Towards reliable and efficient situational awareness in congested waters.

Lars-Christian Tokle, 22nd May 2023.

Autonomous urban passenger ferries

Can substitute bridges and staffed ferries.

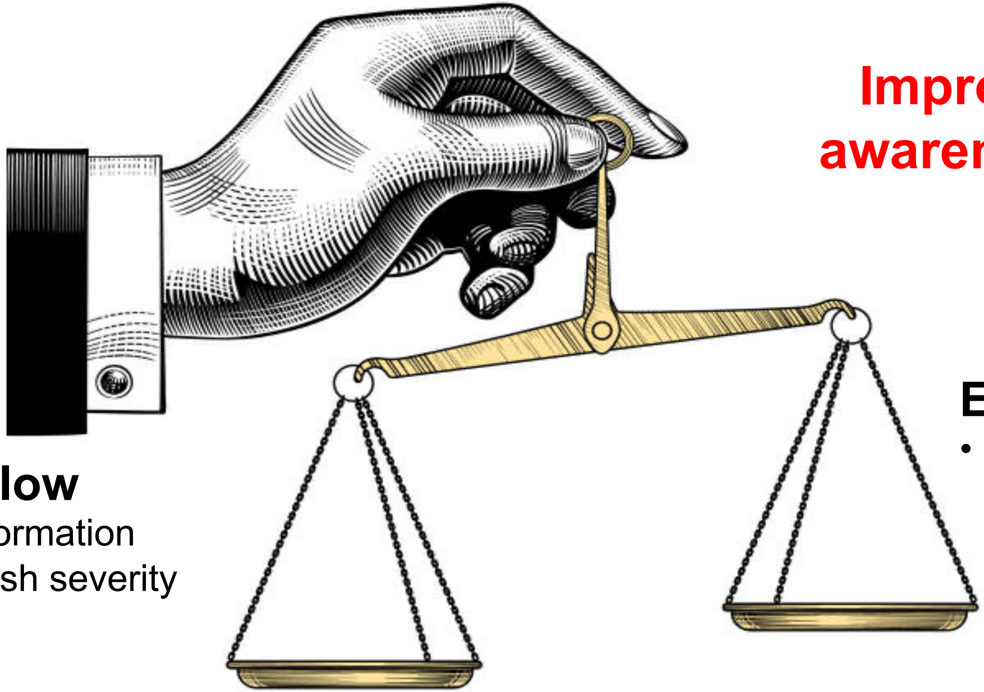
- Cheaper and more flexible.

Situational awareness ***for autonomous ferries***

- Determine route
- Avoid collisions with:
  - land
  - <u>other vessels!</u>

- Requires:
  - Object detection
  - Object tracking
  - Collision avoidance

Avoid collision: Safety vs Efficiency



Improve situational awareness to increase both!

Efficiency

- Get from A to B as quickly as possible

Safety: slow

- Avait information
- Limit crash severity

Topics:

1 Situational awareness and collision avoidance
For NTNU's autonomous ferry prototype

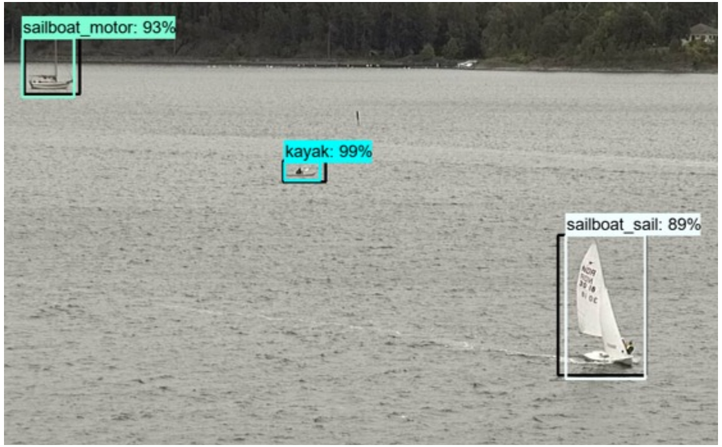
2 Sensor fusion
Combining information according to performance at different ranges

3 Object discovery
Reducing the number of hypotheses to consider

4 As good as it gets?
Improve efficiency of processing information

Collision avoidance using cameras

- 5 frames per second, 6 cameras
- Convolutional neural network detects objects as bounding boxes
- Decides whether to **STOP** or **GO** depending on whether there is an object in the path



Camera only collision avoidance

1 Results

- First time maritime collision avoidance has been done with cameras
- Combines georeferencing with clustering-based multi-camera fusion
- Performance exceeded a lidar benchmark across multiple performance measures

Ø. K. Helgesen, A. Stahl and E. F. Brekke, "Maritime Tracking With Georeferenced Multi-Camera Fusion," in IEEE Access, vol. 11, pp. 30340-30359, 2023, doi: 10.1109/ACCESS.2023.3261556.

Research areas

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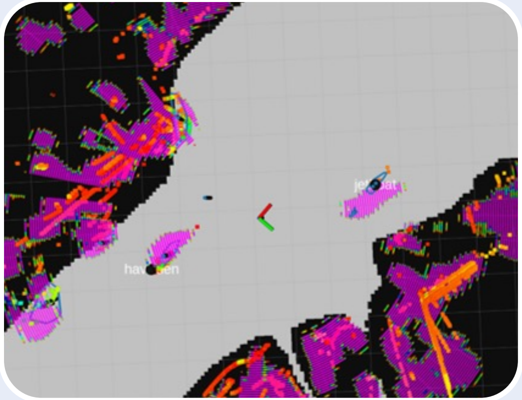
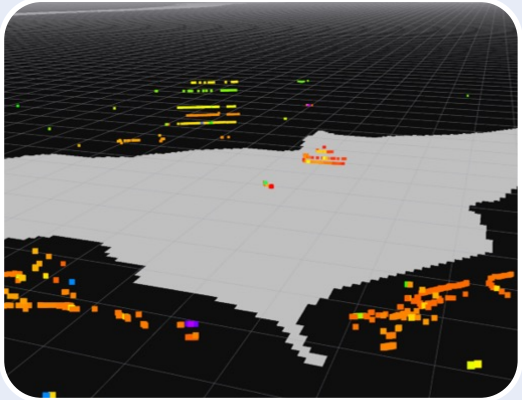
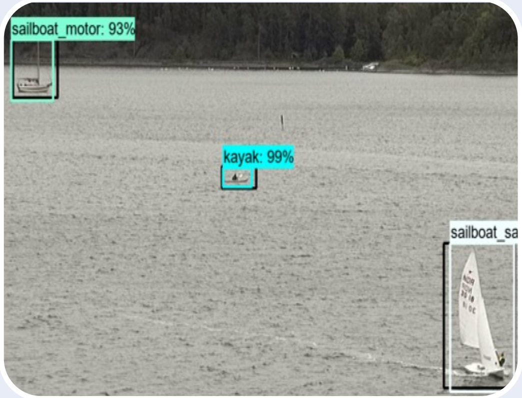
Sensors

- Radar
- Infrared
- Cameras
- Lidar

RADAR (0.8 Hz)	LiDAR (10 Hz)	Camera (5 Hz)
		
Reliable Long range: (kms)	Precise (little noise) Low range: (150 m)	Lots of information Hard to interpret Medium range

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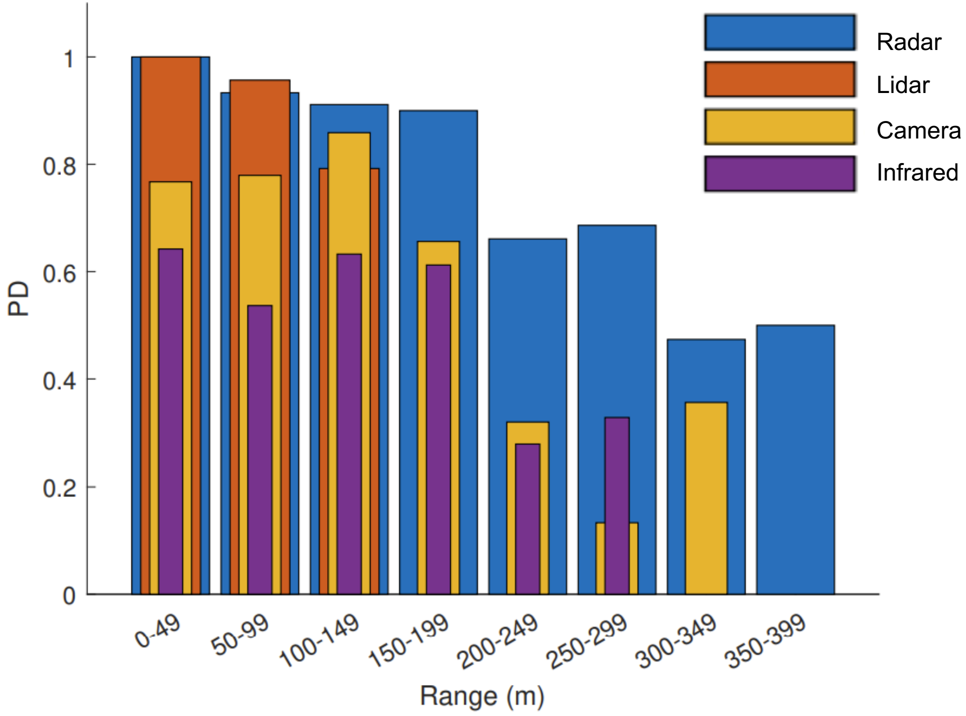
Challenges with tracking objects

- Missed detection: might not detect all objects in all frames
- Clutter / false alarms: might give unwanted detections
- Association uncertainty: no measurement tag or feature that is reliable between frames.
- **<u>→Filtering needed</u>**

Challenges with different sensors

- Different properties
  - information rates
  - Probability of object detection vs erroneous measurements
  - spatial precision
- Wrong model of a weakness might diminish another sensors strength

2 Result: Detection probability per range



Ex: 200-249m, camera says nothing is there 2/3 of the time, but 5 times per second, radar says it is there ¾ off the time but 1 time per second.

Ø. K. Helgesen, K. Vasstein, E. F. Brekke, and A. Stahl, "Heterogeneous multi-sensor tracking for an autonomous surface vehicle in a littoral envi- ronment," Ocean Engineering, vol. 252, p. 111168, 2022

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Problem of discovering new objects.

- However unlikely, *every measurement could be a new object* → Many *potential* objects
- Many potential objects makes associating measurements demanding
- Tradeoff:

  Efficient discovery vs real-time computational feasibility

Problem: Data association complexity

- 1 - 100 frames / second
- N potential objects (1 to 200) and M measurements (0 to 20)
- Number of asssociation events in a single frame:

$$\sum_{i=0}^{\min(M,N)} \binom{M}{i}\binom{N}{i} i!\, 2^{M-i} = \sum_{i=0}^{\min(M,N)} \frac{M!N!}{(M-i)!(N-i)!i!}\, 2^{M-i}$$

M \ N	3	4	5	6	7	8	9	10	11	12	13	14	15
2	22	32	44	58	74	92	112	134	158	184	212	242	274
3	86	152	248	380	554	776	1 052	1 388	1 790	2 264	2 816	3 452	4 178
4	304	648	1 256	2 248	3 768	5 984	9 088	13 296	18 848	26 008	35 064	46 328	60 136
5	992	2 512	5 752	12 032	23 272	42 112	72 032	117 472	183 952	278 192	408 232	583 552	815 192
6	3 040	8 992	24 064	58 576	130 768	270 400	523 072	955 264	1 660 096	2 763 808	4 432 960	6 882 352	10 383 664
7	8 864	30 144	93 088	261 536	671 568	1 586 944	3 479 744	7 141 248	13 828 096	25 448 768	44 795 424	75 826 144	124 002 608
8	24 832	95 744	336 896	1 081 600	3 173 888	8 546 432	21 241 984	49 079 936	106 209 920	216 834 688	420 424 832	778 788 224	1 385 397 376
9	67 328	290 816	1 152 512	4 184 576	13 918 976	42 483 968	119 401 856	310 579 712	752 299 136	1 708 188 416	3 659 700 608	7 443 524 096	14 452 618 112
10	177 664	850 944	3 759 104	15 284 224	57 129 984	196 319 744	621 159 424	1 815 177 984	4 920 975 104	12 443 966 464	29 525 850 624	66 122 856 704	140 558 097 664

Linear Multitarget on subset of objects (LMS)

- Removes low probability objects from the joint data association problem:

$$\Omega^{i}_{t|\underline{t}} = \Lambda_{t|\underline{t}} + \sum_{i' \neq i} \omega^{i'}_{t|\underline{t}}$$

Complex

$$e^{\bar{\Lambda}_{t|\underline{t}}} \sum_{\bigcup_{i'=0}^{N} Z_t^{i'} \subseteq Z_t} \Lambda^{Z_t^0}_{t|\underline{t}} \prod_{\substack{i'=1:\\ i' \neq i}}^{N} B^{\mathbf{z},i'}_{t|\underline{t}}(Z_t^{i'}) \approx e^{\bar{\Omega}^{i}_{t|\underline{t}}} \left(\Omega^{i}_{t|\underline{t}}\right)^{Z_t \setminus Z_t^i}$$

Simpler computation

- More potential objects with low probability now less demanding
- Keeping track of more potentialities gives faster discovery
- Less surprises

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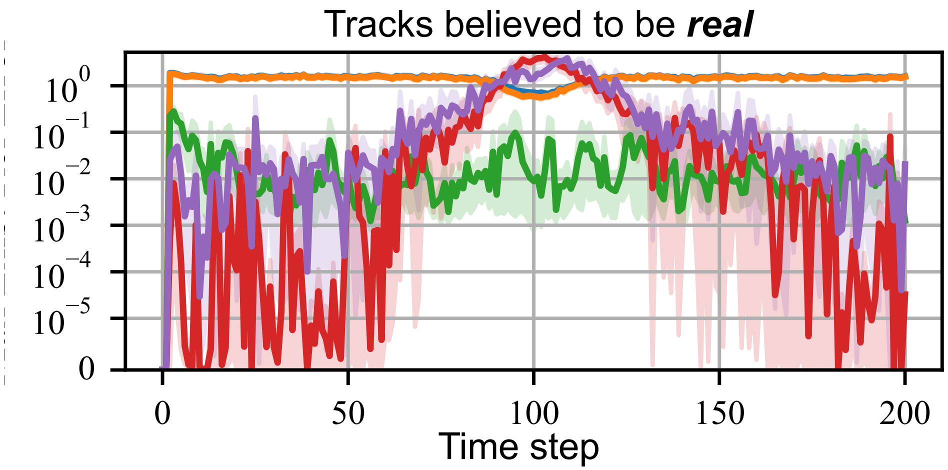
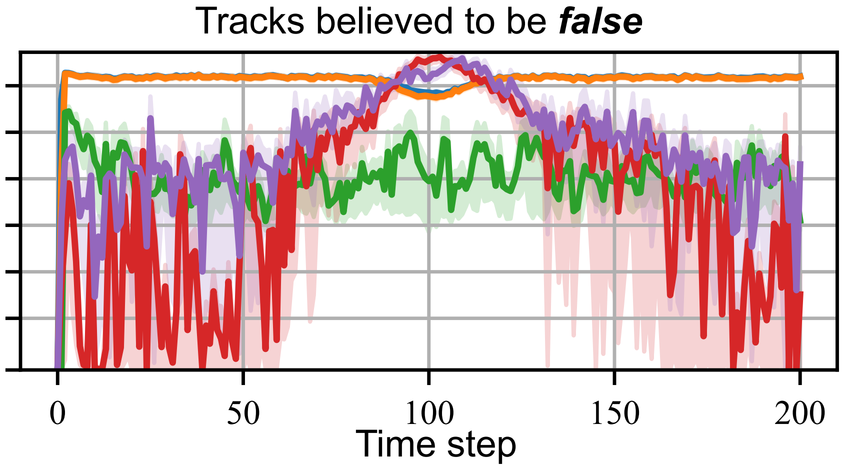
3 Results: Comparison

- Max relative error in calculated probability for potential objects being real
- Simulation scenario: 3 objects starts appart, get into close proximity, and move appart again.
- Our approach has low error, and performance is unaffected by the proximity.





L.-C. Tokle and E. F. Brekke, "The linear multitarget IPDA and its application on only a subset of the tracks." *Proc. 2023 26th International conference on Information Fusion (FUSION).*

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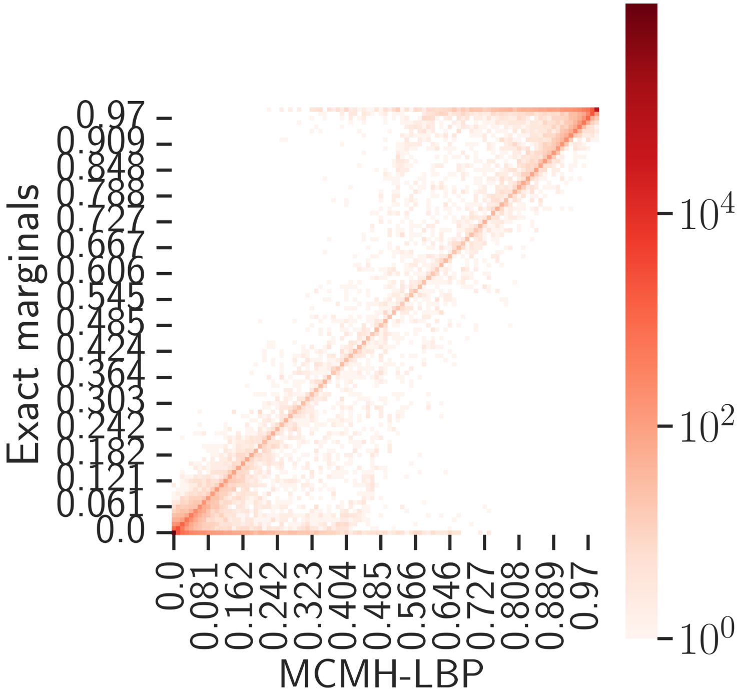
4 **As good as it gets?**
Further improve efficiency

As good as it gets?

- We want to merge two approaches
  1. Keep the K best hypotheses (precise, but might miss)
  2. Average over association hypotheses (currently used, less precise)
- Require multi frame marginal probabilities
  - Enumerate events
  - Event count in multi frame is the product of the single frames
- Approximate probabilities with message passing?
  - Loopy belief propagation (LBP).

4 Results: correlation plot of approx.



- Usually very small error
- Sometimes too large err
- Worst case run time (1000x faster)
  - Exact: 146s
  - LBP: 0.14s than exact
- Average run time (200x faster)
  - Exact: 2.17s
  - LBP: 0.01
- Real-time possible with optimized implementation

O. A. Severinsen, L.-C. N. Tokle and E. F. Brekke, "Belief propagation for marginal probabilities in multiple hypothesis tracking." *Proc. 2023 26th International conference on Information Fusion (FUSION).*

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Ongoing work

- More in depth testing of algorithms
- Track merging to reduce number of tracks while keeping information
- Direct tracking of image features for increased precision.
- In depth study of the trafic patterns in the canal

Thank you!