# Neural Network Rainfall Estimation based on GPM Dual-frequency Precipitation Radar Measurements

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***Abstract*—We implement a novel hybrid machine learning-based hybrid system consisting of two deep neural networks (DNNs) for GPM applications. This architecture estimates rainfall by building a relation between GPM radar observation and rain gauge measurement by using ground radar to bridge the gap between the spaceborne radar and ground rain gauge. The first DNN model is trained from gauge measurements to ground radar rainfall estimations. The second DNN is trained from ground radar rainfall estimation to spaceborne radar rainfall estimation. Using the two DNN models, the entire system can generate a rainfall product by linking spaceborne radar observations to ground rain gauge measurements via ground radar observations.**

## I. Introduction

The Global Precipitation Measurement (GPM) Core Observatory is the successor of TRMM and is expected to provide the next generation of global precipitation products through advanced observations from the GPM Microwave Imager and Dual-frequency Precipitation Radar (DPR). Compared to its predecessor, a key advancement of GPM is an extended capability to observe light rain, solid precipitation and the microphysical properties of precipitation particles. Through overlapping simultaneous measurements on Ka and Ku bands, the DPR is able to quantify precipitation particle distribution and quantitatively measure light rain and falling snow, which account for a significant part of precipitation, particularly in the middle and high latitudes.

As spaceborne radars, GPM DPR needs to validate with ground radar to ensure its performance. However, the different characteristics between space and ground based measuring platforms including viewing angles, frequencies, spatial resolution, and temporal mismatching prevents to make directly comparison between the two observations. Bolen and Chandrasekar have proposed an alignment methodology to match the resolution volumes between space and ground radars to minimize the effects of potential geometric distortion brought by spacecraft [1]. This method has been demonstrated through cross comparison between TRMM Precipitation Radar (PR) and ground radar observations [1, 2].

In this paper, a novel hybrid machine learning-based system consisting of two deep neural networks (DNNs) is developed in order to improve rainfall estimation by building a relation between spaceborne radar observation and rain gauge measurement using ground radar to bridge the gap between the spaceborne radar and the rain gauge. The first DNN model is trained from gauge measurements to ground radar rainfall estimations. The second DNN is trained from ground radar rainfall estimation to spaceborne radar rainfall estimation. Using the two DNN models, the entire system can generate a rainfall product by linking spaceborne radar observations to ground rain gauge measurements via ground radar observations.

## II. Methodology

In this paper, we present the architecture of the hybrid two-stage system using deep neural network to build a relation between rainfall gauge measurements and ground radar observations, then transfer this relationship to GPM DPR observations for rainfall estimation and local rainfall mapping. The hybrid system first trains ground radars for rainfall estimation using rain gauge data and subsequently uses the trained ground radar rainfall estimates to train the GPM DPR-based neural network for space-based rainfall estimation. The system architecture is shown in Fig. 1. This system provides an alternative method for estimating the rainfall from GPM observations based on a non-parametric machine learning method.

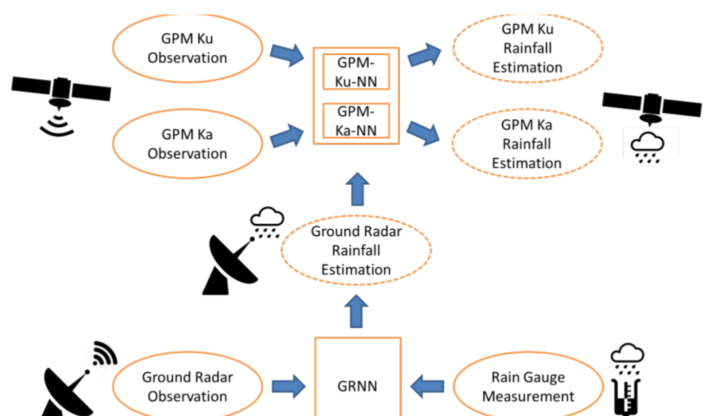


Fig. 1. System diagram of a two-stage hybrid system for GPM DPR rainfall estimation.

The ground radar neural networks (GRNN) were trained using NEXRAD level 2 momentum data around the Melbourne, Florida ground validation site (i.e., KMLB radar) from storm events in 2014. The overpasses at this ground validation site were used as the dataset for training the satellite radar neural networks. There were 40 overpasses for GPM in one year, while only a very small amount of them (around 10 cases) were good precipitation cases and are considered in this study. The entire dataset containing ground and satellite radar observation and gauge measurements were used to train this two-stage neural network. The first network was trained based on ground radar data and its corresponding gauge values. This network was used to generate the rainfall estimation in the entire overpass region as the target label for training the next stage of the neural network. The second network was trained based on satellite radar observation and rainfall estimation from the first network at the time of the overpass. Rainfall estimation of any new data was done based on the network built by previous overpass data. The Training and Estimation processes are similar for GPM Ku and Ka bands. The GPM Ku PR will be used as the example to illustrate the training and estimate processes.

For training purposes, the observation of ground radar and GPM Ku/Ka PR need to match the data pairs (See Fig.2), which are reflectivity profiles with the same space resolution and time stamp. The method developed in [1] is used to align ground and space radar reflectivity profiles despite the difference of viewing angle and spatial resolution from two observation platforms.

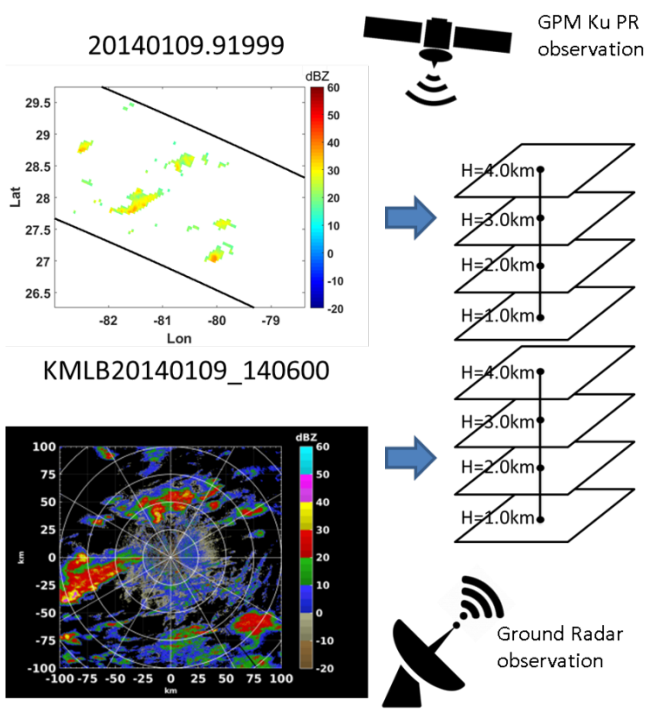


Fig. 2. Training data pair generation.

In the training process, the input features of the space borne radar neural network (SRNN) are GPM DPR reflectivity vertical profiles from 1km to 4km with 1km vertical resolution. These profiles were aligned to ground radar reflectivity vertical profiles using the aforementioned method. The target of the SRNN is the rainfall rate estimation generated by the ground-based radar neural network (GRNN) with the ground radar reflectivity vertical profile aligning with the GPM DPR data at KMLB. This target will be used to train the SRNN. The entire process of training the GPM DRP neural network is shown in Fig. 3.

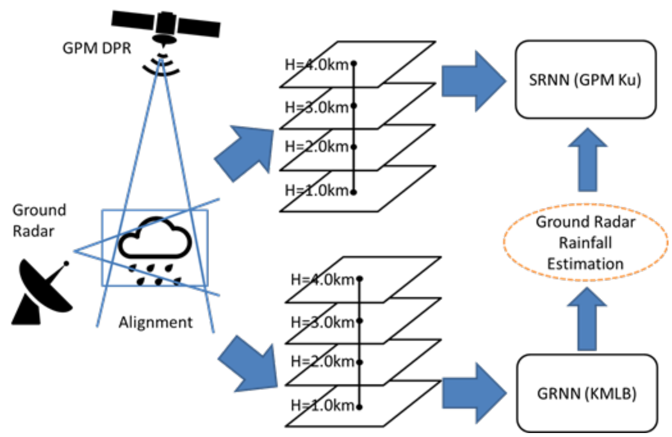


Fig. 3. The tranining process for Ku band Precipitation Radar.

In the estimation process, the input features are the GPM Ku PR profiles, which are not limited to the overpass at the KMLB region. The outputs of the second neural network are rainfall estimation of the GPM Ku PR at the earth's surface. See the details in Fig. 4.

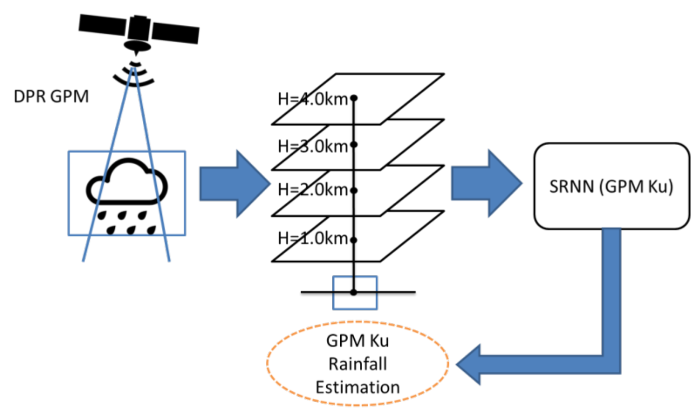


Fig. 4. Rainfall estimation process for Ku band precipitation radar.

## ACKNOWLEDGEMENT

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## REFERENCES

[1] S. Bolen and V. Chandrasekar, "Methodology for Aligning and Comparing Spaceborne Radar and Ground-Based Radar Observations", Journal of Atmospheric and Oceanic Technology, vol. 20, no. 5, pp. 647-659, 2003.

[2] Tan, Haiming, V. Chandrasekar, and Haonan Chen, "Alignment and Comparison between Simultaneous GPM Dual-frequency Precipitation Radar and Ground-based Radar Observations," Proc. Of the 37th AMS Conference in Radar Meteorology, Chicago, Illinois, 2017.