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Advanced Techniques for Polarimetric Radar Estimation of Rainfall

Gianfranco Vulpiani and Frank S. Marzano

Abstract Single-polarization Doppler weather radar systems are known to be very useful tools for the monitoring of precipitation events. Nevertheless, quantitative applications require a careful data processing as several impairments may reduce the reliability of such estimates. Among them, attenuation due to absorption and scattering of the transmitted and received signals in the rain path, hail contamination and the high space-time variability of raindrop size distribution are the most significant. Dual-polarized (polarimetric) radars enable to improve data quality through the use of several additional observables. An ensemble of highly advanced techniques for hydrometeor retrieval, based on the use neural network and fuzzy logic systems, is presented here. Numerical and experimental data set are used to evaluate the proposed methodologies.

Keywords Polarimetric rain rate retrieval · Attenuation correction · Hydrometeor classification · Rain drop size distribution retrieval.

1 Introduction

Rainfall retrieval using ground-based weather radar is achieving an increased relevance for the evaluation of the hydrological cycle and the monitoring of severe events. Nearly all European weather radars operate at C band, mainly due to cost and size constraints (e.g., Alberoni et al., 2002). However, at frequencies higher than S band, path attenuation effects due to rainfall can be significant and need to be compensated for quantitative estimation of rainrate. Moreover, range gates contaminated by hail and wet snow must be accurately identified in order to avoid errors in the attenuation correction procedures and rain rate estimation. Last but not least, rain rate retrieval may be highly inaccurate if only power radar echoes are processed.

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In this regard, dual-polarized (polarimetric) weather radars enable the nature of hydrometeors to be inferred by transmitting and receiving waves at horizontal and vertical polarization (e.g., Bringi and Chandrasekar, 2001). Moreover, the exploitation of the differential phase shift between the two polarization states allows the effective correction of the rain path attenuation. Finally, the estimate of rainfall can be significantly improved if polarimetric radar observables are available and, to some extent, even the drop size distribution can be inferred.

Probably, within the next decade most operational radars will be converted from single-polarization into dual-polarization configuration, apart from Doppler capability which is effective for ground-clutter removal and for wind field retrieval. This contribution is aimed to provide some insights into new advanced techniques capable to exploit the polarimetric radar observations both at S and C band. The text is organized as follows.

- Section 2. Polarimetric radar observables will be defined resorting to a detailed microphysical and electromagnetic model dealing with non-spherical particle ensembles. This coupled model will be used for training physically-based inverse algorithms.
- Section 3. Techniques for rain path attenuation correction at C band will be introduced and a recent iterative methodology, exploiting an embedded neural network and polarimetric constraints, will be described. Numerical tests and error budget will be detailed.
- Section 4. A fuzzy-logic based technique is illustrated for hydrometeor classification exploiting the polarimetric features of new generation radars. It is tuned for C band, generalizing S-band established approaches and resorting to the frequency scaling of the microwave microphysical model. A case study will show the effects at C band and the impact of path attenuation on hydrometeor classification accuracy.
- Section 5. A regularized neural network approach will be described for estimating raindrop size distribution and comparing this new technique with other statistical methods available in literature. The improvement obtained by retrieving the rainfall rate from the retrieved size distribution, instead of a direct estimation, is quantified and discussed.
- Section 6. Conclusions will be drawn emphasizing future developments of radar meteorology research and its operational impacts.

2 Polarimetric Radar Observables

2.1 Rain Model

A normalized Gamma raindrop size distribution (RSD) has been introduced in literature to account for most of the variability occurring in the naturally observed *RSD* (Bringi and Chandrasekar, 2001). The number of raindrops per unit volume per unit size can be written as:

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

where $f(\mu)$ is a function μ only, the parameter D_0 is the median volume drop diameter, μ is the shape of the drop spectrum, and N_w [$\text{mm}^{-1} \text{m}^{-3}$] 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 shape of a raindrop can be described by an oblate spheroid for which the equivalent volume diameter D_e is related to the axis ratio a/b by a relation which has been investigated by several authors. In this study we limited our attention to the relationship introduced by Beard and Chuang (1987). Given a RSD, the rainfall intensity R can be computed as a flux of raindrop volume at a terminal fall velocity $v(D)$, usually parameterized as a power law of D .

2.2 Polarimetric Radar Variables

The copolar radar reflectivity factors Z_{hh} and Z_{vv} [$\text{mm}^6 \text{m}^{-3}$] at H and V polarization state, the cross-polar reflectivity factor Z_{hv} , the differential reflectivity Z_{dr} and the linear depolarization ratio LDR can be expressed as follows:

$$Z_{hh,vv,hv} = \frac{\lambda^4}{\pi^5 |K|^2} < 4\pi |S_{hh,vv,hv}^b(D)|^2 > \quad (2)$$

$$Z_{dr} = \frac{Z_{hh}}{Z_{vv}}, LDR_{vh} = \frac{Z_{vh}}{Z_{hh}} \quad (3)$$

where $S_{hh,vv}$ and S_{hv} [mm] are the backscattering co-polar and cross-polar components of the complex scattering matrix $\mathbf{S}$ of a raindrop, the angular brackets represent the ensemble average over the RSD. K depends on the complex dielectric constant of water estimated as a function of wavelength λ [mm] and temperature.

For a polarimetric radar, the specific differential phase shift K_{dp} , due to the forward propagation phase difference between H and V polarization and co-polar correlation coefficients ρ_{hv} can be obtained in terms of the scattering matrix $\mathbf{S}$ as:

$$K_{dp} = 10^{-3} \frac{180}{\pi} \lambda \cdot \text{Re}[< f_{hh}(D) - f_{vv}(D) >] \quad (4)$$

$$\rho_{hv} = \frac{< S_{vv} S_{hh}^* >}{\sqrt{< |S_{hh}|^2 > < |S_{vv}|^2 >}} = |\rho_{hv}| e^{j\delta} \quad (5)$$

where $f_{hh,vv}$ are the forward-scattering co-polar components of $\mathbf{S}$ and δ (in deg) is the volume backscattering differential phase. The specific attenuation A_{hh} at H polarization and the differential attenuation A_{dp} are finally defined as:

$$A_{hh} = 2 \cdot 10^{-3} \lambda \cdot \text{Im}[< f_{hh}(D) >], A_{dp} = A_{hh} - A_{vv} \quad (6)$$

where specific attenuations are in km^{-1} .

3 Path Attenuation Correction at C Band

For frequencies higher than S-band, path attenuation effects due to rainfall can become significant and need to be compensated for quantitative applications such as rainrate estimation (Bringi and Chandrasekar, 2001; Testud et al., 2000). The iterative approaches (e.g., Hildebrand, 1978) for path attenuation correction are known to be unstable.

A significant improvement to these path-attenuation correction procedures is provided by using the total path-integrated attenuation (PIA) as a constraint. This approach, originally proposed for spaceborne radar applications where the sea or land surface is generally assumed as a reference target, has been extended to ground-based polarimetric radar. Recently, the use of cumulative differential phase (Φ_{dp}) constraint to estimate the PIA and to correct the measured reflectivity Z_{hh} and differential reflectivity Z_{dr} , proposed by Testud et al. (2000), was improved by Bringi et al. (2001) through the use of a self-consistent scheme.

The objective of this work is to introduce an alternative approach with Φ_{dp} utilized as a constraint to retrieve Z_h and Z_{dr} at C band in presence of significant path attenuation and, consequently, rainfall at ground. A model-based data set is used in an embedded neural network to train the retrieval algorithms (Vulpiani et al., 2005). The neural network approach is applied in cascade to estimate rain rate from corrected polarimetric variables. Analysis of model data and numerical tests on synthetic radar data are discussed. The synthetic data are either created by a statistical generator or by spatial conversion of temporal series of disdrometer data.

The proposed retrieval technique, named Neural Iterative Polarimetric Precipitation Estimation by Radar (NIPPER) is illustrated in the next paragraphs. It consists of two steps in cascade where:

- (i) rain path attenuation is corrected by using an iterative scheme with the aid of a total path attenuation constraint and model-based neural-network estimates of the unknown parameters;
- (ii) a neural-network rain retrieval algorithm is applied to the polarimetric observable previously corrected within each single volume bin.

The main features of the NIPPER algorithm is that it does not assume any given analytical relation between the various polarimetric variables and it exploits the neural-network potential as a retrieval tool in a non linear context.

3.1 Iterative Correction of Rain Path Attenuation

Bringi et al. (1990) showed that Φ_{dp} is directly related to path integrated attenuation. It is possible to use the PIA from Φ_{dp} and use it to constraint the attenuation correction procedure (Testud et al., 2000). A_h and A_{dp} (both expressed in dB km⁻¹) are linearly related to K_{dp} (in ° km⁻¹) which is the range derivative of Φ_{dp} . Note that, before applying the attenuation correction scheme the differential phase shift

Φ_{dp} must be filtered from the back-propagation effects which are non negligible at C-band (Scarchilli et al., 1993).

The proposed iterative algorithm is described in the following. The first step is the estimation of the path integrated attenuation $PIA_h(r_N)$, and the path integrated differential attenuation $PIA_{dp}(r_N)$, at the farthest range r_N by using the Φ_{dp} constraint. Therefore the corrected values of Z_{hh} and Z_{dr} are derived at the farthest range volume (here the N^{th}) by:

$$Z_{hh,dr}^C(r_N) = Z_{hh,dr}^m(r_N) + 2PIA_{hh,dp}(r_N) \quad (7)$$

where both reflectivities and PIA are expressed in dB, while the superscripts C and m stand respectively for corrected and measured.

Using the corrected values of Z_{hh} and Z_{dr} , it is possible to estimate the specific attenuation (and the specific differential attenuation), through a neural network, at the N^{th} range volume by mean of:

$$A_{hh,dr}(r_N) = NN_A(Z_{hh}^C(r_N), Z_{dr}^C(r_N)) \quad (8)$$

where NN_A is a Neural Network functional used for the specific attenuation (differential attenuation) estimation. As a consequence we can estimate the PIA at the $(N-1)$ th range bin from:

$$PIA_{hh,dp}(r_{N-1}) = PIA_{hh,dp}(r_N) - A_{hh,dr}(r_N) \cdot \Delta r \quad (9)$$

where Δr is the bin range resolution, while the corrected values of reflectivity and differential reflectivity are

$$Z_{hh,dr}^C(r_{N-1}) = Z_{hh,dr}^m(r_{N-1}) + 2PIA_{hh,dp}(r_{N-1}) \quad (10)$$

Generalizing (9) and (10) for the K th range volume, we can write:

$$PIA_{hh,dp}(r_K) = PIA_{hh,dp}(r_N) - \int_{(r_K-1)\Delta r}^{r_K\Delta r} A_{hh,dr}(s) \cdot ds \quad (11)$$

$$Z_{hh,dr}^C(r_K) = Z_{hh,dr}^m(r_K) + 2PIA_{hh,dp}(r_K) \quad (12)$$

Through (11) and (12) it is possible to iteratively correct the profiles of Z_{hh} and Z_{dr} .

3.2 S-Band Derived Test Data Set

The data set used to test the proposed algorithm has been simulated adopting the rain model specified in sect. 3 where the RSD parameters have been retrieved

from S-band radar measurements. Adopting the procedure proposed in (Gorgucci et al., 2002), the polarimetric variables Z_{hh}^m , Z_{dr}^m and K_{dp}^m , measured by the CSU-CHILL radar during a convective event, have been used to estimate the drop median parameter D_0 and the intercept parameter N_w .

Radar measurements have been performed choosing a Pulse Repetition Frequency (PRF) and a pulse width such that the maximum unambiguous range is about 80 km and the range resolution is 250 m. Fixing the temperature and consequently the relative dielectric constant, a complete volume scan at C-band has been simulated by means of the T-matrix scattering method (Mishchenko, 2000).

A random noise on simulated polarimetric variables has been introduced to realistically reproduce the measurements (Testud et al., 2000), resulting in a 1 dB fluctuation for Z_{hh} , 0.3 dB for Z_{dr} and 2° for Φ_{dp} .

The Plan Position Indicators (PPIs) of the reflectivity and differential reflectivity are shown in Fig. 1.

The intensity of Z_{hh} and Z_{dr} highlights the presence of wide convective areas and stratiform regions. Figure 2 shows the two-way path integrated attenuation as a function of the azimuth. About 50% of rays have a PIA greater than 2 dB. The most attenuated rays are localized in the sectors $70^\circ \leq \varphi \leq 90^\circ$ and $145^\circ \leq \varphi \leq 160^\circ$, where φ is the azimuth angle, with a maximum two-way PIA up to 10 dB.

3.3 Error Analysis

The performance of NIPPER is evaluated in terms of error mean value ($\bar{\varepsilon}_{hh,dr}$) and its standard deviation ($\sigma(\varepsilon_{hh,dr})$), computed as a function of range and for all azimuth profiles. In this work the error is defined as:

$$\varepsilon_{hh,dr}(r) = 10 \log_{10} (\hat{Z}_{hh,dr}(r)) - 10 \log_{10} (Z_{hh,dr}(r)) \quad (13)$$

where $\hat{Z}_{hh,dr}$ indicates the estimate of the attenuation-corrected radar reflectivity.

Figures 3 and 4 show the plot of $\bar{\varepsilon}_{hh,dr}$ and $\sigma(\varepsilon_{hh,dr})$, the metrics of the co-polar reflectivity and differential reflectivity retrieval, as a function of the azimuth for both the self-consistent ZPHI and NIPPER algorithms.

It can be seen from Fig. 3 that the proposed attenuation compensation procedure is characterized by a considerable improvement with respect to the self-consistent rain profiling algorithm. This behaviour is more evident when the attenuation is relatively high (see Fig. 4). If all the processed rays are considered, 78.7% have a mean error less than 0.5 dBZ and a standard deviation less than 0.8 dBZ. Using the self-consistent rain profiling algorithm, the same values of $\bar{\varepsilon}$ and σ_ε are obtained in 43.7% of the cases.

Similarly, the differential reflectivity has been corrected (see Fig. 4) with a mean error less than 0.2 and a standard deviation less than 0.3 for 79.3% of all rays by NIPPER and 52.1% by the self-consistent rain profiling algorithm.

Fig. 1 PPI of the synthetic apparent reflectivity (*upper panel*) and differential reflectivity (*lower panel*) (See also Plate 16 in the Colour Plate Section)

Fig. 2 Two-way Path Integrated Attenuation (PIA) as function of the azimuth

Fig. 3 Reflectivity retrieval. The NIPPER performance (*right panels*) is compared with the rain profiling algorithm one (*left panels*) in case of well-calibrated radar

Fig. 4 Differential reflectivity retrieval. The NIPPER performance (*right panels*) is compared with the rain profiling algorithm one (*left panels*) in case of well-calibrated radar

4 Hydrometeor Classification at C Band

Most scientific literature about hydrometeor classification has been so far devoted to classification techniques designed for S-band dual-polarized weather radars (Vivekanandan et al., 1999) (Zrnić et al., 2001; Lim et al., 2005; Ryzhkov et al., 2005). Only recently some works related to the exploitation of C-band measurements for hydrometeor classification have been presented (Keenan, 2003; Baldini et al., 2004; Galletti et al., 2005; Marzano et al., 2006). The interest of assessing C-band hydrometeor classification may also emerge from the consideration that most mid-to-high latitude weather radars operate and are planned at C-band (Alberoni et al., 2002).

In this section a model-trained supervised fuzzy-logic radar algorithm for hydrometeor classification at C-band (FRAHC-C) is presented. The goal is not to devise a new fuzzy logic algorithm, but using an established approach to: (i) extend it from S-band to C-band radar data; (ii) handle both power and phase measurements giving some details of the approach at C-band; (iii) show the improvements obtained using a C-band tuned algorithm with respect to an S-band based approach; (iv) evaluate the impact of path-integrated attenuation (PIA) exploiting a network radar configuration.

4.1 Hydrometeor Radar Scattering Model at C-band

We limit our attention to copolar reflectivity Z_{hh} , differential reflectivity Z_{dr} and specific differential phase K_{dp} . The analysis of co-polar correlation coefficient ρ_{hv} and linear depolarization ratio L_{dr} is beyond our scopes. Once the particle shape, orientation and dielectric composition together with particle size distribution $N(D_e)$ are known, a numerical solution can be adopted to derive both $\sigma_{hh,vv}$ and $f_{hh,vv}$. The T-Matrix method (Mishchenko, 2000) is an effective numerical solution of the scattering problem for non-spherical particles by means of the electromagnetic equivalence theorem.

A correct microphysical and dielectric modeling of hydrometeors is essential to obtain meaningful simulations of polarimetric radar measurements (Beard and Chuang, 1987). Detailed information about several hydrometeor types can be found in Straka et al. (2000) and here we basically follow their approach. However, in this work only 10 hydrometeor classes have been established as follows: LD (*large drops*), LR (*light rain*), MR (*medium rain*), HR (*heavy rain*), H/R (*hail/rain mixture*), H (*hail*), G/SH (*graupel/small hail*), DS (*dry snow*), WS (*wet snow*), IC (*ice crystals*). Possible temperature ranges for the ten different hydrometeor classes have been derived from Zrnić et al. (2001). In this work we have assumed that all particle shapes may be approximated by spheroids. The size distribution of each hydrometeor has been modeled through a normalized Gamma. Water and ice dielectric constants are derived from Ray's (1972) and Warren's (1984) models, respectively. Ten sets of 300 scattering simulations for each hydrometeor class have been carried out in order to have statistically significant simulated polarimetric signatures. With respect to S-band measurements, C-band signatures are more sensitive to shapes and, in general, present larger values of Z_{dr} and K_{dp} and lower values of co-polar correlation Zrnić et al. (2001). Most relevant differences between the two band behaviors have been found for LD, MR, HR and H/R classes. Specifically, it is worth noting that Z_{dr} at S-band is not usually larger than 3.5 dB, while at C-band LD and HR give rise to Z_{dr} even larger than 5 dB. The key advantage of K_{dp} at C-band is the capability to discriminate between rain and ice hydrometers, but unfortunately the retrieval of K_{dp} is affected by the backscattering differential phase shift δ_{hv} , which is no more negligible at C-band (Iguchi and Meneghini, 1994; Bringi and Chandrasekar, 2001).

4.2 Fuzzy-Logic Classification Method

As previously noted, at C-band path attenuation is relevant and cannot be neglected. All these aspects make fuzzy logic one of the best solutions for the hydrometeor classification problem (Lim et al., 2005). Fuzzy-logic techniques are fairly simple and flexible to set up and their behavior tends to be robust to noisy data (Bringi and Chandrasekar, 2001). A fuzzy logic system basically provides a non-linear mapping of input data vectors into scalar outputs. Any fuzzy-logic algorithm consists of three main stages: (i) fuzzification; (ii) inference; (iii) de-fuzzification (Lim et al., 2005).

In this work we have considered, as input data vector, the combination of reflectivity Z_{hh} , differential reflectivity Z_{dr} and environmental temperature T . This choice is mainly dictated by the network radar system used for algorithm testing. In order to generalize the C-band methodology to polarimetric radars, we have also considered the possible use of specific differential phase K_{dp} .

In the standard FRAHC-C technique the fuzzification stage is characterized by 10 bi-dimensional membership functions (MBFs) for Z_{hh} and Z_{dr} and 10 mono-dimensional MBFs for temperature. Temperature for every radar bin is evaluated by means of a vertical radio-sounding profile realized in proximity of the storm. In absence of this kind of measurement, a standard temperature gradient can be assumed as a first approximation. Definition of MBFs is a fundamental task that affects the classification accuracy. The starting point has been a set of MBFs, originally described in Straka et al. (2000), usually referred as the fuzzy-logic scheme developed for the National Severe Storm Laboratory (NSSL) polarimetric radars at S-band (Zrnić et al., 2001). MBFs adopted in this work have trapezoidal forms and analytical expressions have been derived by means of accurate observations of T-Matrix simulations at C-band. Linear fuzzy thicknesses can be different for each hydrometeor class. Temperature MBFs are also trapezoidal functions, directly derived from Zrnić et al. (2001). The inference rule (I_{Ri}) for the i -th class is based on the product of membership degrees, derived from MBFs as it follows when only Z_{hh} and Z_{dr} are available:

$$I_{Ri} = M_{Zi}(Z_{hh}, Z_{dr})M_{Ti}(T) \quad (14)$$

where $i = 0 - 9$, the M_{Zi} and M_{Ti} are the MBFs for (Z_{hh}, Z_{dr}) and T of the i -th class. The choice of product, instead of linear combination, has the purpose to limit classification errors as far as possible: if, for a given class, one measurement is significantly out of range, the low value of the corresponding MBF will definitely suppress the class.

The defuzzification is carried out by a maximum-value rule applied to (14) giving the estimated hydrometeor class index i_c which the radar bin is assigned to:

$$\hat{i}_c = \text{Max}_i [I_{Ri}] \quad i = 0, 1, \dots, 9 \quad (15)$$

where Max_i is the maximum operator with respect to the i -th class. If two or more rules present the same maximum value, NC (*not classified*) label is assigned to the radar bin.

In order to evaluate the expected classification accuracy, we have generated a training and test data set consisting of 300 independent simulations of Z_{hh} , Z_{dr} , and K_{dp} for each hydrometeor class, with the environmental temperature T uniformly distributed inside specific intervals. Radar measurements at C-band have been simulated by adding a zero-mean Gaussian noise to data with standard deviations equal to 1 dBZ, 0.3 dB and $0.2^\circ/\text{km}$ for Z_{hh} , Z_{dr} and K_{dp} , respectively.

Contingency tables, also known as confusion matrices, are used to evaluate classification accuracy on either real or synthetic data. For comparison, classification

results using S-band MBFs have been computed. Improvements of the hydrometeor classification accuracy w.r.t. the use of S-band designed MBFs (Baldini et al., 2004), measured in terms of overall accuracy (OA) and average non-classified samples percentage (NC_{av}), are noteworthy: OA rises from 48 to 62%, while NC_{av} decreases from 26 to 15%.

4.3 Case Study

Available radar data refer to a convective episode occurred in the region between two dual-polarized C-band radar systems GPM-500C, both located in the Po valley and about 90 km apart: the S. Pietro Capofiume (SPC) and the Gattatico (GAT) radars, both managed by ARPA-SIM Emilia-Romagna. Details about the radar systems and the evolution of the convective event are given by Alberoni et al. (2001), Marzano et al. (2006).

Reflectivity and differential reflectivity data available from the two radars GAT and SPC have been first classified with the previously described FRAHC-C technique, disregarding path-attenuation effects. Temperature vertical average profile has been retrieved from a vertical radio-sounding made at SPC meteorological station. Since truth data regarding the storm on the connection line are unavailable, only qualitative tests can be carried out. This visual inspection is aimed at evaluating the microphysical consistency of the hydrometeor field and the information content of each algorithmic choice (Zrnić et al., 2001). Accuracy improvements can be recognized by direct observations of the RHI diagrams, first with S-band MBFs and then with C-band MBFs. In the latter case the number of non-classified (NC) radar bins considerably decreases, and ice crystals detection (IC) is performed in a more realistic way. Classification results are also physically self-consistent: the hail core (H and H/R) is correctly detected at the centre of the convective storm, graupel (G/SH) is reasonably identified all around the hail core, rain is present only at low altitude while snow and ice crystals (DS, WS, IC) are properly found within the top layers of the storm.

In order to correct for path integrated attenuation (PIA), since differential phase shift measurements are unavailable we can exploit the network radar observation of this convective event by either using a composite field approach or a constrained inversion algorithm (Iguchi and Meneghini, 1994; Vulpiani et al., 2005).

When a network observation of a storm is available, the path integrated attenuation (PIA) can be estimated by looking at the differences between the attenuated measured reflectivity Z_{hhm} , observed from the considered radar, and the non-attenuated reflectivity Z_{hh} , observed by the other radar at the rain-cloud edge. Let us consider the line connecting the SPC and GAT radars at the lowest elevation angle $\theta_0 = 0.5^\circ$. Along this line, an average over 2.5 km (10 range bins) gives a value of 5 ± 2.4 dBZ for the radar reflectivity difference ($Z_{hhm}^{GAT} - Z_{hhm}^{SPC}$) and 7.5 ± 1.5 dBZ for ($Z_{hhm}^{SPC} - Z_{hhm}^{GAT}$). The average value between these two estimates seems to indicate a PIA of about 6.25 dB. In order to reconstruct the equivalent reflectivity range profiles of Z_{hh} and Z_{dr} , we can apply a set of path-attenuation correction algorithms with PIA constraint (Iguchi and Meneghini, 1994; Testud et al., 2000; Vulpiani et al., 2005). Main problems

are that radar data are quite noisy and fluctuating, the two radars may suffer for a different miscalibration and instrumental noise so that the estimate of PIA may be affected by a significant uncertainty. Moreover the various correction algorithms may give different results. In this context, we have decided to perform a maximum likelihood estimation of Z_{hh} and Z_{dr} by assuming a bounded variability of all the previous sources of uncertainty. The goal of the maximum likelihood approach has been to render the reconstructed reflectivity profiles, estimated from SPC and GAT radar data, as close as possible along the considered range line. In order to select the optimal estimate of the corrected reflectivity profile $Z_{xx}^{COR}(r)$, we have minimized, with respect to all uncertainties, an error (cost) function E . It is worth remarking that the global minimum of E has been found for a PIA of about 6 dB – with the three correction algorithms indicating a PIA between 5.5 and 6.5 dB – and a calibration-error bias of about 0 dB. Finally, the reconstructed profile has been evaluated by means of the average between the two minimum-error solutions.

The reconstructed Z_{hh} profile is quite close to the composite profile except for the core region between 31 and 36 km where both measured reflectivities are strongly attenuated. The effect of the reconstruction of the Z_{dr} profile is quite similar.

Once the range profiles of Z_{hh} and Z_{dr} have been corrected, the hydrometeor classification algorithm at C-band can be applied. Figure 5 shows the results obtained by using FRAHC-C technique on corrected data. At the lowest radar elevation we are observing the rain core. This emerges in Fig. 6 from the predominance of LD and HR classes with some H/R on the left edge of the storm. For comparison, Fig. 7 shows classification results obtained using reflectivity profiles measured from SPC radar without any path attenuation correction. We note that attenuation correction tends to remove hail regions, provides a continuity of HR and MR, and reduces the presence of LD and NC bins.

5 Estimation of Raindrop Size Distribution and Rainrate

A new procedure to retrieve the RSD parameters which can be used to estimate the corresponding rainfall rates has been recently proposed (Vulpiani et al., 2006). The polarimetric variables (Z_{hh} , Z_{dr} , and K_{dp}) are used to retrieve the RSD parameters by means of an ad-hoc neural network (NN) technique. The reason for this choice is the ambition to exploit the capability of NNs to approximate strongly non-linear functions such as those describing the relationships between radar observables and RSD parameters. A stochastic model, based on disdrometer measurements, is used to generate realistic range profiles of raindrop size distribution parameters while a T-matrix solution technique is adopted to compute the corresponding polarimetric variables at S band.

5.1 Neural Network Retrieval Technique

An artificial neural network is a non-linear parameterized mapping from an input $\mathbf{x}$ to an output $\mathbf{y} = NN(\mathbf{x}; \mathbf{w}, \mathbf{M})$, where $\mathbf{w}$ is the vector of parameters relating the

Fig. 5 Composite elaboration scheme with FRAHC-C application to the RHI section corresponding to the conjunction line GAT-SPC. Radar data refer to 2003, 20th of May, 16:34 GMT (See also Plate 17 in the Colour Plate Section)

Fig. 6 Hydrometeor classification using FRAHC-C applied to the corrected profile

Fig. 7 Hydrometeor classification using FRAHC-C applied to SPC data without attenuation correction

input to the output while the functional form of the mapping (i.e., the architecture of the net) is denoted as $\mathbf{M}$. The multi-layer perceptron architecture (MLP), considered here, is a mapping model composed of several layers of parallel processors. It has been theoretically proven that one-hidden layer MLP networks may represent any non-linear continuous function (Haykin, 1995), while a two-hidden layer MLP may approximate any function to any degree of non-linearity also taking into account discontinuities (Sontag, 1992). The NN architecture is such that all nodes are fully interconnected to each other and these interconnections are characterized by weights and biases. The hidden and output nodes are characterized by the activation function f which is generally assumed to be a differentiable non-linear function. Here we chose the sigmoidal function, characterized by the node gain and the node bias (Marzano et al., 2004). The network is trained using supervised learning, with a training set $D = (x_i, t_i)$ of inputs and targets. During training, the weights (w) and biases are iteratively adjusted in order to minimize the so called network performance (objective) function, which normally is the summed squared error:

$$E_D = \frac{1}{2} \sum_{i=1}^N (t_i - a_i)^2 \quad (16)$$

where a_i is the neural network response. The minimization is based on repeated evaluations of the gradient of the performance function using back-propagation, which involves performing computations backwards through the network (Rumelhart, 1986). For the weights w_{jj} , that is the weight of the i -th output node associated to the j -th hidden value, the use of the delta rule leads to the following updating equation

$$\Delta w_{ij} = w_{ij}' - w_{ij} = -\eta_0 \frac{\partial E_D}{\partial w_{ij}} \quad (17)$$

where the w_{jj}' indicates the updated (new) value of w_{jj} and η_0 is the output-layer learning rate. The algorithm is very sensitive to the proper setting of the learning rate. For this reason, a back-propagation training with an adaptive learning rate is crucial. Battiti's "bold driver" technique (Battiti, 1989) has been implemented in this work. Gradient descent may get stuck in local minima of the performance function. The best strategy in this case is to orient the search towards the global minimum, but the form of the error function may be such that the gradient does not point in this direction.

The problem can be overcome by including a momentum term m in the weight updates (Fausett, 1994). In the present study a value of $m = 0.9$ has been assumed (Hagan, 1996). The ideal neural network is characterized by small errors on the training set and the capability to respond properly to new inputs. The latter property is called generalization. The procedure to improve generalization, called regularization, adds an additional term to the objective function which becomes $E_R = \gamma E_D + (1 - \gamma) E_W$. E_W is the sum of squares of the networks weights and biases. In addition we note that, in Aires et al. (2002), the authors

have experimentally proven that, for noisy data, a one-hidden layer MLP network may improve the network generalization through the reduction of the number of parameters. In Bishop (1996), the author demonstrated that, assuming low noise conditions, training with input perturbation is closely related to regularization.

5.2 Raindrop Size Distribution Retrieval

Reflectivity and differential reflectivity are commonly used for RSD retrieval (Gorgucci et al., 2002; Brandes, 2002). Specific differential phase shift is a potential predictor for RSD estimation but it may be affected by a high noise which may perturb the results. Consequently, K_{dp} has been used in Gorgucci et al. (2002) setting a lower threshold of 0.2 deg km^{-1} . It has been found that the proposed algorithm performs well even for very low values of K_{dp} . Moreover, in 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 used. 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} . The shape parameter μ is estimated from Z_{dr} and the retrieved values of D_0 (as suggested in Brandes, 2002) using 2-input (i.e., Z_{dr} , D_0) NN. Consequently, its estimate is indirectly dependent on K_{dp} through D_0 . The proposed RSD retrieval technique can be formalized in the following way:

$$\begin{aligned} & NN_{D_0}(Z_{hh}, Z_{dr}, K_{dp}) \\ & NN_{N_w}(Z_{hh}, Z_{dr}, K_{dp}) \\ & NN_{N_\mu}(Z_{dr}, \hat{D}_0) \end{aligned} \quad (18)$$

if K_{dp} is available, $NN_{D_0}(Z_{hh}, Z_{dr})$ and $NN_{N_w}(Z_{hh}, Z_{dr})$ being used otherwise.

The neural network architecture and regularization parameters have been determined according to a heuristic monitoring of the generalization capability on test data, the root mean square error having been used as metric. According to what is suggested in Aires (2002), it has been found that the one-hidden layer configuration improves the generalization capability of the NNs. The number of nodes in the hidden layer has been fixed to 6 for NN_{D_0} and NN_{N_w} , and 12 for NN_{N_μ} . A choice of $\gamma = 0.7$ has been found to be suitable for the retrieval of all the RSD parameters. The input perturbation technique has also been adopted in order to increase the generalization of $NN_{N_\mu}(Z_{dr}, D_0)$.

5.3 Numerical Results on Synthetic Data

The choice of the architecture, learning algorithm and performance function is crucial for the neural network set up. On the other hand, the training data set also plays an important role to guaranty a high generalization capability. In order to

“regularize” the neural network and test its robustness, a large highly heterogeneous data set has been generated by randomly varying the RSD parameters, the axis ratio relationship and the temperature. The validation of the proposed methodology has been accomplished using realistic range profiles of RSDs generated using a modified version of the stochastic simulator proposed by Berne and Uijlenhoet (2005). It is worth mentioning that it is based on a gamma RSD model with fixed μ (i.e., $\mu = 3$). For this reason we have focused on the retrieval of D_0 and N_w only. Once the polarimetric variables have been generated, a zero mean Gaussian noise with standard deviation equal to 1 dBZ, 0.2 dB and $0.3^\circ \text{ km}^{-1}$ has been added to Z_{hh} , Z_{dr} and K_{dp} , respectively.

The sensitivity analysis has been accomplished in terms of mean error ε , root mean square error RMSE and correlation coefficient r . Figure 8 shows the comparison between the proposed technique and those described in Gorgucci et al. (2002) (named β method) and Brandes et al. (2002) (named C-G method). The median volume drop diameter is estimated fairly well by all examined algorithms. The differences in terms of RMSE are small but the proposed approach shows a larger correlation between the estimated and true RSD parameters. We found that $r(\hat{D}_0, D_0)$ is 0.941, 0.856 and 0.796, respectively, for the NN, C-G and β algorithms. Moreover, the estimation of N_w by means of the β algorithm is affected by a larger error standard deviation and smaller correlation coefficient as compared to the other examined methods. The latter have marked differences, especially in terms of correlation, $r(\hat{N}_w, N_w)$ being 0.943 and 0.854, respectively, for the NN and C-G methods. Once the RSD parameters are estimated using the mentioned algorithms, the corresponding rain rates can be computed using (5). R_{NN} , R_β and R_{C-G} denote the rain rate retrieval algorithms based on the neural network, β , and C-G methods, respectively (see Fig. 9). It has been found that the errors are less than 10 mm h^{-1} in about 98.2, 85.8 and 90.6% of the cases respectively for R_{NN} , R_β , and R_{C-G} .

It is worth mentioning that, while the neural network based technique shows a better performance (RMSE $\sim 3.7 \text{ mm h}^{-1}$, $r = 0.951$), the differences among the other algorithms are small. R_β provides better results in terms of RMSE ($\sim 8 \text{ mm h}^{-1}$) but a reduced correlation ($r = 0.758$), the corresponding values for R_{C-G} being about 11.4 and 0.899.

6 Concluding Remarks

Dual-polarized weather radars are becoming precious tools for both mesoscale meteorology and operational monitoring of precipitation events. Several hydro-meteorological and civil protection agencies are converting their radar systems from single-polarization to dual-polarization. This choice is related to the unique potentialities of this new technology which can enhance the data quality control and the accuracy of the retrieved products.

Polarimetric radars can be fully exploited if new advanced techniques are applied to the data processing chain, especially for what concerns the capability of retrieving microphysical properties of precipitation. In this respect, this contribution

Fig. 8 Error histograms of the retrieved RSD parameters. The *upper panels* refer to results obtained applying the NN technique. The *middle and lower panels* to the β and C-G methods, respectively

Fig. 9 Error histograms of the estimated rain rate. The *upper panel* shows the results obtained applying the proposed NN technique. The middle and *lower panels* show the corresponding results for the β and C-G methods, respectively

has introduced some examples of these new methodologies which couple detailed microwave models with sophisticated inversion approaches.

A new stable backward iterative technique to correct for path attenuation and differential attenuation has been presented. The proposed Neural Network Iterative Polarimetric Precipitation Estimator by Radar (NIPPER) is based on a polarimetric model used to train an embedded neural network, constrained by the measurement of the differential phase along the rain path. The adopted polarimetric model is able to simulate amplitude and phase radar response starting from the characterization of raindrop distributions with respect to shape, size and orientation distribution. Numerical simulations have been used to investigate the efficiency, accuracy and robustness of proposed technique. The performances of NIPPER at C-band have been evaluated by using a radar volume scan generated from S-band radar measurements. The latter have been inverted, using a parametric regression algorithm, in order to estimate the raindrop size distribution. Sensitivity analysis has been performed in order to evaluate the expected errors of NIPPER in terms of reconstructed radar observables.

In order to illustrate a hydrometeor classification procedure, a fuzzy logic approach has been introduced. Appropriate MBFs, modified for C-band and constituting the basis of the Fuzzy-logic Radar Algorithm for Hydrometeor Classification at C band (FRAHC-C) approach, have been determined by means of numerical simulations and then tested on synthetic radar data. The overall classification accuracy has considerably increased with respect to the use of S-band MBFs and average not-classified bins percentage has decreased as well. FRAHC-C technique has been successively applied to the available radar data, showing accuracy improvements directly visible by observation of the classified RHIs. A path-attenuation correction algorithm, based on either a composite approach or a constrained correction procedure, has been also applied to the entire vertical section of the precipitating cloud. As expected, the impact on hydrometeor classification is noteworthy: final results appear more robust and microphysically consistent.

Finally, a new neural network algorithm to estimate the raindrop size distribution from S-band dual-polarized radar measurements has been proposed. The neural-network algorithm exhibits enhanced features to improve its efficiency, robustness and generalization capability. Numerical simulations, performed using the detailed hydrometeor scattering model, have been used to investigate the accuracy of the proposed methodology. The precipitation model has been characterized in terms of shape, raindrop size distribution and orientation. A disdrometer-derived stochastic model has been employed to simulate RSD variability and to construct a test data set. The error analysis, performed in order to evaluate the expected errors of this method, have shown an improvement with respect to other methodologies described in the literature to estimate RSD parameters and, consequently, the corresponding rain rates.

Future developments should aim at developing fully-consistent radar approaches, especially at C band where path attenuation is not negligible. As a matter of fact, most European radars are at C band and the capability to extract accurate precipitation product is still an ambition to pursue. In particular, the various processing steps are inherently related and cannot be treated in a separate way. For instance,

path attenuation should be performed not only for rain, but also for graupel and hail radar range volumes, but this means to be able to pre-classify the radar observation. On the other hand, the latter cannot be performed in an accurate manner if path attenuation is not removed. The same applies to rainrate estimation.

Fully-consistent radar approaches should face the entire problem in a systematic way. Finally, we should not forget that radar polarimetry does not solve the problem of the beam occlusion and the need to reconstruct the vertical profile of reflectivity (VPR) to estimate the near-surface rainfall which is crucial for hydrological applications. Indeed, the vertical correlation of radar polarimetric observables might be exploited even for VPR reconstruction.

Other fundamental issues to deal with are also the calibration of polarimetric radars (in this respect, polarimetric self-consistency can help a lot), the ground clutter and non-atmospheric echo removal (in this respect, polarimetric measurements can provide a unique data set for proper filtering when coupled with Doppler features), the beam filling problem which makes the uniform volume assumption not realistic (in this respect, the differential phase shift may show some advantages), and the comparison with surface measurements such as rain gauges or disdrometers (in this respect, the latter can provide direct estimates of the rain drop size distribution, but still remains the problem of point-to-area comparison when comparing gauges with radar data).

In conclusion, microwave radar polarimetry represents a fundamental step forward in geoscience toward an accurate remote measurement of precipitation systems for a variety of applications, from hydrology to radiopropagation, from civil protection to meteorology.

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