Atmospheric Measurement Techniques Discussions

Atmos. Meas. Tech. Discuss., author comment AC2
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Reply on EC1

Andrew Geiss and Joseph C. Hardin

Author comment on "Inpainting radar missing data regions with deep learning" by Andrew Geiss and Joseph C. Hardin, Atmos. Meas. Tech. Discuss., https://doi.org/10.5194/amt-2021-100-AC2, 2021

Thank you to both reviewers and to the editor for your thoughtful comments. We sincerely appreciate you taking the time to review our work and provide constructive comments! We have used your feedback to improve the paper and have responded to each comment in order below:

"It's not clear to me how the potential overfitting issue was faced during training."

The examples shown in Figures 3, 5, and 7 and the error metrics in Figures 4, 6, and 8 were computed on test sets that were held out during training, which indicates the models did not overfit. Because the radar data are temporally correlated, we selected the test sets to be contiguous chunks of observations from the end of the field campaign so information leakage between the training and test sets is unlikely. We noticed early on during this study that overfitting did not occur in general for the inpainting CNNs. This is likely due to a combination of the nature of the inpainting task, the size of the radar datasets used, and the size of the CNN. To overfit, the CNN would have to memorize the radar data in 2D. This corresponds to about $7x10^8$ pixels for KaZR or $6x10^8$ for C-SAPR2, but the CNN has only around $5x10^6$ trainable parameters (depending on which CNN).

"Are the different inpainting techniques fully comparable? E.g., why the interpolation method is not applied in two dimensions? The precipitation field has intrinsic 2-d spatial correlation that cannot be easily reproduced by 1-d linear interpolation."

They are all comparable in the sense that they all fill-in the missing data region and the same error metrics can be applied. We intentionally selected a diverse set of inpainting methods to compare the CNN to. You are correct that the 1-D scheme completely ignores the 2-D structure in the radar data though the Laplace, Telea, Marching Average, and Efros schemes all incorporate 2-D information. An interesting result is that the very simple 1-D interpolation and 1-D 'repeat' schemes performed comparably to the much more complex schemes in terms of pixel-level error. They are much worse qualitatively however. Finally, 2-D interpolation was not used because none of the inpainting scenarios had data on all four boundaries of the missing data region. In the case of beam blockage, the farthest ranges are always missing and so cannot constrain the 2D interpolation properly.

"Relatively simple correction techniques for beam-blockage due to orographic obstacles are available (e.g., Bech et al., 2003). It would be interesting to make a comparison with the proposed method."

We agree. The existing techniques for correcting partial beam blockage typically rely on multiple sweeps or volume coverage patterns however, and here we focused on single sweeps (for C-SAPR) with complete blockage. The success on single sweeps in this study certainly suggests there is potential for handling partial beam blockage with a 3-D CNN using sweeps at multiple levels or a full volume scan which would be more comparable to the partial beam blockage correction methods in the literature. Additionally, this technique tends to be more general as it works on multiple modalities of data and does not necessarily rely on any expert derived techniques. As such, we expect it would likely work for things like lidars and profilers. We leave these as potential areas of future research however.