Weather Radar Ground Clutter. Part II: Real-Time Identification and Filtering

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ABSTRACT

The identification and mitigation of anomalous propagation (AP) and normal propagation (NP) ground clutter is an ongoing problem in radar meteorology. Scatter from ground-clutter targets routinely contaminates radar data and masks weather returns causing poor data quality. The problem is typically mitigated by applying a clutter filter to all radar data, but this also biases weather data at near-zero velocity. Modern radar processors make possible the real-time identification and filtering of AP clutter. A fuzzy logic algorithm is used to distinguish between clutter echoes and precipitation echoes and, subsequently, a clutter filter is applied to those radar resolution volumes where clutter is present. In this way, zero-velocity weather echoes are preserved while clutter echoes are mitigated. Since the radar moments are recalculated from clutter-filtered echoes, the underlying weather echo signatures are revealed, thereby significantly increasing the visibility of weather echo. This paper describes the fuzzy logic algorithm, clutter mitigation decision (CMD), for clutter echo identification. A new feature field, clutter phase alignment (CPA), is introduced and described. A detailed discussion of CPA is given in Part I of this paper. The CMD algorithm is illustrated with experimental data from the Denver Next Generation Weather Radar (NEXRAD) at the Denver, Colorado, Front Range Airport (KFTG); and NCAR’s S-band dual-polarization Doppler radar (S-Pol).

1. Introduction

Mitigation of ground clutter is a long-standing problem in radar meteorology. Scatter from ground-clutter targets contaminates radar returns and mask the desired weather echoes and thus obscure meteorological information from weather forecasters and other users. Ground clutter is usually categorized as either normal propagation (NP) clutter or anomalous propagation (AP) clutter. The former occurs under “normal” atmospheric propagation conditions, while the latter occurs when the atmospheric conditions are such that the radar-transmitted electromagnetic waves are abnormally bent toward the ground because of the vertical gradient of the refractive index \( n \). Mathematically, the propagation of electromagnetic waves is broken down into four regimes depending on the rate of change of the refractivity with height \( dN/dh \):

- **Subrefraction**: \( dN/dh > 0 \text{ m}^{-1} \)
- **Normal Refraction**: \( 0 > dN/dh > -0.0787 \text{ m}^{-1} \)
- **Super-refraction**: \( -0.0787 > dN/dh > -0.157 \text{ m}^{-1} \)
- **Ducting**: \( dN/dh < -0.57 \text{ m}^{-1} \)

where \( N \) is refractivity. The governing equation is

\[
(n - 1)10^6 = N = \frac{77.6p}{T} + \frac{(3.73)10^5e}{T^2},
\]

where \( p \) is the barometric pressure in millibars, \( e \) is the partial pressure of water vapor in millibars, and \( T \) is the temperature in kelvins (Gossard 1977; Skolnik 2001). One typical meteorological condition where AP clutter echoes occur is at the outflows of convective storms where the resulting cold pools of air set up conditions favorable for anomalous radar wave propagation. For a discussion of atmospheric conditions and wave refraction, see Battan (1973) and Steiner and Smith (2002). Both NP and AP clutter have very similar radar signatures and both contaminate weather radar echoes. AP clutter is more problematic since its presence depends on the atmospheric conditions, which are constantly evolving (Pamment and Conway 1998). If ground-clutter
echoes are mistaken for precipitation echoes, rainfall is overestimated and velocity estimates are biased. If clutter filters are mistakenly applied to weather echoes, rainfall is underestimated and again velocities are biased. Both scenarios pose serious problems for forecasters and end users of radar data.

There are several ways to categorize efforts to mitigate clutter. For operational radar applications there have been three levels of mitigation: 1) radar design and physical placement, 2) clutter filtering, and 3) post-processing of the integrated radar moments and products for clutter censoring.

By selectively placing the radar, the amount of clutter seen by the radar can be reduced and the relative strength of the clutter echoes can be reduced by choosing shorter wavelengths (Smith 1972; Mann et al. 1986). Such radar location and wavelength choices can help reduce clutter but by no means solve the problem, and such choices are constrained by other design and radar placement considerations.

The second option typically consists of applying a clutter filter to all collected data so that zero- and near-zero-velocity weather data are lost. The clutter filter can be applied in the time domain (Mann et al. 1986; Michelson and Andersson 1995; Pratte et al. 1995; Torres and Zrnić 1999) or in the frequency domain (Passarelli et al. 1981; Schmid et al. 1991). Recently, adaptive, frequency-domain filters have been introduced that not only have adjustable stop bands but also can interpolate across the gap in the signal’s spectrum caused by the clutter filter, thereby compensating for weather echo that may have been filtered (Siggia and Passarelli 2004). However, such interpolation schemes fail for narrow spectrum width, zero-velocity weather echoes; that is, for such signals the majority of the weather echo is eliminated, leaving little information with which the interpolation algorithm can reconstruct the weather spectrum. Thus, using a clutter filter on all data very effectively mitigates the clutter echoes (typical clutter to signal rejection ratios are about 50 dB; Heiss et al. 1990); however, weather echoes near zero velocity can also be eliminated even with the new adaptive, spectral-based clutter filters. One way to address this problem is to create a priori NP clutter maps that control where clutter filters should be applied. This works fairly well for NP clutter but obviously misses AP clutter. Additionally, the strength of the NP clutter can also be a function of the prevailing refractivity gradient. Ideally one would like to selectivity apply a clutter filter to those places where both AP and NP ground clutter are present and not apply a filter to weather echoes. This is the focus of this paper.

The third option of postprocessing of radar product data encompasses the majority of the AP clutter mitigation research that has occurred since the 1970s. The goal has been to identify clutter-contaminated radar data and then censor it. Clutter filtering was not possible since the base in-phase and quadrature-phase (I and Q data or time series data) were discarded because of lack of communication bandwidth, computer computation speed, and storage space. Clutter is characterized by high power variability in range and azimuth, limited vertical extent, zero-mean velocity, and narrow spectrum width (Sekhon and Atlas 1972; Johnson et al. 1975; Sirmans and Dooley 1980; Moszkowicz et al. 1994; Pratte et al. 1993; Joss and Wessels 1990; Joss and Lee 1993; Lee et al. 1995), and researchers have used these characteristics with various techniques to identify clutter. Schaffner (1972, 1975) recognized the possibility of computer-automated recognition of precipitation and clutter radar echoes. He describes two clutter identification metrics that utilize the pulse-to-pulse power fluctuations. One algorithm measures the difference from peak-to-mean-power differences (PM) over an integration period (referred to as a radar bin or gate) and the second measures the mean value of the power difference from pulse-to-pulse [DM, and we refer to this metric as MVAR in Hubbert et al. (2009, hereafter Part I)]. These algorithms were tested by Schaffner (1975) and Geotis and Silver (1976) and it was found that, for scanning radar, the DM method produced superior results. Distinguishing between clutter and precipitation based on the pulse-to-pulse characteristics of radar samples has been discussed by Johnson et al. (1975), Aoyagi (1978), Sirmans and Dooley (1980), Passarelli (1981), Tatehire and Shimizu (1980), Joss and Wessels (1990). The general idea is that echoes from ground clutter have narrower spectrum widths than precipitation echoes and therefore are correlated in time longer than precipitation echoes. As a result, the pulse-to-pulse power samples of ground clutter for a resolution volume will exhibit less variance than those of precipitation. For a more complete discussion of this topic, see Part I.

Most automated clutter recognition techniques, however, use the integrated radar moments and their spatial texture rather than pulse-to-pulse variability. A neural network approach was examined by Cornelius and Gagnon (1993) and Pratte et al. (1996, 1997). It uses the features of spatial reflectivity texture, mean velocity, mean spectrum width, and standard deviation of velocity over a two-dimensional kernel three beams wide by 2 km in range. In Pratte et al. (1996), three clutter recognition algorithms were tested and compared: 1) empirical, 2) neural network (NN), and 3) fuzzy logic (Kosko 1992). Of the three, the NN approach yielded the best results, but it was noted that it was computationally complex. Grecu and Krajewski (2000) used a
more sophisticated volumetric NN approach that used
nine input features; however, the authors state that it is
not an operational technique. Another more sophisti-
cated NN technique has recently been reported by
Lakshmanan et al. (2007) that differentiates between
nonprecipitation and precipitation echoes and thus also
has the capability to identify biological scatter and other
nonprecipitation scatter in addition to ground clutter.
The algorithm uses 28 input features some of which
characterize the vertical extent of the echoes. To mini-
mize the delay time for the algorithm execution and data
classification, data from previous volume scans are used
to calculate the features dependent on the vertical profile.

The fuzzy logic algorithm in Pratte et al. (1996), which
performed nearly as well as the NN approach, was
designed a more practical approach to automated oper-
ational clutter recognition. The fuzzy logic technique
was further developed by Kessinger et al. (2003) and the
algorithm, termed the radar echo classifier (REC) was
deployed on the National Weather Service’s Weather
More recently, Cho et al. (2006) also use a fuzzy logic
approach similar to Kessinger et al. (2003); however,
they optimize the membership functions through sta-

tistical analyses. Berenguer et al. (2006) also report on a
three-dimensional fuzzy logic algorithm that uses the
features of echo top, vertical reflectivity gradient, spin
change, reflectivity texture, and clutter frequency map.

Another approach to clutter mitigation is parameteric
time-domain estimation of spectral moments (Nguyen
et al. 2008). Simultaneous estimation of the both the
clutter and weather signal properties allowed for accu-
rate retrievals of weather moments for high clutter-to-
signal ratios. Such methods are, however, computa-
tionally expensive and are not practical for real-time
execution at this point in time.

It is useful to categorize clutter mitigation tech-
niques by the number of spatial dimensions required by
the algorithm. The benefit of using fewer spatial di-

mensions for the algorithm is simplification in calculation
and implementation. This is an important consideration
in the development of an operational, real-time clutter
mitigation algorithm. There are four categories: 1) three-
dimensional volumetric algorithms (e.g., Moszkowicz
et al. 1994; Steiner and Smith 2002; Grecu and Krajewski
2000; Berenguer et al. 2006); 2) two-dimensional, in
azimuth and range algorithms (e.g., Pratte et al. 1993,
1995; Kessinger et al. 2003); 3) one-dimensional in range

algorithms (e.g., Hubbert et al. 2007; Dixon et al. 2007);
and 4) point, a single radar gate algorithms (e.g., Geotis
and Silver 1976; Schaffner 1975; Zrnić and Melnikov
2007). To create an operational algorithm, it is advan-
tageous to keep the algorithm as simple as possible while
still obtaining acceptable performance. If a three-
dimensional scheme is used, there can be a relatively long
delay incurred until the clutter identification algorithm is
executed. For example, Next Generation Weather Radar
(NEXRAD) volume scan strategies typically require
about five minutes. Additionally, a volume of time series
would need to be buffered for the subsequent clutter
filtering.

Recent advances in radar processor technology pro-
vide the computational capability to calculate and pro-
cess the spectra of the time series in real time. Cornet
al. (1998) and Morse et al. (2002) calculate the spectra
of each time series along a radar radial and then con-
struct a spectral image by concatenating the spectra in
range; that is, Doppler spectra as a function of range are
constructed. Their method uses mathematical analysis,
fuzzy logic synthesis, and global image processing al-
gorithms to identify atmospheric signals in the presence
of not only clutter but also other contaminants such as
aircraft, biological targets, and radio interference. The
technique exploits the continuity of weather echoes in
range. Once the meteorological echoes are identified,
the radar moments are calculated from the Doppler
spectra by integrating over the part of the spectra that
contain weather echo. The technique has been applied
to profilers where long integration times (i.e., long dwell
times) are the norm.

Newer clutter identification schemes have taken ad-
vantage of dual-polarization parameters. For the same
reason that clutter exhibits large spatial variability of
reflectivity, differential reflectivity (Z_{dp}) is also more
variable spatially in clutter than in precipitation (Hall
et al. 1984; Giulii et al.1991; Straka et al. 2000). Copolar
differential phase (\phi_{dp}) also exhibits large spatial vari-
ability in clutter, and the copolar correlation coefficient
(rh) is typically low in clutter (Ryzhkov and Zrnić 1998;
Zrnić et al. 2006); however, the two quantities, \rho_h and
the variability of \phi_{dp} are not independent. When \rho_h
is low (<0.7), the standard deviation of \phi_{dp} also increases
(>12°) (Hubbert et al. 1993). Zrnić et al. (2006) show
that histograms of \rho_h in clutter completely overlap
histograms of \rho_h in precipitation, and thus \rho_h by itself
is not a robust indicator of clutter. Gourley et al. (2007)
investigated an observation-based approached to derive
fuzzy logic membership functions and objective weights
for the feature fields of the spatial texture of Z_{dr} and \phi_{dp}.
They also included \rho_h and the pulse-to-pulse varia-

ability of reflectivity in their fuzzy logic algorithm.

Faster processors also have the capability to first
identify ground-clutter-contaminated data and then
subsequently filter the data to mitigate ground-clutter
echo in real time, which is the focus of this paper. To
accomplish this, time series data must be stored in a
memory buffer while the clutter identification algorithm is being executed and then recalled after the clutter-affected gates are identified. There are two aspects to consider: 1) the identification of those radar data that contain significant ground-clutter signal and 2) the filtering of those data. The clutter identification technique presented here uses a combination of a pulse-to-pulse variability metric and two measures of the spatial variability of reflectivity along a radar radial as inputs to a fuzzy logic recognition algorithm termed the clutter mitigation decision (CMD) algorithm. It is designed to run in real time on operational radars.

Since zero-velocity weather with narrow spectrum width has spectra very similar to ground clutter, it is difficult to distinguish between the two based solely on the data from one gate. Thus, the spatial texture of reflectivity is used to help distinguish them. After the clutter-contaminated gates are identified, a clutter filter is applied to that gate. We use a spectral domain clutter filter similar to the one reported in Siggia and Passarelli (2004). After filtering, the radar moments are recalculated using the filtered data thereby revealing any weather echo that was obscured by clutter echo. The CMD algorithm effectively identifies and separates clutter from zero-velocity, narrow spectrum width weather echo using single-polarization data and the algorithm is kept as simple as possible for practical, operational, real-time execution.

A new parameter, clutter phase alignment (CPA), which is a measure of pulse-to-pulse phase variability of the time series for a radar gate, is introduced and is shown to have excellent clutter discrimination capability. In Part I, CPA is treated in detail.

Two spectral-based parameters for the identification of clutter are also discussed. While these potential feature fields have not been included in the algorithm reported here, they could be used in the future for enhanced recognition capability, especially in areas of low clutter-to-signal ratio (CSR).

The paper is organized as follows: section 1 gives a general overview of the clutter mitigation problem and previous research. Section 2 describes the fuzzy logic algorithm CMD for both single- and dual-polarization data. Section 3 gives experimental results using data from the Denver NEXRAD, Front Range Airport (KFTG), and section 4 summarizes the results of this paper.

2. Clutter mitigation decision algorithm

The CMD algorithm uses a fuzzy logic approach to combine the information from “feature fields” into a single decision-making field. The feature fields CMD uses for the single-polarization case are 1) texture of reflectivity, 2) the SPINchange of the reflectivity variable as defined by Steiner and Smith (2002, hereafter SPIN), and 3) CPA, with the addition of 4) texture of differential reflectivity and 5) texture of copolar differential phase for the dual-polarization case. The feature fields are transformed to interest values between 0 and 1 using membership functions. The interest values are then combined using decision rules and weights. The final result is normalized to the range 0 to 1 and then a threshold is applied as the clutter classification boundary. The feature fields are calculated from a number of consecutive gates along a radar radial. The series of consecutive gates used is referred to as the “kernel.”

\[ a. \text{Single-polarization feature fields} \]

The texture of the reflectivity (TDBZ) is computed as the mean of the squared reflectivity difference between adjacent gates,

\[ TDBZ = \left( \frac{1}{N} \sum_{i=1}^{M} (dBZ_{i,j} - dBZ_{i-1,j})^2 \right) \]

where dBZ is the reflectivity, \( L \) is the number of radar beams or rays used, \( M \) is the number gates used, and \( N = L \times M \). For CMD, \( L \) is always equal to one; that is, only data along a single radar radial are used to calculate TDBZ (and SPIN), which eliminates the need to buffer adjacent beam information into memory and significantly reduces the algorithm complexity over the use of 2D computations. Also, using a single radar radial eliminates the implementation problem when changing elevation angles. The TDBZ feature field is computed at each gate along the radial, with the computation centered on the gate of interest.

The SPIN feature field is a measure of how often the reflectivity gradient changes sign along a direction in space (in this case the radar radial). For example, if \( X_{i-1}, X_i, \) and \( X_{i+1} \) represent 3 consecutive dBZ values along a radar radial, in order for a SPIN change to occur, two conditions must be met:

1) \[ \text{sign}\{X_i - X_{i-1}\} = -\text{sign}\{X_{i+1} - X_i\}, \]

2) \[ \frac{|X_i - X_{i-1}| + |X_{i+1} - X_i|}{2} > \text{spin\_thres}, \]

where spin_thres is a reflectivity threshold typically set to 5 dBZ. Thus, if both conditions, Eqs. (3) and (4), are met, the SPIN variable increments by 1. Finally, SPIN is converted to a percentage by dividing the SPIN number by the number of gates in the kernel and then multiplied by 100.
CPA is a measure of temporal phase fluctuations of echoes over typical data collection times for a single radar resolution volume. CPA is defined as the magnitude of the vector sum of the individual time series members $x_i$, divided by the sum of the magnitudes of the $x_i$:

$$\text{CPA} = \frac{\left| \sum_{i=1}^{N} x_i \right|}{\sum_{i=1}^{N} |x_i|}.$$  \hspace{1cm} (5)

Thus, CPA ranges from 0 to 1 with 1 indicating a very high probability of clutter. Intuitively, CPA is a good indicator of clutter since by definition it is a metric of the primary characteristic of a stationary ground-clutter target, that is, low variability of backscatter phase. Note that, if the phase of the $x_i$ is a constant, CPA will be 1 regardless of the behavior of the magnitude of the $x_i$. If the target is not completely stationary over the measurement period, the mean velocity may differ from 0 m s$^{-1}$ and/or the spectrum width of the radar return signal may increase, both of which will decrease CPA to below 1. For the very large majority of radar clutter returns examined here (about 77%) CPA is greater than 0.90, whereas CPA is less than 0.5 for noise and weather echo with mean velocity magnitude greater than 3 m s$^{-1}$ (see Fig. 6 in Part I). For a complete description and analysis of CPA, see Part I. As shown in Part I, in the cumulative histograms of CPA for clutter (both experimental and simulated), CPA can be relatively low, though infrequently, and thus some points may be misclassified as precipitation. Such points are nearly always identified as precipitation by SPIN and TDBZ. Also, CPA can be high for zero-velocity narrow spectrum width weather. However, the few times where CMD does misclassify echoes can cause image speckle. To alleviate this, a 5-point median filter is used on CPA in range. It was found that doing this effectively mitigates speckle while no appreciable deleterious effects were observed.

**FUZZY LOGIC ALGORITHM**

The single-polarization feature fields, TDBZ, SPIN, and CPA, are converted to so-called interest fields using the fuzzy logic membership functions. The membership functions used in CMD are shown in Fig. 1. The interest fields vary from 0 to 1 with 1 indicating the strongest clutter likelihood for the given variable. To reduce image speckle caused by high CPA values in the zero-velocity isodop, a 5-point median is used in range on CPA. The TDBZ and SPIN interest field are then combined with a fuzzy “or” rule: the maximum interest value of TDBZ and SPIN is selected. The two remaining interest fields, MAX(TDBZ, SPIN) and CPA, are multiplied by a priori weights of 1.0 and 1.01, respectively, and normalized by the sum of the weights. The weighted sum of interest values yields a probability of clutter between 0 and 1. Finally, gates with values greater than 0.5 probability are classified as clutter.

The chosen weight of 1.01 for CPA can be justified as follows. It sometimes occurs that MAX(TDBZ, SPIN) is zero while the CPA interest is one for clutter-contaminated data. If both interest fields have weights of one, the normalized weighted sum (or probability) would be 0.5, and therefore the point would be classified as not clutter. By giving CPA a weight of 1.01, such data are correctly classified as clutter. Case studies have shown this to improve the performance of the CMD algorithm by removing isolated “speckles’’ of misclassification.

The general steps of the CMD algorithm are as follows:

1) Check if SNR $> 3$ dB; otherwise, no filtering is applied at this gate.
2) Compute feature fields: TDBZ, SPIN, and CPA. TDBZ is computed over 9 consecutive radar gates while SPIN is computed over 11 gates.
3) Apply a 5-point median filter to CPA.
4) Apply membership functions to convert feature fields to interest values.
5) Combine TDBZ and SPIN interest fields using fuzzy “or” rule (maximum interest).
6) Compute normalized weighted sum of interest values (CMD field).
7) Threshold CMD at 0.5 to produce CMD clutter flag.
8) Apply clutter filter where CMD flag is set.
9) Recalculate the radar moments for the clutter-filtered gates.

b. Dual-polarization fuzzy logic

The above clutter mitigation algorithm is designed for use with single-polarization data; however, provision is also made for the inclusion of dual-polarization parameters. The dual-polarization inputs can be either “activated” or “deactivated” depending on the type of data processed. It was found that the spatial texture of copolar differential reflectivity ($Z_{dr}$), $\sigma_{dr}$ and spatial texture of copolar differential phase ($\phi_{dp}$) $\sigma_{\phi_w}$ are excellent discriminators of clutter from weather (Gourley et al. 2007). Spatial texture is calculated as the standard deviation of the field along the radar radial. The $\sigma_{dr}$ is calculated in dB space. In our tests we found that kernels of 7 to 11 gates of data along a radial produced good discrimination between weather and clutter echoes, depending on the parameter. It was also found that the copolar correlation coefficient $\rho_{hv}$ was not as good a discriminator as either $\sigma_{dr}$ or $\sigma_{\phi_w}$ and therefore is not included in the fuzzy logic algorithm. The parameters used in the dual-polarization CMD algorithm are summarized in Table 1, while the membership functions and the weights are summarized in Table 2. The membership functions for $\sigma_{dr}$ and $\sigma_{\phi_w}$ are given in Fig. 2. These weights and membership functions were determined heuristically from experimental data. Also, for the dual-polarization CMD algorithm, a median filter is not used on CPA since the dual-polarization feature fields add sufficient classification skill to CMD to mitigate the possibility of CMD identifying zero-velocity, narrow spectrum width precipitation as clutter.

3. Experimental data

a. Single-polarization data

During the summer and fall of 2006 a radar time series recorder was installed at the National Weather Service (NWS) Denver NEXRAD, KFTG, for the Refractivity Experiment for H2O Research and Collaborative Operational Technology Transfer (REFRACTT; Roberts et al. 2008) and these time series were used to develop and test CMD. Importantly for our data analysis, the CMD-processed moments can be compared directly to the KFTG moment data that are archived at the National Climatic Data Center (NCDC). For the KFTG dataset analyzed here, the comparable NCDC archived data were processed with the Gaussian model adaptive processing (GMAP) spectral clutter filter applied to all the data as specified by the NWS radar operators. As will be seen, large regions of zero-velocity weather data that were effectively eliminated in the NEXRAD operational data by the GMAP clutter filter are preserved through use of the CMD algorithm.

To mitigate the range–velocity ambiguity problem, the NEXRAD radars scan the lower elevation angles twice: once using a long pulse repetition time (PRT; about 3.1 ms) so that the unambiguous range is 460 km but the unambiguous velocity is about $8 \text{ m s}^{-1}$ and once using a much shorter PRT (about 1 ms) to obtain velocity estimates with an unambiguous velocity of about $\pm 25 \text{ m s}^{-1}$ but with an unambiguous range of about 150 km. Velocity estimates obtained from the short PRT scan with overlaid echoes regions are censored using information from the long PRT scan. The following NEXRAD data consist of both long and short PRT scans. We first illustrate CPA using a KFTG clear-air scan and then with a widespread, upslope, rain-mixed-with-snow KFTG data case. The second case has zero-velocity precipitation embedded in the Rocky Mountains and thus is a good test of CMD performance.

<table>
<thead>
<tr>
<th>Field</th>
<th>Weights</th>
<th>Membership function break points</th>
</tr>
</thead>
<tbody>
<tr>
<td>TDBZ</td>
<td>N/A</td>
<td>(20, 0), (40, 1)</td>
</tr>
<tr>
<td>SPIN</td>
<td>N/A</td>
<td>(15, 0), (30, 1)</td>
</tr>
<tr>
<td>MAX_TDBZ_SPIN</td>
<td>1.0</td>
<td>N.A.</td>
</tr>
<tr>
<td>CPA</td>
<td>1.01</td>
<td>(0.6, 1), (0.9, 1)</td>
</tr>
<tr>
<td>$\sigma_{dr}$</td>
<td>0.5</td>
<td>(12.1, 2.4, 1)</td>
</tr>
<tr>
<td>$\sigma_{\phi_w}$</td>
<td>0.5</td>
<td>(10, 1), (15, 1)</td>
</tr>
</tbody>
</table>
1) CLEAR-AIR CASE

First we demonstrate the ability of CPA to identify clutter via a KFTG clear-air reflectivity plan position indicator (PPI) scan, gathered at 2126 UTC 13 October 2006 at 0.5° elevation, shown in Fig. 3a. The feature field CPA, which corresponds to Fig. 3a, is shown in Fig. 3b. A large fraction of the clutter points have CPA values greater than 0.9. Note the ability of CPA to identify some of the ground-clutter features that have low clutter-to-noise ratio (CNR) and are not obvious in the clear-air reflectivity of Fig. 3a. A few features are worth noting. Along the 90° radial (0° is north) there exists a line of elevated CPA values. This line is routinely seen in KFTG data and is due to multiple scatter from the Centennial Airport control tower. Along the 20° radial at about 90 km there is a small area of CPA > 0.9, which is not noticeable in Fig. 3a. Similarly, there are some elevated radial lines of CPA at about 165°. Also discernible in this region is a faint fine line, likely due to a convergence boundary, from about 190°, 60 km to 170°, 90 km. This fine line is not identified as clutter by CPA.

2) SINGLE-POLARIZATION CASE

In the next case, 0.5° elevation angle PPI data were gathered by KFTG at 1202 UTC 26 October 2006 in a widespread snowstorm along the eastern foothills of the Rocky Mountains in Colorado. The time series data were gathered and the CMD algorithm was run during postprocessing. [Note, however, that CMD is designed to run in real time and does so on the National Center for Atmospheric Research’s (NCAR’s) S-band dual-polarization Doppler radar (S-Pol).] Figures 4a and 4b show unfiltered reflectivity and velocity, respectively, from the long PRT scan. The x and y axes span 250 km and the range rings are in 25-km increments. The Rocky Mountains are easily seen in the west portion of the PPIs. Peak reflectivities are about 40 dBZ in the storm (wet snow) while the reflectivity due to the mountain clutter is in excess of 65 dBZ. The velocity plot shows a clear 0 m s⁻¹ isodop through the center of the plot (in gray). The reflectivity plot shows areas marked by black lines that indicate the location of the zero-velocity isodop. The velocity field shows areas, indicated by ovals, where the velocity has folded back to 0 m s⁻¹ (again in gray). This is confirmed by the short PRT velocity (Nyquist velocity is about 25 m s⁻¹), which is shown in Fig. 4c. The power in these areas will be severely attenuated if a clutter filter is applied. It is these zero-velocity weather areas that the CMD should not identify as clutter. (Refer to Fig. 3a for the clear-air
reflectivity that shows the location of ground clutter; that is, it is a clutter map for the region displayed in Figs. 4a,b.) Figure 4d shows the NCDC-recorded long PRT reflectivity that was processed using a clutter filter everywhere as is frequently the case in NEXRAD processing. These are the data that were viewed and used by NWS forecasters, automated algorithms, and outside users. Note the reflectivity that has been eliminated, not only along the zero-velocity isodop, but also in the areas where nonzero-velocity echoes have been aliased to zero velocity as indicated in Fig. 4c. This dataset demonstrates the problem of applying a clutter filter everywhere, even if it is an advanced, adaptive spectral filter.

The feature fields of TDBZ, SPIN, and CPA are calculated from the KFTG time series and are shown in Figs. 5a, 5b, and 5c, respectively. The feature fields can be compared to the clear-air reflectivity of Fig. 3a that shows the location of ground clutter. The membership function for TDBZ gives an interest of 1 when $TDBZ > 40 \text{ dBZ}$.

**Fig. 4.** PPI data gathered with KFTG at 1202 UTC 26 Oct 2006 in a widespread snowstorm along the eastern foothills of the Rocky Mountains in Colorado. The elevation angle is 0.5°. (a) Long PRT (3.1 ms), unfiltered reflectivity. Color scale is in dBZ. The zero-velocity isodop is outlined with black lines where there are obvious clutter echoes and precipitation echoes. (b) Unfiltered long PRT velocity data corresponding to (a). The folding velocity is about 8 m s$^{-1}$. The zero-velocity isodop is marked in gray color scale. Two other regions are circled that have apparent zero velocity but are caused by velocity folding from about ±16 to 0 m s$^{-1}$. If a clutter filter is applied to such data regions, the weather signal will be attenuated. Color scale is in meters per second. (c) Unfiltered velocity from a short PRT scan (about 1 ms) gathered just 3 min before the data corresponding to (a) and (b). The folding velocity is about 25 m s$^{-1}$. The zero-velocity isodop can be seen marked in the gray color scale and the zero-velocity signature of the Rocky Mountains to the west is evident. (d) NCDC-archived KFTG reflectivity data corresponding to (a). A clutter filter was applied to all data. Note how the reflectivity is attenuated along the zero-velocity isodop and the folded zero-velocity regions.
and, from Fig. 5a, values of TDBZ > 40 dBZ$^2$ identify the clear-air clutter regions well. Similarly, when the SPIN feature field is greater than 30 its interest value is 1, and these values of SPIN correspond well to the clutter region of Fig. 3a. The corresponding feature field CPA is shown in Fig. 5c and should be compared to the clear-air CPA field in Fig. 3b. Some of the previously identified clutter areas now have very low CPA values.
since the clutter echoes are dominated by overlaying precipitation echo. However, most of the very strong ground-clutter targets remain, such as those from the Rocky Mountains. Note the elevated CPA values along the zero-velocity isodop that was indicated in Fig. 4c. The CPA is higher in this region since 1) there is zero-velocity narrow spectrum width precipitation and 2) some of this area does contain ground-clutter echo as is seen from Figs. 3a,b. Many of the CPA values are less than 0.8, which is more indicative of precipitation. There are also some pixels with CPA > 0.9 that are in fact precipitation, so the other feature fields of TDBZ and SPIN are needed to properly classify such areas. Many of the radar gates in this area contain both clutter and precipitation echo. The goal is to detect clutter contamination down to a CSR of −10 dB, which is a difficult task. Spectral-based power ratios could help meet this goal (see the appendix for additional details).

After the feature fields are constructed, CMD is then used to create the clutter map shown in Fig. 5d with yellow marking the regions to be filtered. This can be compared to the clear-air reflectivity shown in Fig. 3a. The frequency-domain GMAP clutter filter is applied to the data at those gates specified in Fig. 5d. The resulting reflectivity PPI is shown in Fig. 5e and should be compared to Figs. 4a,d. As can be seen, filtering based on CMD has effectively eliminated most of the ground clutter that is evident in Fig. 4a. Next, compare Fig. 5e to Fig. 4d where a clutter filter was applied everywhere. Note the severe attenuation due to the clutter filter along the zero-velocity isodop and in the two regions of velocity-folded zero-velocity isodop. By using CMD, the majority of the weather echo is preserved. The CMD-filtered reflectivity demonstrates the significant improvement in data quality when compared to the NCDC archive data of Fig. 4d.

3) EVALUATION

To evaluate the performance of the CMD algorithm, the fraction of range gates, which CMD identifies for filtering, is calculated as a function of CSR. The lower the CSR the less likely the radar gate will be identified as clutter. Gates where the SNR is less than 10 dB are excluded. First, GMAP is applied to all the data of Fig. 4a. The clutter power for all gates is estimated by the amount of power removed due to applying GMAP. The remaining power is considered to be weather power. Thus, it is assumed that power at zero velocity is due to clutter, which is, of course, not always true; however, such analysis should indicate the approximate level of clutter power detected by CMD. To reduce this potential error, gates with near-zero-velocity weather (i.e., |vel| ≤ 2 m s⁻¹) are excluded from the analysis because zero- and near-zero-velocity weather power could be classified as clutter power and this would bias the CSR estimate. The results are shown in Fig. 6. The solid line indicates the fraction of gates that are identified by CMD for filtering whereas the dashed line indicates the fraction of gates that are not identified. These are complementary curves: 1 minus the solid line value gives the dashed line value. As can be seen, the crossover point is located at about −8 dB CSR; that is, about 50% of the gates with CSR = −8 dB are identified by CMD for filtering. To detect clutter that is 8 dB below the weather signal is quite good since it would seem that the weather signal would dominate the feature fields. To explain this level of clutter identification performance, consider the mechanics of CMD and the spatial texture of clutter power. CMD operates over a kernel of 7 to 11 gates. Over this interval, the clutter reflectivity is usually highly variable with possible gate-to-gate reflectivity differences of 10–15 dBZ or more. Gates with lower clutter power can have low CSR (CSR < 0 dB) if there is weather present at the appropriate reflectivity level. The surrounding gates, however, can have much higher clutter power (i.e., CSR > 0 dB). Since CMD uses feature fields based on spatial texture for clutter identification, these gates with lower CSR are identified as being clutter contaminated.

Making the 50% crossover CSR value low is important to minimize biases caused by the clutter signal (e.g., see chapter 3 of Federal Handbook 2005). According to this reference, a CSR of about −10 dB would keep
velocity errors to within 1 m $s^{-1}$ for a Nyquist velocity of 25 m $s^{-1}$. The CMD performance as indicated by Fig. 6 is excellent, especially when considered against the alternative of applying a clutter filter everywhere.

b. Dual-polarization case

The following data were gathered by S-Pol at 2118 UTC 24 April 2007 in eastern Colorado along the Front Range. S-Pol was located at the NCAR Marshall field site in Marshall, Colorado, which is only a few kilometers away from the foothills of the Rocky Mountains. The dual-polarization data are collected in fast alternating transmit $H$ and $V$ mode (Bringi and Chandrasekar 2001), the PRT is 0.001 s, the unambiguous range is 150 km, and the unambiguous velocity (Nyquist velocity) is 26.7 m $s^{-1}$. Figure 7a shows unfiltered reflectivity PPI data gathered at 0.5° elevation. There was widespread rain containing embedded higher-reflectivity cells (45–50 dBZ). The Rocky Mountains are clearly seen west of the radar, while several other significant clutter features are seen to the east of the radar. This eastern clutter is entirely embedded in the weather and is difficult to see in the reflectivity data of Fig. 7a. Figure 7b shows the corresponding unfiltered velocity. The zero-velocity isodop runs nearly east–west through the radar location and then veers south at about 60 km in range. Zero m $s^{-1}$ ground-clutter echo from the Rocky Mountains is clearly seen west of the radar marked in gray color scale. For reference, Fig. 7c is a clear-air reflectivity PPI scan at 0.5° elevation that shows the locations of the clutter.

The dual-polarization feature fields of $\sigma^c_{\nu}$, $\sigma^c_{\phi_{\nu}}$, and CPA are shown in Figs. 8a, 8b, and 8c, respectively. Since TDBZ and SPIN were demonstrated in the single-polarization case, they are not given here for brevity.
The membership functions for these feature fields transition to interest values of one at 2.4 dB, 15°, and 0.9 for $\sigma_{dr}$, $\sigma_{dp}$, and CPA, respectively. For each feature field, values greater than these three transition numbers mark areas where clutter is very likely present. Compare these areas to the clear-air reflectivity data of Fig. 7c. Regions of high clear-air reflectivity correspond well to the regions of the feature fields with an interest value of one.

Next, the feature fields are combined using the CMD fuzzy logic algorithm and the CMD flag field of Fig. 7d is the result. Regions marked in yellow are to be filtered. Figure 9a shows the reflectivity data of Fig. 7a but now a filter is applied to the regions identified by CMD in Fig. 8d. The clutter echo due to the Rocky Mountains is removed, but most of the weather located along the zero-velocity isodop east of the radar is preserved. There are several reflectivity “holes” (marked as black) in the zero-velocity isodop located along the 90° azimuth radial at about 30–40-km range. These are areas where the clutter echo dominated the weather echo (in terms of the feature fields) and thus are flagged by CMD for filtering. This can be verified by comparing the unfiltered reflectivity of Fig. 7a to the clear-air reflectivity in Fig. 7c and by examining the feature fields. Since the weather echo mean velocity in these areas is about zero,
the weather is eliminated along with the clutter by the filter. Shown in Fig. 9c is the velocity that accompanies the CMD-filtered reflectivity data of Fig. 9a. As compared to the unfiltered velocity data in Fig. 7b, the CMD-filtered velocity is much smoother. Many of the areas that were contaminated by ground clutter (such as north of the radar between 25 and 75 km) and had biased velocities now have velocities that “match” the surrounding weather data velocities.

For comparison, the data given in Fig. 7a are filtered everywhere, and the result is shown in Fig. 9c. The clutter echo due to the Rocky Mountains has been removed, but much of the weather echo along the zero-velocity isodop has also been severely attenuated. This is clearly an undesirable result and again demonstrates the drawback of applying a clutter filter to all data.

Finally, examine the unfiltered and filtered-everywhere reflectivity plots (Figs. 7a and 9c) between 160° and 180° azimuth and 40–80 km in range. As can be seen, the filtered reflectivity plot shows significant attenuation in this area even though it was not identified by CMD for filtering. The velocities in this region are near the Nyquist velocity of \(-26.7 \text{ m s}^{-1}\) (Fig. 7b), and thus at first glance it would seem that applying a clutter filter to this region should have little effect. The Nyquist velocity is determined from the time difference between the \(H\) and \(V\) pulses with a PRF of 1 ms. However, the filter is applied to the \(H\) and \(V\) data separately and thus, when filtering, the Nyquist velocity is based on a 2 ms, rather than a 1 ms, PRF. Thus, data with velocity near the Nyquist velocity of \(-26.7 \text{ m s}^{-1}\) are folded to near zero velocity when filtering. This is the cause of the observed attenuation.
EVALUATION

As was done in the single-polarization case above, the performance of the dual-polarization CMD algorithm is determined by calculating the fraction of range gates, which CMD identifies for filtering, as a function of CSR. This is shown in Fig. 10 by the solid thick line and the dashed thick line is the complimentary curve. Again, gates where $|\text{vel}| \leq 2 \text{ m s}^{-1}$ are excluded since zero- and near-zero-velocity weather power could be classified as clutter power and this would bias the CSR estimate. Gates where $|\text{vel}| > 24 \text{ m s}^{-1}$ are also excluded, since these velocities are folded to near zero velocity as explained above. The crossover point is at about $-12 \text{ dB CSR}$. For a CSR of $-10 \text{ dB}$, about 65% of the gates are identified for filtering. The dual-polarization data are also processed with the single-polarization CMD algorithm, and the resulting performance curve is shown in Fig. 10 by the thin solid and dashed lines. The crossover point is now at $-10 \text{ dB CSR}$, whereas it was $-8 \text{ dB}$ in the previous, KFTG single-polarization case of Fig. 6. Such performance analysis is dependent on the particular data case examined. Also, the performance of the CMD algorithm will be dependent on the radar characteristics. For example, if the phase noise of the radar is abnormally high, the values of the feature fields will change. The performance curves do indicate the approximate CSR level at which CMD can identify clutter-contaminated data.

4. Summary and conclusions

Both NP and AP ground-clutter echoes routinely contaminate weather radar data, obscuring the desired weather echoes especially at low elevation angles. Previously, either clutter filters have been applied everywhere or clutter echoes have been identified in post-processing with the identified radar gates censored. This paper has presented a practical, operational, real-time fuzzy logic algorithm that first identifies ground-clutter-contaminated data and subsequently applies a clutter filter only to those identified gates. The algorithm, CMD, effectively identifies ground clutter and thus can provide a real-time clutter map on a radar beam-to-beam basis. The algorithm was demonstrated with single-polarization data from the NEXRAD KFTG and with dual-polarization data from NCAR’s S-Pol. For the single-polarization case, the CMD-processed data were compared to the NCDC-archived KFTG data, which had been filtered everywhere. The improvement in CMD-processed data quality was obvious especially along the zero-velocity isodop where the NCDC data showed severe signal attenuation.

It should be noted that, although CMD effectively identifies NP and AP clutter, there are significant other nonweather echoes that affect radar data quality, such as biological scatterers, dust, chaff, smoke, wind turbines, and aircraft. CMD will not effectively identify such echoes.

A new clutter identification feature field, clutter phase alignment (CPA) was introduced and was examined theoretically in Part I. It was shown that CPA is affected by both spectrum width and mean velocity but is a more robust indicator of clutter than either one. An estimate of CMD performance was developed that showed that clutter was robustly identified down to about $0 \text{ dB CSR}$, while zero-velocity weather echoes were not falsely identified. Importantly, CMD is a real-time, operational algorithm. The WSR-88D Radar Operations Center is incorporating the CMD algorithm in the next major release of the operational software, scheduled for May 2009.

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APPENDIX

Detection of Clutter with Low CSR

To keep the bias of velocity estimates to within 1 m s\(^{-1}\) for a Nyquist velocity of 25 m s\(^{-1}\), clutter should be detected down to about \(-10\) dB CSR (Federal Handbook 2005).

Detecting clutter down to \(-10\) dB CSR is very difficult using the feature fields of CPA, TDBZ, and SPIN since the weather echo will dominate. However, detection of clutter at these low CSR should be possible using power ratios obtained from the spectra. A good indicator of clutter is the spectral parameter clutter ratio narrow (CRN) defined as

\[
\text{CRN} = \frac{\sum_{m \in V_1} |X_m|}{\sum_{m \in V_2} |X_m|},
\]

where \(V_1\) and \(V_2\) define velocity regions:

\[
|V_1| < v_1, \quad (A2)
\]

\[
v_1 < |V_2| < v_2, \quad (A3)
\]

where \(v_1\) and \(v_2\) are positive and \(v_1 < v_2\). The index \(m\) is confined to values that correspond to the velocity regions defined by Eqs. (A2) and (A3). Depending on the Nyquist velocity and the number of samples, \(v_1 \approx 0.5\) m s\(^{-1}\) and \(v_2 \approx 2\) m s\(^{-1}\). Since ground-clutter echo is typically centered at zero velocity and has narrow spectrum width, CRN is high in clutter. Note that this ratio will remain high even if there is a large weather spectrum away from the 0 m s\(^{-1}\) area. Figure A1 shows the feature field CRN for the KFTG experimental data shown in Fig. 4a. As can be seen, it also marks well the clutter areas defined in Fig. 3a. CRN identifies clutter well and has the advantage over CPA in that weather echoes away from zero velocity do not change CRN appreciably whereas CPA can be reduced significantly. However, from our experience, CPA is the better discriminator between narrow spectrum width weather and clutter. Thus CPA was used in CMD. However, CRN should help in detecting clutter in low-CSR regions. CRN could be used in conjunction with the parameter

**Fig. A1.** The clutter identification parameter CRN corresponding to Fig. 4a. The color scale is in dB. This parameter can potentially be used to identify clutter-contaminated data for low-CSR data.
power ratio (PR) described in Part I. If CRN is high, then the presence of clutter is possible. In conjunction, if PR is low, this would indicate the presence of a larger weather signal with a smaller clutter signal. This is to be investigated in future research.

REFERENCES


Pramstaller, G., R. Keeler, R. Gagnon, and D. Sirmans, 1995: Clutter processing during anomalous propagation conditions. Preprints,
27th Int. Conf. on Radar Meteorology, Vail, CO, Amer. Meteor. Soc., 139–141.


