IMPROVING NEXRAD DATA
Data Quality Algorithm Progress

FY2006 Annual Report

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Executive Summary

J. Hubbert

This report provides continued analysis of the algorithms for NEXRAD Data Quality and Range-Velocity ambiguity mitigation.

In January of 2006 NCAR delivered a functional description of the CMD algorithm (Clutter Mitigation Decision) for the legacy single polarization NEXRAD radars to the ROC. The CMD provides real time identification of ground clutter contaminated data and the subsequent clutter filtering (with GMAP) of the contaminated data (i.e., weather echoes are not filtered). NCAR has continued to develop and improve CMD over the remainder of FY2006. An important advancement has been the recognition of a new Fuzzy Logic input feature field, CPA (Clutter Phase Alignment). CPA is a direct measure of the defining characteristic of non-moving ground clutter targets: constant backscatter phase angle, i.e., non-moving ground clutter is a coherent target. In contrast, weather is a distributed target and the absolute phase of the received backscatter usually varies significantly from time series data sample to data sample over the dwell time. Thus CPA has proven to be an excellent discriminator of weather and ground clutter. Zero velocity weather with narrow spectrum width can have similar CPA values to ground clutter but this is a fairly infrequent occurrence. Nevertheless, feature fields dependent on the spatial texture of reflectivity need to be retained in order to discriminate this case (zero velocity, narrow spectra weather and ground clutter). CPA has allowed for a significant simplification of the CMD algorithm as it was delivered in January 2006: instead of using a two dimensional region over which to calculate textures, research indicates that calculating texture only along a radar radial is sufficient for excellent discrimination between ground clutter and weather echoes. Practically this means that the CMD algorithm will be much simpler to implement in RVP8 processor architecture.

A version of CMD has also been developed for dual polarization NEXRAD data. The best feature fields for identifying clutter are the spatial texture of differential reflectivity ($Z_{dr}$) and differential phase ($\phi_{dp}$). The copolar correlation coefficient, $\rho_{hv}$, is not an effective discriminator between ground clutter and weather. Even though the dual polarization feature fields improve CMD performance, CPA continues to be an important and indispensable part of the algorithm.

An attractive feature of CPA is that it is calculated in the time domain and should be equally effective for uniform PRT data as well as staggered PRT data. Also, CPA is effective in identifying clutter targets that may be apparent only in part of the received time series due to the radar antenna rotation.

NCAR also investigated dual polarization rainfall algorithms and in particular a NSSL proposed rainfall algorithm for NEXRAD. A total of 19 different rainfall estimators are compared using two S-Pol data sets from the TEFLUN-B experiment in Melbourne, Florida, 1998, and a rainguage network. The NSSL algorithm is composed of three rainfall cases: 1) low rainfall, 2) medium rainfall and 3) heavy rainfall. It is shown that for the TEFLUN data sets, the NSSL proposed initial $Z$-$R$ rainfall for determining which rainfall estimator to use was not optimum. Instead a $Z$-$Z_{dr}$ rainfall estimator is used for this purpose which improved the final agreement between rainguage estimates and radar rainfall estimates. Also, the NSSL algorithms were tuned
for DSDs (drop size distribution) found in Oklahoma. The algorithms we tested were adjusted to accommodate the DSD type likely to be found in Florida. This too improved the agreement between the raingauges and the radar rainfall estimates.

The performance of NSPA (NCAR’s Spectral Processing Algorithm) continues to be improved for application to NEXRAD processing. NSPA uses the principle of continuity of weather echo in range to locate and track weather echoes in plots of spectra versus range along a radar radial. Once the weather echo is found in a spectrum, the radar moments are calculated from only those spectral points that contain weather echo. In this way contaminated echoes (artifacts), if they occupy a different part of the spectrum than the weather, are avoided and thus do not bias the weather radar moments. It is also shown that NSPA can effectively track weather echoes through regions of severe wind shear, e.g. tornados. Examples are shown where NSPA out performs the pulse pair radar moment estimates.

The performance of a three trip SZ-1 phase coding algorithm is investigated. If the SZ-1 algorithm (SZ-1 has no accompanying long PRT scan for unambiguous reflectivity determination) is to be used below about 2.4° elevation, three trips need to be permitted if the NEXRAD requirement of 25 m s\(^{-1}\) minimum unambiguous velocity is to be satisfied. Simulation results show that it is very difficult to correctly separate and locate three overlaid echoes from three different trips. Additionally, if ground clutter echo is present, the signal processing becomes even more difficult. The result is significant deterioration of performance statistics. Much of this data can be censored but large areas of such censored data is not desired but often may be present. It is recommended that a two trip SZ-1 algorithm instead be employed and that the 25 m s\(^{-1}\) requirement be relaxed. Another option for these elevation angles is staggered PRT to retain the Nyquist velocity specification.

NCAR also investigated the problematic SZ-2 spectrum width estimator. The problem was manifest by an excessive number of zero width estimates seen in NEXRAD data sets. Part of this problem is due to the time series Hanning (von Hann) window function employed by the SZ-2 algorithm. The effect is to bias the magnitude of the \(R(1)\) estimator (first lag of the autocorrelation function) high thus causing an excessive occurrence of \(R(1) > R(0)\). When this happens the estimator is undefined (square root of a negative number) and the spectrum width estimate is assigned a value of zero. A correction factor for the bias incurred by the used time series window function is calculated, applied to the data, and thereby mitigates this bias. Still, spectrum width estimators are problematic and better spectrum width estimators for NEXRAD should be investigated.

Improvement in the Radar Echo Classifier (REC) performance is also documented. The REC, unfortunately, has had a rather checkered career since its introduction into the NEXRAD RPG. Most of the observed problems have been due to code translation errors. Unfortunately, effecting the needed corrections has proved arduous. The original design REC contains two separate Fuzzy Logic algorithms for the identification and separation of ground clutter and precipitation: 1) the APDA (Anomalous Propagation Clutter Detection Algorithm) and 2) the PDA (Precipitation Detection Algorithm). These two algorithms are intended to work in conjunction to provide the most robust identification and separation of AP clutter and precipitation echo. The APDA identifies radar data that is most likely ground clutter echoes. The PDA identifies radar data that
is most likely precipitation echo. Thus, the final identification of contaminated data becomes, "if APDA identified or if not PDA identified". The combination of the two algorithms within the REC provides better classification of precipitation data. NCAR recommends that both the APDA corrections and PDA be implemented in the REC for optimum RPG precipitation accumulations.
1 Real Time Clutter Identification and Filtering

M. Dixon and J. Hubbert

1.1 Introduction

CMD (Clutter Mitigation Decision) algorithm is a Fuzzy Logic algorithm for clutter echo identification that is designed to run in real time on RVP8. Times series data are buffered in the RDA (i.e., RVP8) so that the CMD identified clutter contaminated radar data can be clutter filtered and subsequently the radar moments can be calculated. In this way, only the radar gates which are identified as being clutter contaminated are processed by the clutter filter while other gates are not clutter filtered. The goal of CMD is to robustly differentiate between zero velocity weather and ground clutter and thereby not clutter filter desired precipitation data.

Version 1 of the CMD algorithm makes use of spatially-computed quantities in both azimuth and range. Discussions were held at the May 2006 Technical Interchange Meeting (TIM) on how this might be implemented in the RVP8 environment. From those discussions it was clear that the need to buffer adjacent beam data could make the implementation in RVP8 considerably more difficult than if only data along a single beam was used.

Therefore, NCAR developed version 2 of the CMD algorithm, which does not require adjacent beams. All spatially-derived quantities are computed in range only. Obtaining good performance without the advantage of adjacent beam information was accomplished by the addition of the new feature field CPA (Clutter Phase Alignment) to CMD.

1.2 Time series data collection issues

Time series data were recorded using the NCAR S-Pol radar, located at Marshall close to Boulder, as well as an auxiliary host networked to the NWS KFTG NEXRAD situated at the Front Range Airport NE of Denver.

1.2.1 Time series recording on S-Pol

In previous years, time series recording at S-Pol was carried out using the L1RP server and client applications, originally developed by the ROC.

Since most NEXRAD time series data will be stored in the Sigmet TsArchive format, it was considered advantageous to use this format. Therefore the software components on S-Pol were upgraded to accommodate the TsArchive format.

Initial testing was carried out using the Sigmet tsexport and tsimport applications. These applications use UDP (User Datagram Protocol) for transmission of the data. This is a broadcast protocol. The data is broadcast over the local network in packets which have no destination address. The advantage of UDP is that multiple readers can read the same data stream, which minimizes the bandwidth requirements. The disadvantages of UDP are that (a) it is not ‘reliable'
and packets may be dropped, leading to gaps in the data and (b) if configured incorrectly the high-rate data can flood the network with unwanted packets.

Testing with UDP on the S-Pol network showed that a large number of packets were dropped. The situation was improved when some changes were made to the network configuration. However, the problems persisted albeit at a lower severity. For time series data it is unacceptable to drop even one pulse, because this interrupts the time series sequence and the data for an entire beam becomes unusable.

It was therefore concluded that using UDP was not a realistic long-term option for S-Pol. NCAR decided to re-implement the time series applications to make use of TCP/IP (Transmission Control Protocol/Internet Protocol), since the L1RP system used TCP/IP and had proved very reliable. TCP/IP has the advantage of being a point-to-point protocol with error checking, so it is a reliable delivery mechanism for data. The disadvantage is that, being point-to-point, extra bandwidth is used when multiple clients read the same data. However, this was considered an acceptable compromise since modern Giga-bit networks can easily handle multiple time series data streams.

NCAR also obtained from the ROC the `process_driver` application to control the RVP8 at a low level, eliminating the dependence on the Sigmet IRIS software. NCAR modified this code to become the `Rvp8Driver` for S-Pol.

Figure 1 shows the data flow diagram for time series recording on S-Pol.

TsArchive data was collected on S-Pol for the following dates:

2006/04/15
2006/04/18
2006/05/05
2006/05/06
2006/05/08
2006/05/09
2006/05/30
2006/07/20
2006/08/11
2006/08/26
2006/08/27
2006/09/21
2006/09/27
2006/10/05
2006/10/09
2006/10/18
Figure 1: Data flow diagram for time series recording on S-Pol.
Some of this data contains weather cases, while other cases were collected for clutter analysis.

### 1.2.2 Time series recording on KFTG

In preparation for the REFRACTT field experiment, NCAR worked with the NWS to temporarily install an auxiliary IQ host at the KFTG NEXRAD site.

![Data flow diagram for time series recording at KFTG.](image)

Figure 2: *Data flow diagram for time series recording at KFTG.*

Figure 2 shows the setup at KFTG for recording the time series data. Since the RVP8 was under ORDA control, only certified applications could be run on it. Therefore, the Sigmet-supplied `tsexport` application was used to broadcast the time series data using UDP.

For network security purposes, a firewall was installed between the RVP8 and the NCAR auxiliary host. This firewall was configured and managed by NWS personnel.
NCAR developed and ran the \texttt{TsUdp2File} application to read the UDP data stream and save the time series data to files. This worked reasonably well – better than on S-Pol - although large sectors were missing from the time series data quite frequently, about once per volume scan.

The disks on the auxiliary IQ host were large enough to store 24 hours of time series data. NCAR personnel monitored the weather situation for conditions which would be suitable for testing CMD. When such events occurred, NCAR saved selected time series files to an archive location on the auxiliary host and then copied the files to NCAR computers in Boulder via the T1 line.

In this manner, time series files were saved for events at the following dates and times:

- 2006/09/21 03:00Z
- 2006/09/21 05:30Z
- 2006/10/09 18:00Z
- 2006/10/09 22:00Z
- 2006/10/10 10:00Z
- 2006/10/13 21:00Z
- 2006/10/17 21:30Z
- 2006/10/26 12:00Z
- 2006/11/12 15:00Z

This data proved to be extremely useful in the development and testing of CMD version 2.

### 1.3 The CMD single-polarization algorithm

#### 1.3.1 Introduction

The CMD algorithm is similar to the Radar Echo Classifier (REC) (Kessinger et al., 2003) in that it makes use of Fuzzy Logic to combine the information from a number of different fields to derive a single decision-making field. A major difference is that CMD use information derived from the spectra of the radar signals whereas REC does not.

The input data fields (e.g., reflectivity texture) are referred to as \textbf{feature fields} and the units of these data are simply the units of the input field.

The feature fields are then transformed into \textbf{interest fields} by applying a piece-wise linear transfer function, known as a \textbf{membership function}. Values in the interest fields range from 0.0 to 1.0.

Using fuzzy logic, the interest fields are combined into a single \textbf{decision} field, which can be interpreted as the \textbf{likelihood} of clutter at a gate.

A threshold (typically 0.5) is applied to this decision field. A value above 0.5 is interpreted as \textbf{clutter exists}, while values below 0.5 are interpreted as \textbf{clutter does not exist}. 

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1.3.2 CMD Version 1

Version 1 of the CMD algorithm was based on analyses performed during FY2005, under the previous FY2005 Statement of Work. The functional description of version 1 was delivered to the ROC in January 2006. The parameters were tuned to provide the best results possible based on the available data sets at the time.

The CMD Version 1 algorithm utilizes spatial quantities computed over a 2-D computational kernel, typically 5 beams wide and 7 gates long. (These are adjustable parameters.)

![2-D computational kernel, 5 beams wide by 7 gates long.](image)

The following table lists the feature fields used in version 1.

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>TDBZ</td>
<td>Texture of reflectivity</td>
<td>1.0</td>
</tr>
<tr>
<td>SPIN</td>
<td>Reflectivity spin change: the number of significant dBZ sign reversals in range, expressed as a percentage of the maximum number possible</td>
<td>1.0</td>
</tr>
<tr>
<td>SDVE</td>
<td>Standard deviation of velocity over the kernel</td>
<td>0.5</td>
</tr>
<tr>
<td>RATIO_WIDE</td>
<td>The sum of power at the 3 spectral points closest to 0, divided by the sum of the power at the remainder of the spectral points.</td>
<td>0.5</td>
</tr>
</tbody>
</table>

Table 1: Feature fields for version 1.

Figure 4 shows the membership transfer functions for version 1.
Figure 4: Membership functions for version 1.
As mentioned earlier, the feature fields are converted into interest fields and combined into a single decision-making field, which indicates the **likelihood** of clutter at a gate.

An additional spectral based field, RATIO_NARROW, is used to determine the **possibility** of clutter at a gate. If RATIO_NARROW does not exceed a set threshold (say 6 dB) that gate will not be processed by CMD since clutter is not considered possible at the gate.

For complete details of CMD version 1, see Dixon 2006a.

### 1.3.3 CMD version 2

As mentioned in the introduction, one of the problems with version 1 is that it requires information from a 2-D computational kernel, in both range and azimuth (see Figure 3). The dependence on data from adjacent beams complicates the implementation of CMD in the RVP8 ORDA real-time environment.

Therefore, one of the constraints placed on version 2 was that it should use spatial information in range only. In other words it should use a 1-D computational kernel. The length of the kernel in gates is an adjustable parameter.

![1-D kernel using information in range only.](image)

Figure 5: 1-D kernel using information in range only.

Figure 5 shows an illustration of a 1-D kernel, with a length of 9 gates. Because only a single beam is used, the length of the kernel was extended from 7 to 9 to improve the precision of the fields.

The following table lists the feature fields used in version 2.

The set of feature fields changed from version 1 to version 2. RATIO_WIDE was dropped and CPA was added.

TDBZ and SPIN have proved to be very reliable and effective in identifying clutter, so these were retained.
Table 2: Feature fields for version 2.

SDVE was included in both version 1 and version 2. However, it was turned off during the tuning for version 2 by setting its weight to 0. It seems likely that it will be dropped in the future.

CPA appears to be more sensitive to clutter than RATIO_WIDE, hence its inclusion in version 2. The extra sensitivity is needed because of the requirement to use a 1-D kernel. Before CPA was added, it was difficult to achieve satisfactory performance using a single beam of data. The inclusion of CPA made a 1-D configuration feasible with good performance.

Figure 6 shows the membership transfer functions for version 2. One point to notice is that the membership function for SPIN has a different shape from that used in version 1. A mistake was found in the way SPIN had been computed in the Radar Echo Classifier, which led to the use of the previous membership function. After the mistake was corrected, the associated membership function was adjusted accordingly.

To compute the clutter flag at each gate, we proceed through the gates as follows:

- If the Signal-to-Noise Ratio (SNR) < 3 dB, no clutter at this gate, skip to next gate.
- If Clutter Ratio Narrow < 6 dB, no clutter at this gate, skip to next gate.
- If CMD < 0.5, no clutter at this gate, skip to the next gate.
- Otherwise, apply clutter filter at this gate.

For complete details of CMD version 2, see Dixon 2006b (attached in the Appendix).

1.3.4 Selecting the relative weights for the interest fields

The weights applied to each interest field are somewhat dependent upon which fields are included in the fuzzy-logic algorithm. This makes the tuning of the weights more difficult than tuning the membership functions.

The version 2 algorithm was tuned on the 2006/10/26 cases from the KFTG (Denver) NEXRAD and was then tested on six other cases. The performance of the algorithm was quite good and consistent from case to case as determined by visual inspection using knowledge as to the location of NP (Normal Propagation) ground clutter. It appears that the algorithm is well tuned for that radar.
Figure 6: Membership functions for CMD version 2.
However, experience with data sets from other radars will be essential in determining parameter settings suitable for a wide range of radars. Specifically, the algorithm must be tested on sites with tree-covered clutter targets, to determine whether the presence of trees moving in the wind will cause the algorithm performance to suffer.

1.3.5 The Clutter Phase Alignment (CPA) feature field

The CPA field was a major addition to CMD for version 2.

CPA is a measure of how constant the absolute return phase (i.e., the phase of a received I and Q sample) remains for the transmitted pulses which comprise a beam of radar data. For a fix, non moving target, CPA is 1. If the target is not completely stationary over the measurement period, the mean velocity will differ from 0 m/s and/or the width of the spectrum of the radar return signal will increase. Both will decrease CPA from 1. The more constant the absolute phase is, the more likely it is that the gate contains clutter. CPA is defined as

\[
CPA = \frac{\left| \sum_{i=1}^{N} x_i \right|}{\sum_{i=1}^{N} |x_i|} \tag{1}
\]

where \(x_i\) is the received time series and \(N\) is the time series length. Thus CPA is the magnitude of the vector sum of the individual time series members divided by the the sum of the magnitudes of the \(x_i\). CPA is an excellent indicator/identifier of clutter since by definition it is a measure of the primary characteristic of stationary ground clutter, i.e., constant backscatter phase. In fact, if the phase of the \(x_i\) is a constant, CPA will be one regardless of the behavior of the magnitude of the \(x_i\). The backscatter phase is a constant since stationary ground clutter is a coherent target.

There is a close relationship between CPA and the velocity and spectrum width. Figure 7 show this relationship. Time series simulations were made for velocities from -0.6 ms\(^{-1}\) to 0.6 ms\(^{-1}\) at 0.1 ms\(^{-1}\) steps, 100 simulations per step. The simulation parameters are: PRT=1ms, \(\sigma_v = 0.1\) ms\(^{-1}\), 64 points, and SNR=60 dB. For each simulated time series the velocity was estimated via the pulse pair algorithm and CPA was calculated and the result is shown in Figure 7. As can be seen, as velocity magnitude increases, the value of CPA decreases rather quickly. When the velocity magnitude is greater than 0.2 ms\(^{-1}\), the average CPA values are below 0.9. Both velocity and spectrum effect CPA: 1) as the velocity departs from zero, CPA decreases rapidly, 2) as the spectrum width increases the value of CPA decreases, at least for weather signals. Furthermore, no particular spectrum shape is assumed for CPA calculation.

CPA has the following characteristics:

- In clutter, the phase of each pulse in the time series for a particular gate is almost constant since the clutter does not move much and is at a constant distance from the radar.
- In noise, the phase from pulse to pulse is random.
- In weather, the phase from pulse to pulse will vary depending on the velocity of the targets within the illumination volume.
CPA can, however, have high values in weather with a narrow spectrum width and a velocity very close to 0 m s$^{-1}$. In that sense, it can in theory cause the same errors which occur from using velocity and spectrum width to determine clutter likelihood. However, in the case of CPA, the high values in weather are most often limited to a few gates along the zero velocity isodop.

Figure 8 shows conceptually how CPA is computed. Figures 9 and 10 show phasor diagrams for selected gates from the KFTG and S-Pol radars respectively. Each combination of a straight and a curved line represents data for a time series for one gate.

CPA is computed as the ratio of the straight line length to the curved line length.

CPA characteristics include:

- CPA is computed at a single gate.
- It is a normalized value, ranging from 0 to 1.
- In clutter, CPA is typically above 0.95.
- In weather, CPA is often close to 0, but increases in weather with a velocity close to 0 and a narrow spectrum width.
- In weather CPA is above 0.9 only for isolated gates.
- In noise, CPA is typically less than 0.05.

It can be shown that the numerator CPA is equivalent to the magnitude of the zero velocity component of the signal. The denominator of CPA, however, is not easily calculated in the
frequency (i.e., velocity) domain since it is a sum of magnitudes. CPA is somewhat similar to the ratio of the zero velocity power divided by the total signal power but is distinctly different. This is not discussed here but will be addressed in a future report.

1.3.6 Example case study for version 2

As mentioned in section 2, NCAR was able to obtain time series data for selected cases from the KFTG radar NE of Denver.

A case from 1200 UTC on 26 October 2006 will be used to demonstrate CMD version 2. Figures 11 through 24 show this case.

The clutter spike to the east of the radar is caused by 3-body scattering off the large control tower at Front Range airport.

Note that the clutter spike from the 3-body scattering is correctly identified as clutter in Figure 19.
Figure 9: Example phasor diagrams from KFTG.

Figure 10: Example phasor diagrams from S-Pol.
Figure 11: Un-filtered dBZ, KFTG, 2006/10/26 Note the strong mountain clutter to the West of the radar.

Figure 12: Un-filtered velocity, KFTG, 2006/10/26 Note the clear 0 isodop through the weather from West to East.
Figure 13: Un-filtered spectrum width, KFTG, 2006/10/26.

Figure 14: TDBZ, KFTG, 2006/10/26.
Figure 15: SPIN, KFTG, 2006/10/26.

Figure 16: CPA, KFTG, 2006/10/26.
Figure 17: *RATIO-NARROW*, KFTG, 2006/10/26.

Figure 18: *CMD combined interest field*, KFTG, 2006/10/26.
Figure 19: CMD flag field, KFTG, 2006/10/26.

Figure 20: Filtered dBZ, KFTG, 2006/10/26.
Figure 21: Filtered dBZ, filter applied everywhere. Note power removed from the weather along the 0 isodop.

Figure 22: Filtered velocity, KFTG, 2006/10/26.
Figure 23: Filtered spectrum width, KFTG, 2006/10/26.

Figure 24: Clutter power removed, KFTG, 2006/10/26.
Other cases from KFTG, which show similar results, were presented at the TIM in November 2006. CMD version 2 works well on data from KFTG in these stratiform-type events.

1.3.7 Combining CMD version 2 with SZ-2 phase coding

The SZ2 algorithm makes use of data from the following:

- a long-PRT PPI, non phase coded.
- a short-PRT PPI, SZ phase coded.
- a clutter (bypass) map.

In the legacy NEXRAD system, the clutter map is a static map. The problem with this approach is that AP clutter is not handled by the static map.

CMD can be used as an alternative to the static clutter map. CMD would be run on the long-PRT scan to produce a dynamic clutter map. This dynamic clutter would then be used by the SZ2 algorithm in the place of the static clutter map.

1.4 The CMD dual-polarization CMD algorithm

1.4.1 Overview

Two dual polarization versions of the algorithm were tested, corresponding to versions 1 and 2 of the single-polarization algorithm.

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DP-1</td>
<td>Based on CMD version 1</td>
</tr>
<tr>
<td>DP-2</td>
<td>Based on CMD version 2</td>
</tr>
</tbody>
</table>

Table 3: Dual-polarization algorithm versions

1.4.2 Dual-polarization feature fields

The dual-polarization versions of the CMD algorithm extend the single-polarization versions. Feature fields derived from dual-polarization fields are added to increase the skill.

The following dual-polarization feature fields were investigated for use with the dual-polarization algorithm:

For all of these feature fields, only the current beam is used - no adjacent beam data is required. The standard deviation in range computed over a small number of gates, typically 5 or 7. (See Figure 5 for the 1-D kernel.)
<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma_{dr}$</td>
<td>Standard deviation of $Z_{dr}$ in range</td>
</tr>
<tr>
<td>$\sigma_{\phi_{dp}}$</td>
<td>Standard deviation of $\phi_{dp}$ in range</td>
</tr>
<tr>
<td>$\rho_{hv}$</td>
<td>copolar correlation coefficient at the gate</td>
</tr>
<tr>
<td>$\sigma_{\rho_{hv}}$</td>
<td>Standard deviation of $\rho_{hv}$ in range</td>
</tr>
</tbody>
</table>

Table 4: *Dual-polarization feature fields.*

1.4.3 Dual-polarization membership functions

Figure 25 shows the membership functions that were tested for use with the dual-polarization CMD algorithm:

1.4.4 Case demonstrating dual-polarization feature fields

Figures 26 through 35 were generated from an S-Pol case on 2006/05/08. These plots demonstrate the how the various dual-polarization feature fields help to distinguish clutter from weather.
Figure 25: Membership functions for dual-polarization feature fields.
Figure 26: Un-filtered dBZ, dual pol case 2006/05/08.

Figure 27: Un-filtered velocity, dual-pol. case 2006/05/08.
Figure 28: Clutter ratio narrow, dual-pol. case 2006/05/08.

Figure 29: $\sigma_{dr}$, dual-pol. case 2006/05/08 Separates clutter and weather. Good discrimination of clutter from noise.
Figure 30: $\sigma_{\phi dp}$, dual-pol. case 2006/05/08 Detects weather, no discrimination of clutter from noise.

Figure 31: $\rho_{hv}$, dual-pol. case 2006/05/08 Detects weather. Poor discrimination of clutter from noise.
Figure 32: $\sigma_{\text{phv}}$, dual-pol. case 2006/05/08 Detects weather, provides some discrimination of clutter from noise.

Figure 33: CMD, dual-pol. case 2006/05/08 Combined interest field.
Figure 34: CMD flag, dual-pol. case 2006/05/08 Clutter decision after applying of 0.5.

Figure 35: Filtered dBZ, dual-pol. case 2006/05/08 Reflectivity after applying clutter filter.
1.4.5 How well do the dual-polarization feature fields perform?

Based on a review of cases such as that presented above, the utility of the various dual-polarization feature fields may be summarized as follows:

- $\sigma_{dr}$: provides good discrimination of clutter from both noise and weather. Values below about 0.25 indicate weather. Values from 0.25 to about 2.0 indicate noise, and values above 2.0 indicate clutter.

- $\sigma_{\phi_{dp}}$: provides good detection of weather, but does not discriminate clutter from noise. Values below 5.0 indicate the presence of weather. The delineation between weather and non-weather is very sharp. Non-weather values tend to be above 10.

- $\rho_{hv}$: provide detection of weather, but does not discriminate clutter from noise. Values above 0.98 generally indicate weather. However, some clutter targets produce $\rho_{hv}$ values above 0.98.

- $\sigma_{\rho_{hv}}$: provides detection of weather, and some discrimination of clutter from noise. Values below 0.05 generally indicate weather. However, sometimes clutter has a $\sigma_{\rho_{hv}}$ value below 0.05.

$\sigma_{dr}$ is the most useful feature field, because it provides good discrimination of clutter from both noise and weather.

$\sigma_{\phi_{dp}}$ is useful for the detection of weather, but not for the detection of clutter. However, it is a reliable field and does not appear to be prone to errors.

$\rho_{hv}$ and $\sigma_{\rho_{hv}}$ both provide detection of weather, but in a small but significant number of cases clutter is erroneously identified as weather. This is discussed further below.

1.4.6 Detailed example showing problems with using the $\rho_{hv}$ fields

Figure 36 below shows a zoomed view, to the NE of the radar, of the reflectivity field in the example presented above. A yellow line is shown drawn through one region of clutter, and is used as a marker in the figures which follow.

Evidence points to the existence of clutter at most of the gates along the yellow line. The reflectivity field, $\sigma_{dr}$ and $\sigma_{\phi_{dp}}$ fields all indicate the presence of clutter.

However, the $\rho_{hv}$ and $\sigma_{\rho_{hv}}$ fields contain values which indicate weather rather than clutter. If these fields are included in the CMD algorithm, they decrease the CMD value in such situations, so that the clutter filter will not be applied where it should.

Figure 37 shows the RHI, or vertical section, along the yellow line. The regions of clutter clearly show up as having high reflectivity at low levels.

The $\sigma_{dr}$ feature field performs well in identifying the region of clutter.

The $\sigma_{\phi_{dp}}$ field is not particularly helpful in identifying clutter, but it does not incorrectly identify clutter as weather. If $\sigma_{\phi_{dp}}$ identifies a region as weather it is very likely to be so. The
Figure 36: Zoomed view of reflectivity fields from example above
Yellow marker line shows clutter region for the following discussion.

Figure 37: Vertical (RHI) section along the yellow marker line in above figure.
Figure 38: $\sigma_{dr}$ in clutter region.

Figure 39: $\sigma_{dr}$ for vertical section.
Figure 40: $\sigma_{\phi_{dp}}$ for detailed clutter example.

Figure 41: $\sigma_{\phi_{dp}}$ for vertical section.
reverse it not true – if it does not identify weather that does not necessarily imply that weather is absent.

Figure 43 shows how $\rho_{hv}$ can be high in clutter regions. The large blue-gray region to the left of the figure contains clutter, and yet $\rho_{hv}$ has values above 0.99.

Similarly, Figure 45 shows problems with $\sigma_{\rho_{hv}}$. $\rho_{hv}$ is high ($>0.99$), and hence spatially smooth, in parts of the clutter region. As a result $\sigma_{\rho_{hv}}$ is misleadingly low.

1.4.7 Dual polarization algorithm version DP-1

Based on the analysis which led to the discussion in the section above, it was decided to include only $\sigma_{dr}$ and $\sigma_{\phi_{dp}}$ as dual-polarization feature fields. $\rho_{hv}$ and $\sigma_{\rho_{hv}}$ were turned off in the algorithm by setting the weights to 0. It is likely that these fields will not be included in future versions of the algorithm, unless further analysis reveals a better way to make use of them.

The following table lists the feature fields used in version DP-1.

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>TDBZ</td>
<td>Texture of reflectivity</td>
</tr>
<tr>
<td>SPIN</td>
<td>Reflectivity spin change: the number of significant dBZ sign reversals in range</td>
</tr>
<tr>
<td>RATIO_WIDE</td>
<td>Ratio of the sum of power at the 3 spectral points closest to 0, to the sum of the power at the remainders</td>
</tr>
<tr>
<td>$\sigma_{dr}$</td>
<td>Standard deviation of $Z_{dr}$ with range</td>
</tr>
<tr>
<td>$\sigma_{\phi_{dp}}$</td>
<td>Standard deviation of $\phi_{dp}$ with range</td>
</tr>
</tbody>
</table>

Table 5: feature fields for version DP-1.

The SDVE field was not used in this version because it is not very skillful and there are a sufficient number of other fields which do show good skill.

1.4.8 Field testing of version DP-1 during the REFRACTT field experiment

The REFRACTT field experiment was conducted in the Colorado Front Range region during the summer of 2006. The goal of the experiment was to validate the use of the refractivity algorithm for detecting moisture fields with a view to improving convection initiation forecasts.

Four radars were involved in the experiment:

- S-Pol (NCAR)
- KFTG (NWS/NCAR)
- CHILL (CSU)
- Pawnee (CSU)

During the field project, S-Pol was run in fast-alternating dual-polarization mode.
Figure 42: $\rho_{hv}$ for detailed clutter example.

Figure 43: $\rho_{hv}$ for vertical section.
Figure 44: $\sigma_{\rho_hv}$ for detailed clutter example.

Figure 45: $\sigma_{\rho_hv}$ for clutter vertical section.
The DP-1 version of CMD was run on the S-Pol RVP8 time series data throughout the field experiment. The CMD flag field was used to determine at which gates to apply the NCAR version of the GMAP clutter filter. The raw and filtered moments were stored in volume files which were distributed to the operations center at NCAR for display purposes.

The REFRACTT project scientists made extensive use of the filtered moments throughout the field experiment. It was encouraging to learn that the scientists found these fields to be superior when compared with the time-domain filtered fields computed by the S-Pol VIRAQ processor, which produced a parallel data stream.

1.4.9 DP-1 case study – side-lobe clutter from DIA terminal

While analyzing the S-Pol data for the dual-polarization CMD algorithm, it was noticed that a persistent clutter signature existed at many elevation angles at the range and azimuth of the Denver International Airport (DIA) terminal. Further investigation suggested that this was side-lobe clutter from one or more of the structures at DIA.

Figure 46 below shows the region to the east of S-Pol. The yellow line indicates the azimuth along which RHIs were generated for this analysis. Note the linear feature of high reflectivity approximately perpendicular to the RHI line and about half way along it. This is the side-lobe clutter.

Figure 47 shows the same view, but with a map overlay which shows the position of the DIA runways and terminal structures relative to the clutter signature. It appears likely that the clutter is the result of reflections from one or more structures at the airport.

Figures 48 through 56 demonstrate the application of the dual-polarization version DP-1 on this interesting RHI case.

Figure 48 shows the clutter signature from DIA at multiple heights, suggesting side-lobe clutter. The clutter is embedded in a region of stratiform precipitation.

The results for this case are good. It is encouraging to confirm that the algorithm produces smooth results in the vertical dimension as well as the horizontal.
Figure 46: PPI reflectivity with DIA approximately in the center of the image.

Figure 47: Same as Figure 46, but with the DIA terminal and runways shown.
Figure 48: RHI showing the clutter signature from DIA.

Figure 49: Radial velocity along RHI, DIA clutter case.
Figure 50: TDBZ, DIA clutter case.

Figure 51: SPIN, DIA clutter case.
Figure 52: $\sigma_{dr}$, DIA clutter case.

Figure 53: $\sigma_{\phi_p}$, DIA clutter case.
Figure 54: *CMD version DP-1 decision flag field, DIA clutter case.*

Figure 55: *dBZ field again, for comparison, DIA clutter case.*
Figure 56: Filtered dBZ field, DIA clutter case.
1.4.10 Dual-polarization algorithm version DP-2.

The dual-polarization version DP-2 algorithm was developed by combining the single-polarization CMD version 2 with the dual-polarization fields from version DP-1.

The following table lists the feature fields used in version DP-2.

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>TDBZ</td>
<td>Texture of reflectivity</td>
<td>1.0</td>
</tr>
<tr>
<td>SPIN</td>
<td>Reflectivity spin change: the number of significant dBZ sign reversals in range</td>
<td>1.0</td>
</tr>
<tr>
<td>CPA</td>
<td>Clutter Phase Alignment</td>
<td>1.0</td>
</tr>
<tr>
<td>$\sigma_{dr}$</td>
<td>Standard deviation of $Z_{dr}$ with range</td>
<td>1.0</td>
</tr>
<tr>
<td>$\sigma_{\phi_{dp}}$</td>
<td>Standard deviation of $\phi_{dp}$ with range</td>
<td>1.0</td>
</tr>
</tbody>
</table>

Table 6: Feature fields for version DP-2.

An S-Pol case from 2006/05/09 was used to demonstrate the performance of the algorithm. Figure 57 to 70 illustrate this case.

The DP-2 version of the algorithm appears to work well in this case. However, further testing and tuning is required.

1.5 Conclusions

The CMD algorithm continues to be developed and results thus far show excellent performance for real time adaptive clutter filtering on the NEXRAD ORDA. Tests of CMD version 2 on a number of cases from the KFTG radar show that the algorithm is robust and performs well on cases on which it was not tuned.

CMD version 2, which uses data from only the current beam, should be easier to implement on the ORDA than version 1.

The latest dual-polarization version, DP-2, also continues to be developed and will likely perform better than the single polarization version of CMD. The dual polarization algorithm is designed such that the transition from the single to dual polarization algorithm should be straightforward.
Figure 57: S-Pol un-filtered reflectivity, 2006/05/09 2300 UTC.

Figure 58: Unfiltered velocity, DP-2 S-Pol case.
Figure 59: TDBZ, DP-2 S-Pol case.

Figure 60: SPIN, DP-2 S-Pol case.
Figure 61: CPA, DP-2 S-Pol case.

Figure 62: RATIO-NARROW, DP-2 S-Pol case.
Figure 63: $\sigma_{dr}$, DP-2 S-Pol case.

Figure 64: $\sigma_{\phi_p}$, DP-2 S-Pol case.
Figure 65: CMD combined interest field, DP-2 S-Pol case.

Figure 66: CMD decision flag field, DP-2 S-Pol case.
Figure 67: Unfiltered dBZ, DP-2 S-Pol case.

Figure 68: CMD directed cluter filtered dBZ
Figure 69: Unfiltered velocity, DP-2 S-Pol case.

Figure 70: Filtered velocity, DP-2 S-Pol case.
2 Dual-polarization Quantitative Precipitation Estimate

S. Ellis

A new NCAR task added to the fiscal year 2006 statement of work was an independent evaluation of the quantitative precipitation estimation (QPE) algorithm being proposed by NSSL for adoption on the WSR-88D radar network. Although the details of the NSSL algorithm have not been finalized, the validity of the proposed power-law rainrate conversion relationships and use of a synthetic combination of different estimators can be tested in geographic locations other than central Oklahoma – the region used for development. The NCAR S-band dual-polarimetric radar (S-Pol) has been deployed around the country on various field campaigns, making available ideal data sets for this analysis. The results reported here are from the Teflun-B (also known as PRECIP98) field program near Melbourne FL, in August and September of 1998. Two high-density, research-quality rain gauge networks were available for radar-gauge rainfall comparisons similar to those reported by Ryzhkov et al. (2003, RGS03 hereafter) and Ryzhkov et al. (2005, RGS05 hereafter).

2.1 Experiment Design

The rain gauge network was implemented, calibrated and quality controlled by NASA (Brandes et al., 2002) as part of the Teflun-B program. Figure 71 shows the locations of the gauges used in this report relative to the S-Pol radar. There were 14 gauges (two were collocated) over a roughly 5 by 10 km area located 35 to 40 km from S-Pol. The S-Pol radar typically scanned small sectors over the gauge network at an elevation angle of 0.5 degrees. This gave a very high time resolution of radar observations to compare with the gauge measurements. Because these observations were close to ground level and free of contamination by ground clutter, bright-band, and the effects of long range observations, they provide ideal data to test the validity of the rainfall relationships proposed by NSSL. The errors in radar estimated rainfall caused by using radar data at various heights (e.g. construction of HSR due to beam blockage), long ranges etc. can thus be investigated separately and isolated from errors resulting from the rain rate relationships, which depend on DSD and thus rainfall type and geographic location. Without isolating and characterizing these separate sources of error it is impossible to fully understand or optimize the performance of the algorithm.

Analysis tools for the comparison of different rain rate estimators and the radar-gauge comparisons first had to be developed and verified. The code was verified by comparing the results to those found by Brandes et al. (2002) using TEFLUN-B data. Rain rate estimates were computed from 19 different estimators found in the literature and included the NEXRAD Z-R, 6 KDP, 6 Z-ZDR, 4 KDP-ZDR and the 2 synthetic combinations described by RGS03 and RGS05. The 16 dual-polarimetric rainrate estimators are summarized in Fig. 72 and are explained in detail in RGS05. Next, the event-total accumulations were computed for both gauge and radar estimates and the radar range bin at 0.5 deg. elevation angle directly over each gauge was used in the comparison. The height of the radar beam at the location of the rain gauge network was approximately 350 m.
Figure 71: Plot of rain gauge network (blue plus symbols) relative to S-Pol location (red circle) during PRECIP98.

\[
R(K_{DP}) = a |K_{DP}|^b \text{sign}(K_{DP})
\]

<table>
<thead>
<tr>
<th></th>
<th>a</th>
<th>b</th>
<th>Assumptions</th>
<th>Source</th>
</tr>
</thead>
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<tr>
<td>1</td>
<td>50.7</td>
<td>0.85</td>
<td>Simulated DSD, equilibrium shape</td>
<td>BCD01</td>
</tr>
<tr>
<td>2</td>
<td>54.3</td>
<td>0.806</td>
<td>Measured DSD (FL), Brander's shape</td>
<td>BZV02</td>
</tr>
<tr>
<td>3</td>
<td>51.6</td>
<td>0.71</td>
<td>Simulated DSD, Godard's shape</td>
<td>BZV02</td>
</tr>
<tr>
<td>4</td>
<td>44.0</td>
<td>0.622</td>
<td>Measured DSD (OK), equilibrium shape</td>
<td>NSSL</td>
</tr>
<tr>
<td>5</td>
<td>50.3</td>
<td>0.812</td>
<td>Measured DSD (OK), Bringi's shape</td>
<td>NSSL</td>
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<tr>
<td>6</td>
<td>47.3</td>
<td>0.791</td>
<td>Measured DSD (OK), Brander's shape</td>
<td>NSSL</td>
</tr>
</tbody>
</table>

\[
R(Z, Z_{DR}) = a Z_{DR}^b
\]

<table>
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<th>b</th>
<th>Assumptions</th>
<th>Source</th>
</tr>
</thead>
<tbody>
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<td>7</td>
<td>6.70 \times 10^{-3}</td>
<td>0.927</td>
<td>Simulated DSD, equilibrium shape</td>
<td>BCD01</td>
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<tr>
<td>8</td>
<td>7.46 \times 10^{-3}</td>
<td>0.945</td>
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<td>BZV02</td>
</tr>
<tr>
<td>9</td>
<td>7.11 \times 10^{-3}</td>
<td>1.0</td>
<td>Simulated DSD, Godard's shape</td>
<td>BZV02</td>
</tr>
<tr>
<td>10</td>
<td>1.42 \times 10^{-2}</td>
<td>0.770</td>
<td>Measured DSD (OK), equilibrium shape</td>
<td>NSSL</td>
</tr>
<tr>
<td>11</td>
<td>1.59 \times 10^{-2}</td>
<td>0.737</td>
<td>Measured DSD (OK), Bringi's shape</td>
<td>NSSL</td>
</tr>
<tr>
<td>12</td>
<td>1.84 \times 10^{-2}</td>
<td>0.761</td>
<td>Measured DSD (OK), Brander's shape</td>
<td>NSSL</td>
</tr>
</tbody>
</table>

\[
R(K_{DP}, Z_{DR}) = a |K_{DP}|^b Z_{DR}^c \text{sign}(K_{DP})
\]

<table>
<thead>
<tr>
<th></th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>Assumptions</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>13</td>
<td>90.8</td>
<td>0.93</td>
<td>-1.69</td>
<td>Simulated DSD, equilibrium shape</td>
<td>BCD01</td>
</tr>
<tr>
<td>14</td>
<td>136</td>
<td>0.968</td>
<td>-2.86</td>
<td>Measured DSD (FL), Brander's shape</td>
<td>BZV02</td>
</tr>
<tr>
<td>15</td>
<td>52.9</td>
<td>0.852</td>
<td>-0.53</td>
<td>Measured DSD (OK), equilibrium shape</td>
<td>NSSL</td>
</tr>
<tr>
<td>16</td>
<td>63.6</td>
<td>0.851</td>
<td>-0.72</td>
<td>Measured DSD (OK), Bringi's shape</td>
<td>NSSL</td>
</tr>
</tbody>
</table>

* Here, \( c = -8.14 + 1.385 Z_{DP} - 0.1039 Z_{DR} \).

Figure 72: Table of 16 dual-polarimetric rain rate relationships computed (Table 1 from Ryzhkov et al. 2005).
The synthetic algorithm of RGS05 combines three different rainrate estimators depending on the rain rate. This is done to maximize the strengths of each estimator. The proposed combination is given by,

\[ R = \frac{\overline{R(Z)}}{f_1Z_{DR}}, \quad \overline{R(Z)} < 6\text{mm/hr} \]  \tag{2}

\[ R = \frac{\overline{R(KDP)}}{f_2(Z_{DR})}, \quad 6 < \overline{R(Z)} < 50\text{mm/hr} \]  \tag{3}

\[ R = \overline{R(KDP)}, \quad \overline{R(Z)} > 50\text{mm/hr} \]  \tag{4}

where the over-bar indicates a spatial mean, and \( f_1 \) and \( f_2 \) are corrections derived from data in Oklahoma (RGS05). For comparison to the results obtained by RGS05, similar radar/gauge statistical parameters were computed, i.e., fractional bias (FB) and fractional root mean square difference (FRMSD) as,

\[ FB = \frac{TR - TG}{TG}, \]  \tag{5}

\[ FRMSD = \left[ \frac{(TR - TG)^2}{TG} \right]^{0.5}. \]  \tag{6}

where TR and TG are rainfall totals for the radar and gauges respectively and the over-bar indicates mean values computed over all gates.

### 2.2 Results

Two case studies from the Teflun-B data sets are presented, including 17 and 22 September 1998. The fractional bias (percent) calculations for the rainfall event on 17 September are summarized in Fig. 73 by the blue + symbols. For reference the summary results of the Oklahoma data set from RGS05 are also plotted as the red + symbols. The plot is arranged so that each number along the x-axis represents a different radar rainfall estimator and the y-axis represents the computed FB values. The NEXRAD Z-R relationship is plotted at x = 0 and RGS03 RGS05 are plotted at x = 17 and x = 18 respectively, and x = 1 - 16 correspond to the relationships labeled 1 - 16 in Fig. 72. It can be seen in Fig. 73 that the FB values for the RGS05 algorithm are, not surprisingly, slightly worse in Florida than the reported Oklahoma results. This is most likely caused by differences in the prevailing DSD values between the two geographic locations. Differences in radar and gauge calibration may also contribute to differences, however both data sets are of research quality, thus these differences are expected to be minimal. The FB values of the RGS03 and RGS05 algorithms (numbers 17 and 18) are close to the minimum FB of the estimators. The fractional root mean square difference (FRMSD) values (percent) are plotted in Fig. 74. The RGS03 and RGS05 FRMSD values are lower than the other rainfall estimators. Further illustration is provided in Fig. 75, which shows a scatter plots of gauge versus radar
rainfall totals for several of the estimators on the 17 September case. Overall the RGS03 and RGS05 rainfall estimates are the closest to the gauge totals (i.e. near the one to one line).

The next example is from 22 September 1998. The fractional biases for this case are shown in Fig. 76, which is arranged similarly to Fig. 73 with the addition of the results from a modified version of the RGS05 algorithm plotted at $x = 19$. The modifications are discussed below. Again we see that the RGS03 and RGS05 synthetic rain rate estimators yield biases under 5 percent. Only estimate number 6, which is a R-KDP estimate, is significantly lower. However estimate number 6 did significantly worse on the 17 September data set. The inconsistent performance of this KDP rainfall estimator is not too surprising considering that KDP at S-band is only sensitive to heavier rainfall rates. The plot summarizing the FRMSD values for 22 September is shown in Fig. 77. Again the FRMSD values of RGS03 and RGS05 are comparable and slightly lower than most of the other estimators. The Z-ZDR estimators numbers 7, 8 and 9 had lower FRMSD values, but also had significantly higher FB values.

Next we examine the time history of the radar rain rate estimates compared to one gauge for 22 September. Figure. 78 shows rainrate (mm/hr) versus time (UTC) for the gage (red line), Z-R (black dashed line) and the RGS05 (black solid line). The red horizontal lines indicate the Z-R rain rate limits of the estimators used in the RGS05 synthetic computation (Equations 2, 3 and 4). It can be seen that at the beginning of the convective event (near 19.8 UTC) both the RGS05 and Z-R rain rates are significantly overestimated compared to the gage, in fact by more than a factor of 2. This is likely due to the presence of sparse, large drops commonly observed
Figure 74: Plots of fractional root mean square difference of radar rainfall versus gauge for 17 September using S-Pol near Melbourne FL (blue +) and from Ryzhkov et al. (2005) using KOUN near Norman OK using different rainfall relationships.

Figure 75: Scatter plots of rainfall totals from the gauges versus several radar estimates for the 17 September case.
Figure 76: Plots of fractional bias of radar rainfall versus gauge for 22 September using S-Pol near Melbourne FL (blue +).

Figure 77: Plots of fractional root mean square difference of radar rainfall versus gauge for 22 September using S-Pol near Melbourne FL (blue +).
at the edge of convective cells in Florida summer convection (sometimes referred to as a ZDR column). The RGS05 synthetic algorithm used a KDP relationship to estimate rain rates because the Z-R rain rate is greater than 50 mm/hour, even though the gage rain rate indicates using the KDP/ZDR relationship based on the RGS05 synthetic algorithm. Unfortunately the KDP rain estimate will also overestimate rain rate within ZDR columns, as is seen in Figure 78 (solid black line). Conversely, near 20:00 UTC both the RGS05 and Z-R rain rates significantly underestimate the gage measured rain rate. This may be due to differences in DSD’s in Florida as compared to Oklahoma, where the RGS05 relationships were developed.

Coincidentally the RGS05 overestimate at the beginning of the storm and underestimate in the middle of the storm offset, resulting in storm totals that agree well with the gage. However since this will not always be the case, two adjustments were made to RGS05 to improve the performance in this Florida data. First, the criteria for determining the rainfall relationship to be used (Equations 2, 3 or 4) was changed from Z-R to a Z/ZDR rain rate. Second the KDP relationship used was changed to reflect DSD values found in Florida (Brandes et al., 2002). The first change is to ensure the most appropriate rain rate relationship is used, even in the case of ZDR columns and the second change is to ensure the usage of DSD assumptions appropriate for the geographic region. Figure 79 is similar to Fig. 78 except it shows the modified RGS05 (blue line), gage (red line) and the original RGS05 (black line) rain rates. Both RGS05 and the modified RGS05 rainfall totals are similar, however, Figure 79 clearly shows the modified RGS05 rain rate estimates more closely follow the gage measured values. Improvement is realized both in the ZDR column at the beginning of the storm where RGS05 overestimated the rain rate and within the center of the storm where RGS05 underestimated the rain rate. The improvement of the RGS05 performance with these Florida data by implementing the changes described above can also be seen in the storm total fractional bias of 22 September, illustrated in Fig. 76 (estimate number 19 along the x-axis). The modifications of the RGS05 algorithm improve the FB from about -5 percent to about 3.5 percent. Further, it can be seen in Fig. 77 that the fractional rms difference is improved from around 32 percent to less than 28 percent. This indicates it is important to use geographically appropriate DSD assumptions as well as a more accurate method of determining which estimator to use in the synthetic algorithm.
Figure 78: Time history plot of rain rate comparisons for a single gage. Shown are the gage (red line), Z-R (black dashed line) and the RGS05 (black solid line) rain rates. The horizontal red lines indicate the Z-R rain rate limits of the RGS05 synthetic algorithm.

Figure 79: Time history plot of rain rate comparisons for a single gage. Shown are the gage (red line), Z-R (black line) and the modified RGS05 (blue line) rain rates.
3 The Radar Echo Classifier

3.1 REC Improvements: Precipitation Detection Algorithm

S. Ellis

The results of the Radar Echo Classifier (REC) upgraded to include the Precipitation Detection Algorithm (PDA) output within the rainfall accumulation calculation of EPRE were presented at the AMS annual meeting and to later in the spring to the TAC. The TAC approved of the science, but needed to see stronger evidence of improvements realized by adding the PDA and evidence that the PDA did not adversely impact weather echoes. Therefore, longer periods of rainfall accumulation were attempted, but with limited success. The CODE version was updated from version 7 to 8 in the spring of 2007. Unfortunately the NCAR/EOL installation of version 8 never produced rainfall estimates, despite a large, multi-agency debugging effort. The NCAR/RAL, installation of version 8 never produced rainfall either, however they were not interested in rainfall estimates so they were unaffected. To add to the difficulties, the NCAR/EOL version 7 was lost to a disk failure, leaving no options to obtain the required rainfall estimates. Several four hour accumulations were obtained with version 7 before the upgrade and disk failure episodes. These were presented to the TAC at the fall meeting and judged to be insufficient. Recently EOL has received an advance copy of version 9 and used it to successfully make rainfall estimates. Although the code is fairly unstable, probably due to the early release status, it is in principle possible to compute the desired longer accumulation cases before the next TAC meeting. This section will summarize the results obtained with version 7 prior to the software/hardware problems that prohibited any further progress as well as one 8 hour accumulation obtained with version 9. It should be noted that the version 9 results had not been verified against version 7 at the time of these computations. One coding error was discovered in version 9 and will be described. The PDA and APDA and their usage within EPRE are similar as described in the 2005 (Hubbert et al. 2005) annual report, which not be repeated here.

3.1.1 Version 7 results

The first example is from Boston (KBOX) and was sent to EOL by the ROC as a problematic case typical of the complaints about REC performance from the forecast offices. Figure 80 shows reflectivity and radial velocity data for a widespread AP clutter case with stratiform weather in the southern part of the domain on 14 July 2003. It can be seen that much of the Doppler data are obscured by overlaid echoes and some regions have near zero radial velocity making this a challenging case for the REC. In Fig. 81 we see that the REC APDA and PDA algorithms as implemented at EOL do well in separating precipitation from ground clutter echoes. Two Hybrid Scan Reflectivity (HSR) plots using only the APDA as a threshold to remove clutter contamination are shown in Fig. 82, the first provided by the ROC in the left panel and the second using the results from Fig. 81 in the right panel. Although the color scales are different, it is easy to see that the EOL version of APDA removes considerably more ground clutter contamination than the ROC version. This is not surprising given the coding and implementation errors that occurred in the operational version of the APDA. Figure 83 shows that adding a threshold with the PDA (left
Figure 80: PPI plots of reflectivity and radial velocity from Boston for a wide spread AP clutter case with stratiform precipitation to the south of the radar.

Panel) to EPRE results in a further improvement in the removal of ground clutter contamination in the HSR compared to using the APDA by itself (right panel). This is confirmed by the one hour accumulation data in the clutter contaminated region shown in Fig. 84. The left panel shows accumulation with both APDA and PDA thresholds and the right panel shows accumulation with just the APDA. The spurious accumulation when only using the APDA threshold is over 1 inch, while when both PDA and APDA are used it is less than 0.3 inch. Further the spatial extent of the spurious rain accumulation is much greater when only the APDA threshold is used. Importantly the accumulation values in the actual rain echoes are preserved as shown in Fig. 85.

The next example is squall line with clutter mixed with clear air echo from Chicago IL (KLOT), 19 October 1995. Figure 86 shows the reflectivity and radial velocity at an example time. The ground clutter contamination mixed with clear air echoes can be seen near the radar extending to a range of 10 to 20 km. A large squall line with trailing stratiform rain can be seen approaching the radar from the west. It can be seen that a lot of the Doppler velocity has been censored due to overlaid echoes. The radial velocity in the clutter contamination is not necessarily 0 m/s due to the mixture with non-zero velocity of the clear air echoes. This is a situation in which the APDA will not identify the clutter-weather mixture due to the non-zero radial velocity values. The PDA should, however, not identify these echoes as precipitation either. Plots of the HSR’s near the radar using only APDA and both APDA and PDA are shown in Fig. 87. Clearly using only the APDA threshold within EPRE results in considerable clutter contamination in the HSR in this clutter/clear mixture (Fig. 87 left panel). However, adding the PDA threshold (Fig. 87 right panel) removes the majority of the contamination. Most of the contamination that remains is weak clear air return that would ordinarily be removed by the EPRE rain threshold of about 18 dBZ. In these studies the rainfall threshold was removed in order to assess the full performance of
Figure 81: PPI plots of REC APDA and PDA results for the data shown in Figure 80.

Figure 82: PPI plots of the HSR results using APDA only. The left panel shows the results provided by the ROC and right panel shows the results obtained with EOL’s version. Note the different color scales.
Figure 83: PPI plots of the HSR results using APDA only (right panel) and both APDA and PDA (left panel) for the data shown in Figure 80.

Figure 84: Plots of one hour accumulation using APDA only (left panel) and both PDA and APDA (right panel) thresholds within the clutter contamination for the KBOX case.
Figure 85: Plots of one hour accumulation using APDA only (left panel) and both PDA and APDA (right panel) thresholds within the precipitation region for the KBOX case. The color scale is the same as in Fig. 84.

The resulting 4 hour accumulations are shown in Fig. 88. Using both PDA and APDA thresholds (Fig. 88 left panel) results in only traces of spurious accumulation after four hours. Using only the APDA (Fig. 88 right panel) results in much more wide spread spurious accumulation with a maximum that exceeds 2.5 inches. In fact the spurious accumulation is high enough to force the CODE View Graphics (CVG) to automatically rescale the plot resulting in different color scales for the left and right panels of Fig. 88. This results in colors plotted in the left panel of Fig. 88 representing twice the rainfall as the same colors in the right panel of Fig. 88. It is not possible to manually control the color scales of CVG and it took considerable effort to force CVG to plot the proper scale on the color bar to indicate the correct values of the plot. Figure 89 shows a wider view of the 4 hour accumulation. Although comparison is difficult with different color scales, careful examination shows that the rainfall accumulation due to the squall line is preserved using the PDA. A quantitative analysis was attempted, however the instructions (from the ROC) for retrieving the data values using CODE were followed but did not work properly, resulting only in 0’s for all values.

The next example is from Sterling VA (KLWX). Figure 90 shows four hour accumulations using both PDA and APDA (left panel) thresholds, and only the APDA (right panel) threshold. Fortunately the color scales are the same in this case making interpretation easier. It can clearly be seen that the spurious rainfall accumulations near the radar are reduced to trace amounts by using the PDA in addition to the APDA threshold. The maximum spurious rainfall accumulation with only APDA exceeds two inches. The rainfall totals from the real precipitation to the northwest of the radar are preserved when using the PDA.

3.1.2 Version 9 results

The version 9 case was provided by the ROC and contains widespread AP clutter and AP clutter mixed with weather from Houston (KHGX). In this case a squall line passed from northwest to southeast and ground clutter contamination appeared in after the passage. Figure 91 shows reflectivity (left panel) and radial velocity (right panel). The squall line is visible to the far southeast of the radar and AP ground clutter can be seen to the northeast and southwest. Figure
Figure 86: PPI plots of reflectivity and radial velocity from Chicago for a clutter mixed with clear air return case with a squall line to the west of the radar.

Figure 87: PPI plots of the HSR results using APDA only (left panel) and both APDA and PDA (right panel) for the data shown in Figure 86.
Figure 88: Plots near the radar of four hour accumulation using APDA only (left panel) and both PDA and APDA (right panel) thresholds within the precipitation region for the KLOT case.

Figure 89: Plots of four hour accumulation using APDA only (left panel) and both PDA and APDA (right panel) thresholds within the precipitation region for the KLOT case.
Figure 90: Plots of four hour accumulation using APDA only (left panel) and both PDA and APDA (right panel) thresholds within the precipitation region for the KLWX case.

92 shows 8 hour rainfall accumulation results obtained using version 9. Again the spurious rainfall using only the APDA threshold (left panel) exceeds the limit that forces CVG to rescale the plot, therefore similar colors in the left panel represent a factor of 2 more rain than in the right. The contamination by clutter is clearly reduced using the PDA, in addition to the APDA, threshold (left panel). The maximum spurious rainfall using only the APDA threshold exceeds 3.5 inches.

3.1.3 Version 9 code error

An error in the version 9 CODE implementation of the REC was discovered. This error impacts the computation of spatial variance variables such as reflectivity spin and texture. The problem stemmed from the fact that there are several different flags that indicate bad or missing data and the algorithm did not recognize all of them. Thus, in some locations the spin or texture calculations would actually use the bad data values in locations where the computation kernel overlapped the unaccounted for flag at and near the edge of the data. This resulted in erroneously large values of spin and texture at the edges of precipitation echoes. Therefore there were false clutter identifications at the edges and in small isolated precipitation. The results are illustrated in Fig. 93, which shows an example of reflectivity (left panel), the fixed version 9 (middle panel) and the original version 9 (right panel) reflectivity texture. The fixed texture has lower values near the edge of reflectivity data (for example as shown in the white ovals) and in the small echoes to the northwest of the radar.
Figure 91: PPI plots of reflectivity (left panel) and radial velocity (right panel) from KHGX.

Figure 92: Plots of eight hour accumulation using APDA only (left panel) and both PDA and APDA (right panel) thresholds within the precipitation region for the KHGX case.
Figure 93: Plots reflectivity (left panel), corrected texture (middle panel) and original CODE version 9 texture (right panel).
3.2 Spot Blanking and REC-APDA Performance

C. Kessinger

To protect a sensitive asset, the NEXRADs have the ability to turn off the signal transmitter for a few beams while passing over this asset, creating a “spot-blanked” region of beams that are filled with missing data flags. Several radars that use spot-blanking include Kauai, Hawaii (PHKM), Honolulu, Hawaii (PHMO), and Korea.

To test the REC-APDA performance when spot-blanking is being used, Archive-2 data from several cases from the PHKM and PHMO sites were selected and downloaded from the National Climatic Data Center (NCDC) and run through the ORPG CODE available at NCAR. Results from the Radar Echo Classifier-AP Detection Algorithm (REC-APDA) and the Radar Echo Classifier-Precipitation Detection Algorithm (REC-PDA) were examined for artifacts caused by the spot-blanked beams.

The first case is from PHKM on 23 July 1998 at 0804 UTC (Fig. 94). The red arrows in Figure 94 indicate areas where beams have been spot-blanked. This case is a non-precipitation case with low reflectivity values confined to within 10 km range from the radar and with radial velocity values out to 30 km.

After the REC-APDA is computed with the ORPG CODE software, results are shown for this case in Figure 95. Examination of the REC-APDA outputs shows no artifacts appear across the spot-blanking regions.

Figure 94: Plot shows a) reflectivity (dBZ) and b) radial velocity (m/s) from the Kauai (PHKM) NEXRAD on 23 July 1998 at 0804 UTC. Spot-blanked beams are indicated by the red arrows.
Figure 95: REC-APDA, the Clutter Likelihood Reflectivity (%), for the case shown in Figure 94.
Results for the Hybrid Scan Reflectivity (HSR) and the Storm Total Accumulation for this case are shown in Figure 96. No artifacts are apparent.

Using data from the Honolulu (PHMO) NEXRAD containing two areas of spot-blanking, a second case is examined on 14 February 2003 at 1955 UTC. Figure 97 shows that this case has both stratiform and convective precipitation echoes that are widespread within the radar scan and that straddle the two regions of spot-blanking.

Results from the REC-APDA and the REC-PDA (Figure 98) both show that no artifact exists across the regions of spot-blanking.

Results from the Hybrid Scan Reflectivity and the Storm Total Accumulation are shown in Figure 6. No artifacts can be seen across the two regions of spot-blanking.

These two cases show that the performance of the REC-APDA and the REC-PDA are not adversely affected by the use of spot-blanking. The REC-APDA and the REC-PDA both correctly handle missing beams and do not introduce artifacts. The Hybrid Scan Reflectivity and the Storm Total Accumulation fields also show no sign of artifacts after the REC-APDA is used to remove ground clutter contamination.
Figure 97: a) reflectivity (dBZ) and b) radial velocity (m/s) from the Honolulu (PHMO) NEXRAD on 14 February 2003 at 1955 UTC. Spot-blanked beams are indicated by the red and blue arrows.

Figure 98: The a) REC-APDA, the Clutter Likelihood Reflectivity (%), and the b) REC-PDA, Precipitation Likelihood Reflectivity (%), for the case shown in Figure 97.
Figure 99: The a) Hybrid Scan Reflectivity (HSR; dBZ) and the Storm Total Accumulation (inches) for the case shown in Figure 97.
3.3 Sea Clutter Detection Algorithm with Dual-Polarization Variables

C. Kessinger

Discrimination of sea clutter return from precipitation and ground return is a more difficult problem than discriminating ground return from precipitation because of the characteristics of sea clutter return. Its occurrence is dependent upon the sea state which, in turn, is dependent upon wind speed and direction, among other factors. Unlike ground return, sea clutter return is generally moving rather than stationary.

While inland NEXRADs do not suffer from sea clutter return, it can be a significant problem for coastal NEXRADs of the continental US as well as island NEXRADs located in Hawaii, Puerto Rico and Guam. To mitigate this data quality problem, a sea clutter detection algorithm (SCDA) was initially devised using an outside (i.e., non-Radar Operations Center) funding source. Since then, the SCDA has been tested with NEXRAD data and results shown in previous Annual Reports. With the upcoming addition of dual-polarization capability to the NEXRAD systems, the SCDA has been tested with and without dual-polarization variables to ascertain their usefulness in discriminating precipitation return from sea clutter return. Results are presented here.

Ryzhkov et al. (2002) used NCAR SPol dual polarization data from the 2001 IMPROVE-1 field campaign to discern which dual polarization variables were good discriminators of sea clutter return. The radar was located at the Pacific coast in Washington State and was very close to the water’s edge. Results from their investigation are shown in Figure 100. Good discriminators were found to be $\rho_{hv}$, the linear depolarization ratio (LDR) and the standard deviation of signal power (dB). The differential reflectivity ($Z_{dr}$) is not a good discriminator; however, additional investigation showed that the standard deviation of the $Z_{dr}$ field is a good discriminator and it is used within the SCDA.

Using these results, a sea clutter detection algorithm was devised that utilized either single-polarization or dual-polarization variables to ascertain the added value of the dual-polarization variables. Single polarization feature fields that were determined to be useful included: the texture of the reflectivity field (TDBZ; similar to the standard deviation of the signal power field used by Ryzhkov et al. (2002)), the SPIN field, the vertical gate-to-gate difference of the reflectivity field (GDZ; calculated by subtracting the reflectivity value of the higher elevation gate from the corresponding reflectivity of the lower elevation gate), and the vertical derivative of reflectivity ($RSIZ$; calculated as GDZ$/\text{range}\times\sin\{\text{elevation}_{(k)}-\text{elevation}_{(k-1)}\}$). The dual-polarization fields that were used include $\rho_{hv}$ and the standard deviation of $Z_{dr}$. The LDR field was not utilized here because the dual-polarization NEXRAD system will not have this field.

Appropriate membership functions were devised for each feature field, and are shown in Figure 101. After the membership functions are applied to each feature field, the resultant interest fields are used to compute a weighted mean, where each input is given a weight of unity. A threshold of 0.5 is applied such that all values greater than or equal to 0.5 define the location of sea clutter return.

The SCDA has not been implemented within the ORPG CODE at NCAR. For that reason, the version of the REC within the IMAT environment was used to test the SCDA with and without
Figure 100: Scattergrams of $\rho_{hv}$, LDR, ZDR, and SD(P) versus SNR for (a) sea echoes (black dots) and (b) weather echoes (grey dots). The data are taken at the elevation angle of 0.0° on 2 February 2001 from the NCAR S-Pol radar during the IMPROVE-1 field campaign at the coast of Washington state. (Ryzhkov et al., 2002).
Figure 101: Membership functions for each feature field used in the single polarization and the dual-polarization sea clutter detection algorithm.
dual-polarization variables. For the November 2006 Technical Interchange Meeting, results from the SCDA were shown for three cases from the IMPROVE-1 field campaign. Because results were generally similar amongst the three cases, only the 2 February 2001 case is discussed here.

The reflectivity and radial velocity moment data from SPol are shown in Figure 102. The reflectivity data are shown at a) high and at c) low magnification to show the details of the sea clutter return and to show the precipitation return at farther ranges. The radar was positioned along the coast and near a bay. The ground return shows very strong reflectivity (red colors) and outlines these coastal and bay features in Figure 102a. The sea return is a “fan-shaped” echo that extends into the ocean to the west of the radar location and decreases in intensity as range from the radar increases. Note the areas of precipitation return enclosed in the red polygons in Figure 102c.

Thresholded results from the single-polarization and dual-polarization versions of the SCDA are shown in Figure 103 at high magnification (left columns) and at low magnification (right columns). A threshold of 0.5 is applied. Currently, when the SCDA is deployed for operational use, a land-sea mask is applied such that the algorithm is only applied to regions that are over water. This is because, with single-polarization moment data, discrimination between sea clutter and precipitation is more difficult than discriminating between ground return and precipitation. The land-sea mask acts to minimize the amount of precipitation return that might be removed in error due to application of the SCDA. Within the IMAT version of the REC, no land-sea mask is available; therefore, the SCDA was computed at all range gates.

Results from the SCDA show that the fan-shaped echo to the west of the radar location are detected well using both single-polarization and dual-polarization input variables. Both versions also detect the ground return from the coastal areas. At the longer ranges, where precipitation return is present, the value of the dual-polarization data can be realized within the SCDA performance. Within the red polygons, the single-polarization version of the SCDA clearly performs more poorly than the dual-polarization version at discriminating the presence of precipitation return. The dual-polarization SCDA makes many fewer mistakes and has much improved performance.
Figure 102: Plot shows data collected by the NCAR S-Pol radar on 2 February 2001 at 1611 UTC during the IMPROVE-1 field campaign at the coast of Washington state. Fields shown in clue the a) reflectivity (dBZ) shown at high magnification, b) the radial velocity field (m/s) shown at high magnification and c) the reflectivity field (dBZ) shown at low magnification. Regions encircled with red polygons contain precipitation return.
Figure 103: Using the case from Figure 102, SCDA results are shown with single-polarization data (top row) and with dual-polarization data (bottom row) at high magnification (left column) and low magnification (right column). Regions of precipitation return, also indicated in Figure 102, are encircled with red polygons.
3.4 Super-Resolution Data and REC-APDA performance

C. Kessinger

The performance of the ORPG REC-APDA was examined to see what effects, if any, will occur when moment data are available at super-resolution (meaning 0.5 deg azimuth spacing and 250 m range bins for both reflectivity and velocity data).

Using Archive 1 time series data from the National Severe Storms Laboratory KOUN radar (provided by Sebastian Torres) from 8 October 2002 at 1511 UTC, the moment data were processed within the IMAT using 64 samples in each beam with 32 overlapping samples. A Hamming window was utilized. This KOUN case is a mixture of precipitation return and ground clutter return near the radar (Figure 104). No anomalous-propagation ground clutter is present.

After the moment data were created, the IMAT version of the REC-APDA was run using the Build 9 specifications for the membership functions (denoted “legacy” in the following discussions), local area size and reflectivity thresholds. REC-APDA performance was examined to see what differences, if any, were realized and to see what modifications may be required to maintain a high level of performance.

Figure 104 shows the super-resolution moment data (top row) and the various feature fields computed within the REC-APDA (second and third rows). The signal-to-noise ratio field is shown (bottom column, far right) only as a space-filler. Figure 105 shows the interest output fields for each feature field after the legacy, Build 9 version of the membership function was applied, as well as the final output of the REC-APDA as calculated as a weighted mean of all interest fields. The SIGN variable was not used.

Because super-resolution moment data can be expected to contain more variation (i.e., noisier) than normal resolution moment data, it is expected that spatial variations will be larger. Therefore, feature fields that use spatial variations (such as the texture of the reflectivity, the SPIN, and any standard deviation) may differ from the same feature fields computed with “standard” resolution data (meaning 1 degree azimuth spacing, 1.0 km reflectivity range bin spacing, and 0.25 km velocity range bin spacing). If there are large differences, the membership functions devised for the REC-APDA may not be appropriate to discriminate between precipitation and ground clutter. Tuning of the membership functions may be required for super-resolution data.

To accomplish this comparison, the distribution of selected feature field values computed with the super-resolution data are examined and compared to the legacy membership function to see if any adjustment is needed. Also, the feature field and the interest field for each are shown to illustrate the interest field performance. Only those feature fields that compute a spatial variation are examined and include the texture of the reflectivity field, the reflectivity SPIN field and the standard deviation of the radial velocity field. These comparisons are shown in the following figures.

The first feature field to consider is the reflectivity texture. A histogram is shown (Figure 106 of the distribution of texture values within the KOUN super-resolution data. The legacy membership function (indicated by the red line) is over-plotted onto the histogram to show how the data will be scaled to the resultant interest field. The vertical, dashed red line indicates the
Figure 104: Moment data and REC-APDA feature fields are shown from the Norman KOUN radar on 8 October 2002 at 1511 UTC. Moment fields shown include: a) reflectivity (dBZ), b) radial velocity (m/s) and c) spectrum width (m/s). The REC-APDA feature fields shown include: d) reflectivity texture, e) reflectivity SPIN field, f) median-filtered radial velocity (m/s), g) standard deviation of the radial velocity (m/s), h) median-filtered spectrum width (m/s), and i) signal to noise ratio. The cyan oval in a) indicates the location of ground return echo; all return outside of the oval is precipitation.
Figure 105: Using the feature fields shown in Figure 104, the REC-APDA interest output fields are calculated and shown above. Fields shown include the a) interest field for the texture of the reflectivity, b) the interest field for the reflectivity SPIN variable, c) the interest field for the median-filtered radial velocity field, d) the interest field for the standard deviation of the radial velocity field, e) the interest field for the median-filtered spectrum width field, and f) the final, unthresholded interest output of the REC-APDA is computed as a weighted mean of all interest fields.
Figure 106: Histogram plot showing the distribution of reflectivity texture values within the KOUN case shown in Figure 104. Regions of texture values assumed to be precipitation are indicated as are regions assumed to be ground clutter. The legacy membership function is indicated by the red line and is “to scale” with the reflectivity texture values. The vertical dashed line locates the 0.5 interest threshold. The KOUN reflectivity texture feature is shown at the top right while the interest field (derived after application of the legacy membership function) is shown at the bottom right.

The location of the 0.5 interest threshold, which ideally should be the dividing line for discriminating between clutter and precipitation. Some overlap between the two echo types is expected. The reflectivity texture feature field is shown with the resultant interest field to facilitate the performance comparison. For this super-resolution case, the legacy membership function maintains good performance at discriminating between precipitation and clutter. No change in the reflectivity texture membership function is required for super-resolution data.

The next feature field to consider is the standard deviation of the radial velocity field. Again, a histogram is shown (Figure 107) of the distribution of values with an over-plot of the legacy membership function, along with the feature field and the interest output. For this super-resolution case, the legacy membership function maintains good performance at discriminating between precipitation and clutter. No change in the standard deviation of radial velocity membership function is required for super-resolution data.
Figure 107: Same as Figure 106 for the distribution of the standard deviation of the radial velocity values within the KOUN case shown in Figure 104. For this super-resolution case, the legacy membership function maintains good performance at discriminating between precipitation and clutter.
Figure 108: Same as Figure 106 for the distribution of the reflectivity SPIN values within the KOUN case shown in Figure 104. A reflectivity threshold of 3 dBZ is used. For this super-resolution case, the legacy membership function has poor performance at discriminating precipitation from clutter.

Finally, the last feature field to consider is the reflectivity SPIN field. Again, a histogram is shown (Figure 108) of the distribution of values with an over-plot of the legacy membership function, along with the feature field and the interest output. A reflectivity threshold, above which the gate-to-gate difference must exceed, is applied before the SPIN is calculated. As Figure 108 shows, the SPIN feature field does not discriminate between precipitation and clutter return and suggests that a modification is needed. The feature field shows little difference in values between the precipitation and clutter regions; therefore, tweaking the membership function will have little or no effect. Because the super-resolution data are expected to be noisier than standard resolution data, an increase in the reflectivity threshold from 3 dBZ to 6 dBZ is done first.

Results from increasing the reflectivity threshold to 6 dBZ for the SPIN field are shown in Figure 109. Better discrimination is achieved between the precipitation and clutter regions; however, further improvement seems possible.

Next, the reflectivity threshold is increased to 7 dBZ, with results shown in Figure 110. Discrimination achieved with a threshold of 7 dBZ shows the best performance of the three attempts. Notice that no change in the membership function was required, only an increase in the reflectivity threshold.
Figure 109: Same as Figure 106 for the distribution of the reflectivity SPIN values within the KOUN case shown in Figure 104. A reflectivity threshold of 6 dBZ is used. Compared to results shown in Figure 108, the legacy membership function has improved performance at discriminating precipitation from clutter, but more tuning is needed.
Figure 110: Same as Figure 106 for the distribution of the reflectivity SPIN values within the KOUN case as shown in Figure 104. A reflectivity threshold of 7 dBZ is used. Compared to results shown in Figures 108 and 109, the increase in the reflectivity threshold leads to further performance improvements for the legacy membership function.
To conclude, the ORPG REC-APDA should perform well with super-resolution data if the SPIN reflectivity threshold is increased to at least 7 dBZ. Additional testing is needed to complete this investigation. It may be that increasing the threshold to 8, 9 or 10 dBZ produces even better performance, but those tests were not completed at this writing. Additional case studies would increase confidence in these results.
3.5 Dual Polarization Variables in the Radar Echo Classifier

C. Kessinger

As was discussed in last year’s Annual Report, the addition of polarimetric variables to the REC-APDA improves its performance at discriminating ground clutter from precipitation. When the capability for polarimetric data collection is added to the WSR-88D, polarimetric variables can easily be added to all REC algorithms and will improve performance.

The two polarimetric variables that were added to the REC-APDA were the standard deviation of the differential reflectivity field (Zdr) and the standard deviation of the differential phase ($\phi_{dp}$). Two cases from last year’s Annual Report are shown in Figures 111 and 112 and were taken from the IMPROVE-1 and IHOP_2002 field campaigns, respectively. As these two cases show, the addition of polarimetric variables into the REC-APDA leads to improved ground clutter detection, improved discrimination between precipitation and ground clutter especially in mixed conditions, and reduced false alarms (i.e., where precipitation return is incorrectly classified as clutter).

The next step in investigating the utility of polarimetric variables is to input them as feature fields into the REC-Precipitation Detection Algorithm (REC-PDA) and assess their influence on algorithm performance. This is done through the use of the output from the polarimetric Particle Identification algorithm (PID; Vivekanandan et al. 1999). The PID is the forerunner to the Hydrometeor Classification Algorithm (HCA) developed jointly by NCAR and NSSL. This algorithm uses polarimetric variables to determine the type of hydrometeor that is present within the radar illumination volume.

A case study from the winter IMPROVE-1 field campaign in Washington State (Figure 113) is used to test the use of polarimetric variables within the REC-PDA. This case is characterized as having mixed precipitation and ground clutter return, a difficult discrimination situation for the REC-PDA when only single polarization data are used. As shown in Figure 113, this winter case has mainly stratiform precipitation return with maximum reflectivity near 40 dBZ.

The PID algorithm was run on this case and results are shown in Figure 114. Each category of hydrometeor is indicated as a different color. The categories of hydrometeors are numbered from 1 to 16 where each number is assigned a different hydrometeor type. Increasing from values of 1 through 16, the categories are: cloud, drizzle, light rain, moderate rain, heavy rain, hail, rain/hail mixture, graupel/small hail mixture, graupel/rain mixture, dry snow, wet snow, ice crystals, irregular ice crystals, super-cooled liquid drops, insects, second trip and ground clutter, respectively. The PID does not operate where the reflectivity is below 5 dBZ. To input the PID output as a feature field into the REC-PDA, each category is assigned an interest value using the membership function shown in Figure 115. Cloud return is assigned an interest value of 0.5; drizzle is assigned an interest value of 0.75 and all precipitation categories from light rain to super-cooled liquid drops are assigned a value of unity. Non-weather returns are assigned an interest value of zero. After application of the membership function, the output PID interest field is shown in Figure 116.
Figure 111: A comparison of the REC-APDA performance is shown both without and with polarimetric variables. Data are used from the NCAR SPol radar during the IMPROVE-1 field campaign as collected on 8 February 2001 at 1609 UTC. Fields shown include a) and d) the original, unthresholded reflectivity (dBZ), b) the reflectivity (dBZ) with a 0.5 threshold applied from the non-polarimetric REC-APDA, c) the non-polarimetric REC-APDA output thresholded at 0.5, e) the reflectivity (dBZ) with a 0.5 threshold applied from the polarimetric REC-APDA and f) the polarimetric REC-APDA output thresholded at 0.5.
Figure 112: Same as Figure 111 except that the S-Pol data were collected during the IHOP 2002 field campaign on 27 May 2002 at 2203 UTC.
Figure 113: Moment data, from the NCAR SPol radar collected during the IMPROVE-1 field campaign along the coast of Washington State, is shown at two magnifications. Fields shown include a) and c) reflectivity (dBZ) and b) and d) radial velocity (m/s), at high and low magnification, respectively.
Figure 114: Output from the Particle Identification (PID) algorithm, used as a feature field input into the REC-PDA, is shown at a) high and b) low magnification.

Figure 115: Membership function structure is shown as it was applied to each category of the PID algorithm.
To examine the effectiveness of using polarimetric data, the REC-PDA was run both without (i.e., called here the “legacy” ORPG version, meaning that only single polarization moment data are used as input) and with polarimetric data. REC-PDA results from the IMPROVE-1 case are shown in Figure 117. A 0.5 threshold is applied to the interest output, such that all remaining regions are characterized as precipitation. Within the ground clutter that is near the radar (and seen best at high magnification), both versions of the REC-PDA discriminate between precipitation and clutter; however the dual polarimetric version does seem to delete more clutter and to do a slightly better job than the non-polarimetric version near the radar.

Within the precipitation return, the polarimetric version does better than the non-polarimetric version of the REC-PDA in several regions that are encircled with polygons in Figure 117. Within the precipitation return enclosed by the blue polygon, the polarimetric version has higher interest values than the non-polarimetric version of the REC-PDA, leading to a better determination of echo type. The region of mixed clutter (from the Olympia Mountains) and precipitation return is enclosed with the green polygon. Here, the non-polarimetric version incorrectly determines that this region is generally precipitation while the polarimetric version correctly determines that clutter is present within the precipitation return. In short, the addition of polarimetric variables into the REC-PDA leads to better discrimination between precipitation and non-precipitation return.

In summary, the addition of polarimetric variables into the REC-APDA and the REC-PDA has a positive impact on algorithm performance. Adding polarimetric variables is easily accomplished within the REC. After the WSR-88D system is modified to include dual polarization capabilities, the addition of polarimetric variables within all REC algorithms can be easily accomplished.
Figure 117: Thresholded output from the REC-PDA is shown a) and b) without polarimetric feature field from the PID used as input and c) and d) with polarimetric feature field from the PID used as input. Fields are shown at high and low magnification, respectively. A threshold of 0.5 is used.
4 Spectral Processing: Improvements to NSPA

G. Meymaris

4.1 Introduction

The data quality of the spectral (Doppler) moments (power, radial velocity and spectrum width) continues to be an on-going problem for the NEXRAD radar products. Data contaminants that are significant include so-called hard targets like ground clutter (both normal and anomalous propagation), birds, and airplanes. Even with clutter filtering, whether the legacy clutter filters or Gaussian Model Adaptive Parameter (GMAP), Sigmet’s spectral based clutter filter, clutter residue can still bias all moments. However, the new Open RDA system to be deployed on the WSR-88D fleet will allow much more flexibility for processing the so-called level 1, I&Q data. In particular, spectral-domain processing will become a viable method for calculating the moments, thus opening the door to advanced techniques, such as the NEXRAD Spectral Processing Algorithm (NSPA), described in this paper, that can improve moment estimates by isolating weather signals from contaminants, like clutter residue, airplanes, and isolated birds. Improvements to power and velocity estimates would be realized when, for example, weather and strong ground clutter echoes compete. Spectrum width estimates would be improved almost universally by using spectral processing rather than the current pulse pair estimator.

NSPA, like its predecessors NCAR Improved Moment Algorithm (NIMA) (Morse et al. 1995) and NCAR Enhanced Spectra Processing Algorithm (NESPA)(Cornman et al. 1995), use spectral information along a radial, to determine which spectral features are weather rather than contaminants. When contaminants are identified, the algorithm attempts to calculate the spectral moments of only the weather, excluding the contaminants.

Power ($P$), mean radial velocity ($V$), and spectrum width ($W$) can be computed in either the time domain or the spectral domain (Doviak and Zrnić 1993, Cornman et al. 1995, Morse et al. 2002). In the legacy system, there was no choice but to use time-domain processing (pulse-pair) because of limited computational capabilities of hardware at that time. In the new ORDA, SZ-2 will make use of spectral processing but currently the time-domain estimators are to be used.

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 signal-to-noise-ratios (SNR) are larger than 2 or 3 dB. The $W$ estimator is good as long as the signal is approximately Gaussian and SNR’s are larger than 5 dB.
- 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 and in the case of the $R0/R1$ estimator, the value of the noise power is imprecisely known.

Spectral-domain estimators’ advantages:

• 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 can perform at least as well time-domain estimators, and perform better at lower SNR’s and in the presence of contaminants.

• Spectrum width estimators, in particular, perform better.

Spectral-domain estimators’ disadvantages:

• More computationally intensive, although there would be minimal additional overhead if already using SZ.

• Algorithms can be more complex.

• It seems to be necessary to use spectral information from adjacent gates to achieve better results than time-domain methods in many cases

Figure 118 shows a spectrum (simulated) that contains both weather and clutter. The spectra after clutter filtering using the legacy clutter filter, and using the GMAP clutter filter is also shown. The first point is that both clutter filters leave some residual power near 0 m/sec that is comparable to the weather signal near 15 m/sec. The pulse-pair velocity estimator would be biased towards 0 m/sec. But if a spectral processing algorithm only uses the spectral bins from about 5 m/sec to about 25 m/sec, then the velocity estimate would be unbiased. This is one of the two core ideas that make spectral estimators appealing.

The second core idea is illustrated in Figure 119 which shows an example waterfall plot. This type of plot shows all the spectra for a single beam. The $x$-axis is velocity, the $y$-axis is range from the radar, and the color axis shows the range-corrected power of the spectra. The key idea is that in the spectrum domain, algorithms can be written to do feature detection; by looking down the radial, different features can be put in context.

In this report, a spectral-domain moment algorithm that will be referred to as the NEXRAD Spectral Processing Algorithm (NSPA), was developed using ideas from NIMA and NESPA as starting points. NSPA shares much in common with NESPA in particular, since NESPA was developed for forward scanning on-board aircraft weather radar, although the differences in the platform necessitate a different algorithm.

4.2 Algorithm

For the initial implementation of NSPA, the general paradigm is to calculate the spectral moments using a quick and easy spectral estimator (phase 1). Discontinuities are detected, and then repaired using continuity as guidance (phase 2).
Figure 118: Simulated spectrum of a 20 dB signal to noise ratio weather spectrum centered at 15 m/sec with a 60 dB clutter to noise ratio clutter spectrum centered at 0 m/sec. The original spectrum is shown in blue, the spectrum after the high suppression legacy clutter filter is shown in red, and the spectrum after a high suppression GMAP filter is shown in black. The green oval marks the interpolated line across the base of the clutter spike.

Figure 119: Example of a spectral waterfall plot. The x-axis is velocity, the y-axis is range from the radar, and the color scale is spectral power in dB. This example includes both clutter (near 0 m/sec and ranges less than 40 km) and weather that varies in velocity but is generally near −10 m/sec.
NSPA pass 1 To calculate the radial velocity and spectrum width, NSPA simply performs the following calculations:

\[ v = \frac{\sum_{i \in I} (f_i \odot f_c) (S_i - N)}{\sum_{i \in I} (S_i - N)} \oplus f_c \]

\[ w = \frac{\sum_{i \in I} (f_i \odot v)^2 (S_i - N)}{\sum_{i \in I} (S_i - N)} \]

where \( I \) is the range of indices in the spectral domain that the ‘integral’ (sum) is to take place over (in Doviak and Zrnić 1993 and Sirmans and Bumgarner 1975, \( I \) would be taken as the entire spectrum), \( f_i \) is the velocity corresponding to the \( i^{th} \) spectral bin, \( f_c \) is the velocity of the desired ‘center’ of integration (e.g. the peak value of the power spectrum), \( S_i \) is the value of the \( i^{th} \) element in the power spectrum array, and \( N \) is the power of the noise. Note that \( \odot \) is addition using a special modular arithmetic, \( a \odot b \equiv \text{mod} \ (a + b + v_a, 2v_a) - v_a \), which is like modulo arithmetic except that values are forced between \(-v_a\) and \(v_a\), where \( v_a \) is the Nyquist velocity. The symbol \( \ominus \) is defined by \( a \ominus b = a \oplus (-b) \).

Equation 7 is as defined in Doviak and Zrnić. The affect of re-centering (i.e. picking \( f_c \neq 0 \)) is that velocity aliasing of the spectrum is mostly mitigated, depending on the choice of \( f_c \) in relation to the weather spectrum and depending on the spectrum width. Sirmans and Bumgarner (1975) also defines the spectral computation of mean radial velocity this way except without the re-centering, which explains why they found severe biases when the mean velocities approached the Nyquist velocity.

The main problem of NSPA, then, is to decide what values \( f_c \) (for pass 1, \( f_c \) is taken as the velocity of the peak power in the power spectrum), and \( N \) to use, and, most importantly, what indices make up \( I \), the region of integration. Ideally, \( I \) should be the indices where the weather spectrum has power above the noise. For example, in Figure 119 at 60 km, a reasonable range might be the indices that span \(-30 \text{ m/sec}\) to \(-20 \text{ m/sec}\).

Determining the noise powers Two different noise powers are ultimately used by the NSPA to calculate the Doppler moments: a noise level, which we will call the spectral noise floor, \( \hat{P}_{NF} \) is required in order to determine the spectral indices \( I \) over which to integrate, and the spectral noise power, \( \hat{P}_{NP} \), used in equations 7 and 8.

When determining the spectral indices, the spectral noise floor is used to find when the signal reaches the noise and thus the end of the region of integration. Thus it is preferable for the value used be the near the upper bound (but not necessarily at the upper bound) of the noise signal. In Figure 118, a value about -45 dB would be appropriate. Essentially, when the main signal falls below this value, integration would stop. If we required the signal to descend below the average system calibration noise power, \( P_N \), then the integration regions tend to be too wide thus contaminating the estimates.

We assume here that the number of points in the spectrum is divisible by 8. However, if this is not the case other methods could easily be derived. To find the spectral noise floor, break the
power spectrum, denoted $S_k$ for $k = 0, \ldots, n - 1$ ($n$ is the number of points in the spectrum), 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 $L_n = \text{mod} (L_0 + mn/8, n)$ for $m = 1, \ldots, 7$.

For each segment find the maximum value of $S$: The $m^{th}$ segment consists of indices $L_m$ to $L_{m+1} - 1$. Thus

$$M_m = \max_{k=L_m,\ldots,L_{m+1}-1} S_k$$

(9)

Let $\hat{M}_m$ be the sorted list of $M_m$ where $\hat{M}_0$ is the smallest value and $\hat{M}_7$ the largest. Define the spectral noise floor as

$$\hat{P}_{PN} = \frac{1}{N_N} \sum_{m=0}^{N_N-1} \hat{M}_m$$

(10)

where $N_N$ is a constant, currently defined as 2.

One might be tempted to use $\hat{P}_{PN}$ for the spectral noise floor. This is certainly appropriate for narrower spectrum widths, but it is not appropriate for wide spectrum widths. In this case, because there is no good way of estimating the noise in the spectral domain, it is better to use the system calibration noise power. The problem is to determine whether the spectrum is noise or wide spectrum width weather, but unfortunately, a noise spectrum 'looks' much like a spectrum with a wide spectrum width. One fairly good method for determining whether the spectrum 'looks' like a noise spectrum is the spectral censoring metric, first used as a censoring fields of SZ-1, which is defined as

$$H = \frac{1}{N_S} \sum_{l=0}^{N_S-1} \frac{\hat{M}_l}{\hat{M}_7}$$

(11)

where $N_S = 3$. Note that this form is slightly different than what has been described in SZ-1 documentation. This metric compares the peak power to the average peak power over the smallest 3 regions, and thus only depends on the shape of the spectrum.

Looking at $\hat{P}_{PN}$ and $H$ gives us a good indication of what is going on. If $\hat{P}_{PN}$ is large compared to the system calibration noise then there are generally two different possibilities. First, the spectrum could be very strong, like clutter, and so phase errors and/or window effects cause the apparent spectral noise floor to be elevated. In this case, the $\hat{P}_{PN}$ is a good choice for a spectral noise floor. Second, the spectrum width could be very wide compared to the Nyquist velocity and so the values of $\hat{M}_m$ for $m = 0, \ldots, N_N - 1$ are actually part of the weather spectrum. In this case, the system calibration noise is a better choice. In the first case, $H$ will be large, and in the second $H$ will be small (close to 0). If, however, $\hat{P}_{PN}$ is near the system calibration noise power, then it is probably the best choice.
To make the algorithm stable we do not use a hard threshold, but rather transition smoothly between the two modes. Define the spectral noise floor

\[ \hat{P}_{NF} = (1 - \alpha) \hat{P}_{PN} + \alpha P_N \]  

(12)

where \( \alpha \) is a value ranging from 0 to 1 which represents the likelihood that the spectrum is wide (small \( H \)) and strong (large \( \hat{P}_{PN} \)).

The other noise value that is needed for the actual integration is the **spectral noise power**, \( \hat{P}_{NP} \). This is calculated by computing \( \hat{P}_{MN} \) by

\[ M'_m = \frac{1}{L_{m+1} - L_m} \sum_{k=L_m}^{L_m+1} S(k) \]  

(13)

and then sorting these, and denoting the result \( \hat{M}'_m \). Then

\[ \hat{P}_{MN} = \frac{1}{N_N} \sum_{m=0}^{N_N-1} \hat{M}'_m \]  

(14)

and finally

\[ \hat{P}_{NP} = (1 - \alpha) \hat{P}_{MN} + \alpha P_N \]  

(15)

where \( \alpha \) is the identical value as was computed for \( \hat{P}_{NF} \).

**Determining the spectral indices**  
Because the spectra are fairly noisy, it is necessary to first average the spectrum in range to smooth out the spectral features. Referring again to Figure 119, the spectra are averaged in the \( y \)-axis dimension with a Gaussian kernel of length 7. If \( G_i \) for \( i = -3, \ldots, 3 \) is a Gaussian kernel, and \( S(r, v) \) is the power spectrum value at range index \( r \) and velocity index \( v \), then the smoothed spectra is computed as \( \tilde{S}(r, v) = \sum_{i=-3}^{i=3} G_i S(r + i, v) / \sum_{i=-3}^{i=3} G_i \). Other choices of kernel are certainly possible, including using non-linear operations like median filtering. The reasoning behind the choice of kernel was that is is desirable to average “some but not too much”, and that ranges further away from the gate in question should be averaged with less weighting than one that is closer.

The algorithm then starts at \( f_c \), which we have chosen to be the velocity of the maximum value of the non-smoothed power spectrum, and moves to the left, wrapping around the Nyquist edge if necessary, until either a preset number of spectrum values either in a row (currently 3) or total (currently 5) fall below the noise level, or until the loop has iterated \( n/2 \) times. The points between the ‘left’ cutoff and the peak are added to \( I \). The same is now done on the right side. The mean radial velocity and spectrum width can now be calculated as in equations 7 and 8. Note that the \( S_i \) used in these equations are the un-averaged spectral values. For low SNR cases it my be desirable to use the smoothed spectral values, but this has not been studied.
NSPA Pass 2  In the second pass, as in NESPA, NSPA looks for discontinuities and attempts to ‘patch’ them by redefining $I$. The idea is that if the velocity is discontinuous from the surrounding gates then the first pass probably locked onto the wrong feature. By redefining $I$ based on the velocities of the neighboring gates, the velocity of the weather should be recovered.

The technique currently used is to smooth the velocity from pass 1, along each radial, using a wavelet de-noising filter (currently the Haar wavelet is used with a 3 level stationary wavelet transform). The smoothed value is compared to the raw first pass velocities. Outliers are identified by looking at the magnitude of the difference ($\nabla$). When the difference exceeds a threshold, the algorithm recomputes the spectral indices (region of integration), using the smoothed velocity as $f_c$. Then velocity and spectrum width are calculated using equations 7 and 8.

4.3 Results

We present the results from two cases. A clutter map has been determined using REC/CMD methodology, i.e. determine the clutter map by using the spectral moments before clutter filtering. Many of the PPI’s shown have been censored. The censoring is based only on SNR with a threshold of 1 dB. The SNR threshold is normally set higher (3 dB) but we show that by using NSPA we gain some ability to retrieve spectrum widths for smaller SNR’s then are possible with pulse-pair.

4.4 Case 1: 1999/05/03 KOUN

Figures 120-147 show the results from NSPA and pulse-pair. One can see the tornadic hook echo in the uncalibrated radar reflectivity PPI (Figure 120) near $-40$ km east and $-15$ km south. The velocity PPI’s for NSPA (Figure 121) and pulse-pair (Figure 122) are very similar. There are a few places where differences can be seen, especially near the tornado; the NSPA velocity appears to be cleaner than the pulse-pair velocity.

For this particular case, we will discuss some of the intermediate fields. The PPI of the ratio of the spectral noise power from NSPA to the system calibration noise (in dB) is shown in Figure 123. This field should be elevated in places with either strong SNR or wide spectrum width (or both). The spectral censoring field is shown in Figure 124. Small values indicated a noise-like or flat shaped spectrum, which should only occur with very wide spectrum widths, or low SNR. In Figure 125 the areas are shown where the spectrum exhibit ‘strong and wide’ features. In particular, the location of the tornado is prominently shown as well as some areas near the far end of the strong cell to the west-southwest. The value of the strong and wide confidence is the $\alpha$ used in equations 12 and 15. For the elevated values, the noise levels $\hat{P}_{NF}$ and $\hat{P}_{NP}$ preferentially use the system calibration noise.

The velocity PPI after the first pass of NSPA is shown in Figure 126 and its associated confidence in Figure 127. Note that the field has some suspicious velocities; there is one prominent one near the tornado. This shows that the 2nd pass of NSPA is needed, since, referring to Figure 121, the final velocity field does not contain these suspicious velocities.

The spectrum width PPI’s from NSPA and pulse-pair are shown in Figures 128 and 129. First note that pulse-pair returns very small numbers along the edge of censoring regions. This
is because pulse-pair has problems for low SNR’s. The spectrum widths in the NSPA field in the same areas are consistent with those further from the edge.

The waterfall plots for one example radial for NSPA and pulse-pair are shown in Figures 130 and 131, respectively. This radial is very close to the tornado; the strong shear being evident at about 42 km. We can see very good agreement, in general for the velocities from the two algorithms. The largest differences are in the spectrum width estimates; for the lower SNR’s, it is evident that pulse-pair estimators are noisy, and in general seem to underestimate the spectrum width. NSPA, however, at least seem to be consistent and less noisy. To actually verify whether they are ‘good’ fits, we need to look at the spectra and the corresponding fits (see below).

The results from another example radial are shown in Figures 132 and 133. This radial goes right through the rotation center, with the strong shear again very clearly visible at about 42 km. One very important point is that despite the fact that NSPA applies a smoothing filter along the radial for feature detection, NSPA is still able to capture very strong radial shears. A case such as this tests the limits of an algorithm that uses information along a radial.

But to really verify that the fits are ‘good’ as opposed to just being smoothed, it is necessary to look at individual spectra with their associated fits. These are shown in Figures 134-147. The NSPA fits are often very similar to the pulse-pair fits, but, such as in the case shown in Figures 140 and 141, or the case shown in Figures 142 and 143, when pulse-pair and NSPA disagree, the NSPA fit is superior. The case shown in Figures 144 and 145, and the case shown in Figures 146 and 147, both show examples where pulse-pair returns 0 m/sec spectrum widths (and thus there is no fit line), whereas the NSPA fit looks good.
Figure 121: May 3, 1999, KOUN (elevation 0.5°): PPI of mean radial velocity from NSPA pass 2 (final) in m/sec. N = 64, von Hann/Blackman windows for no clutter/clutter, respectively.

Figure 122: May 3, 1999, KOUN (elevation 0.5°): PPI of mean radial velocity from pulse-pair in m/sec. N = 64, von Hann/Blackman windows for no clutter/clutter, respectively.
Figure 123: May 3, 1999, KOUN (elevation 0.5°): PPI of the ratio of the spectral noise power from NSPA to the system calibration noise, in dB. $N = 64$, von Hann/Blackman windows for no clutter/clutter, respectively.

Figure 124: May 3, 1999, KOUN (elevation 0.5°): PPI of spectral censor ratio from NSPA. $N = 64$, von Hann/Blackman windows for no clutter/clutter, respectively.
Figure 125: May 3, 1999, KOUN (elevation 0.5°): PPI of ‘Strong and Wide’ confidence from NSPA. $N = 64$, von Hann/Blackman windows for no clutter/clutter, respectively.

Figure 126: May 3, 1999, KOUN (elevation 0.5°): PPI of mean radial velocity from NSPA pass 1 in m/sec. $N = 64$, von Hann/Blackman windows for no clutter/clutter, respectively.
Figure 127: May 3, 1999, KOUN (elevation 0.5°): PPI of mean radial velocity confidence from NSPA pass 1. N = 64, von Hann/Blackman windows for no clutter/clutter, respectively.
Figure 128: May 3, 1999, KOUN (elevation 0.5°): PPI of spectrum width from NSPA pass 2 (final) in m/sec. $N = 64$, von Hann/Blackman windows for no clutter/clutter, respectively.

Figure 129: May 3, 1999, KOUN (elevation 0.5°): PPI of spectrum width from pulse-pair in m/sec. $N = 64$, von Hann/Blackman windows for no clutter/clutter, respectively.
Figure 130: May 3, 1999, KOUN (elevation 0.5°): Waterfall plot showing $v$ and $w$ from NSPA pass 2 (final). $N = 64$, von Hann/Blackman windows for no clutter/clutter, respectively. The x-axis is radial velocity (m/sec), the y-axis is range from radar (km), and the color axis is range corrected uncalibrated spectral power. The black dots indicate the mean velocity, and the purple lines show $v \pm w$.

Figure 131: May 3, 1999, KOUN (elevation 0.5°): Waterfall plot showing $v$ and $w$ from pulse-pair. $N = 64$, von Hann/Blackman windows for no clutter/clutter, respectively. The x-axis is radial velocity (m/sec), the y-axis is range from radar (km), and the color axis is range corrected uncalibrated spectral power.
Figure 132: May 3, 1999, KOUN (elevation 0.5°): Waterfall plot showing $v$ and $w$ from NSPA pass 2 (final). $N = 64$, von Hann/Blackman windows for no clutter/clutter, respectively. The x-axis is radial velocity (m/sec), the y-axis is range from radar (km), and the color axis is range corrected uncalibrated spectral power. The black dots indicate the mean velocity, and the purple lines show $v \pm w$.

Figure 133: May 3, 1999, KOUN (elevation 0.5°): Waterfall plot showing $v$ and $w$ from pulse-pair. $N = 64$, von Hann/Blackman windows for no clutter/clutter, respectively. The x-axis is radial velocity (m/sec), the y-axis is range from radar (km), and the color axis is range corrected uncalibrated spectral power.
Figure 134: May 3, 1999, KOUN (elevation 0.5°): Spectrum plot showing $v$ and $w$ from NSPA pass 2 (final). $N = 64$, von Hann/Blackman windows for no clutter/clutter, respectively. The $x$-axis is radial velocity (m/sec) and the uncalibrated spectral power. The solid green line indicates the Gaussian fit using the NSPA estimated spectrum moments. The horizontal solid red line indicates the noise power used (from system calibration). The vertical dashed red line shows the location of the mean velocity. The horizontal dashed blue line shows $v \pm 2w$, and the dotted red line shows the spectral indices used in the integration.

Figure 135: May 3, 1999, KOUN (elevation 0.5°): Spectrum plot showing $v$ and $w$ from NSPA pass 2 (final). $N = 64$, von Hann/Blackman windows for no clutter/clutter, respectively. The $x$-axis is radial velocity (m/sec) and the uncalibrated spectral power. The green line indicates the Gaussian fit using the pulse-pair estimated spectrum moments. The horizontal solid red line indicates the noise power used (from system calibration). The vertical dashed red line shows the location of the mean velocity. The horizontal dashed blue line shows $v \pm 2w$. 
Figure 136: May 3, 1999, KOUN (elevation 0.5°): Spectrum plot showing \( v \) and \( w \) from NSPA pass 2 (final). \( N = 64 \), von Hann/Blackman windows for no clutter/clutter, respectively. The \( x \)-axis is radial velocity (m/sec) and the uncalibrated spectral power. The solid green line indicates the Gaussian fit using the NSPA estimated spectrum moments. The horizontal solid red line indicates the noise power used (from system calibration). The vertical dashed red line shows the location of the mean velocity. The horizontal dashed blue line shows \( v \pm 2w \), and the dotted red line shows the spectral indices used in the integration.

Figure 137: May 3, 1999, KOUN (elevation 0.5°): Spectrum plot showing \( v \) and \( w \) from NSPA pass 2 (final). \( N = 64 \), von Hann/Blackman windows for no clutter/clutter, respectively. The \( x \)-axis is radial velocity (m/sec) and the uncalibrated spectral power. The green line indicates the Gaussian fit using the pulse-pair estimated spectrum moments. The horizontal solid red line indicates the noise power used (from system calibration). The vertical dashed red line shows the location of the mean velocity. The horizontal dashed blue line shows \( v \pm 2w \).
Figure 138: May 3, 1999, KOUN (elevation 0.5°): Spectrum plot showing $v$ and $w$ from NSPA pass 2 (final). $N = 64$, von Hann/Blackman windows for no clutter/clutter, respectively. The x-axis is radial velocity (m/sec) and the uncalibrated spectral power. The solid green line indicates the Gaussian fit using the NSPA estimated spectrum moments. The horizontal solid red line indicates the noise power used (from system calibration). The vertical dashed red line shows the location of the mean velocity. The horizontal dashed blue line shows $v \pm 2w$, and the dotted red line shows the spectral indices used in the integration.

Figure 139: May 3, 1999, KOUN (elevation 0.5°): Spectrum plot showing $v$ and $w$ from NSPA pass 2 (final). $N = 64$, von Hann/Blackman windows for no clutter/clutter, respectively. The x-axis is radial velocity (m/sec) and the uncalibrated spectral power. The green line indicates the Gaussian fit using the pulse-pair estimated spectrum moments. The horizontal solid red line indicates the noise power used (from system calibration). The vertical dashed red line shows the location of the mean velocity. The horizontal dashed blue line shows $v \pm 2w$. 

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Figure 140: May 3, 1999, KOUN (elevation 0.5°): Spectrum plot showing $v$ and $w$ from NSPA pass 2 (final). $N = 64$, von Hann/Blackman windows for no clutter/clutter, respectively. The $x$-axis is radial velocity (m/sec) and the uncalibrated spectral power. The solid green line indicates the Gaussian fit using the NSPA estimated spectrum moments. The horizontal solid red line indicates the noise power used (from system calibration). The vertical dashed red line shows the location of the mean velocity. The horizontal dashed blue line shows $v \pm 2w$, and the dotted red line shows the spectral indices used in the integration.

Figure 141: May 3, 1999, KOUN (elevation 0.5°): Spectrum plot showing $v$ and $w$ from NSPA pass 2 (final). $N = 64$, von Hann/Blackman windows for no clutter/clutter, respectively. The $x$-axis is radial velocity (m/sec) and the uncalibrated spectral power. The green line indicates the Gaussian fit using the pulse-pair estimated spectrum moments. The horizontal solid red line indicates the noise power used (from system calibration). The vertical dashed red line shows the location of the mean velocity. The horizontal dashed blue line shows $v \pm 2w$. 

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Figure 142: May 3, 1999, KOUN (elevation 0.5°): Spectrum plot showing $v$ and $w$ from NSPA pass 2 (final). $N = 64$, von Hann/Blackman windows for no clutter/clutter, respectively. The $x$-axis is radial velocity (m/sec) and the uncalibrated spectral power. The solid green line indicates the Gaussian fit using the NSPA estimated spectrum moments. The horizontal solid red line indicates the noise power used (from system calibration). The vertical dashed red line shows the location of the mean velocity. The horizontal dashed blue line shows $v \pm 2w$, and the dotted red line shows the spectral indices used in the integration.

Figure 143: May 3, 1999, KOUN (elevation 0.5°): Spectrum plot showing $v$ and $w$ from NSPA pass 2 (final). $N = 64$, von Hann/Blackman windows for no clutter/clutter, respectively. The $x$-axis is radial velocity (m/sec) and the uncalibrated spectral power. The green line indicates the Gaussian fit using the pulse-pair estimated spectrum moments. The horizontal solid red line indicates the noise power used (from system calibration). The vertical dashed red line shows the location of the mean velocity. The horizontal dashed blue line shows $v \pm 2w$. 

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Figure 144: May 3, 1999, KOUN (elevation 0.5°): Spectrum plot showing $v$ and $w$ from NSPA pass 2 (final). $N = 64$, von Hann/Blackman windows for no clutter/clutter, respectively. The $x$-axis is radial velocity (m/sec) and the uncalibrated spectral power. The solid green line indicates the Gaussian fit using the NSPA estimated spectrum moments. The horizontal solid red line indicates the noise power used (from system calibration). The vertical dashed red line shows the location of the mean velocity. The horizontal dashed blue line shows $v \pm 2w$, and the dotted red line shows the spectral indices used in the integration.

Figure 145: May 3, 1999, KOUN (elevation 0.5°): Spectrum plot showing $v$ and $w$ from NSPA pass 2 (final). $N = 64$, von Hann/Blackman windows for no clutter/clutter, respectively. The $x$-axis is radial velocity (m/sec) and the uncalibrated spectral power. The green line indicates the Gaussian fit using the pulse-pair estimated spectrum moments. The horizontal solid red line indicates the noise power used (from system calibration). The vertical dashed red line shows the location of the mean velocity. The horizontal dashed blue line shows $v \pm 2w$. 
Figure 146: May 3, 1999, KOUN (elevation 0.5°): Spectrum plot showing v and w from NSPA pass 2 (final). N = 64, von Hann/Blackman windows for no clutter/clutter, respectively. The x-axis is radial velocity (m/sec) and the uncalibrated spectral power. The solid green line indicates the Gaussian fit using the NSPA estimated spectrum moments. The horizontal solid red line indicates the noise power used (from system calibration). The vertical dashed red line shows the location of the mean velocity. The horizontal dashed blue line shows v ± 2w, and the dotted red line shows the spectral indices used in the integration.

Figure 147: May 3, 1999, KOUN (elevation 0.5°): Spectrum plot showing v and w from NSPA pass 2 (final). N = 64, von Hann/Blackman windows for no clutter/clutter, respectively. The x-axis is radial velocity (m/sec) and the uncalibrated spectral power. The green line indicates the Gaussian fit using the pulse-pair estimated spectrum moments. The horizontal solid red line indicates the noise power used (from system calibration). The vertical dashed red line shows the location of the mean velocity. The horizontal dashed blue line shows v ± 2w.
4.5 Case 2: 2004/04/09 KJIM

The second case is a stratiform rain case with significant second trip echo. While much of the Doppler moments would be censored because of overlaid echoes, we present uncensored, non-trip-sorted data because, for the purposes of evaluation, we can take the second trip data as widespread contamination. The uncalibrated radar reflectivity PPI is shown in Figure 148. The velocity PPI’s for NSPA and pulse-pair, are shown in Figures 149 and 150, respectively and the spectrum width PPI’s in Figures 151 and 152.

The second trip contamination is evident throughout the north-northwest regions of both velocity PPI plots, but it is especially evident in the pulse-pair velocity field. The second trip is also apparent in the spectrum width plots, but again is more noticeable in the pulse-pair field.

NSPA is unable to completely remove second trip contaminations for a couple of reasons. In some cases there is enough strong second trip in adjacent gates down a radial that NSPA locks onto that signal. In other cases, the two signals can be overlapping somewhat in the frequency domain and so NSPA integrates over both signals. However, it should be noted that the pulse-pair estimators are unable to remove any contaminations other than clutter.
Figure 149: April 9, 2004, KJIM (elevation 0.5°): PPI of mean radial velocity from NSPA pass 2 (final) in m/sec. N = 64, von Hann/Blackman windows for no clutter/clutter, respectively.

Figure 150: April 9, 2004, KJIM (elevation 0.5°): PPI of mean radial velocity from pulse-pair in m/sec. N = 64, von Hann/Blackman windows for no clutter/clutter, respectively.
Figure 151: April 9, 2004, KJIM (elevation 0.5°): PPI of spectrum width from NSPA pass 2 (final) in m/sec. \( N = 64 \), von Hann/Blackman windows for no clutter/clutter, respectively.

Figure 152: April 9, 2004, KJIM (elevation 0.5°): PPI of spectrum width from pulse-pair in m/sec. \( N = 64 \), von Hann/Blackman windows for no clutter/clutter, respectively.
4.6 Conclusions

Advanced spectral-domain processing techniques, such as those employed by NSPA, allow better discrimination between contamination and weather echoes as well as better estimation of the meteorological spectral moments when contamination occurs. As an example, when weather is collocated with ground clutter, spectral-domain processing will result in better estimates of the meteorological spectral moments.

The NSPA spectrum width estimator seems to outperform the pulse-pair estimator \( \frac{R_0}{R_1} \), producing better fits in a variety of cases. In particular, NSPA seems to outperform pulse-pair for low SNR’s, extending the recovery area for this estimator. Simulations studies need to be performed to quantitatively study the performance of the NSPA spectral moments.

In the past, spectral-domain processing with the WSR-88D was not possible in the real-time environment because of limitations in the processing power of the RDA. With the deployment of the RVP8, the ability to perform spectral-domain processing, like NSPA, becomes practical and advantageous.

5 SZ-1 Phase Coding: 3 Trip Evaluation

G. Meymaris

5.1 Introduction

SZ-1 works well in the case of 2 trips. Taking into account beam bending and the curvature of the earth, for elevation angles of 2.4° or above, two unambiguous trips corresponds to a Nyquist velocity of at least 25 m/sec. For elevation angles below this, for which SZ-1 would be employed, either the Nyquist velocity for the Doppler moments would have to be allowed to be smaller than 25 m/sec or else SZ-1 would have to be able to deal with 3 trips. Since the former is not desirable, the feasibility of the latter is investigated.

Because SZ-2 obtains the radar reflectivity (and power) from a long PRT scan, SZ-2 has two advantages over SZ-1 that allows it to process multiple trips. The first advantage is that the long PRT radar reflectivity is not subject to range-folding. In SZ-1, overlaid echoes can in some cases contaminate estimates of power (and therefore reflectivity) as well as velocity and spectrum width. The second is that the the long PRT SZ-2 unambiguous power can be used to estimate clutter power and to trip sort the data. This is not the case for SZ-1 where trip sorting is based solely on \( R_1 \), the first lag of the autocorrelation function. Thus for SZ-1 when there are multiple-trip echoes, there is usually no way to accurately estimate the clutter power. For these cases, censoring the data is often necessary.

5.2 Algorithm changes

The 3 trip version of SZ-1 is the same as the standard SZ-1 algorithm with some additional processing at the end. Namely, after the strong and weak trip moments are recovered \( (P_1, V_1, \)
\(W_1, P_2, \text{ and } V_3\) the 3\(^{rd}\) trip power \((P_3)\) is calculated and \(P_2\) is adjusted since otherwise it would include the power from the 3\(^{rd}\) trip. The PNF notch width must also be changed from \(3/4\) to \(1/2\) because, for example, a 3\(^{rd}\) spatial\(^1\) trip echo will only manifest itself as 4 replicas in the 1\(^{st}\) trip (as opposed to 8). The 3 trip SZ-1 algorithm is as follows:

1. Perform standard SZ-1
2. Apply PNF notch (1/2 only) to the deconvolved weak trip (2\(^{nd}\)) spectrum.
3. Compute the 3\(^{rd}\) strongest trip power by calculating the remaining power (adjusting for the notch).
4. Subtract the 3\(^{rd}\) trip power from the weak (2\(^{nd}\)) trip power.

### 5.3 Case study using simulated data

To evaluate SZ-1 on 3 trips, 3 datasets, recorded at different times (trip 1 from KOUN on May 3, 1999 (Oklahoma City tornado), trip 2 from KNQA on July 8, 1997, and trip 3 from KNQA on June 29, 1997), were combined in 2 ways. The first method simply concatenates the datasets in range. This represents ‘truth’ since there is no overlaid echoes (other than what may have existed in one of the individual datasets). It is processed using standard pulse-pair techniques. The second method is to phase-code each trip, using SZ(8/64), so as to simulate overlaid echoes. This second case is processed using SZ-1. To evaluate SZ-1, the results from the second case (SZ-1 algorithm) are compared to that of the first ‘true’ case.

The results from the ‘truth’ dataset and from the SZ-1 dataset are shown in Figures 153-167. PPI’s of ‘true’ power are shown in Figures 153 and 154 (the latter is zoomed in to an area close to the radar). The SZ-1 recovered powers are shown in Figures 155 and 156. In general, the two results compare fairly well. However, near the radar where there is low SNR (signal-to-noise-ratio) there are phantom echoes in the SZ-1 recovered data. The trip order fields for the two cases are shown in Figures 157-160, where Figures 157 and 158 are from the ‘true’ power (first case) and Figures 159 and 160 are computed using \(R_1\). Blue indicates the location of the strongest trip, gray the 2\(^{nd}\) strongest, and red the 3\(^{rd}\). We can see from looking at Figures 156, 158, and 160 that the phantom echoes in the SZ-1 recovered power corresponds to the 3\(^{rd}\) strongest trip (i.e. the weakest), and thus we see that the cause of these spurious echoes is leakage from the stronger trips. The velocity PPI’s for the two cases are shown in Figures 161-164.

‘Scatter plots’ (2-D histograms) of the ‘true’ power versus the SZ-1 recovered power are shown in Figures 165-167, where the data is limited to the strong trip, the 2\(^{nd}\) strongest trip, and 3\(^{rd}\) strongest trip, respectively, with the trip ordering being determined from the SZ algorithm. The performance of the SZ-1 recovered power for the strong trip (Figure 165) is excellent. Likewise, the performance for the second strongest trip is also very good, although there are certainly more outliers and more spread than in the strong trip case. The performance for the 3\(^{rd}\) trip

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\(^1\)Trips numbers can refer to their spatial distribution (1\(^{st}\) spatial trip is the trip nearest the radar, and so on) or they can refer to their relative strengths (1\(^{st}\) strongest trip is the trip that has the greatest power). If not specified, we refer to the relative strengths as this is the more relevant ordering in SZ-1 processing.
recovered power (Figure 167) however is quite bad. When the true 3\textsuperscript{rd} trip power is larger than \(-30\) dB there is a fairly consistent \(-5\) dB bias. On the other hand, when the true 3\textsuperscript{rd} trip power drops below \(-40\) dB the recovered power is saturating at about \(-40\) dB. Note that the system calibration noise is at about \(-50\) dB. So we can see that the 3\textsuperscript{rd} trip recovered power is quite unreliable, not infrequently producing results that differ substantially from truth. On the one hand, it may be possible to censor the low SNR data where the recovered power is saturating by examining the standard deviation of the velocity around those gates because the recovered velocities are likely to be random. However, there are times that the recovered power is 5 to 10 dB off from truth. The standard deviations are large enough that all 3\textsuperscript{rd} trip power should probably be censored, but it seems be difficult to determine where there are actually echoes that should be censored purple as opposed to no echoes that should be colored black. So all of third trip may have to be censored using the same color, and thus the user would not be able to tell where there were echoes and where there was not.
Figure 153: PPI of uncalibrated power (dB) before overlay. $N = 64$, von Hann window. Data created from concatenation of 3 datasets recorded at different times: trip 1 from KOUN on May 3, 1999 (Oklahoma City tornado), trip 2 from KNQA on July 8, 1997, and trip 3 from KNQA on June 29, 1997.

Figure 154: PPI of uncalibrated power (dB) before overlay. $N = 64$, von Hann window. Data created from concatenation of 3 datasets recorded at different times: trip 1 from KOUN on May 3, 1999 (Oklahoma City tornado), trip 2 from KNQA on July 8, 1997, and trip 3 from KNQA on June 29, 1997.
Figure 155: PPI of uncalibrated power (dB) from SZ-1. $N = 64$, von Hann window. Range un-folded from the overlay of 3 datasets recorded at different times: trip 1 from KOUN on May 3, 1999 (Oklahoma City tornado), trip 2 from KNQA on July 8, 1997, and trip 3 from KNQA on June 29, 1997.

Figure 156: PPI of uncalibrated power (dB) from SZ-1. $N = 64$, von Hann window. Range un-folded from the overlay of 3 datasets recorded at different times: trip 1 from KOUN on May 3, 1999 (Oklahoma City tornado), trip 2 from KNQA on July 8, 1997, and trip 3 from KNQA on June 29, 1997.
Figure 157: PPI of the trip-order field based on the power determined from the data before overlay. Blue indicates the location of the strongest trip, gray the 2nd strongest, and red the 3rd. $N = 64$, von Hann window. Data created from concatenation of 3 datasets recorded at different times: trip 1 from KOUN on May 3, 1999 (Oklahoma City tornado), trip 2 from KNQA on July 8, 1997, and trip 3 from KNQA on June 29, 1997.

Figure 158: PPI of the trip-order field based on the power determined from the data before overlay. Blue indicates the location of the strongest trip, gray the 2nd strongest, and red the 3rd. $N = 64$, von Hann window. Data created from concatenation of 3 datasets recorded at different times: trip 1 from KOUN on May 3, 1999 (Oklahoma City tornado), trip 2 from KNQA on July 8, 1997, and trip 3 from KNQA on June 29, 1997.
Figure 159: PPI of the trip-order field based on the $R_1$ estimator. Blue indicates the location of the strongest trip, gray the 2nd strongest, and red the 3rd. $N = 64$, von Hann window. Range un-folded from the overlay of 3 datasets recorded at different times: trip 1 from KOUN on May 3, 1999 (Oklahoma City tornado), trip 2 from KNQA on July 8, 1997, and trip 3 from KNQA on June 29, 1997.

Figure 160: PPI of the trip-order field based on the $R_1$ estimator. Blue indicates the location of the strongest trip, gray the 2nd strongest, and red the 3rd. $N = 64$, von Hann window. Range un-folded from the overlay of 3 datasets recorded at different times: trip 1 from KOUN on May 3, 1999 (Oklahoma City tornado), trip 2 from KNQA on July 8, 1997, and trip 3 from KNQA on June 29, 1997.
Figure 161: PPI of mean radial velocity using pulse-pair, in m/sec, before overlay. $N = 64$, von Hann window. Data created from concatenation of 3 datasets recorded at different times: trip 1 from KOUN on May 3, 1999 (Oklahoma City tornado), trip 2 from KNQA on July 8, 1997, and trip 3 from KNQA on June 29, 1997.

Figure 162: PPI of mean radial velocity using pulse-pair, in m/sec, before overlay. $N = 64$, von Hann window. Data created from concatenation of 3 datasets recorded at different times: trip 1 from KOUN on May 3, 1999 (Oklahoma City tornado), trip 2 from KNQA on July 8, 1997, and trip 3 from KNQA on June 29, 1997.
Figure 163: PPI of mean radial velocity from SZ-1 in m/sec. N = 64, von Hann window. Range un-folded from the overlay of 3 datasets recorded at different times: trip 1 from KOUN on May 3, 1999 (Oklahoma City tornado), trip 2 from KNQA on July 8, 1997, and trip 3 from KNQA on June 29, 1997.

Figure 164: PPI of mean radial velocity from SZ-1 in m/sec. N = 64, von Hann window. Range un-folded from the overlay of 3 datasets recorded at different times: trip 1 from KOUN on May 3, 1999 (Oklahoma City tornado), trip 2 from KNQA on July 8, 1997, and trip 3 from KNQA on June 29, 1997.
Figure 165: ‘Scatter plot’ (2-D histogram) of uncalibrated power (dB) before overlay (‘truth’) versus uncalibrated power (dB) from SZ-1. The data shown is the strong trip as determined by SZ-1 using $R_1$. The solid white line is the $y = x$ line. The solid black line indicates the mean value for each ‘column’, and the dashed white lines indicate the mean ± one standard deviation (for that column). $N = 64$, von Hann window. Data consisting of 3 datasets recorded at different times: trip 1 from KOUN on May 3, 1999 (Oklahoma City tornado), trip 2 from KNQA on July 8, 1997, and trip 3 from KNQA on June 29, 1997.

Figure 166: ‘Scatter plot’ (2-D histogram) of uncalibrated power (dB) before overlay (‘truth’) versus uncalibrated power (dB) from SZ-1. The data shown is the 2nd (weak) trip as determined by SZ-1 using $R_1$. The solid white line is the $y = x$ line. The solid black line indicates the mean value for each ‘column’, and the dashed white lines indicate the mean ± one standard deviation (for that column). $N = 64$, von Hann window. Data consisting of 3 datasets recorded at different times: trip 1 from KOUN on May 3, 1999 (Oklahoma City tornado), trip 2 from KNQA on July 8, 1997, and trip 3 from KNQA on June 29, 1997.
Figure 167: ‘Scatter plot’ (2-D histogram) of uncalibrated power (dB) before overlay (‘truth’) versus uncalibrated power (dB) from SZ-1. The data shown is the 3rd (weakest) trip as determined by SZ-1 using $R_1$. The solid white line is the $y = x$ line. The solid black line indicates the mean value for each ‘column’, and the dashed white lines indicate the mean ± one standard deviation (for that column). $N = 64$, von Hann window. Data consisting of 3 datasets recorded at different times: trip 1 from KOUN on May 3, 1999 (Oklahoma City tornado), trip 2 from KNQA on July 8, 1997, and trip 3 from KNQA on June 29, 1997.
5.4 Simulation Studies

Simulations studies were performed to further evaluate the 3-trip SZ-1 algorithm. Each ‘sample’ consists of three simulated time-series generated to have specific average statistics. Each trip is phase-coded depending on what trip they are to be in, and then the 3 time-series are added together (i.e. overlaid). For this study, the 2\textsuperscript{nd} trip has an SNR of 40 dB.

Results from simulations studies of the 3-trip SZ-1 algorithm where the weak (2\textsuperscript{nd}) trip to 3\textsuperscript{rd} trip power ratio is 20 are shown in Figures 168-179. For each estimator, the standard deviation and mean bias are calculated. For the strong trip, the performance statistics for power (Figures 168 and 169), velocity (Figures 170 and 171) and spectrum width (Figures 172 and 173) do not show anything new over what has been seen in other SZ reports. The slight negative bias in the power (Figure 168) is due to the fact that we are averaging the power in dB.

For the weak trip, only the power (Figures 174 and 175) and velocity (Figures 176 and 177) are calculated. Note especially that the standard deviation of velocity performs slightly worse than we normally expect for wide strong trip spectrum widths and low strong-to-weak trip power ratios ($P_1/P_2$). This is apparently due to the fact that because there are 3 trips, only a 1/2 width PNF can be applied, and thus there is more leakage from wide spectrum widths in the strong trip. Also there is the additional noise introduced by the 3\textsuperscript{rd} trip.

Finally, for the 3\textsuperscript{rd} trip, only the power (Figures 178 and 179) is calculated. This estimator is severely biased for all but very narrow strong trip spectrum width with low $P_1/P_2$ power ratios. These statistics show that the 3\textsuperscript{rd} trip power is very difficult to estimate for this scenario. There are a couple of reasons for this. First, because the $P_2/P_3$ power ratio is 20 dB, the $P_1/P_3$ ratios are 20 dB more than what is indicated on the y-axis of the plots (so it ranges from 20 to 70 dB). Thus contamination from leakage from the strong trip becomes a large factor. Second, in order to estimate the 3\textsuperscript{rd} trip power, two signals have to be removed via a PNF notch and the weak trip spectrum has to be deconvolved.

We also include for reference the performance statistics plots (Figures 180-191) of the algorithm for the same scenarios just discussed except that the $P_2/P_3$ ratio is 0 dB. We will note only the significant differences with the 20 dB case.

The standard deviation of the weak trip power (Figure 186) is generally very large, probably owing in part to the poor estimates of the 3\textsuperscript{rd} trip power (Figure 190). Oddly enough, the 3\textsuperscript{rd} trip power is estimated better than the weak trip power. This may indicate a bug in the software or there may be something more subtle at work. Note also the general degradation in the recovery of the weak trip velocity (Figure 188). This is expected given the strength of the competing 3\textsuperscript{rd} trip echo.
Figure 168: Standard deviation of strong trip power (dB) from SZ-1. The 2\textsuperscript{nd} to 3\textsuperscript{rd} trip power ratio is 20 dB, the weak trip spectrum width is 2 m/sec, and the 3\textsuperscript{rd} trip spectrum width is 4 m/sec. \( N = 64 \), von Hann window. The data was created using an I&Q simulator. For each sample, 3 time-series were generated with the desired statistics. Each is then phase-coded, and then overlaid. For each pixel, there are 200 samples.

Figure 169: Bias of strong trip power (dB) from SZ-1. The 2\textsuperscript{nd} to 3\textsuperscript{rd} trip power ratio is 20 dB, the weak trip spectrum width is 2 m/sec, and the 3\textsuperscript{rd} trip spectrum width is 4 m/sec. \( N = 64 \), von Hann window. The data was created using an I&Q simulator. For each sample, 3 time-series were generated with the desired statistics. Each is then phase-coded, and then overlaid. For each pixel, there are 200 samples.
Figure 170: Standard deviation of strong trip velocity (m/sec) from SZ-1. The 2nd to 3rd trip power ratio is 20 dB, the weak trip spectrum width is 2 m/sec, and the 3rd trip spectrum width is 4 m/sec. $N = 64$, von Hann window. The data was created using an I&Q simulator. For each sample, 3 time-series were generated with the desired statistics. Each is then phase-coded, and then overlaid. For each pixel, there are 200 samples.

Figure 171: Bias of strong trip velocity (m/sec) from SZ-1. The 2nd to 3rd trip power ratio is 20 dB, the weak trip spectrum width is 2 m/sec, and the 3rd trip spectrum width is 4 m/sec. $N = 64$, von Hann window. The data was created using an I&Q simulator. For each sample, 3 time-series were generated with the desired statistics. Each is then phase-coded, and then overlaid. For each pixel, there are 200 samples.
Figure 172: Standard deviation of strong trip spectrum width (m/sec) from SZ-1. The 2nd to 3rd trip power ratio is 20 dB, the weak trip spectrum width is 2 m/sec, and the 3rd trip spectrum width is 4 m/sec. N = 64, von Hann window. The data was created using and I&Q simulator. For each sample, 3 time-series were generated with the desired statistics. Each is then phase-coded, and then overlaid. For each pixel, there are 200 samples.

Figure 173: Bias of strong trip spectrum width (m/sec) from SZ-1. The 2nd to 3rd trip power ratio is 20 dB, the weak trip spectrum width is 2 m/sec, and the 3rd trip spectrum width is 4 m/sec. N = 64, von Hann window. The data was created using and I&Q simulator. For each sample, 3 time-series were generated with the desired statistics. Each is then phase-coded, and then overlaid. For each pixel, there are 200 samples.
Figure 174: Standard deviation of weak trip power (dB) from SZ-1. The 2\textsuperscript{nd} to 3\textsuperscript{rd} trip power ratio is 20 dB, the weak trip spectrum width is 2 m/sec, and the 3\textsuperscript{rd} trip spectrum width is 4 m/sec. \(N = 64\), von Hann window. The data was created using and I&Q simulator. For each sample, 3 time-series were generated with the desired statistics. Each is then phase-coded, and then overlaid. For each pixel, there are 200 samples.

Figure 175: Bias of weak trip power (dB) from SZ-1. The 2\textsuperscript{nd} to 3\textsuperscript{rd} trip power ratio is 20 dB, the weak trip spectrum width is 2 m/sec, and the 3\textsuperscript{rd} trip spectrum width is 4 m/sec. \(N = 64\), von Hann window. The data was created using and I&Q simulator. For each sample, 3 time-series were generated with the desired statistics. Each is then phase-coded, and then overlaid. For each pixel, there are 200 samples.
Figure 176: Standard deviation of weak trip velocity (m/sec) from SZ-1. The 2nd to 3rd trip power ratio is 20 dB, the weak trip spectrum width is 2 m/sec, and the 3rd trip spectrum width is 4 m/sec. N = 64, von Hann window. The data was created using and I&Q simulator. For each sample, 3 time-series were generated with the desired statistics. Each is then phase-coded, and then overlaid. For each pixel, there are 200 samples.

Figure 177: Bias of weak trip velocity (m/sec) from SZ-1. The 2nd to 3rd trip power ratio is 20 dB, the weak trip spectrum width is 2 m/sec, and the 3rd trip spectrum width is 4 m/sec. N = 64, von Hann window. The data was created using and I&Q simulator. For each sample, 3 time-series were generated with the desired statistics. Each is then phase-coded, and then overlaid. For each pixel, there are 200 samples.
Figure 178: Standard deviation of 3\textsuperscript{rd} weakest trip power (dB) from SZ-1. The 2\textsuperscript{nd} to 3\textsuperscript{rd} trip power ratio is 20 dB, the weak trip spectrum width is 2 m/sec, and the 3\textsuperscript{rd} trip spectrum width is 4 m/sec. \(N = 64\), von Hann window. The data was created using and I\&Q simulator. For each sample, 3 time-series were generated with the desired statistics. Each is then phase-coded, and then overlaid. For each pixel, there are 200 samples.

Figure 179: Bias of 3\textsuperscript{rd} weakest trip power (dB) from SZ-1. The 2\textsuperscript{nd} to 3\textsuperscript{rd} trip power ratio is 20 dB, the weak trip spectrum width is 2 m/sec, and the 3\textsuperscript{rd} trip spectrum width is 4 m/sec. \(N = 64\), von Hann window. The data was created using and I\&Q simulator. For each sample, 3 time-series were generated with the desired statistics. Each is then phase-coded, and then overlaid. For each pixel, there are 200 samples.
Figure 180: Standard deviation of strong trip power (dB) from SZ-1. The $2^{nd}$ to $3^{rd}$ trip power ratio is 0 dB, the weak trip spectrum width is 2 m/sec, and the $3^{rd}$ trip spectrum width is 4 m/sec. $N = 64$, von Hann window. The data was created using an I&Q simulator. For each sample, 3 time-series were generated with the desired statistics. Each is then phase-coded, and then overlaid. For each pixel, there are 200 samples.

Figure 181: Bias of strong trip power (dB) from SZ-1. The $2^{nd}$ to $3^{rd}$ trip power ratio is 0 dB, the weak trip spectrum width is 2 m/sec, and the $3^{rd}$ trip spectrum width is 4 m/sec. $N = 64$, von Hann window. The data was created using an I&Q simulator. For each sample, 3 time-series were generated with the desired statistics. Each is then phase-coded, and then overlaid. For each pixel, there are 200 samples.
Figure 182: Standard deviation of strong trip velocity (m/sec) from SZ-1. The 2nd to 3rd trip power ratio is 0 dB, the weak trip spectrum width is 2 m/sec, and the 3rd trip spectrum width is 4 m/sec. N = 64, von Hann window. The data was created using the I&Q simulator. For each sample, 3 time-series were generated with the desired statistics. Each is then phase-coded, and then overlaid. For each pixel, there are 200 samples.

Figure 183: Bias of strong trip velocity (m/sec) from SZ-1. The 2nd to 3rd trip power ratio is 0 dB, the weak trip spectrum width is 2 m/sec, and the 3rd trip spectrum width is 4 m/sec. N = 64, von Hann window. The data was created using the I&Q simulator. For each sample, 3 time-series were generated with the desired statistics. Each is then phase-coded, and then overlaid. For each pixel, there are 200 samples.
Figure 184: Standard deviation of strong trip spectrum width (m/sec) from SZ-1. The $2^{nd}$ to $3^{rd}$ trip power ratio is 0 dB, the weak trip spectrum width is 2 m/sec, and the $3^{rd}$ trip spectrum width is 4 m/sec. $N = 64$, von Hann window. The data was created using and I&Q simulator. For each sample, 3 time-series were generated with the desired statistics. Each is then phase-coded, and then overlaid. For each pixel, there are 200 samples.

Figure 185: Bias of strong trip spectrum width (m/sec) from SZ-1. The $2^{nd}$ to $3^{rd}$ trip power ratio is 0 dB, the weak trip spectrum width is 2 m/sec, and the $3^{rd}$ trip spectrum width is 4 m/sec. $N = 64$, von Hann window. The data was created using and I&Q simulator. For each sample, 3 time-series were generated with the desired statistics. Each is then phase-coded, and then overlaid. For each pixel, there are 200 samples.
Figure 186: Standard deviation of weak trip power (dB) from SZ-1. The $2^{nd}$ to $3^{rd}$ trip power ratio is 0 dB, the weak trip spectrum width is 2 m/sec, and the $3^{rd}$ trip spectrum width is 4 m/sec. $N = 64$, von Hann window. The data was created using and I&Q simulator. For each sample, 3 time-series were generated with the desired statistics. Each is then phase-coded, and then overlaid. For each pixel, there are 200 samples.

Figure 187: Bias of weak trip power (dB) from SZ-1. The $2^{nd}$ to $3^{rd}$ trip power ratio is 0 dB, the weak trip spectrum width is 2 m/sec, and the $3^{rd}$ trip spectrum width is 4 m/sec. $N = 64$, von Hann window. The data was created using and I&Q simulator. For each sample, 3 time-series were generated with the desired statistics. Each is then phase-coded, and then overlaid. For each pixel, there are 200 samples.
Figure 188: Standard deviation of weak trip velocity (m/sec) from SZ-1. The 2\textsuperscript{nd} to 3\textsuperscript{rd} trip power ratio is 0 dB, the weak trip spectrum width is 2 m/sec, and the 3\textsuperscript{rd} trip spectrum width is 4 m/sec. $N = 64$, von Hann window. The data was created using and I&Q simulator. For each sample, 3 time-series were generated with the desired statistics. Each is then phase-coded, and then overlaid. For each pixel, there are 200 samples.

Figure 189: Bias of weak trip velocity (m/sec) from SZ-1. The 2\textsuperscript{nd} to 3\textsuperscript{rd} trip power ratio is 0 dB, the weak trip spectrum width is 2 m/sec, and the 3\textsuperscript{rd} trip spectrum width is 4 m/sec. $N = 64$, von Hann window. The data was created using and I&Q simulator. For each sample, 3 time-series were generated with the desired statistics. Each is then phase-coded, and then overlaid. For each pixel, there are 200 samples.
Figure 190: Standard deviation of 3\textsuperscript{rd} weakest trip power (dB) from SZ-1. The 2\textsuperscript{nd} to 3\textsuperscript{rd} trip power ratio is 0 dB, the weak trip spectrum width is 2 m/sec, and the 3\textsuperscript{rd} trip spectrum width is 4 m/sec. $N = 64$, von Hann window. The data was created using and I&Q simulator. For each sample, 3 time-series were generated with the desired statistics. Each is then phase-coded, and then overlaid. For each pixel, there are 200 samples.

Figure 191: Bias of 3\textsuperscript{rd} weakest trip power (dB) from SZ-1. The 2\textsuperscript{nd} to 3\textsuperscript{rd} trip power ratio is 0 dB, the weak trip spectrum width is 2 m/sec, and the 3\textsuperscript{rd} trip spectrum width is 4 m/sec. $N = 64$, von Hann window. The data was created using and I&Q simulator. For each sample, 3 time-series were generated with the desired statistics. Each is then phase-coded, and then overlaid. For each pixel, there are 200 samples.
5.5 Conclusions

The three trip version of SZ-1 simply does not work well as-is. In particular, because of the poor performance of the 3rd trip power estimator, it would be necessary to censor 3rd trip power. Because, it would be difficult to tell where there actually is 3rd trip echoes and where there was not, all 3rd trip echoes would likely get the same “color”. If overlaid echo (purple) is chosen, then there will almost always be a 50 km purple ring at 1.8° that will be interspersed between the 3 trips near the beginning of each trip. Recall that the 3 trip situation will only occur in the first 50 km since after that point the beam center will be above 18 km. If the censoring is set as “noise-like”, then instead of purple, there will be simply missing data. This may result weather signals (which occur in the 3rd strongest trip) being indicated either partially or not at all. Neither solution seems desirable.

Because of time constraints, it was not possible to do much algorithm development to determine whether other methods could be found that would perform better than the algorithm we choose. So at this time, it would not be recommended to use the 3 trip version of SZ-1 in an operational setting.
6 Spectrum Width Estimation Considerations

G. Meymaris and J. Hubbert

6.1 Introduction

In Spring of 2006 ROC personnel became aware of apparent bad spectrum widths estimates that occurred within the SZ-2 algorithm. The problem was manifest by the observation of excessive number of zero ms$^{-1}$ velocity estimates. A partial cause of this was the Hanning time series window function used in the SZ-2 algorithm. In this section the spectrum width bias introduced by the window function is evaluated and a correction factor is derived.

There is, however, a more fundamental problem of the typically used pulse pair spectrum width estimators used by NEXRAD. Figure 192 illustrates this. Shown is a histogram of spectrum width estimates from simulated time series. The simulation parameters are: PRT = 1 ms; S-Band, SNR = 60 dB, velocity = 0 ms$^{-1}$, $\sigma_v = 0.5$ ms$^{-1}$. The number of simulations is 50,000. The auto correlation estimate used is the so called unbiased estimate (Doviak and Zrnić 1993):

$$R(i) = \frac{1}{N-i} \sum_{k=1}^{N-i} x(k)x^*(k + i)$$  \hspace{1cm} (16)

where $i$ is the auto correlation lag (i.e., $i = 0$ yields power), and $x(k)$ is a radar time series. The $R(0)/R(1)$ spectrum width estimator is

$$\sigma_v = \frac{\lambda}{2\pi T_s \sqrt{2}} \left[ \ln \left| \frac{R(0)}{R(1)} \right| \right]^{1/2}$$ \hspace{1cm} (17)

where $\lambda$ is the wavelength and $T_s$ is the sampling period. As can be seen, when $|R(1)| > |R(0)|$ the logarithm becomes negative and the square root becomes a complex number, i.e., a nonsensical width estimate is obtained. One strategy is to set the spectrum width to zero under such circumstances. The mean and standard deviation of the data in Figure 192 are 1.1 ms$^{-1}$ and 0.5 ms$^{-1}$, respectively. It can be argued that the data points where $R(1) > R(0)$ should be considered good estimates at 0 ms$^{-1}$ and be included in the histogram. Doing so brings the mean down to about 0.6 ms$^{-1}$. But still these width estimates are not very satisfying with the bulk of estimates either at 0 ms$^{-1}$ or around 1.1 ms$^{-1}$.

One could also use the biased auto correlation estimate defined as

$$R(i) = \frac{1}{N} \sum_{k=1}^{N-i} x(k)x^*(k + i)$$ \hspace{1cm} (18)

Equations (18) and (16) are identical except for the normalization term: $N$ for the biased auto correlation function and $N - i$ for the unbiased correlation function. From signal processing theory, the Fourier transform of the auto correlation function should yield the power spectrum of the signal. It can be shown that if the biased estimator is used, this relationship holds (see
Bringi and Chandrasekar, section 5.7.2, 2001, for a discussion on this topic). Using the biased auto correlation estimate and the same simulation parameters as in Figure 192, the histogram of Figure 193 is obtained. For this histogram of width estimates, \( R(0) \) is always greater than \( R(1) \) which is intuitively satisfying. However, the mean is 1.53 ms\(^{-1}\) and the standard deviation is 0.45 ms\(^{-1}\). It is also interesting that there are no spectrum width estimates below about 0.4 ms\(^{-1}\).

This can be understood by considering a couple of examples. First consider the constant sequence of all ones. Using the biased auto correlation estimate in Eq. (17) yields a width of 1.41 ms\(^{-1}\). For a Hanning window function, using the biased auto correlation estimate, the width is 0.46 ms\(^{-1}\).

Thus, when using the biased auto correlation estimate, it is very difficult to obtain ratios of \( R(0) / R(1) \) that yield width estimates less that about 0.4 ms\(^{-1}\) for 64 point time series at a wavelength of 10 cm.

Based on the two histograms, it seems that neither auto correlation estimates, biased or unbiased, together with the spectrum width estimator of Eq. (17) are very accurate for low spectrum widths. We analyze this issue no farther in this report but we do recommend that alternate spectrum width estimators be investigated. The remainder of this section shows an analysis of the bias incurred when using a Hanning window function.

6.2 Theory

Let \( S \) be the complex-valued time-series signal, \( W \) be the window function, define

\[
R^S_i = \frac{1}{N - i} \sum_{k=0}^{N-i-1} S(k) S^*(k + i)
\]

(i.e, \( R^S_i \) is the \( i^{th} \)-lag of the autocorrelation function of \( S \)) and let \( E[\cdot] \) be the ensemble average, a.k.a. the expected value. The expected value of the windowed data autocorrelation function is

\[
E \left[ R^{SW}_i \right] = E \left[ \frac{1}{N - i} \sum_{k=0}^{N-i-1} S(k) W(k) S^*(k + i) W^*(k + i) \right]
\]

\[
= E \left[ \frac{1}{N - i} \sum_{k=0}^{N-i-1} W(k) W(k + i) S(k) S^*(k + i) \right]
\]

\[
= \frac{1}{N - i} \sum_{k=0}^{N-i-1} E \left[ W(k) W(k + i) S(k) S^*(k + i) \right]
\]

\[
= \frac{1}{N - i} \sum_{k=0}^{N-i-1} W(k) W(k + i) E S(k) S^*(k + i)
\]

\[
= \frac{1}{N - i} \sum_{k=0}^{N-i-1} W(k) W(k + i) E \left[ R^S_i \right]
\]

\[
= E \left[ R^S_i \right] \frac{1}{N - i} \sum_{k=0}^{N-i-1} W(k) W(k + i)
\]

\[
= E \left[ R^S_i \right] R^W_i
\]
Figure 192: Histogram of spectrum width estimates for the unbiased estimator. The requested simulated width is $\sigma_v = 0.5 \text{ ms}^{-1}$. The number of simulations is 50,000.

Figure 193: Histogram of spectrum width estimates for the biased estimator for the same simulation parameters as used in Figure 192. $R(0)$ is always larger than $R(1)$. 
This relates the expected value of the autocorrelation of the windowed time-series to the expected value of the autocorrelation of the time-series and the autocorrelation of the window function:

\[ E[R_{SW}^i] = E[R_S^i] R_W^i \quad (19) \]

Equation 19 shows us that we can remove the bias induced by the window by applying the following “window adjustment”:

\[ \frac{E[R_{SW}^i]}{R_W^i} = E[R_S^i] \]

### 6.3 Theoretical Plots of window bias effect

The figures from this section show the effect of applying a window to an expected autocorrelation function where the Nyquist velocity is \(32 \text{ m s}^{-1}\), \(N = 64\), and \(W = 0.5 \text{ m s}^{-1}\).
Figure 194: Magnitude plot of an example theoretical Gaussian autocorrelation function before any window function is applied, where the Nyquist velocity is $32 \text{ m s}^{-1}$, $N = 64$, and $W = 0.5 \text{ m s}^{-1}$.

Figure 195: Magnitude plot of the 64 point von Hann window.
Figure 196: Magnitude plot of the autocorrelation function of the 64 point von Hann window function.

Figure 197: Magnitude plot of the autocorrelation function of the 64 point von Hann window function.
Figure 198: Magnitude plot of an example theoretical Gaussian autocorrelation function after the von Hann window function is applied. The Nyquist velocity is $32\, m\,s^{-1}$, $N = 64$, and $W = 0.5\, m\,s^{-1}$.

Figure 199: Magnitude plot of an example theoretical Gaussian autocorrelation function after the von Hann window function is applied. The Nyquist velocity is $32\, m\,s^{-1}$, $N = 64$, and $W = 0.5\, m\,s^{-1}$.
In this section, we show the effects of the window on spectrum width estimators via simulation. For what follows, the Nyquist velocity is always about $32 \text{ m s}^{-1}$ and $N = 64$. The lines in each plot correspond to different SNRs as indicated by the legend. There are 3 plot types: bias ($\text{mean}(\hat{W} - W)$), standard deviation ($\left( \text{mean}(\hat{W} - W)^2 \right) M/(M-1)^{1/2}$: note that this is not the standard error which is frequently used in other sources), and percent 0 (the ratio of the observed number of 0’s to the total number of samples). The x-axis corresponds to the spectrum width that is input into the simulator.
Figure 200: *Bias of the R0/R1 spectrum width estimator estimated using simulated Gaussian I&Q time-series for varying input spectrum widths (x-axis) and SNRs (different lines). The Nyquist velocity is about 32 m s$^{-1}$, \( N = 64 \), no window function was applied, and no window adjustment was made.*

Figure 201: *Standard deviation of the R0/R1 spectrum width estimator estimated using simulated Gaussian I&Q time-series for varying input spectrum widths (x-axis) and SNRs (different lines). The Nyquist velocity is about 32 m s$^{-1}$, \( N = 64 \), no window function was applied, and no window adjustment was made.*
Figure 202: Percent of zero values of the $R_0/R_1$ spectrum width estimator estimated using simulated Gaussian I&Q time-series for varying input spectrum widths (x-axis) and SNRs (different lines). The Nyquist velocity is about $32 \text{ m s}^{-1}$, $N = 64$, no window function was applied, and no window adjustment was made.

Figure 203: Bias of the $R_0/R_1$ spectrum width estimator estimated using simulated Gaussian I&Q time-series for varying input spectrum widths (x-axis) and SNRs (different lines). The Nyquist velocity is about $32 \text{ m s}^{-1}$, $N = 64$, the von Hann window function was applied, and no window adjustment was made.
Figure 204: Standard deviation of the $R_0/R_1$ spectrum width estimator estimated using simulated Gaussian I&Q time-series for varying input spectrum widths (x-axis) and SNRs (different lines). The Nyquist velocity is about $32 \text{ m s}^{-1}$, $N = 64$, the von Hann window function was applied, and no window adjustment was made.

Figure 205: Percent of zero values of the $R_0/R_1$ spectrum width estimator estimated using simulated Gaussian I&Q time-series for varying input spectrum widths (x-axis) and SNRs (different lines). The Nyquist velocity is about $32 \text{ m s}^{-1}$, $N = 64$, the von Hann window function was applied, and no window adjustment was made.
Figure 206: Bias of the $R_0/R_1$ spectrum width estimator estimated using simulated Gaussian I&Q time-series for varying input spectrum widths (x-axis) and SNRs (different lines). The Nyquist velocity is about $32 \text{ m s}^{-1}$, $N = 64$, the von Hann window function was applied, and the window adjustment was applied.

Figure 207: Standard deviation of the $R_0/R_1$ spectrum width estimator estimated using simulated Gaussian I&Q time-series for varying input spectrum widths (x-axis) and SNRs (different lines). The Nyquist velocity is about $32 \text{ m s}^{-1}$, $N = 64$, the von Hann window function was applied, and the window adjustment was applied.
Figure 208: Percent of zero values of the $R0/R1$ spectrum width estimator estimated using simulated Gaussian I&Q time-series for varying input spectrum widths (x-axis) and SNRs (different lines). The Nyquist velocity is about $32 \text{ m s}^{-1}$, $N = 64$, the von Hann window function was applied, and the window adjustment was applied.
6.5 Case Study

The data presented from this section is from KCRI 3/19/2006 02:28 Z (VCP 11, elevation 0.5°). Figures 209 through 214 demonstrate the effect of the application of the Hanning window on spectrum width estimates and show the improved performance of the spectrum width estimates when the Hanning window correction factor is applied. Both $R(0)/R(1)$ and $R(1)/R(2)$ width estimators are used. The pixels in black represent 0m s$^{-1}$ or where $|R(0)| > |R(1)|$ or where $|R(1)| > |R(2)|$. For this data set, the $R(1)/R(2)$ estimator seems to perform better than the $R(0)/R(1)$ estimator.

Shown in Figures 215 and 216 are scatter plots of short PRT width estimates versus long PRT spectrum width estimates for the $R(0)/R(1)$ and $R(1)/R(2)$ width estimators, respectively. A Hanning window was applied to the short PRT data but no adjustment to the auto correlation function was used. There is considerable scatter, however, on average both width estimates should be quite similar.

Shown in Figures 217 and 218 are scatter plots of short PRT width estimates versus long PRT spectrum width estimates for the $R(0)/R(1)$ and $R(1)/R(2)$ width estimators, respectively. A Hanning window was applied to the short PRT data and an adjustment to the auto correlation function was used. Comparing Figure 215 to Figure 217 and comparing Figure 216 to Figure 218 shows that when the Hanning window adjustment is used, there is less bias between the short and long PRT spectrum width estimates.
Figure 209: PPI of long PRT uncalibrated power from KCRI 3/19/2006 02:28 Z (VCP 11, elevation 0.5°).

Figure 210: PPI of long PRT (R0/R1) spectrum width from KCRI 3/19/2006 02:28 Z (VCP 11, elevation 0.5°).
Figure 211: PPI of short PRT (R0/R1) spectrum width from KCRI 3/19/2006 02:28 Z (VCP 11, elevation 0.5°). The von Hann window has been applied, but no adjustment for the window was made.

Figure 212: PPI of short PRT (R1/R2) spectrum width from KCRI 3/19/2006 02:28 Z (VCP 11, elevation 0.5°). The von Hann window has been applied, but no adjustment for the window was made.
Figure 213: PPI of short PRT (R0/R1) spectrum width from KCRI 3/19/2006 02:28 Z (VCP 11, elevation 0.5°). The von Hann window has been applied, and the window adjustment was made.

Figure 214: PPI of short PRT (R1/R2) spectrum width from KCRI 3/19/2006 02:28 Z (VCP 11, elevation 0.5°). The von Hann window has been applied, and the window adjustment was made.
Figure 215: ‘Scatterplot’ of long PRT $R_0/R_1$ versus short PRT $R_0/R_1$ spectrum width estimators from KCRI 3/19/2006 02:28 Z (VCP 11, elevation 0.5°). The von Hann window has been applied to the short PRT data and the window adjustment was not made.

Figure 216: ‘Scatterplot’ of long PRT $R_0/R_1$ versus short PRT $R_1/R_2$ spectrum width estimators from KCRI 3/19/2006 02:28 Z (VCP 11, elevation 0.5°). The von Hann window has been applied to the short PRT data and the window adjustment was not made.
Figure 217: ‘Scatterplot’ of long PRT $R_0/R_1$ versus short PRT $R_0/R_1$ spectrum width estimators from KCRI 3/19/2006 02:28 Z (VCP 11, elevation 0.5°). The von Hann window has been applied to the short PRT data and the window adjustment was performed.

Figure 218: ‘Scatterplot’ of long PRT $R_0/R_1$ versus short PRT $R_1/R_2$ spectrum width estimators from KCRI 3/19/2006 02:28 Z (VCP 11, elevation 0.5°). The von Hann window has been applied to the short PRT data and the window adjustment was performed.
7 The SZ(16/128) Algorithm

M. Dixon and J. Hubbert

The SZ(16/128) algorithm was investigated and analyzed in NCAR’s FY2005 Annual Report to the ROC. The argument for the use of the SZ(16/128) instead of the SZ(8/64) algorithm is as follows. Currently SZ-2 is implemented on normal resolution data with non overlapping windows. As shown in NCAR’s FY2005 Annual Report, the use of the Hanning window function (required by the SZ-2 algorithm) reduces the effective beamwidth of the antenna. Thus, instead of using the SZ(8/64) algorithm in such circumstances, the SZ(16/128) should be employed by overlapping the Hanning windows. That is, a 128 point Hanning window would be used at 64 point increments (assuming that 64 point increments yields the desired 1° azimuth resolution). The resulting effective antenna beamwidth is very similar to the effective antenna beamwidth for a 64 point sampling strategy when non overlapping rectangular windows are employed (i.e., equivalent to legacy data resolution). The advantage of using SZ(16/128) over SZ(8/64) is increased data quality: the variance of the radar estimates is reduced by about a factor of $1/\sqrt{2}$. Clutter filtering performance would improve also.

The cost of using SZ(16/128) is increased computation time. The largest time increase is likely due to the FFT (Fast Fourier Transform) used in the SZ algorithm. The computational costs of executing a FFT is related to $N \log(N)$ where $N$ is the length of the sequence. Thus doubling the length of the sequence to $2N$ increases the computational cost by a factor of about 2.3, i.e., more than double. To evaluate the actual increase computation time for use of SZ(16/128), a PPI data set was processed first using the SZ-1(8/64) algorithm and using the SZ-1(16/128) algorithm. The SZ-1 algorithm is applied at every gate whereas the SZ-2 algorithm is only applied to those gates with overlaid echoes as indicated by the long PRT calculated powers. Thus this SZ-1 test should be an upper bound on the increased computation time. The computer used is very similar to an RVP8 - dual 3.2 GHz CPUs. The times include IO and housekeeping, in addition to the raw number-crunching. For the 64-sample case, CPU processing time was 22 seconds. This is 32 beams per second. For the 128-sample case, CPU processing time was 40 seconds. This is about 18 beams per second. Thus, an increased processing time of a little less than a factor of two can be expected if SZ(16/128) is used in place of the SZ(8/64) algorithm. This is a significant increase in computation time and must be weighed against the decrease of about $1/\sqrt{2}$ in radar moment variances.

8 Summary and Conclusions

Real time identification and filtering of both AP and NP ground clutter has been a long standing goal of the NCAR NEXRAD Data Quality program. This goal is now within reach. The new fast RVP8 processor makes possible the real time identification of clutter contaminated data, the buffering of time series data and the subsequent application of a frequency (velocity) domain clutter filter such as GMAP. CMD (Clutter Mitigation Decision) is the NCAR developed Fuzzy Logic algorithm that identifies clutter contaminated data. A new clutter identification feature
field, CPA (Clutter Phase Alignment), was described and tested with both S-Pol and KFTG data. Since non-moving targets produce coherent backscatter, the measured absolute phase angle of the backscatter from such targets is nearly constant assuming the transmit source is coherent. CPA is high (its maximum is 1, the minimum is 0) for coherent backscatter targets and small (< 0.2) for most meteorological targets. The exception is zero velocity weather possessing a narrow spectrum width. As shown, however, even if the mean velocity is only \( \pm 0.3 \text{ms}^{-1} \), CPA decreases to less than 0.8 which is small enough to distinguish from most clutter targets. Moving clutter targets (e.g., blowing trees) may also be difficult to distinguish from weather using only the CPA field. More work needs to be done in this area.

To help distinguish weather from clutter for these two cases (zero velocity weather and blowing trees) the spatial texture of the reflectivity is a good feature field (for the single polarization case). The addition of the new CPA feature field to the CMD algorithm allows CMD to operate along a single ray (beam) of radar data instead of operating on several adjacent beams. This makes implementing CMD in the NEXRAD RPG a much simpler task.

Dual polarization feature fields for identifying clutter were also investigated. It was found that the spatial texture of \( Z_{dr} \) and \( \phi_{dp} \) were excellent clutter identifiers. The copolar correlation coefficient \( \rho_{hv} \), however, was not a good clutter identifier. Even with the addition of these dual-polarization parameters, CPA has proved to be an important feature field for the identification of clutter. When the NEXRAD radars are converted to dual polarization, the dual polarization inputs to CMD can be easily be “turned on”.

Dual polarization rainfall algorithms were investigated using experimental S-Pol data sets from the 1998 TEFLUN-B experiment in Melbourne, Florida and a rainguage network. The performance of 19 different rainfall algorithms were compared. The NSSL proposed algorithm for NEXRAD performed well but several possible improvements were found. The NSSL algorithm consists of three cases: 1) light rain, 2) medium rain, and 3) heavy rain. NSSL used a \( Z-R \) relationship to determine which type of rain case was present. It was shown that using a \( Z, Z_{dr}-R \) relationship to determine the rain case produced better agreement between the radar estimated rainfall and the raingauges, at least for the analyzed data sets. It was also found that tuning the NSSL algorithm for the typical raindrop size distributions found in Melbourne (tropical rain) also improved the performance of the rainfall algorithm. NCAR recommends that such investigations over a wide climatology of data sets be continued in order realize the full potential of dual polarization rainfall algorithms.

Much time and effort was expended in improving the performance of the REC. Unfortunately, the performance of the present RPG version of the REC has been flawed due primarily to coding in its implementation. The errors are a result of translating from NCAR code to AEL code and again to RPG code. Thus, the results of REC performance as seen at NCAR have always been good whereas the performance of the RPG REC code has been flawed. The resolution of this has been compounded by the difficulty of obtaining an operational version of RPG code at NCAR so that the version NCAR was testing was identical to the version the ROC was testing. The REC was originally designed to operate with two Fuzzy Logic algorithms for the identification and

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2 The proposed NSSL rainfall algorithm has apparently been altered in recent months, however, NCAR was not provided with this information so that its performance could be documented.
separation of AP clutter and precipitation: 1) the APDA and 2) the PDA. The APDA identifies clutter and the PDA identifies precipitation. When the two algorithms operate in unison, the best discrimination between non-precipitation and precipitation radar data is achieved, as our tests and evaluations showed. REC was approved and released in the RPG in 2003 with just the APDA functional since its performance was deemed an improvement over the then capabilities of RPG. With the code errors corrected and the addition of PDA, our testing confirms that the REC performs properly and significantly improves RPG rainfall estimation. NCAR recommends that these changes be implemented immediately especially since the current RPG REC’s output is flawed.

Other aspects of the REC were investigated. It was shown that the REC has the ability to correctly process areas of radar data adjacent to “spot blanking”, which are sectors where the transmitter is turned off and thus there is no radar data. Several data cases were examined and the REC is not adversely affected by spot blanking.

REC performance with Super Resolution data was also examined. Histograms of various REC Fuzzy Logic variables were examined in order determine membership functions and thresholds. It was shown that with some minor adjustments to the membership functions, the REC performed well with Super Resolution data.

Improvements continued to be made to NSPA (NCAR’s Spectral Processing Algorithm). The main premise behind NSPA is that weather reflectivity signatures along a radial tend to be more smooth and continuous in range than many forms of contaminating signals such as birds, insects, planes and RF interference\(^3\). Thus, objective use of these “waterfall plots” of spectra versus range can be used to locate and track such contiguous weather signals. Once the weather echo is located, the desired spectral moments are calculated only over the portion of the spectrum where there is weather power. In this way superfluous spectral artifacts are avoided if they occupy a region of the spectrum away from the weather echo. Also, weak echo weather signals and clear air echoes can be tracked via the continuity principle. When the radar moments are calculated only over the region of the spectrum with the desired echo, much noise can be eliminated thus improving the radar moment estimates of these low SNR signals. Examples of data quality improvement were given for several S-Pol cases.

The performance of spectrum width estimators was investigated. When the ROC was testing the new SZ-2 algorithm, it was found that there was an excessive amount of zero ms\(^{-1}\) width data points indicating imaginary spectrum widths. Such data points occur when the real zero lag of the autocorrelation function (\(R(0)\), i.e., the power of a time series) is less that the magnitude of the first lag of the autocorrelation function (\(|R(1)|\)). This can occur when the unbiased autocorrelation estimate (normalized by \(1/(N-i)\)) is used (NEXRAD uses this unbiased estimate). It can not occur if the biased autocorrelation estimate (normalized by \(1/N\)) is used. However, if \(R(0)\) is corrected for noise, as needs to be done for low SNRs, even the biased estimate can produce \(|R(1)| > R(0)\). In any event, both autocorrelation estimates (unbiased and biased) lead to significantly biased spectrum width estimates for low true spectrum widths. The situation is exacerbated when a window function such as the Hanning or Blackman is used: the number of non-physical (zero) spectrum widths increases significantly. Equations were derived

\(^3\)Very large, widespread flocks of birds are an exception and they can be more difficult to discriminate.
that quantified the bias incurred by the window function and a correction factor was given. Modeling studies showed that use of the window correction factor was effective in eliminating this bias. Experimental data examples were given also. However, NCAR recommends that the general problem of biased spectrum width estimators be further investigated with the goal of finding a less biased estimator for narrow spectrum widths.

The performance of the SZ-1 algorithm for the case of three trips was investigated in somewhat more detail than before. If SZ-1 is used at elevation angles less than 2.4°, three trip echoes are possible if the NEXRAD requirement of $v_a = 25 \text{ms}^{-1}$ (Nyquist velocity) is to be met. In other words, if the PRT is increased to so that only two trips are possible at these elevation angles, then the corresponding $v_a$ is less than 25 ms$^{-1}$. Additionally, it is advantageous to increase $v_a$ (shorten the PRT) since the SZ recovery statistics of the radar moments improve. However, the negative effect of having 3 trips is that the SZ-1 algorithm becomes more complicated when three trips instead of two trips need to be sorted and processed. Thus, our goal was to determine whether the increased benefit of a larger $v_a$ is worth the cost of processing three possible echo trips. The basic problem with SZ-1, is that there is no way to ascertain the radar return power for the weakest two trips, even when there are no overlaid echoes present. And if there are overlaid echoes present, it can be difficult to place them in the correct trip. Moreover, it is impossible to detect a weak trip echo that is less than about 40 to 45 dB down from the strong trip echo (this is true for both two trip as well as the three trip SZ-1 algorithm). Recovery problems are exacerbated when clutter is also present. The potential result is excessively censored data. Thus, in our opinion, a better choice would be to relax the $v_a = 25 \text{ms}^{-1}$ requirement to about $v_a = 21.5 \text{ms}^{-1}$ and thus restrict SZ-1 to just two trips. The other alternative is to use staggered PRT at these elevation angles.

Acknowledgments: The authors would like to thank the following people for the technical discussions which helped organize our thoughts for this report: S. Torres, D. Zrnić, R. Rhoton, D. Saxion, D. Berkowitz, D. Zittel, R. Ice, D. Warde and J. Keeler.
References


Table 7: Inputs

<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, in radians, or whatever units are required for $\sin$ and $\cos$, of length $N + 1$, $(-1, \ldots, N-1)$</td>
</tr>
<tr>
<td>$h_C$</td>
<td>The windowing function for use with clutter, of length $N$, $(0, \ldots, N-1)$. Typically this should be the Blackman window.</td>
</tr>
<tr>
<td>$h_O$</td>
<td>The windowing function for use with overlay (no clutter), of length $N$, $(0, \ldots, N-1)$. Typically this should be the von Hann window.</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>

APPENDIX

A  SZ-1 with SIGMET GMAP Filter

G. Meymaris

A.1 Assumptions

1. The phases of the transmitted pulses are modulates 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.2 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 proceeding 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.
<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 ($\approx$ -9 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.5.2</td>
</tr>
<tr>
<td>$K_s$</td>
<td>Strong trip SNR threshold (in linear)</td>
<td>1 ($\approx$ 0 dB)</td>
</tr>
<tr>
<td>$K_w$</td>
<td>Weak trip SNR threshold (in linear)</td>
<td>3.16228 ($\approx$ 5 dB)</td>
</tr>
<tr>
<td>$K_{x0}$</td>
<td>Lower CNR bound for dB-for-dB censoring</td>
<td>10 dB</td>
</tr>
<tr>
<td>$K_{x1}$</td>
<td>Upper CNR bound for dB-for-dB censoring</td>
<td>50 dB</td>
</tr>
<tr>
<td>$K_{s0}$</td>
<td>Rate for smaller CNR region for dB-for-dB censoring</td>
<td>0.15 dB/dB</td>
</tr>
<tr>
<td>$K_{s1}$</td>
<td>Rate for larger CNR region for dB-for-dB censoring</td>
<td>1 dB/dB</td>
</tr>
<tr>
<td>WindowStrongMom</td>
<td>Switch to control when the window function for overlaid signals is applied. TRUE to apply window before computing the spectral moments, and FALSE for afterwards.</td>
<td>FALSE</td>
</tr>
</tbody>
</table>

Table 8: Constants

<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$_P_1$, type$_P_2$</td>
<td>First and second trip Power classification</td>
</tr>
<tr>
<td>type$_v_1$, type$_v_2$</td>
<td>First and second trip Velocity classification</td>
</tr>
<tr>
<td>type$_w_1$, type$_w_2$</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>$P_C$</td>
<td>Power removed by GMAP</td>
</tr>
<tr>
<td>$V_2$</td>
<td>Phase-coded complex time series (raw I &amp; Q) of length $N$, cohered to trip 2. $(0, \ldots, N-1)$</td>
</tr>
<tr>
<td>$r_1$, $r_2$</td>
<td>The first lag of the autocorrelation when cohered to trips 1 and 2, respectively</td>
</tr>
<tr>
<td>$v_a$</td>
<td>Nyquist velocity</td>
</tr>
<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>$\eta_{(window),n}$</td>
<td>Autocorrelation for the 2 different windows, for lags $n = 0, 1, 2$</td>
</tr>
<tr>
<td>WindowApplied</td>
<td>Flag that keeps track of which clutter filter has been applied thus far in the algorithm. Can be NONE, C, or O</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 indicating 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>$V_{wc}$</td>
<td>Windowed 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>$V_{ws}$</td>
<td>Windowed time-series cohered to the strong trip</td>
</tr>
<tr>
<td>$K_{adj}$</td>
<td>Adjustment factor for SNR censoring in the presence of clutter</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.3 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.4 Procedures

A note about the use of < · > in this document: in many cases there are variables that have a value for trip 1 and 2, such as power ($P_1$ 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 (complex) 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 $k_1$ to $k_2$

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

for $0 \leq m < N$ where

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

**Fourier and Inverse Fourier Transforms**: An FFT routine should be used and *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 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

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

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

Let $\hat{M}_n$ be the sorted list of $M_n$ where $\hat{M}_0$ is the smallest value and $\hat{M}_7$ the largest. Define the spectral noise as

$$\tilde{P}_N = \frac{1}{N^N} \sum_{n=0}^{N_N-1} \hat{M}_n$$

and define the spectral censoring metric as

$$H = 10 \log_{10} \left( \frac{\hat{M}_7}{\frac{1}{NS} \sum_{l=0}^{N_N-1} \hat{M}_l} \right)$$

### A.5 Setup

#### A.5.1 Window Adjustment Factors

For each window type used in the algorithm, an adjustment factor needs to be generated for each.

$$\eta_{\text{window},0} = R_0 [h_{\text{window}}]$$

$$\eta_{\text{window},1} = R_1 [h_{\text{window}}]$$

$$\eta_{\text{window},2} = R_2 [h_{\text{window}}]$$

where $\text{window}$ is $C$ or $O$. Define $\eta_{\text{NONE},0} = \eta_{\text{NONE},1} = \eta_{\text{NONE},2} = 1$.

#### A.5.2 Deconvolution

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.

\[
\begin{align*}
X(k) &= S_F(k)F[C](k) \\
Y(k) &= F^{-1}[X](k)C^*(k) \\
D_{inv}(k) &= |F[Y](k)|
\end{align*}
\]

Finally, define the matrix \( D_{invmat}_{n,m} = D_{inv}(n + m) \) where \( n, m = 0, \ldots, N - 1 \) (\( n \) here is the row index and \( m \) is column index) and then compute the matrix inverse \( D_{mat} = (D_{invmat})^{-1} \) (note that this inverse is the matrix inverse and not the component by component operation). The variable \( D_{mat} \) should be stored for the deconvolution block (25).

A.6 Algorithm

1. Initialize

Inputs

Outputs \( P_1, v_1, w_1, P_2, v_2, w_2, \) WindowApplied, \( P_C \)

\[
\begin{align*}
P_1 &= 0 \\
v_1 &= 0 \\
w_1 &= 0 \\
P_2 &= 0 \\
v_2 &= 0 \\
w_2 &= 0
\end{align*}
\]

Also set WindowApplied to NONE and \( P_C = 0 \).

2. Check that there is enough power to warrant any further action

Inputs \( V_1, K_s \)

Outputs \( \text{type}_P_1, \text{type}_P_2, \text{type}_v_1, \text{type}_v_2, \text{type}_w_1, \text{type}_w_2 \)
Calculate the total power

\[ P_T = R_0 [V_1] \]

If \( P_T < K_s \) then set

\[
\begin{align*}
    \text{type}_P_1 &= \text{type}_P_2 = \text{NOISE}_{-}\text{LIKE} \\
    \text{type}_v_1 &= \text{type}_v_2 = \text{NOISE}_{-}\text{LIKE} \\
    \text{type}_w_1 &= \text{type}_w_2 = \text{NOISE}_{-}\text{LIKE}
\end{align*}
\]

and exit the algorithm.

3. **Determine the trip ordering using the \(|R_1|\) estimator**

**Inputs** \( V_1 \)

**Outputs** \( V_2, t_A, t_B, r_1, r_2 \)

Compute \( r_1 = R_1 [V_1] \) for the input time series \( V_1 \), which is cohered to trip 1. Set \( V_2 = C [V_1, 1, 2] \). and compute \( r_2 = R_1 [V_2] \). The trip with the larger magnitude 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. (e.g. if \(|r_1| > |r_2|\) then \( t_A = 1 \), and \( t_B = 2 \))

4. **Determine the clutter status**

**Inputs** Clutter map, \( t_A \)

**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.

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

**Inputs** \( V_1, V_2, \text{ClutterTrip}, h_C, L, C_T \)

**Outputs** ClutterFiltered, \( V_c \)
Set

\[ V_c = V_{(\text{ClutterTrip})} \]

Calculate the so-called narrow clutter ratio test

\[
C = \sum_{k=-L}^{L} \left| \sum_{m=0}^{N-1} h_C V_c(m) \exp(-2\pi imk/N) \right|^2 \]

\[
\frac{(2L+1) R_0 [V_c h_C]}{2 (2L+1) R_0 [V_c h_C]}
\]

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 and proceed to block 9.

6. **Window the time series in preparation for GMAP**

**Inputs** \( V_c, h_C, \eta_C, 0 \)

**Outputs** \( V_{Wc}, \text{WindowApplied} \)

Compute

\[
V_{Wc}(m) = \frac{V_c(m) h_C(m)}{\sqrt{\eta_C 0}}
\]

for \( 0 \leq m < N \). Set WindowApplied to C.

7. **Apply Clutter Filter**

**Inputs** \( V_{Wc}, \text{ClutterTrip} \)

**Outputs** \( \text{ClutterFiltered}, V_{CF1}, V_{CF2}, P_C \)

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

\[ F(k) = F[V_{Wc}](k) \]

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

\[
S(k) = |F(k)|^2
\]

\[
\Phi(k) = \arg(F(k))
\]

Define \( \tilde{P}_N \) as spectral noise level of \( S \), calculated as described in section A.4. Apply GMAP on \( S \), supplying \( \tilde{P}_N \) for the noise power. It is important to provide this noise level to GMAP, rather than letting GMAP calculate it, because the noise calculation used by GMAP assumed that the incoherent signal (i.e. noise) has an exponential distribution at each spectral bin, with
the same average power. In SZ, the incoherent signal does not have the same average power at each spectral bin, which is why you can “see” the replicas from out of trip echoes.

Capture the return from the GMAP code as \( \hat{S} \), and, as in SZ-2, GMAP should return the number of points removed, which we denote \( k_{GMAP} \). We assume here that the indices (though not the values) modified by GMAP will always be symmetric about 0, and therefore \( k_{GMAP} \) will be odd valued. 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

\[
\hat{F}(k) = \sqrt{\hat{S}(k)} \exp\left(i\hat{\Phi}(k)\right)
\]

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

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

Recohere \( V_{CF<\text{ClutterTrip}>} \) to NonClutterTrip (defined as 3-ClutterTrip):

\[
V_{CF<\text{NonClutterTrip}>} = C[V_{CF<\text{ClutterTrip}>}, \text{ClutterTrip}, \text{NonClutterTrip}]
\]

Calculate the clutter power removed (if not provided by GMAP) as

\[
P_C = \begin{cases} 
\sum_{k=0}^{(k_{GMAP}-1)/2} \left( S(k) - \hat{S}(k) \right) + \sum_{k=N-(k_{GMAP}-1)/2}^{N-1} \left( S(k) - \hat{S}(k) \right) & k_{GMAP} > 1 \\
S(0) - \hat{S}(0) & k_{GMAP} = 1 \\
0 & k_{GMAP} = 0
\end{cases}
\]

Finally, set ClutterFiltered to 1.

8. **Determine the trip ordering using the \( |R_1| \) estimator**

**Inputs** \( V_{CF1}, V_{CF2}, \text{ClutterTrip}, \text{WkTripCensorFlag}, t_A, \eta_{<\text{WindowUsed}>}, 1 \)

**Outputs** \( \text{WkTripCensorFlag}, V_{CF1}, V_{CF2}, t_A, t_B, r_1, r_2, \text{type}_P_1, \text{type}_P_2, \text{type}_v_1, \text{type}_v_2, \text{type}_w_1, \text{type}_w_2 \)

Set \( r_1 = R_1 [V_{CF1}] / \eta_{<\text{WindowUsed}>}, 1 \) and \( r_2 = R_1 [V_{CF2}] / \eta_{<\text{WindowUsed}>}, 1 \). As in block 3, the trip with the larger magnitude 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

\[
\text{type}_P_1 = \text{type}_P_2 = \text{OVERLAID\_LIKE} \\
\text{type}_v_1 = \text{type}_v_2 = \text{OVERLAID\_LIKE} \\
\text{type}_w_1 = \text{type}_w_2 = \text{OVERLAID\_LIKE}
\]
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. \textbf{Cohere to Strong trip}

\textbf{Inputs} \( V_{CF1}, V_{CF2}, V_1, V_2, \text{ClutterFiltered}, r_1, r_2 \)

\textbf{Outputs} \( V_s, R_s \)

Set \( V_s = V_{CF<t_A>} \) if ClutterFiltered, otherwise, set \( V_s = V_{<t_A>} \). Set \( R_s = r_{<t_A>} \)

10. \textbf{Window the time series (if not already windowed for clutter filtering purposes)}

\textbf{Inputs} \( V_s, \text{WindowApplied}, h_O, \eta_{O,0}, \text{WindowStrongMom} \)

\textbf{Outputs} \( V_{Ws}, \text{WindowApplied} \)

If WindowStrongMom = FALSE or if WindowApplied is not NONE, set \( V_{Ws} = V_s \) and continue to block 12. Otherwise set

\[
V_{Ws}(m) = \frac{V_s(m) h_O(m)}{\sqrt{\eta_{O,0}}}
\]

for \( 0 \leq m < N \) and set WindowApplied to O.

11. \textbf{Re-compute Strong trip 1st lag autocorrelation function in case WindowStrongMom = TRUE}

\textbf{Inputs} \( V_{Ws}, \text{WindowApplied}, \eta_{<\text{WindowApplied}>,1} \)

\textbf{Outputs} \( R_s \)

\[
R_s = R_1 \left[ V_{Ws} \right] / \eta_{<\text{WindowApplied}>,1}
\]

12. \textbf{Compute Strong trip 2nd lag autocorrelation function}

\textbf{Inputs} \( V_{Ws}, \text{WindowApplied}, \eta_{<\text{WindowApplied}>,2} \)

\textbf{Outputs} \( \rho_s \)

Note regarding nomenclature: for this step, \( V_{Ws} \) may or may not have been windowed, depending on WindowStrongMom and ClutterFiltered.

\[
\rho_s = R_2 \left[ V_{Ws} \right] / \eta_{<\text{WindowApplied}>,2}
\]
13. **Window the time series (if not already windowed for clutter filtering purposes or if WindowStrongMom if TRUE).**

**Inputs** \( V_{Ws}, \) WindowApplied, \( h_O, \eta_{O,0} \)

**Outputs** \( V_{Ws}, \) WindowApplied

If WindowApplied is NONE (note that if WindowStrongMom is TRUE then this should never be NONE), set

\[
V_{Ws}(m) = \frac{V_{Ws}(m) h_O(m)}{\sqrt{\eta_{O,0}}}
\]

for \( 0 \leq m < N \) and set WindowApplied to O. Otherwise leave \( V_{Ws} \) and WindowApplied as-is.

14. **Calculate the dB-for-dB Censoring adjustment**

**Inputs** \( P_C, K_{x0}, K_{x1}, K_{s0}, K_{s1} \)

**Outputs** \( K_{adj} \)

If \( P_C = 0 \), then set \( K_{adj} = 1 \) and continue to the next block. Otherwise, set \( P_{CdB} = 10 \log_{10}(P_C) \) and then

\[
K_{adjdB} = \begin{cases} 
0 & P_{CdB} \leq K_{x0} \\
K_{s0} (P_{CdB} - K_{x0}) & K_{x0} < P_{CdB} \leq K_{x1} \\
K_{s1} (P_{CdB} - K_{x1}) + K_{s0} (K_{x1} - K_{x0}) & K_{x1} < P_{CdB}
\end{cases}
\]

Finally, set \( K_{adj} = 10^{K_{adjdB}/10} \)

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

**Inputs** \( V_{Ws}, K_{adj}, K_s \)

**Outputs** \( \tilde{P}_s, type_{_P1}, type_{_P2}, type_{_v1}, type_{_v2}, type_{_w1}, type_{_w2} \)

Calculate the total power

\[
\tilde{P}_s = R_0 [V_{Ws}]
\]

If \( \tilde{P}_s < K_s K_{adj} \) then set

\[
\begin{align*}
type_{_P1} &= type_{_P2} = NOISE\_LIKE \\
type_{_v1} &= type_{_v2} = NOISE\_LIKE \\
type_{_w1} &= type_{_w2} = NOISE\_LIKE
\end{align*}
\]

and exit the algorithm.
16. **Nyquist velocity**

**Inputs** $T_S, \lambda$

**Outputs** $v_a$

$$v_a = \frac{\lambda}{4T_S}$$

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

**Inputs** $R_s, v_a$

**Outputs** $v_s$

$$v_s = -\frac{v_a}{\pi} \arg(R_s)$$

18. **Calculate the Strong trip spectrum width**

**Inputs** $R_s, \rho_s, v_a$

**Outputs** $w_s$

Use the $R_1R_2$ estimator. Set

$$w_s = \begin{cases} 
\frac{2v_a}{\pi \sqrt{6}} \left( \ln \left( \frac{|R_s|}{|\rho_s|} \right) \right)^{1/2} & |R_s| \geq |\rho_s| \\
0 & |R_s| < |\rho_s|
\end{cases}$$

19. **Apply PNF and compute residual power**

**Inputs** $V_{Ws}, \text{ClutterFiltered}, \text{ClutterTrip}, t_A, v_a$

**Outputs** $V_{SN}, P_R$

Compute the spectrum.

$$F(k) = F[V_{Ws}](k)$$

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

$$k_{\text{ADJ}} = \left( k_{\text{GMAP}} - 1 \right) / 2 + k_{\text{GMAP\_EXTRA}}$$

and then set

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

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

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

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.

Compute $P_R$ here since it requires less computations in the spectral domain because the PNF was just applied:

$$P_R = \frac{1}{N - NW} \sum_{l=NW}^{N-1} |F_{\text{SN}} \left( \text{mod} \left( k_a + l, N \right) \right)|^2$$

Finally, compute the notched time-series

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

for $0 \leq k < N$.

20. **Calculate the Strong trip power**

**Inputs** $P_R, \tilde{P}_s$

**Outputs** $P_s$

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

21. **Compute Weak trip power**

**Inputs** $P_R, P_N$
Outputs $P_w$

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

22. Set the strong trip output values and check that there is reason to warrant any further action

Inputs $P_w$, WkTripCensorFlag, $P_s$, $v_s$, $w_s$, $K_w$, $K_{adj}$

Outputs $type_1 P$, $type_2 P$, $type_1 v$, $type_2 v$, $type_1 w$, $type_2 w$, $P_1$, $v_1$, $w_1$, $P_2$, $v_2$, $w_2$

Set the following:

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

If $P_w < K_w K_{adj}$ then set

$$type_{P_{<t_B>}} = NOISE\_LIKE$$
$$type_{v_{<t_B>}} = NOISE\_LIKE$$
$$type_{w_{<t_B>}} = NOISE\_LIKE$$

and exit the algorithm.

If $P_w \geq K_w K_{adj}$ and WkTripCensorFlag is 1 then set

$$type_{P_{<t_B>}} = OVERLAID\_LIKE$$
$$type_{v_{<t_B>}} = OVERLAID\_LIKE$$
$$type_{w_{<t_B>}} = OVERLAID\_LIKE$$

and exit the algorithm.

23. Cohere to Weak Trip

Inputs $V_{SN}$, $t_A$, $t_B$

Outputs $V_w$
\[ V_w = C[V_{SN}, t_A, t_B] \]

24. **Compute Weak trip mean velocity**

**Inputs** \( V_w, v_a \)

**Outputs** \( v_w \)

Calculate the weak trip mean velocity using the \( R_1 \) estimator. Note that it is not necessary to adjust \( R_W \) for the window function applied since only the complex argument (i.e. angle) is used.

\[
\begin{align*}
R_w &= R_1[V_w] \\
v_w &= -\frac{v_a}{\pi} \arg(R_w)
\end{align*}
\]

25. **Deconvolve the spectrum**

**Inputs** \( V_w, Dmat \)

**Outputs** \( \tilde{S} \)

Compute the magnitude spectrum

\[
S(k) = |\mathbf{F}[V_w](k)|
\]

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

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

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

26. **Compute the Spectral Censoring Metric**

**Inputs** \( \tilde{S} \)

**Outputs** \( H \)

Compute \( H \) as described in section A.4.

27. **Store the results from the weak trip**

**Inputs** \( P_w, v_w \)

**Outputs** \( \text{type}_P_1, \text{type}_P_2, \text{type}_v_1, \text{type}_v_2, \text{type}_w_1, \text{type}_w_2, P_1, v_1, w_1, P_2, v_2, w_2 \)
\[ P_{<t_B>} = P_w \]
\[ v_{<t_B>} = v_w \]
\[ type_{P_{<t_B>}} = SIGNAL\_LIKE \]
\[ type_{v_{<t_B>}} = SIGNAL\_LIKE \]
\[ type_{w_{<t_B>}} = OVERLAI_D\_LIKE \]

B FY2006 Publications

Attached are the following conference publications:


2. Ellis, S., C. Kessinger, J. Van Andel, M. Dixon and J. Hubbert; 2006: Enhancements in Clutter/Precipitation Discrimination for the WSR-88D, \textit{IIPS of Annual AMS Meeting}, Atlanta, GA.


5. Hubbert, J.C., G. Meymaris, S. Ellis and M. Dixon; 2006: Application and issues of SZ phase coding for NEXRAD, \textit{IIPS of Annual AMS Meeting}, Atlanta, GA.