Collaborative Localization in GNSS Denied Environments

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Outline

The Project - People Involved

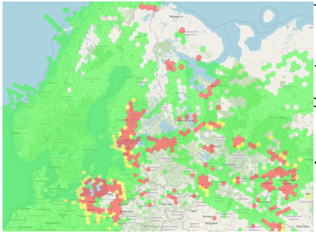
Eric Sevonius
Industrial PhD student
Saab Dynamics

Gustaf Hendeby
Supervisor
LiU

Fredrik Gustafsson
Co-supervisor
LiU

GNSS interference

GNSS is susceptible to interference from malicious actors.



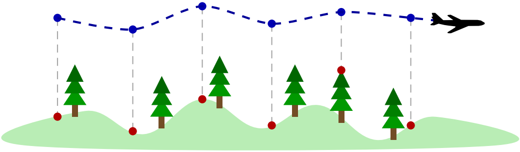
https://gpsjam.org/

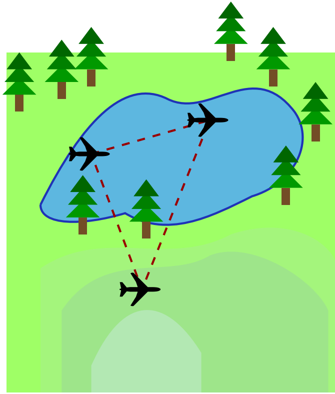
GPS interference reports by airplanes

- $> 10\%$
- $2 - 10\%$
- $0 - 2\%$

Project

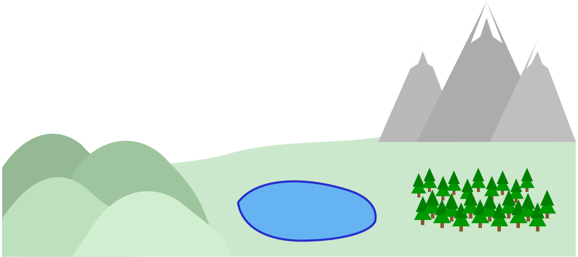
For now: focus on Terrain-Aided Navigation (TAN)





Expected Navigation Performance 1/2

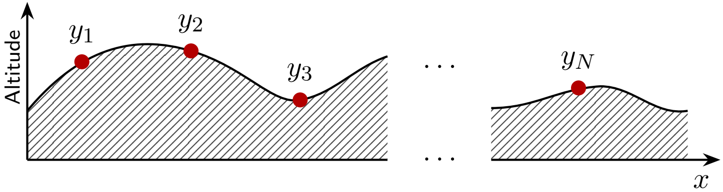
What is expected navigation performance over a *terrain type*?†



† Eric Sevonius, Fredrik Gustafsson, Gustaf Hendeby, "Evaluating the Performance of Terrain-Aided Navigation Using a Stochastic Map Model", Accepted to: 29th International Conference on Information Fusion (FUSION), 2026.

Expected Navigation Performance 2/2

- Cramér-Rao Lower Bound (CRLB) gives measure of achievable performance.



Expected Navigation Performance 2/2

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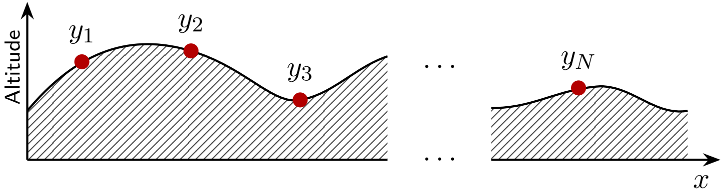
- Given effective estimator, CRLB provides expected performance!



Expected Navigation Performance 2/2

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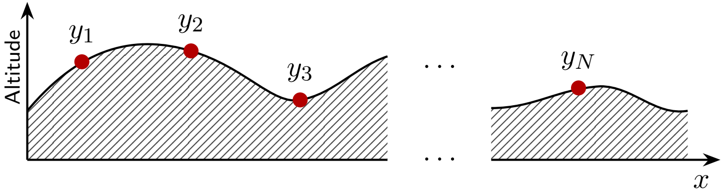

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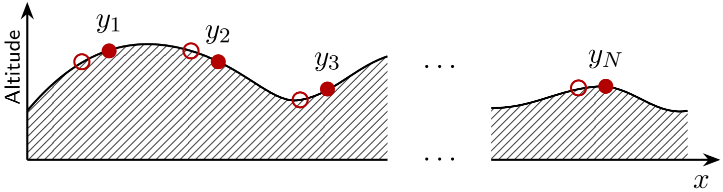


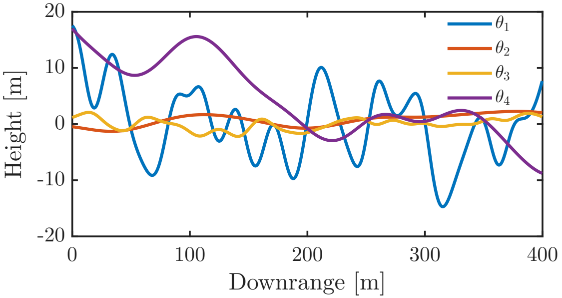
Stochastic Map Model

Let the map, $M(x)$, be a realization of stochastic variable, $\boldsymbol{M}(x)$.

- Associate terrain type with statistical description.
- Turns CRLB into a bound on *expected* performance over the terrain type.
- Note: randomness does *not* enter estimation problem.

Example – 1D Gaussian Process Model 1/2

hyper-parameters	$\boldsymbol{\theta_1}$	$\boldsymbol{\theta_2}$	$\boldsymbol{\theta_3}$	$\boldsymbol{\theta_4}$
ℓ [m]	12	30	12	30
σ_f [m]	8	1	1	8



Example – 1D Gaussian Process Model 2/2

Results from Monte Carlo simulations over the map distribution, $\boldsymbol{M}$.

	Our Method $[\mathrm{m}^2]$	**Mean Map CRLB** $[\mathrm{m}^2]$	**Mean Map MSE** $[\mathrm{m}^2]$
θ_1	0.31 ± 0.22	0.32 ± 0.22	0.32 ± 0.25
θ_2	180 ± 280	180 ± 290	5700 ± 4700
θ_3	20 ± 14	20 ± 13	5200 ± 3700
θ_4	2.9 ± 4.4	2.9 ± 4.4	13 ± 65

Current Work

Go beyond proof of concept in Fusion paper.

- Fit map model to real elevation data.
- More realistic model.
- Generalize properties (*e.g.* 2D).

Thanks for listening!

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