P14.25 EXTENSIVE VALIDATION OF A REGULARIZED NEURAL-NETWORK TECHNIQUE FOR S-BAND POLARIMETRIC RADAR RAINFALL ESTIMATION

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1. INTRODUCTION

Raindrop Size Distribution (RSD) variability is one of the main factors affecting quantitative precipitation estimation from radar measurements. Dual-polarized radar systems enable the use of multi-parametric algorithms that generally improve the rainfall retrieval. Regression-based procedures are largely preferred by the operational community, simplicity being often considered synonymous of robustness. Despite the neural network (NN) capability to represent complex functions is well recognized in the estimation theory, its dissemination to the operational radar community is obstructed by an accompanying mystic halo. Rainfall retrieval problem is an ill-posed strongly non-linear problem. This means that the related inverse problem can be addressed only by resorting to the statistical analysis and by adding a priori information. Within this framework, the NN technique represents a powerful approach to design a retrieval algorithm in a more flexible and robust way than conventional methods such as linearized multivariate regression. Indeed, the selection of a NN topology, very often thought to be a "black box", is theoretically equivalent to the choice of either a regression analytical model or a Bayesian probability model (Haykin, 1995), whereas the NN training and test resembles the optimization step within the parameter estimation of statistical parametric relations.

An attempt to outline the potential benefit derived from the use of such NN approaches in radar rainfall estimation is carried out in the present work. A large radar data and surface gauge observation dataset collected in central Oklahoma during the multiyear Joint POlarization Experiment (JPOLE) field campaign is used to validate two neural network techniques: a) an 'indirect' NN methodology based on the RSD retrieval and rainfall calculation; b) a 'direct' NN methodology based on the rainfall retrieval. Both NN-based rainfall retrieval techniques are trained by a randomly-generated RSD dataset where independent RSD parameters are assumed within a climatological variability range.

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These assumptions ensure a broad applicability including the local expected correlation between the drop number concentration and mean diameter. Rainfall temporal accumulations from RSD retrieval-based methods are shown to be sensitive to the choice of a raindrop fall speed model. To minimize the impact of this choice, a further 'direct' NN approach is tested. Proposed NN-based techniques exhibit bias and root mean square error characteristics comparable with those obtained from parametric relations, specifically optimized for the JPOLE dataset, indicating an appealing generalization capability with respect to the climatological context.

2. NEURAL-NETWORK RADAR RAINFALL ESTIMATION TECHNIQUES

Two neural network techniques for rainfall estimation from polarimetric radar measurements are evaluated in this work. They both assume that the raindrop size distribution $N(D)$ can be approximated by a normalized Gamma function of the form (Bringi and Chandrasekar, 2001)

$$N(D) = N_w f(\mu)\left(\frac{D}{D_0}\right)^{\mu} \exp\left[-(3.67+\mu)\frac{D}{D_0}\right] \qquad (1)$$

where D is the volume-equivalent drop diameter, $f(\mu)$ is a function of μ only, the parameter D_0 is the median volume drop diameter, μ is the shape of the drop spectrum, and N_w [mm^{-1} m^{-3}] is a normalized drop concentration that can be calculated as function of liquid water content W and D_0 (e.g., Bringi and Chandrasekar, 2001).

The first suggested neural network algorithm (R_{RSD}) is based on the use of polarimetric radar observables for the estimation of the Raindrop Size Distribution (RSD). Indeed, radar reflectivity factor at horizontal polarization Z_{hh} and differential reflectivity Z_{dr} are commonly used in RSD retrieval (Gorgucci et al., 2002; Brandes et al., 2002). Specific differential phase shift K_{dp} is another potential predictor for RSD retrieval. However, K_{dp} computations are often noisy and/or negative, which may perturb the results. Consequently, K_{dp}

computations may be considered most reliable after applying a lower threshold of 0.2 deg km^{-1} (e.g., Gorgucci et al. 2002). Notwithstanding, Vulpiani et al. (2006) found that the proposed algorithm may perform well even for very low values of K_{dp}. Moreover, in the case of unreliable or unavailable measurements of K_{dp} (i.e., radars which do not measure differential phase), a 2-input neural-network algorithm can also be successfully applied. Figure 1 shows the block diagram of R_{RSD}.

The median volume drop diameter D_0 and the intercept parameter N_w are independently estimated using distinct NNs with 3 (i.e., Z_{hh}, Z_{dr}, K_{dp}) or 2 inputs (i.e., Z_{hh}, Z_{dr}), according to the availability and reliability of K_{dp} (Vulpiani et al., 2006). The shape parameter μ is estimated from Z_{dr} and the retrieved values of D_0 (as suggested in Brandes, 2002) using a 2-input NN (i.e., Z_{dr}, D_0). Thus, the estimate of the shape parameter is indirectly dependent on K_{dp} through D_0.

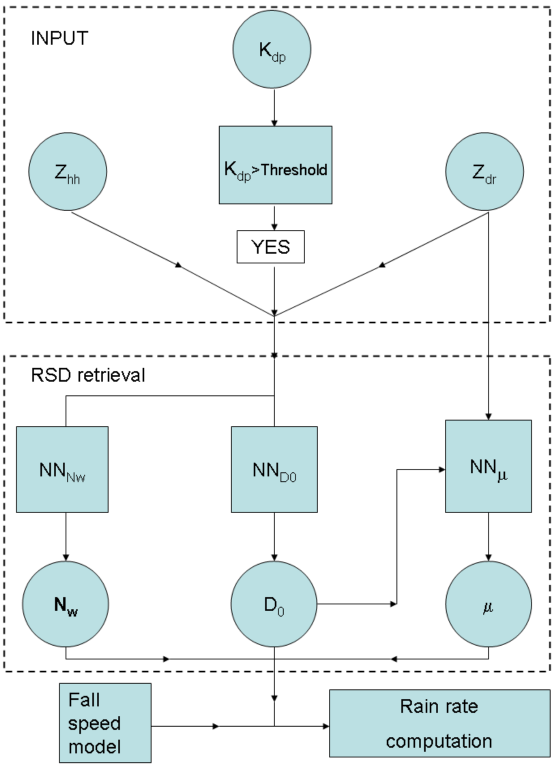

Figure 1 Block Diagram representing the RSD-retrieval based neural network rainfall algorithm.

Once the RSD is retrieved, the rain rate can be simply estimated as (e.g., Bringi et al., 2004; Vulpiani et al., 2006)

$$R_{RSD} = 0.6\pi \times 10^{-3} \int_{D_{\min}}^{D_{\max}} v(D) D^3 N(D; \hat{N}_w, \hat{D}_0, \hat{\mu}) dD \qquad (2)$$

To minimize the importance of the choice of $v(D)$, a new "direct" (without passing through the RSD estimate) neural network rainfall algorithm R_{NN} is also evaluated. Formally, we can write this algorithm as:

$$R_{NN} = NN_R \{Z_{hh}, Z_{dr}, K_{dp}\} \qquad (3)$$

During training, the known neural network output, i.e. D_0, N_w and μ for R_{RSD} and R for R_{NN}, have been randomly generated assuming, for the latter, the Atlas and Ulbrich (1977) terminal velocity relationship. This indicates that both R_{RSD} and R_{NN} are trained without any a priori knowledge of the specific climatology and/or radar measurements of the considered site. It is worth noting that for the 'indirect' NN-based R_{RSD}, the choice of the fall speed model only affects the retrieval phase (e.g., rainfall rate estimates following RSD retrievals), with the NN training dealing only with RSD parameter estimation. In contrast, the training of the 'direct' NN-based R_{NN} could potentially be sensitive to the assumed raindrop terminal velocity. Nevertheless, as briefly discussed later in the text, R_{NN} was found largely insensitive to that assumption used for training.

3. EXPERIMENTAL RESULTS

Validation of the NN methods outlined in the previous section is accomplished using the JPOLE polarimetric radar dataset collected in central Oklahoma (e.g., Ryzhkov et al., 2005a). A total of 42 events observed by the KOUN radar between the years of 2002 and 2005 have been selected for analysis (as in Giangrande and Ryzhkov 2008, Table 1). Concurrent gauge observations were available from the densely-spaced ARS network stations located at ranges of 50-115 km from the KOUN radar. For this study, the ARS Little Washita watershed is the primary location for rain gauges, a basin of about 611 km^2.

For the validation study, we compare hourly gauge and radar rainfall accumulations over gauge locations. In agreement with previous JPOLE studies, hourly radar accumulations are defined as an hourly rainfall estimate centered on a gauge. Radar measurements are averaged using 5 gates centered over the gauge location and two closest azimuths separated by 1 degree. Such averaging produces a radial resolution of 1.0 km and transverse resolution that varies with range. To establish the quality of the radar rainfall algorithms and NN-based methods, absolute differences between radar and gauge estimates (expressed in mm) are examined rather than standard fractional errors, which are heavily weighted towards small accumulations. Rainfall estimates are characterized by the bias B = <ΔT>, standard deviation STD = <|ΔT - B|2>1/2 and the rms error RMSE = <|ΔT|2>1/2, where ΔT = TR – TG is the difference between radar hourly rain-rate totals TR and gauge hourly rain-rate totals TG for any given radar-gauge pair and brackets imply averaging over all such pairs.

3.1 R_{RSD} SENTITIVITY TO FALL SPEED MODEL AND NUMBER OF INPUTS

As it can be argued from (1), any RSD-retrieval based rainfall algorithm is sensitive to the choice of the assumed fall speed. A sensitivity study with respect to the assumed terminal velocity is here performed by considering the following relationships:

- Atlas et al. (1973), here referred as A73;
- Atlas and Ulbrich (1977), here referred as A77;
- Brandes et al. (2002), here referred as B02.

The results obtained by comparing hourly accumulations from ARS rain gauges and NN-based rainfall methods for the raindrop fall speed models are summarized in Table 1 in terms of error Bias, error STD and RMSE. It can be noticed that the assumption of a fall speed relationship plays a non-negligible role for estimating hourly rainfall accumulations from the retrieved RSD. Among the considered relationships, A77 is best matched (Bias= -0.17 mm, STD=3.44 mm, RMSE=3.45 mm) to the observed rainfall accumulations, although we caution this result may be fortuitous for minimizing errors in rainfall estimation and does not necessarily imply that A77 is the best fall-velocity model. The performance of RRSD is similar when considering A73 and B02.

Regarding the performance of the NN-based algorithm with respect to the neural network input configuration, the sensitivity analysis on the observed radar dataset confirms the findings from the simulation environment by Vulpiani et al. (2006); there is a non negligible benefit for using K_{dp} jointly with Z_{hh} and Z_{dr} in estimating rainfall rate. For example, with the A77 fall speed model the performance of the 2-input neural network is inferior compared to the 3-input configuration in terms of standard errors (STD=3.98 mm, RMSE=3.98 mm), with the impact on the bias found negligible (Bias= -0.09 mm).

3.2 COMPARISONS WITH OPTIMAL JPOLE RAINFALL RELATIONS

The following parametric retrieval algorithms, based on empirical regression of measured gauge/disdrometer and radar data, have been chosen for comparison with the proposed neural-network methodology

$$R(Z_{hh}) = 1.7 \cdot 10^{-2}\, Z_{hh}^{\;0.714} \tag{4}$$

$$R(Z_{hh}, Z_{dr}) = 1.42 \cdot 10^{-2} Z_{hh}^{\;0.77} Z_{dr}^{\;-1.67} \tag{5}$$

$$R(K_{dp}) = 44.0 \left|K_{dp}\right|^{0.822} sign(K_{dp}) \tag{6}$$

where Z_{hh} and Z_{dr} are expressed in linear units. Relation (13) is the inversion of the standard NEXRAD rainfall formula for continental (nontropical) application (e.g., Fulton et al. 1998), whereas (14) and (15) are selected because of their optimal performance in rain in central Oklahoma during the JPOLE field campaign (e.g., Ryzhkov et al. 2005b; Giangrande and Ryzhkov 2008).

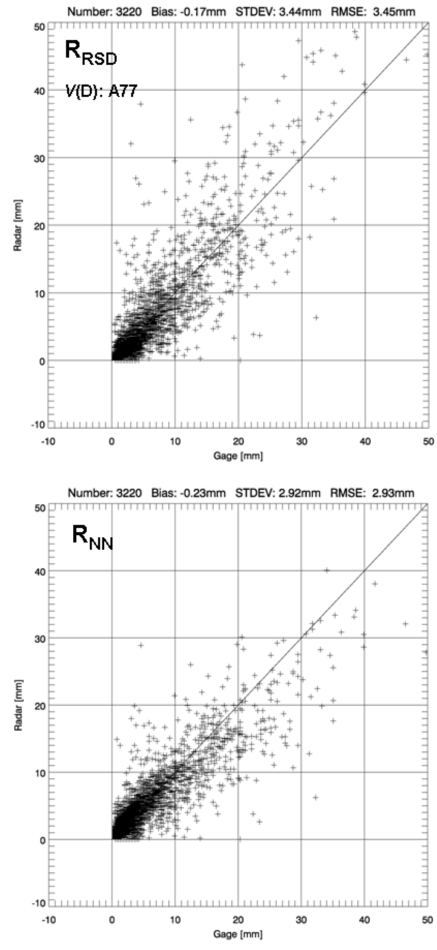

Figure 2 Comparison between gage and radar rainfall estimated through the proposed neural network techniques. The upper panel shows the performance of R_{RSD} assuming the A77 speed model and the three input configuration. The performance of “direct” neural network algorithm R_{NN} is shown on the lower panel.

Rain retrieval using R_{RSD}						
	2-inputs			3-inputs		
	A73	A77	B02	A73	A77	B02
Bias	0.24	-0.09	0.25	0.14	-0.17	0.15
STD	4.26	3.98	4.27	3.66	3.44	3.68
RMSE	4.26	3.98	4.28	3.67	3.45	3.68

Tab. 1. Performance of the RSD-retrieval-based neural network rainfall algorithm (R_{RSD}) with respect to the assumed fall velocity and network configuration (see Vulpiani et al. 2006 for details) relatively to the 42 events observed from 2002 to 2005.

Furthermore, as proposed in Ryzhkov et al. (2005b), we have applied a synthetic algorithm (R_{SYN}). According to the "synthetic algorithm", the choice between various polarimetric rainfall relations is determined solely by the radar reflectivity Z_{hh} or R(Z_{hh}). Such a selection criteria may act as a proxy in the rain medium for rainfall relations contingent on the results polarimetric echo classification, as outlined in Giangrande and Ryzhkov (2008).

We emphasize that the polarimetric algorithms (4), (5) and the 'synthetic' algorithm have been optimized for Oklahoma climatology and the JPOLE dataset. It is noted that JPOLE-'matched' conventional relations have also been tested (e.g., as in Ryzhkov et al. 2005b), but have not shown to offer a significant improvement over optimal polarimetric relations. As recently outlined in Schuur et al. (2008), relationships (4)-(6) may still not be sufficient estimators if "tropical-like" events hit the region. It is worth noting that both R_{RSD} and R_{NN} have been constructed in a simulated framework through a general a priori microphysical parameterization. The consequence is that the estimators R_{RSD} and R_{NN} are potentially robust and may be equally suitable in other precipitation regimes.

An advantage for all polarimetric rainfall methods is confirmed for this study, wherein all of the polarimetric algorithms are found to outperform the single-parameter conventional NEXRAD $R(Z_{hh})$ relation. Results obtained by applying the neural network based algorithms are depicted in Figure 2. Similarly, Figure 3 shows the performance of the parametric techniques. As summarized in Table 2, the conventional NEXRAD $R(Z_{hh})$ relation is characterized by a large bias and the highest standard deviation and rms error when compared with NN-based and JPOLE polarimetric relations. The $R(K_{dp})$ relation slightly outperforms the $R(Z_{hh},Z_{dr})$ and the R_{RSD} NN-method. Contingent on the choice for raindrop fall speed relation (i.e., A77), the RSD-retrieval-based neural network R_{RSD} may perform slightly better than $R(Z_{hh},Z_{dr})$ in terms of STD (STD=3.44, RMSE=3.45) and comparable with R(K_{dp}) for this dataset. The JPOLE optimal synthetic algorithm R_{SYN} ostensibly outperformed $R(Z_{hh},Z_{dr})$, $R(K_{dp})$ and the R_{RSD} method in terms of bias and rms error. Results obtained by applying the "direct" neural network R_{NN} are improved compared to previous R_{RSD} NN-based approach in all configurations.

	R(Z_{hh})	R(K_{dp})	R(Z_{hh},Z_{dr})	RSYN	R_{RSD}	R_{NN}
Bias	1.57	-0.59	-0.18	-0.6	-0.17	-0.23
STD	5.45	3.38	3.59	3.02	3.44	2.92
RMSE	5.67	3.43	3.60	3.08	3.45	2.93

Tab. 2. Comparison between the neural-network based rainfall algorithms (R_{RSD}, R_{NN}) and the parametric ones relatively to the 42 events observed from 2002 to 2005.

For the best-matched fall speed relation (as based on 'indirect' method testing) and 3-input configuration, bias and standard errors are comparable to the published synthetic methodology that we emphasize was optimized for the JPOLE dataset (Bias=-0.23, STD=2.92, RMSE=2.93). During sensitivity testing for various fall speed models in the 'direct' method training, it was determined that the results do not significantly change and even improve slightly, for example, when using the B02 model instead of A77.

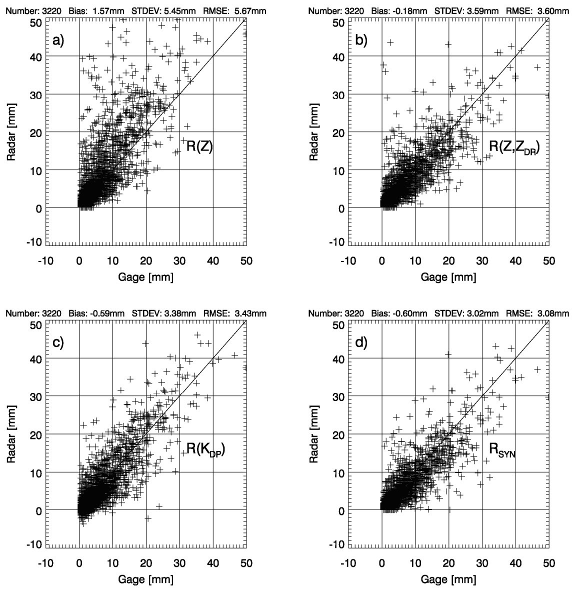

Figure 3 Radar rainfall estimates following a) the NEXRAD conventional Z-R relationship, b) the $R(Z_{hh},Z_{dr})$ relationship shown in (5), c) the $R(K_{dp})$ relationship shown in (6) and d) the synthetic parametric algorithm R_{SYN} proposed by Ryzhkov et al. (2005b).

4. CONCLUSIONS

The variability of the raindrop size distribution represents one of the main physical factors affecting radar-based estimation of rainfall. The use of polarimetric methodologies has been previously found to reduce the impact of such variability. This study evaluates one such polarimetric rainfall technique that uses a neural network algorithm for raindrop size distribution and rainfall retrieval. This technique was only tested previously using simulations as in Vulpiani et al. (2006). For the JPOLE dataset, the ‘indirect’ NN-based R_{RSD} methodology, based on RSD estimation, has shown a non-negligible sensitivity to the assumed fall speed velocity. To reduce this sensitivity, a new ‘direct’ (without passing through the RSD retrieval) NN-based algorithm R_{NN} is also evaluated.

Polarimetric techniques have all outperformed the single-parameter $R(Z_{hh})$ in terms of bias, rms error and standard deviation. Among the polarimetric algorithms, R_{RSD} has shown a performance slightly better than $R(Z_{hh},Z_{dr})$ and comparable with $R(K_{dp})$ over the entire JPOLE dataset. The best results as compared with gauge accumulations were obtained through use of the ‘direct’ NN-based R_{NN} algorithm and JPOLE-optimal R_{SYN} method with a slightly lower bias provided by the former. It is again worth noting that both NN-based R_{RSD} and R_{NN} have been constructed in a simulated framework without any climatologically-driven optimization.

ACKNOWLEDGEMENTS

We express our gratitude to the staff of the Oklahoma Climatological Survey for providing high-quality gauge data. The support from the NSSL and the CIMMS, University of Oklahoma staff who maintain and operate the KOUN WSR-88D polarimetric radar is also acknowledged. Funding for the collection, processing and distribution of the KOUN radar dataset was provided by NOAA/Office of Oceanic and Atmospheric Research under NOAA-University of Oklahoma Cooperative Agreement #NA17RJ1227, U.S. Department of Commerce. Availability of the KOUN radar dataset was also supported by the National Weather Service, the Federal Aviation Administration, and the NEXRAD Product Improvement Program.

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