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IMPROVING THE QUALITY OF DUAL POLARIZATION ESTIMATES USING ADAPTIVE PSEUDOWHITENING

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1. INTRODUCTION

Range oversampling techniques can be utilized to reduce the variance of estimates and/or reduce observation times. Adaptive pseudowhitening is a range oversampling technique that was implemented on the single-polarization National Weather Radar Testbed phased array radar (NWRT PAR) to reduce scanning times. With the advent of the dual polarization upgrade of the NEXRAD (Next Generation Radar) network, it is natural to look at ways to apply range oversampling processing to dual-polarization estimates. Obtaining accurate dual-polarization estimates is a challenge with the current scanning strategies and processing on the WSR-88D (Weather Surveillance Radar – 1988 Doppler), but adaptive pseudowhitening can reduce the standard deviation of estimates by over a factor of two in certain situations. To quantify the performance of this technique, simulations were carried out and analyzed. Oversampled, dual-polarization data were also processed with the new dual-polarization adaptive pseudowhitening algorithm to quantify its performance.

Although this technique was implemented on WSR-88D data, it is also applicable to data collected with phased array weather radars. The electronic scanning capability of phased array antennas lends itself particularly well to range oversampling techniques because any number of pulses can be transmitted at a particular beam position without worrying about antenna rotation. This allows flexibility for shorter dwell times or dwell times that are tailored to particular conditions. If we want to use dwell times that are consistent with the single-polarization dwell times on the WSR-88D, adaptive pseudowhitening can improve the estimates of dual polarization variables without having to increase scan times.

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2. THEORY

Conventional weather radars sample signals at a rate of τ^{-1}, where τ 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 so that *L* complex samples are collected during the time τ. 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 of a class of techniques that applies a linear transform to range-oversampled signals followed by incoherent averaging over *L* oversampled range gates.

The basic structure of the dual-polarimetric adaptive pseudowhitening algorithm follows the efficient implementation introduced in Curtis and Torres (2011). To simplify ground clutter filtering, both the *"H"* and *"V"* time series matrices, $\mathbf{V}_H$ and $\mathbf{V}_V$, are partially transformed using a unitary matrix $\mathbf{U}$. The complex-valued time-series matrices are *L*-by-*M* and correspond to a particular resolution cell that matches the duration of the transmitted pulse τ. The unitary matrix, $\mathbf{U}$, comes from the eigendecomposition of the Hermitian, normalized, range-correlation matrix for the horizontal channel, $\mathbf{C}_{V_H} = \mathbf{U}^*\mathbf{\Lambda}\mathbf{U}^T$. The $\mathbf{\Lambda}$ matrix is the diagonal matrix of eigenvalues, and we assume that the eigenvalues are ordered in size with $\lambda_0 \geq \lambda_1 \geq \ldots \geq \lambda_{L-1} \geq 0$. It is also assumed that the system is using simultaneous transmission and reception of both polarizations, and that the pulses from both channels are matched so that the range-correlation matrices from both channels are equal; i.e., $\mathbf{C}_{V_H} = \mathbf{C}_{V_V}$. In Torres (2009), the case with unmatched channels is addressed which ensures that the dual-polarimetric variables are unbiased. Accurately measuring $\mathbf{C}_{V_H}$ is important because measurement errors can cause biases in reflectivity and reduce the effectiveness of adaptive pseudowhitening (Torres and Curtis 2012).

The equation for the partial transformation is given as follows: $\tilde{\mathbf{X}}_{H,V} = \mathbf{U}^{*T}\mathbf{V}_{H,V}$. This notation is used to show the multiplication of both time series matrices resulting in two partially-transformed matrices $\tilde{\mathbf{X}}_H$ and $\tilde{\mathbf{X}}_V$. A ground clutter filter can be applied to the rows of both of these matrices. It is much more efficient than applying a ground clutter filter to the completely transformed matrices corresponding to each meteorological variable.

Next, we compute L range-oversampled covariances $\hat{R}^{(l)}_{\tilde{X}_H}(k)$, $\hat{R}^{(l)}_{\tilde{X}_V}(k)$, and $\hat{R}^{(l)}_{\tilde{X}_{HV}}(0)$ from the partially-transformed data; the variable k corresponds to the lag. For the classical pulse-pair estimators, we need lags 0 and 1 from $\tilde{\mathbf{X}}_H$ and lag 0 from $\tilde{\mathbf{X}}_V$. Adaptive pseudowhitening utilizes matched-filtered estimates to find the appropriate variable-specific transformation at each range gate. For the single-polarization algorithm the signal-to-noise ratio (SNR) at the output of the digital receiver (SNR_0) and the normailized spectrum width (σ_{vn}) need to be estimated. For the dual-polarization algorithm, it is also necessary to estimate the differential reflectivity (Z_{DR}) and the correlation coefficient (ρ_{HV}). Fortunately, the digital matched filter that maximizes the SNR is given by the eigenvector corresponding to the largest eigenvalue of the normalized range correlation matrix $\mathbf{C}_{V_H}$ (Chiuppesi et al. 1980). Since this eigenvector is a column of $\mathbf{U}$, the first element of each covariance set; i.e., $\hat{R}^{(0)}_{\tilde{X}_H}(k)$, $\hat{R}^{(0)}_{\tilde{X}_V}(k)$, and $\hat{R}^{(0)}_{\tilde{X}_{HV}}(0)$, are the unscaled, matched-filtered covariances corresponding to the largest eigenvalue λ_0. To properly scale the covariances, they each need to be divided by the largest eigenvalue λ_0; this is described in more detail in Curtis and Torres (2011).

We now have the partially-transformed covariances and matched-filtered values of SNR_0, σ_{vn}, Z_{DR}, and ρ_{HV}. The matched-filtered estimates need to be thresholded before the next step to ensure the algorithm works correctly. The σ_{vn} value is thresholded to be above 0.01 and SNR_0 to be above –10 dB. The correlation coefficient, ρ_{HV}, is thresholded to be between 0.01 and 0.999. The Z_{DR} values do not need to be thresholded. Next, the 1-by-L, variable-specific weight vectors, $\mathbf{d}(\theta)$, need to be calculated and applied to the partially-transformed autocovariances as shown:

$$\hat{R}_{X(\theta)}(k) = \sum_{l=0}^{L-1} d_l(\theta)\, \hat{R}^{(l)}_{\tilde{X}}(k) \qquad (1)$$

The variable-specific weight vectors are computed for each of the meteorological variables. In this case, θ can be signal power (S), mean Doppler velocity (v), spectrum width (σ_v), differential reflectivity (Z_{DR}), differential phase (Φ_{DP}), or correlation coefficient (ρ_{HV}). The variable-specific weight vectors combine the variable-specific part of the transformation and the incoherent averaging of the L values of each covariance. The elements of the weight vectors are computed as $d_l = g\lambda_l^+$ where

$$\lambda_l^+ = \frac{\lambda_l}{A\lambda_l^2 + B\lambda_l + C}\,. \qquad (2)$$

The A, B, and C values are variable-specific values and come from an equation in Torres et al. (2004) that minimizes the variance of each meteorological variable estimator. The g term is a power-preserving factor that ensures that the reflectivity estimates are unbiased and can be computed from the λ_l^+ and the eigenvalues using the following expression:

$$g = \left(\sum_{l=1}^{L} \lambda_l^+ \lambda_l\right)^{-1}. \qquad (3)$$

The values of A, B, and C for the spectral moment estimators can be found in Curtis and Torres (2011). The values for the dual polarization estimators are given in the following table:

	A	B	C
Z_{DR}	$\frac{1-\rho_{HV}^2}{\sigma_{vn}\pi^{1/2}}$	$\frac{2(1+Z_{DR})}{\mathrm{SNR}_0}$	$\frac{1+Z_{DR}^2}{\mathrm{SNR}_0^2}$
Φ_{DP}	$\frac{\rho_{HV}^{-2}-1}{2\sigma_{vn}\pi^{1/2}}$	$\frac{1+Z_{DR}}{\rho_{HV}^2\cdot\mathrm{SNR}_0}$	$\frac{Z_{DR}}{\rho_{HV}^2\cdot\mathrm{SNR}_0^2}$
ρ_{HV}	$\frac{1-2\rho_{HV}^2+\rho_{HV}^4}{4\sigma_{vn}\pi^{1/2}}$	$\frac{(1-\rho_{HV}^2)(1+Z_{DR})}{2\cdot\mathrm{SNR}_0}$	$\frac{\rho_{HV}^2(1+Z_{DR}^2)+2Z_{DR}}{4\cdot\mathrm{SNR}_0^2}$

These variable-specific values depend on the four matched-filtered estimates that were computed earlier: SNR_0, σ_{vn}, Z_{DR}, and ρ_{HV}.

Finally, the variable-specific, averaged covariances can be used to compute the six meteorological-variable estimates. An additional issue that needs to be addressed is the noise value at each range gate. Because the transformations are unique for each variable and at each range gate, the noise value is also unique for each variable and each range gate. The change in the noise power is called the noise enhancement factor (NEF) and depends only on the weight vector:

$$\mathrm{NEF}(\theta) = \sum_{l=0}^{L-1} d_l(\theta)\,. \qquad (4)$$

For the meteorological variables that depend on an estimate of the noise power, we can compute the appropriate noise values using the original noise values and the NEF: $N_{H,V}(\theta) = \mathrm{NEF}(\theta) \cdot N_{H,V}$. For both the single-polarization and dual-polarization algorithms, the matched-filtered SNR is used to censor all of the meteorological variable estimates that do not meet an SNR criterion.

This algorithm extends the efficient adaptive-pseudowhitening implementation for single-polarimetric radars from Curtis and Torres (2011) to dual-polarimetric radars. It keeps the partial-transformation step that simplifies the ground clutter filtering process and adds the computation of two matched-filtered dual polarization variables, Z_{DR} and ρ_{HV}, that are needed to calculate the variable-specific *A, B,* and *C* values for the dual polarization variables. The next section will apply this algorithm to simulated data to evaluate its performance.

3. SIMULATIONS

The simulation parameters are based on the scan used to collect the real weather data that are described in section 4. This scan, VCP 11, is used during convective weather events and includes two 360° rotations at an elevation angle of 0.5° using two different pulse repetition times (PRTs). The current dual-polarization processing on the WSR-88D radars computes the dual-polarization variables from the long PRT, which is ~3.1 ms for this scan. There are 17 samples collected at each resolution volume for a dwell time of nearly 53 ms. The frequency is set to 2.7 GHz to correspond to the frequency used on the KOUN radar. To match the real data, the oversampling factor *L* is 5, which gives an oversampled range-gate spacing of ~50 m while the length of the pulse corresponds to a range of ~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 range correlation on the simulated data that closely matches the real data.

Data were simulated with the parameters that were used to define the requirements for the dual-polarimetric variables. These parameters are a spectrum width $\sigma_v = 2\ \mathrm{m\,s^{-1}}$, differential reflectivity $Z_{\mathrm{DR}} = 0.5\ \mathrm{dB}$, and correlation coefficient $\rho_{HV} = 0.99$ which could also be associated with light rain. This is a case where the estimators should have relatively low variances and the dual-polarization estimators should perform well. Fig. 1 shows the results of the simulations for differential reflectivity and correlation coefficient while varying the SNR (from the digital matched filter) from 0 to 35 dB. The SNR for adaptive pseudowhitening 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 top plot is the differential reflectivity (Z_{DR}), and the bottom is correlation coefficient (ρ_{HV}).

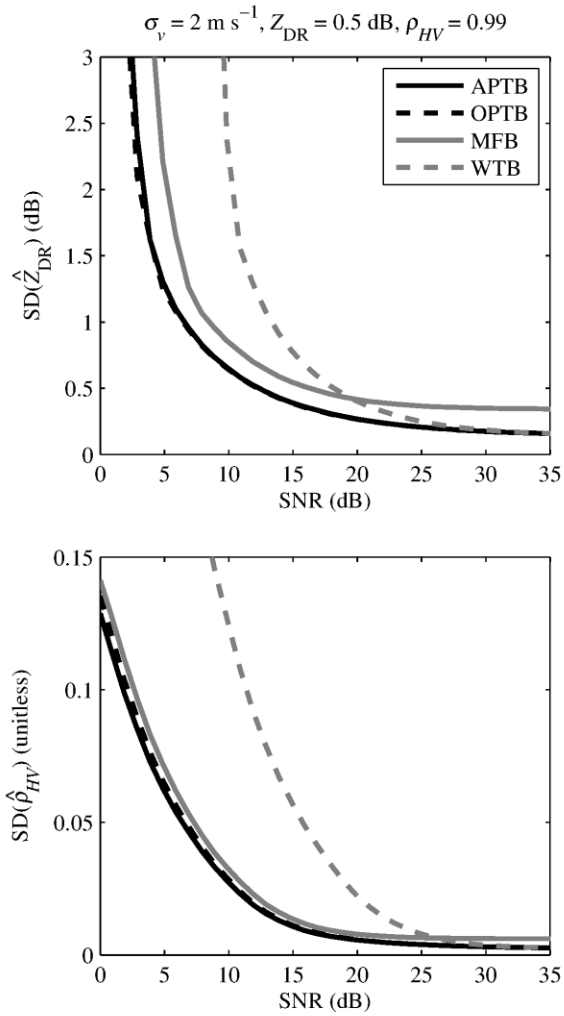

Fig. 1. Standard deviations of polarimetric variable estimators for adaptive pseudowhitening transformation based (APTB), optimal pseudowhitening transformation based (OPTB), matched filtered based (MFB), and whitening transformation based (WTB) processing. The top plot is differential reflectivity (Z_{DR}) and the bottom is correlation coefficient (ρ_{HV}).

The results are shown for four different types of processing. APTB is adaptive pseudowhitening transformation based processing, MFB is digital matched-filter based processing, WTB is whitening transformation based processing using only a pure whitening transformation, and OPTB is optimal pseudowhitening based processing which uses the true values of the matched-filtered parameters to compute the variable-specific transformations rather than estimates. OPTB processing eliminates the errors from estimating the matched-filtered variables but does not address the approximations used in computing the *A*, *B*, and *C* values from section 2. 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 show that using estimates to determine the transformations works well in practice. There are a couple of cases where APTB processing seems to outperform OPTB processing, but APTB processing introduces some small biases which result in lower standard deviations. The APTB biases are smaller than the biases for the MFB processing and are still an improvement.

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 ~0.41 dB which does not meet the requirement, but the result for APTB processing is ~0.27 dB which does meet the requirement. The requirement for ρ_{HV} at 20-dB SNR is a standard deviation of 0.006. The standard deviation of MFB processing is ~0.008 and of APTB processing is slightly below 0.006. At high SNR, adaptive pseudowhitening approaches whitening with a standard deviation improvement factor given, as expected, by $\sqrt{L} \approx 2.24$. Qualitative differences on real data will be shown in section 4.

4. APPPLICATION TO REAL DATA FROM KOUN

In this section, we use data collected by the National Severe Storm Laboratory's KOUN radar to demonstrate how range oversampling can be employed to achieve improved dual-polarimetric data quality 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 pseudowhitening technique described in section 2.

On 12 Aug 2004, the polarimetric, S-band, KOUN radar sampled a severe storm event southwest of Norman, OK. Fig. 2 shows (zoomed in) plan-position-indicator (PPI) displays of differential reflectivity (top row) and correlation coefficient (bottom row) at ~23:37 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 NEXRAD network. The left and right panels in Fig. 2 correspond to fields obtained with digital matched-filter (MFB) and adaptive pseudowhitening (APTB) processing, respectively. Both sets of fields were obtained using the same time-series data and the same ancillary processing functions such as ground clutter filtering and data censoring. It is important to note that both processing modes were based on range-correlation measurements from the data using the technique described by Curtis and Torres (2013).

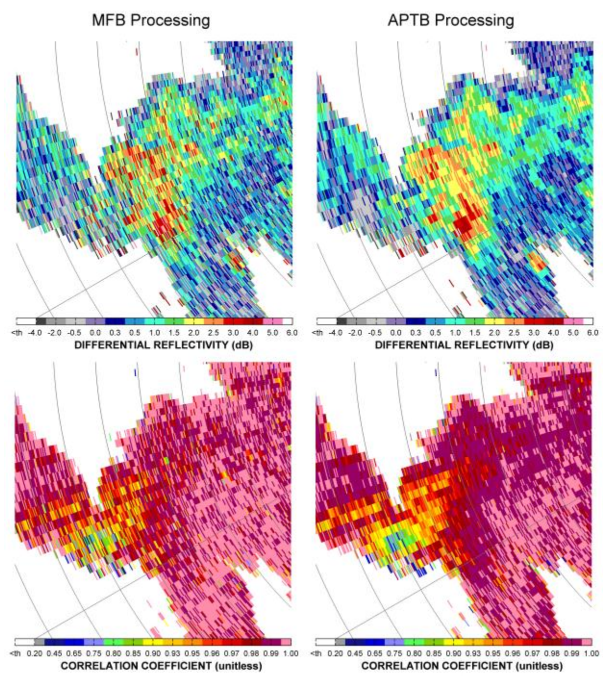

Fig. 2. Plan-position-indicator (PPI) displays of differential reflectivity (top row) and correlation coefficient (bottom row) acquired with the polarimetric, S-band, KOUN radar on 12 Aug 2004 at ~23:37 UTC. The left and right panels correspond to fields obtained with digital matched-filter (MFB) and adaptive pseudowhitening (APTB) processing, respectively.

Corresponding left and right panels of Fig. 2 are useful to qualitatively assess the performance of adaptive pseudowhitening compared to the standard digital matched-filter processing. The significantly smoother texture of fields on the same sampling grid (range and azimuthal spacing) is an indication that, as expected, the variance of APTB estimates is smaller than their MFB counterparts when using the same dwell times. As a result of the variance reduction, data processed using adaptive pseudowhitening exhibit fewer range gates with correlation coefficient values above one.

5. CONCLUSIONS

This paper introduces an extension of the single-polarization adaptive-pseudowhitening algorithm for dual-polarimetric radars. The purpose is to improve the quality of the polarimetric variables while keeping the same dwell times. This is relevant for both conventional parabolic dish antennas and phased array antennas. At high SNR, the standard deviation of the dual-polarization estimators is decreased by approximately a factor of $L^{1/2}$ (L is the range oversampling factor) without changing the scanning strategies used for single-polarization spectral moments.

The dual-polarimetric version of adaptive pseudowhitening 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 pseudowhitening. Although adaptive pseudowhitening 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 pseudowhitening is a practical technique for improving data quality without increasing scan times for dual-polarimetric weather radars.

6. REFERENCES

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