8A.6 ICE PARTICLES CLASSIFICATION USING DUAL-POLARIZATION SPECTRAL OBSERVATIONS

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1. INTRODUCTION

Dual polarization radar measurements are capable of detecting shape, orientation and phase state of hydrometeors. Bringi et al (1984) have shown that by combining reflectivity and differential reflectivity measurements one can discriminate between hail and rain in convective storms. Furthermore it was demonstrated by Hall et al. (1984) that these observations can be used for the detection of the melting layer. The use of a combination of co-polar correlation coefficient, differential reflectivity, specific differential phase, and backscatter differential phase for identification of mixed phase precipitation in severe hailstorms was demonstrated by Zrnic et al. (1993). These studies have demonstrated that dual-polarization measurements provide a powerful tool for the hydrometeor classification.

In relatively recent studies (Liu and Chandrasekar, (2000); Straka et al. (2000); Lim et al (2005)) it was demonstrated that the fuzzy logic approach is well suited for the task of hydrometeor classification. This methodology, however, is restricted to selection of one dominating precipitation type for a given radar volume. This limits our understanding of whether phenomena especially in cases of mixed phase and ice precipitation, where particle of different types can be present within the observation volume.

Spectral decompositions of dual-polarization radar measurements (Unal and Moisseev, 2004) taken at a high elevation angle allows for combining hydrometeor fall velocity and shape information. The spectral decomposition of differential reflectivity is determined as ratio of *hh* and *vv* power spectra, and provides an observation of differential reflectivity for each Doppler spectral line. The spectral decompositions of co-polar correlation coefficient and differential phase are determined by the co-polar coherency spectrum. Since fall velocities and shapes of different ice particle types, such as graupel, aggregates and ice crystals are different, one could discriminate between them by using dual-polarization spectral observations.

Moisseev et al. (2007) have demonstrated that this approach is beneficial for precipitation studies and allows for DSD retrievals. Moisseev et al (2004) and Spek (2005) have extended application of those measurements to the case of ice precipitation. It was demonstrated that dual polarization spectral observations are sensitive to different ice particle types. Therefore, by applying such measurements to ice precipitation studies one could be able to use differential reflectivity, co-polar correlation coefficient and differential phase to improve hydrometeor classification in case of mixed type precipitation.

In this paper we present a new methodology that extends the particle classification scheme of Lim et al. (2005) to the case of spectral observations. Based on CSU-CHILL observations, of the snow storm that took place on December 20th, 2006, it is demonstrated that the new classification approach can be used for a more detailed study of ice precipitation.

2. DUAL POLARIZATION SPECTRAL OBSERVATIONS

2.1 Co-polar coherency spectrum

The co-polar coherency spectrum is defined as:

$$\rho_{hv}(v) = \frac{C_{hv}(v)}{\sqrt{P_{hh}(v)P_{vv}(v)}}, \quad (1)$$

where $C_{hv}(v)$ is the co-polar cross spectrum and $P_{hh}(v), P_{vv}(v)$ are *hh* and *vv* power spectra respectively. The co-polar coherency physical meaning is similar to the co-polar correlation coefficient and can be defined as a spectral decomposition of the co-polar correlation coefficient.

The co-polar coherency is an efficient tool to discriminate between noise and signal. In this

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study we use it to define parts of the spectrum that are dominated by noise.

2.2 Spectral decomposition of differential phase

The spectral decomposition of the differential phase is defined as the argument of the co-polar cross spectrum, $C_{hv}(v)$. For the precipitation signal, at low elevation angles, it is expected that the spectral differential phase would be constant independent of Doppler frequencies. The clutter spectral differential phase on the other hand was observed to vary with Doppler frequency and range.

2.3 Spectral decomposition of differential reflectivity

The spectral decomposition of the differential reflectivity is defined as the ratio of *hh* and *vv* power spectra, $P_{hh}(v)/P_{vv}(v)$. Similar to the differential phase the precipitation signal is characterized by the constant spectral differential reflectivity over all Doppler frequencies. The clutter spectral differential reflectivity, however, varies with the Doppler frequency and range.

3. CLASSIFICATION METHODOLOGY

The new hydrometeor classification scheme uses seven input parameters. Three of those parameters are bulk reflectivity, specific differential phase and linear depolarization ratio. The spectral dual polarization observations are represented by spectral decomposition of differential reflectivity, differential phase and co-polar correlation coefficient. The spectral decomposition of differential phase is used for detection of backscatter differential phase. Because in the absence of the backscatter differential phase the spectral differential phase should be the same for all frequency bins corresponding to the signal. The coherency spectrum, or spectral co-polar correlation coefficient, is used for discrimination between signal and noise spectral parts. The spectral differential reflectivity is sensitive to the shapes of the particles and used to discriminate between particle classes.

Following approach of Lim et al (2005) we use the product rule strength mechanism for reflectivity and height parameters. Furthermore, we have applied the same rule for the spectral decomposition of co-polar correlation coefficient, since it plays a strong role in discriminating between noise and signal.

As a result of the classification we determine a hydrometeor class for each spectral line. In total we define five classes:

1. Aggregates
2. Crystals
3. Vertically oriented crystals
4. Graupel
5. Other

The last class mainly corresponds to the noise. In Fig. 1 the architecture of the classification scheme is shown.

4. DEMONSTRATION ON CSU-CHILL DATA

A new hydrometeor classification scheme was developed based on spectral decompositions of polairmetric observables. This classification scheme was applied to the measurements taken during snowstorm that took place in Colorado on Dec 20, 2006. In Fig. 2 an RHI measurement shows an overview of this storm event. To test this classification scheme time-series data was collected at elevation angles 10, 30 and 50 degrees. In the right panel of Fig. 2 one can see Doppler power spectra and the spectral decompositions of differential reflectivity for different range gates as measured at 50 degree elevation angle. One can see that right side of spectral differential reflectivity contains larger values that are due to scattering from ice crystals that have lower fall velocity. In Fig. 3 a comparison of outcome of Lim et al (2005) and the new classification scheme is shown. One can see that overall there is a rather good agreement, except that the new classification scheme is able to detect ice crystals and aggregates simultaneously present in observation volumes between heights 2.5 to 4.5 km.

Based on this study we can conclude that spectral decompositions of dual-polarization measurements can be used to improve our understanding of mixed hydrometeor type precipitation, such ice precipitation.

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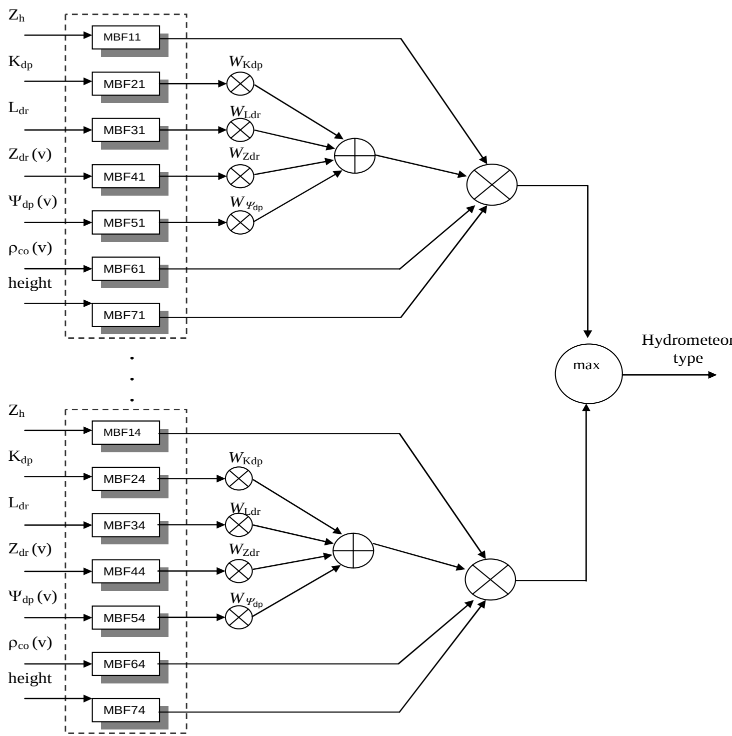

Fig. 1 Architecture of the hydrometeor classification scheme.

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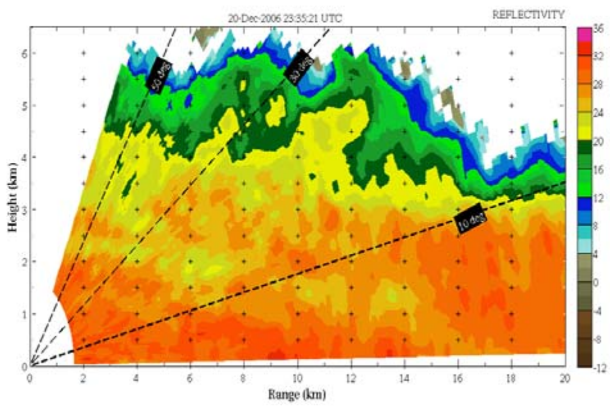

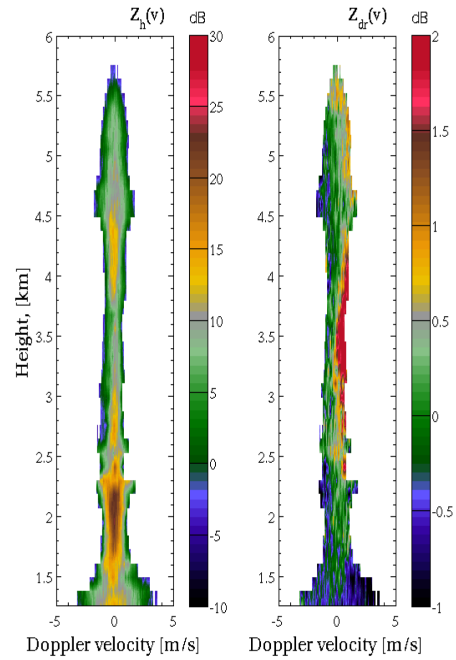

Fig. 2 CSU-CHILL snowstorm observations carried out on Dec. 20, 2006. The top figure shows a RHI measurement. The right figure shows spectrographs of reflectivity and diff. reflectivity measured at 50 degrees elevation angle.

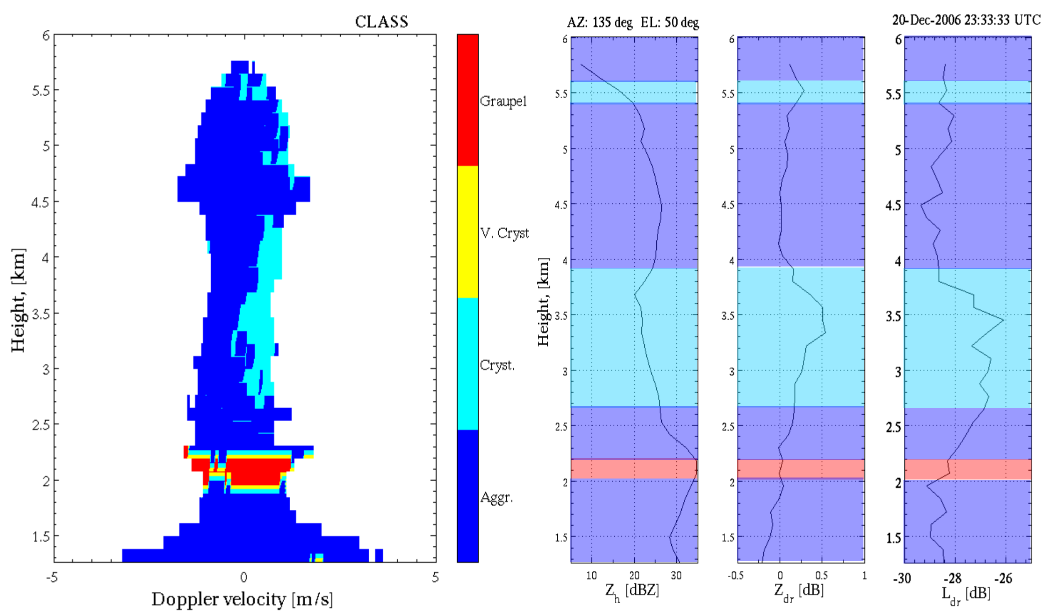

Fig. 3 Comparison between the classification schemes. The right figure shows output of (Lim et al 2005) fuzzy logic classifier. The left figure shows fuzzy logic classifier based on spectral decomposition of polarimetric variables.