ARTIFICIALLY ENHANCING TITAN'S SAR IMAGES USING EARTH SATELLITE IMAGES AND DEEP LEARNING TECHNOLOGY. M. Holland[1], L. Mohlman[1], N. Larson[1], C. Ybañez[1], J. Radebaugh[2], B. Morse[3], D. Broadbent[4] and W. Jeffs[5]. [1]OPAL Labs, Brigham Young University, Provo, UT (mwh1998@byu.edu), [2]Department of Geological Sciences, Brigham Young University, Provo, UT, [3]Computer Science Department, Brigham Young University, Provo, UT, [4]Harold B Lee Library, Brigham Young University, Provo, UT. [5]Springville High School, Springville, UT.

Introduction: Most of the data gathered from the surface of Saturn's moon Titan was produced by the *Cassini* Spacecraft that orbited Saturn from 2004-2017. Because the world has a thick layer of methane haze hiding the surface from the visible light spectrum [1], a 2 cm Synthetic Aperture Radar (SAR) was used to produce images of Titan's geomorphology [2].

One of the drawbacks of the SAR imaging at Titan is that because of the highly scattering properties of the materials and high altitude of orbit, the image resolution and quality was low [3]. Thus, there are likely many geological features present on Titan's surface but at smaller scale than was possible to observe with Cassini SAR [e.g. 4]. In order to better predict what landscapes exist on Titan's surface, we have applied modern machine learning technology to enhance the low resolution and noisy images to produce a high-resolution and denoised version of the data, following on [5]. This method enables us to effectively predict the surface geomorphology and thereby significantly improve our understanding of Titan and its geology.

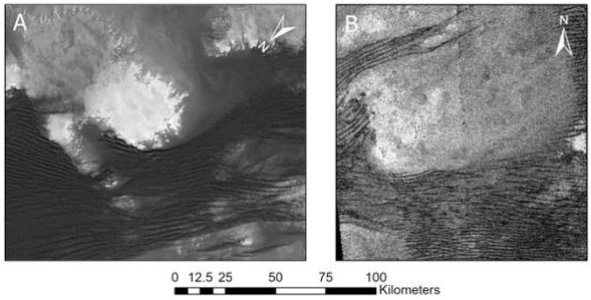

Fig. 1. (A) Dunes on Earth in NIR produced by Landsat 8 (inverted to simulate the SAR imaging) [6] (B) Dunes on Titan from Cassini SAR. Dunes are dark and intervening topography is bright in both images.

Novel Geologic Dataset: One benefit of deep learning is that these methods can analyze data and predict trends based on training on a large dataset. In order to have the predictions as close as possible to what the surface of Titan looks like, the machine learning models are first trained on Earth data with the closest geological analog to Titan (Fig. 1) and then evaluated on lower-resolution *Cassini* SAR data. Earth is the best analog for remotely sensed landforms on Titan because it has an atmosphere and a hydrologic cycle, which leads to the presence of similar geomorphologies, such as rivers, lakes, mountains, and evidence of erosion [7]. Titan is also covered with massive sand dune seas, much like sand seas that we observe on Earth [8].

Multiple areas on Earth were included in the training dataset, these include: The Arabian Peninsula,

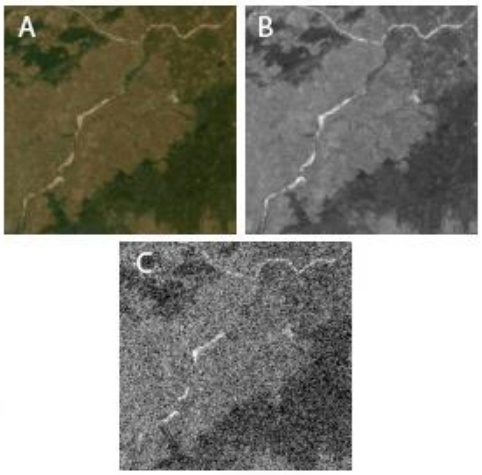

Fig. 2. (A) A color image with three channels of a geographic area on Earth. (B) The same image but in gray scale, meant to represent the denoised version of an image (C) Simulated noise using a gaussian and speckling distribution.

the Namib Sand Sea, the Sahara Desert, Central Australia, and Southern Utah. The dataset includes near-infrared (NIR) images taken by Landsat 8 [6]. Using the NIR images we propose a new dataset in which we select the areas on Earth with the closest geomorphic analog to Titan in order to train deep learning models.

Denoising The Titan SAR Images: The type of noise observed in *Cassini* SAR images is called speckle noise [5]. Using the Novel Geologic Dataset (Fig. 2), synthetic SAR noise was generated using a combination of gaussian distribution and salt and pepper noise and was superimposed onto the image to most efficiently replicate *Cassini* SAR noise (Fig. 2.) Three different deep learning architectures were then selected to attempt to denoise the data. A deep convolutional autoencoder, a traditional autoencoder, and a deep convolutional residual network were all selected for testing the denoising process [9, 10, 11].

Traditional Autoencoder: The traditional autoencoder is a Multi-Layer Perceptron [9] neural network in which the encoder is encoding the input and the decoder is decoding the result from the compressed data after it has been passed through the neural network. It uses fully connected layers, and the output vector is the same size as an input vector.

Convolutional Autoencoder: The convolutional autoencoder [10] is a deep neural network built with an

encoder and a decoder. The encoder transforms the image into a linear vector and then uses convolution layers to decrease the size of the vector. Following the transformation, the decoder "decodes" the image back into an Image

Convolutional Residual Network: The deep residual network [11] is a variation on the convolutional neural network, but it adds the previous input to the output of a specific layer: $g(x) = f(x) + x$. The idea behind using a residual network is that the output (denoised image) of a residual block is fairly like the input, with small variations.

Super Resolution of Titan's SAR Data: The process of super resolving an image is to take a low-resolution image, feed it through a neural network, and then retrieve an artificial high-resolution image. The current state of the art models for super resolution used in this study are Real-ESRGAN, SwinIR, and the Holistic Attention Network [12,13,14].

Real-ESRGAN: Real-ESRGAN [12] uses a generative adversarial network (GAN) in order to predict a high-resolution image based on a low-resolution input image. A GAN is a type of machine learning model which uses a generator network competing with a discriminator network to teach the generator to generate output images with respect to the input images.

SwinIR: SwinIR [13] is a new deep learning architecture that uses the Swin Transformer as layers throughout the network. The model uses a shallow feature extraction network first, then passes the results to a deep feature extraction network that utilizes residual Swin Transformer blocks and uses a high-quality image reconstruction layer to get a high-quality result. This architecture has been shown to be very promising in the field of super resolution.

Holistic Attention Network: The holistic attention network [14] is a modern machine learning architecture that consists of a layer attention module, which transforms the input data with respect to the entire input, instead of convolving each channel individually.

Results: The models are in the early stages of being trained and developed. The current results using the SAR CNN are dramatic and lose some detail, such as lake margins (Fig. 3). Another issue is that the darker parts of the image (i.e. the lakes) still have some noise (Fig. 3). The results using Real-ESRGAN for super resolution enhances the image quality, but it enhances the speckle noise as well. Therefore, the noise needs to be removed prior to the image being super resolved. This is the next step in the project.

Conclusion: Given the similarity in geomorphic processes, even down to the ground-level scale as seen by Huygens, using analogous terrain and topography from the Earth is a viable method for predicting what the surface of Titan should look like at higher resolution. Pitfalls certainly exist in generating predictive images, so we will continue to examine regions, such as the high-contrast margins of lakes, to reveal landscape properties that can be extrapolated across regions. Using these modern computing techniques will enable us to better understand the landforms and histories of regions on Titan, and it can also help us learn more about the selected locations for *Dragonfly* to explore.

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Fig. 3. (A) Original SAR Image from the north polar lakes region, projected to perspective view. (B) Adjacent denoised SAR Image using SAR CNN [9]. The contrast between lakes and intervening terrain is greatly enhanced, though some detail is lost.