Iterative Bayesian radar methodology for hydrometeor classification and water content estimation a X band

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1. Introduction

The increasing importance of dual-polarized weather radar systems is essentially due to their capability to improve data quality by identifying non-meteorological echoes (i.e., ground and sea clutter, insects, birds, chaff), reduce attenuation effects and partial beam blocking using differential phase measurements, and improve rainfall retrieval by exploiting multi-parameter algorithms (Gorgucci et al., 1996; Zrnic and Ryzhkov, 1996; Bringi and Chandrasekhar, 2001; Testud et al., 2002; Marzano et al., 2007). The exploitation of dual-polarization radar measurements has also opened the unique possibility to detect different hydrometeor classes within the observed storm, giving for the first time a physical basis to the remote particle identification (Bringi et al., 2004; Vulpiani et al., 2008). Most applications have been devoted to the retrieval of rain rates, but the estimation of rainfall in terms of water content is, in general, more consistent with the capability of radar remote sensors which are generally unable to retrieve the fall terminal velocity. In case of raindrops, polarimetric radar response has even been used to retrieve their size distribution where liquid water content is one of the most important parameters.

Among the various techniques, a model-supervised Bayesian method for hydrometeor classification, tuned for S- and X-band polarimetric weather radar, can be effectively applied (Marzano et al., 2008). Once estimated the hydrometeor class, the retrieval of their water content can be also statistically carried out. However, the critical issue of rainfall X-band observations is the significant effect of specific copolar ($A_{hh}$) and differential ($A_{dp}$) attenuations. If the radar power measurements are not completely attenuated below the minimum detectable power level, specific correction techniques can be applied in order to restore the radar range profiles. When dealing with a non-uniform distribution of hydrometeor types along the radar ray, adaptive algorithms should be applied to take into account this spatial heterogeneity. In the following sub-sections we will show how to deal with these issues aiming at estimating the water content within each radar bin, adopting a model-supervised approach. A Bayesian hydrometeor classification framework has been developed and will be used throughout this paper (Marzano et al., 2010).

2. Hydrometeor Classification and Retrieval

The critical issue of rainfall X-band observations is the significant effect of specific copolar ($A_{hh}$) and differential ($A_{dp}$) attenuations. If the radar power measurements are not completely attenuated below the minimum detectable power level, specific correction techniques can be applied in order to restore the radar range profiles. When dealing with a non-uniform distribution of hydrometeor types along the radar ray, adaptive algorithms should be applied to take into account this spatial heterogeneity. In the following sub-sections we will show how to deal with these issues aiming at estimating the water content within each radar bin, adopting a model-supervised approach. A Bayesian hydrometeor classification framework has been developed and will be used throughout this paper (Marzano et al., 2010).
2.1 Iterative Final Value Path Attenuation Correction

Several recent studies have developed algorithms that use the two-way differential phase shift $\Phi_d$ as a constraint parameter for the effective estimation of $A_d$ and $A_m$ profiles. This choice is due to the fact that the phase shift is not affected by attenuation (provided that backscattering signals are still received) and it is almost linearly related with the range-integrated copolar attenuations, expressed in dB. We will refer to co-polar reflectivity $Z_{\infty}$ [mm$^3$ m$^{-1}$] where $\infty$ stands for either horizontal ($hh$) or vertical ($vv$) copolar polarization. The co-polar path-attenuation factor $L_{co}$, up to a given range $r$, can be evaluated from the one-way path-integrated attenuation (PIA) by:

$$L_{co}(r_0, r) = \frac{Z_{\text{sw}}(r)}{Z_{\text{sw}}(r_0)} = e^{-\frac{\pi^2}{4} \int_{r_0}^{r} A_d(r)d'r'} = 10^{-0.06 \text{PIA}_{Z_d}(r_0, r)}$$

(1)

where $Z_{\text{sw}}$ is the measured co-polar reflectivity, $A_d$ [dB/km] is the co-polar specific attenuation and $r_0$ is an arbitrary range value less than $r$. The one-way co-polar PIA [dB] can be estimated from the two-way $\Phi_d$ exploiting the linearity between specific attenuation and specific differential phase. A general formula for the computation of the PIA will be given in the next section. The effects of the backscattering differential phase $\delta_{bh}$ are neglected supposing the use of an effective iterative filtering on $\Delta \Phi_{dph}$ (Bringi and Chandrasekar, 2001). We can assume a power-law relation between specific attenuation $A_{\infty}$ and co-polar reflectivity $Z_{\infty}$:

$$A_{\infty} = a_c Z_{\infty}^{b_c}$$

(2)

where $a_c$ and $b_c$ are assumed polarization dependent, but generally range independent. The final value (FV) attenuation correction solution to the radar equation in attenuating media is given by the following corrected polarized reflectivity:

$$\hat{Z}_{\infty}(r) = \frac{Z_{\text{sw}}(r)}{L_{co}^{bh} + I_{\infty}(r_0, r) - I_{\infty}(r_0, r)}$$

(3)

where the integral $I_{\infty}$ is proportional to the integral of $(Z_{\infty})^b$ (e.g., Marzano et al., 2007).

The FV algorithm is one of the hydrometeor profiling constrained techniques to correct for path attenuation (Bringi and Chandrasekar, 2001). Other similar methods are the attenuation adjustment correction (AA) and the constant adjustment correction (CA), the latter formally equivalent to the $Z_{\infty}^{-}\Phi_d$ (ZPHI) solution once the PIA (and then $L_{co}$) is estimated via $\Phi_{dph}$ (Testud et al., 2002). In this work we preferred to implement the FV technique as we proved that is more accurate than CA when the radar is well calibrated and slightly less accurate than CA when there is a system bias.

2.2 Iterative Bayesian Radar Algorithm

The main problem with the straightforward application of the FV attenuation correction algorithm and the other analytical constrained techniques is that it supposes a homogeneous raindrop medium along each radar ray. This assumption is not usually verified when the elevation angle is quite larger than zero and when dealing with medium-to-long range radar bins. Some approaches have been recently developed to face the intrinsic rain variability by selecting the coefficient in the relationship between specific attenuation and differential phase in an adaptive way. To avoid these limitations, an appealing approach is to extend the FV correction method by segmenting the radar range into contiguous intervals, each one containing a uniform hydrometeor class characterized by different couples of regression coefficients. This means that, in order to deal with a heterogeneous distribution of hydrometeors, we can combine the classification step with the PIA correction technique in an iterative way. In a way, this solution is a generalization to the whole radar polar volume of the self-consistent path-attenuation correction valid for rain media, already proposed in literature. The following power-law relation models between radar observables can be defined for each hydrometeor class:

$$A_{\infty} = a_m Z_{\infty}^{b_m}$$

$$A_{\infty} = a_v K_{av}$$

$$K_{av} = e_{av} A_{db}^{f_{av}}$$

(4)

and in this scenario, the PIA can be defined as:

$$\text{PIA}_{xm}(r_0, r_x) = \int_0^{r_x} A_{\infty}(r)d'r = \sum_j A_{\infty}(r_j)K_{av}(r_j)\Delta r = \frac{1}{2} \sum_j \gamma_{av}(r_j)\Phi_{dph}(r_j)$$

(5)

where the integral has been replaced by a sum since the radar bins are discretized.
The following steps characterize the Iterative Bayesian Radar Algorithm (IBRA):

1. The regression coefficients in (4) for each class are computed from T-Matrix simulations within a certain temperature range of variability.
2. The temperature range profile \( T(r) \) is assumed to be known and the range \( r_i \), corresponding to the freezing level along \( r \), is detected.
3. The polarimetric measurements \( Z_{\text{cloud}}(r), Z_{\text{conv}}(r) \) and \( \Phi_{dpm}(r_i, r) \) between the initial range \( r_i \) and the final range \( r_f \) are assumed to be available, after detecting the precipitating-cloud edges at \( r_i \) and \( r_f \) using a reflectivity threshold. Indeed, \( r_f \) can be also set to the maximum radar range in order to preserve some attenuated, but still detectable, signals.
4. The radar range, between \( r_i \) and \( r_f \), is thus divided in \( N \) sub-intervals, depending on the identified hydrometeor class. The \( n \)-th sub-interval contains a given number of radar bins. At each iteration step, these \( N \) sub-intervals are defined by the spatial extension of contiguous range bins characterized by an identical hydrometeor class. The partition of hydrometeors into classes is obtained by applying the BRAHC-X algorithm to the available polarimetric measurements. Since BRAHC will give different results at each iteration, the number \( N \) of the sub-intervals will change consequently.
5. For each sub-interval the FV path-attenuation correction is applied to derive the range profile of the specific attenuation \( A_{\text{sub}}(r) \) and, using (3), the corrected co-polarized reflectivities \( Z_{\text{sub}}(r) \).
6. By using the reconstructed \( Z_{\text{sub}}(r) \), \( Z_{\text{sub}}(r) \) and \( T(r) \), the BRAHC-X approach can be applied to each sub-interval to derive a new range distribution of hydrometeor classes \( c(r) \). This implies that, using (4), we can construct a matrix of the regression parameters, \( \mathbf{p} \), with size \( 5 \times N \), composed of the regression coefficients for each sub-interval.
7. For each range bin belonging to the \( n \)-th sub-interval, the estimated \( K_{dp}(r) \) is recomputed from \( A_{\text{sub}}(r) \) using the identified class \( c \) and the corresponding regressive relations. Thus, the total reconstructed differential phase shift \( \Delta \Phi_{dp}(r_i, r_f) \) can be derived from the estimate of the specific attenuation for each sub-interval through:

\[
\Delta \Phi_{dp}(r_i, r_f) = 2 \left[ \sum_{n} \sum_{k} K_{dp}(r_i) \Delta r = 2 \sum_{n} \sum_{k} e_{\text{p}}(n) \left[ A_{\text{sub}}(r_i) \right]^{e_{\text{p}}(n)} \Delta r \right]
\]

where the index \( k \) refers to the bins within the \( n \)-th sub-interval and the regression coefficients \( e_{\text{p}}(n) \) and \( f_{\text{p}}(n) \) vary according to the class \( c \) within each \( n \)-th sub-interval.
8. If the differences between total reconstructed differential phase shift \( \Delta \Phi_{dp}(r_i, r_f) \) and the measured one \( \Delta \Phi_{dp}(r_i, r_f) \) is assumed to be normally distributed and uncorrelated with a uniform a priori probability, using again the Bayes theorem we can minimize the square distance metrics with respect to the elements of the parameter vector \( \mathbf{p} \):

\[
d^2(\mathbf{p}) = \left| \Delta \Phi_{dpm}(r_i, r_f) - \Delta \Phi_{dp}(r_i, r_f) : \mathbf{p} \right|^2
\]

where the parameter vector \( \mathbf{p} \) has been previously defined (see step 6) and obviously changes at each iteration step.
9. If the distance \( d(\mathbf{p}) \) is less than a specified threshold distance \( d_{\text{th}} \), then the IBRA algorithm is ended and the corresponding parameter vector \( \mathbf{p} \) is chosen has the most probable solution. Otherwise, the steps from 4 to 8 are iterated. In order to avoid algorithm loops, a maximum number \( \text{M}_{\text{max}} \) of iterations is envisaged (typical value of \( \text{M}_{\text{max}} \) is 10 after that the best iteration in terms of distance is selected).

The IBRA algorithm is eventually repeated for both co-polar horizontal and vertical polarization and for each ray \( r(\theta, \varphi) \) along all available elevation \( \theta \) and azimuth \( \varphi \) angles.

Note that information about the texture around the considered radar ray could be also included within the differential phase minimization functional in (7). In principle, any constrained technique for PIA correction either analytical or numerical (e.g., discrete iterative or neural-network based) can be implemented within the iterative Bayesian scheme.

3. Case Study

The International H2O Project (IHOP) experiment lasted about two months, from May to July 2002, and a number of storm cases of various intensity and structure were observed (Weckwerth et al., 2004; Anagnostou et al., 2006). During IHOP, two different weather radars at S band and X band were deployed in western Oklahoma. Several closely matched dual-polarization plan position indicator (PPI) observations were performed using the National Observatory of Athens (NOA) mobile X-band dual-polarization radar (XPOL), together with the National Center for Atmospheric Research (NCAR) S-band polarimetric radar (SPOL).
During storm developments the mobile XPOL radar was deployed a few meters from the SPOL one, and they were operated with synchronized scanning strategies. In the following we will assume that S-band measurements will represent a reference target ("truth") which X-band data will be compared to. This means that we will neglect all geometrical errors due to space-time superimposition of the SPOL and XPOL measured fields. Moreover, in order to avoid differences due to the classification method, we have applied methodologies to S-band data similar to those used for X-band, such as BRAHC and power-law models.

3.1 Retrieval Results

An intense convective event took place during the night between the 15th and 16th of June, 2002. Surface temperature was estimated to be around 20 °C with an average vertical gradient of 7 °C/km. This means that the freezing level is detected around a 3-km height.

A sample of coincident X-band and S-band $Z_{hh}$ plan position indicator (PPI) maps at 1.2° and 6° elevation angle are shown in Fig. 1 on June 16, 2002, at 01:00 UTC. The PPI radius is 60 km. It is worth noting the fairly high X-band co-polar path attenuation occurring in the North-East (NE) quadrant when comparing the S-band image with the X-band one. This $Z_{hh}$ signal attenuation is more pronounced at 1.2° elevation than at 6° elevation, as expected due to the different altitudes of the radar range bins and the relative occurrence of raindrops. At 1.2° the range bin around the FL is beyond 60 km, whereas at 6° is at about 30 km so that, above that range, we expect the presence of less-absorbing ice hydrometeors. PIA correction algorithms have been applied to the XPOL radar data in order to correct for the path attenuation previously observed. Fig. 1 also illustrates, for the same acquisition, what can be obtained using the IBRA attenuation correction technique. The IBRA restoration of $Z_{hh}$ is appreciable within the above mentioned NE sector, especially at 1.2° elevation where the encountered rainfall is more intense.

![Fig. 1](image1.png)

**FIG. 1.** Horizontal copolar reflectivity PPI ($Z_{hh}$) at S (left column), X band (center column) and X band IBRA corrected (right column) at 1.2 (first row) and 6 (second row) degrees elevation measured on June 16, 2002 at 01:00 UTC.

The IBRA correction algorithm can be applied to retrieve differential reflectivity polar volume as well. Fig. 2 shows the same as in Fig. 1, but for the $Z_{dr}$ PPI at S and X band. Again the north-east sector is the most affected by differential attenuation, especially at low elevation angles. Value of X-band $Z_{dr}$ may be as negative as about – 4 dB at far range. After the application of IBRA PIA-correction, the negative regions of X-band $Z_{dr}$ are basically removed as expected when attributed to oblate falling raindrops. It is interesting to note that, at higher elevation, negative values of X-band $Z_{dr}$ are still present even though not visible in the S-band corresponding areas: this might be a residual
error of the IBRA algorithm, but it might also be a response of vertically-oriented ice crystals which are not necessarily detected at longer wavelengths.

![Figure 2](image1.png)

**FIG. 2.** Plan Position Indicator (PPI) of hydrometeor classification PPI at S (left column) and X band corrected with IBRA algorithm (right column) at 1.2° (top panel) elevation measured on June 16, 2002 at 01:00 UTC.

Once reconstructed the X-band polarimetric observables, we can apply the BRAHC classification algorithms to obtain the hydrometeor maps from both S- and X-band PPI's. This is shown in **Fig. 3** where the 12 hydrometeor classes are labeled in different colors. Consistently with what previously guessed at 1.2° elevation, from S-band results the NE sector is characterized by low to heavy rain with embedded some large drops cells. This hydrometeor pattern is well reproduced by the X-band classification with some differences behind the region with the most intense rainfall where path attenuation is more difficult to be restored. At 6° elevation the ice crystal cap has a well distinct signature with some embedded dry-snow retrieved by S-band algorithm only. The wet-snow transition between the rain portion and the ice-crystal region is detected with some differences between S and X band in the northern direction.

![Figure 3](image2.png)

**FIG. 3.** As in Fig. 2, but for the hydrometeor equivalent water content.

The inversion of radar data into water content estimates can be performed using, for each detected hydrometeor class, the outlined power-law regression. This is the last step of the IBRA algorithm. **Fig. 4** shows estimated water content PPI's from SPOL and XPOL IBRA-corrected data of Figs. 1 and 2. Note that the water content may be in water, ice or mixed phase according to the detected hydrometeor class. The S-band water content signature exhibits its peaks where rainfall is dominant. Small regions around the mesoscale convective system show that the water content of large drops, detected in **Fig. 3** at low elevation angle. At X-band we obtain results very similar to the S-band one in the restored-signal regions at both elevations. Extended results and correlation study have been fully described.

4. Conclusion

A supervised hydrometeor classification technique, based on the Bayesian theory, has been illustrated and coupled with path attenuation correction and water content estimation techniques at X band. The overall scheme, called Iterative Bayesian retrieval algorithm (IBRA), has been discussed in detail providing the expected error budget.
of each step. The IBRA methodology is quite flexible as it can, in principle, ingest different path attenuation correction algorithms and hydrometeor classification techniques as well as a priori meteorological information.

Using data from SPOL and XPOL weather radars, during a case study observed within the IHOP campaign, a comparison between the results obtained at the two frequency bands has been discussed, showing some potentials and limitations of the X-band precipitation retrieval. In order to keep the consistency within the algorithm intercomparison, at S band a methodology similar to that used at X band (except for the path attenuation correction) has been developed. The use of the IBRA approach increases the correlation between water content estimates at X and S band from about 70% to about 80% at low elevation angles and from 55% to 60% at higher elevation angles.

The critical issue when applying any PIA correction algorithm to X band measurements is the availability of the signal above the noise at a given range. Our results further confirm, as expected, that when PIA is large and the signal-to-noise ratio is low, any restoration algorithm tends to fail. The way to tackle this problem may be, on the one hand, to expand the receiver dynamics and, on the other hand, to exploit a radar network concept so that any attenuated region may be observed by another radar, probably not affected by the overwhelming PIA.

A systematic validation test of the IBRA methodology on a large set of case studies will be the goal of future work, possibly using co-located S-band measurements (as during IHOP) together with available rain gauge and rain disdrometer data.

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