

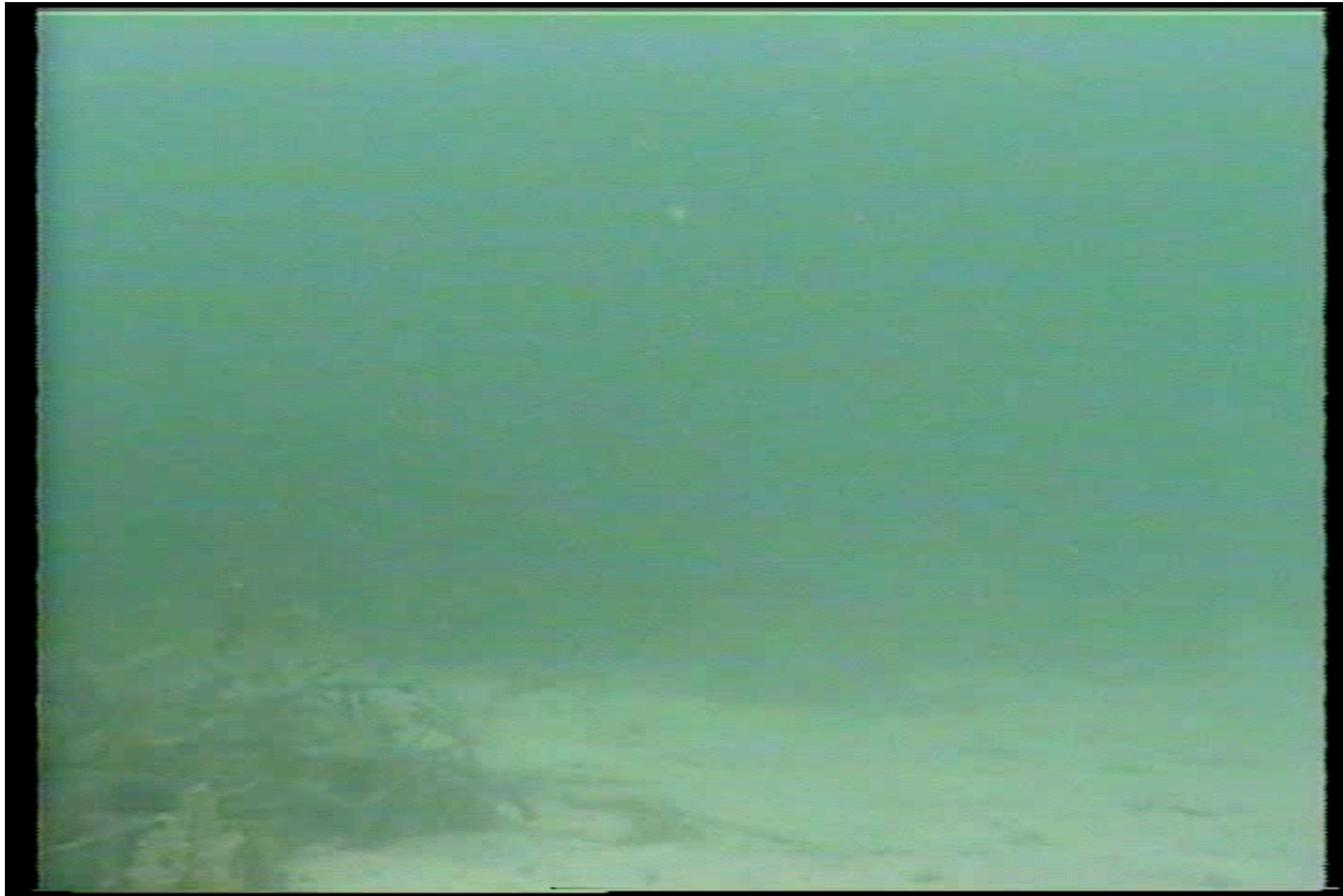
Monitoring Creatures Great and Small: Computer Vision Systems for Looking at Grizzly Bears, Fish, and Grasshoppers

Greg Mori, Maryam Moslemi, Andy Rova, Payam Sabzmeydani,
Jens Wawerla

Simon Fraser University

VAIB workshop - December 7, 2008

Captivating Cinema



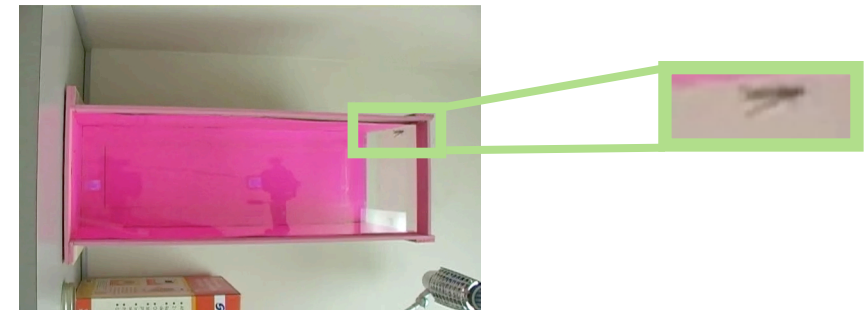
video: Prof. Larry Dill, SFU Biological Sciences

Computer Vision for Data Collection

- “Looking at Animals” problems
 - Sifting through video to find animals
 - Determining what the animals are up to
 - Classifying species of animals
- Symbiotic relationship
 - Natural scientists receive data
 - Computer scientists receive
 - real-world datasets
 - ground truth for quantifiable success/failure

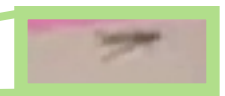
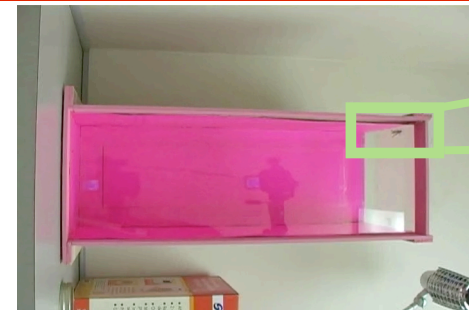
Outline

- Detection of animals in video
 - Grizzly bears
- Analyzing animal behaviours
 - Grasshoppers
- Recognizing animal species
 - Fish



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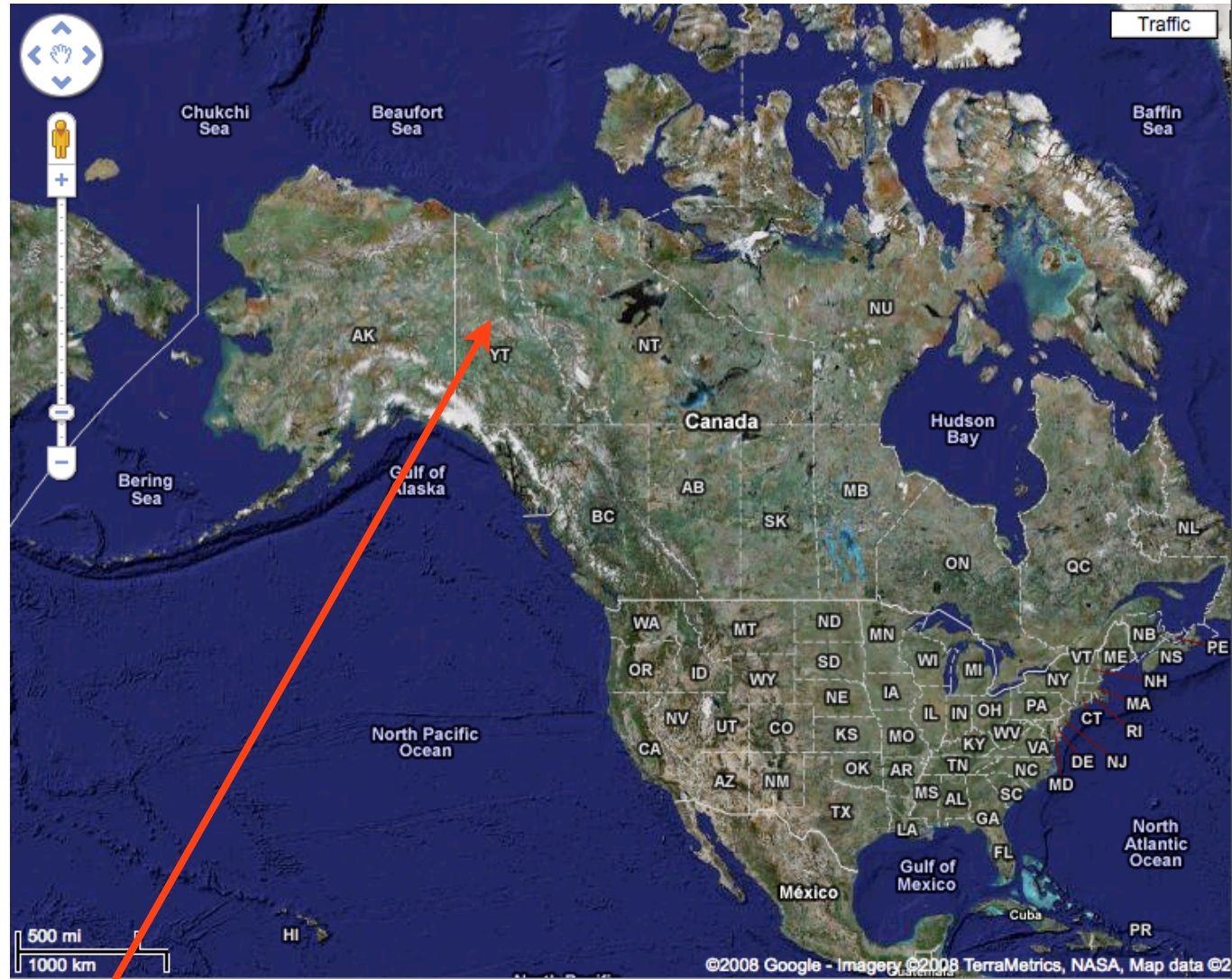
Grizzly Bear Monitoring

- New eco-tourism site on salmon spawning river
 - Grizzly bears feed on salmon
 - Will human presence negatively impact bears?
- “Bearcam” deployed to watch bears on-site in northern Yukon



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Ni'iinlii Njik Park

Bearcam



- Bearcam system recorded approx. 4h video per day for 15 days

Bear Detection



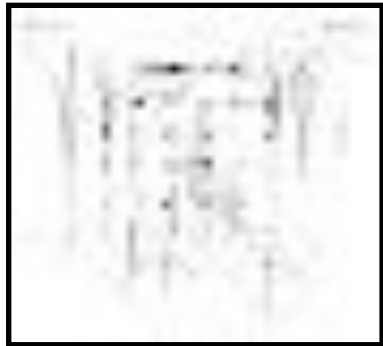
background difference



spatial gradients

- Bears have distinct shape and pattern of motion
 - extract image gradients and background difference
 - build classifier to detect bears

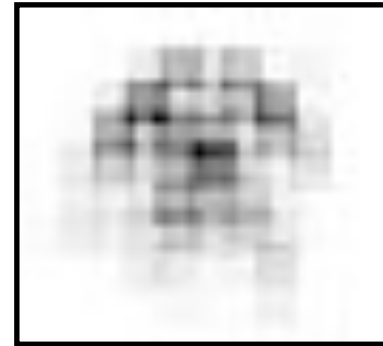
Classifier



pos.
gradient



neg.
gradient



pos.
back. sub.



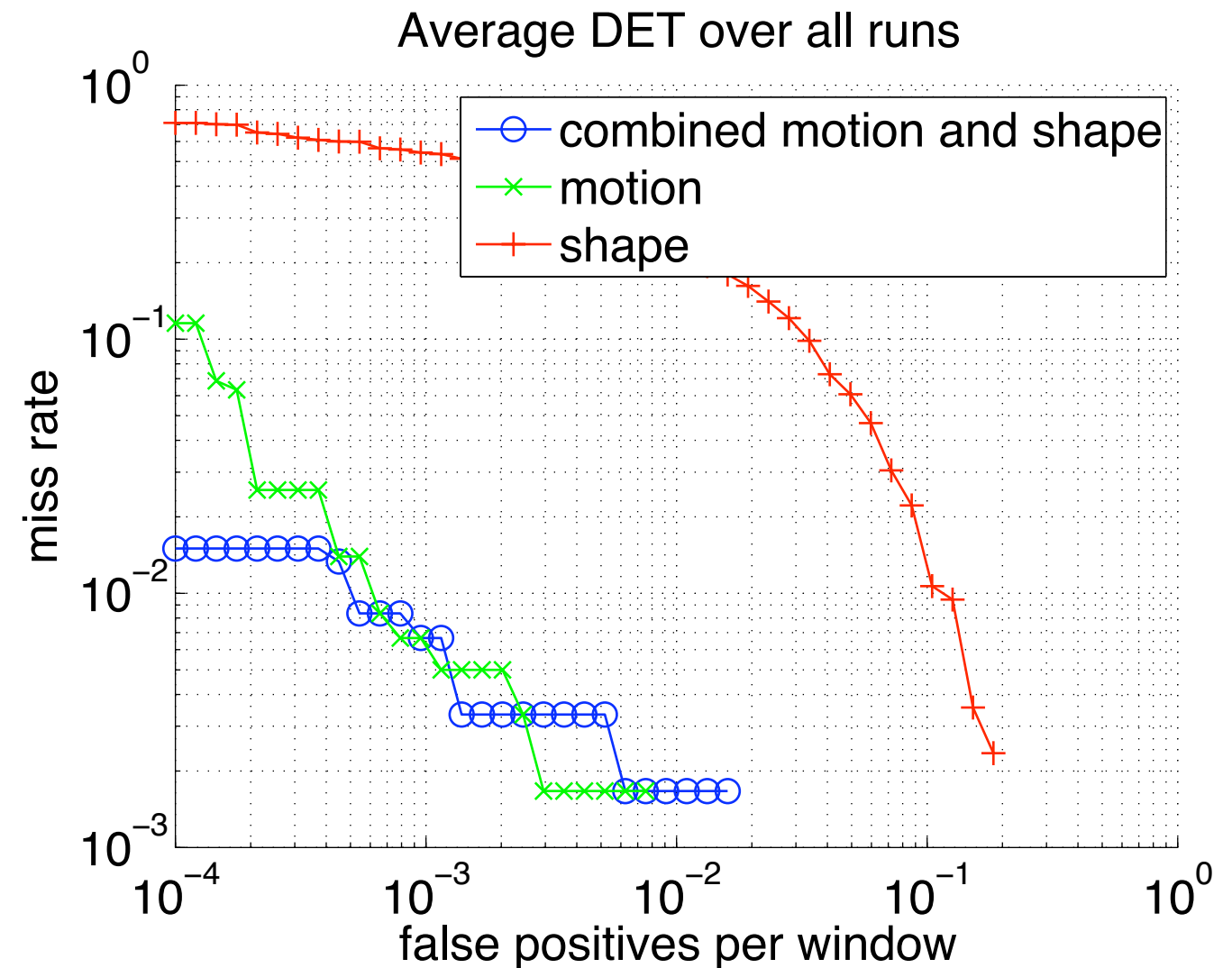
neg.
back. sub.

- Build bear detector using variant of AdaBoost (Viola-Jones)
- A set of weak learners is built from thresholded background subtraction and gradient features

$$h_t(x) = p_t f_t(x) < p_t \theta_t$$

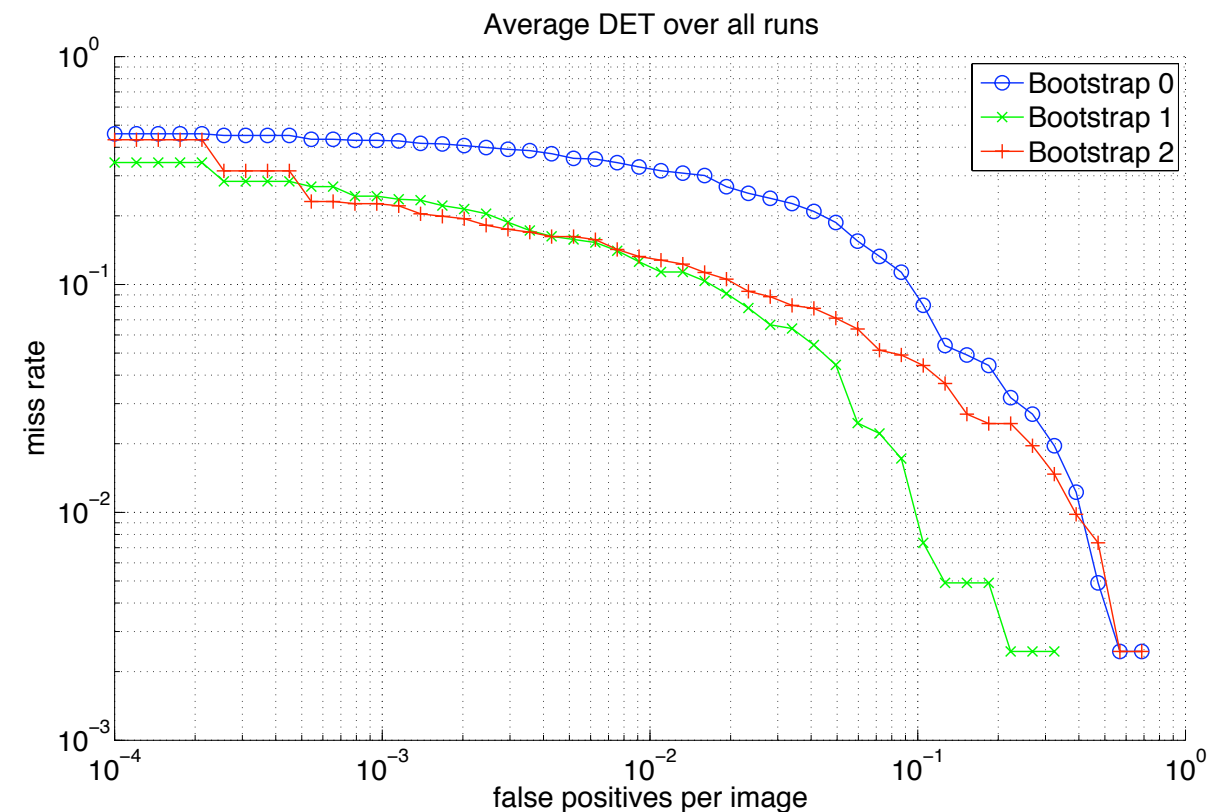
Results

- Crop windows from video frames
- Training set
 - 451 windows containing bears
 - 45100 without bears
- Test set
 - 400 bear windows
 - 40000 without



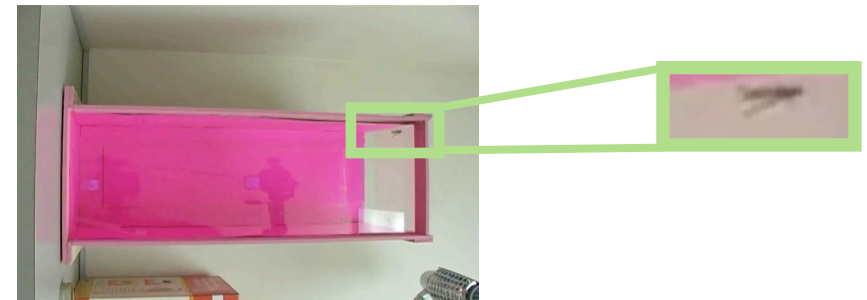
Results on Frames

- Run classifier on entire frame, take highest response
- Same training set
 - bootstrap negative set
- Test set
 - 405 frames with at least 1 bear
 - 16000 with none
 - detect 76% at 0.001 FPPI
 - detect 88% at 0.01 FPPI



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Understanding Insect Actions

- How are grasshoppers' actions affected by spiders?
 - Predator-prey relationship
- Environment variables
 - Temperature
 - Light
 - Presence of food
- Collect data on grasshopper movement rates and actions
 - Lab environment, glass case
 - Calibrated stereo cameras



Tracking

Top Camera

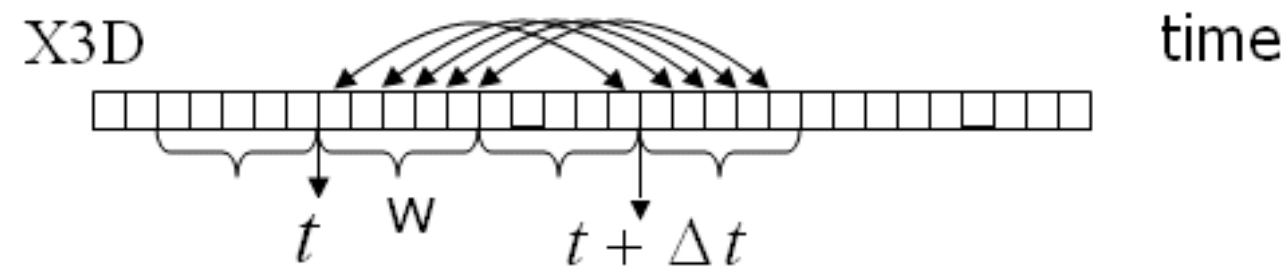
Bottom Camera



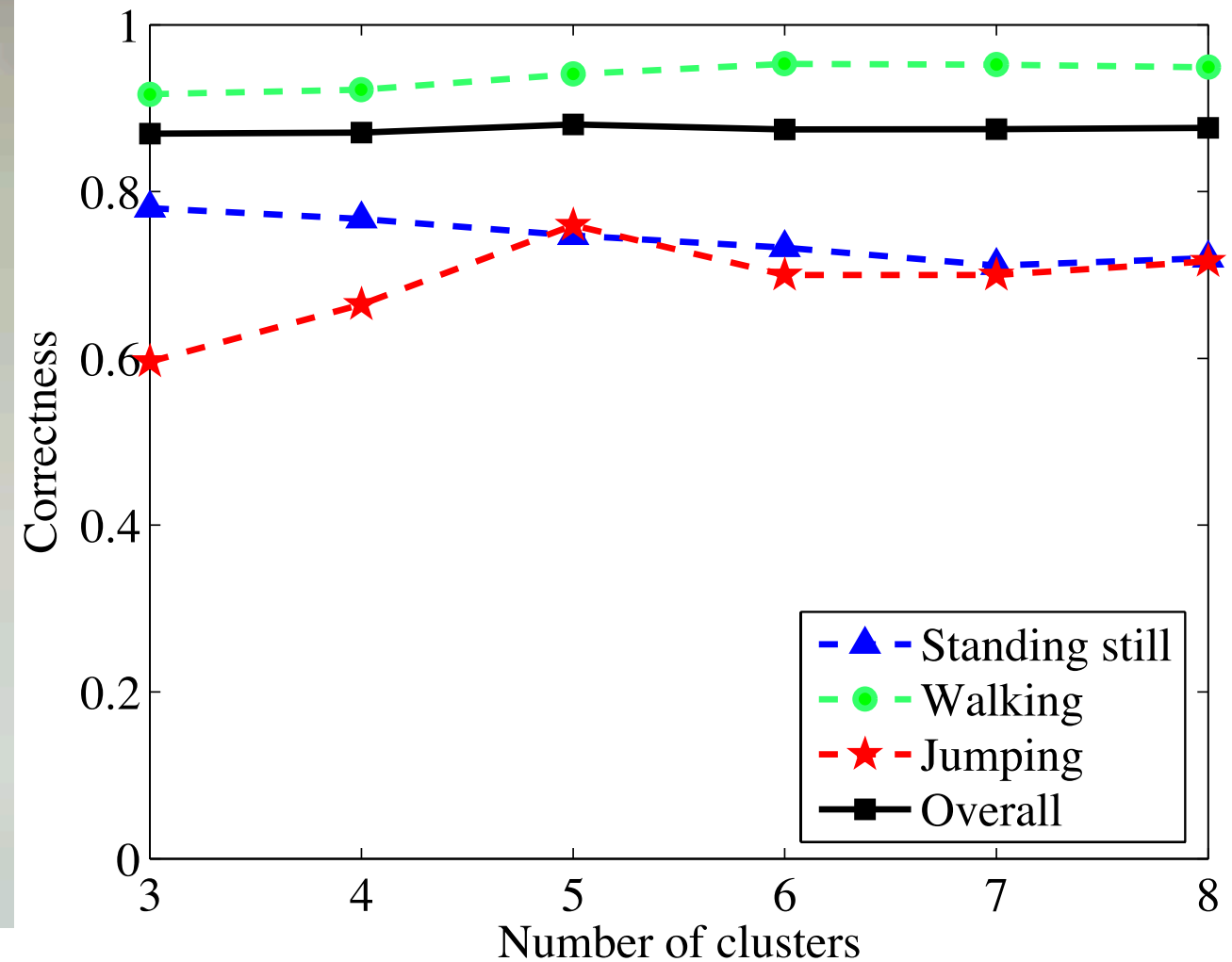
- Background subtraction tracker in each camera

Clustering with Action Features

- Smooth the 3D track
- For each non-overlapping window of size w of track compute the difference between $x(t)$ and $x(t+\Delta t)$
- Use spectral clustering on these features



Clustering Results



- Cluster purity measured
- 3530 hand-labelled frames

Clustering Visualization

- Take all frames in “jump” cluster
- Show all such clips in one shorter video
- Minimize spatial/temporal overlap of clips
- Rav-Acha, Pritch, Peleg CVPR06

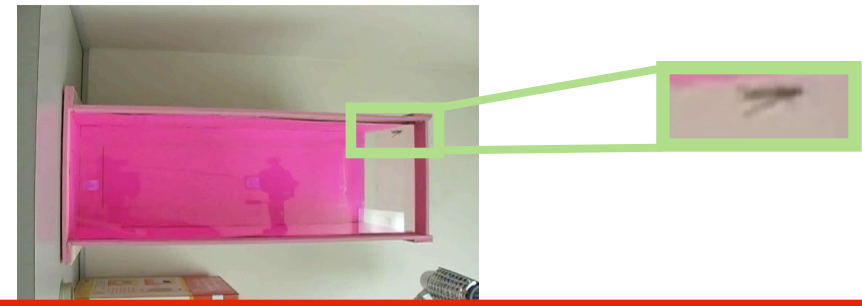
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Counting Fish



- Biologists have many hours of underwater video footage
 - Require count of fish by species
 - Use as proxy for tiger shark count
- Currently, people must watch and manually identify/count
 - Automatic system could save many hours of labour

Challenges

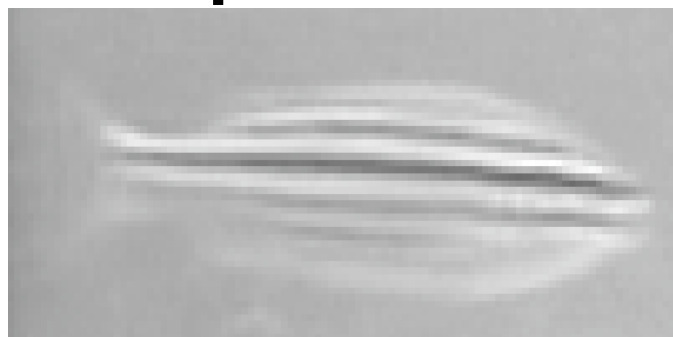
- Video has limited resolution and is interlaced
- Underwater lighting has shifts in intensity and color
- Plants and sediment can cause false positives when detecting movement
- Fish appear with arbitrary locations and poses



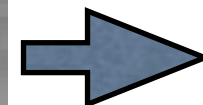
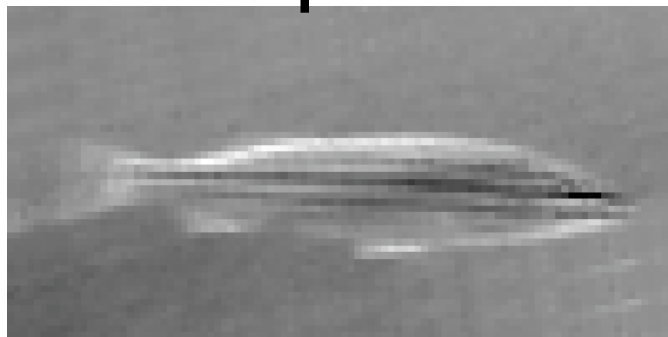
Method overview

1. Preprocess video frames to crop candidate subimages
2. Find correspondences between unknown images and known fish template images
3. Warp unknown images into alignment with the templates
4. Use support vector machines (SVMs) to classify the unknown images by fish species

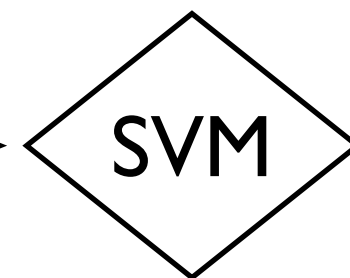
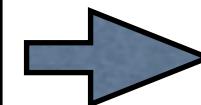
template 1



query warped
to template 1

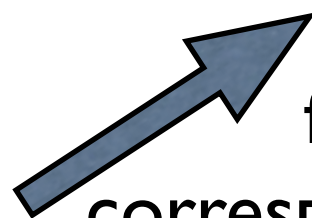
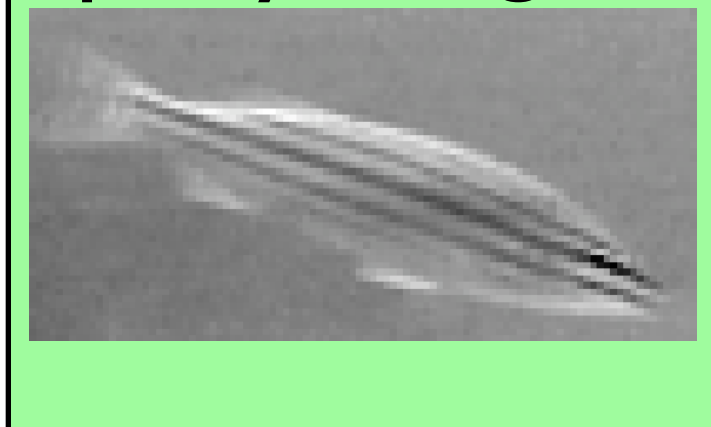


filter responses

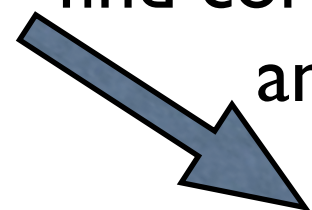


Classification
decision

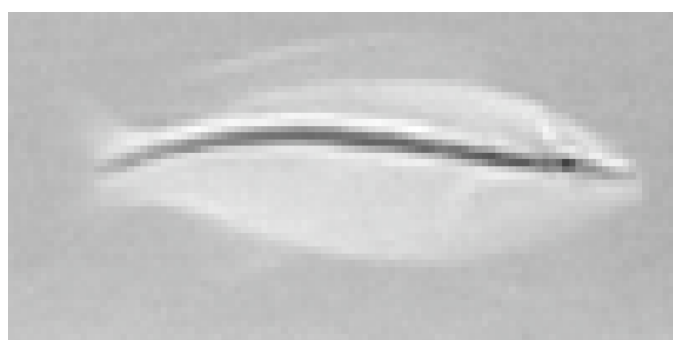
query image



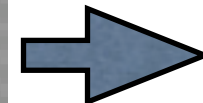
find
correspondences
and warp



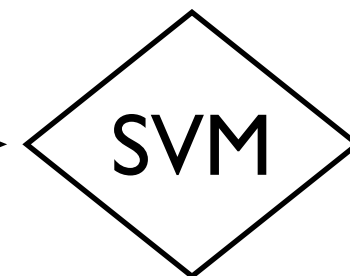
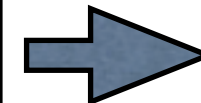
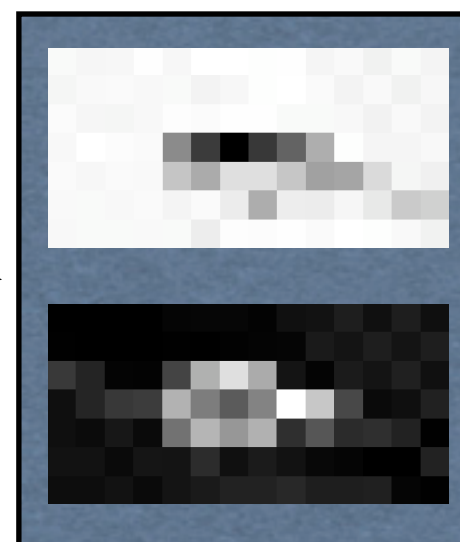
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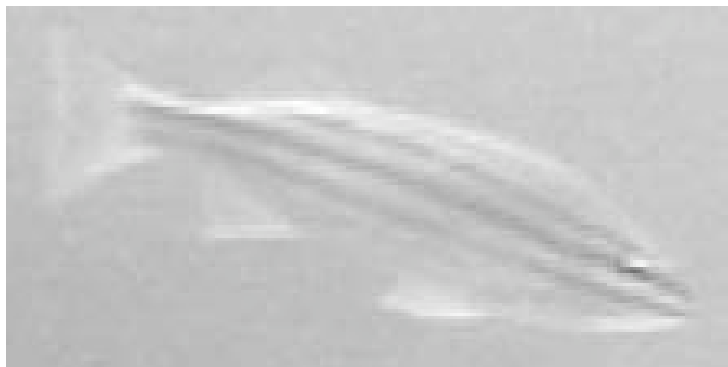
template 2



filter responses



Warping examples



(a) test image



(b) template



(c) warped test image



(d) test image



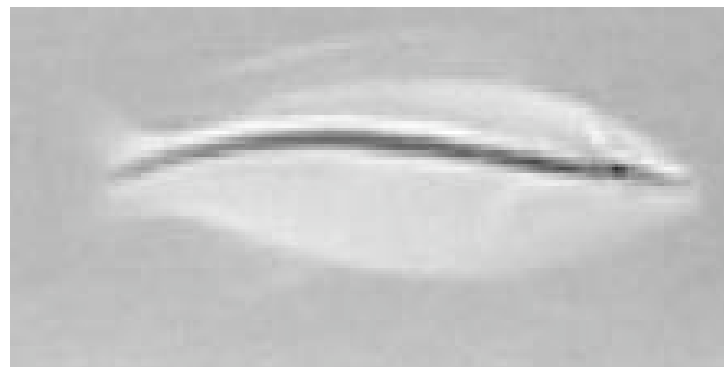
(e) template



(f) warped test image



(g) test image



(h) template

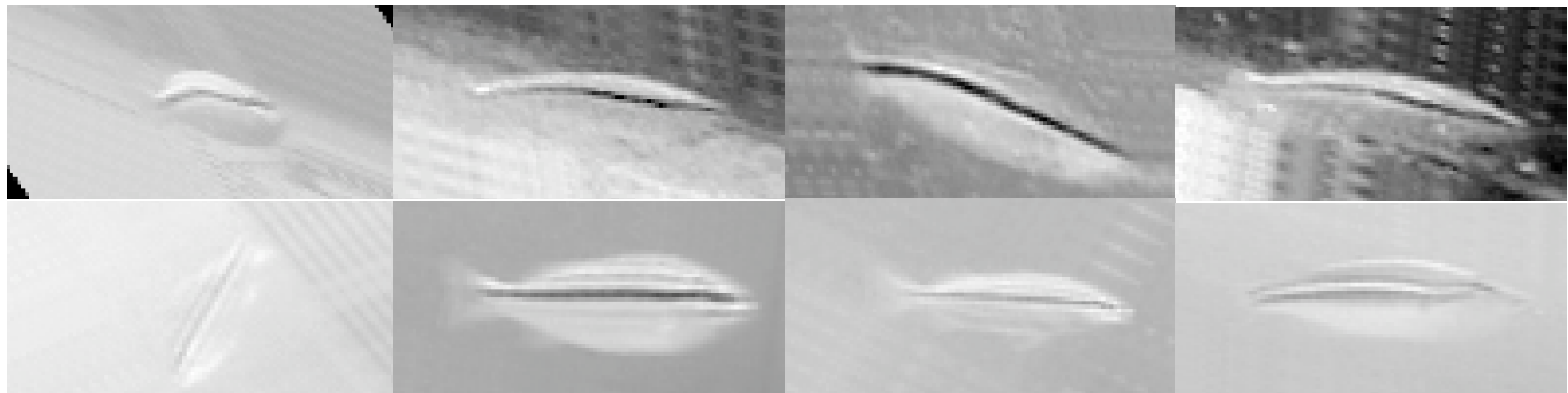


(i) warped test image

Experimental results

Automatic classification of 320 hand-cropped video frames of two fish species

SVM kernel	no warping	warped
linear	84%	90%
polynomial	81%	86%



some misclassifications

Acknowledgements



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Thank you