NEXRAD DATA QUALITY:
SZ Phase Coding Enhancements and Radar Echo Classification Advances

FY2005 Annual Report

Prepared for: WSR-88D Radar Operations Center
By: John Hubbert, Cathy Kessinger, Mike Dixon, Scott Ellis, Greg Meymaris and Joe Van Andel

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Executive Summary

This report provides continued analysis and update of the algorithms for NEXRAD Data Quality improvement and Range-Velocity ambiguity mitigation. Previously, two separate reports were generated but with minimal range-velocity mitigation work this fiscal year, they are combined into this one report.

Two recommended SZ algorithms, SZ-1 and SZ-2, were delivered on 15 August, 2003, in the “Interim Report, NEXRAD Range-Velocity Ambiguity Mitigation SZ(8/64) Phase Coding Algorithm Recommendations” by NSSL and NCAR. In this report, the SZ-1 algorithm is updated with clutter mitigation and the SZ-2 censoring thresholds are modified in anticipation of the low phase noise of the WSR-88D radars. The SZ-1 algorithm assumes that either an a priori input clutter map or the moments generated by the SZ-1 algorithm are processed by the CMD (Clutter Mitigation Decision algorithm) for clutter identification in real time. Either way, a clutter map is passed to the SZ-1 algorithm to indicate special processing in those areas.

This report also investigates improved data quality via overlapping time series windows. Both SZ phase coding algorithms as well as the new clutter filter GMAP require the use of a time series window function, either the Hanning or Blackman window, that limits the spread of power across the spectrum. Due to the window’s strong attenuation of the time series’ beginning and end points, it is possible to use longer overlapping windowed data without significant loss of spatial resolution:

- Overlapping windows allows for the use of longer length time series that reduce the variance of radar moment estimates thereby improving base data quality significantly.

- Overlapping Hanning or Blackman windows are also applied to “Super Resolution” data processing. It is shown that Super Resolution data can be made compatible with SZ(8/64) phase coding so that acceptable moment measurement variances are obtained.

Spatial-spectral processing of radar data is shown to reduce the variance and bias of estimated radar moments. Spectra of radar data are analyzed versus range and the principle of spatial continuity is used to identify meteorological echo. Once the meteorological portions of the spectra are identified, calculation of the radar moments are restricted to that spectral region thereby eliminating superfluous echo and noise. The result is better data quality.

Data quality improvement via upgrades to the REC are also reported. The PDA (Precipitation Detection Algorithm) is improved and is used in conjunction with the APDA (Anomalous Propagation Detection Algorithm) for improved precipitation estimates via EPRE (Enhanced Pre-Processing subsystem). Previously only output from APDA was used in EPRE.

Improvements to the convective/stratiform partitioning algorithm are described. Identifying and separating convective versus stratiform precipitation regions improves precipitation estimates since each type of precipitation is described by different rainfall algorithms.

A significant accomplishment in FY2005 is the development of a real time AP clutter detection and correction algorithm termed the Clutter Mitigation Decision algorithm (CMD). Via Fuzzy Logic, AP clutter (and NP clutter if it is present) is identified in the RDA (i.e, RVP8). Time
series data are buffered in the RDA so that the GMAP clutter filter can be applied to the clutter contaminated areas but not to the other clutter free areas, again in real time. Examples of CMD processing are given using experimental data. Selectively filtering radar data for clutter in real time with CMD has three advantages: 1) clutter filters are applied only to the clutter-affected areas while regions with zero velocity precipitation are not filtered, 2) the algorithm is automated so that operator error is eliminated and 3) weather signatures that are masked or biased by clutter are revealed.
1 Range-Velocity Mitigation

1.1 Introduction

The SZ phase coding algorithm is a technique for the mitigation of the range-velocity ambiguity problem of pulsed radar systems and has been extensively described in previous reports. By attaching predetermined phases to the transmitted pulses, the unambiguous range can be extended while not altering the unambiguous velocity. Two SZ algorithms have been developed and delivered to the ROC in previous reports. SZ-1 was developed for upper elevation scans where there are no supporting long PRT scans. The SZ-2 algorithm is for the lower elevation split cut scans where a long PRT scan is followed by the phased coded short PRT scan. In this report we update the SZ-1 algorithm with clutter filtering. Since there is no long PRT data, the SZ-1 recovered moments must be self-censored. This is done by exploiting the texture of the velocity field and the shape of the recovered spectrum. In contrast, the SZ-2 algorithm uses information from the accompanying long PRT scan to censor the short PRT-recovered velocities. In FY2005 we have integrated clutter filtering into the SZ-1 algorithm and determined that the previously developed SZ-1 censoring technique performs well with data from the updated SZ-1 algorithm. There are two ways in which the clutter-contaminated ranges can be identified: 1) an input clutter bypass map is used or 2) the recovered SZ-1 moments are further processed by the Fuzzy Logic clutter identification algorithm, CMD (Clutter Mitigation Decision) which is described in Section 2.4. In the latter approach the time series data is first buffered (for later possible reprocessing) and then the SZ-1 algorithm is applied. The recovered moments are sent to the CMD algorithm. Range bins that are identified as containing clutter are fed back to the SZ-1 algorithm after clutter removal where only those bins are reprocessed. The resulting moments are reported to the ORPG.

It is expected that the phase noise of the WSR-88D will be significantly lower than 0.5 degrees which was the value used in SZ simulations to determine censoring thresholds. The WSR-88D phase noise is at least -54 dBc and more typically -60 dBc (http://www.roc.noaa.gov/eng/nexradtech.asp) which translates to better than 0.12 degrees of phase noise. This means that there will be less spectral power spread, as compare to 0.5 degrees of phase noise, which means better separation of overlaid echoes. Because of this, the SZ-2 censoring thresholds are updated in this report for improved SZ-2 performance.

Other improvements to the SZ-2 algorithm are also reported here (these improvements are applicable to SZ-1 also). By using extended-length overlapping windows (e.g., 128 points instead of 64 points) the variance of the recovered moments can be reduced. Additionally, clutter filtering is also improved when these extended-length windows are used. The use of overlapping windows also allows for Super Resolution data with SZ(8/64) phase coding and this is addressed in Section 1.5.

1.2 SZ-1 with GMAP Filter

1.2.1 Introduction

Clutter filtering of SZ-1 data is quite similar to clutter filtering of SZ-2 data but because SZ-1 data lacks information from a long PRT scan (which SZ-2 has), the decision of when to apply a clutter
filter is more complicated. Lack of a long PRT scan has three impacts on the SZ-1 algorithm: 1) all base data reflectivity must be estimated from the short-PRT scan, 2) the long PRT power cannot be used to trip sort the range folded short PRT data, and 3) the total power and clutter-filtered power are unknown due to possible overlaid echo and thus cannot be used for censoring criteria. This is particularly problematic in the case of the clutter filters being applied throughout the radar domain due to the original requirement of censoring overlaid clutter echoes.

Of the three impacts, the most serious issue is the third. SZ-1 cannot use an estimate of the clutter power obtained from the long PRT scan as can be done in SZ-2. Thus, SZ-1 has to rely on a given input clutter map. As in SZ-2, when clutter exists in two trips, recovery of one trip is sometimes possible but this has to be determined using the short-PRT data only. The result of the unavailability of long PRT data on clutter filtering of SZ-1 data is that more data will be censored as compared to a SZ-2 algorithm. Fortunately however, since SZ-1 is meant for higher elevation scans, the occurrence of clutter contaminated data is greatly reduced (as compared to low elevation scans) especially for second trip data. For example, for a scan at 2.5° elevation angle, the altitude of the second trip range ring beginning at 115 km is 5 km. Thus, only in very rare circumstances would one need to worry about ground clutter in two overlaid trips.

SZ-1 clutter filtering was implemented with the following paradigm: clutter filter and censor according to a given clutter map and then censor in a second pass (as was previously described in earlier reports) using the texture of the velocity field and the quality of the recovered spectra.

1.2.2 SZ-1 Clutter Filtering Strategies

Recall that in SZ phase-coding, out-of-trip echoes, whether clutter or weather, are modulated so that their power is distributed into equally-spaced and nearly identical replicas in the spectral domain. For SZ-1, since there should only be echoes in two trips, the number of replicas is 8. Because there is no knowledge of how much of the total power is clutter versus weather for SZ-1, it will assist the discussion if we define some new terms. In what follows, the strong total trip refers to the trip with the strongest power, regardless of whether the power is due to clutter or weather. Likewise, the weak total trip refers to the trip with the weakest power. The strong weather trip and the weak weather trip refer to the trips with the strongest or weakest (respectively) power when only the weather power is considered.

Case 1: Clutter exists only in the weak total trip. Since the clutter is in the weak total trip, this implies that the weak total trip is necessarily also the weak weather trip. The decision to make is whether to clutter filter the weak total trip first, or just recover the strong trip. Either way it is not possible to recover any information (P, V, or W) from the weak trip. If it is possible that the clutter filter can remove some power from the clutter, then clutter filtering the weak total trip can improve the quality of the estimates of the strong trip.

Case 2: Clutter exists only in the strong total trip. With the clutter in the strong total trip, it cannot be determined automatically, as in case 1, which trip is the strong weather trip. If the strong total trip is also the strong weather trip, then both trips can be recovered. If, however, the strong total trip is also the weak weather trip, then only the strong weather trip can be recovered.
Case 3: Clutter exists in both trips. Because there is clutter in both trips, at most one trip will be recoverable. If the strong total trip is still the stronger trip after clutter filtering, then that trip is recoverable.

1.2.3 Clutter Map Considerations

From Case 3 above it is seen that if the radar operators specify that the clutter filter be turned on everywhere, very poor data quality would result due to large areas of data being censored. A clutter bypass map will typically not indicate very much, if any, clutter in the second trip since there will not often be much clutter at 150+ km at 2.4° (possible mountains). Thus, the potential problem is that the radar operators could turn the clutter filters on everywhere to try to mitigate AP clutter. Since this causes SZ-1 to censor excessive amounts of data, there are several possibilities to handle AP clutter:

1. If the clutter filters are requested on everywhere, turn them on only in the first trip.

2. Do not allow the user to turn on the clutter filters everywhere, but rather force them to specify regions where the AP exists.

3. Do not allow the operators to specify clutter at all, but rather rely on CMD, or something similar, to determine the existence of AP clutter.

Assuming that CMD’s performance in detecting clutter is shown to be satisfactory (and all indications are that it is), then using item (3.) above would be the best approach for handling AP clutter. Again it should be noted that the presence of AP clutter at elevation angles of 2.4° and above is not common.

1.2.4 NCAR SZ-1 Algorithm

The steps for SZ-1 algorithm with clutter filtering are given via the flow chart of Figs. 1 and 2. The flow chart is similar to the SZ-1 algorithm given in Sachidananda et al. (1998) but is expanded here to include the three clutter cases given above. Details of how the GMAP is applied and how the noise floor is determined is given in the SZ-1 AEL document included in Appendix A. Before applying the GMAP clutter filter, a narrow clutter ratio metric is calculated which indicates whether GMAP should be applied or not. This is done because GMAP was not designed for data containing SZ phase coded overlaid echoes. GMAP will sometimes misinterpret a narrow replica from an off-trip echo as clutter and unnecessarily filtering a replica can cause poor data quality. This narrow clutter ratio metric, $C$, which compares the power of the signal near 0 velocity to the power of the rest of the signal, is defined as

$$P_{nz} = \sum_{k=-L}^{L} \left| \sum_{m=0}^{N-1} V_c(m) \exp \left(-2\pi imk/N\right) \right|^2$$

$$P_a = \sum_{m=0}^{N-1} |V_c(m)|^2$$

(1)
\[ C = \frac{P_{nz}}{P_a - P_{nz}} \]  

where \( V_c \) is the time series, \( L \) is the near-zero width parameter and will typically be about 1 or 2. Note that the \( P_a \) is simply the total power in the spectral bins around 0 velocity.

Because the power spectra is needed only at a few frequencies around 0 velocity, it is faster to simply calculate those spectral values directly using the standard discrete Fourier transform formulas. If \( C < C_T \) where \( C_T \) is the narrow clutter ratio threshold, then do not clutter filter and proceed to the next step as defined in the flow chart. If \( C \geq C_T \) then GMAP will be applied. First, a spectral noise calculation is performed and passed to GMAP. This is necessary because GMAP assumes that the noise is Gaussian and white (i.e. the power is uniformly distributed across all velocities). To find the spectral noise level, the spectrum is broken into 8 equal-sized segments such that the peak of the spectrum is centered in one of the segments. The peak power from each segment \( (P_{seg}(i)) \) is calculated. The spectral noise is set to be the average of the smallest \( P_{seg}(i) \) (currently 2) of the peaks. GMAP is now applied, with this noise power input. As in SZ-2, the number of spectral bins modified by GMAP needs to be returned. The spectrum is reconstructed setting the phases of the spectral points that GMAP modified to 0.

Spectral censoring (described in Hubbert et al. 2004) is used to determine the quality of the weak trip recovered spectrum (i.e., is it a reasonable weather spectrum). The calculation starts exactly like the spectral noise calculation. The spectrum is broken into 8 equally sized segments and the peak value of each segment is determined. The maxima are sorted and denoted \( \hat{M}_n \) where \( n = 0, \ldots, 7 \) and \( \hat{M}_0 \) is the smallest value. Then the spectral censoring metric is defined as

\[ H = 10 \log_{10} \left( \frac{M_7}{\frac{1}{8} \sum_{k=0}^{7} M_k} \right) \]  

### 1.2.5 Statistical Results

The statistical performance of SZ-1 will be comparable to SZ-2 performance. But since there are some small differences between the current discussed SZ-1 algorithm and earlier versions, statistical performance plots were generated, as has been done by Sachidananda and Zrnić (1999) and Hubbert et al. (2003), to verify performance. Though statistical plots were generated for strong and weak trip power, velocity and spectrum width, here we only give the plots for weak trip velocity. The statistics in these plots are all determined using simulated I&Q data. Pairs of I&Q time series are simulated, phase-coded, overlaid, and then processed using SZ-1. The SZ recovered moments are compared to the specified simulation input power, velocity and spectrum width. Table 1 shows the parameter settings for the simulation. The random phase errors are modeled in a similar fashion as done in Sachidananda and Zrnić (1999). The statistics of the weak trip velocity \( (V_2) \) are shown in Fig. 3 with the error (or bias) in the left panel while the standard deviation is in the right panel. The x-axis is strong trip spectrum width \( (W_1) \) and the y-axis is the strong trip to weak trip power ratio \( (P_1/P_2) \) in dB. The weak trip spectrum width is between 3.75 and 4.25 ms\(^{-1}\).

The error (or bias) is near zero and the the standard deviation of \( V_2 \) is similar to previously reported plots. As compared to the plots offered in Sachidananda and Zrnić (1999) the stan-
Figure 1: Flow diagram of SZ-1 algorithm with clutter filtering (continued in next figure).
Figure 2: Flow diagram of SZ-1 algorithm with clutter filtering (continued from previous figure).
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>PRT</td>
<td>988\mu s</td>
</tr>
<tr>
<td>Wavelength</td>
<td>10 cm</td>
</tr>
<tr>
<td>Weak Trip SNR</td>
<td>40 dB</td>
</tr>
<tr>
<td>Number of Simulations per Pixel</td>
<td>200</td>
</tr>
<tr>
<td>Random Phase Distribution</td>
<td>Uniform</td>
</tr>
<tr>
<td>Random Phase Errors</td>
<td>±0.25°</td>
</tr>
<tr>
<td>Number of Pulses/Beam</td>
<td>64</td>
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Table 1: *Table of Simulation Parameters*

Figure 3: *Mean (left) and Standard deviation (right) of Weak Trip Velocity in m\text{s}^{-1} for SZ-1 with W_{2} = 4 m\text{s}^{-1}*

standard deviations are actually smaller and this is due to the 0.25° phase noise used here, whereas Sachidananda and Zrnić (1999) used 0.5° phase noise.

1.2.6 Experimental Results

The developed SZ-1 with clutter filtering algorithm was tested with three data sets listed in Table 2. To determine a clutter map, the data was first processed using SZ-1 with clutter filters off everywhere and then the IMAT version of the REC-APDA was used to define a clutter map. The original data was processed again with clutter filters turned on as dictated by the REC-APDA defined clutter map. Here we only give results for case one of Table 2.

Figures 4 and 5 show a PPI of SNR of case 1 using SZ-1 without and with clutter filtering, respectively. As can be seen in Fig. 4, within 50 km of the radar there is a region of ground clutter indicated by the higher SNRs color coded yellow and red. In Fig. 5 this region of high power has been effectively eliminated by the clutter filter. This is easier to see in Figs. 6 and 7 which show the same data as Figs. 4 and 5 but zoomed in near the radar. The accompanying set of plots for Doppler velocity is given in Figs. 8 to 11. Again, it is seen that the large area of clutter echo has
been eliminated and the underlying storm structure is much more clear. These plots (and the plots for the other two cases not shown) verify that the NCAR developed SZ-1 algorithm with clutter filtering is performing well. Again, the SZ-1 algorithm does not identify clutter but rather depends on a reliable input clutter map.

As seen in SZ-2 data, SZ-1 data will exhibit a ring of censored data along the border between the first and second trip range ring. This ring can be seen in Figs. 4 and 5 in purple (i.e., censored data). The size of the ring, which is caused by strong first trip ground clutter “leaking” through to the weak trip, will vary from radar site to radar site. The size of the this ring seen in data from S-Pol in Boulder, CO seems to be smaller than the clutter ring seen in data from KOUN in Norman, OK. This may be due to stronger ground clutter signatures in KOUN data. However, it may also be that the clutter ring for KOUN is more pronounced because the burst pulse phases were not measured and thus the phase noise of the KOUN data is higher than the phase noise of the S-Pol data. Phase noise causes spectral power spread which in turn leads to more leakage of the strong clutter into the weak second trip. In the new ORDA system, the burst pulse phases will be measured (i.e., phase noise can be minimized) as they were for the S-Pol data, so the clutter ring should be kept to a minimum for NEXRAD data collected with the new ORDA.

Table 2: Test Cases for SZ1 with Clutter

<table>
<thead>
<tr>
<th>Case</th>
<th>Radar</th>
<th>Date</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 2</td>
<td>S-Pol/Boulder, CO</td>
<td>6/29/2003</td>
<td>00:24 Z</td>
</tr>
<tr>
<td>Case 3</td>
<td>KOUN</td>
<td>4/6/2003</td>
<td>04:27 Z</td>
</tr>
</tbody>
</table>

1.2.7 Conclusions

Currently, SZ-1 is designed for data that contain no more than two trips. The NEXRAD Technical Requirements (NTR) state that radar coverage with a Nyquist velocity of 25 ms$^{-1}$ (PRT = 988 µs) must extend to 18 km altitude. With a PRT of 988 µs, the SZ-1 second trip extends to a range of about 300 km. One can use the 4/3 earth radius approximation to determine the range of elevation angles within which the two trip SZ-1 will satisfy the NTR. Such analysis shows that the elevation angle must be $\geq 2.4$ degrees in order for the 300 km range to reach 18 km altitude with a Nyquist velocity of 25 ms$^{-1}$. To be used at lower elevation angles, either SZ-1 needs to be modified to accommodate three trips, or the NTR must be relaxed to accommodate either smaller Nyquist velocities or a lower altitude (e.g. 16 km at 1.8 degrees).
Figure 4: SNR in dB for Case 1 with SZ-1 with no clutter processing.

Figure 5: SNR in dB for Case 1 with SZ-1 with clutter processing.
Figure 6: Zoom in of SNR in dB for Case 1 with SZ-1 with no clutter processing.

Figure 7: Zoom in of SNR in dB for Case 1 with SZ-1 with clutter processing.
Figure 8: $V$ in ms$^{-1}$ for Case 1 with SZ-1 with no clutter processing.

Figure 9: $V$ in ms$^{-1}$ for Case 1 with SZ-1 with clutter processing.
Figure 10: *Zoom in of* $V$ *in ms$^{-1}$ for Case 1 with SZ-1 with no clutter processing.*

Figure 11: *Zoom in of* $V$ *in ms$^{-1}$ for Case 1 with SZ-1 with clutter processing.*
Censoring Threshold | Recommended value | Notes
---|---|---
\(K_s\) | 0.5012 | This is SNR* threshold for the strong trip (= -3 dB)
\(K_w\) | 1.5849 | This is SNR* threshold for the weak trip (= 2 dB)
\(K_r\) | \(C_T = 45\) for \(W_{n2} < 0.243\); \(40\) for \(W_{n2} \geq 0.243\) | These are the P1, P2 power thresholds for different SW

Table 3: \textit{SZ-2 recommended censoring thresholds.}

1.3 \textbf{SZ-2 Algorithm Threshold Update}

The thresholds used in the SZ-2 algorithm are in part based on Sachidananda and Zrnič (1999) who used a phase noise figure of 0.5° in their simulations. There is ample evidence to believe that the phase noise of the WSR-88Ds may well be significantly lower than this. The phase noise of the WSR-88D transmitter is about -70 dBc (Frush 1999). The RVP8 receiver/processor noise is about -55 dBc (private communication with Alan Siggia of SIGMET) and thus the RVP8 will likely be the limiting factor for the overall phase noise of the WSR-88Ds. This -55 dBc figure is equivalent to about 0.1° of phase noise. In light of this phase noise performance of the RVP8 receiver/processor, the strong trip to weak trip power ratio (P1/P2) thresholds can be increased. Thus, new power ratio censoring thresholds (Kr) were tested on the available RVP8 data sets collected using the NCAR S-Pol radar. It was also shown that the thresholds for the out of trip power leakage (SNR*) were too strict, resulting in valid data being censored. Tests were run using the S-Pol data with various SNR* thresholds.

The updated SNR* and power ratio thresholds are listed in the Table 3 following the nomenclature of the NCAR/NSSL interim report of June 2004, table on page 5. The thresholds not listed in Table 3 did not change.

1.4 \textbf{Double Processing Strong Trip Velocity}

1.4.1 Introduction

“Double processing” is additional SZ processing steps that can reduce the variance of the estimates of strong trip velocity (\(V_1\)). It is seen in Fig. 12 that the standard deviation of strong trip velocity estimates increase as the strong-to-weak-trip power ratio decreases below about 3 dB. This suggests that the strong trip velocity estimates could be improved by double processing the strong trip since one could suppress the weak trip power to recover strong trip velocity in the same way that the strong trip power is suppressed to recover the weak trip velocity. The results of this study show that strong trip velocity estimates are indeed improved for \(P_1/P_2 \leq 3\text{ dB}\) when double processing is used.
$W_2 = 2\text{ms}^{-1}$

Figure 12: The performance of $V_1$ (strong trip velocity) via simulation (phase noise $\sigma_\theta = 0.25^\circ$, $\text{SNR} \geq 40 \text{dB}$, Hanning window). The x-axis is the strong trip spectrum width, the y-axis is the strong-to-weak-trip power ratio, and the color axis is the standard deviation of the respective estimator.

1.4.2 Double processing algorithm

Two different approaches to double processing are investigated. The first algorithm executes SZ processing in standard fashion using the coherent power estimator, $|R_1|$, to determine the strong and weak trips and then calculating the the weak trip velocity. The abbreviated processing steps are as follows:

1. Calculate the weak trip velocity in standard SZ fashion.
2. Using the original raw time series, apply a Hanning window and cohere to the weak trip.
3. Calculate the spectrum via an FFT.
4. Apply a PNF (Process Notch Filter; Sachidananda and Zrnić 1999) centered at the weak trip velocity calculated in 1.
5. Apply inverse FFT and cohere to the strong trip.
6. Calculate the strong trip velocity.

In the second algorithm, the above double processing SZ algorithm is simply run twice by switching which trip is considered the strongest. The second algorithm differs in how the “real” weak trip velocity is processed. Simulations show that the first algorithm produces superior placement of the weak trip PNF which results in better velocity estimate statistics. Below we only show the results of the first double processing algorithm.
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>PRT</td>
<td>988µs</td>
</tr>
<tr>
<td>Wavelength</td>
<td>10 cm</td>
</tr>
<tr>
<td>Weak Trip SNR</td>
<td>40 dB</td>
</tr>
<tr>
<td>Number of Simulations per Pixel</td>
<td>200</td>
</tr>
<tr>
<td>Random Phase Distribution</td>
<td>Uniform</td>
</tr>
<tr>
<td>Random Phase Errors</td>
<td>±0.25°</td>
</tr>
<tr>
<td>Number of Pulses/Beam</td>
<td>64</td>
</tr>
</tbody>
</table>

Table 4: Table of Simulation Parameters

The double processing algorithm is tested via simulations using PNF notch-widths of N/4 or N/2 (N is the number of points in the time-series, i.e., 64) and using both the Hanning and Blackman windows. Table 4 shows the parameter settings for the simulations. The random phase noise is modeled in a similar fashion as was the phase noise in Sachidananda and Zrnić (1999). Sachidananda and Zrnić (1999) used phase noise of $\sigma_\theta = 0.5^\circ$ whereas we use a phase noise of $\sigma_\theta = 0.25^\circ$ which should better match the phase noise of the WSR-88D.

1.4.3 Results for double processing with Hanning (von Hann) window

The standard deviation of $V_1$ when using double processing with a weak trip PNF of N/4 (i.e. 1/4 of the Nyquist interval) is shown in Fig. 13 and it is similar to Fig. 12. The difference in standard deviation of $V_1$ with double processing (Fig. 13) minus without double processing (Fig. 12) is shown in Fig. 14. Improvements (seen as negative values) are realized for strong-to-weak trip power ratios ($P_1/P_2$) less than about 5 dB and are on the order of 0.3 ms$^{-1}$ or less. Some improvement can also be seen for narrow strong trip spectrum widths with larger $P_1/P_2$.

The difference in standard deviation of $V_1$ with double processing minus without double processing, with a weak trip PNF of N/2 (i.e. 1/2 of the Nyquist interval) is shown in Fig. 15. Again, improvements (seen as negative values) are realized for strong-to-weak trip power ratios ($P_1/P_2$) less than 5 dB. The performance is slightly better (more negative) for weak trip PNF of N/4. Thus, improvements in $V_1$ estimate standard deviation are only significant when $P_1/P_2 < 5$ dB which will occur infrequently in terms of the total number of pixels in a typical NEXRAD PPI scan. The cost of reducing the standard deviation in $V_1$ by approximately 0.3 ms$^{-1}$ is the additional processing required, mainly 2 FFTs. Since the improvements are small, double processing should be used only when $P_1/P_2 < 3$ dB.

1.4.4 Results for double processing with Blackman window

The following double processing plots are made using the Blackman window instead of a Hanning window. The standard deviation of $V_1$ without double processing is shown in Fig. 16, which should be compared with the results from the Hanning window case, shown in 12. As can be seen, there is a loss of performance (i.e., increase in standard deviation) when the Blackman window is used rather than the Hanning window.
Figure 13: The standard deviation of $V_1$ via simulation of SZ-1/SZ-2 (phase noise $\sigma_\theta = 0.25^\circ$, $\text{SNR} \geq 40\, \text{dB}$, Hanning window) with double processing using a $N/4$ PNF on the weak trip. The $x$-axis is the strong trip spectrum width, the $y$-axis is the strong-to-weak-trip power ratio, and the color axis is the standard deviation of the respective estimator. Left: $W_2 = 2\, \text{ms}^{-1}$. Right: $W_2 = 4\, \text{ms}^{-1}$.

Figure 14: The difference in standard deviation of $V_1$ via simulation of SZ-1/SZ-2 (phase noise $\sigma_\theta = 0.25^\circ$, $\text{SNR} \geq 40\, \text{dB}$, Hanning window) with double processing using a $N/4$ PNF on the weak trip. Negative values indicate an improvement (smaller standard deviation of $V_1$) when using double processing. The $x$-axis is the strong trip spectrum width, the $y$-axis is the strong-to-weak-trip power ratio, and the color axis is the standard deviation of the respective estimator. Left: $W_2 = 2\, \text{ms}^{-1}$. Right: $W_2 = 4\, \text{ms}^{-1}$. 
Figure 15: The difference in standard deviation of $V_1$ via simulation of SZ-1/SZ-2 (phase noise $\sigma_\theta = 0.25^\circ$, $\text{SNR} \geq 40 \text{ dB}$, Hanning window) with double processing using a $N/2$ PNF on the weak trip. Negative values indicate an improvement (smaller standard deviation of $V_1$) when using double processing. The $x$-axis is the strong trip spectrum width, the $y$-axis is the strong-to-weak-trip power ratio, and the color axis is the standard deviation of the respective estimator.

Fig. 17 shows the difference standard deviation of $V_1$ between double processing with a Blackman window (not given) and standard SZ processing with a Blackman window (Fig. 16). Compare Fig. 17 (Blackman) with Fig. 14 (Hanning). As can be seen the benefit from double processing is not as great when using the Blackman window as when using the Hanning window. Thus, the Hanning window should be used for the double processing application.

Although not shown, the performance was also evaluated using a weak trip PNF width of $N/2$ for a Blackman window. The conclusion is the same as with the Hanning case: better performance is realized with use of the $N/4$ weak trip PNF.

1.4.5 Conclusions

An improvement in $V_1$ measurement standard deviation of about 0.3 ms$^{-1}$ is achieved for $P_1/P_2 < 3 \text{ dB}$ when double processing is employed. The computational cost for this improvement is approximately two FFTs for each radar resolution volume. Since double processing would only be used when $P_1/P_2 < 3 \text{ dB}$, this added cost is minimal. The use of a Hanning window in double processing gives better improvement of the standard deviation of $V_1$ estimates than use of the Blackman window.
Figure 16: The standard deviation of $V_1$ (strong trip velocity) via simulation (phase noise $\sigma_\theta = 0.25^\circ$, SNR $\geq 40$ dB, Blackman window). The $x$-axis is the strong trip spectrum width, the $y$-axis is the strong-to-weak-trip power ratio, and the color axis is the standard deviation of the respective estimator.

Figure 17: The difference in standard deviation of $V_1$ via simulation of SZ-2 ($\sigma_\theta = 0.25^\circ$, SNR $\geq 40$ dB, Blackman window) with double processing using a N/4 PNF on the weak trip. Negative values indicate an improvement (smaller standard deviation of $V_1$) when using double processing. The $x$-axis is the strong trip spectrum width, the $y$-axis is the strong-to-weak-trip power ratio, and the color axis is the standard deviation of the respective estimator.
1.5 Window Function Optimization

1.5.1 Introduction

The SZ algorithm to be employed by the NEXRADs uses spectral processing on contiguous blocks of length 64 time series (i.e., the I and Q samples) and the performance of the SZ phase coding algorithm has been reported only for such length 64 time series. Windowing of the time series is done to reduce the spread of power across the velocity spectrum. Below, the statistical performance for SZ phase coding applied to length 32 and length 128 time series is given, i.e., we report the performance statistics for SZ(4/32) and SZ(16/128). Since the time series length is either halved or doubled from the nominal length of 64, it is expected that the standard deviations of the recovered radar moments from SZ(4/32) and SZ(16/128) either increase or decrease by a factor of $\sqrt{2}$, respectively. Thus, for best performance, the time series lengths should be the longest possible.

The NWS is pursuing so called “Super Resolution” data which will increase azimuthal resolution from $1^\circ$ to $1/2^\circ$. If one degree resolution was accomplished by integrating over 64 points, then Super Resolution could be achieved by simply integrating over 32 points for obtaining the radar moments. This presents a problem for the compatibility of the presently-planned SZ algorithm, which requires 64 points. One solution is to simply employ a SZ(4/32) algorithm which would degrade the statistics of the SZ recovered moments. Another solution is to use overlapping time series data, weighted with the Hanning window, but this could lead to some minor “smearing” or loss of resolution of the radar data. Below we show that this smearing effect is negligible and show that using overlapping length 64 Hanning windows can be used to provide both Super Resolution data and range-velocity ambiguity mitigation with SZ(8/64) phase coding.

The concept of overlapping windows has other applications. For example, the current SZ-2 algorithm to be deployed on NEXRAD calls for the use of length 64 times series that are non-overlapping. We show that instead a SZ(16/128) algorithm could be used which would practically maintain the same resolution but would reduce the standard deviation of the recovered moments significantly. Another application for overlapping windows is for clutter filtering. Currently it is planned to use the spectral clutter filter GMAP which requires the use of the Blackman window (Ice et al. 2004, though GMAP has not been tested using the Hanning window). For the long PRT scan of the split cut, there are only about 16 data points per resolution bin, and only about 8 if Super Resolution data is desired! If overlapping windows are employed, the data lengths can be increased to 32 and 16, respectively, which would improve clutter filter performance.

1.5.2 Window Functions

In this section the rectangular, Hanning and Blackman window functions are compared. Mathematically they are defined as,

Rectangular: \[1 \text{ for } 0 \leq n < M; 0 \text{ otherwise}\]

Hanning: \[0.5[1 - \cos\left(\frac{2\pi n}{M - 1}\right)]\]
Figure 18: The rectangular, Hanning (or Von Hann) and Blackman window function plotted over 64 points.

\[
\text{Blackman: } 0.42 - 0.5 \cos \frac{2\pi n}{M-1} + 0.08 \cos \frac{4\pi n}{M-1}
\]

where M is the window length and n is the index. Figure 18 shows plots of the window functions for M=64 (the rectangular window function is difficult to see since it is just a straight line at 1 on the ordinate axis). As can be seen, when applying the Hanning or Blackman window to a time series, the magnitude of time series members are reduced and thus, some signal power is lost. In fact the begin and end segments of the time series contribute very little to the total power of the signal. Also shown in Fig. 18 are the window functions divided into three regions: 1) the first 16 points, labeled \( P_1 \), 2) the middle 32 points, labeled \( P_2 \) and the last 16 points, labeled \( P_3 \). We define: \( P_R \) as the total power under the rectangular curve, i.e., \( P_R = 64 \), \( P_w \) as the total power of a window function, and \( P_1, P_2, P_3 \) as the power of a window function in the first 16, middle 32 and last 16 points, respectively. Table 1 shows some interesting power ratios. The middle column shows the ratio of the total power of a window to the power in the Rectangular window. The Hanning and Blackman windows contain 38.1% and 30% of the power of the rectangular window, respectively, which corresponds to 4.19 dB and 5.23 dB reductions in power. Thus, when using these windows

<table>
<thead>
<tr>
<th>WINDOW</th>
<th>( P_w/P_R )</th>
<th>( P_2/(P_1 + P_2 + P_3) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rectangular</td>
<td>100%</td>
<td>50%</td>
</tr>
<tr>
<td>Hanning</td>
<td>38.1%</td>
<td>91.9%</td>
</tr>
<tr>
<td>Blackman</td>
<td>30%</td>
<td>97%</td>
</tr>
</tbody>
</table>

Table 5: Ratios of window function powers corresponding to Fig. 18.

on time series, power estimates must be compensated by these reduction factors. The third column
Figure 19: Overlapping window strategy.

shows the power ratio of the middle 32 points of a window to the total power in a window. For Hanning and Blackman windows this ratio is 91.9% and 97%, respectively. Thus, the middle 32 points of a 64 point time series contains a very large majority of the total power in the windowed time series. Taking 10log of these ratios yields -0.37 dB and -0.13 dB (assuming equal distributed power across the time series). Thus, even if we neglected the power in the $P_1$ and $P_2$ areas, the bias of the calculated power would be less than a half of a dB (assuming equal distributed power across the time series). This then suggests using overlapping windows for SZ phase coding.

Figure 19 illustrates the overlapping window strategy as it would be used to obtain Super Resolution data simultaneously with SZ(8/64) phase coding. Shown are length 64 time series sequences that are gathered along a particular range ring as the radar scans. The top portion of Fig. 19 shows the traditional 64 point windowing strategy, i.e., contiguous non-overlapping windows. Each 64 point window corresponds to a radar resolution bin. The bottom portion of Fig. 19 shows the overlapping window strategy. The center of the 64 point window is advanced only 32 points for each new resolution volume. The number in parenthesis corresponds to the consecutive windows. In the overlapping strategy, twice the number of resolution bins are created, i.e., Super Resolution data, thus increasing the resolution of the processed radar data without smearing the data significantly (this is shown below). Figure 20 gives an alternative depiction of the overlapping windowing strategy. Shown in Fig. 20a are contiguous non-overlapping windows versus time or azimuth angle for some radar range. Each “bump” represents a Hanning type window applied to the underlying time series and thus each “bump” corresponds to a radar resolution volume or bin. Figure 20b shows the same time series windows moved closer together so that there is now an overlap of time series data points for each processed bin of radar data. In this way SZ phase coding can be made compatible with Super Resolution data.

Super Resolution could also be made compatible with SZ phase coding by converting the SZ(8/64) phase coding scheme to a SZ(4/32) scheme, i.e., only length 32 time series could be used in the algorithm. This would, however, result in inferior statistics of the recovered radar moments as is shown below. Next we compare the statistics of the SZ(8/64) algorithm to the SZ(4/32) and SZ(16/128) algorithms.
1.5.3 SZ statistics for SZ(4/32) and SZ(16/128)

The recovery statistics for the weak trip velocity have been shown in Sachidananda and Zrnić (1999). The standard deviation of the recovered weak trip velocity ($V_2$) is calculated as a function of the ratio of the strong to weak trip power ($P_1/P_2$) and of the strong trip spectrum width ($W_1$) using the weak trip spectrum width ($W_2$) as a parameter. The statistics are compiled using simulated data as was done in Sachidananda and Zrnić (1999). Shown in Figs. 21, 22 and 23 is the standard deviation of $V_1$ for SZ(4/32), SZ(8/64) and SZ(16/128), respectively. As the sequence length increases, the standard deviation of $V_1$ (strong trip velocity) decreases as expected. The benefit of using longer sequence lengths is clearly seen. Shown in Figs. 24, 25 and 26 is the standard deviation of $V_2$ for SZ(4/32), SZ(8/64) and SZ(16/128), respectively, for weak trip spectrum widths of 3.75 to 4.25 ms$^{-1}$. In this case, since $V_2$ is a SZ recovered moment ($V_1$ is calculated directly from the time series before any SZ processing) and is affected by spectral overlap from the strong trip as well as the overlap of the weak trip replica spectra (see Sachidananda and Zrnić 1999 for details), the effects of lengthening the time series sequence is less certain. Figures 24, 25 and 26, however, again clearly show the reduction of standard deviation of $V_2$ as the sequence length increases. The result is a significantly extended region of acceptable $V_2$ recovery, i.e., the recovery region is increased to higher $P_1/P_2$ power ratios, wider $W_1$ spectrum widths and wider $W_2$ spectrum widths for a constant acceptable level of $V_2$ standard deviation. Thus again, this demonstrates the advantage of using longer length times series. In the case of Super Resolution data and SZ phase coding, using overlapping length 64 windows is clearly superior to using non-overlapping length 32 time series sequences.
Figure 21: The standard deviation of strong trip velocity for SZ(4/32) algorithm.

Figure 22: The standard deviation of strong trip velocity for SZ(8/64) algorithm.
Figure 23: The standard deviation of strong trip velocity for SZ(16/128) algorithm.

Figure 24: The standard deviation of weak trip velocity for SZ(4/32) algorithm.
Figure 25: The standard deviation of weak trip velocity for SZ(8/64) algorithm.

Figure 26: The standard deviation of weak trip velocity for SZ(16/128) algorithm.
1.5.4 Effective beamwidth analysis

To quantitatively assess the effect of increased window lengths on data resolution, we next calculate effective radar beamwidths for one degree and half degree azimuth resolution with window weighting included.

Shown in Fig. 27 is an illustration of the calculations used for one degree azimuth resolution. Shown on the left hand side are the 64 beam patterns that are summed over a one degree resolution volume as the radar scans. This resultant represents the effective beam pattern, i.e., how the scatterers across the one degree resolution volume are weighted by the effective radar beam. This beam pattern can then be weighted by the desired window function which then yields the overall effective radar beamwidth.

Figure 28 shows several effective antenna beamwidths for one degree resolution using the NEXRAD VCP 11 parameters of $PRT = 780\mu s$ and a scan rate of $18.66^\circ s^{-1}$. The antenna pattern is modeled as Gaussian shaped with one degree beamwidth. The blue curve is the two way radar antenna pattern. The green curve represents the legacy effective antenna pattern, i.e., 64 point integration using a rectangular window function weighting. This can be used as a comparison baseline for the remaining curves. The red curve shows the effective beam pattern when using Hanning window weights, e.g., the effective beam pattern when using SZ(8/64). As is seen, the red curve is significantly narrower than the legacy green curve. The black curve shows the effective beam pattern if 128 points are used with Hanning window weights. As can be seen the black curve matches very well the green legacy curve down to about -20 dB. At two degrees off center, the difference between the green and black curves is about 8 dB but the black curve is about 60 dB down from its peak at this point. Thus, the loss in azimuthal resolution introduced by using 128 points weighted by a Hanning window will be minimal as compared to the legacy 64 point samples weighted by a rectangular window. The conclusion is: if Hanning windows are required by any of the signal processing techniques (SZ(8/64) or GMAP), one can double the window length and maintain resolution of a "legacy" scan which uses rectangular window weights.

Figure 29 is similar to Fig. 28 and shows several effective beamwidths for one-half degree resolution data. Again, the blue curve shows the 2-way antenna pattern while the green curve shows the legacy 32 point effective beamwidth, i.e., rectangular window weights are used over 32 points to attain one-half degree resolution. As should be, the 32 point legacy effective beamwidth is broader than the 2-way beamwidth but this broadening is not as great as in the prior one degree resolution case. The red line shows the effective beamwidth for 32 point integration using Hanning window weights (e.g., if SZ(4/32) is used). The black line shows the effective beamwidth for 64 point integration with Hanning window weights. As can be seen the black curve very closely matches the legacy 32 point green curve. Thus, the resolution when using SZ(8/64) is nearly identical to the resolution when using 32 point integration and a rectangular window. This then shows that Super Resolution data (i.e., 32 point legacy resolution) can be attained using 64 point integration with Hanning window weighting and therefore Super Resolution data is fully compatible with SZ(8/64) phase coding.

We next illustrate the use of the overlapping window strategy using data gathered with KOUN, NSSL’s research radar.
Figure 27: Effective beamwidth calculation.
Figure 28: Effective beamwidth for one degree resolution NEXRAD scanning.

Figure 29: Effective beamwidth for one half degree resolution NEXRAD scanning.
1.5.5 Data examples for Super Resolution

We next use experimental radar data to illustrate Super Resolution data and Super Resolution data with SZ phase coding for the purpose of investigating possible loss of resolution (i.e., smearing) when using overlapping time series windows. The following data was gathered by KOUN on 3 May, 1999, in times series format without phase coding. Via post processing, two PPI sector scans can be phase coded for first and second trip and then overlaid. The combined data set then can be processed using the SZ recovery algorithm. The advantage of this technique is two-fold; 1) experimental data is used and 2) the SZ recovered moments can be compared to or “truthed” against the original non-overlaid data moments. Shown in Fig. 30 are two concatenated PPI scans of uncalibrated power. The border between the two PPIs is seen as an arc of discontinuity in the center of the plot. The PPIs are phase coded for first and second trip and then overlaid and combined into one PPI scan. We next focus our attention on the features at about (-40km, -10 km) where there are some sharp power gradients and smearing effects will be most evident.

We first show Super Resolution data without overlapping windows and without SZ phase coding. Next we show Super Resolution data with overlapping windows and finally we show Super Resolution data with overlapping windows and SZ phase coding. Shown in Fig. 31 are zoomed-in power PPIs of Fig. 30 for the purpose of illustrating Super Resolution data in an area of high reflectivity gradients. No phase coding is applied (i.e, no overlay of data), a non-overlapping rectangular window is used to process the radar moments. Figure 31a shows the power calculated over 64 points in the conventional manner. Figure 31b shows power calculated from 32 points (i.e., double the resolution). Indeed the hook echo does have more detail and forecasters would like to have such data. But if phase coding is to be used in conjunction with Super Resolution data, then only 32 points are available if non-overlapping windows are used. In other words, SZ(4/32) would
Figure 31: Close up of Fig. 30. Power is calculated over non-overlapping windows; A. 64 point window integration; B. Super Resolution data, i.e., power is integrated over 32 points.
be used but that would degrade signal statistics significantly as shown above. Figure 32 shows the velocity plots that accompany the power plots of Fig. 31. Some folding is evident but again the Super Resolution plot (Fig. 32b) offers more storm detail.

Next, loss of data resolution due to using overlapping windows is examined where again no phase coding is used. Figure 33 shows power when using a 64 point overlapping Hanning window that slides 32 points for each resolution bin, i.e., the resolution is comparable to Fig. 31b. Figure 34 shows the same as Fig. 33 except a Blackman window is used. As can be seen, Figs. 33 and 34 are very similar to the 32 point Super Resolution data of Fig. 31b. Looking very closely at regions of highest power gradient does show that there is some smearing of the data but it appears to be minimal, at least for this case. Also, the smearing appears to be slightly less for the Blackman window of Fig. 34 as compared to the Hanning window of Fig. 33.

The concatenated PPI scans of Fig. 30 are now SZ phase coded, overlaid and separated via the SZ(8/64) algorithm in order to demonstrate the compatibility of SZ(8/64) phase coding and Super Resolution data. Results are compared to the moments calculated from the non-overlaid data. First, Fig. 35 shows the ratio of first trip power to second trip power for the same region as Figs. 31 to 34. The entire area displayed in Figs. 31 to 35 lies in the first trip region. The red areas in Fig. 35 are strong trip regions and the green areas are weak trip regions. As can be seen the power ratios vary considerable over the PPI of Fig. 35 and thus the recovery limits of the SZ algorithm are well tested by this data set. Figure 36 shows SZ recovered power when using a 64 point Hanning window centered every 32 points, i.e., it shifts 32 points per each new resolution bin. Comparing Fig. 36 to the Super Resolution data of Fig. 33, it is difficult to discern visually any degradation of the data.

Figure 37 shows the velocity that accompanies Fig. 36. Comparing Fig. 37 with Fig. 32b it is seen that the variance in the velocity field is greater (i.e., Fig. 37 looks “noisier” than Fig. 32b, the simple 32 point integrated velocity). This is to be expected since the process of separating the strong and weak trip moments with phase coding will increase the variance of the recovered velocity in Fig. 37. However, it is more appropriate to compare the velocities recovered with a SZ(8/64) algorithm to the velocities recovered with a SZ(4/32) algorithm. Shown in Fig. 38 is the velocity recovered with a SZ(4/32) algorithm. Comparing Fig. 38 to the SZ(8/64) recovered velocities of Fig. 37, it is seen that the variance of the velocities in Fig. 37 is less than those in Fig. 38. To summarize, the small amount of data smearing that occurs due to the use of overlapping windows is a small penalty for the significant reduction in variance that is gained.

1.5.6 Implications for overlapping windows

Using longer length windows that overlap can increase data quality in several applications while preserving the desired data resolution. Currently the SZ algorithm slated to be deployed on the NEXRAD network (at the existing 1° resolution data) will use non-overlapping 64 point Hanning windows. Instead overlapping 128 point Hanning windows could be used. The resulting data will be smeared minimally but the recovered SZ signal statistics will improve significantly. More velocity data should be recoverable with reduced variance. For example, comparing Fig. 38 (SZ(4/32) recovered velocity) to Fig. 37 (SZ(8/64) SZ recovered velocity) shows that the variance of the 64
Figure 32: Radial velocity plots that correspond to Fig. 31. A. Velocity from 64 point integration; B. Super resolution velocity from 32 point integration.
Figure 33: Power calculated using a 64 point Hanning window but at 32 point intervals. No phase coding is applied.

Figure 34: Power calculated over 64 point Blackman window but at 32 point intervals. No phase coding is applied.
The new clutter filter to be deployed on ORDA is the spectral-based (i.e., operates on the individual spectra) GMAP which requires the use of the Blackman window function (Ice et al. 2004). Here again the overlapping window strategy can be employed so that GMAP will have twice as many samples to use and thus clutter suppression will be improved (Ice et al. 2004). For example, at low elevations angles where a split cut scan is used, a long PRT scan will precede a short PRT SZ phase coded scan. The long PRT scan has approximately 16 non-overlapping data points per resolution bin. Instead the window length should be increased to 32 points with overlapping Blackman windows used (or possibly Hanning window). This would improve the clutter rejection performance of the GMAP filter.

1.5.7 Conclusions

SZ phase coding of of radar-transmitted pulses has been shown to be an effective method to mitigate range-velocity ambiguities. Application of the SZ decoding algorithm requires the use of a Hanning time series window or the equivalent. When using such window functions, it was shown that the large majority of the measured power results from the middle half of the windowed points. Thus, instead of applying the window to non-overlapping time series points, it was shown that overlapping windows could be used to either 1) increase the resolution of the data or 2) increase the window length to improve SZ recovered moment statistics. Using overlapping windows makes doubling the resolution of the radar data possible so that SZ(8/64) phase coding an be used in conjunction with Super Resolution data. Also, by using increased-length windows, clutter filters, such as GMAP, would have better performance.
Figure 36: Power calculated over 64 point Hanning window but at 32 point intervals. PPI scans in Fig. 30 are SZ phase coded, overlaid and separated via SZ algorithm.

Figure 37: Corresponding velocity plot for Fig. 36.
Figure 38: Velocity calculated from a non-overlapping 32 point windows using SZ phase coding, i.e., PPI scans in Fig. 30 are SZ phase coded, overlaid and separated via SZ algorithm.

2 Data Quality for NEXRAD

2.1 Introduction

The data quality tasks are primarily concerned with the identification of radar echoes. Previous reports have mostly focused on the Radar Echo Classifier (REC) which is a Fuzzy Logic-based algorithm for identifying 1) AP clutter 2) precipitation and 3) sea clutter. Other topics addressed in this report are stratiform versus convective rain partitioning and spectral processing for improved data quality.

The REC was designed to run on the ORPG but with the arrival of SIGMET RVP8 some of the REC functionally can migrate to the ORDA, most notably the AP clutter detection. In this section we describe CMD (Clutter Mitigation Decision algorithm), NCAR’s new Fuzzy Logic-based AP clutter identification algorithm which is specifically designed to run real time on ORDA. Also, the processing power of the RVP8 makes possible the calculation of the power spectra in real time. This means that the actual power near 0 velocity (or other variables calculated from spectra) is available for input to Fuzzy Logic algorithms (e.g., both REC and CMD) which is in contrast to simply estimating mean velocity via the pulse pair technique. The former quantity is a much better identifier of the existence of ground clutter which by definition is the presence of power at 0 and near 0 velocity. Such spectral variables are investigated in this report and they do improve the performance of clutter identification algorithms.

Perhaps most important, however, is the computational power of the RVP8 which allows for the identification of clutter and the subsequent application of a clutter filter in real time. The
improvement in data quality will be dramatic as is shown in this report. Not only is AP clutter eliminated in real time but also the underlying masked weather signature is revealed. Figure 39 shows a signal flow diagram of the ORDA with CMD. The digitized I and Q base data (time series) flow into the ORDA and is buffered for later possible use. A NP (Normal Propagation) clutter map may be input, however, CMD could also be used to identify NP as well as AP clutter thus eliminating the necessity of generating NP clutter maps. The I and Q samples may be from a long PRT scan, short PRT phase coded scan or any other uniform PRT scan. If a clutter map has been specified, then a clutter filter will be applied in those regions. If the input is phase coded, then the SZ decoding algorithm would also be applied here. In any case, moments are generated and then passed on to the CMD algorithm which identifies regions with ground clutter present. The clutter-contaminated gates are then fed back to the moments calculation algorithm where a clutter filter is applied and the moments are recalculated. All moments (base data) are then passed on to the ORPG. Again, an interesting possibility is that when the input I and Q data come from a long PRT scan, CMD could be used to identify both NP as well as AP clutter. This clutter map then could be used as input to the succeeding short PRT phase coded scan.

The Precipitation Detection Algorithm (PDA) is further developed in this report and coupled with the APDA to better identify those gates that contain precipitation. These results are then used in EPRE for better precipitation estimates.

Spectral processing is also further developed in this report. Spectral processing of radar echoes allows for the separation of precipitation echoes from point targets, interference and noise thereby providing improved weather base data estimates (i.e., reduced bias and reduced variance). This is done by processing spectra versus range and first identifying precipitation echoes (and clear air echoes) using spatial continuity of precipitation echoes. Then the radar moments are calculated by integrating only over desired meteorological portions of the spectra. Several examples are given to illustrate this. The end objective will be to automate this processing.

We first report on modifications, improvement and status of ORPG/CODE at NCAR.

### 2.2 Software Issues for ORPG/CODE and the Radar Echo Classifier

In FY05, NCAR made several corrections to the REC algorithm.

![Figure 39: Block diagram of the CMD (Clutter Mitigation Decision) algorithm in the ORDA.](image-url)
Bug fixes: NCAR fixed several coding errors in the REC. The Spin calculation did not correctly identify sign changes in reflectivity, and incorrectly used the integer function “abs()”, rather than the floating point function “fabs()”. NCAR also changed the spin and sign algorithms to return missing values if less than 25% of the values in the surrounding region are valid. These corrections cause the REC to produce the same results as our reference implementation.

New diagnostic feature: NCAR added the ability to write computed features and the outputs of membership functions to a netCDF file. This feature allowed NCAR to view results in Matlab and in SOLO (NCAR’s radar data viewer/editor), which aided us in validating that REC was producing correct results, as show in Fig. 40.

Multi-point membership functions: The original REC only supported membership functions defined by 2 points. NCAR has added a more general Fuzzy Logic membership lookup function that allows an arbitrary number of points, which is necessary to implement more flexible Fuzzy Logic recognizers.

Figure 40: NetCDF diagnostic output from Radar Echo Classifier
Precipitation detection algorithm: NCAR added a precipitation detection algorithm (PDA) to the REC. The PDA requires one additional feature - standard deviation of width; and uses the same Fuzzy Logic structure as the AP recognition algorithm.

NCAR has also modified the REC to correctly process Open RDA tilts, which now contain precisely 360 indexed radials. The REC now correctly finds adjacent radials for the first and last radial.

Furthermore, NCAR has started to merge the double precision changes made by Steve Smith that allow the Linux and Solaris versions of the REC to produce the same results.

### 2.2.1 Changes to the Enhanced Pre-Processing Subsystem (EPRE)

NCAR modified EPRE to use the PDA as well the APDA to decide which gates will be used for the Hybrid Scan array. A gate’s reflectivity value is included only in the hybrid scan if it is not clutter/AP and is classified as precipitation. The original algorithm is shown in Fig. 41. The modified algorithm is shown in Fig. 42. The additions to the algorithm are shaded blue. Note that EPRE algorithm now keeps track of missing gates to avoid erroneously using reflectivity values from higher tilts.
Figure 42: EPRE Modified to use PDA
2.2.2 Sea Clutter Algorithm

NCAR investigated adding a Sea Clutter Detection Algorithm (SCDA) to the REC. The SCDA would require the following interest fields:

- Vertical Gradient of Reflectivity (GDZ)
- Range Weighted GDZ (RGDZ)
- GDZ/sine(delta elevation angle)

The SCDA would require adding a 660 Kb buffer to the REC to store the previous tilt’s reflectivity to enable calculating the vertical gradient.

2.3 The REC

2.3.1 The APDA and PDA

The Anomalous Propagation Detection Algorithm (APDA) and the Precipitation Detection Algorithm (PDA) are relatively mature algorithms and are described in detail in Kessinger et al. (2003) and Kessinger et al. (2002). The APDA has already been implemented into the RPG as a criterion for the construction the Hybrid Scan Reflectivity (HSR). Thus, optimization of the algorithms requires only minor changes to the Fuzzy Logic membership functions and weights. The membership functions and weights for the APDA and PDA algorithms were slightly modified from previous annual reports (Kessinger et al., 2003, Kessinger et al., 2002), as described in this section. Also, the use of the long PRT radial velocity data is proposed within the APDA and initial results are provided. A version of the ORPG CODE has been installed at NCAR and utilized for this study allowing research within the WSR-88D environment.

An evaluation of the sign variable revealed that, as implemented, it had virtually no skill in separating clutter from precipitation. This is clearly shown in Fig. 43, which displays PPI images of a) radial velocity, b) reflectivity c) the sign variable and d) the sign interest field or membership output. There are strong ground clutter echoes embedded within precipitation return to the north and northeast of the radar, as evidenced by the high reflectivity and zero radial velocity values. The sign variable appears to have values ranging from -1 to 1 scattered throughout the radar domain, with no preferred value within the clutter or the precipitation regions. Accordingly, applying the sign membership function does not result in an interest field which discriminates the clutter from the precipitation. Inclusion of the sign variable in the APDA or PDA results in poorer performance (not shown) than when excluding it from the analysis. It is recommended the sign variable weight be set to zero, similar to the 2002 and 2003 reports (Kessinger et al., 2003, Kessinger et al., 2003), for all REC algorithms, unless a new version is computed and found to have benefit.

The following changes affected only the PDA algorithm. The mean reflectivity variable was removed from the PDA for the following experiments since the reflectivity values of ground clutter contamination and precipitation have significant overlap. Also, the 18 dBZ threshold of the PDA for rain removes any weak echoes that should not be classified as precipitation. Next, the standard
Figure 43: PPI images of a) radial velocity, b) reflectivity, c) the sign variable, and d) the sign interest field or membership function output.
deviation of radial velocity (SDVE) membership function was tuned, utilizing the new multiple point membership function capability in the ORPG CODE (Section 2.2). The SDVE membership functions for the new (red line) and old (black line) versions are shown in Fig. 44. The new membership function has a high interest for data with higher standard deviation velocity values than the old one in order to be more inclusive of variable precipitation such as convection. Also, the weight for the standard deviation of spectrum width was reduced to 0.25.

There were changes to the computation and membership functions of the spin variable feature field after bug-fixes to the ORPG CODE were implemented. The spin threshold was changed from 11 dB to 3 dB. This is much more consistent with the 2 dB that Steiner and Smith (2002) used. The membership functions were also tuned for REC APDA and PDA, and are shown in Fig. 45.

Preliminary experiments have been conducted to show the utility of using the long PRT radial velocity data within the APDA. The idea is to use long PRT radial velocity data in regions where the Doppler scan velocity data are not available due to censoring. Even though the long PRT velocities may be aliased, they can reliably show considerable regions of echo that do not have zero velocity and thus cannot be clutter. This useful information has the potential to improve the performance of the APDA in regions missing the standard Doppler data. As a proof of concept, experiments were run using the IMAT (Matlab based) version of the APDA. Currently the long
PRT velocity data are not available in the RPG, but discussions with the ROC indicate that the data could be made available, if proven to be of use.

In the data presented below, SZ phase coded time series data were used as the short PRT data with only the strong trip being recovered to simulate current WSR-88D processing. Long PRT data were also available and Fig. 46 shows a) the long PRT power (uncalibrated) and b) the short PRT radial velocity. This illustrates a case where large regions of echo are void of Doppler data for the APDA to utilize. The ground clutter contamination is highlighted by the black ovals. In order to illustrate the benefit of the long PRT radial velocity, we ran the APDA first using no Doppler data anywhere in the domain and then using long PRT data everywhere in the domain. Figure 47 shows the APDA results with a) no Doppler data and b) long PRT velocity used throughout the domain. Both methods identify the clutter near the radar, however the use of the long PRT data dramatically reduces the number of false clutter identifications in the weather echoes. Clearly the addition of the long PRT radial velocity, shown in Fig. 48 adds valuable information to the APDA despite the obvious folding. One caveat is that a zero value in the long PRT velocity may be in fact a non-zero velocity (e.g., velocities at $\pm 2 \times V_{\text{Nyquist}}$) folded to zero. Thus it is recommended that the long PRT velocity data only be used if it is not zero, to avoid using potentially misleading data in the APDA. One solution is to use only the long PRT velocity if the interest field is $< 0.5$, thus indicating the echo is not clutter, otherwise the weight should be set to zero. These results clearly show significant benefit to using the long PRT with the APDA. Intuitively this is satisfying since zero velocity estimates are a strong indicator of clutter.

### 2.3.2 Precipitation Estimation Improvements with EPRE

Improving precipitation estimation within EPRE by adding the Precipitation Detection Algorithm (PDA) output to the criteria for hybrid scan reflectivity (HSR) construction is discussed in this section. In order for a range gate to be included in the HSR, it must be unblocked, “unexcluded”, identified as NOT clutter by the APDA and positively identified as precipitation by the PDA. The
Figure 47: PPI plots of the APDA results with a) no Doppler data and b) long PRT velocity used throughout the domain.

Figure 48: PPI plot of the long PRT radial velocity.
benefit of using the PDA output is realized in regions of mixed clutter and precipitation or clear air echoes, and in regions of pure clutter in which random speckles of clutter may not be identified as clutter and thus contribute to noise in the rainfall estimates. In mixed clutter/weather regions, the APDA generally correctly does not identify the region as pure clutter because the radial velocity may not be zero, the spectrum width is too wide, etc., due to the contribution from weather. However, the PDA can recognize that the moment estimates are too noisy to be pure precipitation and thus correctly identify the echo as not being pure precipitation either. Thus by including the PDA criterion to the HSR, the contamination of the clutter mixed with precipitation is excluded from the HSR. In pure clutter regions there may be small, isolated areas that are misclassified by the APDA. The PDA may correctly indicate that these echoes are, in fact, not precipitation, and should not be included in the HSR. This significantly reduces the number of clutter gates included in the HSR. The required changes in the EPRE are described in Section 2.2.1 and the results are presented below. In the experiments presented below, the normal threshold for the PDA (typically 18 dBZ in rain) is not used in order to fully examine the algorithm performance. In practice echoes below the threshold would not be included in the HSR or the rainfall estimate.

Results of using the PDA within EPRE are shown from five WSR-88D data sets from separate locations. The radars and dates are St Louis MO (KLSX) 1 November 2004, Boston MA (KBOX) 14 July 2003, Sterling VA 17 August 2003, Amarillo TX 25 May 1994, and Chicago IL 19 October 1995.

Figure 49 shows an example of ground clutter and weather echoes mixed together. The ovals indicate regions in which the clutter and weather echoes have competing magnitudes. This results in clutter contaminated reflectivity, but with non-zero radial velocity. Thus, it is (correctly) not classified as clutter echo by the APDA, as seen in the lower left panel of Fig. 49. In the regions of competing clutter and weather echo the radial velocity and reflectivity have much higher variance and texture values than is expected for pure weather echoes. Thus the PDA does not classify the contaminated regions as weather. Using the newly-developed criteria to build the HSR, in this case, results in exclusion of the clutter contamination and the use of a higher scan reflectivity to fill in the contaminated regions. This is illustrated in Fig. 50, which shows, a) the HSR scan using only the APDA threshold and b) the resulting HSR scan using both APDA and PDA thresholds. Notice the considerable decrease in clutter contamination near the radar and to the north in the mixed clutter/weather region, when both criteria are used (there are still a few misclassified points).

The next example is from Boston (KBOX) on 14 July 2003 and demonstrates the pure clutter case. Figure 51 shows a) the reflectivity and b) the radial velocity at 12:01 GMT. Notice the only weather echo is the region of stratiform precipitation to the south of the radar and there are strong clutter echoes nearby and to the north. In this case clutter actually extends to the end of the displayed range. This case was of particular interest to the ROC as an example of desired improvement in the rainfall estimate. A comparison of the original HSR from the ROC and the HSR resulting from the improved method are shown in Fig. 52a and b, respectively, (note the different color scales). It can be seen that the majority of the contamination that leaked through the original algorithm is removed by the new algorithm. A minor point is that the original data was produced without the changes to the APDA membership functions described in the previous section.
Figure 49: PPI images of radial velocity (upper left), reflectivity (upper right), APDA output thresholded at 50 (lower left), and PDA output thresholded at 50 (lower right).

Figure 50: PPI images of the HSR with a) APDA threshold only and b) both APDA and PDA thresholds applied.
Figure 51: PPI images of a) reflectivity and b) radial velocity from KBOX on 14 July 2003.

Figure 52: PPI images of a) the original HSR with APDA criterion only, and b) HSR resulting from using both APDA and PDA criteria, from KBOX on 14 July, 2003. Note that the color scales are slightly different.
There is strong clutter leakage in both HSR displays in Fig. 52 at the edge of the radar range in the northern part of the display, denoted by the white circles. Further examination reveals that the APDA correctly identified the echo as clutter and that the PDA correctly identified the echo as not being precipitation as shown in Fig. 53. It was discovered that the APDA and PDA are not being computed to the end of the range of the radar while the HSR is. Figure 54a shows the APDA output and 54b shows the HSR. Notice that the end of the data for the two scans, indicated by the white arrows, is different. This results in range gates at the edge, which have no APDA or PDA output, never being excluded from the HSR and the consequent precipitation estimate. The number of range gates at the edge of the domain without REC classification probably depends on the size of the data region chosen to compute the Fuzzy Logic feature fields. The one-hour precipitation estimate resulting from using both the APDA and PDA criteria for computing the HSR is shown in Fig. 55.

The next example is from Sterling VA (KLWX), 17 August 2003. Figure 56a shows the reflectivity and Fig. 56b shows radial velocity from 10:51 GMT. Notice the clutter mixed with clear air echoes near and to the west of the radar. The clutter contamination does not necessarily have zero radial velocity and thus is not all classified as clutter, as can be seen in Fig. 57 which displays the APDA output in panel (a) and the PDA output in panel (b). It can also be seen that the PDA does not classify the echoes as precipitation. Thus the HSR constructed using only the APDA criterion contains more clutter contamination than when both APDA and PDA criteria are used. This is illustrated in Fig. 58 which shows the HSR using only APDA criterion in panel (a) and both APDA and PDA in panel (b). The white ovals highlight the region of improvement. The resulting one-hour rainfall accumulation estimates are shown in Fig. 59. It can be see that the false accumulation due to clutter contamination is not present when both criteria are used (part b), but that the rest of the precipitation estimates are the same.
The next example again shows the benefit of using both APDA and PDA criteria to build the HSR in a case with clutter mixed with clear air echo, which may not have zero velocity. The data are from Amarillo TX (KAMA) on 25 May, 1994. Figure 60 shows the reflectivity in panel (a) and radial velocity in panel (b) with the white oval indicating the region of ground clutter contamination. Notice the non-zero velocity values mixed in with the clutter. The APDA and PDA results are plotted in Fig. 61 and it can be seen that both algorithms are performing well. However, the small areas with non-zero velocity are not identified as clutter by the APDA, nor are they identified as precipitation by the PDA. Thus, using both criteria to build the HSR is advantageous. This is illustrated in Fig. 62 which shows reduced clutter contamination using both criteria (b) as opposed to only the APDA (a). The resulting one hour rainfall accumulations are shown in Fig. 63. Clearly the addition of the PDA criterion reduces the clutter contamination.

Figure 64 shows a squall line approaching Chicago (KLOT, 19 October 1995) with ground clutter echo mixed with clear air echo close to the radar. The HSR scans shown in Fig. 65 clearly demonstrate improvement in clutter removal using both PDA and APDA criteria (b) over APDA alone (a). The 1.5 hour rainfall accumulation estimates are shown in Fig. 66. The two plots are nearly indistinguishable except there is slightly more clutter contamination in the APDA threshold only (a). It is important to note that the rainfall accumulation using both APDA and PDA thresholds (Fig. 66b) is not degraded within the convective squall line compared to the APDA threshold only.
Figure 55: One hour accumulation rainfall estimate using both APDA and PDA criteria.
Figure 56: PPI images of a) reflectivity and b) radial velocity from KLWX at 10:51 GMT.

Figure 57: PPIs of one-hour rainfall accumulation using the a) APDA and b) PDA from KLWX at 10:51 GMT.
Figure 58: PPI images of the HSR resulting from using a) APDA and b) both APDA and PDA criteria, from KLWX at 10:51 GMT.

Figure 59: PPI images of a) clutter likelihood from the APDA and b) precipitation likelihood from the PDA from KLWX at 10:51 GMT.
Figure 60: PPI images of a) reflectivity and b) radial velocity from KAMA at 00:04 GMT.

Figure 61: PPI images of a) clutter likelihood from the APDA and b) precipitation likelihood from the PDA from KAMA at 00:04 GMT.
Figure 62: PPI images of the HSR resulting from using a) APDA and b) both APDA and PDA criteria, from KAMA at 00:04 GMT.

Figure 63: PPI images of output from the a) APDA and b) PDA from KAMA at 00:04 GMT.
Figure 64: PPI images of a) reflectivity and b) radial velocity from KLOT, 19 October 1995, at 23:13 GMT.

Figure 65: PPI images of the HSR resulting from using a) APDA and b) both APDA and PDA criteria, from KLOT, 19 October 1995, at 23:13 GMT.
Figure 66: PPI images of the rainfall accumulation for 1.5 hours using a) APDA and b) both APDA and PDA criteria, from KLOT, 19 October 1995.

2.3.3 Super Resolution and REC

Super Resolution data for the WSR-88D consists of beams spaced 0.5 degrees in azimuth and with a gate spacing of 0.25 km for all moments. Testing the performance of the REC-APDA using Super Resolution data is necessary to ensure that no performance degradation occurs once these data are available within the ORPG. Using the I & Q data from the KJIM radar on 4 April 2004, two data sets were processed and moment fields created within IMAT for one elevation scan at 0.4 degrees. The first represents WSR-88D data as it currently exists where beams are 1 deg apart in azimuth and are formed using 64 samples. The second represents future Super Resolution WSR-88D data where the beams are 0.5 deg. apart in azimuth and are formed using only 32 samples. A gate spacing of 0.25 km was used for all moment data within both data sets. Due to the fewer number of samples in the Super Resolution data, it is expected that the moment fields will be statistically noisier.

Once the two sets of moment fields were created, netCDF output files were written by IMAT and then converted to DORADE format for input into the REC-APDA that resides within the Python Environment for Radar Processing (PERP). The PERP contains the developmental versions of algorithms within the REC and can directly ingest DORADE formatted data sets, whether from a WSR-88D or S-Pol or other radars.

A visual comparison of the moment fields derived from 64 samples (Figure 67) versus 32 samples (Fig. 68) is instructive. While it is expected that the 32 sample data is noisier than the 64 sample data, it is difficult to discern this from the plots shown in Figs. 67 and 68. The effect of the increased number of beams gives the appearance that the 32 sample data set has less noise than the 64 sample data set. A formal, statistical comparison of the two moment data sets is needed to fully explore their differences. Also, selection of alternate color tables could show the differences
more clearly.

The performance of the REC-APDA is examined using the two data sets (panel b within both figures). Within the ground clutter region near the radar, the REC-APDA has comparable values as indicated by the yellow and brown areas and suggests that significant performance differences are not a problem. However, comparison of the REC-APDA performance within the precipitation area and within the low-signal area suggests some tuning of the algorithm may be necessary. Within the precipitation and the low-signal areas, the REC-APDA returns clutter likelihood values that are approximately 10 to 15% higher in the 32 sample data than for the 64 sample data. This difference could lead to a negative performance impact on the REC-APDA if it results in areas being falsely classified as clutter. The REC-APDA differences, while reasonably small, will be most noticeable when the interest values are near the threshold value of 0.5. A place that this occurs is within the precipitation area located near 260 degrees azimuth and 100-140 km in range. The REC-PDA is below the 0.5 threshold value in the 64 sample data set and is at the threshold for the 32 sample data set.

Future work will include an examination of the feature fields and their membership functions as used within the REC-APDA to determine what modifications may be necessary to accommodate the Super Resolution data. It is expected that the modifications will be slight and will focus on the size of the local area used to calculate the feature fields. Further comparisons of the REC-APDA performance using super resolution data will be derived from S-Pol IQ data sets.

2.3.4 Use of Polarimetric Variables in the APDA

When the capability for polarimetric data collection is added to the WSR-88D, it will be possible to add polarimetric variables to the REC algorithms and vastly improve its performance. The advantage of using the polarimetric REC-APDA is that it will be in place within the ORPG and modifications to EPRE will not be needed.

To test this concept, the REC-APDA was modified to include two polarimetric variables as additional feature fields and run within the PERP. The new variables are the standard deviation of the differential reflectivity field \( Z_{dr} \) and the standard deviation of the differential phase \( \phi_{dp} \). These variables (plus additional ones) are also used by the polarimetric Particle Identification Algorithm (PID; Vivekanandan et al. 1999) within its classification for detection of ground clutter. Membership functions were devised for each variable, based on visual inspection of a few scans, and are shown in Fig. 69. These membership functions are somewhat different to the ones used by the PID. Refinements in the membership functions may be needed after more scans are examined. As Fig. 69 shows, values \( \geq 2 \text{dB} \) of the standard deviation of \( Z_{dr} \) indicate a high likelihood of ground clutter while values \( \geq 14 \text{ deg.} \) of the standard deviation of \( \phi_{dp} \) indicate a high likelihood of clutter. Smaller values for each variable indicate less to no likelihood of clutter.

Using these membership functions, the two polarimetric variables were added to the REC-APDA as feature fields; hereafter the REC-APDA version with polarimetric variables added as feature fields will be called the “polarimetric REC-APDA”. Four scans from the S-Pol radar at two locations were utilized to see what, if any, performance improvements might occur. For each case, the reflectivity data are shown without any thresholding, with the original REC-APDA applied
Figure 67: This figure and Fig. 68 compare current and super resolution WSR-88D data and its effect on the REC-APDA performance. The data were processed from IQ data collected by the KJIM radar on 4 April 2004, using 64 samples. Each figure shows the a) reflectivity (dBZ), b) the REC-APDA interest output, c) the radial velocity (ms$^{-1}$) and d) the spectrum width (ms$^{-1}$) fields.
Figure 68: Same as Fig. 67 except that the I&Q data are processed using 32 samples. Fields shown include the a) reflectivity (dBZ), b) the REC-APDA interest output, c) the radial velocity (ms$^{-1}$) and d) the spectrum width (ms$^{-1}$) fields.

Figure 69: Membership functions are shown for the standard deviation of the $Z_{dr}$ (left panel) and the standard deviation of the $\phi_{dp}$ (right panel).
as a threshold and with the polarimetric REC-APDA applied as a threshold. Algorithm outputs from the original REC-APDA and the polarimetric REC-APDA are shown with the 0.5 threshold applied.

The first case was collected during the IMPROVE-I field campaign on 8 February 2001 and was selected due to the prominent ground clutter surrounding the coastal bay and from the Olympic Mountains to the northeast of the radar. Figure 70a shows stratiform precipitation mixed with ground clutter return from the bay and the mountains. Reflectivity values within the stratiform precipitation vary between zero and 40 dBZ while ground clutter echo has values between 20 and 55+ dBZ (the maximum reflectivity values are off the color scale and cannot be more precisely determined from this figure). In Figs. 70b and 70d, a 0.5 threshold is applied to the reflectivity to remove the ground clutter contamination as determined by the original REC-APDA and by the polarimetric REC-APDA, respectively. Figures 70c and 70e show the output from the original REC-APDA and from the polarimetric REC-APDA, respectively, after application of a 0.5 threshold.

As Fig. 70 shows, the polarimetric REC-APDA has improved performance over the original REC-APDA at removing ground clutter in mixed clutter/precipitation conditions, as indicated by the fewer number of high reflectivity gates (typically shaded red or brown) seen within the Olympic Mountains and around the bay (compare Figure 70b to Fig. 70d). Identifying mixed clutter and precipitation echo is difficult with only the three moment fields as input. The addition of polarimetric variables improves the discrimination that the REC-APDA is able to achieve.

The next three examples use S-Pol data taken during the IHOP 2002 field campaign when the radar was located in the Oklahoma panhandle. The ground clutter was not as strong as was observed at the IMPROVE-I site, but is a persistent feature at close ranges surrounding the radar and to the northwest of the radar.

The first IHOP 2002 case was collected on 27 May 2002 (Fig. 71a) and shows a region of precipitation to the south and east of the radar with ground clutter regions near and to the northwest of the radar. The polarimetric REC-APDA (Fig. 71e) performs better than the original REC-APDA (Fig. 71c) at discriminating ground clutter return from precipitation return. The reflectivity field is shown after the respective version of the REC-APDA is used to remove ground clutter, as determined by application of a 0.5 threshold using the original REC-APDA (results shown in Fig. 71b) and using the polarimetric REC-APDA (results shown in Fig. 71d). Within the red shape (where a mixture of clutter and precipitation resides), the original REC-APDA does not remove nearly as many clutter-contaminated gates of reflectivity data as the polarimetric REC-APDA. The polarimetric REC-APDA is also better able to discriminate precipitation return (as indicated within the cyan shape) and does not incorrectly classify precipitation return as clutter. In the relatively-pure clutter return to the northwest of the radar, both algorithms achieve good results at classifying and removing ground clutter with the polarimetric REC-APDA classifying a somewhat larger area of clutter as compared to the original REC-APDA.

The second and third IHOP 2002 cases were collected on 13 June 2002 at 1100 and 1230 UTC. As can be seen at the first time (Fig. 72a) intense convective cells are near the radar within the eastern and southern quadrants. In addition to the ground clutter that is normally present, some AP clutter can be seen to the west of the radar location. After applying the 0.5 threshold using the original REC-APDA (Fig. 72c) to the reflectivity field (Fig. 72b) the clutter to the northwest
Figure 70: Data collected by the NCAR S-Pol radar on 8 February 2001 data 1609 UTC during the IMPROVE-I field campaign near the coast of Washington. Fields shown are the a) reflectivity (dBZ) field, b) the reflectivity field with a 0.5 threshold applied from the original REC-APDA, c) the output from the original REC-APDA after a 0.5 threshold is applied, d) the reflectivity field with a 0.5 threshold applied from the polarimetric REC-APDA and e) the polarimetric REC-APDA after a 0.5 threshold is applied. The locations of the coastal bay and the Olympic Mountains are indicated. The 0.5 degree elevation angle is shown with range rings at 15 km intervals.
Figure 71: Same as Fig. 70 for S-Pol data taken on 27 May 2002 at 2203 UTC during the IHOP_2002 field campaign. The red shape encircles a region of ground clutter mixed with precipitation while the cyan shape encircles a region of precipitation. The 0.0 degree elevation angle is shown with range rings at 15 km intervals.
Figure 72: Same as Fig. 70 for S-Pol data taken on 13 June 2002 at 1100 UTC during the IHOP_2002 field campaign. The 0.0 degree elevation angle is shown. The red shape encircles a region of ground clutter mixed with precipitation while the cyan shape encircles a region of mostly precipitation.
Figure 73: Same as Fig. 70 for S-Pol data taken on 13 June 2002 at 1230 UTC during the IHOP_2002 field campaign. The 0.0 degree elevation angle is shown. The red shape encircles a region of mostly precipitation with a region of strong clutter at its southern edge.

and near the radar (area enclosed by the red oval) is removed. Some precipitation regions are also removed within the area enclosed by the cyan shape. The polarimetric REC-APDA (Fig. 72c) removes even more ground clutter within the red shape when compared to the original REC-APDA and does not remove the precipitation regions within the cyan shape. Within the green shape, the polarimetric REC-APDA removes more gates of data than the original REC-APDA and reflects its improved discrimination of mixed precipitation and clutter situations.

The fourth and last comparison the the original REC-APDA and the polarimetric REC-APDA was also collected on 13 June 2002 during IHOP_2002. A region of precipitation with a maximum reflectivity value of about 40 dBZ is centered over the radar with extension of the echo towards the southeast (Fig. 73a). Anomalous Propagation (AP) ground clutter has appeared to the west of the radar at and beyond 45 km in range. Both the original REC-APDA (Fig. 73c) and the polarimetric REC-APDA (Fig. 73e) do a good job of removing the AP ground clutter with the strongest reflectivity values when the threshold of 0.5 is applied to the reflectivity field (Figs. 73b and d, respectively). The original REC-APDA leaves more of the gates that have low reflectivity than the polarimetric REC-APDA. Within the red oval, the original REC-APDA incorrectly classifies...
some of the precipitation return to the northwest of the radar as clutter and it is removed during the thresholding process. A region of clutter mixed with precipitation lies to the south of the radar within the red oval and has reflectivity values in excess of 45 dBZ. Both algorithms are able to remove most of this mixed clutter area; however, the polarimetric REC-APDA removes more.

In summary, the addition of two polarimetric variables to the REC-APDA has a positive impact on the algorithm performance. When the WSR-88D system includes the capability to measure dual polarization, the addition of polarimetric variables within the REC is easily accomplished and should be considered. The dual polarization REC will provide a base line against which other possible algorithms can be compared.

2.3.5 Convective/Stratiform Partition

Partitioning precipitation regions into convective versus stratiform regions is of value when computing radar-derived rainfall estimates because each precipitation regime can have a different Z-R relationship. For the WSR-88D Enhanced Precipitation Pre-processing Subsystem (EPPRE), it would be useful to determine regions of each precipitation type such that the appropriate Z-R equation can be used for each. A method proposed by Steiner et al. (1995) (here after referred to as S1995) has been implemented within the Python Environment for Radar Processing (PERP) the NCAR prototype development environment for the ORPG. The S1995 methodology uses radar data in Cartesian space; the PERP methodology uses radar data in polar space. A full description of the S1995 algorithm follows. As originally envisioned, the idea was to devise a Fuzzy Logic algorithm to discriminate between convective and stratiform regions in a similar manner as is done in the AP clutter Detection Algorithm (APDA). However, feature fields derived from the base radar fields of reflectivity, radial velocity and spectrum width that discriminate sufficiently between convective and stratiform regions are few. For this reason, it was decided to try to improve the existing rule-based algorithm.

2.3.6 Steiner et al. (1995) Methodology

The S1995 methodology examines the horizontal structure of the precipitation field to separate the convective and stratiform regions. This method searches for peaks in reflectivity and applies specific criteria regarding the ratio of the peak reflectivity to the background reflectivity to separate the echo types. Mean reflectivity is linearly computed over two regions: the convective radius that varies in length and the background radius of 11 km (Fig. 74). The separation is performed on reflectivity data in Cartesian space at 3 km AGL to be above possible bright band contamination. The specific criteria used by their methodology are as follows.

**Intensity:** Any grid point with reflectivity \( > 40 \) dBZ is convective

**Peakedness:** Of the remaining grid points, those that exceed the average reflectivity computed over the background radius by at least the reflectivity difference shown in Fig. 75 are convective.
Figure 74: Schematic diagram showing how convective grid points are identified. For a specific grid point, the lightly shaded circular area indicates the region of the “background reflectivity”, computed over an 11 km radius. The darker shaded area indicates the “convective region” if the center grid point is identified as convective. Figure provided by courtesy of S1995.

**Surrounding area:** For each grid point identified as convective, all surrounding grid points within an intensity dependent convective radius (Fig. 76) are also identified as convective. All grid points not classified as convective are categorized as stratiform.

### 2.3.7 Biggerstaff and Listemaa (2000) Modifications to S1995 Methodology

The Steiner technique is used operationally with the ground validation radars for the Tropical Rainfall Measurement Mission (TRMM) to verify the satellite rainfall estimates. Satellite echo classification is achieved with an algorithm that is partly based on S1995. Biggerstaff and Listemaa (2000) (hereafter referred to as BL2000) modified certain aspects of the S1995 methodology to improve the discrimination between convective and stratiform regions. These modifications were based on the three dimensional reflectivity characteristics of the storms. The changes that they made to the algorithm corrected two main causes of error: heavy rain areas within the stratiform regions that were classified as convective and the edges of convective cells originally classified as stratiform.

Briefly, the changes that they made were to calculate the vertical lapse rate of reflectivity, the bright band fraction (BBF), and the magnitude of the two-dimensional horizontal gradient of reflectivity. The vertical lapse rate of reflectivity is calculated as the decrease in reflectivity with increasing height above the ground in the 3 km layer above the height of maximum reflectivity, which will occur in the mixed-phase region between 0°C Celsius and -20°C Celsius for a well-developed stratiform region. In BL2000, lapse rates for convective (stratiform) regions were defined as being less (greater) than 3.5 dB km⁻¹. The BBF is calculated similar to Rosenfeld et al. (1995a) but with the added conditions that the maximum reflectivity in the grid column must occur within ±1.5 km of the melting level and that the reflectivity lapse rate indicates stratiform precipitation. The magnitude of the two-dimensional gradient of reflectivity was computed using the log-scale reflectivity.
Figure 75: The reflectivity difference (reflectivity value minus the background reflectivity value, computed at each gate) is plotted versus the mean background reflectivity. The curved line shows the criteria used to evaluate the peakedness criteria. At low mean background reflectivity values, the reflectivity difference must be greater than at a high mean background reflectivity to classify a point as “convective”. Figure provided by courtesy of S1995.

Figure 76: Three convective area radii are shown as a function of the mean background reflectivity for the “surrounding area” criteria. The three radii determine how much of the surrounding area is defined as convective, whether it is “small”, “medium” or “large”. Figure provided by courtesy of S1995.
and with a threshold of 3.0 dB km\(^{-1}\) selected such that values less (greater) than the threshold indicate stratiform (convective) precipitation. Further, they removed the 40 dBZ convective criteria used by S1995 and found that this decreased the amount of bright band contamination.

Using the new fields, they devised additional rules to refine the convective/stratiform partition. First, convective grid points (as classified by S1995) were reclassified to stratiform if the following conditions were met:

1. The horizontal reflectivity gradient was weak (< 3 dBZ km\(^{-1}\)), the reflectivity lapse rate was steep (> 3.5 dB km\(^{-1}\)), and the reflectivity values were low (< 35 dBZ), or if:
2. There are low reflectivity values aloft (< 28 dBZ at about twice the altitude of the reflectivity maxima), a weak horizontal reflectivity gradient (< 3 dBZ km\(^{-1}\)) and a high BBF (> 0.6).

Second, stratiform grid points (as classified by S1995) were reclassified as convective if the following conditions were met:

1. There exists a strong horizontal reflectivity gradient (> 3 dBZ km\(^{-1}\)), or if
2. There is a weaker horizontal reflectivity gradient (> 2 dBZ km\(^{-1}\)) and a low BBF (< 0.4).

Three example cases have been included from BL2000 to illustrate the improvements that they achieved using their modified S1995 technique. Two of the cases are for large, mesoscale convective systems (MCS) and are shown in Figs. 77 and 78 while the third is for scattered convective cells with no particular organization (Fig. 79). As shown in Figs. 77 and 78, the changes made by BL2000 result in significant performance improvement at discriminating stratiform and convective precipitation regions. In particular, note for the two MCS cases that the leading edges that had been classified as stratiform are now correctly identified as convective and that the identification of the trailing stratiform region is much improved. The first case, shown in Fig. 77, retains considerable area defined as convective in the trailing stratiform region but overall has improved performance with the partitioning. For the case with scattered convective cells (Fig. 79), the BL2000 technique improves the classification results. Convective cells that are dissipating are correctly identified as stratiform precipitation and the edges of convective cells are correctly identified as convective rather than stratiform.

2.3.8 NCAR Algorithm

For the algorithm under development at NCAR, it is desired to remain in polar space rather than interpolate the data to Cartesian space as is done in S1995 or to use constant altitude plane PPIs (CAPPIS) as is done in BL2000. However, some of the modifications made by BL2000 can also be applied to radar reflectivity data in polar space. For the NCAR algorithm, the one-dimensional horizontal gradient of reflectivity (along the radial) is added to the convective/stratiform partitioning algorithm in a similar fashion as the BL2000 scheme and is used to reclassify points initially identified as convective to stratiform. In addition, the inclusion of polarimetric data is desired to better plan for the future deployment of this capability on radars in the NEXRAD network.
Figure 77: A case study from the Houston WSR-88D (KHGX) for 2132 UTC on 23 May 1993 that illustrates the improvement made by applying changes to the S1995 methodology as suggested by BL2000. Fields shown are a) radar reflectivity (dBZ), b) the classification difference between the S1995 methodology and the BL2000 methodology, c) the S1995 classification using the original algorithm and d) the BL2000 classification of the reflectivity field that uses c) as the first guess.
Figure 78: Same as Fig. 77 except the data are taken from 10 May 1993 at 0706 UTC.
Figure 79: Same as Fig. 77 except the data are taken from 3 June 1994 at 2004 UTC.
Figure 80: Flow chart showing the modifications that NCAR has made to the S1995 algorithm such that it now uses polarimetric variables and the radial gradient of the reflectivity.

Polarimetric variables can be used to discriminate various hydrometeor types (Vivekanandan et al. 1999), and are useful in determining if a bright band is present. Frequently, the bright band will create errors in the convective/stratiform partitioning process due to the high reflectivity values that may be present. Two polarimetric variables have been selected for inclusion in the convective/stratiform process: the differential reflectivity ($Z_{dr}$) and the copolar correlation coefficient ($\rho_{hv}$). Within the bright band, the differential reflectivity will be positive because the melting snow flakes form raindrops which are characterized by positive $Z_{dr}$. Since the bright band is characterized by mixed-phase particles, $\rho_{hv}$ values are reduced typically below 0.96 (See Hubbert et al. 2000 for a description of polarimetric variables in the context of a Colorado Eastern Plains storm) whereas $\rho_{hv}$ is typically greater than 0.96 in rain.

The modifications that NCAR has made to the S1995 technique are shown in Fig. 80. The first step is to calculate the S1995 algorithm on an elevation scan using the technique as described earlier. The second step is to apply the polarimetric criteria in regions where the reflectivity is between 25 and 45 dBZ. A median filter (5 beams by 16 gates; recall that the S-Pol uses 0.15-km gate spacing) has been applied to the reflectivity field to remove small scale irregularities in the data and is called the “smoothed reflectivity” in Fig. 80. The polarimetric fields ($Z_{dr}$ and $\rho_{hv}$) were tested for use in their original, unsmoothed form and after a median filter (1 beam by 3 gates) had been applied to smooth the data. Gates where the reflectivity is between 25-45 dBZ, where $Z_{dr} > 0.3$ dB and where $\rho_{hv} < 0.96$ were classified as stratiform. The third and last step is to re-test those gates that have been classified as “convective”. If the radial, horizontal gradient of the reflectivity ($\delta dBZ km^{-1}$) is $< 6 dBZ km^{-1}$ and the smoothed reflectivity is $< 35 dBZ$, then that gate is reclassified from “convective” to “stratiform”.

Results from this modified convective/stratiform partitioning algorithm are shown for six scans using data taken by the NCAR S-Pol radar. Each figure has the same arrangement of three rows...
and 4 columns. The first row contains the a) original reflectivity, b) the median-filtered reflectivity, c) the background reflectivity averaged over a 11-km radius and d) the one-dimensional horizontal gradient of reflectivity (along a radial). The second row contains the differential reflectivity ($Z_{dr}$) in its e) original state and f) after having a 1x3 median filter passed through field along the radial. Likewise the copolar correlation coefficient ($\rho_{hv}$) is shown in its g) original state and h) after having a 3-point median filter passed through the field along the radial. The third and last row shows the results from the convective/stratiform partitioning algorithm tests. In i), the final results from S1995 are shown after the convective radius is applied. In j), the intermediate results from S1995 are shown before the convective radius is applied. This step is shown because software engineering work to apply the convective radius to the test algorithm has not yet been completed.

Results from the convective/stratiform algorithm under development at NCAR are shown in two versions: in k) the median filter is not applied to the polarimetric fields before being input into the algorithm and in l) the median filter is applied to the polarimetric fields before being input. The first case was taken on 8 February 2001 during the IMPROVE-1 field campaign in Washington State and consists of stratiform snow (Fig. 81). The 1.5 degree elevation angle is shown. The bright band is easily seen in the differential reflectivity field (Fig. 81e and 81f) and in the copolar correlation coefficient field (Fig. 81g and 81h) although it is not as easily seen in the reflectivity field (Fig. 81a). Results from the original S1995 algorithm (Fig. 81i and 81j) show the effect of the bright band contamination as illustrated by the incorrect convective classifications that occur within the bright band. In the NCAR modified algorithm, results for the unfiltered (also termed unsmoothed; Fig. 81k) and filtered (also termed smoothed; Fig. 81l) versions show the improvements made by adding the polarimetric variables and the one-dimensional reflectivity gradient. Considerable improvement in the classification is achieved for this case with much of the incorrect convective classifications being removed. The median filter removes a few incorrectly classified points.

The second case was taken on 27 May 2002 during the IHOP 2002 field campaign in the Oklahoma Panhandle and consists of convective cells mixed with stratiform precipitation (Fig. 82). The 0.0 degree elevation angle is shown. At these low altitudes above the ground, the bright band is not present and cannot be seen in the differential reflectivity fields (Fig. 82e and 82f) or the copolar correlation coefficient field (Fig. 82g and 82h). Results from the original S1995 algorithm (Fig. 82i and 82j) show many convective classifications. In the NCAR modified algorithm, results for the unfiltered (Fig. 82k) and filtered (Fig. 82l) versions show the improvements made by adding the one-dimensional reflectivity gradient; the polarimetric variables do not contribute much in this example. Regardless, considerable improvement is achieved in the classification with the removal of many of the incorrect convective classifications. Use of the median filter does not change the performance significantly.

The third example (Fig. 83) was taken during the same volume scan as the previous IHOP 2002 example except that the 2.0 degree elevation angle is shown. At this higher elevation, the bright band can be easily seen in the differential reflectivity field (Fig. 83e and 83f) and the copolar correlation coefficient field (Fig. 83g and 83h). Results from the original S1995 algorithm (Fig. 83i and 83j) show many incorrect convective classifications caused by the bright band. In the NCAR modified algorithm, results for the unfiltered (Fig. 83k) and filtered (Fig. 83l) versions show the improvements made by adding the polarimetric variables and the one-dimensional reflectivity
Figure 81: This plot shows the results of the convective-stratiform partition for 8 February 2001 at 1610 UTC using a 1.5 deg elevation angle. Data were collected by the NCAR S-Pol during the IMPROVE-1 field campaign. Fields shown include a) reflectivity (dBZ), b) reflectivity after application of a median filter, c) the background reflectivity field that is smoothed over an 11 km radius, d) the change in reflectivity over 1 km (δdBZ km$^{-1}$), e) the differential reflectivity ($Z_{dr}$) field, f) same as e) but after application of a median filter, g) the copolar correlation coefficient ($\rho_{hv}$) field, h) same as g) but after application of a median filter, i) final output from S1995 where purple is stratiform and red is convective, j) intermediate output from S1995 before application of the convective radius, k) intermediate output from S1995 after the addition of polarimetric variables, and l) same as k) except that the polarimetric variables were filtered with a median filter. Panels a), b) and c) share the color table in c); panels e) and f) share the color table in f); panels g) and h) share the color table in h); and panels i) through l) are shaded where purple shapes are classified as stratiform regions and red shapes are classified as convective regions.
gradient. Considerable improvement is achieved in the classification with the removal of many of the incorrect convective classifications. The median filter removes a few of the isolated points that are classified as convection and does improve the performance somewhat.

The fourth example (Fig. 84) was also taken on 27 May 2002 except at 2300 UTC, about an hour later than the previous two examples. The 0.0 degree elevation angle is shown. At this time, additional convective cells have formed to the east of the older cells and many of the cells to the west of the radar have dissipated. Similar to the previous scan shown at 0.0 degree, the bright band cannot be easily seen in the differential reflectivity field (Fig. 84e and 84f) or the copolar correlation coefficient field (Fig. 84g and 84h) since the radar beam does not intersect the bright band. Results from the original S1995 algorithm (Fig. 84i and 84j) show many incorrect convective classifications, especially in the regions to the west of the radar where the cells are dissipating. In the NCAR modified algorithm, results for the unfiltered (Fig. 84k) and filtered (Fig. 84l) versions show the improvements made by adding the polarimetric variables with the removal of many of the incorrect convective classifications. The median filter removes isolated points that are classified as convection. For this case, the convective cells to the east of the radar are not as well-defined in the NCAR algorithm; a detailed examination is needed. Figure 85 shows an RHI scan along the 89.7 deg azimuth taken at 2302 UTC that clearly shows the bright band. The increased reflectivity (Fig. 85a) within and below the bright band is easily seen. Within the differential reflectivity field (Fig. 85b), the increase in values due to melting hydrometeors is seen below the bright band.
Likewise, the lowering of values within the copolar correlation coefficient field (Fig. 85c) is seen at the level of the bright band.

The fifth example (Fig. 86) was also taken during IHOP_2002 on 13 June 2002 at 1104 UTC. The 4.0 degree elevation angle is shown to emphasize the bright band contamination. Since the Hybrid Scan Reflectivity can be constructed from many elevation angles, the convective/stratiform partition will need to be applied to all elevation angles. At this time, there are convective cells within the radar range as well as considerable stratiform regions. The bright band can be easily seen in the differential reflectivity field (Fig. 86e and 86f) and the copolar correlation coefficient field (Fig. 86g and 86h). Results from the original S1995 algorithm (Fig. 86i and 86j) show many incorrect convective classifications, especially in the regions to the west of the radar where the cells are dissipating. In the NCAR modified algorithm, results for the unfiltered (Fig. 86k) and filtered (Fig. 86l) versions show the improvements made by adding the polarimetric variables with the removal of many of the incorrect convective classifications. The median filter removes isolated points that are classified as convection. For this case, the convective cells to the east of the radar are not as well-defined in the NCAR algorithm; a detailed examination is needed to discern any possible problems.

The sixth example (Fig. 87) was also taken during IHOP_2002 on 13 June 2002 at 1304 UTC, about two hours later than the previous case. The 4.0 degree elevation angle is shown to emphasize
Figure 84: Same as Fig. 81 for data collected by the S-Pol during the IHOP 2002 field campaign on 27 May 2002 at 2300 UTC for the 0.0 degree elevation angle.

Figure 85: An RHI scan showing data collected by the S-Pol on 27 May 2002 at 2302 UTC along the 89.7 deg azimuth angle. Fields shown are a) reflectivity (dBZ), b) differential reflectivity ($Z_{dr}$) and c) copolar correlation coefficient ($\rho_{hv}$).
Figure 86: Same as Fig. 81 for data collected by the S-Pol during the IHOP_2002 field campaign on 13 June 2002 at 1104 UTC for the 4.0 degree elevation angle.
the bright band contamination. For this case, there are no convective cells present, only stratiform precipitation and the bright band. The bright band is easily seen in the reflectivity (Fig. 87a), the differential reflectivity field (Fig. 87e and 87f) and the copolar correlation coefficient field (Fig. 87g and 87h). Results from the original S1995 algorithm (Fig. 87i and 87j) show that the bright band has been incorrectly classified as convective. In the NCAR modified algorithm, results for the unfiltered (Fig. 87k) and filtered (Fig. 87l) versions show the improvements made by adding the polarimetric variables with the removal of many of the incorrect convective classifications. The median filter improves the algorithm performance by removing the isolated points classified as convection.

To summarize, the use of polarimetric variables can help to discriminate convective from stratiform precipitation and will help to remove bright band contamination. This should prove useful when computing rainfall accumulations. Continued efforts to improve the S1995 algorithm with the BL2000 modifications plus the polarimetric variables are needed. Future work includes:

1. Complete the application of the convective radius to the NCAR-modified algorithm,
2. Modify the one-dimensional reflectivity gradient to be two-dimensional,
3. Continue to examine the BL2000 methods for incorporation into the NCAR-modified algorithm.
2.4 Real Time Clutter Echo Suppression: The Clutter Mitigation Decision (CMD) system

2.4.1 Introduction

The Radar Echo Classifier (REC) (Kessinger et al., 2003) is a general-purpose decision engine designed to classify radar echoes into categories such as ground clutter, sea clutter, and stratiform precipitation or convective precipitation.

Recognizing clutter independently from a clutter map is important for the ORDA in order to ensure that the GMAP clutter filter is not applied to weather echo with velocity close to 0 and narrow spectrum widths. Over the past year we have developed a decision system, based on the REC, specifically to identify normal propagation (NP) and anomalous propagation (AP) ground clutter returns. The Clutter Mitigation Decision (CMD) system is designed to identify echo regions which are likely to contain clutter, so that we can apply the clutter filter only to those regions, thereby avoiding the problem of removing power from weather echoes.

The desirable properties of the CMD are that:

- it should be sufficiently fast and efficient to operate in real-time in the WSR-88D ORDA.
- it should accept time series data, so that the algorithm can perform spectral processing.
- it should be suitable for detecting both AP and NP clutter.

The CMD was programmed in C++ to read time-series data in LIRP\(^1\) format. It was tested primarily on a KJIM case containing stratiform weather echo. It was also run on SZ(8/64) phase-coded S-Pol data and some dual-polarization S-Pol data.

2.4.2 Clutter filtering with zero velocity weather

Consider Fig. 88 which shows an example of a 64-point spectrum containing power from both clutter and weather. (This simulated spectrum is re-constructed from clutter and weather components). The red line shows the weather spectrum, the green line shows the clutter spectrum and the blue line shows the combined spectrum. The radial velocity is plotted on the X axis and the power is plotted on the Y axis using a log scale. The zero-velocity point is plotted at the center of the X axis, with motion away from the radar plotted on the right side and motion towards the radar on the left side. In Fig. 88 the clutter peak and the weather peak are separate and distinct. The clutter feature lies at the center of the plot and the weather feature to the right hand side, and they do not overlap significantly. Identifying the clutter and removing it from the weather is reasonably simple.

Fig. 89 shows the same clutter, combined with a weather spectrum with a velocity of \(5 \text{ ms}^{-1}\) instead of \(20 \text{ ms}^{-1}\). There is considerable overlap between the clutter and weather features. Nevertheless, the peaks are still separate. Furthermore, the weather has a wide spectrum while the

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\(^1\)LIRP files are time-series files which are in binary format. The LIRP format was developed by the ROC at the beginning of the RVP8 project prior to the time at which SIGMET released the TsArchive data format.
clutter spectrum is narrow, which means that much of the weather power lies outside the clutter spectrum. As it turns out, adaptive clutter filters can do a good job of separating clutter power from weather power for these types of spectra, too.

Fig. 90 shows the same clutter spectrum as in the previous cases, combined with a weather spectrum with a velocity of 1 ms$^{-1}$ (quite close to 0) and a narrow width of 0.5 ms$^{-1}$. For this case, the weather and clutter peaks merge into a single feature and it is clear that separating the components using only the information in the combined spectrum at a single gate would be difficult if not impossible.

Even in the absence of the ground clutter echo, the narrow width stratiform rain signal near 0 velocity depicted in Fig. 90 is problematic for adaptive spectral clutter filters as the weather signal may be treated as clutter and removed thus biasing the weather moment estimates. Such stratiform rain echoes occur near 0 velocity quite commonly and would be routinely removed by the adaptive filters. Therefore, a comprehensive clutter mitigation strategy, which considers information other than just the spectrum at a gate, is required to robustly differentiate between 0 velocity precipitation and clutter echoes.

### 2.4.3 Fixed notch clutter filters

Typically clutter filters used operationally employed a fixed bandwidth time domain filter (Stanley 1975, Bringi and Chandrasekar 2001). These filters are designed to have a 3 dB bandwidth that would correspond to typical clutter spectral widths. Standardized time domain filters have bandwidths, bandstop and rejection design criteria. In contrast, spectral filters can not only simply notch out the desired spectral points but they can also interpolate across the notched-out regions in order to compensate for weather signal that might have been eliminated.
Figure 89: Combined clutter with weather spectrum. CSR 20 dB, Clutter width 0.5 ms$^{-1}$. Weather velocity 5 ms$^{-1}$, width 2.5 ms$^{-1}$.

Figure 90: Combined clutter with weather spectrum. CSR 20 dB, Clutter width 0.5 ms$^{-1}$. Weather velocity 1 ms$^{-1}$, width 0.5 ms$^{-1}$.
Figure 91 shows the result of applying a simple spectral notch filter to the combined clutter and weather spectrum from Fig. 89. Typically a spectral notch filter has a fixed width. As this example shows, there is a tendency for such fixed bandwidth filters to remove more than just the clutter power, since some of the weather power has also been removed.

Fixed bandwidth time domain filters have the advantage of simplicity and speed. The latter was of particular importance in the 1980s and 1990s because affordable computers were not fast enough to perform sophisticated spectral processing for each radar gate. Since clutter time domain filters (typically Infinite Impulse Response (IIR) filters) operate directly on the I and Q time samples, this was a computationally efficient and practical way to reduce clutter signatures.

The disadvantage of fixed notch width filters is that, when used in isolation and applied everywhere, they often can remove power from the weather echoes. For example, these filters will remove valid weather reflectivity from areas of stratiform precipitation with velocities close to 0.

### 2.4.4 Adaptive clutter filters

As computer costs have decreased and computing power increased, it has become practical to apply more sophisticated spectral-domain clutter filtering on a gate-by-gate basis for scanning radars. Adaptive spectral-base filters analyze the shape of the spectra and adaptively decide where to reduce the clutter power. The potential of frequency domain filtering has been recognized earlier (Passarelli et al. 1981, Keeler et al. 2003).

The Gaussian Model Adaptive Processing (GMAP) filter was developed by Sigmet and is described by Siggia and Passarelli (2004). As indicated by its name, GMAP assumes that the clutter and weather spectra have approximately Gaussian shapes. The spectrum width of the clutter is specified by the user. Given the clutter spectrum width and the power from the near-zero velocity
spectral points, a suitable Gaussian curve is estimated for the clutter. This curve intersects the noise floor at two points. The interval between these two points defines the initial notch for the filter. A Gaussian curve is fitted to the points outside of the notch, which are assumed to represent the weather. The Gaussian curve is then used to estimate the weather power at the points within the initial notch. The Gaussian fit and power estimation are then repeated until the power and velocity of the filtered spectrum do not change significantly.

GMAP is an effective filter and has been shown to meet the specifications for the WSR-88D (Ice et al., 2004). However, the implementation (i.e. computer code) is proprietary. Therefore NCAR decided to develop a similar algorithm - the Spectral Stationary Echo Filter (SSEF) with a publicly available implementation so that it could be freely used for testing and research purposes.

There are two primary differences between SSEF and GMAP: (a) rather than using a Gaussian model to determine the initial notch, an aggressive notch (typically 1.5 ms\(^{-1}\) wide) is used; and (b) logic was added to identify the location of the weather peak. This was done in order to center the final Gaussian fit on the weather peak.

2.4.5 Applying an adaptive filter to various spectrum types

Figures 92, 93 and 94 show the results of applying SSEF to the spectra in Figs. 88, 89 and 90. The adaptive filter works well in the first two cases, removing the clutter power while leaving the weather power largely unaffected. In the third case, however, the result is not as good and some of the weather power is removed as well. It is difficult to separate the two spectra that have very similar characteristics.
Figure 93: SSEF applied to combined spectrum in Fig. 89. The adaptive filter works well.

Figure 94: SSEF applied to combined spectrum in Fig. 90. The adaptive filter has problems separating the peaks of the component spectra.
2.4.6 Applying an adaptive filter in a situation with stratiform precipitation

Figs. 95, 96 and 97 show the unfiltered reflectivity, velocity and spectrum width, respectively, for a case from the KJIM radar, which is a WSR-88D test-bed located in Norman, OK.

The data were taken at 10:50 UTC on 2004/04/09. A band of stratiform precipitation lies to the W and NW of the radar. There is ground clutter around the radar and to the south of the radar.

Figure 98 shows the reflectivity after application of the SSEF filter at every gate. Fig. 99 shows the clutter power as determined by SSEF.

The filter does a good job of correctly identifying clutter and removing it in most parts of the PPI. However, there are three regions where weather power was removed in error. These are high-lighted by the magenta ellipses. Referring to Figs. 96 and 97, it can be seen that these are regions with velocities close to 0 and narrow spectrum widths.

This is precisely the situation mentioned earlier, of stratiform precipitation exhibiting low spectrum widths and velocities close to 0 ms\(^{-1}\). This demonstrates that it is not sufficient to use the clutter filter alone to make decisions about where to remove clutter.

In the sections which follow, we introduce the Clutter Mitigation Decision (CMD) system which is designed to help make the decision about where to apply an adaptive filter.
Figure 96: Unfiltered velocity for KJIM case.

Figure 97: Unfiltered spectrum width for KJIM case.
Figure 98: KJIM Reflectivity after application of the SSEF filter at all gates. Magenta ellipses indicate regions where reflectivity was decreased by the filter in error.

Figure 99: Clutter for KJIM case as computed by applying SSEF at all gates. The magenta ellipses indicate the regions where weather power has been incorrectly identified as clutter.
The following interest fields are considered possible candidates for use in the CMD:

<table>
<thead>
<tr>
<th>Field</th>
<th>Description</th>
<th>Spatial?</th>
<th>Will we use it?</th>
</tr>
</thead>
<tbody>
<tr>
<td>TDBZ (from REC)</td>
<td>DBZ texture</td>
<td>Range/azimuth</td>
<td>Yes</td>
</tr>
<tr>
<td>SPIN (from REC)</td>
<td>DBZ Spin change</td>
<td>Range/azimuth</td>
<td>Yes</td>
</tr>
<tr>
<td>SDVE (from REC)</td>
<td>Standard deviation of velocity</td>
<td>Range/azimuth</td>
<td>Probable not</td>
</tr>
<tr>
<td>Clutter Ratio arrow CRN (ratio 1)</td>
<td>Ratio of power at 0 to power close to 0</td>
<td>No</td>
<td>Possibly</td>
</tr>
<tr>
<td>Clutter Ratio Wide CRW (ratio 2)</td>
<td>Ratio of power at 0 to power in rest of spectrum</td>
<td>No</td>
<td>Probably</td>
</tr>
<tr>
<td>Clutter-to-weather peak ratio CWPR</td>
<td>Ratio of clutter peak power to weather peak power</td>
<td>No</td>
<td>Possibly</td>
</tr>
<tr>
<td>Clutter-to-weather peak separation CWPS</td>
<td>Separation between clutter and weather peak expressed as a fraction of the Nyquist</td>
<td>No</td>
<td>Probably</td>
</tr>
<tr>
<td>NSPA</td>
<td>NEXRAD Spectral Processing Algorithm</td>
<td>Range only</td>
<td>Under development</td>
</tr>
</tbody>
</table>

Table 6: CMD fields

2.4.7 The CMD system: Real time clutter mitigation

The CMD uses some of the interest fields of the REC, which are based on radar moments computed from non-filtered spectra. In addition, a number of new interest fields based on the spectral shape are used.

Table 6 shows the interest fields which are considered candidates for use in the CMD. Refer to Kessinger et al 2003, and previous reports for details on computing TDBZ and SPIN. SDVE is the standard deviation of the velocity computed over the kernel. The clutter ratio and peak separation fields are new and it is these fields which distinguish the CMD from the REC.

NSPA is a spectral method using 2-D pattern recognition to find coherent features in the spectra along a radar radial. It is under development and is dealt with elsewhere in this report. It is not currently used in CMD but it is likely that aspects of NSPA will be added to CMD in the future.

2.4.8 Computing the spectral fields

Let us examine two examples of mixed weather and clutter. Figure 100 shows a spectrum with two distinct peaks, while the spectrum in Fig. 101 has only a single peak, centered at 0 ms$^{-1}$.

The spectral-based fields of Clutter Ratio Narrow and Clutter Ratio Wide measure how much power resides in the part of the spectrum close to zero compared to the power in other parts of the spectrum. Refer to Fig. 102. Clutter Ratio Narrow is computed as the power in the region A,
Figure 100: *Clutter and weather clearly separated*

Figure 101: *Clutter and weather not separated*
Figure 102: Computing Clutter Ratio Narrow (ratio 1)

Figure 103: Computing Clutter Ratio Wide (ratio 2)
For the computation of the Clutter to Weather Peak Ratio refer to Fig. 104. The ratio is computed as A divided by B, expressed in dB.

The computation of the Clutter to Weather Peak Separation field is shown in Fig. 105. The peak separation is computed as the absolute value of (A-B), expressed as a fraction of the Nyquist interval. The separation field provides information related to the spread of the peaks, independent of the power in each peak.

2.4.9 Computations over the CMD kernel

As shown in Table 6, TDBZ, SPIN and SDVE are based on values not only from the gate of interest but from surrounding gates as well. For NEXRAD the spacing in azimuth is 1° and in range it is 250 m. The CMD is set up to use a computational kernel 7 gates long in range (i.e. about 2 km) and 5° wide in azimuth. This setup is shown in Fig. 106.

2.4.10 Converting the fields to interest values.

The CMD computes each field, and then converts the field value into an interest value between 0 and 1 using so-called membership functions, just as is done in the REC. Typical membership functions are shown in Fig. 107. The interest values from all fields are combined into a weighted mean, which is interpreted as a measure of clutter probability. Gates with a clutter probability exceeding 0.5 are considered likely clutter points.
Figure 105: Computing the Clutter to Weather Peak Separation

Figure 106: Computation of spatially-based fields over a kernel
2.4.11 Pulse and beam processing sequence

Because the CMD uses data from 2 adjacent beams on either side, for real-time operations a beam queue of 5 beams must be used as shown in Fig. 108. The interest fields are then computed for the center beam, as shown in Fig. 109.

2.4.12 High-level functional description of the CMD

Refer to Fig. 106. The CMD clutter likelihood value is computed for the gate at the center of the kernel by moving the kernel along the center beam.

For each gate in the beam at the center of the kernel, perform the following:

1. For each point in the kernel, sum the various quantities needed to compute TDBZ, SPIN and SDVE.
2. Compute TDBZ, SPIN and SDVE.
3. Compute power ratios CRN, CRW, CWPR.
4. Compute peak separation CWPS.
5. For each CMD field (TDBZ, SPIN, SDVE, CRN, CRW, CWPR, CWPS), (a) convert the field value to an interest value using the relevant interest map, (b) multiply by the field weight (c) add to interest sum.
Figure 108: Beam queue processing required to run the CMD in real-time using time-series data.

Figure 109: Computing the CMD and moments for the center beam in the queue.
6. Compute the weighted mean of the interest sum. (the clutter flag is a boolean variable: 1 denotes presence of clutter, 0 denotes no clutter)

7. If the weighted mean exceeds a set threshold, set the clutter flag for that gate.

### 2.4.13 Incorporating the CMD into the SZ-2 scheme as a dynamic clutter map

SZ-2 is designed to work with a clutter map. A problem with this approach arises if the operator defines a region which effectively turns on the clutter map everywhere. If this occurs SZ-2 executes as if all trips have clutter. In that case, a “dynamic” clutter map is needed to take the place of the static clutter map. An adaptive filter such as GMAP can be run on each gate to determine if clutter exists there. However, this must be coupled with a system such as CMD to ensure that stratiform weather power is not removed in error.

The following processing sequence could be used to provide S-Z2 with a dynamic clutter map:

1. Compute the long-PRT moments without any clutter filtering.
2. Compute the CMD clutter likelihood and clutter flag for each point in the beam.
3. Use the CMD clutter flag to generate a dynamic clutter map.
4. Apply SZ-2 using the dynamic map.

### 2.4.14 Example of using the CMD to identify clutter

Refer back to Figs. 95, 96 and 97. These show the unfiltered moments (reflectivity, velocity and width) for the case from the KJIM radar on April 9 2004.

Figures 110 through 116 show the raw fields for the CMD for this case.

Figure 117 shows the result of computing the mean weighted interest field, and Fig. 118 shows the decision flag field after applying a threshold of 0.5 to the weighted field. (There is an ‘edge effect’ at long range which is the result of not handling the last few gates correctly. This will be taken care of in future versions.)

Figure 119 shows the clutter removed by applying the clutter filter at all points in Fig. 118. Figure 120 shows the filtered reflectivity and Fig. 121 shows the filtered velocity field.

Figure 122 shows the unfiltered velocity in the region close to the radar, where ground clutter exists at many gates. Figure 123 shows filtered velocity in the same area while Fig. 124 shows the peak separation field for that area. The peak separation field detects many of the same features as the filtered velocity field, indicating that it is suitable for detecting velocity-related signatures in the unfiltered spectrum.

### 2.4.15 Using dual polarization data for identifying clutter

Dual-polarization fields, if available, are a useful additional source of information for the identification of clutter. In particular the $p_{hv}$ field and the spatial variability of $Z_{dr}$ and $p_{hv}$, are
Figure 110: TDBZ CMD field for KJIM case

Figure 111: SPIN CMD field for KJIM case
Figure 112: SDVE CMD field for KJIM case

Figure 113: Clutter Ratio Narrow CMD field for KJIM case
Figure 114: **Clutter Ratio Wide CMD field for KJIM case**

Figure 115: **Clutter-to-weather Peak Ratio for KJIM case**
Figure 116: Clutter-to-weather Peak Separation for KJIM case

Figure 117: CMD clutter likelihood, computed as the weighted mean interest field.
Figure 118: CMD clutter flag resulting from applying a threshold of 0.5 to the clutter likelihood field.

Figure 119: KJIM clutter removed by applying the filter at those points indicated by the clutter flag.
Figure 120: Filtered reflectivity

Figure 121: Filtered velocity
Figure 122: Unfiltered velocity close to the radar.

Figure 123: Filtered velocity close to the radar.
good indicators of the likelihood of weather as opposed to clutter (Vivekanandan et al., 1999). In the case of $Z_{dr}$ and $\rho_{hv}$, the spatial variability is computed in range only, rather than over the range/azimuth kernel. The advantage of this technique is that it eliminates the smearing in azimuth which is apparent in the TDBZ and SPIN fields.

The above three dual-polarization fields were tested in the CMD using data from the NCAR S-Pol radar collected in Mexico during the North American Monsoon Experiment (NAME) field campaign conducted in the summer of 2004. The membership functions applied for each of these three fields are shown in Fig. 125.

Figure 126 shows the CMD clutter likelihood (weighted mean interest) field without the dual polarization fields while Figure 127 shows the result with the dual-polarization fields included. (There is a test pulse close to the maximum range of the data, so the concentric rings should be ignored.)

The two fields are similar, confirming that the information contained in the various CMD fields is complementary. The advantages of including the dual polarization fields are that (a) the dual polarization fields are an independent measure of clutter likelihood, and therefore improve the confidence of the result and (b) because the dual polarization statistics are applied in range only, rather than across adjacent azimuths, the smearing in azimuth evident in Fig. 126 is somewhat reduced.

### 2.5 Spectral Processing

#### 2.5.1 Introduction

The computational power of the NEXRAD ORDA makes real time spectral analysis feasible. One type of spectral processing is to analyze weather spectra versus range along a radar radial. Since significant weather phenomena are usually relatively wide spread (as compared to a single radar resolution volume), weather echoes are characterized by continuity in range which makes them distinguishable from contaminating signals such as point targets. An example of radar spectra versus range is shown in Fig. 128 with some of the spectral features labeled. The experimental data was phased coded and cohered to the first trip and only the first trip echo range is shown. The weather echo is evident in the top right hand portion of the plot. Below the weather is a much weaker echo, likely some sort of clear air echo (e.g., bugs). High power is seen in red along the 0 velocity line which is due to ground clutter. Across the top and across the bottom of the figure are signatures due to second trip and third trip echoes. Looking closely at these areas one can see eight power peaks across the top and four power peaks across the bottom. Recall the spectral character of second and third trip echoes. Second trip echoes are characterized by eight spectral replicas whereas third trip echoes are characterized by four spectral replicas. In the central low reflectivity portion of the figure, several higher power point-type scatterers are also evident.

Two thin black lines are drawn on each side of the weather and clear air echo regions of the figure. Automated definition of such boundaries is possible by identifying the meteorological areas of such plots and then identifying the noise or low echo areas on each side of the weather power. The weather moments are then calculated by only integrating over the region between the two thin black
Figure 124: Clutter-to-weather peak separation field close to the radar. The patterns in this field mirror those in the filtered velocity field.

Figure 125: Membership functions for dual polarization variables.
Figure 126: CMD clutter likelihood, without dual-polarization fields.

Figure 127: CMD clutter likelihood, including dual-polarization fields
The thicker dashed black line represents the mean velocity estimate of the weather and clear air portions of the spectra. By excluding the point targets, noise, etc. from the moment calculations, better moment estimates are obtained. This is the central idea of the spectral processing presented here. Such spectral processing has been developed by NCAR for wind profiling radars (Corinne et al. 2002) and for airborne weather warning radar (Cornman et al. 2002).

Time-domain estimators have several advantages:

- Computationally very efficient
- The estimators for $P$ and $V$ are good as long as there is only 1 echo and SNRs are larger than 2 or 3 dB. The $W$ estimator is good as long as the spectrum is approximately Gaussian, the SNRs are larger than 5 dB and the widths are not too wide.
- Simple to implement.

But they also have disadvantages:

- Only noise and clutter are easily separable from the rest of the signal
- $W$ is frequently not estimated well because the Gaussian assumption is violated.

The spectral-domain estimator advantages are:

- Echoes are separated by their radial velocities. This allows for contaminants that are moving at different speeds to be separated and thus suppressed.
- Spectral-domain estimators usually perform at least as well time-domain estimators, and perform better at lower SNRs and in the presence of contaminants.
- Spectrum width estimators, in particular, perform better.

Spectral-domain estimator disadvantages are:

- More computationally intensive, although there would be minimal additional overhead if already using SZ phase coding.
- Algorithms can be more complex.

We next illustrate the advantage of spectral domain moment estimation via an individual spectrum. Figure 129 shows a spectrum (simulated) that contains both weather and clutter with the blue line. A weak weather signal exist at about 15 ms$^{-1}$. The spectra after clutter filtering using the legacy clutter filter (in red) and using the GMAP clutter filter (black circles) are shown. Both clutter filters leave some residual power near 0 ms$^{-1}$ that is comparable to the weather signal near 15 ms$^{-1}$. Because of the residual clutter power, the pulse-pair velocity estimator would be biased towards 0 ms$^{-1}$. But if a spectral processing algorithm only uses the spectral bins from about 5 ms$^{-1}$ to
Figure 128: Spectra versus range example.
Figure 129: Example of a spectrum that includes both clutter (near 0 m/sec) and weather (near 15 m/sec). The blue line shows the original spectrum, the red shows the spectrum after the legacy clutter filter is applied, and the black shows the spectrum after the GMAP clutter filter is applied. Note the clutter residue near 0 m/sec for both clutter filtered spectra has about the same power as the weather.

about 25 ms$^{-1}$ then the velocity estimate would be unbiased. This illustrates an advantage of spectral estimators.

In this study, a prototype spectral domain moment algorithm that will be referred to as the NEXRAD Spectral Processing Algorithm (NSPA), was developed using NIMA (NCAR Improved Moment Algorithm; Corinne et al. 2002) and NESPA (NCAR Enhanced Spectral Processing Algorithm; Cornman et al. 2002), both developed at NCAR, as starting points. NSPA shares much in common with NESPA since NESPA was developed for forward scanning on-board aircraft weather radar, although the differences in the platform necessitate a new algorithm.

2.5.2 The NEXRAD Spectral Processing Algorithm (NSPA)

The NSPA algorithm is executed in two phases: 1) initial moment estimates are calculated after clutter filtering, and 2) the spectra versus range are further processed to detect continuity features.

In phase 1 first, the power spectra for a radar radial are computed and if there is clutter, then the spectra are clutter filtered. The velocity of the peak power, $V_p$, for each spectrum is saved. The spectra are then smoothed by using a 7 point Gaussian weighted filter in range for each velocity bin. This smoothed spectrum is used only for feature detection and identifying the bounds of integration for the spectral moments. At the end of the processing, when the moments are recalculated, the original spectra are one again used. Using the smoothed spectrum, the bounds of integration are determined by computing the spectral noise level, and then starting at the peak spectrum power, (previously determined from the raw spectra) the algorithm examines adjacent spectral points until
the average power falls below the noise level. The average velocity and spectrum width are then calculated as:

\[
V = \frac{\sum_{l=0}^{N-1} (v_l \oplus V_p) S_l}{\sum_{l=0}^{N-1} S_l} \oplus V_p \tag{5}
\]

\[
W^2 = \frac{\sum_{l=0}^{N-1} (v_l \oplus V)^2 S_l}{\sum_{l=0}^{N-1} S_l} \tag{6}
\]

where \(N\) is the number of points in a spectrum (nominally 64), \(v_l\) is the velocity of the \(l^{th}\) bin (only depends on the Nyquist velocity and \(N\)), \(\oplus (\ominus)\) is circular addition (subtraction) with respect to the Nyquist interval, and \(S_l\) is the power spectrum.

In phase 2, the velocities along a radar radial are smoothed using a wavelet filter. Wavelet filters are effective at reducing high frequency fluctuations but still preserve large scale trends without significant distortion of the data (Donoho 1995). Discontinuities are identified by comparing the smoothed versus raw velocities. The velocity and spectrum width are then recalculated using the smoothed velocity, rather than \(V_p\), to both identify the new integration bounds, and in the formulas of velocity and spectrum width.

### 2.5.3 Results

We will present two different cases to show the qualitative performance of NSPA versus pulse-pair. The first case is data from KOUN on April 5, 2003. Figure 130 shows an uncalibrated power PPI of the data. The velocities from pulse-pair and from NSPA (phase 2) are shown in Figs. 131 and 132, respectively. As can be seen, the velocities due to the NSPA algorithm in general appear smoother, i.e., the variance of the velocity estimates has been reduced (the noisy streak of data on the right
hand side of the figures is second trip echo). Once the NSPA algorithm “locks” onto the weather signal, superfluous echoes are ignored and the result is less variance or speckle in the data.

A significant issue is the ability of NSPA to smooth the velocities down a radial but still track large power and velocity shears, like those of a tornado. A possible problem for NSPA is locking on to the incorrect signal by being fooled by data with large velocity shears and discontinuities. A good test case is the KOUN May 3, 1999 tornado data. The uncalibrated power PPI scan is shown in Figure 133. The velocities from pulse-pair and from NSPA (phase 2) are shown in figures 134 and 135, respectively. The two algorithms produce very similar velocity scans. The NSPA velocity PPI shows the tornado signature more distinctly and in general the velocities again appear more smooth.

2.5.4 Conclusions

The prototype NSPA produces velocities that are generally less biased and that have lower variance than the pulse-pair estimate. NSPA performs well at eliminating individual outliers (i.e., point scatterers) and reducing the noise contribution to radar moment estimates. Further work needs to be done to

1. further evaluate, refine and test the NSPA tracking decisions
2. mitigate clutter
3. test the algorithm on other contaminants like radio frequency interference (RFI)
4. automate the algorithm.
Figure 131: Pulse-pair Velocity (V) PPI scan from KOUN on April 5, 2003.

Figure 132: NSPA phase 2 Velocity (V) PPI scan from KOUN on April 5, 2003.
3 Summary and Conclusions

There were two major achievement in FY2005 in the area of Range-Velocity mitigation work: 1) the analysis of SZ phase coding in conjunction with Super Resolution data and 2) the analysis and delivery of an SZ-1 phase coding algorithm with clutter filtering. It was shown that due to the nature of the Hanning and Blackman time series window functions used with SZ phase coding and with the GMAP clutter filter, such processed data can be thought of as “under-sampled” in azimuth. For a Hanning window function, 91.7% of its “power” is contained in the middle 32 points of a 64 point window. For a Blackman window it is 97%. Because of this, the windows can be overlapped in azimuth (e.g., a 64 point window is only advanced 32 points for each new radar resolution volume) without significantly degrading the resolution of the radar data. This means that Super Resolution data can be gathered simultaneously with the SZ(8/64) algorithm. The GMAP clutter filter requires the use of of the Blackman or Hanning window function also. This means that if 32 point non-overlapping time series data are used with GMAP, 64 point overlapping time series data can be used instead while maintaining the same resolution. The use of longer data sets mean better clutter rejection and reduced variance of the radar moment estimates. Thus, we have shown that GMAP, SZ phase coding and Super Resolution data are all compatible.

An SZ-1 algorithm with clutter filtering was developed which requires an input clutter map. The clutter map can be either generated a priori (for NP clutter) or the CMD algorithm can be used to first identify clutter contaminated regions (both AP and NP clutter) and then the SZ phase coded data is reprocessed using the CMD defined clutter map.

Spatial-spectral processing was developed and it was demonstrated how such processing can reduce the variance of the radar moments. Spectra were plotted versus range and it was seen that meteorological echoes frequently have the feature of range continuity. Thus, using range continuity,
Figure 134: Pulse-pair Velocity ($V$) PPI scan from KOUN on April 5, 2003.

Figure 135: NSPA phase 2 Velocity ($V$) PPI scan from KOUN on April 5, 2003.
the meteorological echo was identified and this allowed for the calculation of the radar moments only over sub-portions of the spectra that contained the meteorological echo of interest. Point type targets are in this way eliminated (if they are outside the velocity spread of the meteorological echo) as well as noise and therefore the moments estimated are improved, especially Doppler velocity and spectrum width.

Double processing for the SZ phase coding algorithm was also modeled and performance statistics analyzed. Double processing uses the estimate of the weak trip velocity to recalculate the strong trip velocity. It was found that standard deviation of strong trip velocity estimates is reduced by about 0.3 ms\(^{-1}\) for \(P_1/P_2 < 3\) dB. The computational cost of this improvement is the execution of two additional FFTs. The Hanning window function performed better than the Blackman window for double processing.

A major accomplishment in FY2005 was the development of the Clutter Mitigation Decision algorithm (CMD). CMD is a Fuzzy Logic based algorithm that identifies clutter in real time. Due to the computational power of the new NEXRAD ORDA, clutter-identified data can then be reprocessed with a clutter filter so that not only is clutter echo eliminated, but also, the radar moments can be recalculated after clutter filtering so that any underlying weather is revealed. This promises to dramatically increase the data quality of NEXRAD radars. Only a few data sets have been analyzed so that further testing needs to be done.

Another accomplishment was the improvement of the EPRE algorithm by the addition of the PDA (Precipitation Detection Algorithm). Previously only the output of the APDA was used in EPRE to construct the hybrid-scans. It was found that there were data used in the hybrid scan that were not precipitation and thus precipitation estimates were biased. To remedy this, the output from the new PDA algorithm was used in EPRE and most of the data bins that were previously misclassified as precipitation were eliminated thus improving the performance of EPRE and in turn improving precipitation estimates.

Progress was also made with the convective versus stratiform precipitation classification algorithm. Techniques developed by Biggerstaff and Listemaa (2000) were adapted and resulted in better discrimination. Polarimetric variables were also used in the algorithm and evaluated and it was shown that they too improve the discrimination between stratiform and convective rain.

In an endeavor to look forward to the dual polarimetric era for NEXRAD, NCAR has been evaluating dual polarimetric variables in the various Fuzzy Logic classification algorithms developed at NCAR. This has been done for three reasons: 1) to improve the performance of the algorithms and to use the output of the “dual polarized” algorithms as a performance baseline for the non-dual polarized algorithms, 2) to make ready these algorithms for possible implementation in the NEXRAD dual polarized system and 3) to use these algorithms as a performance baseline for other dual polarized algorithms that may be implemented in NEXRAD.

**Acknowledgments:** We would like to thank the ROC staff, Sebastian Torres, Dusan Žrnić, Darcy Saxion, Rick Rhoton, Rich Ice and Jeff Keeler for the many technical discussions that made this report possible.
References


<table>
<thead>
<tr>
<th>Inputs</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( V_1 )</td>
<td>Phase-coded complex time series (raw I &amp; Q) of length ( N ), cohered to trip 1. ((0, \ldots, N-1))</td>
</tr>
<tr>
<td>( N )</td>
<td>The length of the phase-coded time series ( V )</td>
</tr>
<tr>
<td>( \psi )</td>
<td>Measured switching code angles of length ( N+1 ), ((-1, \ldots, N-1))</td>
</tr>
<tr>
<td>( h )</td>
<td>The windowing function of length ( N ). ((0, \ldots, N-1))</td>
</tr>
<tr>
<td>( P_N )</td>
<td>Noise Power (in same units as the power of ( V ))</td>
</tr>
<tr>
<td>( T_S )</td>
<td>Pulse Repetition time in seconds</td>
</tr>
<tr>
<td>( \lambda )</td>
<td>Wavelength of the radar in meters (i.e. ( \sim 0.10 ) meters for WSR-88D)</td>
</tr>
</tbody>
</table>

Table 7: Inputs

<table>
<thead>
<tr>
<th>Constant</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( L )</td>
<td>Near 0 radius, in bins for the narrow clutter ratio test</td>
<td>2</td>
</tr>
<tr>
<td>( N_N )</td>
<td>Number of smallest “peaks” to average in spectral noise calculation</td>
<td>2</td>
</tr>
<tr>
<td>( N_S )</td>
<td>Number of smallest “peaks” to average in spectral censoring</td>
<td>3</td>
</tr>
<tr>
<td>( C_T )</td>
<td>Threshold for the narrow clutter ratio test</td>
<td>0.12589 ( (\sim -9 \text{ dB}) )</td>
</tr>
<tr>
<td>( k_{GMAP, EXTRA} )</td>
<td>Additional buffer for PNF Clutter Adjustment</td>
<td>1</td>
</tr>
<tr>
<td>( Dmat )</td>
<td>The ( N \times N ) deconvolution matrix</td>
<td>see section A.6</td>
</tr>
<tr>
<td>( K_s )</td>
<td>Strong trip SNR threshold (in linear)</td>
<td>1 ( (\sim 0 \text{ dB}) )</td>
</tr>
<tr>
<td>( K_w )</td>
<td>Weak trip SNR threshold (in linear)</td>
<td>3.16228 ( (\sim 5 \text{ dB}) )</td>
</tr>
</tbody>
</table>

Table 8: Constants

APPENDIX

A SZ-1 with SIGMET GMAP Filter

A.1 Algorithm

Refer to in Figs.1 and 2 for a flow chart of the algorithm.

The algorithm is much the same as it has been, with only additions made at the beginning to handle clutter.
<table>
<thead>
<tr>
<th>Constant</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_1, P_2$</td>
<td>First and second trip average Power</td>
</tr>
<tr>
<td>$v_1, v_2$</td>
<td>First and second trip average radial velocity</td>
</tr>
<tr>
<td>$w_1, w_2$</td>
<td>First and second trip spectrum width</td>
</tr>
<tr>
<td>$type_{P1}, type_{P2}$</td>
<td>First and second trip Power classification</td>
</tr>
<tr>
<td>$type_{v1}, type_{v2}$</td>
<td>First and second trip Velocity classification</td>
</tr>
<tr>
<td>$type_{w1}, type_{w2}$</td>
<td>First and second trip Spectrum width classification</td>
</tr>
<tr>
<td>$H$</td>
<td>Spectral Censoring Metric</td>
</tr>
</tbody>
</table>

Table 9: Outputs

<table>
<thead>
<tr>
<th>Constant</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$t_A$</td>
<td>Trip number of the strong trip</td>
</tr>
<tr>
<td>$t_B$</td>
<td>Trip number of the weak trip</td>
</tr>
<tr>
<td>$V_{W1}, V_{W2}$</td>
<td>First and second trip windowed time-series</td>
</tr>
<tr>
<td>WkTripCensorFlag</td>
<td>Flag that indicates whether weak trip should be censored or not</td>
</tr>
<tr>
<td>ClutterTrip</td>
<td>Trip containing the clutter to clutter filter</td>
</tr>
<tr>
<td>ClutterFiltered</td>
<td>Flag indicating if the trip that was to be clutter filtered was actually clutter filtered</td>
</tr>
<tr>
<td>$V_c$</td>
<td>Time-series cohered to the trip to be clutter filtered</td>
</tr>
<tr>
<td>$V_{CF1}, V_{CF2}$</td>
<td>First and second trip clutter filtered time-series</td>
</tr>
<tr>
<td>$V_s$</td>
<td>Time-series cohered to the strong trip</td>
</tr>
<tr>
<td>$P_s$</td>
<td>Total power of signal only excluding the clutter filtered power</td>
</tr>
<tr>
<td>$R_s$</td>
<td>The first lag of the autocorrelation when cohered to the strong trip</td>
</tr>
<tr>
<td>$V_{SN}$</td>
<td>Time-series of the strong trip after the PNF is applied</td>
</tr>
<tr>
<td>$P_R$</td>
<td>The total residual power after PNF is applied</td>
</tr>
<tr>
<td>$V_w$</td>
<td>Time-series cohered to weak trip</td>
</tr>
<tr>
<td>$S$</td>
<td>The magnitude spectrum of the weak trip after deconvolution</td>
</tr>
</tbody>
</table>

Table 10: Intermediate Variables
A.2 Assumptions

1. The phases of the transmitted pulses are modulated with the SZ(8/64) switching code, and that these transmitted phase angles are measured.

2. The number of pulses in each beam is 64, i.e. \( N = 64 \).

3. The algorithm operates on one range cell of \( M \) samples of time-series at a time, but the censoring algorithm operates on several beams at a time.

A.3 Inputs

The inputs are listed in table 7. In order for the SZ-1 algorithm to be able to recover two trips, it is necessary for the measured transmitted phase code to be of length \( N + 1 \), with the transmitted phase angle \( \psi(m) \) corresponding to the pulse from which \( V_1(m) \) is measured. The extra phase measurement corresponds with the pulse immediately preceding the \( N \) pulses, and is thus denoted \( \psi(-1) \). The constants in table 8 also are inputs into the algorithm but they are suitable for a parameter table.

A.4 Outputs

The outputs are listed in table 9. The type variables classifies the signal for that variable and trip. There are three possibilities:

- **SIGNAL\_LIKE**: The variable contains an estimate of a significant return.
- **OVERLAID\_LIKE**: The variable is being censored because of contamination from an overlaid echo (can be caused, for example, by clutter contamination or because of poor recovery)
- **NOISE\_LIKE**: The variable is being censored because there is no significant return.

A.5 Procedures

A note about the use of \(<\cdot>\) in this document: in many cases there are variables that have a value for trip 1 and 2, such as power \( (P_1 \text{ and } P_2) \). By \( P_{<n>} \), it is meant \( P_1 \) if \( n = 1 \), \( P_2 \) if \( n = 2 \), etc. This is to distinguish \( P_N \) (which is the noise power), from \( P_{<N>} \) which means the \( N^{th} \) trip power (here \( N \) is being used as a variable not as the input variable in table 7).

First, define some functions that will be used within the algorithm more than once.

**Auto-correlation function**: The \( i^{th} \)-lag value of the auto-correlation function:

\[
R_i[v] = \frac{1}{N-i} \sum_{k=0}^{N-i-1} v^*(k) v(k+i)
\]

where \( v \) is a time-series.
Recohere: To cohere a time-series \( v \) from trip \( k_2 \) to \( k_1 \)

\[
v' (m) = v(m) \exp (j \phi_{k_1,k_2} (m))
\]

for \( 0 \leq m < N \) where

\[
\phi_{k_1,k_2} (m) = \psi (m - k_2 + 1) - \psi (m - k_1 + 1)
\]

Fourier and Inverse Fourier Transforms: An FFT routine should be used and \textit{not} the equations below. Because different FFT routines could conceivably index the Fourier transforms differently and/or have different normalizations, the equations given show what this document assumes. If a given FFT routine uses different conventions, then wrappers should be built around the routine to conform to the conventions here. The Fourier transform is

\[
F[v] (m) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} v(n) \exp (-2\pi j mn/N)
\]

for \( 0 \leq m < N \) and the inverse Fourier transform is

\[
F^{-1}[v] (m) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} v(n) \exp (2\pi j mn/N)
\]

Spectral Noise Calculation/Spectral Censoring Metric: To find the spectral noise level, break the power spectrum, denoted \( S \), into 8 equal sized segments such that the maximum of the power spectrum is centered. To do this, find the index \( K \) such that \( S(K) = \max_k (S(k)) \). Let \( L_0 = \text{mod} (K + \text{round} (N/16), N) \). This is the starting index for the first segment. The starting indices for the 7 other segments are \( L_n = \text{mod} (L_0 + nN/8, N) \) for \( n = 1, \ldots, 7 \).

For each segment find the maximum value of \( S \): The \( n^{th} \) segment consists of indices \( L_n \) to \( L_{n+1} - 1 \). Thus

\[
M_n = \max_{k=L_n,...,L_{n+1}-1} S(k)
\]

Define the spectral noise as

\[
\tilde{P}_N = \frac{1}{N} \sum_{n=0}^{N-1} M_n
\]

and define the spectral censoring metric as

\[
H = 10 \log_{10} \left( \frac{M_7}{N \sum_{l=0}^{N_S-1} M_l} \right)
\]
A.6 Deconvolution Setup

The following computation needs to be performed only once and can be stored for later use. In fact, this can be done off-line and the results can simply be stored in with the constants. Compute the PNF filter, define for $0 \leq k < N$ where $NW = 3N/4$.

$$S_F(k) = \begin{cases} 
0 & \text{if } k < NW \\
1 & \text{if } NW \leq k < N
\end{cases}$$

and let

$$C(k) = \exp\left(j\hat{\phi}_{1,2}(k)\right)$$

where $\hat{\phi}_{1,2}(k) = \pi k^2/8$, the theoretical modulation code for SZ(8/64). It should be noted that the deconvolution matrix does not depend on what index the actual code begins versus the theoretical code, where the PNF notch was located, or whether the strong trip was trip 1 or 2. The only important requirement is that the magnitude of the actual modulation code spectrum is very similar to that of the actual modulation code and that the PNF notch is $3/4$ of the spectrum.

$$X(k) = S_F(k) F[C](k)$$
$$Y(k) = F^{-1}[X](k) C^*(k)$$
$$Dinv(k) = |F[Y](k)|$$

Finally, define the matrix $Dinvmat_{n,m} = Dinv(n + m)$ where $n, m = 0, \ldots, N - 1$ ($n$ here is the row index and $m$ is column index) and then compute the matrix inverse $Dmat = (Dinvmat)^{-1}$ (note that this inverse is the matrix inverse and not the component by component operation). The variable $Dmat$ should be stored for the deconvolution block (20).

A.7 Algorithm

1. Initialize moments

Inputs

Outputs $P_1, v_1, w_1, P_2, v_2, w_2$

$$P_1 = 0$$
$$v_1 = 0$$
$$w_1 = 0$$
$$P_2 = 0$$
$$v_2 = 0$$
$$w_2 = 0$$
2. Check that there is enough power to warrant any further action

**Inputs** $V_1$

**Outputs** $type\_P_1, type\_P_2, type\_v_1, type\_v_2, type\_w_1, type\_w_2$

Calculate the total power

$$P_T = R_0 [V_1]$$

If $P_T < K_s$ then set

$$type\_P_1 = type\_P_2 = NOISE\_LIKE$$
$$type\_v_1 = type\_v_2 = NOISE\_LIKE$$
$$type\_w_1 = type\_w_2 = NOISE\_LIKE$$

and exit.

3. Determine the trip ordering using the $|R_1|$ estimator

**Inputs** $V_1$

**Outputs** $t_A, t_B$

Compute $|R_1 [V_1]|$ for the input time series $V_1$, which is cohered to trip 1. Cohere to trip 2. Compute $|R_1 [V_2]|$. The trip with the larger value is the strongest total trip. Define $t_A$ to be the number of the strongest trip. Then define $t_B = 3 - t_A$, i.e the weak trip.

4. Window the time series

**Inputs** $V_1$

**Outputs** $V_{W1}$

Compute

$$G_h = \frac{1}{N} \sum_{m=0}^{N-1} |h(m)|^2$$

and then set

$$V_{W1}(m) = \frac{V_1(m) h(m)}{\sqrt{G_h}}$$

for $0 \leq m < N$. 
5. **Determine the clutter status**

**Inputs** Clutter map

**Outputs** WkTripCensorFlag, ClutterTrip, ClutterFiltered

At this point, we assume that all clutter map sources have been combined to form a final clutter map for SZ1 to work with. Set the WkTripCensorFlag to 1 if there is clutter in the weak total trip, otherwise set it to 0. If there is no clutter in either trip, set ClutterFiltered to 0 and proceed to block 9. If there is clutter in only 1 trip, set ClutterTrip to that trip. If there is clutter in both trips, set the ClutterTrip to $t_A$, i.e. the strong total trip from block 3.

6. **Test applicability of applying clutter filter**

**Inputs** $V_{W1}$, ClutterTrip

**Outputs** ClutterFiltered, $V_{CF1}$, $V_{CF2}$, $V_c$

If ClutterTrip is 2, then cohere $V_{W1}$ to trip 2 and save as $V_c$, otherwise set $V_c$ to $V_{W1}$. Calculate the so-called narrow clutter ratio test

$$C = \frac{\sum_{k=-L}^{L} \sum_{m=1}^{N-1} V_c(m) \exp(-2\pi imk/N)}{(2L + 1) R_0[V_c]}$$

where $L$ is as the near-zero width parameter and will typically be about 1 or 2. If $C < C_T$ where $C_T$ is the narrow clutter ratio threshold, then set ClutterFiltered to 0, proceed to block 9.

7. **Test applicability of applying clutter filter**

**Inputs** $V_c$, ClutterTrip

**Outputs** ClutterFiltered, $V_{CF1}$, $V_{CF2}$

Otherwise, to prepare to apply GMAP, we need to compute the spectrum, and calculate a spectral noise level.

$$F(k) = F[V_c](k)$$

for $0 \leq k < N$. The power and phase spectra is then

$$S(k) = |F(k)|^2$$

$$\Phi(k) = \text{arg}(F(k))$$

Define $\bar{P}_N$ as spectral noise level of $S$. 

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Apply GMAP on $S$, supplying $\tilde{P}_N$ for the noise power. Capture the return from the GMAP code as $\tilde{S}$, and, as in SZ-2, GMAP should return the number of points removed, which we denote $k_{GMAP}$. Define

$$\hat{\phi}(k) = \begin{cases} 
\Phi(k) & (k_{GMAP} - 1)/2 < k < N - ((k_{GMAP} - 1)/2) \\
0 & \text{otherwise}
\end{cases}$$

Thus the reconstructed spectrum is

$$\hat{F}(k) = \sqrt{\hat{S}(k)} \exp\left(ik\hat{\phi}(k)\right)$$

and thus the clutter filtered time-series is the inverse Fourier transform

$$V_{CF<\text{ClutterTrip}}(k) = F^{-1}\left[\hat{F}\right](k)$$

Finally, set ClutterFiltered to 1.

8. Determine the trip ordering using the $|R_1|$ estimator

Inputs $V_{CF1}, V_{CF2}, \text{ClutterTrip}, WkTripCensorFlag, t_A$

Outputs $WkTripCensorFlag, V_{CF1}, V_{CF2}, t_A, t_B, \text{type}_P_1, \text{type}_P_2, \text{type}_v_1, \text{type}_v_2, \text{type}_w_1, \text{type}_w_2$

Compute $|R_1[V_{CF1}]|$ and $|R_1[V_{CF2}]|$. Note that the current trip is ClutterTrip, rather than trip 1 as in block 3. Thus $|R_1|$ is first calculated for $V_{CF<\text{ClutterTrip}}$. The NonClutterTrip is defined as $3 - \text{ClutterTrip}$. Cohere to NonClutterTrip, saving the time-series as $V_{CF<\text{NonClutterTrip}}$. Compute $|R_1|$ on this time-series. The trip with the larger value is the stronger trip, so set $t_A'$ to that trip.

If there was clutter in both trips and the new strong total trip is different then the old strong total trip ($t_A \neq t_A'$), then this implies that we are in the worst possible case, and that neither trip is recoverable. In this eventuality set

$$\text{type}_P_1 = \text{type}_P_2 = \text{OVERLAI.D\_LIKE}$$
$$\text{type}_v_1 = \text{type}_v_2 = \text{OVERLAI.D\_LIKE}$$
$$\text{type}_w_1 = \text{type}_w_2 = \text{OVERLAI.D\_LIKE}$$

and stop processing. If there was clutter in only 1 trip and the new strong total trip is different then the old strong total trip, then this implies that the clutter was in the weak weather trip and thus the weak trip needs to be censored; set WkTripCensorFlag to 1. Set $t_A = t_A'$ and since there are only 2 trips $t_B = 3 - t_A$.

9. Cohere to Strong trip

Inputs $V_{CF1}, V_{CF2}, V_{W1}, V_{W2}, \text{ClutterFiltered}$
**Outputs** $V_s$

Set $V_s = V_{CF < t_A}$ if ClutterFiltered, otherwise, set $V_s = V_{W < t_A}$.

10. **Calculate the Strong trip total power (including noise) and check that there is enough power to warrant any further action**

**Inputs** $V_s$

**Outputs** $\tilde{P}_s, type_P_1, type_P_2, type_v_1, type_v_2, type_w_1, type_w_2$

Calculate the total power

$$\tilde{P}_s = R_0 [V_s]$$

If $\tilde{P}_s < K_s$ then set

$$type_P_1 = type_P_2 = NOISE.LIKE$$
$$type_v_1 = type_v_2 = NOISE.LIKE$$
$$type_w_1 = type_w_2 = NOISE.LIKE$$

and exit.

11. **Calculate the Strong trip mean velocity using the $R_1$ estimator.**

**Inputs** $V_s$

**Outputs** $v_s, R_s$

Store both $v_s$ as well as $R_s$ for later use for calculating the spectrum width.

$$R_s = R_1 [V_s]$$
$$v_s = -\frac{v_a}{\pi} \arg (R_s)$$

where $v_a = \lambda / (4 T_s)$

12. **Apply PNF**

**Inputs** $V_s$, ClutterFiltered, ClutterTrip, $t_A$

**Outputs** $V_{SN}$
Compute the spectrum.

\[ F(k) = F[V_s](k) \]

for \( 0 \leq k < N \).

Compute the central spectral coefficient:

\[
k_0 = \begin{cases} 
\text{round} \left( -v_s \frac{N}{2v_a} \right) & \text{if } v_s \leq 0 \\
\text{round} \left( N - v_s \frac{N}{2v_a} \right) & \text{if } v_s > 0 
\end{cases}
\]

If ClutterFiltered and \( t_A = \text{ClutterTrip} \), then perform PNF center adjustment. To do this, set

\[
k_{\text{ADJ}} = (k_{\text{GMAP}} - 1)/2 + k_{\text{GMAP,EXTRA}}
\]

and then set

\[
k_0 = \begin{cases} 
\left\lfloor \frac{NW-1}{2} \right\rfloor - k_{\text{ADJ}} & \text{if } \left\lfloor \frac{NW-1}{2} \right\rfloor - k_{\text{ADJ}} < k_0 < \frac{N}{2} \\
N - \left\lceil \frac{NW-1}{2} \right\rceil + k_{\text{ADJ}} & \text{if } \frac{N}{2} \leq k_0 < N - \left\lceil \frac{NW-1}{2} \right\rceil + k_{\text{ADJ}} \\
k_0 & \text{otherwise}
\end{cases}
\]

where \( NW = 3N/4 \).

Now, apply PNF. Let \( k_a = \text{mod} \left( N + k_0 - \left\lfloor \frac{NW-1}{2} \right\rfloor , N \right) \). Then set

\[
F_{SN}(\text{mod}(k_a + l, N)) = \begin{cases} 
0 & \text{if } l < NW \\
NF \cdot F(\text{mod}(k_a + l, N)) & \text{if } NW \leq l < N
\end{cases}
\]

where \( NF = 1/\sqrt{1 - 3/4} = 2 \). \( NF \) normalizes the filtered signal to preserve the power of the weak trip. Note that if SZ-1 is upgraded to accommodate 3 trips, then \( NF \) will have to adapt with the situation. For now, we are hard coding the notch width.

Finally, compute the notched time-series

\[ V_{SN}(k) = F^{-1}[F_{SN}](k) \]

for \( 0 \leq k < N \).

13. Calculate the residual power.

Inputs \( V_{SN} \)

Outputs \( P_R \)

\[ P_R = R_0[V_{SN}] \]
14. Calculate the Strong trip power

Inputs $P_R, \tilde{P}_s$

Outputs $P_s$

$$P_s = \tilde{P}_s - P_R$$

15. Calculate the Strong trip spectrum width

Inputs $P_s, R_s$

Outputs $w_s$

Use the $R_0R_1$ estimator.

$$w_s = \begin{cases} \frac{v_s}{\pi} \left( \ln \left( \frac{P_s^2}{|R_s|^2} \right) \right)^{1/2} & P_s \geq |R_s|^2 \\ 0 & P_s < |R_s|^2 \end{cases}$$

16. Compute Weak trip power

Inputs $P_R, P_N$

Outputs $P_w$

$$P_w = \max(P_R - P_N, 0)$$

17. Check that there is reason to warrant any further action

Inputs $P_w, \text{WkTripCensorFlag}, P_s, v_s, w_s$

Outputs $\text{type}_P_1, \text{type}_P_2, \text{type}_v_1, \text{type}_v_2, \text{type}_w_1, \text{type}_w_2, P_1, v_1, w_1, P_2, v_2, w_2$

Set the following regardless

$$P_{<t_A>} = P_s$$
$$v_{<t_A>} = v_s$$
$$w_{<t_A>} = w_s$$
$$\text{type}_{P_{<t_A>}} = \text{SIGNAL\_LIKE}$$
$$\text{type}_{v_{<t_A>}} = \text{SIGNAL\_LIKE}$$
$$\text{type}_{w_{<t_A>}} = \text{SIGNAL\_LIKE}$$

If $P_w < K_w$ then set
and stop processing. 

If $P_{w} \geq K_{w}$ and WkTripCensorFlag is 1 then set

$$
type_{P_{<t_{B}>}} = OVERLAIKD\_LIKE \\
type_{v_{<t_{B}>}} = OVERLAIKD\_LIKE \\
type_{w_{<t_{B}>}} = OVERLAIKD\_LIKE
$$

and stop processing.

18. **Cohere to Weak Trip**

**Inputs** $V_{SN}$, $t_{A}$, $t_{B}$

**Outputs** $V_{w}$

Recohere from trip $t_{A}$ to $t_{B}$ and denote the new time-series $V_{w}$.

19. **Compute Weak trip mean velocity**

**Inputs** $V_{w}$

**Outputs** $v_{w}$

Calculate the weak trip mean velocity using the $R_{1}$ estimator.

$$
R_{w} = R_{1} [V_{w}] \\
v_{w} = -\frac{v_{a}}{\pi} \arg (R_{w})
$$

where $v_{a} = \lambda / (4T_{s})$

20. **Deconvolve the spectrum**

**Inputs** $V_{w}$

**Outputs** $\tilde{S}$
Compute the magnitude spectrum

\[ S(k) = |F[V_w](k)| \]

for \( 0 \leq k < N \).

Perform the magnitude deconvolution \( \tilde{S} = Dmat \cdot S \), i.e.

\[ \tilde{S}(k) = \sum_{n=0}^{N-1} Dmat_{k,n} S(n) \]

21. Compute the Spectral Censoring Metric

Inputs \( \tilde{S} \)

Outputs \( H \)

Break the spectrum \( \tilde{S} \) into 8 equally sized segments and determine the maximum value over each segment, exactly as is done in the spectral noise calculation. Sort these maxima, and denote \( \hat{M}_n \) where \( n = 0, \ldots, 7 \) and \( \hat{M}_0 \) is the smallest value. Then

\[ H = 10 \log_{10} \left( \frac{M_7}{\frac{1}{N_S} \sum_{l=0}^{N_S-1} M_l} \right) \]

22. Store the results from the weak trip

Inputs \( P_w, v_w \)

Outputs \( \text{type}_P_1, \text{type}_P_2, \text{type}_v_1, \text{type}_v_2, \text{type}_w_1, \text{type}_w_2, P_1, v_1, w_1, P_2, v_2, w_2 \)

\[ P_{<t_B>} = P_w \]
\[ v_{<t_B>} = v_w \]
\[ \text{type}_P_{<t_B>} = \text{SIGNAL\_LIKE} \]
\[ \text{type}_v_{<t_B>} = \text{SIGNAL\_LIKE} \]
\[ \text{type}_w_{<t_B>} = \text{OVERLAID\_LIKE} \]
B Publications

The following publications are attached to this report. They can also be found at http://www.atd.ucar.edu/rsf/NEXRAD/nexrad_publications_links.html


- Dixon, M., C. Kessinger and J. Hubbert, Echo classification within the spectral domain to discriminate ground clutter from meteorological targets, 22nd IIPS, AMS, Atlanta, GE, 2006.


