Autoencoders for Denoising Atmospheric Profiles from ICESat-2

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Abstract: The 2[nd] generation Ice, Cloud, and land Elevation Satellite (ICESat-2) is an altimetry mission designed primarily for measuring ice sheet elevation and sea ice thickness, provides atmospheric profiles of clouds and aerosols at 532 nm using a photo counting detection approach. While highly sensitive for the detection of tenuous aerosol and cloud features, during the day signal-to-noise-ratio (SNR) photon counting detectors are adversely impacted by solar contributions to the total signal. Averaging the data to coarser horizontal resolutions has been the standard way to increase SNR and thus allow clouds and aerosols to be more easily detectable. Recent work has demonstrated success in boosting SNR without decreasing resolution using advanced filtering techniques [Yorks et al., 2021], however, rapid advancements in Deep Learning based image denoising algorithms can further improve the SNR. Here, we present results using a state-of-the-art Deep Learning autoencoder applied to noisy daytime ICESat-2 data to improve SNR and discuss implications for atmospheric feature detection, classification, and optical property retrievals.

1. Introduction

The 2[nd] generation Ice, Cloud, and land Elevation Satellite (ICESat-2) was launched in 2018 as an altimetry mission focused on measuring elevation of ice sheets, glaciers, and sea-ice using the Advanced Topographic Laser Altimeter System (ATLAS) [1]. ICESat-2 was designed using a single 532 nm wavelength, utilizing 6 beams for enhanced spatiotemporal coverage and dynamic range.

While not a primary focus of ICESat-2 and with the end of Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observations (CALIPSO) [2] in 2023, ICESat-2 is currently the only spaceborne lidar currently providing atmospheric profiles of clouds and aerosols despite providing only one wavelength and no depolarization ratio measurement.

Vertical profiles of clouds and aerosols are key measurements necessary to better understand the Earth's radiation budget, complex weather interactions, aerosol transport, and can help assess nose-level air quality that impacts human health. Traditionally, photon-counting elastic backscatter lidars such as ICESat-2, as well as the Cloud-Aerosol Transport System (CATS) [3] on the International Space Station from 2015-2017 are adversely impacted by the contributions from solar background (Bs in equation (1)), which is exacerbated further in ICESat-2 owing to its high pulse repetition rate (PRF) of 10 kHz.

$$N(r) = \frac{C_{bks}}{r^2} \times (P_P(\pi, r) B_P(r)) + P_M(\pi, r) B_M(r)) e^{-2\int_0^r \sigma(r\prime) dr\prime} + B_S + B_D \quad (1)$$

Contributions from the solar background to the total signal reduces the signal-to-noise ratio (SNR) and traditionally has required signal averaging to enable atmospheric feature detection and optical property retrievals.

Recent efforts have shown SNR improvements to permit higher-resolution feature detection at native raw data resolution during daytime viewing conditions [4] using observations from CATS. Machine learning techniques applied to lidar data are rapidly evolving and more recent advancements in Deep Learning based image denoising [5,6] have shown further promise toward eliminating solar background contributions to total signal, and thereby increasing SNR.

2. Method

Using profiles of backscatter and extinction provided by the airborne Cloud Physics Lidar (CPL) [7] to serve as truth, the GSFC lidar simulator [8] was used to simulate the same scenes as CATS would observe at day assuming a Poisson noise distribution. Using these simulated cases, along with actual CATS nighttime data, a state-of-the-art Deep learning image denoising algorithm was applied to the CATS curtains to train and develop a DDUNet neural network to remove solar signal at 1064 nm. These results are promising and have shown a factor of 2 increase in daytime SNR.

For this work, we propose to invoke the same methodology applied to ICESat-2. Two airborne CPL underpasses of ICESat-2 were obtained using the NASA ER-2 on October 29 and 30, 2019 off the coast of California. While under ICESat-2, CPL measured both cloud and elevated smoke aerosol fields during both flights.

For simulations of ICESat-2, CPL level 2 observations of particulate backscatter and extinction were used as inputs for the scene. Along with scene inputs, ICESat-2 instrument parameters from [9] are provided in Table 1 were used to simulate the daytime and nighttime ICESat-2 signal using the GSFC lidar simulator.

ATLAS instrument parameter	Nominal value
Laser repetition rate	10 kHz
Laser energy (strong; weak)	100; 25 μJ
Telescope effective area	0.43 m^2
Telescope FOV	83 μr
Detector quantum efficiency	0.15
Detector dead time	3 ns
Detector dark count rate	1–10 kHz
Bandpass filter width	30 pm
Receiver transmission	0.4
Nominal orbit height	495 km
Orbit inclination; repeat	92°; 91 days
Laser/telescope FOV spot size (on ground)	17 m/45 m

Table 1. From Palm et al., 2021. ICESat-2 Instrument Parameters input into GSFC lidar simulator.

Using the CPL observations from both flights, a training dataset was created that included noisy and noise-free pairs. Using these pairs, the DDUNet model was trained to identify Poisson noise and remove from the noisy image using the noise-free image as “truth”. This process yields a denoised version of the image with improved SNR.

3. Results

Figure 1 shows the observed CPL 532 nm total attenuated backscatter obtained from the NASA ER-2 on 30 October 2019. During the flight, a smoke plume originating from California was sampled as part of the ICESat-2 underpass.

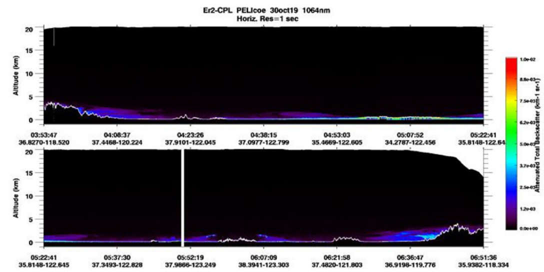

Figure 1. Total attenuated backscatter observed by CPL for a smoke events on 30 October 2019.

Figure 2 shows an example of the DDUNet denoising model applied to simulated noisy daytime ICESat-2 data for the 30 October 2019 flight. Comparing the simulated noisy input (top) to the DDUNet denoised signal (center), we find much better agreement and improved SNR compared to the scene “truth” (bottom).

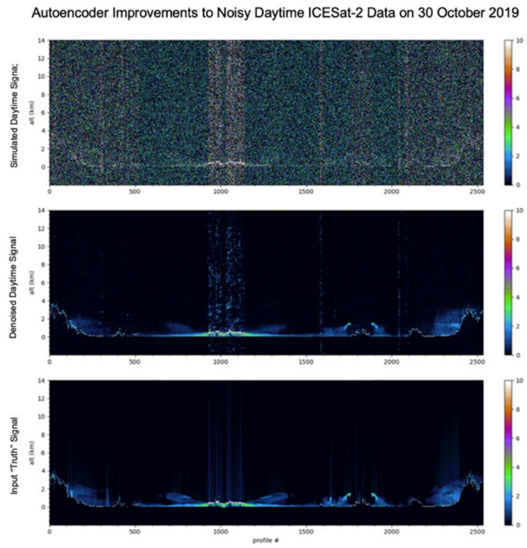

Figure 2. Simulated noisy daytime ICESat-2 signal (top), DDUNet denoised signal (center), and scene truth (bottom) on 30 October 2019.

4. Discussion

While we have only shown one example of applying DDUNet autoencoders to simulated ICESat-2 data, results are extremely promising, despite the higher PRF and consequently lower daytime SNR compared to CATS. Work to be done includes quantifying improvements to daytime SNR and assessing any distortions to the true signal.

This method looks to be a viable path forward for denoising ICESat-2 daytime data, this work will enable higher resolution atmospheric spaceborne lidar data products for the Earth science community going forward, as there currently are not any spaceborne lidar missions planned to launch this decade.

5. References

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