Tip & Cue AIS-Assisted Gaussian Process Regression for Ship Dynamics Modeling and Cognitive SAR Tasking

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Motivations and Challenges

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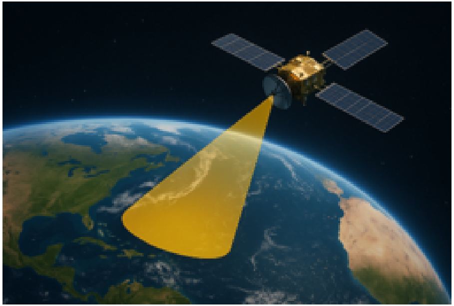
- Maritime surveillance as application scenario for Cognitive SAR design
- AIS data for vessel selection and trajectory fitting
- Tip & Cue enables extended monitoring period



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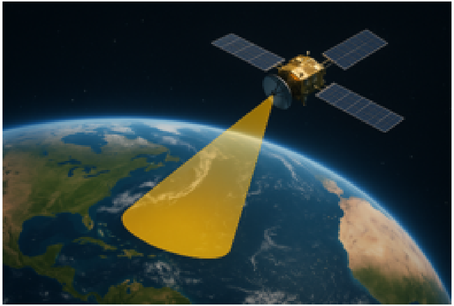


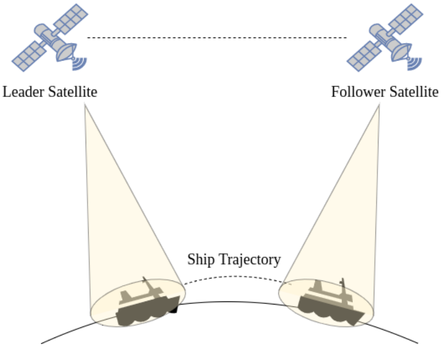
Challenge

- Fit vessel track with sparse AIS messages and observability gap

Tip & Cue Framework

Tip & Cue involves cooperation among satellites

- Leader satellite selectes Area of Interest (*Tip*)
- Follower satellite focuses on selected area (*Cue*)
- Surveillance and emergency response applications



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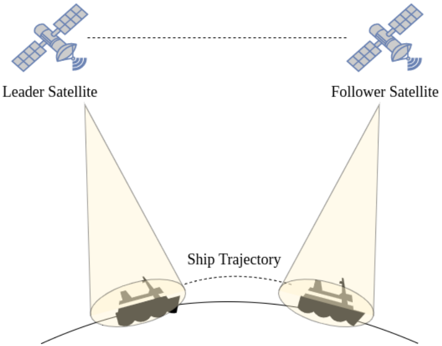

Pros: Extended monitoring of target of Interest
Cons: Non-observability period of target of Interest

Received AIS data to fit overall trajectory

AIS Data

AIS data are

- Provided by cooperative vessels to share their status
- Divided into static and kinematic informations

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Kinematic AIS data useful for trajectory fitting

ID	UNIX Times-tamp	Longitude	Latitude	Heading	Speed	Course
2f0f2613	1524381344000ms	23.6deg	37.96deg	167deg	0kn	167deg

Gaussian Process Regression

Gaussian Process: collection of variables, any finite number of which have a joint Gaussian distribution

A GP is completely define by its *mean function* $m(x)$ and *kernel* $k(x, x')$

$$f(x) \sim GP(m(x), k(x, x'))$$

with

$$\begin{aligned} m(x) &= \mathbf{E}[f(x)] \\ k(x, x') &= \mathbf{E}[(f(x) - m(x))(f(x') - m(x'))] \end{aligned}$$

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The function $f(x)$, in this work, is the longitude and latitude time evolution

Gaussian Process Regression

Gaussian Process Regression: a supervised learning problem

- Training dataset $D = \{X, y\}$: feature X (time instants) and label y (longitude / latitude)
- Goal: predict output $f^\star$ for new features $X^\star$

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Output $f^\star$ obtained by maximizing the Log-Marginal-Likelihood and with distribution

$$f^\star \mid X, y, X^\star \sim \mathcal{N}(\mu^\star, \sigma^{\star 2})$$

where, for unseen time instant X:

- $\mu^\star$ *mean value* of longitude/latitude
- $\sigma^\star$ associated *standard deviation*

Simulation Set-Up

Leader and *Follower* spacecrafts

- AIS observability of 300s each
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- Leader sends AIS messages via inter-satellite link

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AIS dataset provided by [1]

- Freely available, real ground-based AIS dataset
- Only vessels with speed at least of 3kn and sending messages for at least 1100s considered
- Only 25% of available data used to simulate data packet loss

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Kernel employed: sum of Radial Basis Function and Dot Product

$$k(x, x') = k_{rbf}(x, x') + k_{dp}(x, x') = \sigma_f^2 \text{exp}\left(\frac{-\|x - x'\|^2}{2l^2}\right) + \sigma_0^2 x \cdot x'$$

where GPR learns the legnth scale l and the variances σ_f^2 and σ_0^2

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Results - Mean Absolute Error

Fitting quality on both longitude and latitude evaluted in terms of *Mean Absolute Error*

$$\text{MAE} = \sum_{n=0}^{N_{\text{trajectories}}} \frac{|p_{\text{fit}} - p_{\text{true}}|}{n_{\text{samples}}}$$

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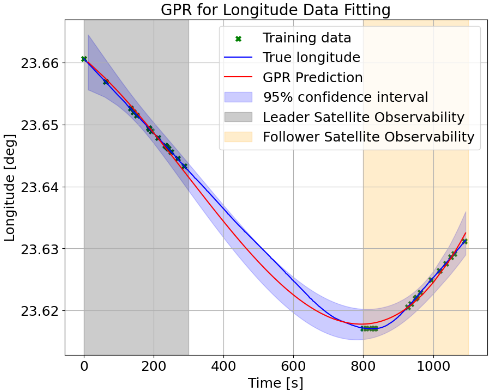
	MAE Longitude	MAE Latitude
Test Set	0.00124deg	0.00102deg
Non-Obs Test Set	0.00167deg	0.00138deg



Results - Confidence Interval

Fitted output $y^\star$ lies in *Confidence Interval* if

$$y^\star \in [\mu^\star - \alpha\sigma^\star, \mu^\star + \alpha\sigma^\star]$$

where α depends on selected C.I.

Higher C.I.

- Higher α, e.g, larger interval
- More test points are contained within the C.I.

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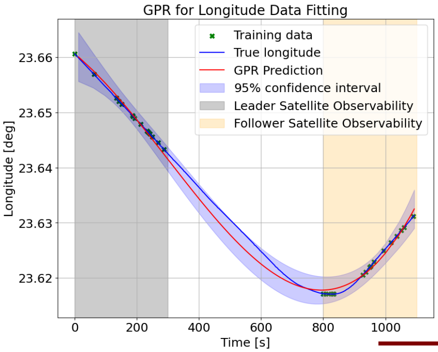
	Longitude Test Data	Latitude Test Data
99%	88.19%	92.79%
95%	82.49%	87.28%
90%	77.80%	82.71%



FPGA Porting

Gaussian Process Regression algorithm porting

- Zynq UltraScale+ and Versal Edge FPGAs
- ZCU102 and VE2303 development kits
- VE2302 outperforms ZCU102

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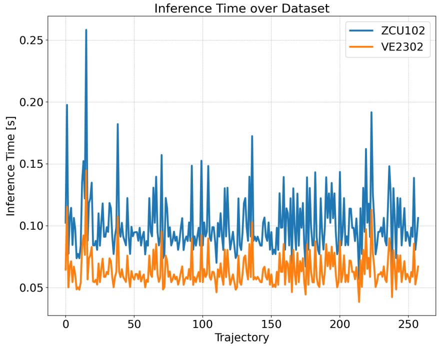

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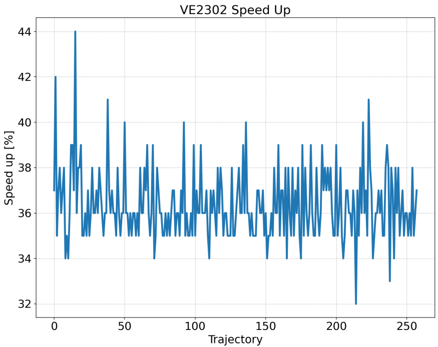
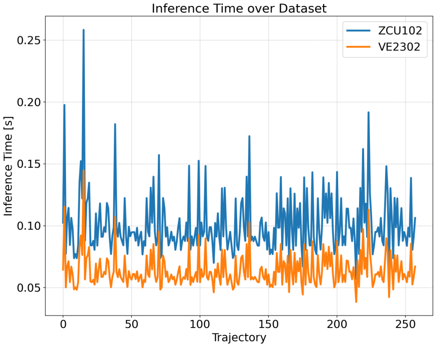
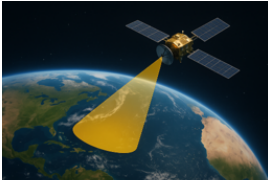
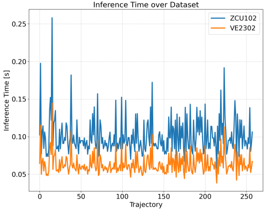




Conclusions

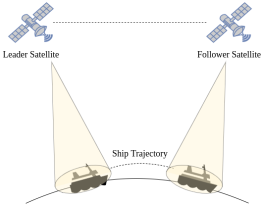




Tip & Cue as maritime surveillance set-up

Gaussian Process Regression applied to AIS data fitting

Fitting results in terms of Mean Absolute Error and Confidence Interval



Algorithm porting on two space-qualified FPGAs