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Deep Learning for Computational Imaging

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Background

- Professor of Electrical Computer and System Engineering at Rensselaer Polytechnic Institute, Troy, NY

Research Interests

- Applied mathematics
- Statistical signal processing, machine learning, optimization
- Wave-based imaging, inverse scattering & tomography
  - Radar, sonar, diffuse optical imaging

Computational Imaging Laboratory at RPI

- Prof. Birsen Yazıcı
- Supervised 12 PhD thesis, 8 MS thesis
- Dr. Il-Young Son, post-doc
- PhD students
  - Bariscan Yonel
  - Samia Kazemi
  - Sean Thammakoune
  - Airas Akhtar

MS students
  - Ziya Su
  - Jianyu Yang

Outline

- Fundamentals of Deep Learning
  - Basic concepts and ideas in Deep Learning
  - Traditional machine learning vs Deep Learning
  - Advantages and problems of Deep Learning
- Deep Learning for Inverse Problems in Imaging
- Deep Learning based for Synthetic Aperture Imaging
  - Passive SAR Imaging
  - ATR-aware Synthetic Aperture Imaging
- Conclusion

Why Deep Learning?

- Staggering performance in difficult classification tasks

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- Abundance of data
- Minimal upfront engineering
- Fundamental connections to iterative processes, optimization and Bayesian decision making
- A framework to combine modeling and data synergistically

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Basic Concepts in Deep Learning

- Perceptron (Rosenblatt, 1957)

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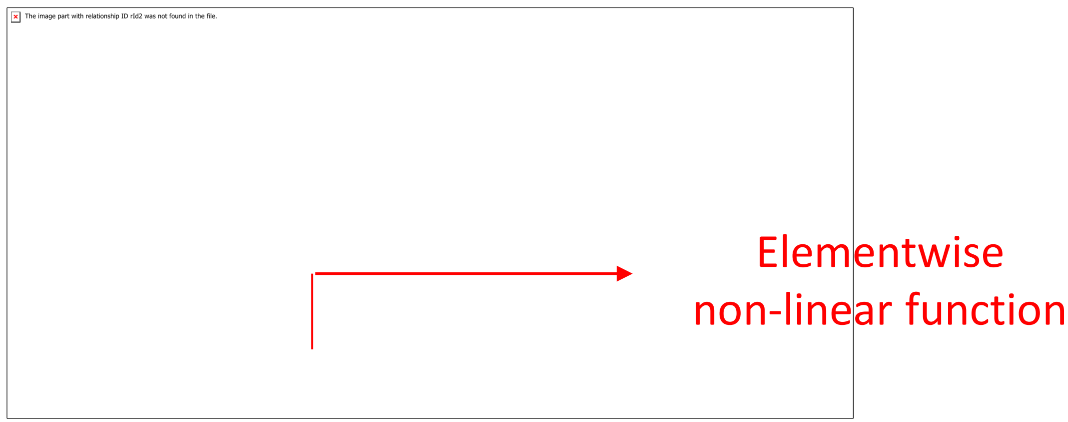
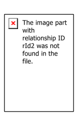
- Concept of a “neuron”
- Building block of machine learning methods

Basic Concepts in DL - Layer

- Parallel implementation of neurons: “layer”
- Layer – A processing block



- Parametrized by a matrix **A** and a bias vector **b**
- 

called a representation of **x** which lies in a “feature space”.

Traditional Machine Learning

- Inductive learning – learn from examples
  - Classification: learning class boundaries in data
  - Regression: learn a function to fit data
- Classifiers are “shallow”, 2-layer architectures
- Features are hand crafted

Deep Learning vs Traditional Machine Learning

- More Layers – Forward Propagation

- Many more layers – Deep Networks
- Each layer produces a representation of the output from the previous layer

- Hierarchical feature spaces as features get more abstract
- Raw data processed directly – no hand crafting of features beforehand

Breakthroughs in Deep Learning – Convolutional Networks

- First Convolutional Neural Network, 1980 (Fukushima)

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LeCun, Bengio, and Hinton. “Deep learning" Nature 2015

Breakthroughs in Deep Learning – Backpropagation

- Backpropagation algorithm, Hinton (1987)
- Fundamental way of learning in deep models

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Learning with Backpropagation

- "Train" with examples
- Network operator The image part with relationship ID rId3 was not found in the file.
- The image part with relationship ID rId3 was not found in the file. parametrized by the weight matrices and bias vectors

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- "Learning": estimating/updating network parameters so that produces desired output
  - Given a set of data The image part with relationship ID rId3 was not found in the file. and ground truth The image part with relationship ID rId3 was not found in the file. , update network parameters

Loss function

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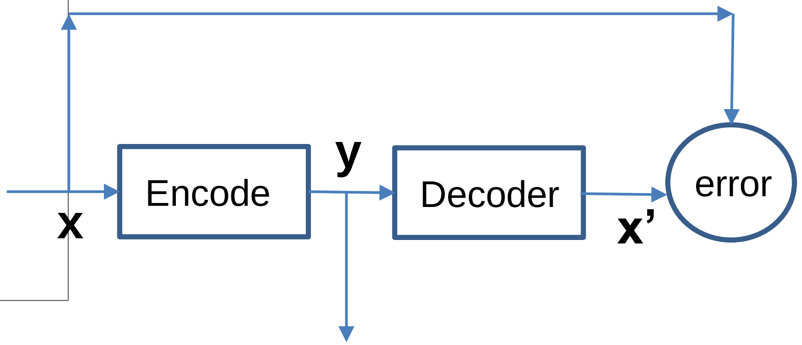
Deep Learning Architectures



- Recurrent Neural Networks (RNNs)
  - Widely used in natural language processing and speech generation
  - Great imitators of iterative processes
- Auto-encoders
  - $\|\cdot\|^2$ of error is backpropagated for learning
  - Output layer folds back, suitable for denoising

Breakthroughs in Deep Learning

- LeNet-5, LeCun, Bottou, Bengio (1998)
  - An improved CNN structure, demonstrated for character recognition.
- Deep Belief Nets, Hinton (2006)
  - Introduced the term "Deep Learning", and unsupervised pre-training
- Deep Neural Network - Hidden Markov Models for speech recognition, Dong Yu, Microsoft (2011)
  - Record breaking performance in speech recognition
- AlexNet, Krizhevsky, Sutskever, Hinton (2012)
  - Record breaking performance in ImageNet classication.

Advantages of Deep Learning

- Big data
- Faster computation power
- Bypassing feature engineering
- Ability to approximate very complex mappings
- Learns goal driven representations
- Software infrastructure

Problems in Deep Learning

- Learning is very high dimensional and highly non-convex optimization
- Many hyper-parameters and heuristic tuning
- Training requires large data sets and high computation power
- Vague theoretical understanding
- Overfitting, generality

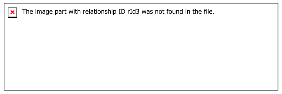
Outline

- Fundamentals of Deep Learning
- Deep Learning for Inverse Problems in Imaging
  - Image reconstruction as a machine learning task
  - Deep Learning as an inverse solver
  - Bayesian and optimization inspired Deep Learning
- Deep Learning based for Synthetic Aperture Imaging
- Conclusion

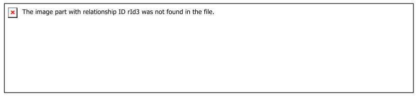
[1] Yonel, Bariscan, Eric Mason, and Birsen Yazıcı. "Deep learning for passive synthetic aperture radar." *IEEE Journal of Selected Topics in Signal Processing* 12.1 (2018): 90-103.

Problems in Imaging

- **Forward model**: derived from underlying physics



  – Can we learn the model from data via DL?
- **Inversion**: obtain estimate



  – How can we implement inversion methods with DL?
- **Efficient algorithm design**
  – Can DL offer faster convergence?
- **Automatic Target Recognition**
  – Can we design DL based inversion methods guided by the goals of ATR?

Deep Network as a Forward Solver

- **Conventional forward modeling -** Similar to 2-layer conventional machine learning

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- **DL-based forward modeling -** Insert hidden layers

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  - Learn non-linear forward models from data
  - Improve over linearized/idealized forward models
  - Potential applications in high fidelity data generation

Image Reconstruction as a Machine Learning Task

- **Image:** A desired representation of measurements in image space
- **Conventional image reconstruction:** Similar to 2-layer conventional machine learning
  - **Backprojection:** A representation of measurements in the range of adjoint operator

- **Deep Learning-based image reconstruction:** Use deep layers to form a new representation at each layer, progressively approaching to desired output

Deep Network as an Inverse Solver

- Insert hidden layers

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The image part with relationship ID rId3 was not found in the file.

- **"Model-free" inverse solver**
  - Learn the inverse mapping from training data

    The image part with relationship ID rId3 was not found in the file.
  - Initialize network with physics-based backprojection, i.e.,

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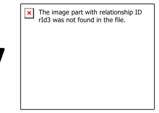
  - Requires extensive training data to avoid over fitting

Bayesian and Optimization Inspired DL-based Image Reconstruction

- How to choose the network non-linearity 

?
  – Based on a priori information
- Why?
  – Formulate reconstruction as a constrained least square optimization problem
  – Address optimization via proximal gradient descent method
- Build layers of deep network from iterations of a proximal gradient descent method
  – Affine mapping - Gradient descent step
  – Non-linearity - Proximity operator of the constraint

Bayesian and Optimization Inspired DL-based Image Reconstruction

- **Bayesian formulation**

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- **Proximal gradient descent**
  - Gradient descent over the smooth The image part with relationship ID rId3 was not found in the file. term:

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  - Project onto the feasible set of the regularization term

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RNN as a Proximal Gradient Descent Optimization

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- Rewriting The image part with relationship ID rId3 was not found in the file.

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- Unfold a fixed number of iterations to obtain an RNN
  - **Weight matrix:** The image part with relationship ID rId3 was not found in the file. → filter
  - **Bias vector:** The image part with relationship ID rId3 was not found in the file. → backprojection
  - **Activation function:** The image part with relationship ID rId3 was not found in the file. → network non-linearity

Deep Learning for Image Reconstruction

- Image reconstruction - viewed as learning a representation of measurements in image space
- DL framework suitable for blind deconvolution
- Refine the unknowns in the forward model and perform reconstruction simultaneously
  - Initialization – partially known forward model
  - Forward propagation – image reconstruction
  - Backpropagation – refinement of forward model
- Use training to drive the network towards goals and to learn the information implicit in the measurement data

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SAR Imaging

- Configurations (a) Monostatic, (b) Bistatic

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SAR Forward Model

- Received signal –

Range

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Scene to be imaged

<u>*Bistatic range*</u>

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Transmitter and receiver trajectories

<u>*Ground topography*</u>

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Height

SAR Forward Model

- Measurements - Generalized Radon Transform (GRT) of scene reflectivity
  - GRT - Filtered projections of reflectivity onto some smooth manifolds
  - Manifold - Phase of the kernel
  - Weight - Amplitude of the kernel

Range

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Scene to be imaged

Bistatic range

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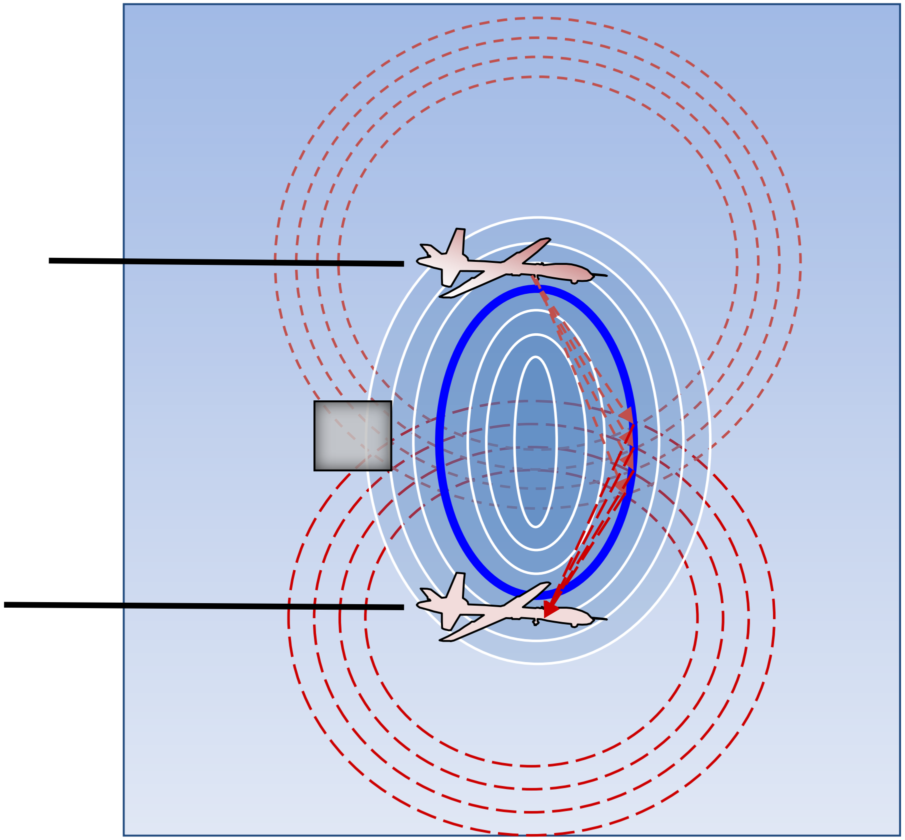
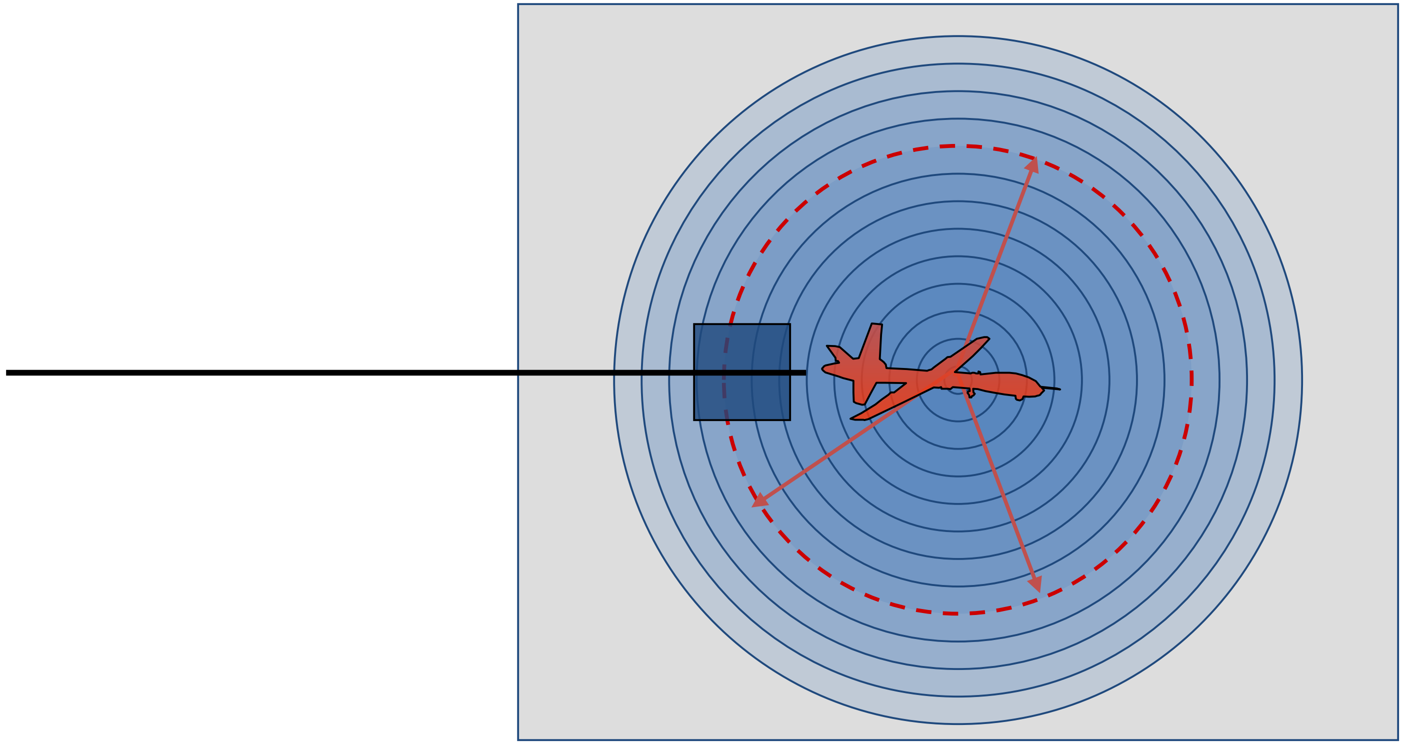
Transmitter and receiver trajectories

Bi-static SAR Forward Model



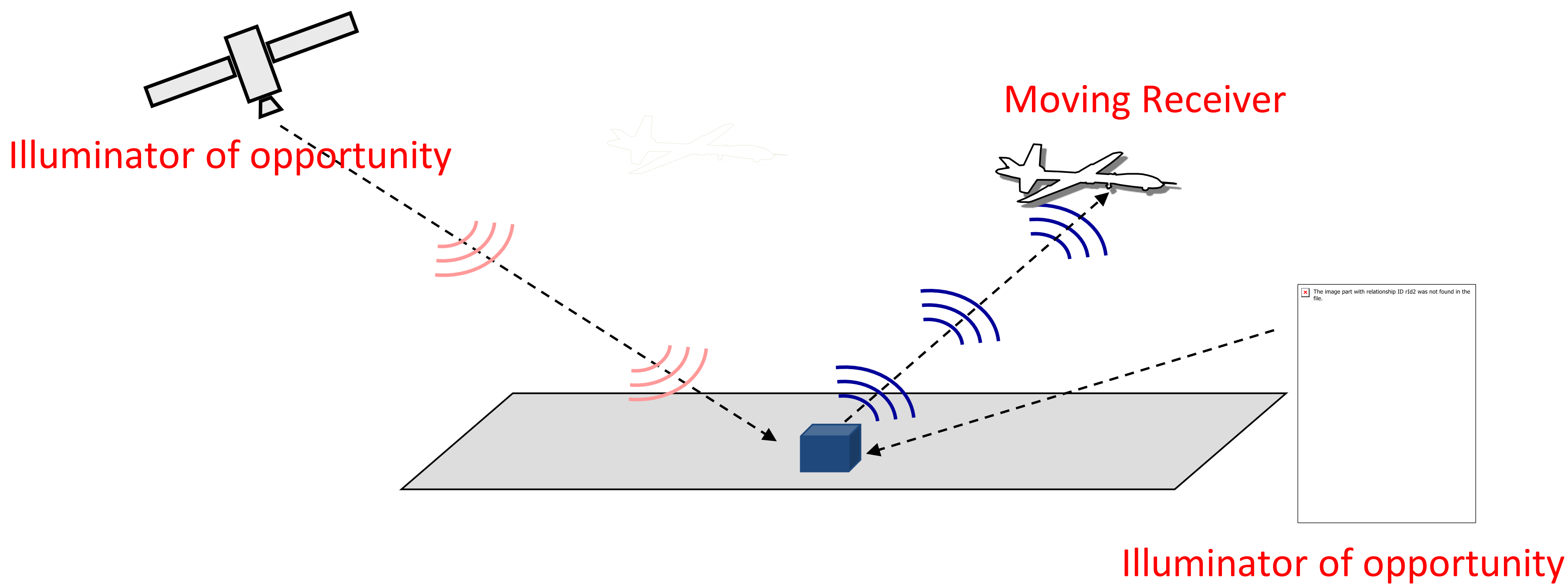
- *Iso-range surfaces - Ellipsoids*
- *Iso-range contours - Intersection of ellipsioids with topography*
- *Flat topography → Ellipses*

Mono-static SAR Forward Model



- *Iso-range surfaces - Spheres*
- *Iso-range contours - Intersection of spheres with topography*
- *Flat topography → Circles*

Passive SAR



- Scene illuminated by transmitters of opportunity: TV, cell-phone stations etc.
- Receive only airborne antenna uses backscattered measurements to make an image of the scene

Motivations and Challenges

- Rapid growth in the number of RF sources of opportunity
  - *Radio signals, TV signals, communication signals, WiFi, WiMAX…*
- Requires receivers only
  - Inexpensive, mobile, versatile, and suitable for rapid deployment
  - Less vulnerable to electronic counter measures

Challenges

- Transmitter is not in user control
- The location of the transmitter may not be known
- Waveforms may not have sufficient bandwidth

Passive Synthetic Aperture Imaging [1,2]

- <u>Forward model</u> –

Unknown bistatic range

Unknown scene

Unknown waveform

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- <u>Model</u> – The image part with relationship ID rId3 was not found in the file.

- Discretized model – $\mathbf{d} \approx \mathbf{F}\boldsymbol{\rho}$ + noise

- Neither $\mathbf{F}$ nor $\boldsymbol{\rho}$ is known – Blind deconvolution

[1] Yonel, Bariscan, Eric Mason, and Birsen Yazıcı. "Deep learning for passive synthetic aperture radar." *IEEE Journal of Selected Topics in Signal Processing* 12.1 (2018): 90-103.

[2] Yonel, Bariscan, Eric Mason, and Birsen Yazici. "Deep Learning for Waveform Estimation and Imaging in Passive Radar." *in the special issue of IET on High Resolution Passive Imaging, 2019.*

Passive Synthetic Aperture Radar

- **Forward model –**

Unknown waveform

scene

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- Discretize the scene –

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- **Known component –**

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  – Bistatic range –

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  – Geometric spreading –

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- **Discretized forward model –**

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Network Parametrization and Backpropagation

- **Network architecture –** Recurrent auto-encoder

- **Network parameters –**
    - Bias –
    - Filter –

- Network operator approximates an identity operator

- Train the network in an unsupervised manner to estimate

Training by Projected Stochastic Gradient Descent

- Network operator –

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- Learn **w** and λ by minimizing

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given training set The image part with relationship ID rId3 was not found in the file.

- Include prior information on w and λ; in the form of constraints.

- Minimize by projected SGD of the form:

Training by Projected Stochastic Gradient Descent

- Learn **w** and λ by minimizing

The image part with relationship ID rId3 was not found in the file.

given training set The image part with relationship ID rId3 was not found in the file.

- Include prior information on w and λ; in the form of constraints and update by stochastic gradient descent

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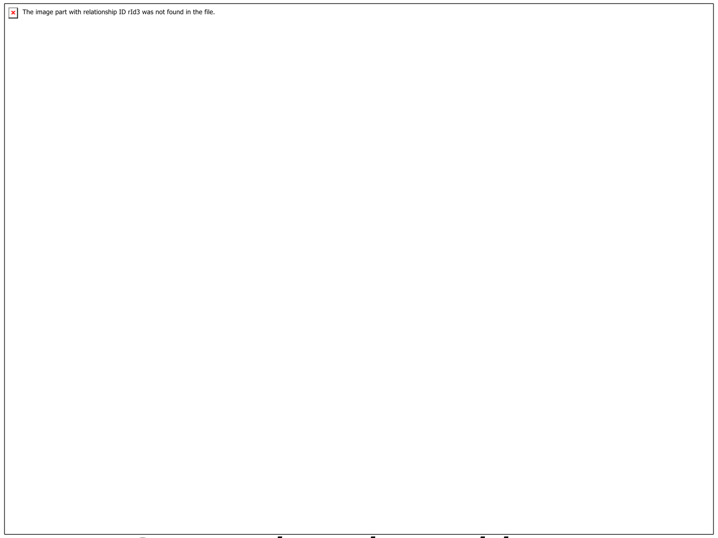
Numerical Simulations

- Bandwidth = 8 MHz, f_c = 760 MHz
- Unknown transmitted waveform = QPSK signal, A=1
- 620 x 620 meter flat scene,
- 20m range resolution, 32 x 32 pixels
- Initialization of **w**: random QPSK symbols



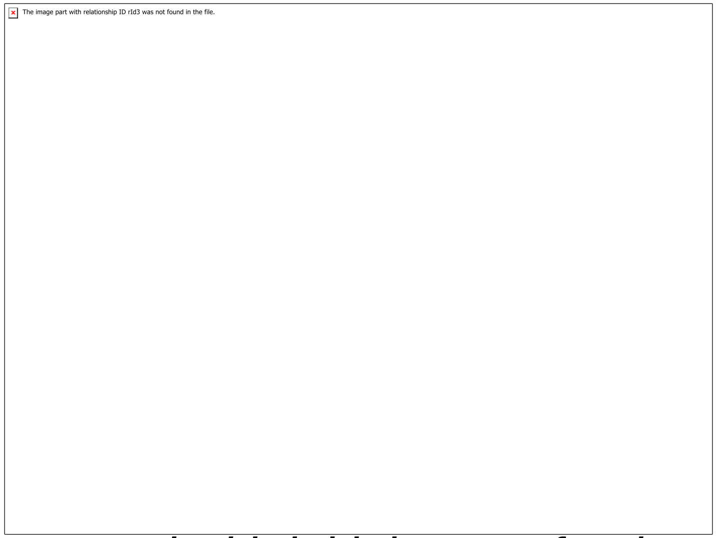


Figure: *Ground truth and image reconstructed with initial guess for the QPSK waveform*

Numerical Simulations

Network Properties

- The image part with relationship ID rId2 was not found in the file.
- Number of layers $L = 4$
- Training size $T = 10$
- Number of epochs $I = 1,2, \dots, 10$
- Initial learning rate $\eta_0 = 1e-4, \eta_{I+1} = \eta_I/(I+1)$
- Threshold ($\tau = \alpha\lambda$) learning rate $\eta_I \times 1e-7$

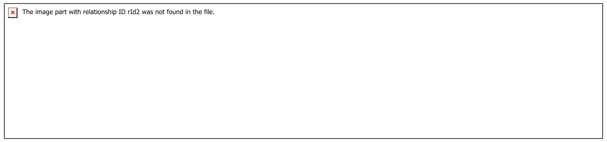
Numerical Simulations

- Different SNR levels for training and test data: -15, -10, -5, 0 dB SAR measurements.
- Training set: Sparse scene with single extended target of varying rectangular shape and location.
- Length and width: picked randomly in [1,6]x[1,6] range.
- Target placement: random in [3,28]x[3,28] range of pixels.
- Test set: 20 different realization of SAR measurements of the scene of interest under corresponding training noise level.

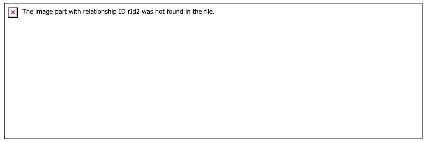
Numerical Simulations

Figures of merit

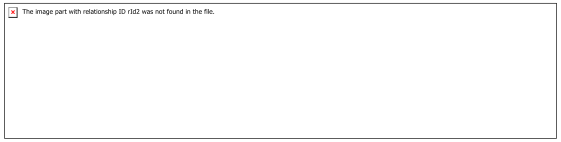
- Data Mismatch



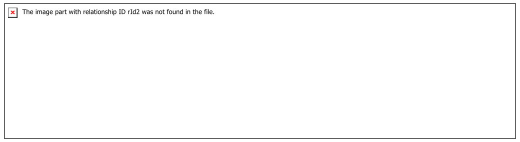
- Image domain error



- Image contrast



- Waveform error



Numerical Simulations

Reconstructed Images from the Test Set

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Numerical Simulations

Error Curves: Data Mismatch, Image Mismatch, Contrast, Waveform Error

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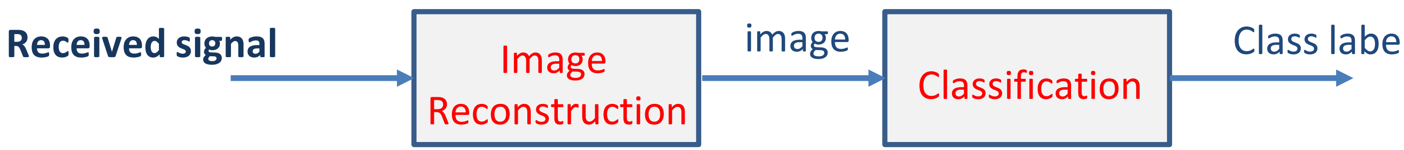
ATR Directly from Received Signal bypassing Image Reconstruction [3]

- DL has shown staggering performance in ATR applications from images
- <u>Conventional approach</u>



- <u>ATR directly from received signal</u>

- Combine ATR and image reconstruction into a single step to
  - Reduce computational complexity
  - Improve ATR performance

[3] S. Kazemi, B. Yonel, B. Yazici, "Deep Learning for Direct Automatic Target Recognition from SAR Data," to appear in 2019 Radar Conf.

Network Architecture Inspired by Sparse Dictionary Learning

- Inspired by classification via sparse representation

- **Underlying optimization problem**:

- – Dictionary: A set of basis vectors along the columns of a matrix

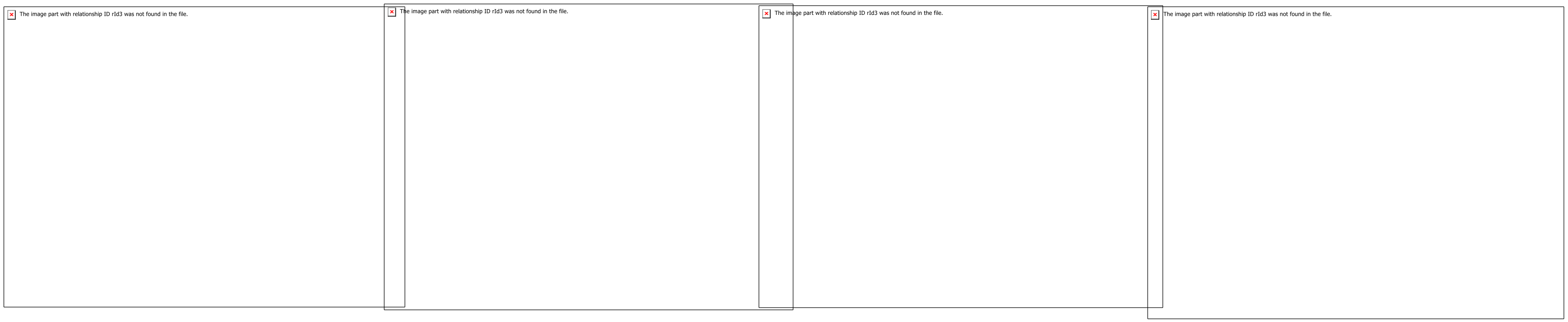
- – sparse coefficient: Represents samples of its own category more sparsely than samples from a different category

- and

- – Network weights → **Function of D**

- – Non-linear function

Numerical Simulations



Sample scenes with square and triangular objects

- **Significantly sparsely sampled imaging data -** No. of slow-time and fast-time samples – 4 and 20 , respectively
- Random scenes are synthesized by placing two types of objects at different locations, orientations and on different backgrounds.

- Training set: 28x28 pixels with single extended target of rectangular and triangular shape.
- Target placement: random in [1,25]x[1,25] range of pixels.
- No. of dictionary columns – 200

Numerical Simulations

Original scene

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Reconstructed image

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Original scene

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Reconstructed image

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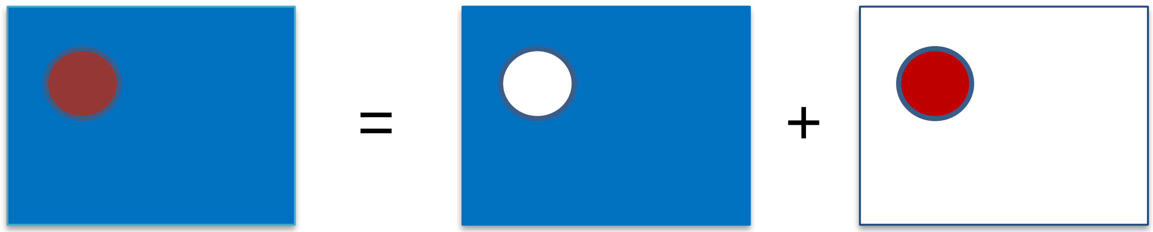
- **Polar format reconstruction followed by sparse dictionary method -**

SNR (dB)	Classification accuracy (%)	
	DL classification	Image reconstruction + classification
-3	84.6	50.7
0	90.2	50.8
3	91.6	52

Reconstruction of Foreground/Background Images



Original image $\boldsymbol{\rho}$ | Background image $\boldsymbol{\rho}_b$ | Foreground image $\boldsymbol{\rho}_f$

- <u>Reconstruct two images</u>:
  - A foreground image $\boldsymbol{\rho}_f$ including one or more objects of interest (mines) and
  - A background image, $\boldsymbol{\rho}_b$
- <u>Two approaches</u>:
  - Supervised: Training – $\mathbf{d}$, $\boldsymbol{\rho}_f$ and $\boldsymbol{\rho}_b$ available, Testing – Only $\mathbf{d}$ is available
  - Unsupervised: Training – $\mathbf{d}$ and **label** available, Testing – Only $\mathbf{d}$ is available

Numerical Simulations - Supervised

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Original scene

($\boldsymbol{\rho}$)

=

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Original background

($\boldsymbol{\rho}_b$)

+

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Original foreground

($\boldsymbol{\rho}_f$)

Input sonar data → Recursive Neural Network →

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Reconstructed background image

&

The image part with relationship ID rId3 was not found in the file.

Reconstructed foreground image

Numerical Simulations - Unsupervised

The image part with relationship ID rId6 was not found in the file.

Original scene
($\boldsymbol{\rho}$)

=

The image part with relationship ID rId6 was not found in the file.

Original background
($\boldsymbol{\rho}_b$)

+

The image part with relationship ID rId6 was not found in the file.

Original foreground
($\boldsymbol{\rho}_f$)

Input sonar data → Generative Adversarial Network →

The image part with relationship ID rId6 was not found in the file.

Reconstructed background image

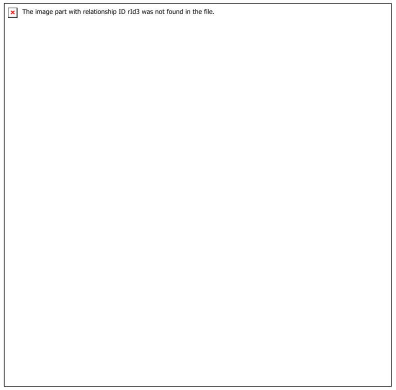
&

The image part with relationship ID rId6 was not found in the file.

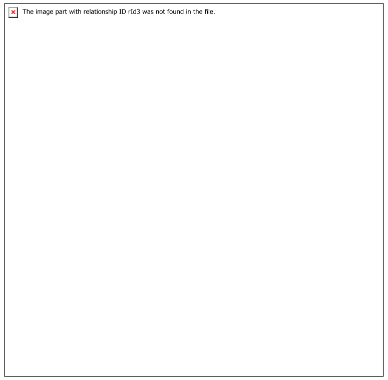
Reconstructed foreground image

Comparison with Conventional Approach

- **Foreground separation using proposed model**

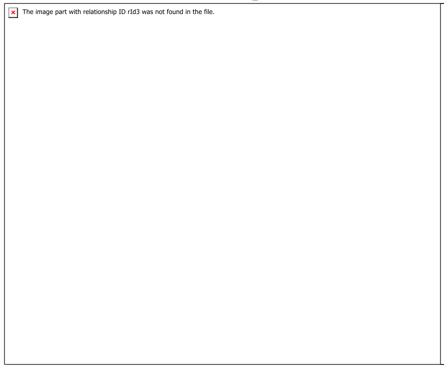


Original image

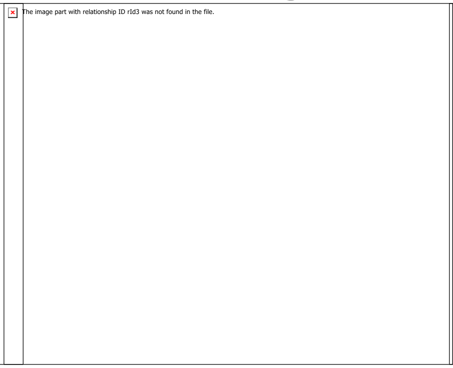


Reconstructed foreground image

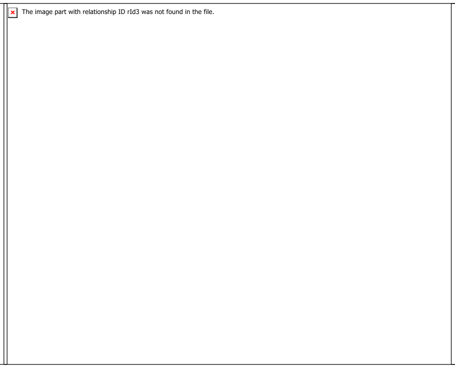
- **Image formation + edge detector**



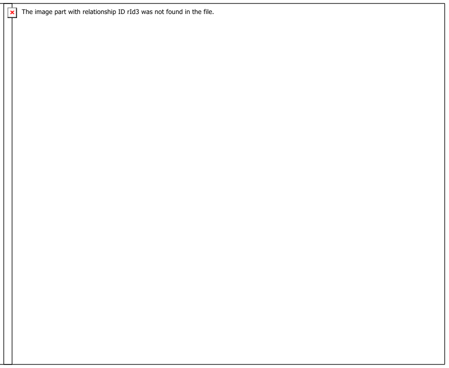
‘Canny’ edge detection



‘Sobel’ edge detection



‘Roberts’ edge detection



‘LoG’ edge detection

Conclusions

- DL framework: a joint estimation & classification tool for blind deconvolution combining a model based ánd data driven approaches
- Accurate reconstruction performance: good geometric fidelity, background suppression. Accurate estimation of the waveform only given a priori functional form
- Classification using sparse synthetic aperture data directly from received sparse signal
- Accurate reconstruction of background and foreground images from sparse received data