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Discussions

Interactive comment on "Retrieval of optical thickness and droplet effective radius of inhomogeneous clouds using deep learning" *by* Rintaro Okamura et al.

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Comments on "Retrieval of optical thickness and droplet effective radius of inhomogeneous clouds using deep learning" by Okamura et al.

This paper documents a retrieval algorithm based on the deep learning neural network (DNN) for retrieving the cloud optical thickness and cloud effective radius from spectral cloud reflectance observations. The DNN algorithm is trained by synthetic cloud fields from LES and simulated cloud reflectances using 3D radiative transfer models. It is shown that a great advantage of the DNN algorithm is its apparent immunity to the so-called 3-D radiative transfer effects. The "traditional" Look-up-table method suffers from

significant biases due to the illuminating and shallowing effects, while the retrievals from the DNN algorithm are less affected by these biases and agree better with the "ground truth" from LES.

Overall, I found this paper interesting and exciting, and certainly suitable for AMT. On the other hand, I do have a few questions/suggestions that are listed below and hope they can help the author further improve the paper. For full disclosure, I know almost nothing about neural network or machine learning. So, my comments will be mostly from the perspective of cloud remote sensing which is my research field.

1) Robustness of the results: I'm very excited to see that the DNN-based algorithm is able to overcome the influence of 3-D effects (illuminating and shadowing) and yield retrievals in close agreement on LES. My biggest concern is that if this result is robust enough. I hope I am not mistaken, but it seems the DNN in this study is trained using only two LES cases in Figure 1 and moreover only applied to these two cases. If so, frankly, I not completely convinced if the algorithm will generate same successful retrievals if it is applied to other LES scenes or real satellite images. To convince me and the readers, the authors should consider a "blind test", in which they apply the algorithm to the LES cases other than the two training cases. For example, the authors can tweak the meteorological conditions in the LES (e.g., inversion strength, large-scale forcing etc.) to generate different cloud types/scenes, and then apply the DNN algorithm to assess and report its performance. r Overall, the authors need to demonstrate the robustness of their algorithm and results.

2) Complexity of the training: Note that 3-D radiative effects depend on many factors, not only just COT, CER and solar geometry, but also cloud top inhomogeneity, cloud geometrical thickness and surface reflectance among others [Várnai and Davies, 1999; Várnai and Marshak, 2001; 2002] as well as instrument characteristics. I'm wondering which ones of these factors have to be part of the training and which ones do not need to be. Take surface reflectance for example. Can we train the algorithm using only one surface reflectance and then it will work for all other types of surface? In addition to 3-D

effects, the retrievals are also affected by many other factors, the presence of drizzle, atmospheric absorption, surface reflectance etc. It is not clear from the paper to what extent these factors are considered in the DNN algorithm training, and which ones are not. Overall, I'm trying to figure out how "smart" the algorithm is. If we have to worry about all the above-mentioned details in the training, then the practical usefulness of the algorithm becomes questionable.

3) Cloud mask: It is not clear from the paper how cloud masking is treated in the retrieval/training. If retrievals are done at the resolution coarser than the LES grid, then some pixels are inevitably partly cloudy. How are the partly cloudy pixels treated in the retrievals and training?

4) Definitions of CER: When cloud microphysics varies both vertically and horizontally, then the definition of CER can be very tricky. For example, Eq. (1) applies well to a single LES cell, no problem. (the root and meaning of the parameter need to be explained in detail though). The equation (2) for column-mean CER becomes tricky. First of all, does the vertical average takes into account any vertical weighting for example due to photon penetration depth [Platnick, 2000; Miller et al., 2016]? Some explanations are needed either way. Second, what the column-mean ? How to compute it? Third, what is the significance of the column-mean CER in Eq. (2)? Does it help understand the cloud radiative effects? Does it help the modelers validate their cloud microphysics simulations? Can it be used in combination of COT retrieval to estimate LWP?

After defining the column-mean CER for a single column, the authors also need to explain how to aggregate/define the CER over multiple LES columns horizontally. For example, if the retrievals are done at 10x10 pixels, and each pixel has a slightly different column-mean CER, then what is the CER for the 10x10 pixel ensemble?

There are a few recent studies that discussed this topic. Maybe they are helpful [Miller et al., 2016] and [Alexandrov et al., 2012]

5) Plane-parallel albedo bias: This study focuses on the impacts caused by IPA, but

there is another type of bias, plane-parallel-albedo bias (PPHB). It is not clear to me if the DNN described in this study could also take care of the PPHB. Note that recently, Zhang et al. [Zhang et al., 2016] described a novel method to correct the PPHB, which might be helpful for this study.

6) Lack of technique details: I agree with the other reviewer that many important technique details are lacking from the current paper. Currently, the paper is rather short, so there is plenty of space to add in more detailed description and discussion, especially for Section 3 Method. Just to give an example, what are the meaning of Eq. (8) and (9)? Why do they provide the "relationships between inputs and outputs variables" of DDN, what kind of relationship?

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