

 **R**-Package `robKalman` —
 R. Kalman's revenge or
 Robustness for Kalman Filtering  Revisited



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Peter Ruckdeschel¹ Bernhard Spangl²

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Rennes, July 9, 2009

Euclidean State Space Models

Definitions and Assumptions:

— Time-Discrete, Euclidean Setup ideal model:

$$\mathbf{x}_t = F(\mathbf{x}_{t-1}, \mathbf{t}) + \mathbf{v}_t, \quad \mathbf{v}_t \stackrel{\text{indep.}}{\sim} (\mathbf{0}, \mathbf{Q}_t), \quad [\rho\text{-dim}],$$

$$\mathbf{y}_t = Z(\mathbf{x}_t, \mathbf{t}) + \varepsilon_t, \quad \varepsilon_t \stackrel{\text{indep.}}{\sim} (\mathbf{0}, \mathbf{V}_t), \quad [q\text{-dim}],$$

$$\mathbf{x}_0 \sim (\mathbf{a}_0, \mathbf{Q}_0), \quad [\rho\text{-dim}],$$

$\{\mathbf{v}_t\}, \{\varepsilon_t\}, \mathbf{x}_0$ indep. as processes

functions F, Z smooth with known derivatives;
hyper-parameters $\mathbf{Q}_t, \mathbf{V}_t, \mathbf{a}_0$ known

extensible to:

- continuous time (SDE's)
- incorporate user-specified controls

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Types of Outliers

exogenous outliers affecting only singular observations

$$\text{AO} \quad :: \quad \varepsilon_t^{\text{re}} \sim (1 - r_{\text{AO}})\mathcal{L}(\varepsilon_t^{\text{id}}) + r_{\text{AO}}\mathcal{L}(\varepsilon_t^{\text{di}})$$

$$\text{SO} \quad :: \quad \mathbf{y}_t^{\text{re}} \sim (1 - r_{\text{SO}})\mathcal{L}(\mathbf{y}_t^{\text{id}}) + r_{\text{SO}}\mathcal{L}(\mathbf{y}_t^{\text{di}})$$

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Different and competing goals

- AVSO attenuation of "false alarms"
- IO tracking: detect structural changes as fast as possible;
 recovering: clean data from structural changes
- AVSO & IO identification problem:
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Classical Method: Kalman–Filter

Filter Problem

$$E |x_t - f_t(y_{1:t})|^2 = \min_{f_t} !,$$

$$\text{with } y_{1:t} = (y_1, \dots, y_t), \quad y_{1:0} := \emptyset$$

General solution: $E[x_t|y_{1:t}]$ —difficult to compute

Kalman–Filter assuming $F(x, t) = F_t x$, $Z(x, t) = Z_t x$

optimal solution among linear filters — Kalman/[Bucy] [60/61]:

Initialization: $x_{0|0} = a_0$

Prediction: $x_{t|t-1} = F_t x_{t-1|t-1}, \quad [\Delta x_t = x_t - x_{t|t-1}]$

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and corresponding recursions for the prediction/filtering error covariances $\Sigma_{t|t[-1]}$ and the Kalman gain M_t^0

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Features of the Kalman-Filter

- + an easy, understandable structure:
initialization, prediction, correction step
- + correction step is easily evaluable and interpretable: it is linear !
- + strict recursivity / Markovian structure:
all information from the past useful for the future is captured in
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R-package robKalman — Contents

- Kalman filter: filter, Kalman gain, covariances
- ACM-filter: filter, multivariate version, GM-estimator
- rLS-filter: filter, calibration of clipping height
 - AO/SO-robust version
 - IO-robust version
 - with a certain delay joint treatment of AO/SO's & IO's
- extensible to further recursive filters:
 - ↔ general interface `recursiveFilter`
 - with arguments:
 - data
 - state space model (hyper parameters)
[will be: object of class SSM]
 - **functions for the `init./pred./corr.step`**
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Implementation concept

- Programming language
 - completely in S, perhaps some code in C later (↔ FKF)
- Use existing infrastructure: zoo, timeSeries
 - for: graphics, diagnostics, management of date/time
- Code in different layers
 - internal functions: no S4-objects, no time stamps
(helps bringing in code by “non-S4-people”)
 - user interface: S4-objects, time stamps
- Use generating functions for encapsulation
 - without using structured arguments:
 - ★ too many arguments ↔ user loses track
 - ★ prone to name mis-matchings (positional, partial matching)
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Implementation so far

Interfaces so far

- preliminary, “S4-free” interfaces
 - Kalman filter (in our context) `KalmanFilter`
 - rLS: `rLSFilter` (= `rLS.AO.Filter`),
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 - ACM: `ACMfilt`, `ACMfilter`, `mACMfilter`
 - all realized as wrappers to `recursiveFilter`
- availability: `robKalman` version 0.3 (incl. demos)

<http://r-forge.r-project.org/projects/robkalman/>

Almost ready:

• `robKalman` (S4) for `recursiveFilter` (S4) (see `robKalman` package)
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- interfaces between S4-layer and S4-free layer
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to `robotLayer` (Roland Fried & K. Scheuflinger)

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Work in process

Release Plans

- package `robKalman` should be on **CRAN** by UseR! 2009, but...
- at least: release on **CRAN** by end of August
- till then: refer to **r-forge**

Extensions

- robust smoothing (80% done)
- robust EM-Algorithm to estimate unknown hyper parameters
(extending Shumway/Stoffer) (70% done)
- interpretation as random coefficient regression
↔ robust regression-type approach (**rlc**, **mlc**) (30% done)
- connection to particle filters —
theory and computer interface (10% done)
- speeding up things / bridging to fast Kalman filter of
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Some experiences on collaborative programming on r-forge

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 - **very neat** for collaborative R package development
 - version management (`svn`)
 - mail-forwarded `log`-files of committed code
 - ↪ keep track of work of others
 - bug tracker, archived mailing lists, . . .
 - see slides by **Stefan Theussl**
 - needs serious conceptual preparations
 - for separating/modularizing tasks
 - consistency: coding & documentation conventions
 - helpful: scheduling, reminders/deadlines for collaborators. . .
 - summarizing:

Collaborative programming is enjoyable and very exciting!

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References

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