Deep Learning Transformers for Retrieval of Cloud Optical Properties

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Motivation

Retrieving cloud microphysics or optical properties from cloud reflectance is an inverse problem. Traditional physics-based method such as Nakajima and King[3] uses 1D inversion to retrieve cloud properties based on the cloud's three-dimensional (3D) radiative transfer effects. But this method suffers from **significant gap between retrieved cloud properties and real cloud properties** since

- ❖ No one-to-one relationship between radiance and cloud properties exist[2].
- ❖ 3D radiance depends on the spatial context of nearby cloud elements[1].

Recent works have shown promising results using the deep neural network approaches[2,4]. However, they do not make use of the spatial characteristics and obtain sub-optimal results.

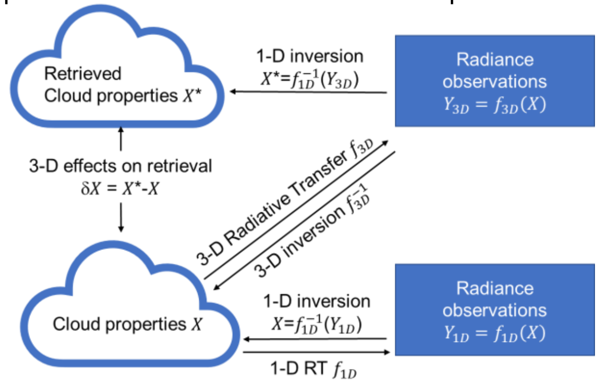


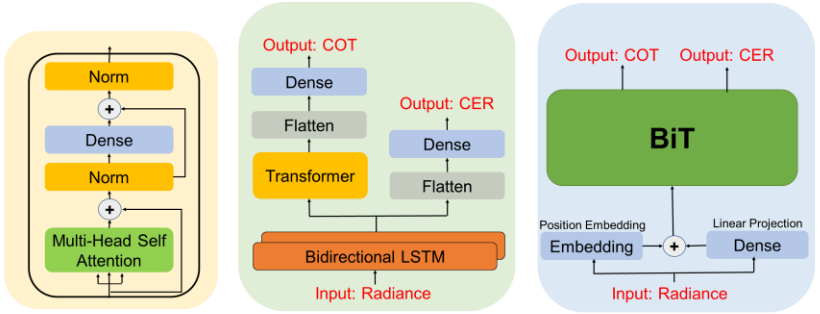
Figure 1: Conceptual framework to show spatial context between radiance and cloud properties under 3D radiative transfer effect.

Our Proposed Models

We propose recurrent neural network-based transformer models as they can capture spatial and temporal information using attention mechanisms:

- **Bi-LSTM with Transformer and Embedding (BiTE)**
- **Bi-LSTM with Transformer (BiT)**

Our Proposed Model Architectures



Transformer block structure with Attention

Bi-LSTM with Transformer (BiT)

Bi-LSTM with Transformer and Embedding (BiTE)

Experiments

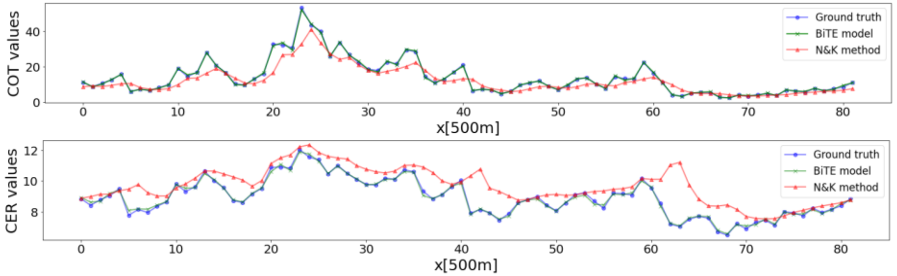
Datasets: 4 datasets each containing 4000 fractal clouds were generated with varying/fixed Cloud Top Height (CTH), Cloud Effective Radius (CER) and Cloud Optical Thickness (COT) at one or two 0.865µm and 2.13µm wavelengths at different Solar Zenith Angles(12) and Viewing Zenith Angles(6).
Retrieval experiments: Single view (SZA 60, VZA 0): datasets 1 and 2; Multi-view: datasets 3 and 4
Settings: 5-fold cross validation, Adam optimizer
Evaluation metrics of retrieval errors: mean square error (MSE), root mean square error (RMSE), mean absolute percentage error (MAPE)

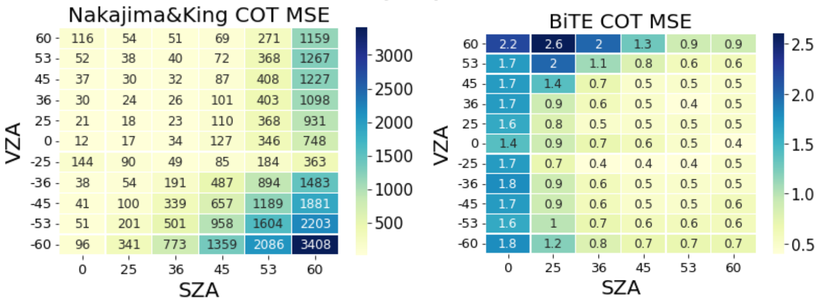
Experimental Results: Quantitative

	Models	Dataset 1 COT MSE	Dataset 2 COT MSE	Dataset 3 COT MSE	Dataset 3 CER MSE	Dataset 4 COT MSE	Dataset 4 CER MSE
Physics–based baseline model	1-D retrieval	75.3	635.66	-	-	-	-
	Nakajima and King[3]	-	-	74.7	7.11	164	31.6
Deep learning-based baseline models	Okamura DNN-2r[4]	8.29	6.63	8.66	0.57	11.74	0.68
	CNN[2]	1.27	5.45	10.09	0.09	11.84	0.10
	LSTM	0.58	0.92	0.35	0.03	3.15	0.06
	Bi-LSTM	0.40	0.76	0.35	0.01	2.24	0.05
	BiLSTM with Embedding	0.40	0.73	0.34	0.02	2.23*	0.05*
Our proposed models	Bi-LSTM with Transformer (BiT)	0.33	0.55	0.30	0.01	1.50*	0.03*
	Bi-LSTM with Transformer and Embedding (BiTE)	0.28	0.42	0.23	0.01	1.12	0.03

Experimental Results: Visualization

Multi-view COT and CER retrieval of a sample fractal cloud with fixed CTH, varying CER, and varying COT by **BiTE model vs Nakajiama and King vs Ground truth.**





Comparison of multi-view COT retrieval results at each angle of fractal clouds with varying CTH, varying CER, and varying COT for (Left) Nakajima and King (Right) BiTE.

Summary

- ➢ First work to demonstrate transformer-based neural networks for using 3D radiative transfer for cloud property retrieval
- ➢ Our proposed models, BiT and BiTE, outperform state-of-the-art physics-based and deep learning-based methods

References

[1]Angelof, K., et. al. (2020) Machine Learning for Retrieving Cloud Optical Thickness from Observed Reflectance: 3D Effects. Cybertraining Project, UMBC Faculty Collection.
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