National Aeronautics and Space Administration

Machine-Learned Information-Theoretic Optimal Data Compression for Outer Solar System Missions

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Program: FY22 R&TD Topics

Strategic Focus Area: Data: Acquisition, Storage, and Analytics

Objectives

The objective of this project was to develop advanced compression algorithms for outer solar system instrument concepts by using machine learning to augment and advance traditional compression methods. We sought to keep our models portable and quickly trainable to allow for uploads of new parameters, and to assess their effect on the scientific results.

In a collaborative effort between data scientists and Cassini science team members, we identified several ways to assess the quality of lossy compression on images from the Cassini Imaging Science Subsystem (ISS). These included maintaining the ability to accurately 1) measure the atmospheric haze density in images of the moon Titan, 2) perform tie point matching between successive images of the icy satellite Tethys, and 3) detect and measure the shape of "propeller" structures in Saturn's rings [1].

Background

The Cassini ISS carried a hardware-implemented JPEG compressor, which was found to introduce large artifacts in camera images, leading to overly conservative compression. A previous study [2] found that if Cassini science teams had been able to update their compressors during flight after evaluating downloaded data, they could have achieved compression ratios 3-30 times larger than those seen on the actual mission, while still reaching their science goals. The study employed well-chosen wavelet transforms under which Cassini images had sparse relatively representations. Entropy coding a small number of transformed coefficients yielded very low bit rates.

Machine learning gives us the tools to automate this problem by training models to optimize the data transformations and bit allocations.

Approach and Results

We developed a neural network model inspired by the wavelet transform's filterbank implementation. Our model's encoder/decoder replaces the filters with levels of trainable convolutional kernels. Gaussian distributions with trainable parameters are fit to the encoded coefficients to minimize a loss based on reconstruction error and compressibility. The coefficients are quantized and entropy-coded.

We tested this on 32x32 pixel image patches of Tethys. The dominant structure was preserved when compressing below 1.5 bits per pixel (bpp), while avoiding compression artifacts arising from the wavelets employed in [2]. A similar test on images of propellers in Saturn's rings showed that they were still visible when compressing down to about 0.62 bpp, and generally allowed for more accurate retrievals of the propeller shapes than the original algorithm at bit rates >2 bpp.

Going further, we combined this network with SPyNet [4] to estimate the optical flow between images of a flyby sequence and achieve even even lower bit rates and error. We also implemented a convolutional discriminator network to distinguish between compression error and intrinsic image noise. We trained it adversarially [5] against our encoder/decoder network, creating an implicit distortion function based on our understanding of the instrument noise. For images of Tethys, this approach succeeded in reconstructing the main features when compressing down to 1.5 bpp.

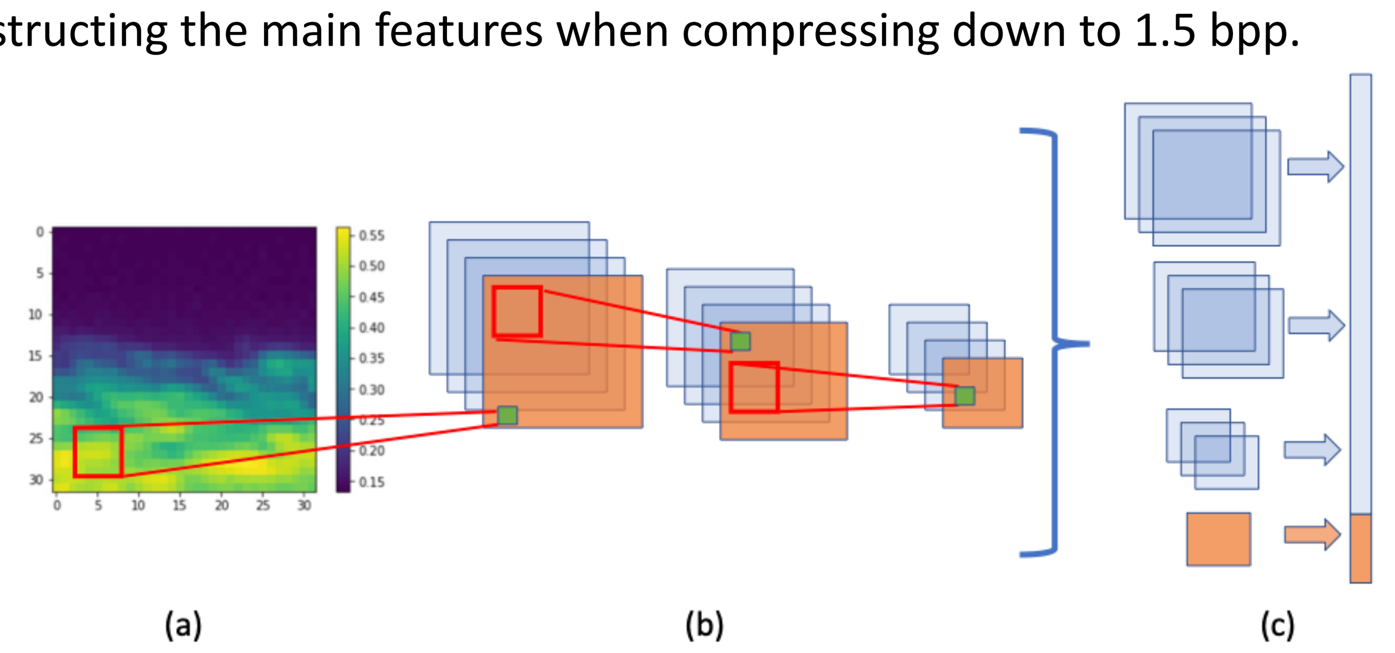

Figure 1. A neural network encoder generalizing the wavelet transform. (a) A 32 x 32 pixel image is passed through four 8 x 8 convolutional kernels. (b) At each layer, the output of the first kernel is iteratively passed through four more convolutional kernels. (c) The final layer's first-kernel output is combined with all layers' second/third/fourth kernel outputs, and vectorized into 1024 coefficients.

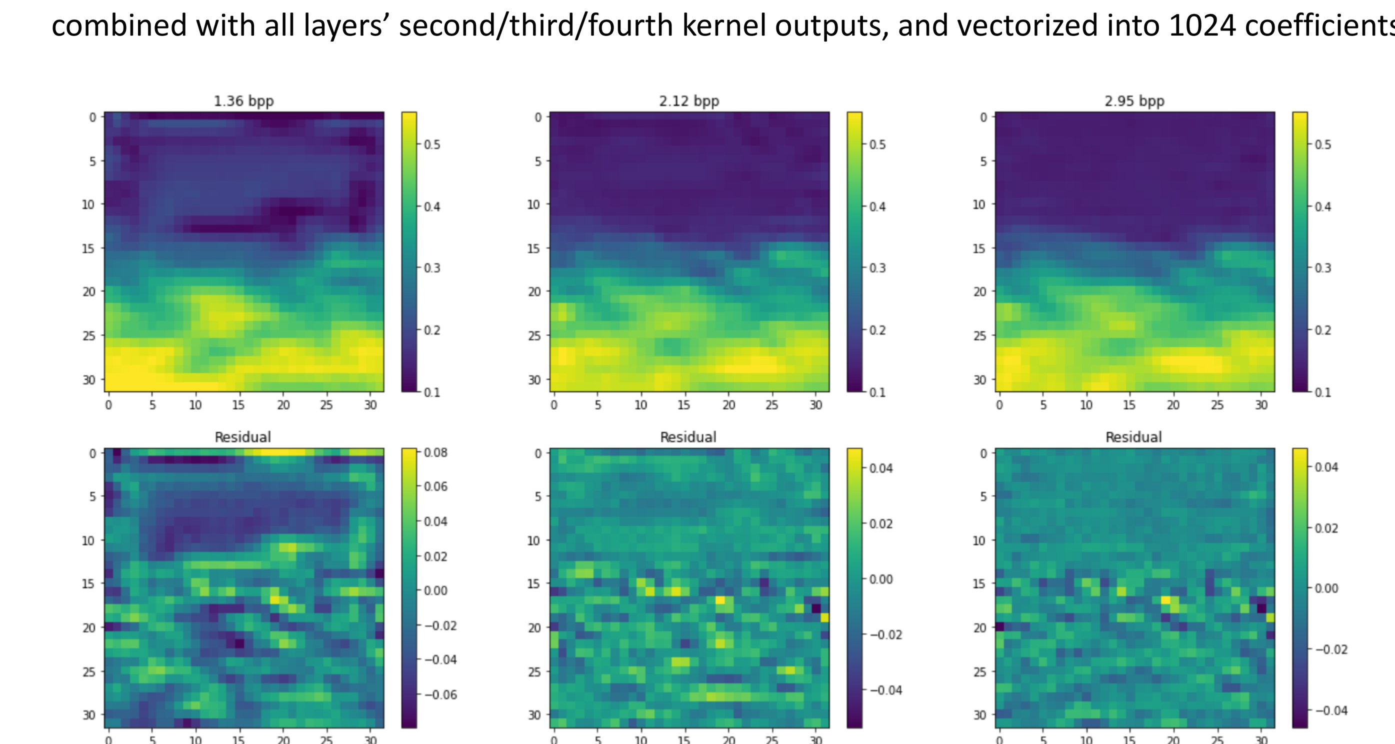

Figure 3. Compressing and recovering an image subpatch of Tethys using the neural network generalized wavelet transform encoder. Top row depicts the same image compressed to 1.36 bpp (left), 2.12 bpp (center), and 2.95 bpp (right). Bottom row depicts the associated residual error.

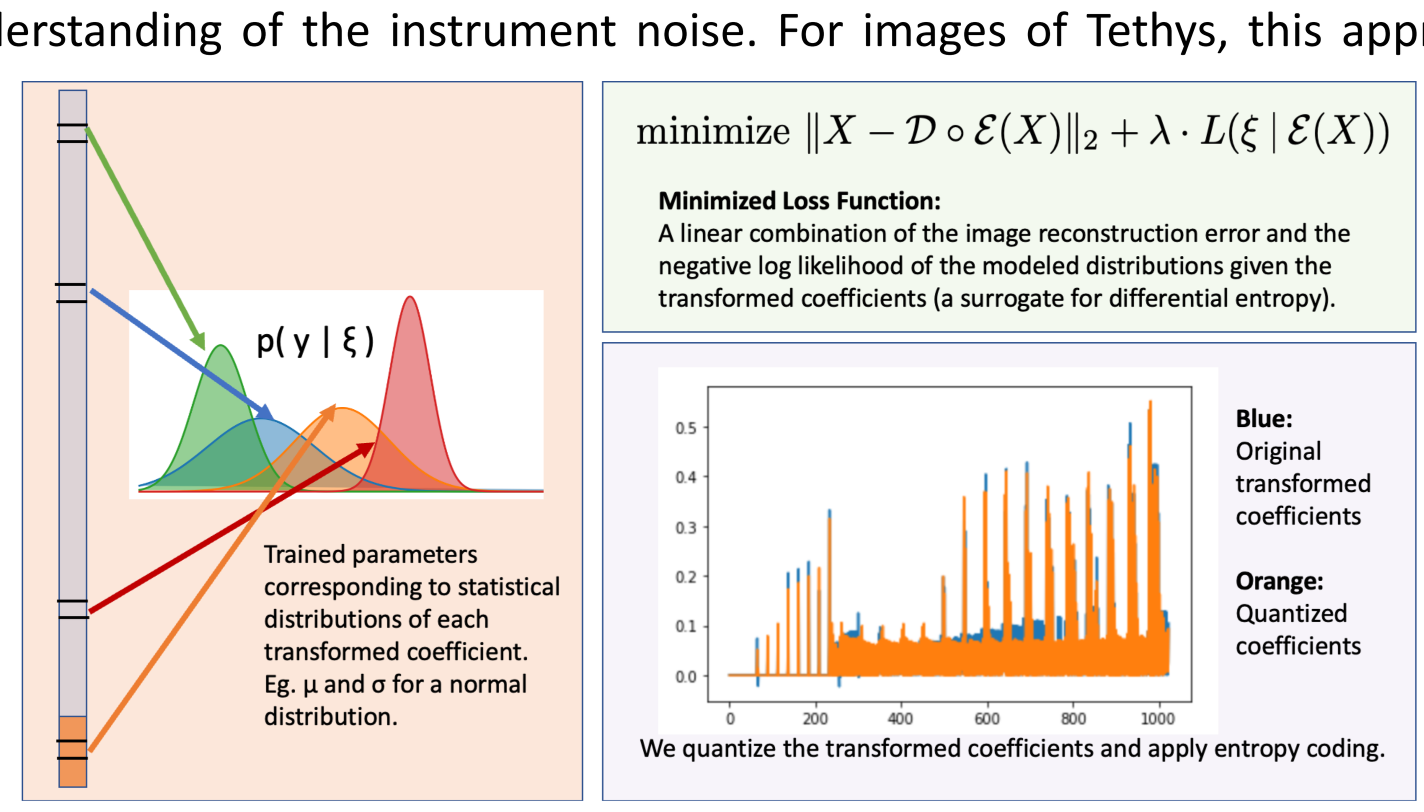

Figure 2.

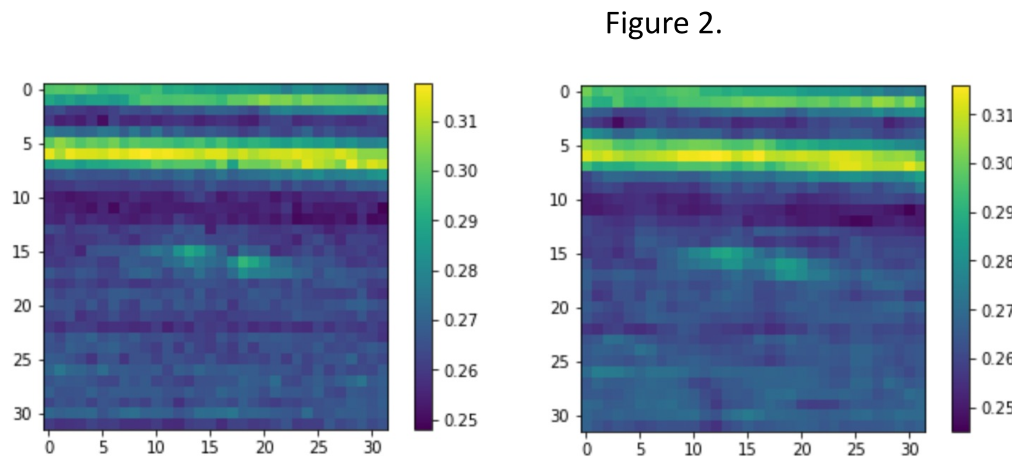

Figure 4. Example of a Saturn ring image patch containing a propeller (left), and the results of compressing to 1.53 bpp using our neural network compressor (right). The two lobes of the propeller are successfully restored by the network.

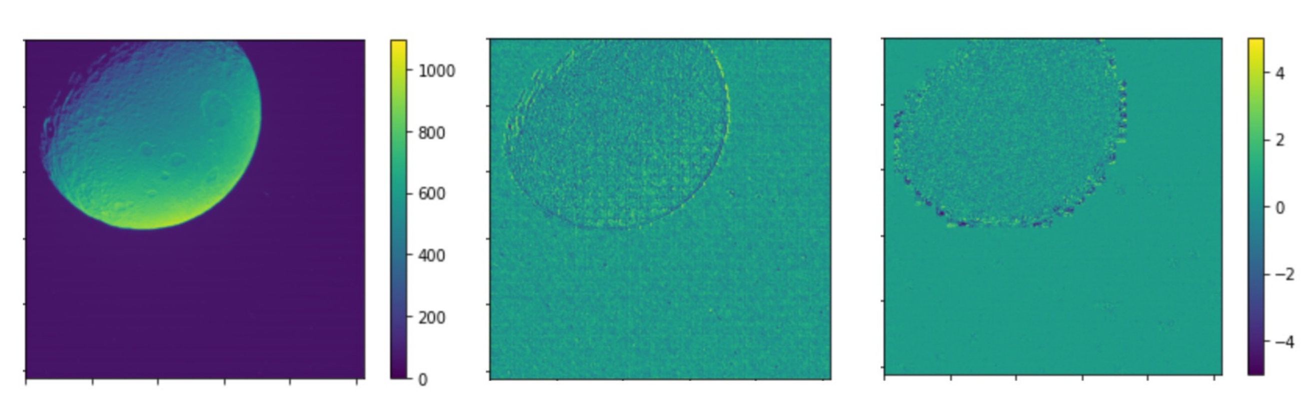

Figure 5. Left: A full image of Tethys, stored at 12 bpp. Center: The error residual after compressing the image with the neural network wavelet compressor (2.95 bpp). Right: The residual after compressing the image using the previous image from the flyby, along with the optical flow and error residual, altogether compressed to 2.69 bpp.

Significance of Results and Benefit to JPL

The methods we have developed throughout this study can enable future outer solar system missions to overcome severe constraints on mass (limiting antenna size) and power (limiting signal strength) to deliver significantly more data for scientific retrievals or to allow for more instruments by trading antenna mass for instrument mass. We envision a new paradigm for data compression, in which scientists will be provided with a toolkit of our algorithms to build and fine tune a custom compressor suited to their retrievals, with guidance from data scientists. Ultimately, JPL could supply a spacecraft facility compressor hosting a library of compression schemes optimized for all high data volume instruments on future missions.

Publications:

[A] Thill, M., West, R., Xie, H., Jewell, J., Dumont, P., Helfenstein, P., Tiscareno, M., "Machine-Learned Data Compression for Outer Solar System Missions," *OBPDC*, Athens, Greece, Sept. 28-30, 2022.

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[4] A. Ranjan and M. J. Black. "Optical flow estimation using a spatial pyramidal network." *CVPR*, 2017.

[5] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio. "Generative Adversarial Nets." *NIPS*, 2014.

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