Towards Robust ATR in Sonar Imagery

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Outline

1. Introduction
   - The future of Mine Counter Measures (MCM) in the UK
   - Object Recognition
   - The Detection /Classification Problem
   - The Clutter Issue

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   - Fusion Techniques
   - High Resolution Imaging - What do we need?

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   - Fusion Techniques
   - High Resolution Imaging - What do we need?
4. Recent Developments
   - SAS
   - Acoustic Cameras
   - New Algorithms

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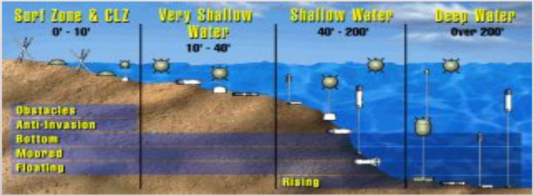
An (brief) introduction to Mine and Counter Measures

What is MCM?

The ability to detect, identify and neutralise mines. Mines can be floating, mid-water (moored) or on the bottom.



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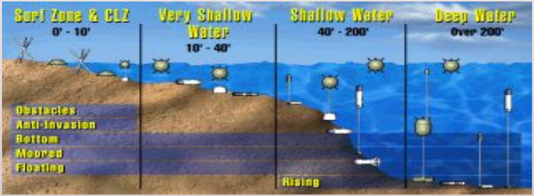
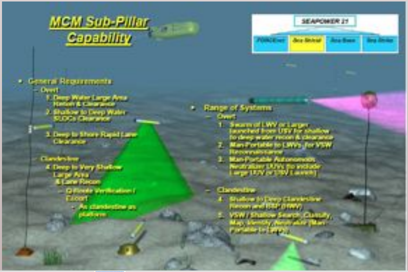


Why does it matter?

Mines are cheap and can cause damage to large assets (asymetric threat). Modern warfare has recently focused on external intervention. 90% of the world's trade is carried by sea, including oil...

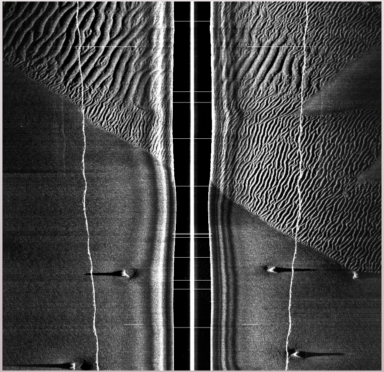
A paradigm shift in MCM

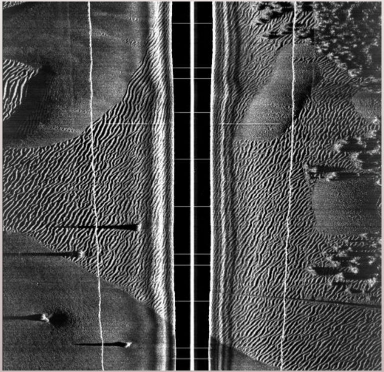
- Traditional MCM is done using dedicated ships with hull mounted sonars.
- These are expensive to run and maintain and need to be able to run over minefields for sweeping.
- New doctrine based around multi-purpose metallic ships with unmanned systems to support the MCM function
- renewed emphasis on automatic target recognition to support in-stride detection, identification and neutralisation



Typical Conops for autonomous systems based MCM

- Vehicle is doing a Search / Classify / Map mission
- Sensor of choice is Sonar
- It is a signal and image processing problem
- Typical sonar image with targets:





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- Validation and Comparison of algorithms remains a real issue in underwater.

Object Recognition - Methods

Techniques Based on Appearance:

- Require high resolution data (Side Scan, SAS)
- 3D information (Bathymetry, Interferometry)
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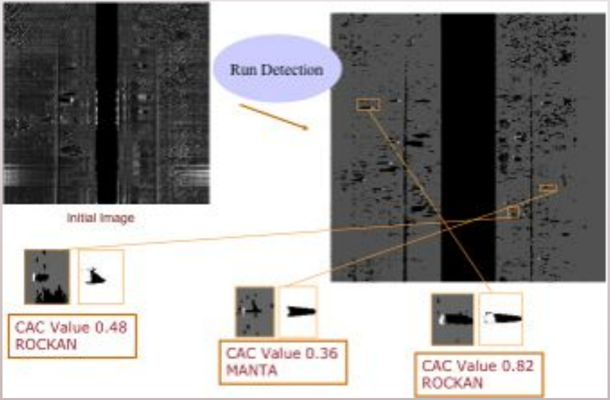
Object Recognition - Steps to Identification

Generally 3 Steps but can be combined:

- **Detection:** Is this a possible Mine Like Contact?
- **Classification:** Is this a Mine?
- **Identification:** Which Type of Mine is this?



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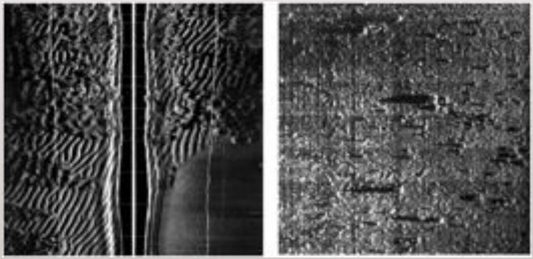

Example of textured seabed (Left) and flat seabed cluttered with small rocks (Right)

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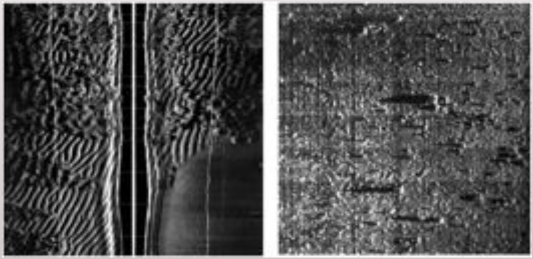

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- We now start to have good models of clutter and can use context to drive algorithms behaviours [26]
- But estimation of model parameters is difficult.

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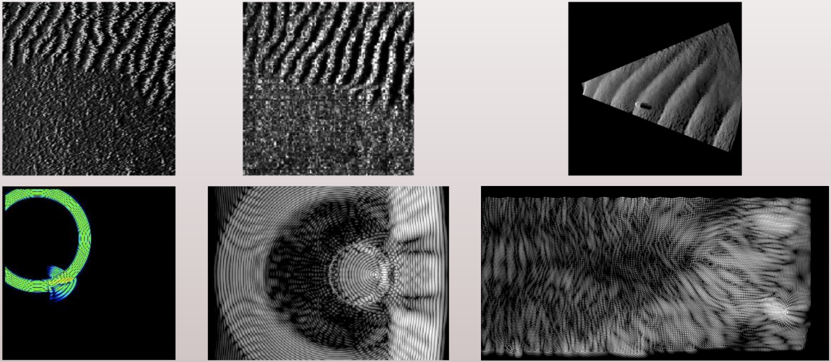
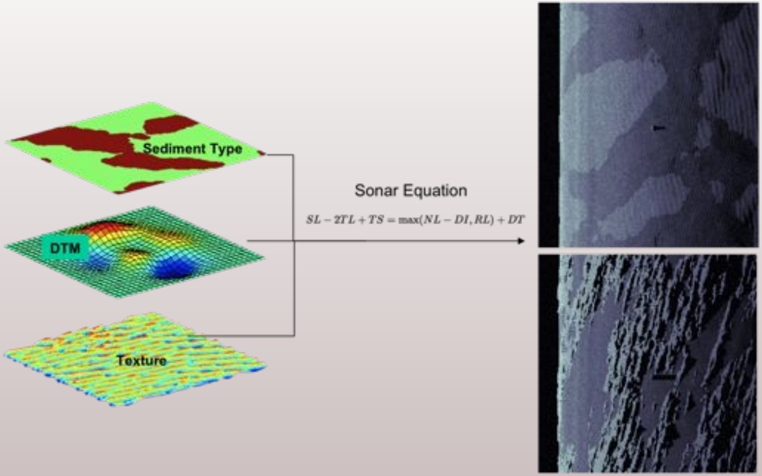
Simulation Tools - Examples



Ray Tracing Simulation (top) and PSTD simulation (bottom)

Simulation Tools - Energy Based Approach [26]

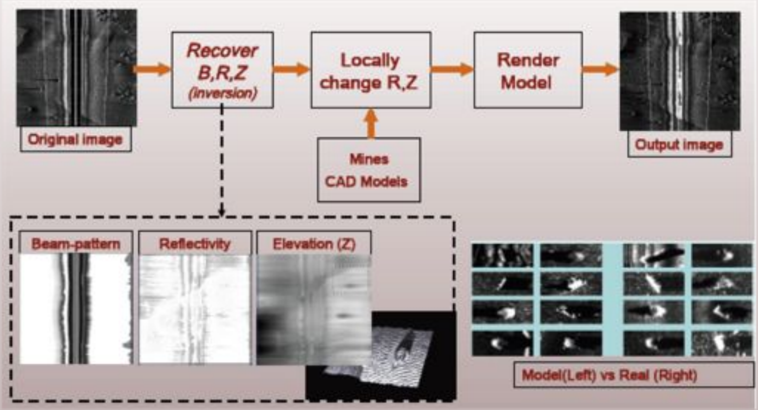


SL: Source Level for the projector, DI : Directivity Index, TL :Transmission Loss, NL :Noise Level, RL : Reverberation Level, TS : Target Strength and DT : Detection Threshold.

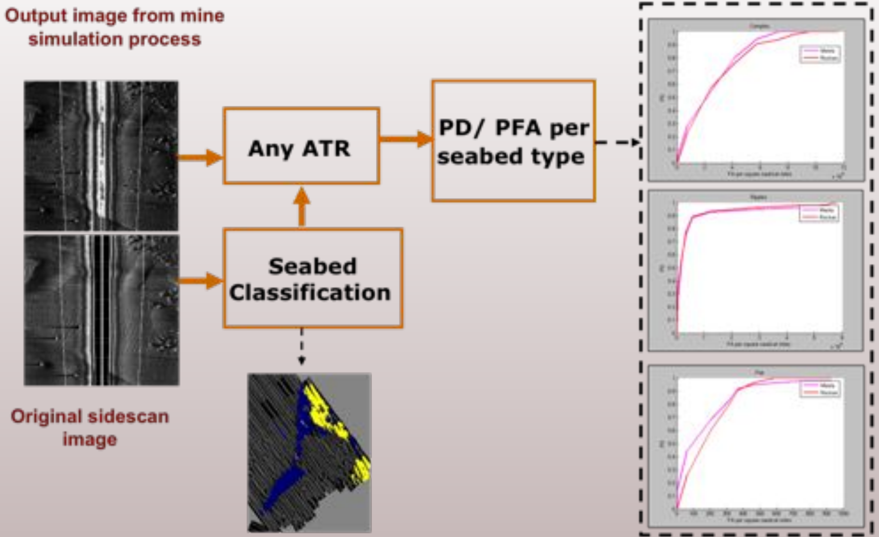
Augmented Reality [9]

Idea:

Insert simulated targets in real data from real environments.

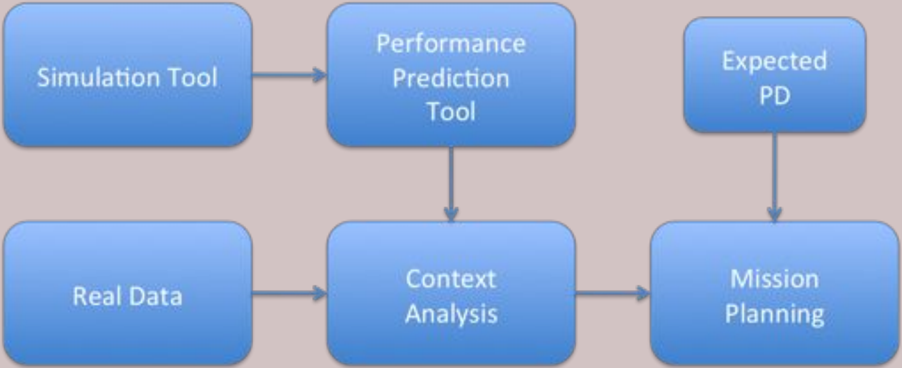


Route to systematic evaluation



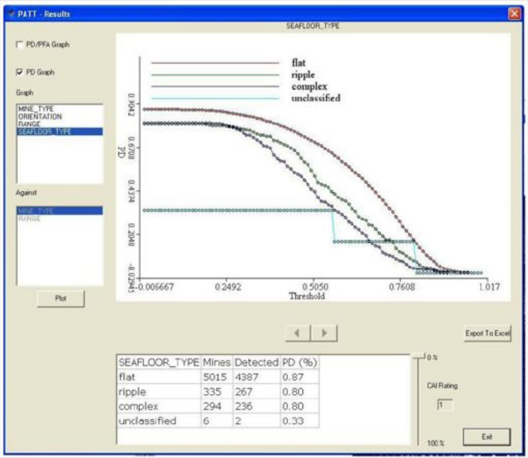
Route to optimised mission planning

Optimal Planning for ATR



Route to optimised mission planning

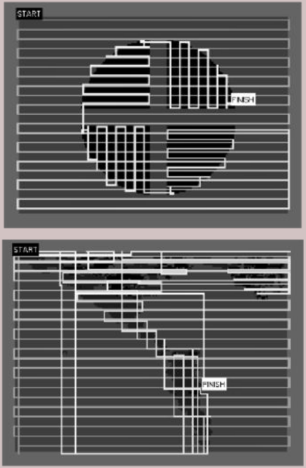
Performance Prediction Tool



Route to optimised mission planning

Optimal Planning Examples

Context Map

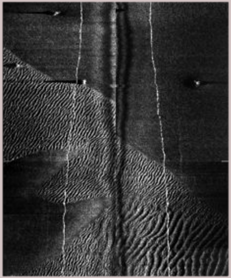


Generated Trajectories for $P_d >= 0.9$

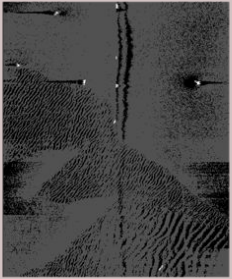
Model Based Approaches

Markov Random Field Based Detection / **Mathematical morphology** [23, 2, 31]

- Segmentation of images based on priors (highlight / shadow pairs).
- Works well on easy seabed types



Original Image

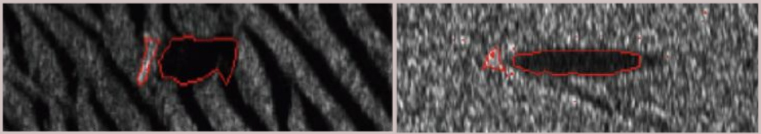


Segmented Image using Target Priors

Model Based Approaches

Snake Based Detection [10, 30]

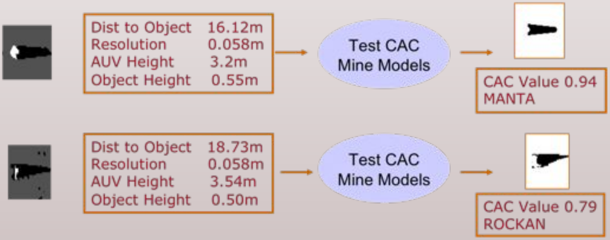
- Extracts shadow shape for classification.
- Works well on lowly textured seabed
- Can be extended to use both echo and shadow



Model Based Approaches

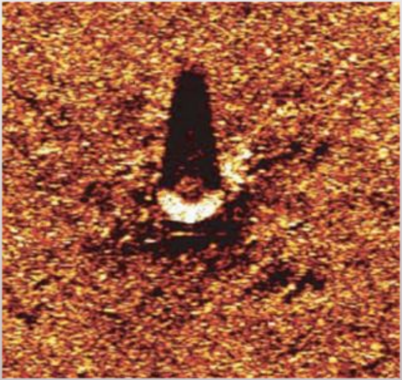
Simulation Based Classification [19]

- Use simulation of compare highlights and shadows of potential targets
- Generally poor results on side-scan sonar (resolution is too low)



Model Based Approaches

This can be extended to Synthetic Aperture Sonar
Issue is the definition of a robust image to image distance function in presence of noise



SAS Real Target Image (Courtesy NATO CMRE) [24]

Simulated Target using a Lambertian Model (3cm)

Learning Based Approaches [9, 5, 25, 16, 17, 32, 8, 7]

- Use large datasets (simulated or real).

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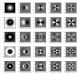

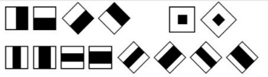

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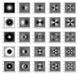
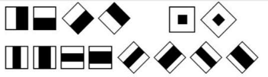




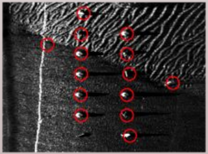
- Results on Simulated and Real Data:

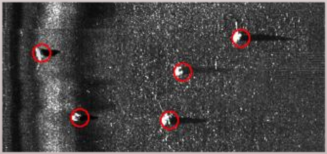
%	Non-t.	Cyl.	Manta	Rockan
Non-t.	92	4	4	0
Cyl.	11	80	9	0
Manta	1	2	97	0
Rockan	0	0	6	94

%	Non-t.	Cyl.	Manta	Rockan
Non-t.	96	4	0	0
Cyl.	0	19	81	0
Manta	0	12	88	0
Rockan	0	0	20	80

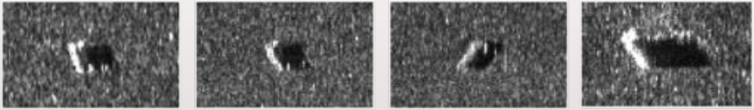
Error(simulation) : 9%

Error(real) : 18%





MultiView Fusion [29]

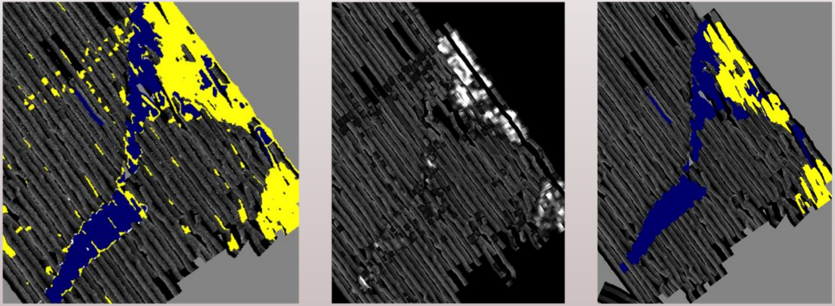


Mono-Image Belief					Fused Belief				
Obj	Cyl	Sph	Cone	Clutt	Objs Fused	Cyl	Sph	Cone	Clutt
1	0.70	0.00	0.00	0.21	1	0.70	0.00	0.00	0.21
2	0.83	0.00	0.00	0.08	1,2	0.93	0.00	0.00	0.05
3	0.83	0.00	0.00	0.08	1,2,3	0.98	0.00	0.00	0.01
4	0.17	0.00	0.00	0.67	1,2,3,4	0.96	0.00	0.00	0.03

Dempster-Shafer Fusion Example

Context Analysis [28]

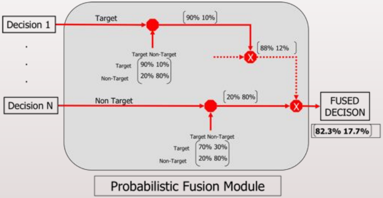
- Use texture features to segment / classify seabed (Flat, Ripples, Complex)
- Use Clutter Density to Clean Maps and extract difficult areas.



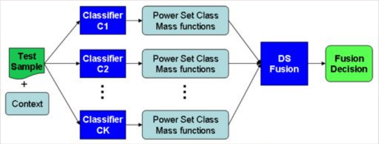
Texture Based Classification | Clutter Density | Fused Map

Courtesy of SeeByte Ltd and NATO CMRE

Context Dependent Classifiers Fusion [22, 34, 33, 12]



Probabilistic Fusion Architecture



PD/PFA	PFA	PD
Off-line Conf Mat for All Sea-Bed	0.0025 (3/1214)	0.917 (760/829)
Off-line Conf Mat for Each Sea-Bed	0.0008 (1/1214)	0.891 (739/829)

Context Aware Fusion Architecture

High Resolution - What do we need? [26]

Idea

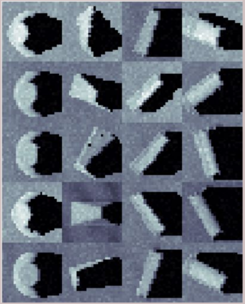
Study the minimum resolution required to perform detection and classification.
Performance estimation using eigen-spaces methods for object classification.

Consider a set of k images for an object of class L:

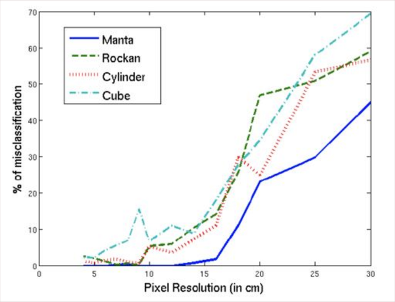
- Each images M_i of size $m \times n$ is first rasterized in a vector $M_i^{'}$ of size mn
- For each class, the mean and standard deviation of the class is calculated.
- Normalise each training vector: $T_i = \dfrac{M_i^{'} - M_{mean}}{std(M_i^{'})}$
- Compute the covariance matrix of $\{T_i\}$ and extract the first p eigenvectors. This generates a subspace Θ_L
- For each new target I_n, project it onto each subspace Θ_L and allocate the class as: $Targ = min_L \|I_n - P_{\Theta_L}(I_n)\|$, where $P_{\Theta_L}(I_n)$ is the projection of I_n on subspace Θ.

High Resolution - What do we need? [26]

Influence of Resolution



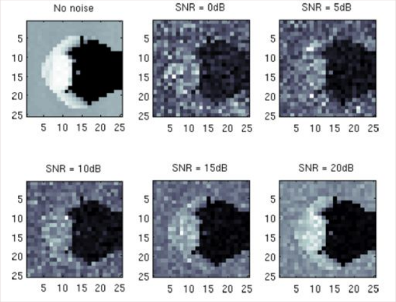
Subset of training images

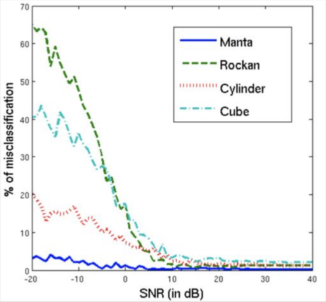


Influence of Resolution on classification

High Resolution - What do we need? [26]

Influence of Noise



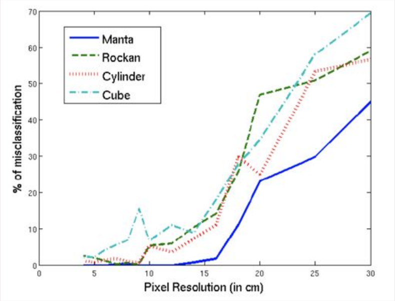


Images for various SNRs

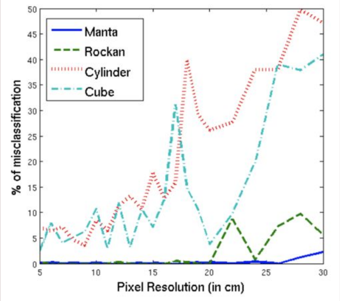
Influence of Noise on classification

High Resolution - What do we need? [26]

Highlights or Shadows?



Classification Performances for Highlight



Classification Performances for Shadow

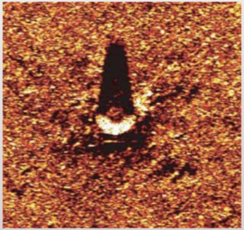
High Resolution - What do we need? [26]

Summary

- Highlights should be used for very high resolution imagery (SAS, VHF Sonar 1MHz+)
- Shadows are better (and easier) for mid resolution imagery
- In practice, noise level is not an issue but clutter is
- Target is P_{fa} of 10^{-8} or less!

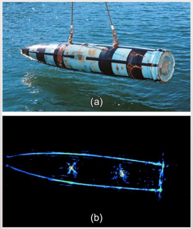
SAS for ATR. Do we Need anything else?

- Image quality of latest SAS sensors is extraordinary.
- Little difference between HF SAS and Lambertian Based Simulation.



SAS Real Target Image [1]

Simulated Target using a Lambertian Model (3cm)



Circular SAS Image [11]

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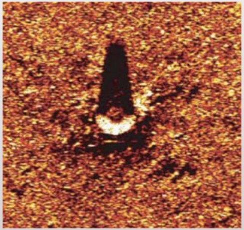

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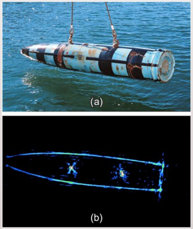

Circular SAS Image [11]

- But not widely available

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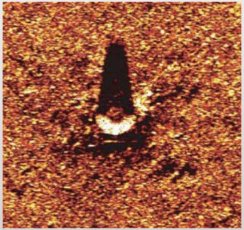

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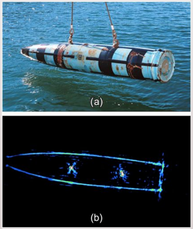

Circular SAS Image [11]

- But not widely available
- Requires expensive platforms and sensors

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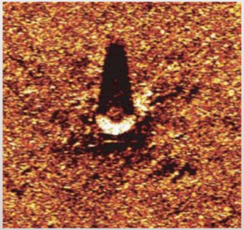

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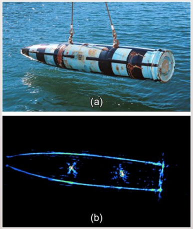

Circular SAS Image [11]

- But not widely available
- Requires expensive platforms and sensors
- Still does not provide sufficient performances in complex environments

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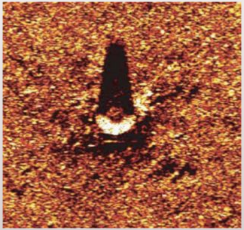

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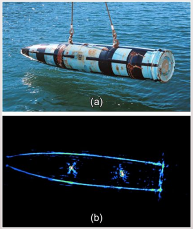
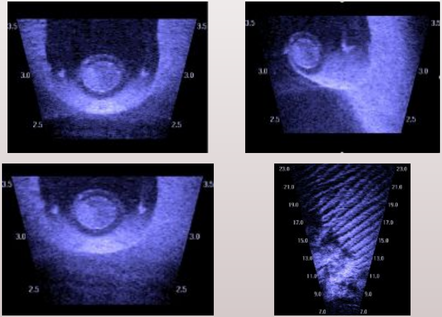


Circular SAS Image [11]

- But not widely available
- Requires expensive platforms and sensors
- Still does not provide sufficient performances in complex environments
- Coherence is necessary for image formation. This can be destroyed by multipath in shallow water.

New Video-Rate Acoustic Sensors for Identification

- Image quality ever improving



Various DIDSON Images, Courtesy of Sound Metrics

- Target Tracking and Bayesian Filtering now possible.
- Multiple angles on targets. MultiView, 3D reconstruction.

Examples

(Manta.avi)

Tracking and Identification of objects in Blueview Data

Video Courtesy of SeeByte Ltd

Cascade Classifiers for High Resolution Sensors

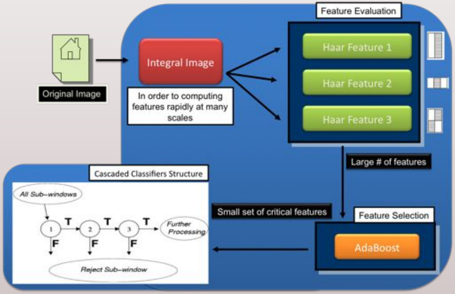
Cascade Classifier

- Proposed by Viola and Jones for video processing [35].
- Coarse to fine approach.
- Explicit use of sequences of classifiers with increasing complexity.

Key features

- Feature extraction: use of Haar features and integral images. Very Fast.
- Efficient Feature Selection Algorithms. Adaboost.
- Ability to process large amount of data in real time. Cascades.

Cascade Framework



Conclusions

What's available?

- Current ATR algorithms have probably reached their limits.
- High resolution is there (and needed!): SAS, Acoustic Cameras. We need to use it!
- Simulation tools can be useful for training, prediction, classification and validation.
- Multi-aspect / Multiple classifier fusion should be used.

Conclusions

What's missing - Algorithms & Data

- New ATR techniques using high resolution(SAS) and video rate(Acoustic cameras).
- Much to learn from recent developments in machine vision.
- Use of Low-Frequency Wideband for classification [6] must be fully explored
- Context must be taken into account in algorithm on-line tuning
- Operators' feedback (implicit or explicit) must be used in an incremental /transfer learning framework.
- Performance evaluation (assigning a confidence to the classification outputs is critical for autonomous deployment. Recent developments using Gaussian Processes are encouraging.
- Large datasets are required to train algorithms if machine learning is to be of used.

Conclusions

What's missing - Concepts of Operations and & Data acquisition

- **Clear CONOPS** to use all the possible modalities optimally.
- **Reactive data gathering** to optimise P_d and P_{fa} online (See [36]).
- **Goal Based Planning** to move towards more autonomy.
- **Open Standards** to enable easy multiple-vehicle operations (resources are sparse).
- **Open Platforms** to test algorithm and autonomy solutions.

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