



Enhancing Vessel Estimated Time of Arrival Prediction through Vessel Event Detection and Data Augmentation

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1. Introduction: Importance & Challenges



Crucial role in maritime logistics

- Operational Efficiency:
 - Help ports optimize docking schedules
 - $\,\circ\,$ Minimize waiting times and streamline cargo handling
- Supply Chain Impact: increase visibility and facilitate downstream planning
- Commercial Advantage: Companies that can predict ETAs more accurately can improve customer satisfaction and gains a competitive edge.

Challenges:

- Dynamic factors: Weather, ocean currents, etc.
- **Global-scale ETA prediction**: Expanding prediction models to accommodate global maritime networks is a significant challenge.

1. Introduction: Objective and Overview



Objective

- Develop a framework to enhance vessel ETA prediction accuracy
- Applicable to Global-scale ETA prediction: Given a position in the sea and a target port (destination), predict the travel time between them
- Dynamically update and refine ETA predictions as voyages progress

Overview: two-step development

- Step 1: Vessel event detection
- Step 2: Data processing and machine learning pipeline selection

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2. Vessel Event Detection





3. Data extraction and feature expansion



- Extract AIS data for the identified travel legs
 - o A vessel's trajectory between two ports and its travel time
- Feature expansion:
 - Vessel type
 - Dimensions: vessel's length and width
 - Vessel current position
 - Vessel destination: the lat and lon of a port
 - SOG (current speed over ground)
 - Draft: loading
 - Month: ocean current information)

3. Example of training data



Vessel Type	Vessel lat	Vessel lon	Destination lat	Destination lon	Length	Width	Draught	SOG	Month	Remaining_Travel_Time[h]
Cargo	-20.418645	113.130748	-33.31790479	115.6555239	190	28	6.3	10.2	5	75.51
Cargo	-20.76018	113.05003	-33.31790479	115.6555239	190	28	6.3	10.5	5	73.52
Cargo	-21.114613	112.96827	-33.31790479	115.6555239	190	28	6.3	9.8	5	71.35
Cargo	-21.43374	112.900167	-33.31790479	115.6555239	190	28	6.3	9.4	5	69.33
Cargo	-21.706898	112.841097	-33.31790479	115.6555239	190	28	6.3	9.4	5	67.51
Cargo	-22.045553	112.762337	-33.31790479	115.6555239	190	28	6.3	10.3	5	65.33
Cargo	-22.379438	112.683188	-33.31790479	115.6555239	190	28	6.3	10.8	5	63.45
Cargo	-22.717872	112.610652	-33.31790479	115.6555239	190	28	6.3	11	5	61.52
Cargo	-23.110263	112.505717	-33.31790479	115.6555239	190	28	6.3	11.1	5	59.34

Features

ETA

Case Studies



Period: January 2020 to June 2023

AIS data resolution: bi-hourly

Use cases

- Singapore-China Shipping Line
- Europe Asia-pacific Maritime Corridor

Machine learning pipelines

- XGBoost, ANN, Random Forest
- After fine tuning, XGBoost performs the best in all use cases

Singapore-China Shipping Line (47 ports)



- 355 vessels
- 965 travel legs
- 27,302 lines of training data
- Testing MAE: 2.43 hours

NORMA NO





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Europe Asia-pacific Maritime Corridor



- 1,208 vessels
- 3,694 travel legs
- 272,558 lines of training data
- Testing MAE: 3.3164 hours

Only show feature with importance > 0.01









Conclusion



- Proposed a framework from AIS data to effective ETA prediction
 - Event detection from AIS data for identifying travel legs
 - Feature expansion
- Future work: Global-scale Maritime Network







THANK YOU