



Signal and Systems Matlab Toolbox  
Sensor Fusion

**Fredrik Gustafsson**

`fredrik.gustafsson@liu.se`

Gustaf Hendeby

`gustaf.hendeby@liu.se`

Linköping University

# Background

## Goals

1. Reproducible examples in theory and exercise books
2. Possibility to vary parameters in the examples
3. Possibility to extrapolate to similar use cases

It is really not a general purpose toolbox that covers all problems that can occur in sensor fusion.

However, many applications can be recast into the standard framework covered by the toolbox.

# Model framework

- Sensor fusion as pattern recognition: rewrite problem into standard form

$$\begin{aligned}x(t+1) &= f(t, x(t), u(t), v(t); \theta), & v(t) &\in p_v(v) \\ y(t) &= h(t, x(t), u(t), e(t); \theta), & e(t) &\in p_e(e).\end{aligned}$$

- Toolbox use is also pattern recognition, with restriction to additive noises

$$\begin{aligned}x(t+1) &= f(t, x(t), u(t); \theta) + v(t), & v(t) &\in p_v(v) \\ y(t) &= h(t, x(t), u(t); \theta) + e(t), & e(t) &\in p_e(e).\end{aligned}$$

- Model specified by

- the functions  $f, h$ ,
- the dimensions of the signals in alphabetical order (and order of appearance)  
 $n = [n_x, n_u, n_y, n_\theta]$ ,
- and the noise distributions  $p_v, p_e$  which are default Gaussian.

# Main ideas

- The use of classes to define objects
  - sensor for sensor models and sensor networks  $y(t) = h(t, x(t), u(t); \theta) + e(t)$
  - nl, lss for motion models with or without sensor  $x(t+1) = f(t, x(t), u(t); \theta) + v(t)$
  - pdfclass for distributions such as  $p_v, p_e$
  - sig for signal objects  $(y(t), x(t), u(t))$
- Try to reuse a few standard methods, e.g.  
disp, simulate, ls/wls/ml, plot/xplot/xplot2
- Plenty of standard models pre-defined in e.g. exsensor, exnl, exmotion

# Installation

- Download the zip-file from `https://www.control.isy.liu.se/student/tsrt14/`
- Unzip the file structure and save it to a convenient folder
- Place Matlab in the same folder and run `initSigSys` to set the path to all subfolders

# Sensor models

General form:  $y(t) = h(x, u, \theta) + e$

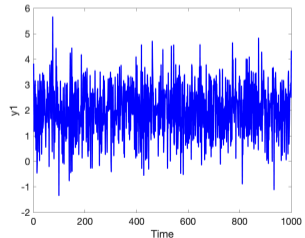
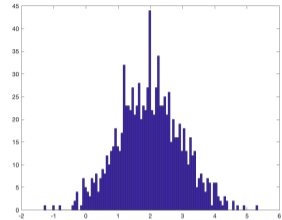
Dimensions:  $n=[n_x, n_u, n_y, n_\theta]$

Used for simulation, calibration of  $\theta$ , estimation of  $x$  or

$x, \theta$ , and to create state space models

Simulation creates a SIG object

```
s=sensormod('x(1)^2+x(2)^2',[2 0 1 0]).      % Simplest
s=sensormod('x(1,:).^2+x(2,:).^2',[2 0 1 0])% Preferred
s.x0=[1;1];                                % Set x
data=simulate(s,1:3)                         % Simulate y(1:3)
data.y                                       % Display y(t)
s.pe=1                                       % Set pe to N(0,1)
data=simulate(s,1:3)                         % Simulate with noise
data.y                                       % Display y(t)
data=simulate(s,1:1000);                    % Generate 1000 y
hist(data.y,100)                             % Histogram
plot(data)                                   % Plot y(t)
```



# Sensor networks: calibration

Sensor networks is a special case of SENSORMOD.

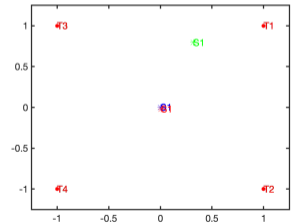
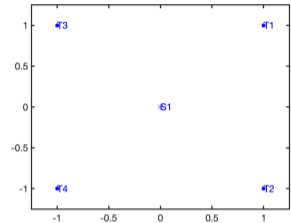
The parameters  $\theta$  used to represent sensor positions.

Many example networks in `exsensor(type,M,N)`:

TOA, TDOA, DOA, RSS, etc.

$M$  targets and  $N$  sensors.

```
s=exsensor('toa',1,4);           % Standard TOA network
s.x0=[1 1 1 -1 -1 1 -1 -1];     % Set the 4 target pos
s.th=[0 0]; s.pe=0.001*eye(4);   % Sensor pos and dist
y=simulate(s,1);                 % Simulate one meas
s0=s; s0.th=s.th+0.5*randn(2,1); % Perturb sensor pos
shat=calibrate(s0,y);            % Estimate sensor pos
plot(s,s0,shat)                  % Compare all three
```



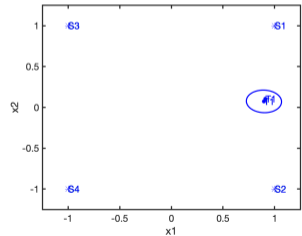
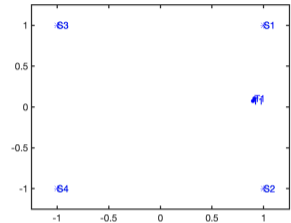
# Sensor networks: estimation

Estimate  $x$  using `wls`, `ls`, `ml`.

Two outputs: `SIG` and `SENSORMOD` (incl.  $P_x, P_\theta$ ) objects.

The method `estimate` estimates any mix of  $x$  and  $\theta$

```
s=exsensor('toa',4,1)           % TOA now with 4 sensors
s.th=[1 1 1 -1 -1 1 -1 -1];    % Sensor positions
s.pe=0.01*eye(4);              % Sensor noise N(0,0.01)
y=simulate(s,1)                 % Simulate one data point
[xhat,shat]=wls(s,y);          % Estimate target with WLS
                                % Output both SIG and SENSOR
                                % Plot both networks
plot(s,shat)
hold on
xplot2(xhat,'conf',90)         % SIG provides covariance
```





# State space models

LSS denotes the class of linear models where the method `kalman` can be applied

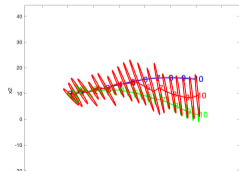
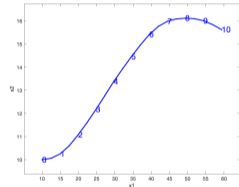
NL is the more general class of nonlinear models

Many examples of motion and sensor models in `exnl`, `exsensor`

Motion models and sensor models can be mixed

Filters can be applied to simulated data e.g. `ekf`, `ukf`, `pf`, `crlb`

```
randn('state',2), rand('state',3)
fx=exmotion('ctcv2d') % Motion model without sensor
hx=exsensor('radar',1) % Radar sensor
ss=addsensor(fx,hx) % Add sensor to motion model
yx=simulate(ss,10); % Simulate 10 seconds
xplot2(yx) % Plot state trajectory X,Y
xhat1=ekf(ss,yx); % Apply EKF
ss.pv=2*ss.pv; % Dithering noise since fx nonlin
ss.pe=2*ss.pe; % Also hx nonlinear
xhat2=ekf(ss,yx); % Second try
xplot2(yx,xhat1,xhat2,'conf',90)
axis('equal') % Compare filters
```



# Summary

- Sensor fusion has a very complex scope
- Strict model syntax

$$\begin{aligned}x(t+1) &= f(t, x(t), u(t); \theta) + v(t), & v(t) &\in p_v(v) \\ y(t) &= h(t, x(t), u(t); \theta) + e(t), & e(t) &\in p_e(e).\end{aligned}$$

- Start with working examples from `help`, book, exercises or manual to save time debugging syntax
- The goal with the toolbox is to get problem intuition
- Write your own code is also an important part of the learning process