RDAnet: A Deep Learning Based Approach for Synthetic Aperture Radar Image Formation

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Abstract

Synthetic Aperture Radar (SAR) imaging systems operate by emitting radar signals from a moving object, such as a satellite, towards the target of interest. Reflected radar echoes are received and later used by image formation algorithms to form a SAR image. There is great interest in using SAR images in computer vision tasks such as automatic target recognition. Today, however, SAR applications consist of multiple operations: image formation followed by image processing. In this work, we show that deep learning can be used to train a neural network able to form SAR images from echo data. Results show that our neural network, RDAnet, can form SAR images comparable to images formed using a traditional algorithm. This approach opens the possibility to end-to-end SAR applications where image formation and image processing are integrated into a single task. We believe that this work is the first demonstration of deep learning based SAR image formation using real data.

1. Introduction

Synthetic Aperture Radar (SAR) [1], [2] is a remote sensing imaging technique used to form images from radar signals. During imaging, a moving device such as a satellite or an unmanned aerial vehicle [3] emits high frequency radar signals in the direction of a region of interest to image. These signals reflect off the target region and are received by an antenna on the same imaging device. After a sufficient number of signal echoes have been received, they are used as input to an image formation algorithm to produce an image. Image contrast is determined by variations in reflectivity of the region being imaged. SAR imaging has many applications including mapping [4], change detection [5], automatic target recognition [6], and environmental monitoring [7].

Over time, there have been many different algorithms developed to form SAR images from echo data. These algorithms use several different approaches such as backprojection [8], compressed sensing [9], or signal processing [10]. Although there has been interest [11], [12], in the development of deep learning based SAR image formation, to our knowledge as of yet there has not been a demonstration of a fully functional approach.

Instead, much deep learning based SAR work has been conducted in the fields of classification [13] and target segmentation [14] [15]. In these works, however, the neural networks that perform target classification operate on images that have already been formed using other SAR image formation approaches. Nevertheless, there are many cases where a deep learning based approach to SAR image formation could be very beneficial. For instance, a neural network could be trained to output fully formed SAR images that are automatically annotated with identified targets of interest. Additionally, there may be imaging configurations where simultaneous image formation and target classification may result in improved target classification rate [11] when compared to the case when image formation and target classification are performed sequentially.

There are also potential computational advantages in using a deep learning based approach for SAR image formation. Traditional SAR formation algorithms make use of both well-established data transforms such as the FFT as well as SAR specific data corrections. To achieve high throughput SAR image formation, all components of the image formation algorithm must be efficiently implemented. In comparison, a deep learning based approach can largely be implemented through matrix multiplication. Therefore, rather than needing to optimize many different components of the image formation algorithm, optimization can be focused on a single key function. Furthermore, a deep learning based implementation can take advantage of the many processing gains that have been developed by the deep learning community, as well as any gains developed in the future, through the use of commonly used deep learning platforms such as TensorFlow [16] or PyTorch.[17].

In this work, we present RDAnet, a neural network trained to focus SAR images from raw radar data. This network has been trained to match performance of the Range Doppler Algorithm [10], a well-known signal processing based SAR image formation algorithm. Briefly, the algorithm performs the following set of operations to generate a focused SAR image. During processing, echo
data is stored in a 2D complex matrix. After the matrix is formed, a matched filter is applied to each matrix row. Once filtering is complete, a 1D FFT is taken along column of the matrix, followed by interpolation along each row of the transformed data. Finally, a second set of matched filters are applied to each column of the matrix. After this, the matrix is transformed back to the spatial domain by an inverse FFT. Finally, the complex magnitude of each pixel is calculated. In some cases, an additional processing step called ‘multilooking’ is also performed [18]. There are different approaches to how this step is handled, but the purpose of multilooking is to reduce image speckle. Regardless, the end result is a focused SAR image that can be used for visualization or further processing.

As will be discussed, we trained RDA\textsuperscript{net} to generate the output of the complete set of operations of the Range Doppler Algorithm by treating the SAR formation problem as a supervised learning problem. We built a dataset containing pairs of raw echo data collected by a research satellite and the echo’s corresponding focused image. These echo/image pairs were then used to train RDA\textsuperscript{net}.

Taken as a whole, the major contribution of this paper is to demonstrate that formation of SAR images through deep learning is feasible. Due in part to the challenges in obtaining sufficient training data, but largely to identifying an appropriate network architecture, we believe that this is the first demonstration of a deep learning based approach to SAR image formation. Our results demonstrate that, after training, RDA\textsuperscript{net} generalizes well and can generate focused SAR images with image quality that is comparable to images generated using the Range Doppler Algorithm in terms of image contrast and resolution. Perhaps most importantly, this work paves the way towards advanced deep learning based SAR applications, such as simultaneous image formation and automatic target recognition.

The remainder of this paper is laid out as follows: Section 2 details the methods used to build our dataset, the RDA\textsuperscript{net} architecture, and RDA\textsuperscript{net} training details. Section 3 shows key results, including comparison of images produced with RDA\textsuperscript{net} and a traditional approach. Section 4 discusses these results and their implications, Section 5 discusses potential future work, and Section 6 concludes the paper.

## 2. Methods

In this section, we discuss the approach used to collect and preprocess SAR data used for training, the RDA\textsuperscript{net} architecture, and the steps taken to train the RDA\textsuperscript{net}. The two key components of the RDA\textsuperscript{net} architecture are shown in Fig. 1: a Deep Convolutional Encoder (DCE) followed by a Deep Residual Network (DRN). At a high level, the purpose of the DCE is generate a mapping from raw SAR echo data to a first pass at a focused SAR image. However, we found that SAR images formed by the DCE had poor image resolution and contrast, compared with SAR images formed by traditional approaches. For this reason, the output of the DCE is passed directly to the DRN. The DRN then uses single image super-resolution techniques [19] to upsample the image and improve focused image quality in terms of image resolution and image contrast. Together, the end result is a model that generates focused SAR images from raw echo data.

### 2.1. Data collection and preprocessing

Raw SAR echo data was obtained from the Alaska Satellite Facility (ASF) [20], an organization that allows researchers to access both raw and processed remote sensing data, including SAR data, from a set of satellites. For this work, data collected from the European Remote Sensing (ERS) [21], [22] satellite was used. The ERS-2 was a research satellite launched by the European Space Agency in 1995 and collected data through 2011. The ASF Vertex tool [23] was used to download frames of raw SAR data collected by the ERS-2. In total, 4451 frames were downloaded, containing raw data collected by the ERS-2 while it was orbiting over Alaska. The ERS-2 collected mapping data, therefore, SAR images used in this work consist of mountain landscapes.

To build a training dataset, each radar frame was divided up into unique 4096x4096 segments, resulting in a total of 35641 segments. Each segment was downsampled using

![Complex raw echo data collected by satellite](image1.png)

**Figure 1:** A high level view of the RDA\textsuperscript{net} architecture. Echo data is input into network, and final output is a focused SAR image. In this work, training data was collected from a mapping satellite, so images produced are of mountain landscapes.
MATLAB’s resample function [24] to size 256x256. After downsampling the raw data segment, a SAR image was formed using the Range Doppler Algorithm. Finally, to reduce noise, each reconstructed image was smoothed using a Gaussian kernel with sigma of 0.75. After all images were formed, SAR image pixel values were scaled such that all pixel values ranged linearly between 0 and 1 throughout the entire dataset.

SAR raw radar data is complex, containing both real and imaginary components. Representative raw echo data is seen in Fig. 1. As seen, before processing, the data is nearly unintelligible from the perspective of a person. It is very difficult to see any sort of feature or pattern within the data, highlighting the need for approaches to focus SAR images. For training, all raw data was normalized by the highest complex magnitude in the dataset, bounding the data between -1 and 1. Finally, the raw data was zero centered by calculating the mean of each pixel across the entire dataset and then subtracting each pixel in each echo by its respective mean. Raw data was then stored in 256x256x2 arrays, where the real component of the raw was stored in the first channel while the imaginary component was stored in the second channel. After all processing was complete, 33641 echo/image pairs were used for model training, while the remaining 2000 echo/image pairs were used for model validation.

2.2. Deep Convolutional Encoder architecture

To map the raw SAR echo data to the SAR image, a convolutional encoder similar to VGG11 [25] was used. The architecture of the convolutional encoder is shown in Fig. 2. As shown, the encoder consists of four sets of convolutional blocks with increasing number of filters, from 64 up to 512, each with kernel dimensions 3x3. Every convolutional layer is connected to the next via a leaky rectified linear unit function [26]. Following each convolutional block, two-dimensional max-pooling with stride 2 was used, to reduce the dimensionality of the encoded data by two in each dimension. After the final convolutional block, two-dimensional spatial dropout [27] is used to provide regularization and prevent overfitting. Unlike standard dropout [28], where each unit is set to 0 with a chosen probability at each training iteration, with spatial dropout entire convolutional feature maps are set to 0 instead. For this work, feature maps were set to 0 with probability 0.5. The spatial dropout layer is then connected to two fully connected layers, with 2014 hidden units each. The first fully connected layer is connected to the second via a leaky rectified linear unit function. Finally, the output of the second fully connected layer is reshaped such that the network output is 19x106, which is half the size of the focused SAR image in each dimension. The output of the Deep Convolutional Encoder is then passed to the Deep
2.3. Deep Residual Network architecture

To improve image resolution, an approach inspired by the EDSR single image super resolution technique [29], was used. The network architecture for the Deep Residual Network, also shown in Fig. 2, contained 16 residual encoder [30] blocks. As shown, each residual block contains two convolutional layers, with the first connected to the second through a rectified linear unit function. The output of the second convolutional layer is then added to a scaled copy of the input to the first convolutional layer. Each convolutional layer contains 64 filters. Following the last residual block, there is a convolutional layer with 256 filters. As in the DCE, here again each filter uses a 3x3 convolutional kernel. The output of this last convolutional layer is then reshaped using TensorFlow’s ‘depth to space’ function [31] such that image size is upsampled by a factor of two in each dimension. After this, the final layer contains a convolution with a single 3x3 filter.

2.4. RDAnet training details

The RDAnet was implemented using TensorFlow [16] and trained using the Adam optimizer [32] to minimize the mean absolute error between the output of the network and SAR images reconstructed using the Range Doppler Algorithm. The initial optimizer learning rate was set to 1e-4, all other parameters were left as default. Training minibatch size was 32. Fig. 3 shows the mean absolute error of both the training and validation set plotted over each training epoch. As seen, the mean absolute error of the validation set tracks closely with the mean absolute error of the training set throughout the training process, suggesting that the RDAnet generalizes well and that training was stable.

3. Results

3.1. Comparison to RDA SAR images

SAR images formed using the Range Doppler Algorithm were compared with images generated by the RDAnet. Representative results are shown in Fig. 4, which contains side by side comparison between images produced from the same echo data using the Range Doppler Algorithm and RDAnet. As is demonstrated, our model produces SAR images of comparable image quality. The same landscape features are seen in both images, indicating that the raw echo data is being properly focused after passing through the network.

Interestingly, we are able to generate these images without providing the model with any direct information about the satellite or radar used to collect imaging data (e.g. antenna size, distance from target, orbital height, signal wavelength, or data sampling rate). In fact, the first component of RDAnet, the deep convolutional encoder, uses standard neural network layers (convolutional layers, pooling layers, and fully connected layers) as well as a well-known architecture, albeit with modified layer activation functions and model regularization approach. Instead, this data is only provided to the model indirectly, through the focused images used to train the model. Additionally, the model did not receive any direct information about the algorithm used to form SAR images used as input to train the model. This suggests that our approach can be applied to other SAR imaging configurations or image formation algorithms, provided that there is sufficient training data.

3.2. Impact of Deep Residual Network on image quality

To evaluate the impact of the Deep Residual Network on the quality of images formed by RDAnet, we compared the output RDAnet to two other cases: In the first case, we trained a Deep Convolutional Encoder by itself and applied standard bilinear interpolation to reach the correct image dimensions. For the second case, we used a Deep Residual Network with the same number of layers and filters used in the final RDAnet, but trained it separately from the Deep Convolutional Encoder. Results are shown in Fig. 5. Fig. 5a shows the SAR image formed using the Range Doppler Algorithm, Fig. 5b shows the upscaled output directly from the Deep Convolutional Encoder, Fig. 5c shows the output from the Deep Residual Network that was trained separately, while Fig. 5d shows the output from RDAnet.

As can be seen by comparing Fig. 5b with Fig. 5c or Fig. 5d, there is clear improvement in image resolution when using the Deep Residual Network single image super resolution approach over standard bilinear interpolation of the output of the Deep Convolutional Encoder. Although

![Figure 3: Training and validation loss reported at each training epoch. Mean absolute error was used as the loss function to minimize.](image-url)
the broad structures of the mountain landscape are recovered with the Deep Convolutional Encoder, finer details in the image are blurred together and lost when the Deep Residual Network is not used. Image resolution is further improved when the Deep Convolutional Encoder and Deep Residual Network are trained concurrently. An example of this is seen when the boxed region in Fig. 5a is compared with the same region in the other three images. Here, as shown, landscape features are more clearly resolved and the formed image has improved contrast when both components of the complete model are trained together.

To quantitatively assess the impact of the Deep Residual Network, PSNR was calculated for each image in the validation set for each of the three cases. Calculation results, which show the average PSNR from the three sets of calculations, are shown in Table 1, show that validation set PSNR is highest when the Deep Convolutional Network is trained simultaneously with the Deep Residual Network, which tracks with the qualitative observations discussed above.

| Interpolation Type         | Average PSNR |
|----------------------------|--------------|
| DCE+Bilinear               | 16.59 dB     |
| DCE+DRN, trained sequentially | 34.68 dB     |
| DCE+DRN, trained together  | 36.2 dB      |

Figure 4: Representative images formed using the Range Doppler Algorithm (left column) and RDAnet (right column). As seen, both images have comparable image quality in terms of resolution and contrast.

4. Discussion

In this work, we demonstrated that SAR images can be formed directly from raw radar data through the use of a deep learning architecture. Unlike [11], which discusses a potential framework for deep learning based SAR image formation but does not contain imaging results from real data, we do not require a forward model of the radar imaging system in the loss function to minimize while training the network. Instead, our network was trained using a standard mean absolute error loss function. This suggests that it should be straightforward to train a RDAnet for any other SAR imaging system with minimal modification to the network design, provided that there is sufficient data for training.

While developing the RDAnet architecture, one challenge we came across was that noise in the raw echo data can cause networks to quickly overfit to the training data. For example, early in the development of RDAnet, we attempted an architecture similar to what is used by AUTOMAP [33] for reconstruction of MRI images from k-space data. This architecture consists of two fully connected layers followed by a sparse convolutional autoencoder. However, we found that regardless of the regularization techniques that we tried, any network trained using an AUTOMAP style architecture did not generalize well when trained with using our echo/image pairs. It is for this reason that we ultimately decided to use a VGG [25] style convolutional encoder for this work. With this architecture, the fully connected layers are below several convolutional...
suggests that running the network in inference mode to backpropagation to update the network weights, that this timing measurement includes both forward and our network at a rate of ~50 samples per second. Assuming the training process, TensorFlow reported that we trained RDAn

signal processing needed to form a SAR image. We trained FPGAs

Currently, many solutions for real

purpose computing platform equipped with a GPU. (36)

Dataset

availability SAR data obtained using a modern SAR imaging

obtaining SAR data for deep learning research. A publicly

available SAR data is not publicly available. (35)

this dataset have already been formed, and the raw echo
data is not publicly available. A similar publicly available

dataset containing SAR echo data of different targets would be beneficial to the research community. Likewise, the fact that researchers are still publishing using the MSTAR
database [35] despite the fact that it was collected over twenty years ago again highlights the challenge of obtaining SAR data for deep learning research. A publicly available SAR data obtained using a modern SAR imaging system would also be of great value to the research community

The RDAnet architecture also opens the possibility for real-time or near real-time SAR imaging using a general-purpose computing platform equipped with a GPU. Currently, many solutions for real-time SAR make use of FPGAs [36] or specialized electronics [37] to perform the signal processing needed to form a SAR image. We trained RDAnet using an NVIDIA Tesla V100 GPU [38]; during the training process, TensorFlow reported that we trained our network at a rate of ~50 samples per second. Assuming that this timing measurement includes both forward and backpropagation to update the network weights, this suggests that running the network in inference mode to process newly acquired data should be able to operate at an even faster rate, allowing for real-time SAR imaging without specialized hardware. It is intended to collect RDAnet timing measurements using other GPU models soon.

A final interesting aspect of the RDAnet architecture is that the Deep Residual Network component enables a tradeoff between formed image resolution and processing time. In this work, we used 16 residual blocks in our Deep Residual Network. However, the architecture could potentially include fewer blocks, or blocks with fewer filters per block. In either case, we believe this would result in a reduction in image quality in terms of resolution, but also a reduction in time to form the image. Therefore, if the user is interested in real-time or near-real-time SAR imaging at a certain frame rate, the number of residual blocks used in the RDAnet can be adjusted in order to meet timing requirements, potentially at the expense of image quality.

5. Future Work

During the development of RDAnet, raw SAR echo data was downsampled prior to training to reduce the problem size. This was done to enable rapid experimentation of different neural network architectures with a dedicated GPU server, to demonstrate the feasibility of generation of SAR images through a deep learning approach. However, this also had impact on the resolution of the images reconstructed using the Range Doppler Algorithm that were then used to train our model. Going forward, it would be interesting to train an RDAnet using larger echo/image pairs with less, if any, downsampling to enable formation of even higher resolution SAR images. To maintain the possibility of real-time SAR with larger data size, we will investigate the usage of dilated convolutions [39], which will enable us to increase convolution filter size without increasing the number of calculations that are made.

Another interesting possibility is to investigate the use of GAN [40] style loss functions to train our network.

Figure 5: Demonstration of the impact the Deep Residual Network has on formed image quality. a) shows an image formed by the Range Doppler Algorithm, b) shows an image formed with only the Deep Convolutional Encoder, c) shows an image formed by training the Deep Convolutional Encoder and the Deep Residual Network separately, and d) shows an image formed by RDAnet. Image features in the boxed region of 5a are more clearly resolved in 5d than they are in 5b or 5c due to the inclusion and joint training of the deep residual network.
Currently, the RDAnet is trained to minimize mean absolute error. Adding a discriminator term into the loss function could help to further improve the quality of images formed using the trained RDAnet.

6. Conclusions

In this work, we presented RDAnet, a deep learning architecture for the formation of SAR images from raw radar data. After training the RDAnet using real echo data and contrast, when compared with images produced using traditional approaches. As far as we know, this is the first demonstration of using a deep learning based approach to form SAR images.

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