Atmospheric Measurement Techniques Discussions

Atmos. Meas. Tech. Discuss., author comment AC1
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Reply on RC1

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-AC1, 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:

130: Flips and rotations of images are used. Is there any way to quantify whether these add skill? Are there any downsides to flipping a meteorological image, thereby including physically impossible weather patterns in the training set?

This is a good point, and we think data augmentation deserves a more thorough treatment in the manuscript. We moved the discussion of data augmentation to the end of Section 3.4 (“Training” Lines 271-282) and expanded it. Many of the data augmentation schemes used in the deep learning literature were designed for use with images and, if applied to radar data, would result in weather features that are physically impossible, so we were careful here to only use augmentations that produce physically plausible samples. For KaZR data, flips were performed with respect to time (not in the vertical). For most cloud features that are embedded in the large-scale flow this results in a physically plausible sample and approximates large scale flow in the opposite direction. For weather features whose shape is heavily determined by the large-scale flow (e.g. fall streaks) this results in an unlikely but still very realistic looking sample. For C-SAPR2, we flipped only with respect to azimuth (not range) and performed rotations with respect to azimuth. Likewise, these augmentations still result in physically plausible radar data because they simulate an altered scan strategy or coordinate convention without changing the physical structure of the weather in the scan.

335: The performance on blank space is dismissed as trivial. What about the performance on a sparsely speckled background? In real time radar applications, masks can be leaky due to atmospheric and instrumental variations. The CGAN's creativity in hallucinating weather patterns could pose risks if the presence of speckle or other faint, spurious data could trigger inpainting of weather patterns that do not exist.

The expected use case for this involves scenarios where a blockage/outage/low-quality data is known to exist, and the inputs to the CNN require a pre-defined mask and setting the input fields to constant values in the region where inpainting is required, so we do not expect the algorithm to be used to inpaint speckle alone. This would be similar to fitting noise, so the pixel-level skill for any scheme would likely be low. There are cases in our test set where a missing data region contained a weather feature and speckle in different locations. In these cases, the conventional CNN is typically very conservative and does not interpolate speckle from the boundaries into the inpainting region. The CGAN will hallucinate similar speckle in the inpainting region to that near the boundary. We have attached a sample case from the KaZR dataset below, where there is some speckle that was not removed by the reflectivity threshold near the ground with a weather feature above.

410, 420, 455: The CGAN success should be discussed a little more. It has the poorest performance, underperforming all the non-NN techniques on certain metrics. Also, it's skill has risks as mentioned above. I know this is addressed a bit already, but I think the outstanding qualitative skill of the CGAN (while poor quantitative skill) requires a bit more discussion of the risks, how they might be addressed for applications, and some speculation on how to leverage the relative skills of the two novel techniques.

Additional discussion was added to section 5 (Lines 583-59).

Please also note the supplement to this comment:
https://amt.copernicus.org/preprints/amt-2021-100/amt-2021-100-AC1-supplement.pdf