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IMPLEMENTATIONS OF CSU HYDROMETEOR CLASSIFICATION SCHEME FOR C-BAND POLARIMETRIC RADARS

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1. INTRODUCTION

Dual-polarization radar measurements are sensitive to hydrometeor properties such as shape, phase state, and fall behaviour (Bringi and Chandrasekar 2001) so that they can be used for hydrometeor classification purposes. The differential reflectivity (Z_{dr}) is sensitive to the shape and orientation of precipitation particles: it can discriminate rain from spherical hail. The linear depolarization ratio (LDR) is sensitive to shape and orientation, canting, and dielectric constant of precipitation particles, so that tumbling wet nonspherical particles result in large LDR, while drizzle and dry ice particles are associated with low LDR. The magnitude of the co-polar correlation coefficient (ρ_{co}) can be useful to identify melting particles or mixed precipitation. The specific differential phase (K_{dp}) can isolate anisotropic hydrometeors from isotropic ones. The reflectivity factor (Z_h) is used to further enhance classification.

However, the mapping from polarimetric radar measurement space to hydrometeor classes is not one to one so that Boolean classification techniques cannot be successfully applied. Fuzzy logic represents an attractive approach, since it can a) combine objective knowledge and subjective knowledge, b) manage classification in the presence of imprecisely defined class output, c) cope with overlapping conditions, and d) deal with approximate reasoning.

Fuzzy logic based hydrometeor classification systems (HCS) have been successfully applied and evaluated mainly with S-band polarimetric radars (Vivekanandan et al. 1999, Liu and Chandrasekar 2000, Zrnić et al. 2001, Ryzhkov et al. 2005, Lim and Chandrasekar 2005). Adaptation of such classification schemes to C-band is becoming increasingly important, especially because of the extensive use of C-band dual polarization radar systems in Europe. For example, in Italy, the new national radar network will include several C-band radars with the ability to measure Z_h, Z_{dr} and differential phase shift. Consequently, HCSs working at C-band may also be used for deployment in operational weather services.

Examples of HCSs used at C band are reported in the literature. Höller et al. (1994) applied a decision tree classification to study the evolution of a hail-generating event. Keenan (1999) introduced a fuzzy logic classification scheme based on an additive inference engine which is used in a quasi-operational mode in Australia. Cremonini et al. (2004) studied the sensitivity of two different fuzzy logic classification approaches using Z_h and Z_{dr} measurements from different C-band radars in Northern Italy.

This paper transforms the CSU algorithm for hydrometeor classification (Liu and Chandrasekar 2001, Lim and Chandrasekar 2005) for C-band applications. Modifying the CSU classification scheme to C-band requires some adaptations, which include both the adjustment of the membership functions and the adoption of implementations for the reduced set of measurements available in current C-band radars. Implementations of the C-band version of the CSU hydrometeor classification scheme to two different C-band radars, namely the Polar 55C radar (Rome, Italy) and the ARMOR (Huntsville, AL) are presented and discussed in the paper.

2. THE CSU HYDROMETEOR CLASSIFICATION SYSTEM

A fuzzy logic system (FLS) provides a non linear mapping of input data vector (“crisp” inputs) into scalar output (“crisp” outputs). The *fuzzifier* is a block which converts crisp inputs (objective measurements) into fuzzy sets. Crisp inputs can belong to different fuzzy sets with different degrees of membership, defined by a membership function (MF). The *inference engine* is a block governed by a number of *a priori* established rules mapping fuzzy sets into fuzzy sets according to the *rule strength*. 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 classification of hydrometeors, crisp inputs are polarimetric radar measurements and crisp output is an index corresponding to a specific hydrometeor class. Implementations of FLSs for hydrometeor classification can differ from a) The choice of crisp inputs, b) the choice of the hydrometeor classes (Crisp outputs).c) the form of the membership functions d) the inference engine.

The CSU hydrometeor classification system was proposed by Liu and Chandrasekar (2000), who presented arguments for synthesizing all the knowledge base of polarimetic radar measurements, using fuzzy

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logic to perform robust, hydrometeor classification and provided validation with in-situ aircraft data. A learning mechanism, based on a neural network approach was also considered to tune the membership functions. The system uses as input the (Z_h, Z_{dr}, LDR, ρ_{co}, K_{dp}, h) set, h denoting the height of the measurement. The fuzzifier block of the model uses Beta membership functions, characterized by a continuous derivative, a property that becomes useful to implement adaptive mechanisms. At the inference engine stage the strength of each rule was obtained as the product of the strength of individual preposition. The 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 rule strength. Other models (Vivekanandan et al. 1999, Keenan et al. 1999), adopt an additive approach which allow maximizing 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.

The CSU model has evolved in order to embody both approaches. In its latest version (Lim and Chandrasekar 2005), the rule strength is expressed as:

$$RS_j = \left[W_j^{Zdr} B_j^{Zdr}(Z_h, Z_{dr}) + W_j^{Kdp} B_j^{Kdp}(Z_h, K_{dp}) + W_j^{\rho_{hv}} B_j^{\rho_{hv}}(\rho_{hv})\right] \times B_j^{Z_h}(Z_h) \times B_j^{a}(a) \qquad j = 1,..,M \tag{1}$$

where W_j^X and B_j^X represent the weight and the beta membership function associated with hydrometeor class j and measurement X; a, which replaces h, indicates the height relating to environmental melting layer, which is derived from the vertical profile of Z_{dr}. Weights allow to adapt the system to different radars. By setting $W_j^X = 0$ j=1,..,M, the input X is not considered, thus allowing implementation of the HCS with a reduced set of input measurements. Usually, ρ_{co} has the lowest weight, while the (Z_h, Z_{dr}) pair takes the highest one.

The choice and the number of hydrometeor classes are usually *a priori* determined according to the applications and available data. The classification scheme adopted here considers a first output set (preliminary output) composed by 1) drizzle, 2) rain 3) heavy rain, 4) wet snow, 5) vertical ice, 6) dry snow, 7) graupel/s. hail, 8) wet graupel, 9) small hail, 10) large hail, 11) small hail-rain mixture, 12) large hail-rain mixture. Combining potentially overlapping categories, this set can be reduced to the final output set of 9 classes (final output) composed by 1) drizzle; 2) rain; 3) wet snow; 4) dry snow; 5) graupel/s. hail; 6) Small hail, 7) large hail 8) small hail-rain mixture 9) large hail-rain mixture.

3. ADAPTING THE CSU MODEL TO C-BAND RADAR DATA

In general, the extension of hydrometeor classification methods to C-band is not straightforward (Baldini et al. 2004). Two main issues should be taken into consideration:

1) synthesizing new membership functions taking into account different scattering properties of the hydrometeors at C-band
2) taking in to account propagation and resonance effects

Membership functions adopted within the CSU and other schemes at S-band were derived from the existing knowledge base concerning 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, affect radar measurements. In rain, for example, resonance effects result in different range of polarimetric measurements for a given range of DSD parameters. These effects have been analyzed using also theoretical simulations in order to synthesize membership functions for the C-band case. Main findings are summarized below.

As far as rain is concerned, Z_h at C-band is affected by resonance effects only in case of intense rainfall, while for Z_h greater than 40 dBZ, Z_{dr} can achieve greater excursions at C- then at S-band: when Z_h=50dBZ, Z_{dr} varies between 1.3 and 3dB at S-band, while it can reach values around 4 dB at C-band. These range of variability at C-band is considered in the membership functions for the plane (Z_h-Z_{dr}). Higher values of LDR can be found in heavy rain at C-band, bordering with boundaries that can be expected for graupel. Z_{dr} will help in the discrimination here. In rain, lower values are expected for ρ_{co} at C-band, where it can achieve a minimum of 0.94. For K_{dp} the scaling with the frequency can be adopted. The phase shift on backscattering δ_{hv} is also significant at C-band.

For low density ice, such as dry graupel, same MFs can be used at S- and C- band. For hail also the membership functions are similar, except for melting hail; there LDR values are higher by a couple of dB at C-band. Higher values are also expected for Z_{dr}. Similar effects occur in the presence of mixed phase precipitation.

The need to correct C-band radar reflectivity and differential reflectivity for attenuation effects has long been recognized for quantitative rainfall estimation. However, attenuation effects can lead to wrong hydrometeor classification as well. Here a method based on a rain profiling algorithm (Testud et al. 2000) and a simple linear relation between attenuation at horizontal polarization and differential attenuation with parameters estimated from simulation has been adopted to correct rain attenuation.

4. IMPLEMENTATIONS OF THE MODEL AND RESULTS

The CSU scheme has been adapted and tested for the ARMOR and Polar 55C radars.

ARMOR is a scanning dual-polarimetric Doppler radar operating at C-band (5625 MHz) with a beam width of 1 deg. It was originally deployed in Huntsville by the National Weather Service as a local warning radar. It was refurbished and upgraded to Doppler in 1991. The radar was donated to the UAH Dept. of Atmospheric Science in 2002 and upgraded to dual-polarimetry in fall 2004. It provides real time estimate of Z_h, Z_{dr}, K_{dp}, ρ_{co}, and the moments of the Doppler velocity spectrum.

The classification scheme has been applied to data collected on 21 February 2005 when a slow-moving cold front determined several hailstorms in the region observed by the radar. Some of these hailstorms were characterized by large (dime or golf-ball sized) hailstones.

The radar adopted a volume scan strategy with 19 PPI sweeps. Figs. 1(a-d) show polarimetric measurement interpolated on a 0.4×0.4 km grid in range-height coordinates. The weights adopted by Lim and Chandresekar (2005) for the scheme without LDR have been used in the HCS. The final output of the HCS is shown in Fig. 1e. Contours refer to corrected reflectivity factor. A heavy precipitation cell embodying a region of hail mixed is shown. A core of large hail mixed with rain close to the ground is detected by the classification scheme.

The second case refers to the C-band Polar 55C radar installed in Rome (Italy). In its current configuration, the radar implements the alternating polarization scheme using a single receiver to provide real time estimates of Z_h, Z_{dr}, K_{dp}, and the moments of the Doppler velocity spectrum.

Observations concern a summer convective precipitation system, characterized by the presence of sparse intense rain cells, occurring in Central Italy on 26 July 2004. Some of these cells were studied through RHI scans collected by the Polar 55C radar. The CSU classification system was implemented for Z_h and Z_{dr} only. In this case the rule strength in (1) is expressed by the product of the membership functions.

Figs. 2ab show Z_h and Z_{dr} measurements of a single cell, while Fig. 2c shows the results of classification. This cell did not produce hail at ground. The classification, based on just two measurements can make known the structure of the cell.

5. ACKNOWLEDGMENTS

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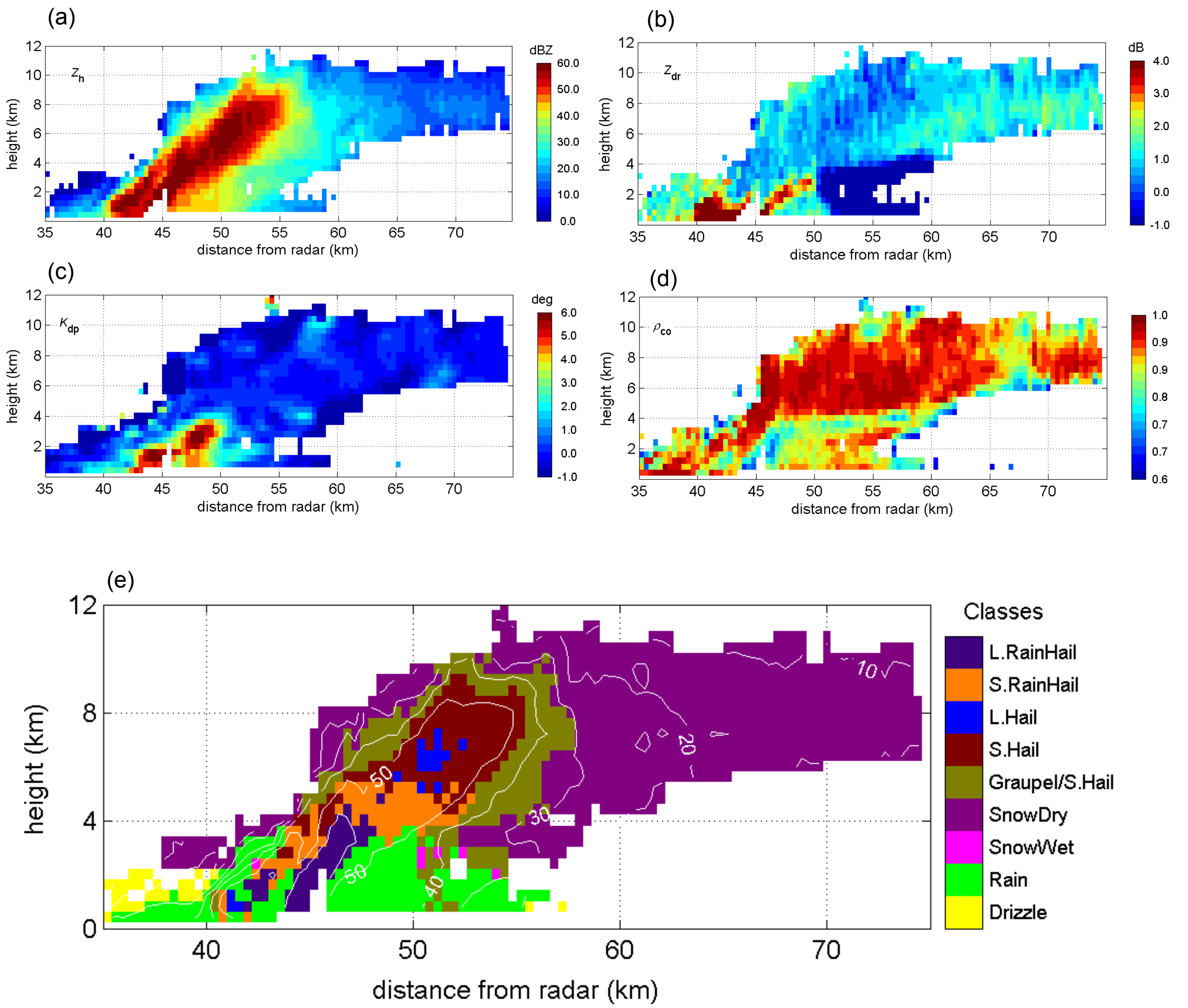

Fig.1. Z_h (a), Z_{dr} (b), K_{dp} (c), ρ_{co} (d), and hydrometeor classification (e) for the case of 21 February 2005 (Alabama) observed by ARMOR.

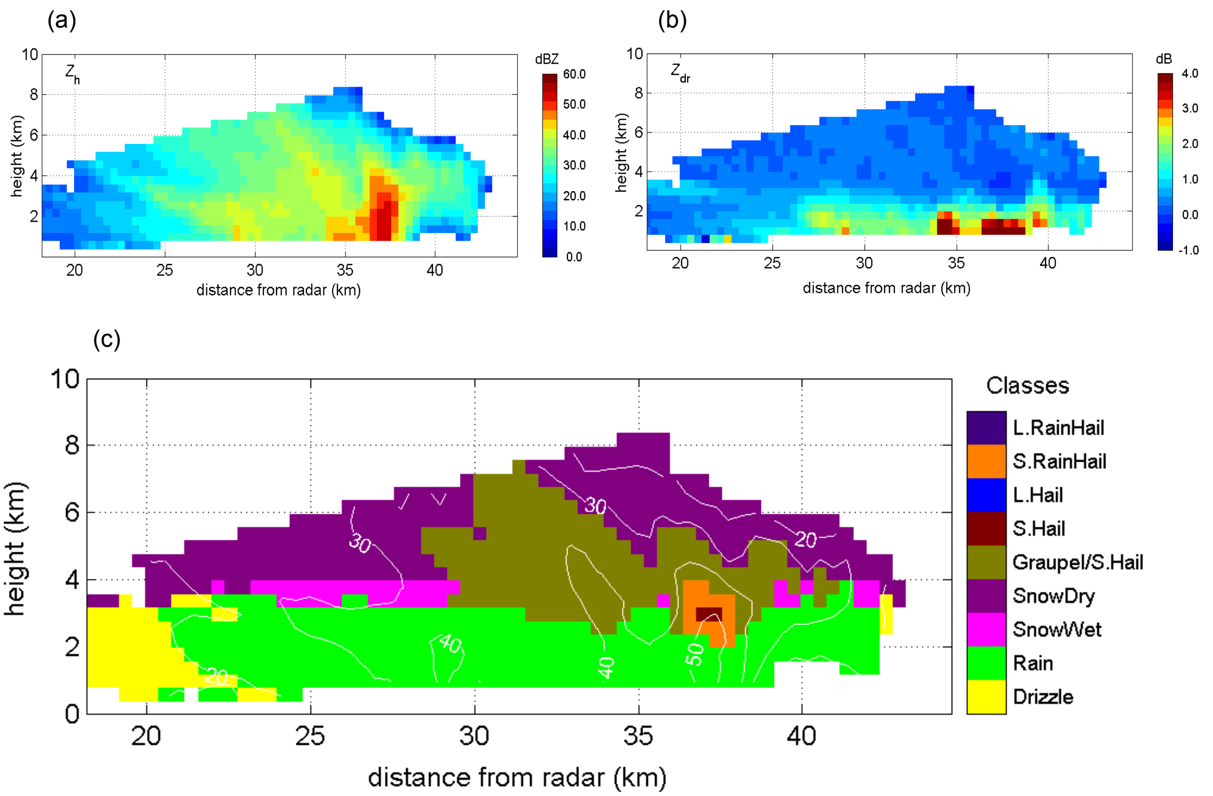

Fig. 2: Z_h (a), Z_{dr} (b), and hydrometeor classification (c) for the case of 26 July 2004 (Central Italy) observed by Polar 55C