DEDS Summer School Presentation

ESR#2.4 Analytic Operators for Trajectories

7 July 2023

Song WU

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AALBORG UNIVERSITY
DENMARK

Agenda

Current Status

Scientific Content

- Semantic segmentation of AIS trajectories
- Evaluation of Vessel CO_2 Emissions Methods
- Fusion of trajectories from AIS and Camera (onging secondment)

Current Status: where & progress

Courses

- all ECTS are finished

Relocation

- (home) ULB, 1 Sep 2021 - 31 Aug 2022
- (host) AAU, 1 Sep 2022 - 31 May 2023
- Secondment at MarineTraffic in Athens, 01 June 2023 - 31 Aug 2023 (ongoing)

Research Output

- one 6-page workshop paper at the MDM'2022 conference (before DPP)
  Semantic Segmentation of AIS Trajectories for Detecting Complete Fishing Activities
- one 10-page research paper accepted at SSTD'2023 conference (after DPP)
  Evaluation of Vessel CO_2 Emissions Methods using AIS Trajectories

Semantic segmentation of AIS trajectories

Motivation

Illegal, unreported and unregulated (IUU) fishing is becoming an increasing concern[1].
So it is important to know when & where a ship may have performed fishing activities.

Definition

trajectory T: $(p_1, t_1), (p_2, t_2), \cdots, (p_{n-1}, t_{n-1}), (p_n, t_n)$, an ordered sequence of timestamped points where p_i is the coordinate of a moving object at the timestamp t_i.

Problem Statement

Given a trajectory T, this works aims to split T into a sequence of labelled segments $<(S_1,l_1), \ldots, (S_k,l_k)>$, where S_i is a continuous sequence of points in T, and l_i is the label of segment $\in$ {fishing, non-fishing}.

[1] https://ec.europa.eu/oceans-and-fisheries/fisheries/rules/illegal-fishing_en

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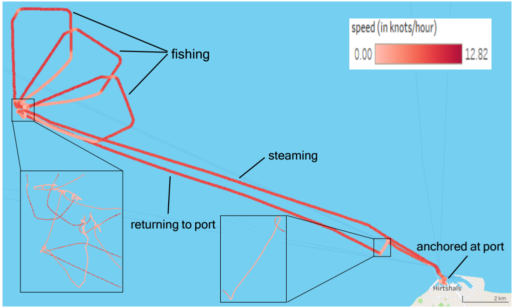
Semantic segmentation of AIS trajectories

Limitations of existing approaches

- some work simply treat trajectories as a sequence of stops and moves, such as CB-SMoT[11] and DB-SMoT[12].
- segments are returned without labels, such as W-Kmeans[6], SWS[1].
- Many studies assume that that returned segments should have high homogeneity w.r.t. some spatiotemporal criteria or features of points, such as GRASP-UTS[13].



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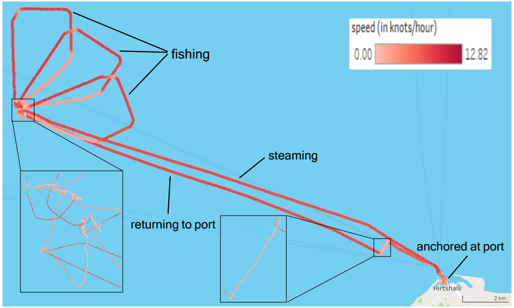

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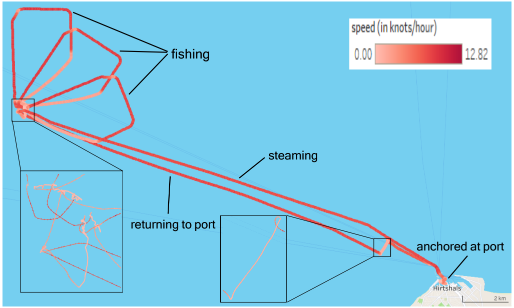


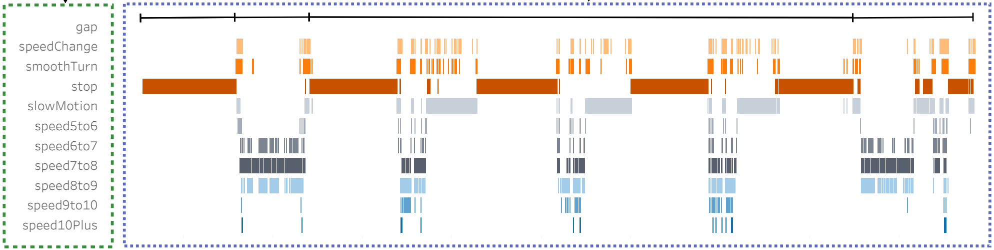
Semantic segmentation of AIS trajectories

Proposed solution

part#1: feature design by TPoSTE (Temporal Profiling of Spatio-Temporal Events)

Step#1: choose spatial-temporal events

Step#2: draw all occurrences of events



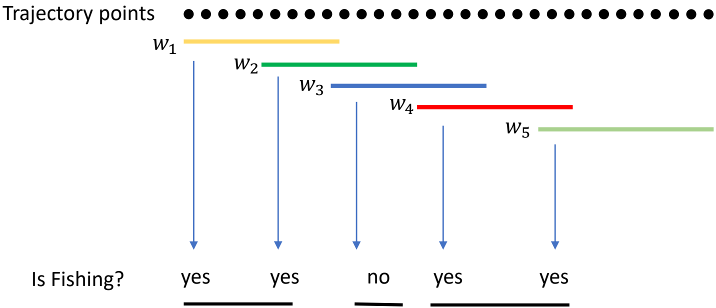
Step#3: gain some insights that help design features capturing movement patterns

Semantic segmentation of AIS trajectories

Proposed solution

part#2: Window-Based Trajectory Segmentation using Run-Length Encoding

- a window is required to contain at least $\boldsymbol{size_w}$ points and its duration is larger than a time threshold $\boldsymbol{t_w}$.
- two adjacent windows have some overlap indicated by ***ratio***.



Semantic segmentation of AIS trajectories

Proposed solution

part#2: Window-Based Trajectory Segmentation using Run-Length Encoding
(an alternating sequence of counts $\ldots, a_{fishing}, b_{sailing}, c_{fishing}, \ldots$ is obtained.)

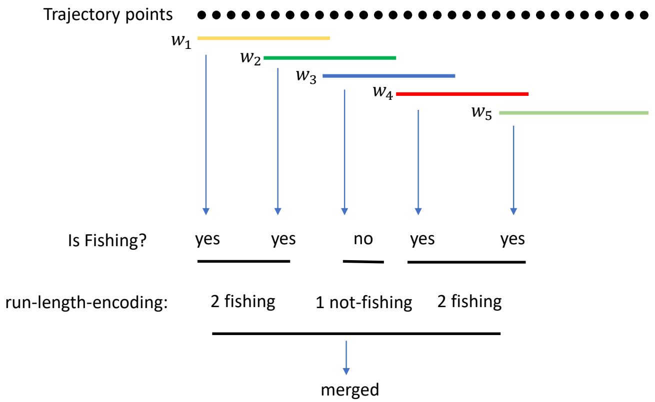
A complete fishing activity A is a maximal subsequence of counts that:

- A starts and ends with fishing counts.
- each triplet $< a_{fishing}, b_{sailing}, c_{fishing} >$ in A fulfills $a \geq b$ and $b \leq c$ to correct occasional classification errors.

Semantic segmentation of AIS trajectories

Proposed solution

part#2: Window-Based Trajectory Segmentation using Run-Length Encoding

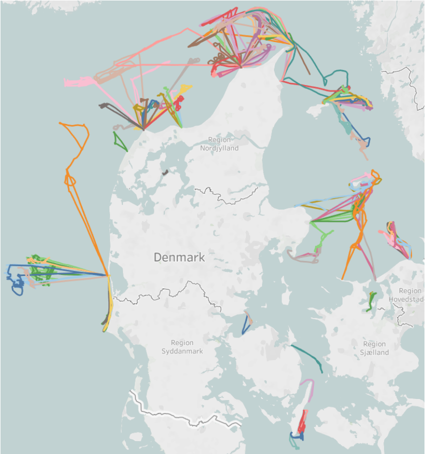


Semantic segmentation of AIS trajectories

Datasets

We manually labeled 128 trajectories that are likely to contain fishing activities.

- publicly available from Danish Maritime Authority
- average sampling frequency: 10.63 seconds
- # of points: 1,080,220
- 31 trajs for training, 97 trajs for testing

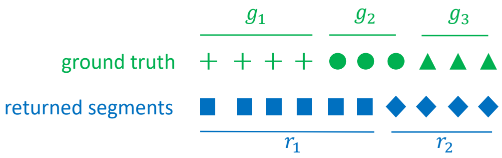


Semantic segmentation of AIS trajectories

three state-of-the-art for comparison: CB-SMoT, W-Kmeans, SWS

Four metrics are used:

- Purity (introduced in [13])
- Coverage (introduced in [13])
- Harmonic Mean of Purity and Coverage
- # of returned segments



Purity = (4/6 + 3/4) / 2

Coverage = (4/4 + 2/3 + 3/3) / 3

Semantic segmentation of AIS trajectories

Results

WBS-RLE achieves:

- the highest harmonic mean
- the closest number of segments w.r.t ground truth, except WKMeans (k=3)

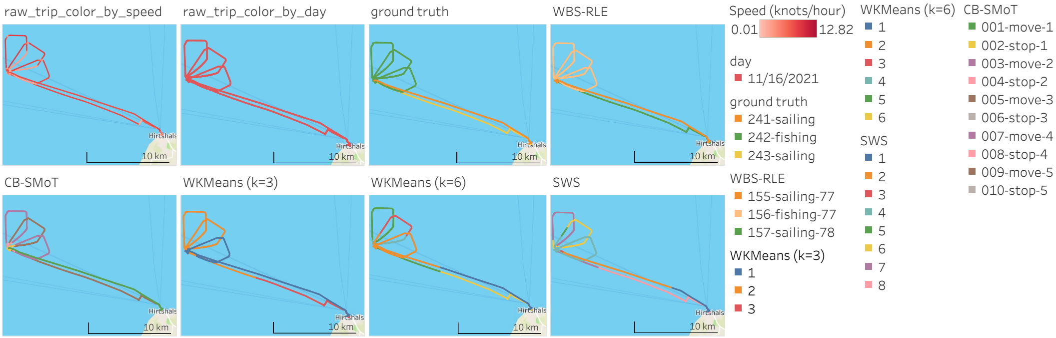
method	purity	coverage	harmonic mean	# of segments
WBS-RLE	0.890	0.974	0.927	2.670
CB-SMoT	0.859	0.885	0.859	5
WKMeans (k=3)	0.878	0.840	0.855	3
WKMeans (k=6)	0.932	0.619	0.741	6
SWS	0.954	0.759	0.837	9.855

Table: average performance on the 97 trajectories

* all segmentation results are available online

Semantic segmentation of AIS trajectories

Segmentation result for the trajectory #220051000-2



Evaluation of Vessel CO_2 Emissions Methods

Motivation

1. growing interest of society in environmental friendliness and sustainability
2. about **90%** of global trade is fulfilled by shipping
3. In 2018, shipping CO_2 emissions were estimated to be **1,056 million tons** by IMO
4. accurate estimation of shipping CO_2 emissions is important for developing regulations

Research gap:

- None of the review studies [2, 15, 14] does a quantitative comparison of models
- The comparative studies [8, 9] are limited to a small area near the Strait of Gibraltar

Contribution

- a general data-driven framework to compare/validate ship emission models
- extensive experiments are conducted and insights are presented

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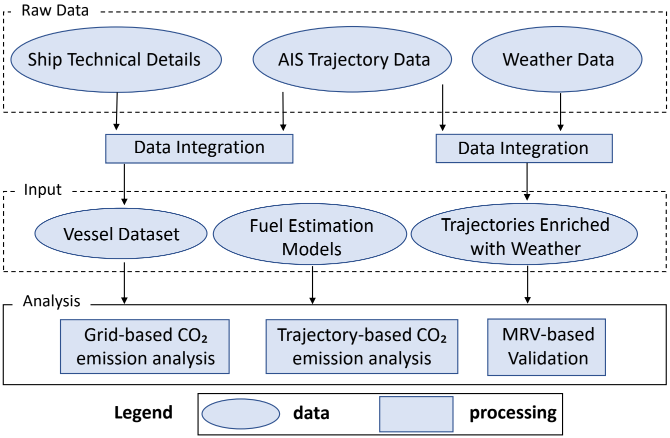

Figure: Overview of the Evaluation Framework

Evaluation of Vessel CO_2 Emissions Methods

Currently, five models are considered in our framework.

- **Baseline**: assumes a certain amount of CO_2 are emitted per metric ton of cargo per kilometer of transport, 3 grams CO_2 / (ton · km) [3].
- **GrossTonnage [7]**: The daily fuel consumption C is linearly related to the gross tonnage of a ship, and the CO_2 emissions per ton of fuel depends on operation mode.
- **SpeedCubic [4]**: speed is considered, and the emission factor (gCO_2/kWh) depends on engine type and fuel type.
- **IMO [10]**: speed and draught are considered. The emission factor (gCO_2/kWh) depends on engine type/load/generation and fuel type.
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Evaluation of Vessel CO_2 Emissions Methods

summary of required input by the five models

Models	TPC	DWT	D	P	S	GT	RPM	Year	Length	Beam	Wave
Baseline	✓	✓	✓								
GrossTonnage					✓	✓					
SpeedCubic				✓	✓		✓				
IMO			✓	✓	✓		✓	✓			
STEAM				✓	✓				✓	✓	✓

TPC: tons per centimeter
D: maximum draught
S: maximum speed
RPM: revolutions per minute

DWT: deadweight
P: maximum power
GT: gross tonnage

Evaluation of Vessel CO_2 Emissions Methods

AIS data

One-month data from May 2022 was downloaded from the Danish Maritime Authority[2]. 41,024,724 records from 1,571 cargo ships were used.

Ship Technical Details

Public information in six websites were collected.
① BalticShipping ② Bureau Veritas ③ FleetMon
④ MarineTraffic ⑤ ShipAtlas ⑥ VesselTracker

Wave Data (wave height and direction)

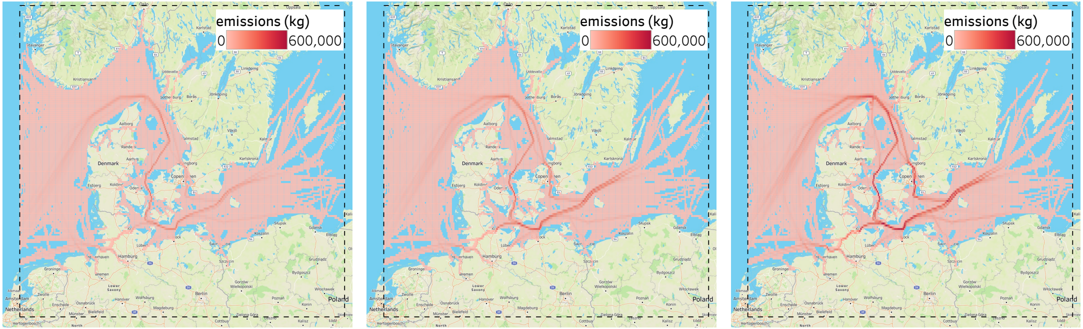
Two products were used from the Copernicus Marine Service.
- Baltic Sea[3]: spatial res. 1nm $\times$ 1nm ; temporal res. 1 hour
- North Sea[4]: spatial res. 3km $\times$ 1.5km ; temporal res. 1 hour

[2] https://web.ais.dk/aisdata/
[3] https://goo.by/FKzLj
[4] https://goo.by/vPwnP

Evaluation of Vessel CO_2 Emissions Methods

Grid-based analysis

The area of interest in divided into 0.05 ° by 0.05 ° grids



(a) Baseline (b) IMO (c) GrossTonnage

Figure: Spatial distribution of CO_2 emissions by each model

Evaluation of Vessel CO_2 Emissions Methods

Grid-based analysis

Comparison of absolute emissions by each model

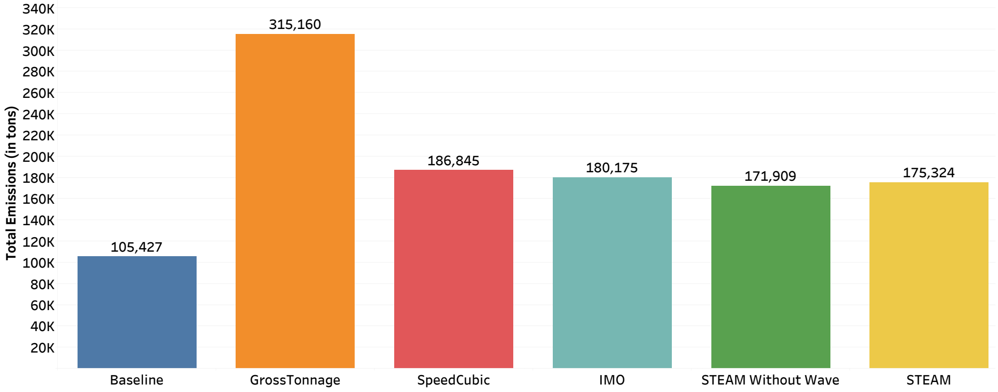
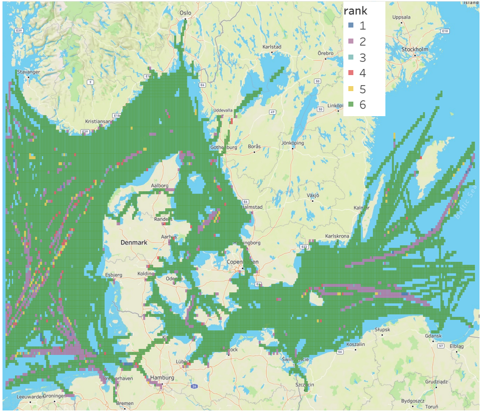


Figure: Total CO_2 emissions of the 1,571 ships by each model

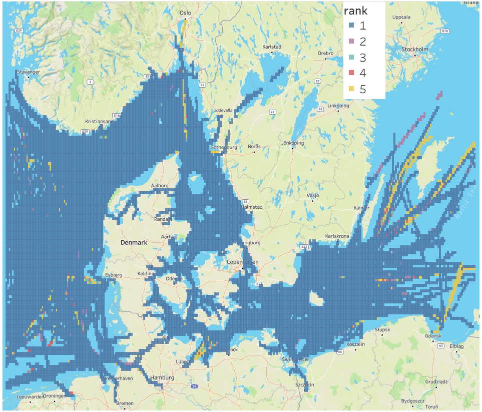
Evaluation of Vessel CO_2 Emissions Methods

Grid-based analysis

Grid-level ranking of each model: "1" highest ("6" lowest) emissions



(a) Baseline

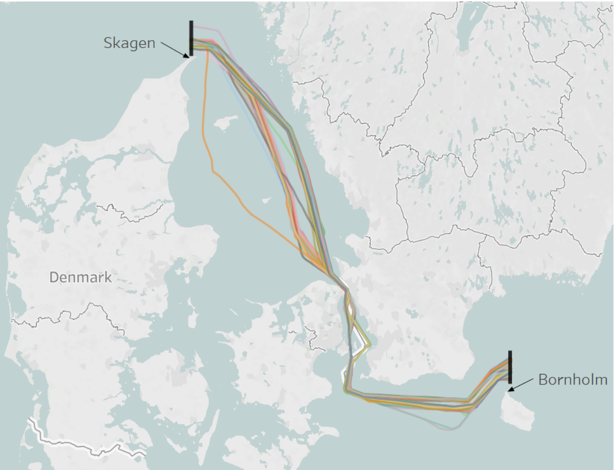


(b) GrossTonnage

Evaluation of Vessel CO_2 Emissions Methods

Trajectory-based analysis

192 trips are selected travelling between Skagen and Bornholm



Evaluation of Vessel CO_2 Emissions Methods
Trajectory-based analysis

Statistic of the 192 trips

min. / avg. / max. length (km)	478.4 / 488.8 / 507.9
min. / avg. / max. duration (hours)	13.8 / 23.3 / 32.9
min. / avg. / max. passing speed (knots/hour)	8.0 / 11.7 / 19.0

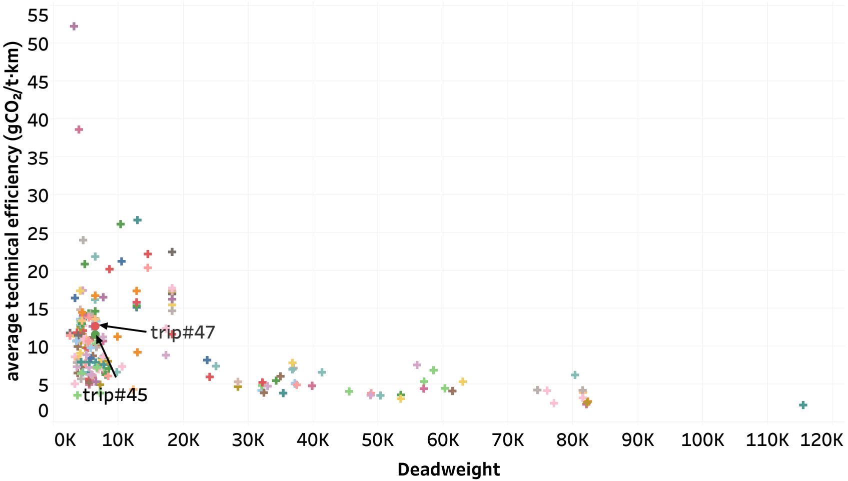
Equivalent CO_2 efficiency for each trip

$$E_{CO_2,i} = \frac{CO_{2\_IMO}}{Cargo_i * Length_i}, 1 \leq i \leq 192$$

Evaluation of Vessel CO_2 Emissions Methods

Trajectory-based analysis

Equivalent CO_2 efficiency of the 192 trips



Evaluation of Vessel CO_2 Emissions Methods

Trajectory-based analysis

trip#45 and trip#47 by the same ship (DWT = 6,410 t, S = 19 knots/h)

	trip#45	trip#47
length (km)	489.8	489.6
avg. passing speed (knots/hour)	13.17	14.15
CO_2 emissions (kg)	36,372	39,798
CO_2 efficiency ($gCO_2/t{\cdot}km$)	11.58	12.68

A 5.2% decrease in speed leads to a 8.7% increase in CO_2 efficiency

- it suggests that shipowners can probably improve CO_2 efficiency of their fleet by speed optimization.

Evaluation of Vessel CO_2 Emissions Methods

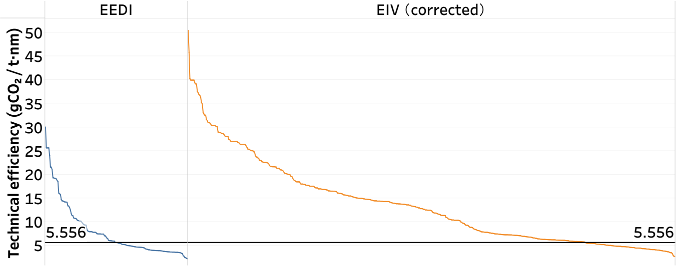
MRV-based validation

The EU's Monitoring, Reporting and Verification (MRV) system

- ship above 5,000 gross tonnage should report CO_2 emissions data for their maritime transport activities in the EU waters.
- 760 out of the 1,571 ships have matching entries in the MRV dataset.

CO_2 efficiency of the 760 ships based on MRV

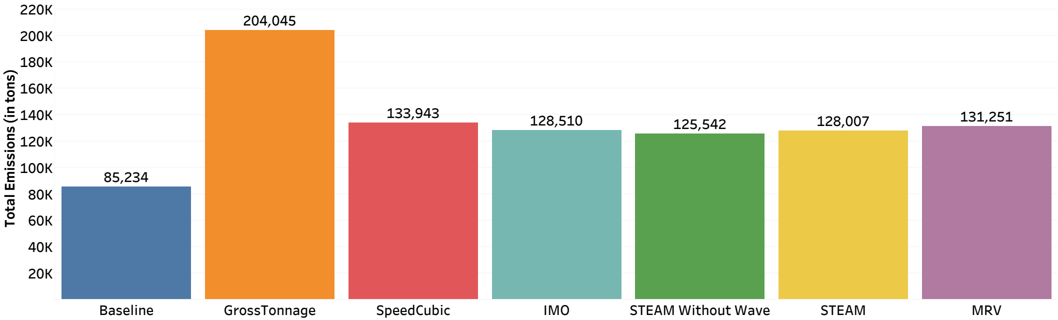
- - EEDI: Energy Efficiency Design Index
- - EIV: Estimated Index Values



Evaluation of Vessel CO_2 Emissions Methods

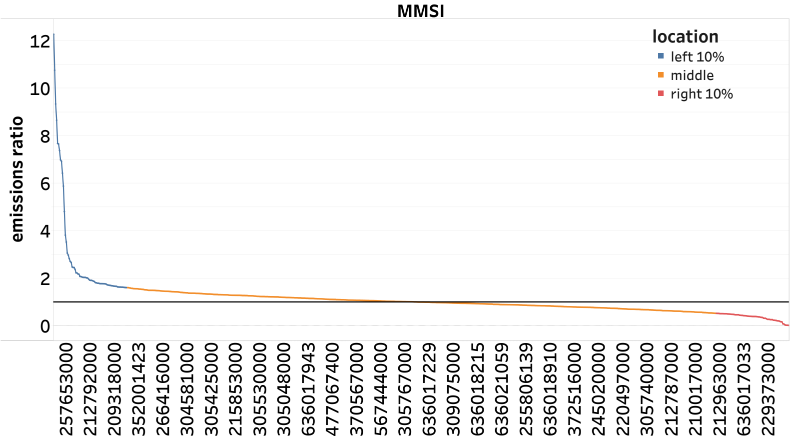
MRV-based validation

Total CO_2 emissions of the 760 ships by each model



Evaluation of Vessel CO_2 Emissions Methods
MRV-based validation

Ship-level CO_2 efficiency ratio between the IMO method and MRV dataset



Fusion of trajectories from AIS and Camera

Motivation

- Installation of AIS devices is not mandatory for small boats
- AIS can be manually switched off by crew onboard. (dark vessels)
- Different sensors have their own pros and cons:
  AIS: vessel identify, position, speed, etc
  Camera images: visual appearance of vessels, but without identify and so on
- It is promising to do fusion of AIS data and Camera data for better tracking of vessels

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Fusion of trajectories from AIS and Camera

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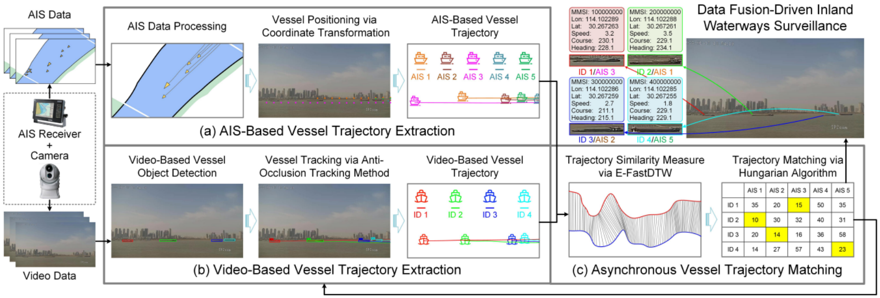

	AIS 1	AIS 2	AIS 3	AIS 4	AIS 5
ID 1	35	20	15	50	35
ID 2	10	30	32	40	31
ID 3	20	14	16	36	58
ID 4	14	27	57	43	23

Fig. 1. The architecture of the proposed deep learning-based simple online and real-time vessel data fusion method (termed DeepSORVF). The DeepSORVF consists of AIS-based vessel trajectory extraction, video-based vessel trajectory extraction, and asynchronous vessel trajectory matching.

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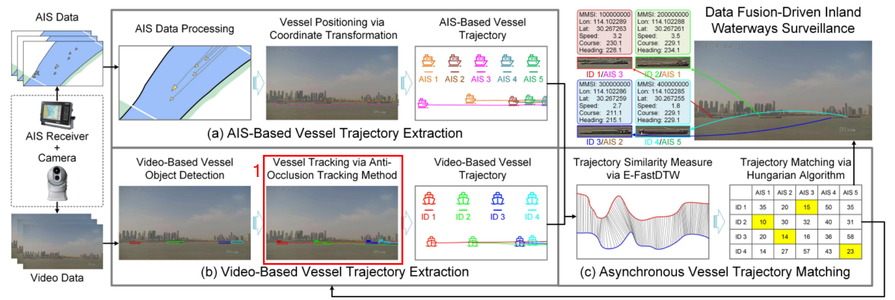

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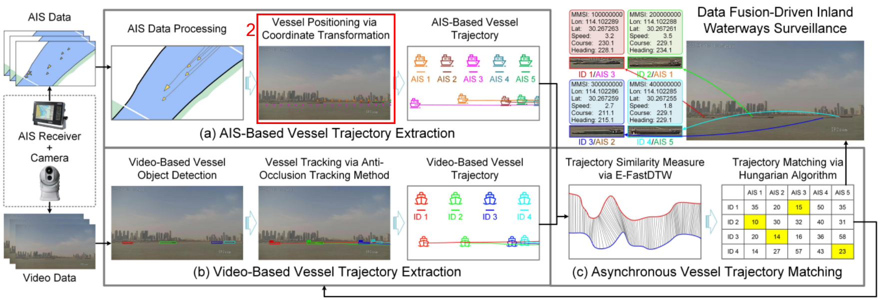

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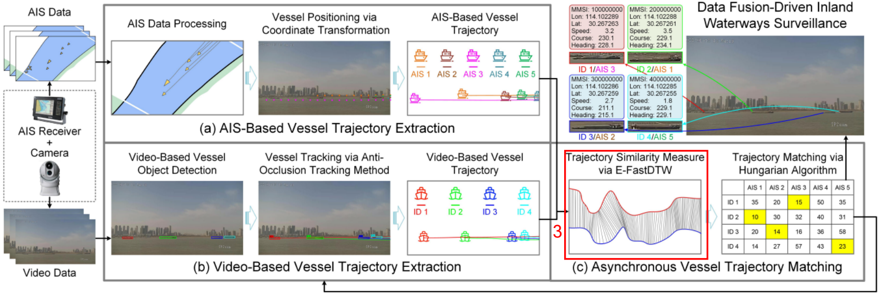

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Thank for your attention! Feel free to ask any questions.

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Reference I

[1] M. Etemad, A. Soares, E. Etemad, J. Rose, L. Torgo, and S. Matwin.
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