

Hydrometeor classification methodology for C-band polarimetric radars

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Abstract. Classification of hydrometeors has a wide variety of applications such as validation of cloud microphysical models, choice of algorithm for precipitation estimation and evaluation of assumptions made in the precipitation retrieval processes as well as validation of space borne observations. Dual-polarization radar measurements are sensitive to hydrometeors properties such as size, shape, phase state and fall behavior, they can be used for hydrometeor classification purposes. Over the last decade the topic of dual-polarization radar measurements to classify hydrometeors has been investigated extensively at S-band. Fuzzy logic based approaches to perform robust hydrometeor classification have emerged because of their ability to provide distinct decisions with overlapping conditions and noisy data. Essentially, two classes of independent models, for hydrometeor classification have evolved, namely the CSU model and the NCAR/NSSL model.

Most of available literature on this topic is from S-band radar observations. Only recently, some work related to hydrometeor classification at C-band is being initiated. Adapting a hydrometer scheme devised for S-band to C-band measurements is not straightforward. Different backscattering and propagation properties, attenuation effects on radar observations should be taken into account in the classification scheme. This paper discusses issues related to advancing the CSU hydrometeor classification scheme for C-band frequencies. Results of preliminary development are presented.

ments to retrieve microphysical properties and to identify hydrometers. Classification of hydrometeors has a wide variety of applications such as:

- initialization and validation of cloud microphysical models
- choice of the proper algorithm for precipitation estimation
- choice of the proper algorithm for attenuation correction
- evaluation of assumptions made in the precipitation retrieval processes.

The mapping from polarimetric radar measurement space to hydrometeor classes is not one to one. Boolean classification techniques, such as decision tree cannot be applied. Fuzzy Logic Systems (FLS) represents an attractive approach, because of their ability to:

- combine objective knowledge and subjective knowledge
- manage linguistic a-priori knowledge
- manage classification in the presence of imprecisely defined class output
- cope with non mutually exclusive conditions
- cope with approximate reasoning.

1 Introduction

Hydrometeor types, shapes and size distributions as well as fall behaviors determines polarimetric radar measurements. Extensive information about the microphysics of hydrometeors is thus embodied in the polarization diversity radar measurements. This lends the utility to utilize these measure-

Straka et al. (2000) tried to synthesize the a-priori knowledge about polarimetric radar measurements of the prevailing (in radar sense) hydrometeor type into a set of “fuzzy” relations. These fuzzy relations were derived from published studies at S-band, but some of them were extrapolated from studies concerning different bands, including the C-band. Liu and Chandrasekar (2000) presented arguments for synthesizing all the knowledge base of polarimetric radar measurements, using fuzzy logic to perform robust, hydrometeor

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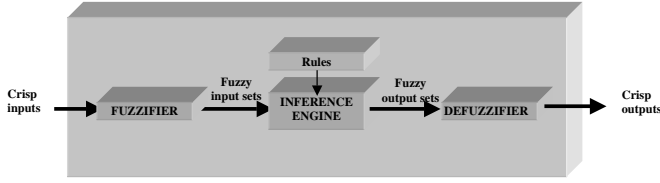


Fig. 1. General scheme of a Fuzzy Logic System.

classification. They also provided validation with in-situ aircraft data (this method will be henceforth referred as the CSU model). A learning mechanism, based on a neural network approach was also considered to tune the membership functions. Vivekanandan et al. (1999) and Straka and Zrni (2001) have also presented and evaluated a different approach (hereafter referred as the NCAR/NSSL model) for hydrometeor classification.

CSU and NCAR/NSSL models differ in the input measurements, the choice of membership function and the inference engine. An improved version of the CSU model was proposed later by Lim et al. (2001).

All the mentioned approaches were devised, proposed and tested for S-band. Most of the European radar network is at C-band. Therefore it is important to have similar methods for polarimetric radars operating at C-band. C-band systems have larger differential phase measurements, reduced antenna size, and, finally, an overall low cost with respect to that of a S-band system with similar resolution characteristics. Moreover, in Italy, the new national radar network will include several C-band radars with the ability to measure Z_h , Z_{dr} and Φ_{dp} . Consequently, hydrometeor classification systems for C-band have also perspective for deployment in operational weather services.

Recent papers refer about some classification schemes adapted for C-band polarimetric radars. Höller et al. (1994) proposed a classification method based on a decision tree approach to study the evolution of a hail-generating event. Keenan (1999) introduced a fuzzy logic classification scheme based on an additive inference engine. Z_h , Z_{dr} , K_{dp} and ρ_{co} were employed to define membership functions in two-dimensional subspaces, coupled with a temperature-dependent membership function. Alberoni et al. (2002) investigated some summer storms through a straightforward application of the NCAR/NSSL model to the C-band polarimetric data (Z_h and Z_{dr} only) from the GPM 500C operational radar managed by the environmental agency of the Emilia-Romagna (Italy) regional government.

In general, the extension of hydrometeor classification methods to C-band is not straightforward. Two main issues should be taken into consideration:

- synthesizing new membership functions taking into account different scattering properties of the hydrometeors at C-band
- correcting propagation effects

The objective of this study is to devise a methodology to extend the CSU model for C-band applications.

In the following section the knowledge base for Hydrometeor classification will be recalled. Next, basic schemes for hydrometeor classification will be introduced and discussed. Eventually, the last section will deal with the specific problems related to the C-band implementation.

2 Polarimetric radar measurements and their potential for discriminating hydrometeors

Both CSU and NCAR/NSSL models adopt a set of polarimetric measurements constituted by the reflectivity factor (Z_h), the differential reflectivity (Z_{dr}), the linear depolarization factor (LDR), the co-polar correlation coefficient (ρ_{co}), and specific differential phase shift (K_{dp}) (see Bringi and Chandrasekar, 2001 for definitions).

Z_h , Z_{dr} and LDR are real (power) measurements and, at C-band, are affected by propagation effects. Z_h alone has a limited usefulness for discriminating hydrometeor. Anyway, the presence of high values of Z_h can be adopted to reduce misclassification of hydrometeors like drizzle and ice crystals which determine low Z_h . Z_{dr} is very sensitive to the shape and orientation of precipitation particles. Therefore, it is a good discriminator between oblate rain and spherical hail. LDR depends on nonsphericity, orientation, canting, and dielectric constant of precipitation particles. Tumbling wet nonspherical particles such as melting graupel can be identified with large LDR values, whereas drizzle and dry ice particles are associated with low LDR values. The complex co-polar correlation coefficient has amplitude and phase. From amplitude, we define ρ_{co} adopted in the classification model. ρ_{co} does not depend on radar calibration. It decreases as particle diversity increases and can be useful to identify melting particles or mixed precipitation.

At radar frequencies where the attenuation is negligible such as S-band, the main outcome of propagation through precipitation is the differential phase shift Φ_{dp} . At C-band, the measured differential phase shift includes also the backscattering component usually indicated as δ_{hv} that is typically neglected at S-band, but it is not at C-band. The propagation differential phase K_{dp} is half of the range derivative of Φ_{dp} and is proportional to the water content in a rain path, and is one of the important parameters measured. K_{dp} can be used to isolate anisotropic hydrometeors such as rain from isotropic hydrometeors such as tumbling hail. K_{dp} estimators at C-band should however filtered out the δ_{hv} contribution (Bringi and Hubbert, 1995). K_{dp} scales with frequency and, therefore, at C-band an improved sensitivity to power and differential phase measurements is expected.

S-band polarimetric research radars usually provide several measurements which include Z_h , Z_{dr} , LDR, ρ_{co} and Φ_{dp} , used to derive K_{dp} . Usually C-band meteorological radars provide only a subset of these measurements. Reduced implementation of the schemes proposed at S-band should be adopted for C-band.

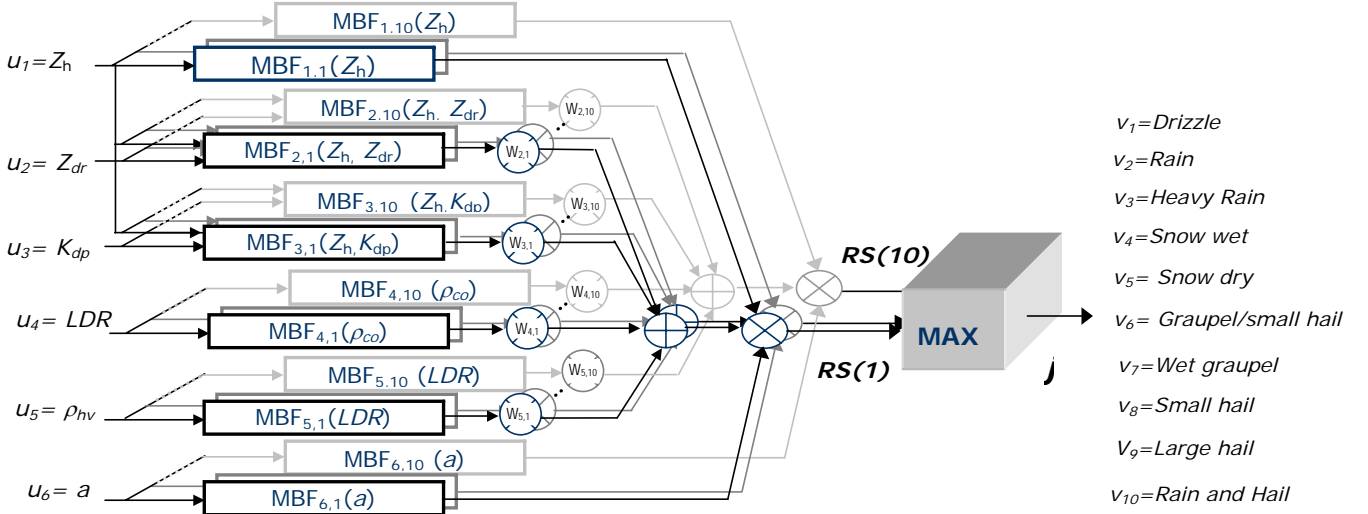


Fig. 2. The current CSU hydrometeor classification model.

3 Fuzzy logic approach for hydrometeor classification

A Fuzzy Logic System (FLS) provides a non linear mapping of input data vector (“crisp” inputs) into scalar output (“crisp” outputs) (Mendel, 1995). A FLS can be explained with reference to Fig. 1, where the FLS is decomposed into three parts, which are the Fuzzifier, the Inference engine, and the Defuzzifier. The fuzzifier is a block which converts crisp inputs (objective measurements) into fuzzy sets. A crisp inputs can belong to different fuzzy sets with different degrees of membership, defined by a membership function (MBF). The inference engine is a block governed by a number of a-priori established rules mapping fuzzy sets into fuzzy sets according to the set of rules, assessing the strength of the rule. The defuzzifier is a process that finds the crisp output which best represents the fuzzy output set determined according to the inference engine. When this scheme is applied to the hydrometeor classification system case, crisp inputs are polarimetric radar measurements and the crisp output is an index corresponding to a specific hydrometeor class. Implementations of FLSs for hydrometeor classification can differ from:

- The “crisp” inputs.
- The hydrometeor classes (Crisp outputs).
- The form of membership function.
- Inference engine.

The CSU model described in Liu and Chandrasekar (2001) uses as input the measurements ($Z_h, Z_{dr}, LDR, \rho_{co}, K_{dp}, h$), h denoting the height of the measurement, thus avoiding exogenous inputs. NCAR/NSSL model uses the same set of polarimetric measurements and the temperature instead of h .

In the fuzzifier block of the CSU model, one-dimensional Beta membership functions were adopted. These functions are characterised by a continuous derivative, a property

which become useful to implement adaptive mechanisms. Only in the case of Z_{dr} , a specific 2-D membership functions based on (Z_h, Z_{dr}) is adopted.

At the inference engine stage the strength of the rule j is obtained as the product of the strength of individual proposition as:

$$RS_j = B_j^{Z_h}(Z_h) B_j^{Z_{dr}}(Z_h, Z_{dr}) B_j^{K_{dp}}(K_{dp}) B_j^{\rho_{hv}}(\rho_{hv}) B_j^{LDR}(LDR) B_j^h(h) \quad j = 1, \dots, M \quad (1)$$

where B_j^X represents the membership function for hydrometeor class j and measurement X . This multiplicative approach minimizes the occurrence false classification: if, for a given class, one measurement is significantly out of range, the low value of the corresponding MBF will suppress the class. No weighting functions are adopted, so that radar measurements are considered equally reliable. The crisp output is given by the index corresponding to the maximum of the RS_j .

On the other hand, the NCAR/NSSL model adopts an additive approach which allow to maximize the probability of correct classification. This is a classical problem of balancing probability of error and probability of detection. The defuzzification is based on the search of the index of the class which determines the strongest rule.

Weights and 2-D Beta function have been adopted CSU model described by Lim et al. (2001). The rule strength becomes:

$$RS_j = \left[W_j^{Z_{dr}} A_j^{Z_{dr}}(Z_h, Z_{dr}) + W_j^{K_{dp}} A_j^{K_{dp}}(Z_h, K_{dp}) + W_j^{\rho_{hv}} A_j^{\rho_{hv}}(\rho_{hv}) \times W_j^{LDR} A_j^{LDR}(LDR) \right] \times A_j^{Z_h}(Z_h) \times A_j^a(a) \quad j = 1, \dots, M \quad (2)$$

where W_j^X and A_j^X represent the weight and the membership function associated with hydrometeor class j and measurement X , and a , which replaces h , indicates the height of the

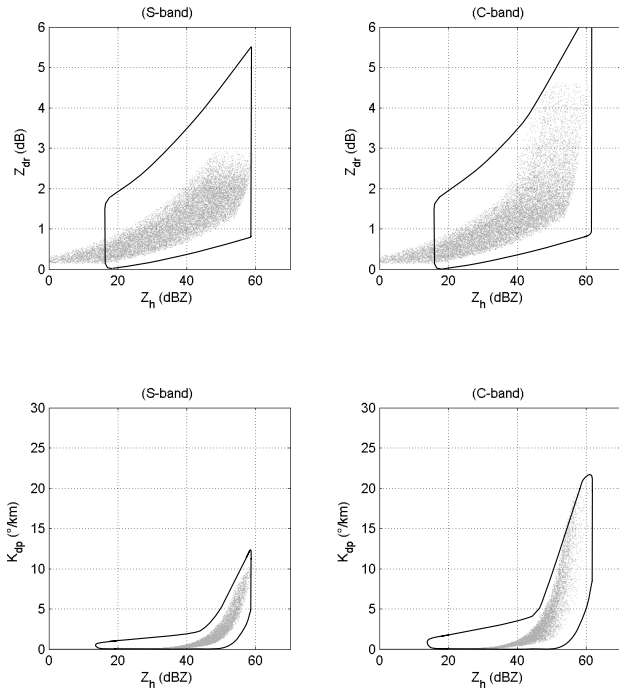


Fig. 3. (Z_h, Z_{dr}) and (Z_h, K_{dp}) membership functions for rain at S-band and C-band. Contour lines at 0.99.

melting layer, derived from the vertical profile of Z_{dr} . The weights of LDR depend on the cross-polar signal to noise ratio. If it is below 10 dB the weight of LDR is set to zero, implying that LDR measurement is discarded. Usually, ρ_{co} has the lowest weight, while Z_{dr} has the highest. Figure 2 illustrates the scheme of this classifier.

4 Extending the CSU model to C-band radar data

In this section we refer to the specific problem of membership function modification. The choice and the number of hydrometeor classes are usually determined a priori according to the applications and available data. Current CSU hydrometeor classification scheme considers this reduced set of hydrometeor type:

- Drizzle
- Rain
- Wet Snow
- Dry Snow
- Graupel / Small Hail
- Hail
- Rain/hail mixture

Membership functions adopted within the CSU and other schemes at S-band are derived taking into account the existing knowledge base for this band. These functions cannot be

applied directly to C-band, since at this band, the resonance effects due to Mie scattering, usually neglected at S-band, notoriously affect radar measurements. Differences in the measurements at C- and S-band were analysed by Bringi et al (1991), who presented and validated results from simulated measurements at C- and S-band. In case of rain, resonance effects result in different range of polarimetric measurements for a given range of DSD parameters. In the previously mentioned paper, differences between radar measurements at C- and S-band were highlighted in the (Z_h, Z_{dr}) plane, in ρ_{co} , which can achieve a minimum of 0.94 at C-band, and, finally, in δ_{hv} , which, however, is not taken into account in the classification schemes. Similar effects occur in the presence of mixed phase precipitation. Membership functions at C-band should take into account these effects. To illustrate these consequence on membership functions, we have chosen the 2D-Membership used in the CSU model, properly scaled for C-band. Scatterplots of simulated radar measurements are obtained according to Bringi and Chandrasekar (2001). Figure 3 shows the difference between the 2-D membership functions for rain at C- and S-band.

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