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Fast Trajectory Forecasting With Automatic Identification System (AIS) Broadcasts

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Motivation: Automatic Identification System (AIS)

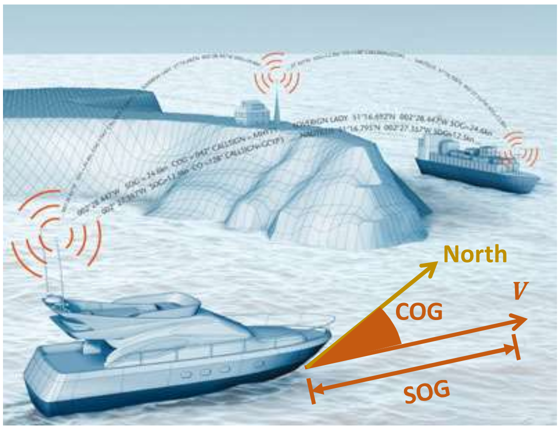

Figure 1. Illustration of the “Revised guidelines for the onboard operational use of shipborne automatic identification systems (AIS)”, 2015, International Maritime Organization (IMO) (source: https://www.imo.org/).

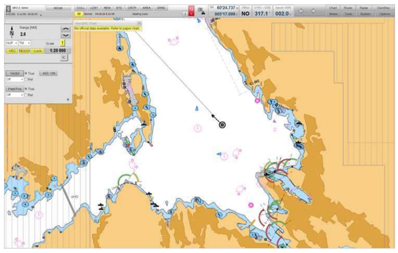

Figure 2. Screenshot from an onboard Electronic Chart Display and Information System (ECDIS) screen (source: https://www.kongsberg.com/.).

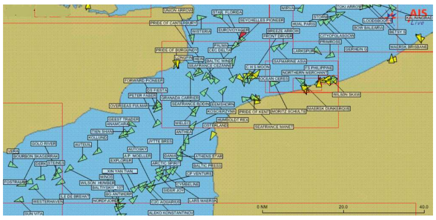

Figure 3. Maritime traffic display based on AIS messages (source: https://en.wikipedia.org/wiki/Automatic_identification_system.).

Motivation: Trajectory forecasting with AIS

- AIS messages collected over time are discrete observations of trajectory.
- Prediction of future position and the associated uncertainty is desirable in maritime safety and security application.

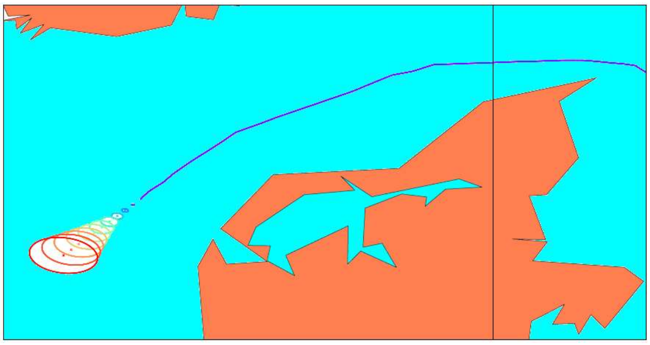

Figure 4. Example location forecasts and uncertainty ellipses for multiple time steps separated by 1,000 s starting from the last message.

Contents

- **A (generative) trajectory model with six parameters**
- **Fast sub-optimal maximum likelihood estimation**
- **Performance Study**
- **Conclusion**

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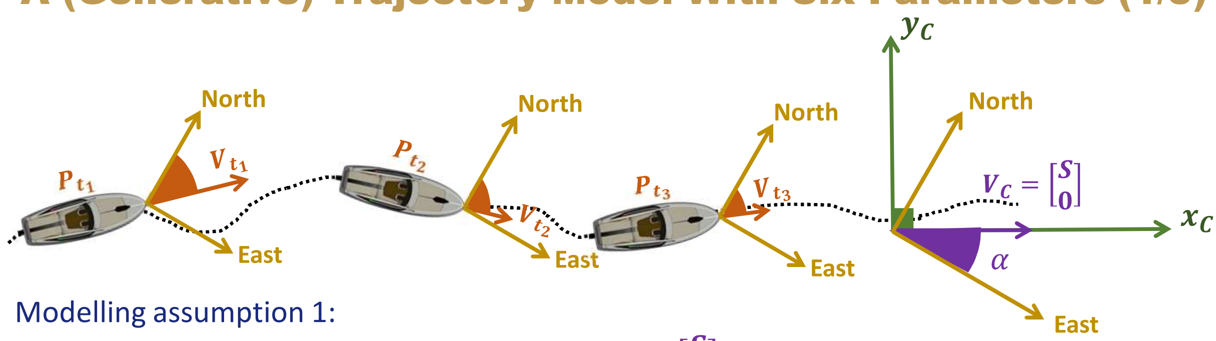
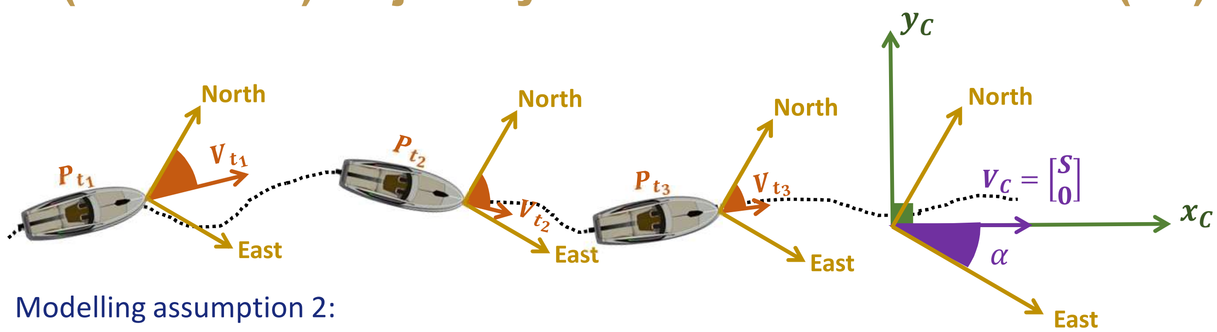
A (Generative) Trajectory Model With Six Parameters (1/5)



Modelling assumption 1:

- The motion maintains an average velocity $\boldsymbol{V_C} = \begin{bmatrix} S \\ 0 \end{bmatrix}$ in a cruise coordinate system specified by the rotation angle α.
- In the East-North plane, this mean velocity is $V = \begin{bmatrix} v_E \\ v_N \end{bmatrix} = \begin{bmatrix} \cos\alpha & -\sin\alpha \\ \sin\alpha & \cos\alpha \end{bmatrix} \boldsymbol{V_C}$.
- The parameters α and $\boldsymbol{S}$ encode this assumption.

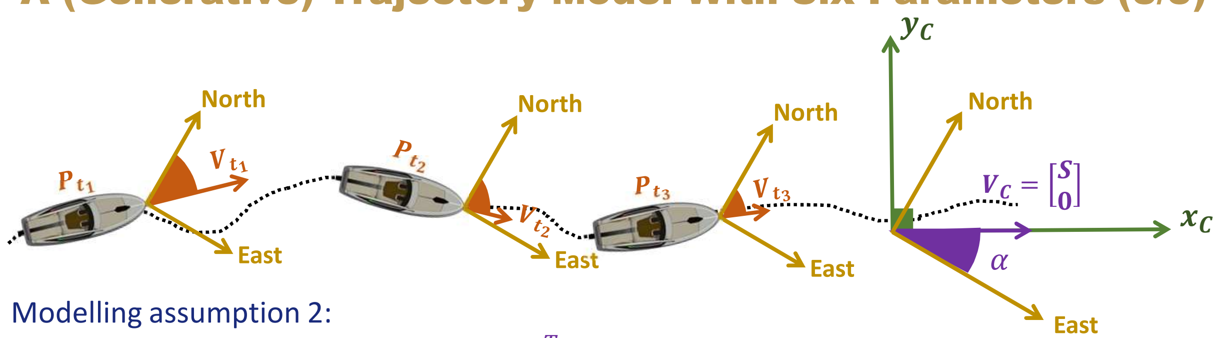
A (Generative) Trajectory Model With Six Parameters (2/5)



Modelling assumption 2:

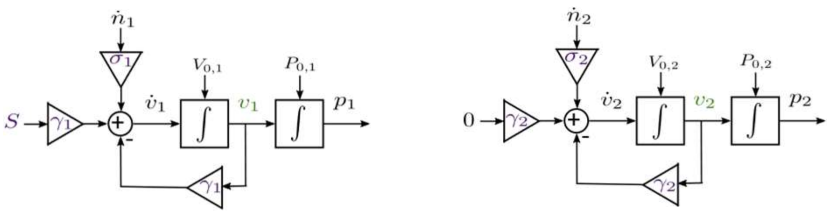
- The deviations of the two components of the instantaneous velocities $\boldsymbol{V}_{t_1}, \boldsymbol{V}_{t_2}, \ldots$ in the cruise coordinate frame $(\boldsymbol{x}_C, \boldsymbol{y}_C)$ from $\boldsymbol{V}_C = \begin{bmatrix} \boldsymbol{S} \\ \boldsymbol{0} \end{bmatrix}$ are due to independent continuous time random walk; and the processes revert to the mean of $\boldsymbol{S}$ and $\boldsymbol{0}$.

A (Generative) Trajectory Model With Six Parameters (3/5)



Modelling assumption 2:

- Equivalently $[\boldsymbol{V}_t]_C = \begin{bmatrix} \cos\alpha & -\sin\alpha \\ \sin\alpha & \cos\alpha \end{bmatrix}^T \boldsymbol{V}_t = \begin{bmatrix} v_1 \\ v_2 \end{bmatrix}$ and v_1 and v_2 are Ornstein-Uhlenbeck (OU) processes with parameters (σ_1, γ_1) and (σ_2, γ_2) , respectively.



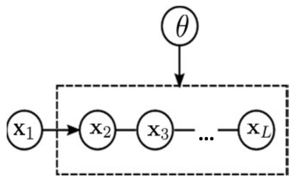
A (Generative) Trajectory Model With Six Parameters (4/5)

- The model parameters for the continuous state trajectory $x(t) = [p_1(t), p_2(t), v_1(t), v_2(t)]^T$ are thus $\theta = [S, \alpha, \sigma_1, \gamma_1, \sigma_2, \gamma_2]$.
- Given (discrete time) state trajectory observations (as, e.g. AIS messages) $\mathbf{x} = [\mathbf{x}_1, \ldots, \mathbf{x}_L]$ collected at $\boldsymbol{t} = [t_1, \ldots, t_L]$, i.e. $\mathbf{x}_k = x(t_k)$ for $k = 1, \ldots, L$.
  1. The parameter likelihood induced by the OU processes is a product of multi-normal densities:

$$\Delta t_k \triangleq t_k - t_{k-1}$$

$$l(\mathbf{x}|\theta; \boldsymbol{t}) = \prod_{k=2}^{L} \underbrace{l(\mathbf{x}_k|\mathbf{x}_{k-1}, \theta; \Delta t_k)}$$

$$l(\mathbf{x}_k|\mathbf{x}_{k-1}, \theta; \Delta t_k) = \mathcal{N}(\mathbf{x}_k; \mu(S, \alpha, \gamma_1, \gamma_2, \mathbf{x}_{k-1}, \Delta t_k), \mathbf{\Sigma}(\Delta t_k, \gamma_1, \gamma_2, \sigma_1, \sigma_2))$$



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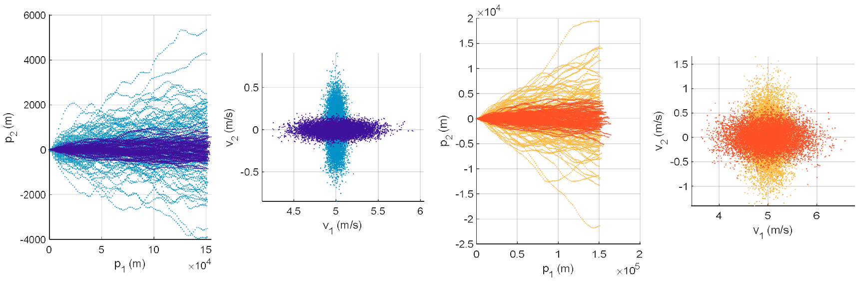
  1. The parameter likelihood induced by the OU processes is a product of multi-normal densities:

$$l(\mathbf{x}|\theta; \boldsymbol{t}) = \prod_{k=2}^{L} l(\mathbf{x}_k|\mathbf{x}_{k-1}, \theta; \Delta t_k)$$

#	S (m/s)	α (deg)	γ_1	γ_2	σ_1	σ_2
1	5	0	1.0e-3	1.0e-3	1.0e-2	0.25e-2
2	5	0	1.0e-3	1.0e-3	0.25e-2	1.0e-2
3	5	0	1.0e-3	0.25e-3	1.0e-2	1.0e-2
4	5	0	0.25e-3	1.0e-3	1.0e-2	1.0e-2



A (Generative) Trajectory Model With Six Parameters (5/5)

2. The probability density of a future state $\mathbf{x}_{t_f}$ at time t_f given
   I. $\mathbf{x} = [\mathbf{x}_1, ..., \mathbf{x}_L]$,
   II. An estimate of the parameters $\hat{\theta}(\mathrm{x})$ is a multivariate normal:

$$l(\mathbf{x}_{t_f}|\mathbf{x}, \hat{\theta}(\mathbf{x}); t_f, \mathbf{t}) = \mathcal{N}(\mathbf{x}_k; \mu(\hat{S}, \hat{\alpha}, \hat{\gamma}_1, \hat{\gamma}_2, \mathbf{x}_L, t_f - t_L), \mathbf{\Sigma}(t_f - t_L, \hat{\gamma}_1, \hat{\gamma}_2, \hat{\sigma}_1, \hat{\sigma}_2))$$

- The mean of this density $\mu(\hat{\theta})$ is the MMSE estimate of the future state $\mathbf{x}_{t_f}$.
- The covariance matrix $\Sigma(\hat{\theta})$ quantifies the uncertainty.

Fast Sub-Optimal Maximum Likelihood Estimation (1/5)

- The maximum likelihood estimation* of the parameters $\theta = [S, \alpha, \sigma_1, \gamma_1, \sigma_2, \gamma_2]$ given state observations (e.g. AIS messages) $\mathbf{x} = [\mathbf{x}_1, ..., \mathbf{x}_L]$ is a constrained optimisation problem:

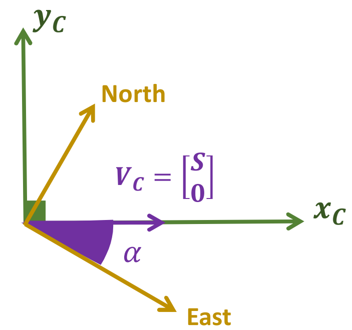
$$\begin{aligned} \hat{\theta} &= \arg\max_{\theta} l(\mathbf{x}|\theta; \boldsymbol{t}) \\ &= \arg\max_{\theta} \log l(\mathbf{x}|\theta; \boldsymbol{t}), \\ &\quad \text{subject to} \end{aligned}$$
$$0 \leq S, 0 < \alpha < 2\pi, 0 < \gamma_1, 0 < \gamma_2, 0 < \sigma_1,\ 0 < \sigma_2$$

1. Solutions are iterative (e.g. the interior point algorithm): $\hat{\theta}_0 \rightarrow \hat{\theta}_1 \rightarrow \cdots \rightarrow \hat{\theta}_i \rightarrow \cdots$ and require the evaluation of a non-trivial gradient and Hessian*.
2. Optimal solution requires a good initial estimate $\hat{\theta}_0$.

* Uney, et al. "Maximum likelihood estimation in a parametric stochastic trajectory model," SSPD'19, Brighton, 2019.

Fast Sub-Optimal Maximum Likelihood Estimation (1/5)

Reminder: The model has two independent OU processes:
Along $\boldsymbol{x_C}$ with a mean of S and along $\boldsymbol{y_C}$ with a mean of 0.



1. Find $\hat{S}, \hat{\alpha}$ using sample averages of $\mathbf{x} = [\mathbf{x}_1, \ldots, \mathbf{x}_L]$
2. Find the samples of the two OU processes:
   1. Rotate the state observations: $\mathbf{x}_C = \mathbf{E}(\hat{\alpha})^T \mathbf{x}$
   2. Use the results in [*] for the ML estimation of σ, γ for $\Delta t_2 = \Delta t_3 = \cdots = \Delta t_k = \Delta T$ and zero-mean OU processes:
      1. Find $y = \mathbf{x}_{C,3} - \hat{S}$ and find the estimates $\hat{\gamma}_1$and $\hat{\sigma}_1$ using closed form equations.
      2. Use $\mathbf{x}_{C,4}$ and find the estimates $\hat{\gamma}_2$and $\hat{\sigma}_2$ using closed form equations.

* T. Karvonen, F. Tronarp, and S. Sarkka, "Asymptotics of maximum likelihood parameter estimates for gaussian processes: The Ornstein-Uhlenbeck prior," in 2019 IEEE 29th International Workshop on Machine Learning for Signal Processing (MLSP), 2019, pp. 1–6.

Performance Study

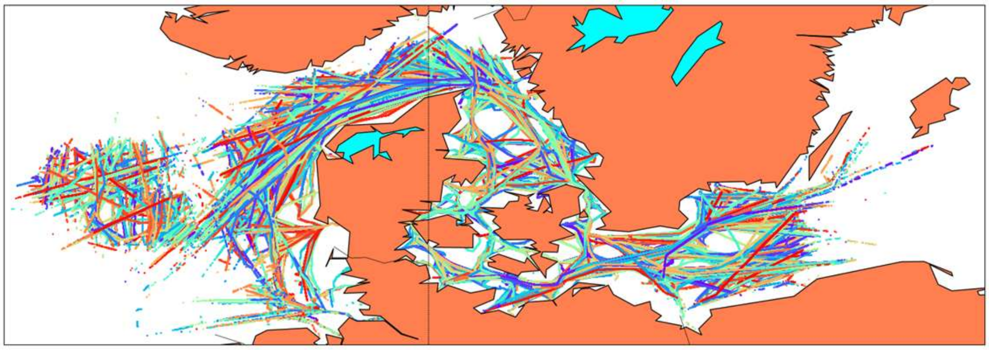


Figure 5. Cargo-ship trajectories recorded in February 2022 by the Danish Maritime Authority (URL: https://dma.dk/safety-at-sea/navigationalinformation/ais-data). A total of 6194 trajectories are depicted.

	Time length (h)	Number of AIS messages per MMSI trajectory	Speed (ms^{-1})
Average	13.76	4,576.52	5.46
Maximum	23.99	31,367	11.95
Minimum	0.21	101	0

Performance Study

- Let us consider the error in predicted position.
- The distance to horizon is approximately 10km for an observer 8m above the sea level.

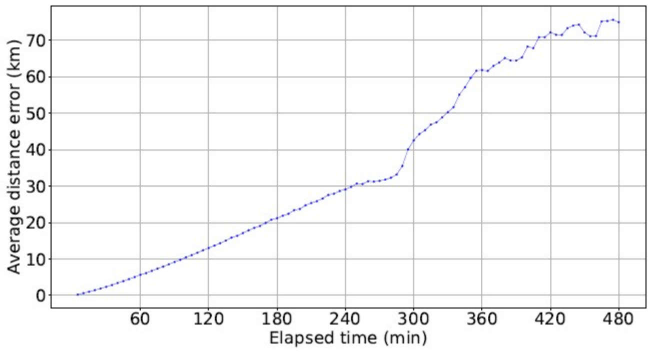


Figure 6. Average prediction error versus the length of time step into the future.

Performance Study

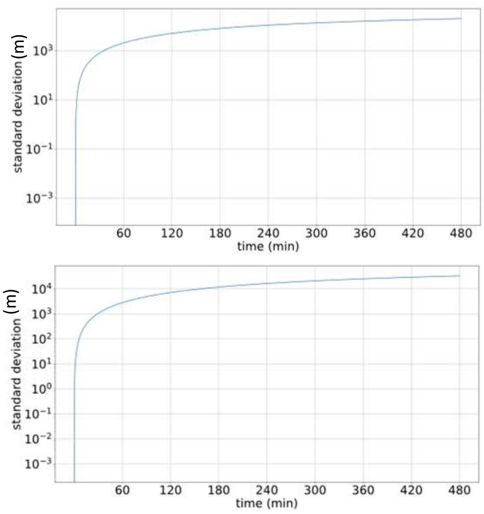


Figure 7. Predictive model standard deviation along the cruise direction (top) and the perpendicular direction (bottom).

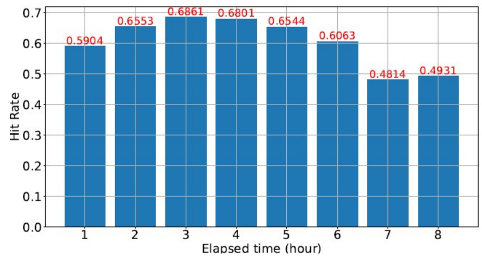
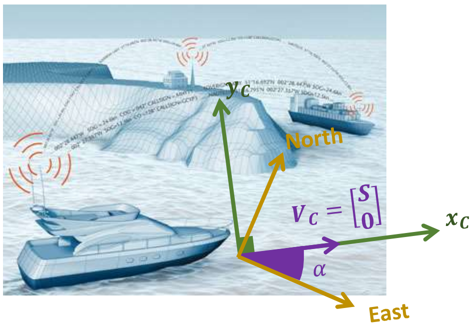


Figure 8. Prediction hit rate versus prediction time.

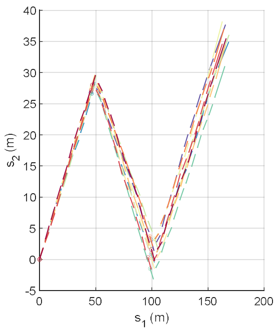
- Let us consider the error in prediction uncertainty.
- The hit rate is the ratio of the trajectories for which the ground truth falls in the 4σ uncertainty ellipse of the prediction.
- The prediction models are overconfident.

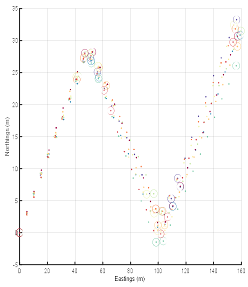
Conclusions

- This work considered an Ornstein-Uhlenbeck process based trajectory model with six-parameters.
- We introduced a fast sub-optimal method for the estimation of model parameters.
- To handle piece-wise stationarity of trajectories, future work includes incorporating the fast estimator to a dynamic programme for joint segmentation and parameter estimation.



- Future work includes incorporating the fast estimator to a dynamic programme for trajectory segmentation.





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