New Study on the Application of Convolutional Neural Network to Vertical CALIPSO Profile Measurements

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ABSTRACT

The Cloud-Aerosol Lidar with Orthogonal Polarization (CALIOP), on-board the Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observations (CALIPSO) is a satellite-borne polarization sensitive lidar. It has been providing the vertical distributions of clouds and aerosols along with their microphysical and optical properties since 2006. One of its important Level 2 products, feature classification, has been determined using the lidar information from 532 nm parallel and perpendicular channels, and 1064 nm channel measurements of layer integrated backscatter. Deep machine learning methods which combine both the channel and texture information to recognize feature patterns is uniquely beneficial when applied to this data. In this study, we will use Convolutional Neural Network (CNN), a deep machine learning method, to classify lidar aerosol subtypes by using the lidar profile observations. This method uses additional information from the vertical texture of the feature instead of using only the layer information. Note that in the integrated layer properties, the texture information has been masked due to averaging. Our results will show how the texture information plays a role in the classification. This preliminary work explores the benefits and potential of deep machine learning methods for lidar retrievals and focuses on the aerosol subtype classification. The broader application extends to the classification of other feature types. Future applications include the developing deep machine learning methods with neural networks to retrieve properties of the features, and studies of indirect effect of cloud-aerosol interaction from lidar measurements.

Machine Learning Models: Segmentation CNN

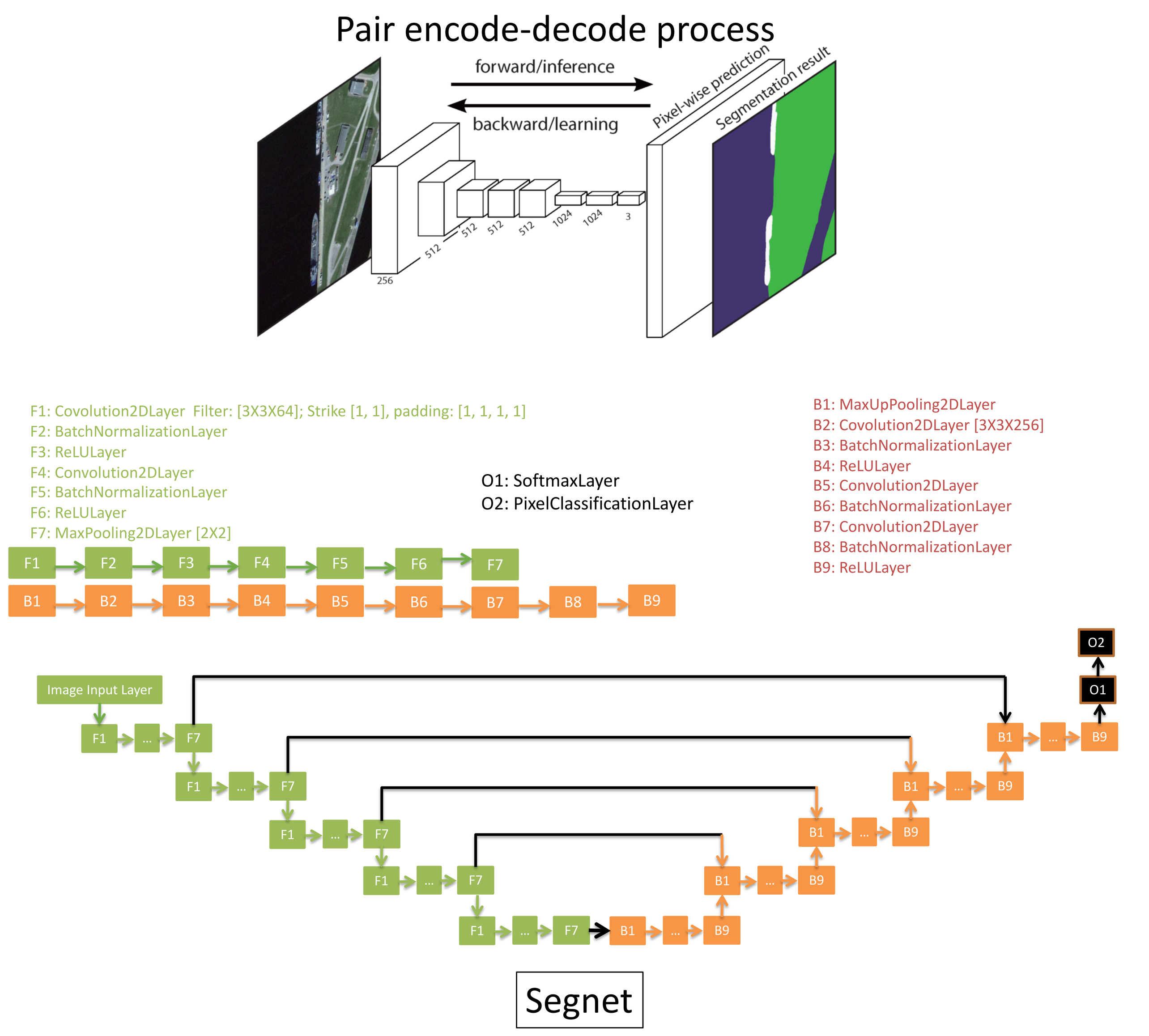

Figure 1: Flowchart of CNN for Segmentation Classification of Aerosol types

Input: Observations for the Classification

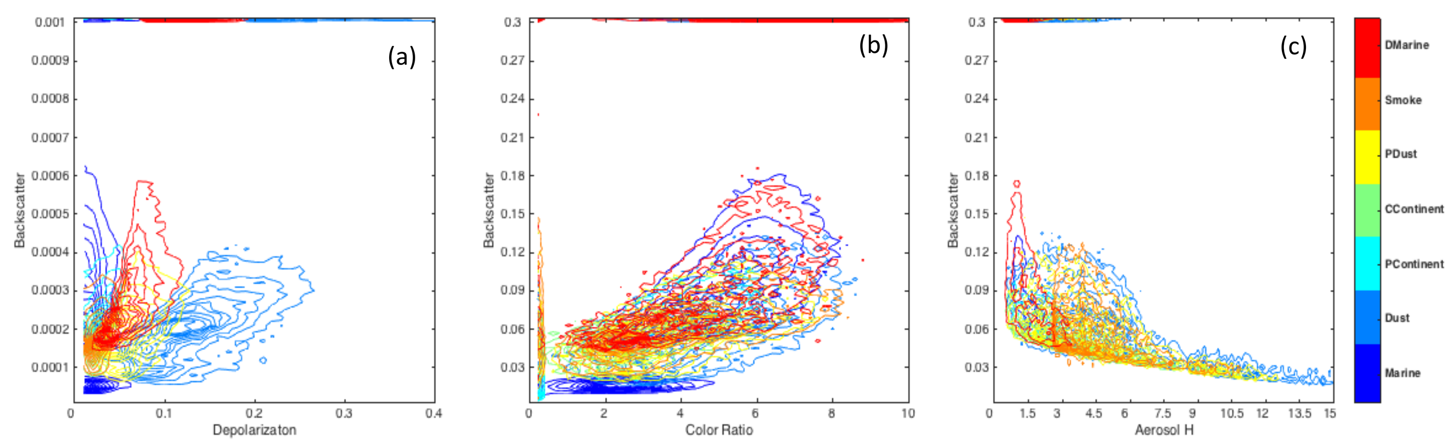

Figure 2: Relationship of backscatter-depolarization (a), backscatter-color ratio (b) and backscatter – altitude (c) for different aerosol types

Case Study: Preparation

Weighting the lost function according to sample (PDF of each class)

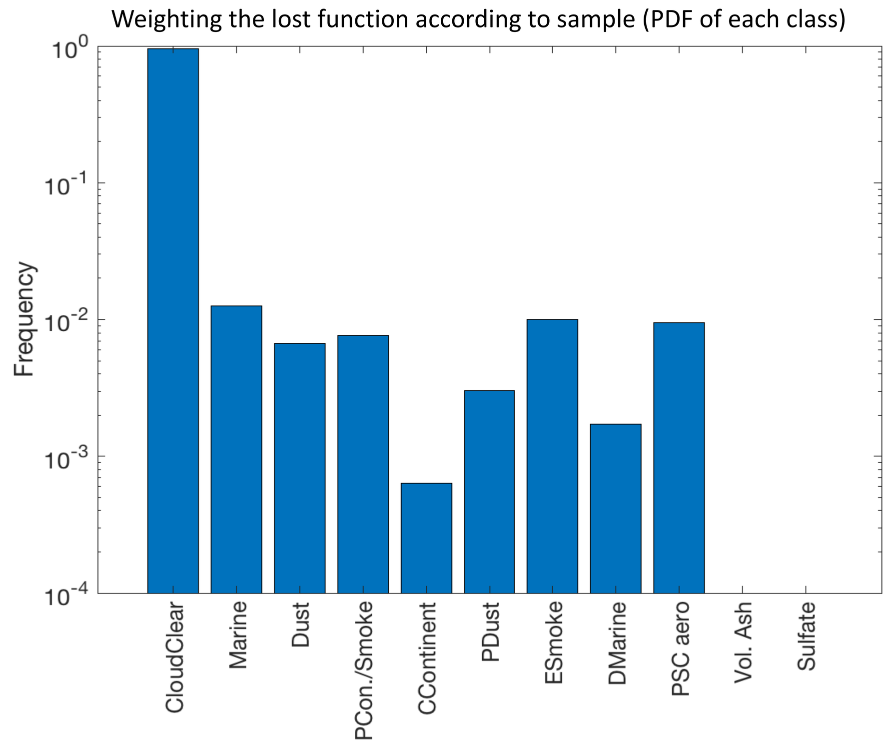

Figure 3: Histogram of different aerosol subtypes

Class	Weight
Cloud/Clear	79.5980
Marine	150.1924
Dust	131.4168
Pcon/Smoke	1.5779E03
Pdust	331.1944
ESmoke	99.3542
DMarine	581.3953
PSC Aerosol	105.7711

Table 1: Weighting coefficients for different aerosol subtypes

Data Training

- Size of input: all cut to [4000, 400, 3]
- Options:
- Training model: Vgg16 (can change to a better model)
- InitialLearnRate = 5e-1
- Momentum optimizer with momentum = 0.9
- MaxEpoches = 600
- MiniBatchSize = 16

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Loss: maxsoft function (Y–Ŷ) be the minimun

def softmax(X):
exps = exp(X)

return exps / sum(exps)
```

One orbit Training Speed and accuracy   Total Time Training: 22h

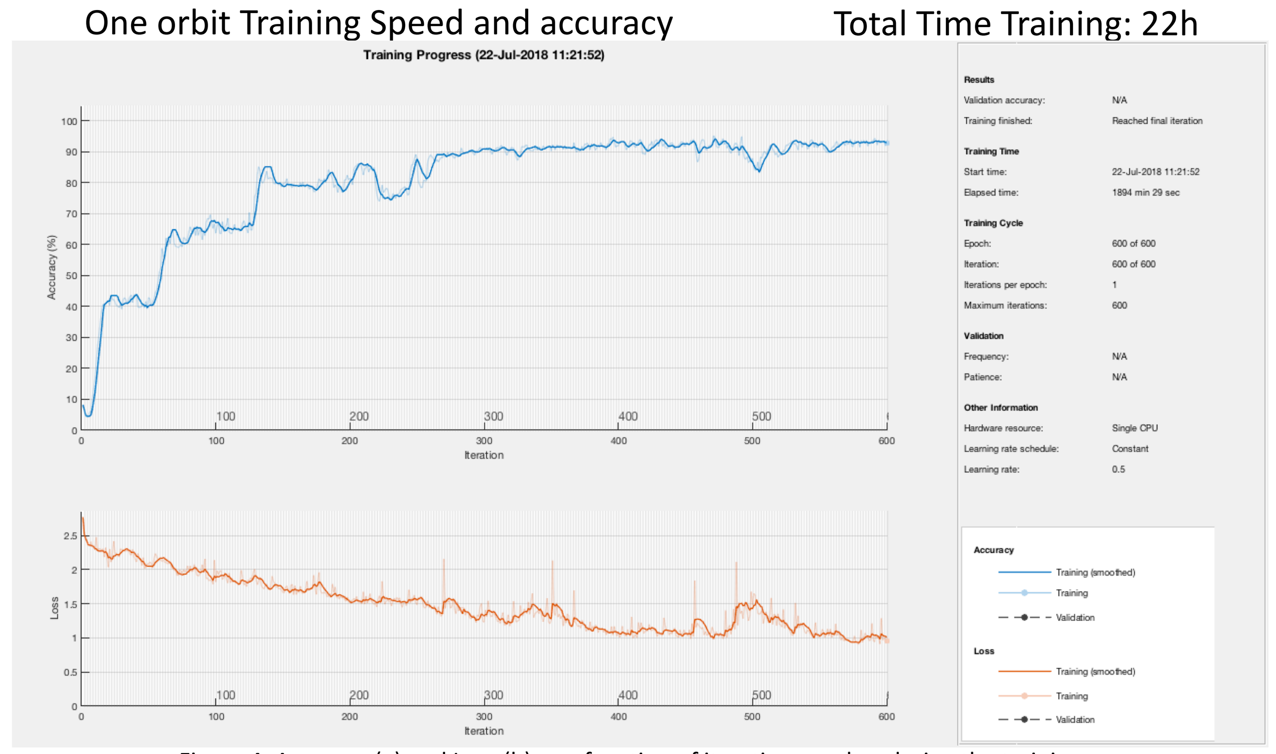

Figure 4: Accuracy (a) and Loss (b) as a function of iteration number during the training

Classification Results

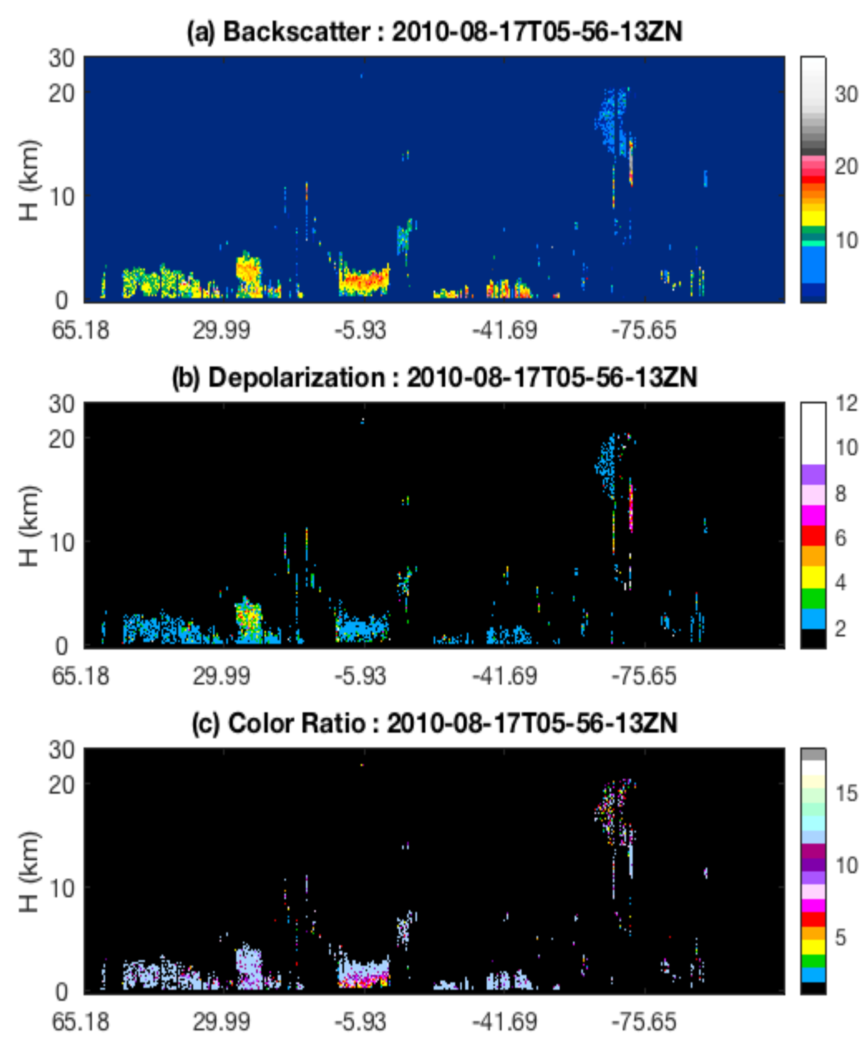

Figure 5: Backscatter (a), Depolarization (b) and Color ratio (c) for granule 2010-08-17T05-56-13ZN

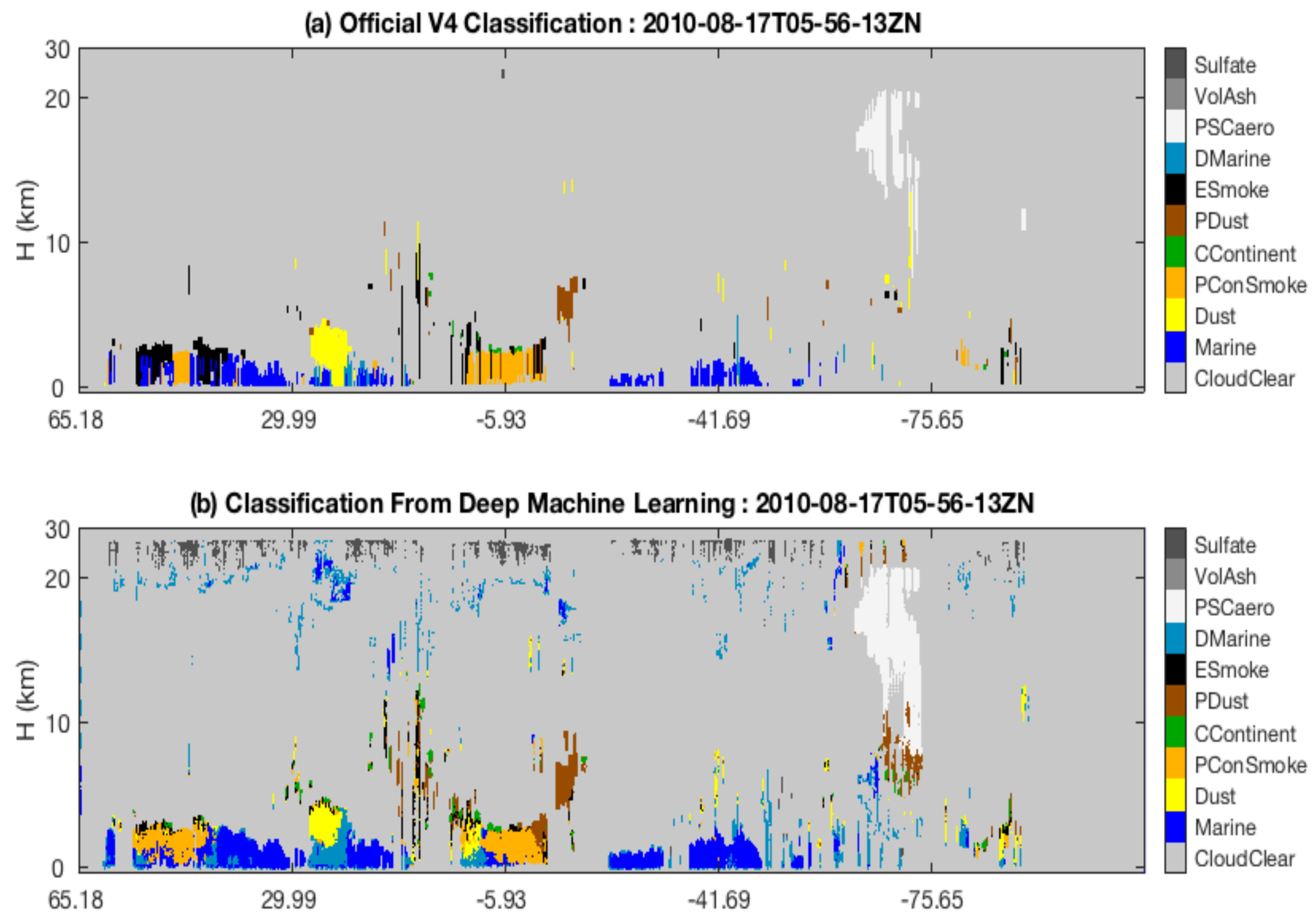

Figure 6: Operational V4 aerosol subtypes (a) and Classification results from CNN (b)

CNN / V4	Clear/Cloud	Marine	Dust	Pcont./Smoke	Ccont.	PDust	ESmoke	DMarine	PSC Aero	Vol. Ash	Sulfate
Clear/Cloud	93%	1.7%	0.3%	0.3%	0.2%	0.6%	0.3%	1.7%	1.1%	0%	1.1%
Marine	0.7%	81%	0.2%	7.4%	0%	0.1%	0.1%	10%	0%	0%	0.1%
Dust	2%	2%	41%	1.1%	1.1%	7.4%	6.2%	33.8%	5.4%	0	0.2%
Pcont./Smoke	0.3%	13.8%	6.8%	61.2%	0.1%	1%	3.7%	12.9%	0%	0%	0%
Ccont.	0%	0%	3.1%	8.4%	60.6%	11.1%	16.4%	0.5%	0%	0%	0%
PDust	1.2%	~0%	6.6%	3.5%	2.6%	72.6%	10.2%	3.3%	~0%	0%	0%
ESmoke	0.5%	14.5%	11%	25.6%	3.8%	12.3%	21.5%	10.7%	0.2%	0%	~0%
DMarine	1.5%	44%	0.8%	0.1%	0%	0%	~0%	53.6%	0%	0%	0%
PSC Aero	0.1%	~0%	2.1%	0%	0%	0.8%	0%	0.5%	96.5%	0%	0%
Vol. Ash	-	-	-	-	-	-	-	-	-	-	-
Sulfate	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%

Table 2: Confusion Matrix for different aerosol subtypes from operational V4 algorithm and CNN

Conclusion:

Using Deep Machine Learning CNN method, lidar for the first time can use the vertical profile texture information for feature classification. This brings in additional/independent information observed from lidar that are used to be hided due to averaging. More training data in the future are still needed and more discussions about using this method for the retrievals of atmosphere radiative/optical properties are in the close future. Machine Learning definitely expend the benefit of space lidar for observation of the atmosphere/Earth and monitoring the global radiative forcing.