

Inferring hand-object configuration directly from tactile data

Robert Platt
MIT

Frank Permenter
Oceaneering Space Systems

Joel Pfeiffer
Purdue University



Problem



Track “haptic features” in a flexible material by touch

- Buttons/grommets sewn into cloth
- Divots in flexible plastic



Today, I focus on the localization problem only...

Tools: compliance and tactile sensing

Yesterday's talk:

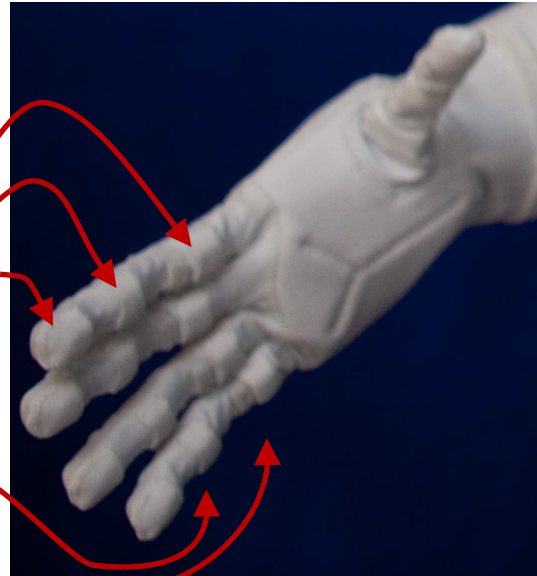
- Used compliance and tactile sensing to localize an inflexible object



Robonaut 2:

Six-axis load cells

Actively compliant
finger joints



Mode of interaction

1. Hold material between thumb and forefingers
2. Squeeze and pull such that fingers slide over material



As a consequence of mode of interaction:

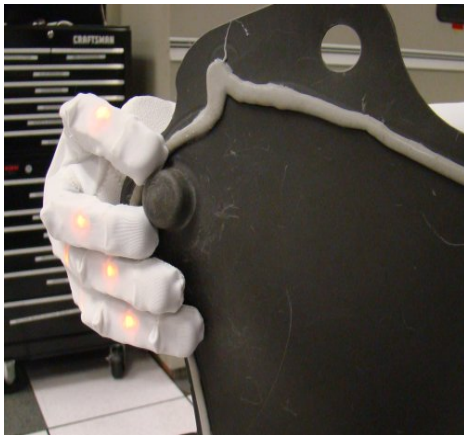
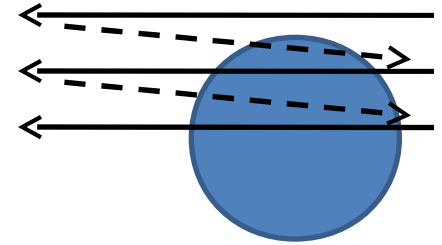
1. State space: 2-d coordinates on flexible material
2. Always pulling in one direction means that we can eliminate velocity component of state



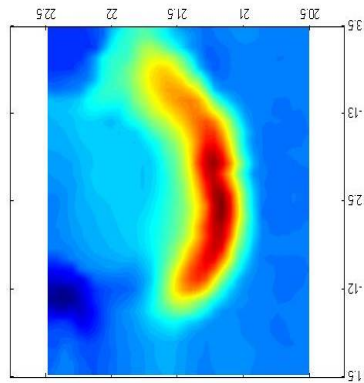
Sensor model

Goal: model expected sensor measurements as a function of hand-feature state.

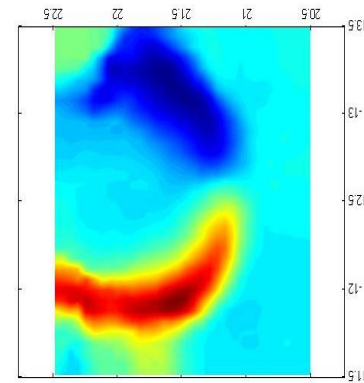
- Training phase where multiple “swipes” are performed.
- Measurements: 8 signals per phalange



Signal 1



Signal 2



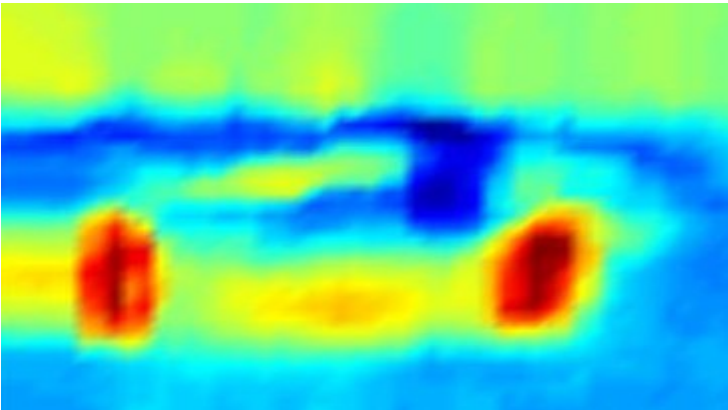
...

“Haptic Map”: mean signal as a function of 2-d state:

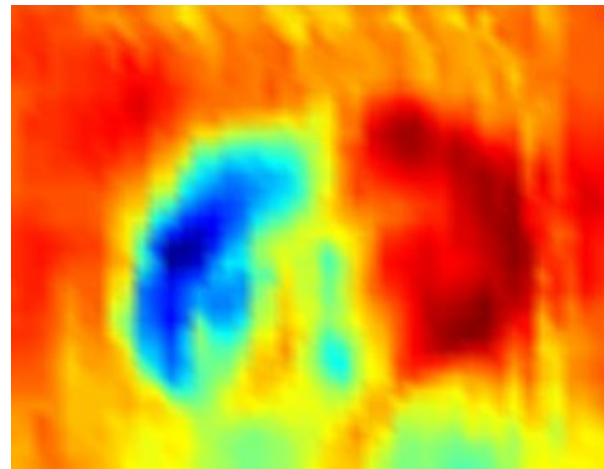
$$\hat{z}(x) = \frac{1}{k} \sum_{z \in N_k(x)} z$$

More haptic maps

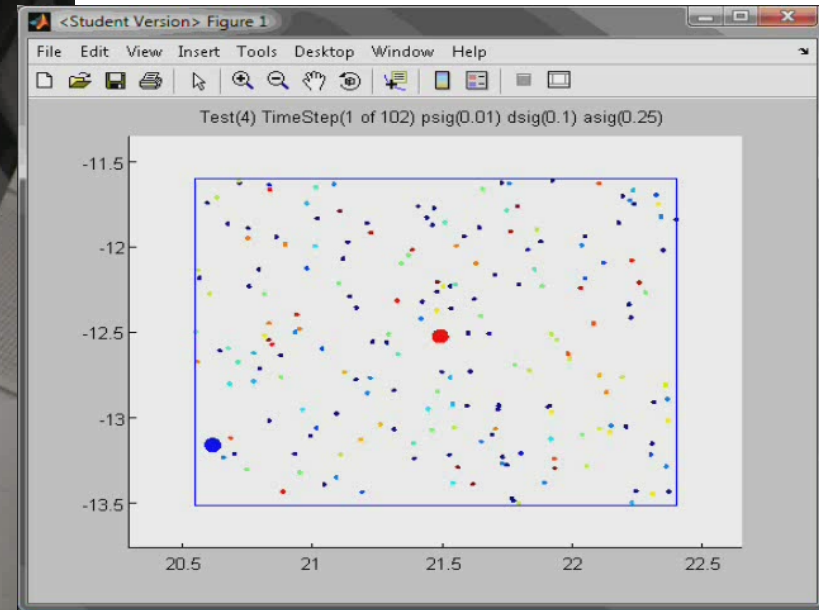
Grommet



Snap



Application of particle filter



Measurement model: Gaussian over measurements
fit to nearest neighbors in state space:

Mean and covariance
calculated over k
nearest neighbors

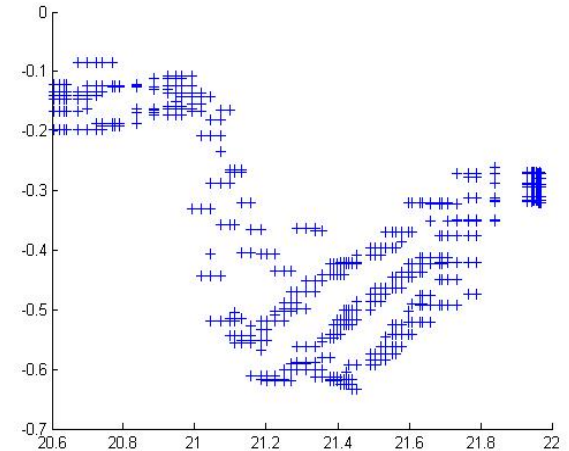
$$P(z | x) = N(z | \hat{z}(x), \Sigma(x))$$
$$\hat{z}(x) = \frac{1}{k} \sum_{z \in N_k(x)} z$$



Different models

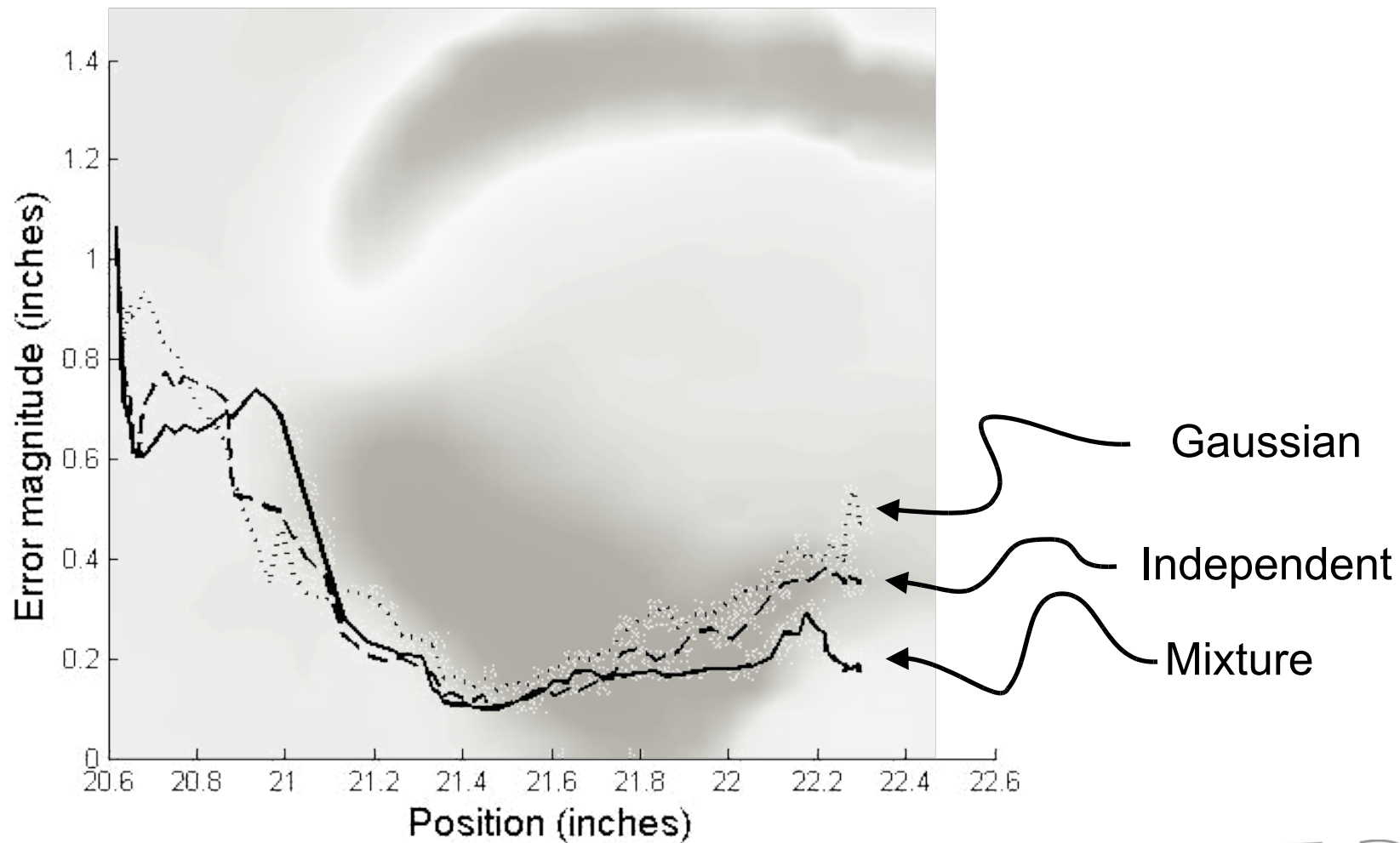
Gaussian model: $P(z | x) = N(z | \hat{z}(x), \Sigma(x))$

Independent fingers: $\Sigma(x) = \begin{bmatrix} \Sigma_1(x) & 0 \\ 0 & \Sigma_2(x) \end{bmatrix}$

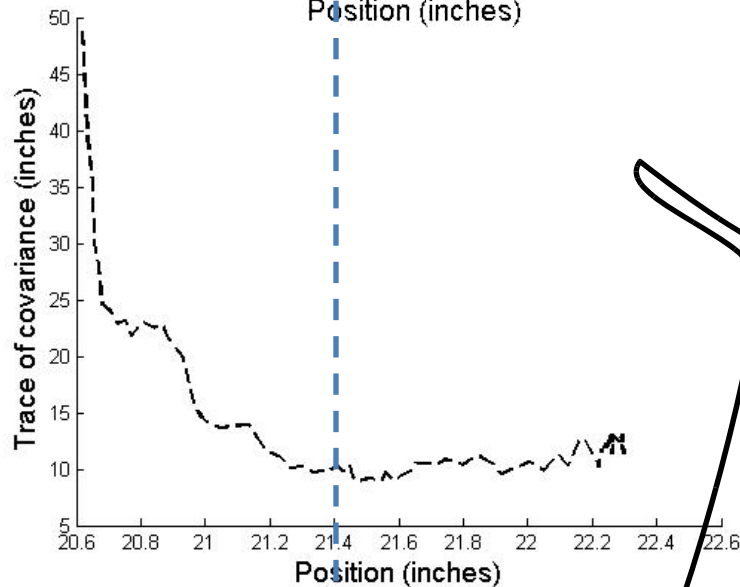
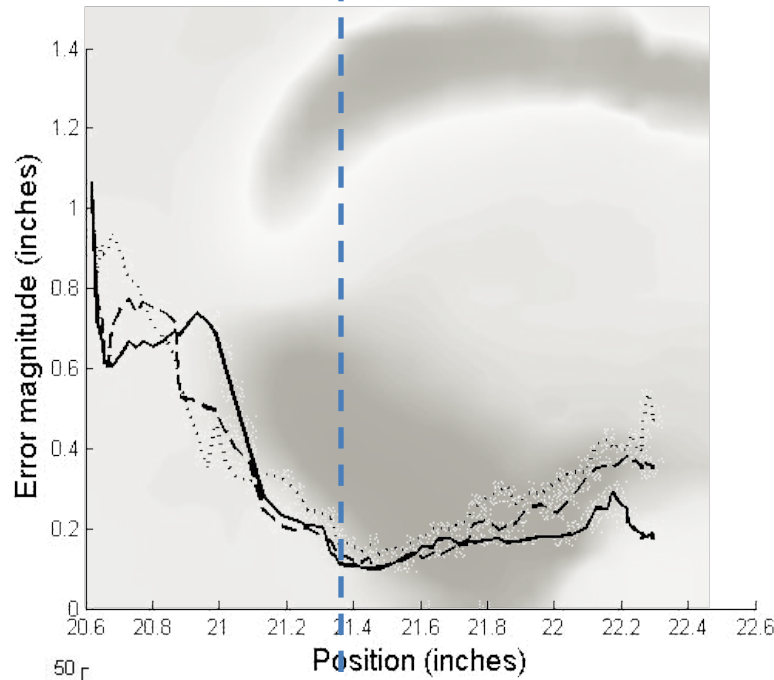


Mixture of Gaussians: $P(z_i | x_i) = \sum_{(x,z) \in D} N \left(\begin{matrix} x_i \\ z_i \end{matrix} \middle| \begin{matrix} x \\ z \end{matrix}, \begin{pmatrix} \Sigma_x & 0 \\ 0 & \Sigma_z \end{pmatrix} \right)$

Performance



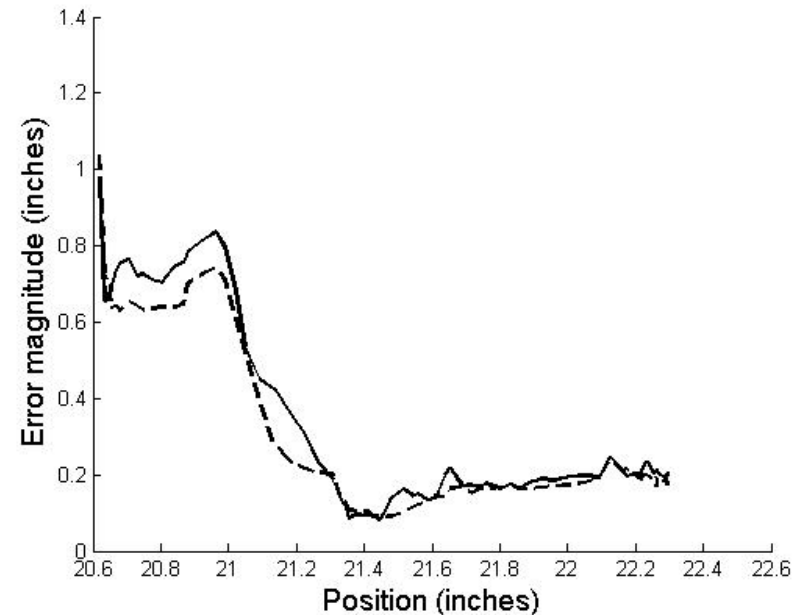
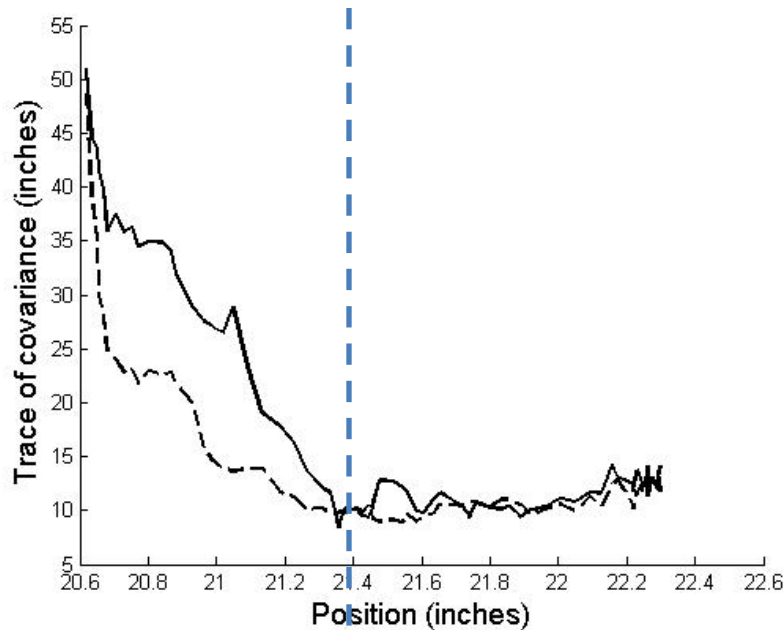
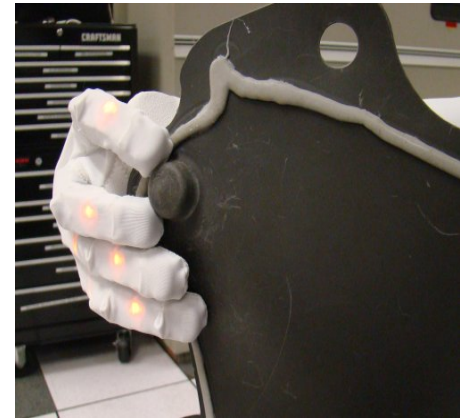
How do you know you got it right?



How do you know that you're not here?

Reduce overfitting via on-off bump model

1. Factor likelihood by phalange: $P(z | x) = \prod_k P(z^k | x)$
2. Enforce a uniform distribution over “off bump” region:



Grommet application

Fabric pivots freely



Contributions

1. Accurate localization (0.1 inch) of features in fabric for the first time.
2. Propose a mode of interaction that simplifies the dimensionality of state estimation problem
3. Propose relevant measurement models



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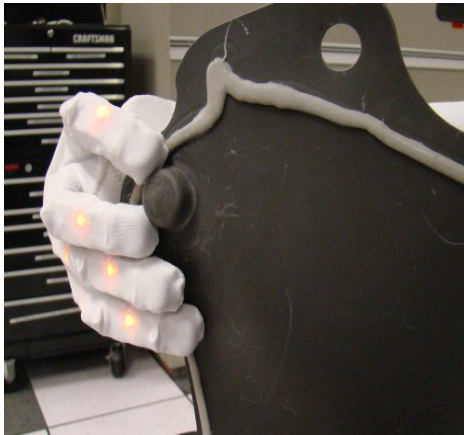
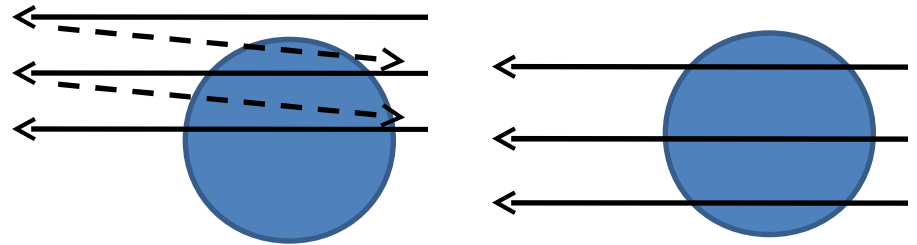
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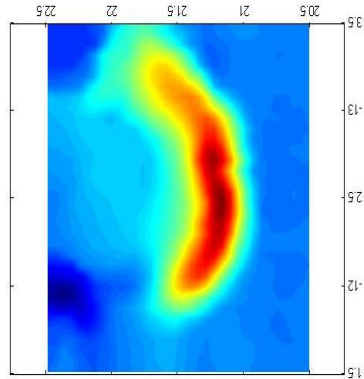


Measurement model: the “haptic map”

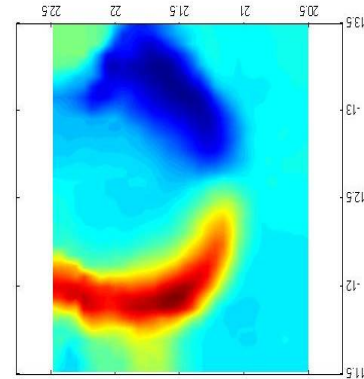
Training swipes:



Signal 1



Signal 2



...

$$P(z | x) = N(z | \hat{z}(x), \Sigma(x)) \quad \hat{z}(x) = \frac{1}{k} \sum_{z \in N_k(x)} z$$

Approach: particle filter

1. Training phase: model relation between finger positions and sensor data
2. Test phase: estimate state based on sensor data



Gaussian measurement model:

$$P(z | x) = N(z | \hat{z}(x), \Sigma(x))$$

High-DOF sensor measurements

2-DOF state

Mean and covariance calculated over k nearest neighbors