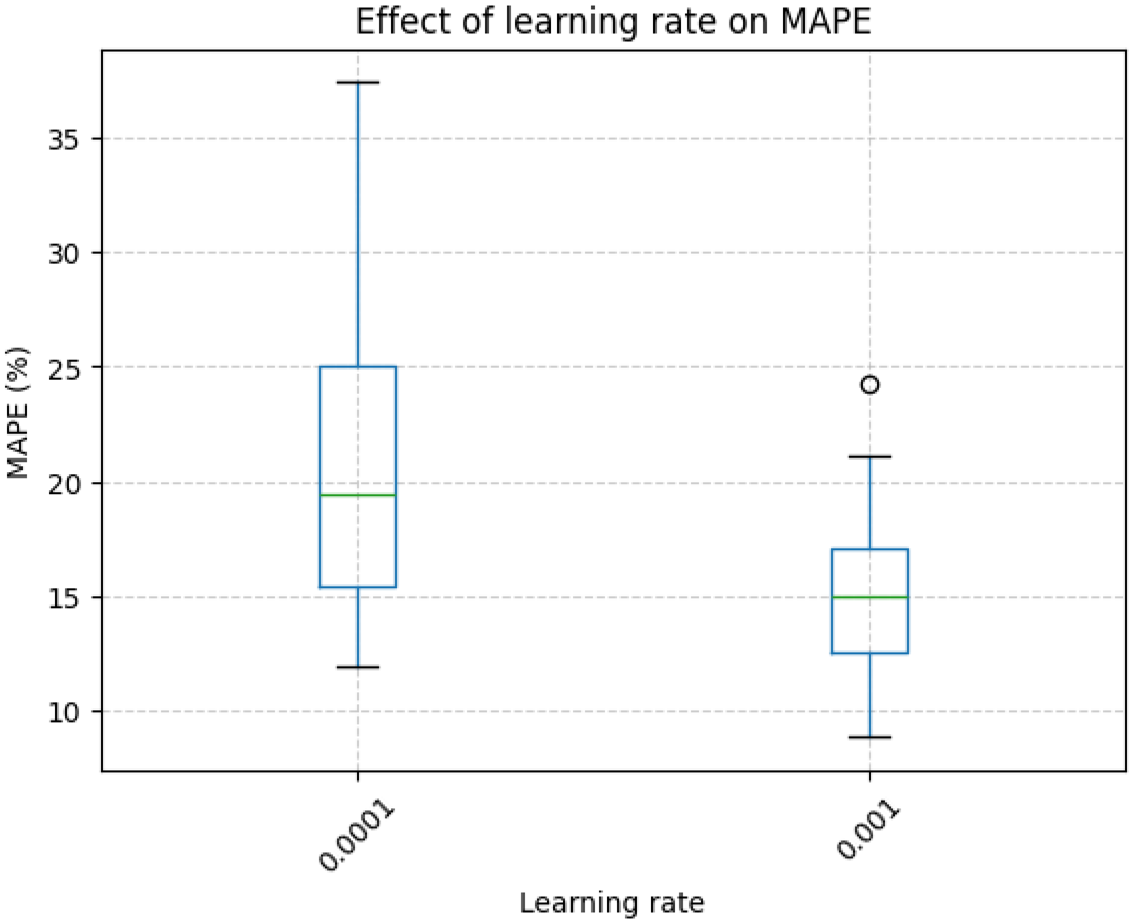
Model	MAPE (%)	Angular score (°)
MLP	34.35	5.27
Transformer [9]	11.66	2.85
ResNet 18 [7]	28.43	5.67
CNN [8]	33.42	5.23
mLSTM [10]	11.7	2.86
Proposed model	**10.52**	**2.77**

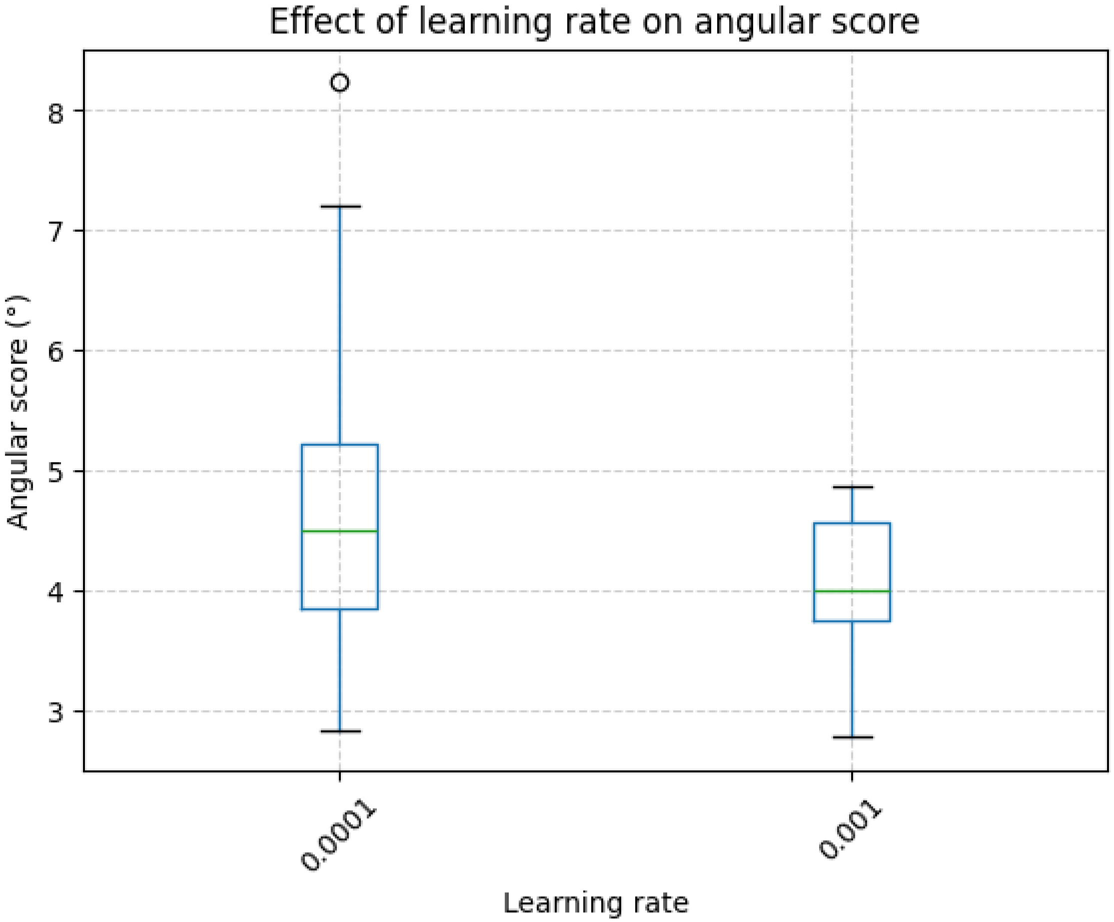
Hyperparameters tuning





Hyperparameters tuning





Hyperparameters tuning