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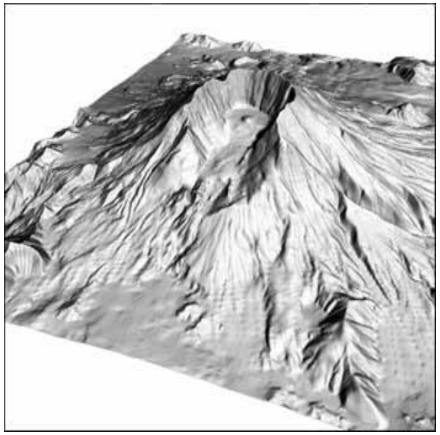
Automatic Target Recognition (ATR) via Deep Learning Techniques

Vito Pascazio

Seminario CESMA

Roma, 7 giugno 2022



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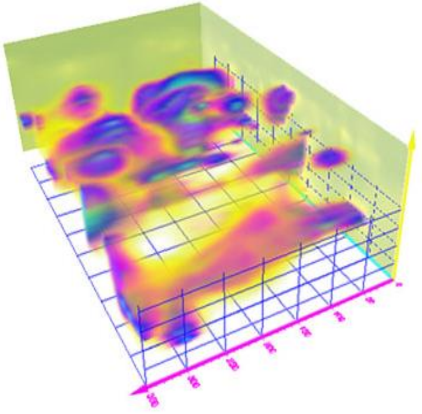

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Staff

Vito Pascazio	professor
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+ 5 PhD Students……

Main Areas of Activity

- Imaging Radars
  - Synthetic Aperture Radar (SAR) Imaging (1986)
  - SAR Interferometry - across and along track (1996)
  - SAR Tomography (3D) (2009)
  - SAR Tomography (5D) (2019)
  - Automotive Imaging Radars (2010)
  - SAR Image Compression (1993, 2001)
  - Image Restoration (1995)
- Non-Invasive MWI Applications
  - Microwave imaging systems – GPR – TtWR (1993)
  - Millimeter wave body scanners (2015)
- Deep Learning Application (2017)
  - to Image Restoration
  - to TomoSAR
  - to ATR
  - to Gesture Recognition
  - …..

Main Areas of Activity

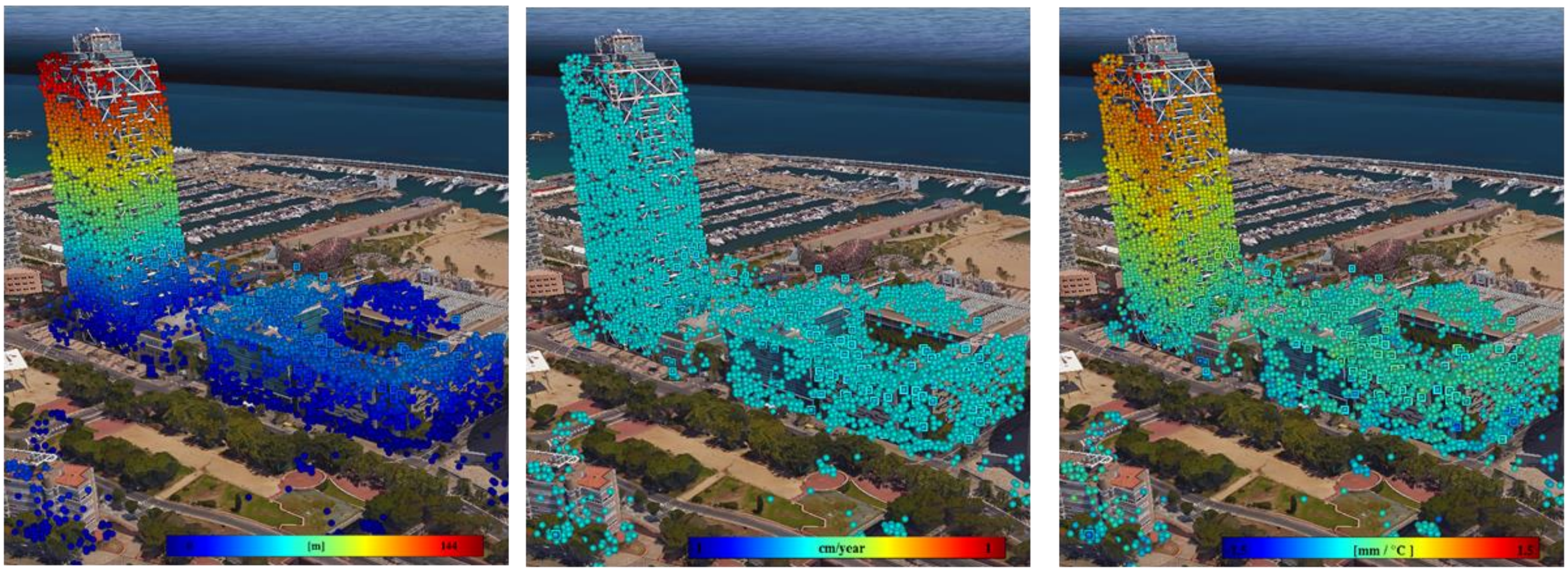
- SAR Imaging

Main Areas of Activity

- SAR Imaging

Main Areas of Activity

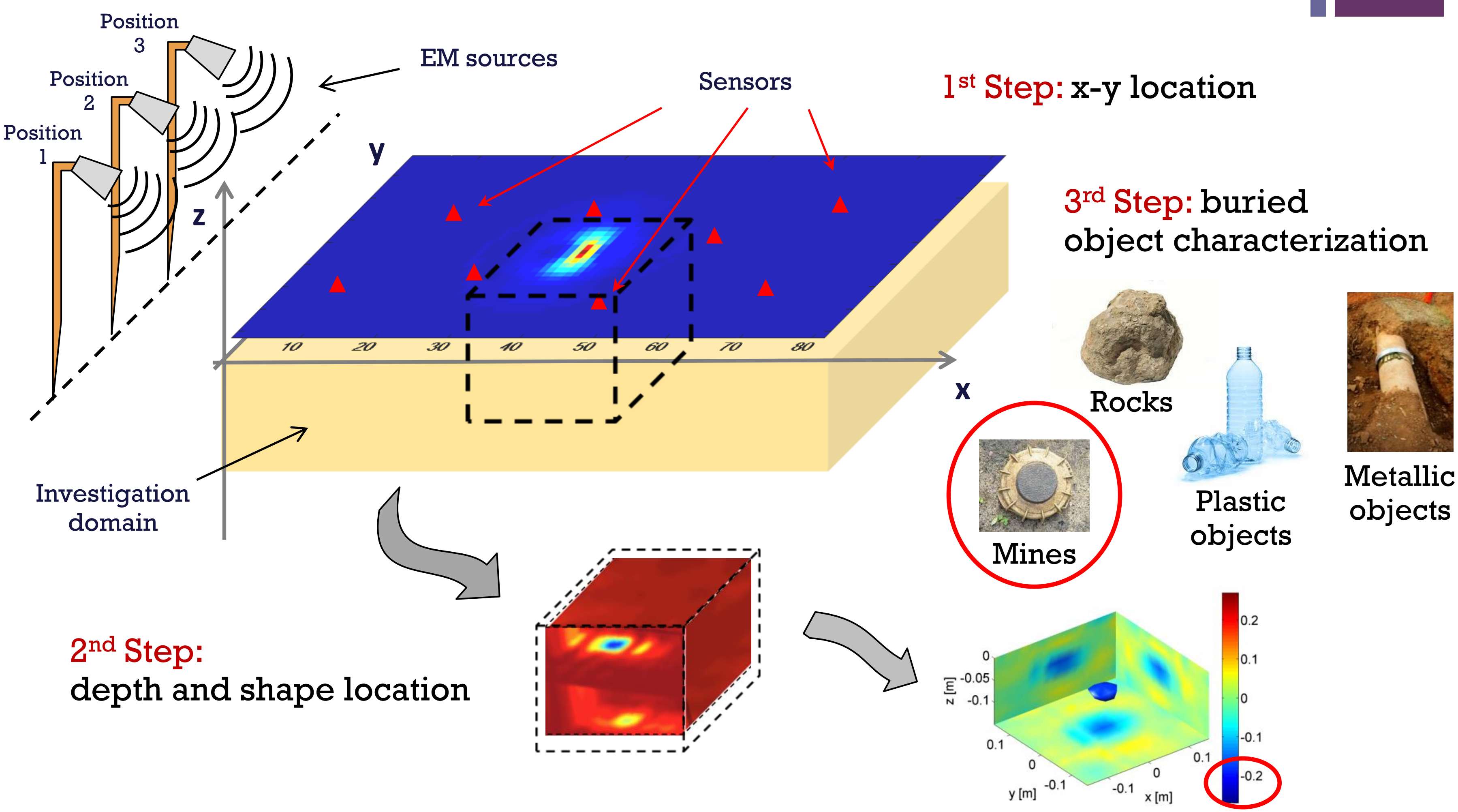
- SAR Tomography 3D->5D



(Left) Height Estimation; (Middle) Surface Deformation; (Right) Thermal Dilation

Main Areas of Activity

- GPR Demining



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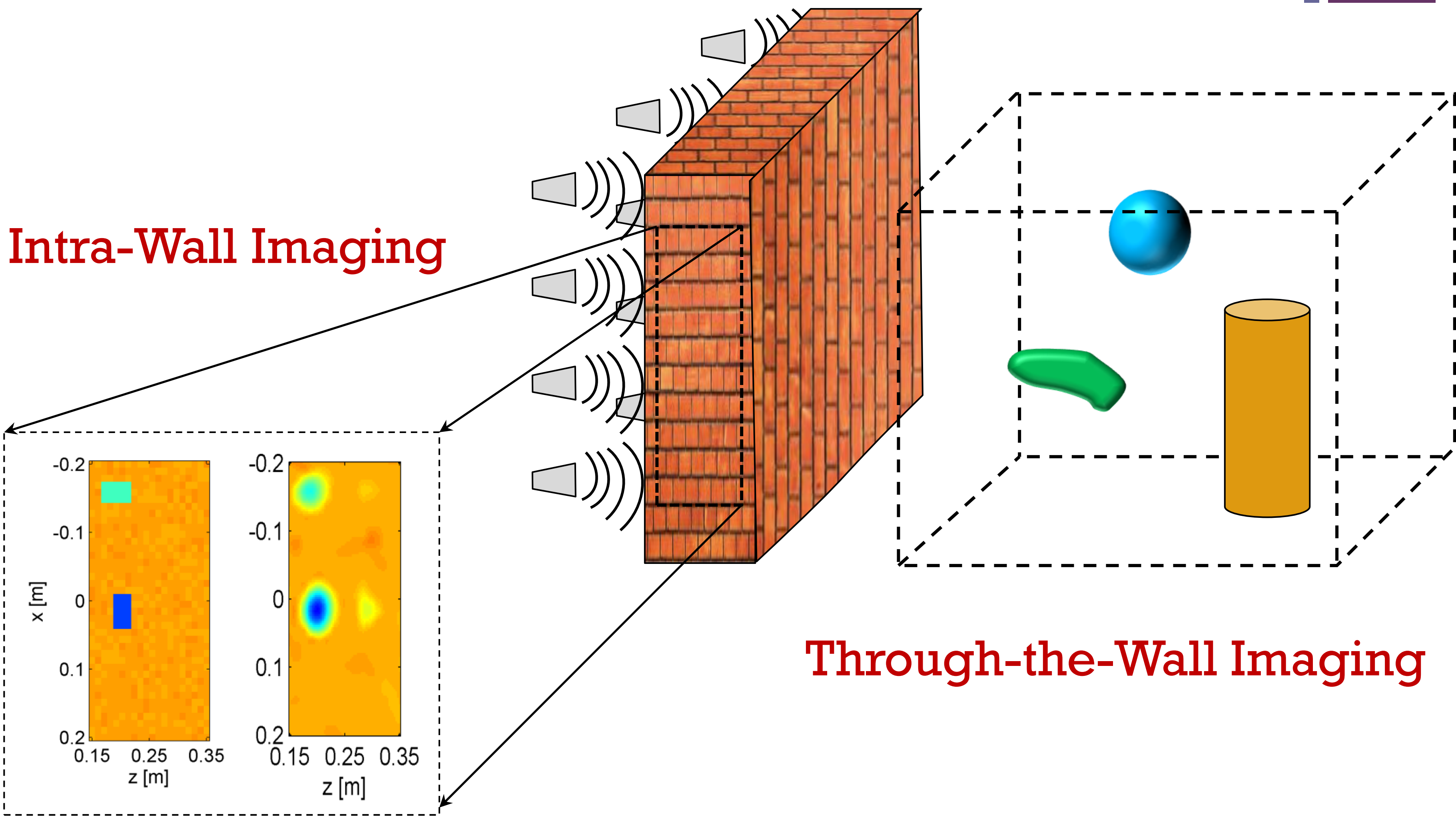
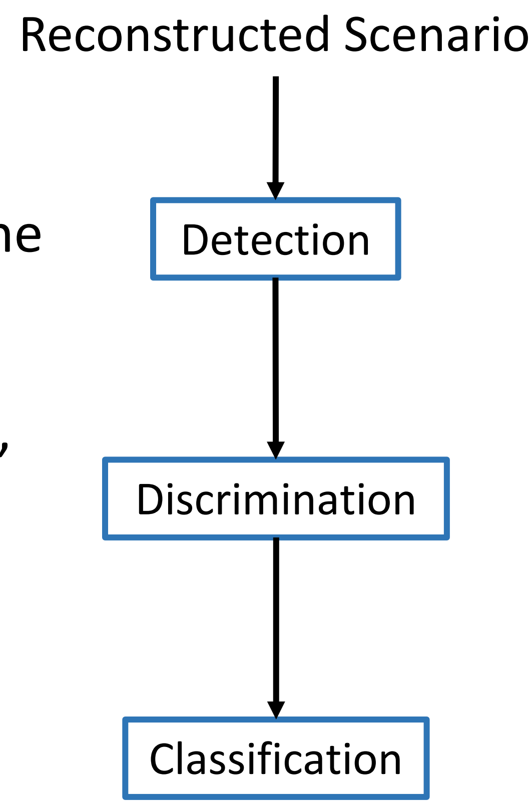
Main Areas of Activity

- IW & TtW



Automatic Target Recognition (ATR) workflow

Automatic target recognition (ATR) is the ability for an algorithm or device to recognize targets or other objects based on data obtained from sensors.



- *Detection*: locate a possible target within the scene
- *Discrimination*: distinguish between clutter (trees, buildings cars, etc…) and target of interest such tanks
- *Classification*: categorise inputs into a specific target type

ATR Sensors

- LIDAR – Active sensor, operating day and night, high cost, size, power consumption and processing time, maximum operative distance (not so large).
- Infrared – Passive sensor, operating day and night, low cost, size, power consumption and processing time, maximum operative distance (not so large).
- Optical – Passive sensor, light dependence, low cost, size, power consumption and processing time, maximum operative distance (large).
- SAR – Active sensor, operating day and night, high cost, size and power consumption, low processing time, maximum operative distance (large).

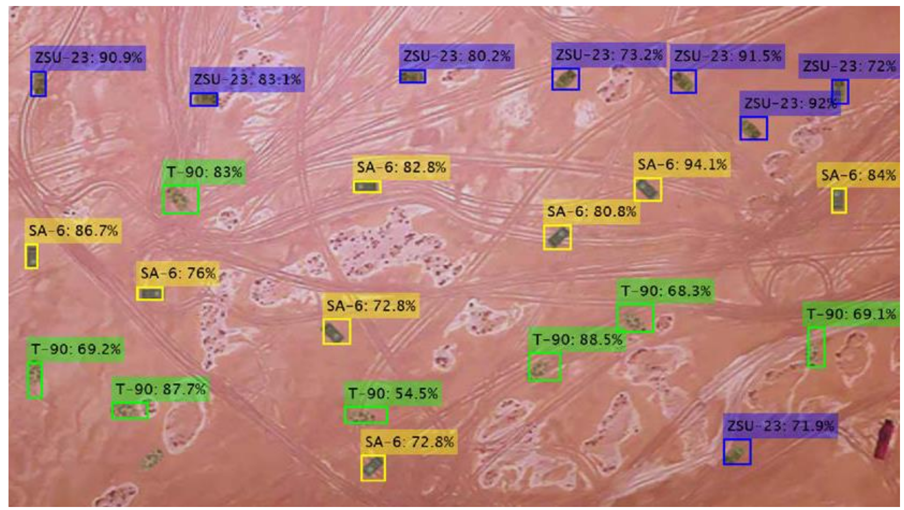
ATR via Optical sensors, an example

ATR via Optical sensors relies on the spectral signatures of the target.

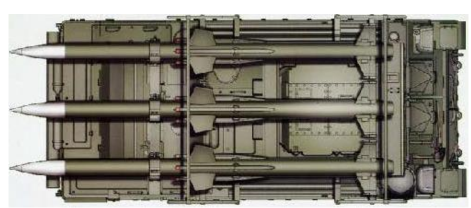
Different target produce a different response in the frequency spectrum that can help in their discrimination and classification

This approach is efficient but too much sensible to environment issues (clouds, day light, atmosphere).

T-90



SA-6



ZSU-23

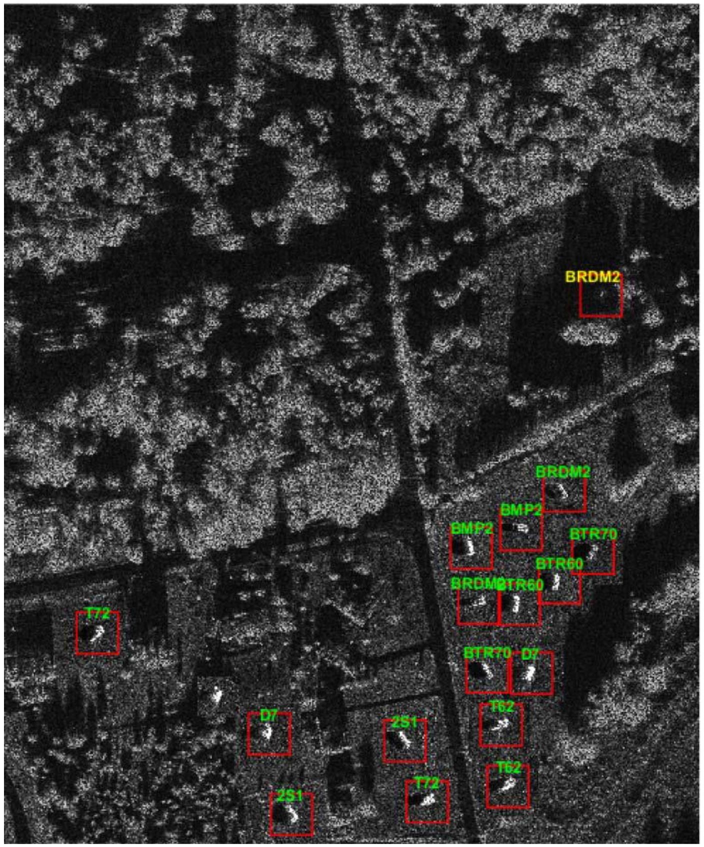
H. W. Chen, et al., *"Advanced automated target recognition (ATR) and multi-target tracker (MTT) with electro-optical (EO) sensors,"* Applications of Machine Learning, 2020.

ATR via SAR sensors, an example

ATR via SAR sensors is complicated by the SAR imaging system (geometrical distortions, speckle noise)

<u>SAR sensors overcome the environment issues.</u> Acquiring data during day&night and in any wheatear condition.

The discrimination relies on the different textural signatures each target produce in the SAR domain.



+ Dataset MSTAR (Moving and Stationary Target Acquisition and Recognition)

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MSTAR dataset, created in 1995, is a dataset containing targets (tanks) acquired by a SAR sensor.

- X- band SAR images
- 1 ft resolution (30 cm approx.)

Different kind of tanks are presents and for each of them, different variants

E. R. Keydel, S. W. Lee, and J. T. Moore, *“MSTAR extended operating conditions: A tutorial,”* in Proc. 3rd SPIE Conf. Algorithms SAR Imagery, 1996.

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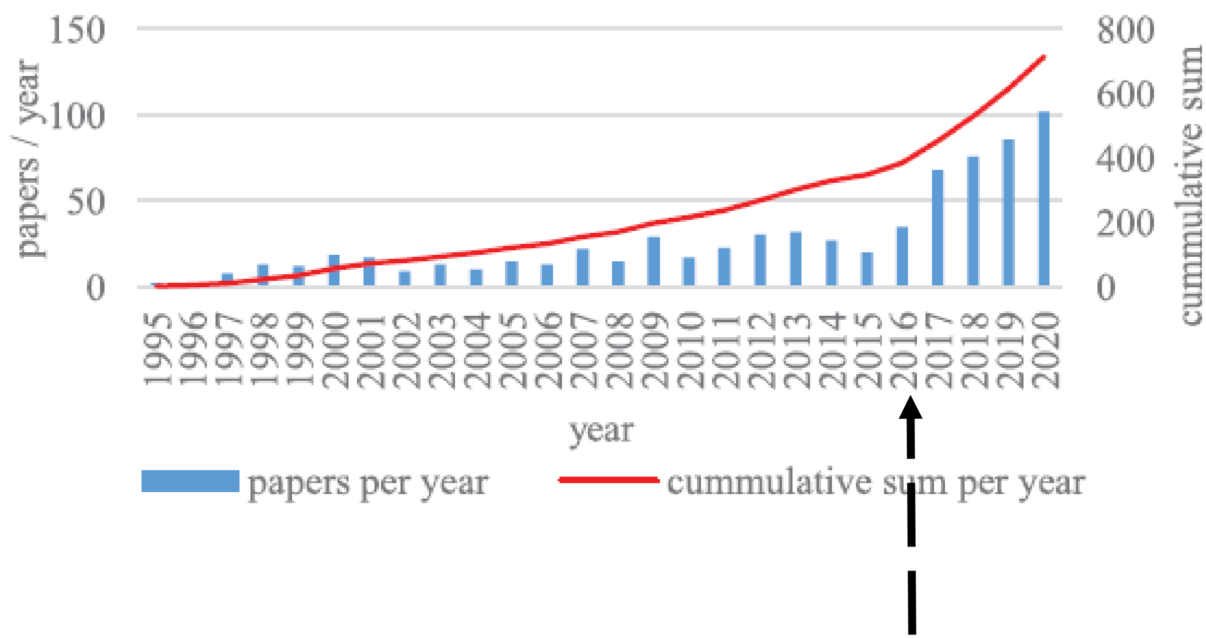
Dataset MSTAR (Moving and Stationary Target Acquisition and Recognition)

The presence of this publicly available dataset has lead to the risen of many algorithm, allowing a growing interest and performance in the research for ATR in the SAR community

Following the trend of the last decade, the great performance of DL methods has boosted the proliferation of methods for ATR in the SAR domain



First Neural Network approach

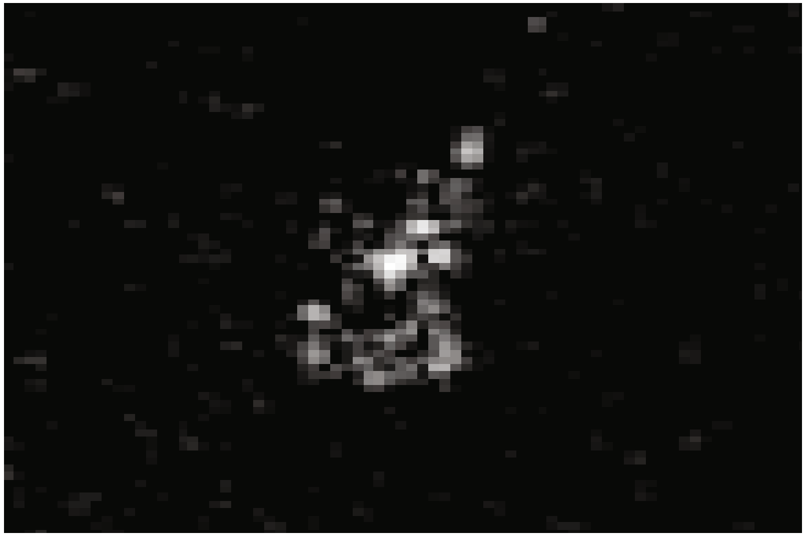
Dataset MSTAR (Moving and Stationary Target Acquisition and Recognition)

MSTAR dataset allows to efficiently build and compare methods for ATR

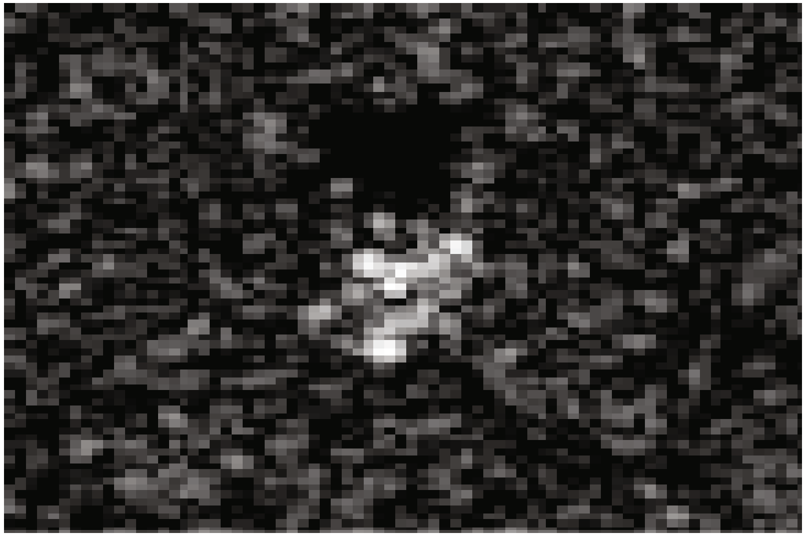
- Configuration variance: the configurations of the target for classification may be different (e.g. shield and spare barrels may be equipped or removed for different applications
- Depression angle variance: the test samples to be classified may be collected at different depression angles
- Noise corruption: The measured SAR data may be contaminated by the background clutters or system noises
- Partial occlusion: The target may be occluded by nearby obstacles
- Resolution variance: The resolution of the target patches may be different

E. R. Keydel, S. W. Lee, and J. T. Moore, *"MSTAR extended operating conditions: A tutorial,"* in Proc. 3rd SPIE Conf. Algorithms SAR Imagery, 1996.

Depression Angle Variation

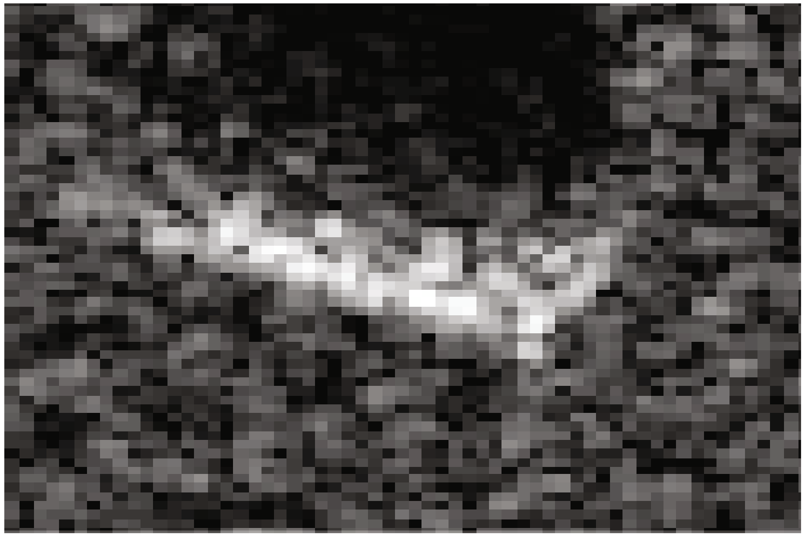


17 degrees

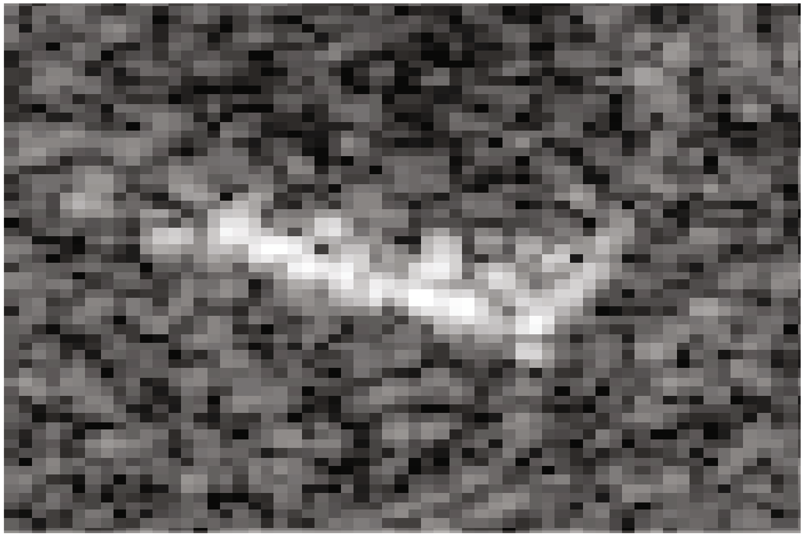


45 degrees

Noise Corruption

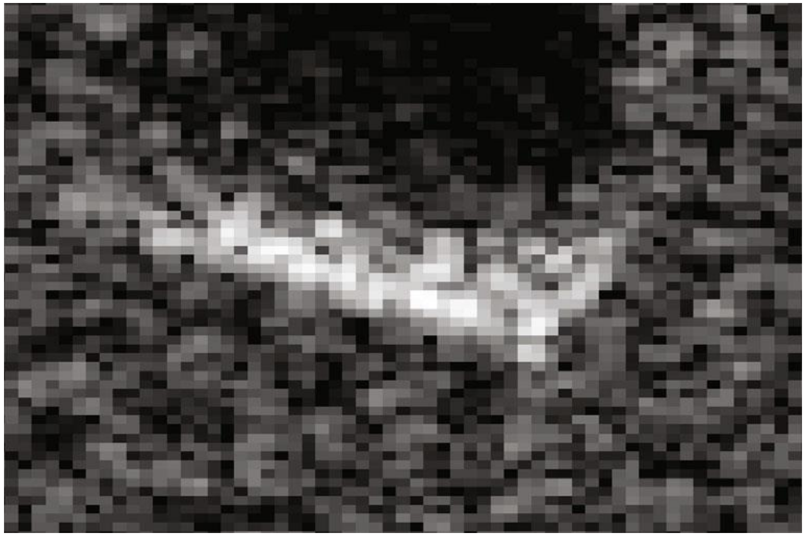


Original

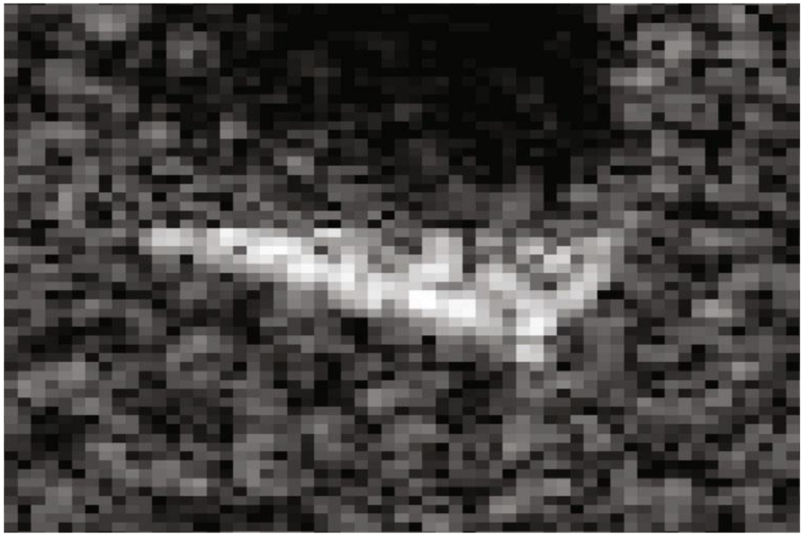


Noisy (0 dB SNR)

Partial Occlusion



Original



Occluded

Comparison of methods in SOC and EOC

Compared Operative Condition
- SOC (Standard Operative Condition):
  - Configuration variant
- EOC (Extended Operative Condition):
  - Depression Angle
  - Noise Corruption
  - Partial Occlusion
  - Resolution Variation

Compared Methods
- Convolutional Neural networks (CNN)
- Attributed Scattering centers (ASC)
- Sparse Representation Classification (SRC)
- Low-rank Matrix Factorization (LMF)
- Hybrid reflectivity attribute
- Compressive Sensing (CS)

Overall Performance

Scenario	most robust architectures
SOC 10-class	CNN, SRC
SOC 3-class	CNN, SRC
EOC depression angle variation	CNN, SRC, ASC, CS, Hybrid reflectivity attribute, LMF
EOC Gaussian noise level variation	CNN, SRC, ASC, CS, Hybrid reflectivity attribute
EOC resolution variation scenario	CNN, SRC, ASC, CS, Hybrid reflectivity attribute
EOC target version variation	SRC, CNN, LMF, ASC
EOC occlusion level variation	ASC, SRC, CNN, CS, features

O Kechagias-Stamatis, N. Aouf, "*Automatic Target Recognition on Synthetic Aperture Radar Imagery: A Survey*," IEEE Aerospace and Electronic Systems Magazine, 2021.

Comparison of methods in SOC and EOC

Compared Operative Condition

- SOC (Standard Operative Condition):
  - Configuration variant
- EOC (Extended Operative Condition):
  - Depression Angle
  - Noise Corruption
  - Partial Occlusion
  - Resolution Variation

CNN based solution have become the more robust and versatility method for ATR achieving best performance in almost all challenging case: Standard, Depressiong angle variations, Noise corruption, etc…

At the moment, CNN are not the best for partial occlusion, mostly because of the lack of good training dataset

Overall Performance

Scenario	most robust architectures
SOC 10-class	CNN, SRC
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EOC depression angle variation	CNN, SRC, ASC, CS, Hybrid reflectivity attribute, LMF
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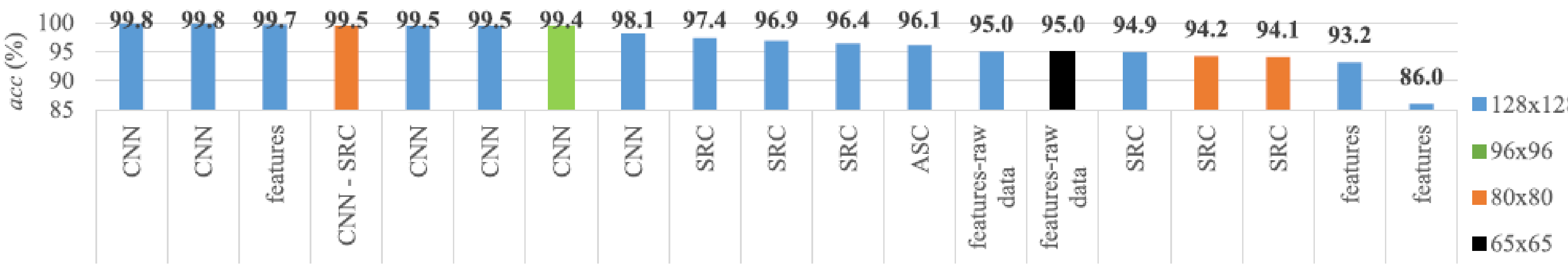
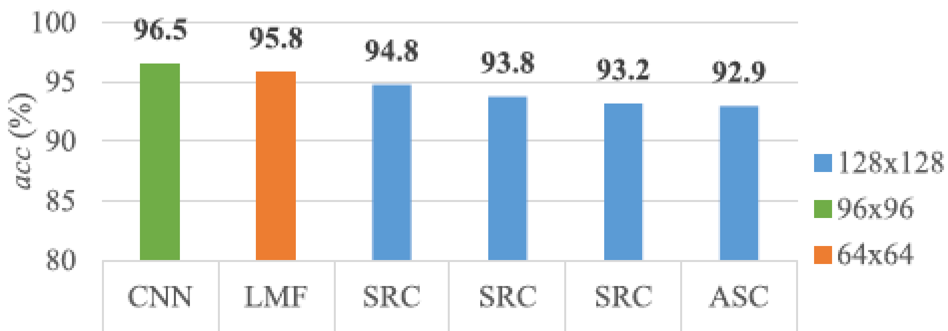
Comparison of methods in SOC and EOC



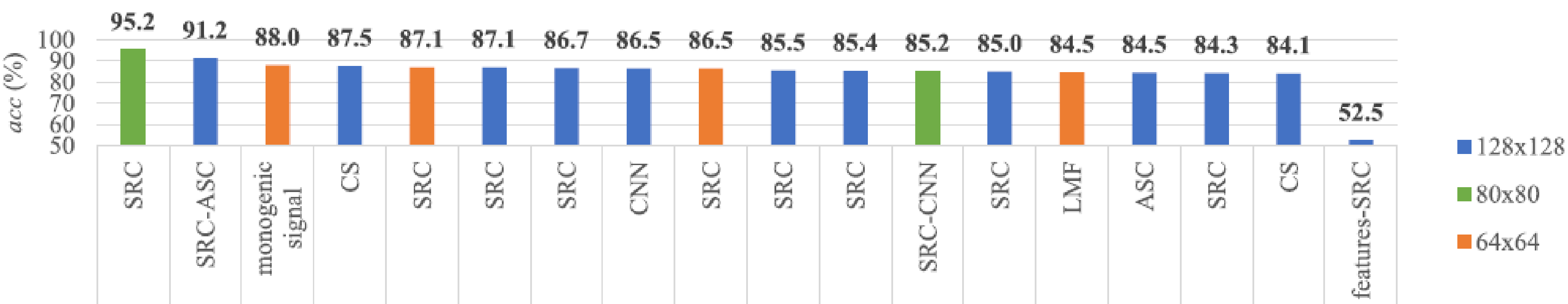
SOC



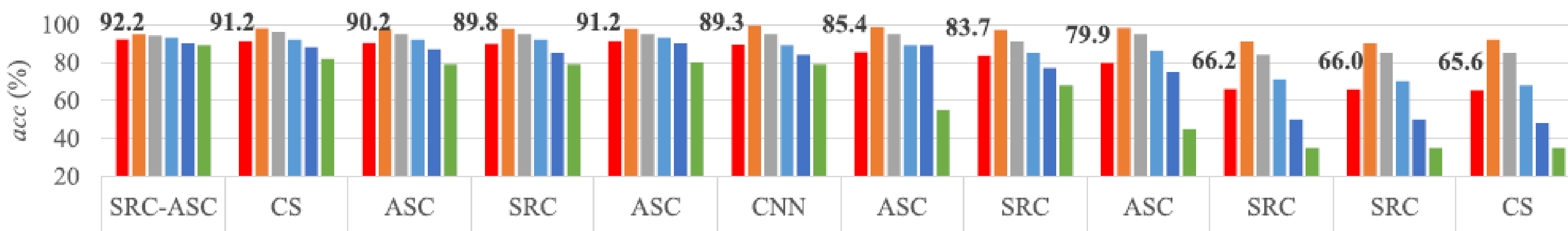
SOC: Configuration Variant

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

Comparison of methods in SOC and EOC



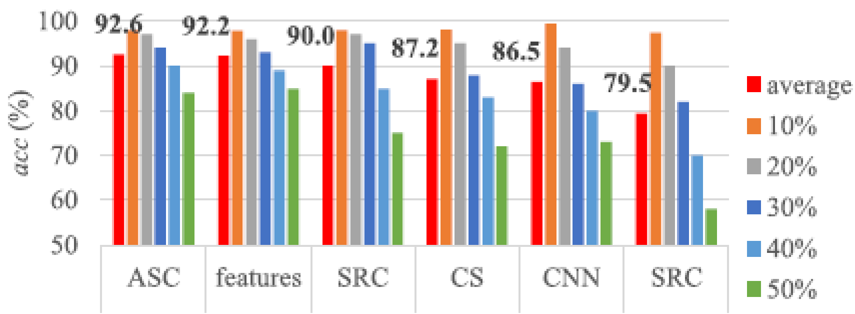
EOC: Depression Angle Variant



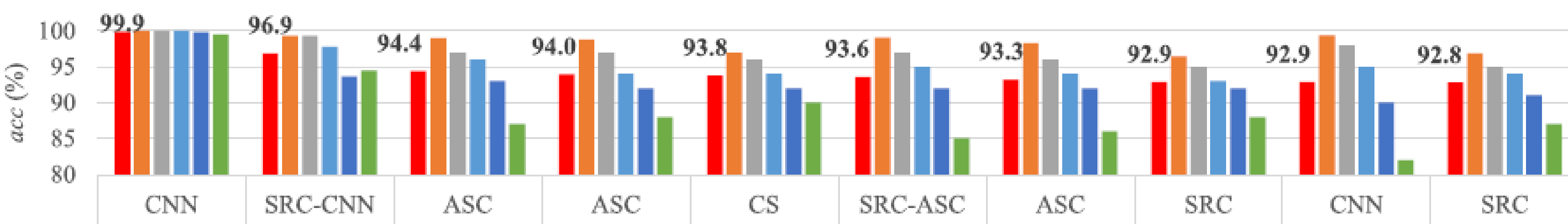
EOC: Noise Corruption (red=average, orange=10dB SNR, grey=5dB SNR, light blue=0dB SNR, dark blue=-5 dB SNR, green=-10dB SNR)

O Kechagias-Stamatis, N. Aouf, "*Automatic Target Recognition on Synthetic Aperture Radar Imagery: A Survey*," IEEE Aerospace and Electronic Systems Magazine, 2021.

Comparison of methods in SOC and EOC



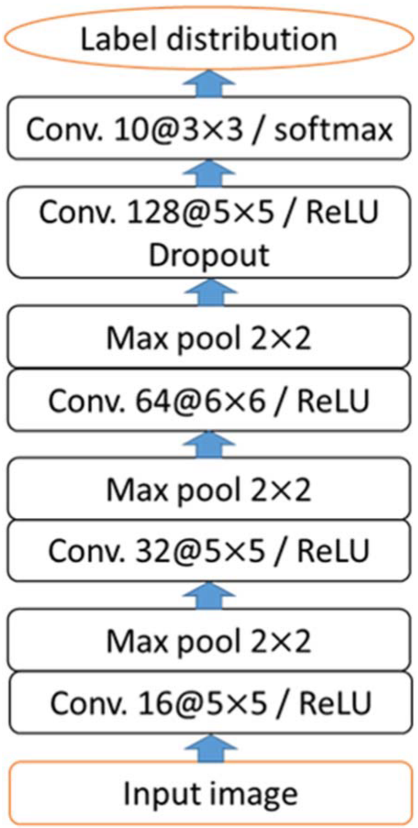
EOC: Partial Occlusion



EOC: Resolution Variant (Red= average, orange=0.3 X 0.3 m, grey=0.4 X 0.4 m, light blue=0.5 X 0.5 m, dark blue=0.6 X 0.6 m, green= 0.7 X 0.7 m)

O Kechagias-Stamatis, N. Aouf, "*Automatic Target Recognition on Synthetic Aperture Radar Imagery: A Survey*," IEEE Aerospace and Electronic Systems Magazine, 2021.

ATR SAR via CNN, an example



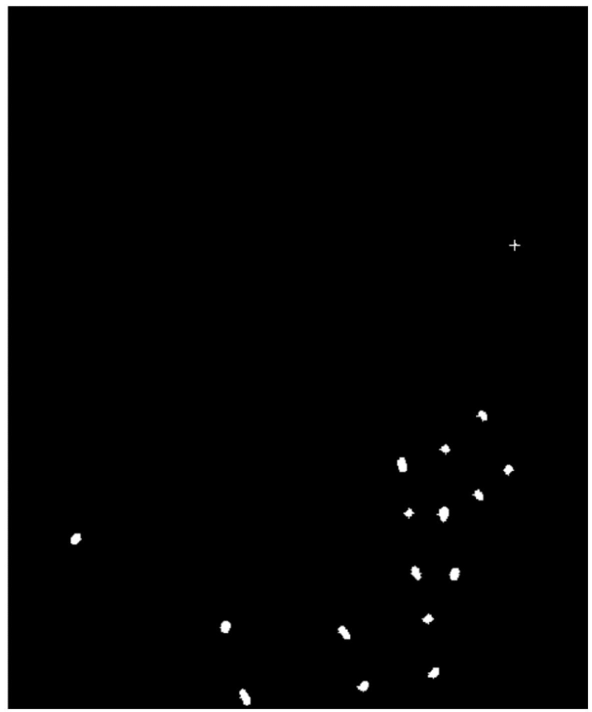
Class	BMP-2	BTR-70	T-72	BTR-60	2S1	BRDM-2	D7	T62	ZIL131	ZSU234	P_{cc}(%)
BMP-2	194	0	1	0	1	0	0	0	0	0	98.98
BTR-70	0	195	0	0	0	1	0	0	0	0	99.49
T-72	0	0	196	0	0	0	0	0	0	0	100
BTR-60	1	0	0	188	0	0	0	1	1	4	96.41
2S1	0	0	0	0	269	4	0	0	0	1	98.18
BRDM-2	0	0	0	0	0	272	0	0	0	2	99.27
D7	0	0	0	0	0	0	272	1	1	0	99.27
T-62	0	0	0	0	0	0	0	272	1	0	99.64
ZIL-131	0	0	0	0	0	0	0	0	273	1	99.64
ZSU-234	0	0	0	0	0	0	1	0	0	273	99.64
Total											99.13

S. Chen, H. Wang, F. Xu, Y. Q. Jin, "*Target Classification Using the Deep Convolutional Networks for SAR Images*," IEEE Transaction on Geoscience and Remote sensing, 2016.

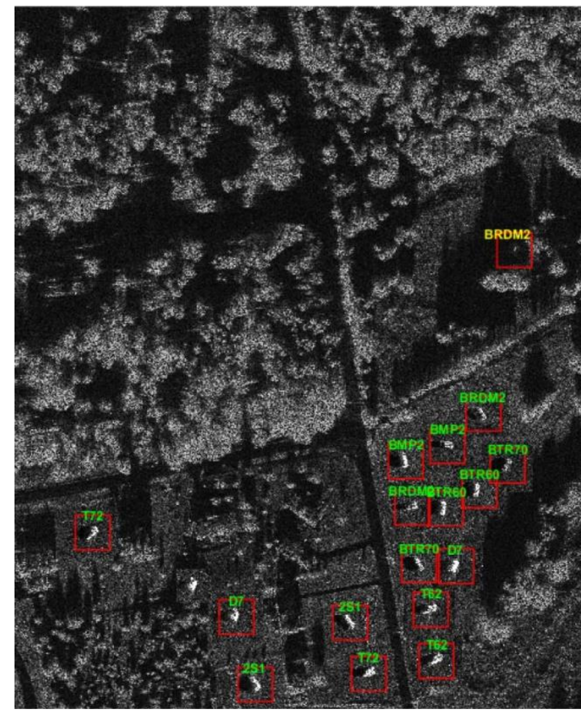
ATR SAR via CNN, an example

Scenario

Detection



Classification



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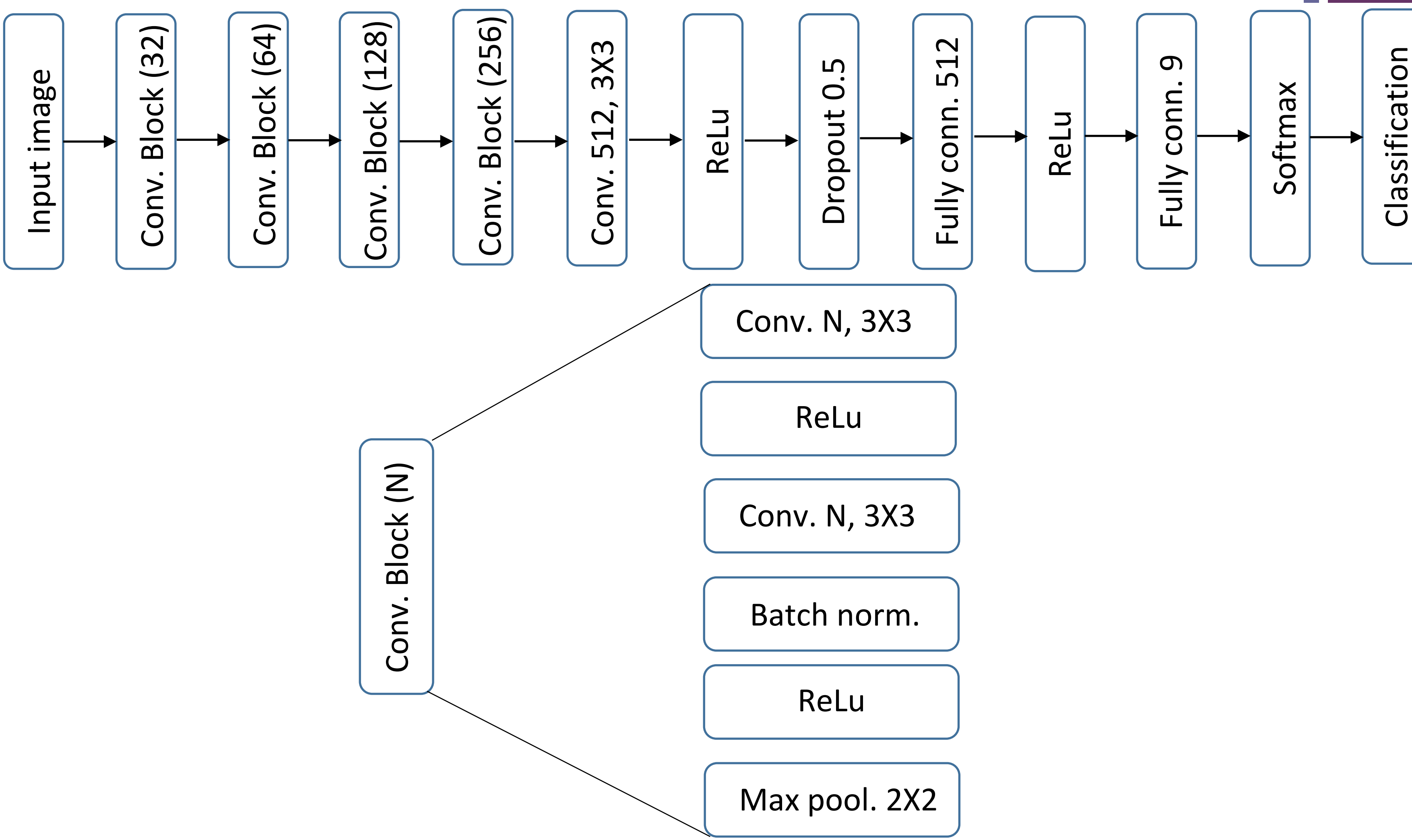
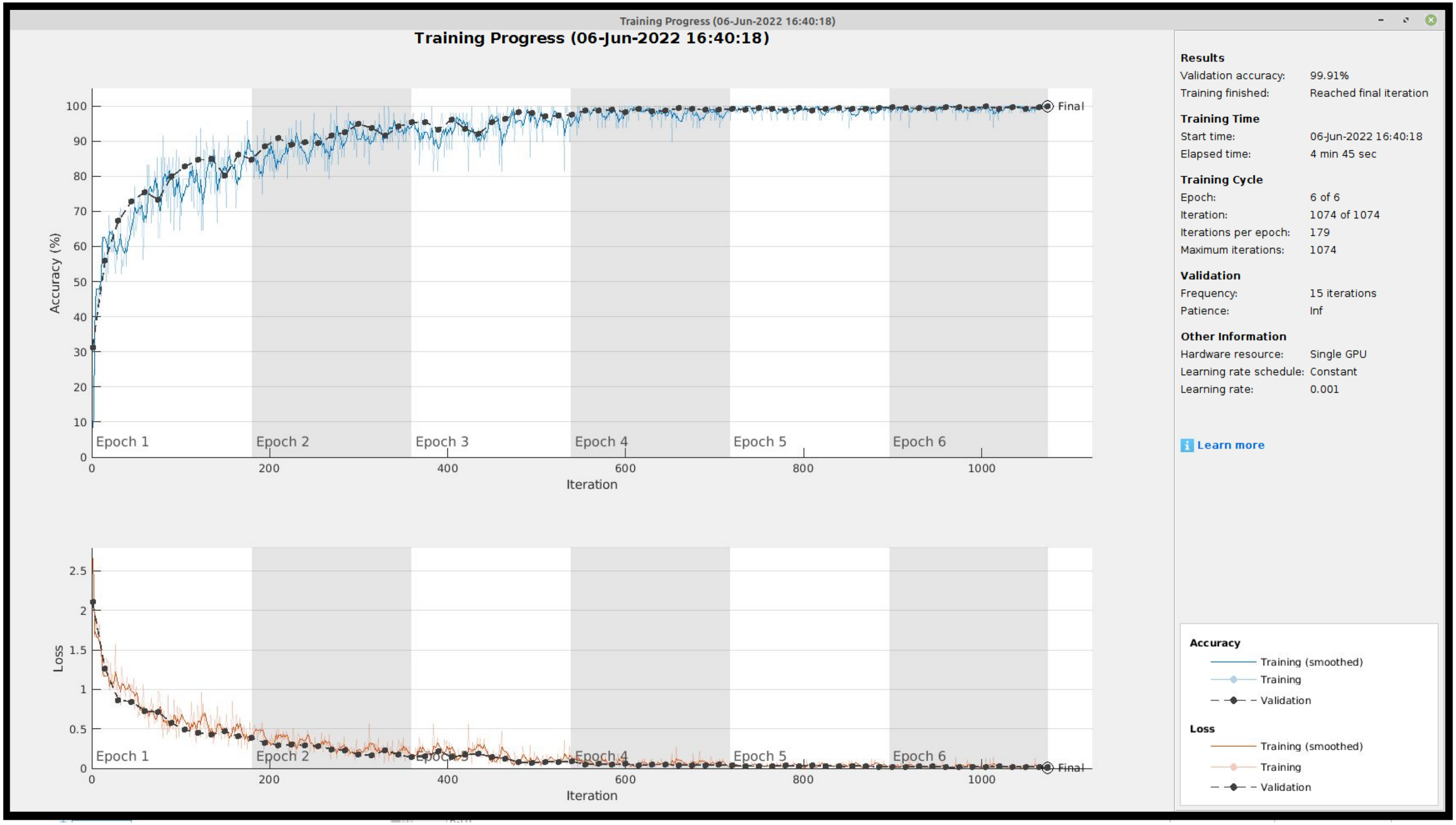
ATR SAR via CNN, proposed example



ATR SAR via CNN, proposed example



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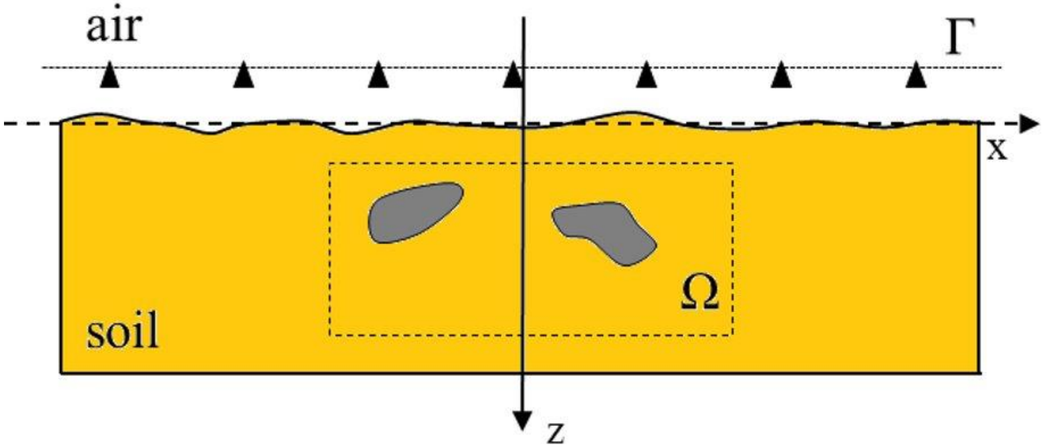
ATR SAR via CNN, proposed example

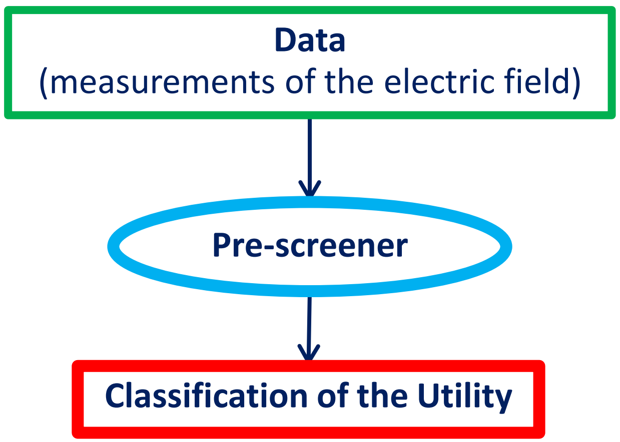
SAR Target Classification Confusion Matrix

True Class \ Predicted Class	2S1	BRDM_2	BTR_60	Clutter	D7	SLICY	T62	ZIL131	ZSU_23_4		
2S1	116							1	2	97.5%	2.5%
BRDM_2		141								100.0%	
BTR_60			45							100.0%	
Clutter				214						100.0%	
D7					57			1	1	96.6%	3.4%
SLICY						253				100.0%	
T62							57			100.0%	
ZIL131								55		100.0%	
ZSU_23_4									137	100.0%	

MIMO GPR

MIMO GPR





Two-step process:

- Anomaly detection (prescreener)
  (spectral features to model the interested target patterns)

- Classification of the buried target
  (supervised learning)

Aim of the work*: a deep learning approach for the classification of urban underground utilities via exploiting multistatic GPR data.*

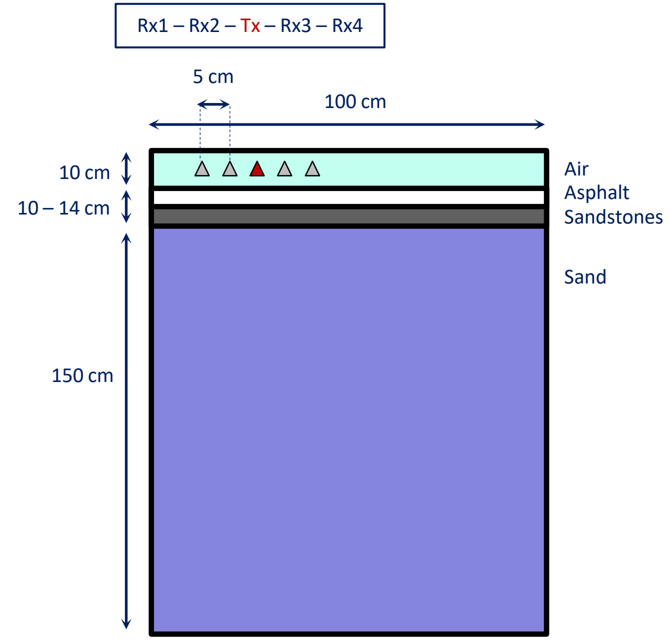
MIMO GPR

ANTENNAS INFORMATION:

- Type of Antennas: wire
- Central Frequency: 600 MHz
- Bandwidth: 500 MHz
- Array Height: 5 cm from the interface
- Array positions: 15 in 60-cm length

Buried Targets Details

Utility	Pipe Material	External Diameter [cm]	Thickness [cm]	Depth [cm]
Water	Plastic/Metallic	20 – 60	1 – 4	100 – 150
Natural Gas	Plastic	10 - 15	1 – 1,5	50 - 150



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MIMO GPR

Some strategies usually employed to face the limited amount of GPR data:

- ➢ synthetically generated signatures
- ➢ data augmentation
- ➢ pretraining
- ➢ transfer learning

Training Details:

- Mini-batch size: 32
- Training of epochs: 32
- Optimization method: SGDM
- l_2-regularization factor: 10^{-3}
- Momentum factor: 0.9
- Initial learning rate: 10^{-3}

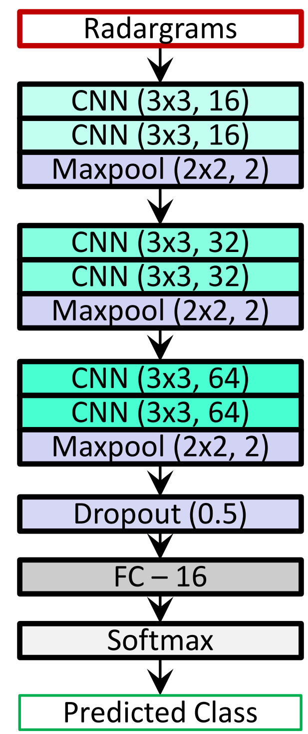
PROCESSING:

- Training using time-gated radargrams with no noise
- Testing with SNR = 30dB

List of the Classes Adopted in the Classification Problem

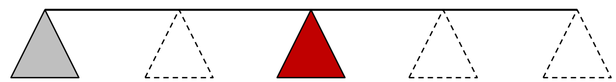
Class ID	Infill	Pipe Material	Depth
I	Gas	Plastic	Deep
II	Water	Metallic	Deep
III	Water	Plastic	Deep
IV	Gas	Plastic	Shallow
V	Water	Metallic	Shallow
VI	Water	Plastic	Shallow

Data Set Information:



MIMO GPR

Rx1 – Rx2 – Tx – Rx3 – Rx4

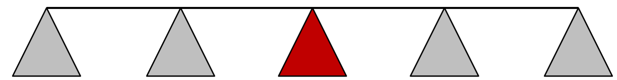


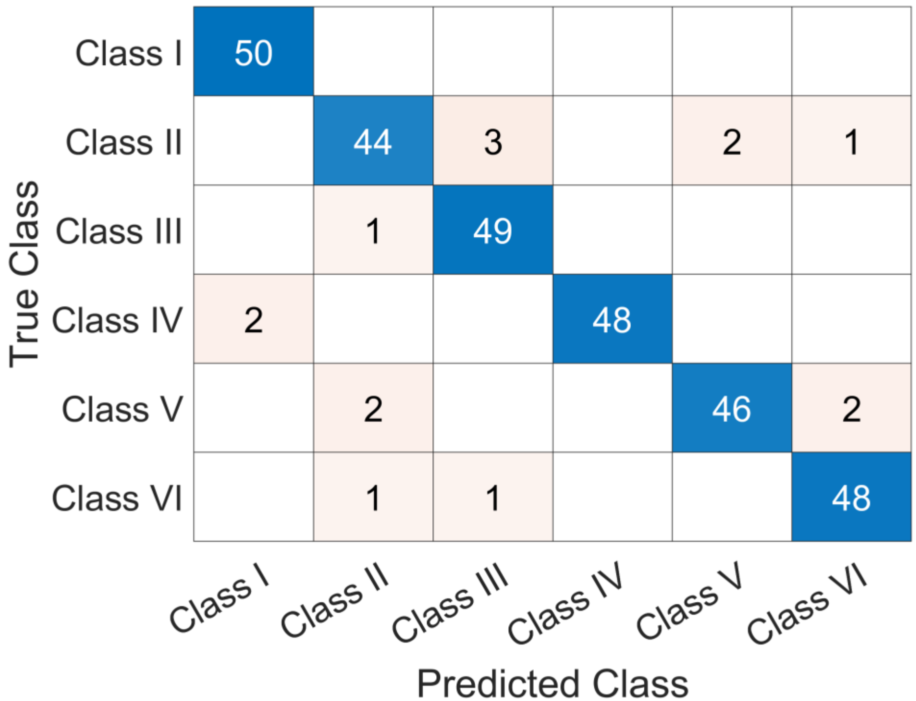
True Class \ Predicted Class	Class I	Class II	Class III	Class IV	Class V	Class VI
Class I	50					
Class II	3	41	3		2	1
Class III		1	48			1
Class IV	2			48		
Class V		5			39	6
Class VI		1	4		3	42

Testing accuracy ≈ 89%

MIMO GPR

Rx1 – Rx2 – Tx – Rx3 – Rx4





Testing accuracy ≈ 95%

MIMO GPR

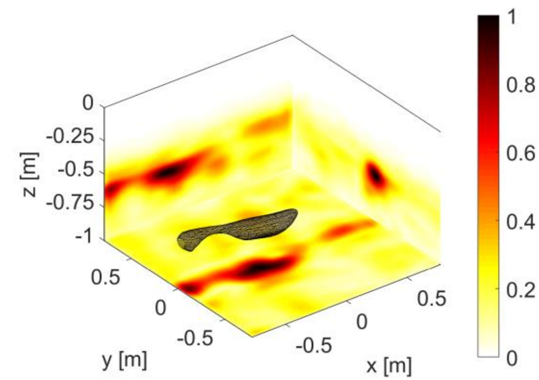
ON-GOING WORK:

- Testing the proposed approach in more realistic scenarios
- Improving the detection performance (both database and network architecture)
- Complete the localization with a three-dimensional map
- Drone-based

Classification of the Utility

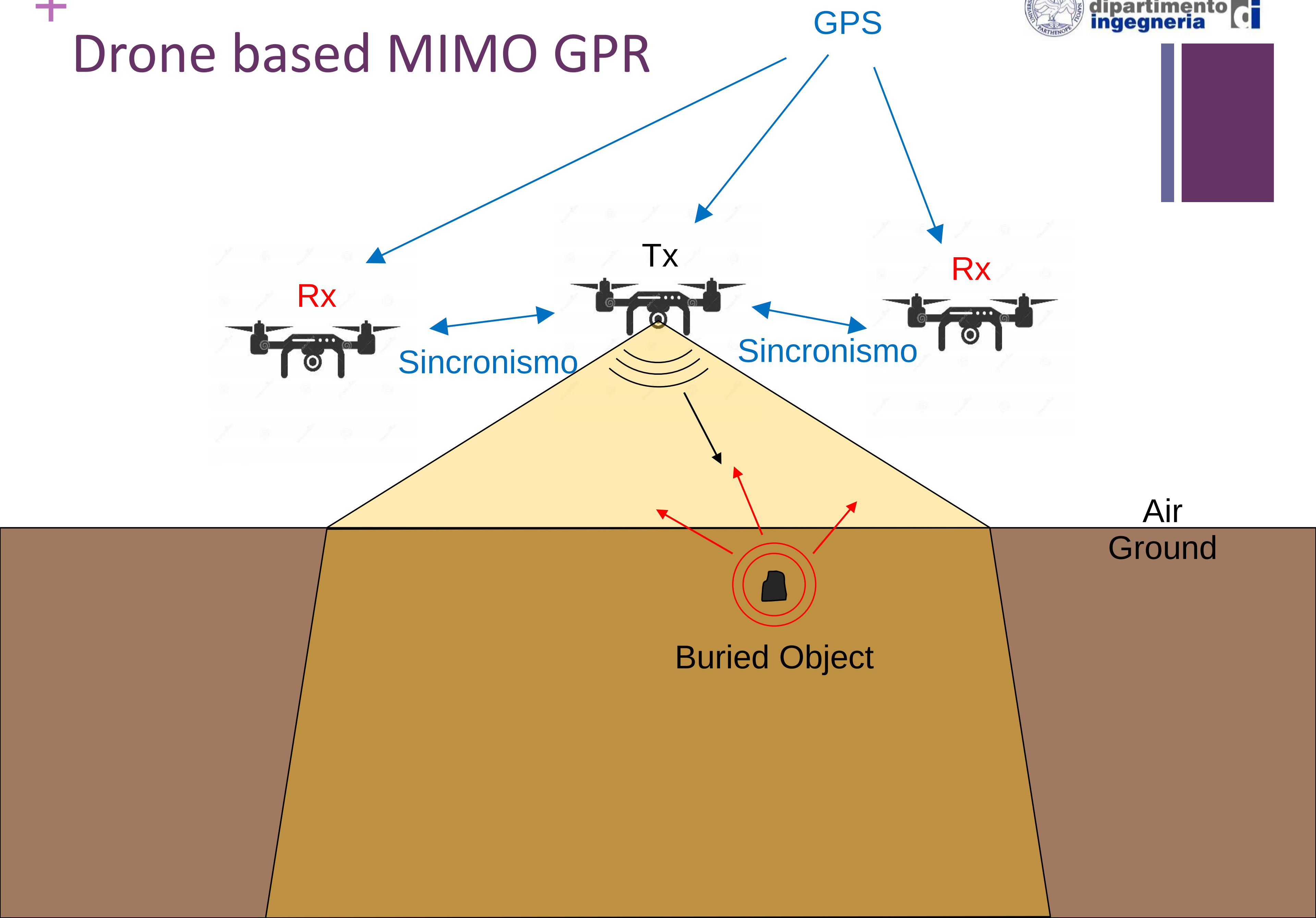
↓

3D map



Ambrosanio et Al., «Performance Analysis of Tomographic Methods Against Experimental Contactless Multistatic Ground Penetrating Radar», *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *14*, pp. 1171-1183, 2020.

Drone based MIMO GPR



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Grazie per l'attenzione!