A Machine Learning System for Rainfall Estimation from Spaceborne and Ground Radars

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Abstract

Rainfall measured by Tropical Rainfall Measuring Mission (TRMM) Precipitation Radar (PR) is important for studying precipitation distribution in the tropical regions. The ground validation of TRMM PR is difficult because the ground sensing systems have different characteristics from TRMM PR in terms of resolution, scale, view aspect and sensing environments. In this paper, we introduce a machine learning system to train ground radars for rainfall estimation using rain gauge data and subsequently using the trained ground radar rainfall estimation to train TRMM PR. This system can build a connection between ground gauge measurements and ground radar observations, and transfer this connection to TRMM PR observations for rainfall estimation. The rain gauge, ground radar and satellite data collected from Melbourne, Florida are used for demonstration purposes. The rainfall estimation product derived from this new system is compared against the TRMM standard products, which shows improvement brought by the new machine learning system.

1. Introduction

Rainfall estimation based on radar measurements has been pursued for a few decades. In principle, rainfall on ground can be represented by four-dimensional radar observations. However, the relation between rain rate and radar observation is difficult to express in a simple form. The simple empirical relations are not sufficient to capture the space-time variability of precipitation microphysics in term of raindrop size distribution (DSD). On the other hand, Machine Learning, a nonparametric method which can be used to estimate ground rainfall directly from radar observations has been demonstrated in a number prior research for rainfall rate estimation [1,2].

TRMM RP is capable to provide a high-resolution vertical profile of precipitation. However, fundamental challenges exist in comparison analysis between the TRMM PR and ground gauges. First, the TRMM PR has 4.5km horizontal resolution which is much coarser than rain gauge spatial resolution. Second, available data pairs for comparison are scarce in single weather event because of the limited coincident overpasses. Unlike the rain gauge, the ground radar have a reflectively similar resolution as TRMM PR and can measure rainfall over large spatial extent to obtain more coincident samples comparing with ground rain gauge.

This paper approaches a new machine learning system consisted two Multilayer Perceptron (MLP) models to build a relation between TRMM PR rainfall estimation and rain gauge. This will be done with ground radar to bridge the gap between the TRMM PR and rain gauge. The first MLP is trained from gauges measurement to ground radar rainfall estimation. The second MLP is trained from the ground radar rainfall estimation to TRMM PR rainfall estimation. Via two MLP models, the entire system can generate a rainfall product by linking TRMM PR observations to ground rain gauge measurements via ground radar observations. Figure 1 shows the conceptual diagram of entire system. Figure 2 shows the ground validation neural network MLP1 design. Figure 3 shows the TRMM-PR neural network MLP2 design.

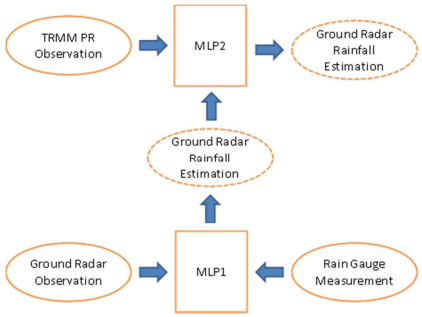

Figure 1. Conceptual diagram of the MLP-based machine learning model for TRMM PR rainfall estimation.

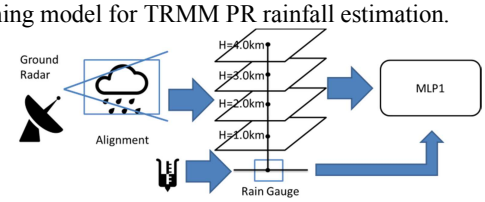

Figure 2. Conceptual diagram of ground validation neural network MLP1.

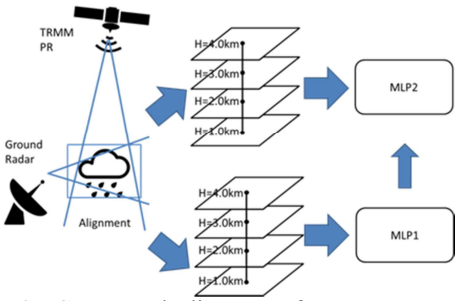

Figure 3. Conceptual diagram of TRMM PR neural network MLP2 including Ground Radar and TRMM PR data alignment.

2. Preliminary Result

In this section, the ground gauge measurements, ground radar observations, and TRMM PR observations collected during the storm events in 2007 at Melbourne FL region were selected for implementation of the two MLP models. Radar data are first mapped to Constant Altitude Plan Position Indicator (CAPPI) at multiple vertical levels with a spatial resolution of 1km by 1km. The MPL1 is designed to estimate rainfall rates with the CAPPI data from 1km to 4km vertical levels (see also Figure 2). Rainfall measurements from three rain gauge networks are used for training and validating purposes, including Kennedy Space Center (KSC), South Florida Water Management District (SFL), and St. Johns Water Management District (STJ), which include 33, 46, and 99 rain gauge stations, respectively. The total numbers of the training pairs for MLP1 are 67312 and validate pairs are 7480. TRMM data were collect from coincident overpasses in the same area. It will align with the ground radar data to have the common grid (see Figure 3). We only choose the overpass that contains some precipitation event to train the MLP2 model. The total numbers of the training pairs for MLP2 are 5416 and validate pairs are 602. Finally, we have 106 valid data pairs between ground gauge and TRMM PR. Those data pairs were used to evaluate the performance of the entire system.

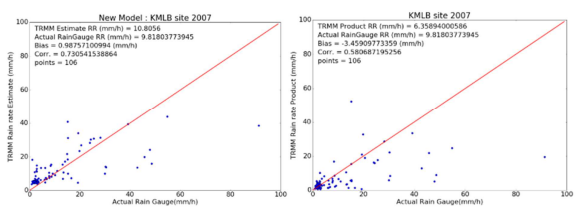

Figure 4. (left) TRMM PR rainfall estimates based on the machine learning system vs. rainfall measurements from validation gauges. (right) TRMM rainfall product vs. rainfall measurements from validation gauges.

Figure 4 shows the scatter plots of rainfall estimates based on TRMM PR observations versus the rainfall measurements from the validation gauge stations. Comparing the preliminary results in Figures 4, it is concluded that the proposed machine learning system has great potential for TRMM rainfall estimation. In order to further evaluate the rainfall performance, the biases are computed for both TRMM PR products and the products derived from the proposed machine learning system.

$$Bias = < R_G - R_R > \quad (1)$$

where R_R and R_G denote rainfall observations from spaceborne radar and validation gauge, respectively; the angle brackets stand for sample average.

The biases of TRMM rainfall estimates based on the new model and TRMM products are 0.99 mm/hr and -3.46 mm/hr, Obviously, the new model has much better performance.

The machine learning system also can used to generate rainfall maps after training. Figure 5 shows the example that one precipitation event observed by both ground radar and TRMM PR. The top row of figure shows maps of reflectivity from KMLB and TRMM PR. The second row of figure shows maps of rainfall estimation from KMLB and TRMM PR. The third row shows the maps of rainfall product from TRMM.

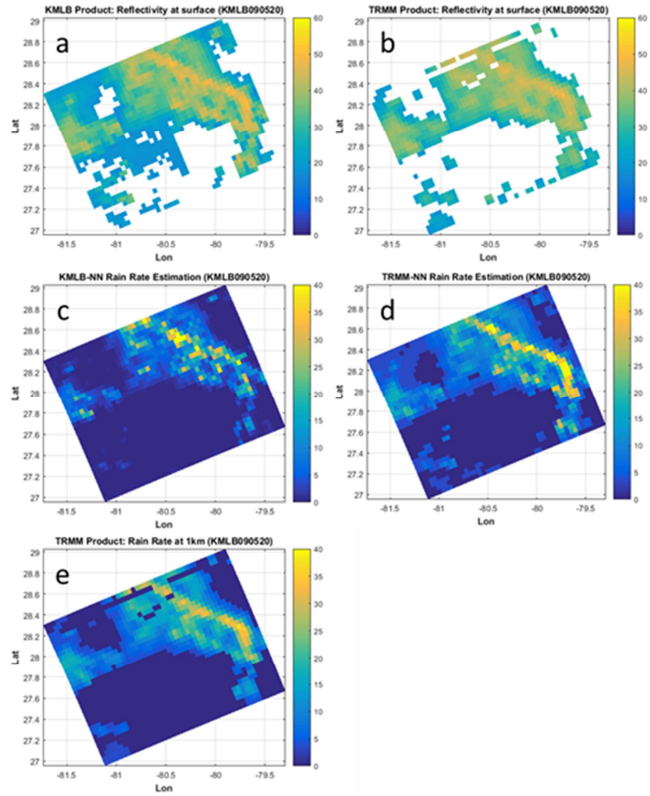

Figure 5. (a) KMLB reflectivity: unit dbz (b) TRMM PR reflectivity: unit dbz (c) KMLB rain rate estimation by MLP1 model: unit mm (d) TRMM rain rate estimation by MLP2 model: unit mm (e) TRMM PR rain rate product: unit mm (Case: KMLB: 05/20/ 2009)

3. Acknowledgements

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4. References

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