Towards Robust ATR in Sonar Imagery

Yvan Petillot

Joint Research Institute in Signal and Image Processing
Heriot-Watt University
Scotland

June 23rd 2014
1 Introduction
- The future of Mine Counter Measures (MCM) in the UK
- Object Recognition
- The Detection /Classification Problem
- The Clutter Issue
Outline

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   - Introduction
   - Fast Simulation
   - Augmented Reality
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   - Fusion Techniques
   - High Resolution Imaging - What do we need?
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4 Recent Developments
- SAS
- Acoustic Cameras
- New Algorithms

ATR in Sonar Imagery  Yvan Petillot  Joint Research Institute in Signal and Image Processing
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   - Fusion Techniques
   - High Resolution Imaging - What do we need?

4. **Recent Developments**
   - SAS
   - Acoustic Cameras
   - New Algorithms

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

Why does it matter?
Mines are cheap and can cause damage to large assets (asymmetric 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:
Object Recognition - Definition

Aim

*Object Recognition* aims at associating a semantic label to a subset of an image.
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- **Structural analysis** (Physical Components, Interactions with probing signals)
- **However**, despite the vast literature, performances of most of the algorithms still fall far behind human perception!
- **Validation** and **Comparison** of algorithms remains a real issue in underwater.
Techniques Based on Appearance:

- Require high resolution data (Side Scan, SAS)
- 3D information (Bathymetry, Interferometry)
- Is it sufficient for identification?
Object Recognition - Methods

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- Require low frequency wideband sonar to penetrate inside targets
- Require very good acoustic models and understanding of acoustic propagation
- Can it also be used for detection?
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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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Detection & Classification of Possible Targets

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

- 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.
Simulation Tools - Objectives [18, 20, 26]

Aim:

To simulate seabed or targets for algorithms development, validation and prediction of performances.
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Classical approaches:

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- Ray Tracing: simulate propagation of sound by rays [18]. Can model multipath. **Slow.**
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Classical approaches:
- Energy based approach: Uses Sonar equation [26].
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- Augmented Reality: Places simulated objects into real scenes [9]. No need to simulate complex seabeds. Fast but not very accurate.
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**Aim:**
To simulate seabed or targets for algorithms development, validation and prediction of performances.

**Classical approaches:**
- **Ray Tracing:** simulate propagation of sound by rays [18]. Can model multipath. *Slow.*
- **PSTD based approach:** Solves the full wave equation [20]. Can handle resonances and complex interfaces. *Very Very Slow.*
- **Augmented Reality:** Places simulated objects into real scenes [9]. No need to simulate complex seabeds. *Fast but not very accurate.*
Simulation Tools - Examples

Ray Tracing Simulation (top) and PSTD simulation (bottom)
Augmented Reality [9]

**Idea:**
Insert simulated targets in real data from real environments.
Route to systematic evaluation

Output image from mine simulation process

Any ATR

Seabed Classification

PD/ PFA per seabed type

Original sidescan image

15 / 29
Route to optimised mission planning

Optimal Planning for ATR

- Simulation Tool
- Performance Prediction Tool
- Expected PD
- Real Data
- Context Analysis
- Mission Planning
Route to optimised mission planning

Performance Prediction Tool
Route to optimised mission planning

Optimal Planning Examples

Context Map

Generated Trajectories for $P_d \geq 0.9$
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.
**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).
Learning Based Approaches [9, 5, 25, 16, 17, 32, 8, 7]

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- Extract features (Central filters, Haar) and Train.
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Results on Simulated and Real Data:

<table>
<thead>
<tr>
<th>%</th>
<th>Non-t.</th>
<th>Cyl.</th>
<th>Manta</th>
<th>Rockan</th>
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</thead>
<tbody>
<tr>
<td>Non-t.</td>
<td>92</td>
<td>4</td>
<td>4</td>
<td>0</td>
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<tr>
<td>Cyl.</td>
<td>11</td>
<td>80</td>
<td>9</td>
<td>0</td>
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<tr>
<td>Manta</td>
<td>1</td>
<td>2</td>
<td>97</td>
<td>0</td>
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<tr>
<td>Rockan</td>
<td>0</td>
<td>0</td>
<td>6</td>
<td>94</td>
</tr>
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Error(simulation) : 9%

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<td>0</td>
<td>20</td>
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Error(real) : 18%
**MultiView Fusion [29]**

![MultiView Fusion Example](image_url)

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<th>Fused Belief</th>
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<tr>
<td><strong>Obj</strong></td>
<td>Cyl</td>
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<tr>
<td>1</td>
<td>0.70</td>
</tr>
<tr>
<td>2</td>
<td>0.83</td>
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<tr>
<td>3</td>
<td>0.83</td>
</tr>
<tr>
<td>4</td>
<td>0.17</td>
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**Dempster-Shafer Fusion Example**
- Use texture features to segment / classify seabed (Flat, Ripples, Complex)
- Use Clutter Density to Clean Maps and extract difficult areas.
Context Dependent Classifiers Fusion [22, 34, 33, 12]

Probabilistic Fusion Architecture

Context Aware Fusion Architecture
Idea

Study the minimum resolution required to perform detection and classification.

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

- Each image $M_i$ 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: $T_i = \frac{M'_i - M_{\text{mean}}}{\text{std}(M'_i)}$.
- Compute the covariance matrix of $\{T_i\}$ and extract the first $p$ eigenvectors. This generates a subspace $\Theta_L$.
- For each new target $I_n$, project it onto each subspace $\Theta_L$ and allocate the class as: $\text{Targ} = \min_L \| I_n - P_{\Theta_L}(I_n) \|$, where $P_{\Theta_L}(I_n)$ is the projection of $I_n$ on subspace $\Theta$. 
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
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.

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- 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.
- 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.
- 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.
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.
Acknowledgments

- Oceans Systems Laboratory: Yan Pailhas, Judith Bell, Scott Reed, P.Y. Mignotte, Chris Capus, Jamil Sawas, Enrique Coiras, Keith Brown, David Lane.
- SeeByte Ltd: Scott Reed, Pierre Yves Mignotte, Jose Vasquez, Francois Chataignier.
- NATO Undersea Research Centre.
- DSTL & ONR for supporting us over the years.


[16] I. Quidu, Ph. Malkasse, G. Burel, and P. Vilbe. Mine classification using a


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