Adaptive Range Oversampling to Improve Estimates of Polarimetric Variables on Weather Radars

CHRISTOPHER D. CURTIS AND SEBASTIÁN M. TORRES

Cooperative Institute for Mesoscale Meteorological Studies, University of Oklahoma, and NOAA/OAR/National Severe Storms Laboratory, Norman, Oklahoma

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ABSTRACT

One way to reduce the variance of meteorological-variable estimates on weather radars without increasing dwell times is by using range oversampling techniques. Such techniques could significantly improve the estimation of polarimetric variables, which typically require longer dwell times to achieve the desired data quality compared to the single-polarization spectral moments. In this paper, an efficient implementation of adaptive pseudowhitenning that was developed for single-polarization radars is extended for dual polarization. Adaptive pseudowhitenning maintains the performance of pure whitening at high signal-to-noise ratios and equals or outperforms the digital matched filter at low signal-to-noise ratios. This approach results in improvements for polarimetric-variable estimates that are consistent with the improvements for spectral-moment estimates described in previous work. The performance of the proposed technique is quantified using simulations that show that the variance of polarimetric-variable estimates can be reduced without modifying the scanning strategies. The proposed technique is applied to real weather data to validate the expected improvements that can be realized operationally.

1. Introduction

Range oversampling was introduced by Torres and Zrnić (2003a,b) as a means to reduce the variance of meteorological-variable estimates on weather radars without increasing observation (or dwell) times. The technique relies on the fact that radar returns sampled at a rate faster than the inverse of the transmitter pulse width exhibit a correlation that (for all practical purposes) depends only on the transmitter pulse shape and the receiver impulse response. Thus, range-oversampled signals can be efficiently combined to increase the equivalent number of independent samples (Eq. 6.12 in Doviak and Zrnić 1993) without increasing the number of radar pulses per dwell. A whitening transformation can be used to maximize the equivalent number of independent samples by decorrelating the weather signal samples in range (Torres and Zrnić 2003a,b); however, this process artificially increases the noise power. Thus, its application is limited to situations where the signal-to-noise ratio (SNR) is relatively large. As a way to mitigate this effect, Torres et al. (2004) introduced pseudowhitenning transformations that trade a lesser degree of decorrelation for reduced noise enhancement. In general, the largest variance reduction for a given meteorological-variable estimator can be achieved with a pseudowhitenning transformation tailored to specific signal characteristics (e.g., SNR), which naturally calls for an adaptive technique. Curtis and Torres (2011) introduced a real-time adaptive pseudowhitenning algorithm and implemented it on the single-polarization National Weather Radar Test Bed Phased Array Radar (NWRT PAR). This led to update times that were twice as fast with no significant degradation in data quality.

The U.S. network of weather surveillance radars has been recently upgraded to dual polarization, which has been shown to provide significant improvements to rainfall estimation, precipitation classification, data quality, and weather hazard detection. While this upgrade resulted in significant hardware and software modifications, none of the operational scanning strategies were changed. Thus, the Weather Surveillance Radar-1988 Doppler (WSR-88D) computes polarimetric variables (differential reflectivity, differential phase, and magnitude of the copolar cross-correlation coefficient) using the dwell times from the pre-dual-polarization era. However, their

Corresponding author address: Christopher Curtis, National Weather Center, 120 David L. Boren Blvd., Norman, OK 73072.

E-mail: chris.curtis@noaa.gov

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quantitative use for key applications (e.g., quantitative precipitation estimates) would benefit significantly if they had higher fidelity than presently achieved, but this is challenging under current operational conditions. For example, at the lowest elevation angle of volume coverage pattern (VCP) 11, the WSR-88D uses a dwell time of 53.38 ms that, at the benchmark condition of an SNR of 20 dB, a spectrum width of 2 m s$^{-1}$, and a cross-correlation coefficient of 0.99, results in standard deviation of differential reflectivity estimates of $\sim$0.4 dB, not quite the required 0.3 dB for dwell times longer than 50 ms (Baron Services Inc. 2008). As will be shown later, application of adaptive pseudowhitening to range-oversampled signals under the same conditions reduces the standard deviation of differential reflectivity estimates to $\sim$0.25 dB.

In this paper, we extend the efficient implementation of adaptive range oversampling introduced by Curtis and Torres (2011) to the dual-polarization WSR-88D with the goal of reducing the variance of meteorological-variable estimates without increasing the dwell times. The rest of the paper is organized as follows. Section 2 reviews the theory behind adaptive range oversampling and proposes an efficient implementation for the dual-polarization WSR-88D. In section 3, simulations are used to quantify the improvement realized with this technique under typical operational conditions. Section 4 illustrates the performance of the proposed technique on real data collected in an experimental mode on the National Severe Storms Laboratory’s research WSR-88D (KOUN) radar. Finally, conclusions and recommendations for operational implementation are presented in section 5.

2. Theory

The purpose of this section is to provide background information on range oversampling processing culminating in the description of an efficient adaptive pseudowhitening algorithm for dual-polarization radars. The basic ideas behind adaptive pseudowhitening will initially be described in terms of the application of a linear transformation followed by incoherent averaging. Next, the details of an efficient adaptive pseudowhitening implementation will be addressed, building on the earlier linear transformation framework. Finally, the steps of the algorithm will be given along with some discussion.

Conventional weather radars typically sample signals at a rate of $\tau^{-1}$, where $\tau$ is the duration of the transmitted pulse. Range oversampling by a factor of $L$ is accomplished by sampling the time series data at an increased rate ($L\tau^{-1}$) so that $L$ complex samples are collected during the time $\tau$. These range-oversampled signals can then be processed with a digital matched filter or some other type of range oversampling technique. In this case, adaptive pseudowhitening will be used to improve the quality of meteorological variables. Adaptive pseudowhitening is one in a class of techniques that applies a linear transform to range-oversampled signals followed by incoherent averaging over $L$ oversampled range resolution volumes. The processing steps will be described for an $M$-pulse dwell and a given resolution cell, where the complex-valued, oversampled time series matrices $V_H$ and $V_V$ are each $L$ by $M$. The subscripts $H$ and $V$ denote the horizontal and vertical polarization channels, respectively. The algorithm is designed to work with a system that uses simultaneous transmission and reception of both polarizations; modifications would be needed for other transmission/reception schemes.

Initially, the oversampled signals from a given resolution cell are transformed using a linear transformation matrix $W$:

$$X_{H,V} = WV_{H,V}.$$  

Both the horizontal and vertical channel data are multiplied by $W$, resulting in the transformed matrices $X_H$ and $X_V$, respectively. In this case, it is assumed that the dual-polarization channels are matched so the transformation is the same for both channels. In Torres (2009), the case with unmatched channels is addressed, which ensures that the polarimetric variables are unbiased. In general, $W$ can be any $L$ by $L$ complex-valued matrix that satisfies the “power-preserving criterion”

$$\text{tr}(W^*C_{V_H}W^T) = L,$$  

where $\text{tr}(\cdot)$ is the matrix trace operation, the superscript asterisk (*) denotes complex conjugation, the superscript $T$ denotes matrix transpose, and $C_{V_H}$ is the normalized range-correlation matrix for the original time series data corresponding to the horizontal polarization (subscript $V_H$). Because of the assumption of matching channels, the range correlation matrix is the same for both polarizations, that is, $C_{V_H} = C_{V_V}$. Accurately measuring $C_{V_H}$ is important because measurement errors can cause biases in reflectivity estimates (Torres and Curtis 2012); $C_{V_H}$ is also critical because it is normally used to compute the transformation matrix $W$ that determines the overall performance of range oversampling processing. One way of computing $W$ is through adaptive pseudowhitening, which is a nearly optimal technique for choosing the best possible transformation matrix for each of the meteorological variables.

After the data are transformed, $L$ values are computed for each covariance (and each lag) needed to
estimate the meteorological variables. The covariances at lag $k$ are computed using the following formula with a different set of transformed data needed for each variable ($\theta$):

$$
R_{X_{HV}}(k) = (M - |k|)^{-1} \sum_{m=0}^{M-|k|-1} X_{HV}(\theta)(l,m)X_{HV}(\theta)(l, m + k),
$$

(3)

where $l$ is the range oversampling index ($0 \leq l < L$) and $m$ is the sample time index ($0 \leq m < M$). On dual-polarization radars, the signal processor typically computes autocovariances of both the $H$ and $V$ channels for the first few lags plus at least one cross covariance between the two polarization channels (normally at lag 0). Regardless of the particular covariances (type and lag) required to estimate all meteorological variables in a given implementation, $L$ estimates for each covariance are then averaged to get the final estimate for the resolution cell. These are the basic steps needed to perform range oversampling processing. However, using a separate $W$ matrix for each meteorological variable is not the most efficient way to process the data. The rest of the discussion focuses on how adaptive pseudowhitenning is used to find a nearly optimal transformation for each meteorological variable and how range oversampling processing is efficiently implemented on dual-polarization radars based on an extended version of the single-polarization algorithm introduced by Curtis and Torres (2011).

As mentioned previously, one of the main goals of range oversampling processing is to decrease the variance of meteorological-variable estimates. Adaptive pseudowhitenning accomplishes this goal by minimizing an equation for the variance of each meteorological-variable estimator (Torres et al. 2004):

$$
\text{Var}(\hat{\theta}) = D\{A \text{ tr}[(W^*C_{V_H}W^T)^2]
+ B \text{ tr}[(W^*C_{V_H}W^T)(W^*W^T)]
+ C \text{ tr}[(W^*W^T)^2]\},
$$

(4)

where $\theta$ is the meteorological variable under consideration. In this case, $\theta$ can be signal power ($S$), mean Doppler velocity ($v$), spectrum width ($\sigma_v$), differential reflectivity ($Z_{DR}$), differential phase ($\Phi_{Dp}$), or correlation coefficient ($\rho_{HV}$). The constants $A$, $B$, $C$, and $D$ are variable specific and depend on the SNR for the horizontal polarization at the output of the digital receiver ($\text{SNR}_0$), the normalized spectrum width ($\sigma_v$), the differential reflectivity ($Z_{DR}$), and the correlation coefficient ($\rho_{HV}$). The normalized spectrum width is the spectrum width divided by twice the Nyquist velocity ($\sigma_v = \sigma_v/2v_q$). For each meteorological variable, the optimal $W(\theta)$ matrix is found that minimizes Eq. (4) as described in Torres et al. (2004). The values of $\text{SNR}_0$, $\sigma_v$, $Z_{DR}$, and $\rho_{HV}$ are estimated from digitally matched-filtered data, and $C_{V_H}$ is measured from the original range-oversampled data (Curtis and Torres 2013). Sometimes the transformation is described as “nearly optimal” because of its dependence on estimates; there are also approximations in Eq. (4) that can cause the transformation to be less than optimal. One approximation is the assumption that the horizontal and vertical noise powers are equal. Also, the expressions for the variance of some of the meteorological variables (derived using perturbation analysis) are less accurate for a small number of samples or for relatively wide spectrum widths. Even though each of the nearly optimal transformation matrices $W(\theta)$ depends on estimates and approximations, the process works well over a wide range of conditions. The values of the constants $A$, $B$, $C$, and $D$ are given in Table 1 for both the spectral moments and the polarimetric variables. Note that these values directly correspond to the particular estimator listed in the table.

The basic outline of the algorithm has been presented, but the actual implementation splits each variable-specific transformation matrix $W(\theta)$ into two parts to enable a computationally efficient version of the algorithm when applying ground clutter filtering and other ancillary signal-processing techniques. The details of the single-polarization implementation can be found in Curtis and Torres (2011), but the key insight comes from writing the transformation matrix in the following form:

$$
W = \gamma(A^+)^{1/2}U^*T,
$$

(5)

where $C_{V_H} = U^*\Lambda U^T$ is the eigendecomposition of the Hermitian matrix $C_{V_H}$, $\gamma$ is a power-preserving factor, and $A^+$ is computed from the diagonal matrix of eigenvalues $\Lambda$. We assume that the eigenvalues are ordered in size with $\lambda_0 \geq \lambda_1 \geq \cdots \geq \lambda_{L-1} \geq 0$. Based on the minimization of (4), the equation for the elements of $A^+$ is given as

$$
\lambda_i^* = \frac{\lambda_i}{A\lambda_i + B\lambda_i + C},
$$

(6)

where the variable-specific $A$, $B$, and $C$ values depend on the match-filtered estimates of $\text{SNR}_0$, $\sigma_v$, $Z_{DR}$, and $\rho_{HV}$ (Table 1).

The application of the transformation matrix can be done in two steps by splitting out the variable-independent
part of the equation, \( U^{\ast T} \), and the variable-specific part, \( \gamma(\Lambda^+)^{1/2} \). Thus, the time series data can be “partially transformed” using \( U^{\ast T} \) to produce two new matrices, \( X_H \) and \( X_V \), where \( X_{HV} = U^{\ast T} X_{HV} \). At this point, the data can be ground clutter filtered before the variable-specific part of the transformation is applied, which represents a significant savings in computations compared to applying the clutter filter once per meteorological variable. Next, \( L \) estimates are produced for each required covarion as in (3), except that \( X_H \) and \( X_V \) are substituted for \( X_H \) and \( X_V \), respectively, resulting in \( \hat{R}_X^{(i)}(k) \), \( \hat{R}_X^{(0)}(k) \), and \( \hat{R}_X^{(1)}(k) \) (for all needed lags). Before doing the variable-specific part of the processing, the matched-filtered values of SNR, \( \sigma_{\text{env}} \), \( Z_{\text{DR}} \), and \( \rho_{\text{HV}} \) need to be computed. Conveniently, the digital matched filter that maximizes the SNR is given by the eigenvector corresponding to the largest eigenvalue of the normalized range correlation matrix \( C_{\bar{\nu} \nu} \) (Chiuppesi et al. 1980). Since this eigenvector is a column of \( U \), the first elements of each covariance set—that is, \( \hat{R}_X^{(i)}(k) \), \( \hat{R}_X^{(0)}(k) \), and \( \hat{R}_X^{(1)}(k) \)—are the unscaled, matched-filtered covariances corresponding to the largest eigenvalue \( \lambda_i \). To properly scale the covariances, each need to be divided by the largest eigenvalue \( \lambda_i \); this is described in more detail in Curtis and Torres (2011). The values of SNR, \( \sigma_{\text{env}} \), \( Z_{\text{DR}} \), and \( \rho_{\text{HV}} \) that are needed to calculate the variable-specific \( A \), \( B \), and \( C \) values can then be estimated and used for adaptive pseudowhitenning.

The \( L \) values of each covarion are then combined using a variable-specific weight vector \( d(\theta) = [d_0 \ d_1 \ \cdots \ d_{L-1}] \). This weight vector combines the variable-specific part of the transformation and the averaging into one step as follows:

\[
\hat{R}_X(k) = \sum_{i=0}^{L-1} d_i R_X^{(i)}(k),
\]

where \( d_i = g \lambda_i^+ \). The \( \lambda_i^+ \) depend on the \( A \), \( B \), and \( C \) values that were computed earlier. By acting on covariances instead of time series data, the square root in Eq. (5) disappears and a new power-preserving factor \( g \) is used that incorporates the division-by-\( L \) averaging step. This power-preserving factor is also variable specific, and the following equation shows its relationship to the power-preserving factor from Eq. (5) and the power-preserving criterion from Eq. (2):

\[
g = \frac{\gamma^2}{L} = \frac{[\text{tr}(W^\ast C_{\nu \nu} W^T)]^{-1}}{[\text{tr}(A^+ A)]^{-1}} = \left( \sum_{i=1}^{L} \lambda_i^+ \right)^{-1}.
\]
The power-preserving factor from Eq. (5) is squared because the weighting factor is applied to the covariances, and the division-by-$L$ is apparent. The last two parts of the equation show the relationship between the power-preserving criterion in Eq. (2) and the eigenvalues of $C_{V_H}$. More details of this efficient implementation can be found in appendix A of Curtis and Torres (2011).

One last implementation issue that needs to be addressed is the effect of the weight vector $d(\theta)$ on the noise power. The multiplication by $U^T$ does not affect the noise power because $U$ is a unitary matrix, but the weight vector does change the noise power. This is critical for meteorological-variable estimators that depend on an estimate of the noise power. In general, the change in the noise power is called the noise enhancement factor (NEF). This terminology was introduced in Torres and Zrnić (2003a) and was expressed in the form we need in Curtis and Torres (2011):

$$\text{NEF}(\theta) = \sum_{l=0}^{L-1} d_l(\theta).$$

(9)

This equation relates the change in the noise power directly to the elements of the weight vector. Even though this is called the noise enhancement factor, it can, in some cases, be less than one, which leads to a reduction in noise power. One example of this is the matched-filtered case where the only nonzero element of the weight vector is the $l = 0$ element, resulting in a variable independent $\text{NEF} = \lambda_0^{-1}$. For an adaptive pseudowhitenning example, the signal power for the horizontal polarization can be computed as $S_H = R_{X_H}(0) - \text{NEF}(S)N_H$, where $N_H$ is the noise power for the horizontal polarization at the output of the digital receiver and $\text{NEF}(S)$ is the signal-power-specific noise enhancement factor. Because of the nature of adaptive pseudowhitenning, the noise power can change at each range resolution volume, and this needs to be taken into account when estimating the meteorological variables.

Based on this description of the algorithm, the particular steps of the dual-polarization version are given as follows:

1) Compute the partially transformed matrices of time series data, $\tilde{X}_{H,V} = U^T V_{H,V}$, using the $U$ computed from the eigendecomposition of $C_{V_H} = U^T A U^T$. Ground clutter filtering can be applied to these two partially transformed data matrices.

2) Compute $L$ range-oversampled covariances $R_{X_H}(k)$, $R_{X_H}(k)$, and $R_{X_H}(k)$ from the partially transformed data. Required covariances for the classical pulse-pair estimators are lags 0 and 1 from $\tilde{X}_H$, lag 0 from $X_V$, and lag 0 for the cross correlation.

3) Compute the matched-filter-based (MFB) estimates of $\text{SNR}_0$, $\sigma_w$, $Z_{DR}$, and $\rho_{HV}$ from $\tilde{R}_{X_H}(0)/\lambda_0$, $\tilde{R}_{X_H}(0)/\lambda_0$, and $\tilde{R}_{X_H}(0)/\lambda_0$ using the appropriate lags and the matched-filtered noise powers for both polarizations $N_{MF_{H,V}} = N_{H,V}/\lambda_0$. Threshold the $\sigma_w$ value to be above 0.01 and $\text{SNR}_0$ to be above −10 dB. Threshold $\rho_{HV}$ to be between 0.01 and 0.999. The $Z_{DR}$ values do not need to be thresholded.

4) Calculate the nearly optimal variable-specific weight vectors $d(S)$, $d(V)$, $d(\sigma_w)$, $d(Z_{DR})$, $d(\Phi_{DR})$, and $d(\rho_{HV})$ using $d_l(\theta) = g(\theta)\lambda_l^*(\theta)$, and Eqs. (6) and (8).

5) Compute the required covariance estimates (shown in the estimator column of Table 1): $\tilde{R}_{X_H}(0)$, $\tilde{R}_{X_H}(0)$, $\tilde{R}_{X_H}(0)$, $\tilde{R}_{X_H}(0)$, $\tilde{R}_{X_H}(0)$, $\tilde{R}_{X_H}(0)$, $\tilde{R}_{X_H}(0)$, $\tilde{R}_{X_H}(0)$, $\tilde{R}_{X_H}(0)$, $\tilde{R}_{X_H}(0)$, $\tilde{R}_{X_H}(0)$, $\tilde{R}_{X_H}(0)$, and $\tilde{R}_{X_H}(0)$ from $\tilde{R}_{X_H}(0)$, $\tilde{R}_{X_H}(0)$, $\tilde{R}_{X_H}(0)$, $\tilde{R}_{X_H}(0)$, and $\tilde{R}_{X_H}(0)$ using the weight vectors from step 4 as shown in Eq. (7).

6) Compute adaptive-pseudowhitenning-transformation-based (APTB) meteorological-variable estimates from the variable-specific averaged covariances. Use the appropriate variable-specific noise values where necessary, where $N_{H,V}(\theta) = \text{NEF}(\theta)N_{H,V}$.

To summarize, the first step is the application of the variable-independent part of the transformation $U$. Ground clutter filtering (or other signal processing prior to the covariance estimation step) can be applied to the data from both the $H$ and $V$ polarizations so that it need not be applied to each of the variable-specific completely transformed data matrices. In the second step, $L$ values of each covariance estimate needed to compute the meteorological variables are calculated. The set of covariances could change based on the particular estimators used for the meteorological variables. The classical pulse-pair estimators are utilized in this implementation, which matches the processing on the WSR-88D. This could be extended to other estimators that employ higher autocovariances and/or that combine autocovariances from both polarizations, but new expressions for the $A$, $B$, and $C$ values would need to be derived for the alternative estimators. In step 3, the matched-filtered covariances and the corresponding values of the matched-filtered $\text{SNR}_0$, $\sigma_w$, $Z_{DR}$, and $\rho_{HV}$ are computed. Some of these values need to be thresholded to ensure reasonable values of $A$, $B$, and $C$ in the next step. Step 4 is the key adaptive-pseudowhitenning step, where the variable-specific weights are computed, and the weights are then applied in step 5. The last step is the actual computation of the meteorological variables based on the adaptive-pseudowhitenning covariance estimates. For this implementation, censoring...
is applied based on the matched-filtered SNR₀, but other approaches could be employed.

This algorithm extends the efficient adaptive-pseudowhitening implementation for single-polarization radars from Curtis and Torres (2011) to dual-polarization radars. It keeps the partial-transformation step that simplifies the signal processing prior to the estimation of covariances and adds the computation of two matched-filtered polarimetric variables, \( Z_{DR} \) and \( \rho_{HV} \), that are needed to calculate the variable-specific \( A, B, \) and \( C \) values for the polarimetric variables (based on the expressions in Table 1, a matched-filtered estimate of \( \Phi_{DP} \) is not required). The next section will apply this algorithm to simulated data to evaluate its performance.

3. Simulations

The simulation parameters are based on the scanning strategy used to collect the real weather data, which are analyzed in section 4. This scan, VCP 11, is used during convective weather events and includes two 360° azimuthal rotations at a constant elevation angle of 0.5° each using a different pulse repetition time (PRT). The current processing on the WSR-88D radars computes the polarimetric variables from the long-PRT scan, which is \( \sim 3.1 \) ms for this strategy (the maximum unambiguous range is \( \sim 460 \) km). There are 17 samples collected at each resolution volume for a dwell time of nearly 53 ms. The transmit frequency is set to 2.7 GHz, corresponding to the frequency used on the KOUN radar (the maximum unambiguous velocity is \( \sim 8.9 \) m s\(^{-1} \)). To match the real data, the oversampling factor \( L \) is 5, which gives an oversampled range gate spacing of \( \sim 50 \) m, while the length of the pulse corresponds to a range of \( \sim 250 \) m. The data are simulated as described in Zrnić (1975) with a range gate spacing of 50 m and are then convolved with a modified pulse measured from the KOUN data. This imposes a range correlation on the simulated data that closely matches the real data.

Data were simulated for three different cases to show the performance of adaptive pseudowhitenning under varied conditions. The first case uses a spectrum width \( \sigma_v = 2 \) m s\(^{-1} \), a differential reflectivity \( Z_{DR} = 0.5 \) dB, and a correlation coefficient \( \rho_{HV} = 0.99 \), which could be associated with light rain. This is a case where the estimators should have lower variances and is close to a best-case scenario for the polarimetric-variable estimators. The second case with \( \sigma_v = 4 \) m s\(^{-1} \), \( Z_{DR} = 2 \) dB, and \( \rho_{HV} = 0.9 \) could be associated with wet snow and results in higher variances for all polarimetric variables. The last case with \( \sigma_v = 6 \) m s\(^{-1} \), \( Z_{DR} = 4 \) dB, and \( \rho_{HV} = 0.7 \) could be associated with melting hail and leads to the highest variances. Figure 1 shows the results of the simulations for all three cases while varying the SNR (at the output of the digital matched filter) from 0 to 35 dB. The corresponding SNR for adaptive pseudowhitenning is not used because it varies from range gate to range gate and from variable to variable because of the variable-specific NEF described in section 2. The three different cases are in the three columns from left to right, from lowest to highest variance of estimates. The three polarimetric variables comprise the rows with \( Z_{DR} \) at the top, \( \Phi_{DP} \) in the middle, and \( \rho_{HV} \) at the bottom.

The results are shown for four different types of processing: APTB processing; MFB processing; whitening-transformation-based (WTB) processing (using only a pure whitening transformation); and optimal-pseudowhitenning-based (OPTB) processing using the true values of the matched-filtered parameters to compute the variable-specific transformations). OPTB processing eliminates the errors from estimating the matched-filtered variables but does not address the approximations in calculating the variances [Eq. (4)]. In all cases, APTB processing outperforms MFB processing and matches WTB processing at high SNRs. The APTB results are very close to the OPTB results, which illustrates that using estimates to determine the transformations works well in practice. If the technique were especially sensitive to errors in the match-filtered estimates of \( \rho_{HV} \), \( \sigma_v \), \( Z_{DR} \), and \( \rho_{HV} \), we would expect significant differences between the APTB and OPTB results. There are a couple of cases where APTB processing seems to outperform OPTB processing, but APTB processing introduces some small biases that result in artificially lower standard deviations. The APTB biases are smaller than the biases for MFB processing and are still an improvement.

To get an idea of the differences in performance, we begin with the first case in the leftmost column of Fig. 1. The parameters in this case correspond to the parameters used to define the dual-polarization requirements. At an SNR of 20 dB, the requirement for \( Z_{DR} \) is a standard deviation of less than 0.3 dB. The result for MFB processing is \( \sim 0.41 \) dB, which does not meet the stated requirement, but the result for APTB processing is \( \sim 0.27 \) dB, which does meet the requirement. There is a similar result for \( \Phi_{DP} \). The requirement at 20-dB SNR is a standard deviation of 2.5°. MFB processing has a value of \( \sim 2.8° \), while AFTB processing has a value \( \sim 1.8° \). Finally, the requirement for \( \rho_{HV} \) at 20-dB SNR is a standard deviation of 0.006. The standard deviation of MFB processing is \( \sim 0.008 \) and of APTB processing is slightly below 0.006. In all cases, adaptive pseudowhitenning results in polarimetric-variable estimates that meet the specified data-quality requirements. Although the improvements are larger in an absolute sense for the higher-variance cases in the middle and
rightmost columns, the relative improvement is similar for all cases. This is especially true at high SNRs, where the performance of adaptive pseudowhitening approaches that of pure whitening with a standard deviation improvement factor given, as expected, by $\sqrt{L} \approx 2.24$. At low SNRs, adaptive pseudowhitening continues to outperform matched-filtered processing because matched-filtered processing maximizes the SNR rather than minimizing the variance of the estimators.

An additional topic that can help illustrate the differences between adaptive pseudowhitening and whitening performance is the notion of crossover SNR ($\text{SNR}_c$). This is the SNR value at which the standard deviation curve for WTB processing crosses the curve for MFB processing, which can take on different values for different variables and for different conditions. If we focus on the first column in Fig. 1, which corresponds to commonly occurring values for the polarimetric variables, we see that the SNR$_c$ for both $Z_{DR}$ and $\Phi_{DP}$ is less than 20 dB, while it is greater than 25 dB for $\rho_{HV}$. Since adaptive pseudowhitening performs like whitening at high SNR values and like the digital matched filter at low SNR values, the SNR$_c$ gives us some insight into where that transition will occur. We would expect adaptive pseudowhitening to perform more like the matched filter at 20 dB for $\rho_{HV}$ than for either $Z_{DR}$ or $\Phi_{DP}$ because of the higher SNR$_c$ for $\rho_{HV}$. In general, the SNR$_c$ values for the spectral moments are lower than those for the polarimetric variables. If we examined real data

Fig. 1. Standard deviations of polarimetric-variable estimators under varying conditions for APTB, OPTB, MFB, and WTB processing. Each of the three columns denotes different weather conditions, and the corresponding parameters are provided at the top of each column. The rows show results for the different polarimetric variables with (top) $Z_{DR}$, (middle) $\Phi_{DP}$, and (bottom) $\rho_{HV}$.
comparing adaptive pseudowhitenning and whitening processing at SNR values around 15 dB, we would see more differences on the $\rho_{HV}$ plots than for $Z_{DR}$ or $\Phi_{DP}$ and fewer differences for the spectral moments than for the polarimetric variables. In section 4, we will examine real data to explore the performance of adaptive pseudowhitenning with respect to both whitening and matched-filter processing.

4. Application of adaptive pseudowhitenning to real data from KOUN

In this section, we use data collected by the National Severe Storms Laboratory’s KOUN research radar to demonstrate how range oversampling can be exploited to achieve improved quality of dual-polarization data without increasing observation times. Time series data are processed to illustrate and compare the performance improvement that could be realized using an operational implementation of the adaptive pseudowhitenning technique described in section 2.

On 12 August 2004, the dual-polarization S-band KOUN radar sampled a severe storm event southwest of Norman, Oklahoma. Figure 2 shows (zoomed in) plan position indicator (PPI) displays of MFB estimates of SNR$_{0}$ (top left), $\sigma_{c}$ (top right), $Z_{DR}$ (bottom left), and $\rho_{HV}$ (bottom right) at ~2337 UTC. Data shown in this figure correspond to the lowest elevation scan at an elevation of 0.5°. At this elevation, 17 samples were collected at each range resolution volume using a long PRT of ~3.1 ms, which matches the operational parameters of VCP 11 on the Next Generation Weather Radar (NEXRAD) network. MFB fields depicted in Fig. 2 drive the performance of the adaptive algorithm described in section 2; thus, they provide context to the results shown in Fig. 3.

PPI displays of $Z$ (Fig. 3a), $Z_{DR}$ (Fig. 3b), $\Phi_{DP}$ (Fig. 3c), and $\rho_{HV}$ (Fig. 3d) from MFB (top left), APTB (middle left), and WTB (bottom left) estimates are shown. All fields were obtained using the same time series data as in Fig. 2 and the same ancillary signal processing functions such as ground clutter filtering and data thresholding. Also, transformations for the three processing modes (MFB, APTB, and WTB) were based on range-correlation measurements from the data using the technique described by Curtis and Torres (2013). Corresponding left panels of Fig. 3 are useful to qualitatively assess the performance of adaptive pseudowhitenning compared to those of the standard digital matched-filter and whitening processing. The local spatial variability of fields can be used to assess the variance of estimates, which are primarily correlated with the field of MFB SNR (repeated in the top-right panel of each figure for convenience). Thus, when comparing the fields produced from each of the three processing techniques, significantly smoother spatial textures could be used as an indicator for lower variance of estimates. As expected, for high SNR and when using the same dwell times, the variance of APTB estimates is smaller than their MFB counterparts but similar to that of WTB estimates. On the other hand, for low SNR, APTB estimates exhibit the quality of MFB estimates, which is superior to that of WTB estimates. A clear example of this is shown in the weak isolated echoes in the southwest corner of the display, where the performance of WTB estimates is noticeably degraded compared to that of either MFB or APTB estimates. Overall, the same type of behavior is evidenced in the four meteorological variables shown in Fig. 3; however, an additional benefit is realized in APTB estimates of the correlation coefficient (Fig. 3d). In this case, as a result of the variance reduction achieved by APTB processing, the corresponding fields exhibit fewer range gates with invalid correlation coefficient values above one (denoted by a light pink color).

A more quantitative comparison of these fields can be seen in the two bottom-right panels of Fig. 3. Spatial variances were estimated for the fields of MFB, APTB, and WTB (left panels) using a $3 \times 3$ mask, and ratios were taken between the MFB spatial variances and the corresponding APTB (middle right) and WTB (bottom right) ones. The resulting fields are loosely termed as variance reduction factors (VRF); however, they estimate not only the true VRF but also the spatial variability inherent to the fields. If the fields are uniform, then their inherent variance is much smaller than the variance of estimates, and the ratios approach the true VRF. However, when the fields exhibit significant gradients, their inherent variance dominates, and the ratios approach a value of one. Thus, interpretation of the spatial VRF fields computed in this manner is not straightforward, but it is possible to derive useful information from them.

Patches of range gates in the spatial VRF fields with values between 0 and 1 (gray color) are evidence of situations in which MFB estimates are more precise than either APTB or WTB estimates. Comparing APTB and WTB VRFs, one can see that the latter exhibit more gray patches, particularly in regions of low SNR. This is because below the SNR$_{c}$ (defined in the previous section), WTB estimates are less precise than their MFB counterparts, but APTB estimates gradually change toward MFB as the SNR decreases. The spatial VRF fields also confirm the fact that different meteorological variables have different SNR$_{c}$ values. For example, as mentioned in the previous section, the SNR$_{c}$ for $\rho_{HV}$ estimates is larger than those of $Z_{DR}$ or $\Phi_{DP}$ estimates,
and this is evident in the larger areas of gray in Fig. 3d compared to Figs. 3b,c. Of the four variables shown, reflectivity is the one with the smallest SNR, as made evident by the almost nonexistent gray areas in Fig. 3a.

Whereas spatial VRF values around one would indicate dominance of the variance as a result of the inherent spatial structure of the fields, VRF values significantly larger than one represent true improvement of APTB and WTB over MFB processing. However, since the spatial VRF measurement is affected by the spatial gradients in the fields, the values cannot be used as a direct quantitative measure of performance improvement.

FIG. 2. PPI displays of (top left) MFB SNR, (top right) spectrum width, (bottom left) differential reflectivity, and (bottom right) correlation coefficient acquired with the dual-polarization S-band KOUN radar at about 2337 UTC 12 Aug 2004. Range rings are 10 km apart.
FIG. 3. (a) PPI displays of (left) reflectivity; (top right) SNR; and (middle right), (bottom right) spatial VRF for the same data as in Fig. 2. Shown are (left top) MFB, (left middle) APTB, and (left bottom) WTB estimates. The (right middle) and (bottom) show the VRF for APTB and WTB estimates, respectively, using MFB estimates as a reference. Gray range gates in the VRF fields correspond to cases in which MFB estimates are more precise than either APTB or WTB estimates.
FIG. 3. (b) Same as in (a), but for differential reflectivity.
FIG. 3. (c) Same as in (a), but for differential phase.
Fig. 3. (d) Same as in (a), but for the correlation coefficient.
to validate the simulation results in the previous section. In addition, saturation of the fields and limitations of the color scales could produce counterintuitive results, such as the apparent improvement in $\rho_{HV}$ in the low SNR, isolated region in the southeast corner of the image. Still, there is enough evidence in these images to validate the fact that VRFs of up to five are realizable and that APTB estimates exhibit the best of both worlds: WTB performance at high SNRs and MFB performance at low SNRs.

5. Conclusions

This paper introduces an extension of the single-polarization adaptive-pseudowhitening algorithm for dual-polarization radars. The purpose is to improve the quality of the polarimetric variables while keeping the same dwell times. This is especially relevant in light of the recent dual-polarization upgrade to the U.S. network of weather radars. After the upgrade, the same scanning strategies are used that were implemented in the pre-upgrade single-polarization era. In fact, the standard deviations of the polarimetric variables do not always meet the current requirements for polarimetric-variable estimates. We show that adaptive pseudowhitenning processing does lead to polarimetric-variable estimators that meet the requirements and also improves the quality of estimates under a wide variety of atmospheric conditions. The improvement in the standard deviation of meteorological variable estimates is more than a factor of 2 at high SNRs (with $L = 5$), and smaller but still significant improvement can be seen at low SNRs.

The dual-polarization version of adaptive pseudowhitenning utilizes an efficient implementation similar to the one used for the single-polarization version. This leads to a significant reduction in computational complexity compared to a brute-force implementation of adaptive pseudowhitenning. With the efficient approach, only the partially transformed matrices need to be ground clutter filtered compared to all of the variable-specific data matrices that would need to be filtered in a brute-force approach. The efficient implementation reduces the number of computations by roughly a factor of 6 (because of the six meteorological variables being calculated). Although adaptive-pseudowhitenning processing does increase the computational load compared to matched-filtered processing, the benefits can be substantial as shown through both simulations and real weather data.

In short, adaptive pseudowhitenning is a practical technique for improving data quality without increasing scan times for dual-polarization weather radars. The main challenge is the additional computational load, which should be relatively easily achievable with current computer technology.

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