

# Nonlinear Estimation Framework in Target Tracking

Ondřej Straka<sup>1</sup>, Miroslav Flídr<sup>1</sup>, Jindřich Duník<sup>1</sup>, Miroslav Šimandl<sup>1</sup> and Erik Blasch<sup>2</sup>

<sup>1</sup> Department of Cybernetics & Research Centre Data - Algorithms - Decision making  
Faculty of Applied Sciences, University of West Bohemia, Czech Republic

<sup>2</sup> Defence R&D Canada-Valcartier  
2459 Pie-XI Blvd. North  
Québec City, QB G3J 1X5

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# Outline

- 1 Nonlinear Estimation Framework (NEF)
- 2 NEF modelling component
- 3 NEF estimation component
- 4 NEF performance evaluation component
- 5 Case study – tracking a ship
- 6 Concluding remarks

# Introduction of the Nonlinear Estimation Framework (NEF)

## Goal of the paper

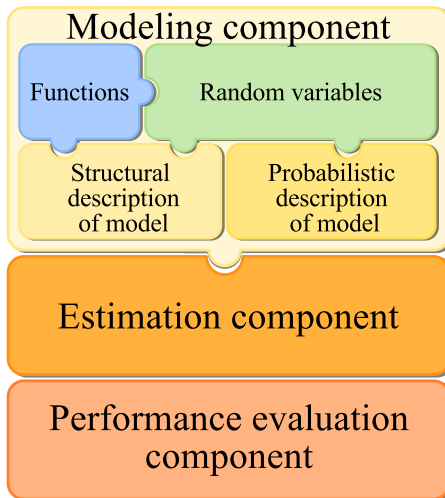
to introduce NEF and illustrate its use in target tracking problems

- a collection of MATLAB classes and functions for
  - modelling system behavior
  - state estimation
  - evaluation of the results
- development driven by the need for a tool that can
  - evaluate the quality of a state estimation method in arbitrary case
  - compare performance of several state estimators
  - provide means for effortless rapid prototyping of new state estimators
- most recent generation of software toolboxes developed by authors (former NFTools and NFToolsCD).

# Key features of the NEF

- structural and probabilistic modelling,
- support for time-varying models,
- support for filtering, multi-step prediction and fixed-lag smoothing,
- implementation of both standard and numerically stable estimation algorithms,
- full estimator parametrization by means of the standard MATLAB property-value mechanism,
- complete evaluation of estimate quality.

# Components of the NEF



# Modelling component

## Structural description

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

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

$$p(\mathbf{w}_k), p(\mathbf{v}_k), p(\mathbf{x}_0)$$

- $\mathbf{x}_k \in \mathcal{R}^{n_x}, \mathbf{z}_k \in \mathcal{R}^{n_z}, \mathbf{u}_k \in \mathcal{R}^{n_u}, \mathbf{w}_k \in \mathcal{R}^{n_x}, \mathbf{v}_k \in \mathcal{R}^{n_z}$

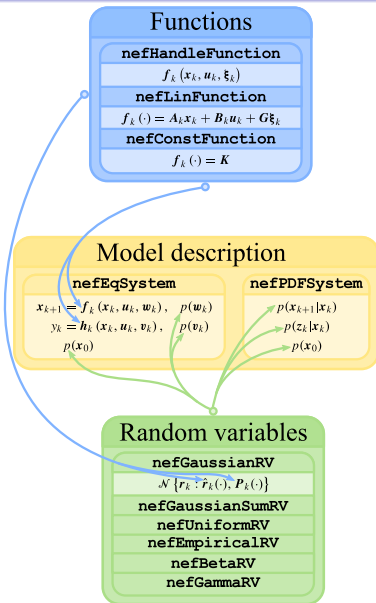
## Probabilistic description

$$p(\mathbf{x}_{k+1} | \mathbf{x}_k, \mathbf{u}_k), k = 0, 1, \dots,$$

$$p(\mathbf{z}_k | \mathbf{x}_k, \mathbf{u}_k), k = 0, 1, \dots$$

$$p(\mathbf{x}_0)$$

# Scheme of NEF modelling component



# Estimation

## The estimate of the state $\mathbf{x}_k$

given by the posterior pdf  $p(\mathbf{x}_k | \mathbf{z}^\ell, \mathbf{u}^\ell)$ , where  $\mathbf{z}^\ell$  is the sequence of measurements up to time instant  $\ell$ , i.e.,  $\mathbf{z}^\ell \triangleq [\mathbf{z}_0^T, \mathbf{z}_1^T, \dots, \mathbf{z}_\ell^T]^T$ .

- If  $\ell = k$ , the problem is called *filtering*.
- If  $\ell < k$ , the problem is called *prediction*.
- If  $\ell > k$ , the problem is called *smoothing*.

## Solution to the estimation problem

- provided by the Bayesian functional relations (BFR)
- analytically tractable for a few special models
- mostly an approximate solution is being looked for
- BFR idea is embodied by `nefEstimator`



# Estimators implemented in the NEF estimation component

**nefKalman,**  
**nefSKalman**  
**nefUDKalman**

(extended) Kalman filter (standard, square-root and UD versions)

**nefDD1,**  
**nefSDD1,**  
**nefDD2**

central difference Kalman filter, divided difference filter (1<sup>st</sup> and 2<sup>nd</sup> order) (standard and square-root version)

**nefUKF,**  
**nefSUKF**

unscented Kalman filter (standard and square-root version), cubature Kalman filter

**nefItKalman**

iterated Kalman filter

**nefGSM**

Gaussian sum filter

**nefPF**

bootstrap filter, generic particle filter, auxiliary particle filter, unscented particle filter

**nefEnKF**

ensemble Kalman filter.

# Estimation tasks supported by individual estimators

estimator	filtering	prediction	smoothing
<b>nefKalman</b>	✓	✓	✓
<b>nefSKalman</b>	✓	✓	✓
<b>nefUDKalman</b>	✓	✓	
<b>nefItKalman</b>	✓	✓	✓
<b>nefDD1</b>	✓	✓	✓
<b>nefSDD1</b>	✓	✓	✓
<b>nefDD2</b>	✓	✓	✓
<b>nefUKF</b>	✓	✓	✓
<b>nefSUKF</b>	✓	✓	✓
<b>nefGSM</b>	✓	✓	
<b>nefPF</b>	✓	✓	
<b>nefEnKF</b>	✓	✓	

# Performance evaluation

## Aim

- to measure estimation error
- to compare performance of several estimators against the true value of the state

## Steps to measure performance

- 1 collecting data from Monte Carlo simulations,
- 2 extracting appropriate indicators from the conditional distribution of the state provided by individual estimators
- 3 evaluating the performance index

# Performance indices implemented in the NEF

## ABSOLUTE ERROR MEASURES

MSEM      mean squared error matrix

RMSE      root mean squared error

AEE      average Euclidean error

HAE      harmonic average error

GAE      geometric average error

MEDE      median error

MODE      mode error

## RELATIVE ERROR MEASURES

RMSRE      root mean squared relative error

ARE      average Euclidean relative error

BEEQ      Bayesian estimation error quotient

EMER      estimation error relative to measurement error

## PERFORMANCE MEASURES

NCI      non-credibility index

ANEES      average normalized estimation error squared

# NEF in target tracking

- Tracking a ship with unknown control

- $\mathbf{x}_k = [x_k, y_k, \dot{x}_k, \dot{y}_k]$

- 

$$\mathbf{x}_{k+1} = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \mathbf{x}_k + \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix} \mathbf{u}_k + \mathbf{w}_k$$

- $T = 0.02$ ,  $\mathbf{w}_k$  is a Gaussian zero mean white noise with  $Q = 10^{-6} \cdot \mathbf{I}$
- the control  $\mathbf{u}_k$  is unknown  $\implies$  will be appended to the state variable

# NEF in target tracking – modelling dynamics

dynamics function:

```
F = [1 0 T 0;  
     0 1 0 T;  
     0 0 1 0;  
     0 0 0 1];  
G = [0 0 1 0;  
     0 0 0 1]';  
Fm = [F G; zeros(2,4) eye(2)];  
fm = nefLinFunction(Fm, [], eye(6));
```

state noise:

```
Q = 1e-6*eye(4);  
Qm = [Q zeros(4,2); zeros(2,4) 1e-3*eye(2)];  
wm = nefGaussianRV(zeros(6,1), Qm);
```

# NEF in target tracking – measurement

position measured in polar coordinates

$$z_k = \begin{bmatrix} \arctan \frac{y_k}{x_k} \\ \sqrt{y_k^2 + x_k^2} \end{bmatrix} + \mathbf{v}_k,$$

$\mathbf{v}_k$  Gaussian zero mean white noise with covariance matrix

$$R = \text{diag}[4 \cdot 10^{-4}(\pi/180); 1 \cdot 10^{-4}]$$

measurement function:

```
hm = nefHandleFunction(@ (x,u,v,t) ...  
[atan(x(2)/x(1));sqrt(x(1)^2+x(2)^2)] + v,[6 0 2 0]);
```

measurement noise:

```
R = [4e-4*(pi/180)^2 0; 0 1e-4];  
v = nefGaussianRV(zeros(2,1),R);
```

# NEF in target tracking – measurement

intial condition:

```
m0 = [20 50 0 -12 0 0]';  
P0 = diag([1e1 1e1 1e1 1e1 1e-1 1e-1]);  
x0m = nefGaussianRV(m0,P0);
```

model:

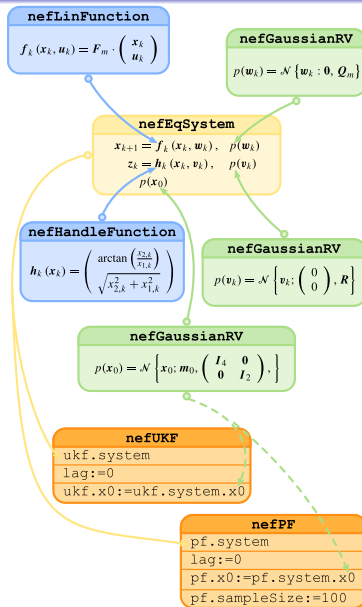
```
model = nefEqSystem(fm,hm,wm,v,x0m,'logLikelihood',LLH);
```

estimators (PF and UKF)

```
PF = nefPF(model,'sampleSize',1000);  
UKF = nefUKF(model);
```



# NEF in target tracking – experiment setup



# NEF in target tracking – performance evaluation

performance evaluators:

```
filters = 2;; mcrun = 10;
RMSE_PE = nefPerformanceEvaluator(...
model,K,mcrun,filters,'method','RMSE','idxState',[1:4]);
NCI_PE = nefPerformanceEvaluator(...
model,K,mcrun,filters,'method','NCI','idxState',[1:4]);
```

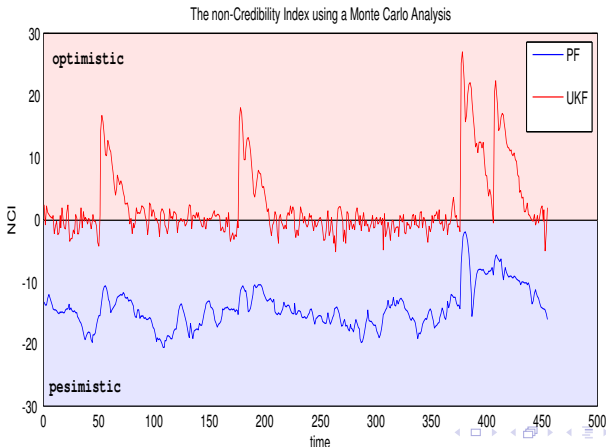
performing 10 Monte Carlo simulations:

```
for i = 1:mcrun
    [val_PF] = estimate(PF,z,u);
    [val_UKF] = estimate(UKF,z,u);
    for k = 1:K
        Data.state{1,k} = [x(:,k); u(:,k)];
        estData{1,1,k} = val_PF{k};
        estData{2,1,k} = val_UKF{k};
    end
    processData(RMSE_PE,Data,estData);
    processData(NCI_PE,Data,estData);
end
```

# NEF in target tracking – performance evaluation (cont.)

performance evaluators: obtaining the performance indices:

```
rmse = performanceValue(RMSE_PE);  
nci = performanceValue(NCI_PE);
```



# Concluding remarks

a suitable tool for testing estimator performance in target-tracking problems

- it provides:
  - versatile description of discrete-time dynamic stochastic systems with continuous state,
  - a number of estimators,
  - a number of performance indexes.

## Concluding remarks (cont.)

- Benefits for:
  - beginners:** problem specification which is reduced to its absolute minimum
  - advanced users:** the property-value mechanism to fully customize the experiment parameters
- In addition (not shown):
  - rapid prototyping of user-defined estimators
  - complex models or performance evaluators

`http://nft.kky.zcu.cz/`