Intelligent

Sensor-Actuator-Systems

Hot Topics in Multisensor Data Fusion

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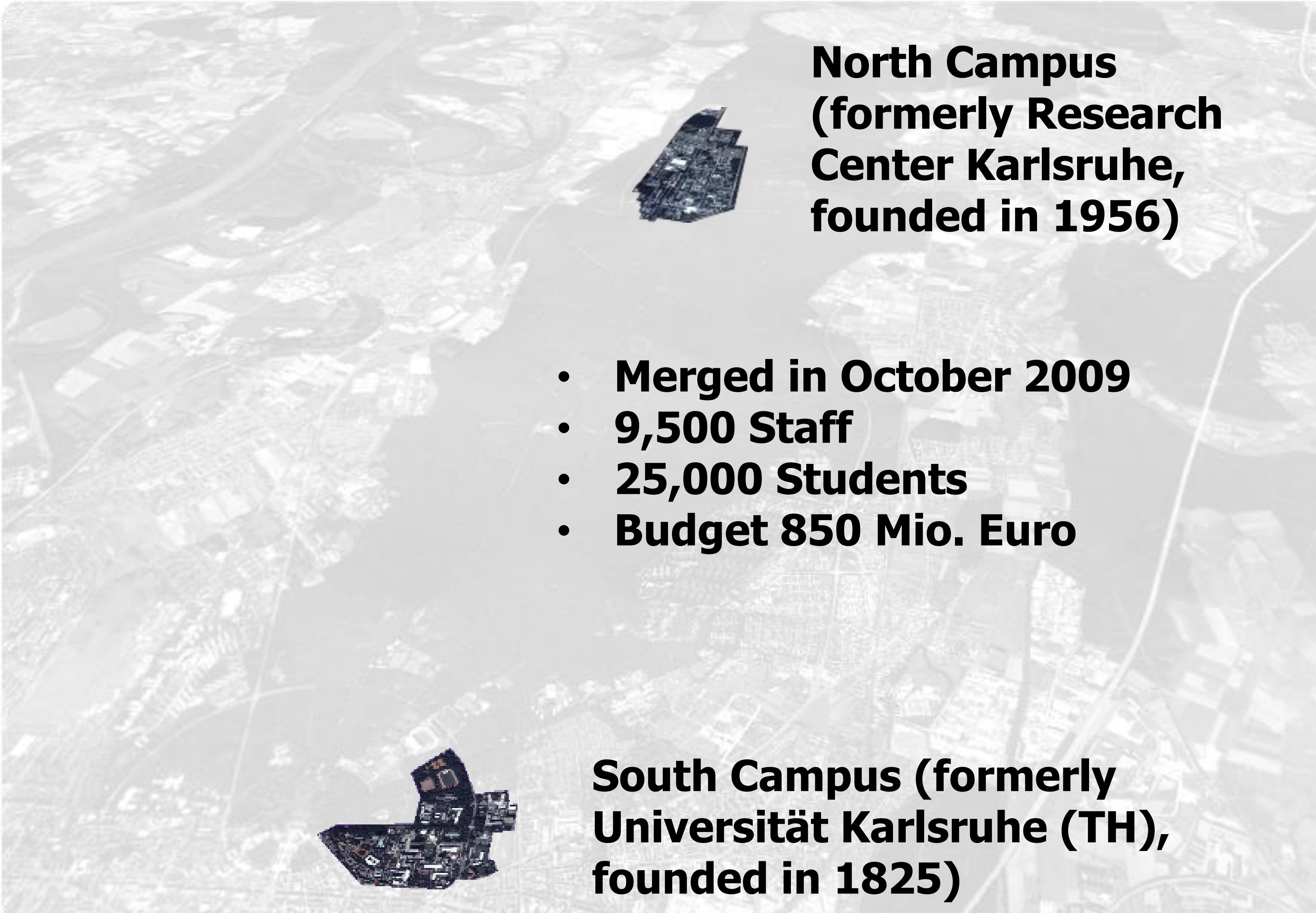
Intelligent Sensor-Actuator-Systems

Karlsruhe in Germany

Karlsruhe Institute of Technology (KIT)



North Campus (formerly Research Center Karlsruhe, founded in 1956)

- **Merged in October 2009**
- **9,500 Staff**
- **25,000 Students**
- **Budget 850 Mio. Euro**

South Campus (formerly Universität Karlsruhe (TH), founded in 1825)

Motivation

3) Measurement association unknown

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Association-free filter

1. **Nonlinear filter:**
   Sample-based nonlinear Kalman filter

2. **Combination:**
   Direct fusion of empirical estimates

3. **Association-free filter:**
   Symmetrization of measurement equation

1) Nonlinear motion / measurement models

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Nonlinear filter

2) Several estimates

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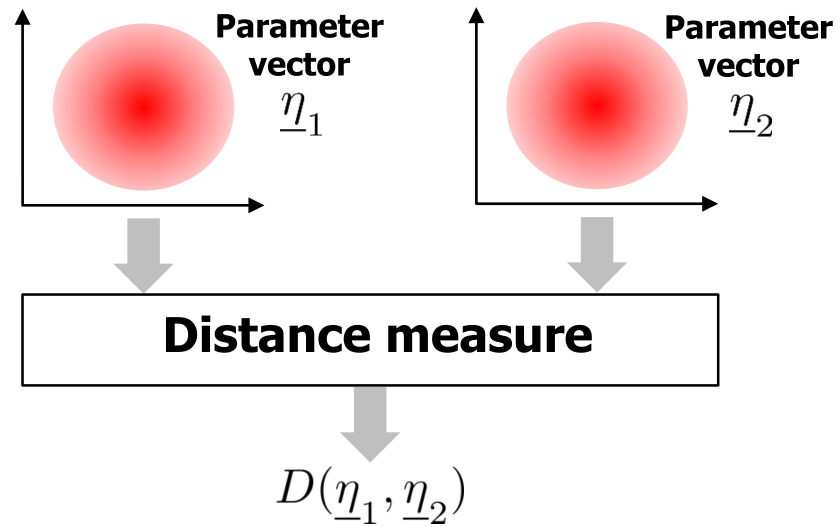
Combination

Foundation: Distance Measure

- All methods based on novel distance measure
- Comparison of densities
  - Continuous / continuous
  - Continuous / discrete
  - Discrete / discrete
- Continuously differentiable

$$\underline{G}(\underline{\eta}_1, \underline{\eta}_2) = \frac{\partial D(\underline{\eta}_1, \underline{\eta}_2)}{\partial \underline{\eta}_2}$$



- Discrete / discrete case:
  - Invariant to permutations of points

$$D(\underline{\eta}_1, \underline{\eta}_2) = D(P_1(\underline{\eta}_1), P_2(\underline{\eta}_2)) \quad \text{with permutations} \quad P_1(.), P_2(.)$$

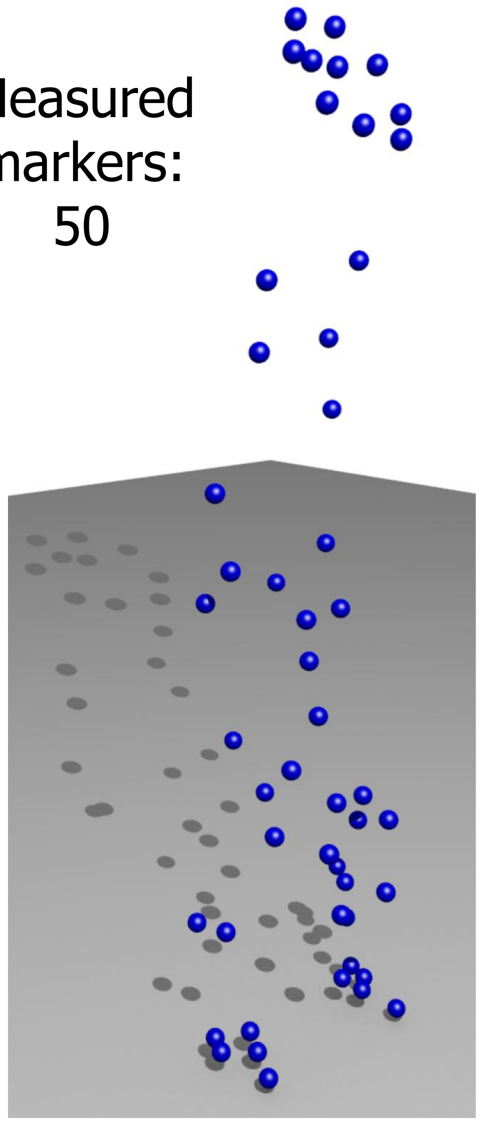
  - Efficient closed-form calculation
- Uses generalized cumulative distributions for comparison

Reference: [1]

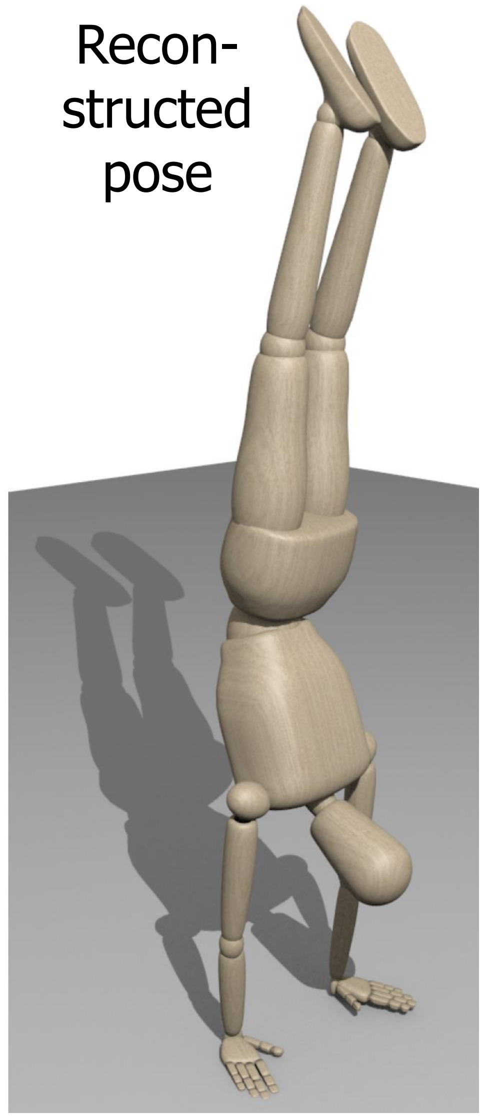
Sample-based Nonlinear Kalman Filtering

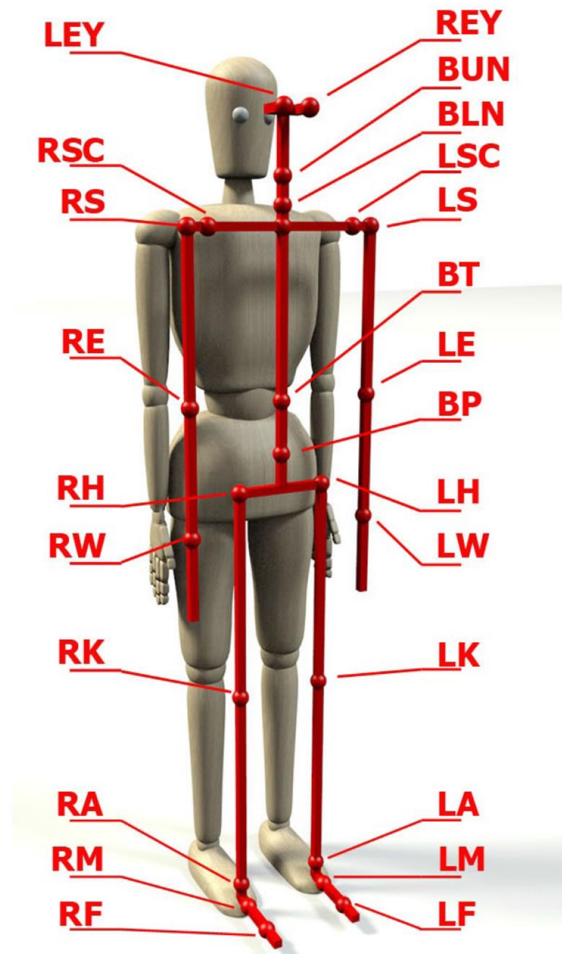
Application: Human Tracking (1)

Measured markers: 50



Recon-structed pose

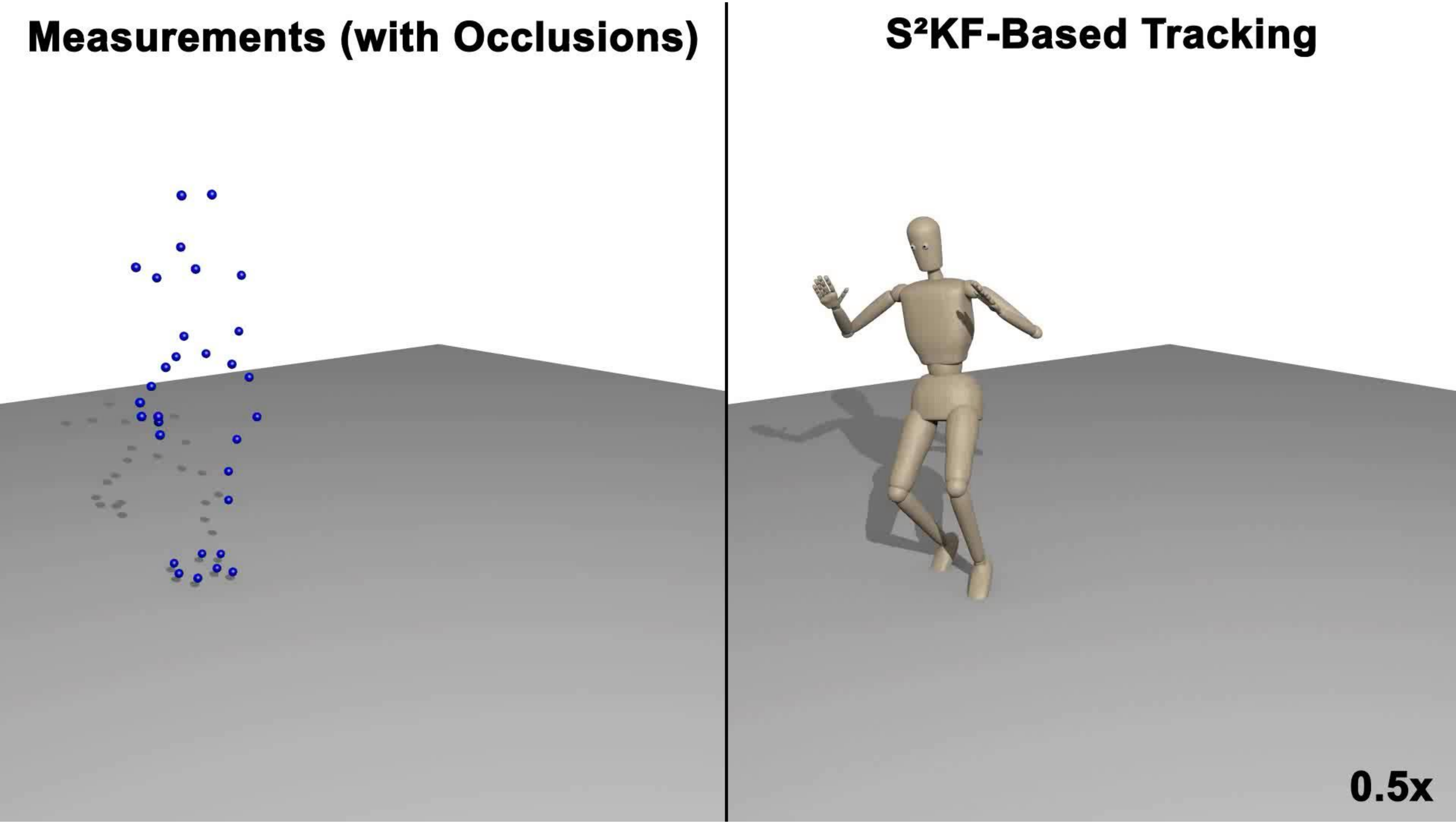




Kinematic model: state dimension: 46

Reference: [2], [3]

Application: Human Tracking (2)



Reference: [2], [3]

Nonlinear Filtering: Problem

- Given:
  - Nonlinear measurement equation $\underline{y} = \underline{h}(\underline{x}) + \underline{v}$
  - Gaussian prior density for $\underline{x}$: $f_p(\underline{x})$
  - Measurement noise $\underline{v}$ with Gaussian density: $f_v(\underline{v})$
  - Specific measurement $\hat{\underline{y}}$
- Desired:
  - Gaussian posterior density for $\underline{x}$: $f_e(\underline{x})$
- Complicated problem: Exact solution rarely possible
- Simplification:

Additional Gaussian assumption
between state and measurement

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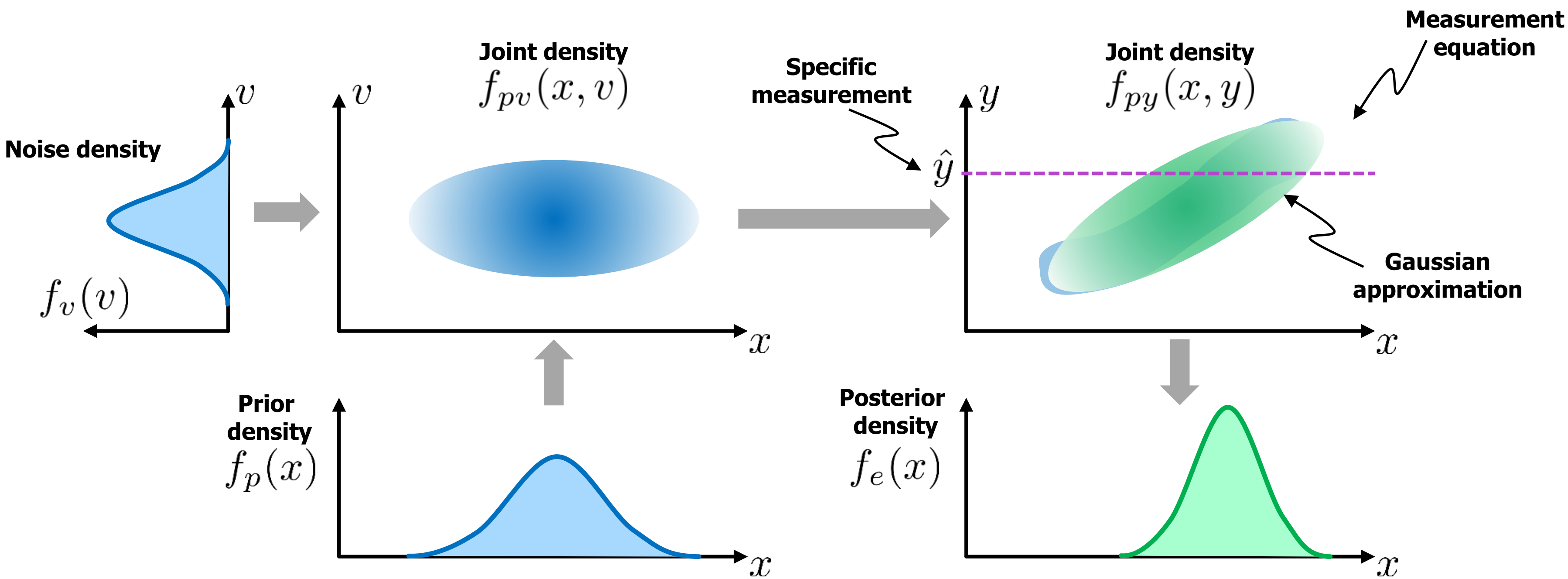
Nonlinear Kalman Filter

Our Matlab Toolbox available.
See reference [4]

Analytic Nonlinear Kalman Filter

- Calculate joint density of $\underline{y}, \underline{z}$ by augmented measurement equation
$$\begin{bmatrix} \underline{y} \\ \underline{z} \end{bmatrix} = \begin{bmatrix} \underline{h}(\underline{x}) + \underline{v} \\ \underline{x} \end{bmatrix} \quad \text{and} \quad \underline{z} = \underline{x}$$

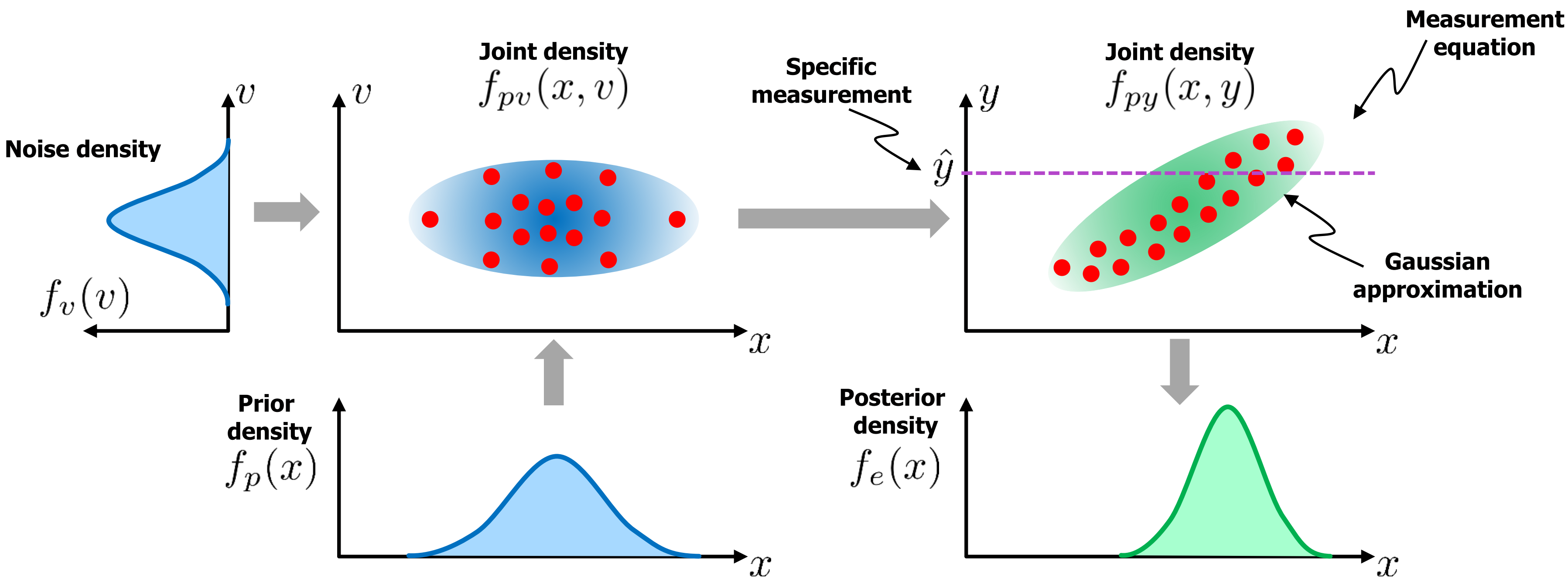


- Gaussian approximation cannot always be analytically calculated → Simplifications inevitable

Reference: [5]

Sample-based Nonlinear Kalman Filter

- Use samples to approximate Gaussian prior and noise
- Samples can easily be propagated



- Remaining challenge: Suitable sample approximation
- Standard approximations: Random sampling, quadrature

Reference: [3]

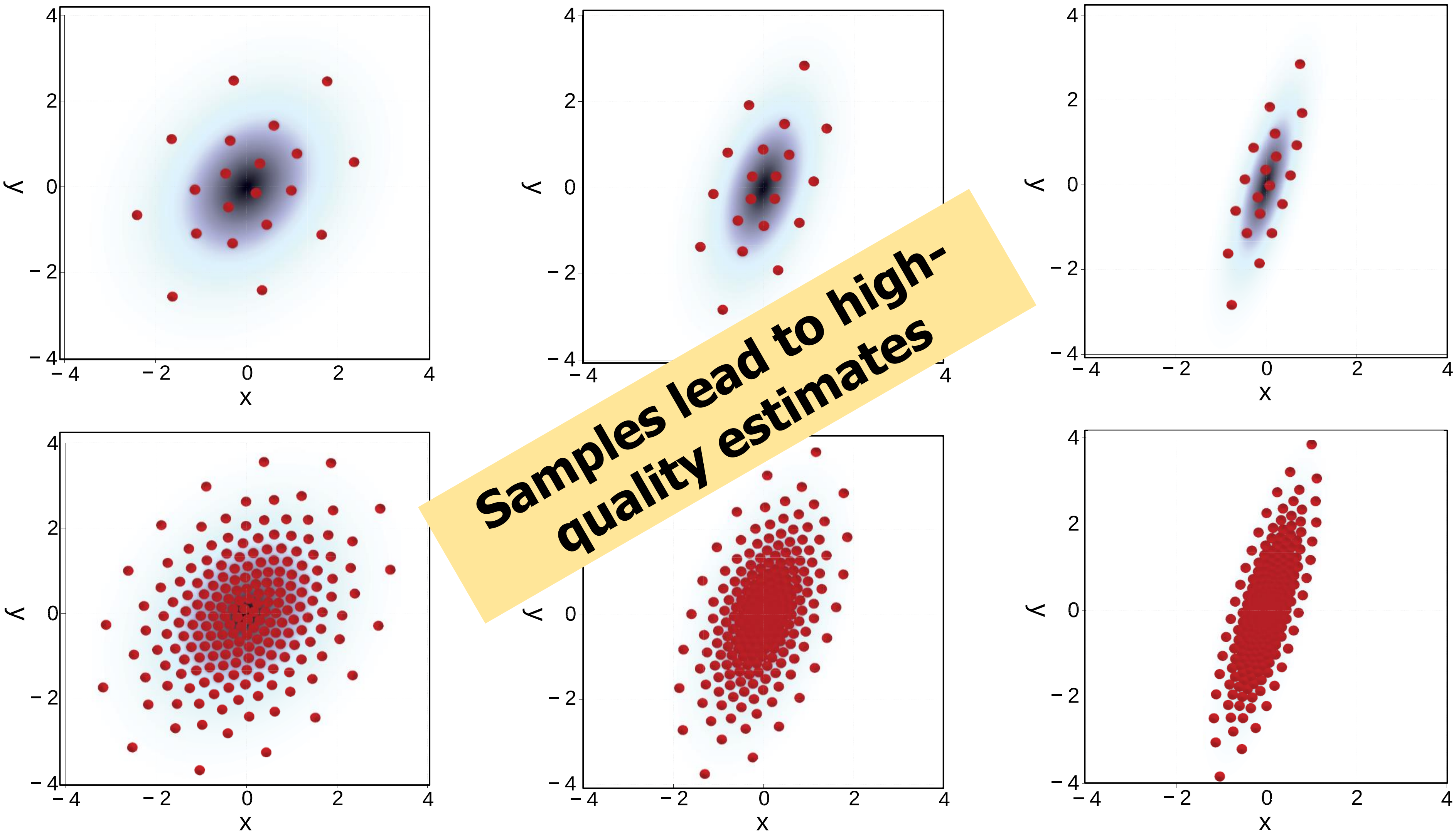
New Sampling Method: Idea

- Goal:
  - Arbitrary number of samples
  - Homogeneous coverage of given Gaussian density
  - Systematic approximation by minimization of distance measure
- Challenge:
  - Standard distance measures typically not suitable for comparing continuous / discrete densities
  - Wasserstein distance suitable, but very complex (distance requires optimization itself)
- Here:
  - Employ novel distance measure
  - Use optimization method to minimize distance between given Gaussian and desired Dirac mixture

  → Yields sample positions

Reference: [6], [7]

New Sampling Method: Results

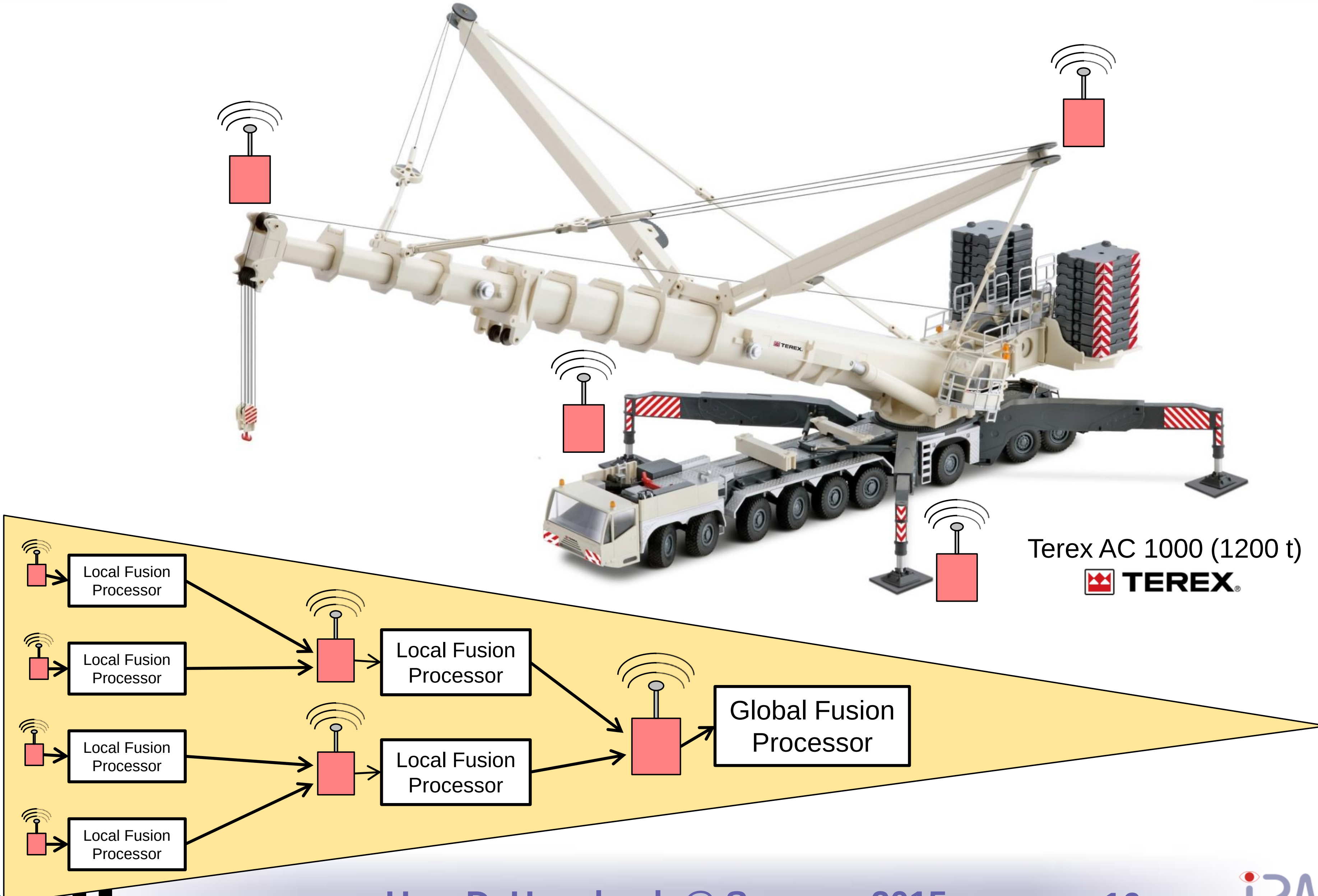


Samples lead to high-quality estimates

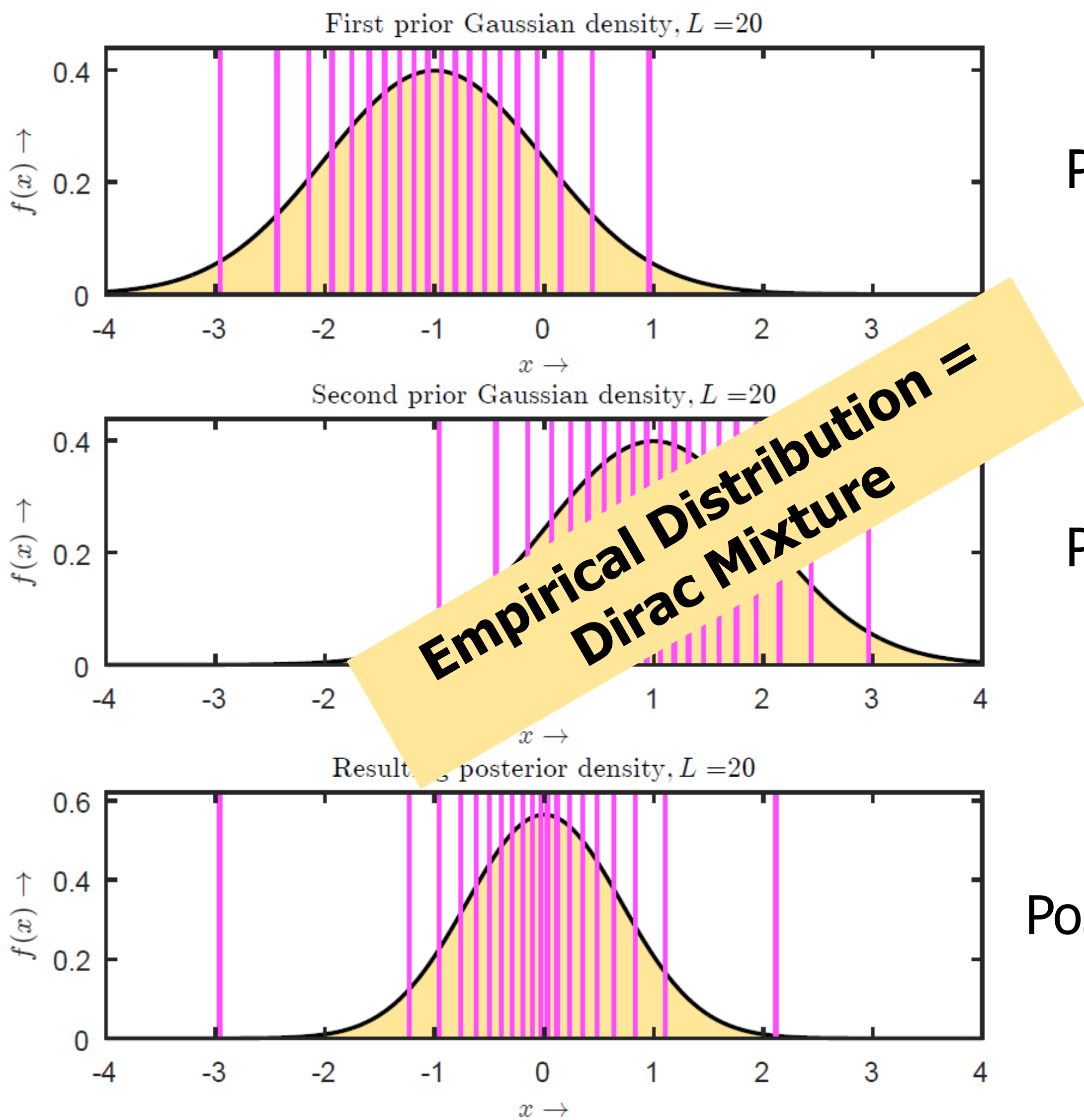
Reference: [6], [7]

Direct Fusion of Two Empirical Estimates

Application: Crane Monitoring



Direct Fusion: Problem Formulation (1)



Prior Density 1

Prior Density 2

Posterior Density

Reference: [8]

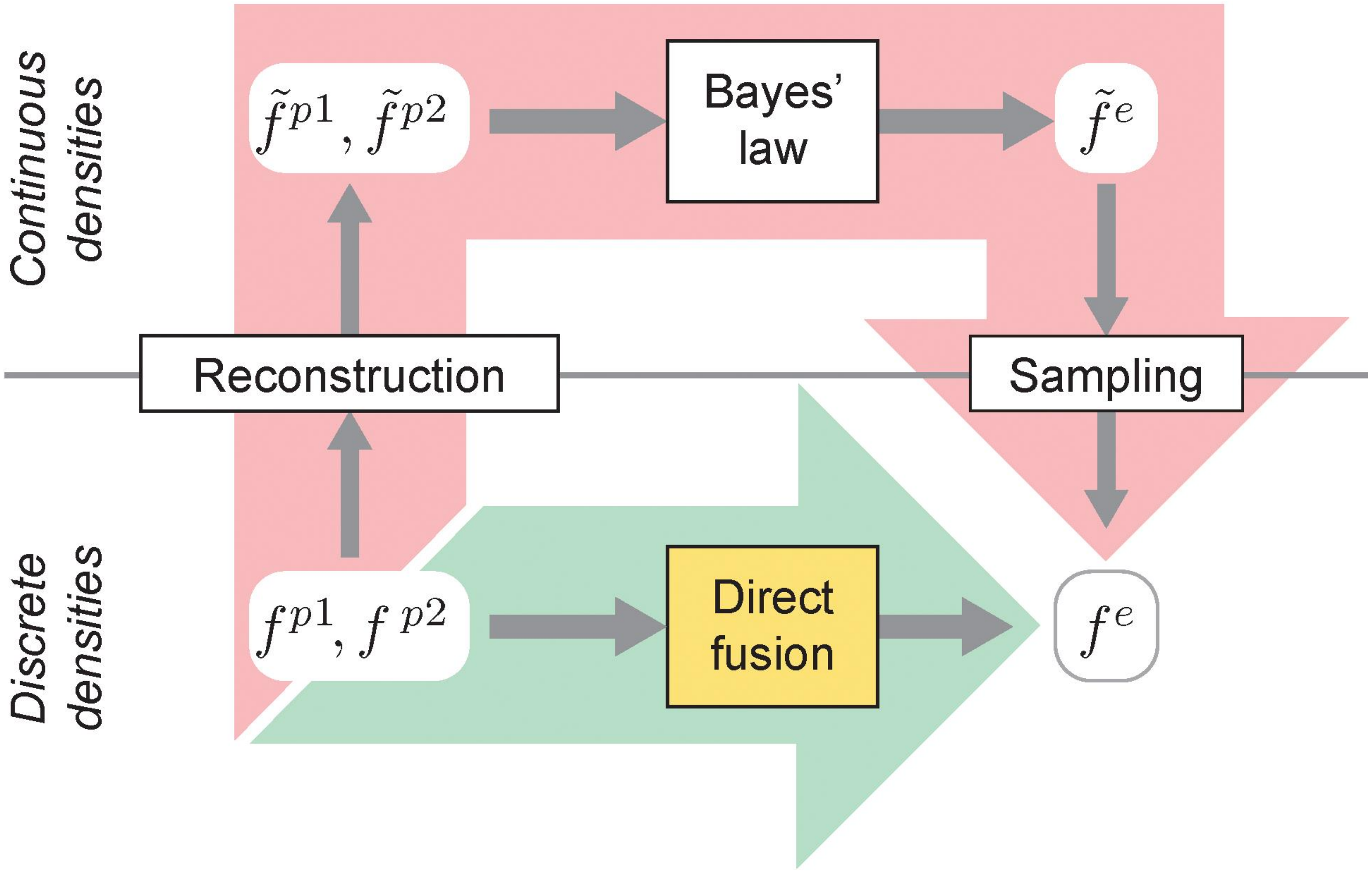
Direct Fusion: Problem Formulation (2)

- **Goal: Direct Bayesian Fusion**
- However, multiplication not well defined for Dirac mixtures
- For Dirac mixture: „Density" coded in distances and weights (when non-equally weighted)
- Both given densities are discrete
- In general: No joint support

- What we do not want:
  - Reconstruct both continuous underlying densities
  - Multiply the continuous densities
    $\rightarrow$ Posterior continuous density
  - Discretize posterior

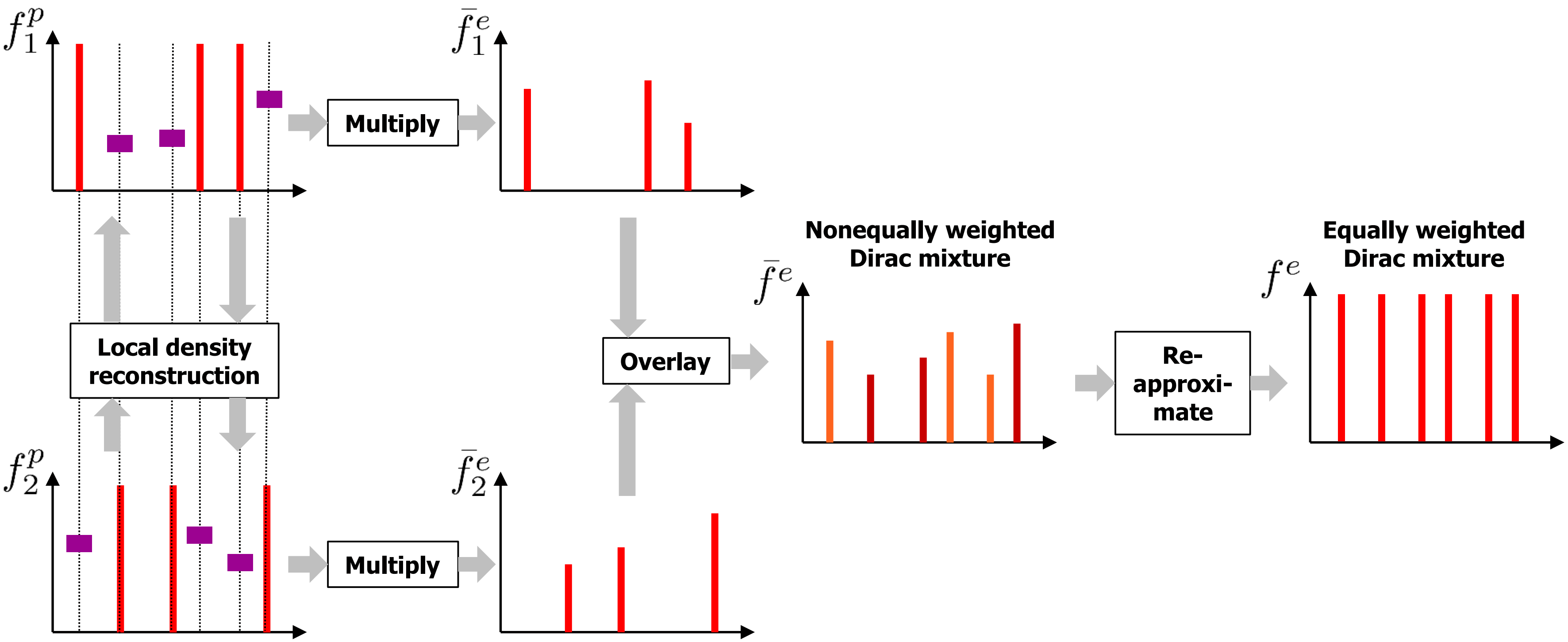
Reference: [8]

Direct Fusion: Problem Formulation (3)



Reference: [8]

Direct Fusion: Solution

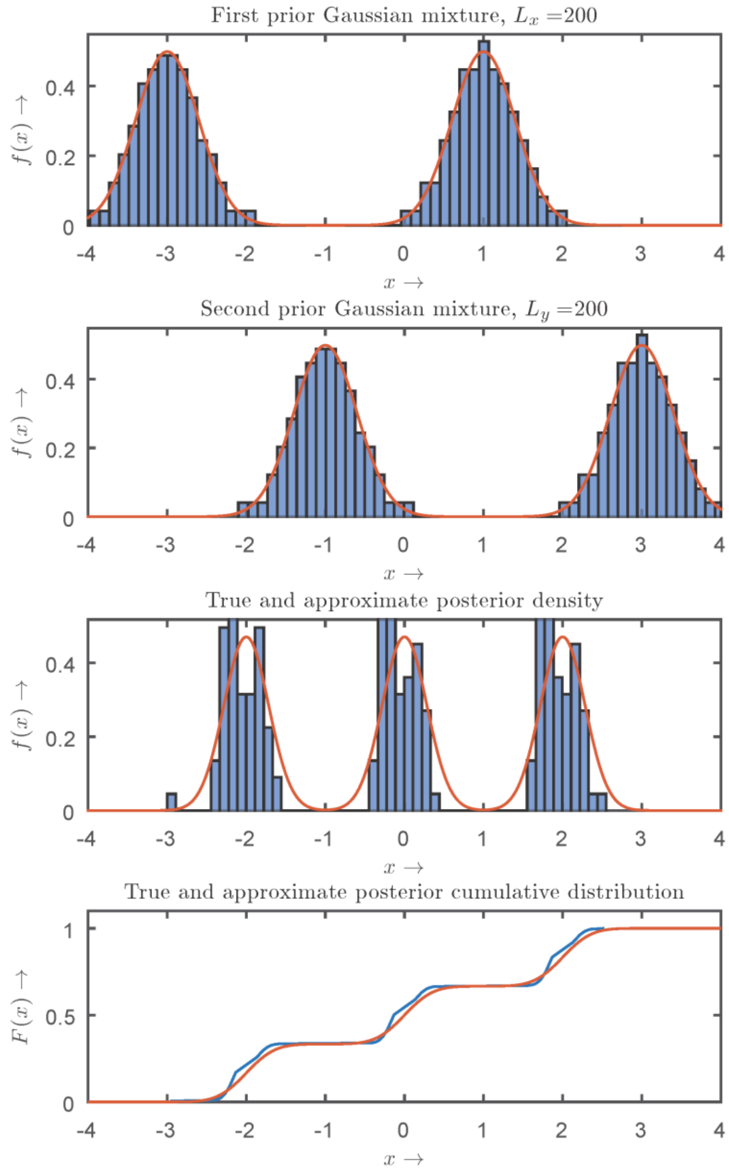


Reconstruct density values at component locations (use k-nearest neighbors)

Minimize distance measure between $\bar{f}^e$ and f^e

Reference: [8]

Direct Fusion: Results



Red: True densities (unknown to the filter)

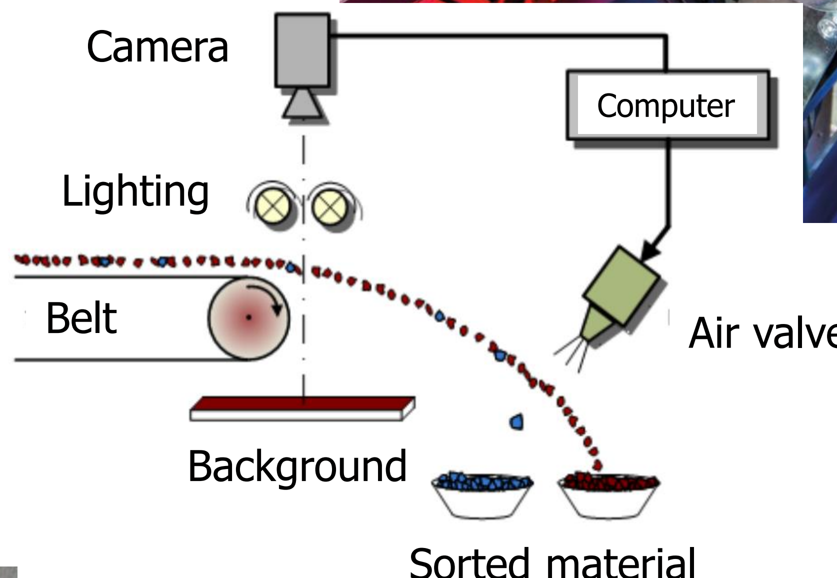
Blue: Histogram of samples

Reference: [8]

Association-free Data Fusion

Application: TrackSort (1)

- Sorting bulk material
- Belt sorter
- Use camera for tracking objects on belt
- Challenge: Many objects and high belt speed



Reference: [9]

Application: TrackSort (2)

Reference: [9]

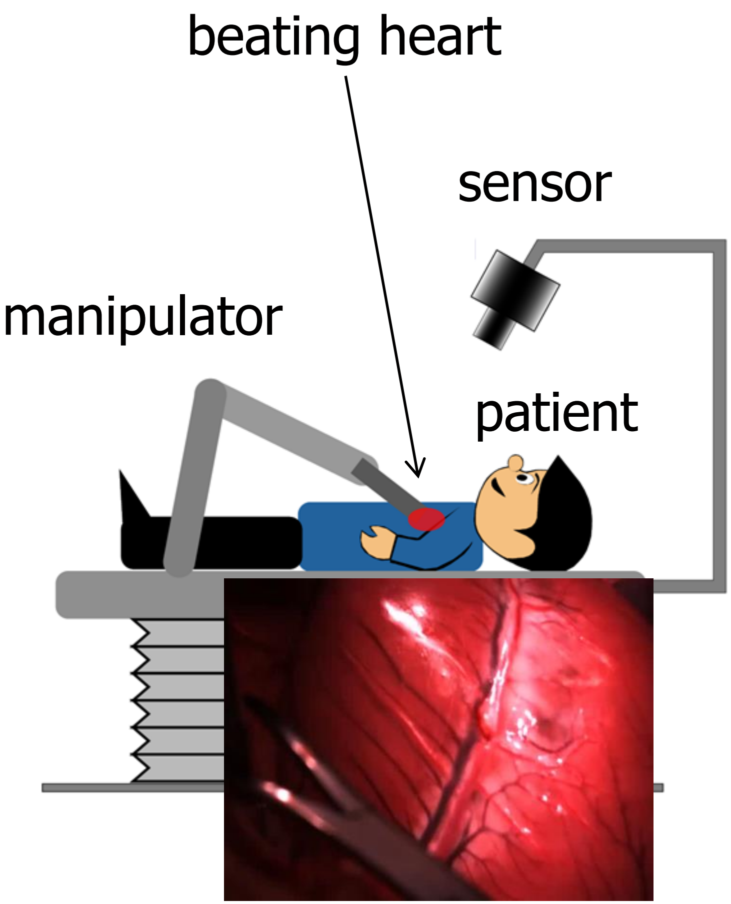
Application: Beating Heart Surgery (1)

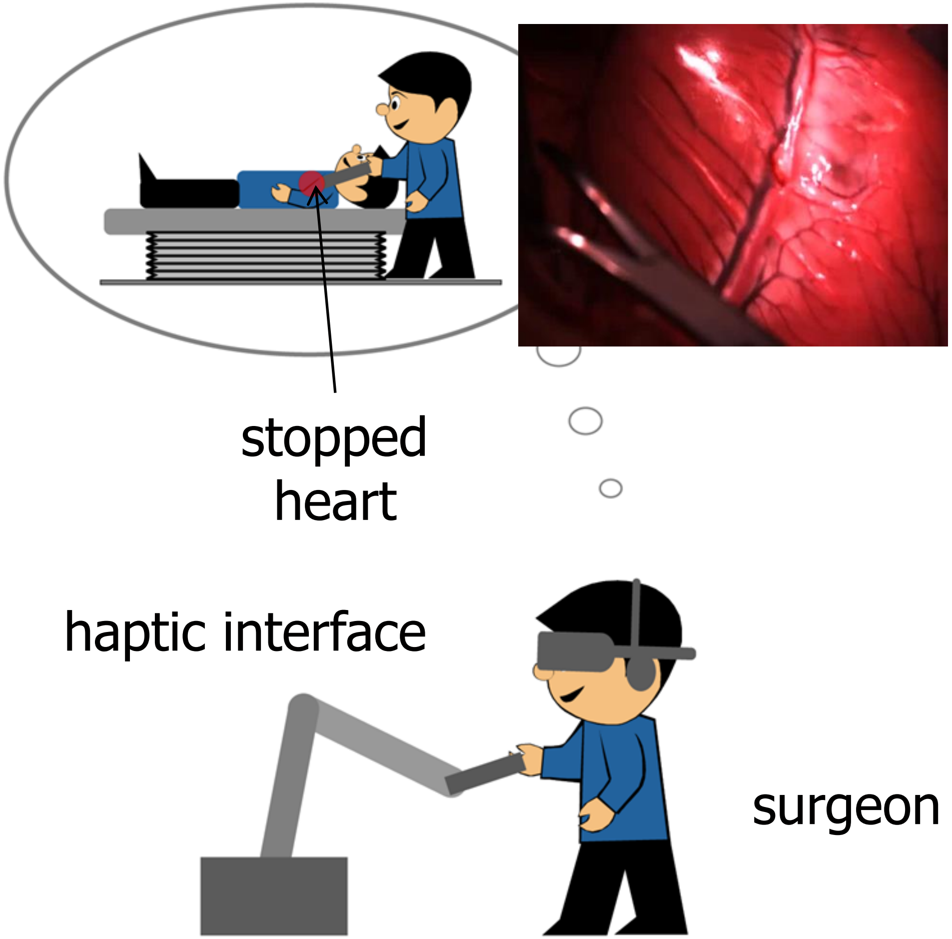
- Beating Heart Surgery
  - coronary artery bypass
- Stopped heart
  - use of heart lung machine
  - additional risks for patient
- Beating heart
  - more difficult for surgeon

Goal: Robot automatically compensates for heart motion

Reference: [10]-[12]

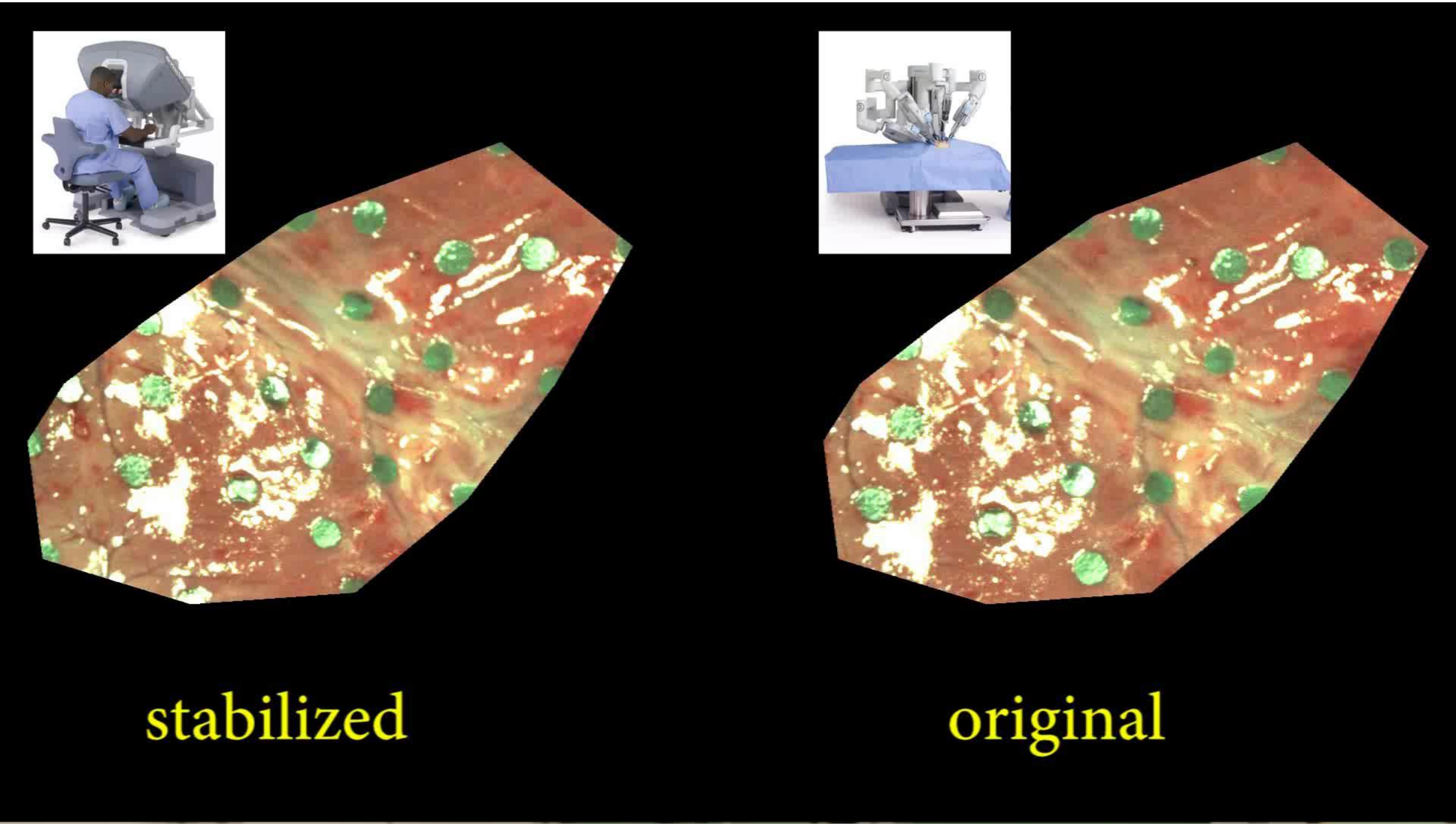
Application: Beating Heart Surgery (2)





Reference: [10]-[12]

Application: Beating Heart Surgery (3)



Reference: [10]-[12]

Association-free Data Fusion: Problem

- Given:
  - Prior estimates of N objects $\mathcal{X}^p = \{\underline{x}_1^p, \underline{x}_2^p, \ldots, \underline{x}_N^p\}$
  - Set of measurements $\hat{\mathcal{Y}} = \{\hat{\underline{y}}_1, \hat{\underline{y}}_2, \ldots, \hat{\underline{y}}_N\}$
  - Association of measurements to objects is unknown: Taken care by unknown permutation P
  - Measurement equations

$$
\begin{aligned}
\hat{\underline{y}}_{P(1)} &= h_1(\underline{x}_1) + \underline{v}_1 \\
\hat{\underline{y}}_{P(2)} &= h_2(\underline{x}_2) + \underline{v}_2 \\
&\vdots \\
\hat{\underline{y}}_{P(N)} &= h_N(\underline{x}_N) + \underline{v}_N
\end{aligned}
$$

- Desired:
  - Posterior estimates of objects $\mathcal{X}^e = \{\underline{x}_1^e, \underline{x}_2^e, \ldots, \underline{x}_N^e\}$

Reference: [13]

Association-free Data Fusion: Challenge

- Number of permutations: $N!$ e.g. $10! = 3,628,800$
- Standard approaches
  - Hard assignment
    - Local nearest neighbors (simple)
    - Global nearest neighbors (complex)
  - Soft assignment
    - Probabilistic matching (exponential grow over time)
- **Here:** no assignment at all

Association-free data fusion

↓

Based on permutation-invariant
distance measure

Reference: [13]

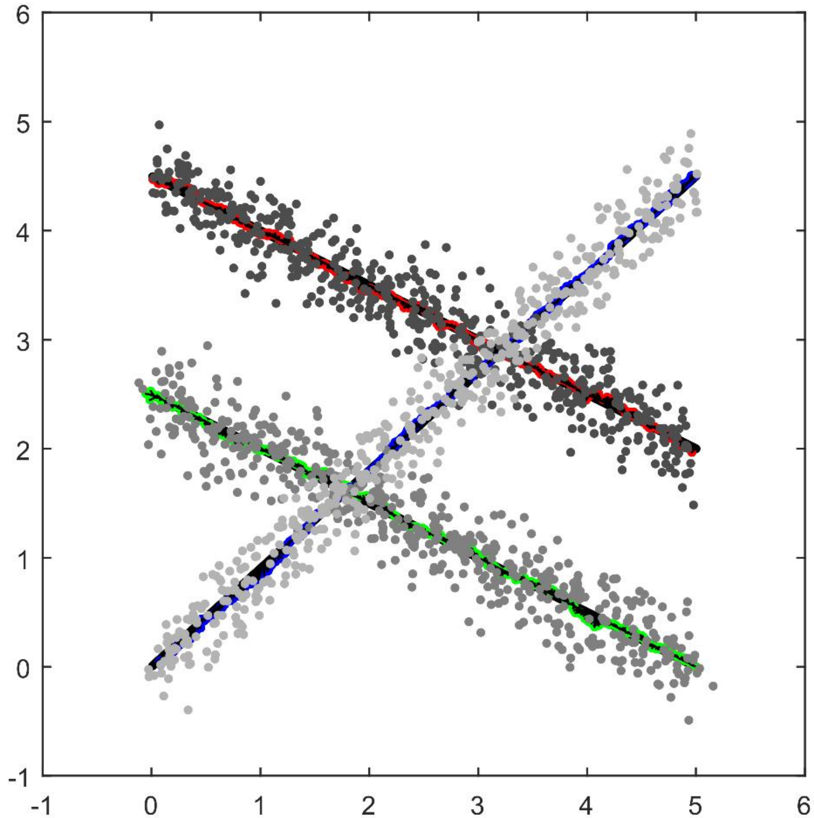
Association-free Data Fusion: Solution

- Several fundamental approaches possible, e.g., integral design of filter
- **Here:** Transformation of measurement equation to get rid of unknown permutation (literature: SME)
- Idea:
  - Consider set of given measurements
  $$\hat{\mathcal{Y}} = \{\hat{\underline{y}}_1, \hat{\underline{y}}_2, \ldots, \hat{\underline{y}}_N\}$$
  - Calculate predicted measurements based on $\mathcal{X}^p$
  $$\mathcal{Y}^p = \{\underline{y}_1^p, \underline{y}_2^p, \ldots, \underline{y}_N^p\}$$
  - Minimize distance measure (is permutation invariant)
  $$D(\hat{\mathcal{Y}}, \mathcal{Y}^p)$$
- Gradient vector gives new set of measurement equations without unknown permutation
- Apply standard filter to estimate object states

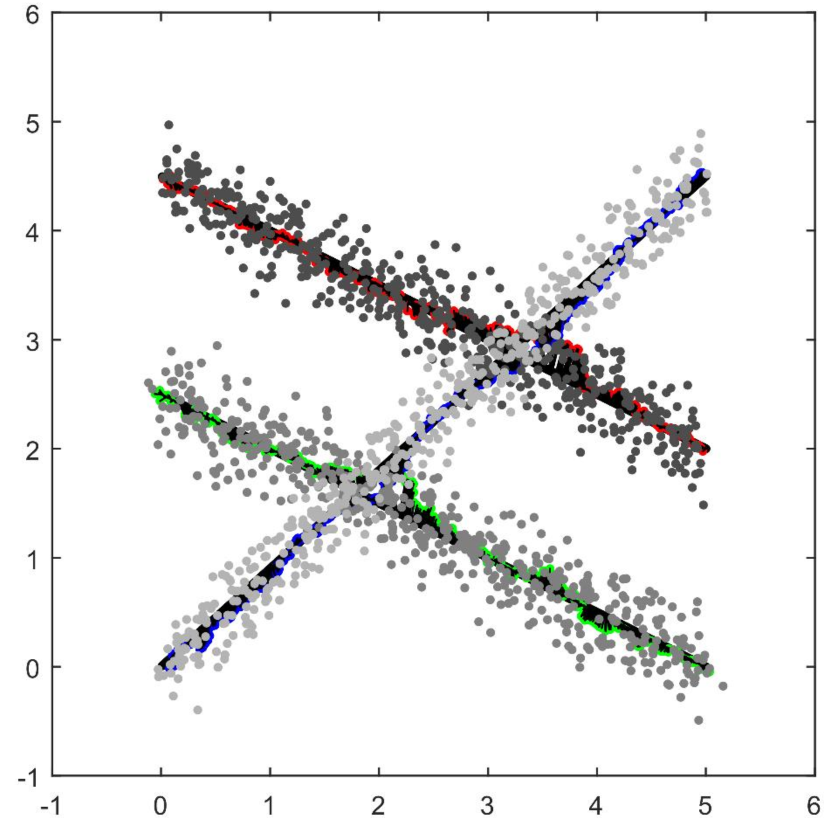
Reference: [13]

Association-free Data Fusion: Result

Three moving objects, high noise



Association fully known



Association unknown

Reference: [13]

Conclusions

Three hot topics:

1. Nonlinear filter:
   Sample-based nonlinear Kalman filter

2. Combination:
   Direct fusion of empirical estimates

3. Association-free filter:
   Symmetrization of measurement equation

All methods based on:

Novel distance measure for continuous / discrete densities

- permutation invariant
- continuously differentiable

Thank You for Your Attention !

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The End

References

[1] *Uwe D. Hanebeck and Vesa Klumpp*,
Localized Cumulative Distributions and a Multivariate Generalization of the Cramér-von Mises Distance
Proceedings of the 2008 IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems (MFI 2008), August 2008.

[2] *Jannik Steinbring, Christian Mandery, Nikolaus Vahrenkamp, Tamim Asfour, and Uwe D. Hanebeck*
High-Accuracy Real-Time Whole-Body Human Motion Tracking Based on Constrained Nonlinear Kalman Filtering
(submitted) also available as arXiv preprint: Systems and Control (cs.SY), November 2015

[3] *Jannik Steinbring and Uwe D. Hanebeck*
LRKF Revisited: The Smart Sampling Kalman Filter (S2KF)
Journal of Advances in Information Fusion, 9(2):106 - 123, December 2014.

[4] Jannik Steinbring
Nonlinear Estimation Toolbox
Available at: https://bitbucket.org/nonlinearestimation/toolbox

[5] *Marco F. Huber, Frederik Beutler, and Uwe D. Hanebeck*
Semi-Analytic Gaussian Assumed Density Filter
Proceedings of the 2011 American Control Conference (ACC 2011), June 2011.

[6] *Uwe D. Hanebeck, Marco F. Huber, and Vesa Klumpp*
Dirac Mixture Approximation of Multivariate Gaussian Densities
Proceedings of the 2009 IEEE Conference on Decision and Control (CDC 2009), December 2009.

[7] *Igor Gilitschenski, Jannik Steinbring, Uwe D. Hanebeck, and Miroslav Simandl*
Deterministic Dirac Mixture Approximation of Gaussian Mixtures
Proceedings of the 17th International Conference on Information Fusion (Fusion 2014), July 2014.

[8] *Uwe D. Hanebeck*
Bayesian Fusion of Empirical Distributions Based on Local Density Reconstruction
Proceedings of the 2015 IEEE International Conference on Multisensor Fusion and Information Integration (MFI 2015), September 2015.

[9] *Florian Pfaff, Marcus Baum, Benjamin Noack, Uwe D. Hanebeck, Robin Gruna, Thomas Längle, and Jürgen Beyerer*
TrackSort: Predictive Tracking for Sorting Uncooperative Bulk Materials
Proceedings of the 2015 IEEE International Conference on Multisensor Fusion and Information Integration (MFI 2015), September 2015.

[10] *Gerhard Kurz, Marcus Baum, and Uwe D. Hanebeck*
Real-time Kernel-based Multiple Target Tracking for Robotic Beating Heart Surgery
Proceedings of the Eighth IEEE Sensor Array and Multichannel Signal Processing Workshop (SAM 2014), June 2014.

[11] *Gerhard Kurz, Geneviève Foley, Péter Hegedüs, Gábor Szabó, and Uwe D. Hanebeck*
Evaluation of Image Stabilization Methods in Robotic Beating Heart Surgery
13. Jahrestagung der Deutschen Gesellschaft für Computer- und Roboterassistierte Chirurgie (CURAC14), September 2014.

[12] Video Footage [0:00-0:17] and Images: da Vinci Surgical System, Intuitive Surgical, Inc. (http://www.intuitivesurgical.com/)

[13] *Uwe D. Hanebeck and Marcus Baum*
Association-Free Direct Filtering of Multi-Target Random Finite Sets with Set Distance Measures
Proceedings of the 18th International Conference on Information Fusion (Fusion 2015), July 2015.