

Prof.Dr.

Backward filter and smoothing

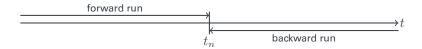
Backward filter and smoothing

The forward (real time) Kalman filter requires $t_{n-1} < t_n$ and updates the state vector and its variance by

$$\hat{x}_{n|n} = \hat{x}_{n|n-1} + K_n \left(z_n - H_n \hat{x}_{n|n-1} \right)$$

$$P_{n|n} = (I - K_n H_n) P_{n|n-1}$$
(8.1)

As long as we apply the correct state transition model one can run also the Kalman filter in time-backward direction.



This is of course only possible in post-processing, i.e. non-real time. We denote the estimated states from the backward run with $\hat{x}^b_{n|n}$ and $P^b_{n|n}$.

Question: How to combine the results from the forward run for an optimal estimate based on all data?

Backward filter and smoothing - cont'd

Linear combination (weighted average)

$$\hat{x}_n = A\hat{x}_{n|n} + (I - A)\hat{x}_{n|n}^b$$

$$P_n = AP_{n|n}A^T + (I - A)P_{n|n}^b(I - A)^T$$
(8.2)

 $m{A}$ and $(m{I}-m{A})$ are the weight matrices.

Question: How to choose A?

Selection of an optimality criterion. Minimize the trace of covariance matrix of the result.

$$\operatorname{tr}(P_n) = \operatorname{tr}\left(AP_{n|n}A^T + (I - A)P_{n|n}^b(I - A)^T\right) \to \min.$$
 (8.3)

Take the derivative of equ. (8.3) w.r.t. the matrix A and equate to zero.

Backward filter and smoothing - cont'd

A useful relation (see also previous lecture) is the following, given that the matrix ${\cal C}$ is symmetric.

$$\frac{\partial \text{tr}(ACA^T)}{\partial A} = 2AC \tag{8.4}$$

With that we start with

$$\operatorname{tr}\left(\boldsymbol{A}\boldsymbol{P}_{n|n}\boldsymbol{A}^{T} + (\boldsymbol{I} - \boldsymbol{A})\boldsymbol{P}_{n|n}^{b}(\boldsymbol{I} - \boldsymbol{A})^{T}\right) = \operatorname{tr}\left(\boldsymbol{A}\boldsymbol{P}_{n|n}\boldsymbol{A}^{T}\right) + \operatorname{tr}\left((\boldsymbol{I} - \boldsymbol{A})\boldsymbol{P}_{n|n}^{b}(\boldsymbol{I} - \boldsymbol{A})^{T}\right)$$
(8.5)

and then compute the partial derivative w.r.t. A

$$\frac{\partial}{\partial \mathbf{A}} \operatorname{tr} \left(\mathbf{A} \mathbf{P}_{n|n} \mathbf{A}^{T} + (\mathbf{I} - \mathbf{A}) \mathbf{P}_{n|n}^{b} (\mathbf{I} - \mathbf{A})^{T} \right) =
\frac{\partial}{\partial \mathbf{A}} \operatorname{tr} \left(\mathbf{A} \mathbf{P}_{n|n} \mathbf{A}^{T} \right) + \frac{\partial}{\partial \mathbf{A}} \operatorname{tr} \left((\mathbf{I} - \mathbf{A}) \mathbf{P}_{n|n}^{b} (\mathbf{I} - \mathbf{A})^{T} \right)$$
(8.6)

which we then evaluate and equate to 0, i.e.

$$2AP_{n|n} + 2(I - A)P_{n|n}^{b}(-I) = 0$$
(8.7)

Backward filter and smoothing - cont'd

From equ. (8.7) we get

$$A = P_{n|n}^{b} \left(P_{n|n}^{b} + P_{n|n} \right)^{-1}$$
 and $I - A = P_{n|n} \left(P_{n|n}^{b} + P_{n|n} \right)^{-1}$ (8.8)

Inserting equ. (8.8) in equ. (8.2) gives

$$P_{n} = P_{n|n}^{b} \left(P_{n|n}^{b} + P_{n|n} \right)^{-1} P_{n|n} \left(P_{n|n}^{b} \left(P_{n|n}^{b} + P_{n|n} \right)^{-1} \right)^{T} + P_{n|n} \left(P_{n|n}^{b} + P_{n|n} \right)^{-1} P_{n|n}^{b} \left(P_{n|n} \left(P_{n|n}^{b} + P_{n|n} \right)^{-1} \right)^{T}$$

$$(8.9)$$

If we use the matrix identity $A(A+B)^{-1}B=(A^{-1}+B)^{-1})^{-1}$ we get

$$P_{n} = \left((P_{n|n}^{b})^{-1} + (P_{n|n})^{-1} \right)^{-1}$$

$$\hat{x}_{n} = P_{n} \left((P_{n|n})^{-1} \hat{x}_{n|n} + (P_{n|n}^{b})^{-1} \hat{x}_{n|n}^{b} \right)$$
(8.10)

You will find the examples discussed in this lecture as Jupyter notebook under https://github.com/spacegeodesy/ParameterEstimationDynamicSystems/blob/master/example08.ipynb