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Neural Network Scheme for Radar Rainfall Estimation

Devendra Bairagi
bairagidevendra020888@gmail.com

Pankaj Bhoite
pankajbhoitebpr@gmail.com

Abstract— **In the last years, the artificial neural networks (ANN) have proved an attractive approach to non-linear regression problems arising in environmental modeling, such as short-term forecasting of atmospheric pollutant concentrations, rainfall run-off modeling and precipitation now casting using radar, satellite or meteorological data. This neural network scheme enables the network to account for any variability in the relationship between radar measurements and precipitation estimation. This precipitation estimation scheme is a good compromise between the competing demands of accuracy and generalization.**

Keywords — **RADAR, Rainfall, Neural Network, Rain Gauge.**

I. Introduction

Radar is a useful remote sensing tool for precipitation estimation on the ground. The development of algorithms for the remote estimation of precipitation based on radar measurements has been an active research topic for many years. The problem of rainfall estimation on the ground based on radar measurements is complicated because of the space–time variability of the rainfall field. The rainfall rate R obtained on the ground can be potentially dependent on the four-dimensional structure of precipitation aloft (three spatial dimensions and time). In principle, one can obtain a functional approximation between the rainfall on the ground and the 4D radar reflectivity observations Z aloft. This function will be more complicated than a simple Z–R algorithm or a multi parameter radar rainfall algorithm. Therefore the ground rainfall estimation can be viewed as a complex function approximation problem.

Neural networks are well suited for this problem, and the theoretical basis is provided by the universal function approximation theorem (Funahashi 1989). Recent research has shown that neural network techniques can be used successfully for ground rainfall estimation from radars (Xiao and Chandrasekar 1995, 1997) and other such applications (Krasnopolsky et al. 1995). This technique includes two stages, namely, 1) the training and validation stage and 2) the application stage. In the training stage, the neural network learns the potential relationship between the rainfall rate and the radar measurements from a training dataset. When a radar measurement set is applied to the neural network, the network yields a rainfall-rate estimate as output. This output is compared with the rain gauge measurement, and their difference or the error is propagated back to adjust the parameters of the network. This learning process is continued until the network converges. Once the training process is complete, a relationship between the rainfall rate and the radar measurement is established and the network is ready for operation. When a radar measurement vector subsequently is applied to the network, it yields a rainfall-rate estimate.

Neural networks have many advantages in the context of rainfall estimation from radar measurements. The relationship between radar measurements and rainfall rate on the ground is derived directly from a training dataset, and therefore it is not influenced by systematic variations in the radar system characteristics. The neural network can be tuned very well for one specific kind of storm or for several storms. Once the neural network is trained, it represents a relation between radar measurements and rainfall rate. If the training dataset is large enough and representative enough, the neural network can perform very well [1].

II. Neural Network

The structure of the ANN system used in this paper consists of three node layers: an input layer, a hidden layer and an output layer. The nodes in the input layer transfer the input data (average reflectivity measurements) to all the nodes the hidden layer. The great power of neural networks stems from the fact that it is possible to "train" them. Training is affected by continually presenting the networks with the "known" inputs and outputs (targets) and modifying the connection weights between the individual nodes and the biases. The output of the network is a weighted sum of the outputs of the hidden layer. In our case, the ANN network was trained with the learning algorithm based on the back-propagation of errors.

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Learning by error back-propagation (like in all supervised methods) is carried out in cycles, called “epochs”. One epoch is a period in which all input-target pairs are presented once to the network. The weights are corrected after each input-target pair produces an output vector and the errors from all output components *are* squared and summed together. The back-propagation algorithm follows the gradient descent on the error surface. This process is controlled by two parameters: the learning rate and momentum. The learning rate scales the magnitude of each step, down the error surface, taken after each complete calculation in the network (epoch). The momentum acts like a low pass filter, smoothing out progress over some small bumps in the error surface by remembering the previous weight change. The neural networks are often affected by the effect called overtraining or over fitting. An over trained neural network memorizes the small training set instead of generalizing the data and consequently performs badly on new data *e.g.* on the validation set. In this work, the overtraining (or over fitting) was anticipated by the so-called early stopping. Early stopping was implemented by stopping the training when the error of cross-validation of the training data starts going up, as the neural network may lose its generalization ability at this moment.

III. Simulation

The data to train the neural network is collected from Hydromet division, India Meteorological Department for Indore district.

The Neural Network has built using Neural Network toolbox of MATLAB (R2009a).

From the data the neural network has trained and tested.

IV. Result

The Neural Network trained using the rain gauge data and the radar input data from year 2007 to 2010 as shown in below:

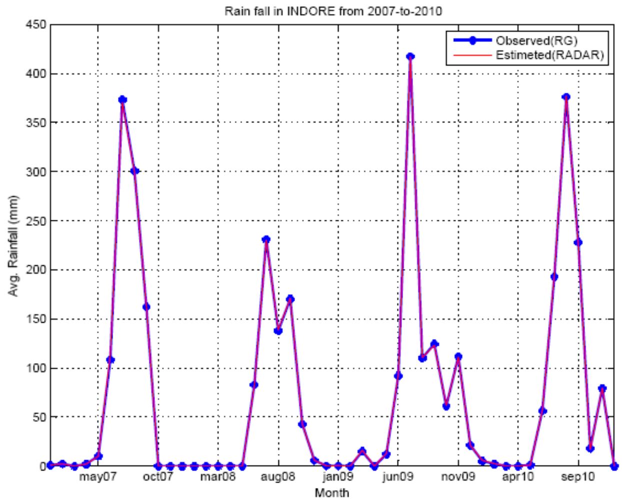

Figure1: Training Data

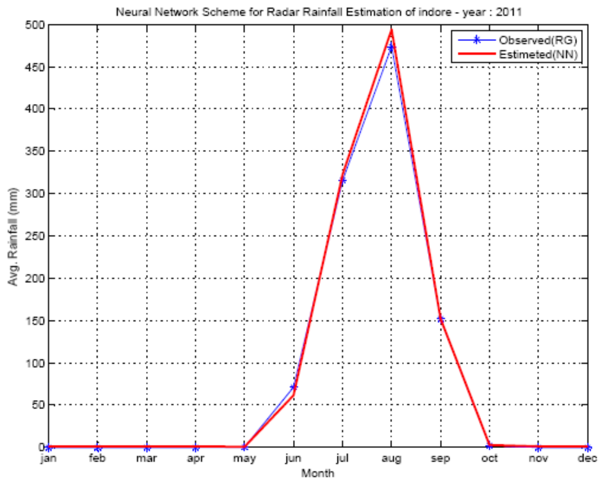

Figure2: Test Results

V. Conclusion

The Rainfall estimation based on neural network to estimate rainfall is described here. This technique can be used for rainfall estimation. Data from years 2007, 2008, 2009 and 2010, 2011 over Indore were used to evaluate the performance of this technique against rain gauge measurements.

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