

Multisensor Constrained Estimation with Unscented Transformation

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Constrained Estimation

Problem Formulation

Density Framework

Estimate Fusion and Constraints

Unconstrained Fusion

Problems of Nonlinear Constraints

Derivative-free Solution

Example – Ground Tracking

Introduction

classical state estimation

system described by a stochastic model exactly

state estimation with constraints

system only approximated by a stochastic model

BUT

some extra knowledge available, for example

- ▶ train follows railway
- ▶ ship cruises the sea
- ▶ mass is non-negative

i.e. some unmodelled physical constraints exist

Problem Formulation

a linear multisensor system is *described* by

$$\begin{aligned}\mathbf{x}_{k+1} &= \mathbf{F}_k \mathbf{x}_k + \mathbf{G}_k \mathbf{w}_k, \\ \mathbf{z}_k^{(j)} &= \mathbf{H}_k^{(j)} \mathbf{x}_k + \mathbf{v}_k^{(j)}, \quad j = 1, \dots, N,\end{aligned}$$

where $\mathbf{x}_k \in \mathbb{R}^{n_x}$ is the state, $\mathbf{z}_k^{(j)} \in \mathbb{R}^{n_z^{(j)}}$ are local measurement coming from j -th sensor, the noises \mathbf{w}_k , \mathbf{v}_k are independent, ... the system state obeys equality or inequality constraints given by

$$\begin{aligned}c_e(\mathbf{x}_k) &= 0, \\ c_n(\mathbf{x}_k) &\leq 0\end{aligned}$$

the goal is to combine estimates based on the local data and to respect the constraints

Enforcing Constraints

the model approximates the system dynamics

⇒

the estimate need not to obey the constraints

various approaches to restore the constraints exist

- ▶ model projection or reduction
- ▶ modification of measurement model
constraint = additive information, dynamics model considered to be accurate ⇒ this approach **removes** inadmissible states
 - ▶ pdf truncation (inequality constraints)
 - ▶ pseudomeasurements (equality constraints)
- ▶ estimate projection
⇒ this approach **refines** the approximation

Proposed Density Interpretation

Problem Formulation

true system state follows unknown densities

$$p(\mathbf{x}_{k+1}^\dagger | \mathbf{x}_k^\dagger), p(\mathbf{x}_0^\dagger)$$

but the set \mathcal{C}_k of admissible system states is known for each time k

$$\mathcal{C}_k = \{\forall \mathbf{x}_k^\dagger : p(\mathbf{x}_k^\dagger) \neq 0\}$$

and some *approximation* of the system dynamics is available,

$$p(\mathbf{x}_{k+1} | \mathbf{x}_k), p(\mathbf{x}_0)$$

The true measurement probability density is given by

$$p(\mathbf{z}_k^{(1)\dagger}, \dots, \mathbf{z}_k^{(N)\dagger} | \mathbf{x}_k^\dagger)$$

The model usually assumes that the density exists also for $\mathbf{x}_k \notin \mathcal{C}_k$,

$$p(\mathbf{z}_k^{(1)}, \dots, \mathbf{z}_k^{(N)} | \mathbf{x}_k)$$

Proposed Density Interpretation

Enforcing Constraints

- ▶ model projection or reduction = transition density transformation

$$C_S : p(\mathbf{x}_{k+1}|\mathbf{x}_k) \rightarrow p_C(\mathbf{x}_{k+1}|\mathbf{x}_k), \quad p_C(\mathbf{x}_{k+1}|\mathbf{x}_k) \neq 0 \Rightarrow \mathbf{x}_{k+1} \in \mathcal{C}_{k+1}$$

- ▶ modification of measurement model – fictive measurement \mathbf{c}_k

$$p(\mathbf{x}_k|\mathcal{Z}_k, \mathbf{c}_k) \propto I_{C_k}(\mathbf{x}_k)p(\mathbf{x}_k|\mathcal{Z}_k),$$

where I_{C_k} is the indicator function, the relation results from

- ▶ fusion with noninformative constraining density

$$p(\mathbf{x}_k|\mathbf{c}_k) \propto I_{C_k}(\mathbf{x}_k)$$

- ▶ zero noise measurements $\mathbf{c}_k = 0$

$$p(\mathbf{c}_k|\mathbf{x}_k) = \delta(\mathbf{c}_k - \mathbf{c}_k(\mathbf{x}_k))$$

- ▶ estimate projection = estimated density transformation

$$C_k : p(\mathbf{x}_k|\mathcal{Z}_k) \rightarrow p(\mathbf{x}_k|\mathcal{Z}_k, \mathbf{c}_k), \quad p(\mathbf{x}_k|\mathcal{Z}_k, \mathbf{c}_k) \neq 0 \Rightarrow \mathbf{x}_k \in \mathcal{C}_k$$

Fusion Problem

fusion of estimates

local measurements → local estimates
local estimates → fused estimate

unconstrained fusion

- ▶ fusion of decorrelated information
- ▶ computing the dependences of estimates
- ▶ respecting the unknown dependences

constrained estimation – the meaning of dependences unclear
⇒ respecting the dependences

Covariance Intersection

- ▶ having consistent local estimates $\{\hat{\mathbf{x}}_1, \mathbf{P}_1\}$, $\{\hat{\mathbf{x}}_2, \mathbf{P}_2\}$, the fused estimate $\{\hat{\mathbf{x}}, \mathbf{P}\}$ is consistent, i.e. $\mathbf{P} - \mathbb{E}[(\mathbf{x} - \hat{\mathbf{x}})(\mathbf{x} - \hat{\mathbf{x}})^T] \geq 0$, regardless the dependence of the local estimates

$$\begin{aligned}\mathbf{P}^{-1}\hat{\mathbf{x}} &= \omega\mathbf{P}_1^{-1}\hat{\mathbf{x}}_1 + (1 - \omega)\mathbf{P}_2^{-1}\hat{\mathbf{x}}_2, \\ \mathbf{P}^{-1} &= \omega\mathbf{P}_1^{-1} + (1 - \omega)\mathbf{P}_2^{-1},\end{aligned}$$

for $\omega \in [0, 1]$

- ▶ works well for unconstrained estimates (regular covariances)
- ▶ equality constrained estimates have singular covariances if a linearised projection have been used

Fusion of Singular Densities

estimates constrained in the same direction

fusion of approximated constrained estimates

$$\left(\begin{bmatrix} 1 & 0 \\ 0 & 0.01 \end{bmatrix}^{-1} + \begin{bmatrix} 2 & 0 \\ 0 & 0.01 \end{bmatrix}^{-1} \right)^{-1} \doteq \begin{bmatrix} 0.666 & 0 \\ 0 & 0.005 \end{bmatrix}$$

the pseudoinverse solution is OK

$$\left(\begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}^{-1_{MP}} + \begin{bmatrix} 2 & 0 \\ 0 & 0 \end{bmatrix}^{-1_{MP}} \right)^{-1_{MP}} = \begin{bmatrix} \frac{2}{3} & 0 \\ 0 & 0 \end{bmatrix}$$

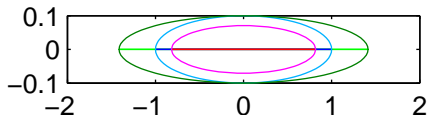


Figure: Covariance ellipses, $\mathbf{x}^T \mathbf{P} \mathbf{x} = 1$ (lines for singular covariances)

Fusion of Singular Densities

estimates constrained in different directions

the approximation gives approximative results

$$\left(\begin{bmatrix} 1 & 0 \\ 0 & 0.01 \end{bmatrix}^{-1} + \begin{bmatrix} 0.01 & 0 \\ 0 & 1 \end{bmatrix}^{-1} \right)^{-1} \doteq \begin{bmatrix} 0.01 & 0 \\ 0 & 0.01 \end{bmatrix} \rightarrow \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

while the use of pseudoinverses spoils the fusion

$$\left(\begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}^{-1_{MP}} + \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}^{-1_{MP}} \right)^{-1_{MP}} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \ggg \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

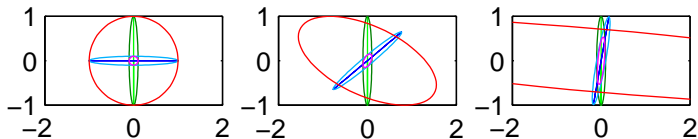
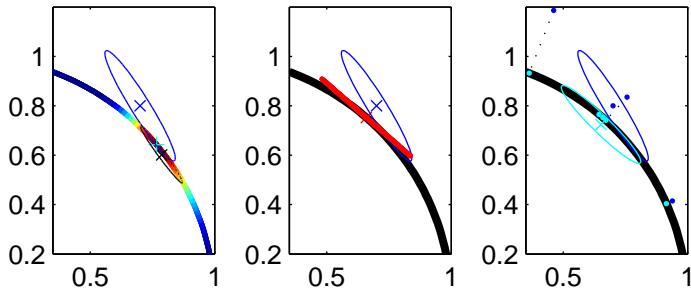


Figure: Closer constrained direction \Rightarrow worse pseudoinverse solution

Projection by Unscented Transformation

nonlinear equality constraint \Rightarrow nonlinear projection needed



(a) pdf truncation

(b) linear projection

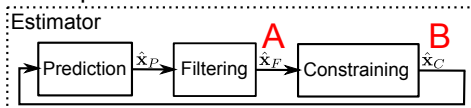
(c) projection by UT

- a) pdf truncation (pseudomeasurements) gives inadequate results
- b) linear projection leads to singular covariances
- c) unscented transformation respects the constraint nonlinearity

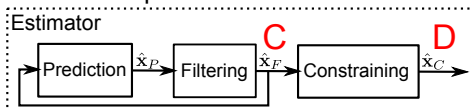
Estimators Architecture

Local Estimators

constraint in the loop



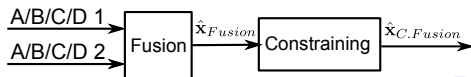
constraint outside the loop



Fusion at the centre

A, C fusion of unconstrained estimates

B, D fusion of constrained estimates



Ground Tracking Example

- ▶ nearly constant velocity model – state $\mathbf{x} = [x, v_x, y, v_y]^T$
- ▶ position measured by two sensors (different error covariances)
- ▶ circular road, tangent velocity

$$x^2 + y^2 - R^2 = 0$$

position constraint

$$xv_x + yv_y = 0$$

velocity constraint

- ▶ estimate projection approach

$$\pi(\mathbf{x}) = \left[\frac{R_x}{\sqrt{x^2+y^2}} \quad \frac{v_x y^2 - v_y xy}{x^2+y^2} \quad \frac{R_y}{\sqrt{x^2+y^2}} \quad \frac{-v_x xy + v_y x^2}{x^2+y^2} \right]^T$$

- ▶ the proposed approaches compared

Example Results

Table: Mean position and velocity errors at local estimator

	C in the loop	C outside the loop
$\bar{\epsilon}(\hat{\mathbf{x}}_P)_{position/velocity}$	4.34/2.41	12.78/6.90
$\bar{\epsilon}(\hat{\mathbf{x}}_F)_{position/velocity}$	A 3.52/2.45	C 7.65/5.00
$\bar{\epsilon}(\hat{\mathbf{x}}_C)_{position/velocity}$	B 3.29/1.34	D 3.76/1.51

Table: Mean position/ velocity errors after the fusion of local estimates

approach	A	B	C	D
$\bar{\epsilon}(\hat{\mathbf{x}}_{Fusion})_{pos./vel.}$	2.75/2.27	2.40/1.01	6.88/4.86	2.91/1.20
$\bar{\epsilon}(\hat{\mathbf{x}}_{C.Fusion})_{pos./vel.}$	2.49/1.04	2.39/1.01	3.53/1.43	2.91/1.20

+ opened questions (divergence between model and system, incomplete constraint utilisation, projection design)

Summary

- ▶ constrained estimation formulated in density framework
- ▶ estimate projection preferred to pseudomeasurements
- ▶ problems with singular densities referred
- ▶ derivative-free solution proposed
- ▶ various estimators designed
- ▶ their performance compared

Thank you for the attention.