

7.5 RANGE OVERSAMPLING TECHNIQUES FOR POLARIMETRIC RADARS WITH DUAL TRANSMITTERS

Sebastián M. Torres

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

1. INTRODUCTION

Range oversampling followed by a decorrelation transformation is a novel method for increasing the number of independent samples from which to estimate the Doppler spectrum, its moments, as well as several polarimetric variables on pulsed weather radars (Torres and Zrníc 2003a, 2003b). Range oversampling techniques rely on the precise knowledge of the range correlation of oversampled signals, which is a function of the transmitter pulse envelope, the receiver filter impulse response, and the reflectivity field illuminated by the radar. Theoretical and simulation studies demonstrating the advantages of these techniques have been successfully verified on weather data collected with a single-transmitter dual-polarization radar (Ivić et al. 2002, Torres and Ivić 2005). In contrast, recent experimental results on a dual-transmitter system have been rather negative; if the amplitude and/or phase mismatch between transmission pulses is disregarded in the formulation of the decorrelation transformation, processing of range oversampled dual-polarization signals with the standard whitening transformation can produce biased polarimetric variable estimates (Choudhury and Chandrasekar 2007). This paper demonstrates that, by properly accounting for the amplitude and/or phase differences in the two polarization channels, it is always possible to obtain unbiased polarimetric variable estimates. However, the accuracy of these estimators may degrade as the degree of mismatch between the horizontally and the vertically polarized transmitted pulses increases.

2. RANGE OVERSAMPLING IN DUAL POLARIMETRIC RADARS

Traditional sampling of weather radar signals (V) occurs at a rate of τ^{-1} , where τ is the duration of the transmitted pulse. Oversampling in range entails acquiring polarimetric time series data at increased rates so that L complex samples are collected during time τ . This is termed as oversampling by a factor of L and has become feasible with the advent of commercial, single-board digital receivers (Ivić et al. 2003) and digital signal processors (Torres and Zahrai 2002).

Let $\mathbf{v}_H^{(m)}$ and $\mathbf{v}_V^{(m)}$ be the set of L oversampled signals for the horizontal and vertical polarization channels for a given sample time m . In vector notation,

$$\mathbf{v}_{H,V}^{(m)} = \left[V_{H,V}^{(m)}(0) \quad V_{H,V}^{(m)}(1) \quad \dots \quad V_{H,V}^{(m)}(L-1) \right]^T, \quad (1)$$

where the superscript T denotes matrix transposition.

If the resolution volume is uniformly filled with scatterers and the effects of receiver noise are ignored, the correlation coefficient of the oversampled range samples is solely determined by the transmitted pulse shape and the receiver filter impulse response. Let p_H and p_V be the normalized “modified” pulse envelopes for the horizontal (H) and vertical (V) channels (i.e., the transmitted pulses after each channel’s receiver filter) such that $\sum_{l=0}^{L-1} |p_{H,V}(l)|^2 = 1$. Then, the correlation coefficient for range samples can be obtained as (Torres and Zrníc 2003a)

$$\rho_{V,V}^{(R)}(l) = p_V(l) * p_V^*(-l), \quad (2)$$

where the superscript (R) denotes range-time correlation, $*$ is the convolution operation, and the superscript $*$ denotes complex conjugation. Y and Z can be either H or V (e.g., $\rho_{V,V}^{(R)}$ is the range autocorrelation for the horizontal channel, and $\rho_{V,V}^{(R)}$ is the range cross-correlation between the horizontal and vertical channels). Normalized correlation matrices can be constructed as

$$\{ \mathbf{C}_{V,V} \}_{i,j} = \rho_{V,V}^{(R)}(j-i), \quad (3)$$

where $\{ \mathbf{C} \}_{i,j}$ denotes the element in the i -th row and j -th column of the matrix \mathbf{C} .

3. ESTIMATION OF SPECTRAL MOMENTS AND POLARIMETRIC VARIABLES

Oversampled signals in range can be used to improve the quality of meteorological variable estimates without increasing volume acquisition times. Because the objective is to produce better-quality estimates for the traditional (non-oversampled) range gate spacing, a set of signals at L oversampled range gates are suitably combined. With this technique, auto- and cross-correlations are estimated at each of the L oversampled range gates. These L correlation estimates are averaged to produce one covariance estimate with reduced statistical errors. As with traditional sampling, averaged auto- and cross-correlations are used to compute the spectral moments and the polarimetric variables.

Auto- and cross-correlation estimation from oversampled signals is given in general by

$$\hat{R}_{V,V}(k) = \frac{1}{(M-k)L} \sum_{l=0}^{L-1} \sum_{m=0}^{M-k-1} \left[V_V^{(m)}(l) \right]^* V_V^{(m+k)}(l), \quad (4)$$

Corresponding author address: Sebastián Torres, NSSL, 120 David L. Boren Blvd., Norman, OK 73072; email: Sebastian.Torres@noaa.gov

where k is the correlation lag, M is the number of samples in the dwell time, and again, Y and Z can be either *Hor* or *V*. Equation (4) can be rewritten as

$$\begin{aligned}\hat{R}_{V_Y V_Z}(k) &= \frac{1}{(M-k)} \sum_{m=0}^{M-k-1} \left\{ \frac{1}{L} \sum_{l=0}^{L-1} [V_Y^{(m)}(l)]^* V_Z^{(m+k)}(l) \right\} \\ &= \frac{1}{(M-k)} \sum_{m=0}^{M-k-1} \hat{y}_{V_Y V_Z}(m, k),\end{aligned}\quad (5)$$

where it is more evident that it is possible to produce correlation estimates with smaller errors by reducing the errors of the range averaged correlations $\hat{y}_{V_Y V_Z}$. In other words, we would like to transform the range oversampled signals to produce uncorrelated data that can be exploited to maximize the variance reduction through averaging (Torres and Zrnić 2003a).

Assuming stationarity and using the vector representation of the signals, the expected value of (5) is

$$\begin{aligned}E[\hat{R}_{V_Y V_Z}(k)] &= E[\hat{y}_{V_Y V_Z}(k)] \\ &= E\left\{ \frac{1}{L} \sum_{l=0}^{L-1} [V_Y^{(m)}(l)]^* V_Z^{(m+k)}(l) \right\} \\ &= \frac{1}{L} E\left[(\mathbf{v}_Y^{(m)})^* \mathbf{v}_Z^{(m+k)} \right] \\ &= \frac{1}{L} E\left\{ \text{tr} \left[(\mathbf{v}_Y^{(m)})^* (\mathbf{v}_Z^{(m+k)})^T \right] \right\} \\ &= \frac{1}{L} \text{tr} \left\{ E \left[(\mathbf{v}_Y^{(m)})^* (\mathbf{v}_Z^{(m+k)})^T \right] \right\} \\ &= \frac{1}{L} \text{tr} (\mathbf{R}_{V_Y V_Z}^{(k)}),\end{aligned}\quad (6)$$

where \mathbf{R} is the correlation matrix with no normalization (e.g., $\mathbf{R}_{V_H V_H}^{(0)} = S_H \mathbf{C}_{V_H V_H}$, where S_H is the signal power in the horizontal channel) and $\text{tr}(\cdot)$ is the trace of a matrix.

4. TRANSFORMATION OF RANGE OVERSAMPLED DATA

A whitening transformation on range oversampled time-series data can be used to decorrelate these signals before averaging. That is, through a linear transformation, a set of L correlated complex samples is transformed into a set of L decorrelated (or whitened) complex samples. Because data are uncorrelated, averaging covariances from whitening oversampled signals reduces the variance of estimates by a factor of L (Torres and Zrnić 2003a).

The whitening transformation \mathbf{W} can be constructed as

$$\mathbf{W} = \mathbf{H}^{-1}, \quad (7)$$

where $\mathbf{C}_{V_H V_H} = \mathbf{H}^* \mathbf{H}^T$. Then, transformed oversampled data are obtained as

$$\mathbf{x}_{H,V} = \mathbf{W} \mathbf{v}_{H,V}. \quad (8)$$

Range correlations for the transformed data (\mathbf{x}) can be derived as follows:

$$\begin{aligned}\mathbf{R}_{X_Y X_Z}^{(k)} &= E \left[(\mathbf{x}_Y^{(m)})^* (\mathbf{x}_Z^{(m+k)})^T \right] \\ &= \mathbf{W}^* E \left[(\mathbf{v}_Y^{(m)})^* (\mathbf{v}_Z^{(m+k)})^T \right] \mathbf{W}^T \\ &= \mathbf{W}^* \mathbf{R}_{V_Y V_Z}^{(k)} \mathbf{W}^T = R_{V_Y V_Z}(k) \mathbf{W}^* \mathbf{C}_{V_Y V_Z} \mathbf{W}^T,\end{aligned}\quad (9)$$

where again, Y and Z can be either *Hor* or *V*.

4.1. Matched Channels

For a radar system with perfectly matched channels, $\rho_H = \rho_V$. This is not an unrealistic assumption for dual polarization radars with one transmitter. In this situation, the normalized auto- and cross-correlation matrices are the same; i.e., $\mathbf{C}_{V_H V_H} = \mathbf{C}_{V_V V_V} = \mathbf{C}_{V_H V_H}$.

4.1.1 Autocorrelation Estimation

Analogous to (6), the expected value of the autocorrelation estimator on transformed data is

$$\begin{aligned}E[\hat{R}_{X_H X_H}(k)] &= \frac{1}{L} \text{tr} (\mathbf{R}_{X_H X_H}^{(k)}) \\ &= \frac{R_{V_H V_H}(k)}{L} \text{tr} (\mathbf{W}^* \mathbf{C}_{V_H V_H} \mathbf{W}^T) \\ &= \frac{R_{V_H V_H}(k)}{L} \text{tr} (\mathbf{I}) = R_{V_H V_H}(k).\end{aligned}\quad (10)$$

Hence, the autocorrelation estimator on transformed data is unbiased with the transformation defined by equation (7). The same is true for the V channel autocorrelation estimator on transformed data, since $\mathbf{C}_{V_H V_H} = \mathbf{C}_{V_V V_V}$ and \mathbf{W} also whitens the data in the V channel.

4.1.2 Cross-Correlation Estimation

Again, from (6),

$$\begin{aligned}E[\hat{R}_{X_Y X_H}(k)] &= \frac{1}{L} \text{tr} (\mathbf{R}_{X_Y X_H}^{(k)}) \\ &= \frac{R_{V_Y V_H}(k)}{L} \text{tr} (\mathbf{W}^* \mathbf{C}_{V_Y V_H} \mathbf{W}^T) \\ &= \frac{R_{V_Y V_H}(k)}{L} \text{tr} (\mathbf{I}) = R_{V_Y V_H}(k).\end{aligned}\quad (11)$$

The cross-correlation estimator on transformed data with the transformation defined by (7) is also unbiased since $\mathbf{C}_{V_H V_H} = \mathbf{C}_{V_V V_V}$.

4.2. Mismatched Channels

For a radar system with mismatched channels, $\rho_H \neq \rho_V$. This is more likely to occur in dual polarization radars with dual transmitters. In this case, auto- and cross-correlation matrices are generally different. Therefore, a whitening matrix that works for the H channel may not work for the V channel, and vice versa. Then, it makes sense to consider two independent transformations, \mathbf{W}_H and \mathbf{W}_V , one for each channel. Transformed data (\mathbf{x}) are obtained as [c.f. (8)]

$$\mathbf{x}_{H,V} = \mathbf{W}_{H,V} \mathbf{v}_{H,V}, \quad (12)$$

and range correlations are [c.f. (9)]

$$\mathbf{R}_{X_V X_Z}^{(k)} = R_{V_V Z} \mathbf{W}_V^* \mathbf{C}_{V_V Z} \mathbf{W}_Z^T. \quad (13)$$

4.2.1 Autocorrelation Estimation

Repeating the process in 4.1.1, the expected value of the autocorrelation estimator on transformed data is

$$\begin{aligned} E[\hat{R}_{X_H X_H}(k)] &= \frac{1}{L} \text{tr}(\mathbf{R}_{X_H X_H}^{(k)}) \\ &= \frac{R_{V_H V_H}(k)}{L} \text{tr}(\mathbf{W}_H^* \mathbf{C}_{V_H V_H} \mathbf{W}_H^T) \\ &= \frac{R_{V_H V_H}(k)}{L} \text{tr}(\mathbf{I}) = R_{V_H V_H}(k); \end{aligned} \quad (14)$$

hence, the estimator is unbiased with \mathbf{W}_H defined by (7). The same is true for the V channel autocorrelation estimator, with \mathbf{W}_V derived from an analogous decomposition of $\mathbf{C}_{V_V V_V}$.

4.2.2 Biased Cross-Correlation Estimation

Repeating the process in 4.1.2,

$$\begin{aligned} E[\hat{R}_{X_V X_H}(k)] &= \frac{1}{L} \text{tr}(\mathbf{R}_{X_V X_H}^{(k)}) \\ &= \frac{R_{V_V V_H}(k)}{L} \text{tr}(\mathbf{W}_H^* \mathbf{C}_{V_V V_H} \mathbf{W}_V^T); \end{aligned} \quad (15)$$

Hence, the cross-correlation estimator is biased because, in general, $\text{tr}(\mathbf{W}_H^* \mathbf{C}_{V_V V_H} \mathbf{W}_V^T) / L \neq 1$ and $E[\hat{R}_{X_V X_H}(k)] \neq R_{V_V V_H}(k)$.

4.2.3 Unbiased Cross-Correlation Estimation

The result in (15) is useful for constructing transformations that lead to unbiased cross-correlation estimates. As suggested before, the condition for unbiased estimates is given by

$$\text{tr}(\mathbf{W}_H^* \mathbf{C}_{V_V V_H} \mathbf{W}_V^T) = L, \quad (16)$$

and this is easily achieved by properly scaling the H and V transformation matrices. That is, let a new set of scaled transformation matrices be $\tilde{\mathbf{W}}_{H,V} = \gamma_{H,V} \mathbf{W}_{H,V}$. With these new transformations, (16) becomes

$$\gamma_H^* \gamma_V \text{tr}(\mathbf{W}_H^* \mathbf{C}_{V_V V_H} \mathbf{W}_V^T) = L, \quad (17)$$

and the scaling factors have to be chosen such that

$$\gamma_H^* \gamma_V = \frac{L}{\text{tr}(\mathbf{W}_H^* \mathbf{C}_{V_V V_H} \mathbf{W}_V^T)}. \quad (18)$$

A solution to this equation is

$$\gamma_H^* = \gamma_V = \sqrt{\frac{L}{\text{tr}(\mathbf{W}_H^* \mathbf{C}_{V_V V_H} \mathbf{W}_V^T)}}. \quad (19)$$

Note that with this formulation, the transformation matrices used in the autocorrelation estimators are different from the ones used in the cross-correlation estimator.

4.2.4 General Unbiased Correlation Estimation

In the general case, we would like to determine the best transformation matrices for any given situation without being constrained to choosing a whitening transformation. For example, pseudowhitening has been proposed as a way to increase the effective number of independent samples while minimizing the noise enhancement effects inherent to the whitening transformation (Torres et al. 2004). Hence, we need a general formulation that produces unbiased auto- and cross-correlation estimates for any transformation matrix structure.

Let, $\mathbf{W}_{H,V}^A$ be the set of transformations for the autocorrelation estimator, and $\mathbf{W}_{H,V}^C$ the one for the cross-correlation estimator, where the basic structure of each matrix can be determined using different criteria (e.g., $\mathbf{W}_{H,V}^A$ can be chosen as the whitening matrices for the H and V channel data, while $\mathbf{W}_{H,V}^C$ can be chosen as the matrices that diagonalize the range cross-correlation matrix $\mathbf{C}_{V_V V_H}$). To produce unbiased estimates, these four matrices require scaling given by $\gamma_{H,V}^{AC}$, which could be determined as

$$\gamma_H^A = \sqrt{\frac{L}{\text{tr}[(\mathbf{W}_H^A)^* \mathbf{C}_{V_H V_H} (\mathbf{W}_H^A)^T]}}, \quad (20)$$

$$\gamma_V^A = \sqrt{\frac{L}{\text{tr}[(\mathbf{W}_V^A)^* \mathbf{C}_{V_V V_V} (\mathbf{W}_V^A)^T]}}, \quad (21)$$

and

$$(\gamma_H^C)^* = \gamma_V^C = \sqrt{\frac{L}{\text{tr}[(\mathbf{W}_H^C)^* \mathbf{C}_{V_V V_H} (\mathbf{W}_V^C)^T]}}. \quad (22)$$

Note that with the scaling in the previous three equations auto- and cross-correlation estimates are always unbiased. However, the variance of these estimators depends on the basic structure chosen for each transformation matrix.

5. SIMULATION RESULTS

Simulated polarimetric time-series data were used to validate the unbiasing scaling presented in the previous section. Signals are simulated as described by Torres and Zrnić (2003a, b) using varying degrees of mismatch between the modified pulses of the H and V channels. The modified pulse for the H channel was fixed with rectangular amplitude and zero-phase

$$p_H(l) = \begin{cases} L^{-1/2} & 0 \leq l < L \\ 0 & \text{otherwise} \end{cases}, \quad (23)$$

whereas the one for the V channel was varied to obtain different degrees of mismatch as

$$p_V(l) = \begin{cases} \tilde{a}(l)e^{j\alpha l} & 0 \leq l < L \\ 0 & \text{otherwise} \end{cases}. \quad (24)$$

Note that the phase of p_V is linear with slope α , and the amplitude function 'a' was chosen as either a linearly increasing function from A to 1:

$$a(l) = A + (1 - A) \frac{l}{L-1}, \quad l = 0, \dots, L-1, \quad (25)$$

or as a "raised" triangular function¹:

$$a(l) = A + (1 - A) \frac{2}{L-1} \left(\frac{L-1}{2} - \left| l - \frac{L-1}{2} \right| \right), \quad l = 0, \dots, L-1, \quad (26)$$

and

$$\tilde{a}(l) = a(l) \left[\sum_{l'} a^2(l') \right]^{-1/2} \quad (27)$$

so that $\sum_{l=0}^{L-1} |\tilde{p}_V(l)|^2 = 1$. The pattern for these mismatches was based on Choudhury and Chandrasekar's work (2007) on the Colorado State University's CHILL radar and on our observations from the National Severe Storms Laboratory's NEXRAD polarimetric prototype (Ivić et al. 2003). An amplitude mismatch could be due to miscalibrated pulse-forming networks or different overall gains in each channel. A phase mismatch might be attributed to a known effect with klystron amplifiers. It has been observed that these devices exhibit an AM-to-PM conversion whereby voltage variations in the transmitted pulse envelope are converted into phase variations of the carrier (Ivić et al. 2003).

Amplitude and phase mismatches were evaluated independently. Figures 1 and 2 show the magnitude and phase of the H and V channel autocorrelation functions for only a phase mismatch and only an amplitude mismatch, respectively.

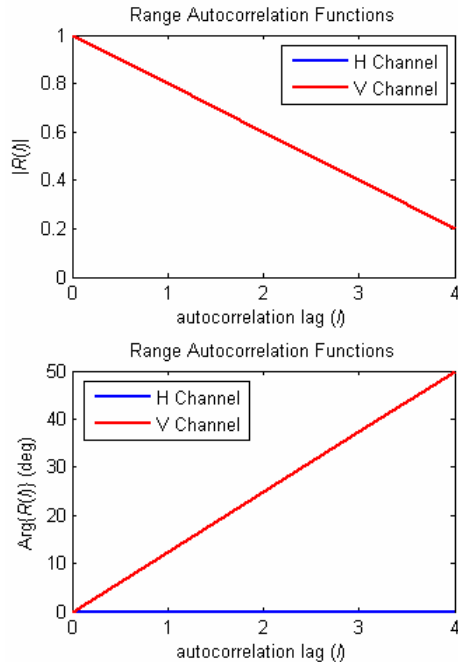


Fig. 1. Magnitude and phase of the H and V channel normalized autocorrelation functions for $a(l)=1$, and $\alpha=50$ deg. The oversampling factor L is 5. Note that magnitude curves are on top of each other.

Figures 3 and 4 show the bias and standard deviation of the spectral moments corresponding to varying degrees of phase and amplitude mismatch (only the case in (25) is shown here), respectively. Figures 5 and 6 depict the same for the polarimetric variables. To generate these figures, range oversampled data were processed using four matrix transformation sets:

1. Matched filtering (MFB), in which range oversampled signals are run through a matched filter and decimated to simulate the standard, non-oversampling processing,
2. Oversampling and averaging (OAB), in which oversampled signals are not transformed; i.e., $\mathbf{W}_{H,V}^A = \mathbf{W}_{H,V}^C = \mathbf{I}$,
3. "Biased" whitening (WTB), in which the same whitening transformation (the one for the H channel) is used disregarding channel mismatch; i.e., $\mathbf{W}_{H,V}^A = \mathbf{W}_{H,V}^C = \mathbf{H}^{-1}$ (where $\mathbf{C}_{V_H V_H} = \mathbf{H} \mathbf{H}^T$), and
4. Unbiased whitening (UWTB), in which the proper scaling factors are applied, $\mathbf{W}_{H,V}^A$ are the whitening transformations for each channel, and $\mathbf{W}_{H,V}^C$ diagonalize the normalized range cross-correlation matrix $\mathbf{C}_{V_H V_H}$.

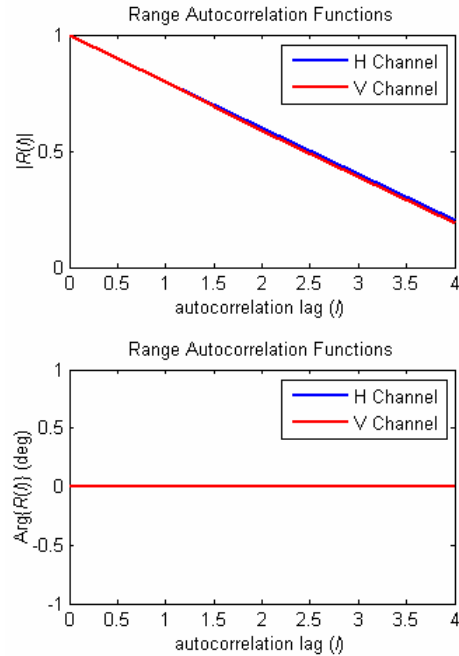


Fig. 2. Magnitude and phase of the H and V channel normalized autocorrelation functions for $a(l)=0.8+0.05l$ and $\alpha=0$. The oversampling factor L is 5. Note that phase curves are on top of each other.

¹ This formula is for odd L

Fig. 3 and 4 show that spectral moments (which are based on the H channel autocorrelation function) are unbiased, and the performance of the different range oversampling techniques is independent of the degree of mismatch between the H and V channels (which is obvious since the estimates are computed from signals in only one channel.) Performance of both WTB and UWTB are the same; both of these are much better than MFB or OAB, as predicted by the theory.

Fig. 5 and 6 show that although WTB has the lowest errors, it produces biased estimates of all polarimetric variables as the degree of mismatch between the H and V channels increases. On the other hand, UWTB has almost the same variance reduction as WTB but produces unbiased estimates irrespective of the degree of mismatch between the H and V channels. Notice however that the errors of estimates with UWTB (and WTB) increase relative to those of OAB or MFB as the degree of mismatch between the H and V channels increases. Indeed, for large degrees of mismatch (mainly observed for phase mismatches with α larger than about 5) UWTB performs worse than OAB! In such cases, we argue that we could use a different structure for the transformation matrices (based on the proper optimum criterion to achieve maximum variance reduction of cross-correlation estimates). This, however, is beyond the scope of this work and is the subject of ongoing research.

6. CONCLUSIONS AND FUTURE WORK

This paper demonstrates that, by properly accounting for the amplitude and/or phase differences in the transmission channels (i.e., by proper scaling of the transformation matrices), it is always possible to obtain unbiased spectral moment and polarimetric variable estimates. However, as shown by the simulations, the accuracy of these estimators degrades as the degree of mismatch between the horizontally and the vertically polarized transmitted pulses increases.

We are currently investigating other transformation structures that result in unbiased auto- and cross-correlation estimates and at the same time achieve maximum variance reduction. The fact that this is always possible for the autocorrelation and for the cross-correlation with matched channels suggests that by properly accounting for the mismatch in the two polarimetric channels, it might be possible to produce optimum cross-correlation estimates.

ACKNOWLEDGMENT

This conference paper was prepared by Sebastián Torres with funding provided by NOAA/Office of Oceanic and Atmospheric Research under NOAA-University of Oklahoma Cooperative Agreement #NA17RJ1227, U.S. Department of Commerce. The statements, findings, conclusions, and recommendations are those of the authors and do not necessarily reflect the views of NOAA or the U.S. Department of Commerce.

REFERENCES

- Choudhury, S. and V. Chandrasekar, 2007: Wideband reception and processing for dual-polarization radars with dual transmitters. *J. Atmos. Oceanic Technol.*, **24**, 95-101.
- Ivić, I., S. Torres, and D.S. Zrnić, 2002: Demonstration of Optimum Processing of Oversampled Data in Range to Improve Doppler Spectral Moment Estimates. Preprints, *18th International Conf. on IIPS*, Orlando, FL, Amer. Meteor. Soc., 142-144.
- Ivić, I., A. Zahrai, and D. Zrnić, 2003: Digital IF receiver – capabilities, tests, and evaluation. *Preprints 31th Conf. on Radar Meteorology*, Seattle, WA, Amer. Meteor. Soc., pp. 732-734.
- Ivić, I., D. Zrnić, and Torres, S., 2003: Whitening in range to improve weather radar spectral moment estimates. Part II: Experimental evaluation. *J. Atmos. Oceanic Technol.*, **20**, 1449-1459.
- Torres, S. and D. Zrnić, 2003a: Whitening in range to improve weather radar spectral moment estimates. Part I: Formulation and simulation. *J. Atmos. Oceanic Technol.*, **20**, 1433-1448.
- Torres, S. and D. Zrnić, 2003b: Whitening of signals in range to improve estimates of polarimetric variables. *J. Atmos. Oceanic Technol.*, **20**, 1776-1789.
- Torres, S., C. Curtis, and J. R. Cruz, 2004: Pseudowhitening of weather radar signals to improve spectral moment and polarimetric variable estimates at low signal-to-noise ratios. *IEEE Trans. Geosci. Remote Sensing*, **42**, 941-949.
- Torres, S. and I. Ivić, 2005: Demonstration of range oversampling techniques on the WSR-88D. Preprints, *32nd International Conf. on Radar Meteorology*, Albuquerque, NM, Amer. Meteor. Soc., Paper 4R.5.
- Zahrai, A., S. Torres, I. Ivić, and C. Curtis, 2002: The open radar data acquisition (ORDA) design for the WSR-88D. *Preprints 18th International Conf. on IIPS*, Orlando, FL, Amer. Meteor. Soc., paper 5.10.

Spectral Moments

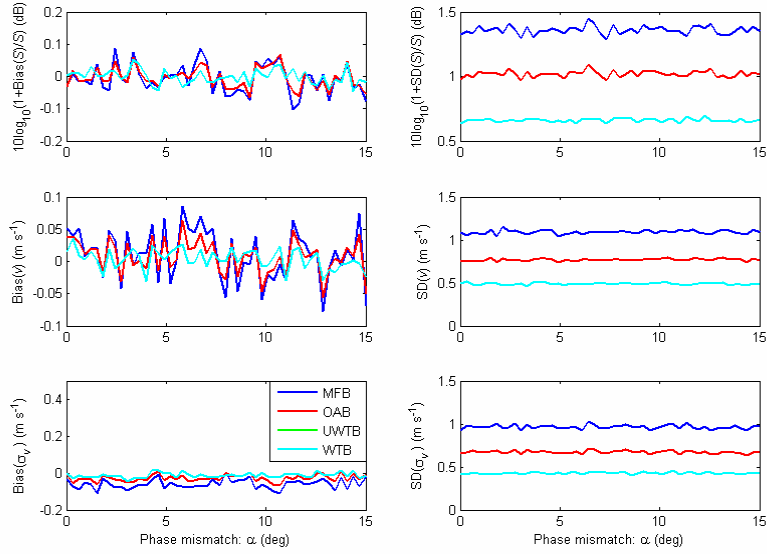


Fig. 3. Bias (left) and standard deviation (right) of spectral moment estimates for oversampled data processed using: (1) a matched filter (MFB), (2) oversampling and averaging (OAB), (3) biased whitening (WTB), and (4) unbiased whitening (UWTB). H and V channels exhibit a progressively increasing phase mismatch with α varying from 0 to 15.

Spectral Moments

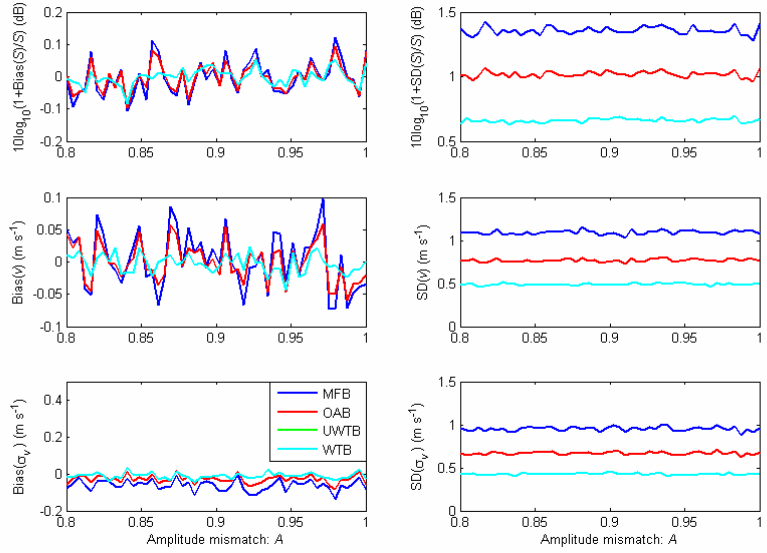


Fig. 4. Bias (left) and standard deviation (right) of spectral moment estimates for oversampled data processed using: (1) a matched filter (MFB), (2) oversampling and averaging (OAB), (3) biased whitening (WTB), and (4) unbiased whitening (UWTB). H and V channels exhibit a progressively increasing amplitude mismatch with A varying from 0.8 to 1.

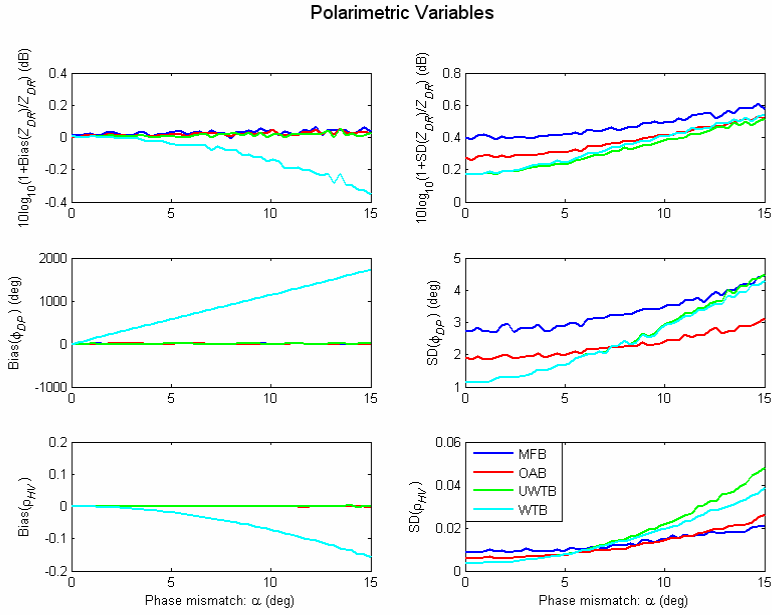


Fig. 5. Bias (left) and standard deviation (right) of polarimetric variable estimates for oversampled data processed using: (1) a matched filter (MFB), (2) oversampling and averaging (OAB), (3) biased whitening (WTB), and (4) unbiased whitening (UWTB). H and V channels exhibit a progressively increasing phase mismatch with α varying from 0 to 15.

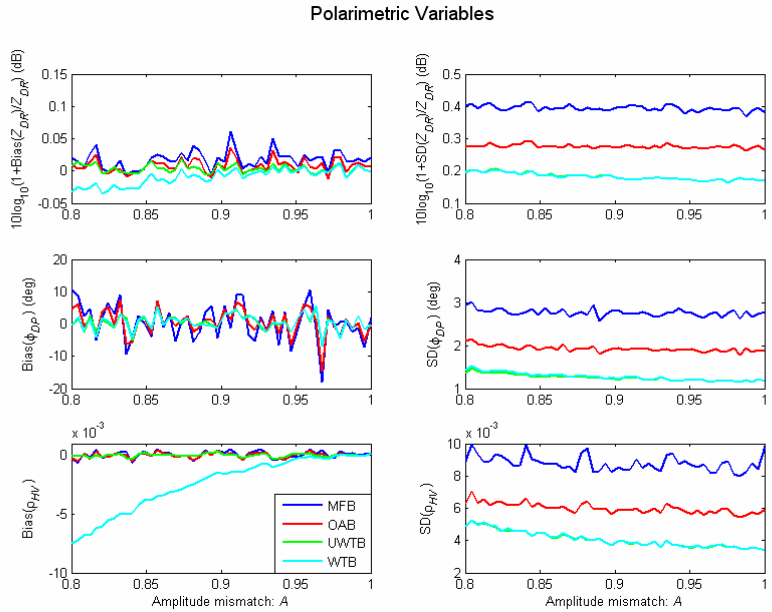


Fig. 6. Bias (left) and standard deviation (right) of polarimetric variable estimates for oversampled data processed using: (1) a matched filter (MFB), (2) oversampling and averaging (OAB), (3) biased whitening (WTB), and (4) unbiased whitening (UWTB). H and V channels exhibit a progressively increasing amplitude mismatch with A varying from 0.8 to 1.