Tracking of Animals Using Airborne Cameras

Clas Veibäck

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Introduction

- Tracking of animals

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- Tracking of animals
- Overhead cameras

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- Applicable to other target types

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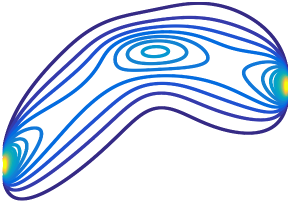
- Tracking of animals
- Overhead cameras
- Applicable to other target types
- Applications to demonstrate theory

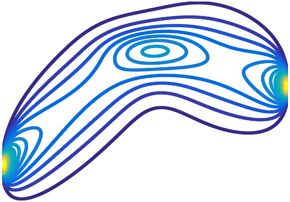
Main Contributions

Uncertain Timestamps



Main Contributions

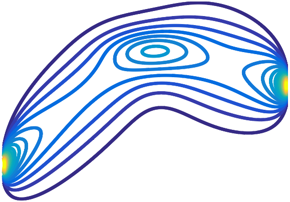
Uncertain Timestamps



Constrained Motion Model

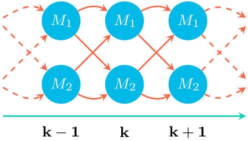
Main Contributions

Uncertain Timestamps



Constrained Motion Model

Mode Observations



Dolphin Application

- Dolphinarium at Kolmården Wildlife Park

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- Dolphinarium at Kolmården Wildlife Park
- Fisheye camera with occlusions

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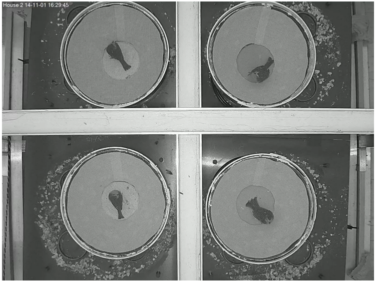
- Fisheye camera with occlusions
- Reflections and changing light conditions

Dolphin Application

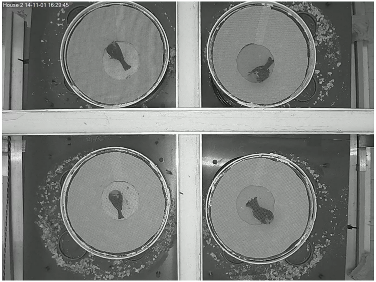
- Dolphinarium at Kolmården Wildlife Park
- Fisheye camera with occlusions
- Reflections and changing light conditions
- Constrained to basin

Bird Application



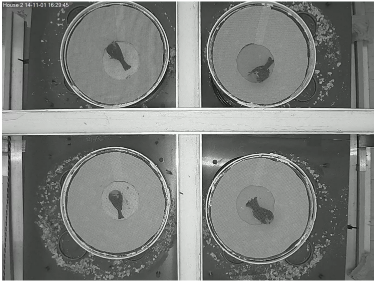
- Recording of birds in Emlen funnels

Bird Application



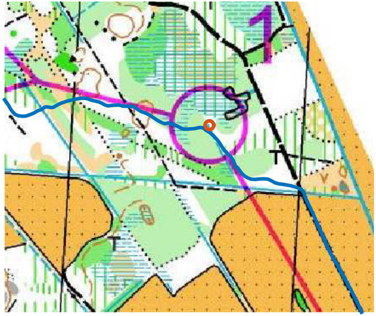
- Recording of birds in Emlen funnels
- Detect take-off times

Bird Application



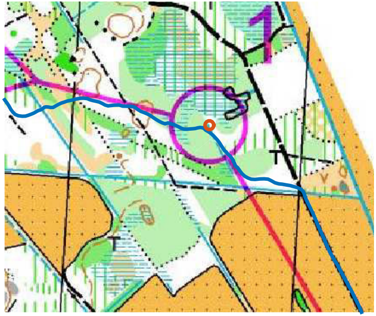
- Recording of birds in Emlen funnels
- Detect take-off times
- Estimate take-off directions

Orienteering Application



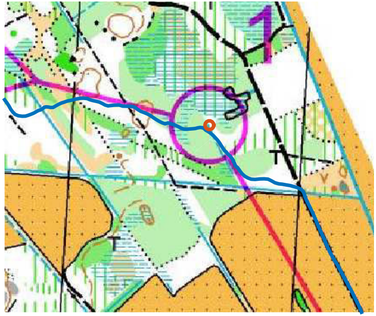
- GPS trajectory

Orienteering Application



- GPS trajectory
- Control position known

Orienteering Application



- GPS trajectory
- Control position known
- Improve position estimate

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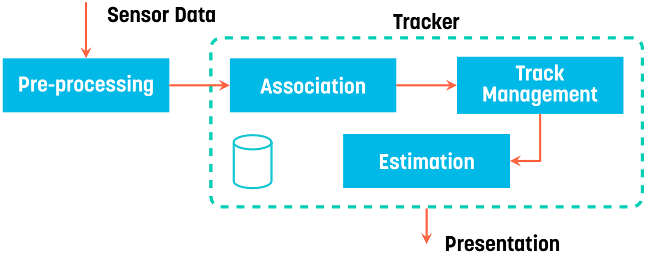
Target Tracking



Target Model

Linear Gaussian state-space model

$$\mathbf{x}_k = \mathbf{F}_k \mathbf{x}_{k-1} + \mathbf{w}_k,$$

Target Model

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$$\mathbf{x}_k = \mathbf{F}_k \mathbf{x}_{k-1} + \mathbf{w}_k, \qquad \mathbf{w}_k \sim \mathcal{N}(0, \mathbf{Q}_k),$$

Target Model

Linear Gaussian state-space model

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$$\mathbf{y}_j = \mathbf{H}_j \mathbf{x}_j + \mathbf{v}_j,$$

Target Model

Linear Gaussian state-space model

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Target Model

Linear Gaussian state-space model

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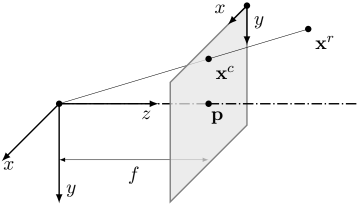
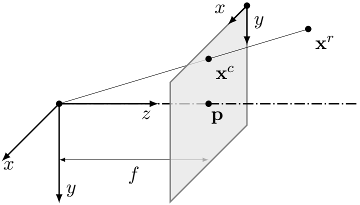
Camera Model



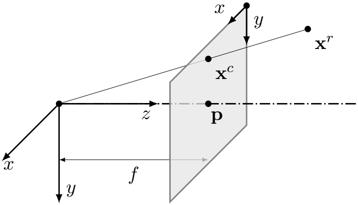
- Camera extrinsics

Camera Model



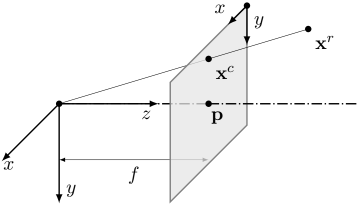
- Camera extrinsics
- Camera intrinsics

Camera Model



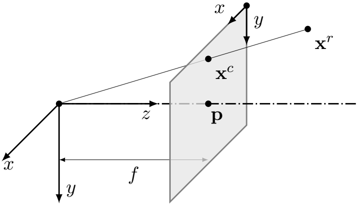
- Camera extrinsics
- Camera intrinsics
- Projection

Camera Model



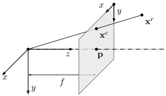
- Camera extrinsics
- Camera intrinsics
- Projection
- Perspective compensation

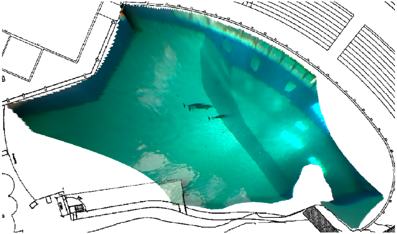
Camera Model



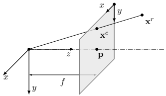
- Camera extrinsics
- Camera intrinsics
- Projection
- Perspective compensation
- Lens distortion

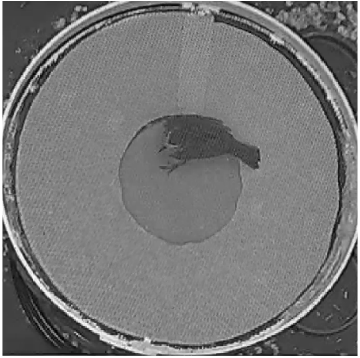
Dolphin Camera





Bird Camera





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Constrained Motion Model

Constrained Motion Model

- Targets constrained to region

Constrained Motion Model

- Targets constrained to region
- Feasible predictions

Constrained Motion Model

- Targets constrained to region
- Feasible predictions
- Similar behaviour

Turning Model

$$\omega(\mathbf{x}) = d_r(\mathbf{x}) \int_{\mathbf{N}} \Big(\beta_d + \beta_a \big(\dot{\mathbf{p}}_\perp \cdot \mathbf{l}(\mathbf{n})\big)\Big) w(\mathbf{x},\, \mathbf{n})\, d\mathbf{n}$$

Turning Model

$$\omega(\mathbf{x}) = d_r(\mathbf{x}) \int_{\mathbf{N}} \Big(\beta_d + \beta_a \big(\dot{\mathbf{p}}_\perp \cdot \mathbf{l}(\mathbf{n})\big)\Big) w(\mathbf{x},\, \mathbf{n})\, d\mathbf{n}$$

- Nearly constant speed

$$\mathbf{x} = \begin{pmatrix} \mathbf{p} \\ \dot{\mathbf{p}} \end{pmatrix} = \begin{pmatrix} x \\ y \\ \dot{x} \\ \dot{y} \end{pmatrix}$$

Turning Model

$$\omega(\mathbf{x}) = d_r(\mathbf{x}) \int_{\mathbf{N}} \Big(\beta_d + \beta_a \big(\dot{\mathbf{p}}_\perp \cdot \mathbf{l}(\mathbf{n})\big)\Big) w(\mathbf{x},\, \mathbf{n})\, d\mathbf{n}$$

- Nearly constant speed
- Influence by edges

$$w(\mathbf{x},\, \mathbf{n}) = \frac{1}{\|\mathbf{p} - \mathbf{n}\|^2}$$

Turning Model

$$\omega(\mathbf{x}) = d_r(\mathbf{x}) \int_{\mathbf{N}} \Big(\beta_d + \beta_a \big(\dot{\mathbf{p}}_\perp \cdot \mathbf{l}(\mathbf{n}) \big) \Big) w(\mathbf{x},\, \mathbf{n})\, d\mathbf{n}$$

- Nearly constant speed
- Influence by edges
- Avoid collision with edges

Turning Model

$$\omega(\mathbf{x}) = d_r(\mathbf{x}) \int_{\mathbf{N}} \Big(\beta_d + \beta_a \big(\dot{\mathbf{p}}_\perp \cdot \mathbf{l}(\mathbf{n})\big)\Big) w(\mathbf{x},\, \mathbf{n})\, d\mathbf{n}$$

- Nearly constant speed
- Influence by edges
- Avoid collision with edges
- Align with edges

Turning Model

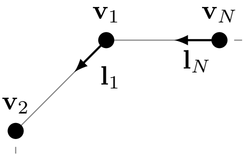
$$\omega(\mathbf{x}) = d_r(\mathbf{x}) \int_{\mathbf{N}} \Big(\beta_d + \beta_a \big(\dot{\mathbf{p}}_\perp \cdot \mathbf{l}(\mathbf{n})\big)\Big) w(\mathbf{x},\, \mathbf{n})\, d\mathbf{n}$$

Clockwise
or
Counterclockwise

- Nearly constant speed
- Influence by edges
- Avoid collision with edges
- Align with edges
- Preferred direction

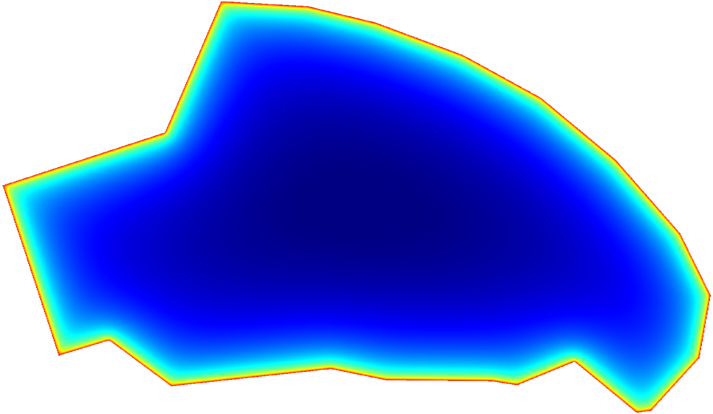
Turning Model

$$\omega(\mathbf{x}) = d_r(\mathbf{x}) \sum_{i=1}^{N} \big(\beta_d + \beta_a(\dot{\mathbf{p}}_\perp \cdot \mathbf{l}_i)\big) w_i(\mathbf{x})$$

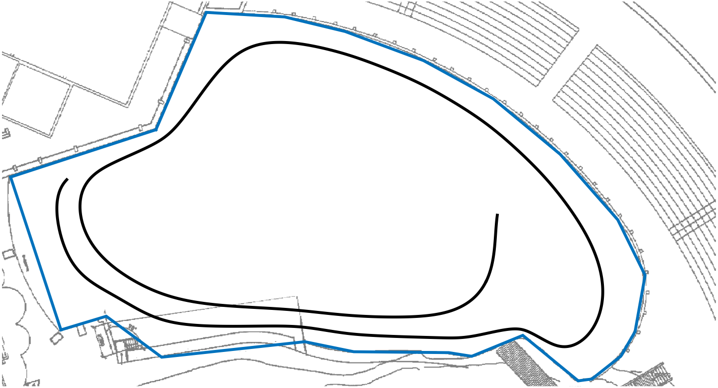


- Nearly constant speed
- Influence by edges
- Avoid collision with edges
- Align with edges
- Preferred direction
- Polygon region

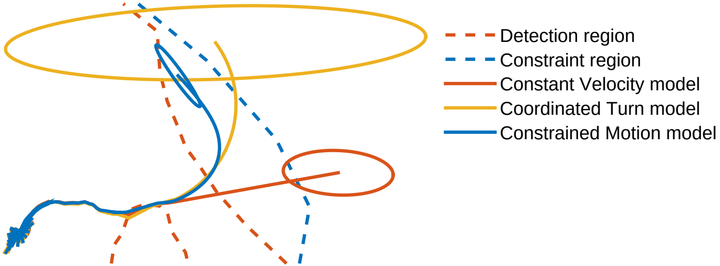
Potential Field



Dolphin - Model Simulation



Dolphin - Model Comparisons



Dolphin - Complete Framework

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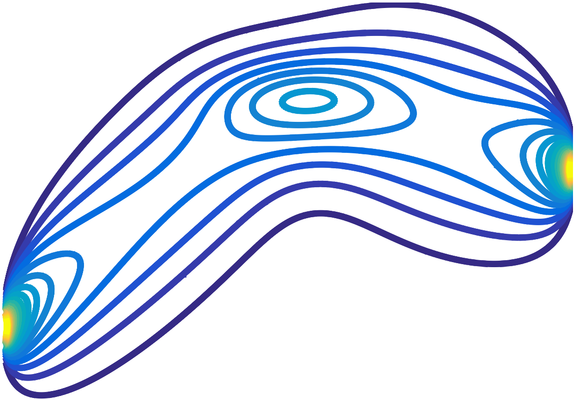
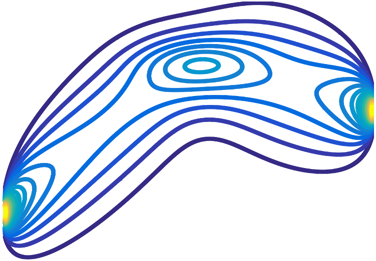
Uncertain Timestamp Model

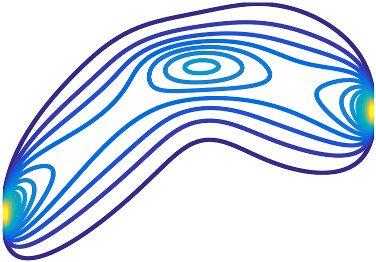


Uncertain Timestamp Model



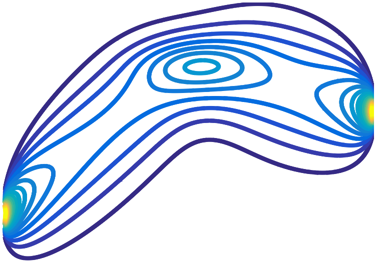
- Traditional measurements

Uncertain Timestamp Model



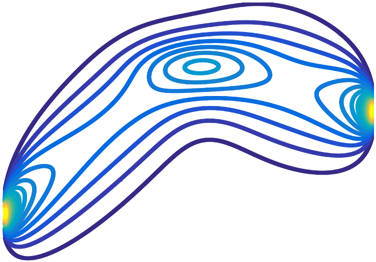
- Traditional measurements
- Observations sampled at an uncertain time

Uncertain Timestamp Model



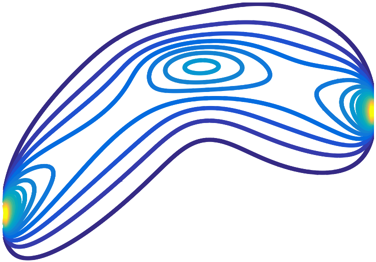
- Traditional measurements
- Observations sampled at an uncertain time
- Crime scene investigations

Uncertain Timestamp Model



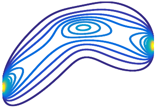
- Traditional measurements
- Observations sampled at an uncertain time
- Crime scene investigations
- Traces from animals

Uncertain Timestamp Model



- Traditional measurements
- Observations sampled at an uncertain time
- Crime scene investigations
- Traces from animals
- Bottlenecks in mines

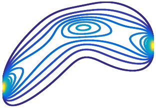
Uncertain Timestamp Model



Consider a linear Gaussian state-space model,

$$
\begin{aligned}
\mathbf{x}_k &= \mathbf{F}_k \mathbf{x}_{k-1} + \mathbf{w}_k, & \mathbf{w}_k &\sim \mathcal{N}(0, \mathbf{Q}_k),\\
\mathbf{y}_j &= \mathbf{H}^y_j \mathbf{x}_j + \mathbf{v}^y_j, & \mathbf{v}^y_j &\sim \mathcal{N}(0, \mathbf{R}^y_j),\\
\mathbf{x}_0 &\sim \mathcal{N}(\bar{\mathbf{x}}_0, \mathbf{P}_0), & &
\end{aligned}
$$

Uncertain Timestamp Model



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Extend the model with

$$\mathbf{z} = \mathbf{H}^z \mathbf{x}_\tau + \mathbf{v}^z, \qquad \mathbf{v}^z \sim \mathcal{N}(0, \mathbf{R}^z), \qquad \tau \sim p(\tau).$$

Simple Uncertain Time Scenario

Consider the simple model,

$$
\begin{aligned}
x_k &= x_{k-1} + w_k, & w_k &\sim \mathcal{N}(0, Q), \\
y_j &= x_j + v_j^y, & v_j^y &\sim \mathcal{N}(0, R^y)
\end{aligned}
$$

for $k \in \{1, \ldots, N\}$ and two measurements y_1 and y_N.

Simple Uncertain Time Scenario

Consider the simple model,

$$x_k = x_{k-1} + w_k, \qquad w_k \sim \mathcal{N}(0, Q),$$
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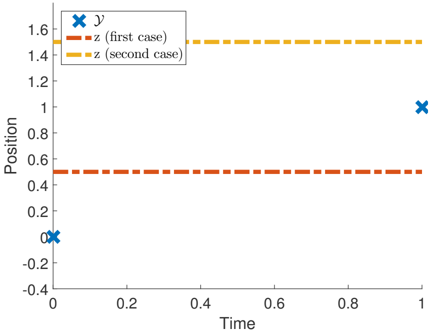
for $k \in \{1, \dots, N\}$ and two measurements y_1 and y_N.

Extend the model with

$$z = x_\tau + v^z, \qquad v^z \sim \mathcal{N}(0, R^z), \qquad \tau \sim p(\tau).$$

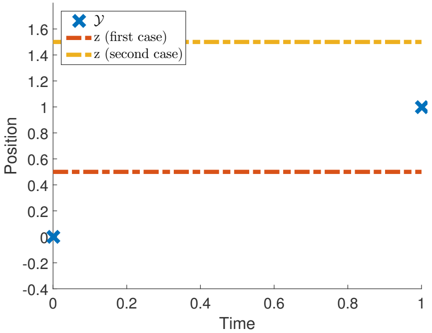
Simple Uncertain Time Scenario



The measurements are

- $y_1 = 0,$
- $y_N = 1.$

Simple Uncertain Time Scenario



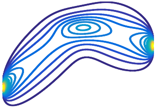
The measurements are

- $y_1 = 0$,
- $y_N = 1$.

The two cases of observations are

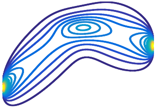
- $z = 0.5$ with flat prior.
- $z = 1.5$ with non-flat prior.

Posterior Distributions - Time

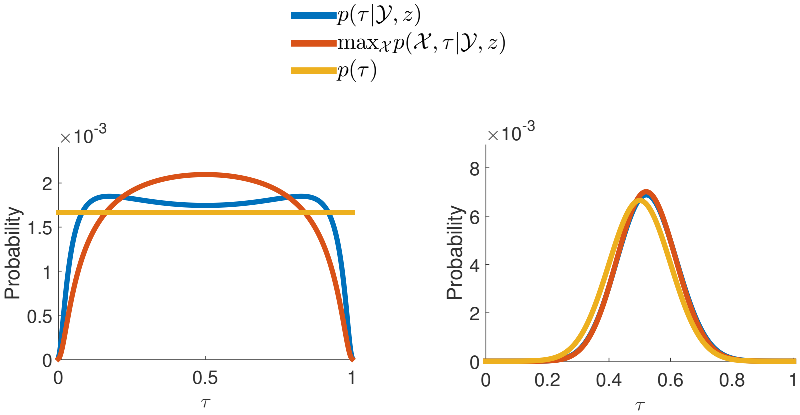


The posterior distribution of the uncertain time is

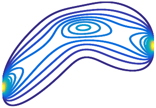
$$w_\tau \triangleq p(\tau|\mathcal{Y}, \mathbf{z}) \propto p(\tau)\mathcal{N}(\mathbf{z}|\,\hat{\mathbf{z}}_\tau,\, \mathbf{S}_\tau).$$



Posterior Distributions - Time



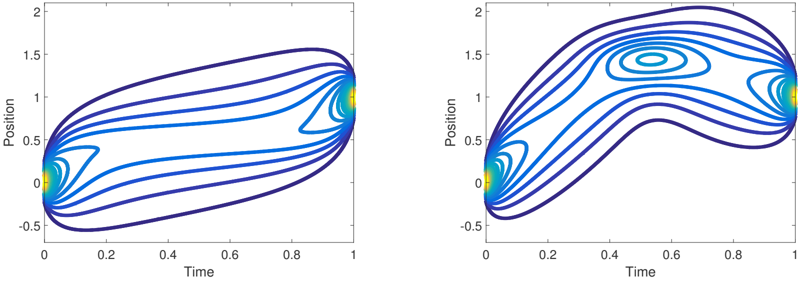
Posterior Distributions - States



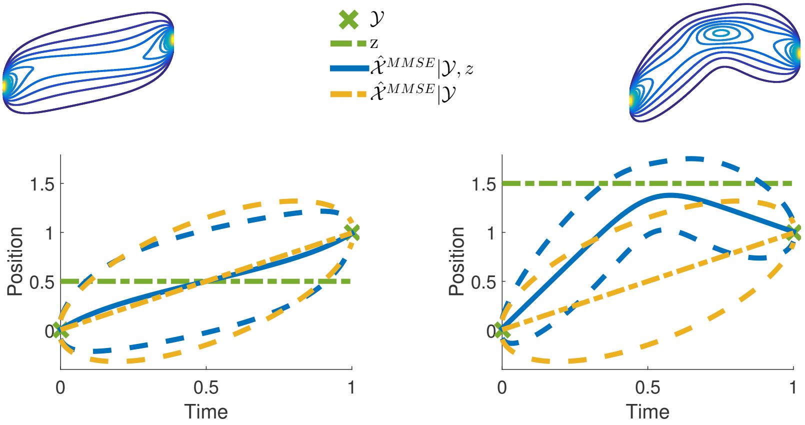
The posterior distribution of the state is

$$p(\mathbf{x}_k|\mathcal{Y}, \mathbf{z}) = \sum_{\tau=1}^{N} w_\tau \cdot \mathcal{N}(\mathbf{x}_k|\hat{\mathbf{x}}_k^\tau, \mathbf{P}_k^\tau).$$

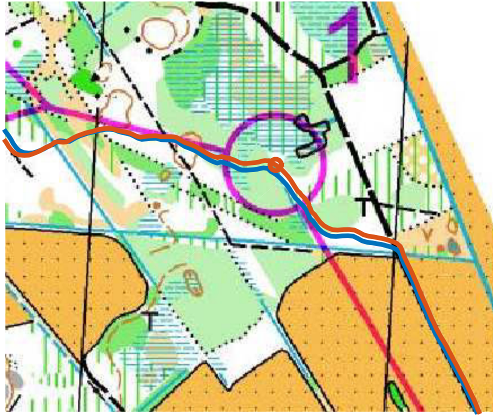
Posterior Distributions - States



Estimators - Minimum Mean Squared Error

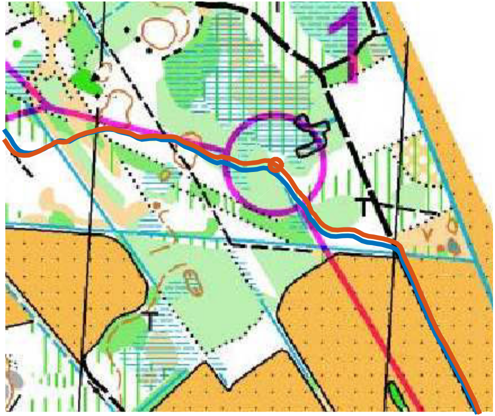


Orienteering



- Adjusted trajectory

Orienteering



- Adjusted trajectory
- Single control point

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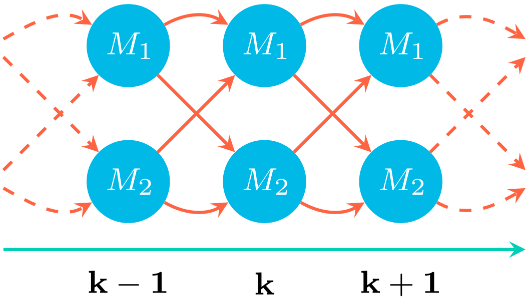
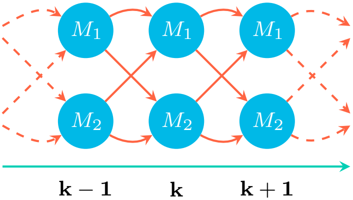
Mode Observations

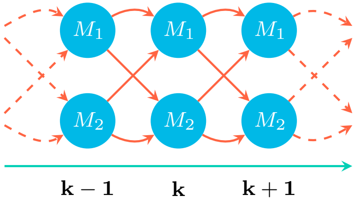


Mode Observations



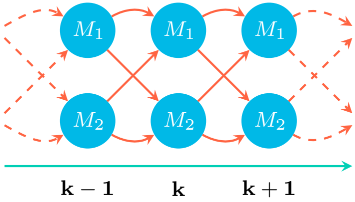
- Jump Markov model

Mode Observations



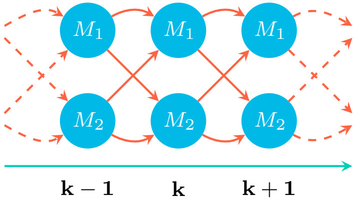
- Jump Markov model
- Model target behaviour

Mode Observations

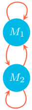


- Jump Markov model
- Model target behaviour
- Probability of switching

Mode Observations



- Jump Markov model
- Model target behaviour
- Probability of switching
- Direct mode observation



Jump Markov Model

The jump Markov linear model is

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\begin{aligned}
\mathbf{x}_k &= \mathbf{F}_k(\delta_k)\mathbf{x}_{k-1} + \mathbf{w}_k, & \mathbf{w}_k &\sim \mathcal{N}(\mathbf{0},\, \mathbf{Q}_k(\delta_k)),\\
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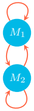

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$$p(\delta_k \mid \delta_{k-1}) = \mathbf{\Pi}_k^{\delta_k, \delta_{k-1}}, \qquad \delta_k \in \mathcal{S}.$$

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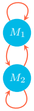
Augmented is the direct mode observation,

$$\mathbf{z}_k \sim p(\mathbf{z}_k \mid \delta_k).$$

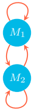
Posterior Distribution - Mode Sequence



The posterior probability of a mode sequence $\{\delta_j^i\}_{j=1}^k$ is computed recursively by

$$w_k^i \propto w_{k-1}^i \cdot \mathbf{\Pi}_k^{\delta_k^i, \delta_{k-1}^i} \cdot \mathcal{N}(\mathbf{y}_k \,|\, \hat{\mathbf{y}}_k^i, \, \mathbf{S}_k^i) \cdot p(\mathbf{z}_k \,|\, \delta_k^i).$$

Posterior Distribution - Mode Sequence



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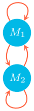


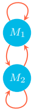
Posterior Distribution - State

The posterior distribution of the state is given by

$$p(\mathbf{x}_k \mid \{\mathbf{y}_j\}_{j=1}^k, \{\mathbf{z}_j\}_{j=1}^k) = \sum_{i=1}^{|\mathcal{S}|^k} w_k^i \cdot \mathcal{N}(\mathbf{x}_k \mid \hat{\mathbf{x}}_k^i, \mathbf{P}_k^i).$$

Bird - Model

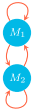
The modes are $\mathcal{S} = \{s,\ f\}$.



Bird - Model

The modes are $\mathcal{S} = \{s,\ f\}$.

The state variables are $$\mathbf{x} = \begin{pmatrix} x \\ y \\ b^s \\ b^f \end{pmatrix} = \begin{pmatrix} \mathbf{p} \\ b^s \\ b^f \end{pmatrix}.$$



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The state-space model is

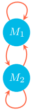
$$\mathbf{x}_k = \mathbf{x}_{k-1} + \mathbf{w}_k, \qquad \mathbf{w}_k \sim \mathcal{N}(\mathbf{0},\ \mathbf{Q}(\delta_k)),$$

$$\mathbf{y}_k = \begin{pmatrix} \mathbf{h}(\mathbf{p}_k) \\ b_k^{\delta_k} \end{pmatrix} + \mathbf{v}_k, \qquad \mathbf{v}_k \sim \mathcal{N}(\mathbf{0},\ \mathbf{R}),$$

Bird - Model Extension

The direct mode observation is the radial position

$$z_k = \sqrt{x_k^2 + y_k^2},$$



Bird - Model Extension

The direct mode observation is the radial position

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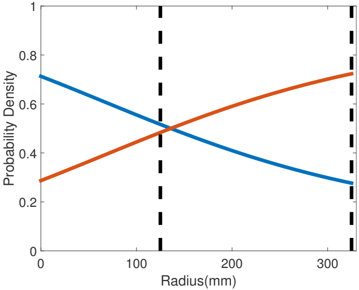
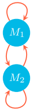
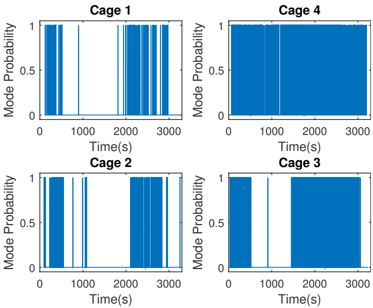
where $p(z_k|\delta_k)$ is given by:

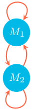




Bird - Results



- Estimated modes



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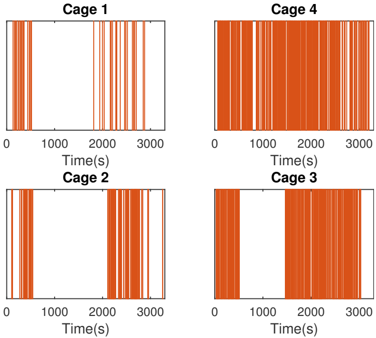
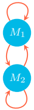
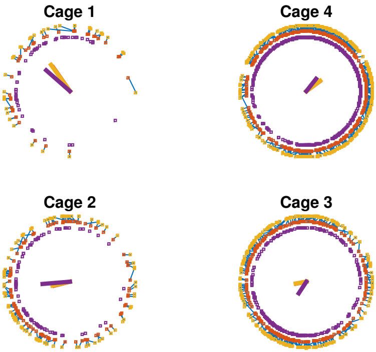


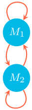
- Estimated modes
- Extracted takeoffs



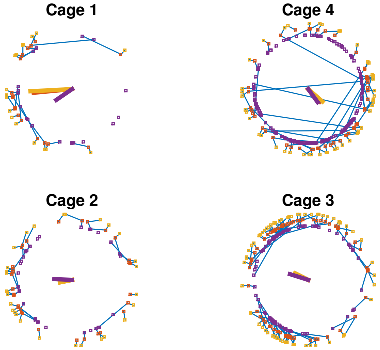
Bird - Results



- Estimated modes
- Extracted takeoffs
- Takeoff directions

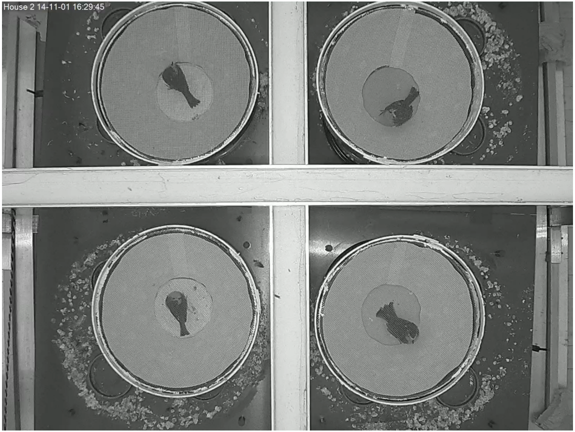


Bird - Results



- Estimated modes
- Extracted takeoffs
- Takeoff directions
- Matched takeoffs

Bird - Complete Framework



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Conclusions

Theory is presented on

- a constrained motion model

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Theory is demonstrated to work in applications

Questions?

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