Automatic Target Recognition

The Technical Challenge for Autonomous Weapons

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Autonomous Weapons are a Legal & Ethical minefield

A classification of Weapon systems

Automated

Semi-Autonomous

Autonomous

Automated

System is <u>pre-programmed</u> in a specific manner and <u>cannot adapt</u> its function outside those parameters.

"Fire-and-forget"

Semi-Autonomous

A system is essentially an automated weapon or that has some degree of self-function but this function is permanently supervised by a human operator.

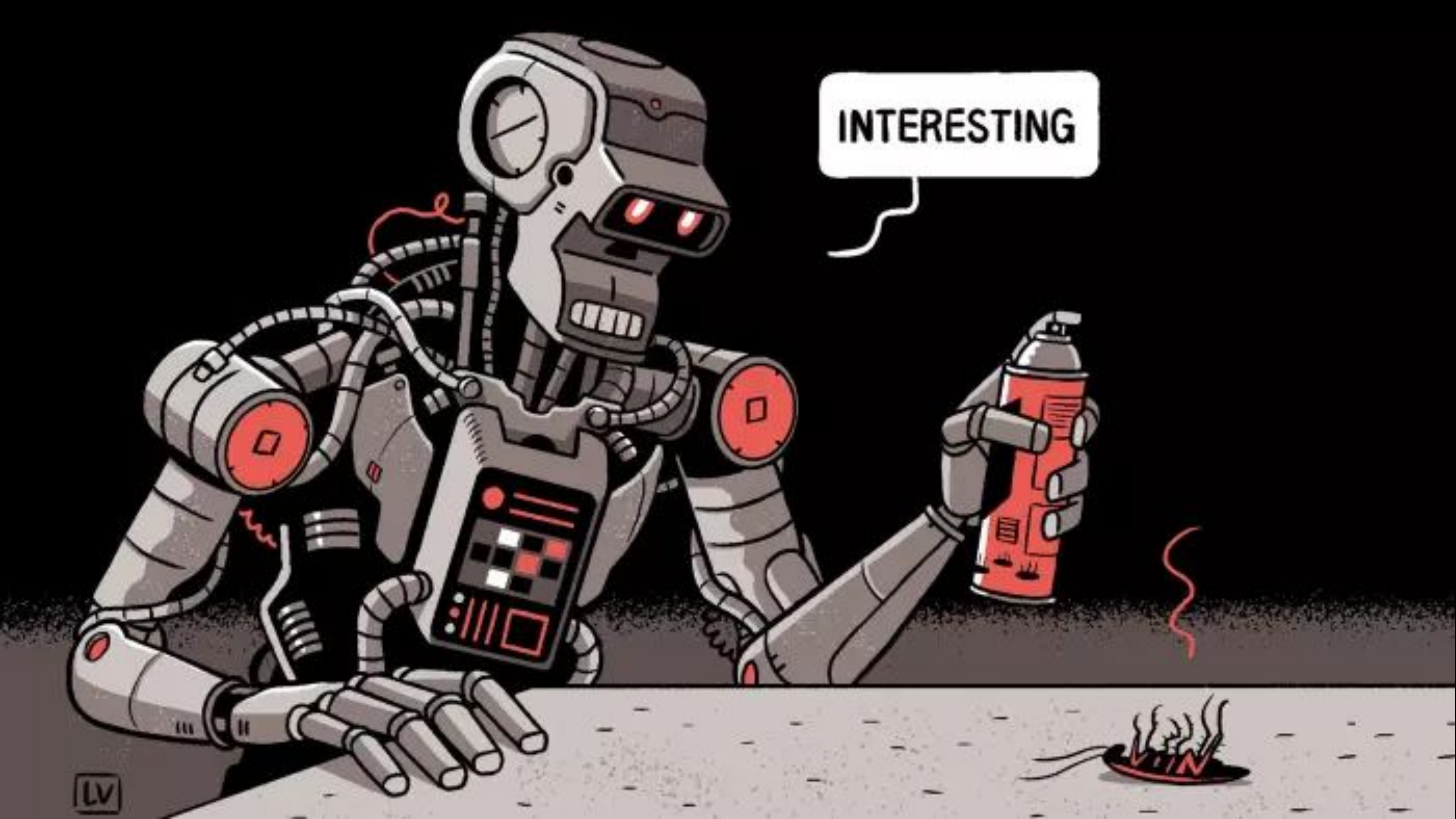
"human in the loop"

"human on the loop"

Autonomous

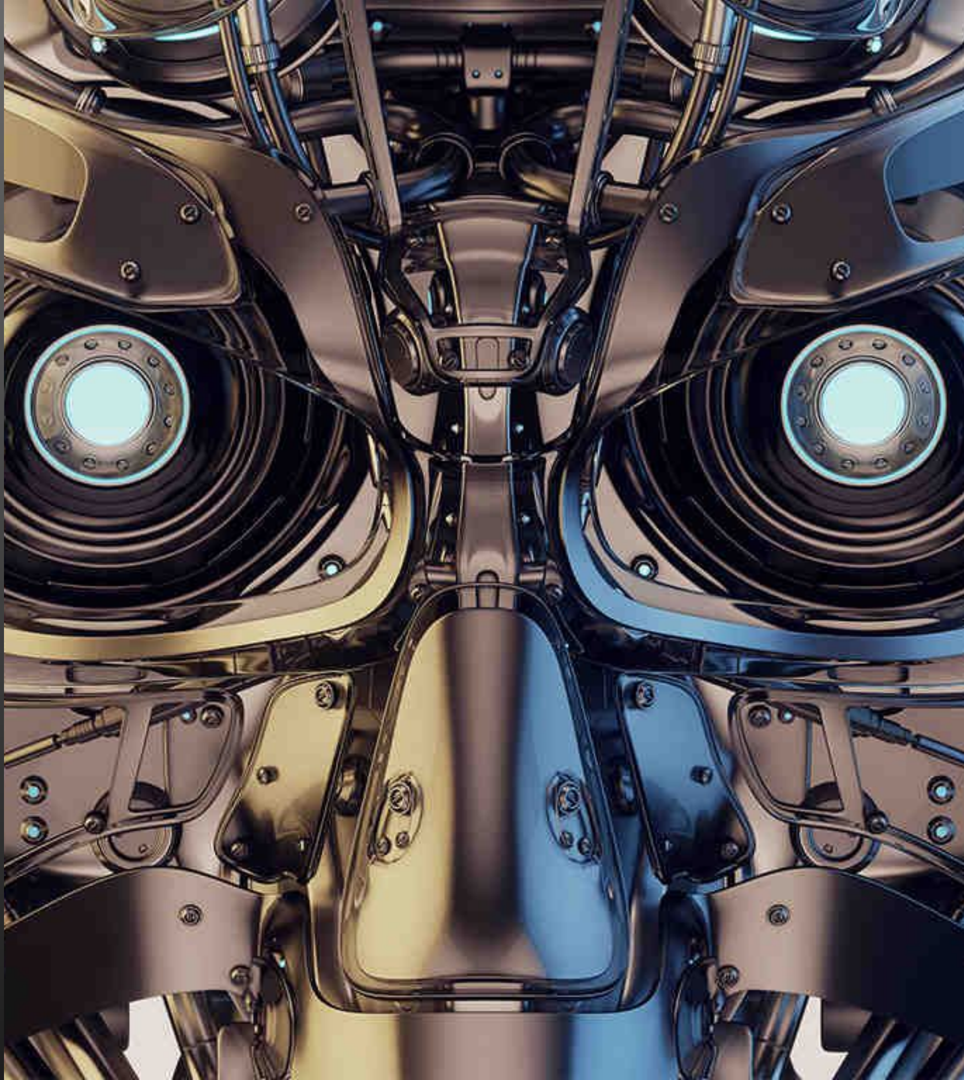
An automated weapon that can adapt its function to changing circumstances.

AI…


INTERESTING
LV

Why is Automatic Target Recognition (ATR) important?

It’s the eye



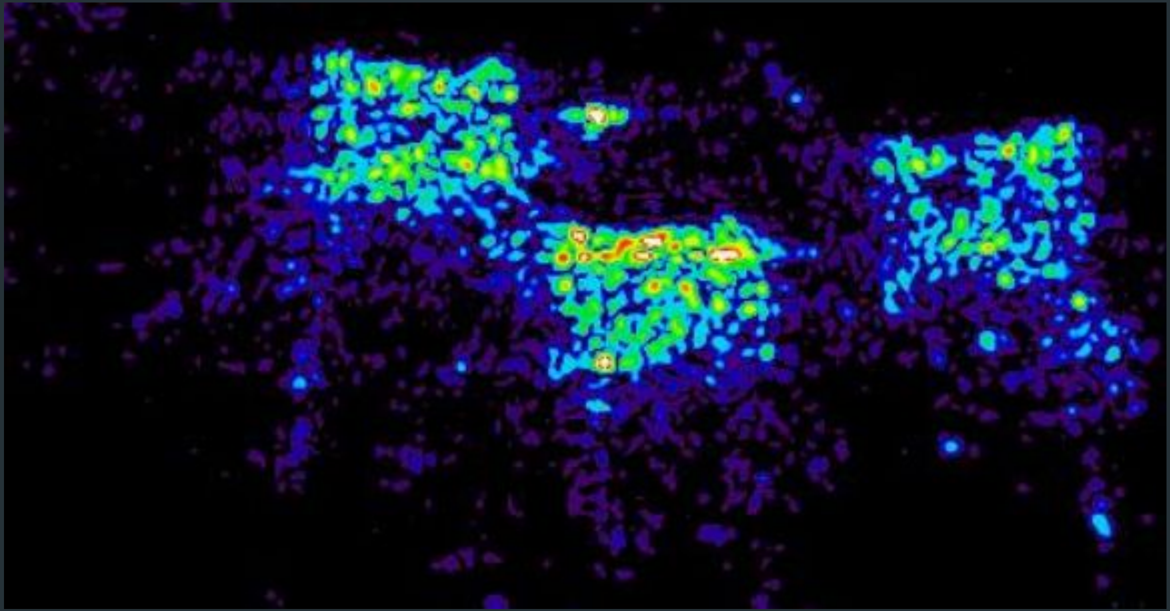
ATR of Ground Targets

A general-purpose automatic target recognition system does not exist.

— Steven K.Rogers

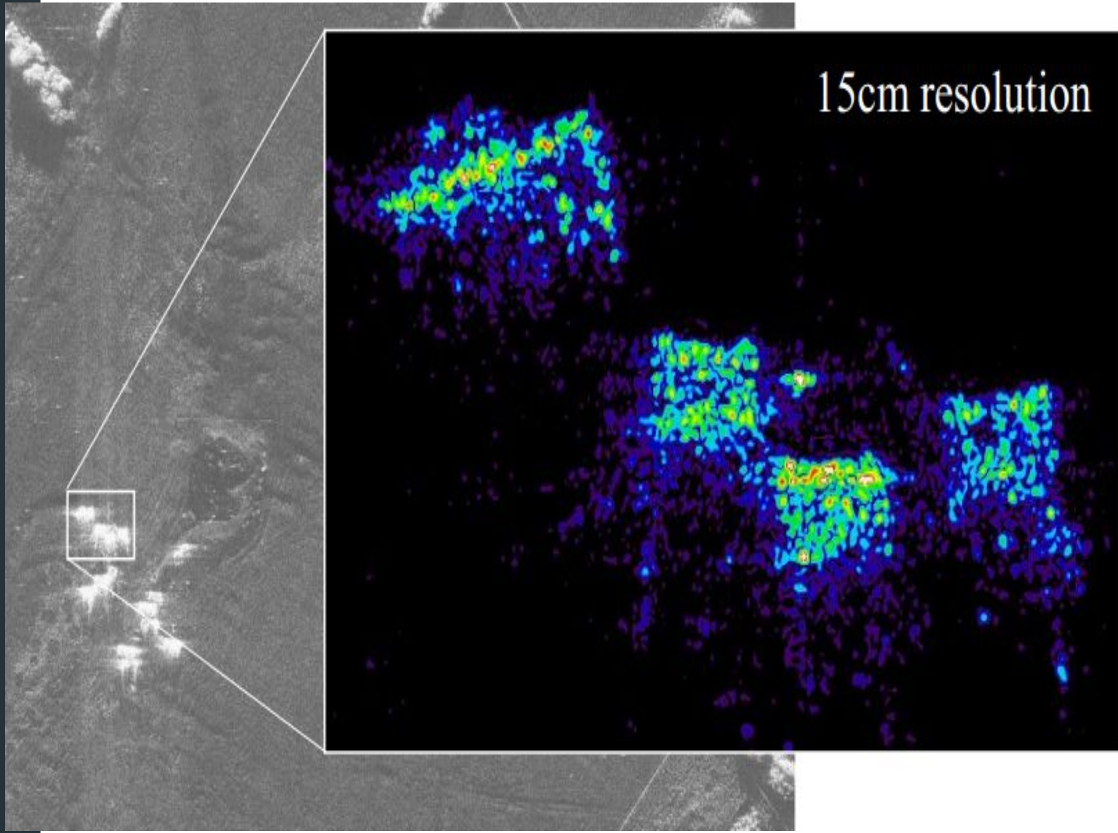
(Air Force Institute of Technology, USA)

Why not human-only?



- Radar images are not interpretable by humans

- But computers can, and they are more efficient



How does it work?

Image processing

+

Maching learning

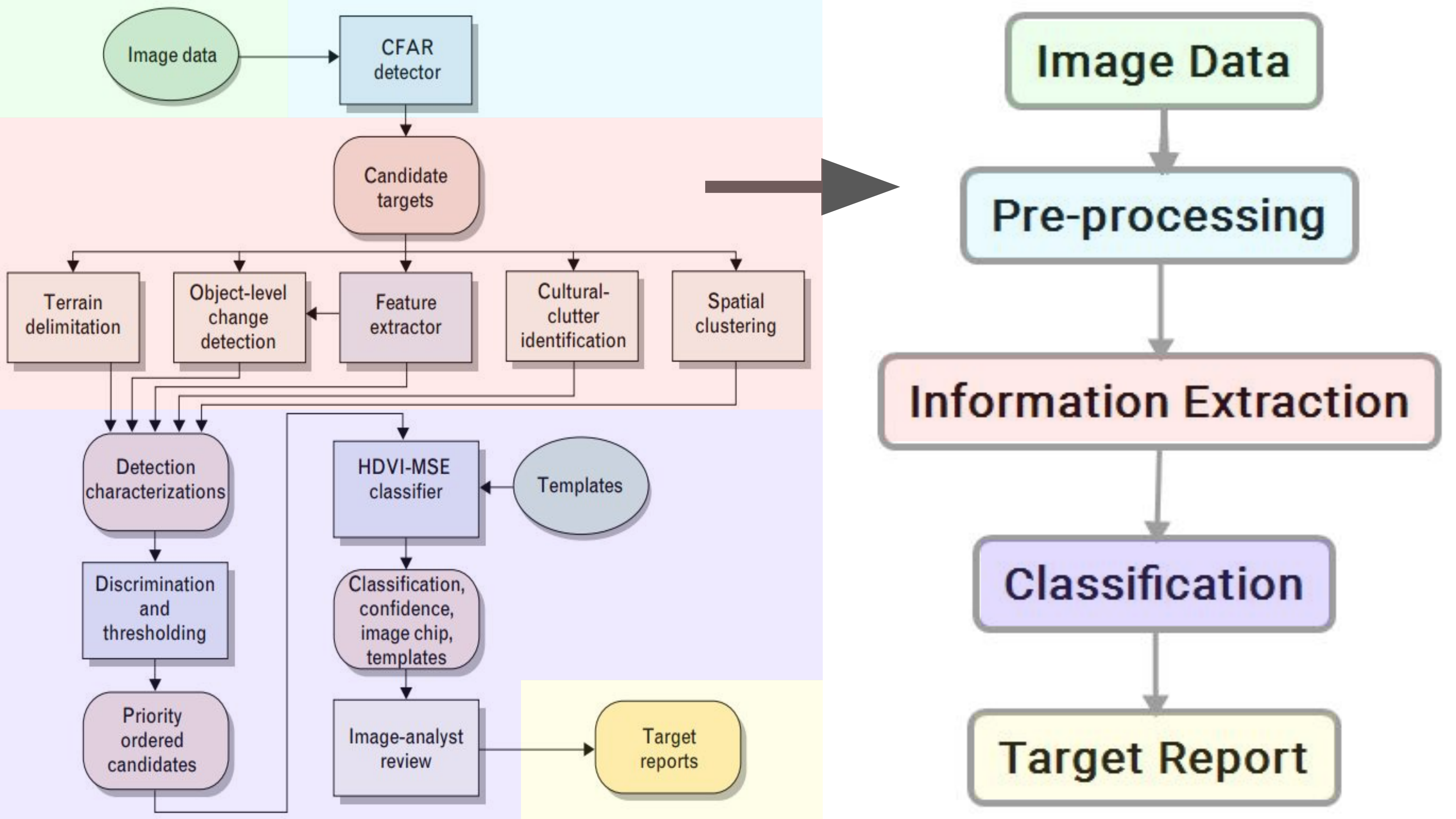
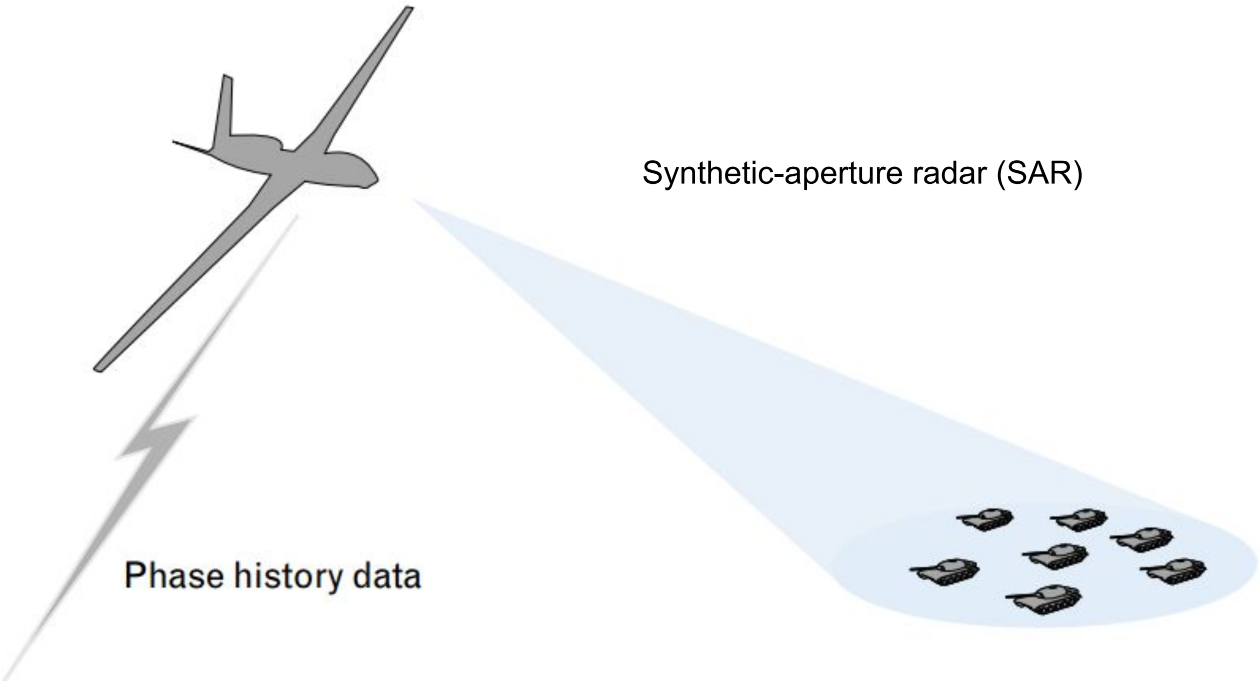


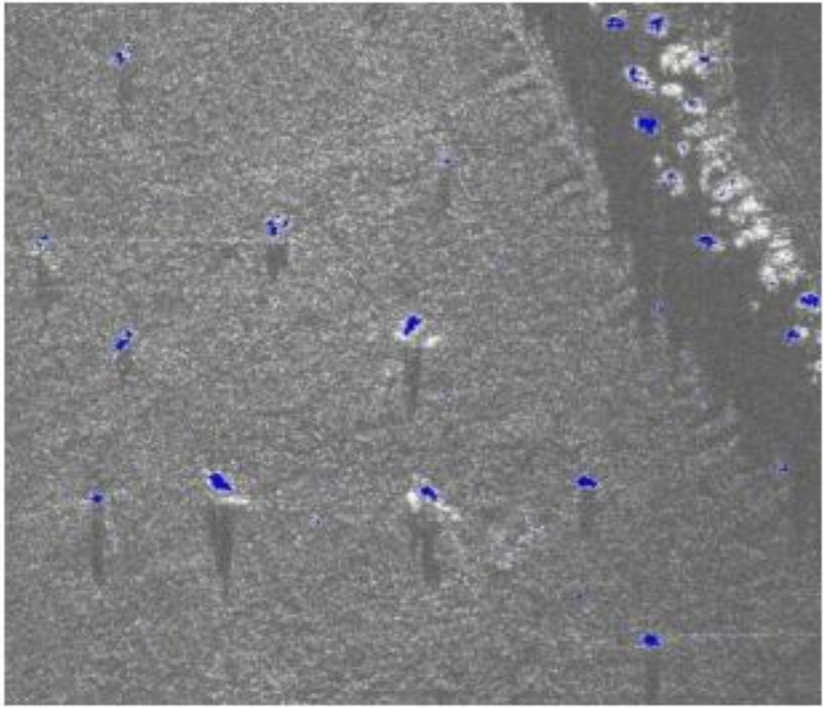
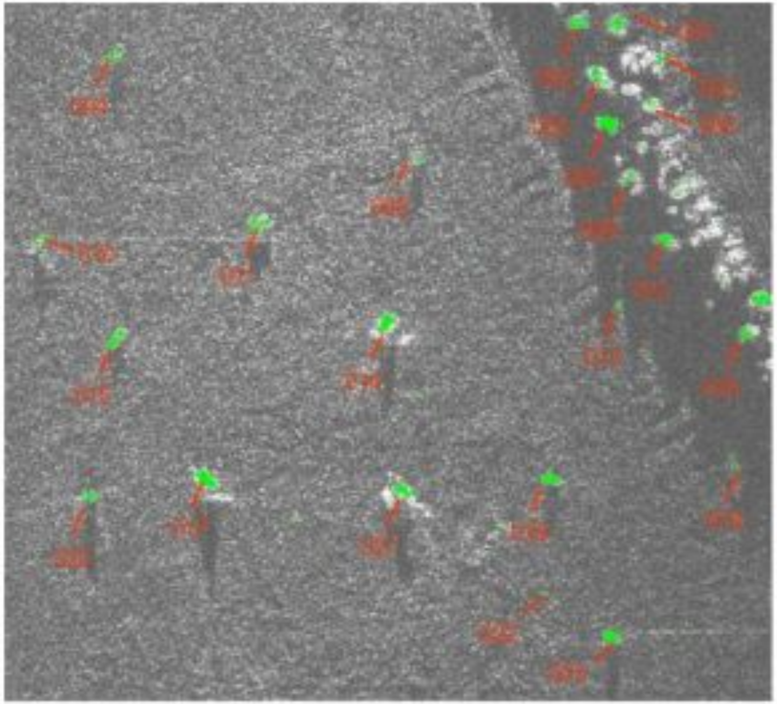
Image data
CFAR detector
Candidate targets
Terrain delimitation
Object-level change detection
Feature extractor
Cultural-clutter identification
Spatial clustering
Detection characterizations
HDVI-MSE classifier
Templates
Discrimination and thresholding
Classification, confidence, image chip, templates
Priority ordered candidates
Image-analyst review
Target reports
Image Data
Pre-processing
Information Extraction
Classification
Target Report

(Collect) image data

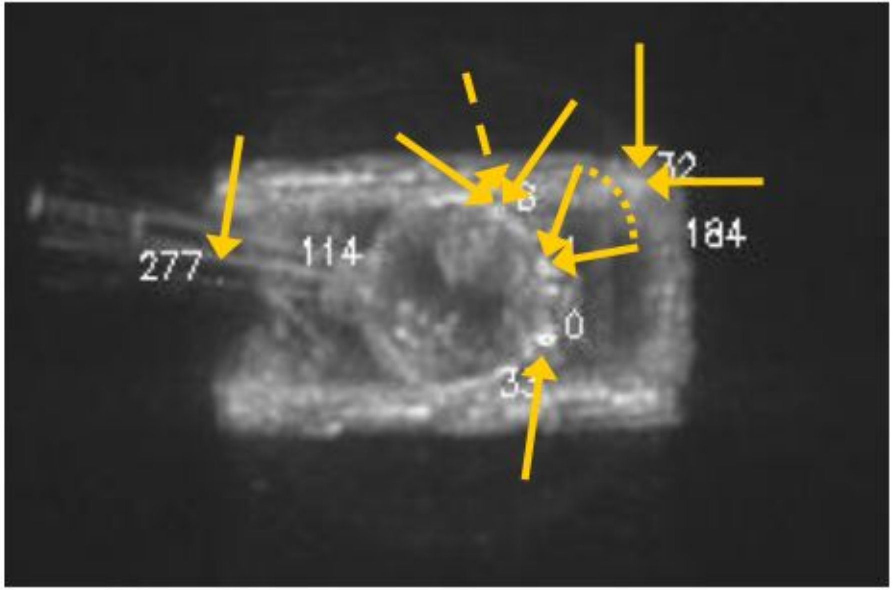
Using UVA (drone) to generate a profusion of data

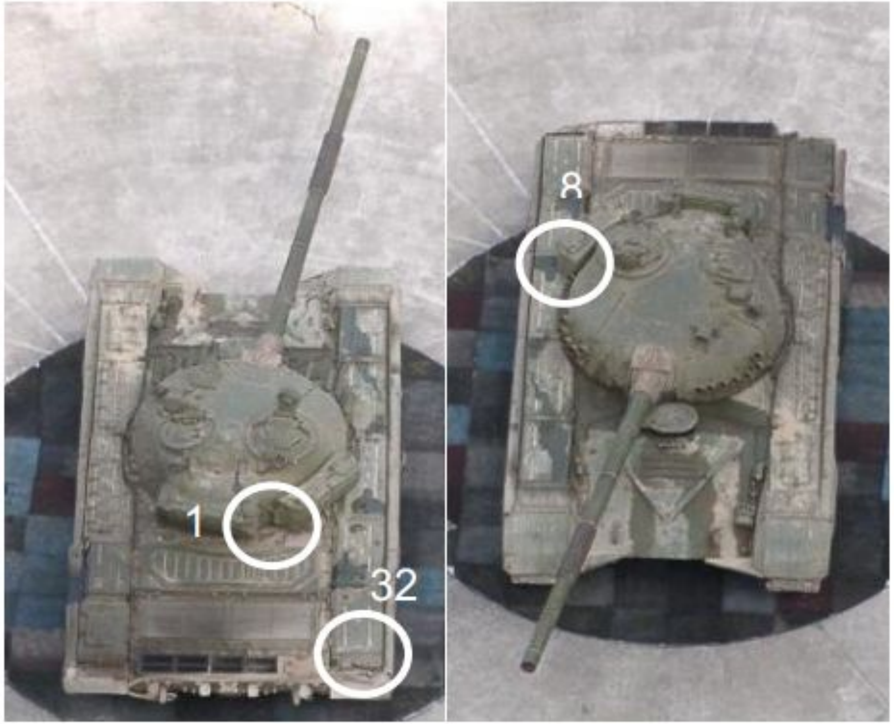


Pre-processing (images)

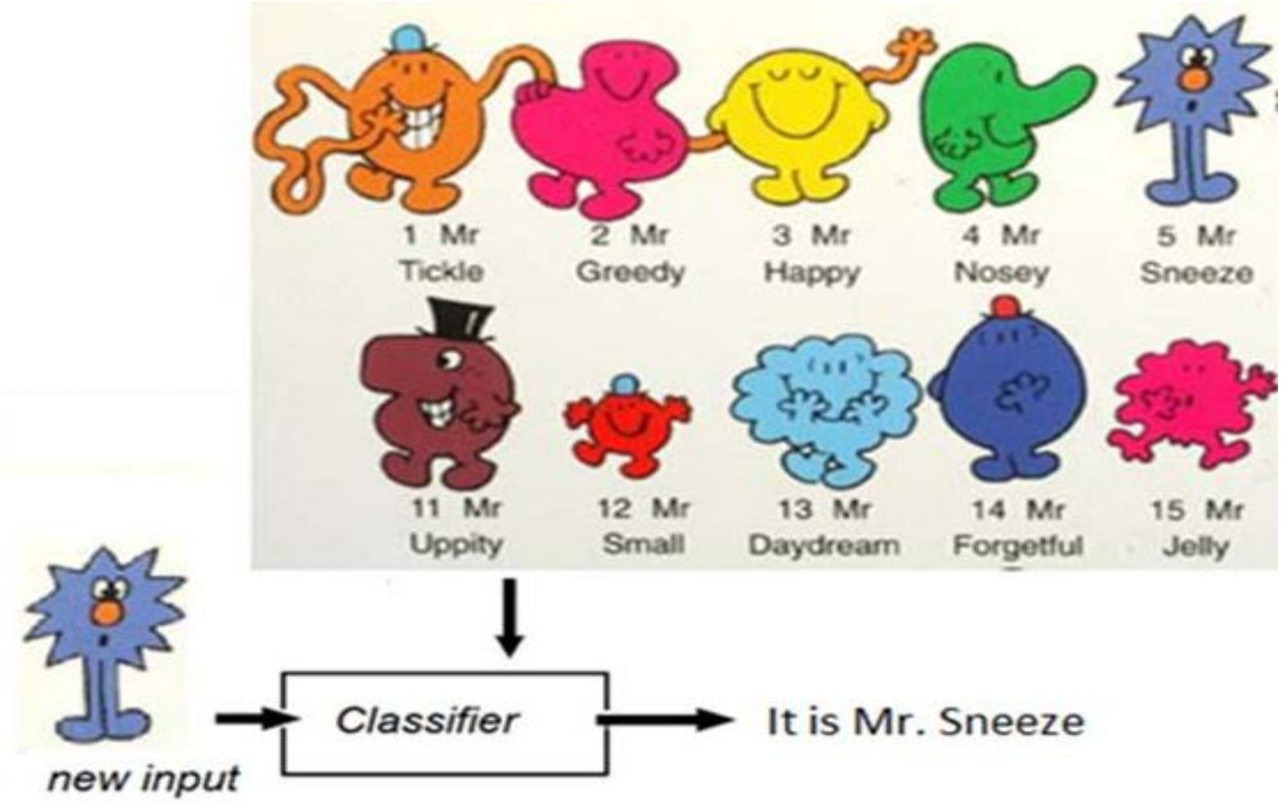
Detection	Clustering
	

Information Extraction

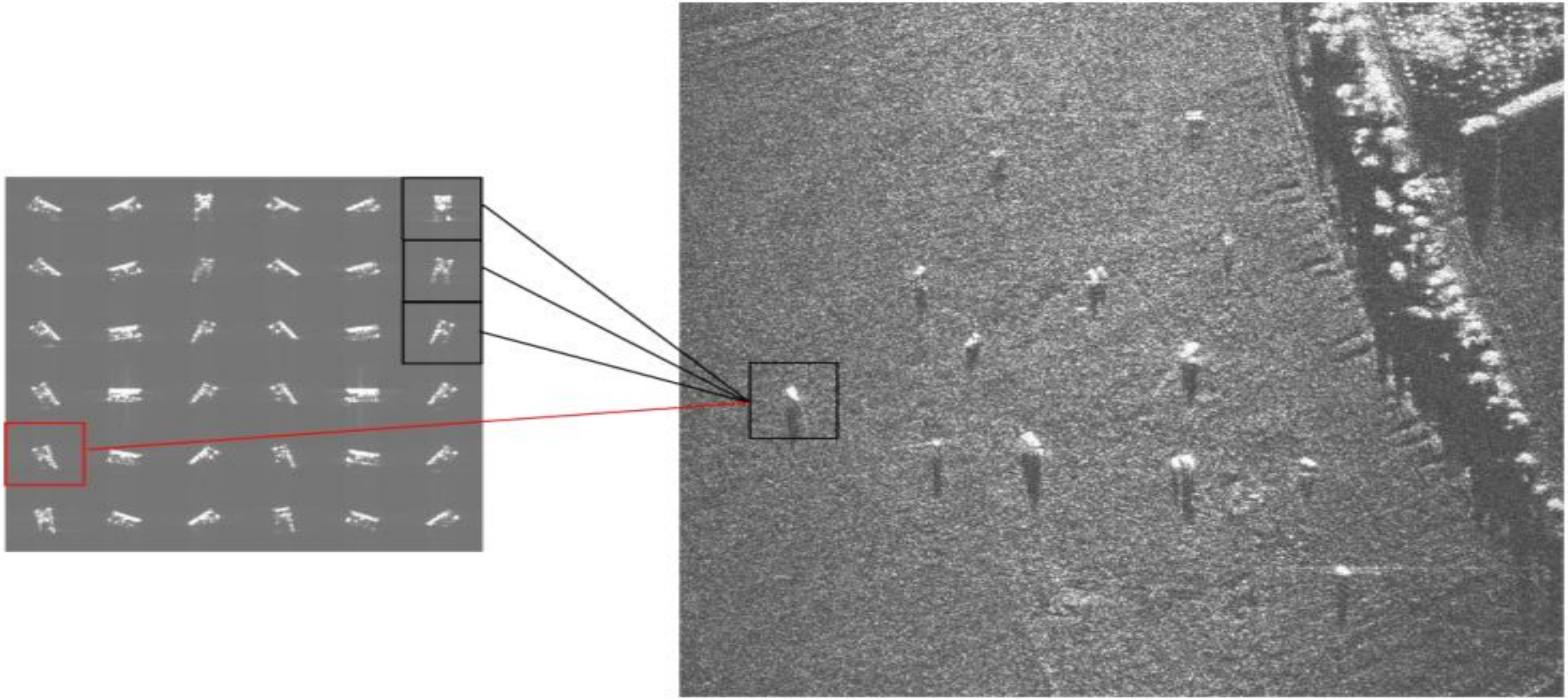




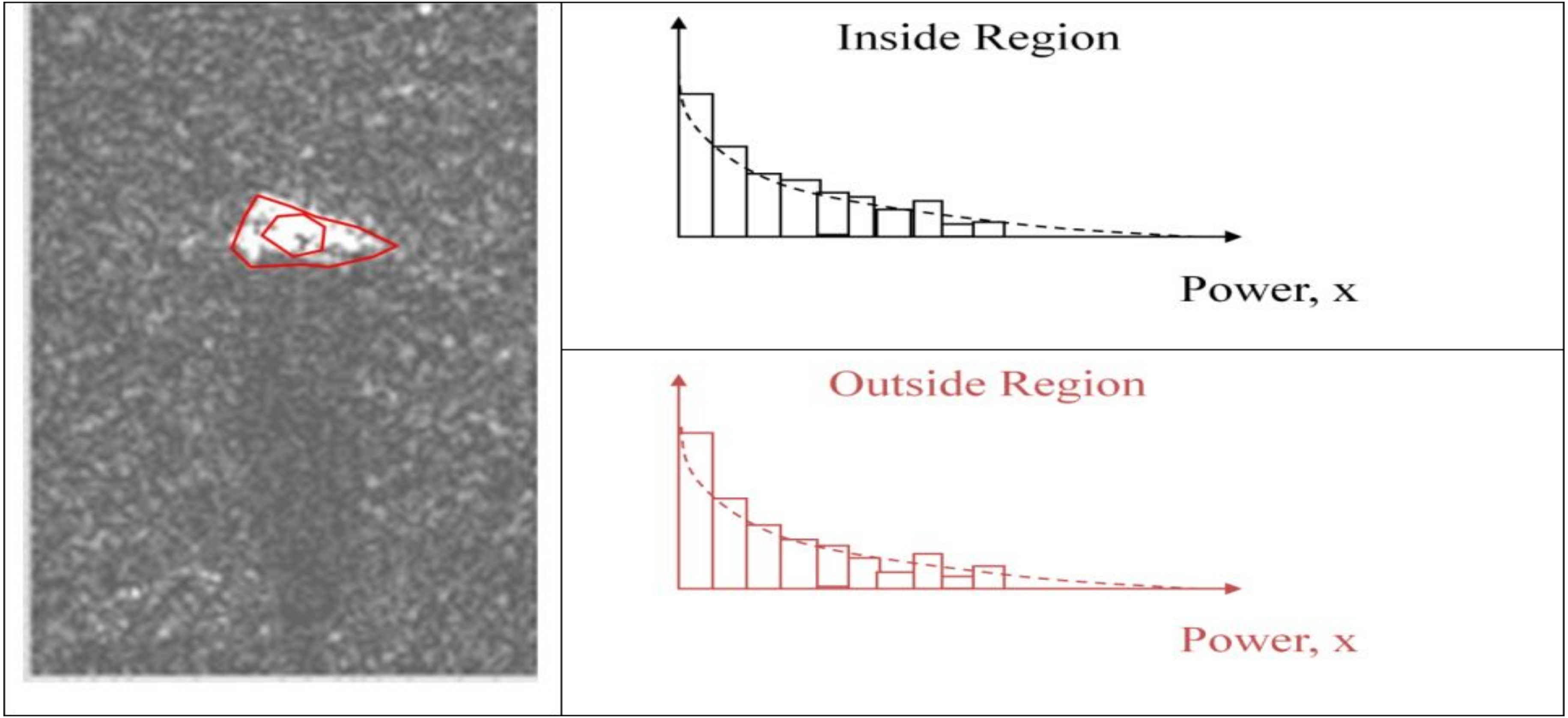
Classification: Method 1 - Template Matching



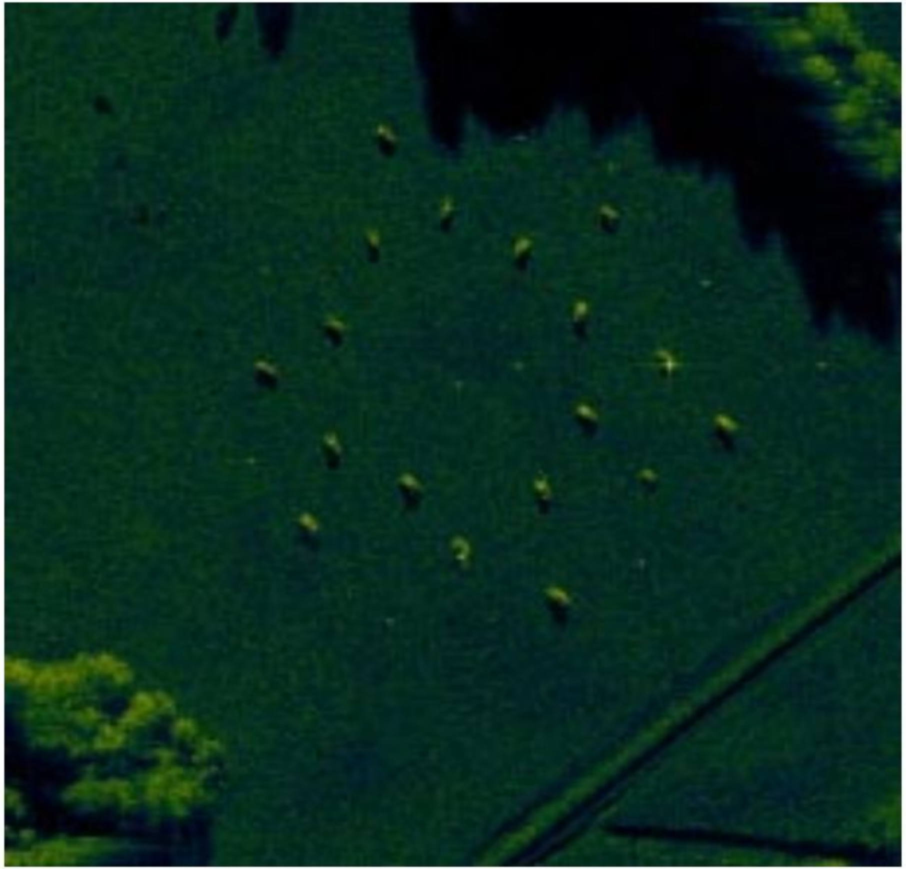
Classification: Method 1 - Template Matching

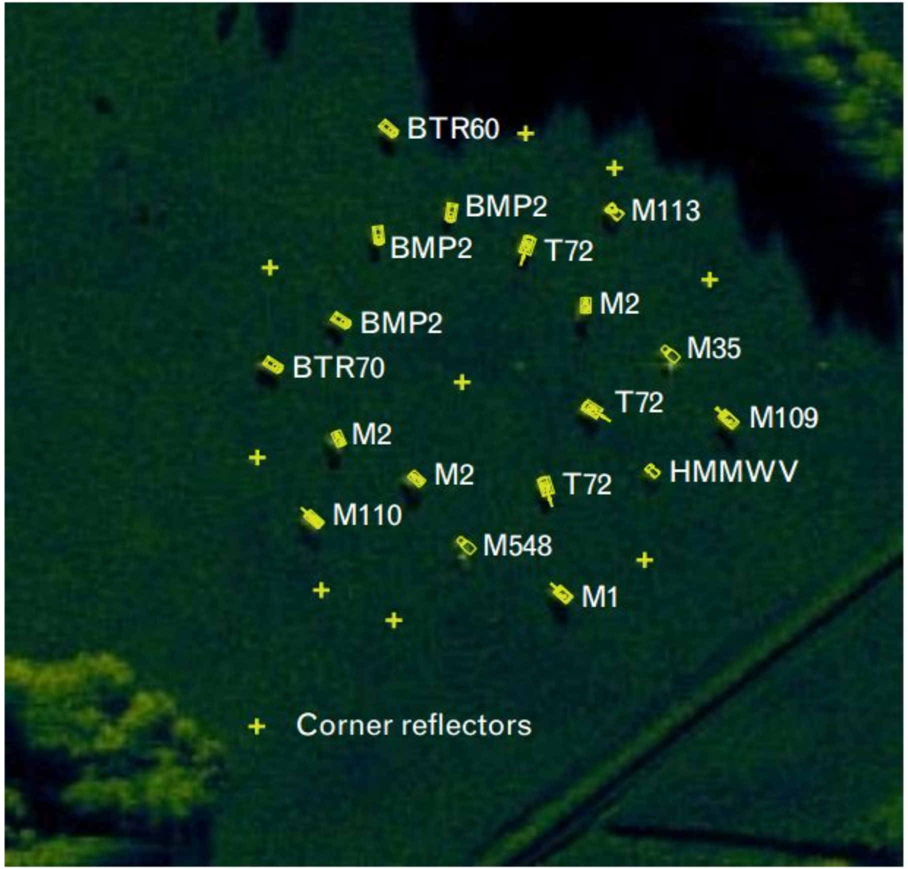


Classification: Method 2 - Feature-based



Classification: Performance





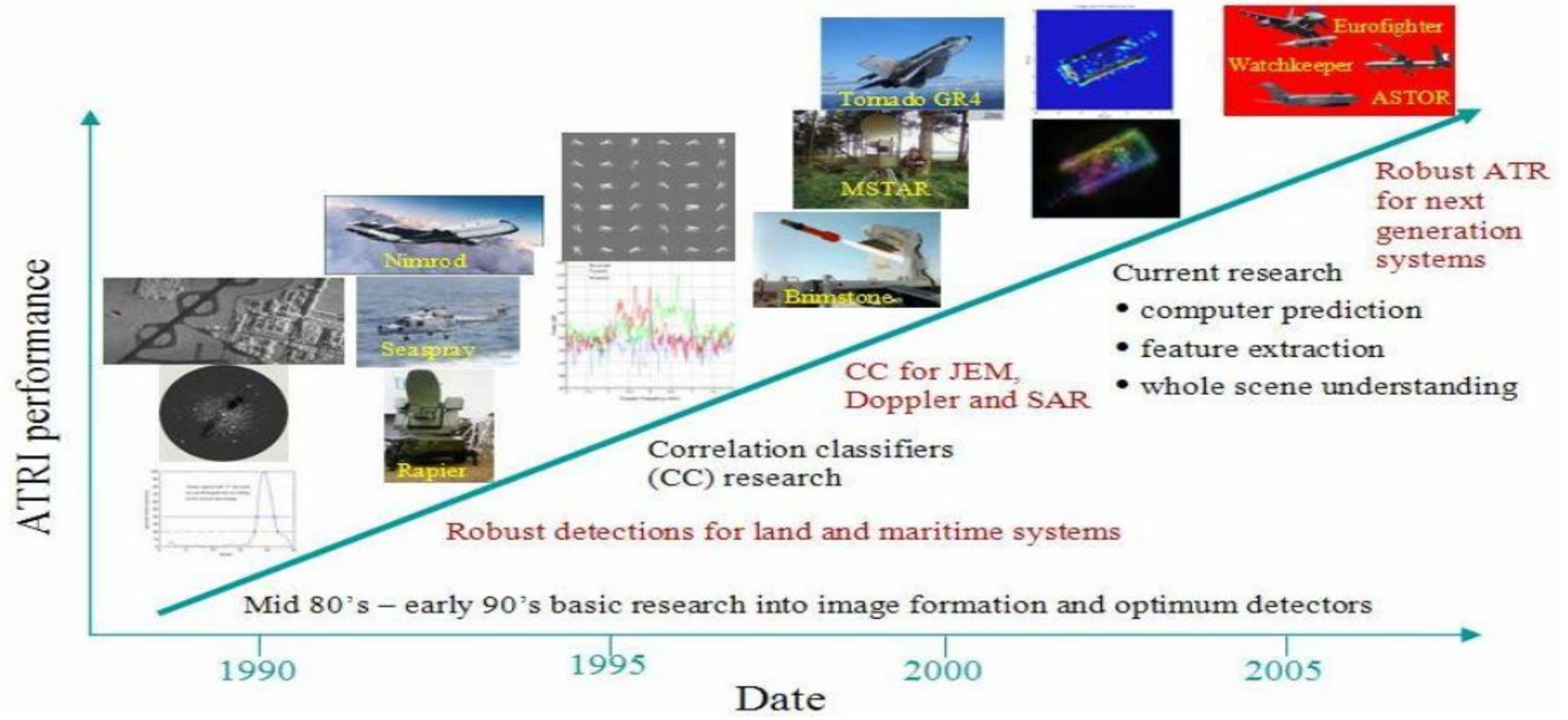
Performance

Target Truth

Target Called

	M1	T80	T72	M60	M551
M1	.80	.03	.01	.06	.02
T80	.06	.76	.06	.01	0.0
T72	.02	.18	.92	.03	0.0
M60	.12	.01	.01	.88	.03
M551	0.0	.02	0.0	.02	.95

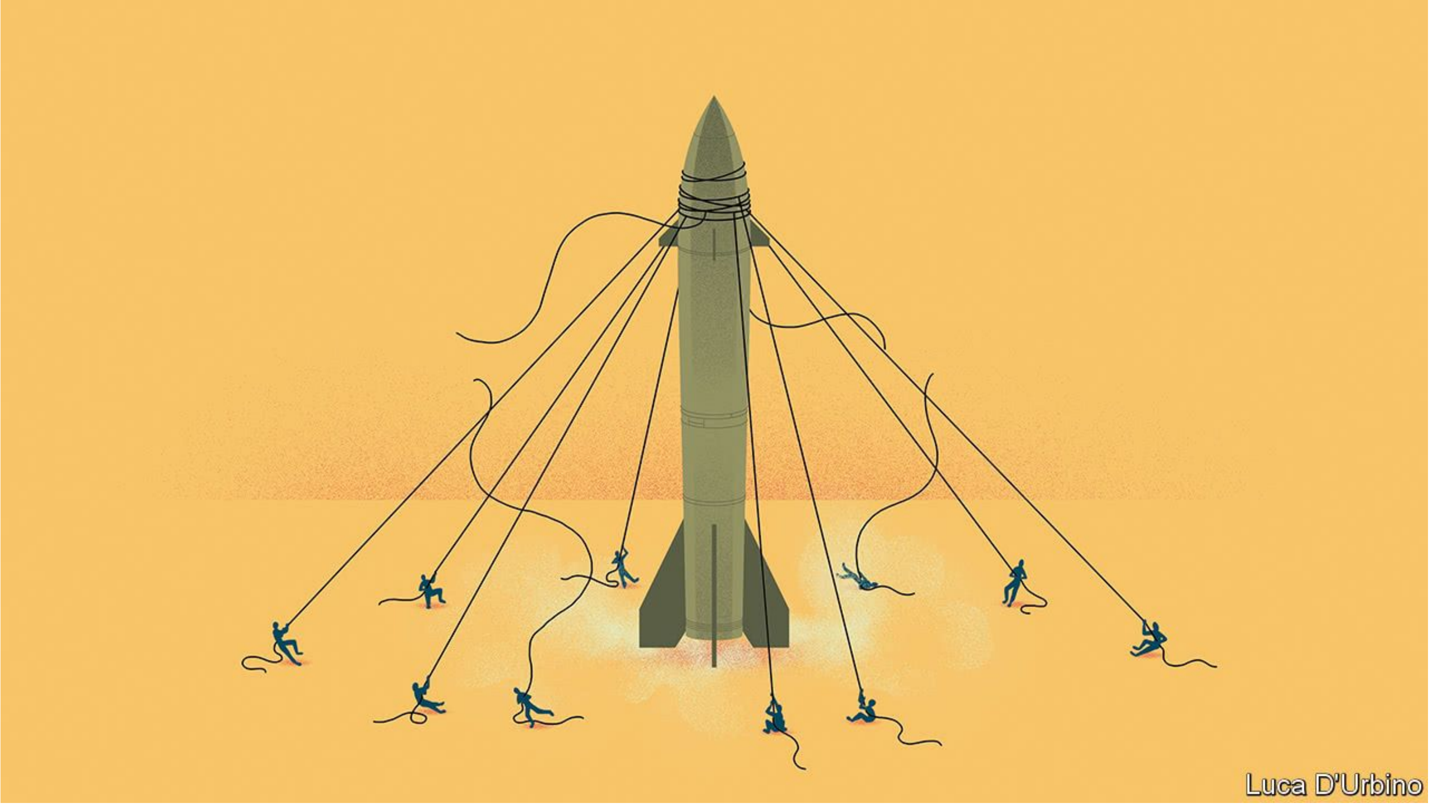
Performance



Send Target Reports

ATR searched for target
ATR identified target
ATR sent target to analysts
Why doesn't ATR kill the target?

Semi-Autonomous not Autonomous !!!



Existing benefits of automated processing

Number of people required

Using ATR

Time required

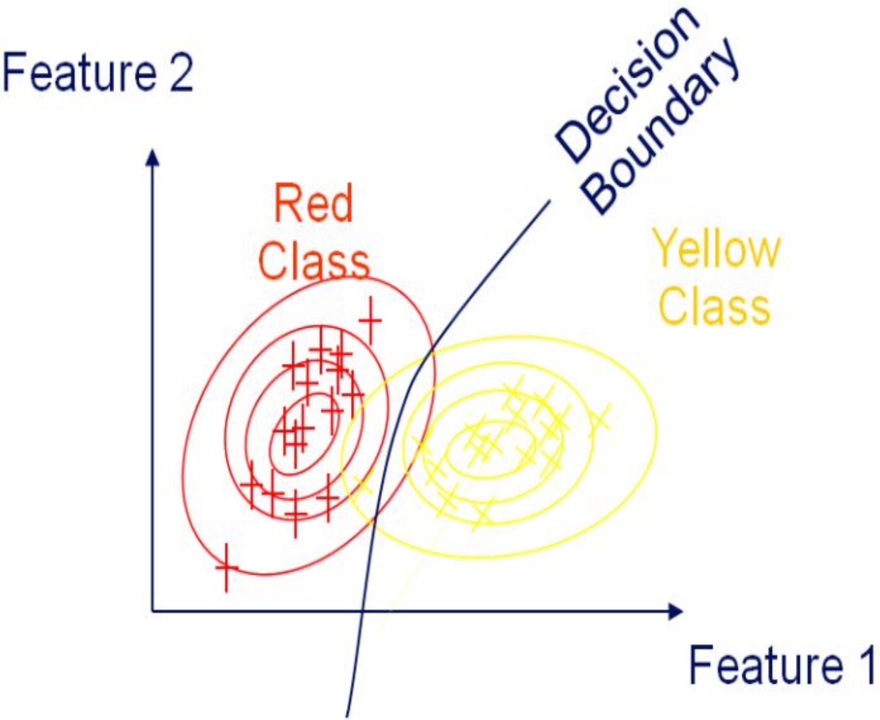
> 30 min

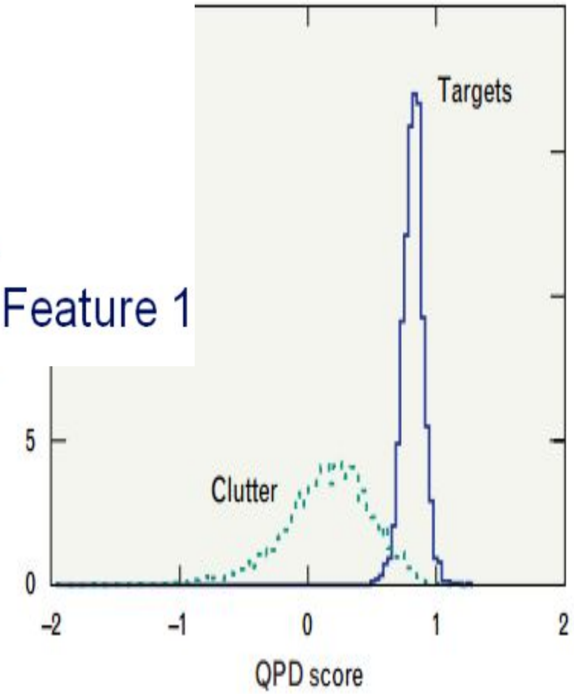
≈ Real time

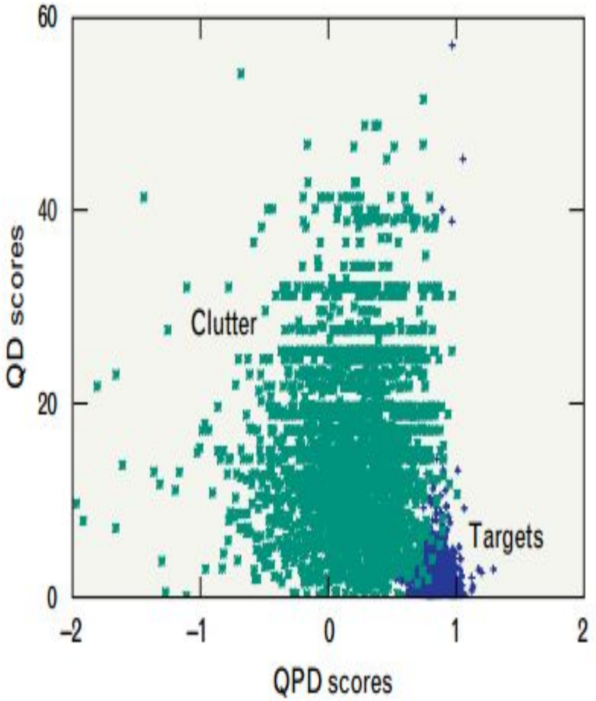
Why not Fully-Autonomous?

Challenge 1: Easy to be confused

Overlap!!!


Feature 2
Decision Boundary
Red Class
Yellow Class
Feature 1

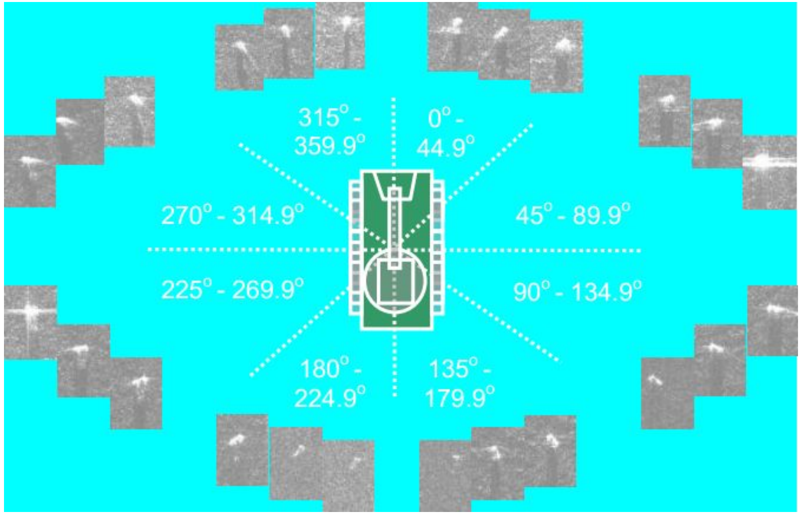

Targets
Clutter
5
0
-2
-1
0
1
2
QPD score


60
40
20
0
QD scores
Clutter
Targets
-2
-1
0
1
2
QPD scores

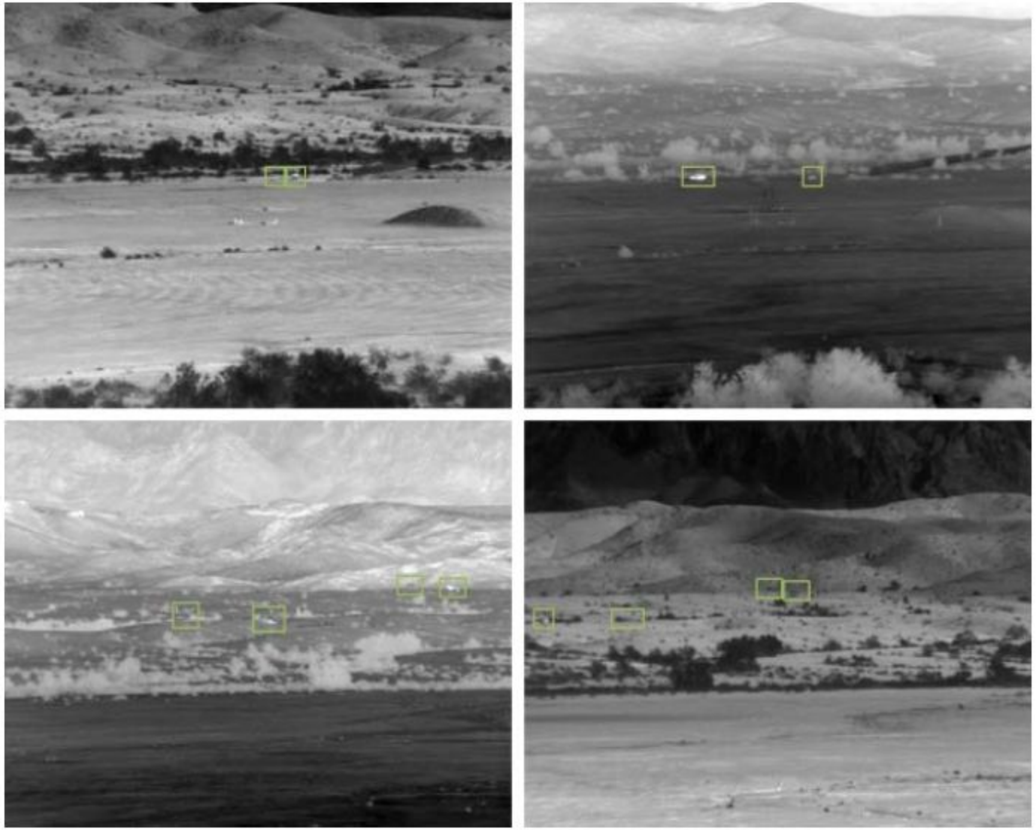
Truth	ATR System Output Declaration				
	Blue1	Blue2	Red1	Red2	PCC
Blue1	0.78	0.03	0.06	0.13	0.78
Blue2	0.01	0.95	0.02	0.02	0.95
Red1	0.10	0.03	0.83	0.04	0.83
Red2	0.02	0.01	0.03	0.95	0.95
PCL	0.86	0.93	0.88	0.83	

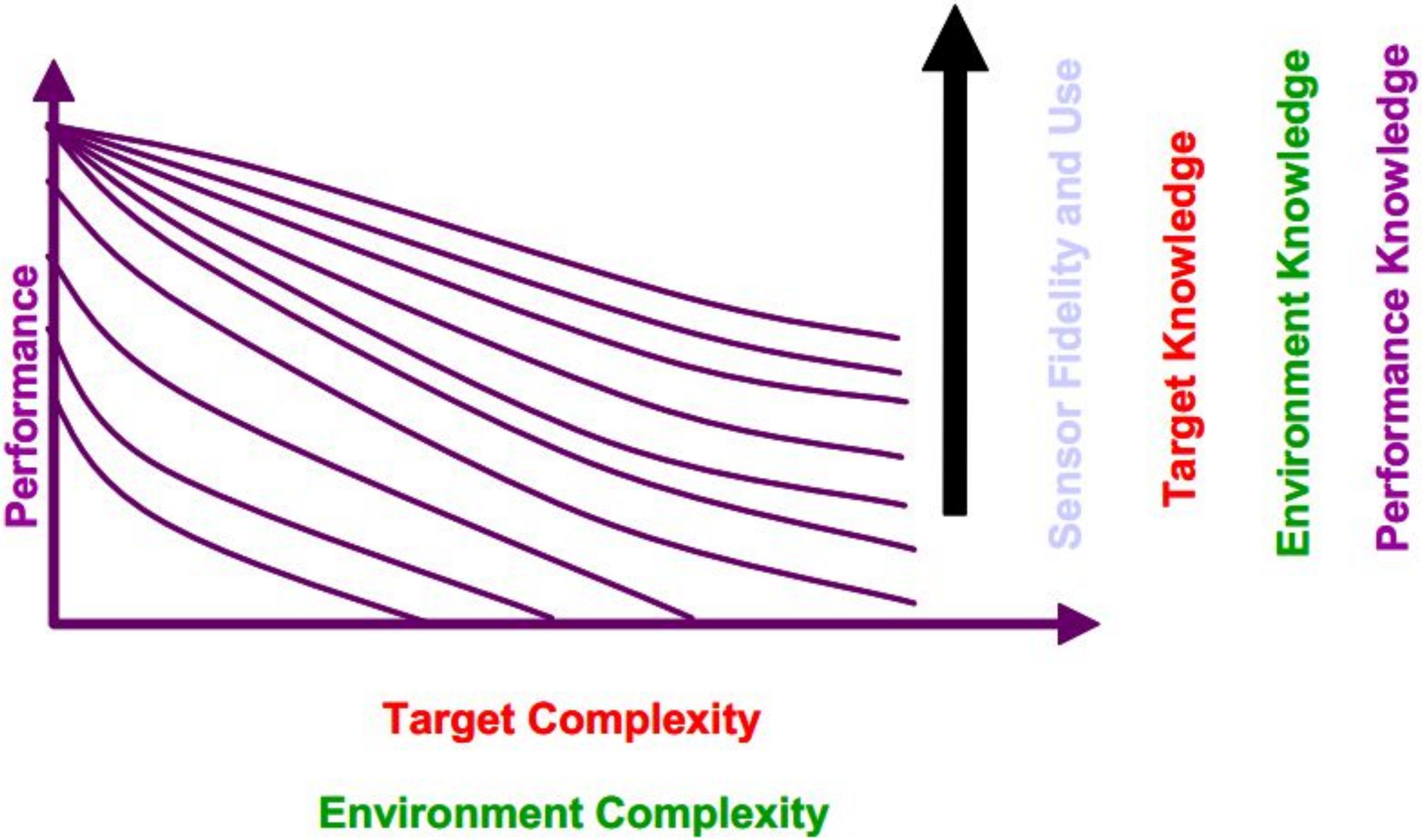
Truth	ATR System Output Declaration				
	Blue1	Blue2	Red1	Red2	PCC
Blue1	0.78	0.03	0.06	0.13	0.78
Blue2	0.01	0.95	0.02	0.02	0.95
Red1	0.10	0.03	0.83	0.04	0.83
Red2	0.02	0.01	0.03	0.95	0.95
Conf1	0.24	0.28	0.22	0.27	N/A
Conf2	0.28	0.16	0.31	0.25	N/A
PCL	0.55	0.65	0.56	0.57	

Challenge 2: The enormous variability of targets



Challenge 3: The enormous variability in environments

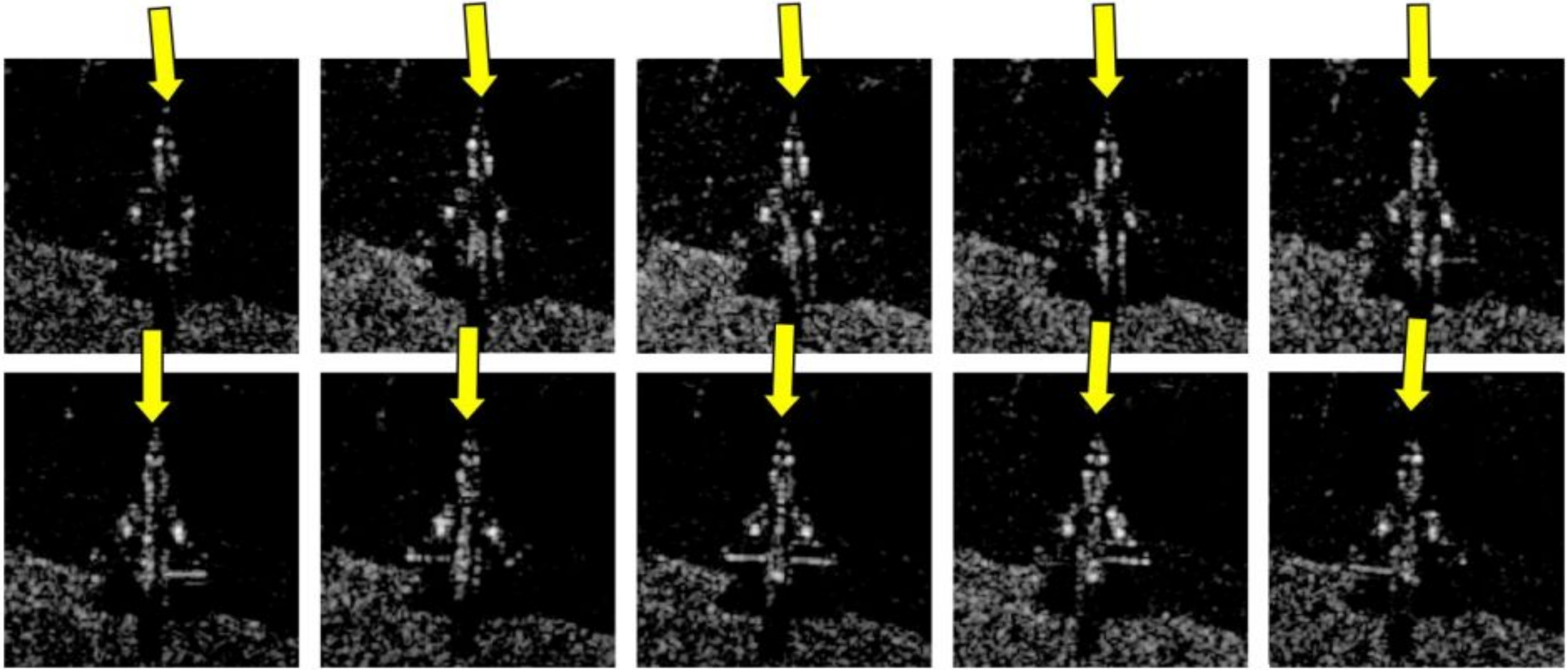



Performance
Sensor Fidelity and Use
Target Knowledge
Environment Knowledge
Performance Knowledge
Target Complexity
Environment Complexity

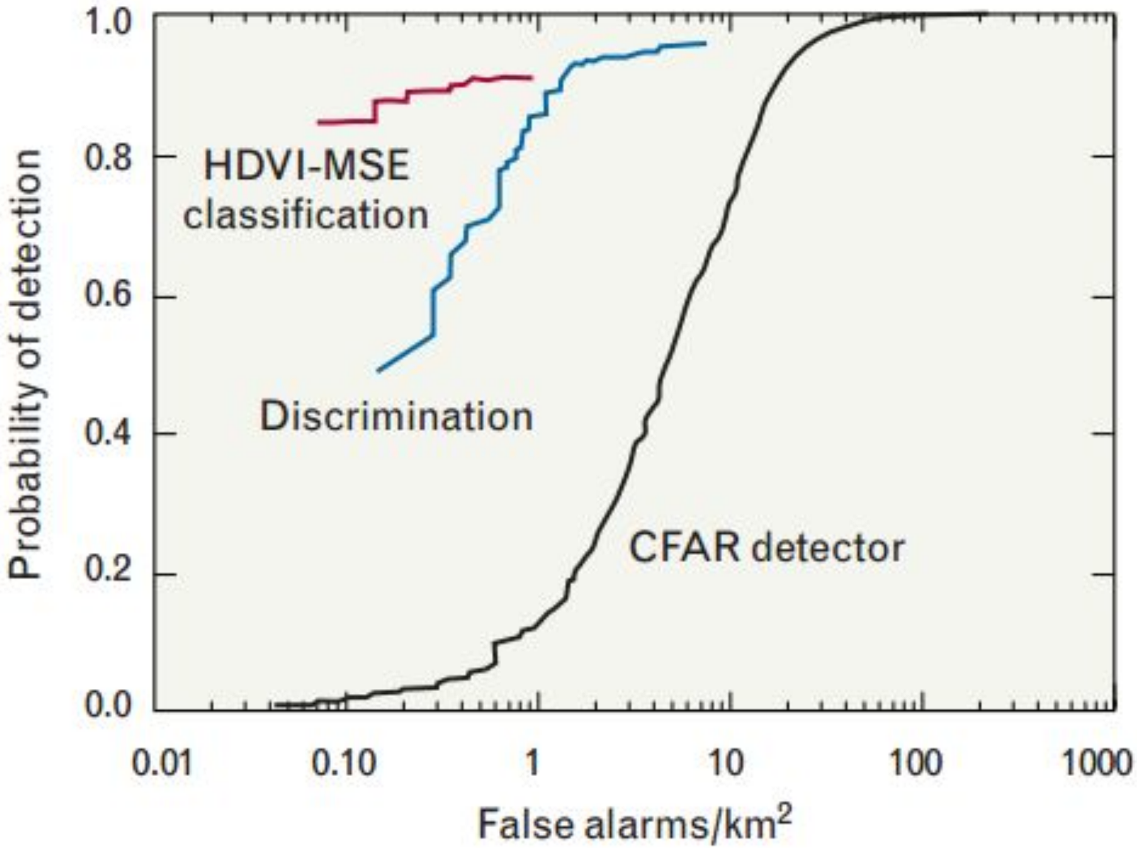
Scene :	
Nb. targets	0 1 … 10 … unknown
Nb. variants	1 … known … estimated … unknown
Clutter	uniform (field) … dense & complex (urban, forest)
Performance :	
Level	detection … classification (rough … fine) … identification … technical analysis
Nb.Target/class	1 … 10 … all targets on scene
Time to	days … hours … minutes … real time
Error (PFA)	10% … 1% … 5e-3%
Success (PD)	50% … 80% … 90% … ~100%
Cost	« Free » … radar cost … multi radars &/ collections
Reference :	
Ref. Data	Photos … expert … 3D CAD (rough … fine) ISAR/turntable SAR
Radar(s) mode	monolook … multi-looks … multi-aspects …
Side orders	bandwidth … channels (freq., polar., InSAR …) … multi sensors

Challenge 4: The target is moving

Challenge 4: The target is moving

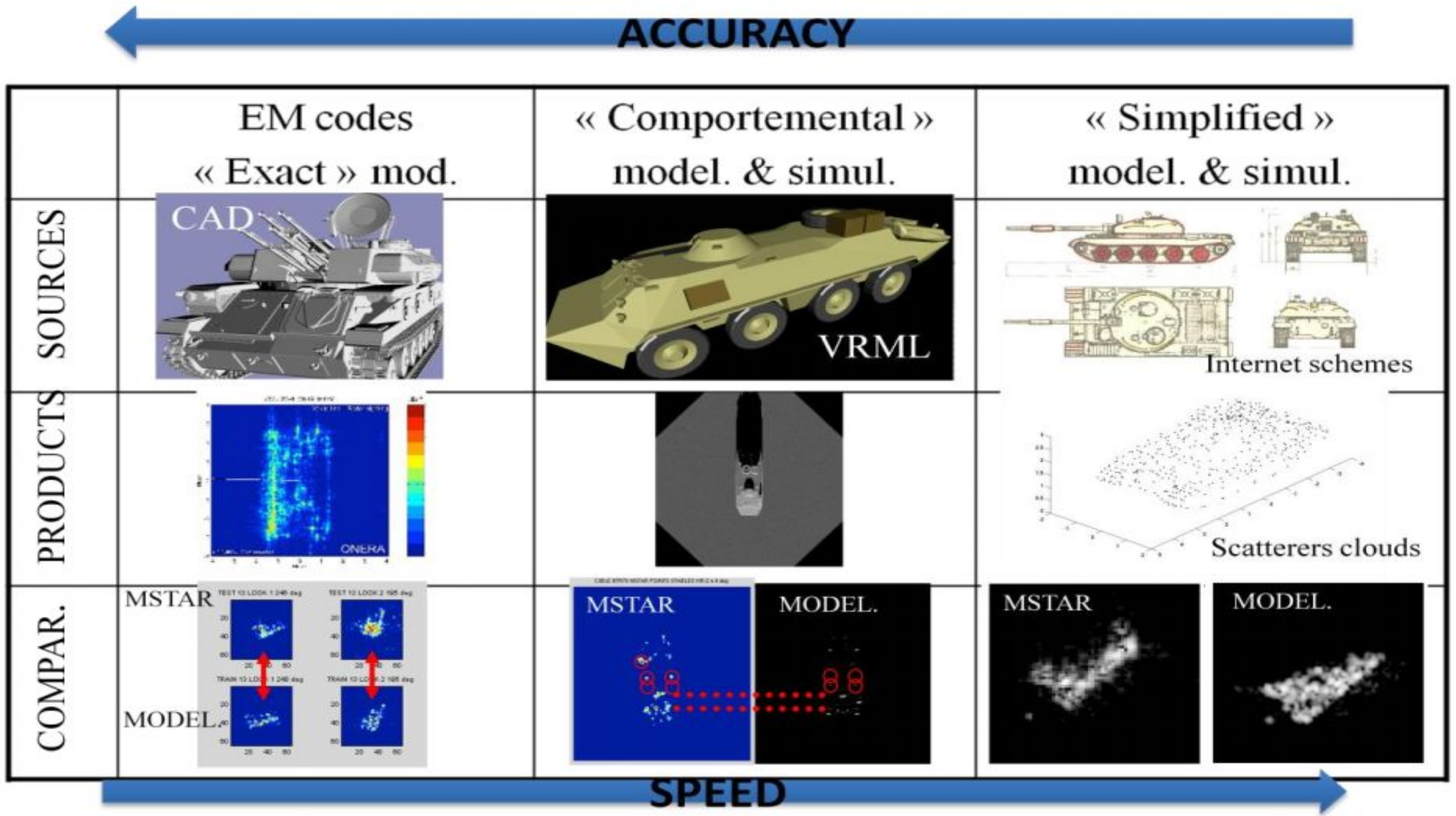


Challenge 5: Tradeoffs - FA, Accuracy and Speed



True-positive:
an instance of class A is correctly classified as class A

False-Alarms:
an instance that is not from A is wrongly classified as in A
Dangerous !!!


ACCURACY
EM codes
« Exact » mod.
« Comportemental »
model. & simul.
« Simplified »
model. & simul.
SOURCES
CAD
VRML
Internet schemes
PRODUCTS
ONERA
Scatterers clouds
COMPAR.
MSTAR
MODEL.
MSTAR
MODEL.
MSTAR
MODEL.
SPEED

State-of-the-art image recognition perform on par with humans

Relative Confusion	A1	A2
Human succeeds, GoogLeNet succeeds	1352	219
Human succeeds, GoogLeNet fails	72	8
Human fails, GoogLeNet succeeds	46	24
Human fails, GoogLeNet fails	30	7
Total number of images	1500	258
Estimated GoogLeNet classification error	6.8%	5.8%
Estimated human classification error	5.1%	12.0%

【1】Russakovsky, O., Deng, J., Su, H. et al. Int J Comput Vis (2015) 115: 211. https://doi.org/10.1007/s11263-015-0816-y

But accuracy depends on operating conditions

	Original image	Image with noise
VGG-16	91.24%	44.02%
GoogLeNet	94.10%	34.02%
AlexNet	84.00%	19.29%
Human	80.50%	75.13%

【2】Geirhos, Robert & H. J. Janssen, David & Schütt, Heiko & Rauber, Jonas & Bethge, Matthias & Wichmann, Felix. (2017). Comparing deep neural networks against humans: object recognition when the signal gets weaker.

But accuracy depends on operating conditions

	Original image	Image with noise
VGG-16	91.24%	44.02%
GoogLeNet	94.10%	34.02%
AlexNet	[illegible]	19.29%
Human	80.50%	75.13%

How close are we to deploying fully-autonomous Lethal Autonomous Weapon Systems?

【2】Geirhos, Robert & H. J. Janssen, David & Schütt, Heiko & Rauber, Jonas & Bethge, Matthias & Wichmann, Felix. (2017). Comparing deep neural networks against humans: object recognition when the signal gets weaker.

Summary

- ATR can dramatically improve weapon systems’ efficiency and **decrease unnecessary casualties.**
- But many crucial challenges still exist.
- Profound nderstanding the limitations of AI is.
- ATR is still a Semi-Autonomous process: i.e. not able to support autonomous weapons yet (or classified).

Thank you!

Questions?

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