IEEE ICRA Workshop on Uncertainty in Automation, May 9, 2011

A PODS-based Extended Kalman Filter: Quantifying Sensing Uncertainties in Automatic Bird Species Detection

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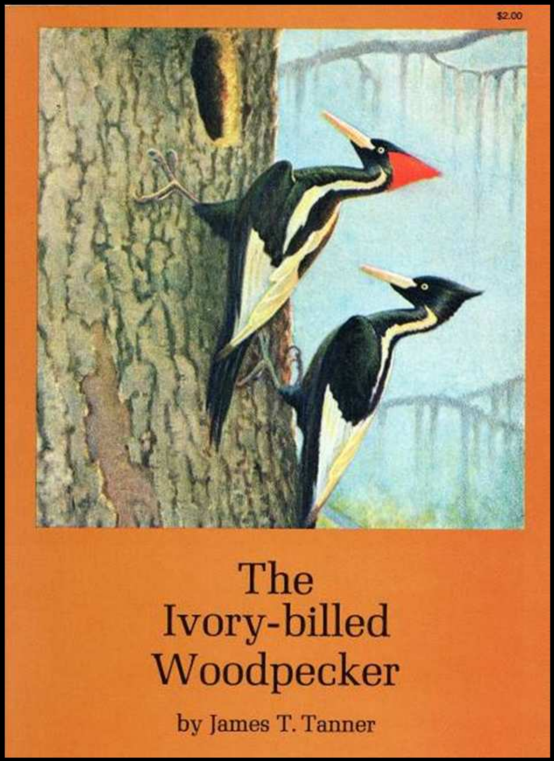
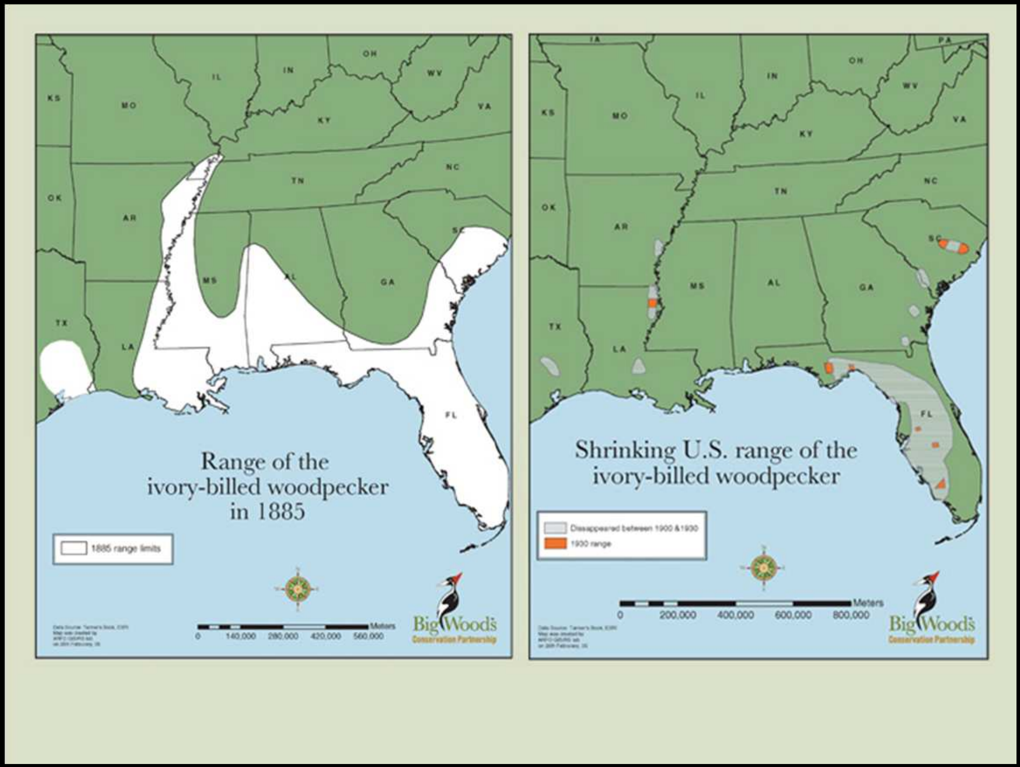
Thanks to:

Ni Qin, Yiliang Xu, Chang Young Kim, Wen Li, TAMU
Ken Goldberg, UC Berkeley
Ron Rohrbach, Cornell Lab of Ornithology
John Fitzpatrick, Cornell Lab of Ornithology
David Luneau, U Arkansas
Hopeng Wang and Jingtain Liu, Nankai University
John Rappole, Smithsonian
Selma Glasscock, Welder Wildlife Foundation
National Science Foundation
The Nature Conservancy
Arkansas Game and Fish Commission
U.S. Fish and Wildlife Service
Arkansas Electric Cooperative
Cache River National Wildlife Refuge

Biological observation is
arduous, expensive, dangerous, lonely

Assisting the search for IBWO



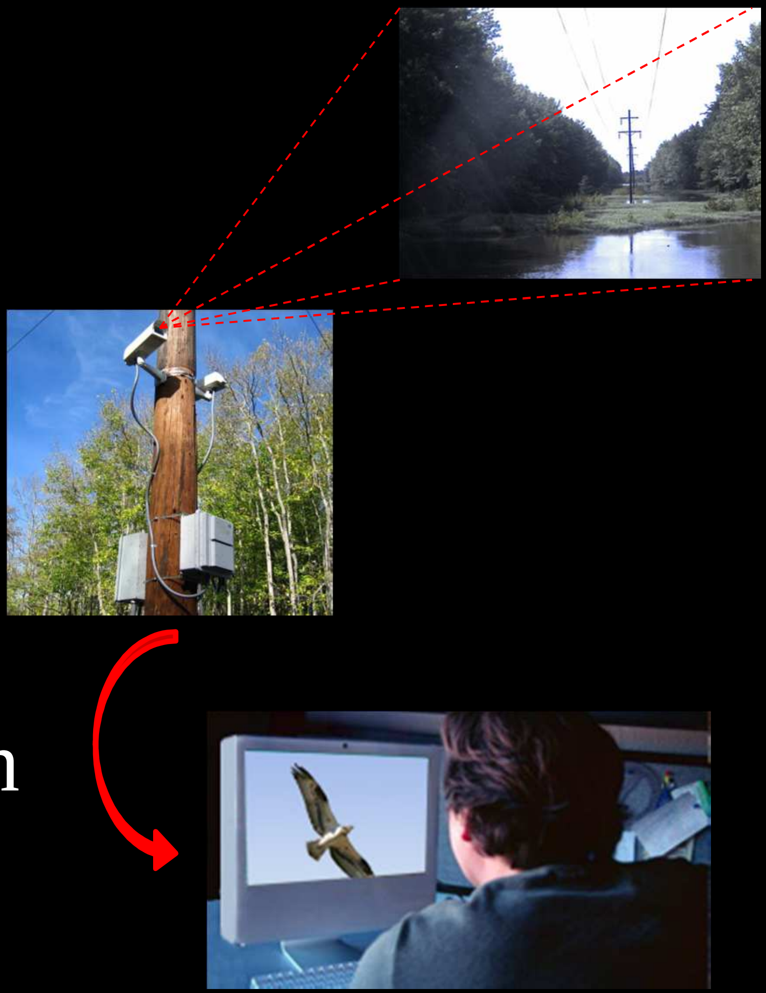


Detecting Rare Birds

- Low occurrence (e.g., <10 times per year)
- Short duration (e.g., < 1 sec. in FOV)
- Huge video data for human identification.
- Setup and maintenance in remote environments.

Design Goals

- Accuracy
  – low false negative
- Data reduction
  – filtering the targeted bird
- Easy to setup and maintain
  – monocular vision system



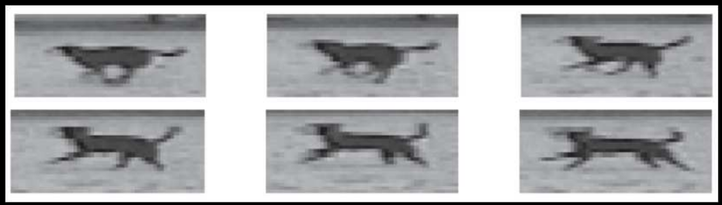
Related Work

- Natural cameras
  - DeerCam
  - Africa web cams at the Tembe
  - Elephant part
  - Tiger web cams
  - James Reserve Wildlife Observatory
  - Crane Cam
  - Swan Cam

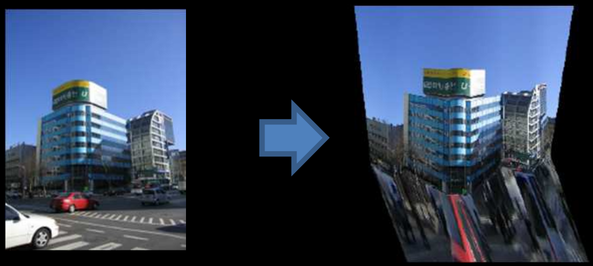
Related Work

- Motion detection and tracking
  - Elgammal, Grimson, Isard …

- Periodic motion detection
  - Culter, Ran, Briassouli …



- 3D inference using monocular vision
  - Ribnick, Hoiem, Saxena …



Related Work

- Kalman Filter
  - SLAM, tracking, recognition …
  - Convergence
    - ample observation data
    - manageable noise

- less than 11 data points
- significant image noise

Bird detection problem

- Input
  - targeted bird body length l_b and speed range $\mathcal{V}$=[v_{min},v_{max}].
  - a sequence of *n* images containing a moving object

- Output
  - to determine if the object is a bird of targeted species

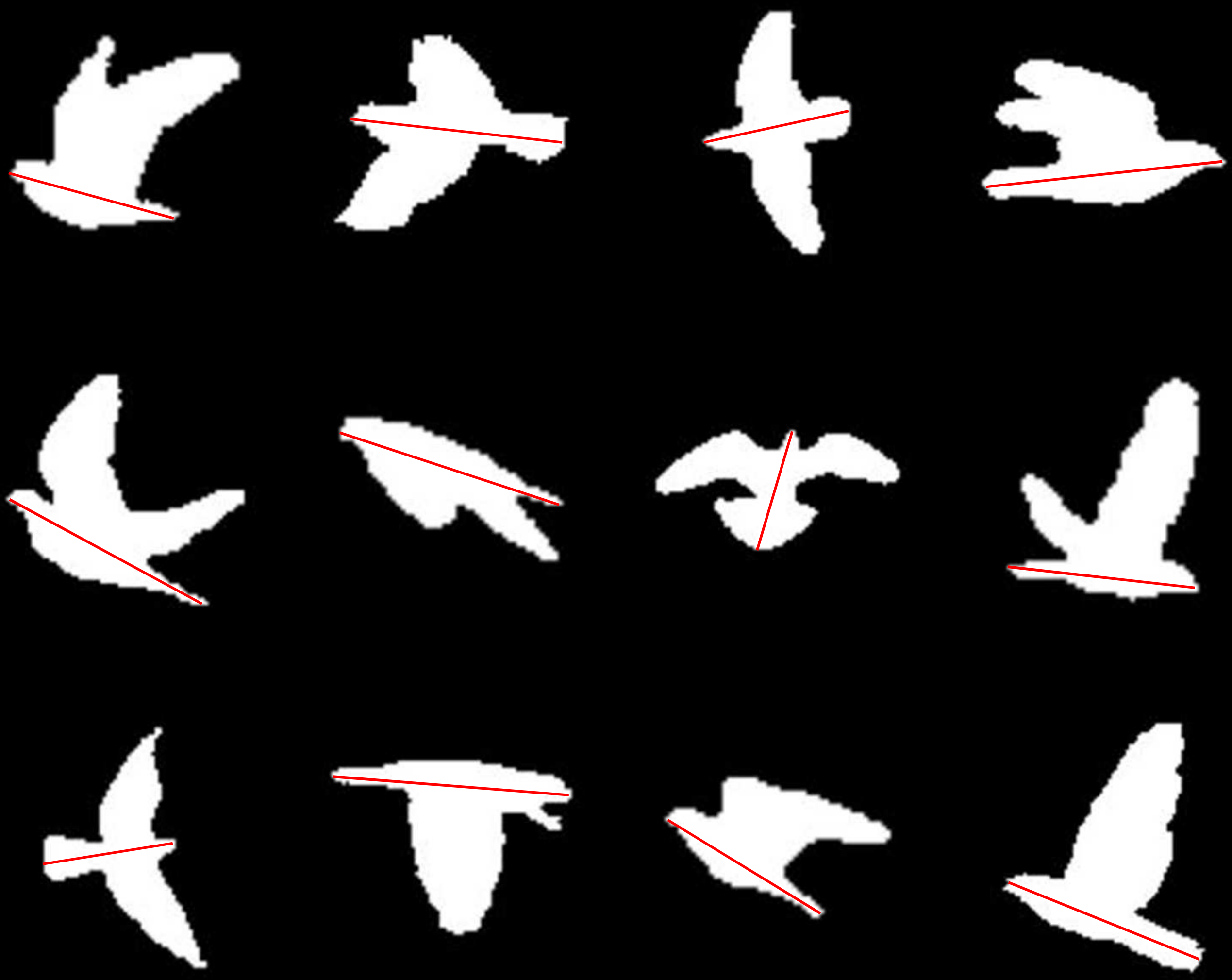
Assumptions

- Static monocular camera
  - High resolution
  - Narrow FOV

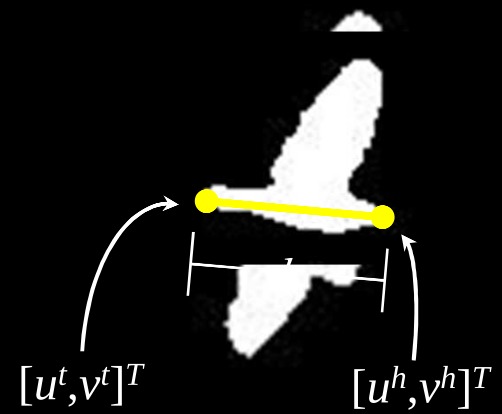
- Single bird in FOV
  - Motion segmentation

- Constant bird velocity
  - High flying speed
  - Narrow camera FOV

Observation 1: Invariant body length in Steady flight



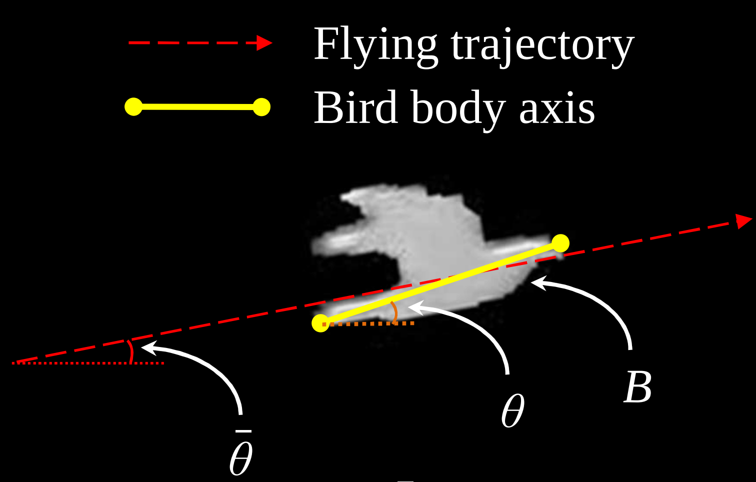
Invariant body length in steady flight



$\mathbf{z}=[u^h,v^h,u^t,v^t]^T$ (observation)

Bird Body Axis Filtering

- Observation 2: Body axis orientation close to tangent line of trajectory during steady flight

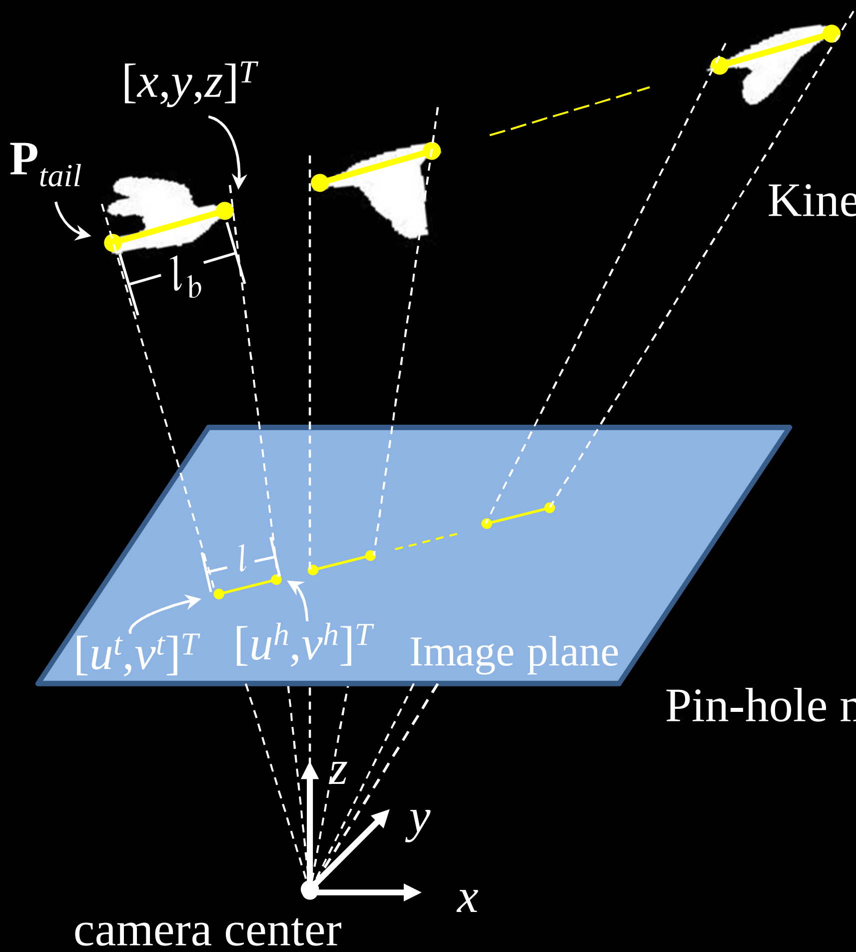


Difference between θ and $\bar{\theta}$ on 61bird sequences:

$$\mu_b = 0.8^\circ; \qquad \sigma_b = 8.3^\circ$$

$$z = \underset{\substack{(u^h, v^h) \in B \\ (u^t, v^t) \in B}}{\operatorname{argmax}} \; l, \text{ s.t. } \theta \in [\bar{\theta} - 2\sigma_b, \bar{\theta} + 2\sigma_b]$$

Modeling A Flying Bird



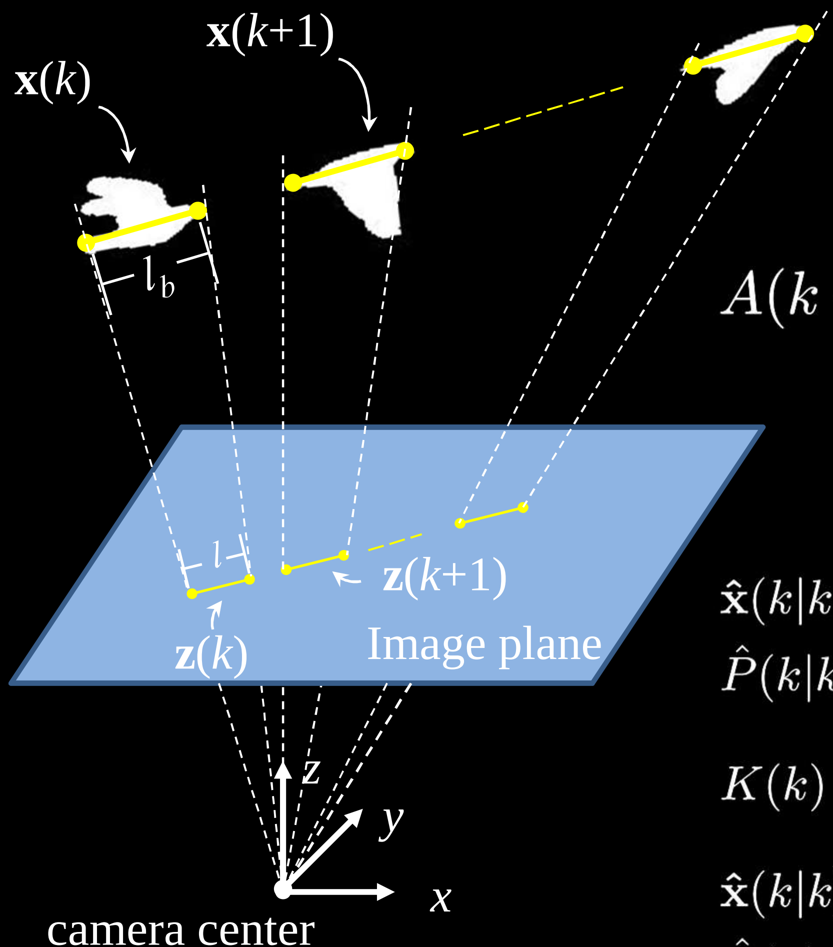
$$\mathbf{p} = [x, y, z]^T \qquad \mathbf{v} = [\dot{x}, \dot{y}, \dot{z}]^T$$

Kinematics: $\boxed{\dot{\mathbf{x}} = \begin{bmatrix} \dot{\mathbf{p}} \\ \dot{\mathbf{v}} \end{bmatrix} = [\dot{x}, \dot{y}, \dot{z}, 0, 0, 0]^T = \begin{bmatrix} \mathbf{v} \\ \mathbf{0} \end{bmatrix}}$

Tail: $\mathbf{P}_{tail} = [x^t, y^t, z^t]^T = \begin{bmatrix} x - \dot{x} l_b / \|\mathbf{v}\| \\ y - \dot{y} l_b / \|\mathbf{v}\| \\ z - \dot{z} l_b / \|\mathbf{v}\| \end{bmatrix}$

Pin-hole model: $\boxed{\begin{aligned} \mathbf{z} &= \begin{bmatrix} fx/z \\ fy/z \\ fx^t/z^t \\ fy^t/z^t \end{bmatrix} = \begin{bmatrix} fx/z \\ fy/z \\ f\frac{x\|\mathbf{v}\| - l_b \dot{x}}{z\|\mathbf{v}\| - l_b \dot{z}} \\ f\frac{y\|\mathbf{v}\| - l_b \dot{y}}{z\|\mathbf{v}\| - l_b \dot{z}} \end{bmatrix} + \mathbf{w} \\ &:= h(\mathbf{x}) + \mathbf{w} \end{aligned}}$

Extended Kalman Filter



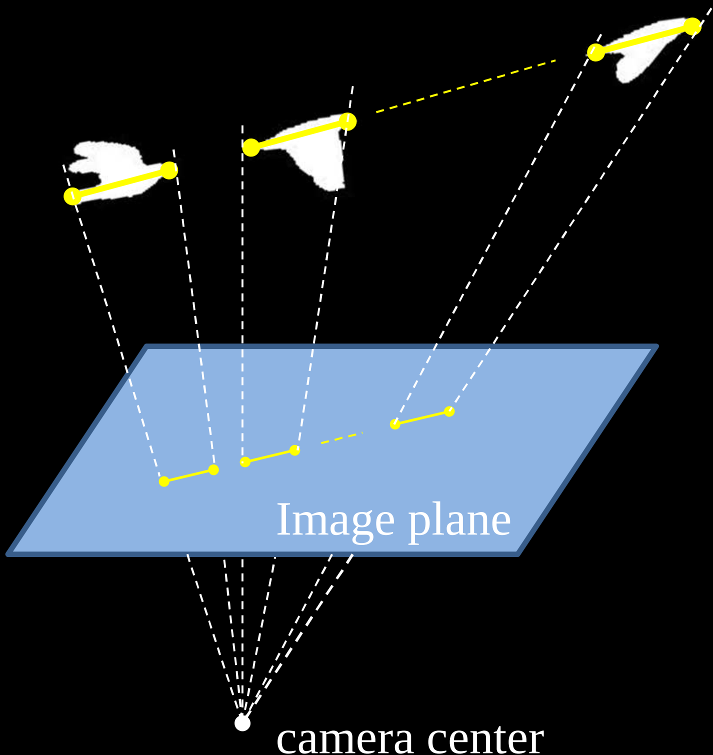
$$\mathbf{x}(k+1) = A(k+1)\mathbf{x}(k) + \mathbf{q}(k),$$
$$\mathbf{z}(k) = h(\mathbf{x}(k)) + \mathbf{w}(k),$$

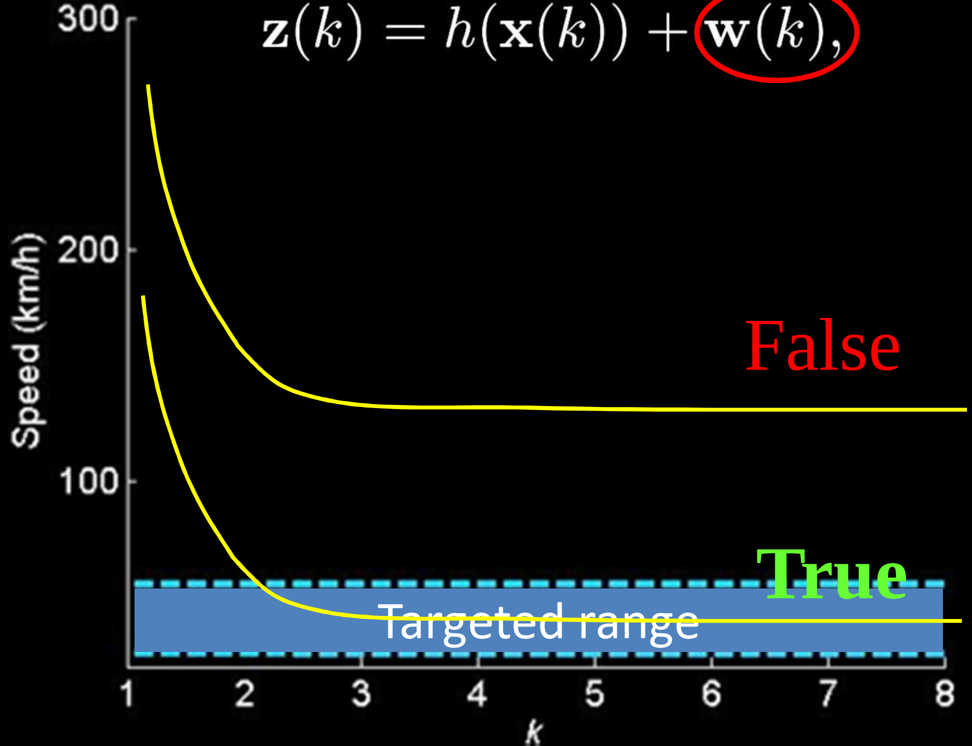
$$A(k+1) = \begin{bmatrix} \mathbf{I}_{3\times 3} & \Delta T(k+1|k)\mathbf{I}_{3\times 3} \\ \mathbf{0}_{3\times 3} & \mathbf{I}_{3\times 3} \end{bmatrix}$$

$$\hat{\mathbf{x}}(k|k-1) = A(k)\hat{\mathbf{x}}(k-1|k-1),$$
$$\hat{P}(k|k-1) = A(k)\hat{P}(k-1|k-1)A^T(k) + Q(k),$$
$$K(k) = \frac{\hat{P}(k|k-1)H^T(k)}{H(k)\hat{P}(k|k-1)H^T(k) + W(k)},$$
$$\hat{\mathbf{x}}(k|k) = \hat{\mathbf{x}}(k|k-1) + K(k)(\mathbf{z}(k) - h(\hat{\mathbf{x}}(k|k-1))),$$
$$\hat{P}(k|k) = (\mathbf{I}_{6\times 6} - K(k)H(k))\hat{P}(k|k-1),$$

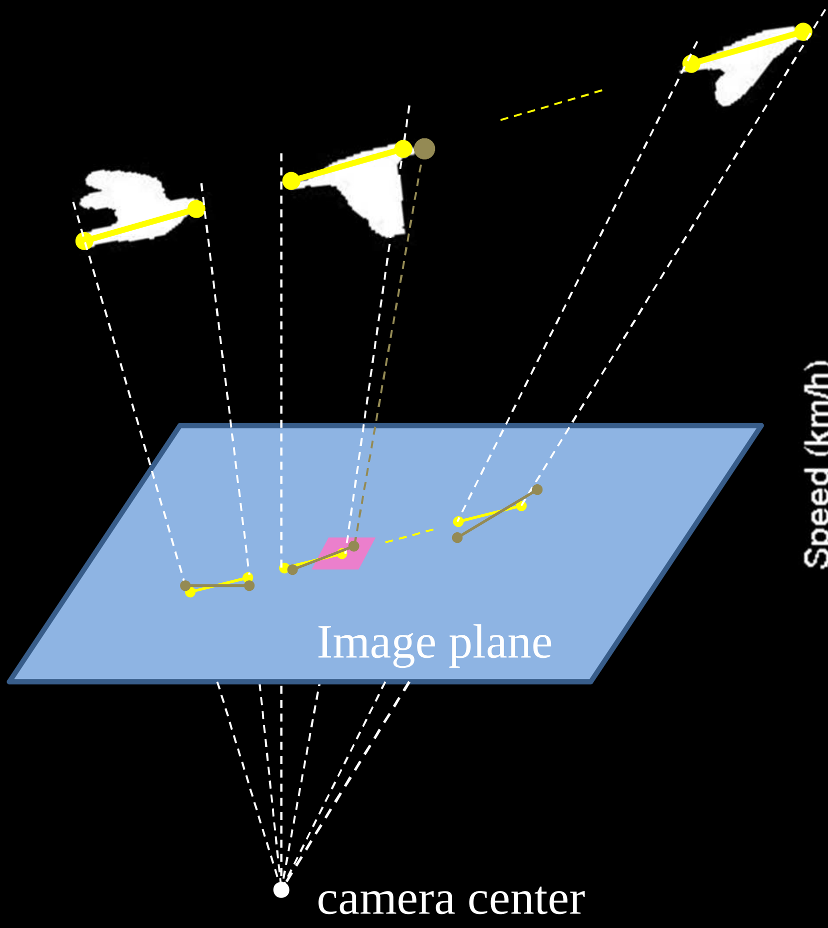
Determine Species for Noise-free Cases

$$\mathbf{x}(k+1) = A(k+1)\mathbf{x}(k) + \mathbf{q}(k),$$
$$\mathbf{z}(k) = h(\mathbf{x}(k)) + \mathbf{w}(k),$$

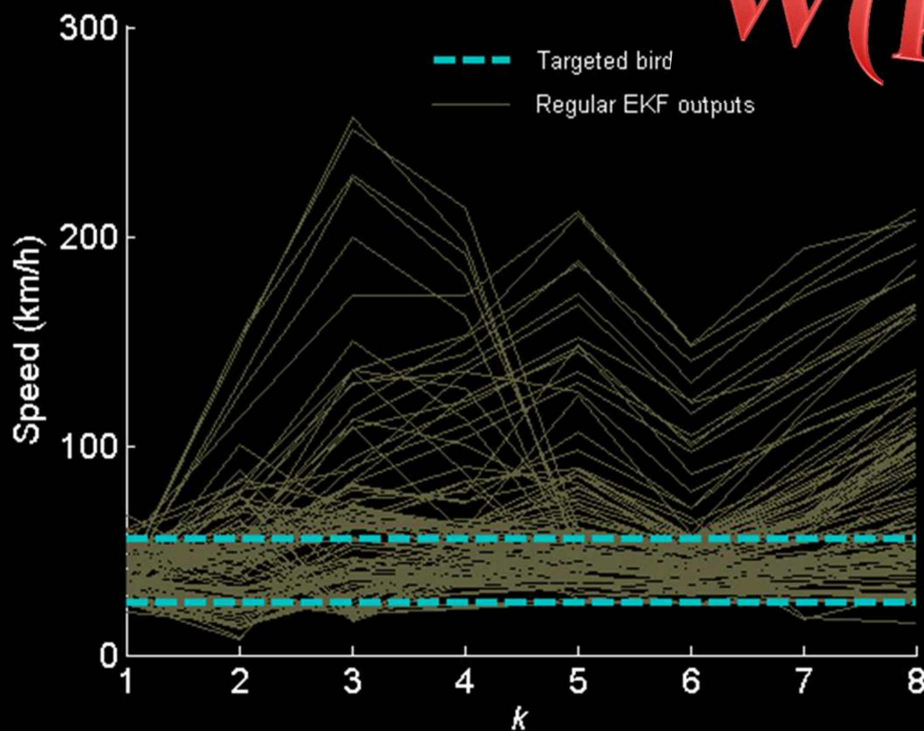




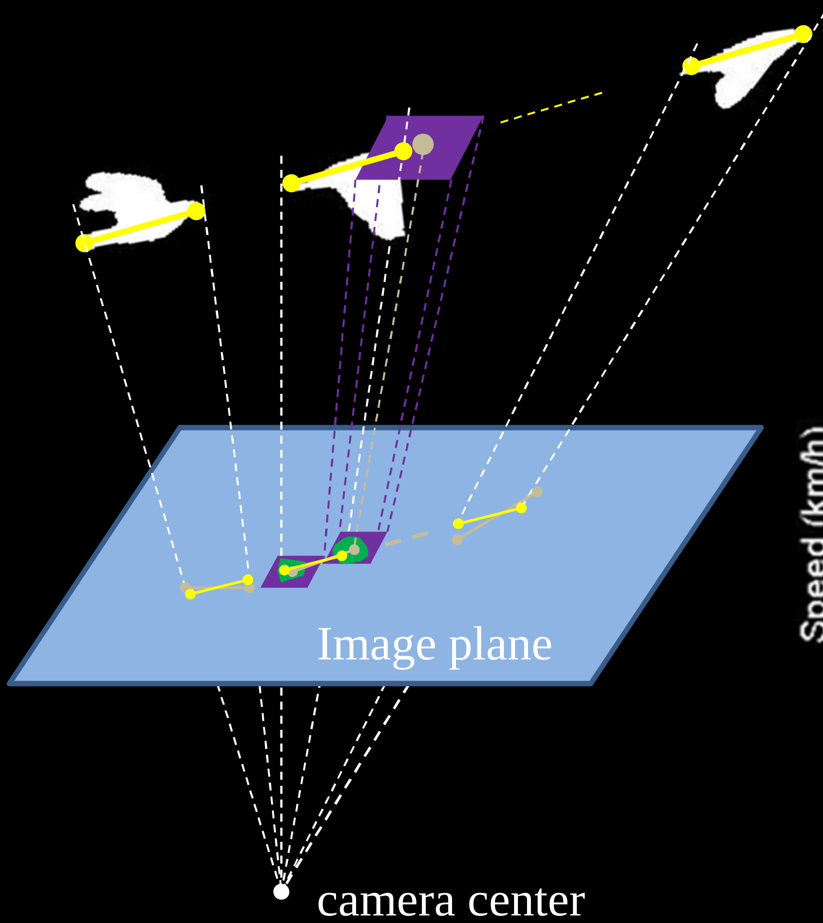
Estimation with Observation Noises



$$\mathbf{x}(k+1) = A(k+1)\mathbf{x}(k) + \mathbf{q}(k),$$
$$\mathbf{z}(k) = h(\mathbf{x}(k)) + \mathbf{w}(k)$$



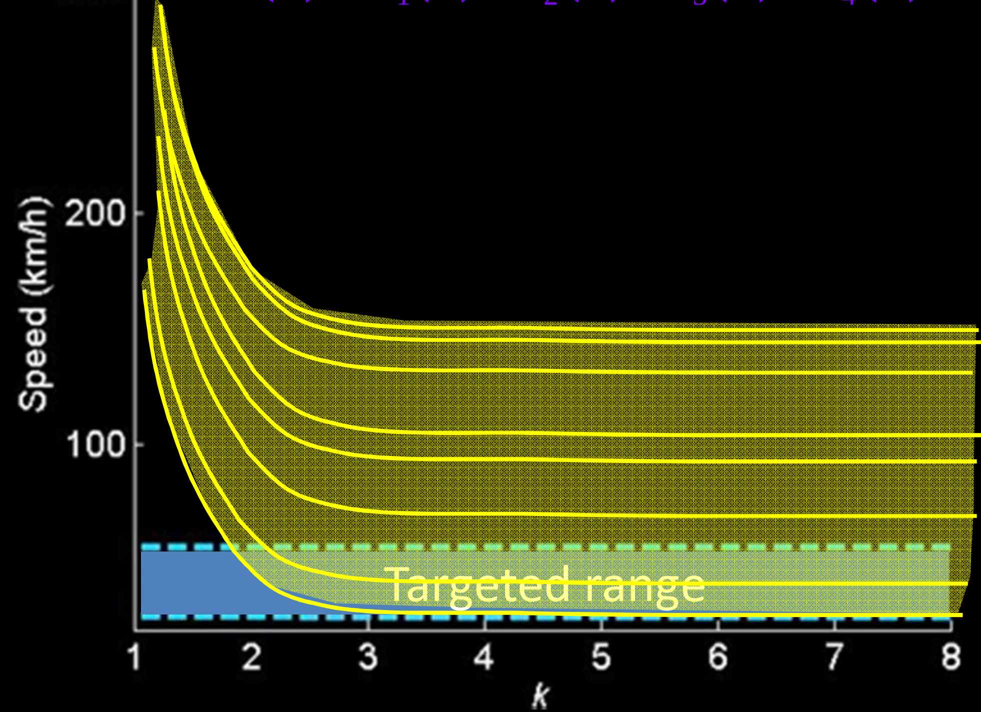
Probable Observation Data Set (PODS)



$S_1(k)=[u^h(k)\pm\tau]$ $S_2(k)=[v^h(k)\pm\tau]$

$S_3(k)=[u^t(k)\pm\tau]$ $S_4(k)=[v^t(k)\pm\tau]$

$$\mathbb{S}(k)=S_1(k)\times S_2(k)\times S_3(k)\times S_4(k)$$



$$\varepsilon(\mathbf{X}^{1:n})<\delta$$

EKF Convergence Metrics

$$\text{EKF converges} \iff \|\hat{\mathbf{v}}(k|k) - \hat{\mathbf{v}}(k-1|k-1)\| \to 0$$

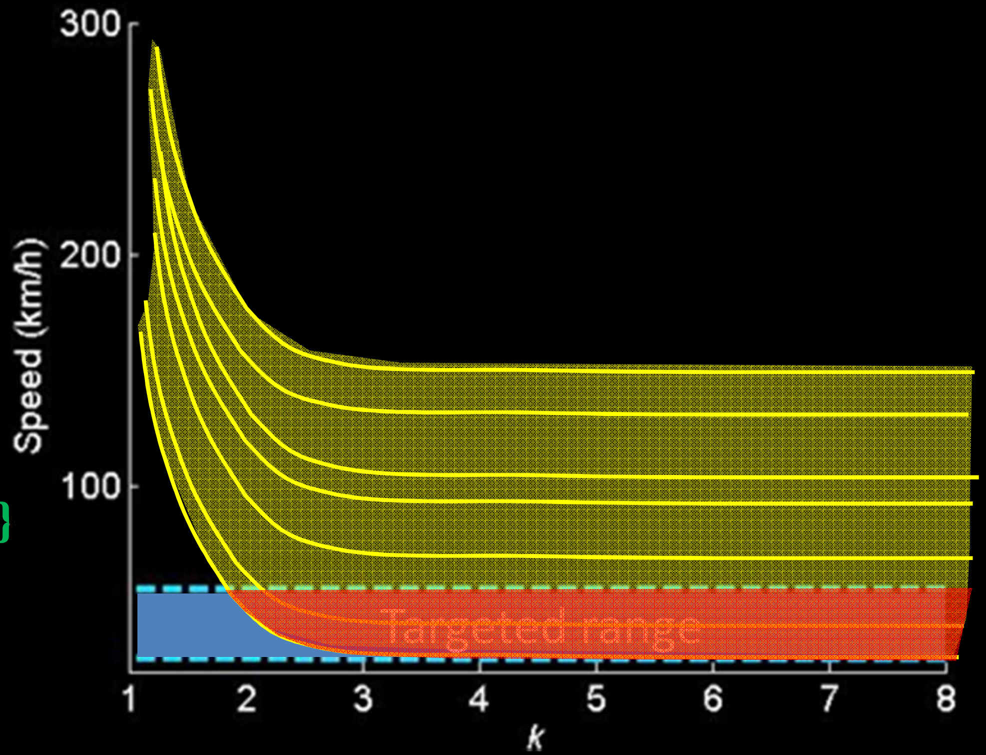
$$\boxed{\varepsilon(\mathbf{X}^{1:n}) = \sum_{k=2}^{n} \omega(k) \|\hat{\mathbf{v}}(k|k) - \hat{\mathbf{v}}(k-1|k-1)\|}$$

$$\omega(k) = E\left(\frac{\|\hat{\mathbf{v}}\|}{\|\hat{\mathbf{v}}(k|k) - \hat{\mathbf{v}}(k-1|k-1)\|}\right)$$

PODS-EKF

Decision-making:

$$I(\mathbf{Z}^{1:n}) = \begin{cases} 1 \text{ (accept) if } \mathbb{V} \cap \mathcal{V} \neq \Phi \text{ and } \mathbb{Z}^{1:n} \neq \Phi \\ 0 \text{ (reject) otherwise} \end{cases}$$



PODS:

$$\mathbb{Z}^{1:n} = \{\mathbf{Z}^{1:n} \mid \mathbf{z}(k) \in \mathbb{S}(k) \text{ and } \varepsilon(\mathbf{X}^{1:n}) < \delta\}$$

Dezhen Song and Yiliang Yu, *Low False Negative Filter for Detecting Rare Bird Species from Short Video Segments using a Probable Observation Data Set-based EKF Method*, IEEE Transactions on Image Processing, vol. 19, no. 9, Sept. 2010, pp. 2321-2331

PODS-EKF Approximate Computation

$$\tilde{\mathbf{Z}}^{1:n} = \arg\min_{\mathbf{z}(k)\in\mathbb{S}(k)} \varepsilon(\mathbf{X}^{1:n})$$

$$\hat{\mathbf{x}}(k|k-1) = A(k)\hat{\mathbf{x}}(k-1|k-1),$$

$$\hat{P}(k|k-1) = A(k)\hat{P}(k-1|k-1)A^T(k) + Q(k),$$

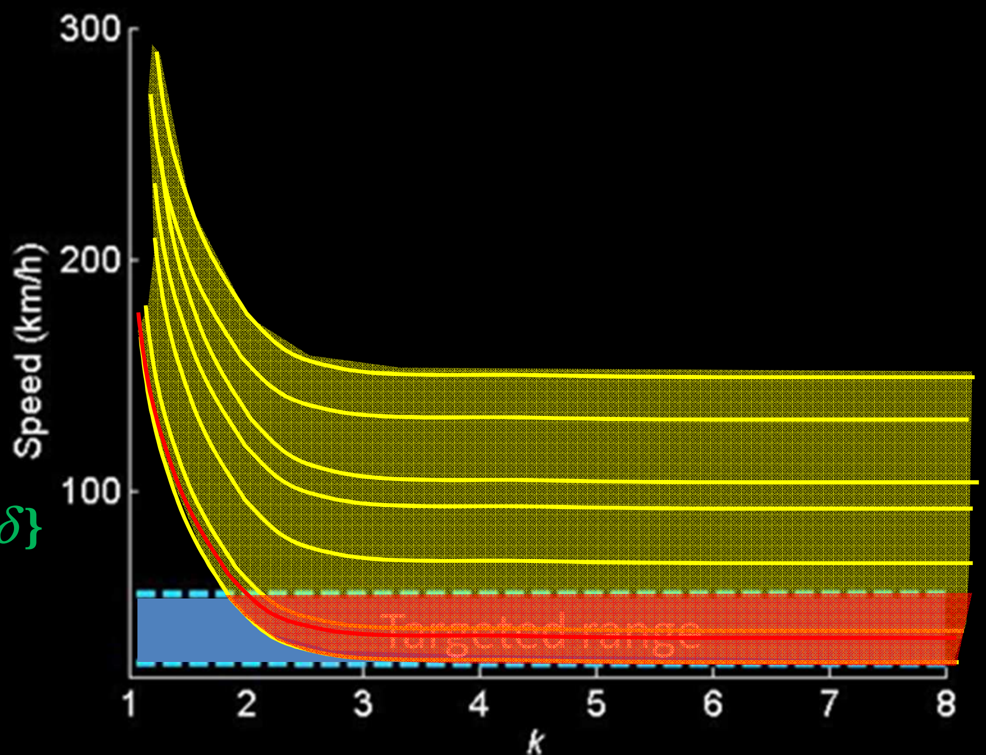
$$K(k) = \frac{\hat{P}(k|k-1)H^T(k)}{H(k)\hat{P}(k|k-1)H^T(k) + W(k)},$$

$$\hat{\mathbf{x}}(k|k) = \hat{\mathbf{x}}(k|k-1) + K(k)(\mathbf{z}(k) - h(\hat{\mathbf{x}}(k|k-1))),$$

$$\hat{P}(k|k) = (\mathbf{I}_{6\times6} - K(k)H(k))\hat{P}(k|k-1),$$

$$\mathbb{Z}^{1:n} = \{\mathbf{Z}^{1:n} \mid \mathbf{z}(k)\in\mathbb{S}(k) \text{ and } \varepsilon(\mathbf{X}^{1:n}) < \delta\}$$

$$\|\tilde{\mathbf{v}}(n|n)\| \in \mathcal{V}$$



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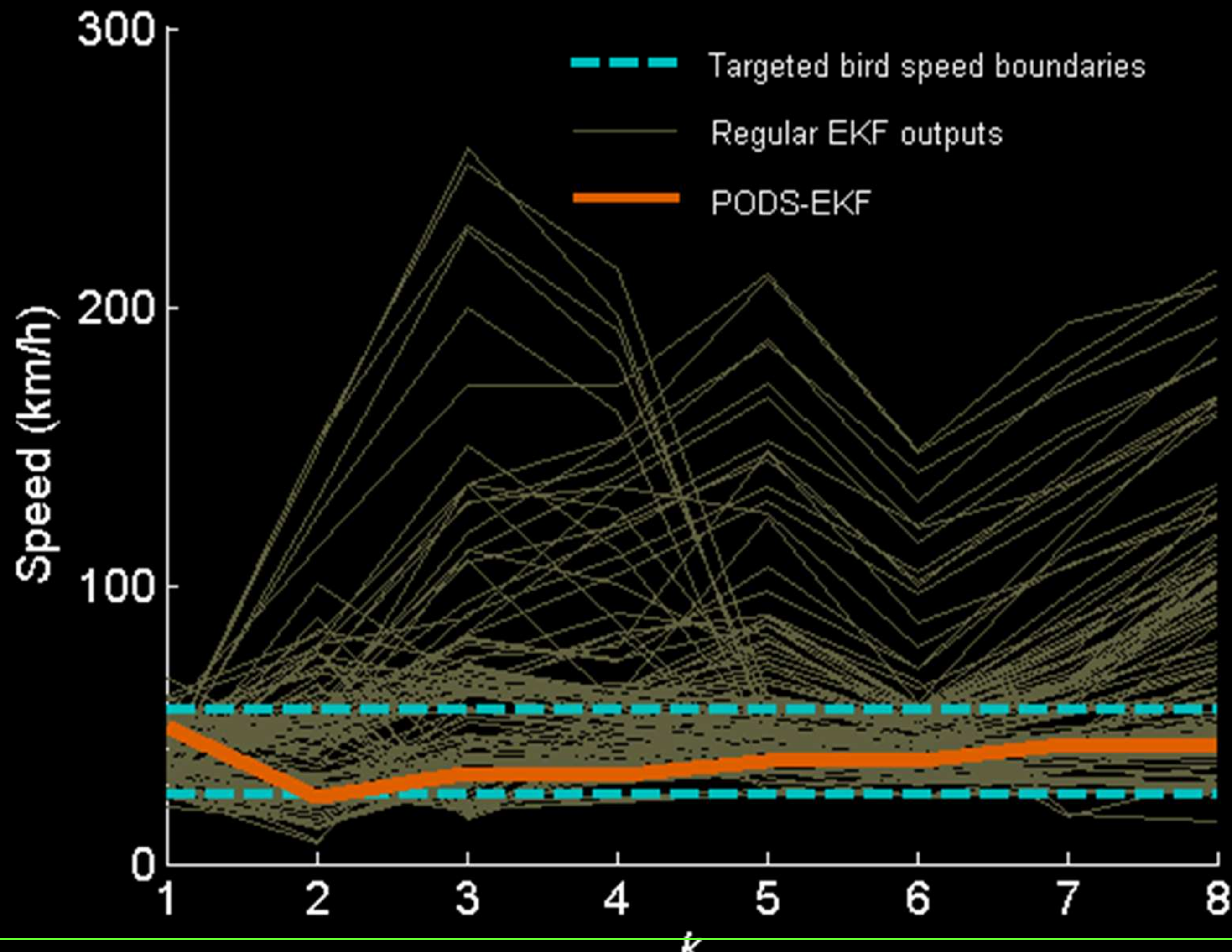
PODS-EKF Approximate Computation



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Algorithm

Algorithm 1: PODS-EKF based Bird Detection Algorithm

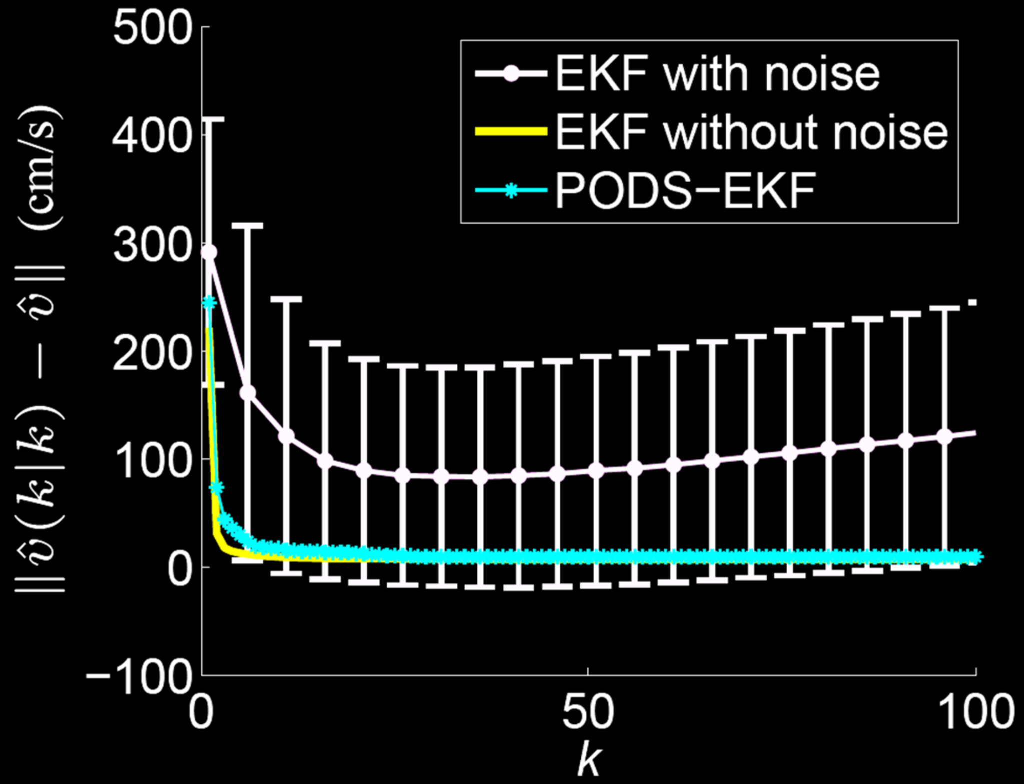
input : n frames with a segmented motion sequence
output: TRUE or FALSE for the targeted species.
for *the segmented motion block in i-th frame* **do**
  calculate the geometric center point C_i of the bird;
Connect $C_i,\ i = 1, 2, ..., n$ to generate a piecewise linear trajectory;
Obtain $\bar{\theta}$ from the trajectory;
for *the segmented motion block in i-th frame* **do**
  Obtain $\mathbf{z}(i)$ using the BBAF in (2);
Initialize the EKF using (20) and (21);
Solve the constrained nonlinear optimization problem in (14);
if $\|\widetilde{\mathbf{v}}(n|n)\| \in \mathcal{V}$ ***AND*** $\varepsilon(\widetilde{\mathbf{X}}^{1:n}) < \delta$ **then**
  return TRUE;
else
  return FALSE;

Experiments

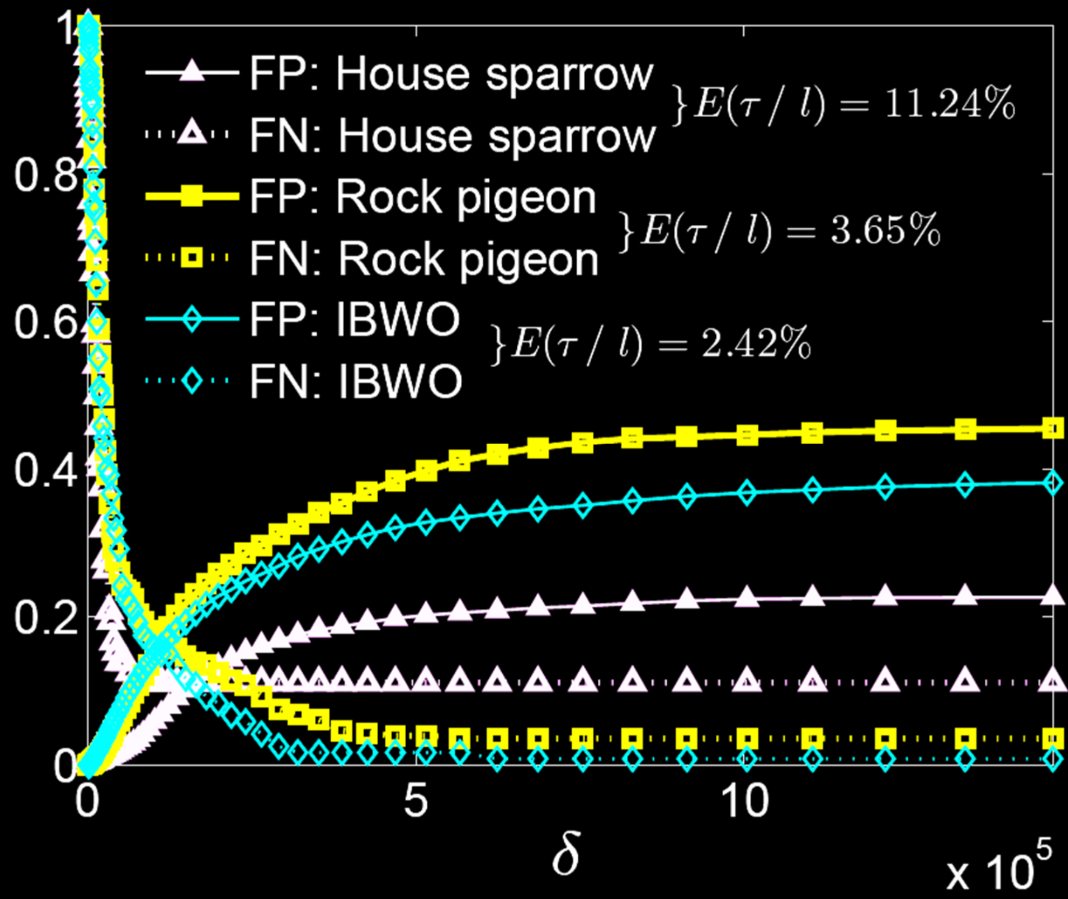
- Both simulated and real data
- A desktop PC with an Intel Core 2 Duo 2.13GHz CPU and 2GB RAM
- Matlab 7.0 (motion detection) and Visual C++ 8.0 (PODS-EKF)
- Arecont AV3100 camera
- Bird species tested:

Species	l_b (cm)	$\mathcal{V}$ (km/h)
House sparrow	15	[29, 40]
Rock pigeon	33	[24, 56]
Ivory-billed woodpecker(IBWO)	48	[32, 64]
Red-tailed hawk	56	[32, 64]

Convergence of different EFKs on Rock Pigeon

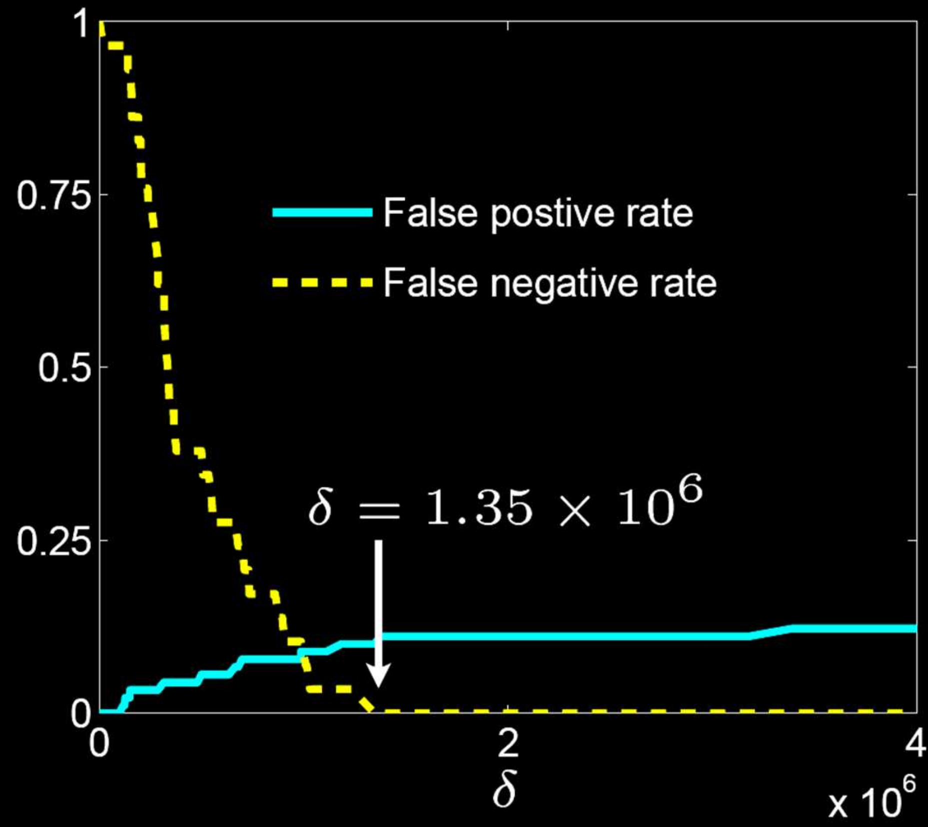


Simulation on three birds



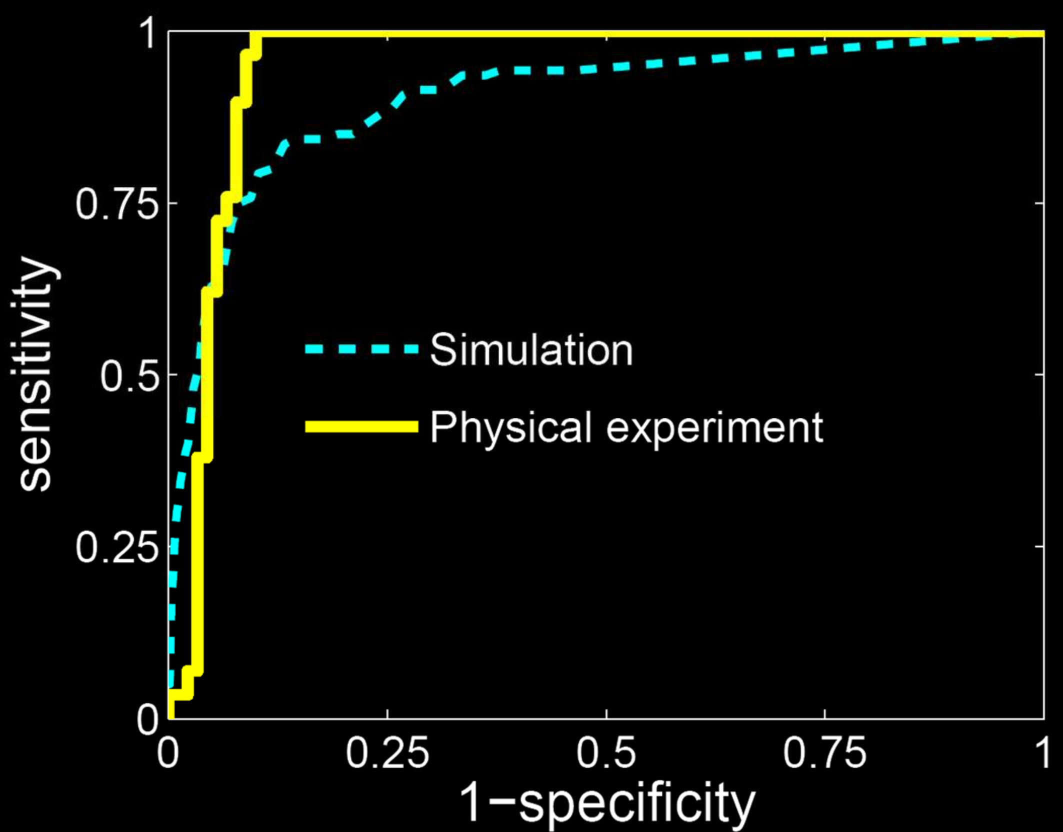
Physical Experiment on Rock Pigeon

	Pigeon	Not pigeon
Predicted pigeon	29	9
Predicted not pigeon	0	81



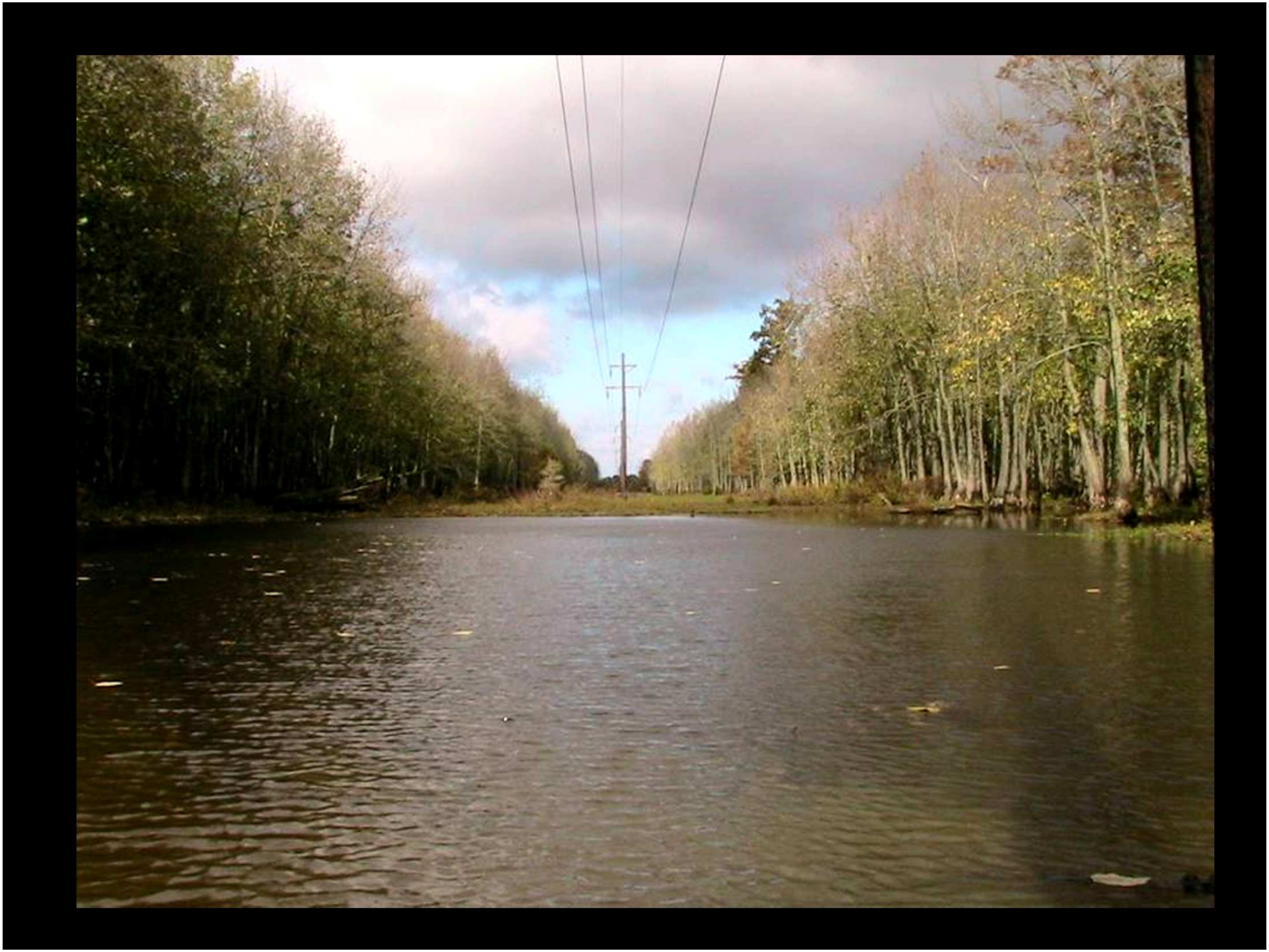
Insects, falling leaves, other birds, etc.

ROC Curves for Rock Pigeon

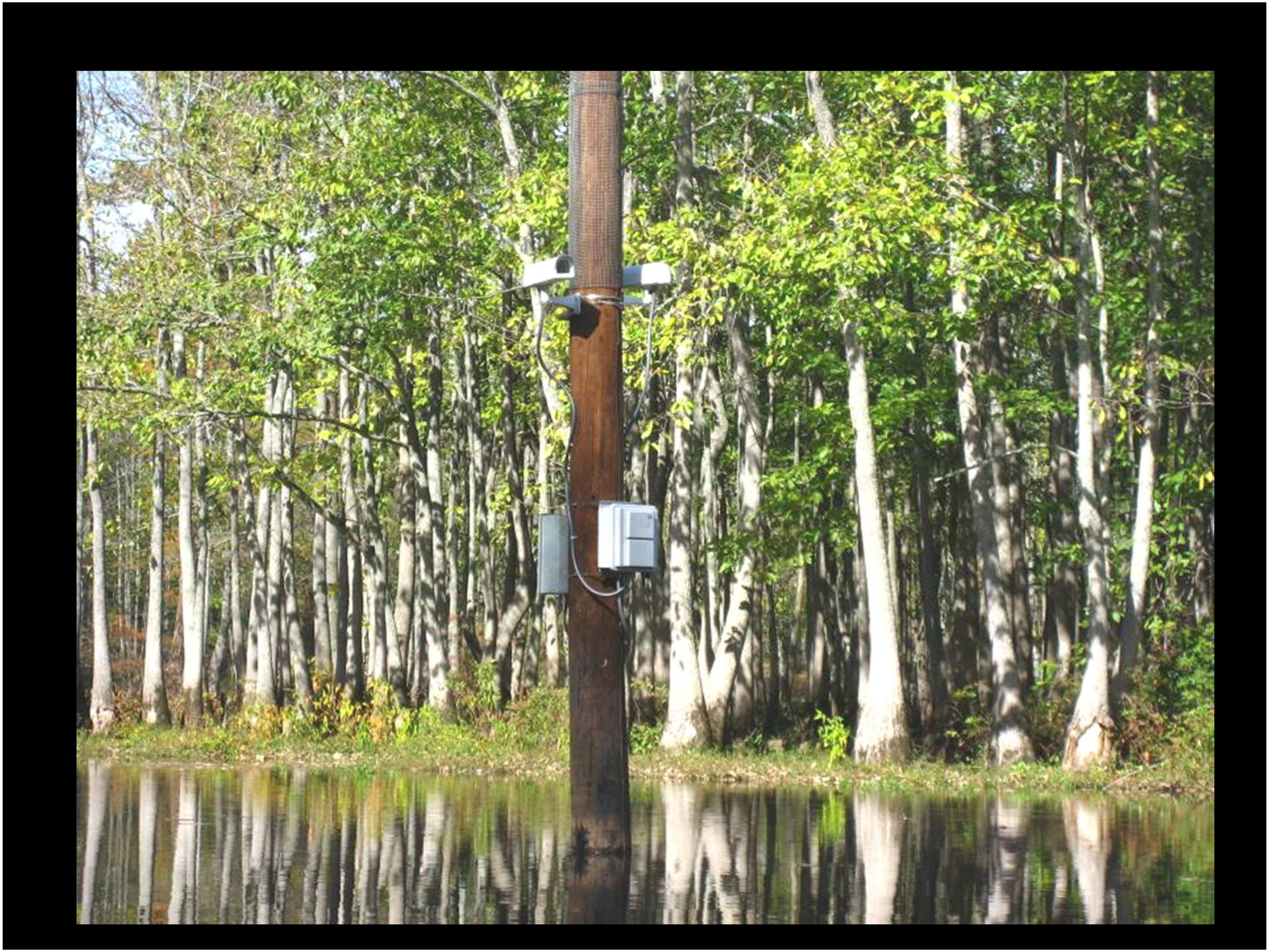


Area under ROC curve: 91.5% in Simulation; 95.0% in Experiment.

Powerline cut
49
17
40
70
Brinkley, AR




DANGER



Data reduction

- Oct. 2006 – Oct. 2007
- Motion detection: 29.41 TB to 27.42 GB
- PODS-EKF: 27.42 GB to 146.7 MB (~960 images)
- Overall reduction rate: 99.9995%

What we found

Pileated woodpecker (cousin of IBWO)

Northern flicker (smaller than IBWO)

Red-tailed Hawk (larger than IBWO)

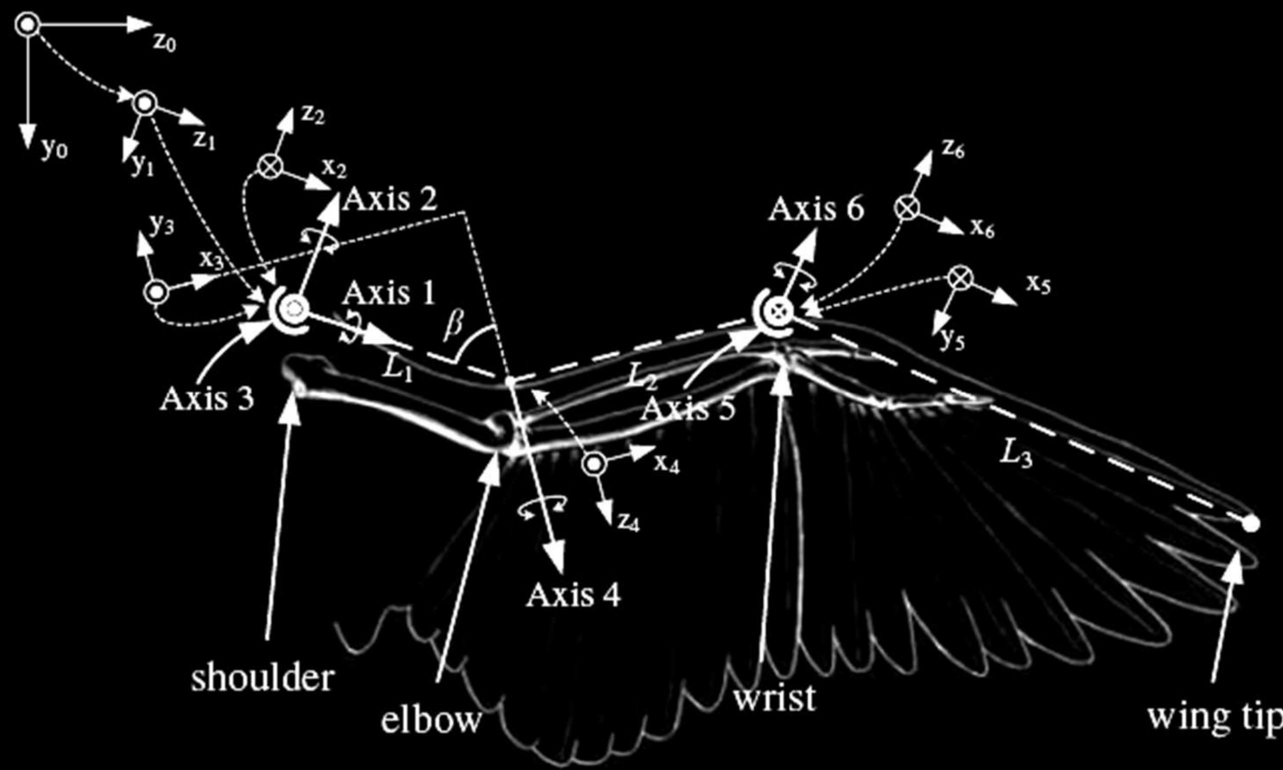
Conclusion

- Low false negative bird filter: PODS-EKF
- Cope with insufficient noisy observation data
- 95% area under ROC curve
- 99.9995% data reduction

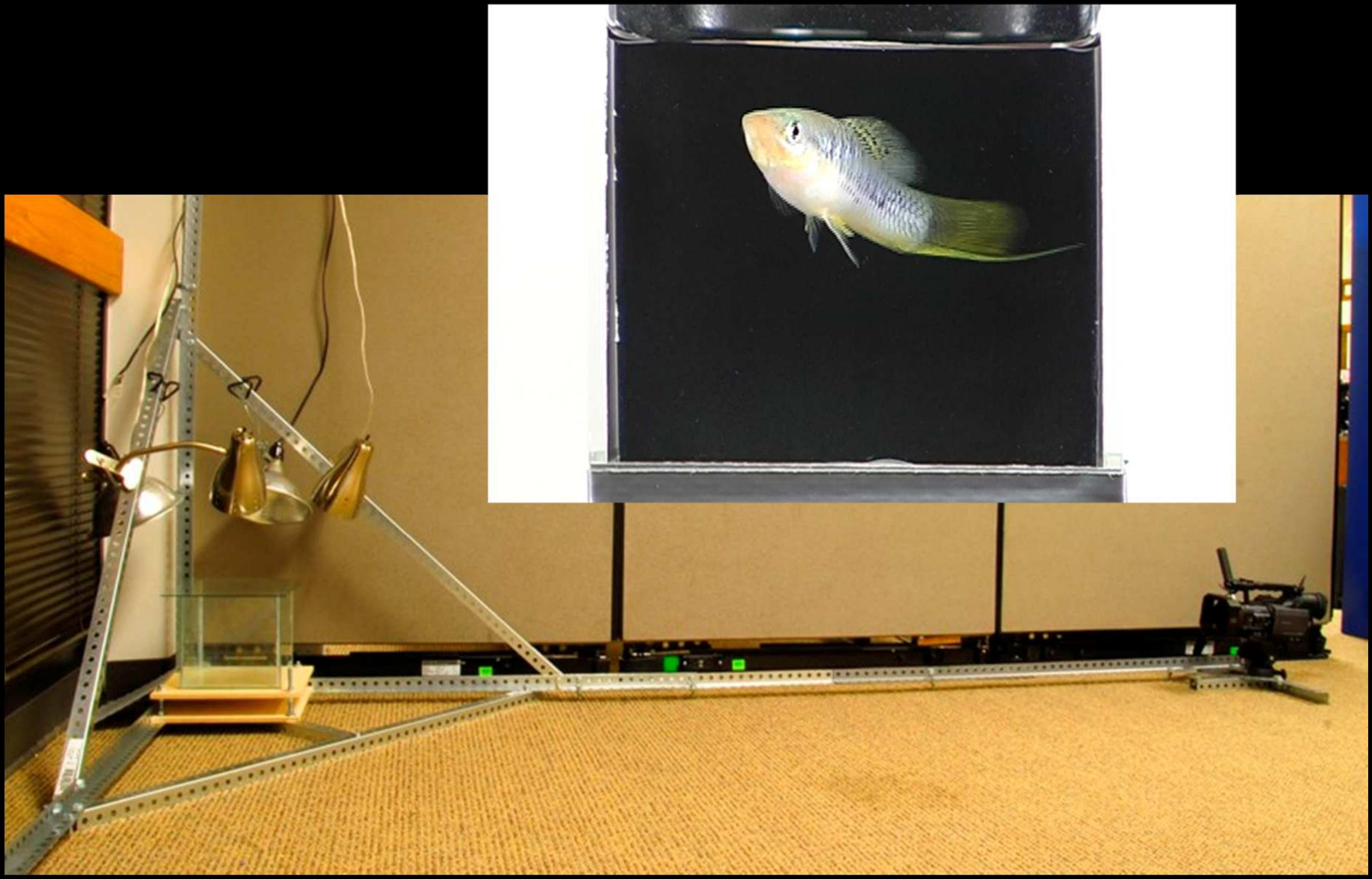
Current and Future Work

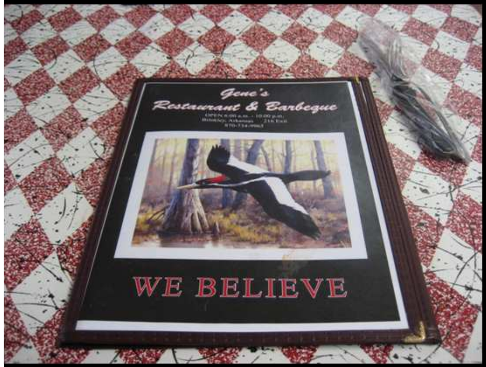
- Examine wing-flapping motion
  - Wingbeat frequency is unique for each species

Wing Kinematic Model



Current & Future Work: AnyFish





Thanks!

Websites:

http://telerobot.cs.tamu.edu

http://rbt.cs.tamu.edu/


gettyimages
1174-76

Seagull: Mean 2.74 Hz

S.D. 0.22 Hz