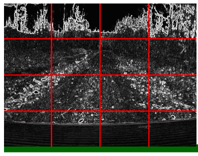
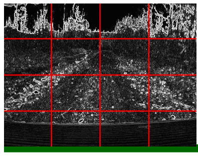


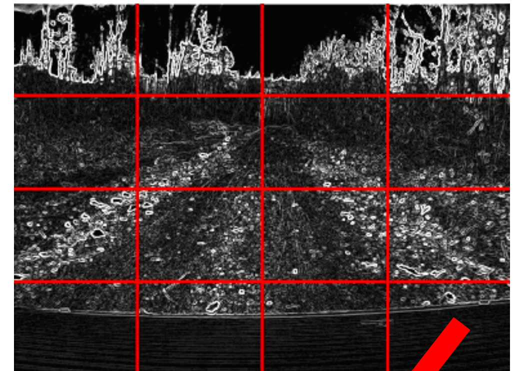
Real-Time Image-based Topological Localization in Large Outdoor Environments

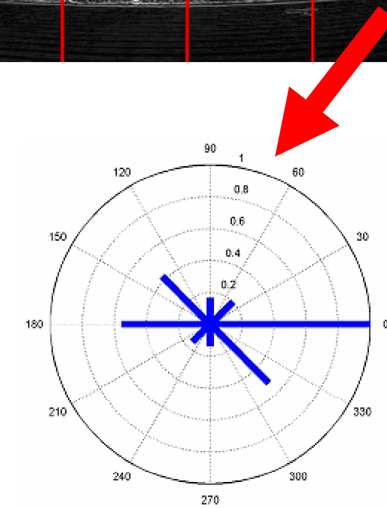
David M.Bradley, Rashmi Patel, Nicolas Vandapel, Scott M. Thayer
Carnegie Mellon University
IROS August 5th, 2005

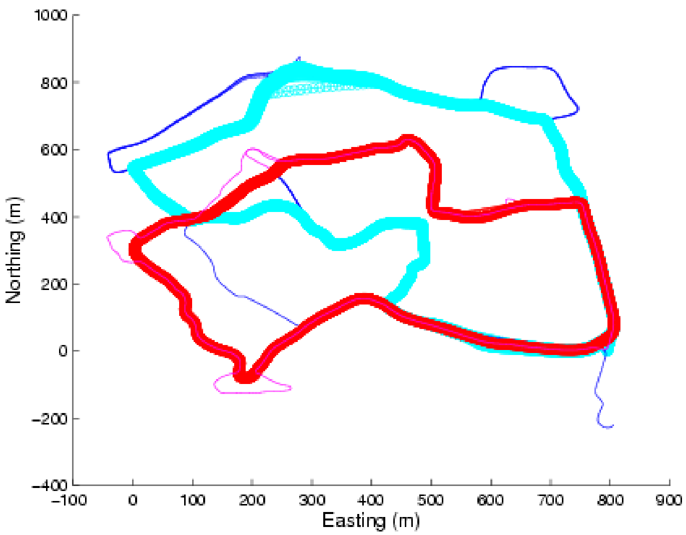


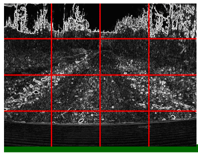
Localization in Large Unstructured Environments

- Large scale environments
- Variable lighting conditions
- Demonstrated real-time localization
- Image-based feature matching
- On-board local sensing with prior map
- Research philosophy:
  - →Data association is the weak link

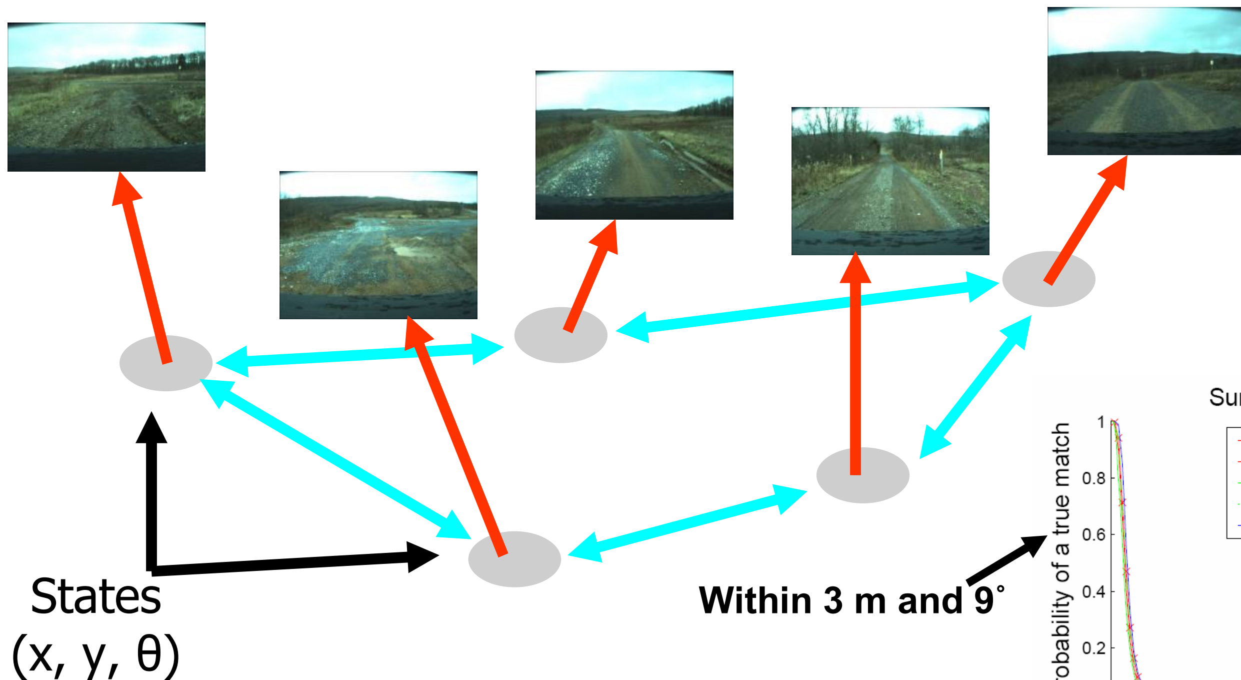


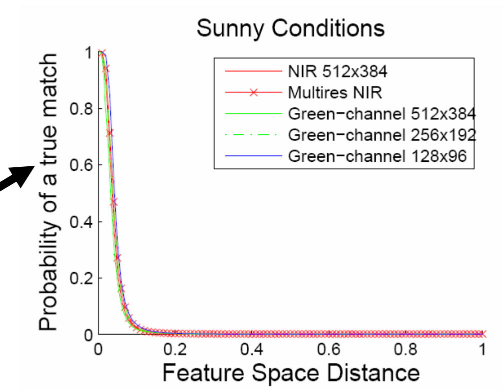




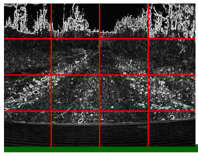


Localization to a prior map





- **Camera image varies continuously as camera moves**
  - → **3D manifold in high-dimensional image space**
- **Image feature vectors are stored for each location** (x, y, θ)
  - → **Reduced storage and matching costs**
  - → **Reduce sensitivity to noise**
- **Close in feature space → close in physical space**

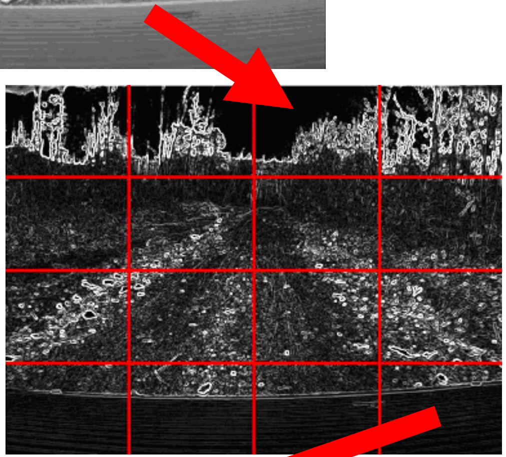


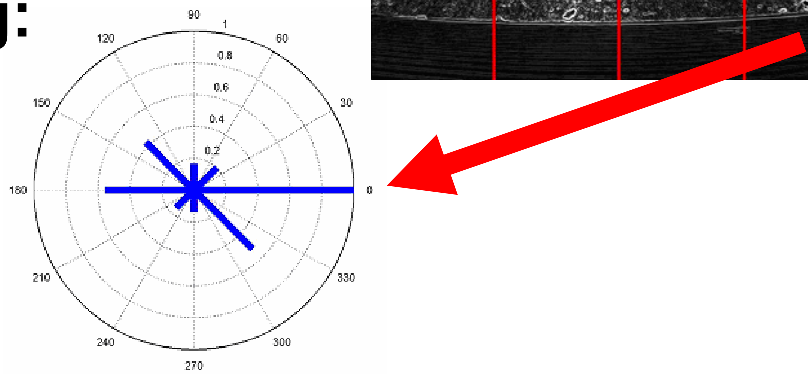
Gradient Orientation Histograms

- Divide image into sub-regions
- Histogram the image gradient orientation weighted by its magnitude
- Concatenate histograms into one vector
- Threshold and normalize
- Inspired by [1] and Similar to feature used in [2]
- Compare descriptors using:

$$d(X_i, X_j) = 1 - X_i X_j^T$$

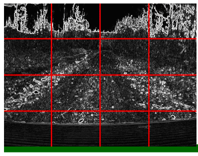
IR image



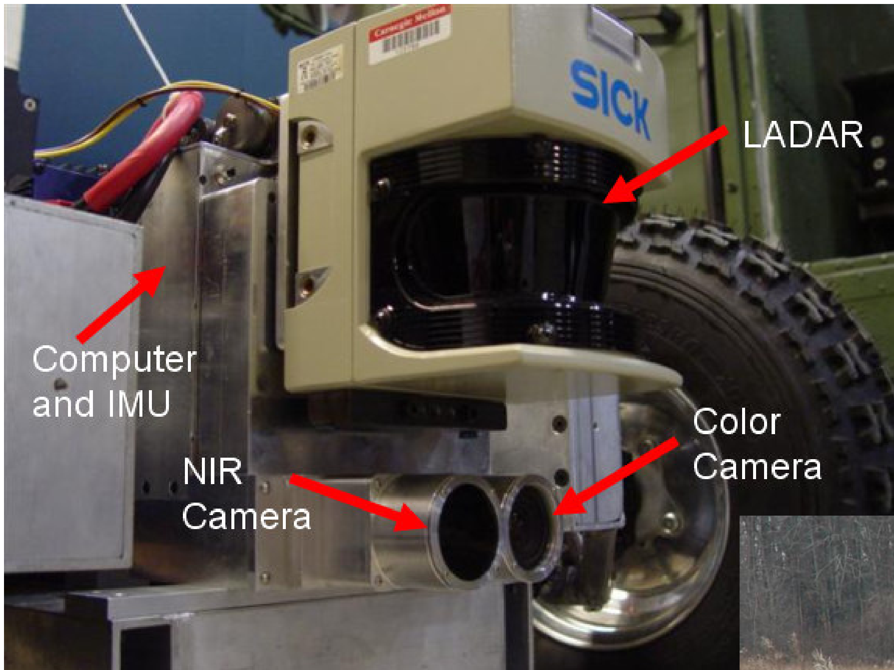


[1] David G. Lowe. Distinctive image features from scale-invariant keypoints. *IJCV*, 2004.

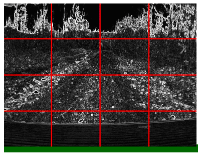
[2] J. Kosecka et al. Qualitative Image-Based Localization in Indoors Environments. *CVPR* 2003.



Fort Indiantown Gap Test



- **100k pairs of GPS-tagged images**
- **70 km accumulated driving**

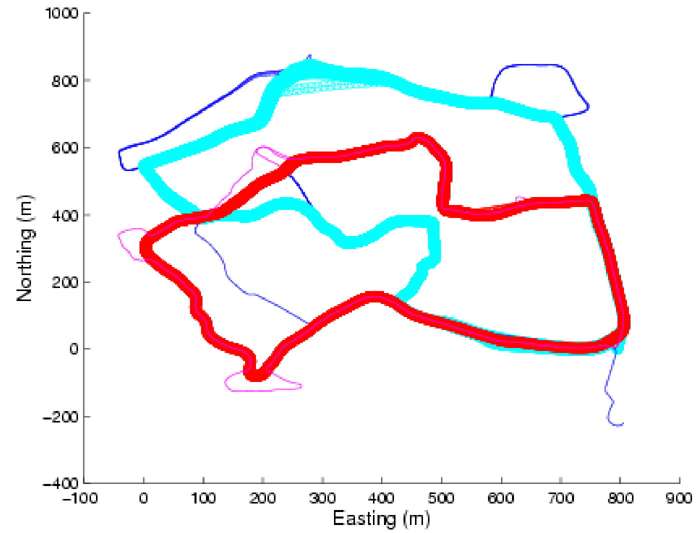


Fort Indiantown Gap Data Set

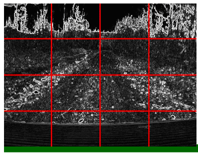
Sunny

Dusk

Paths Driven



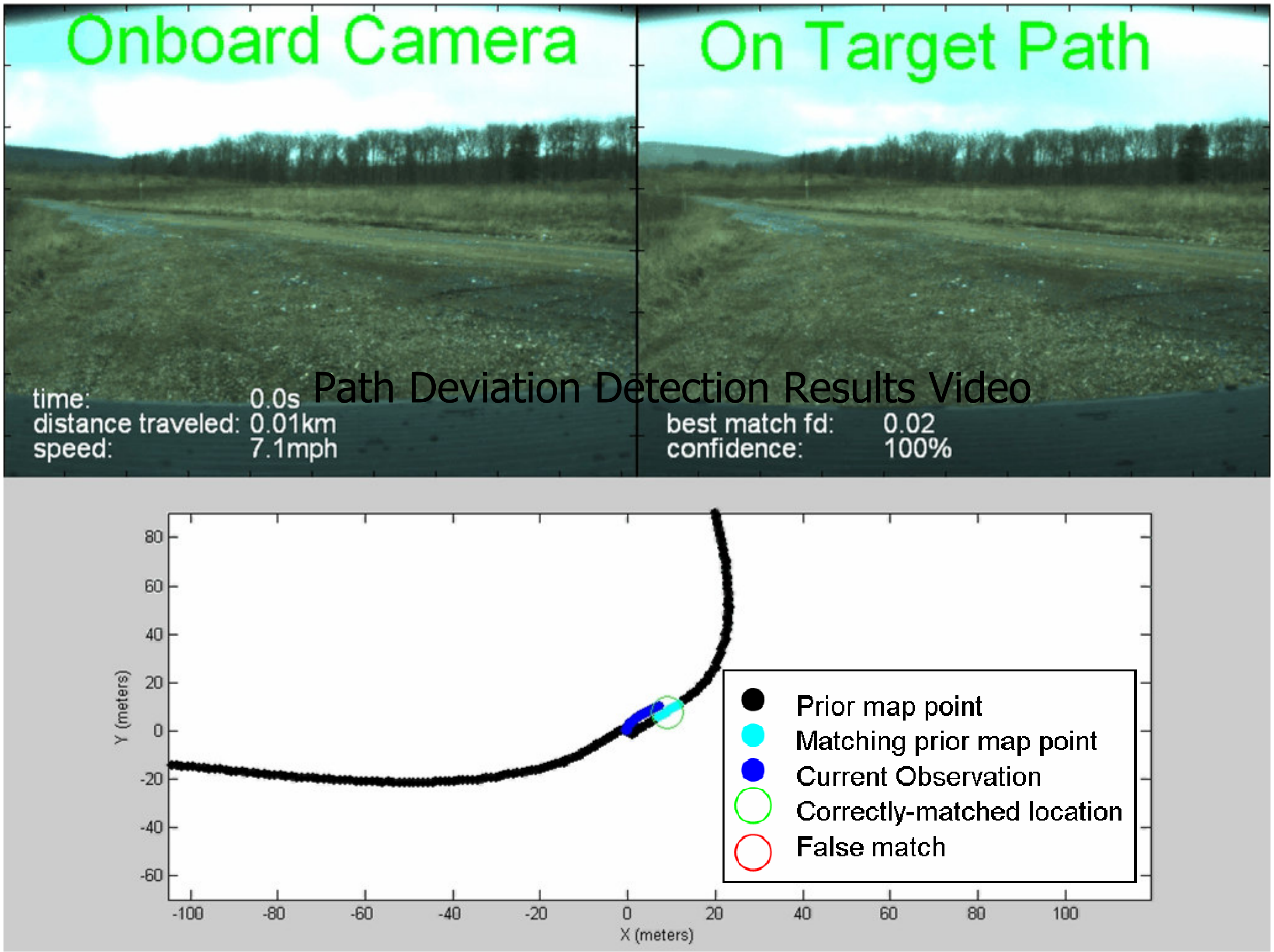
Weather	# of runs	Avg. # of images	Avg. path length
Sunny	10	4723	2.8 km
Overcast	8	4919	3.05 km
Dusk	2	4333	2.8 km
Night	3	4044	3.1 km

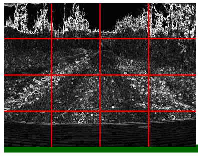


Real-time Localization

- **Nearest neighbor found for each new observation**
- **If feature-space distance < threshold, accept match**
- **7 Hz operation with a prior map of 4700 images**
  - **→Limited by feature creation, not comparison**

Sample Matching Results



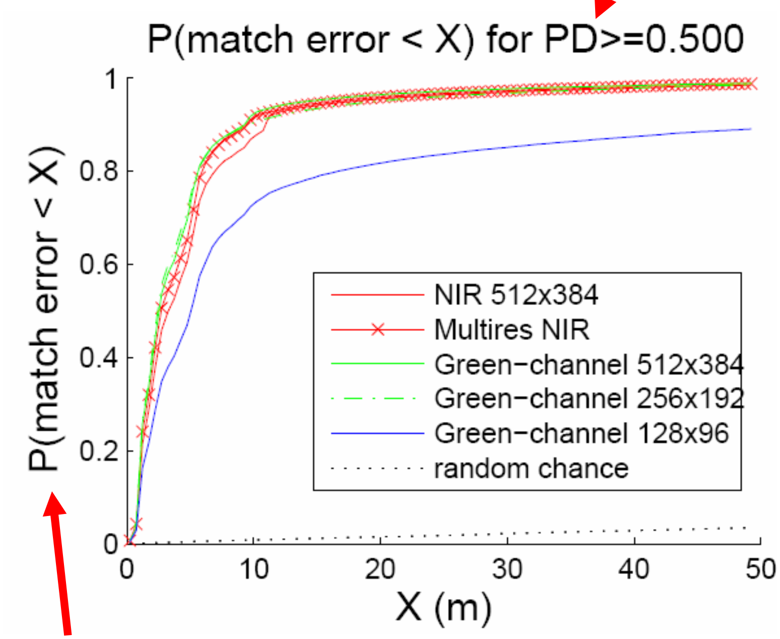


Probabilistic Localization Error Bounds

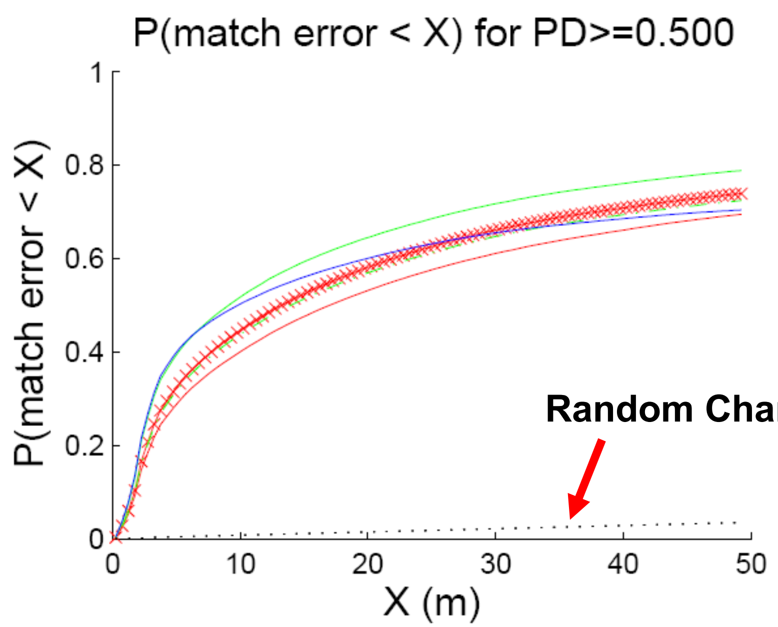
Feature space threshold set to detect

%50 of pairs within 3 m and 9˚

Overcast



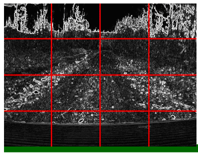
Sunny



Random Chance

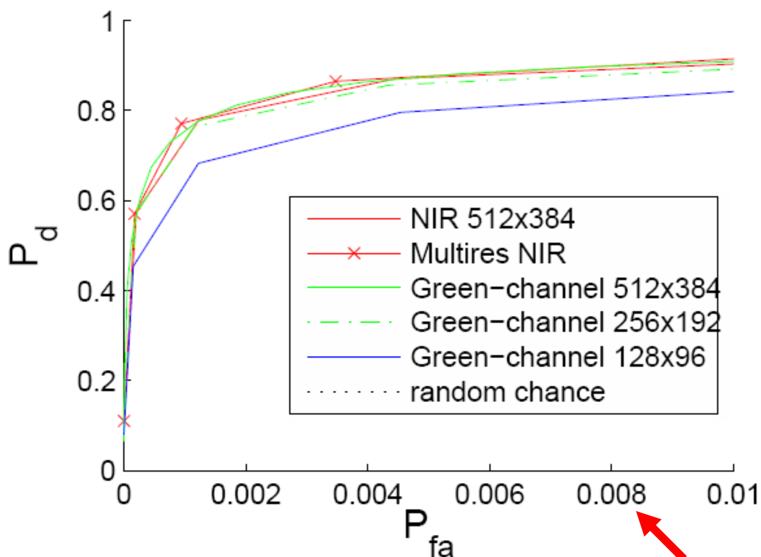
Probability that feature-space

matches were taken within X m

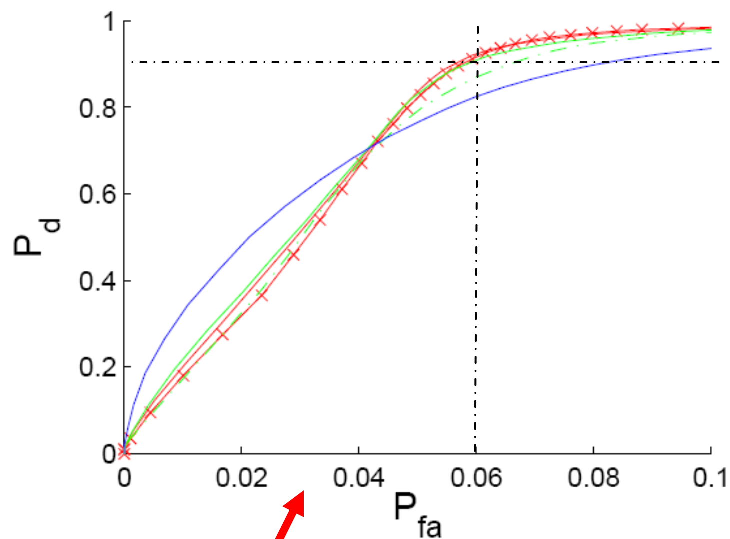


Overcast Conditions

All pairs

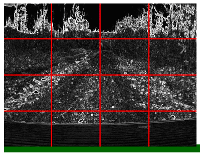


Closest Match Only

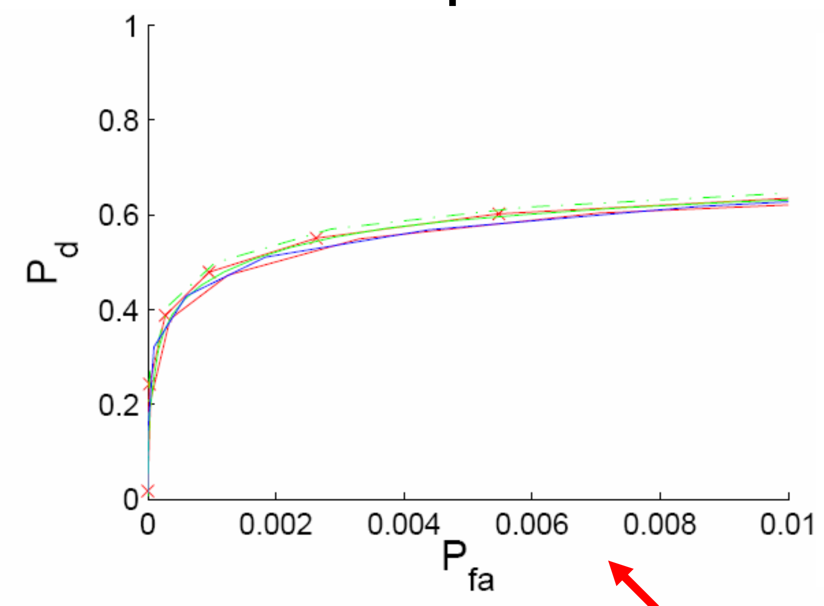


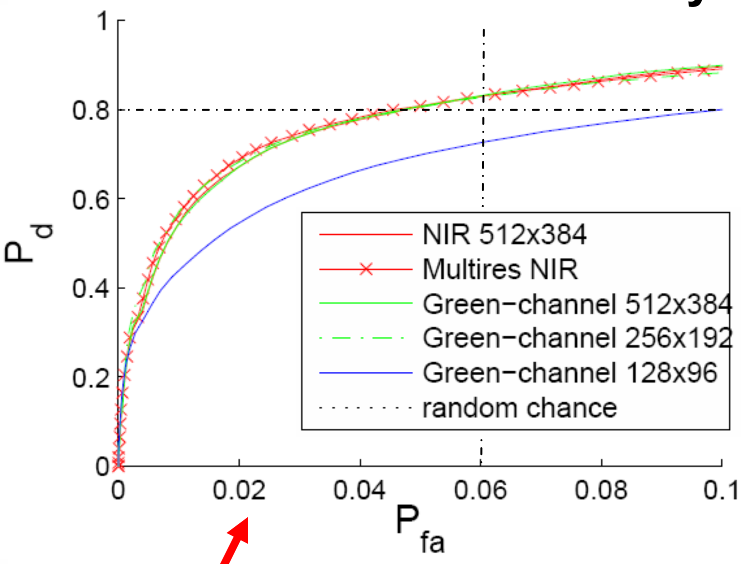
Note change in scale

- **> 90% probability of detection with 6% false alarm rate**
- **Similar performance across imaging frequency bands and resolutions**



Sunny Conditions

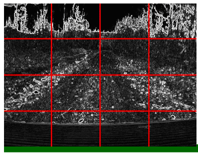




Note change in scale

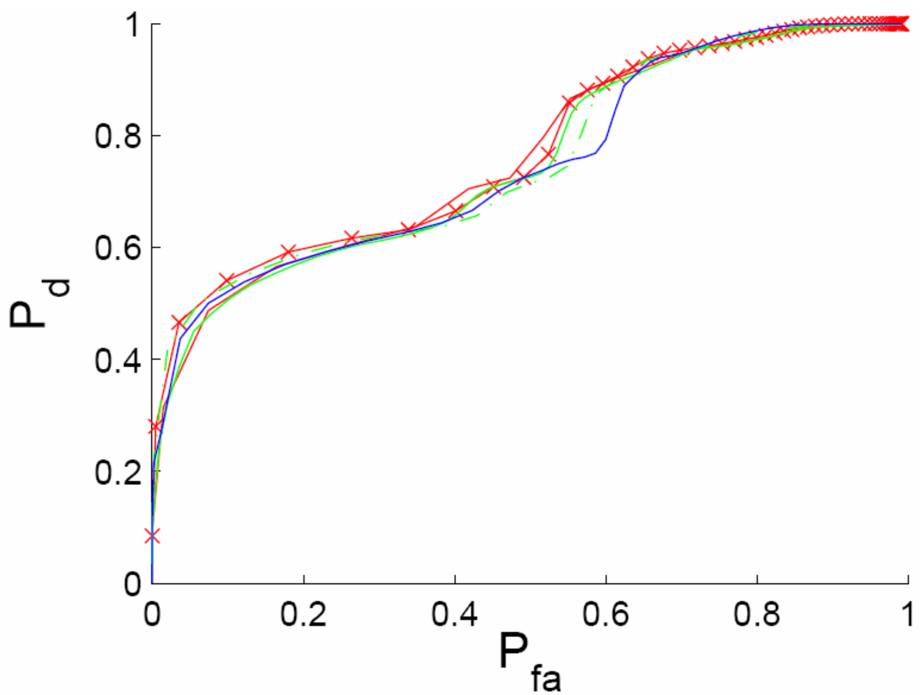
- > 80% probability of detection with 6% false alarm rate
- Strong shadows change as the sun moves
- CCD saturates when sun is in FOV

  → High Dynamic range environment

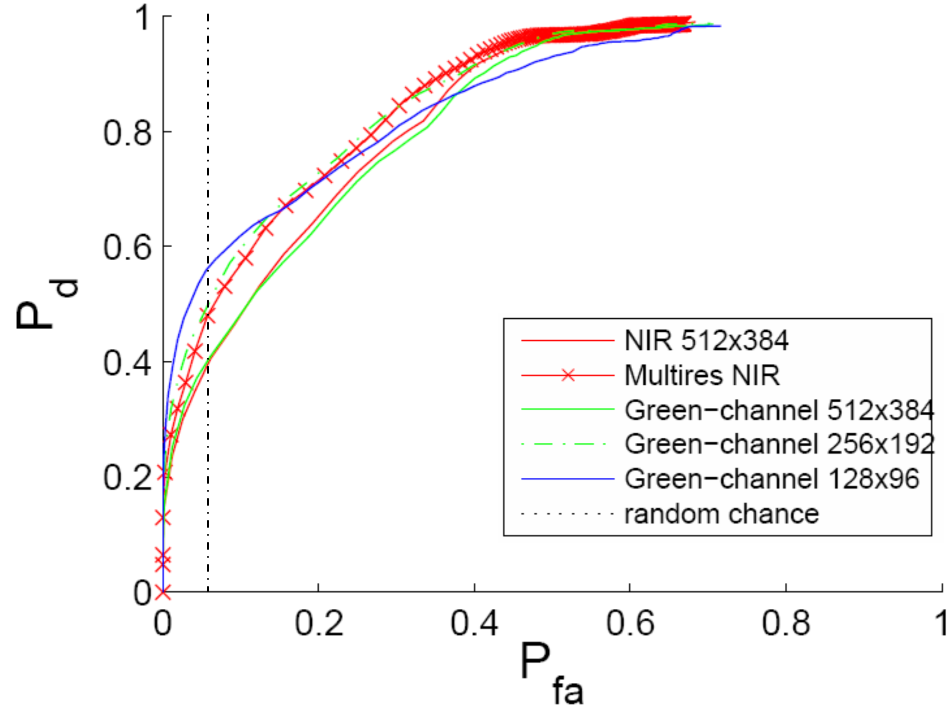


Night-time Conditions

All pairs

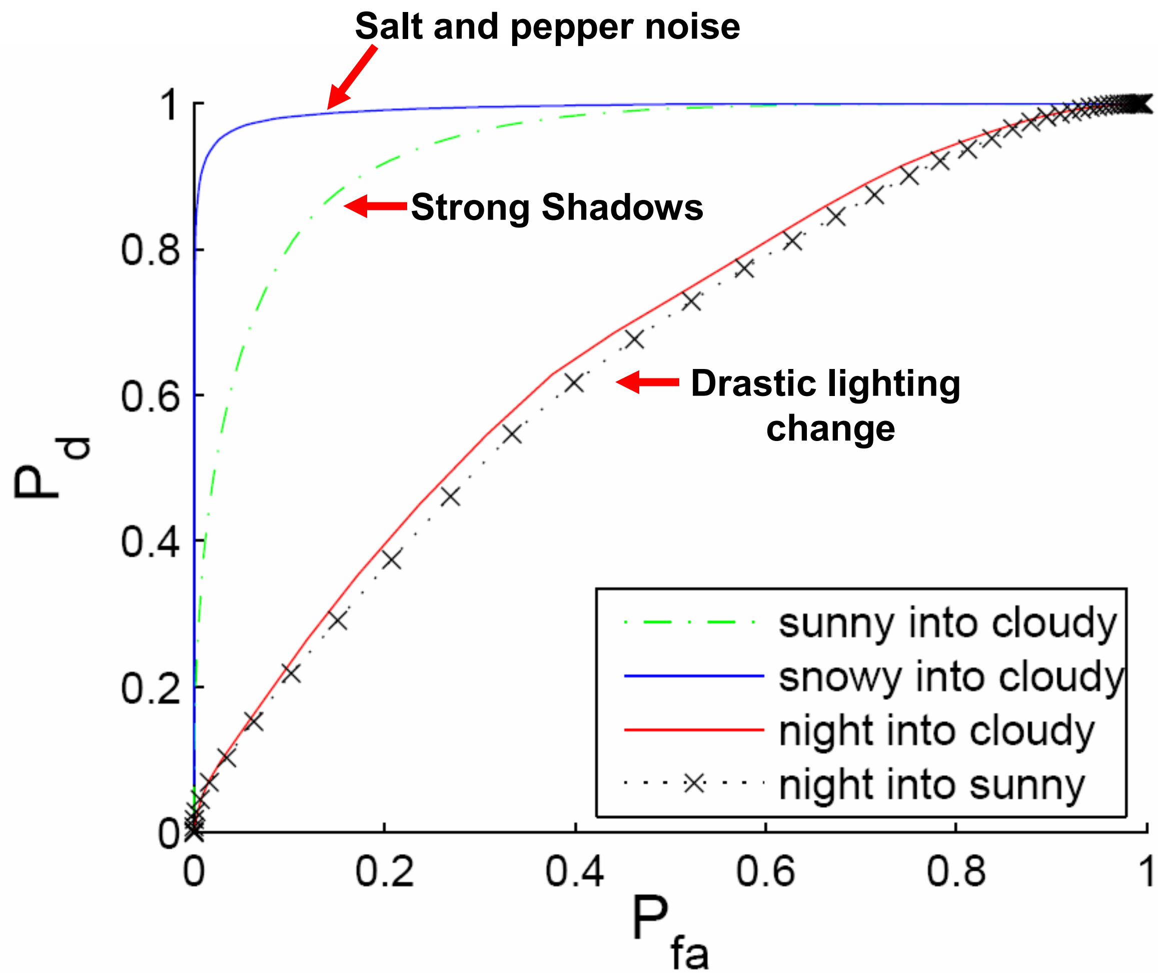


Closest Match Only



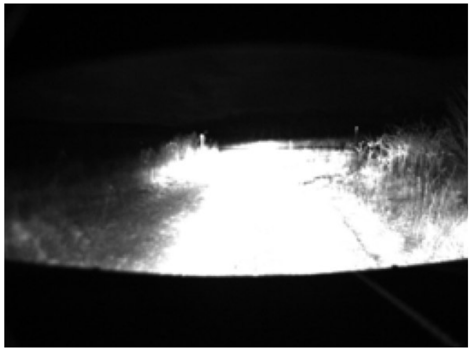
- >50% probability of detection with 6% false alarm rate

Performance Between Environmental Conditions

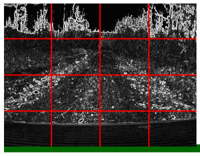


Day

Night



Night - NIR

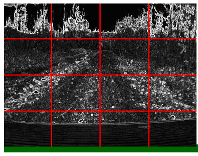


Perceptual Aliasing

Location 1

Location 2 (>50 m away)

- Robot kidnapping problem at every iteration
- Similar areas require filtering over time to reject false positives

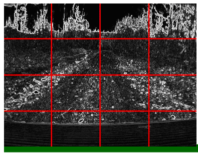


Conclusions

- **Pruning method**
  - →**Low computational and storage requirements**
- **Sufficient Accuracy for large environments**
- **Resolve ambiguities with more expensive:**
  - →**Temporal Filtering**
    - **HMM [3]**
    - **Maximum Likelihood [4]**
  - →**Perceptual features**
    - **SIFT**
- **Helpful if the environment constrains the robots configuration space**
- **Currently working on increasing feature robustness across illumination changes**

[3] A. Torralba et al. Context-based vision system for place and object recognition. ICCV, 2003.

[4] P. Rybski et al. A Comparison of Maximum Likelihood Methods for Appearance-Based Minimalistic SLAM. *ICRA,* 2004.



Acknowledgements

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- U.S. Army Tank-automotive and Armaments Command
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- Anthony Stentz and Marc Zinck
- Martial Hebert

Why have RGB and NIR?