IMPROVING NEXRAD DATA
Data Quality Algorithm Progress

FY2009 Annual Report

S-Pol Z_{dr} data: Left, FHV data. Right, corresponding SHV data

Prepared for: WSR-88D Radar Operations Center

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EXECUTIVE SUMMARY

This report provides continued analysis and evaluation of data quality issues for the National Weather Services network of WSR-88D radars. Specifically addressed are uniform PRT ground clutter mitigation, staggered PRT clutter mitigation, spectrum width estimation and $Z_{dr}$ bias caused by cross-coupling of the horizontal and vertical transmitted waves for dual polarization operations.

NCAR’s clutter mitigation algorithm, CMD (Clutter Mitigation Decision) has now been deployed across the entire NEXRAD network. Though CMD has been largely successful, some sites have reported anomalous data. This has lead to efforts to further improve the fuzzy logic used in CMD. Some anomalous signatures are due to moving targets, such as motor vehicle traffic, which CMD is not designed to detect. Some, however, are due to ground clutter targets which produce atypical radar signatures. The majority of these atypical signatures are due to the presence of two dominate clutter targets in the radar resolution volume which has been verified with model simulations (see Hubbert et al. (2009a) for clutter model details). This can cause both the magnitude and phase of the I and Q time series to change significantly during the radar dwell time so that clutter metric CPA (Clutter Phase Alignment) is abnormally low and causes a miss detection. In this report, several possible enhancements to CMD are discussed and analyzed which will mitigate such confounding, anomalous signatures. CMD has been designed and tested to include dual polarization variables so that the transition to dual polarization will be seamless. Such atypical radar signatures from ground clutter, as mentioned above, will be much better detected with the addition of the dual polarization feature fields.

NCAR’s new hybrid spectrum width estimator has recently been approved by the TAC (Technical Advisory Committee) for deployment consideration on the NEXRADS. This new hybrid spectrum width estimator combines several known spectrum width estimators. Different estimators perform better depending on the relative breadth of the Doppler spectrum. In this report, the
performance characteristics of the several spectrum width estimators, including the pulse-pair estimator currently used in the WSR-88D, are reviewed. A hybrid algorithm combining three spectrum width estimators is discussed, and it is shown that this algorithm, while slightly more computationally intensive, is more accurate and robust than any single estimator method.

Even though ground clutter mitigation using polynomial regression filters has been investigated (Torres and Zrnić 1999) little additional analysis and testing have been reported. Stationary ground clutter targets produce time series signals (in-phase (I) and quadrature(Q)) that vary little over the radar dwell period as compared to weather signals. In fact a completely stationary target illuminated by a stationary (non-rotating) radar would produce constant I and Q time series. Thus, to eliminate such slowly varying signals from radar time series, a polynomial can be fitted to the data. Such a polynomial can then be subtracted from the time series. This is referred to as a polynomial regression filter. The appeal and benefit of the polynomial regression filtering technique is that it does not require the use of an aggressive time series window such as the Von Hann or Blackman which are required by GMAP (used by NEXRAD). Thus, in general, polynomial regression filters can sufficiently attenuate the clutter signal while attenuating weather signal very little as compared to GMAP. Since an aggressive time series window is not used, this can result in improved signal statistics (reduced variance) by a factor of two or more. Additionally, polynomial regression filters do not require time series with uniform spaced samples. Experimental data is given that show the viability of this technique.

Also investigated is a simplified staggered PRT (SSPRT) clutter filtering technique. The staggered PRT time series are separated into even and odd numbered samples thereby creating two times series with uniform time spacing. These two new time series then can be clutter filtered via standard techniques, e.g., using GMAP. The two time series are then recombined and the radar moments are calculated from the single recombined time series using typical staggered PRT techniques. This technique is interesting since it is relatively simple to understand as compared
to SACHI. The performance of SSPRT and SACHI is comparable.

Finally, $Z_{dr}$ biases are examined that result from the simultaneous transmission of the horizontal (H) and vertical (V) polarized waves (termed SHV mode). If the H and V transmitted waves cross-couple, significant $Z_{dr}$ bias can occur. The two primary ways this cross-coupling can occur is via antenna polarization errors and the propagation medium. The latter occurs when the propagation medium is characterized by a non-zero mean canting angle (Ryzhkov and Zrnić 2007; Hubbert et al. 2009b). The effects of the antenna polarization errors on SHV mode $Z_{dr}$ are not well understood. In this report we document SHV mode $Z_{dr}$ bias using experimental S-Pol data. This data set is unique because SHV mode data was gathered in close time proximity to fast alternating H and V transmit (FHV mode) data which is relatively free of the above mentioned cross-coupling biases. Thus the FHV mode data can be used as truth for the SHV mode data. The SHV mode $Z_{dr}$ biases are clearly demonstrated. Additionally, an SHV mode KOUN data set is analyzed. Again, the SHV mode $Z_{dr}$ biases are clearly demonstrated.
1 SHV $Z_{dr}$ Bias Caused by Cross-coupling

a Introduction

In the NCAR’s 2009 Annual Report to the ROC, the effect cross-coupling between the H and V channels when operating a radar in the simultaneous H and V transmit mode were reported. The two primary sources of cross-coupling are 1) non-zero mean canting angle of the particles in the propagation medium and 2) antenna polarization errors. The effects of non-zero mean canting angle of the propagation medium have been shown by other authors, e.g., (Ryzhkov and Zrnić 2007). However, the data shown in last year’s annual report consisted of both SHV (Simultaneous H and V transmit) as well as corroborating FHV (Fast Alternating H and V) data in close time proximity. Thus, the FHV data can be used as truth data by which to judge the SHV data. SHV $Z_{dr}$ data in the ice phase clearly showed anomalous radial stripes whereas the FHV data showed no evidence of these bias stripes. Also shown were SHV $Z_{dr}$ biases in a region of pure rain that were caused by antenna polarization errors. Such biases might be difficult to identify without the accompanying FHV data which is void, for all practical purposes, of such biases caused by antenna polarization errors. Here we extend this work. The S-Pol antenna polarization errors are estimated and then used in the scattering model to predict the SHV $Z_{dr}$ bias as a function of $\phi_{dp}$. The predicted errors are then used to correct the bias in SHV $Z_{dr}$.

A data set from KOUN where there is over 300 degrees of $\phi_{dp}$ is analyzed for antenna polarization errors. This interesting case has both positive and negative SHV $Z_{dr}$ bias along a single radial.

All reflector type antennas will introduce some distortion to the desired H and V transmit polarization states causing cross-coupling between the H and V polarization states. This will bias polarization measurements of precipitation and these errors are similar to the cross-coupling problem reported in Ryzhkov and Zrnić (2007). In this report the impact of antenna induce
cross-coupling $Z_{dr}$ bias caused by the non ideal radar antenna are investigated. The radar model introduced by Hubbert and Bringi (2003) is used to quantify the impact of polarization errors on $Z_{dr}$ and $\phi_{dp}$. Transmit errors are also included separately in the model by specifying the transmit polarization state that is fed to the antenna. Finally experimental data from S-Pol, NCAR’s S-band polarimetric radar, and KOUN, NSSL’s experimental S-ban radar, are used to illustrate the theory. These data clearly illustrate the effects of antenna polarization errors on $Z_{dr}$. It will be critical for the NEXRAD dual polarization program to understand and estimate the magnitude of $Z_{dr}$ bias caused by antenna polarization errors.

b. Antenna Errors

Antenna errors are quantified in the model by the complex numbers $\xi_h$ and $\xi_v$ (Hubbert et al. 2009b). These errors can be equivalently defined by the tilt and ellipticity angles, i.e., $\alpha_{h,v}$ and $\epsilon_{h,v}$ respectively, of the polarization ellipse as shown in Fig. 1. $E_h$ and $E_v$ are the horizontal and vertical electric field components. Ideally if only an H polarized field is sent to the antenna, only H polarization would emerge from the antenna and be propagated into space. This pure H polarized wave would be represented as a horizontal line on the H axis of Fig. 1. However, due to the non-ideal feedhorn and antenna dish, some of the H polarized wave is coupled to the V channel. This error is characterized by the complex number $\xi_h$ and is equivalently represented by the tilt and ellipticity angles $\alpha_h$ and $\epsilon_h$, respectively. Similarly for the vertical channel, $\xi_v$ is the antenna error which can be equivalently represented by $\alpha_v$ and $\epsilon_v$. Mathematically,

\[
\begin{bmatrix}
E_{rh}^{\text{rad}} \\
E_{rv}^{\text{rad}}
\end{bmatrix} =
\begin{bmatrix}
i_h & \xi_v \\
\xi_h & i_v
\end{bmatrix}
\begin{bmatrix}
E_h^t \\
E_v^t
\end{bmatrix}
\]  

(1)

where $E_h^t$ and $E_v^t$ are the electric fields input to the OMT and feedhorn, $E_{rh}^{\text{rad}}$ and $E_{rv}^{\text{rad}}$ are the electric fields radiated into free space, $i_{h,v}$ are real numbers such that $|\xi_h|^2 + i_h^2 = 1$ and $|\xi_v|^2 + i_v^2 = 1$. Representing the antenna polarization errors in terms of the the tilt and ellipticity
A description of the radar scattering model can be found in Hubbert et al. (2009b); Hubbert and Bringi (2003). First the model is used to illustrate the different effects that tilt and ellipticity angle errors individually have on $Z_{dr}$ bias. Figure 3 shows $Z_{dr}^{shv}$ for one-degree, orthogonal polarization tilt errors (upper panel) and one-degree orthogonal polarization ellipticity errors (lower panel), both versus $\phi_{dp}^\theta$, principal plane $\phi_{dp}$ (see Hubbert et al. (2009b) for a discussion of $\phi_{dp}^\theta$). The $\theta$ (mean canting angle of the propagation medium) is zero and $E^t_v = E^t_h$ ($E^t_{h,v}$ are the H and V electric fields input to the antenna at the reference plane (See Fig. 2)). The magnitude of these errors, i.e, $|\xi_h + \xi_v|$, corresponds to an LDR system limit of about -30 dB. The solid straight lines represent non-biased $Z_{dr}$ that would be measured in fast alternating H and V transmit mode. The figure shows that $Z_{dr}$ bias is significant with a maximum error of about 0.6 dB when $\phi_{dp}^\theta = 180^\circ$.

Actual antenna errors can be some combination of tilt and ellipticity angle errors and thus we present the following again as an illustrative example of how antenna errors affect $Z_{dr}^{shv}$. Figure 4 shows $Z_{dr}^{shv}$ bias for the H and V tilt and ellipticity error angles given in Table 1. The antenna errors are orthogonal, i.e., $\xi_v = -\xi_h^*$. The figure shows that the character of the $Z_{dr}$ bias is quite different for each curve with a maximum bias about 0.4 dB. These antenna errors all correspond
Figure 2: A block diagram showing the elements of the radar model. TX is the transmitter block, PD is the power division network and $R_H$ and $R_V$ are the vertical and horizontal receiver chains.

to about a -31 dB $LDR$ system limit.

These same antenna errors from Table 1 are used again in Fig. 5, but for circular transmit polarization. The $Z_{dr}$ biases curves have changed dramatically and demonstrate the importance of the phase difference between the H and V components of the transmit wave. The transmit wave is defined here at the reference plane shown in Fig. 2.

As shown in Hubbert et al. (2009b), S-Pol’s antenna polarization errors are fairly well characterized by orthogonal ellipticity angles and by H and V tilt angles of 0° and 90°, respectively, (i.e., no tilt angle errors). Using this restriction, for an $LDR$ system limit value, the ellipticity error angle can be calculated. Table 2 gives the error ellipticity angles for several $LDR$ system limit values. The corresponding values for the $Im\{\xi_h\}$ (or equivalently $\epsilon_h$ in radians) are also given.

We next examine SHV $K_{dp}$ biases caused by polarization errors given in Table 3. These antenna polarization errors correspond to a $LDR$ system limit of -25 dB. Shown in Fig. 6 is $K_{dp}^{shv}/K_{dp}^{P}$ as a function of principal plane $\phi_{dp}$. The $K_{dp}$ bias is fairly small, always being less than 3%. If the $LDR$ system limit is less than -30 dB, the $K_{dp}$ error is within 2%.

The biases of SHV $\rho_{hv}$ for $LDR$ system limits as high -25 dB are less than 1% and are not plotted.
Table 1: The H and V tilt and ellipticity error angles corresponding to Fig. 4.

<table>
<thead>
<tr>
<th></th>
<th>H tilt</th>
<th>H ellip.</th>
<th>V tilt</th>
<th>V ellip.</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>-0.5°</td>
<td>-0.7°</td>
<td>89.5°</td>
<td>0.7°</td>
</tr>
<tr>
<td>B</td>
<td>0.5°</td>
<td>-0.7°</td>
<td>90.5°</td>
<td>0.7°</td>
</tr>
<tr>
<td>C</td>
<td>-0.5°</td>
<td>0.7°</td>
<td>89.5°</td>
<td>-0.7°</td>
</tr>
<tr>
<td>D</td>
<td>0.5°</td>
<td>0.7°</td>
<td>90.5°</td>
<td>-0.7°</td>
</tr>
</tbody>
</table>

c **SHV Z\text{dr} as a Function of LDR System Limit**

As shown in Hubbert et al. (2009b), the antenna polarization error terms appear as $\xi_h + \xi_v$ in the expression for LDR system limit and SHV $Z_{dr}$ in drizzle. Thus, the LDR system limit for a radar can be related to the SHV $Z_{dr}$ bias as a function of $\phi_{dp}^P$ with differential transmit phase as a parameter. Based on the antenna errors for S-Pol, the antenna errors are modeled as orthogonal ellipticity angles with no tilt angle errors. This is shown in Fig. 7 for (a) slant 45° linear transmit polarization (i.e., $E_t^h = E_t^v$) and (b) circular transmit polarization. The shown $\epsilon$ denotes the sign of the H polarization ellipticity angle. The values of the ellipticity angle corresponding to each curve are given in Table 2. Note how not only the shape of bias curves changes but also the maximum $Z_{dr}$ bias increases significantly for circular transmit polarization. The model shows that the most stringent crosspolar isolation criteria results for the circular polarization transmit condition. As can be seen, if SHV $Z_{dr}$ bias is to be kept under 0.2 dB, the LDR system limit needs to be about -40 dB. Practically, if one of the circular transmit bias curves characterized a radar, the $Z_{dr}$ bias at $\phi_{dp} = 0$ would likely be detected by the user and a $Z_{dr}$ offset correction factor would be used. Then, the maximum $Z_{dr}$ bias would occur for $\phi_{dp}^P = 180^\circ$ instead of at $\phi_{dp}^P = 0^\circ$.

d **S-Pol Experimental SHV Data**

During May and June of 2008, S-Pol was deployed in Southern Taiwan for the field experiment TiMREX (Terrain-influenced Monsoon Rainfall Experiment). S-Pol was operated in the FHV
Figure 3: SHV mode $Z_{dr}$ for one degree antenna polarization errors. The upper panel shows $\pm 1^\circ$ tilt errors while the lower panel shows $\pm 1^\circ$ ellipticity errors.

Figure 4: SHV mode $Z_{dr}$ for mixed tilt and ellipticity antenna error angles which are given in Table 1. The antenna errors are orthogonal and the $H$ and $V$ transmit signals are equal, i.e., $E_h = E_v$. These antenna errors correspond to a system LDR limit of -31 dB.
Figure 5: SHV mode $Z_{dr}$ for mixed tilt and ellipticity antenna error angles which are given in Table 1, however, the transmission polarization state is circular. The antenna errors are orthogonal. These antenna errors correspond to a system LDR limit of -31 dB.

Figure 6: Normalized SHV mode $K_{dp}$ as a function of principal plane $\phi_{dp}$ for the antenna error angles given in Table 3.
Figure 7: SHV mode $Z_{dr}$ bias as a function of principal plane $\phi_{dp}$ with LDR system limit as a parameter. The antenna polarization errors are assumed to be orthogonal ellipticity angles. The sign of the $H$ ellipticity angle is given in each quadrant. (a) The transmit polarization is $45^\circ$ linear, i.e., $E_t^h = E_t^v$. The curves all mimic a sine wave shape. (b) The transmit polarization is circular. The curves are symmetric about the vertical line through $180^\circ$. The corresponding antenna errors are given in Table 2.
Table 2: Antenna polarization errors as a function of system LDR limit. The antenna errors are assumed to be orthogonal and elliptical.

<table>
<thead>
<tr>
<th>LDR (dB)</th>
<th>( \Im { \xi_h } \approx \epsilon ) (rad.)</th>
<th>( \epsilon ) (deg.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>-25</td>
<td>0.0281</td>
</tr>
<tr>
<td>B</td>
<td>-30</td>
<td>0.016</td>
</tr>
<tr>
<td>C</td>
<td>-35</td>
<td>0.009</td>
</tr>
<tr>
<td>D</td>
<td>-40</td>
<td>0.005</td>
</tr>
<tr>
<td>E</td>
<td>-45</td>
<td>0.003</td>
</tr>
</tbody>
</table>

Table 3: The H and V tilt and ellipticity error angles corresponding to Fig. 6. The corresponding LDR system limit is -25 dB.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0°</td>
<td>1.61°</td>
<td>90°</td>
<td>-1.61°</td>
</tr>
<tr>
<td>B</td>
<td>0°</td>
<td>-1.61°</td>
<td>90°</td>
<td>1.61°</td>
</tr>
<tr>
<td>C</td>
<td>0°</td>
<td>1.61°</td>
<td>90°</td>
<td>-1.61°</td>
</tr>
<tr>
<td>D</td>
<td>0°</td>
<td>-1.61°</td>
<td>90°</td>
<td>1.61°</td>
</tr>
</tbody>
</table>

(fast alternating H and V polarization) transmit mode for the majority of the project (normal operation mode), however, limited data were collected in the SHV (simultaneous H and V transmit) mode interleaved with the FHV data. Thus, SHV and FHV data that were gathered only minutes apart can be compared. Higher elevation PPIs illustrate radial \( Z_{dr}^{shv} \) bias stripes similar to the ones shown in Ryzhkov and Zrnić (2007) caused by canted ice-phase particles. See Hubbert et al. (2009b) for a discussion of the TiMREX higher elevation cuts.

Figures 8 and 9 show S-Pol FHV mode reflectivity (Z) and differential reflectivity (\( Z_{dr} \)) gathered during TiMREX on 2 June 2008, 6:17:06 UTC at 2.0° elev. Figures 10, 11 and 12 show SHV Z, \( Z_{dr} \) and \( \phi_{dp} \) gathered at 6:11:28 UTC at 2.0° elev. The SHV and FHV \( Z_{dr} \) data appear fairly comparable but in fact there is a bias in the SHV data. To show this, we employ the self consistency Z calibration technique of Vivekanandan et al. (2003). The technique is based on the relationship of Z, \( Z_{dr} \) and \( \phi_{dp} \) in rain. Assuming a typical range of rain drop size and shape distributions, \( \phi_{dp} \) can be estimated from measured Z and \( Z_{dr} \). This estimated \( \phi_{dp} \) (\( \hat{\phi}_{dp} \)) is compared to the measured \( \phi_{dp} \) (\( \phi_{dp}^{m} \)). A scatter plot is generated and a straight line fit is calculated. If the calculated mean line differs from the 1-to-1 line, this indicates a reflectivity
bias. The technique assumes that $Z_{dr}$ is well calibrated (S-Pol $Z_{dr}$ is calibrated via vertical pointing data in light rain). The self-consistancy technique can also be used to investigate $Z_{dr}$ bias as is done below.

Shown in Fig. 13 is a scatter plot of $\phi_{dp}^e$ versus $\phi_{dp}^m$ for TiMREX data. The $Z$ bias is about 0.03 dBZ, i.e., negligible. Note the tight scatter about the 1-to-1 line. This indicates that S-Pol is well calibrated and such self consistency plots are the norm for S-Pol. Biases in either $Z$ or $Z_{dr}$ result in changes in the slope of the data in the scatter plot of Fig. 13, but not in significant changes in the shape of data, i.e., the data are still tightly scattered around a straight line. This is illustrated in Fig. 14 which shows the same data as Fig. 13 but with an offset of 1 dB added to $Z$ (a) and an offset of 0.5 dB added to $Z_{dr}$ (b). Both $Z$ and $Z_{dr}$ offsets result in tight scatter around a straight line that is not the 1-to-1 line.

Fig. 15 is similar to Fig. 13 except the data was gathered in SHV mode. The scatter is rather tight about the 1-to-1 line for $\phi_{dp} < 50^\circ$ but for $\phi_{dp} > 70^\circ$ the computed $\phi_{dp}$ are biased low. The different biases at different values of $\phi_{dp}$ is not due to biases in $Z$ or $Z_{dr}$ but is rather due to $Z_{dr}$ bias caused by antenna errors.

To further illustrate this SHV $Z_{dr}$ bias, $Z_{dr}$ is averaged under the constraint $20 \text{ dBZ} < Z \leq 25 \text{ dBZ}$. These $Z_{dr}$ data are partitioned into three categories: 1) $20^\circ < \phi_{dp} < 40^\circ$, 2) $40^\circ < \phi_{dp} < 70^\circ$, and 3) $70^\circ < \phi_{dp} < 100^\circ$. The results are given in Table 4. For low $\phi_{dp}$ the SHV and FHV $Z_{dr}$ values are about equal. For $40^\circ < \phi_{dp} < 70^\circ$, the $Z_{dr}$s differ by 0.11 dB and for $70^\circ < \phi_{dp} < 100^\circ$ the $Z_{dr}$s differ by 0.27 dB. The data is not corrected for differential attenuation (which could potentially add error). This increasing difference between FHV and SHV $Z_{dr}$ as a function of $\phi_{dp}$ is consistent with the $Z_{dr}$ bias predicted for antenna errors of radar systems with $LDR$ limit in the -30 dB to -35 dB range.
Figure 8: FHV mode PPI reflectivity for 2.0° elevation. Data were gathered by S-Pol on 2 June 2008 at 06:17:06 UTC during the Field Campaign TiMREX in southern Taiwan. Range rings are in 15 km increments.

Figure 9: FHV mode PPI $Z_{dr}$ for 2.0° elevation corresponding to Fig. 8.
Figure 10: *SHV mode PPI reflectivity for 2.0° elev.* Data were gathered by S-Pol on 2 June 2008 at 06:11:28 UTC during the Field Campaign TiMREX in Southern Taiwan. Range rings are in 15 km increments.

Figure 11: *SHV mode PPI Z_{dr} for 2.0° elev.* corresponding to Fig. 10.
<table>
<thead>
<tr>
<th>Total $\phi_{dp}$</th>
<th>Mean $Z_{dr}$ (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FHV</td>
</tr>
<tr>
<td>between 20 and 40 deg.</td>
<td>0.17</td>
</tr>
<tr>
<td>between 40 and 70 deg.</td>
<td>0.15</td>
</tr>
<tr>
<td>between 70 and 100 deg.</td>
<td>-0.07</td>
</tr>
</tbody>
</table>

Table 4: A comparison of $Z_{dr}$ values for FHV and SHV modes as a function of $\phi_{dp}$. Reflectivities are limited to between 20 and 25 dBZ.

Figure 12: SHV mode PPI $\phi_{dp}$ for 2.0° elevation corresponding to Fig. 8.

Figure 13: Scatter plot of calculated $\phi_{dp}$ (from $Z$ and $Z_{dr}$) versus measured $\phi_{dp}$ from TiMREX FHV data corresponding to Figs. 8 and 9. The $Z$ bias is about 0.03 dBZ.
Figure 14: Scatter plot of calculated \( \phi_{dp} \) (from \( Z \) and \( Z_{dr} \)) versus measured \( \phi_{dp} \) from TiMREX FHV data similar to Fig. 13 with a) 1 dB offset added to \( Z \) and b) 0.5 dB offset added to \( Z_{dr} \).

Figure 15: Scatter plot of calculated \( \phi_{dp} \) (from measured \( Z \) and \( Z_{dr} \)) versus measured \( \phi_{dp} \) from TiMREX SHV data. Data above approximately 50° are biased low (consistently fall below the ono-to-one line). This is a manifestation of the \( Z_{dr} \) bias caused by antenna polarization errors.
The antenna polarization errors, $\xi_h$ and $\xi_v$, are difficult to quantify and are not typically given by the manufacturer. The errors can be estimated, however, from radar data as shown in Hubbert et al. (2009b). The technique uses an estimate of the $LDR$ system limit and solar scan data. The S-Pol antenna polarization errors, in terms of tilt and ellipticity of the polarization ellipse, are $\alpha_h = 0^\circ$, $\epsilon_h = -0.91^\circ$ and $\alpha_v = 90^\circ$, $\epsilon_v = 0.69^\circ$ which corresponds to $\xi_h = -j0.0159$ and $\xi_v = -j0.0120$. These estimated antenna errors are now used in the radar scattering model and the results are shown in Fig. 16. There are no transmit errors (i.e., $E^h_t = E^v_t$, (see Hubbert et al. (2009b))), the mean canting angle of the propagation medium is zero, and the backscatter medium is drizzle. As is seen, the $Z_{dr}$ bias becomes more positive with increasing $\phi_{dp}$ in a similar fashion to that in the above experimental data. The model also predicts that in FHV mode, the measured $LDR_h$ ($LDR$ for H polarization transmission) decreases with increasing $\phi_{dp}$ instead of increasing due to differential attenuation as normally expected. This type of $LDR_h$ behavior is observed with S-Pol data for long paths of increasing $\phi_{dp}$. Thus, the model predicts well the general behavior of the observed SHV $Z_{dr}$ bias and FHV $LDR_h$. A more precise estimate of the antenna errors could be made if the transmit polarization state could be measured and if the differential phase shift incurred from the reference plane to the I and Q samples were determined. While in principle this can be done, in practice it is not straightforward. To do this, the impedance mismatch of the measurement system and waveguide coupler to the radar system would need to be determined. This would require a vector network analyzer and such a measurement was not attempted. However, the present analysis demonstrates the magnitude and the characteristics of antenna polarization errors and their deleterious effect on SHV mode $Z_{dr}$.

Next, the SHV experimental data of Fig. 15 are corrected using the the modeled $Z_{dr}$ bias values from Fig. 16 as a function of measured $\phi_{dp}$. The self consistency technique is then again
applied to the corrected data and the result is shown in Fig. 17. As can be seen the data are now better clustered around the one-to-one line as compared to the uncorrected data of Fig. 15. Finally, the $Z_{dr}$ bias values from Fig. 16 are added to the FHV data to simulate the expected antenna polarization errors that occur in SHV transmit mode and the self-consistency results are shown in Fig. 18. The self-consistency results from the FHV data that have had the expected SHV $Z_{dr}$ biases added look very similar to the self-consistency results from the measured SHV data in Fig. 15, lending strong evidence that the estimates of $Z_{dr}$ errors are accurate.

f **KOUN Data**

The following section uses data gathered by KOUN, NSSL’s (Nation Severe Storms Laboratory) S-band research radar, on 30 March 2007 through a convective line that produced over 300° of $\phi_{dp}$ accumulation and serves as another example of SHV $Z_{dr}$ bias caused by antenna polarization errors. This rain event was described by local meteorologists as being more tropical in nature with fewer large drops than typically occur in Oklahoma rain storms\(^1\). This is confirmed by the

\(^1\)Personal communications with Terry Schuur Ph.D., of the Cooperative Institute for Mesoscale Meteorological Studies, University of Oklahoma, Norman Oklahoma.
Figure 17: Scatter plot of calculated $\phi_{dp}$ (from measured $Z$ and $Z_{dr}$) versus measured $\phi_{dp}$ from TiMREX SHV data from Fig. 15 except the $Z_{dr}$ is corrected as a function of measured $\phi_{dp}$ using the relationship in Fig. 16.

Figure 18: Similar to Fig. 13 except the predicted SHV biases have been added to $Z_{dr}$.
National Weather Service sounding data for the time period that shows a moist profile through a deep layer, low vertical wind shear, and relatively low convective available potential energy (CAPE = 834 J). Furthermore there were no hail reports in Oklahoma from the National Weather Service or the Community Collaborative Rain, Hail and Snow Network (CoCoRaHS). Thus, this is an excellent data set for the analysis of antenna polarization errors. The KOUN antenna is similar to the antennas used on the NWS’s operational radars (i.e., NEXRAD) except it has a dual-polarized feed horn. It has a center-fed parabolic reflector with three support struts. The 1.5° elevation angle data are used in our analysis to avoid the influence of partial beam blockage.

Since KOUN does not operate in FHV mode, only the SHV data are available and no FHV mode data are available for comparison. Nevertheless, the self consistency $Z$ calibration technique can be used to ascertain the presence of $Z_{dr}$ bias due to cross-coupling between the H and V channels. To calibrate KOUN data, PPI plots of $Z$ and $Z_{dr}$ are inspected in regions of light rain/drizzle with low reflectivity and very low $\phi_{dp}$ accumulation so that intrinsic $Z_{dr}$ should be about 0 dB. From this data, the $Z_{dr}$ bias is estimated to be 0.6 dB. Next, using the self consistency principle, the scatter plot of $\phi_{dp}^c$ versus $\phi_{dp}^m$ is calculated using only data with $\phi_{dp}^m$ less than 50°, which yields a $Z$ bias of 4.7 dB. To verify these estimated calibration numbers, a scatter plot of $Z_{dr}$ versus $Z$ is made for data with $\phi_{dp} < 30°$ (to minimize possible bias caused by the antenna polarization errors) and is shown as the solid line in Fig. 19. The experimental data are put into 5 dBZ bins, averaged, and then standard deviations are calculated. The mean and standard deviation are calculated in linear units and converted back to dB (see Rinehart (2004) for details). The solid vertical lines represent the standard deviations plotted at the midpoints of the 5 dB bins. For comparison, the curve found by Illingworth and Caylor (1989) is plotted in Fig. 19 as the dashed line. The corrected data compare well with the line from Illingworth and Caylor (1989).

The method of Vivekanandan et al. (2003) is applied to the KOUN data calibrated as de-
scribed above. Once again, the scatter plot of \( \phi_{dp} \) calculated from \( Z \) and \( Z_{dr} \) versus measured \( \phi_{dp} \) should cluster around the one-to-one line. Figure 20 shows this plot for the KOUN data. The data points are clustered around the one-to-one line for measured \( \phi_{dp} \) less than about 50° but data points are biased low for measured \( \phi_{dp} \) greater than about 50°. Since there are no reference FHV data for comparison, data self consistency is used to demonstrate the \( Z_{dr} \) bias in the KOUN data.

The \( Z_{dr} \) attenuation correction as well as the \( Z \) correction for attenuation will affect the nature of the scatter and there is a degree of uncertainty to these corrections. However, Vivekanandan et al. (2003) show that the scatter plots of \( \phi_{dp}^m \) versus \( \phi_{dp}^e \) for both 1) poorly calibrated \( Z \) data and 2) non-attenuation corrected data remain scattered about a mean straight line which has a significantly different slope as compared to 1. Thus, if the scatter of \( \phi_{dp}^e \) versus \( \phi_{dp}^m \) do not cluster well about a straight line, this indicates a \( Z_{dr} \) bias caused by antenna polarization errors. Assuming that the KOUN data are well calibrated for data where \( \phi_{dp}^m < 50^\circ \), the data of Fig. 20 shows a negative bias of the \( \phi_{dp}^e \) for \( \phi_{dp}^m > 50^\circ \). This in turn indicates that \( Z_{dr} \) is biased high (see Eq.(16) of Vivekanandan et al. (2003)). Following Vivekanandan et al. (2003) the mean \( Z \) bias assuming a well calibrated \( Z_{dr} \) and the mean \( Z_{dr} \) bias assuming a well calibrated \( Z \) measurement were computed for different ranges of \( \phi_{dp} \). The results are tabulated in Table 5. It can be seen that there are negligible biases of \( Z \) and \( Z_{dr} \) for total \( \phi_{dp} \) values less than 50, with large biases for \( \phi_{dp} \) between 50 and 150 deg, and reduced biases for larger \( \phi_{dp} \) values. The inconsistency of the results can be explained by a \( \phi_{dp} \) dependent bias in \( Z_{dr} \). To make sure that removing the overall bias would not improve the consistency of the results, it was removed from the data and the self-consistency calibration rerun. Table 6 shows the results for the different \( \phi_{dp} \) ranges. It can be seen that the bias values have changed in their magnitude there is essentially no relative change in biases between the \( \phi_{dp} \) ranges. In other words the results are still inconsistent over varying \( \phi_{dp} \). These large differences in computed \( Z \) and \( Z_{dr} \) biases as a function of \( \phi_{dp} \) indicate
<table>
<thead>
<tr>
<th>Total $\phi_{dp}$</th>
<th>Z bias</th>
<th>ZDR bias</th>
</tr>
</thead>
<tbody>
<tr>
<td>less than 50 deg.</td>
<td>0.026</td>
<td>-0.013</td>
</tr>
<tr>
<td>between 50 and 150 deg.</td>
<td>-0.70</td>
<td>0.34</td>
</tr>
<tr>
<td>greater than 150 deg.</td>
<td>-0.19</td>
<td>0.10</td>
</tr>
</tbody>
</table>

Table 5: Results of the self-consistency calibration for different $\phi_{dp}$ ranges. The Z bias is computed assuming an unbiased $Z_{dr}$ and the $Z_{dr}$ bias is computed assuming an unbiased $Z$. The data were calibrated based on the results with total $\phi_{dp}$ less than 50 deg.

<table>
<thead>
<tr>
<th>Total $\phi_{dp}$</th>
<th>Z bias</th>
<th>ZDR bias</th>
</tr>
</thead>
<tbody>
<tr>
<td>less than 50 deg.</td>
<td>0.44</td>
<td>-0.21</td>
</tr>
<tr>
<td>between 50 and 150 deg.</td>
<td>-0.28</td>
<td>0.14</td>
</tr>
<tr>
<td>greater than 150 deg.</td>
<td>0.22</td>
<td>-0.11</td>
</tr>
</tbody>
</table>

Table 6: Results of the self-consistency calibration for different $\phi_{dp}$ ranges. The Z bias is computed assuming an unbiased $Z_{dr}$ and the $Z_{dr}$ bias is computed assuming an unbiased $Z$. The data were calibrated based on all of the results regardless of $\phi_{dp}$ value.

antenna errors in $Z_{dr}$ rather than a constant bias of Z or $Z_{dr}$.

g Estimating KOUN Antenna Errors

While it is impossible to calculate the KOUN antenna polarization errors, as was done for S-Pol, a rough estimate can be made based on the data displayed in Fig 20 using trial and error and the model described in Part I. The antenna polarization error parameters are varied and the model is used to generate $Z_{dr}$ bias curves. The KOUN $Z_{dr}$ is then corrected and scatter plots of $\phi_{dp}^e$ versus $\phi_{dp}^m$ are calculated. The $Z_{dr}$ bias curve that best aligns the scatter of such plots around the one-to-one line is judged to yield the best estimate of the KOUN antenna errors. This $Z_{dr}$ bias curve is shown in Fig. 21 and the antenna errors are $\alpha_h = 1.7^\circ$, $\epsilon_h = -0.7^\circ$, $\alpha_v = 91.7^\circ$ and $\epsilon_v = 0.7^\circ$. The transmit polarization ellipse is characterized by $\alpha = 45^\circ$ and $\epsilon = -30^\circ$. The true KOUN antenna errors may be significantly different and still result in a similar $Z_{dr}$ bias curve as Fig. 21. Nevertheless, inevitably KOUN does possess antenna polarization errors as all center-fed parabolic antennas must. Furthermore, the magnitude of the errors must significantly
bias SHV $Z_{dr}$ as evidenced by the radar model given in Part I, unless the crosspolar isolation is better than 40 dB. Without a concerted design and development effort, this is extremely unlikely.

The suggested $Z_{dr}$ bias correction curve of Fig. 21 is now used to correct the KOUN $Z_{dr}$ KOUN data. That was corrected using $\phi_{dp}$ values less than 50 deg. As can be seen in Fig. 22, the character of the self consistency plot has improved: the scatter points are now more closely distributed around the one-to-one line as compared to the uncorrected data of Fig. 20. The self-calibration results using the corrected $Z_{dr}$ were computed for the $\phi_{dp}$ ranges listed in Table 5 and Table 6 and are shown in Table 7. It can be seen that the computed biases are much smaller and more consistent with $\phi_{dp}$ than if the antenna errors are not corrected. Thus, these estimated antenna errors are judged to be reasonable approximations of the true KOUN antenna errors.

Additional evidence of the validity of the antenna error corrections is provided by Figs. 23 and 24. The data in both figures were corrected for attenuation and differential attenuation using Eqs. (17) and (18) from Vivekanandan et al. (2003). Figure 23 shows a scatter plot of uncorrected mean $Z_{dr}$ versus $Z$ in 5 dB reflectivity bins for $\phi_{dp} > 175^\circ$ (thick solid line) and $\phi_{dp} < 175^\circ$ (thin solid line). The relationship of Illingworth and Caylor (1989) is again plotted as the dashed line in both Figs. 23 and 24. Figure 24 is similar to Fig. 23 except $Z_{dr}$ has now been corrected for antenna polarization errors by using the curve from Fig. 21. Figure 23 shows that the thin and thick plotted lines are significantly above and below, respectively, the theoretical dashed curve. The observed bias is consistent with $Z_{dr}$ being biased high for data where $\phi_{dp}$ is

<table>
<thead>
<tr>
<th>Total $\phi_{dp}$</th>
<th>Z bias</th>
<th>ZDR bias</th>
</tr>
</thead>
<tbody>
<tr>
<td>less than 50 deg.</td>
<td>0.2</td>
<td>-0.12</td>
</tr>
<tr>
<td>between 50 and 150 deg.</td>
<td>-0.12</td>
<td>0.059</td>
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<tr>
<td>greater than 150 deg.</td>
<td>-0.11</td>
<td>0.056</td>
</tr>
</tbody>
</table>

Table 7: Similar to Table 5 except the antenna error corrections of Fig. 21 were applied to the $Z_{dr}$ data.
Figure 19: $Z_{dr}$ versus $Z$ for KOUN data (solid line) and the theoretical curve given in Illingworth and Caylor (1989). The vertical bars represent one standard deviation of the KOUN data.

less than 175° and being biased low for data where where $\phi_{dp}$ is greater than 175° as predicted by Fig. 21. In comparison, the corrected data of Fig. 24 now yields curves that are much more consistent and agree with the theoretical curve of Illingworth and Caylor (1989). Note that there are less data available with $\phi_{dp}$ greater than 175° than less than 175°, resulting in the smaller data coverage of the thick black lines in Figs. 23 and 24.

**Summary and Conclusions**

Simultaneous transmission of H and V polarized waves (termed SHV mode) is now a popular way to construct dual-polarization radar systems largely because of lower cost and technical simplicity: an expensive, fast, high-power polarization switch is avoided. This report has shown that data quality issues will likely limit the cost-benefit of the SHV technique unless antenna polarization errors can be reduced so that the crosspolar isolation is better than 40 dB, a figure difficult to achieve for center-fed parabolic reflector antennas.

S-Pol data from TiMREX (Terrain-influenced Monsoon Rainfall Experiment) and from KOUN were used to demonstrate the $Z_{dr}$ bias in rain. The S-Pol SHV data were compared to FHV (fast
Figure 20: Scatter plot of calculated $\phi_{dp}$ (from $Z$ and $Z_{dr}$) versus measured $\phi_{dp}$ from KOUN SHV data gathered 30 March 2007. The slope of the straight line can be changed but the scatter points do not cluster symmetrically about the line. This is likely caused by antenna polarization errors.

Figure 21: SHV mode $Z_{dr}$ bias estimated from the model for KOUN data. The antenna polarization errors are $\alpha_h = 1.7^\circ$, $\epsilon_h = -0.7^\circ$ and $\alpha_v = 91.7^\circ$, $\epsilon_v = 0.7^\circ$. The transmit polarization ellipse is characterized by $\alpha = 45^\circ$ and $\epsilon = -30^\circ$. 
Figure 22: Scatter plot of calculated $\phi_{dp}$ (from $Z$ and $Z_{dr}$) versus measured $\phi_{dp}$ from KOUN SHV data gathered 30 March 2007 similar to Fig. 20 except the $Z_{dr}$ data have been corrected using the $Z_{dr}$ bias curve from Fig. 21.

Figure 23: Scatter plot of SHV mode $Z_{dr}$ versus $Z$ from KOUN data gathered 30 March 2007. The thin(thick) solid line shows data with $\phi_{dp}$ less than(greater than) 175 degrees and the dashed line is the relationship of Illingworth and Caylor (1989). The data have been calibrated based on data with low accumulated $\phi_{dp}$, corrected for attenuation and differential attenuation, but have not been corrected for antenna polarization errors.
alternating H and V transmit) data which is relatively free of biases caused by inter-channel cross-coupling (Wang and Chandrasekar 2006). S-Pol SHV mode $Z_{dr}$ bias was shown to be about 0.3 dB after about 80° of $\phi_{dp}$ accumulation in pure rain. Fortunately, small antenna polarization errors such as those found on S-Pol, do not significantly bias $K_{dp}$ nor $\rho_{hv}$. For the antenna errors considered in this paper, the radar model showed that biases in $K_{dp}$ or $\rho_{hv}$ are both within about 3% of their nominal unbiased values.

SHV radar data from KOUN were also analyzed for antenna polarization errors. This was more difficult since there was no FHV truth data for comparison. Nevertheless, the antenna polarization errors were estimated using the radar model, the principle of self consistency among $Z$, $Z_{dr}$, and $\phi_{dp}$ and $Z - Z_{dr}$ scatter plots. The KOUN data analyzed contained over 300° of accumulative $\phi_{dp}$ and therefore was an excellent case to examine for $Z_{dr}$ bias in rain caused by antenna polarization errors. Using the radar model, $Z_{dr}$ biases were shown to be positive (about 0.5 dB maximum) for $\phi_{dp} < 180^\circ$ and to be negative (about $-0.5$ dB minimum) for $\phi_{dp} > 180^\circ$.

Mitigation of the SHV mode $Z_{dr}$ bias caused by antenna errors will be difficult. First of all they are very difficult to quantify precisely. If the errors were known exactly, then the data could be corrected. This would only be valid in regions of homogeneous distributions of precipitation.
particles since antenna errors are not constant across the antenna beam. Thus, reflectivity gradients will affect the magnitude of the $Z_{dr}$ bias. Additionally, radome seams and irregularities as well as radome wetting will also cause polarization errors and measurement biases. Such errors were not considered here (S-Pol operates without a radome hence is free of these errors). The most promising path to reduction of the SHV mode $Z_{dr}$ bias is to reduce the antenna polarization errors via antenna design. However, our model shows that if $Z_{dr}$ bias is to be kept below 0.2 dB, assuming antenna polarization errors are similar in character to S-Pol’s antenna errors, the system LDR limit must be reduced to about -40 dB. This is largely in agreement with Wang and Chandrasekar (2006) who quote a similar requirement of -44 dB system LDR limit. Our estimated antenna errors are not worst case as was used by Wang and Chandrasekar (2006). Such a low LDR limit figure may not be cost-effective to achieve with center-feed parabolic antennas and this cost must be considered against the afore-mentioned cost-benefits of implementing SHV mode dual-polarization.

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Alternative approaches to staggered PRT clutter filtering

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1. Introduction

Staggered PRT (pulse repetition) is a popular technique to mitigate the range-velocity dilemma of weather radars. The unambiguous range is based on the longer PRT while the largest time interval that divides evenly the two PRTs (when the stagger is \(m/(m + 1)\) for some positive integer \(m\)) gives the unambiguous velocity (Zrnić and Mahapatra 1985). The major limitation of the staggered PRT technique has been clutter filtering. Since the time-series for a resolution volume is not equi-spaced, traditional filtering techniques such as time domain IIR (infinite impulse response) filtering or spectral domain filtering (based on the Discrete Fourier Transform (DFT)) are not immediately applicable. Recently Sachidananda and Zrnić (2000; 2002) introduced a staggered PRT clutter filtering algorithm based on the interpolation of the time-series to equi-spaced samples. This is done by interleaving zeros into the time-series to create equi-spaced time-series. The interpolated time-series is then transformed with a DFT. The resulting spectrum contains 5 replicas of the intrinsic underlying spectrum. Fairly complicated matrix mathematics is used to filter the spectra and estimate the power, mean velocity, and spectrum width.

In this paper we discuss a novel technique in which the time-series is separated into two equi-spaced time-series and then a spectral notch clutter filter can be employed. The two filtered sequences are then recombined to once again create a staggered PRT sequence. The velocity and power can then be calculated in standard fashion. Another similar technique based on regression filtering (Torres and Zrnić 1999) is also proposed.

2. Alternative SPRT Clutter Filtering Techniques

A typical staggered PRT sequence is shown in Fig. 1. Sequence (A) is the staggered PRT sequence with the two staggers periods \(T_1\) and \(T_2\); in this paper, the \(2/3\) stagger is assumed, which means that \(T_1 = 2T_2/3\). Denote the time-series samples \(s_1, s_2, \ldots, s_M\) (where \(M\) is the total number of samples). Two sequences are created by taking alternate samples and separating them as indicated by the red and blue lines and the even and odd samples. The resulting two sequences have have a period of \(T_1 + T_2\). These equi-spaced sequences can then be filtered in the time domain or the frequency domain. If they are filtered in the frequency domain, the sequences are subsequently transformed using an inverse DFT. The resulting time-series are then interleaved to produce the filtered staggered PRT sequence corresponding to Fig. 1A.

It is instructive to compare the Sachidananda and Zrnić (2002) technique (SACHI) and the simplified staggered PRT technique (SSPRT) via a numerical example. Let \(T_1 = 785 \mu s\) and \(T_2 = 1177 \mu s\) so that \(T_1 + T_2 = 1962 \mu s\). The SACHI zero-interpolated sequence has a period \(T_u = 393 \mu s\). Therefore, the unambiguous velocity for SACHI is 67 m s\(^{-1}\) while the unambiguous velocity for SSPRT sequence, based on period of 1962 \(\mu s\), is 13 m s\(^{-1}\). The SACHI technique creates 5 “replicas” (phase and amplitude modulated) of the true clutter signal spectrum equi-spaced over the entire unambiguous velocity range of 134 ms\(^{-1}\). Thus the spectrum replicas are separated 27 ms\(^{-1}\) intervals. The performance of the SACHI clutter filter degrades when there is weather located at these 27 ms\(^{-1}\) intervals (i.e., weather can be eliminated by the clutter filter causing biased velocity and reflectivity estimates). For SSPRT, if weather signal is located close to 0 ms\(^{-1}\), this weather signal can also be attenuated causing biased estimates. Since the unambiguous velocity is 13 ms\(^{-1}\), weather with \(27k\) ms\(^{-1}\), where \(k\) is an integer, will “wrap back” to 0 ms\(^{-1}\)
and thus these weather signals can also be attenuated by the clutter filter. Therefore, both SACHI and SSPRT can suffer performance degradation when weather has velocity close to $27k \text{ ms}^{-1}$ (depending on the width of the clutter filter).

Figures 2-5 show various spectral representations for a simulated weather and overlaid clutter case. The original spectra sampled at 393 $\mu$s with 160 samples is shown in figure 2. This can be thought of as the spectrum that the staggered PRT techniques are trying to recover. In figure 3, the spectra from the SACHI technique is shown (i.e. the original time-series is down-sampled using SPRT, the missing values are then “interpolated” back in with 0’s, and then the spectrum is calculated). With the SSPRT technique, the SPRT time-series was separated into even and odd time-series, and the spectra are calculated. The resulting spectra are shown in figure 4, zoomed into the $13 \text{ ms}^{-1}$ Nyquist interval, and in figure 5, shown on the extended Nyquist interval like figures 2 and 3.

### 3. Algorithms

#### a. SSPRT

The SSPRT method works as follows. The time-series is separated into even and odd time-series (each with PRT $T_1 + T_2$). The time-series are windowed using von Hann window function, and the FFT is computed. To filter the clutter, we used Gaussian Model Adaptive Processing (GMAP) clutter filter (Siggia and R. Passarelli 2004). If GMAP determines that clutter exists, then GMAP not only attempts to remove the clutter power, it also attempts to reconstruct the weather by assuming a Gaussian shape. However, care must be taken for staggered PRT data because it is necessary to also reconstruct the phases as well. Or more precisely the difference between the phases of the two complex spectra, since this contains important information. Before GMAP is applied, using the phase angle between the complex spectra at a spectral bin as well as the velocity value at that bin, a determination can be made as to which of the 5 intervals the data in that bin likely came from. There is some noise in the estimate so a de-speckle type filter is applied to fix isolated misclassifications. Continuing the simulated clutter and weather case above, figure 6 shows the interval determination for the spectra in figure 4. In theory, the spectrum can then be de-aliased, which is
Figure 2: Spectrum of a simulated weather and clutter echo. The simulation parameters are $\lambda = 10.5$ cm, PRT of 393 $\mu$s, 160 samples, 20 dB SNR.

Figure 3: SACHI Spectrum of a simulated weather and clutter echo. The simulation parameters are $\lambda = 10.5$ cm, $T_1 = 785$ $\mu$s, 64 staggered PRT samples, 20 dB SNR.

Figure 4: SSPRT Spectra (even and odd) of a simulated weather and clutter echo. The simulation parameters are $\lambda = 10.5$ cm, $T_1 = 785$ $\mu$s, 64 staggered PRT samples, 20 dB SNR.
shown in figure 7. GMAP could then be applied and the moments could then be calculated.

Alternatively, GMAP can be applied to each spectrum (even and odd), and then the interval determination (made before applying GMAP) can be used to assign the phases between the complex spectra for the bins that GMAP modified. An inverse FFT is then applied to each spectrum, and the time-series are “zippered” back together. The power, mean velocity and spectrum width can then be calculated using the standard techniques (Zrnić and Mahapatra 1985; Sachidananda et al. 1999; Torres et al. 2004).

b. Regression Filter

Another approach which has some significant promise is to use a regression filter as described by Torres and Zrnić (1999), instead of GMAP. Because the regression filter is a time-domain filter, a few details change. A least-squares polynomial fit is subtracted from the time-series data (real and imaginary parts are treated separately). This is a time-domain high-pass filter. Spectral reconstruction can then be performed. To do this the time-series can again be split into even and odd time-series and the spectra calculated for each. An advantage of the regression filter is that it effectively removes, or at least reduces, the need to use a window function when calculating the spectra. For the spectral reconstruction, the 3 or 5 points centered at 0 velocity can be linearly interpolated over. Something more complex like what is done in GMAP could also be done. The phases and then finally spectral moments are computed as in SSPRT.

The even and odd spectra from the same example after the regression filter (order 5 polynomial) has been applied is shown in figure 8. This is analogous to 4 except that the filter has already been applied. The interval determination is shown in figure b, and the de-aliased spectrum is shown in figure 9. Again, the moments could then be calculated on this de-aliased spectrum.

Alternatively, the interval determination can be used to assign the phases between the complex spectra for the bins that the regression filter modified. An inverse FFT is then applied to each spectrum, and the time-series are “zippered” back together. The power, mean velocity and spectrum width can then be calculated using the standard techniques.

4. Conclusions

The SSPRT and regression filtering techniques are promising clutter filtering techniques in at least some scenarios. It has the advantage that it is quite simple to understand, building from more standard techniques than does SACHI. A detailed study of the scenarios in which these techniques are better than SACHI, and vice versa, needs to be performed.

5. Acknowledgment

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Figure 5: SSPRT Spectra (even and odd) of a simulated weather and clutter echo on the extended Nyquist interval. The simulation parameters are $\lambda = 10.5$ cm, $T_1 = 785$ $\mu$s, 64 staggered PRT samples, 20 dB SNR.

Figure 6: SSPRT interval determination of a simulated weather and clutter echo shown in figure 4. The simulation parameters are $\lambda = 10.5$ cm, $T_1 = 785$ $\mu$s, 64 staggered PRT samples, 20 dB SNR.

Figure 7: SSPRT de-aliased spectrum of a simulated weather and clutter echo shown in figure 4. The simulation parameters are $\lambda = 10.5$ cm, $T_1 = 785$ $\mu$s, 64 staggered PRT samples, 20 dB SNR.
Figure 8: SSPRT Regression Spectra (even and odd), with no window used, of a simulated weather and clutter echo. The simulation parameters are $\lambda = 10.5$ cm, $T_1 = 785$ $\mu$s, 64 staggered PRT samples, 20 dB SNR. The polynomial order used was 5.

SSPRT Regression interval determination of a simulated weather and clutter echo. The simulation parameters are $\lambda = 10.5$ cm, $T_1 = 785$ $\mu$s, 64 staggered PRT samples, 20 dB SNR. The polynomial order used was 5.
Figure 9: SSPRT de-aliased regression Spectra (even and odd), with no window used, of a simulated weather and clutter echo. The simulation parameters are $\lambda = 10.5$ cm, $T_1 = 785 \mu s$, 64 staggered PRT samples, 20 dB SNR. The polynomial order used was 5.
References


An improved hybrid spectrum width estimator

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1. INTRODUCTION

With the advent of the Open Radar Data Acquisition (ORDA) system on WSR-88D radars and the introduction of significantly more powerful signal processing hardware comes the opportunity to improve the method used for estimating the spectrum width, a measure of the variability of radial wind velocities within a measurement pulse volume. In addition, the implementation of new operational modes for improved data quality, including SZ phase coding and staggered PRT, will involve very different signal processing techniques and hence may require novel methods to meet the WSR-88D specifications. While spectrum width has not been used extensively by radar meteorologists in the past, the NEXRAD Turbulence Detection Algorithm (NTDA), developed under direction and funding from the FAA’s Aviation Weather Research Program, uses the WSR-88D spectrum width as a key input for providing in-cloud turbulence estimates (eddy dissipation rate, EDR) for an operational aviation decision support system (Williams et al. 2005). Achieving improved spectrum width estimator performance would directly benefit the accuracy of the NTDA product.

In this report, the performance characteristics of the several spectrum width estimators, including the pulse-pair estimator currently used in the WSR-88D, are reviewed. A hybrid algorithm combining three spectrum width estimators is discussed, and it is shown that this algorithm, while slightly more computationally intensive, is more accurate and robust than any method alone.

2. Methodology

To evaluate and compare different spectrum width estimators we generated random complex time-series data for various true spectrum width, signal-to-noise ratio (SNR) and overlaid power ratio (PR) scenarios. We used an I&Q simulation technique based on the method described in Frehlich and Yadlowsky (1994); Frehlich (2000); Frehlich et al. (2001) except that the autocorrelation function is that of a weather echo as defined in Doviak and Zrnić (1993, p. 125). This is a preferable method for generating complex time-series with a given average autocorrelation function, as opposed to what is described by Zrnić (1975), because it is not necessary to generate as long of a time-series in order to get the correct temporal statistics.

In what follows, the simulator input (“true”) spectrum width will be denoted as $W$, while the estimated spectrum width will be denoted as $\hat{W}$ with a modifying subscript specifying the estimation technique used. Estimation errors were calculated by subtracting the simulator input values from the estimated values (i.e. $\hat{W} - W$). It should be noted that biases and standard deviations have different implications for turbulence detection since bias cannot be mitigated by averaging while random unbiased errors can.

Another way that we evaluated the performance was to compare $R0/R1$ to the hybrid estimator on case studies. This was done by comparing PPIs. Where the two estimators differed, Gaussian fits of the empirical spectrum using the estimated power ($\hat{P}$), velocity ($\hat{V}$), and spectrum widths were compared.
3. Spectrum Width Estimators

In this section, we used the simulator to generate short PRT data with the following characteristics: wavelength $\lambda = 10.5$ cm, the number of samples per time-series ($M$) is 88, PRT is 913 $\mu$s and varying signal-to-noise ratios (SNR) and input spectrum widths. This corresponds to the NEXRAD volume control pattern (VCP) 21.

a. The $R_0/R_1$ Pulse Pair Estimator

The standard spectrum width estimator currently used in the WSR-88D radars on short PRT data is the $R_0/R_1$ estimator (Doviak and Zrnić 1993), so named because it utilizes the ratio of the first two lags of the autocorrelation function:

$$\hat{W}_{s01} = \left(\frac{\sqrt{2}}{\pi}\right) V_a \left| \log \left( \frac{P_S}{|R_1|} \right) \right|^{1/2}$$  

The “s” in the subscript “s01” indicates that the short PRT data are used. Here $V_a$ is the Nyquist velocity, $P_S$ is the average power of the signal with noise removed, and $R_1$ is the first lag of the autocorrelation function (i.e., $R_1 = (n-1)^{-1} \sum_{k=1}^{n-1} V^*(k) V(k+1)$ where $V(k)$ are the complex-valued I&Q radar time-series). In the event that $|R_1| < P_S$, in which case the log has a negative argument, the spectrum width is set to 0 as is done on the WSR-88D.

The performance statistics obtained via simulation for the short PRT (913 $\mu$s) $R0/R1$ spectrum width estimator in the case of (essentially) no overlaid echoes is shown in Figure 1 for various input spectrum widths and SNRs. The biases are shown in Figure 1a, and the standard deviation of the errors $\hat{W}_{s01} - W$ is depicted in 1b. The error standard deviation plot agrees reasonably well with that in Doviak and Zrnić (1993), although there are some differences. These may be caused by different approaches to dealing with the cases where $|R_1| < P_S$, or to different methods used to generate time-series segments for analysis. The biases and standard deviations show that for low SNRs (0 and 4 dB) this estimator is very poor, with large error standard deviations and large and variable bias values. As SNR increases to 10 dB and greater, the bias relative to the input spectrum width improves dramatically for all but rather small or quite large input spectrum widths, and the error standard deviations improve for small and, especially, medium spectrum width values. For large input spectrum widths, the spectrum width estimator eventually saturates, as can be seen from the increasing negative bias for all SNR levels.

b. Other Estimators

Another estimator described by Doviak and Zrnić (1993) is the $R1/R2$ estimator, which is based on the ratio of the first and second lags of the autocorrelation function:

$$\hat{W}_{s12} = \left(2 / \left(\pi \sqrt{6}\right)\right) V_a \left| \log \left( |R_1/R_2| \right) \right|^{1/2}$$  

where $R_2$ is the second lag of the autocorrelation function:

$$R_2 = (n-2)^{-1} \sum_{k=1}^{n-2} V^*(k) V(k+2)$$

In the event that $|R_2| < |R_1|$, the spectrum width is set to 0. The performance is discussed by Meymaris et al. (2009). The important point is that this estimator as a whole performs better than $R0/R1$ until it saturates (at about 1/3 of the Nyquist velocity), leading to severe negative biases.
Figure 1: Bias and error standard deviation plots of the short PRT (913 µs) R0/R1 spectrum width estimator for varying input spectrum widths and SNRs (0, 4, 10, 15 and 20 dB shown). The PR in this data is set at 30 dB, low enough such that the weak trip does not significantly impact the statistics.

The $R1/R3$ estimator, is derived in the same way as the above pulse-pair estimators. It is based on the ratio of the first and third lags of the autocorrelation function:

$$\hat{W}_{s13} = \frac{1}{(2\pi)} V_a \log (|R_1/R_3|)^{1/2}$$

where $R_3$ is the second lag of the autocorrelation function:

$$R_3 = (n-3)^{-1} \sum_{k=1}^{n-3} V^*(k) V(k + 3)$$

In the event that $|R_3| < |R_1|$, the spectrum width is set to 0. This estimator behaves much like the $R1/R2$ estimator except that it performs better at very narrow spectrum widths, but also saturates very quickly (Meymaris et al. 2009).

Like the above models, the pulse pair least squares estimator (PPLS2) assumes that the autocorrelation function is a Gaussian. In the above estimators the fit of the Gaussian is exactly determined by 2 points (lags). However, PPLS2 uses 3 points, lags 0, 1, and 2, and is thus over-determined. The log of the autocorrelation function, if Gaussian, is a concave-down quadratic, and thus a least squares fit can be found efficiently. This estimator behaves somewhere between the $R0/R1$ and the $R1/R2$, as might be expected. It performs better than $R0/R1$ for narrow spectrum widths, although not as good as $R1/R2$, and worse than $R0/R1$ for wide spectrum widths, although better than $R1/R2$ (Meymaris et al. 2009).

c. The Hybrid Spectrum Width Estimator

The three estimators ($\hat{W}_{s01}$, $\hat{W}_{s12}$, and $\hat{W}_{s13}$) each performs well in certain regimes. $\hat{W}_{s01}$ performs well in higher SNRs and for larger spectrum widths, whereas $\hat{W}_{s12}$ performs well for slightly lower
SNRs and medium-valued spectrum widths. The estimator $\hat{W}_{s13}$ performs the best for very narrow spectrum widths. These complementary regimes of relatively good performance suggest that a hybrid approach where the appropriate estimator is used depending on the true (but unknown) spectrum width, might achieve good overall performance. Because the true spectrum width is unknown, a guess is made by calculating different estimators ($R_0/R_1$, $R_1/R_3$, and PPLS2) and then using a heuristic algorithm. Once the decision (guess) is made whether the true spectrum width is narrow, medium, or wide, then the appropriate estimator ($R_1/R_3$, $R_1/R_2$, and $R_0/R_1$, respectively) is used to calculate the final spectrum width estimate.

- The spectrum width estimators $\hat{W}_{s01}$, $\hat{W}_{s13}$, and $\hat{W}_{sPPLS2}$ are calculated.

- Based on $n$, the number of samples in the time-series, a table lookup of the wide normalized spectrum width threshold, $w_{tw}$ is performed. By normalized we mean that the spectrum width threshold must be multiplied by $V_a$ in order to be directly compared to the spectrum width estimators.

- If $\frac{1}{2}(\hat{W}_{s01} + \hat{W}_{sPPLS2}) > V_au_{tw}F_H$, where $F_H$ is an adaptable parameter to tune the algorithm (currently set to 0.9), then the spectrum width is guessed to be large. In which case, $\hat{W}_{s01}$ is the final output.

- Otherwise, another table lookup is performed (again based on $n$) to find the narrow normalized spectrum with threshold, $w_{tn}$.

- If $\hat{W}_{s13} < V_au_{tn}F_L$, where $F_L$ is an adaptable parameter to tune the algorithm (currently set to 1), then the spectrum width is guessed to be small. In which case, $\hat{W}_{s13}$ is the final output. For smaller values of $n$ ($n \leq 58$), $w_{tn}$ is set to $-1$, in which case this comparison is always false, and the algorithm proceeds to the next step. This is done because for smaller values of $n$, the capabilities of any tested estimator (including $\hat{W}_{s13}$) for discriminating between narrow and medium spectrum widths is poor. Since it is better to guess that a narrow spectrum width is medium-sized than vice verse, the algorithm errs on the side of guessing that the spectrum width is medium-sized.

- Otherwise, the spectrum width is guessed to be medium-sized. $\hat{W}_{s12}$ is calculated and returned as the final output.

In figure 2, the thresholds as a function of $n$ are shown. These thresholds were obtained in an automated way by running simulation data through a classification decision tree. The costs associated with misclassifications were set to reflect the fact that guessing that a spectrum width is too big is, in general, better than guessing that a wide spectrum width is narrow. This is true both from an estimator comparison standpoint as well as from the fact that wide spectrum widths are associated with hazards and so occasional over-warning is generally better than under-warning.

### 4. Results

#### a. Statistical Comparison

Plots of the performance statistics from simulations are shown in figures 3-42. Note that there are idealized in that the simulations produce I&Q data that are on average Gaussian and have on
average the correct noise level. In reality, both of these are often not satisfied. One type of statistical comparison for various regimes are shown in figures 3-32. These are 2-D histograms comparing the true input spectrum width versus the estimated spectrum width, which is similar to a scatter plot comparison of the data. The color scale is log. The plots are ordered by increasing SNRs and number of points, \( N \). These simulations cover the worst case scenario with respect to the number of points for each standard NEXRAD VCP for the short PRT. It is clear from these plots that the hybrid estimator performs much better than \( R0/R1 \). It is possible to see a few more outliers here and there which is caused by incorrect diagnoses of general size of the spectrum width. However, the number of outliers is quite small.

Another type of statistical comparison of the \( R0/R1 \) estimator and the proposed hybrid estimator is shown in figures 33-42 (see Meymaris et al. (2009) for more). The top panel in each plot shows the mean and the bottom the standard deviation for the estimators. The same regimes are shown as in the 2-D histogram plots. As can be seen, there are substantial improvements, in both bias and standard deviation, for narrower spectrum widths. It would not be expected to see improvements for larger spectrum widths because the \( R0/R1 \) is used in the hybrid estimator for wide spectrum widths because it performs the best of all the estimators tested in that regime.
Figure 3: 2-D Histogram of true input spectrum width versus the hybrid spectrum width estimate. Color scale represents frequency in log scale. The black line shows the mean per “column”, the solid white line shows the 1-1 line, and the dashed white line shows the standard deviation per “column”. Parameters: $\lambda = 10.5$ cm, PRT = 780 $\mu$s, $N = 37$, rectangular window was applied, and SNR = 5 dB.

Figure 4: 2-D Histogram of true input spectrum width versus the $R_0/R_1$ spectrum width estimate. Color scale represents frequency in log scale. The black line shows the mean per “column”, the solid white line shows the 1-1 line, and the dashed white line shows the standard deviation per “column”. Parameters: $\lambda = 10.5$ cm, PRT = 780 $\mu$s, $N = 37$, rectangular window was applied, and SNR = 5 dB.
Figure 5: 2-D Histogram of true input spectrum width versus the hybrid spectrum width estimate. Color scale represents frequency in log scale. The black line shows the mean per “column”, the solid white line shows the 1-1 line, and the dashed white line shows the standard deviation per “column”. Parameters: $\lambda = 10.5$ cm, PRT = 780 $\mu$s, $N = 37$, rectangular window was applied, and SNR = 10 dB.

Figure 6: 2-D Histogram of true input spectrum width versus the $R0/R1$ spectrum width estimate. Color scale represents frequency in log scale. The black line shows the mean per “column”, the solid white line shows the 1-1 line, and the dashed white line shows the standard deviation per “column”. Parameters: $\lambda = 10.5$ cm, PRT = 780 $\mu$s, $N = 37$, rectangular window was applied, and SNR = 10 dB.
Figure 7: 2-D Histogram of true input spectrum width versus the hybrid spectrum width estimate. Color scale represents frequency in log scale. The black line shows the mean per “column”, the solid white line shows the 1-1 line, and the dashed white line shows the standard deviation per “column”. Parameters: $\lambda = 10.5$ cm, PRT = 780 $\mu$s, $N = 37$, rectangular window was applied, and SNR = 20 dB.

Figure 8: 2-D Histogram of true input spectrum width versus the $R0/R1$ spectrum width estimate. Color scale represents frequency in log scale. The black line shows the mean per “column”, the solid white line shows the 1-1 line, and the dashed white line shows the standard deviation per “column”. Parameters: $\lambda = 10.5$ cm, PRT = 780 $\mu$s, $N = 37$, rectangular window was applied, and SNR = 20 dB.
Figure 9: 2-D Histogram of true input spectrum width versus the hybrid spectrum width estimate. Color scale represents frequency in log scale. The black line shows the mean per “column”, the solid white line shows the 1-1 line, and the dashed white line shows the standard deviation per “column”. Parameters: $\lambda = 10.5$ cm, PRT = 780 $\mu$s, $N = 50$, rectangular window was applied, and SNR = 5 dB.

Figure 10: 2-D Histogram of true input spectrum width versus the $R0/R1$ spectrum width estimate. Color scale represents frequency in log scale. The black line shows the mean per “column”, the solid white line shows the 1-1 line, and the dashed white line shows the standard deviation per “column”. Parameters: $\lambda = 10.5$ cm, PRT = 780 $\mu$s, $N = 50$, rectangular window was applied, and SNR = 5 dB.
Figure 11: 2-D Histogram of true input spectrum width versus the hybrid spectrum width estimate. Color scale represents frequency in log scale. The black line shows the mean per “column”, the solid white line shows the 1-1 line, and the dashed white line shows the standard deviation per “column”. Parameters: $\lambda = 10.5$ cm, PRT = 780 $\mu$s, $N = 50$, rectangular window was applied, and SNR = 10 dB.

Figure 12: 2-D Histogram of true input spectrum width versus the $R_0/R_1$ spectrum width estimate. Color scale represents frequency in log scale. The black line shows the mean per “column”, the solid white line shows the 1-1 line, and the dashed white line shows the standard deviation per “column”. Parameters: $\lambda = 10.5$ cm, PRT = 780 $\mu$s, $N = 50$, rectangular window was applied, and SNR = 10 dB.
Figure 13: 2-D Histogram of true input spectrum width versus the hybrid spectrum width estimate. Color scale represents frequency in log scale. The black line shows the mean per “column”, the solid white line shows the 1-1 line, and the dashed white line shows the standard deviation per “column”. Parameters: $\lambda = 10.5$ cm, PRT = 780 $\mu$s, $N = 50$, rectangular window was applied, and SNR = 20 dB.

Figure 14: 2-D Histogram of true input spectrum width versus the $R_0/R_1$ spectrum width estimate. Color scale represents frequency in log scale. The black line shows the mean per “column”, the solid white line shows the 1-1 line, and the dashed white line shows the standard deviation per “column”. Parameters: $\lambda = 10.5$ cm, PRT = 780 $\mu$s, $N = 50$, rectangular window was applied, and SNR = 20 dB.
Figure 15: 2-D Histogram of true input spectrum width versus the hybrid spectrum width estimate. Color scale represents frequency in log scale. The black line shows the mean per “column”, the solid white line shows the 1-1 line, and the dashed white line shows the standard deviation per “column”. Parameters: $\lambda = 10.5$ cm, PRT = 2240 $\mu$s, $N = 87$, rectangular window was applied, and SNR = 5 dB.

Figure 16: 2-D Histogram of true input spectrum width versus the $R_0/R_1$ spectrum width estimate. Color scale represents frequency in log scale. The black line shows the mean per “column”, the solid white line shows the 1-1 line, and the dashed white line shows the standard deviation per “column”. Parameters: $\lambda = 10.5$ cm, PRT = 2240 $\mu$s, $N = 87$, rectangular window was applied, and SNR = 5 dB.
Figure 17: 2-D Histogram of true input spectrum width versus the hybrid spectrum width estimate. Color scale represents frequency in log scale. The black line shows the mean per “column”, the solid white line shows the 1-1 line, and the dashed white line shows the standard deviation per “column”. Parameters: $\lambda = 10.5$ cm, PRT = 2240 $\mu$s, $N = 87$, rectangular window was applied, and SNR = 10 dB.

Figure 18: 2-D Histogram of true input spectrum width versus the $R0/R1$ spectrum width estimate. Color scale represents frequency in log scale. The black line shows the mean per “column”, the solid white line shows the 1-1 line, and the dashed white line shows the standard deviation per “column”. Parameters: $\lambda = 10.5$ cm, PRT = 2240 $\mu$s, $N = 87$, rectangular window was applied, and SNR = 10 dB.
Figure 19: 2-D Histogram of true input spectrum width versus the hybrid spectrum width estimate. Color scale represents frequency in log scale. The black line shows the mean per “column”, the solid white line shows the 1-1 line, and the dashed white line shows the standard deviation per “column”. Parameters: $\lambda = 10.5$ cm, $\text{PRT} = 2240 \mu s$, $N = 87$, rectangular window was applied, and $\text{SNR} = 20 \text{ dB}$.

Figure 20: 2-D Histogram of true input spectrum width versus the $R0/R1$ spectrum width estimate. Color scale represents frequency in log scale. The black line shows the mean per “column”, the solid white line shows the 1-1 line, and the dashed white line shows the standard deviation per “column”. Parameters: $\lambda = 10.5$ cm, $\text{PRT} = 2240 \mu s$, $N = 87$, rectangular window was applied, and $\text{SNR} = 20 \text{ dB}$. 
Figure 21: 2-D Histogram of true input spectrum width versus the hybrid spectrum width estimate. Color scale represents frequency in log scale. The black line shows the mean per “column”, the solid white line shows the 1-1 line, and the dashed white line shows the standard deviation per “column”. Parameters: $\lambda = 10.5 \text{ cm}$, PRT = 780 $\mu$s, $N = 88$, rectangular window was applied, and SNR = 5 dB.

Figure 22: 2-D Histogram of true input spectrum width versus the $R_0/R_1$ spectrum width estimate. Color scale represents frequency in log scale. The black line shows the mean per “column”, the solid white line shows the 1-1 line, and the dashed white line shows the standard deviation per “column”. Parameters: $\lambda = 10.5 \text{ cm}$, PRT = 780 $\mu$s, $N = 88$, rectangular window was applied, and SNR = 5 dB.
Figure 23: 2-D Histogram of true input spectrum width versus the hybrid spectrum width estimate. Color scale represents frequency in log scale. The black line shows the mean per “column”, the solid white line shows the 1-1 line, and the dashed white line shows the standard deviation per “column”. Parameters: $\lambda = 10.5 \text{ cm}$, $\text{PRT} = 780 \mu s$, $N = 88$, rectangular window was applied, and $\text{SNR} = 10 \text{ dB}$.

Figure 24: 2-D Histogram of true input spectrum width versus the $R_0/R_1$ spectrum width estimate. Color scale represents frequency in log scale. The black line shows the mean per “column”, the solid white line shows the 1-1 line, and the dashed white line shows the standard deviation per “column”. Parameters: $\lambda = 10.5 \text{ cm}$, $\text{PRT} = 780 \mu s$, $N = 88$, rectangular window was applied, and $\text{SNR} 10 \text{ dB}$. 
Figure 25: 2-D Histogram of true input spectrum width versus the hybrid spectrum width estimate. Color scale represents frequency in log scale. The black line shows the mean per “column”, the solid white line shows the 1-1 line, and the dashed white line shows the standard deviation per “column”. Parameters: \( \lambda = 10.5 \text{ cm} \), \( \text{PRT} = 780 \mu \text{s} \), \( N = 88 \), rectangular window was applied, and \( \text{SNR} = 20 \text{ dB} \).

Figure 26: 2-D Histogram of true input spectrum width versus the \( R_0 / R_1 \) spectrum width estimate. Color scale represents frequency in log scale. The black line shows the mean per “column”, the solid white line shows the 1-1 line, and the dashed white line shows the standard deviation per “column”. Parameters: \( \lambda = 10.5 \text{ cm} \), \( \text{PRT} = 780 \mu \text{s} \), \( N = 88 \), rectangular window was applied, and \( \text{SNR} = 20 \text{ dB} \).
Figure 27: 2-D Histogram of true input spectrum width versus the hybrid spectrum width estimate. Color scale represents frequency in log scale. The black line shows the mean per “column”, the solid white line shows the 1-1 line, and the dashed white line shows the standard deviation per “column”. Parameters: $\lambda = 10.5$ cm, PRT = 780 $\mu$s, $N = 278$, rectangular window was applied, and SNR = 5 dB.

Figure 28: 2-D Histogram of true input spectrum width versus the $R_0/R_1$ spectrum width estimate. Color scale represents frequency in log scale. The black line shows the mean per “column”, the solid white line shows the 1-1 line, and the dashed white line shows the standard deviation per “column”. Parameters: $\lambda = 10.5$ cm, PRT = 780 $\mu$s, $N = 278$, rectangular window was applied, and SNR = 5 dB.
Figure 29: 2-D Histogram of true input spectrum width versus the hybrid spectrum width estimate. Color scale represents frequency in log scale. The black line shows the mean per “column”, the solid white line shows the 1-1 line, and the dashed white line shows the standard deviation per “column”. Parameters: $\lambda = 10.5$ cm, PRT = 780 $\mu$s, $N = 278$, rectangular window was applied, and SNR = 10 dB.

Figure 30: 2-D Histogram of true input spectrum width versus the $R_0/R_1$ spectrum width estimate. Color scale represents frequency in log scale. The black line shows the mean per “column”, the solid white line shows the 1-1 line, and the dashed white line shows the standard deviation per “column”. Parameters: $\lambda = 10.5$ cm, PRT = 780 $\mu$s, $N = 278$, rectangular window was applied, and SNR = 10 dB.
Figure 31: 2-D Histogram of true input spectrum width versus the hybrid spectrum width estimate. Color scale represents frequency in log scale. The black line shows the mean per “column”, the solid white line shows the 1-1 line, and the dashed white line shows the standard deviation per “column”. Parameters: $\lambda = 10.5$ cm, PRT = 780 $\mu$s, $N = 278$, rectangular window was applied, and SNR = 20 dB.

Figure 32: 2-D Histogram of true input spectrum width versus the $R_0/R_1$ spectrum width estimate. Color scale represents frequency in log scale. The black line shows the mean per “column”, the solid white line shows the 1-1 line, and the dashed white line shows the standard deviation per “column”. Parameters: $\lambda = 10.5$ cm, PRT = 780 $\mu$s, $N = 278$, rectangular window was applied, and SNR = 20 dB.
Figure 33: Mean (top panel) and standard deviation (bottom panel) of the hybrid spectrum width estimator. The x-axis corresponds to the true input spectrum width, and the colors to different SNRs. Parameters: $\lambda = 10.5$ cm, PRT = 780 $\mu$s, $N = 37$, and the rectangular window was applied.
Figure 34: Mean (top panel) and standard deviation (bottom panel) of the hybrid spectrum width estimator. The x-axis corresponds to the true input spectrum width, and the colors to different SNRs. Parameters: $\lambda = 10.5$ cm, PRT = 780 $\mu$s, $N = 37$, and the rectangular window was applied.
Figure 35: Mean (top panel) and standard deviation (bottom panel) of the hybrid spectrum width estimator. The x-axis corresponds to the true input spectrum width, and the colors to different SNRs. Parameters: $\lambda = 10.5 \text{ cm}$, $\text{PRT} = 780 \mu\text{s}$, $N = 50$, and the rectangular window was applied.
Figure 36: Mean (top panel) and standard deviation (bottom panel) of the hybrid spectrum width estimator. The x-axis corresponds to the true input spectrum width, and the colors to different SNRs. Parameters: $\lambda = 10.5$ cm, PRT = 780 $\mu$s, $N = 50$, and the rectangular window was applied.
Figure 37: Mean (top panel) and standard deviation (bottom panel) of the hybrid spectrum width estimator. The x-axis corresponds to the true input spectrum width, and the colors to different SNRs. Parameters: $\lambda = 10.5$ cm, PRT = 2240 $\mu$s, $N = 87$, and the rectangular window was applied.
Figure 38: Mean (top panel) and standard deviation (bottom panel) of the hybrid spectrum width estimator. The x-axis corresponds to the true input spectrum width, and the colors to different SNRs. Parameters: $\lambda = 10.5$ cm, PRT $= 2240 \, \mu s$, $N = 87$, and the rectangular window was applied.
Figure 39: Mean (top panel) and standard deviation (bottom panel) of the hybrid spectrum width estimator. The x-axis corresponds to the true input spectrum width, and the colors to different SNRs. Parameters: $\lambda = 10.5$ cm, PRT = 780 $\mu$s, $N = 88$, and the rectangular window was applied.
Figure 40: Mean (top panel) and standard deviation (bottom panel) of the hybrid spectrum width estimator. The x-axis corresponds to the true input spectrum width, and the colors to different SNRs. Parameters: $\lambda = 10.5 \text{ cm}$, PRT $= 780 \text{ ms}$, $N = 88$, and the rectangular window was applied.
Figure 41: Mean (top panel) and standard deviation (bottom panel) of the hybrid spectrum width estimator. The x-axis corresponds to the true input spectrum width, and the colors to different SNRs. Parameters: $\lambda = 10.5 \text{ cm}$, PRT $= 780 \mu s$, $N = 278$, and the rectangular window was applied.
Figure 42: Mean (top panel) and standard deviation (bottom panel) of the hybrid spectrum width estimator. The x-axis corresponds to the true input spectrum width, and the colors to different SNRs. Parameters: $\lambda = 10.5$ cm, PRT = 780 $\mu$s, $N = 278$, and the rectangular window was applied.
Table 1: List of cases given in this report

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*VCP 22 was a test VCP that, for our purposes, is the same as VCP 21.

b. Case Studies

Seven case studies, listed in table 1, are shown in figures 43-114. For each case, plots of long range reflectivity (e.g. figure 43), short range reflectivity (e.g. 44), velocity (e.g. 45), rectangular windowed hybrid spectrum width (e.g. 46), rectangular windowed $R_0/R_1$ spectrum width (e.g. 47), von Hann windowed hybrid spectrum width (e.g. 48), and von Hann windowed $R_0/R_1$ spectrum width (e.g. 49). All of these plots, with the exception of the long range reflectivity, are from the short PRT data and have not been range un-folded. For these plots, areas of severe overlaid echo or severe clutter contamination have been censored purple. In some cases, plots are shown from the output of the NEXRAD turbulence detection algorithm using the hybrid spectrum width (e.g. 50) and using the $R_0/R_1$ spectrum width (e.g. 51). Also, in some cases, plots that include the comparison of the Gaussian fits using the two different spectrum width estimators are shown (e.g. 52-58). These spectral plots reflect cases where the two spectrum widths were visibly different and in general occurred in places of low SNR, narrow spectrum width, or non-Gaussian spectra. In the latter cases (e.g. 72) it is interesting to note that the hybrid estimator generally locks on to the strongest 20 or so dB signal.

The hybrid estimator clearly outperforms the $R_0/R_1$ estimator in areas with low SNR where that latter estimator very clearly suffers from a negative bias. In areas of smaller spectrum width, the hybrid estimator can be seen to be smoother. Also very evident is the larger regions of coverage of usable spectrum widths from the hybrid estimator versus the $R_0/R_1$ estimator.
Figure 43: PPI of long range reflectivity from Case 1.

Figure 44: PPI of short range reflectivity from Case 1.
Figure 45: PPI of velocity from Case 1.
Figure 46: PPI of hybrid spectrum width from Case 1. Rectangular window was applied.

Figure 47: PPI of $R_0/R_1$ spectrum width from Case 1. Rectangular window was applied.
Figure 48: PPI of hybrid spectrum width from Case 1. von Hann window was applied.

Figure 49: PPI of $R_0/R_1$ spectrum width from Case 1. von Hann window was applied.
Figure 50: PPI of NEXRAD turbulence detection algorithm output from the hybrid spectrum width from Case 1. Rectangular window was applied.

Figure 51: PPI of NEXRAD turbulence detection algorithm output from the $R0/R1$ spectrum width from Case 1. Rectangular window was applied.
Figure 52: Analysis plot of a gate from case 1. The top panel is an “A-scope” plot (power as a function of range). The next panel contains the empirical spectrum (light red), Gaussian fit line based on estimated power, velocity, and hybrid spectrum width (green), and Gaussian fit line based on estimated power, velocity, and $R_0/R_1$ spectrum width (orange). If either of the Gaussian fits is not visible, that means the corresponding spectrum width estimator is 0. A good fit indicates a good spectrum width estimate. The third panel shows power as a function of time. And the bottom panel shows phase as a function of time.
Figure 53: Analysis plot of a gate from case 1. The top panel is an “A-scope” plot (power as a function of range). The next panel contains the empirical spectrum (light red), Gaussian fit line based on estimated power, velocity, and hybrid spectrum width (green), and Gaussian fit line based on estimated power, velocity, and $R_0/R_1$ spectrum width (orange). If either of the Gaussian fits is not visible, that means the corresponding spectrum width estimator is 0. A good fit indicates a good spectrum width estimate. The third panel shows power as a function of time. And the bottom panel shows phase as a function of time.
Figure 54: Analysis plot of a gate from case 1. The top panel is an “A-scope” plot (power as a function of range). The next panel contains the empirical spectrum (light red), Gaussian fit line based on estimated power, velocity, and hybrid spectrum width (green), and Gaussian fit line based on estimated power, velocity, and $R_0/R_1$ spectrum width (orange). If either of the Gaussian fits is not visible, that means the corresponding spectrum width estimator is 0. A good fit indicates a good spectrum width estimate. The third panel shows power as a function of time. And the bottom panel shows phase as a function of time.
Figure 55: Analysis plot of a gate from case 1. The top panel is an “A-scope” plot (power as a function of range). The next panel contains the empirical spectrum (light red), Gaussian fit line based on estimated power, velocity, and hybrid spectrum width (green), and Gaussian fit line based on estimated power, velocity, and \( R_0/R_1 \) spectrum width (orange). If either of the Gaussian fits is not visible, that means the corresponding spectrum width estimator is 0. A good fit indicates a good spectrum width estimate. The third panel shows power as a function of time. And the bottom panel shows phase as a function of time.
Figure 56: Analysis plot of a gate from case 1. The top panel is an “A-scope” plot (power as a function of range). The next panel contains the empirical spectrum (light red), Gaussian fit line based on estimated power, velocity, and hybrid spectrum width (green), and Gaussian fit line based on estimated power, velocity, and $R_0/R_1$ spectrum width (orange). If either of the Gaussian fits is not visible, that means the corresponding spectrum width estimator is 0. A good fit indicates a good spectrum width estimate. The third panel shows power as a function of time. And the bottom panel shows phase as a function of time.
Figure 57: Analysis plot of a gate from case 1. The top panel is an “A-scope” plot (power as a function of range). The next panel contains the empirical spectrum (light red), Gaussian fit line based on estimated power, velocity, and hybrid spectrum width (green), and Gaussian fit line based on estimated power, velocity, and $R_0/R_1$ spectrum width (orange). If either of the Gaussian fits is not visible, that means the corresponding spectrum width estimator is 0. A good fit indicates a good spectrum width estimate. The third panel shows power as a function of time. And the bottom panel shows phase as a function of time.
Figure 58: Analysis plot of a gate from case 1. The top panel is an “A-scope” plot (power as a function of range). The next panel contains the empirical spectrum (light red), Gaussian fit line based on estimated power, velocity, and hybrid spectrum width (green), and Gaussian fit line based on estimated power, velocity, and $R_0/R_1$ spectrum width (orange). If either of the Gaussian fits is not visible, that means the corresponding spectrum width estimator is 0. A good fit indicates a good spectrum width estimate. The third panel shows power as a function of time. And the bottom panel shows phase as a function of time.
Figure 59: PPI of long range reflectivity from Case 2.

Figure 60: PPI of short range reflectivity from Case 2.
Figure 61: PPI of velocity from Case 2.
Figure 62: PPI of hybrid spectrum width from Case 2. Rectangular window was applied.

Figure 63: PPI of $R_0/R_1$ spectrum width from Case 2. Rectangular window was applied.
Figure 64: PPI of hybrid spectrum width from Case 2. von Hann window was applied.

Figure 65: PPI of $R_0/R_1$ spectrum width from Case 2. von Hann window was applied.
Figure 66: PPI of NEXRAD turbulence detection algorithm output from the hybrid spectrum width from Case 2. Rectangular window was applied.

Figure 67: PPI of NEXRAD turbulence detection algorithm output from the $R_0/R_1$ spectrum width from Case 2. Rectangular window was applied.
Figure 68: Analysis plot of a gate from case 2. The top panel is an “A-scope” plot (power as a function of range). The next panel contains the empirical spectrum (light red), Gaussian fit line based on estimated power, velocity, and hybrid spectrum width (green), and Gaussian fit line based on estimated power, velocity, and $R_0/R_1$ spectrum width (orange). If either of the Gaussian fits is not visible, that means the corresponding spectrum width estimator is 0. A good fit indicates a good spectrum width estimate. The third panel shows power as a function of time. And the bottom panel shows phase as a function of time.
Figure 69: Analysis plot of a gate from case 2. The top panel is an “A-scope” plot (power as a function of range). The next panel contains the empirical spectrum (light red), Gaussian fit line based on estimated power, velocity, and hybrid spectrum width (green), and Gaussian fit line based on estimated power, velocity, and $R_0/R_1$ spectrum width (orange). If either of the Gaussian fits is not visible, that means the corresponding spectrum width estimator is 0. A good fit indicates a good spectrum width estimate. The third panel shows power as a function of time. And the bottom panel shows phase as a function of time.
Figure 70: Analysis plot of a gate from case 2. The top panel is an “A-scope” plot (power as a function of range). The next panel contains the empirical spectrum (light red), Gaussian fit line based on estimated power, velocity, and hybrid spectrum width (green), and Gaussian fit line based on estimated power, velocity, and $R_0/R_1$ spectrum width (orange). If either of the Gaussian fits is not visible, that means the corresponding spectrum width estimator is 0. A good fit indicates a good spectrum width estimate. The third panel shows power as a function of time. And the bottom panel shows phase as a function of time.
Figure 71: Analysis plot of a gate from case 2. The top panel is an “A-scope” plot (power as a function of range). The next panel contains the empirical spectrum (light red), Gaussian fit line based on estimated power, velocity, and hybrid spectrum width (green), and Gaussian fit line based on estimated power, velocity, and $R_0/R_1$ spectrum width (orange). If either of the Gaussian fits is not visible, that means the corresponding spectrum width estimator is 0. A good fit indicates a good spectrum width estimate. The third panel shows power as a function of time. And the bottom panel shows phase as a function of time.
Figure 72: Analysis plot of a gate from case 2. The top panel is an “A-scope” plot (power as a function of range). The next panel contains the empirical spectrum (light red), Gaussian fit line based on estimated power, velocity, and hybrid spectrum width (green), and Gaussian fit line based on estimated power, velocity, and $R_0/R_1$ spectrum width (orange). If either of the Gaussian fits is not visible, that means the corresponding spectrum width estimator is 0. A good fit indicates a good spectrum width estimate. The third panel shows power as a function of time. And the bottom panel shows phase as a function of time.
Figure 73: PPI of long range reflectivity from Case 3.

Figure 74: PPI of short range reflectivity from Case 3.
Figure 75: PPI of velocity from Case 3.
Figure 76: PPI of hybrid spectrum width from Case 3. Rectangular window was applied.

Figure 77: PPI of $R_0/R_1$ spectrum width from Case 3. Rectangular window was applied.
Figure 78: PPI of hybrid spectrum width from Case 3. von Hann window was applied.

Figure 79: PPI of $R_0/R_1$ spectrum width from Case 3. von Hann window was applied.
Figure 80: PPI of long range reflectivity from Case 4.

Figure 81: PPI of short range reflectivity from Case 4.
Figure 82: PPI of velocity from Case 4.
Figure 83: PPI of hybrid spectrum width from Case 4. Rectangular window was applied.

Figure 84: PPI of $R_0/R_1$ spectrum width from Case 4. Rectangular window was applied.
Figure 85: PPI of hybrid spectrum width from Case 4. von Hann window was applied.

Figure 86: PPI of $R_0/R_1$ spectrum width from Case 4. von Hann window was applied.
Figure 87: Analysis plot of a gate from case 4. The top panel is an “A-scope” plot (power as a function of range). The next panel contains the empirical spectrum (light red), Gaussian fit line based on estimated power, velocity, and hybrid spectrum width (green), and Gaussian fit line based on estimated power, velocity, and $R_0/R_1$ spectrum width (orange). If either of the Gaussian fits is not visible, that means the corresponding spectrum width estimator is 0. A good fit indicates a good spectrum width estimate. The third panel shows power as a function of time. And the bottom panel shows phase as a function of time.
Figure 88: Analysis plot of a gate from case 4. The top panel is an “A-scope” plot (power as a function of range). The next panel contains the empirical spectrum (light red), Gaussian fit line based on estimated power, velocity, and hybrid spectrum width (green), and Gaussian fit line based on estimated power, velocity, and $R_0/R_1$ spectrum width (orange). If either of the Gaussian fits is not visible, that means the corresponding spectrum width estimator is 0. A good fit indicates a good spectrum width estimate. The third panel shows power as a function of time. And the bottom panel shows phase as a function of time.
Figure 89: Analysis plot of a gate from case 4. The top panel is an “A-scope” plot (power as a function of range). The next panel contains the empirical spectrum (light red), Gaussian fit line based on estimated power, velocity, and hybrid spectrum width (green), and Gaussian fit line based on estimated power, velocity, and $R_0/R_1$ spectrum width (orange). If either of the Gaussian fits is not visible, that means the corresponding spectrum width estimator is 0. A good fit indicates a good spectrum width estimate. The third panel shows power as a function of time. And the bottom panel shows phase as a function of time.
Figure 90: Analysis plot of a gate from case 4. The top panel is an “A-scope” plot (power as a function of range). The next panel contains the empirical spectrum (light red), Gaussian fit line based on estimated power, velocity, and hybrid spectrum width (green), and Gaussian fit line based on estimated power, velocity, and $R_0/R_1$ spectrum width (orange). If either of the Gaussian fits is not visible, that means the corresponding spectrum width estimator is 0. A good fit indicates a good spectrum width estimate. The third panel shows power as a function of time. And the bottom panel shows phase as a function of time.
Figure 91: Analysis plot of a gate from case 4. The top panel is an “A-scope” plot (power as a function of range). The next panel contains the empirical spectrum (light red), Gaussian fit line based on estimated power, velocity, and hybrid spectrum width (green), and Gaussian fit line based on estimated power, velocity, and \( R_0/R_1 \) spectrum width (orange). If either of the Gaussian fits is not visible, that means the corresponding spectrum width estimator is 0. A good fit indicates a good spectrum width estimate. The third panel shows power as a function of time. And the bottom panel shows phase as a function of time.
Figure 92: Analysis plot of a gate from case 4. The top panel is an “A-scope” plot (power as a function of range). The next panel contains the empirical spectrum (light red), Gaussian fit line based on estimated power, velocity, and hybrid spectrum width (green), and Gaussian fit line based on estimated power, velocity, and \( R_0/R_1 \) spectrum width (orange). If either of the Gaussian fits is not visible, that means the corresponding spectrum width estimator is 0. A good fit indicates a good spectrum width estimate. The third panel shows power as a function of time. And the bottom panel shows phase as a function of time.
Figure 93: Analysis plot of a gate from case 4. The top panel is an “A-scope” plot (power as a function of range). The next panel contains the empirical spectrum (light red), Gaussian fit line based on estimated power, velocity, and hybrid spectrum width (green), and Gaussian fit line based on estimated power, velocity, and $R0/R1$ spectrum width (orange). If either of the Gaussian fits is not visible, that means the corresponding spectrum width estimator is 0. A good fit indicates a good spectrum width estimate. The third panel shows power as a function of time. And the bottom panel shows phase as a function of time.
Figure 94: PPI of long range reflectivity from Case 5.

Figure 95: PPI of short range reflectivity from Case 5.
Figure 96: PPI of velocity from Case 5.
Figure 97: PPI of hybrid spectrum width from Case 5. Rectangular window was applied.

Figure 98: PPI of $R_0/R_1$ spectrum width from Case 5. Rectangular window was applied.
Figure 99: PPI of hybrid spectrum width from Case 5. von Hann window was applied.

Figure 100: PPI of $R_0/R_1$ spectrum width from Case 5. von Hann window was applied.
Figure 102: PPI of short reflectivity from Case 6.
Figure 103: PPI of velocity from Case 6.
Figure 104: PPI of hybrid spectrum width from Case 6. Rectangular window was applied.

Figure 105: PPI of $R_0/R_1$ spectrum width from Case 6. Rectangular window was applied.
Figure 106: PPI of hybrid spectrum width from Case 6. von Hann window was applied.

Figure 107: PPI of $R_0/R_1$ spectrum width from Case 6. von Hann window was applied.
Figure 108: PPI of long range reflectivity from Case 7.

Figure 109: PPI of short range reflectivity from Case 7.
Figure 110: PPI of velocity from Case 7.
Figure 111: PPI of hybrid spectrum width from Case 7. Rectangular window was applied.

Figure 112: PPI of $R0/R1$ spectrum width from Case 7. Rectangular window was applied.
Figure 113: PPI of hybrid spectrum width from Case 7. von Hann window was applied.

Figure 114: PPI of $R_0/R_1$ spectrum width from Case 7. von Hann window was applied.
5. Conclusions

A hybrid approach that combines different spectrum width estimators shows great improvement in overall performance over $R_0/R_1$. While knowledge of the true spectrum width would allow determining the ideal estimator, an alternative that uses spectrum width estimates to try to decide the general magnitude of the true spectrum width was proposed as a practical alternative. The hybrid estimator presented in this report was shown to outperform the $R_0/R_1$ spectrum width estimator in most cases, and at the least did no worse than the $R_0/R_1$ estimator. Computationally, the hybrid algorithm is fairly modest, requiring fewer operations than the FFT needed by a spectral technique.

Future work could include improving the performance by using other spectrum width estimators such as spectral or maximum likelihood methods. This hybrid approach also needs to be adapted for staggered PRT.

6. Acknowledgment

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References


Meymaris, G., J. K. Williams, and J. C. Hubbert: 2009, Performance of a proposed hybrid spectrum width estimator for the nexrad orda. AMS 25th International Conference on Interactive Information and Processing Systems for Meteorology, Oceanography and Hydrology, Phoenix, AZ.

HYBRID SPECTRUM WIDTH ESTIMATOR
Updated 2/26/2010

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Inputs | Description
---|---
\( V \) | Complex (windowed or non-windowed) time series (raw I & Q) of length \( N \), \((0, \ldots, N-1)\)
\( N \) | The length of the cohered time series \( V \)
\( h \) | The windowing function used previously on \( V \), of length \( N \), \((0, \ldots, N-1)\). If no window was previously used, this should be all 1’s.
\( C \) | 1 if the ground clutter filter was applied, otherwise 0.
\( P_N \) | Noise Power (in same units as the power of \( V \))
\( T_S \) | Pulse Repetition time in seconds
\( \lambda \) | Wavelength of the radar in meters (i.e. \( \sim 0.105 \) meters for WSR-88D)

Table 1: Inputs

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Table 2: Threshold Table

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<th>Parameter</th>
<th>Description</th>
<th>Value</th>
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<tr>
<td>( F_L )</td>
<td>Adjustment factor for the low cutoff</td>
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Table 3: Parameter Table

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<th>Description</th>
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<td>( w )</td>
<td>spectrum width</td>
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Table 4: Outputs
Table 5: Intermediate Variables

1 Assumptions

1. The I&Q are cohered to the desired trip.
2. Ground clutter has been filtered.
3. The pulse repetition interval is constant for the entire gate.
4. The window function is never identically 0. (This assumption can be relaxed without much additional work.)
5. The mean power of $V$ is greater than $P_N$.
6. The auto-correlation function used is linear not circular (see section 5).
7. Censoring (e.g., signal-to-noise ratio or reflectivity) is handled by elsewhere.

2 Notes

1. Table 2, the threshold table, has been carefully crafted so that the missing value, $-1$, needs no special treatment in the code. In particular, if the table returns $-1$ for a threshold, then the corresponding inequality check in 7 will be false for the low cutoff check and true for the high cutoff check, which are the desired behaviors. To force the interpolated thresholds from the table to never interpolate $-1$, the missing value, with a real threshold, the transitions were designed to occur on adjacent integers. For example, for the high cutoff, $N = 24$ has the missing value while $N = 25$ does not. For the low cutoff, the transition occurs from $N = 58$ to $N = 59$.

2. For SZ phase-coded time, this technique should only be used in regions of no overlay. See assumption 1. In regions of overlay, the default SZ spectrum width should be used.

3 Inputs

The inputs are listed in table 1. There is also a table containing the thresholds for determining whether the spectrum width is probably small, medium, or large (see table 2). Finally, there are a few adjustable parameters shown in table 3.

4 Outputs

The only output is $w$, the spectrum width. See table 4. Intermediate variables are shown in table 5.
5 Procedures

First, define a function that will be used within the algorithm more than once.

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

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

where $v$ is a time-series. This is the linear autocorrelation. It is not equivalent to computing the autocorrelation from the spectrum, even if it is windowed. This is especially true for larger lags ($i \geq 2$). The circular version is a biased estimator of the signal's true autocorrelation function since it assumes that the frequencies comprising the time-series are periodic over the length of the time-series. This is almost always not the case. If the spectrum must be used to compute the autocorrelation lags, it is possible to compute the linear autocorrelation by zero-padding the time-series before computing the spectrum, and then scaling the computed autocorrelation values appropriately.

6 Algorithm

1. **Un-window the time-series, if the clutter filter was not applied.**

   **Inputs** $V, C, h$
   
   **Outputs** $V_u$
   
   If $C = 0$, un-window by
   
   $$V_u[i] = V[i]/h[i]$$
   
   for $i = 0, \ldots, N-1$. If $C = 1$, then set
   
   $$V_u[i] = V[i]$$

2. **Calculate the auto-correlation function to 4 lags**

   **Inputs** $V_u, C$
   
   **Outputs** $r$
   
   If $C = 0$, for $i = 0, \ldots, 3$. If $C = 1$,
   
   $$r[i] = |R_i[V_u]/R_i[h]|$$
   
   for $i = 0, \ldots, 3$.

3. **Calculate normalized $R_0/R_1$ estimator**

   **Inputs** $r, P_N$
   
   **Outputs** $w_{01}$
   
   If $r[1] \geq r[0] - P_N$ then $w_{01} = 0$. Otherwise
   
   $$w_{01} = \frac{\sqrt{2}}{\pi} \sqrt{\ln \left( \frac{r[0] - P_N}{r[1]} \right)}$$

4. **Calculate normalized $R_1/R_2$ estimator**

   **Inputs** $r$
   
   **Outputs** $w_{12}$
If \( r[2] \geq r[1] \) then \( w_{12} = 0 \). Otherwise

\[
 w_{12} = \frac{\sqrt{2}}{\pi \sqrt{3}} \sqrt{\ln \left( \frac{r[1]}{r[2]} \right)}
\]

5. **Calculate normalized \( R_1/R_3 \) estimator**

**Inputs** \( r \)

**Outputs** \( w_{13} \)

If \( r[3] \geq r[1] \) then \( w_{13} = 0 \). Otherwise (written to show the general formula)

\[
 w_{13} = \frac{\sqrt{2}}{\pi \sqrt{3^2 - 1^2}} \sqrt{\ln \left( \frac{r[1]}{r[3]} \right)}
\]

6. **Calculate normalized \( R_0/R_1/R_2 \) estimator**

**Inputs** \( r \)

**Outputs** \( w_{012} \)

The idea is that if we take the ln of the autocorrelation, a Gaussian becomes a concave down quadratic. The 0\(^{th}\)-order term corresponds to the power, and the 2\(^{nd}\)-order term is related to the width:

\[
 w_{012} = \frac{1}{\pi} \sqrt{-2 \min (0, -0.1923 \ln (r[0] - P_N) - 0.0769 \ln (r[1]) + 0.2692 \ln (r[2]))}
\]

7. **Determine what regime (small, medium, and large)**

**Inputs** \( w_{01}, w_{012}, w_{13}, N, F_H, F_L \)

**Outputs** \( M \)

First lookup the surrounding values in the threshold table for \( N \). In other words, let \( N_1 \) be the largest value smaller or equal to \( N \), and let \( L_1 \), and \( U_1 \) be the corresponding lower and upper thresholds, respectively. Let \( N_2 \) be the smallest value larger or equal to \( N \), and let \( L_2 \), and \( U_2 \) be the corresponding lower and upper thresholds, respectively.

If \( N_1 = N_2 \) then let \( L = L_1 \) and \( U = U_1 \). Otherwise let \( U = (1 - \alpha) U_1 + \alpha U_2 \) and \( L = (1 - \alpha) L_1 + \alpha L_2 \) where \( \alpha = (N - N_1) / (N_2 - N_1) \). Then set \( M = 2 \) if \( (w_{01} + w_{012})/2 \geq F_H U \). Otherwise, set \( M = 0 \) if \( w_{13} < F_L L \). Otherwise, set \( M = 1 \).

8. **Determine final spectrum width**

**Inputs** \( w_{01}, w_{12}, w_{13}, T_a, \lambda, M \)

**Outputs** \( w \)

Calculate the Nyquist velocity: \( v_a = \lambda / (4T_a) \). Then set

\[
 w = \begin{cases} 
 v_a w_{13} & M = 0 \\
 v_a w_{12} & M = 1 \\
 v_a w_{01} & M = 2 
\end{cases}
\]

7 **Acknowledgment**

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NCAR 2009 NEXRAD Data Quality Report

Clutter Mitigation Decision (CMD)
Investigation of improvements to the single-polarization algorithm

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Clutter Mitigation Decision (CMD)
Investigation of improvements to the single-polarization algorithm

1 Introduction

The single-polarization version of CMD (4.1) was deployed on the NEXRAD network in early 2009 as part of build 11. It has proved to be quite robust, and provides good performance in a wide range of conditions.

However, as the users gained experience with CMD, they noted some problem areas of concern. This report highlights some of these problems, and proposes possible solutions to them.

The problems which have been noted by the users are:

- occasional missed detections of clutter, which leaves some gates unfiltered when they contain clutter.

- occasional false detections of clutter, which causes the filter to be applied where it should not be. This problem is amplified by the manner in which the dynamic clutter maps are handled in the ORDA, causing the error to be spread from a single gate to surrounding gates.

- occasional multi-modal spectra, thought to be caused by surface transportation targets such as cars and trucks.

Although the problems tend to be isolated to just a few gates in a scan, the visual result can be disconcerting to the user, because the errors show up clearly as speckle in an otherwise smoothly-varying image. Developing solutions to the problems is a high priority for the data quality team.

In addition to investigating these problem cases, NCAR also researched the possible use of a polynomial regression filter, particularly for use in staggered-PRT operations.
2 Missed detections and false detections

2.1 Overview

The following figure shows an example scan with **missed detections** and **false detections**. This is the familiar snow-storm case at KFTG, on 10/26/2006. The yellow ellipse encloses a region with reflectivity speckle, caused by the fact that CMD did missed gates which have clutter. On the other hand, the white ellipse highlights gates, along the 0-isodop, which were incorrectly identified as having clutter. When the filter is applied to these gates, part of the weather signal is incorrectly removed.

![Figure 1: Problems with CMD version 4.1](image)

Yellow ellipse – missed detections
White ellipse – false detections
The following figure shows the result of false detections from an operational NEXRAD site. This is the velocity field. Incorrect application of the filter has biased the velocity away from zero. The relatively large patches of incorrect velocity are the result of the procedure by which the dynamic clutter map, as determined by CMD on the long-range tilt, is applied to the Doppler tilt. This procedure exaggerates the problem, taking a single false detection and spreading its effect to surrounding gates.

Figure 2: Operational NEXRAD velocity case showing the result of false detections

2.2 Incremental improvements to CMD

The following techniques offer relatively straight-forward improvement to CMD, with good results:

- Improving the CMD flag gap infill filter
- Adding a CMD flag speckle filter
- Computing the off-zero SNR (OZSNR), and using a lower CMD threshold for those areas where OZSNR > 6 dB

2.3 Improving the CMD flag gap (infill) filter – reducing missed detections

The CMD flag gap filter is intended to fill in gaps between correct clutter detections, on the assumption that if a gate is surrounded by clutter gates, it does not make sense to leave that gate unfiltered. In other words, the infill filter is intended to address the problem of missed detections.

The implementation of the existing infill filter in CMD version 4.1 has some flaws and leaves some gaps where they should logically have been filled in.
Figure 3: Schematic of CMD version 4.1 infill filter

The figure above shows a schematic view of the version 4.1 gap infill filter. The filter is designed to fill in gaps of the type shown above. Specifically, it will fill in gaps of the following type:

1 un-flagged gate between adjacent flagged gates;
2 un-flagged gates with at least 2 flagged gates on either side;
3 un-flagged gates with at least 3 flagged gates on either side.

However, there are circumstances in which this filter does not perform well. As an example from KEMX, the following figures show the CMD flag field, before and after applying the version 4.1 gap filter. It is clear that some gates are left un-flagged when realistically they should be flagged.

Figure 4: KEMX example: CMD flag field before applying the version 4.1 gap infill filter
To solve this problem, a new gap filter is proposed. The following figure shows schematically how this filter is set up.

The filter works as follows:

- One each side of the gate in question, construct a computational kernel with weights decreasing with distance from the gate.
- In the forward direction, if the CMD flag is set, sum up (weights * CMD val) at that gate
- In the reverse direction, if the CMD flag is set, sum up (weights * CMD val) at that gate
- IF forward_weight >= threshold AND reverse_weight >= threshold, set CMD_flag at center gate to TRUE
- IF not, set CMD_flag at center gate to FALSE
From testing, it was determined that a threshold value of 0.35 seems to work well.

2.4 Adding a CMD flag speckle filter – reducing false detections

In CMD version 4.1, the problem of false detections is (supposed to be) handled by the application of the NEXRAD reflectivity spike filter. The problem with this approach is that, in the ORDA, the spike filter is applied well downstream of CMD, after a series of intermediate steps in which the flag field becomes spread out from a single gate into surrounding gates. Therefore, the NEXRAD spike filter does not work as it should.

As an alternative, a speckle filter is proposed specifically for CMD, and is applied in the CMD algorithm itself. The figure below shows the speckle filter schematically.

![Schematic of speckle filter](image)

The filter works as follows:

- Consider speckle to be CMD flags over 1, 2 or 3 consecutive gates, surrounded by unflagged gates.
- In these cases, use a higher CMD threshold to determine whether the CMD flag should be set at those gates.
- If the CMD value is less than this higher value, set the CMD flag to false to remove the speckle.

During testing, it was found that the following values work well:

<table>
<thead>
<tr>
<th>N gates</th>
<th>Modified Threshold</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.75</td>
</tr>
<tr>
<td>2</td>
<td>0.65</td>
</tr>
<tr>
<td>3</td>
<td>0.55</td>
</tr>
</tbody>
</table>

By way of comparison, the normal CMD threshold is 0.50.

2.5 Effects of applying the new gap and speckle filters

The figures below compare the effects of applying the original filter, as opposed to both the new gap filter and the speckle filter, to a KFTG case.
Figure 8: KFTG example – no infill filter

Figure 9: KFTG example – version 4.1 infill filter
As can be seen by comparing the above figure, the new filters perform better with respect to (a) filling in the missing detections and (b) removing isolated false detections.

### 2.6 Removing clutter speckle in weather regions – use of the off-zero SNR field

#### 2.6.1 Overview

Sometimes CMD misses detections in regions of combined weather and clutter. If significant weather signal power is present in regions having radial velocity well away from 0 m/s, it is safe to apply the filter even if clutter is not present.

If in such regions we can use a reduced CMD threshold, the probability of missed detections is reduced.

#### 2.6.2 Method

In the spectral domain, we apply a generous notch around 0 m/s, with a width of say 6 m/s (half-width 3 m/s). This will remove any signal close to DC.

Using the power remaining after the notch is applied, we compute the signal to noise ratio. We call this the Off-Zero Signal-to-Noise Ratio (OZSNR).

If the OZSNR exceeds 6dB, we can be confident that there is weather (with significant velocity) mixed with the clutter. We can therefore reduce the CMD flag threshold from 0.5 to 0.25, which will reduce the probability of missed detections, thereby reducing speckle in the regions of weather with non-zero velocity.
2.6.3 Results

The following figures illustrate the OZSNR technique on the KFTG snow case.

Figure 11: Reflectivity with speckle

Figure 12: Off-zero-velocity SNR, computed by applying a wide notch of 6 m/s
For gates where the off-zero SNR > 6 dB, use a lower CMD threshold of 0.25. This reduces the number of missed detections – see following figure.

![Figure 13: Reflectivity with speckle removed](image)

### 2.7 Summary – proposed incremental CMD improvements

The following are proposed as incremental improvements to the version 4.1 single-polarization CMD algorithm:

- Improved gap filter for CMD flag.
- New speckle filter for CMD flag.
- Use of off-zero-velocity SNR to lower the CMD threshold in areas of weather.
3 Potential improvements which require further research

The following ideas were implemented and tested, with a view to improving the performance of the single-polarization version of CMD.

In some cases, it was shown that these do not significantly improve CMD. In others, further testing is required to determine whether they can be used in practice.

3.1 Two-dimensional TDBZ and SPIN

3.1.1 Overview

In the predecessor to CMD, the Radar Echo Classifier (REC), the TDBZ and SPIN feature fields are computed in 2 dimensions – i.e. both in range and azimuth. This makes them somewhat more robust than in CMD, where they are computed in range only.

One option is to try to recover the 2-D nature of TDBZ and SPIN, by dividing the dwell into parts (say thirds), computing the reflectivity for each third, and then computing the 2-D versions of TDBZ and SPIN.

This was coded and tested using the familiar KFTG snow case.

3.1.2 Results

It was found that this technique does not improve the CMD performance. The reason is that when reflectivity is computed on a partial dwell, the estimator is more noisy, because fewer samples are used. This in turn makes TDBZ and SPIN more noisy.

The following figures show the DBZ field and TDBZ from the full dwell, and from the partial dwell. You can see the increased noise in the DBZ field from the partial dwells. It is also clear that the TDBZ field has increased variability, making it less suitable as a feature field.
Figure 14: DBZ from full dwell

Figure 15: DBZ from 1/3 dwell.
Note the increased speckle in the region of the ellipse.
Figure 16: TDBZ from full dwell

Figure 17: TDBZ from 1/3 dwell. Note increased variability.
3.2 CPA computed on partial dwell

3.2.1 Overview

Some gates with low CPA have varying phase for only part of the time series. It is considered likely that this is caused by different and distinct clutter targets coming into view and disappearing from view as the radar scans.

For example, the figure below shows the spectrum and time series of a clutter target with a low CPA value (0.19):

![Example - spectrum of clutter point with low CPA](image)

**Figure 18:** details of clutter targets with low CPA and varying phase as targets come in and out of view

Therefore, one option is to compute CPA using the best fraction of the time series – i.e. that which will produce the highest CPA. For weather, it should not matter which half is used since the phase change in the time series is more evenly distributed with time.

3.2.2 Implementation of partial-dwell CPA

The prototype for the modified CPA implements the following steps:

- Divide the time series into 8 parts.
- Compute the CPA factors for each part.
- Compute CPA using some fraction of the parts which yield a maximum value.

This procedure for computing CPA leads to higher values and a generally smoother result. The membership function for CPA must be adjusted to account for the higher values.
The following 2 figures show the results of testing the partial-dwell CPA on KEMX data. There is no weather echo in this case, all of the echo is clutter.

![Image of KEMX clutter case - original CPA](image1.png)

**Figure 19:** KEMX clutter case - original CPA

![Image of KEMX clutter case – partial-dwell CPA](image2.png)

**Figure 20:** KEMX clutter case – partial-dwell CPA

In this case the improvement in CPA looks promising.

On the other hand, the following figures show the result of applying the partial-dwell CPA method to weather-only data at a high elevation angle, using the KFTG snow case.
3.2.3 Summary

- Method: compute CPA using some fraction of the parts which yield a maximum value.
- This leads to higher values of CPA and a generally smoother result.
• In addition to being smoother, this version of CPA shows higher values in both clutter and weather.

• Therefore, further tuning and testing is required.
3.3 Adding a new feature field: TPT/CPD = TCLUT

3.3.1 Overview

- Some time series show a significant change in power over the dwell.
- This is caused by clutter targets coming into and out of view as the antenna turns.
- This behavior does not occur in weather.
- The Time-series Power Trend – TPT – identifies this behavior.
- A second feature – the cumulative difference in phase across the dwell (CPD) – also has skill for identifying clutter.
- These 2 features appear to be complementary. The combined feature field (TCLUT) shows promise as an additional feature field.
- One important caveat should be mentioned up-front. The following examples show the fields computed on a 2-degree dwell. The skill decreases with narrower dwells.

3.3.2 Time-series Power Trend – TPT

TPT is a measure of the trend in time series power across the dwell. The higher the TPT value, the higher the probability of clutter.

TPT is computed as follows:

- Divide the time series into 8 parts
- Find the 3 consecutive parts which yield the lowest mean power
- Find the 3 consecutive parts which yield the highest mean power
- TPT = (max power) / (min power) expressed in dB

The following figure shows 2 time series plots, for weather on the left and clutter on the right. For the weather case, TPT is 7 dB, while for the clutter case, TPT is 27 dB. These values are typical.
3.3.3 Cumulative phase difference (CPD)

CPD is defined as the cumulative phase difference across the dwell, taking wrapping into account. It is computed in degrees. In clutter, CPD will be low (say less than 90), because the phase tends to be stable in clutter. In moving weather, CPD will be very high (greater than 360).

The following figure shows CPD computed for weather on the left and clutter on the right.

Figure 23: TPT computed for weather (left) and clutter (right)
The 3 panels are (a) ASCOPE – yellow, (b) spectrum – red, and (c) time series of power (green).
Figure 24: CPD for weather (left) and clutter (right)
The 4 panels are (a) ASCOPE – yellow, (b) spectrum (red)
(c) phase (orange), (d) cumulative phase difference (pink)

The following figures show TPT and CPD for the KFTG snow case:

Figure 25: Time-series Power Trend (TPT) for KFTG snow case
Figure 26: Cumulative Phase Difference (CPD) for KFT snow case

The following figures show how TPT and CPD are somewhat complementary – when TPT is active, CPD is less so, and vice versa. The figures highlight 3-body scattering for the Centennial Airport control tower target to the east of KFTG.

Figure 27: TPT – identifies target coming in and out of view
3.3.4 TCLUT – the maximum of TPT interest and CPD interest

Since TPT and CPD appear to be somewhat complementary in nature, in terms of identifying clutter, we can derive a third field, TCLUT, which is defined as the maximum of the TPT interest and CPD interest. This derived field should then be a good indicator of clutter.

The following figure shows TCLUT for the KFTG snow case.
Figure 29: TCLUT = max of TPT interest and CPD interest

Compare this to the following figure, which shows the CMD flag field computed for the same case. It is clear that TCLUT has considerable skill in identifying clutter.

Figure 30: CMD flag field for KFTG snow case
Computed using CMD version 4.1
3.4 Summary – TPT/CPD = TCLUT shows promise, needs tuning and testing

- This set of fields shows promise.
- More testing and tuning is needed.
- An important caveat – these examples show the fields computed on a 2-degree dwell. The skill decreases with narrower dwells.
4 Multi-modal spectra from surface traffic

4.1 Overview - problems at KEMX, Tucson, Arizona

The Radar Operations Center (ROC) received reports of problems, in some limited regions at KEMX. The ROC requested that NCAR investigate the poor performance of CMD. For this purpose the ROC provided NCAR with a weather-free time series case from KEMX.

NCAR ran their version of CMD and the clutter filter on this case to investigate the performance problems. NCAR was able to duplicate some of the problems indicated by the ROC.

The KEMX long-PRT data was processed in super resolution mode, using the following parameters:

- PRT 3.1 ms (long PRT)
- Elevation 0.5 deg
- 64 samples
- 0.5 degree indexed beams
- Von Hann window for CMD
- Von Hann window for moments computations

The following problems were identified:

- Some multi-modal spectra were identified. These lead to missed detections and poor clutter filter performance. These may be related to echoes from surface transportation.
- The CMD in-fill filter sometimes does not fill in missing flag gates as expected and should be improved. This problem is addressed in previous sections of this report.
The problems with KEMX were isolated to 2 regions, as highlighted by the yellow ellipses in the following figure:

![Figure 31: Regions of problems at KEMX](image)

This is a clear-air case, so all of the echoes are caused by clutter of one type or another.

It appears that some of the missed detections and poor clutter filter performance are caused by traffic echoes. The traffic echoes exhibit multi-modal spectra. This makes them both difficult to detect as clutter, and difficult to filter with the current adaptive filters.
4.2 Region 1, centered on 75 degrees azimuth, 45 km range, from KEMX

Figure 32: Region 1 – Unfiltered reflectivity
Note interstate 10 – shown in bold – traversing this area, and other smaller roads

Figure 33: region 1, unfiltered velocity showing the region is dominated by clutter
The figure below shows the filtered reflectivity. This is a clear-air case, so we do not expect weather echoes. The ellipse shows speckle indicating that the clutter filter was either not applied, or the filter failed to perform properly.

Examination of the spectra for these gates shows that some of them are multi-modal. i.e. they contain targets moving at different velocities. Given the proximity of the targets to interstate highway 10, it seems very likely that these are caused by reflection from vehicles on the interstate.

Figure 34: Region 1 – filtered reflectivity showing gates at which CMD and the clutter filter failed
The following figures show spectra from normal clutter echoes and from suspected traffic echoes.

Figure 35: Normal-propagation clutter signature
Panels are (a) ASCOPE – yellow, (b) spectrum (red) (c) time series power (green), (d) time series phase (orange) (e) pulse-to-pulse phase difference in time (yellow)
Figure 36: Multi-modal spectrum of suspected traffic targets (red) example 1

Figure 37: Multi-modal spectrum of suspected traffic targets (red) example 2
4.3 Region 2, centered on 340 degrees azimuth, 55 km range

The second region exhibiting problems at KEMX is just to the NE of Tucson. There is mountainous terrain in the area, with a road up the side of the higher terrain.

Figure 38: Region 2 – unfiltered reflectivity

Figure 39: Region 2 – unfiltered velocity
Figure 40: Region 2 – filtered velocity

The ellipse highlights clutter from traffic and some missed detections

The following figures show the multi-modal nature of the spectra from two of the problem gates. This indicates probable contamination from traffic echoes.

Figure 41: Multi-modal spectrum from traffic (red)
4.4 Conclusions – traffic clutter spectra:

- It appears that some of the missed detections and poor clutter filter performance are caused by traffic echoes.

- Some of the spectra are multi-modal, which suggests multiple targets are illuminated in the sample volume.

- The CPA value can be quite low, leading to missed detections.

- The multi-modal spectra presents a challenge to the clutter filter. Further work is required to develop a strategy to deal with this type of clutter.
5 Evaluating a polynomial regression filter

5.1 Overview

A polynomial regression filter was proposed in the 1990s by Sebastian Torres and Dusan Zrnic. See the following reference for details:


An advantage of this filter is that it does not require application of a window, which in turn means that all of the returned power is used in computing the moments. This improves the statistics associated with the moments.

This filter was evaluated, in a slightly modified form, in combination with CMD, for effectiveness in both normal and staggered-PRT operations.

5.2 Modifications to the polynomial regression filter

The filter proposed by Torres and Zrnic was modified in the following manner:

- Apply the regression filter in the time domain
- Apply an FFT, with a rectangular window
- Interpolate across the notch created by application of the filter
- Constrain the filtered spectrum magnitudes to be less than or equal to the original spectrum
- Invert the FFT
The following figure shows the application of the modified regression to a clutter target. The panel on the left shows, in orange, the regression filter spectrum, without any interpolation across the notch. The panel on the right shows the regression filter spectrum after interpolation across the notch.

![Example of application of regression filter to clutter gate](image)

**Figure 43:** Application of modified regression filter to clutter target.  
Top panel (yellow): ASCOPE  
Third panel (white): regression fit to I time series.  
Lower panel (magenta): regression fit to Q time series  
Left: without notch interpolation. Right: with notch interpolation.

### 5.3 Why is this filter interesting so interesting?

The filter seems to be more benign than the spectral adaptive filter when CMD makes false detections, which results in the filter being applied inappropriately. This can be demonstrated by applying both filters to all gates, and determining how much weather power suppression occurs along the 0 isodop.

The figures below show a comparison between the results of the spectral adaptive filter and the regression filter when applied to all gates. Inspection of these results indicates that the regression filter is more benign when applied in the 0-isodop region. The regression filter produces, on the whole, a narrower region in which the weather power is removed by the filter.
It is not clear why the regression filter seems more benign than the spectral filter. The figures below show results from applying the filter to gates at or close to the 0-isodop, contrasted with gates at which clutter is definitely present. Some differences are apparent, but a full explanation of those differences will require further research.
Examples of regression filter in weather close to or at the 0-isodop

Figure 46: Spectra and time series of regression filter applied to gates near the 0-isodop

Examples of regression filter in clutter

Figure 47: Spectra and time series of regression filter applied to gates with clutter
5.4 Applying the polynomial regression filter to staggered PRT

5.4.1 Overview

Because the regression filter operates in the time domain, it can readily be applied to data from staggered PRT operations. In this case, interpolation across the notch is not (yet) performed, though this will be added in the future.

Greg Meymaris has evaluated this filter using modeled data – the results will be presented in a different part of this report.

The regression filter was tested on two staggered-PRT cases: (a) a simulated staggered PRT case using KFTG short-prt time series, in which pulses were selectively dropped to simulate staggered mode, and (b) a real staggered PRT case from an operational NEXRAD radar.

5.4.2 Staggered-PRT simulated using KFTG short-PRT data

KFTG time series data was used to simulate staggered PRT operations. This was achieved by dropping pulses, using the following sequence:

1 0 1 0 0 1 0 1 0 0 1 0 1 0 0 ....

where 1 indicates that the pulse is used and 0 indicates that it is not used.

This will be demonstrated on the KFTG snow case, the unfiltered reflectivity of which is shown below for context.

Figure 48: KFTG – unfiltered reflectivity, fixed short PRT
The following series of figures shows the results, with the filtered, retrieved velocity compared with the original filtered measured velocity.

**Figure 49:** KFTG - simulated velocity, long-PRT

**Figure 50:** KFTG – simulated velocity, short-PRT
Comparison of the previous 2 figures shows that the retrieved velocity values are comparable, for the most part, with the measured data. There is no significant bias in velocity along the 0-isodop. Some velocity retrieval errors do occur, but they are related to the staggered-prt algorithm rather than the clutter filter.
5.5 Actual staggered PRT case

The following plots show application of the filter to data collected in staggered PRT mode on an operational NEXRAD.

Figure 53: Unfiltered retrieved velocity

Figure 54: Filtered retrieved velocity
Some velocity bias away from 0 is apparent along the 0 isodop.
The filtered velocity is biased away from zero in the 0 isodop region, because notch interpolation is not performed. (This will be added to a later version).

5.6 Summary – regression filter

- The regression filter appears to be more benign than the spectral filter, with respect to CMD errors.
- The regression filter may be suitable for staggered PRT.
- Since no window is required for this filter, data quality is improved.
- The filter is somewhat faster to run than the spectral filter.
- In the staggered PRT case, notch interpolation must be added to remove the velocity bias.