Autoencoders for Denoising Atmospheric Profiles from ICESat-2

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Abstract: The 2nd 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 ICESat-2 data to improve daytime SNR and discuss implications for atmospheric feature detection, classification, and optical property retrievals.

1. Introduction

The 2nd 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. Airborne CPL underpasses of ICESat-2 were obtained using the NASA ER-2 in October 2019 off the coast of California and include measurements of both cloud and elevated smoke aerosol fields. These underpasses will be used to simulate the ICESat-2 signal using the GSFC lidar simulator, and, along with ICESat-2 nighttime data, a truth dataset will be obtained to assess improvements in daytime SNR for ICESat-2.

3. Results

Preliminary results will be included as part the extended abstract for ILRC once available. Current efforts are focused on confirming ICESat-2 instrument parameters to enable proper simulation of the ICESat-2 daytime signal. CPL underpasses have already been indentifed and the DDUNet architecture developed for CATS will be adjusted for differences in data resolution.

4. Discussion

In this section, results will be discussed in further detail, including an evaluation of the suitability of using DDUNet Deep Learning techniques applied to ICESat-2 daytime data. Owing to the higher PRF of ICESat-2, we anticipate that the daytime SNR improvements will be drastic, however, we will also present an evaluation of any signal distortion or loss owing to using this method. Additionally, we will provide an assessment of DDUNet training and processing metrics, as a key goal of this work will be to provide denoised ICESat-2 data as quickly as possible for near-real-time products for the research and application communities.

If this method proves to be a viable path forward, 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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