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Machine Learning Techniques for Radar ATR

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Chapter 1: Introduction to Radio Frequency ATR



Presenter Information



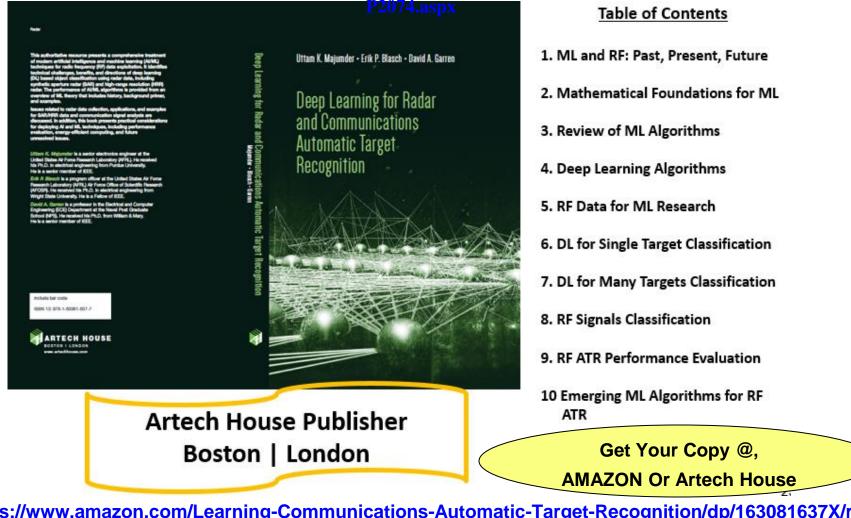
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Outline of the Short Course

The Presentation will follow our RF ATR Monograph (published in July 2020)

https://us.artechhouse.com/Deep-Learning-for-Radar-and-Communications-Automatic-Target-Recognition-

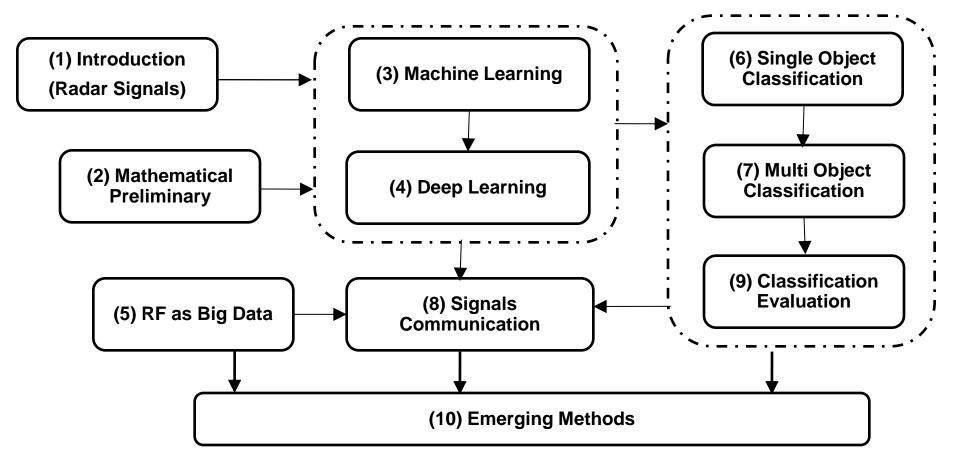


https://www.amazon.com/Learning-Communications-Automatic-Target-Recognition/dp/163081637X/r ef=sr_1_3?crid=3QGCWTJ59ETIP&dchild=1&keywords=deep+learning+for+radar&qid=159651 2219&s=books&sprefix=deep+learning+for+radar%2Caps%2C151&sr=1-3

Lecture Outline

- Radio Frequency ATR: Past, Present, and Future:
 20 min
- Mathematics for Machine Learning / Deep Learning:
 20 min
- 3. Review of ML Algorithms: 30 min
- 4. Deep Learning Algorithms: 30 min
- 5. RF Data for ML Research: 15 min
- 6. DL for Single Target Classification: 25 min
- 7. DL for Many Targets Classification: 20 min
- 8. RF Signals Classification: 15 min
- 9. RF ATR Performance Evaluation: 25 min
- 10. Emerging ML Algorithms for RF ATR: 35 min

Teaching/Learning Deep Learning Based Radio Frequency (RF) Automatic Target Recognition (ATR)



Learning Outcomes

- An understanding of machine learning (ML) algorithms
- ✓ Identifying objects in radio frequency (RF) imagery
- ✓ Construct a machine learning (ML) system to classify objects from RF imagery
- ✓ Compare technical challenges involving radar and video image classification
- ✓ Benefits of deep learning (DL) based RF object classification
- ✓ RF ATR Evaluation
- ✓ Emerging RF ATR Algorithms

Introduction to ML

Over the years, Machine Learning (ML) algorithms have evolved

- Improved accuracy
- Real-time execution
- Solving more complex problems

- Top ML Tools/Software

- TensorFlow (Google), Caffe (UC Berkley)
- Theano, Torch (Facebook)

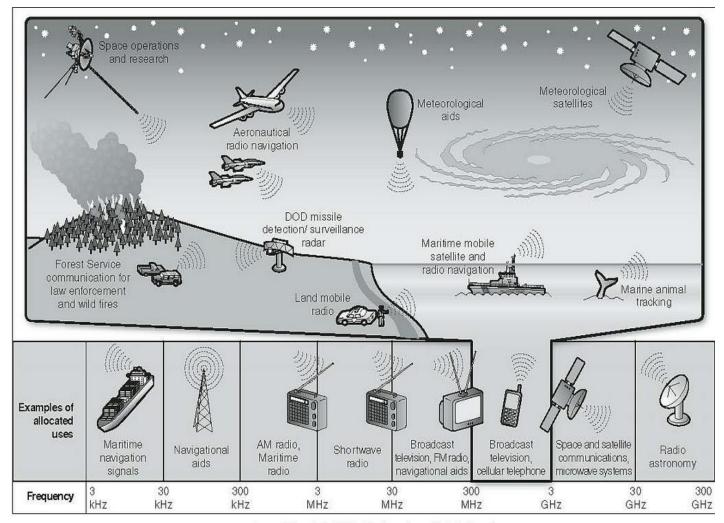
- ML for Big Data Analytics

- Image Classification
- Natural Language Processing
- Autonomous Systems
- Sentiment Analysis
- Biomedical Applications

This Short Course....

- Applying ML to Radio Frequency (RF) Signals
 - Object Classification from Synthetic Aperture Radar (SAR) imagery
 - Communication signal classification
- ML for object classification from video imagery is more known to the researcher
 - These algorithms could be applied to the RF domain

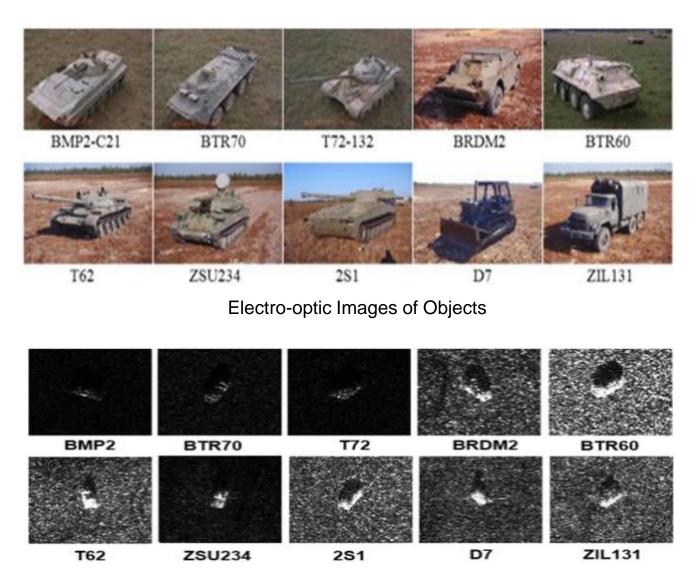
Radio Frequency Applications



Source: GAO analysis of NTIA, federal agencies, and industry information.

From(labeled reuse): https://www.flickr.com/photos/usgao/5727623528

Electro-Optics Vs. Radar Imagery



SAR Images of Objects

RF (SAR) Imagery Example:

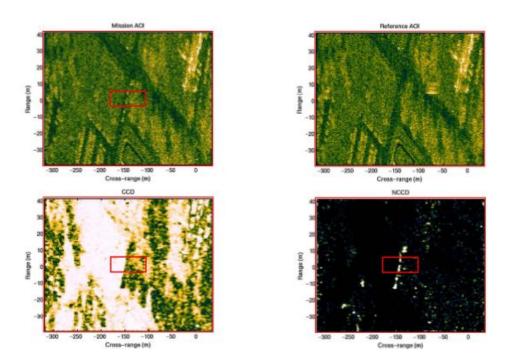
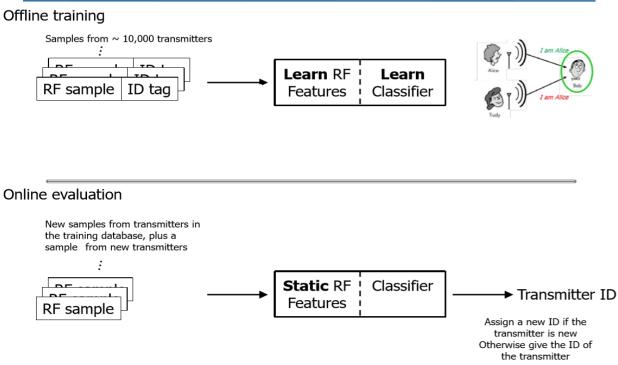


Figure: Objects in SAR Imagery

<u>**Reference**</u>: S. Scarborough, et. al. "A challenge problem for SAR-based GMTI in urban environments" Algorithms for Synthetic Aperture Radar Imagery XVI, edited by Edmund G. Zelnio, Frederick D. Garber, Proc. of SPIE Vol. 7337, 73370G

RF Signal Example:

RF Feature Learning



Reference:

DARPA Public Release: RF Machine Learning Systems (RFMLS) Industry Day https://www.darpa.mil/attachments/RFMLSIndustryDaypublicreleaseapproved.pdf

<u>Previous Approach for SAR Object</u> <u>**Classification: DARPA MSTAR Program (1998)**</u>

Template-based Matching Approach:

 The training/template formation process consists of registering and estimating the mean target signature over small aspect windows (10 deg)

$$(x_{opt}, y_{opt}) = \operatorname{argmin}_{x_s y_s} (\sum_{x=1}^{N} \sum_{y=1}^{N} |w(x, y)(M_k(x, y) - S(x - x_s, y - y_s))|)$$

where;

(x_s,y_s) = Translation Variable w(x,y) = Binary Mask S(x,y) = Chip Magnitude

and

 $M_{k}(x,y) = [(k-1)^{*}M_{k-1}(k-1)/k + k^{*}S(x-x_{opt},y-y_{opt})]$

(k = 1 ... Number Chips/Template)

Classification Cost Measure: Data Processing, Storage, Collection

Reference:

Timothy D. Ross, Steven W. Worrell, Vincent J. Velten, John C. Mossing, Michael Lee Bryant, "Standard SAR ATR evaluation experiments using the MSTAR public release data set," Proc. SPIE 3370, Algorithms for Synthetic Aperture Radar Imagery V, (15 September 1998); doi: 10.1117/12.321859

Previous Approach for SAR Object Classification: MSTAR

Resul	ts

	BMP2	BTR70	T72	Rejections	Confidence
BMP2-1	0.8256	0.0923	0	0.0821	+/- 0.020
BMP2-2	0.7653	0.1582	0	0.0765	+/- 0.020
BMP2-3*	0.8929	0.0408	0	0.0663	+/- 0.020
BTR70-1	0.0073	0.9197	0.0073	0.0657	+/- 0.017
BTR70-2*	0	0.9890	0	0.0110	+/- 0.017
BTR70-3	0.0182	0.8869	0.0036	0.0912	+/- 0.017
BTR70-4	0.0204	0.8418	0	0.1378	+/- 0.020
T72-1*	0.0051	0.0102	0.9592	0.0255	+/- 0.020
T72-2	0.0667	0.1795	0.5744	0.1795	+/- 0.020
T72-3	0.0419	0.1466	0.6859	0.1257	+/- 0.020

Table _. Fractional Classification and Rejection Rates (PD = 0.9)

*: denotes trained object

Reference:

Timothy D. Ross, Steven W. Worrell, Vincent J. Velten, John C. Mossing, Michael Lee Bryant, "Standard SAR ATR evaluation experiments using the MSTAR public release data set," Proc. SPIE 3370, Algorithms for Synthetic Aperture Radar Imagery V, (15 September 1998); doi: 10.1117/12.321859

Current Deep Learning Approach for SAR Object Classification: DARPA TRACE Program (2016)

Public MSTAR

Ground Plane

REAL	Accuracy	
BASELINE / Real network		0.9961

COMPLEX	Accuracy
Mag_64	0.9639
Hybrid_64	0.9961
Complex_64_5Z	0.9941
Complex_64	0.9939
Complex_128	0.9971
Hybrid_128***	0.9922

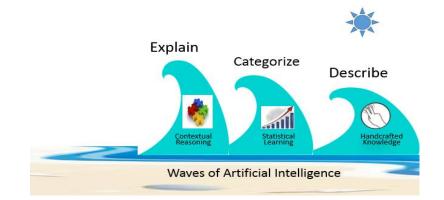
Results based on the public MSTAR CDs. 10% of data used for validation. Obtained from https://www.sdms.afrl.af.mil/index.php?collection=mstar&page=targets

Reference:

SPIE DSS 2016: Public Release, Approved by DARPA

History of Learning

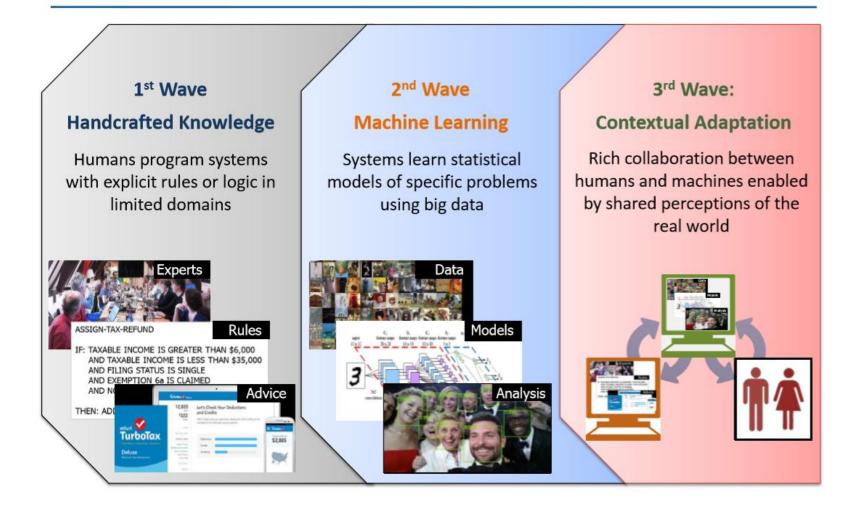
- AI Machines to think/behave/react ANN
- ML Data for (Machines) to learn RL, BN, ILP
- **DL Brain-Inspired** NN for robust methods CNN, RNN
 - (mostly supervised from labeled data)



AI: Artificial Intelligence ANN: Artificial Neural Networks RL: Reinforcement Learning BN: Bayesian Networks ILP: Inductive Logic Programming CNN: Convolutional Neural Networks RNN: Recurrent Neural Networks

Reference: Andrew Fogg, A histroy of Deep Learning, (import.io)

Three Waves of Artificial Intelligence



Reference:

DARPA Public Release: RF Machine Learning Systems (RFMLS) Industry Day https://www.darpa.mil/attachments/RFMLSIndustryDaypublicreleaseapproved.pdf

Summary

- ✓ We provided an overview of RF ATR
 - Past: Template Based Approach
 - **Present**: Deep Learning Approach
 - Future: Reinforcement Learning / More Autonomous Decision Making, Explainable ATR, Secure and Trusted ATR, Quantum Neural Networks, Real-time on-board ATR