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A Deep Learning Approach to Dual-Polarization Radar Rainfall Estimation

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Abstract

Traditionally, radar rainfall algorithms are derived through nonlinear regression of rain rates and simulated radar observables from raindrop size distribution (DSD). The performance of such empirical relations is highly dependent on the physical model of DSD and the parametric relation between the physical model and radar parameters. Such algorithms also have large uncertainties that need to be adaptively adjusted based on local DSD properties. In this research, we propose an alternative approach to dual-polarization radar rainfall estimation. In particular, a non-parametric machine learning model is designed and trained using simulated radar data based on DSD measurements in different climatological regimes. The trained model is applied to real radar measurements to produce rain rate estimates. Preliminary results show the promising performance of this novel method compared to traditional parametric rainfall relations.

1. Introduction

In principle, rainfall on the ground is dependent on the four-dimensional distribution of precipitation aloft. The functional relation between rain rate on the ground and the four-dimensional radar observations aloft can be obtained from measurements (e.g., [1, 2, 9]). However, it is difficult to express this functional relation in a simple form due to the complex space time variability in precipitation microphysics. The performance of radar-derived quantitative precipitation estimation greatly relies on the physical model of the raindrop size distribution (DSD) and the relation between the physical model and radar parameters [3-5]. Conventional parametric relationships between radar observables and rain rate are not sufficient to capture such variabilities, and the empirical relations have large uncertainties that need to be adaptively adjusted based on local DSD properties [5, 6].

Prior research has shown that neural networks can be used to estimate surface rainfall from ground radar measurements [7]. This nonparametric approach can explore the complex functional relation from high dimension input space (i.e., radar data) to the target space (i.e., rain gauge measurements). However, the utilization of neural networks in rainfall estimation is subject to many factors such as the representativeness and sufficiency of the training dataset. In addition, most of the previous studies focused on single polarization radar (i.e., reflectivity). Similar application of dual-polarization radar is yet to be explored. In [8], Chen and Chandrasekar have designed a machine learning system for dual-polarization radar rainfall estimation, and showed the promising performance using pseudo radar observations simulated from DSD data. This study aims to extend the research in [8] and demonstrate the radar rainfall estimation performance using deep learning approach in real experiments.

2. Methodology

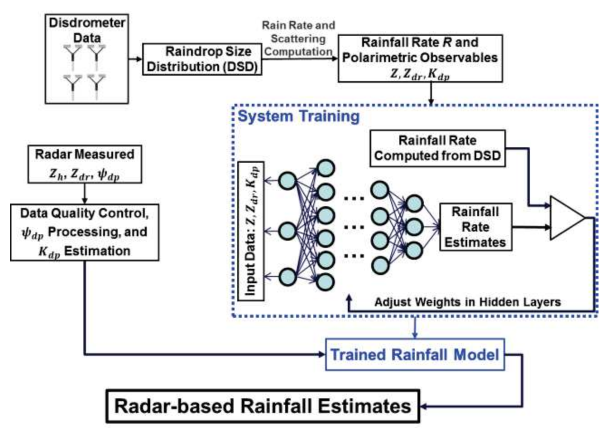

Figure 1. Deep-learning system diagram for dual-polarization-based radar rainfall applications.

Figure 1 illustrates the architecture of the deep learning-based rainfall estimation and application system. The key component is a machine learning model trained using polarimetric radar moments and corresponding rain rates computed from DSD data. The model equation can be expressed in the following form:

$$\mathbf{y_1} = f(\mathbf{w}_1\mathbf{x} + \mathbf{b}_1) \quad (1a)$$
$$\mathbf{y_2} = f(\mathbf{w}_2\mathbf{y_1} + \mathbf{b}_2) \quad (1b)$$
$$\mathbf{y_3} = f(\mathbf{w}_3\mathbf{y_2} + \mathbf{b}_3) \quad (1c)$$
$$\mathbf{z} = f(\mathbf{w}_4\mathbf{y_3} + \mathbf{b}_4) \quad (1d)$$

where $\mathbf{x} = [\mathrm{Z}, Z_{\mathrm{dr}}, K_{\mathrm{dp}}]$ is the input vector consisting of simulated polarimetric observables; $\mathbf{y_1}$, $\mathbf{y_2}$, and $\mathbf{y_3}$ are the outputs of example three hidden layers; $\mathbf{w}_1$, $\mathbf{w}_2$, $\mathbf{w}_3$, and $\mathbf{w}_4$ are the weight vectors at the input layer and hidden layers, respectively; $\mathbf{b}_1$, $\mathbf{b}_2$, $\mathbf{b}_3$, and $\mathbf{b}_4$ are the bias terms associated with the input layer and hidden layers, respectively; and $\mathbf{z}$ is the output of estimated rain rate, which will be compared with rain rates computed directly from the DSD data. Note that the model equations in (1) are only for illustration purposes. In real applications, the number of hidden layers and nodes associated with each layer is determined using grid search method.

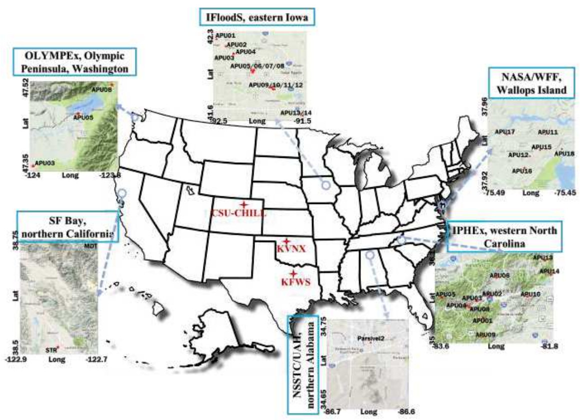

Figure 2. Locations of disdrometers (red dots) used in model training and three radars (red crosses) used for model applications.

In this paper, simulated radar moments are used for training the deep learning model. The simulated data are derived from a large scale of real DSD measurements from disdrometers deployed in different climatological regimes. Figure 2 illustrates the locations of disdrometers used for model training and three radars that will be used for generic applications in real experiments. We select these disdrometers in different regimes mainly to represent different DSD properties as much as possible.

3. Case Studies and Preliminary Results

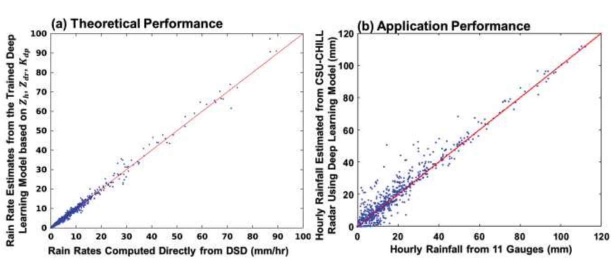

Figure 3. (a) Scattergram of rainfall rates estimated using the optimal deep learning model versus rainfall rates computed from DSD data; (b) Deep learning-model based hourly rainfall estimates from CSU-CHILL radar at 11 gauge locations versus hourly rainfall measurements from rain gauges on 11 June 2015.

In order to demonstrate the performance of the designed rainfall model, we use both DSD data for theoretical evaluation and radar data for real applications. Figure 3 illustrates scatter plots of rainfall estimates from both theoretical and experimental perspective. In particular, Figure 3(a) shows the rain rate estimates from the trained model versus rain rates computed directly from the independent testing DSD data. Compared to traditional parametric rainfall relations, the deep learning model can greatly reduce the parameterization errors associated with the empirical non-linear regress. Figure 3(b) shows the hourly rainfall estimates from CSU-CHILL radar at 11 gauge locations versus hourly rainfall measurements from rain gauges on 11 June 2015, demonstrating promising performance of the proposed algorithm.

4. Acknowledgements

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