Extended target tracking using Gaussian processes

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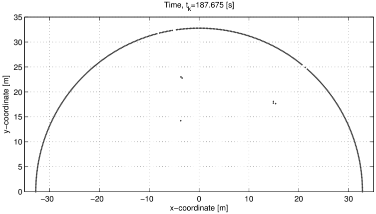
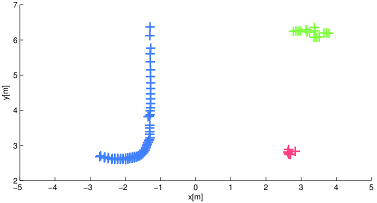
Extended target tracking

Many sensors generates more than one measurement per target





Extended target (definition)

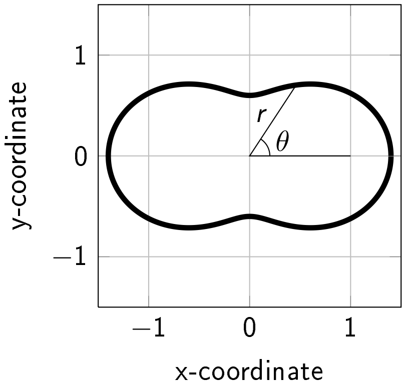
Targets that potentially give rise to multiple measurements at each time step

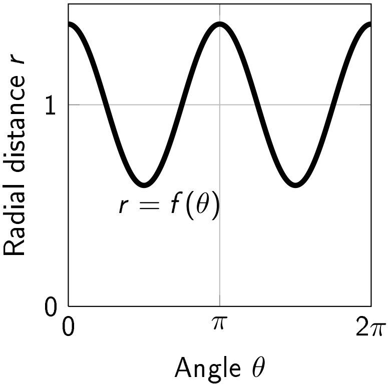
Goal: We want to estimate target position, target orientation and target extent *jointly*.

Related work

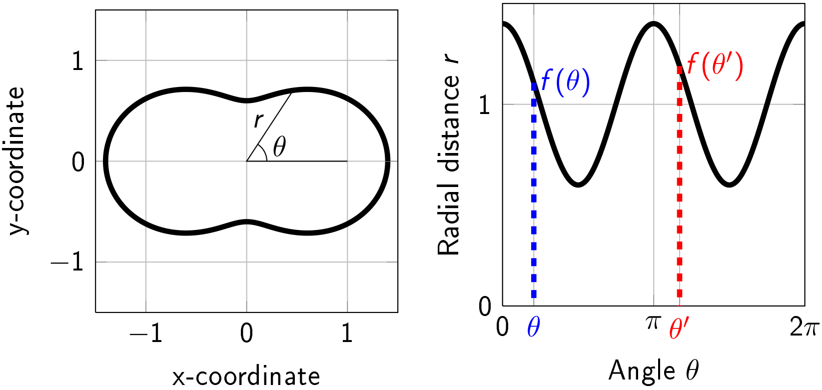
- Elliptical targets using inverse Wishart prior
  - First paper (Koch, Trans. Aerospace 2008).
  - Multiple ellipses per target (Lan and Li, Fusion 2012).
  - Encoding orientation (Granström and Orguner, Trans. Aeorspace 2014)
- Parametrized objects, rectangles, ellipses etc. (Granström, Fusion 2011)
- Random hyper-surface model (Baum and Hanebeck, Fusion 2011)
- Computer vision: B-splines (Blake et al., 1993, 1995, 1998)

Modeling using polar coordinates





Modeling using polar coordinates

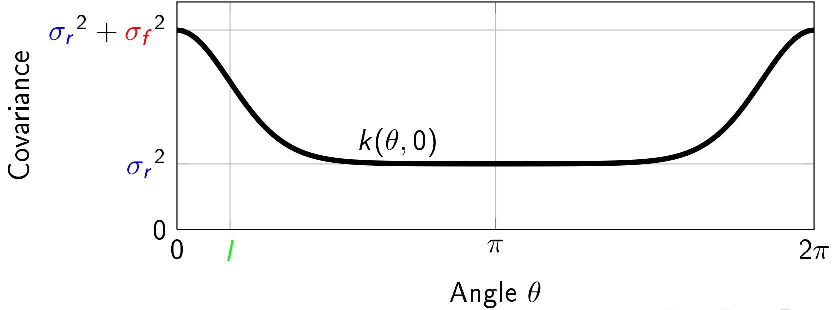


We model $f(\theta)$ using a Gaussian process.

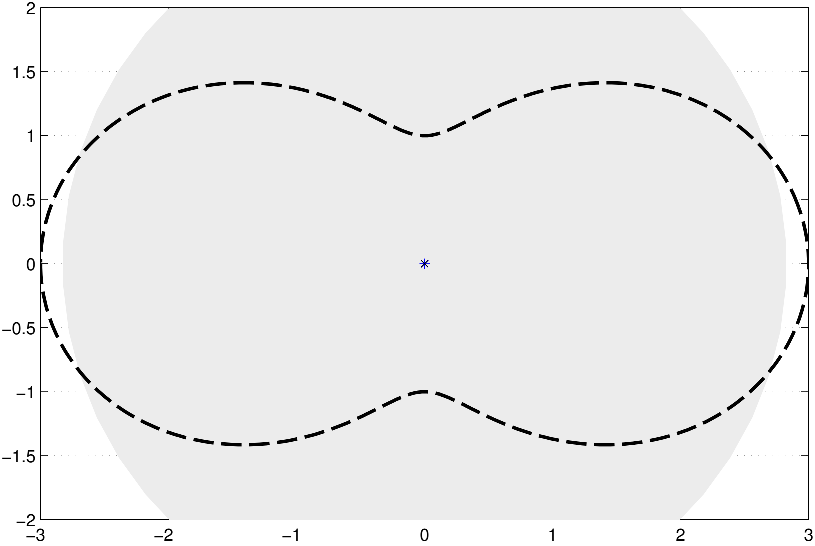
$$f(\theta) \sim \mathcal{GP}(0, k(\theta, \theta')), \qquad \mathbb{E}[f(\theta)f(\theta')] = k(\theta, \theta')$$

- We use a periodic covariance function to model the periodicity
- We use a additional constant covariance to model a constant (but unknown) mean, corresponding to the mean radius of the target

$$k(\theta, \theta') = {\sigma_f}^2 e^{-\frac{2\sin^2\left(\frac{|\theta-\theta'|}{2}\right)}{l^2}} + {\sigma_r}^2$$



Example

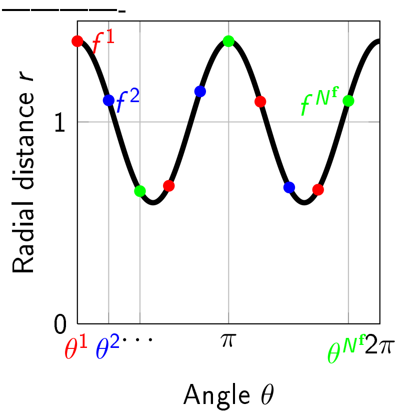


Idea: Consider function values $f^1, f^2, \dots, f^{N^{\mathrm{f}}}$ to be the state components

$$\mathbf{x}^{\mathrm{f}} = \begin{bmatrix} f^1 \\ f^2 \\ \vdots \\ f^{N^{\mathrm{f}}} \end{bmatrix}$$

This can be cast into a state space model

$$\mathbf{x}^{\mathrm{f}}_{k+1} = \mathbf{x}^{\mathrm{f}}_k$$
$$\mathbf{y}_k = H\mathbf{x}^{\mathrm{f}}_k + \mathbf{e}_k$$
$$\mathbf{x}^{\mathrm{f}}_0 \sim \mathcal{N}(0, P^{\mathrm{f}}_0)$$



Recursive GP regression

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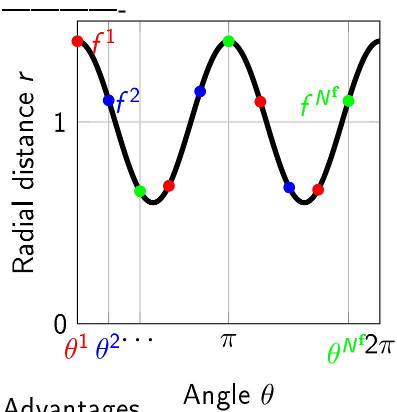

Advantages

- Recursive update with KF

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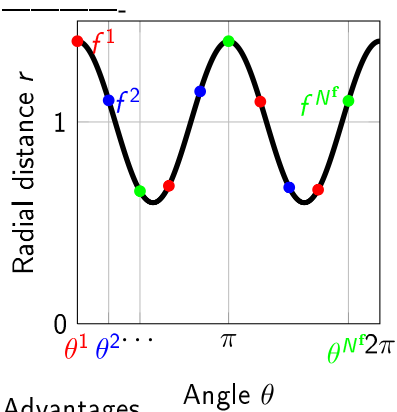

Advantages

- Recursive update with KF
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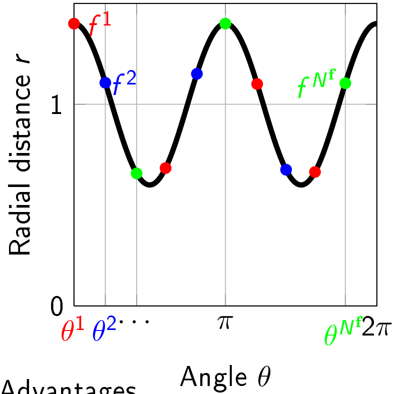
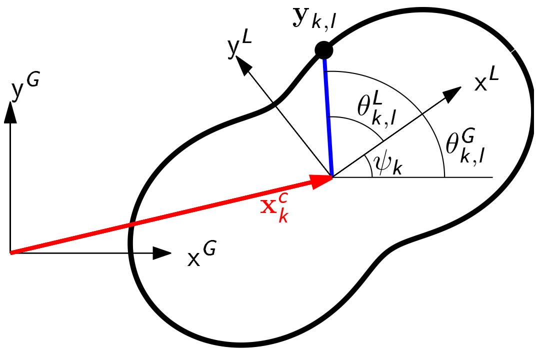


Advantages

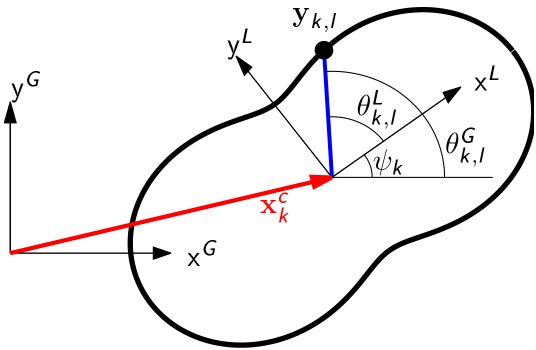
- Recursive update with KF
- Add process noise
- $\mathbf{x}^{\mathrm{f}}_k$ can be augmented with target position $\mathbf{x}^c_k$ and



Measurement is the sum of target position and offset due to target extent

$$\mathbf{y}_{k,l} = \mathbf{x}^c_k + \begin{bmatrix} \cos(\theta^G_{k,l}) \\ \sin(\theta^G_{k,l}) \end{bmatrix} f(\theta^L_{k,l}) + \mathbf{e}_{k,l}, \qquad \theta^G_{k,l} = \theta^G_{k,l}(\mathbf{x}^c_k)$$

$$\theta^L_{k,l} = \theta^L_{k,l}(\mathbf{x}^c_k, \psi_k)$$



Measurement is the sum of target position and offset due to target extent

$$\mathbf{y}_{k,l} = \mathbf{x}^c_k + \begin{bmatrix} \cos(\theta^G_{k,l}) \\ \sin(\theta^G_{k,l}) \end{bmatrix} H(\theta^L_{k,l})\mathbf{x}^{\mathbf{f}}_k + \mathbf{e}_{k,l}, \qquad \theta^G_{k,l} = \theta^G_{k,l}(\mathbf{x}^c_k)$$

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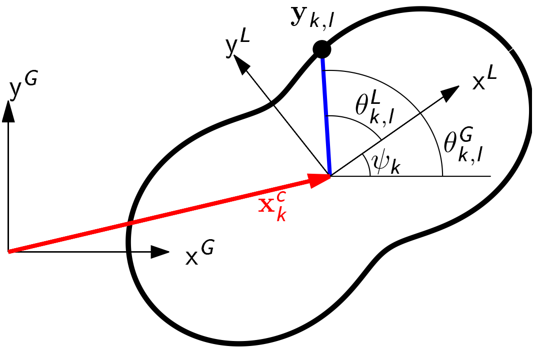


This can be summarized into a non-linear sensor model

$$\mathbf{y}_{k,l} = \mathbf{x}^c_k + H(\mathbf{x}^c_k, \psi_k)\mathbf{x}^{\mathbf{f}}_k + \mathbf{e}_{k,l}$$

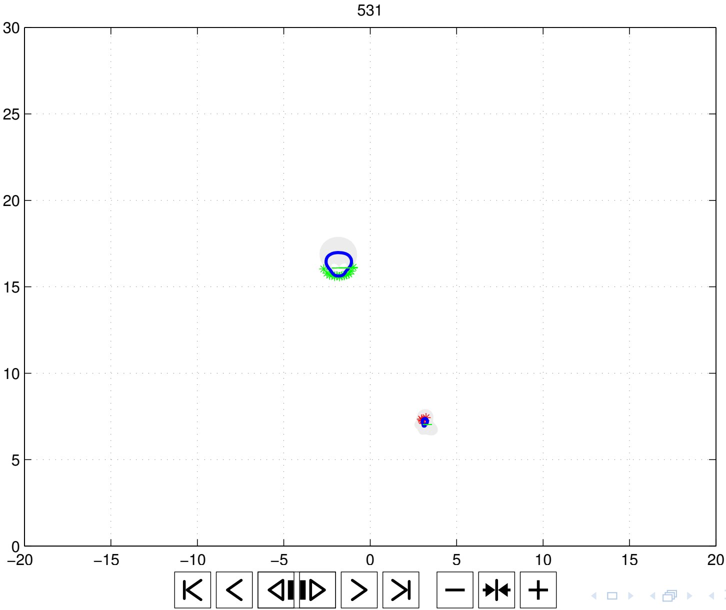
Real data experiment

- Laser range data
- Multi-target scenario (cars, bicycles, humans)
- Almost no clutter

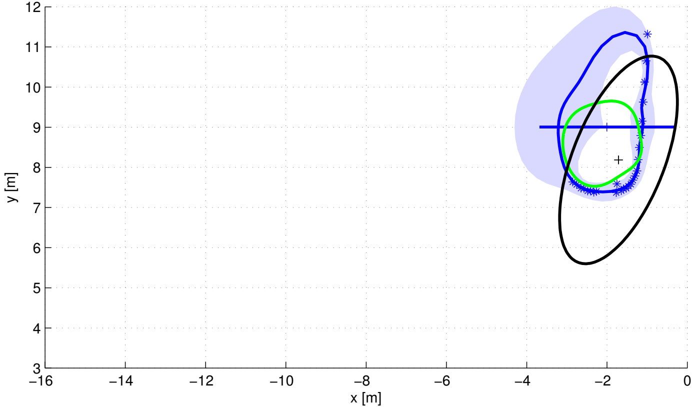
We used a simple logic-based multi-target tracker:

- Gating based likelihood
- Associate a measurement with the most likely target
- Cluster all ungated measurements and form new targets

Real data experiment -result

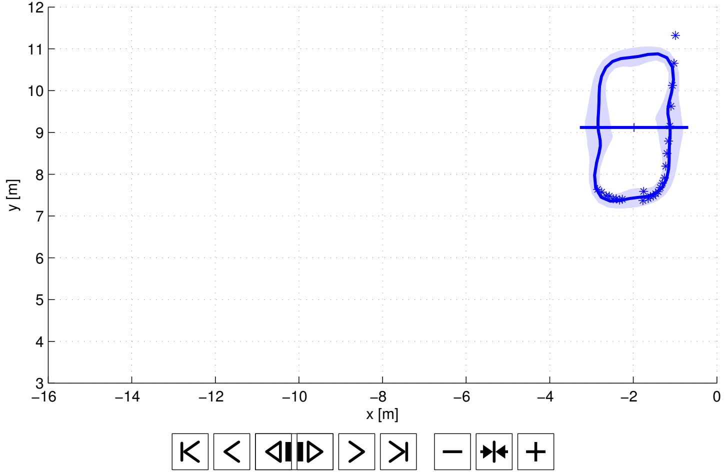


Green: RHM (Baum and Hanebeck). Black: Elliptical target (Koch...), Blue: proposed model



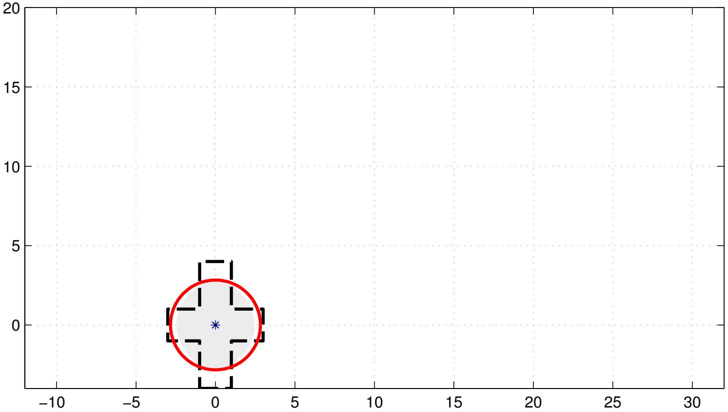
Extension - Symmetry assumptions

If we assume that $f(\theta)$ has a period of π instead of 2π, we can encode symmetry assumptions.



If the measurements originate from the target interior, we can add a random scalar to compensate for that

$$\mathbf{y}_{k,l} = \mathbf{x}_k^c + s_{k,l} H(\mathbf{x}_k^c, \psi_k)\mathbf{x}_k^{\mathbf{f}} + \mathbf{e}_{k,l}, \quad s_{k,l} \in [0, 1]$$



Conclusions and Future work

Conclusions

- Model the target extent with a Gaussian process
- Estimate target extent and kinematic state jointly
- Fully recursive update provided

Future work

- Use Rao-Blackwellized PF - target extent state can be marginalized
- Exploit target symmetry properties even further
- A more sophisticated multi-target tracker

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