PARTICLE IDENTIFICATION USING THE METEO-FRANCE C-BAND POLARIMETRIC RADAR

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1. INTRODUCTION

Meteo-France has been collecting measurements from a C-band radar with polarization capabilities in an operational setting for over a year. There are three main goals in this project: 1) improving quantitative precipitation estimates for hydrologic purposes, 2) improving radar data quality, and 3) retrieving microphysical properties in clouds. The second and third objectives will be useful to the numerical modeling community by providing high quality observations of precipitation types and concentrations for model assimilation and validation purposes. Traditionally, distinct outputs of different hydrometeor classes are produced using algorithms that employ fuzzy logic. This approach is attractive in that it incorporates an ensemble of descriptions for the hydrometeors one wishes to identify. These descriptions, or membership functions, often have preconceived shapes and may be adapted using a neural network approach (Liu and Chandrasekar 2000).

Several countries are now considering upgrading their operational C-band radars with polarization capabilities. A majority of particle-typing development work has been undertaken at S-band. Different membership functions need to be considered for application at C-band due to the deleterious effects of attenuation and resonance at C-band, and properties of backscattered radiation and propagation through rainfall media are different than at S-band. This study presents a new approach in deriving membership functions that is based entirely on a priori observations. Probability distribution functions (pdfs) are shown for stratiform rain and are compared to pdfs produced from common contaminants to radar reflectivity products, such as echoes from ground clutter and anomalously propagating beams (anaprop), chaff, and clear air echoes.

2. BACKGROUND

It is well known that the values of polarimetric variables for different hydrometeor types or non-hydrometeors are typically not mutually exclusive. For example, the pdf of radar reflectivity ($Z_i$) may be similar for rainfall as it is for ground clutter. Use of this variable alone is thus limited in separating the two and thus eliminating ground clutter from $Z_i$ images and derived products. Additional polarimetric observations and their spatial derivatives may yield pdfs that begin to differ, yet still overlap. This prohibits us from relying on strict thresholds in a decision tree method. A fuzzy logic system can be constructed to integrate the information from several observations to make a distinct decision regarding hydrometeor type. The success of these algorithms is highly dependent on the specification of the membership function. The shapes of these functions have been defined as trapezoidal (Vivekanandan et al. 1999) and as Beta functions (Liu and Chandrasekar 2000) in the polarized radar community. The use of a beta function may be preferred for some applications because their derivatives are continuous. Nonetheless, they are constructed using a priori knowledge regarding the behavior of the input for the given fuzzy set, or particle type.

A new approach is developed which relies almost entirely on observations of the phenomena of interest. Instead of imposing conditions based on incomplete knowledge or simulations performed at S- or C-band, membership functions are produced from observation-based pdfs for each input corresponding to each fuzzy set. This empirical approach to deriving membership functions offers the following advantages:

- derived pdfs are directly applicable for specifics of atmospheric conditions at radar location, radar wavelength, scanning strategy, and volume coverage pattern
- functions may be updated as new observations of weather phenomena become available
- analysis of functions leads to a posteriori understanding of backscatter and propagation properties of hydrometeors

3. METHODOLOGY

3.1 Definition of distinct inputs

The polarization variables the Trappes radar collects are backscattered reflectivity at horizontal polarization ($Z_i$), differential reflectivity ($Z_{DR}$), copolar cross-correlation coefficient at zero time lag due to simultaneous transmission and reception ($\rho_{hv}$), and differential propagation phase ($\phi_{DP}$). A detailed study has been undertaken in order to identify and correct for the effects of noise, miscalibration, attenuation, and resonance. Thus, each polarimetric measurement represents the intrinsic value. The additional inputs of radial velocity ($V_r$), pulse-to-pulse variability of $Z_i$ ($\sigma$), and temperature ($T$) are considered in the fuzzy logic algorithm under development. It was discovered that the textures of several variables were quite different, especially for discriminating between hydrometeors and non-hydrometeors. For this reason, the root mean
squared error of all variables is computed in a 3x3 pixel window (corresponding to 1.5' x 720m). Many of these derivatives are redundant with one another and may be neglected or at least minimized in the inference step.

3.2 Identification of hydrometeor and non-hydrometeor species

Membership functions are required for each crisp input (14 total) characterizing each hydrometeor class. These hydrometeor and non-hydrometeor classes may be chosen according to geographic region and anticipated application. For the purposes of this study, we only consider the following five classes: stratiform rain, anomalous propagation (anaprop), ground clutter, chaff, and clear air echoes. The latter four classes are common contaminants toZH products and their removal is desired. In the near future, several hydrometeor types will be included in the classification scheme.

First, an expert analyst identifies a case where a given class is obvious and prevalent. For example, in order to identify a case where there is significant ground clutter, the radar analyst searches low elevation angles near the radar on sunny days, especially during morning hours. Care must be exercised in order to unambiguously isolate the phenomenon of interest. The analyst specifies the search domain by defining the ranges, azimuths, elevation angles, altitudes, and times at which the hydrometeor or non-hydrometeor species is prevalent. This search domain is thus limited only by its spatial and temporal coordinates. It is important to note that no thresholds based on polarimetric variables are employed during this step. This enables the computation of the membership pdfs to remain unconditional, an attractive property in classical probability theory.

3.3 Gaussian kernel density estimation

The pdf of each distinct input is computed for the hydrometeor type using Gaussian kernel density estimation (Silverman 1986). The kernel density estimate is defined as:

$$\hat{f}(x) = \frac{1}{n \sqrt{2\pi}} \sum_{i=1}^{n} e^{-\frac{1}{2} \left[ \frac{f(x, x_i)}{\sigma} \right]^2}$$

(1),

where \( \hat{f}(x) \) is an estimate of the data density, \( \sigma \) is the smoothing parameter or bandwidth, \( n \) is the total number of data points, and \( X_i \) is the \( f(x) \) value. The bandwidth controls the number of bumps or the smoothness in the estimation of \( f(x) \). This parameter is estimated using the so-called Silverman’s rule, which is based on the standard deviation of the data sample. In effect, a Gaussian curve is produced at each observation along the abscissa. The width of these curves is determined by the value of \( \sigma \). Next, linear superposition is used to sum up all the curves in order to arrive at a continuous estimate of the data density.

4. RESULTS

The pdfs of all 14 variables have been computed for stratiform rain, anaprop, ground clutter, chaff, and clear air echoes. The duration of the analyses vary from 6-24 hours. It was observed that the pdfs exhibited stability after a single time step. Fig. 1 shows the pdfs of ZH for all five classes. Because the latter four are common contaminants to ZH images and products, the overlap of the pdfs with stratiform rain is not unexpected.

![Fig. 1. Estimated probability density functions based on observations of ZH for classes listed to the left.](image1)

![Fig. 2. Estimated probability density functions based on observations of ZDR for classes listed to the left.](image2)

The pdfs of ZDR (fig. 2) also have significant overlap with wider distributions associated with the non-hydrometeor classes. This characteristic of the pdfs is used more
explicitly in the calculation of spatial textures. It is also noted that the $Z_{DR}$ values associated with chaff are larger in the mean compared to the other classes. The large width of the distribution is due to the effects of air turbulence on the chaff particles, while the large mean value is a result of the elongated strands falling slowly with a horizontal orientation. Improved data quality has been anticipated through the use of $\rho_{HV}$ data. As is shown in fig. 3, indeed there is better PDF separation between hydrometeors and non-hydrometeors. It is a bit surprising, however, that $\rho_{HV}$ in anaprop and ground clutter is relatively high with mean values greater than 0.9.

![Fig. 3. Estimated probability density functions based on observations of $\rho_{HV}$ for classes listed to the left.](image)

Additional information is provided through PDFs of the pulse-to-pulse fluctuations of $\sigma$ in fig. 4. The stratiform and clear air PDFs of this parameter overlap, yet there is a distinct separation with the ground-based echoes. The $\sigma$ values are quite low with anaprop and ground clutter because the scattering mechanisms are fixed, thus there is very little change in reflectivity from pulse-to-pulse. Lastly, the texture of $\Phi_{DP}$ (fig. 5) reveals significant differences in PDFs from hydrometeors and non-hydrometeors. The most probable values in stratiform rain are $5^\circ$, while distribution modes are greater than $75^\circ$ for the other classes.

5. SUMMARY

A method has been developed to empirically derive probability distribution functions for all available polarimetric variables with the intent of discriminating hydrometeors and non-hydrometeors. The method initially relies on an expert to identify observations of interest and then the PDFs are derived using Gaussian kernel density estimation. The resulting PDFs have reasonable shapes, are differentiable everywhere, are derived empirically, and are not conditioned on the values of other variables. We believe these PDFs will serve the purpose as membership functions in the development of fuzzy logic algorithms for C-band radar. This study has compared PDFs between common artifacts such as anaprop, ground clutter, chaff, and clear air echoes versus real stratiform rain. The following conclusions can be drawn:

- There is significant overlap between real and false precipitation echoes when considering PDFs of $Z_H$ and $Z_{DR}$.
- $\rho_{HV}$ may be useful in removing chaff and clear air echoes, but not necessarily anaprop or ground clutter

- pulse-to-pulse variability in $Z_H$ is useful in removing artifacts except clear air echoes

- texture of $\Phi_{DP}$ may be used to separate precipitation echoes from non-hydrometeorological data

- the combination of the above rules will be successful in removing radar-based artifacts in a fuzzy logic framework

Future work involves the development of a fuzzy logic algorithm to produce distinct outputs of hydrometeor and nonhydrometeor types. In addition, we will investigate the physical reasoning behind many of the observations. For instance, at this time, the exact scattering mechanism producing the clear air echoes is not known.

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7. REFERENCES

