

This paper describes objective technical results and analysis. Any subjective views or opinions that might be expressed in the paper do not necessarily represent the views of the U.S. Department of Energy or the United States Government.

MLDL

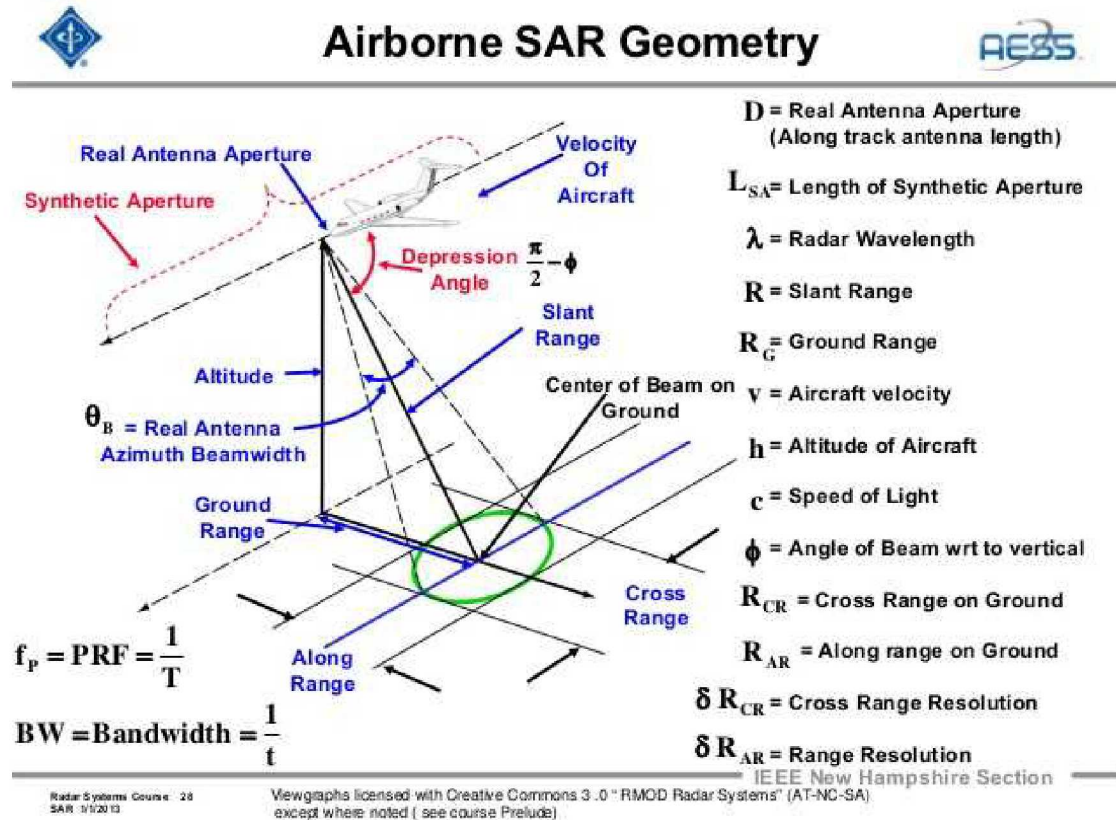
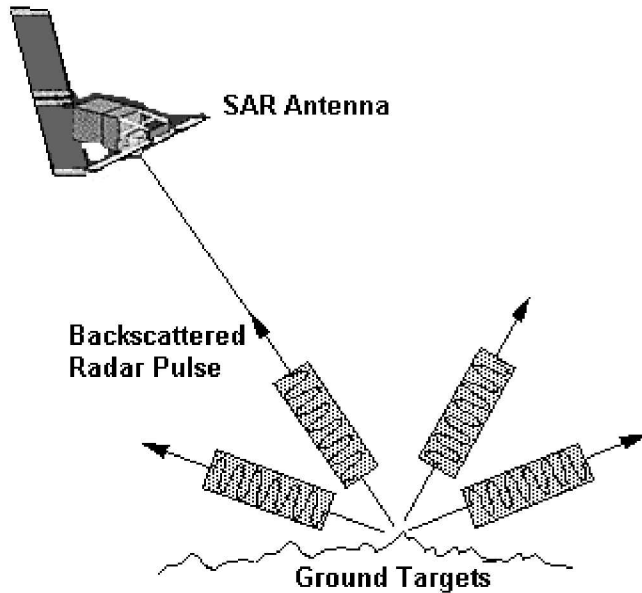
SAND2018-8249C

Machine Learning and Deep Learning Conference 2018

“Synthetic Aperture Radar image generation using Generative Adversarial Networks”

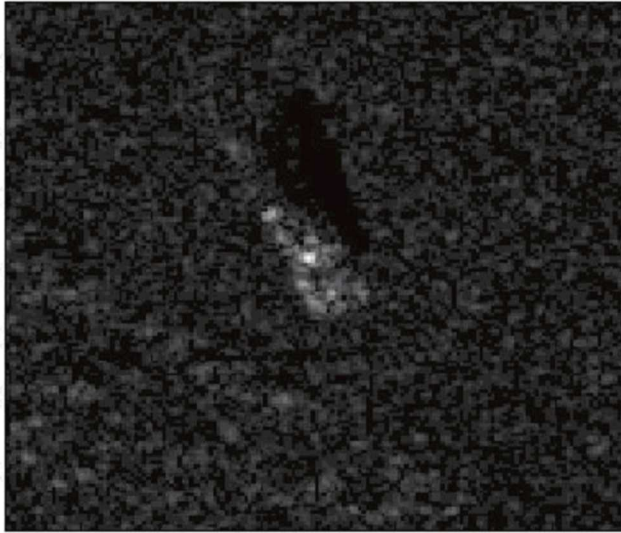
- Joshua Coon/5448
- Mark Louie/5448
- Daniel Moser/1516
- Mary Moya/5448
- Darren Rodriguez/5448
- Alex Schwing/UIUC
- Theodore Stangebye/5448
- Derrek Yager/5448

Synthetic Aperture Radar (SAR) overview

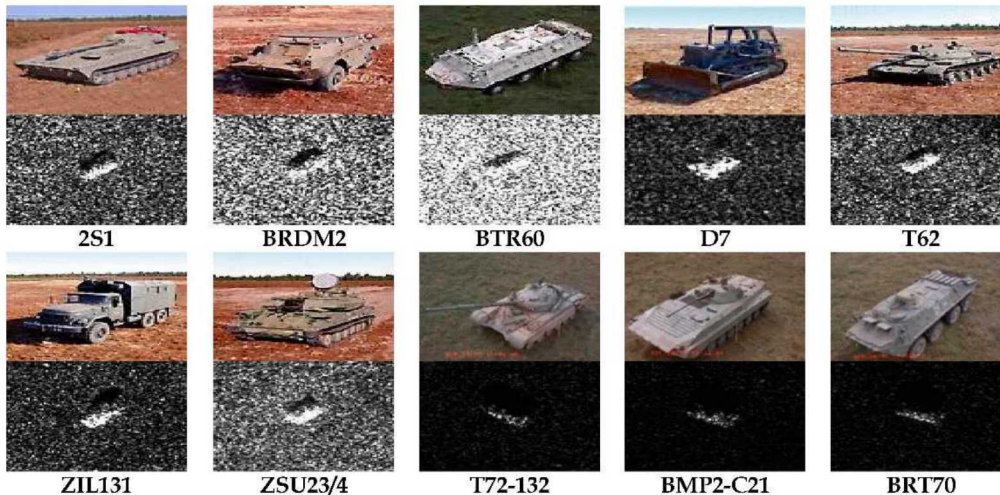


Generating SAR Images with GANs

Example image from MSTAR dataset



- Examples of SAR images on left
- SAR images have different statistics from optical images
 - Patches of bright and dark spots called “speckle”
- Convolutional Neural Networks (CNNs) that work for optical images need adaptation to work for SAR images
 - Loss function of CNNs

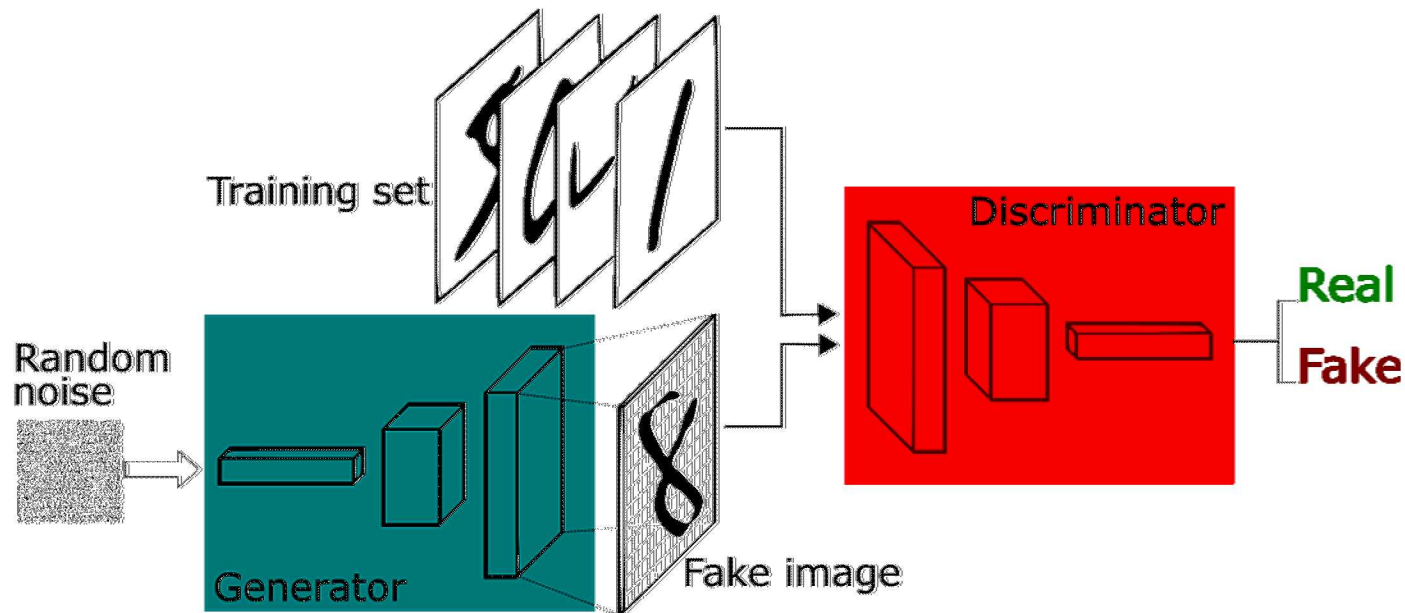


Research questions



- Style transfer: Can we make synthetic images look more like real images without human intervention?
- Change elevation: Can we train a GAN on a set of 30 degree elevation images and generate a 15 degree elevation image (for example)?
- Denied target: Can we generate SAR image for denied target by only training on group of similar images and a few images of the target?
- Other parameters: Can we generate images that account for changes in other variables, such as squint angle?

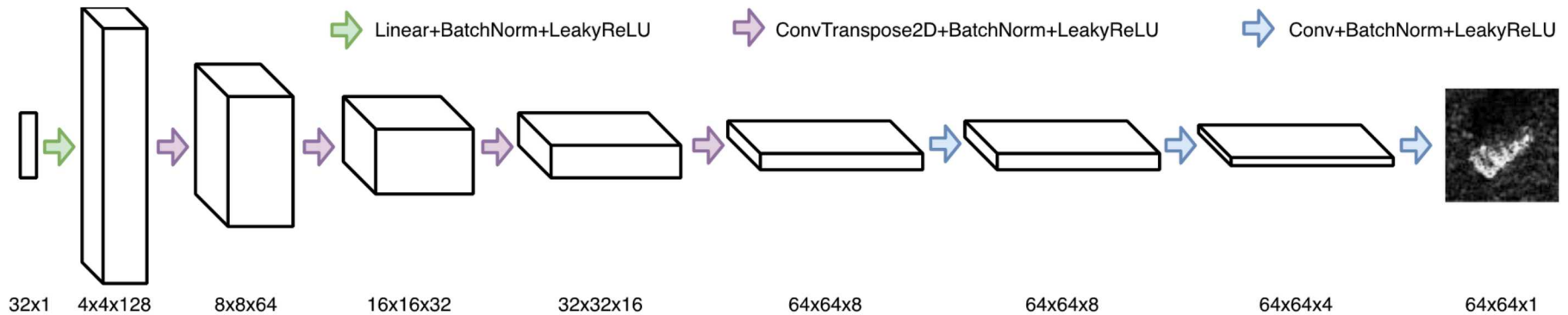
Algorithmic approach of your solution



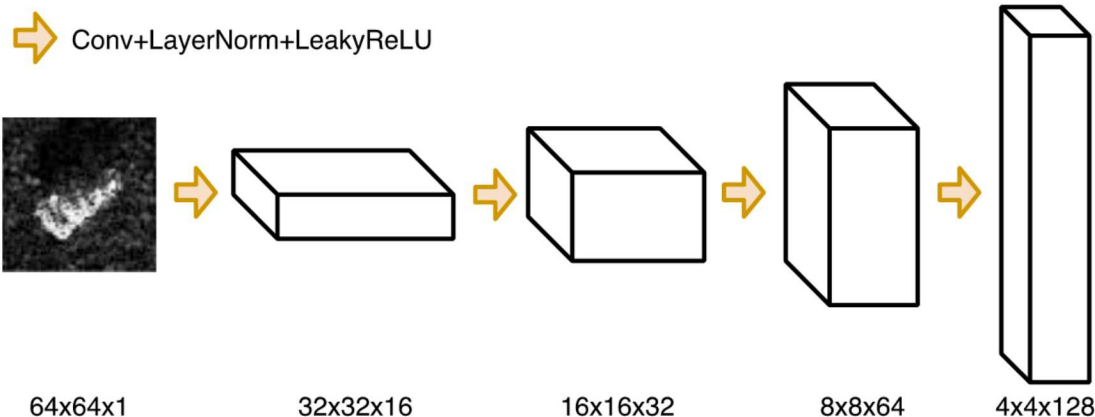
- Generative Adversarial Networks (GANs) train two neural networks in a “game” against each other
- The generator is equivalent to a forger
- The discriminator is equivalent to an expert trying to decide if the generators work is real or fake
- Nash equilibrium when 50/50 chance that generated images are labelled real by discriminator
 - Discussed in <https://arxiv.org/abs/1710.08446>

GAN Architectures

Generator



Discriminator



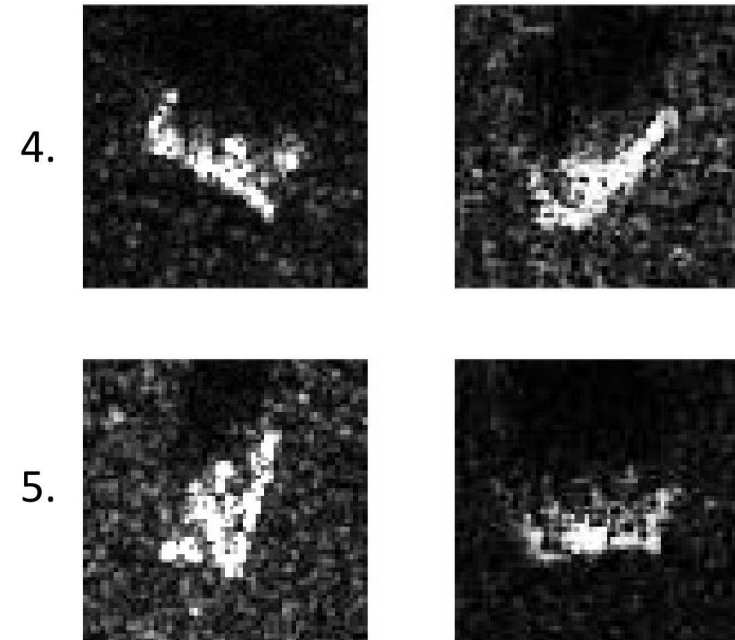
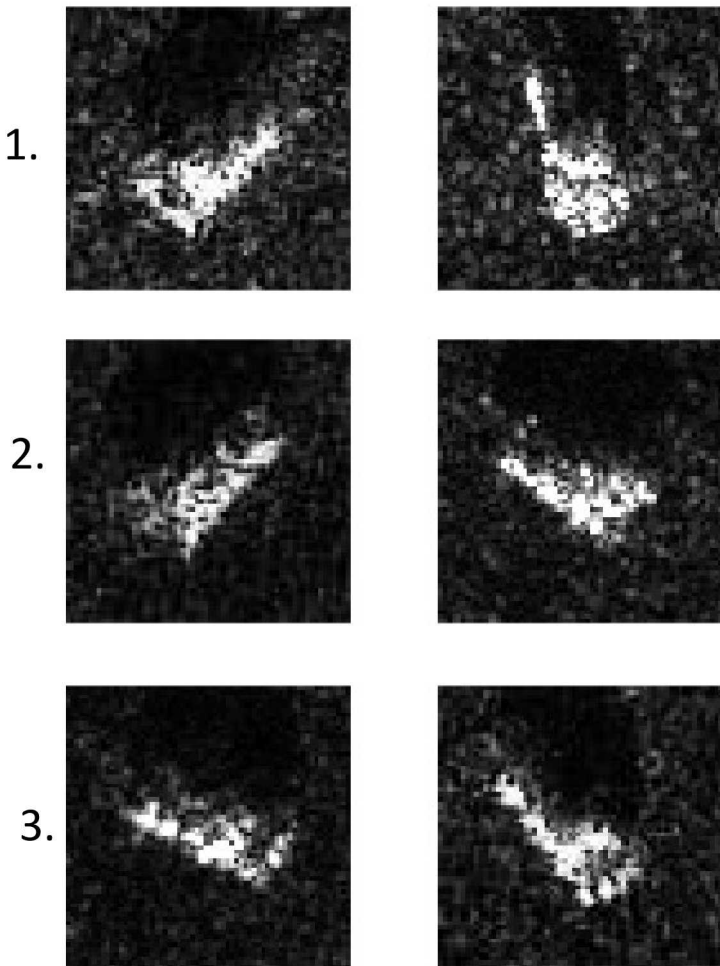
https://github.com/vdumoulin/conv_arithmetic
for some cool illustrations of convolutional filters

32x1 vector is noise input

Conditional GANs (cGANs) concatenate additional tunable variables onto the end of noise vector

SAR Turing Test

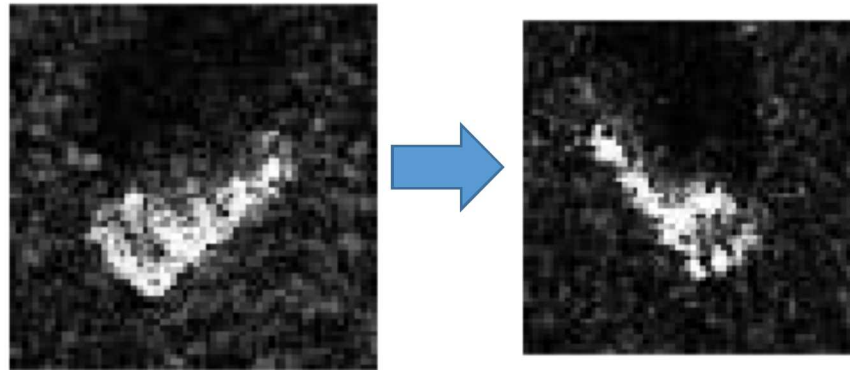
Which one is real/fake?



Answers: 1. R/F 2. F/R 3. R/F 4. R/F 5. R/F

Lessons Learned

Example of Lesson Learned:



- Fixed generated images (above) to make them more “blocky” by changing activation function on generator network from sigmoid to ReLU
- SAR SMEs say blocky images more realistic
- Example of changes in network architecture producing better images

Lessons Learned:

- The quality of images is sensitive to network architecture and hyperparameter tuning.
- Off-the-shelf solutions don’t produce good results without modifications
- Using a sliced Wasserstein loss function seems superior to L2 loss function
- SME feedback on images critical for improving data

Additional Results and Future Directions



- Additional results from using Pix2Pix and CycleGAN on improving synthetic SAR images
 - Can show examples later if interested
 - Dan Moser
- Examining several improvements on ‘vanilla’ GANs
 - Sliced Wasserstein GAN: Replace loss function with Sliced Wasserstein loss function
 - Cost to transform one pile of dirt into a different pile of dirt
 - Mathematical arguments support Wasserstein being a better loss function
 - Derrek Yager
 - Data Augmentation: Expand data set by translating pictures, adding noise, etc.
 - Theo Stangebye
 - Network Architecture: More layers? Pooling -> Capsule Network?
 - Alex Schwing and Dan Moser
 - Examine Automatic Target Recognition (ATR) properties of generated images
 - Mary Moya
- Other staff members developing statistical tests for comparing SAR images
 - Michelle Hummel