Kalman Filter Bank Applications

Sensor Fusion

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Purpose

Illustrate a Kalman filter bank by tracking vehicles with two magnetometers.

- Car is approximated by one magnetic dipole.
- Good approximation the the magnetometer is placed some meters away.
- Sensor model based on Maxwell's equations

$$y_k = \frac{\mu_0}{4\pi|\mathbf{r}_k|^5}\left((\mathbf{r}_k^T \mathbf{m})\mathbf{r}_k - |\mathbf{r}_k|^2 \mathbf{m}\right),$$

where r is the vector between sensor and magnetic dipole characterized by its dipole moment $\mathbf{m}$.

Experiment Setup

- Measured 3D magnetic field

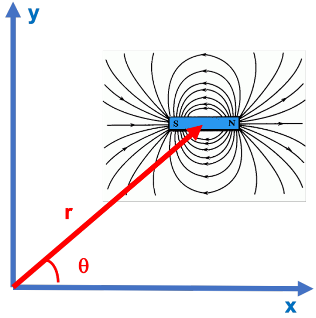
$$y_k = \frac{\mu_0}{4\pi|\mathbf{r}_k|^5}\left((\mathbf{r}_k^T\mathbf{m})\mathbf{r}_k - |\mathbf{r}_k|^2\mathbf{m}\right),$$

- For motion on a horisontal 2D plane, the measurement can be transformed and the model simplified

$$\bar{y}_k^1 = \sqrt{(y_k^x)^2 + (y_k^y)^2} = \frac{\mu_0}{4\pi|r_k|^3}\sqrt{1 + 3\sin^2(\theta_k)},$$

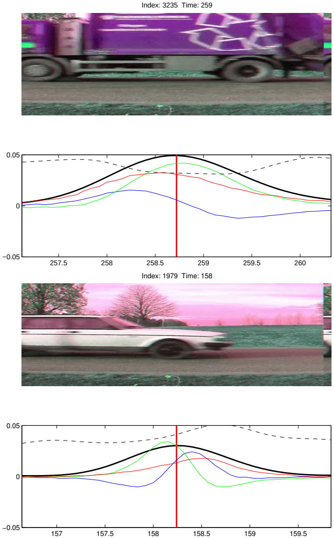
$$\bar{y}_k^2 = \frac{y_k^x}{y_k^y} = \frac{x + x^2 + y^2}{y}.$$

- However, the original model with $z = 0$ in r is to prefer, since it has additive sensor noise.



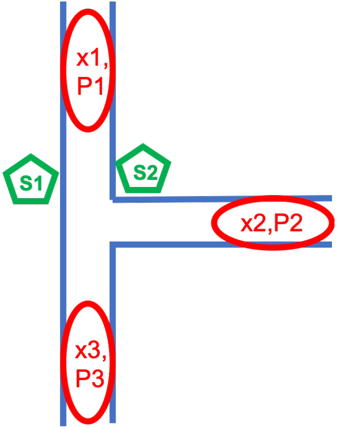
Measurement Example

- Figure shows y_t from one magnetometer and its magnitude (thick black line)
- Dashed line shows magnitude from the accelerometer just for comparison
- The magnitude peaks when the vehicle passes
- Larger vehicle gives larger peak
- Different vehicles have different dipole moment. This can be used to identify cars by its estimated $\hat{m}$ as a point in 3D space.



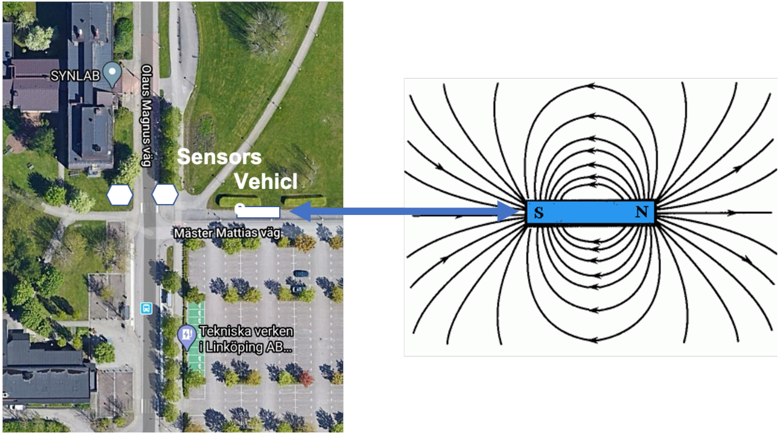
Experimental setup

- Traffic intersection with three possible entrances
- Network with two magnetometers
- Vehicles are coming one by one from different directions
- Kalman filter bank where each filter is matched to each hypothesis by having a different x_0, P_0.



Experiment Setup

The actual place is on campus close to Vallfarten



Kalman Filter Model

- A standard 2D constant velocity model with an augmented state $x = (p^T, v^T, \mathbf{m}^T)^T$ is used

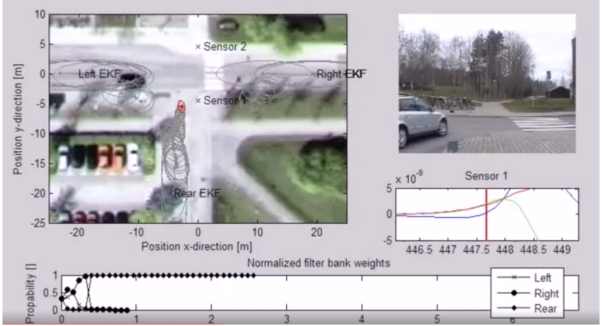
$$x_{k+1} = \begin{pmatrix} I_2 & TI_2 & 0 \\ 0 & I_2 & 0 \\ 0 & 0 & I_3 \end{pmatrix} x_k + \begin{pmatrix} T^2/2I_2 \\ TI_2 \\ 0 \end{pmatrix} w_k$$

- The initial state is x_0^i, P_0, where p_0^i corresponds to points at the entrance roads, further away from the sensors, with a velocity vector v_0^i towards the intersection.
- The sensor model for sensor i at position q_i is

$$y_k^i = \frac{\mu_0}{4\pi|q^i - p_k|^5}(((q^i - p_k)^T\mathbf{m})(q^i - p_k) - |q^i - p_k|^2\mathbf{m}),$$

Result

- Upper left panel: each Kalman filter estimate is overlaid on an aerial image
- Lower panel: relative probability of each hypothesis
- Upper right panel: video facing Vallfarten
- Upper middle panel: measured signal



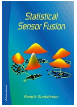
https://youtu.be/0-UE05aq8fs

Video shows how first each filter tries to track the vehicle,
after a few seconds the relative probability for the rear EKF hypothesis is almost one,
and the Kalman filter ellipsoid for this filter decreases quickly.

Summary

Automotive target tracking applications using a network of two magnetometers, illustrating

- Sensor modelling based on Maxwell's equations.
- How a Kalman filter bank can resolve an unknown initial state with a countable number of alternatives.
- In this case, there is no exponential growth in the filter bank, so no pruning or merging is needed.
- Both the position and magnetic dipole moment are estimated, solving both the tracking problem and vehicle identification problem in one filter.



Section 14.2.4