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4 Workshop: Signal and Track Processing
Oliver E. Drummond, Consulting Engineer (United States)
Eric Hallenborg, Space and Naval Warfare Systems Center Pacific (United States)

Workshop Topic:

Signal and Data Processing

Presentation Titles:

Action windows with resource limits

and

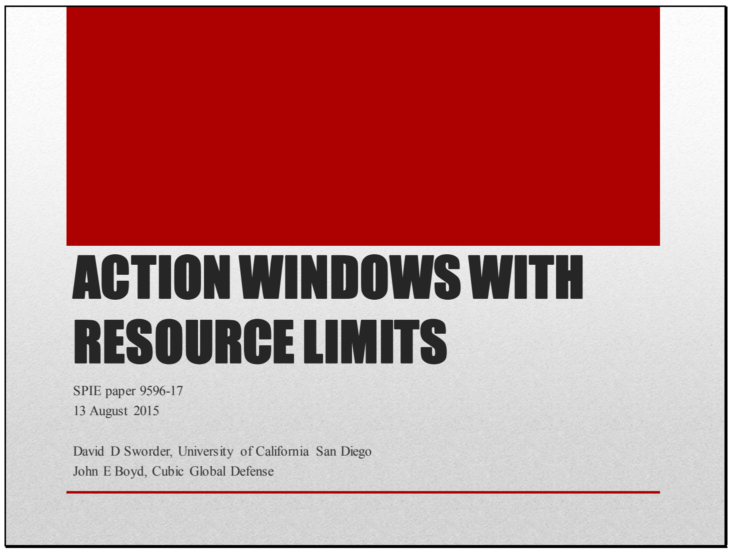
Implementation and evaluation of a detector of clutter embedded resolved targets in optical and infrared maritime video

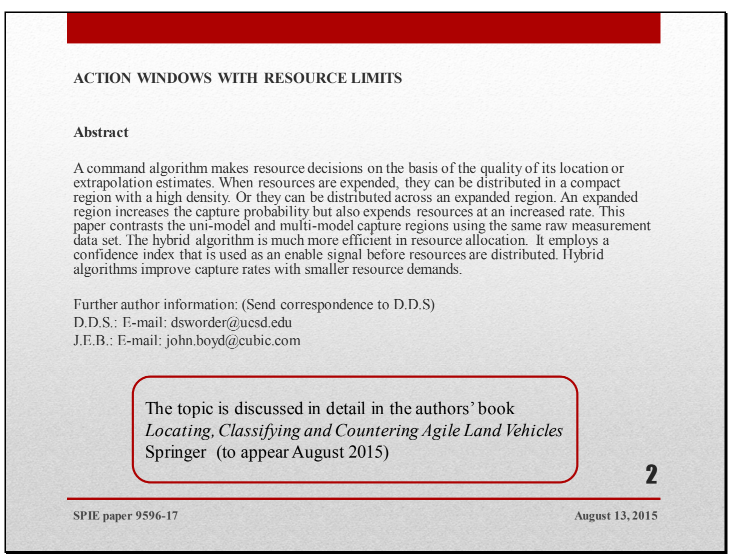
This Series of Conferences Has Added A Daytime Workshop.

The conference proceedings and the SPIE Digital Library will use a copy of each author's PowerPoint file instead of a manuscript.

Workshop I:
Action Windows with Resource Limits

David D. Sworder[1] and John E. Boyd[2]
[1]University of California, San Diego
[2]Cubic Global Defense Applications, Inc.





- Target tracking frequently supports tactical decisions in a command architecture
- Real-world actions must recognize constraints:
  - Limited available energy
  - Deployment and location of sensors
  - Detectability of expended energy
  - Processing resources
  - Time
  - Type and quantity of countermeasures
- This paper studies the ability of uni-model and multi-model tracking algorithms to support command algorithms in constrained deployment of sensing and countermeasure

Introduction

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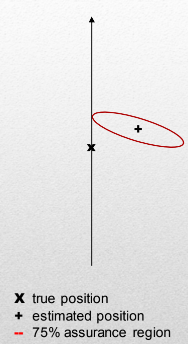
- A target of uncertain intent moves along a road grid
- Emplaced sensors determine range and bearing to the target at regular intervals
- We seek to determine target intent with the aid of a classifying sensor
  - The sensor can be directed to regions of varying size
  - Sensor accuracy is improved if the interrogated region is small
  - If target is classified hostile, countermeasures may be deployed, with greater effectiveness in smaller regions
- Thus, we seek small regions of assured target location
- Action windows (*assurance regions*) are ellipses containing a specified probability of target presence
  - Circular error probable (CEP) is a 50% *assurance region* constrained to equal axes.



The Topic

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- Single motion mode
- Standard CV plant dynamics model
- Range-bearing measurements are translated to lat-lon using estimated target position (extension)
- Plant noise is augmented to account for nongaussian maneuver modes (extension)

Uni-model Estimator:

Extended Kalman Filter

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SPIE paper 9596-17 August 13, 2015

- Explicitly allows for CV and CT motion
  - Maneuver modes are left (L), straight (S), and right (R)
- Accepts position, modal, or both observations as available
- Models each possible mode history for *l* time steps
  - For example, an *l*=3 path might be L| L | S -- (27 modes)
- Estimates probability of each modal *l*-path to generate the composite state estimate (path and position-velocity)
  - Estimator output estimate is a weighted Gaussian sum across all *l*-path estimates (a wavelet)

Multi-model Estimator:

Gaussian Wavelet Estimator

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- Each estimator provides an estimate of target position and an estimate error covariance
- To compare estimator performance, we normalize the position error and obtain the unit Gaussian white sequence $\tilde{\chi}_F[k] = F_{\chi\chi}[k]\tilde{\chi}[k] \sim \mathrm{N}(0,I)$
- We refer to the units of norm of $\tilde{\chi}_F[k]$ as σ; *e.g.*, if the norm of $\tilde{\chi}_F[k]$ is 2, we say the tracker estimate is off by 2σ.
- Action is directed to the interior of a σ-multiple of the centered covariance ellipse.
    - An action window of size 1.18σ should capture the target 50% of the time
- Larger action windows require more power
    - To increase capture probability to 95%, a 2.5σ ellipse is required with more than 6 times the power of a 1σ ellipse
- Comparison statistics are therefore
    - The number of hits (action window actually contains the target)
    - Area illuminated (a measure of required emitted power, detectability, or countermeasures)

Action Window Statistics

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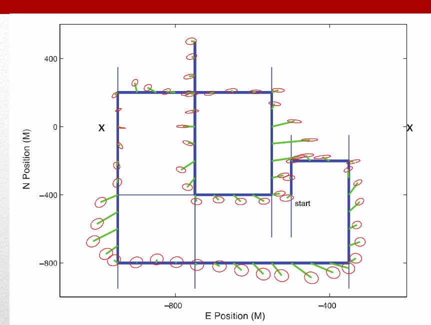

- **x** marks sensor locations
- Problem: Illuminate the target given tracker position and derived action window estimates

1: TARGET ILLUMINATION

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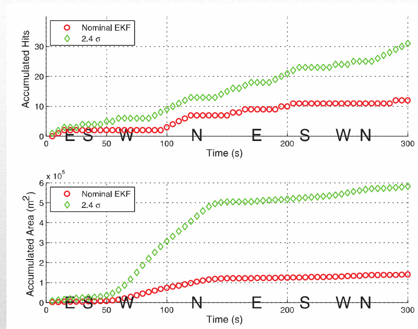
- 95% coverage is expected from 2.5σ windows.
- Actual coverage achieved is little better than 50%
- Area covered (energy) is more than 4 times that of a 1σ EKF



The Nominal EKF Illuminator

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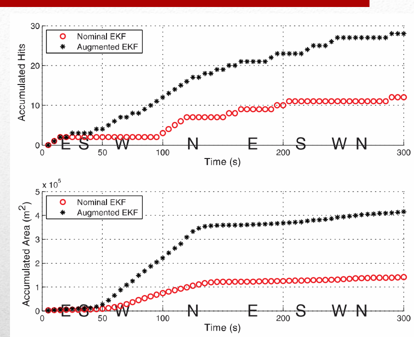
- Pseudonoise improves tracker performance but generates large action windows
- A-EKF windows contain the target about half the time
- It misses 9 straight points (probability of this event is 0.2%)
- It uses 71% of the energy required by the nominal EKF, still large



Augmented EKF Illuminator

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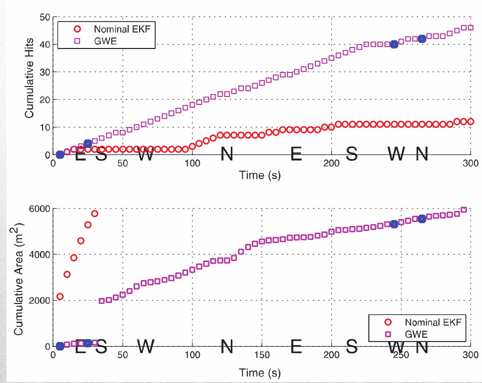
- GWE has more information than EKF
  - A crude speed measurement
  - Map-constrained motion
- Compared to nominal EKF,
  - Miss rate is far smaller
  - Energy is orders of magnitude smaller



The GWE Illuminator

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- Nominal and augmented EKFs achieved similar performance with similar energy expenditure
- GWE misses few illuminations
- GWE uses 99% less energy than the nominal EKF

Problem 1 Conclusions

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2: BALLISTIC FIRE CONTROL

Range measurement error: 2 m

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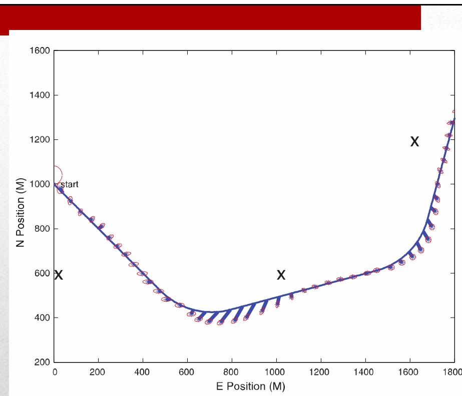
- A hostile target maneuvers in the plane
- We seek to neutralize the target with ballistic particles having range-dependent time of flight
- The tracker must predict the target position at the time of impact



2: BALLISTIC FIRE CONTROL

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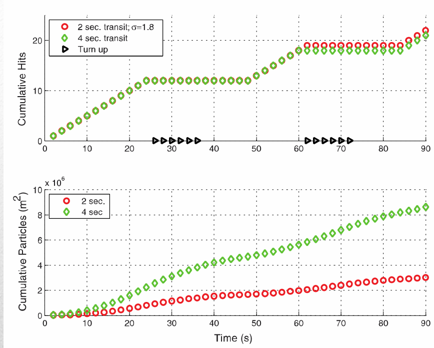
- Goal: 95% probability of fewer than 10 misses
  - Leads to 80% cover probability
  - Again, resources are constrained
- Simplifications
  - Fixed 2-s and 4-2 predictions
  - Hit probability is independent of location within action window
  - Cover sequence is iid
- EKF misses are more than double the specified 10
- Over 9 million particles are expended with uniform firing



EKF Tracker (1.8 σ-windows) 15

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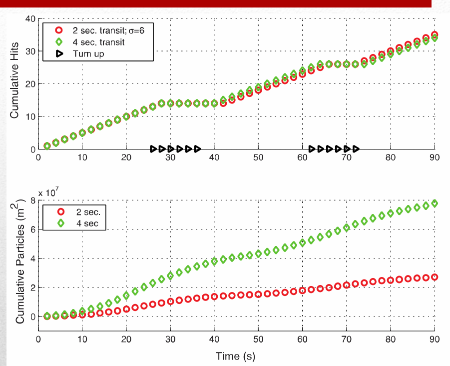
- Goal: 95% probability of fewer than 10 misses
  - Leads to 80% cover probability
  - Again, resources are constrained
- Simplifications
  - As before
- The 11 EKF-6 misses nearly meet the spec
- Over 80 million particles are expended with uniform firing



EKF Tracker (6 σ-windows) 16

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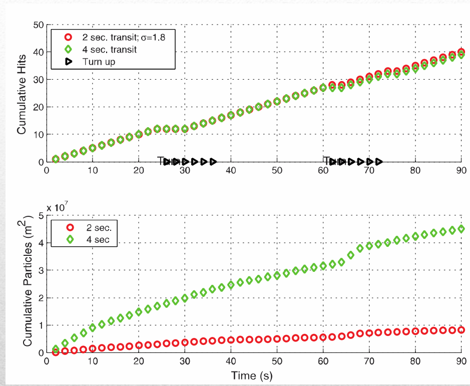
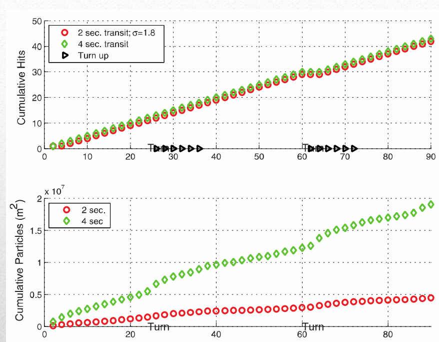
xviii

- GWE uses the same measurements as EKF
- Fewer misses (5) than the 6σ EKF (11)
- Expends fewer particles than EKF



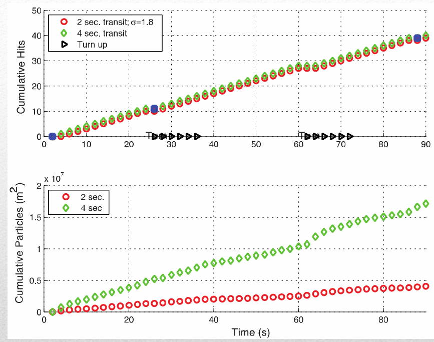
GWE Tracker [1.8σ windows] 17

- Augmented GWE uses more information
  - Modal measurement; 80% correct
- GWE fires on every measurement, using 20 million particles
- Misses 3 times, 2 for the 4-2 predictor



Augmented GWE Tracker [1.8σ windows] 18

- Same GWE, but with modified firing strategy
  - If modal confidence is above 75%, use 1.8σ action window
  - If not, do not fire
- There are three more misses, still fewer than the specified 10
- Particles expended reduced about 25%



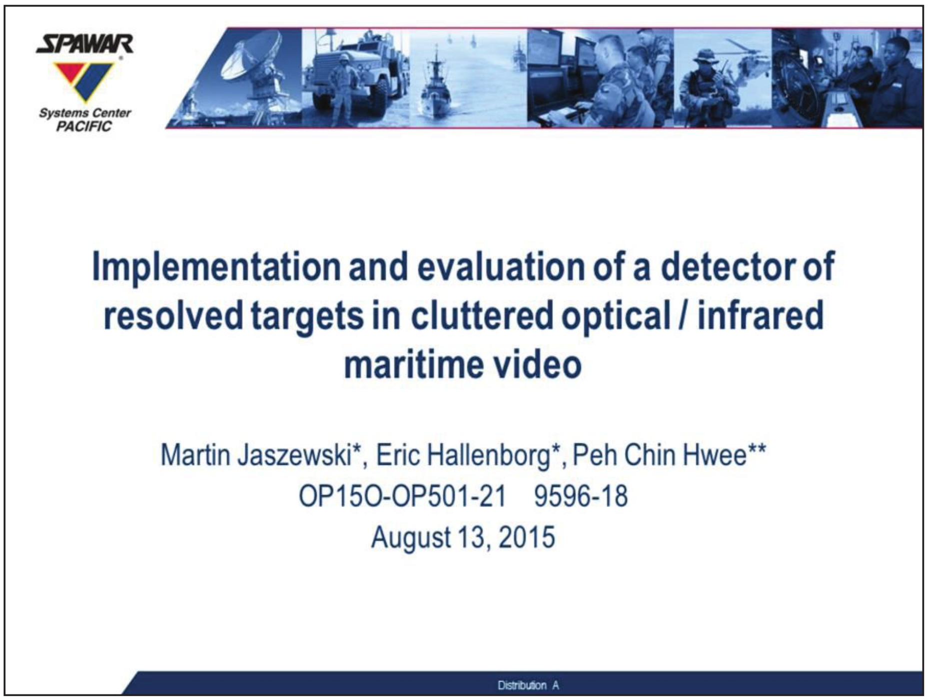
Augmented GWE Tracker [fire when confident]

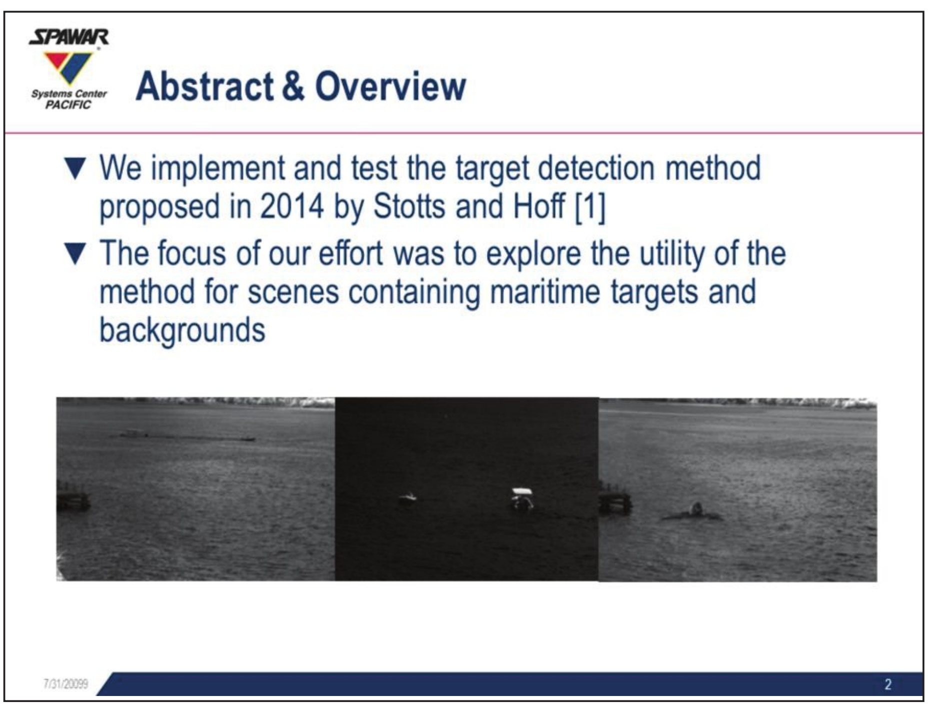
- A hybrid tracking algorithm demonstrated substantial advantages over the uni-model EKF in both problems studied
  - Location estimates and predictions are much more accurate with the GWE
  - Action windows have higher fidelity
  - Defensive resource expenditure is reduced an order of magnitude
- Use of a para-measurement can further improve the hybrid tracker performance
  - Benefit is more from reduced uncertainty (smaller action windows) than from improved prediction accuracy
- The fire-when-confident strategy further reduced resource consumption at a small increase in number of misses
- The augmented GWE is harder to implement than EKF or GWE, but in applications where particle cost or inventory is considerable, the more nuanced approach may be warranted

Conclusions

Workshop II:
Implementation and evaluation of a detector of resolved targets in cluttered optical/infrared maritime video

Martin Jaszewski*, Eric Hallenborg*, and Peh Chin Hwee**
*Space and Naval Warfare Systems Center Pacific, San Diego, USA
**ST Dynamics Pte Ltd., Singapore, Republic of Singapore





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Abstract Full Text

We implement the method proposed in 2014 by Stotts and Hoff (SH14) [1] to automatically detect resolved targets embedded in background clutter. The SH14 method provides a test statistic which emphasizes comparing apparent contrast rather than signal to noise ratio. The SH14 authors demonstrated through analysis and simulations that their method can detect low or even zero contrast targets in clutter if the background variance is greater than the common system noise variance.

We apply this detector to the maritime domain in which marine vessels are typically found amid clutter such as waves, glint, whitecaps, wakes, port and harbor infrastructure, etc. Our implementation provides an estimate of the common system noise variance whereas SH14 uses a fixed value in their theoretical validation. We estimate the system noise from the video directly without any prior knowledge of the imaging sensor parameters. After considering several noise models with different assumptions about the spatiotemporal variance of system noise we will compare the results to justify our model selection. Further, we provide a means to compute the background statistics needed by the SH14 detector, following the approach in [2] by using a sliding annulus with a guard band and distinct background mean and variance estimation bands.

Finally, we will evaluate the detection accuracy of our implementation of the SH14 detector using a video dataset depicting marine vessels in real world maritime environments using the PASCAL VOC Challenge evaluation framework. We will analyze the computational performance of our detector as a function of various input parameters.

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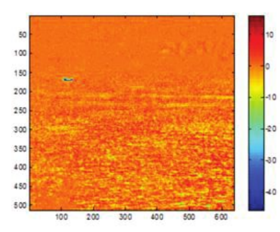
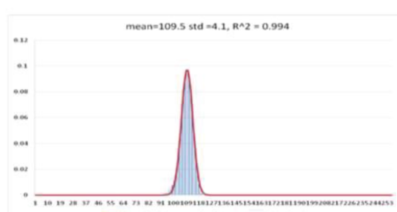
Statistical Resolved Target Detection (1/3)

- Statistical detection aims to make a reasoned and firm decision about the presence/absence of a target based on:
  - Measurements from an image or video frame
  - A statistics based model of noise/clutter





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Statistical Resolved Target Detection (2/3)

- What is "resolved" detection? How is it distinct from the unresolved model?
  - Unresolved target detection assumes that pixels containing targets are composed of Target + Noise + Clutter
  - Resolved target detection assumes that pixels containing targets are composed of Target + Noise, and pixels containing clutter are composed of Clutter + Noise
    - Also known as "extended" targets
    - Used by Stotts and Hoff (2014) for their target detector

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Statistical Resolved Target Detection (3/3)

- What are the key predictions of SH14?
  - Detection performance depends on apparent contrast, not SNR
  - Detection performance depends on background clutter to common system noise ratio
- What are the open questions?
  - How to obtain appropriate target signature?
  - How to estimate system noise?
  - Can background clutter be modeled as Gaussian?
- What are the questions we can address by using real-world video?
  - It gives us a path to validate of the theory using incremental crawl-walk approach

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Experiment

- Goal, Scope
  - Explore the utility of the method for scenes containing maritime targets and backgrounds
- Methodology:
  - Evaluate assumption that background clutter is Gaussian
  - Our crawl/walk approach moves past simulated targets in simulated background clutter:
    - Crawl: simulated target in real background clutter
    - Walk: real target in real clutter
  - How do our results compare to predictions of SH14?
- Limitations?

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EO/IR Surveillance Video from Singapore

- Electro-optical
- IR (short/mid/long-wave)
  - Low contrast boats
  - Gaussian clutter background

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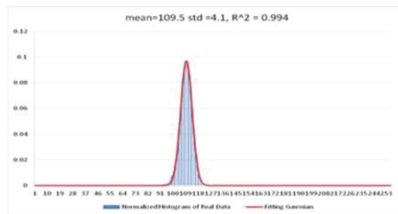
EO/IR Surveillance Video from Singapore

- ▼ Electro-optical
- ▼ IR (short/mid/long-wave)
  - Low contrast boats
  - Gaussian clutter background



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Clutter Analysis

- ▼ Analyzed example LWIR and SWIR videos
- ▼ Spatial and temporal
  - 20x20, 40x40, 80x80, 120x120
  - Compare results for single frame vs. averaged across 100 frames
- ▼ Gray level histograms can be adequately approximated by a Gaussian distribution
  - As expected, fit was better when sampling with a larger window and/or across more frames
  - Poorest R^2 measure: 0.854 (1 frame, 20x20 window)

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Crawl/walk approach

- Stotts and Hoff (2014) demonstrated their method using a grid of simulated targets on simulated background
- We used a crawl-walk approach to progressively add more realistic conditions
  - Crawl: simulated target in real background clutter
  - Walk: real target in real clutter

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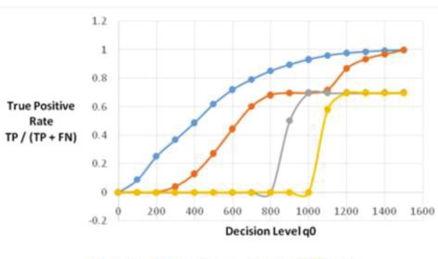
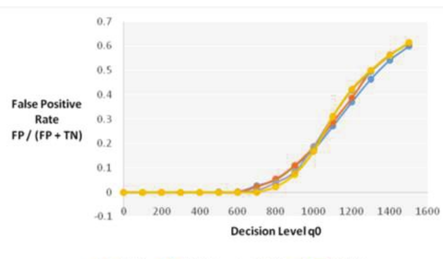
Results: Crawl

- SWIR-31148, frame 269





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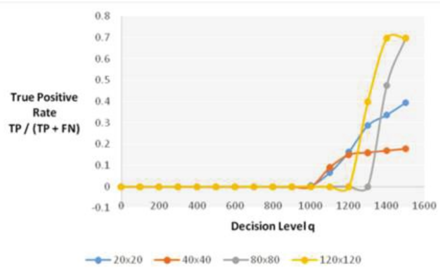
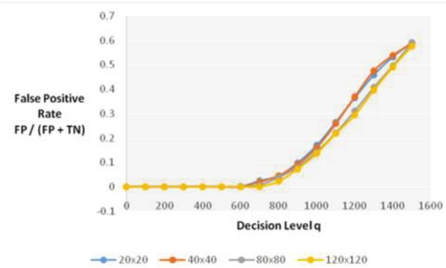
Results: Walk

- SWIR-31148, frame 269





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Conclusions

- Summary
  - Detection performance also depends on target signature selection, which may be scale/pose variant
- Acknowledgements
  - US Office of the Secretary of Defense (OSD), Coalition Warfare Program (CWP)
  - Republic of Singapore, Ministry of Defence (MINDEF), Defence Research and Technology Office (DRTech)
- References
1. Stotts, L., and Hoff, L., "Statistical detection of resolved targets in background clutter using optical/infrared imagery," Applied Optics, July 2014.
2. Vondrick, C., Ramanan, D., and Patterson, D. "Efficiently scaling up video annotation with crowdsourced marketplaces," European Conference on Computer Vision, Crete, Greece, September 2010.

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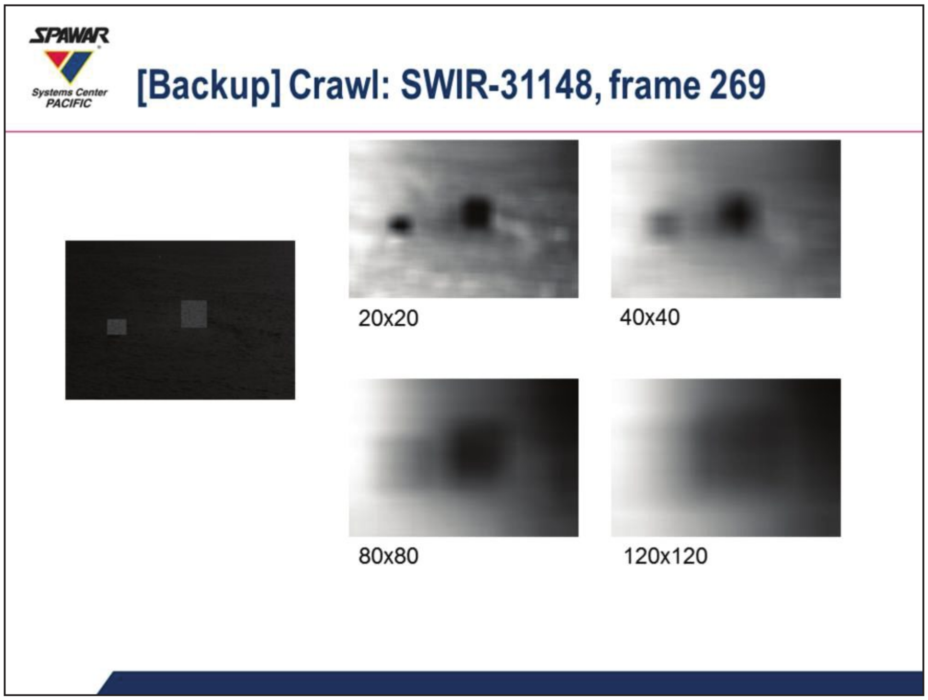
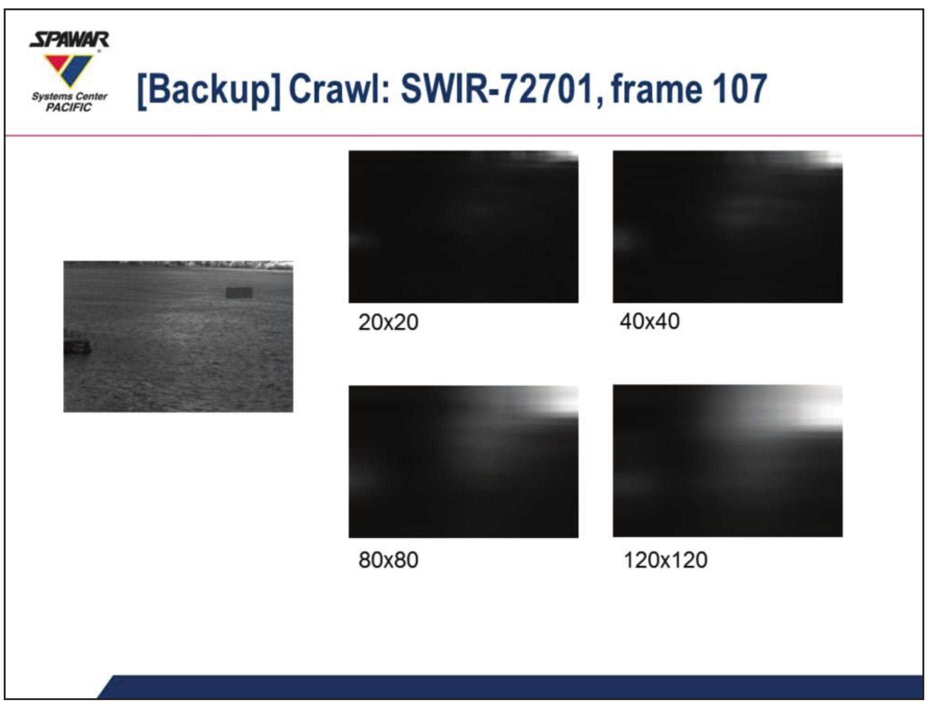


Test statistic images have been normalized for viewing purposes. The pixel intensity values represent the relative confidence that the pixel contains anomalies (targets). Darker values represent relatively higher confidence that an anomaly is present.



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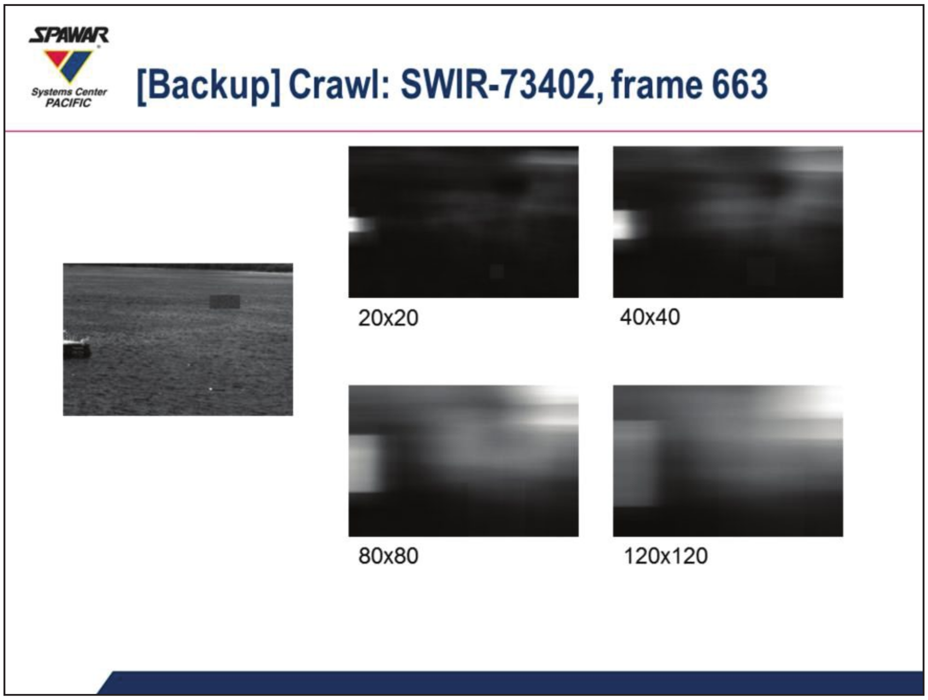

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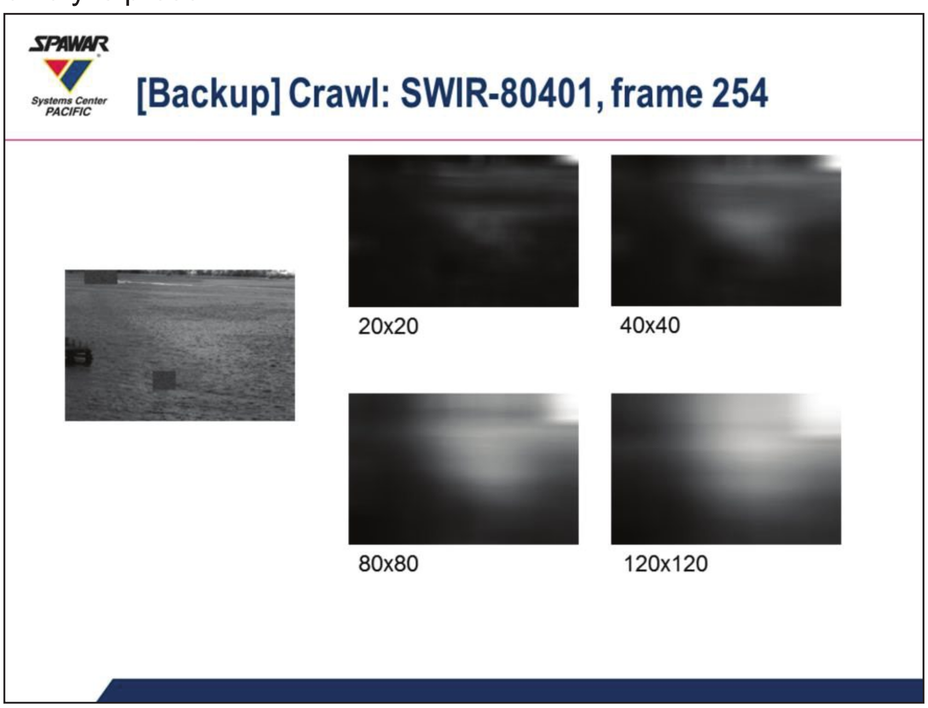

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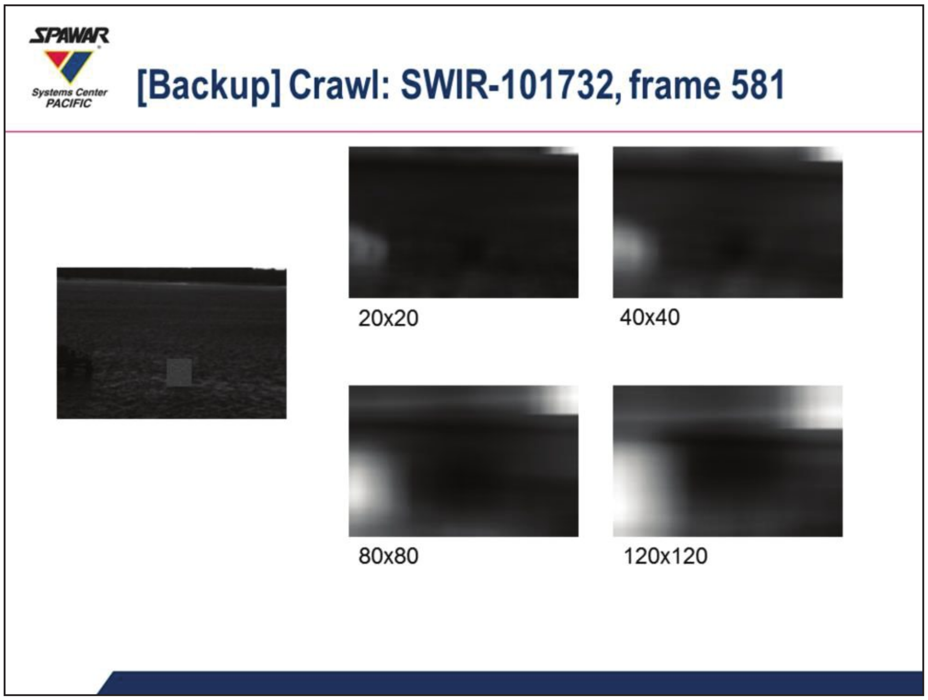

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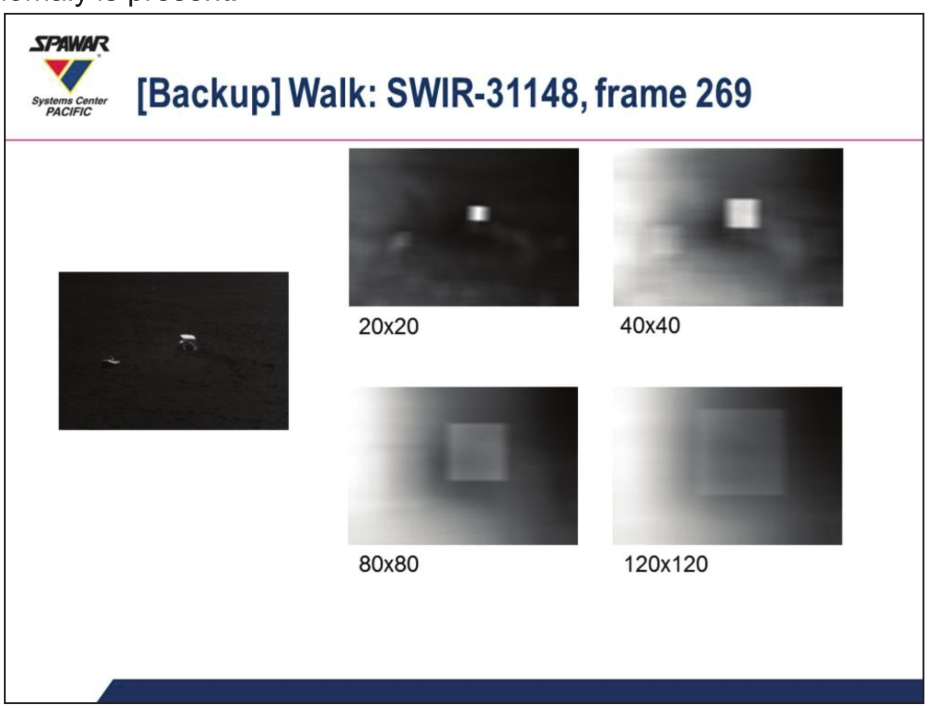

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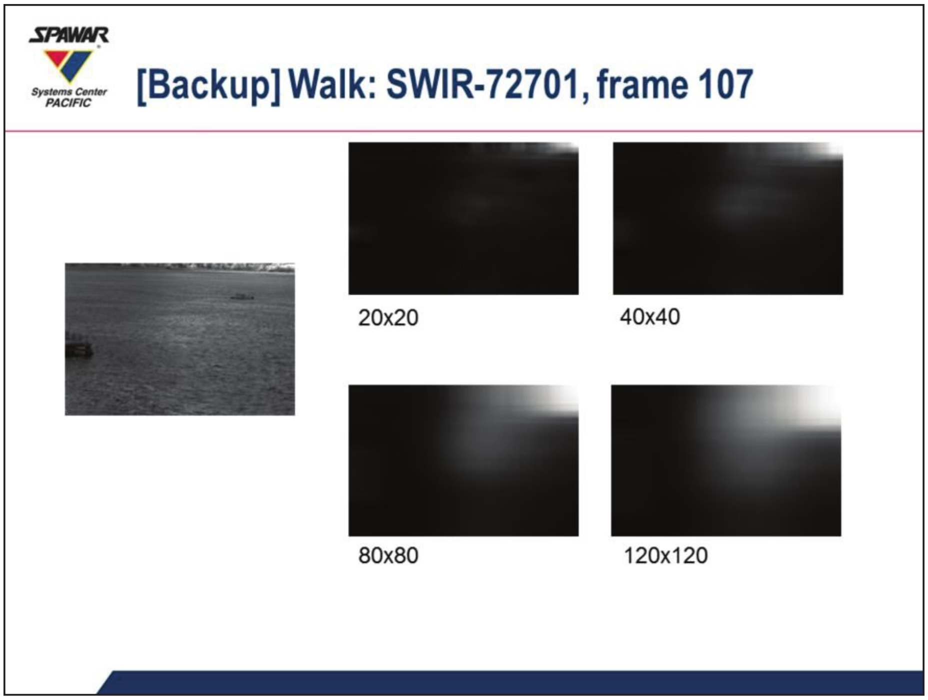

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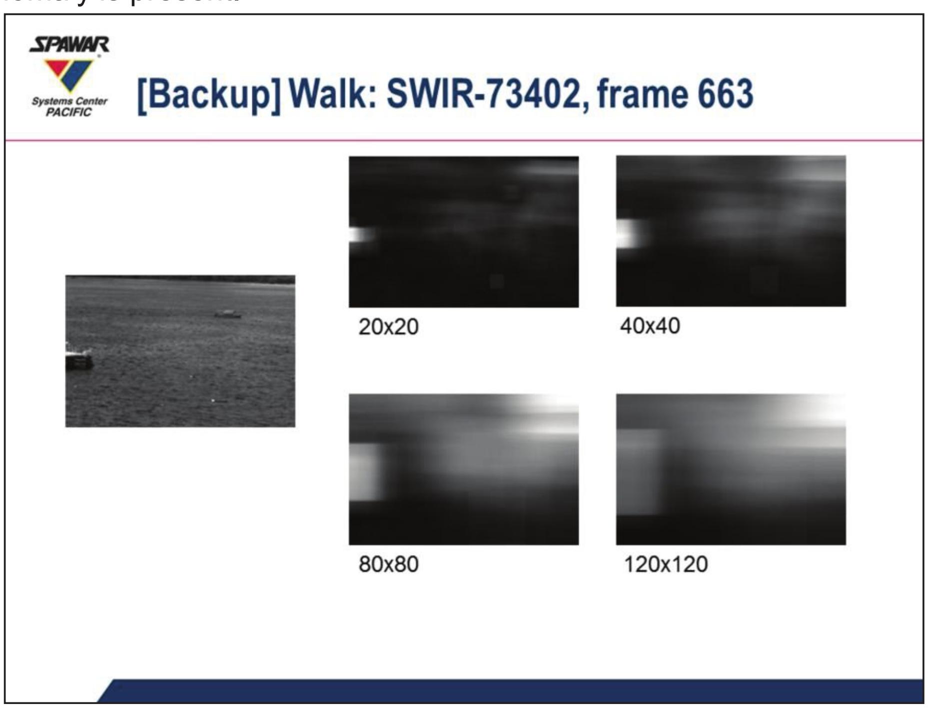

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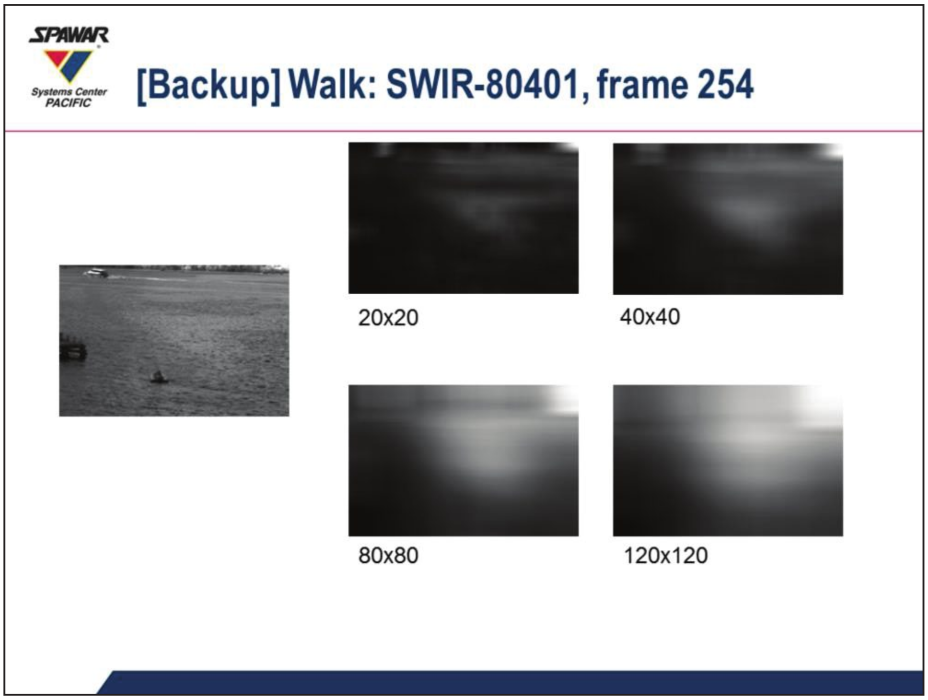

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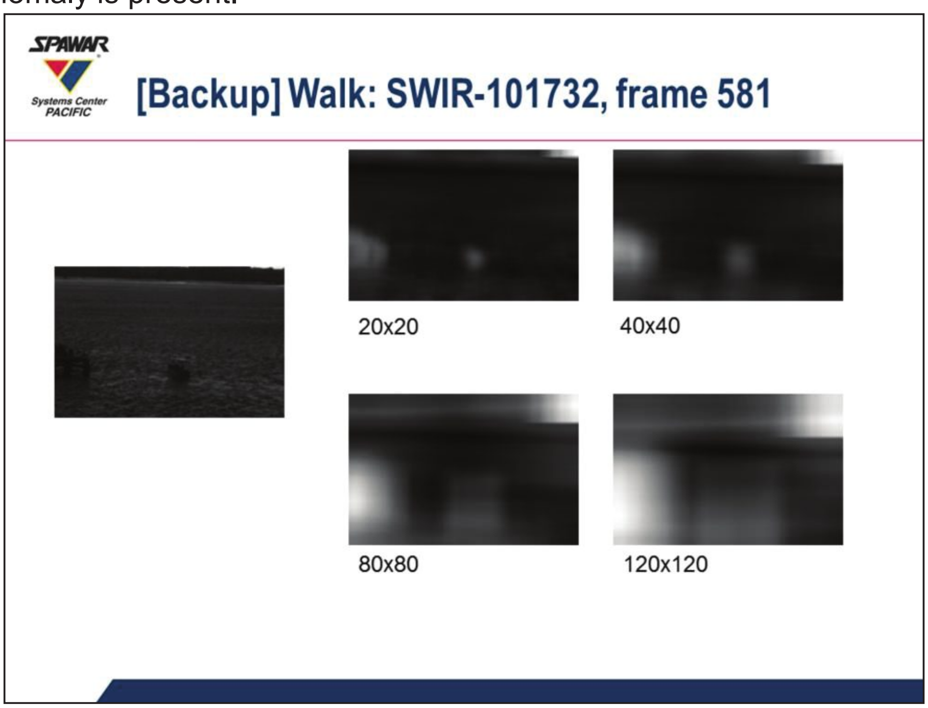

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