Radar Beam Blockage Correction for Improved QPE over Complex Terrain

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***Abstract*—In weather radar data, partial beam blockage is caused by the obstruction of the beam filling by mountains or buildings, which often leads to incomplete and/or distorted radar quantitative precipitation estimation (QPE). In this paper, a novel deep learning approach using Generative Adversarial Networks to correct radar beam blockage effects is presented and demonstrated using radar observations over complex terrain in Northern California. The model is trained and tested using historical radar data collected during a number of precipitation events. The testing results show that the precipitation patterns are better captured by the beam blockage corrected data, and the corrected radar reflectivity measurements agree better with ground-based disdrometer data. In addition, radar QPE products are derived using radar reflectivity before and after correction, and the QPE results are evaluated using rainfall rates derived from the disdrometer data. The improved QPE indicates the potential of the proposed beam blockage correction model for quantitative applications over complex terrain regions.**

I. Introduction

Weather radars are crucial for monitoring and forecasting precipitation and other hydro-meteorological events. However, the accuracy of radar data can be compromised by partial beam blockage, where physical obstructions impede the radar signal, resulting in incomplete data and inaccuracies in weather forecasting and quantitative precipitation estimation (QPE) [1]. Traditional methods for addressing beam blockage, such as statistical interpolation or multi-radar data fusion, often struggle with complexity, cost, and reliance on external data sources, which limits their effectiveness. To address these limitations, this paper introduces a data-driven approach using deep learning techniques—specifically, a Generative Adversarial Network (GAN) [2] to correct the impact of beam blockage on weather radar data. The GAN model is conditioned to learn from historical radar data affected by beam blockage and to generate corrected radar images by recovering the precipitation information that has been lost or distorted. This methodology is performed over complex terrain regions such as Northern California. The corrected radar data are validated against ground-based disdrometer measurements; this manner of validation ensures that these improvements are both statistically significant and meteorologically meaningful.

II. Methodology

A. Study Domain

The study area is in Northern California, known for its diverse topography that includes the Coast Ranges, Central Valley, and Sierra Nevada Mountains, making any weather radar system particularly challenging for complete radar coverage [3]. Located in Davis, CA, the KDAX radar is especially

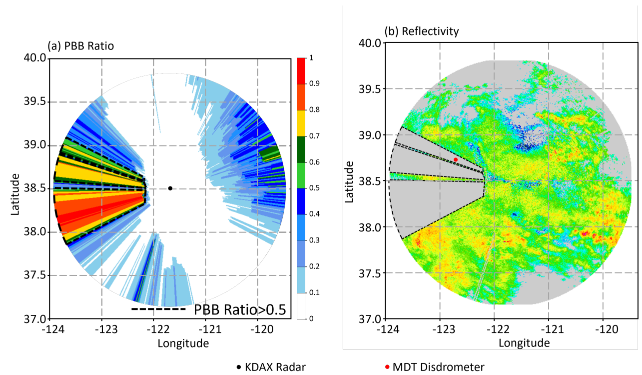

Fig. 1. (a) Partial beam blockage (PBB) ratio of KDAX radar observations; (b) Reflectivity observation after applying a PBB mask.

susceptible to partial beam blockage because of the close proximity of mountainous terrain [6]. As depicted in Fig. 1a, the areas where the radar signal experiences the most significant obstruction are predominantly located to the west of the radar. For this study, we utilized regions with a blockage ratio exceeding 0.5 as the final blockage mask. During the wet seasons, precipitation in this area is often shallow and stratiform. When combined with low radar beam elevation angles and complex topography, significant data gaps are observed.

The disdrometer data from Middletown (shown in Fig. 1b) are utilized as an in-situ reference to validate the corrected radar data using a deep learning model. The training dataset of the deep learning model comprises radar observations collected over three consecutive storm seasons, from 2019 to 2022, encompassing 26 precipitation events. This diverse dataset allows the model to discern intricate patterns of radar beam blockages.

B. Deep Learning Model

As shown in Fig. 2, the designed deep learning framework is centered around a Conditional Generative Adversarial Network (CGAN). In this model, the generator and discriminator are defined as components. The generator is constructed upon a 5-layer UNet++ architectural framework, a variant of UNet that incorporates skip connections and multi-scale feature extraction to retain intricate details while generating precise radar data. Its objective is to rectify distorted precipitation data through the utilization of preprocessed radar information. The discriminator, functioning as a classifier, discerns between the corrected data from UNet++ and label radar data through the deployment of convolutional layers. Training these GAN

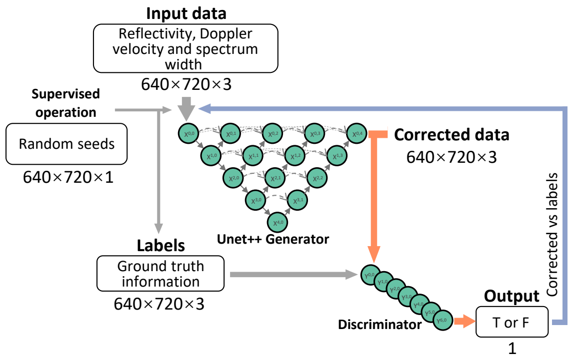

Fig. 2. CGAN-based deep learning model for radar beam blockage correction.

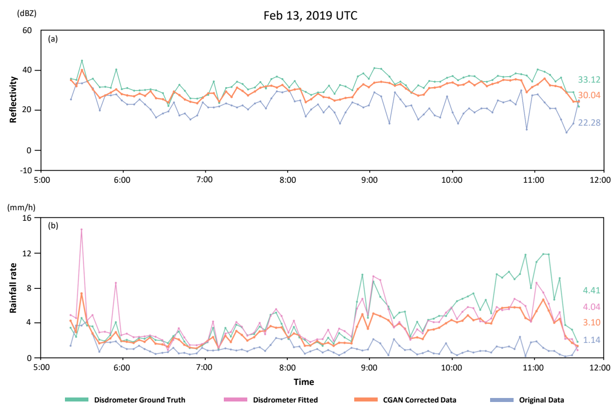

Fig. 3. Evaluation results of the beam blockage correction performance: (a) Radar reflectivity; (b) QPE during the precipitation event on Feb 13, 2019. The mean values are illustrated in the figure to highlight the performance.

models involves the generator and discriminator entering a form of adversarial scenario where they learn to beat each other. The generator improves to the point that it can play tricks on or introduce random noise to fool the discriminator. Concurrently, this process ensures that the discriminators also improve in their ability to distinguish between data that was corrected and data that was not. This adversarial loop compels the generator to produce more precise corrections by discriminator feedback [4] [5].

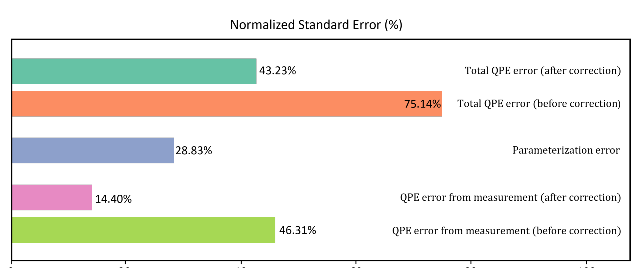

Fig. 4. Radar QPE errors before and after beam blockage correction.

III. Results and Conclusion

The CGAN-based beam blockage correction model was evaluated using a precipitation event on February 13, 2019. We aligned the precipitation data from 88 radar profiles and disdrometers while ensuring that radar data could be collected at the disdrometer. Fig. 3a illustrates the performance of correction on reflectivity, the green line represents the disdrometer data, which serves as the ground truth. The orange line represents the CGAN-corrected data, and the blue line represents the original, blocked radar data. Quantitative evaluation of the reflectivity data reveals that the CGAN-corrected data closely aligns with the disdrometer ground truth. Before the correction, the raw radar data significantly underestimated reflectivity profiles. In addition, we fitted a $Z - R$ relationship to the data for the entire event utilizing the disdrometer measurements and derived a comparison curve for rainfall rate estimates (Fig. 3b). We used precipitation data from three different cases for fitting the $Z - R$ relation. The green line represents the true rainfall rate recorded by the disdrometer, and the pink, orange, and blue lines represent the fitted truth data, the fitted CGAN-corrected data, and the fitted raw data, respectively. The mean of the CGAN-corrected data closely approximates the mean of the disdrometer data in reflectivity evaluation. While there is a slight difference in the evaluation of rainfall rate, both are greatly improved over the original data. In order to address the measurement errors presented in the evaluation, we derive the measurement error by removing the parameterization error from the total QPE error. The results are displayed in 4. Overall, the CGAN correction model reduced the measurement QPE error from 46.31% to 14.4%.

Acknowledgement

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