

TK8117 Multivariate Data Analysis

Week 10 Advanced Topic 3:

Kalman Filters for Non-Gaussian Noises

Simen Dymbe, Saygin Ileri, Anette Fagerheim Bjerke, Torstein Nordgård-Hansen 30.10.2024



Outline

Non-gaussian noise

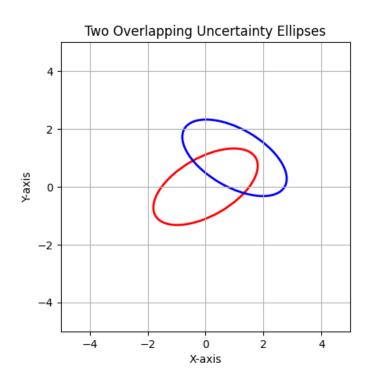
- Using "normal" filters
- H_∞ filter

- Estimates using IRLS method
- Sources



Non-gaussian noise

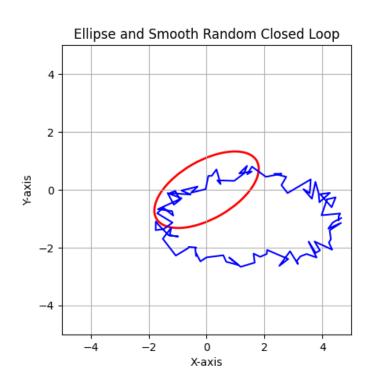
- Kalman filters propagate noise
- Assumes nice noise curves





Non-gaussian noise

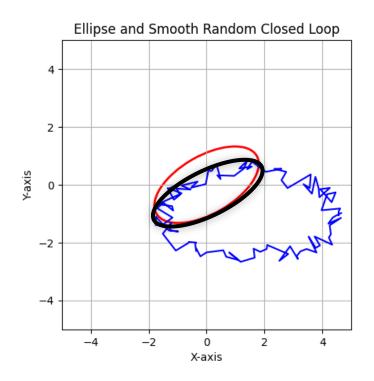
- Ugly noise is ugly
- Kalman filters requires:
 - Finite first and second moments





Using "normal" filters

- Normal filters often work
- Ensemble and unscented filters are also good





H_∞ filter

Also called minimax filter

Minimize the maximum estimation error

when we maximize the noise

Makes no assumption about the noise



H_∞ filter

$$min_{\widehat{x}} max_{w,v} J$$

w, v – noise J – measure of how good our estimator is

$$J = \frac{ave||x_k - \hat{x}_k||_Q}{ave||w_k||_W + ave||v_k||_V}$$

 $min_{\widehat{x}} max_{w,v} J$ – difficult to solve Instead we solve:

$$J < \frac{1}{\gamma}$$

 γ – constant chosen by us



H_∞ filter equations

The state estimate that forces $J < \frac{1}{\gamma}$ is given as:

$$L_{k} = (I - \gamma Q P_{k} + C^{T} V^{-1} C P_{k})^{-1}$$

$$K_{k} = A P_{k} L_{k} C^{T} V^{-1}$$

$$\hat{x}_{k+1} = A \hat{x}_{k} + B u_{k} + K_{k} (y_{k} - C \hat{x}_{k})$$

$$P_{k+1} = A P_{k} L_{k} A^{T} + W$$

 K_k - Gain matrix, will converge after a few steps and can be used as a constant matrix for Steady-state H_{∞}

 γ – must be chosen such that the eigenvalues of P_k has a magnitude less than 1. A too large γ will result in no solution for H_{∞}

 γ , Q, P_0 , V & W are the tuning parameters



H_∞ filter Key points

Minimax filter

 Assumes Murphy's Law – the noise we have is the worst possible noise

No statistical assumption about the noise



A Modified Kalman Filter for Nongaussian Measurement Noise

Kalman Filter with Robust Sequential Estimator (RSE)

Using RSE to handle non-Gaussian data as outliers



How it works...

measurements with noise

modeling non-gaussian part as <u>outliers</u>

how modeling works..

one sample

maximum likelihood estimates for t-distribution error model

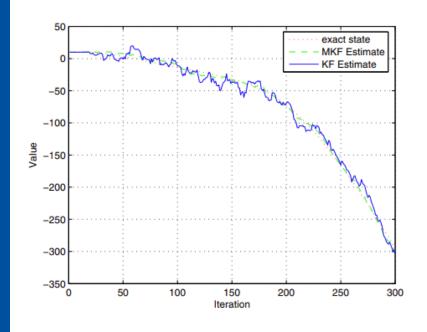
update the sample via Iteratively Reweighted Least Squares (IRLS)

Outlier classification with weights done by RSE

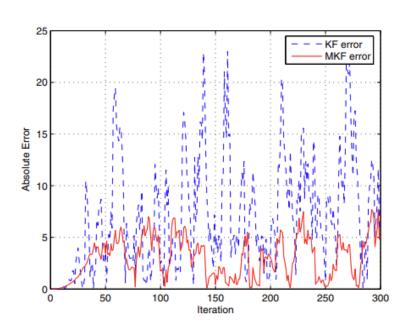
updates the state only with valid data



Results



standart vs. modified Kalman Filter <u>estimates</u>



standart vs. modified Kalman Filter mean square errors



Sources

- Mirza J. Muhammed, 2011 "A Modified Kalman Filter for Non-gaussian Measurement Noise"
- Dan Simon, 2001, "From Here to Infinity"