UiO : Department of informatics
University of Oslo

Target recognition techniques in SAR and SAS

Trial lecture for PhD disputation

Stig Asle Vaksvik Synnes
Oslo, 2021.06.22

Outline

Introduction

- **Background**
  - SAS and SAR
  - Target recognition
  - Applications
- **Automatic target recognition**
  - Motivation
  - Processing chain
  - Literature surveys

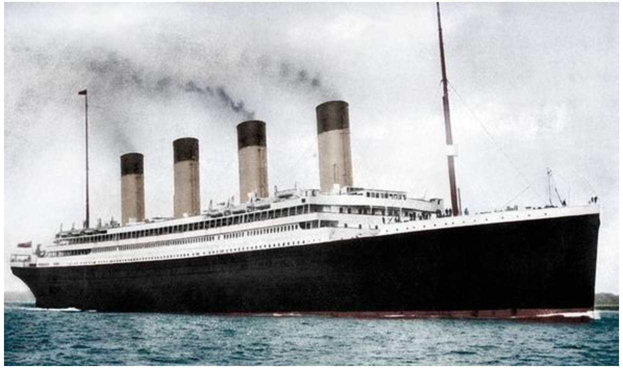
Techniques

- **Input data**
  - Data type
  - Data domains
- **Machine learning**
  - Feature extraction
  - Deep learning

Image: SAR targets from the MSTAR classification dataset SDMS - US Air Force

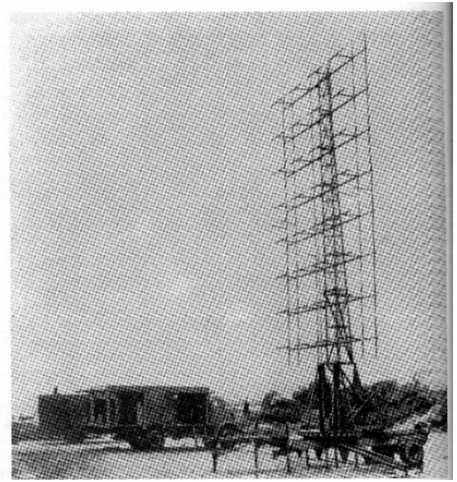
Sonar and radar

- Sonar
  - Acoustic pressure field in water
  - Long range detection



Titanic, Image: Daily Express

- Radar
  - Electromagnetic vector field in air/vacuum
  - All weather, day and night



WWII radar system, Image: ETHW

Synthetic aperture radar and sonar

- Synthetic aperture radar (SAR) [1]
  - Invented in the 1950s
  - Space since 1978
  - Surveillance planes

- Synthetic aperture sonar (SAS) [2]
  - Invented in the late 1960s
  - Commercial since early 2000s

[1] The Engineering and Technology History Wiki (ETHW), ethw.org

[2] Sternlicht et al, "Historical development of seabed mapping synthetic aperture sonar", 4th Conf. SAS/SAR, Proc. Institute of Acoustics, Vol 40 Pt2, 2018

Seasat
Image: NASA/JPL

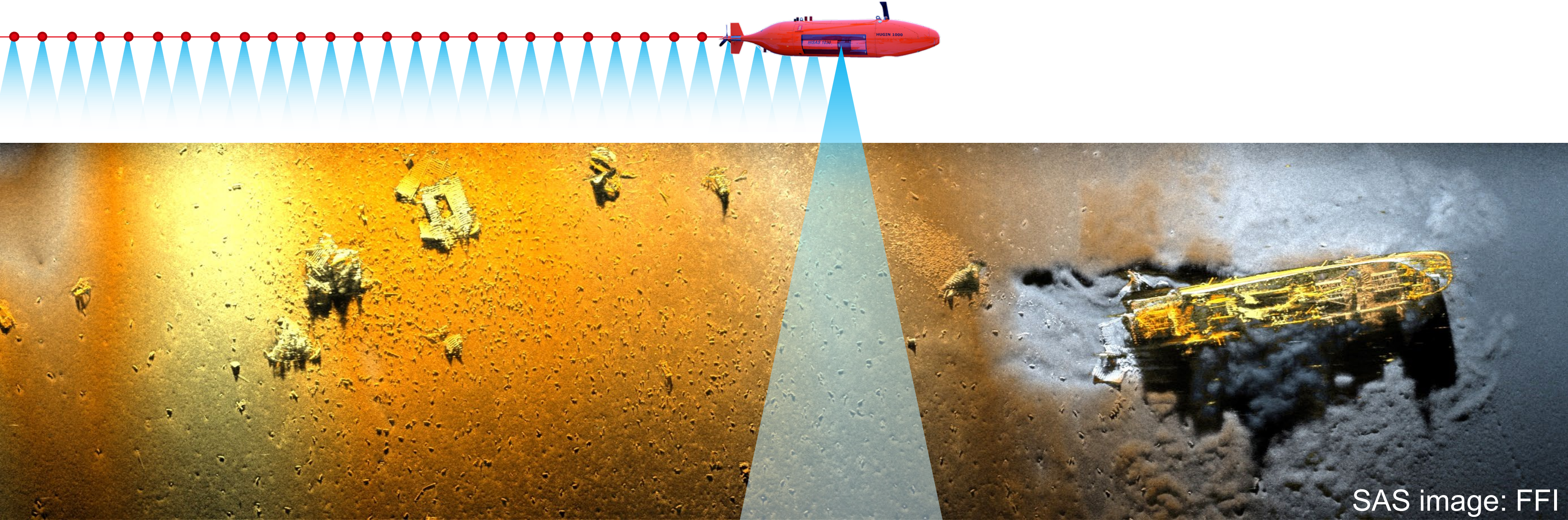
SR-71 Blackbird
Image: US Air Force

KM Hugin with HISAS
Image: Ole Lorentzen, FFI

Synthetic aperture technique

- High resolution AND large area coverage rate
- Synthesizes a long array by platform motion

- Combines all
  - Frequencies, by matched filtering
  - Aspect angles, by integrating over measurements



SAS image: FFI

Target recognition

- ***Target recognition*** $\rightarrow$ ***Automatic target recognition (ATR)***
  The ability for an algorithm or device to recognize targets or other objects based on data obtained from sensors [1]
- ***Recognition***: The determination of the nature of a detected person, object or phenomenon, and possibly its class or type [2]

Target

[1] Wikipedia, "Target recognition", 2021
[2] NATO AAP-06; Glossary of Terms and Definitions; 2020

ATR on SAR/SAS

Military applications

- Infrastructure: buildings, roads, etc
- **Vehicles** and vessels
- **Naval mines**
- Unexploded ordnanse

Civilian applications

- Vegetation classification
- Oil spill monitoring

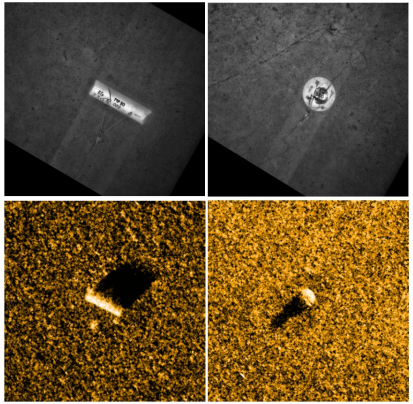


Image: SAS dummy mines, FFI [1]

Targets from the SAR MSTAR ’95 and ’96 datasets, US Air Force’ SDMS

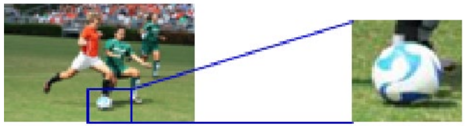
[1] Krogstad et al, “Autonomous survey and identification planning for AUV MCM operations”, UDT 2014

ATR processing chain

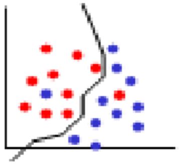
Sensor Data — SAR or SAS images and data products

Preprocessing — Suppression of background variations, etc

Detection — Anomaly detector, matched filter, etc



Classification — Target recognition



Target list — Class or type, and potentially identity

Photo illustration from Stack, Proc SPIE, Vol 8017, 2011

ATR motivation

- Increase efficiency
  - Performance
  - Speed
  - Coverage
  - Endurance
- Operator support
  - Area coverage map
  - Target list for validation
- Autonomous operations
  - Automatic detection and classification
  - Reactive behavior

Manual naval mine target recognition on SAS images
Photo: Kongsberg Martime [1]

Photo: Kongsberg Martime [1]

[1] Hagen et al, "Military operations with HUGIN AUVs: Lessons learned and the way ahead", OCEANS Europe 2005

ATR algorithms

Requirements [1,2]

- Good **performance** in most environments
- Accurate quality assessment
  - Estimated performance and coverage
  - Estimated classification confidence
- Gain trust from operator and management
  - Accurate performance estimates might be more important than high performance

Performance drivers

- Environment, sensor and geometry
- The **ATR algorithm**

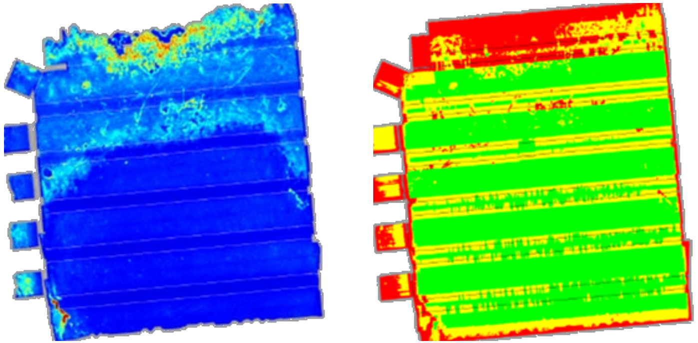


Image: Estimated complexity and condensed performance map [2]

[1] Stack, "Automation for underwater mine recognition: current trends and future strategy", Det. Sens. Mines., Proc of SPIE, 2011

[2] Geilhufe et al, "Through-the-Sensor Performance Evaluation for Modern Mine Hunting Operations" Underw. Defence Tech., 2016

Technology Surveys

ATR on SAS

Stack, “Automation for underwater mine recognition: current trends and future strategy”, Detection and Sensing of Mines, Explosive Objects, and Obscured Targets XVI, Proc of SPIE, 2011

ATR on SAR

Blacknell & Griffiths (eds), ”Radar automatic target recognition (ATR) and non-cooperative target recognition (NCTR)”, The Institute of Engineering and Technology, 2013

Kechagias-Stamatis & Aouf, “Automatic Target Recognition on Synthetic Aperture Radar Imagery: A Survey”, IEEE Aerospace and Electronic Systems Magazine, 2021

ATR techniques – categorized by input data

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ATR on 1. & 2. Single look images

1. **Intensity images**

A. Feature-based
- Geometry, statistics, etc

B. Template matching
- Coherence

C. Sparse representation
- Compressive sensing, TSVD, etc

D. Deep learning
- Convolutional neural network (CNN)

2. **Complex data** (intensity, aspect and frequency)

A. Attributed scattering centers (ASC)
- Reflector shapes

1.A Intensity images: Feature-based [1, 2, 3]

Features intended to uniquely classify the target

Segmentation → **Feature extraction** → **Classification**

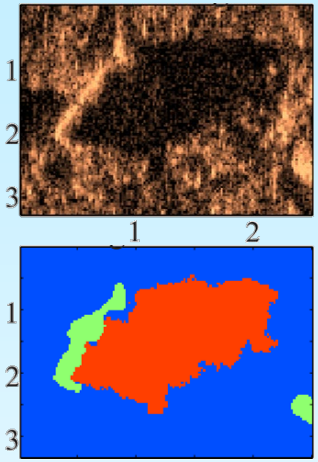


Image: Fandos [3]

Geometric metrics
- Elongation, volume, shape

Textural metrics
- Wavelet components

Statistical metrics
- Number above threshold
- Skewness, kurtosis

Moments and
principal components

Mahalanobis' classifier,
k-nearest neighbor, neural networks,
support vector machines, etc

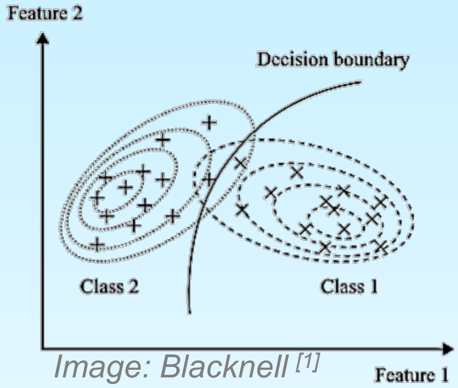


Image: Blacknell [1]

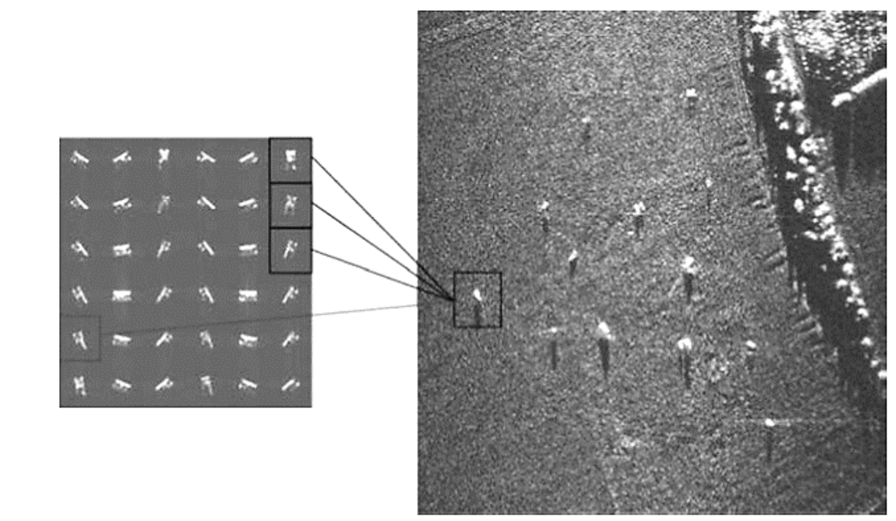
[1] Blacknell & Vignaud, in Blacknell & Griffiths (eds), "Radar ATR and NCTR", ch 2.3.3, 2013
[2] Kechagias-Stamatis, "ATR on SAR: A survey", IEEE Aerosp. Elec. Sys. Mag., 2021
[3] Fandos et al, "(…) Feature-Based (…) Mine Hunting Using SAS", IEEE Trans. Geosc. Remote Sens., 2014

1.B Intensity Images: Template-matching [1, 2]

Compares with templates for all targets and geometries

- most applicable to relatively constrained problems [2]

- Optional segmentation
  - Target, shadow and background
- Target database
  - Measurements and/or simulations
- Classification by computing similarity between test-image and templates:
  - Coherence



SAR template matching. Image from [2]

[1] Middelfart et al, "Robust Template Matching for Object Classification", Proc. Underw. Acoust. Meas., 2011
[2] Blacknell & Vignaud, in Blacknell & Griffiths (eds), "Radar ATR and NCTR", ch 2.3.2, 2013

1.C Intensity Images: Sparse Representations [1,2]

Exploits sparse representations to focus on salient features

- Sparse and lossy representation
- Sparse coding
  - Represents a signal y (of N samples) as a **linear** combination of a few atoms, i.e., entries of a dictionary D.

    $$y = Dx$$

  - Minimize number of non-zero entries of x (through l_0-norm optimization)
  - In practice solved using **compressive sensing** (solve l_1-norm optimization)
- Classification
  - Example using SAR training images as dictionary [2]

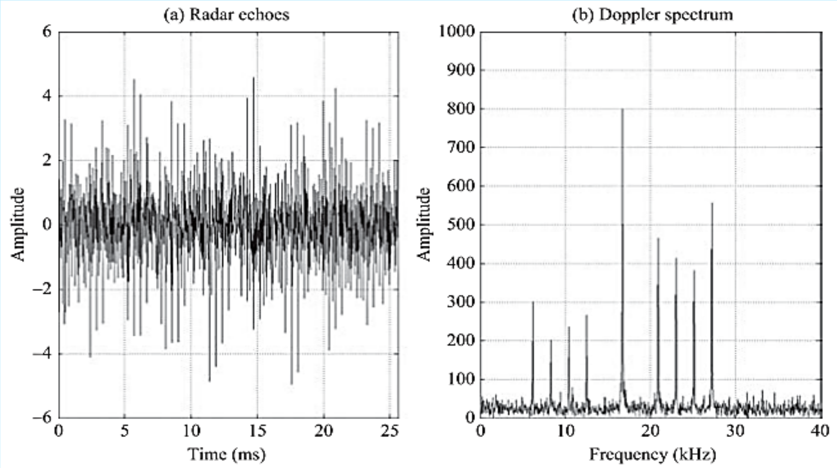


Image: representing a signal by its frequency components [1]

[1] Huizing and Tan, in Blacknell&Griffiths (eds), ch 8.2, 2013
[2] Kechagias-Stamatis, "Fusing Deep Learning and Sparse Coding for SAR ATR", IEEE Trans. Aerosp. Elec. Sys., 2019

1.D Intensity images: Deep learning [1,2]

Automatically learns relevant features from the training data

Deep learning

- Neural networks with multiple layers

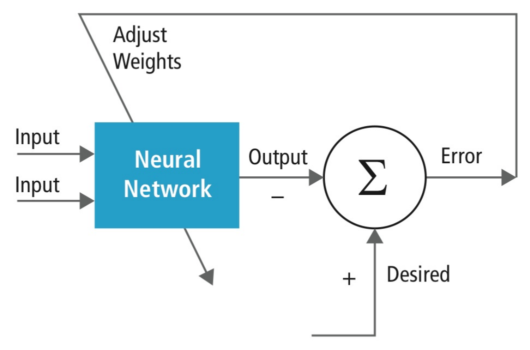
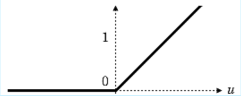


Image: "edge ai + vision alliance" [2]

- Breakethrough in 2012 by use of "AlexNet" Convolutional neural network (CNN) on the "ImageNet" optical database

Convolutional neural networks

- Manually chosen architectures
  - Convolutional layers (shift invariant)
  - Pooling layers
  - Connectivity
  - Non-linear activation function (ReLU)



- Automatically learns by extracting from small-scale to increasingly large-scale features
- Needs BIG datasets
  - ImageNet: 14 million images, 1000 labeled classes
- CNNs architectures (trained on ImageNet): AlexNet, VGG, GoogleNet, etc

[1] Wikipedia, "Deep learning" and "Convolutional neural network", 2021
[2] Edge ai + vision alliance, https://www.edge-ai-vision.com/2015/11/using-convolutional-neural-networks-for-image-recognition/

1.D Intensity images: Deep learning [1,2]

Automatic learning

- Skips the difficult step of feature identification
- Performance increases with amount of data
  - Recording, augmentation (shift, flip, etc)
  - Modeling and simulation, target insertion …

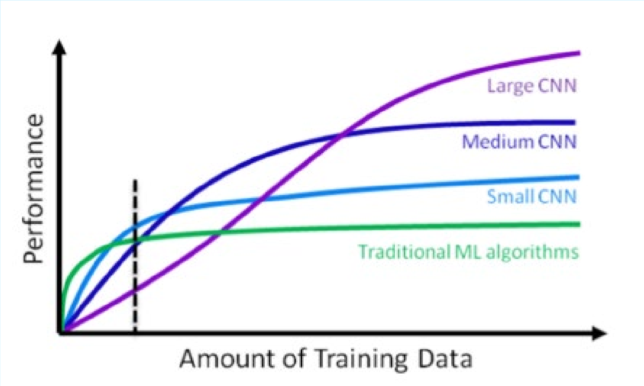


Image: Williams 2021 [1]

Transfer learning to SAR/SAS

- Fine-tune CNN architectures trained on ImageNet
  - Last layer: Tune to classify into desired classes
  - First layer: Tuned to input type
  - All layers: Overall performance

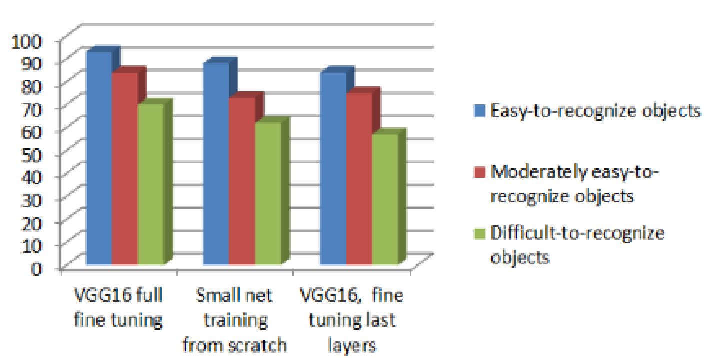


Image: Warakagoda 2018 [2]

[1] Williams, "On the Use of Tiny Convolutional Neural Networks …", IEEE Journal of Oceanic Engineering, 2021
[2] Warakagoda et al, "Transfer-learning with deep neural networks for mine recognition in sonar images", Proc. Inst. Acoust., 2018

1.A-D Summary: ATR on intensity images

- **Feature-based**: Manually designed features
  - \+ Potentially robust to orientation
  - \- Difficult to obtain good features
- **Template-based**: Compares candidate with templates
  - \+ Reduces the need of manually designed features
  - \- Based on templates for all targets and geometries. Mainly feasible on constrained problems
- **Sparse representations**: Uses compressive sensing to extract information from objects
  - \+ Replaces the difficult step of manually designing features
  - \- The approach is lossy, and some of the important information might be lost
- **Deep learning**: Automatically learns features from the training data
  - \+ Transfer learning to adapt CNNs trained on the ImageNet optical database
  - \- Needs a huge amount of training data

2.A Complex images: Attributed scattering centers (ASC)

3D characterization of prominent scatterers

Description

- Scatterer properties / features [1]
  - Azimuth-dependency
  - Frequency-dependency
- Distributed object: sum of scatterers

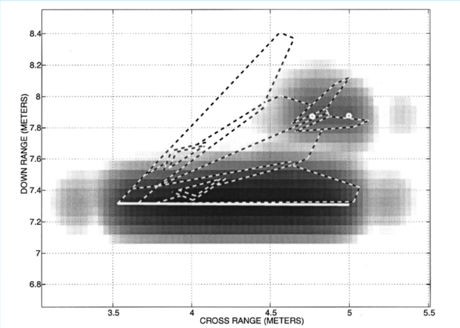


Image: [1]

Features [2]

$$[A_i, x_i, y_i, L_i, \overline{\varphi_i}, \alpha_i, \gamma_i]^T$$

- Relative amplitude
- Location
- Length
- Orientation
- Aspect dependence
- Frequency dependency {-1,- ½, 0, ½, 1} relates to geometry (outside corner, edge, point-symmetric, axis-symmetric, plane)

[1] Gerry et al, "A parametric model for synthetic aperture radar measurements", Trans Ant prop Mag, 1999
[2] Ding et al, "An Efficient and Robust Framework for SAR Target Recognition …", IEEE Trans Image Proc, 2018

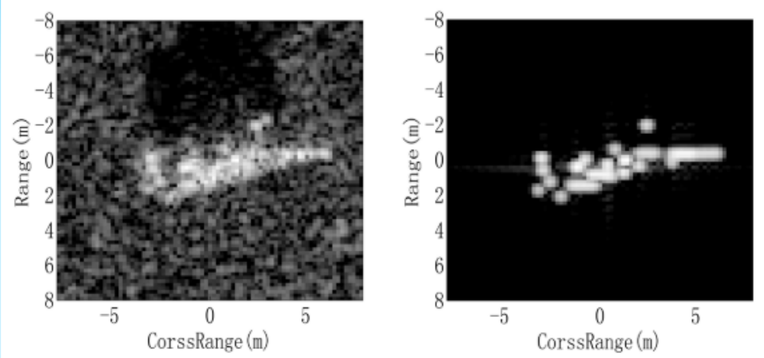
2.A Complex images: Attributed scattering centers (ASC)

Classification

- Classical [1]
  - Hungarian algorithm finds the correspondence between ASC and template
- Deep learning [2]

Properties

- Sparse representation of intensity and 3D-geometry
- Could emphasize **man-made objects**
- Favors broadband & wide-aspect data
  - Wavelength smaller than scatterer
  - Demonstrated with 3 deg beamwidth, 10% bandwidth and 5 dB SNR [2]
- SAR ATR: Among top performances on MSTAR [2]



T72 from [1]

[1] Ding et al, "An Efficient and Robust Framework for SAR Target Recognition …", IEEE Trans Image Proc, 2018
[2] Kechagias-Stamati et al, "Fusing Deep Learning and Sparse Coding for SAR ATR", IEEE Trans. Aerosp. Elec. Sys., 2019

ATR techniques – categorized by input data

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Advanced ATR input

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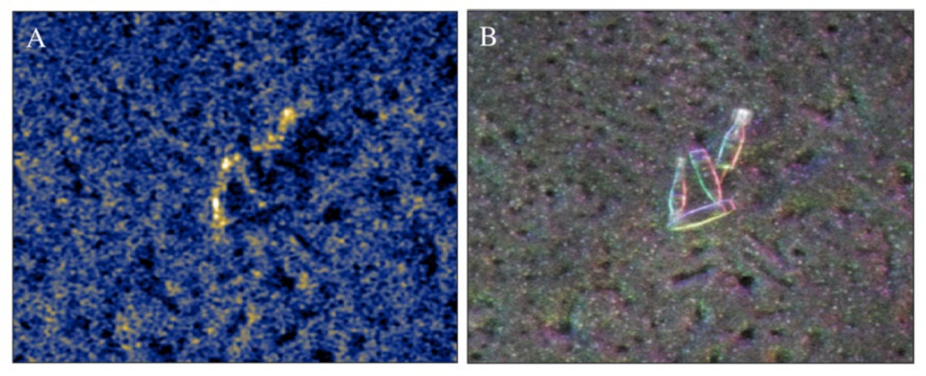
3. Aspect coverage: circular aperture, widebeam or multi-aspect

Classification of small or occluded scatterers

- Properties [1]
  - Specular reflections
  - Azimuth-dependency
- Detection and segmentation
  - on SAR [2]
  - using DL on SAS [3]
- Classification
  - ATR on SAR [4]



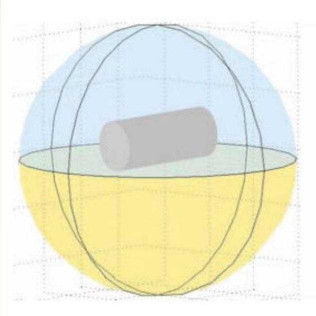
UXOs, imaged with A) short aperture and B) circular SAS aperture. Image: [5]

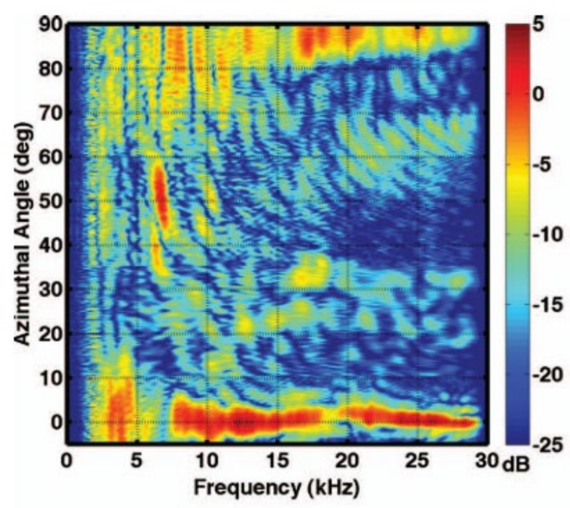
[1] Plotnik et al, "Utilization of Aspect Angle Information in Synthetic Aperture Images", IEEE Trans. Geosc. Remote Sens., 2018
[2] Allen et al, "Wide-angle SAR matched filter image formation for enhanced detection performance", SPIE 2093, 1994
[3] Sledge et al, "Target Detection and Segmentation in Circular-Scan SAS Images using Semi-Supervised Convolutional Encoder-Decoders", arXiv.org (submitted to IEEE Journal of ecanic engineering)
[4] Allen et al, "FOPEN-SAR detection by direct use of simple scattering physics", IEEE International Radar Conference, 1995
[5] Marston et al, "Spatially variant autofocus for circular synthetic aperture sonar", Journ. Acoust. Soc. Am., 2021

4. Low frequency

Captures resonances

- Both scattering and resonances
  - Frequency- and aspect domain data [1]
- Classification
  - Matched filtering [2]
  - CNN [2,3]





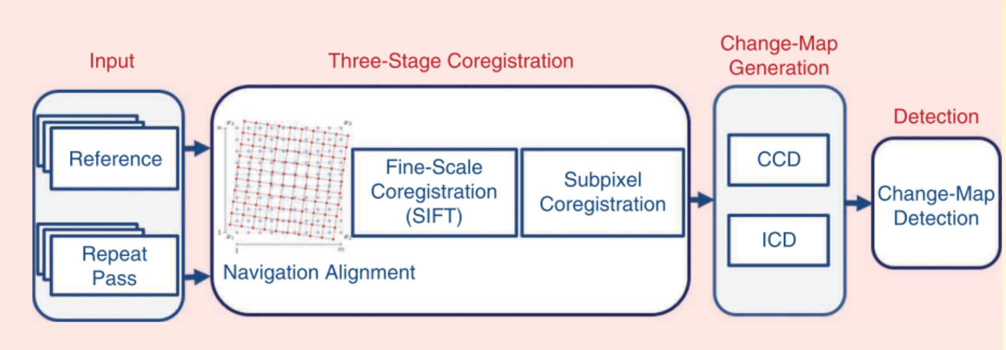
Images: Williams 2010 [1]

[1] Williams K, et al, "Acoustic scattering from a solid aluminum cylinder in contact with a sand sediment (…)", J.A.S.A., 2010
[2] Fawcett et al, "Classification experiments with the PONDEX and TREX13 datasets", DRDC report, 2018
[3] Williams D, "Acoustic-color-based CNN for uxo classification with low-frequency sonar david", UACE, 2019

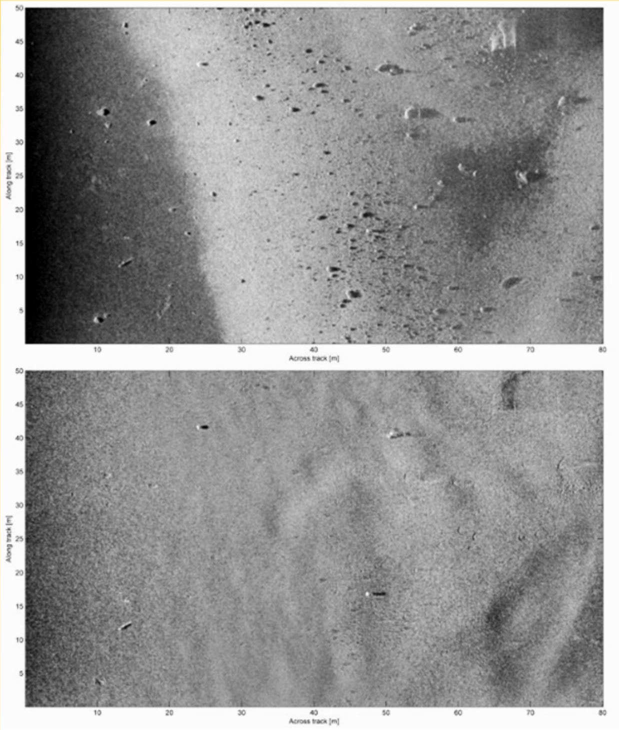
5. Change detection

Hugely simplifies segmentation

- Gain: Minimizes the number of **false alarms**
- Cost: Pre-survey, co-registration, geometriy-restraints
- Coherent: Short time, small targets (pixel-level)
- Incoherent: Long time, larger targets



G-Michael et al, "Automated Change Detection - Applications for Synthetic Aperture Sonar and Future Capabilities", IEEE Systems, Man, & Cybernetics Magazine, 2019



Img2

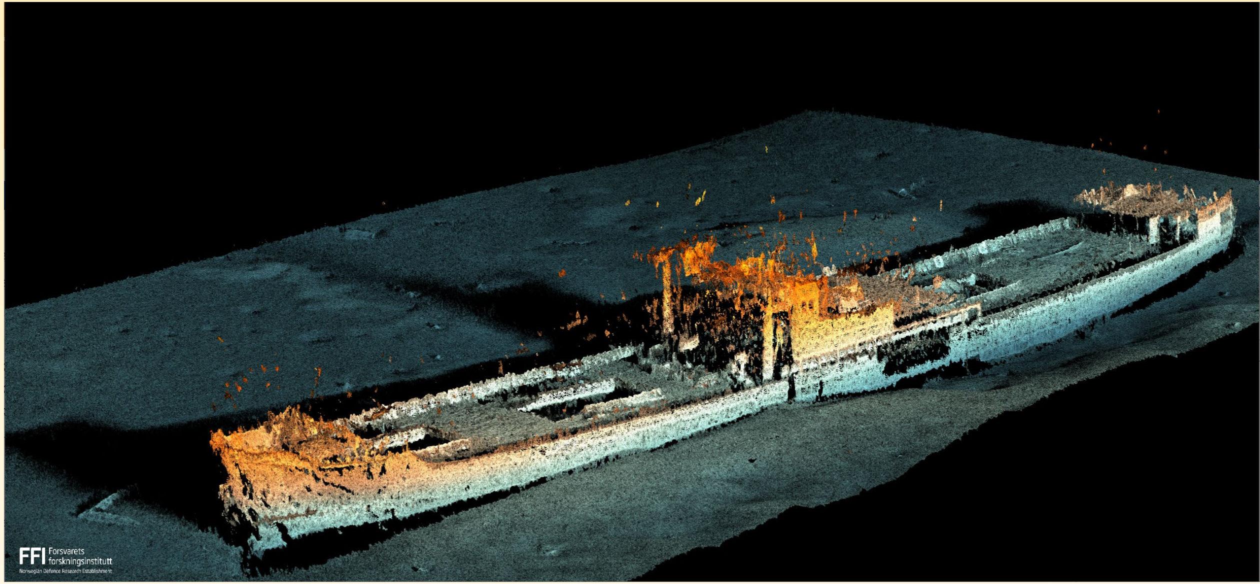
Img2
-
Img1

Midtgaard et al, "Change detection using synthetic aperture sonar: Preliminary results from the Larvik trial", Proceedings of Oceans 2011 MTS/IEEE

6. Interferometer (vertical sampling)

Provides height information

- Lower resolution than image
- Might improve detection and classification [1]



SAS image with color-coded depth. Image: FFI

[1] Williams, "SAS and Bathymetric Data Fusion for Improved Target Classification", ICoURS, 2012

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ATR information and performance

1.	**Intensity image**	**Backscattering from one aspect**	Commonly used information
2.	Complex image	3D characterization of prominent scatterers	Potential information
3.	Wide aspect	Specular reflection, small or occluded targets	
4.	Low frequency, wideband	Resonances and material	
5.	Change detection	Simple segmentation	
6.	Interferometry	Height distribution	
7.	Polarimetry (SAR)	Material and orientation	
8.	Redundant sampling	Moving targets	

Conclusion on the future of ATR on SAR and SAS

ATR development will focus on

- Good performance in more difficult and diverse environments
  - **Exploiting deep learning**
  - **Using more of the collected information**
  - **Collecting more information**
- Accurate performance estimates
- Gaining trust from operator and management

ATR on SAS versus SAR

- SAS continues to learn from SAR
  - ATR technology
- SAR might learn from SAS
  - Transition to autonomous systems

Illustration: Stig A. V. Synnes