2nd URSI AT-RASC, Gran Canaria, 28 May – 1 June 2018

A Machine Learning-based Approach to Pseudo-Radar Rainfall Estimation Using Disdrometer Data

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Abstract

This paper introduces a non-parametric machine learning algorithm for dual-polarization radar rainfall estimation. The machine learning model is trained and tested using pseudo radar observations simulated using *in situ* raindrop size distribution data. Preliminary results show the superior performance of the proposed approach to traditional parametric radar rainfall relations.

1. Introduction

Radar has been used for rainfall estimation since its earliest application in meteorology. Traditionally, rainfall estimation with radar has been accomplished by relating the backscattered power to rainfall rate through the so-called *Z-R* relations [1-3]. Since the introduction of polarization diversity in meteorological radar, a large amount of research effort has been devoted to polarimetric radar system and its weather applications [1, 4-6]. Through the dual-polarization measurements, including reflectivity Z_h, differential reflectivity Z_{dr}, and specific differential propagation phase K_{dp}, various empirical rainfall relations can be derived at different frequencies [6-9], including $R(Z_h)$, $R(Z_h, Z_{dr})$, $R(K_{dp})$ and $R(Z_{dr}, K_{dp})$. However, these relations greatly depend on raindrop size distribution (DSD), which varies across different rainfall regimes, even within a single storm. For illustration purposes, Figure 1 shows the scatter plot of rainfall rate R versus reflectivity Z_h computed using DSD data collected during the National Aeronautics and Space Administration (NASA) Integrated Precipitation and Hydrology Experiment (IPHEx) field campaign. The black curve indicates the best-fitting power-law relation of $R(Z_h)$. The grey bars stand for the mean and standard deviation of the binned data. Obviously, it is a challenging task to remove the parametrization error in the non-linear regression. To this end, this paper develops a novel non-parametric radar rainfall system based on machine learning approaches. The architecture of the deep learning system is designed to extract the relation between rainfall rate and polarimetric radar measurements. For demonstration purposes, this paper uses pseudo radar observations simulated from DSD data in the training and testing analysis. The trained model can be applied to real radar measurements.

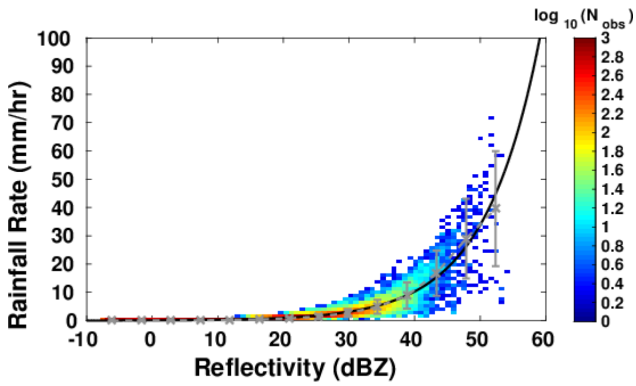

Figure 1. Scattergram of rainfall rate R versus reectivity Z_h. Both are computed based on DSD data collected during the NASA IPHEx field experiment. The black curve indicates the best-fitting power-law relation. The grey bars stand for the mean and standard deviation of the binned data.

2. Methodology and Preliminary Results

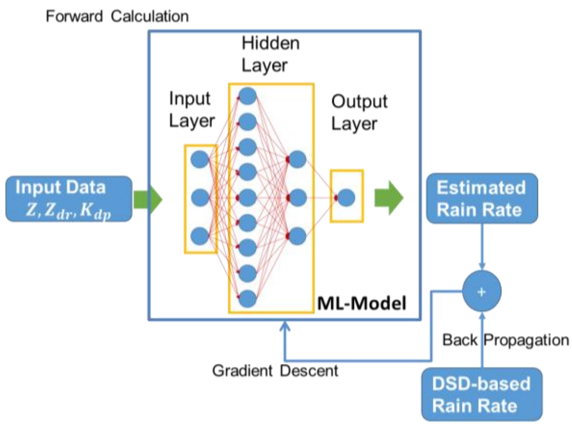

Figure 2. Architecture of the machine learning-based radar rainfall system.

Figure 2 illustrates the architecture of the proposed machine learning-based radar rainfall system. The input data include all the polarimetric radar observables. Ground-based rainfall measurements from disdrometers are used as targets to train the machine learning model. In particular, the model can be trained for any individual polarimetric observable or combinations of different variables.

In this study, pseudo-radar measurements simulated using DSD data are used to train and test the machine learning model. It is worth noting that the test dataset is independent from the training dataset. Figure 3 illustrates scattergrams of rainfall rates estimated using the proposed machine learning model versus rainfall rates directly computed from the independent DSD data. The good agreement demonstrates the excellent performance of the deep learning system for radar rainfall estimation.

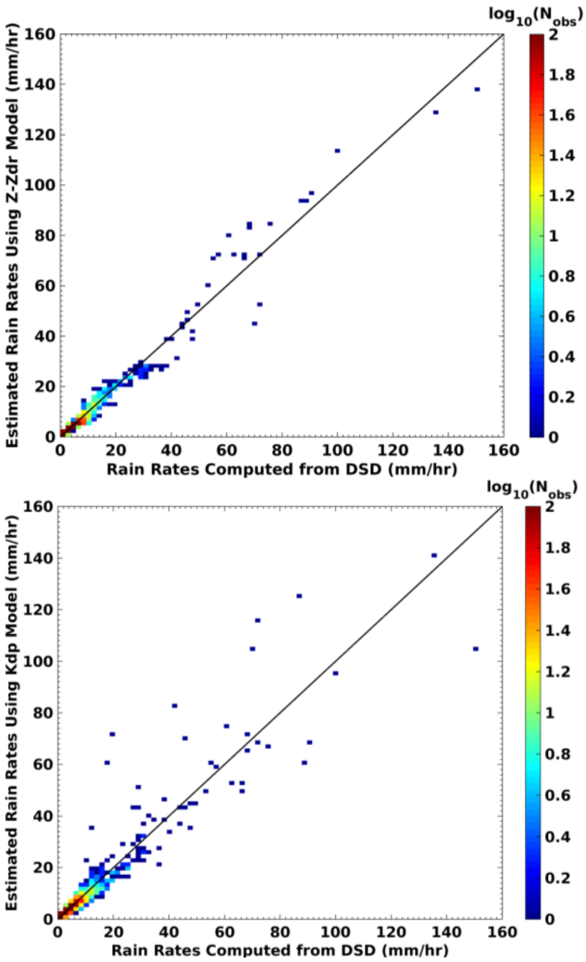

Figure 3. Scattergram of rainfall rates estimated using the proposed machine learning model versus rainfall rates directly computed from DSD data: (upper) model trained for Z_h and Z_{dr}; (lower) model trained for K_{dp}.

3. Summary

In this study, a novel deep learning system has been developed for polarimetric radar rainfall estimation. Compared to traditional parametric rainfall relations, the deep learning model can greatly reduce the parameterization errors involved in the empirical non-linear regress. Analyses based on pseudo radar observations have demonstrated the promising performance of the proposed system. Future work will focus on implementation of the machine learning algorithm using real radar data.

4. Acknowledgements

This research was primarily supported by the Physical Sciences Division (PSD) at NOAA's Earth System Research Laboratory (ESRL) and the National Science Foundation Hazards Science, Engineering and Education for Sustainability (SEES) program. The APU DSD data were kindly provided by NASA.

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