

# Framework for implementing and testing nonlinear filters

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# Problem formulation

Consider multivariate nonlinear stochastic system

$$\mathbf{x}_{k+1} = \mathbf{f}_k(\mathbf{x}_k, \mathbf{u}_k, \mathbf{w}_k), \quad k = 0, 1, 2, \dots$$

$$\mathbf{z}_k = \mathbf{h}_k(\mathbf{x}_k, \mathbf{v}_k), \quad k = 0, 1, 2, \dots$$

$\mathbf{x}_k \in \mathbb{R}^{n_x} \dots$  non-measurable state

$\mathbf{w}_k \in \mathbb{R}^{n_x} \dots$  state white noise

$\mathbf{z}_k \in \mathbb{R}^{n_z} \dots$  measurement

$\mathbf{v}_k \in \mathbb{R}^{n_z} \dots$  measurement white noise

$\mathbf{u}_k \in \mathbb{R}^{n_u} \dots$  control

- ✓ Both noises are mutually independent and they are also independent of the known initial state  $\mathbf{x}_0$  pdf  $p(\mathbf{x}_0)$ .
- ✓ The vector mappings  $\mathbf{f} : \mathbb{R}^{n_x} \rightarrow \mathbb{R}^{n_x}$ ,  $\mathbf{h} : \mathbb{R}^{n_x} \rightarrow \mathbb{R}^{n_z}$  are known

**The aim:** to estimate the non-measurable state  $x_k$

The posterior pdf  $p(\mathbf{x}_k | \mathbf{z}^\ell, \mathbf{u}_{k-1})$  is sought!

$\mathbf{z}^\ell \triangleq [\mathbf{z}_0, \mathbf{z}_1, \dots, \mathbf{z}_\ell] \dots$  set of measurements

# General Solution

## General solution obtainable by Bayesian approach

➤ solution of the **filtering problem** ( $\ell = k$ )

$$p(\mathbf{x}_k | \mathbf{z}^k, \mathbf{u}_{k-1}) = \frac{p(\mathbf{x}_k | \mathbf{z}^{k-1}, \mathbf{u}_{k-1}) p(\mathbf{z}_k | \mathbf{x}_k)}{\int p(\mathbf{x}_k | \mathbf{z}^{k-1}, \mathbf{u}_{k-1}) p(\mathbf{z}_k | \mathbf{x}_k) d\mathbf{x}_k},$$

$$p(\mathbf{x}_k | \mathbf{z}^{k-1}, \mathbf{u}_{k-1}) = \int p(\mathbf{x}_{k-1} | \mathbf{z}^{k-1}, \mathbf{u}_{k-2}) p(\mathbf{x}_k | \mathbf{x}_{k-1}, \mathbf{u}_{k-1}) d\mathbf{x}_{k-1}$$

➤ solution of the **multistep prediction problem** ( $\ell < k$ )

$$p(\mathbf{x}_k | \mathbf{z}^\ell, \mathbf{u}_{k-1}) = \int p(\mathbf{x}_{k-1} | \mathbf{z}^\ell, \mathbf{u}_{k-2}) p(\mathbf{x}_k | \mathbf{x}_{k-1}, \mathbf{u}_{k-1}) d\mathbf{x}_{k-1}$$

➤ solution of the **multistep smoothing problem** ( $\ell > k$ )

$$p(\mathbf{x}_k | \mathbf{z}^\ell, \mathbf{u}_{k-1}) = p(\mathbf{x}_k | \mathbf{z}^k, \mathbf{u}_{k-1}) \int \frac{p(\mathbf{x}_{k+1} | \mathbf{z}^\ell, \mathbf{u}_k)}{p(\mathbf{x}_{k+1} | \mathbf{z}^k, \mathbf{u}_k)} p(\mathbf{x}_{k+1} | \mathbf{x}_k, \mathbf{u}_k) d\mathbf{x}_{k+1}$$

# Solutions of Bayesian recursive relations for filtering, prediction and smoothing problems

## Exact solutions - valid only for special class of systems

- Kalman filter
- Gaussian sum filter
- Daum filter

## Approximate local methods

- Extended Kalman filter
- Divided difference filter
- Unscented Kalman filter

## Approximate global methods

- Gaussian sum filter
- Point-mass method
- Particle filters

# The objective: To design toolbox facilitating easy estimator design and testing

## What criteria should the toolbox meet?

- ✓ to be highly modular, easily extensible and user friendly
- ✓ to provide multi-step prediction, filtering and multi-step smoothing
- ✓ to be build in MATLAB environment

## Which tasks should be provided by the toolbox?

- ✓ complete description of the system
- ✓ simulation of the system
- ✓ choice and application of the suitable estimator
- ✓ easy extensibility with new estimators

# Aren't there already Matlab toolboxes for nonlinear estimation?

- **KALMTOOL**  
([HTTP://SERVER.OERSTED.DTU.DK/PERSONAL/OR/KALMTOOL3/](http://SERVER.OERSTED.DTU.DK/PERSONAL/OR/KALMTOOL3/))
- **ReBEL** ([HTTP://CHOOSH.ECE.OGI.EDU/REBEL/](http://CHOOSH.ECE.OGI.EDU/REBEL/))

## Advantages & disadvantages of those toolboxes

- ✓ the computational demands of estimation process are moderate
- ✓ KALMTOOL has Simulink support
- ✗ suitable only for filtering problem
- ✗ not easily reusable code (monolithic design)
- ✗ provides only point estimate

*However, both mentioned toolboxes doesn't fully meet specified demands!!*

# Features of the Nonlinear Filtering Toolbox (NFT)

## Advantages of presented framework

- takes advantage of Matlab **object oriented** programming features
- can handle filtering and multistep prediction and smoothing
- estimators provide conditional probability density functions
- provides means for easy control of the whole estimation process
- easy addition of new estimators

## Structure of NFT

- probability density function (pdf's) classes
- system classes
- estimator classes
- auxiliary classes

# Probability density function classes

## Pdf's classes features

- all random quantities represented as objects of corresponding pdf class
- generic class defining mandatory interface of all pdf classes and making them distinguishable as pdf's within toolbox
- pdf classes provide methods such as:
  - ◇ resetting and reading of pdf parameters,
  - ◇ evaluation of pdf in arbitrary point of state space,
  - ◇ generating of random samples, ...

## Illustration of creation of Gaussian pdf object

$$p(\mathbf{x}) = \mathcal{N} \left\{ \mathbf{x} : \begin{pmatrix} -1 \\ 5 \end{pmatrix}, \begin{pmatrix} 0.1 & 0 \\ 0 & 0.2 \end{pmatrix} \right\}, \quad (1)$$

```
>> px = gpdf([-1;5],diag([.1,.2]));  
>> x = sample(px);
```

# System classes

## Classes provided for system creation and handling

- two classes for definition of multivariate functions  $f(\cdot)$  and  $h(\cdot)$ 
  - ◇ `nfFunction` - general class defining interface for user defined functions
  - ◇ `nfSymFunction` - utilizes Symbolic toolbox  $\Rightarrow$  slow computations
- several classes for various type of system - (Non)Linear (Non)Gaussian with (Non)Additive noises

## Illustration of creation and use of nonlinear system with additive noises

```
>> f = nfSymFunction(' [x1*x2+w1;x2+w2]', ...
>>                  ' ', 'x1,x2', 'w1,w2' );
>> h = nfSymFunction('x1*x2+v', ' ', 'x1,x2', 'v' );
>> system = nlga(f,h,pw,pv,px0);
>> [z,x,system] = simulate(system,u,n);
```

# Estimator classes

## Main task of the estimator classes

The estimator classes essentially implement algorithms necessary to obtain  $p(\mathbf{x}_k | \mathbf{z}^k, \mathbf{u}_{k-1})$ ,  $p(\mathbf{x}_k | \mathbf{z}^\ell, \mathbf{u}_{k-1})$  and even possibly  $p(\mathbf{x}_k | \mathbf{z}^\ell, \mathbf{u}_{k-1})$ , i.e. filtering, predictive and smoothing conditional pdf's, respectively.

## Features of the general class `estimator`

- its virtual methods sets the interface of actual estimator classes
- provides method `estimate` that controls the whole estimation process  
⇒ the designer of the estimator doesn't need to care
- `estimator` stores the data of multistep operations in dynamical list
- the lists can hold arbitrary content, however, they are primarily used to store conditional pdf's
- implements commonly used methods (e.g. Ricatti equation) ⇒ decreases redundancy and makes possible easy future improvements

# Estimator classes

## Estimators currently implemented in NFT

Method	NFT class
Kalman filter	kalman
Extended Kalman filter	extkalman
Iterating Kalman filter	itekalman
Second order Kalman filter	seckalman
Gaussian sums filter	gsm
Particle filter	pf
Point mass filter	pmf
Divide difference filter 1st order	dd1
Unscented Kalman filter	ukf

## Illustration of creation and use of DD1 estimator object

```
>> filter = dd1(system,0);
>> [est,filter] = estimate(filter,z,NaN);
```

# Example of NFT usage

## Considered nonlinear non-Gaussian system

$$\begin{pmatrix} x_{1,k+1} \\ x_{2,k+1} \end{pmatrix} = \begin{pmatrix} x_{1,k} \cdot x_{2,k} \\ x_{2,k} \end{pmatrix} + \mathbf{w}_k$$
$$z_k = x_{1,k} \cdot x_{2,k} + v_k$$

## The description of stochastic quantities

$$p(\mathbf{w}_k) = \mathcal{N} \left( \mathbf{w}_k : \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0.49 & 0 \\ 0 & 0.01 \end{bmatrix} \right)$$

$$p(v_k) = \mathcal{N}(v_k : 0, 0.5)$$

$$p(x_0) = 0.7 \cdot \mathcal{N} \left( x_0 : \begin{bmatrix} 10 \\ -5 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \right) +$$
$$+ 0.3 \cdot \mathcal{N} \left( x_0 : \begin{bmatrix} -10 \\ 5 \end{bmatrix}, \begin{bmatrix} 18 & 0 \\ 0 & 18 \end{bmatrix} \right)$$

## Example of NFT usage (continuation)

The task is to obtain two-step prediction  $p(x_k|z^{k-2})$

- ⇒ definition of the random variables

```
pw = gpdf([0;0],diag([0.49 0.01]));  
pv = gpdf(0,0.5);  
px0 = gspdf(0.7,[10;-5],diag([1 1]),...  
            0.3,[-10;5],diag([18 18]));
```

- ⇒ definition and simulation of the system

```
f = nfsymfunction(' [x1*x2+w1;x2+w2]',...  
                '' , 'x1,x2' , 'w1,w2' );  
h = nfsymfunction(' x1*x2+v' , '' , 'x1,x2' , 'v' );  
system = nlga(f,h,pw,pv,px0);  
[z,x,system]=simulate(system,zeros(1,10));
```

- ⇒ choice of the estimator and the estimation process itself

```
filter = gsm(system,2,5);  
[est,filter] = estimate(filter,z,NaN);
```

# Concluding remarks

## Current contribution of the NFT

- provides all necessary tools for estimator design, testing and employment
- the toolbox is easily extensible thanks to object oriented approach
- includes all the basic estimator implementing filtering, prediction and smoothing methods

## Future directions

- implementation of additional estimators
- fully probabilistic description of the system
- support for time varying systems
- possibility to automatically approximate pdf's
- refactoring and conversion to the new Matlab class system