Online Determination of Noise Level in Weather Radars

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1. Introduction

All receivers detect signals that are at some level above the limit imposed by the random voltage (i.e., the noise) inherent in every electronic device. Consequently, proper measurement of noise power is of paramount importance for the estimation and censoring of the weather radar data, which, in turn, is essential for the correct operation of automated algorithms and accurate forecasts derived from such data. Incorrect noise power measurements may lead to reduction of coverage in cases where noise power is overestimated or to radar data images cluttered by noise speckles if the noise power is underestimated. Consequently, the correct noise measurement is essential for proper operation of censoring techniques in both single and dual-polarized radars (Ivić and Torres 2009, Ivić et al. 2009). Moreover, when an erroneous noise power is used at low signal-to-noise ratios (SNR), estimators usually produce biased meteorological variables such as in the case of reflectivity and spectrum width. Typically, the noise in weather radars can be measured in several ways. For instance, on the National Weather Surveillance Radar – 1988 Doppler (WSR-88D) the noise is measured as part of the system online calibrations performed after each volume scan. Such measurement takes place at a high antenna elevation angle and the result is adjusted for other antenna elevations. In systems that do not have the capability to perform online calibrations (e.g., the National Weather Radar Testbed Phased-Array Radar) the noise must be measured offline. Clearly the downside of such approach is that it does not capture the temporal variations of noise power. Moreover, the nature of the noise sources in radar data is such that noise can have angular dependence in both azimuth and elevation (e.g., noise from cosmic radiation and from the oxygen and water vapor molecules) (Doviak and Zrnić 1993). Consequently, the benefit of noise measurements at each antenna position becomes obvious. The only way such measurement can be performed operationally is in parallel with data collection. Thus, an efficient approach that estimates noise power from measurements that contain both signal and noise is needed.

Ideally, noise power estimates should be computed for every sampling volume, for example, by using spectral noise estimation methods. In the past several methods have been proposed. Hildebrand and Sekhon (1974) describe a method that subjects the Fourier coefficients to a series of tests whereby coefficients are recursively discarded until statistical conditions suggest only noise samples remain. Urkowitz and Nespor (1992) used the Kolmogorov-Smirnov (K-S) test applied to the periodogram by successively discarding the Fourier spectral lines until the criterion for the noise hypothesis is satisfied. Siggia and Passarelli (2004) used rank order statistics on power spectral density estimate to dynamically determine the noise level. Common to all these approaches is discarding excess Fourier coefficients until the remaining ones satisfy conditions for noise. Inevitably, each approach introduces bias in noise level determination even when no signal is present and particularly for radar volumes with weather signals that have wide spectrum widths or if using a small number of samples in the dwell time. This can not be avoided and the only question is how significant the bias is. Hence, a need arises for a more precise and continuous system noise power calibration that is robust and feasible for real-time implementation on weather radars. In this paper, we propose a novel method to estimate the system noise power dynamically from the in-phase and quadrature data for every antenna position (radial). The technique uses a novel criterion to detect radar volumes that do not contain significant weather signals and uses those to estimate the system noise power. The proposed method overcomes the limitations of the previous work in cases when the numbers of samples at each range position is small because it does not use the Fourier coefficients. Moreover, this is usually the case in the surveillance mode where the unambiguous range is long and the number of range positions devoid of signal is more than sufficient for quality noise estimation resulting in the algorithm performing very well.

This technique is evaluated using a time-series collected with the National Weather Radar Testbed Phased-Array Radar (NWRT) and the research WSR-88D KOUN radar, both located in Norman, OK. Results show that the proposed technique produces noise power estimates that are closely matched to the ones obtained from manually identified, signal-free radar volumes at far ranges from the radar; thus, providing empirical validation. A real-time implementation of this technique is expected to significantly improve the data quality of operational weather radars which often rely on accurate noise power estimates.

2. Noise estimation algorithm

Unlike the previously discussed approaches to noise estimation, the algorithm presented in this paper does not produce a noise power estimate for each radar volume. Rather, it attempts to discard all samples at range locations where the presence of signal is detected. The assumption is that there are enough range bins devoid of signal to yield noise estimates with satisfactory accuracy. This is almost always true when using long pulse repetition times (PRT), which result in unambiguous ranges in excess of 300 km. On the other hand, when the PRT yields shorter unambiguous ranges, it is possible that the majority of samples contain signal as storms span or exceed the entire unambiguous range. In such cases, the algorithm is unable to produce reliable noise estimates. For dual PRT scans (i.e., those using a long PRT for range coverage and a short PRT for Doppler velocity measurements), if the noise power at a given antenna position can not be estimated from the short PRT data, it is usually readily available from the long PRT.

To illustrate the steps of the noise estimation algorithm we will use data collected with the National Weather Radar Testbed Phased-Array Radar (NWRT PAR) in Norman, OK. This particular set of data was collected with a long PRT with unambiguous range of 465.6 km. Radar echoes are oversampled by a factor of 4, where samples are 60 m apart and the transmitted pulse is roughly 240 m long. The number of samples in the dwell time is 15. This radar does not perform online calibrations so the default noise level is ascertained by offline measurements. The test power profile is shown in FIG. 1. By visual inspection, we see that there should be no signal beyond the 5000-th sample. By averaging the power of all samples beyond 5000, 5500, and 6000 we get 18.06, 17.64 and 17.6. Thus, we assume that the "true" noise power is 17.6 (12.46 dB) in this case.

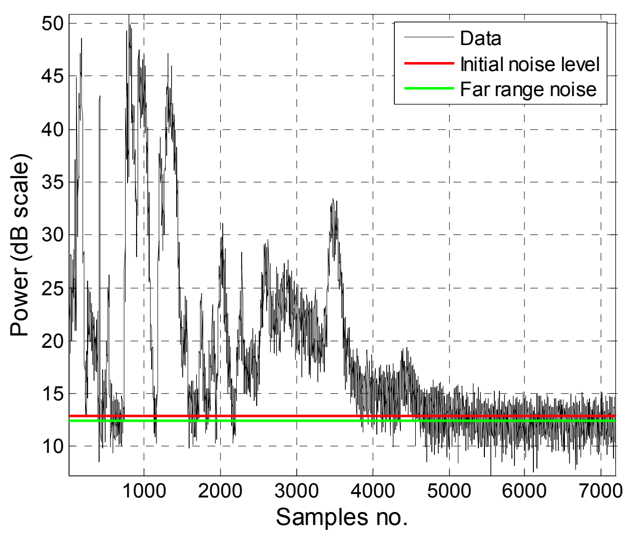

FIG. 1 Received power as a function of range at the elevation angle of 0.5 deg. The number of samples at each range position is 15 and the range sample spacing is 60 m. The initial and "true" noise values are indicated with a red and green line, respectively. This data was collected using the NWRT PAR in Norman, OK.

The first step in the algorithm requires an initial knowledge of the noise power (herein referred to as the initial noise level for the purposes of the algorithm) which should be a rough estimate in the vicinity of the true noise power (e.g., within ±2 dB). This initial noise level is used to obtain the coherency-based threshold (CBT) (Ivić and Torres 2009) by simply multiplying it with the value chosen from the look-up table (where the number of samples is used as an entry into the table). Then, all samples at range positions classified to contain signal-like returns are discarded. In this particular case the threshold produces the false alarm rate of 4.4×10^{-6}; hence, if the initial noise value were the true noise value, such threshold would produce about 44 false signal detections in 10 million. Because the true noise power is lower than the initial one, the number of false signal detections is even smaller. On the other hand, if the initial noise value were lower than the true one, the number of false detections would be higher. Here, we are interested in those samples that are classified as noise (i.e., those that are censored by the CBT). Thus, it is important that the number of false detections is not too high to prevent too many noise samples being classified as signals (hence not used for noise estimation) which can potentially bias the noise estimate. Choosing a CBT threshold that yields low false detection rate ensures this does not occur for a wide range of initial noise values. In this case, however, the default absolute noise power for the NWRT PAR is 19.5 (12.29 dB); hence, the initial noise power is overestimated by the offline procedure.

The second step refines the outcome of the first one by using the autocorrelation coefficient (ACF) at lag 1. In this step, the lag-1 ACF is calculated at each range position and those for which it is larger than the predetermined threshold are deemed to contain signal and related samples are consequently discarded. The ACF threshold is set to pass 99% of the noise samples so it does not bias the noise estimate. The threshold value depends on the number of samples in the dwell time (M) and in this particular case it is 0.55. Because the autocorrelation coefficient is not dependent on the noise and signal powers, this step discards samples at range positions containing highly correlated signals. After applying the first two steps, the remaining "noise-like" range bins are shown in FIG. 2 (a). It is obvious that a significant amount of range positions still contain signal-like returns. This is reflected by the mean power of this data set which is 23.02 (13.62 dB); thus, it is still well above the far range or "true" noise level.

The next step is to apply a "range persistence" filter. The filter finds 10 or more consecutive power values that are larger than the median power in the set and discards them along with 10 samples on either side. The rationale for choosing 10 consecutive samples is as follows. The probability that one power sample is larger than the median is 0.5; hence, the probability that 10 randomly chosen independent samples are larger than the median is $0.5^{10} = 9.76\times10^{-4}$. Consequently, this filter should detect and remove larger sample powers (evident of signal-like returns) that exhibit some continuity in range while leaving those in predominantly in noise areas. After applying the range persistence filter to our sample data set, we obtain FIG. 2 (b). The mean power of the resulting set is 19.69 (or 12.94 dB), which is still higher than the "true" noise power for this case.

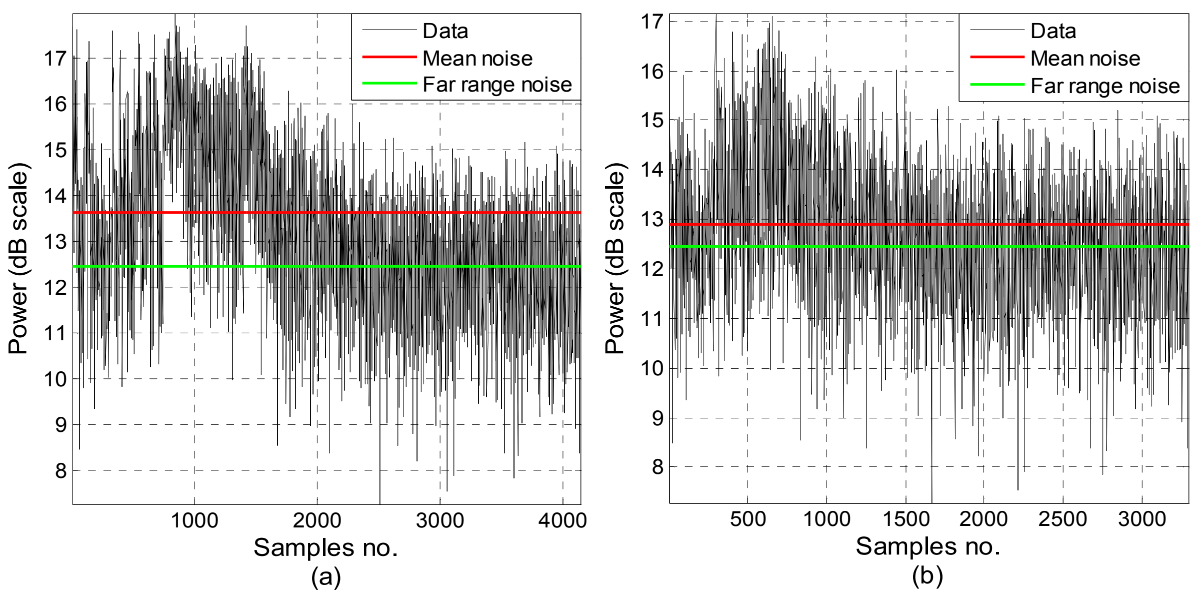

FIG. 2 (a) Power of range bins after the first two steps of the algorithm. (b) Power of range bins after the third step of the algorithm.

In the fourth step, the matrix of samples (range time vs. sample time) is reshaped into a vector where the samples from 1 to M belong to the first column of the matrix, samples M+1 to 2M belong to the second column of the matrix and so on. Then, a running average of K samples is performed as

$$RAVG(m) = \frac{1}{K}\sum_{k=0}^{K-1}\left|V(m-k)\right|^2 \text{, for } m \geq K, \tag{1}$$

where $V(k)$ are the elements of the reshaped samples vector. Because $m \geq K$, the first K elements are always discarded. K is chosen to be 750. FIG. 3 (a) shows the results of this step on the sample data set. Note that this makes the part of the range profile where signal is still present more evident. In a noise-only case the probability that one averaged point is larger than the mean N times D is (Ivić and Zrnić 2009)

$$\frac{K}{N\cdot(K-1)!}\int_{D\cdot N}^{\infty}\left(\frac{K}{N}p\right)^{K-1} e^{-p\frac{K}{N}}dp = \Gamma_{inc}\left(D\cdot K, K\right). \tag{2}$$

When *D* is 1.1 (or 110% of the mean noise power) and *K* is 750 this probability is 0.38%. The mean is found from the data after the range persistence filter. Averaged points that are larger by more than 10% of the so found mean (herein referred to as "outliers") are detected and all samples that went into the averaged points are discarded. This is repeated while the number of discarded samples is larger than 0.0038 times the total number of samples or up to a maximum of five iterations. In this particular case the outlier filtering is performed twice. The results are shown in FIG. 3 (b). The mean power of this data set is 17.728. Finally, instead just using plain average, the mean power is obtained using rank ordered statistics as described in

Appendix *A*. In this particular case this yields a noise power estimate of 17.672, which is in almost perfect agreement with the "true" or far range noise level.

The steps of the algorithm are summarized below:

1) *Censor using coherency based thresholding (Ivić and Torres 2009) with the initial noise level.*
2) *Censor using the autocorrelation coefficient (ACF) with the threshold set to pass 99% of noise samples based on the number of pulses per dwell (M).*
3) *Run range persistence filter that detects 10 or more consecutive samples with power larger than the median and discards them plus 10 surrounding samples on each side.*
4) *Reshape all samples into a one dimensional array.*
5) *Obtain mean power.*
6) *Perform running average of 750 points.*
7) *Discard samples used to obtain outlier averaged points (i.e., those larger than 1.1 times the mean power from 5).*
8) *If the number of discarded samples is smaller than 0.0038 times the total number of samples or the number of iterations of steps 5, 6, and 7 is 5, proceed to step 9. Otherwise, go back to step 5.*
9) *Estimate the noise power using rank ordered statistics as described in*
10)
11) *Appendix* A.

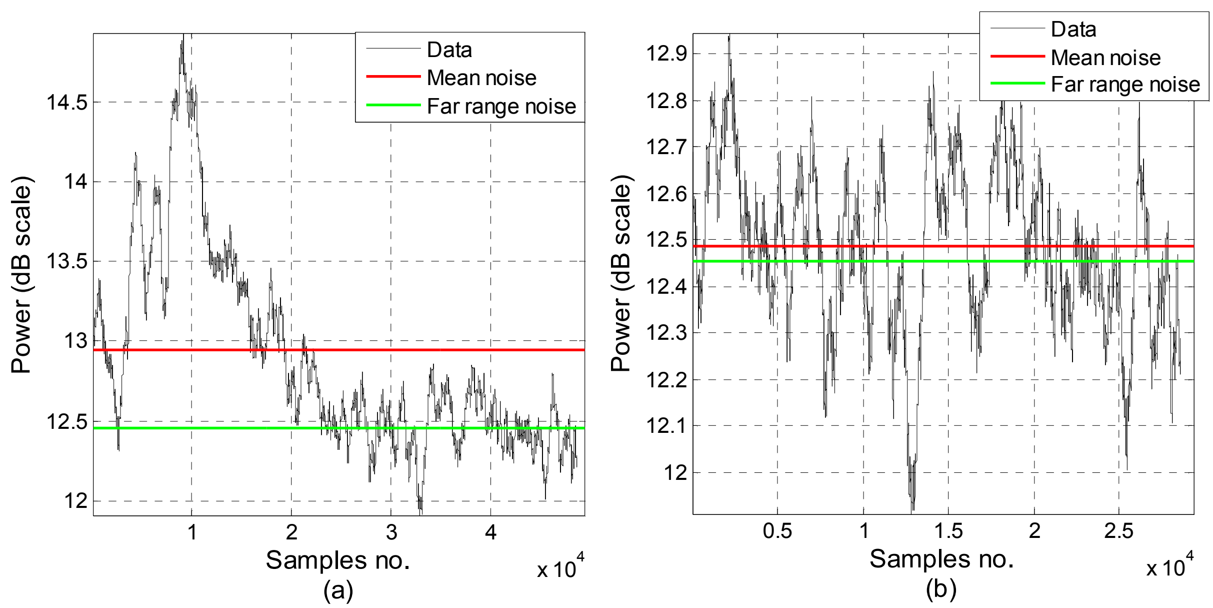

FIG. 3. (a) Power of range bins after the first iteration of the fourth step of the algorithm. (b) Power of range bins after the second iteration of the fourth step of the algorithm.

3. Performance examples

In this section, examples of the algorithm performance on time-series are presented. The first set of data is collected with the National Weather Radar Testbed Phased-Array Radar (NWRT). This radar does not perform online calibrations thus if noise is not estimated from data the initial value of 19.5 (obtained by offline measurements) is used for product generation. The presented data is from a dual PRT tilt with a long PRT of 3.104 ms and a short PRT of 0.896 ms, at an elevation of 0.51 deg.

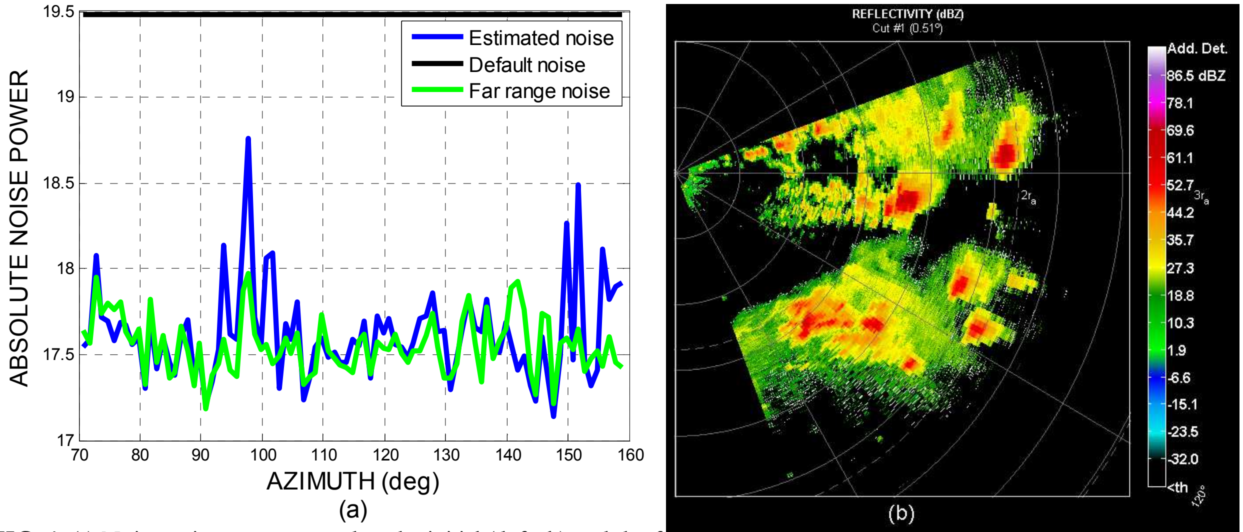

FIG. 4. (a) Noise estimates compared to the initial (default) and the far range ("true") noise, and (b) reflectivity field with additional detections obtained using estimated noise highlighted in white.

The algorithm is set so that if fewer than 1000 samples remain in step 8, the estimator reports it is unable to produce an estimate. By imposing the requirement that the estimates are made from at least 1000 samples, the algorithm is prevented from producing results when the majority of samples contain signal. Additionally, if exactly 1000 samples are used for estimation, the estimate is within ±10% of the true mean with 0.998 probability. In this particular case, the algorithm fails to produce results from the short PRT data rather often. Consequently, if the short PRT estimate is not available, the one from the long PRT is used. In this example however, even in the cases when the algorithm produces results from the short PRT data, the samples are usually heavily inundated with signal so the noise power is frequently overestimated. Consequently, the short-PRT and long-PRT estimates are compared and the two results are combined only if they are within 10% of each other. Otherwise, only the long PRT estimate is used. In FIG. 4 (a), the estimated noise is plotted with the one obtained from the distant ranges free of visible signals (the "true" noise). This shows that the proposed noise power estimator is reliable and robust as it produces values close to the true noise power. FIG. 4 (b) shows the reflectivity field obtained using the estimated noise power and using CBT for detection (Ivić and Torres 2009). The additional detections obtained using the estimated noise power as opposed to the default one are highlighted in white.

Another example shows the surveillance scan data collected by the dual polarized KOUN WSR-88D research radar in Norman, OK. The PRT used for this scan was 3.1 ms with 17 samples (M = 17) per dwell. This radar performs online calibrations which attains the initial noise value. The comparison between the far range and the estimated noise is given in FIG. 5 (a). As in the previous case, it is apparent that the estimated and the "true" noises agree very well. Moreover, the noise estimation procedure filters out the jumps in the far range noise (most likely caused by point target interferences). FIG. 5 (b) shows the reflectivity field obtained using the coherency based censoring technique for dual-polarized radars (Ivić et al. 2009). Additional detections resulted from the use of the noise estimation algorithm are highlighted in white. In this particular case, the noise obtained by the online calibration is about 1 dB larger than the one produced by the dynamic estimation.

4. Summary

A method to estimate noise power dynamically from data was presented. Through a set of steps, the algorithm classifies samples as containing signal or not. The approach requires an initial rough guess on the noise power. In systems that use online calibrations such value is already available. Other possibility is to have it measured offline. First, coherency based detection using the initial noise guess is applied to the data. Then, the range positions which exhibit strong correlations along sample-time are discarded using the measured autocorrelation coefficient. Range positions with powers that are consecutively higher than the median one are disposed of next. At this point all the remaining samples are rearranged into a long vector and the running average is performed to make the remaining weak signal areas more visible. To dispense with the remaining signal, all samples associated with the averaged points, larger than 10% of the mean power, are discarded. The last step is repeated until the ratio of the number of the discarded samples and the total ones falls under the probability that the averaged point exceeds 1.1 times the mean power value (i.e., 0.0038). The noise estimate is produced from the remaining samples using rank ordered statistics. In the implementation presented in this paper, the minimum number of the remaining samples required to produce reliable estimate is set to be 1000. The algorithm accuracy was verified by comparing its results to the noise powers obtained from the data at the far range positions devoid of visible signals. Such comparison shows that the technique produces noise powers with improved accuracy as opposed to offline and online calibrations with minimal bias.

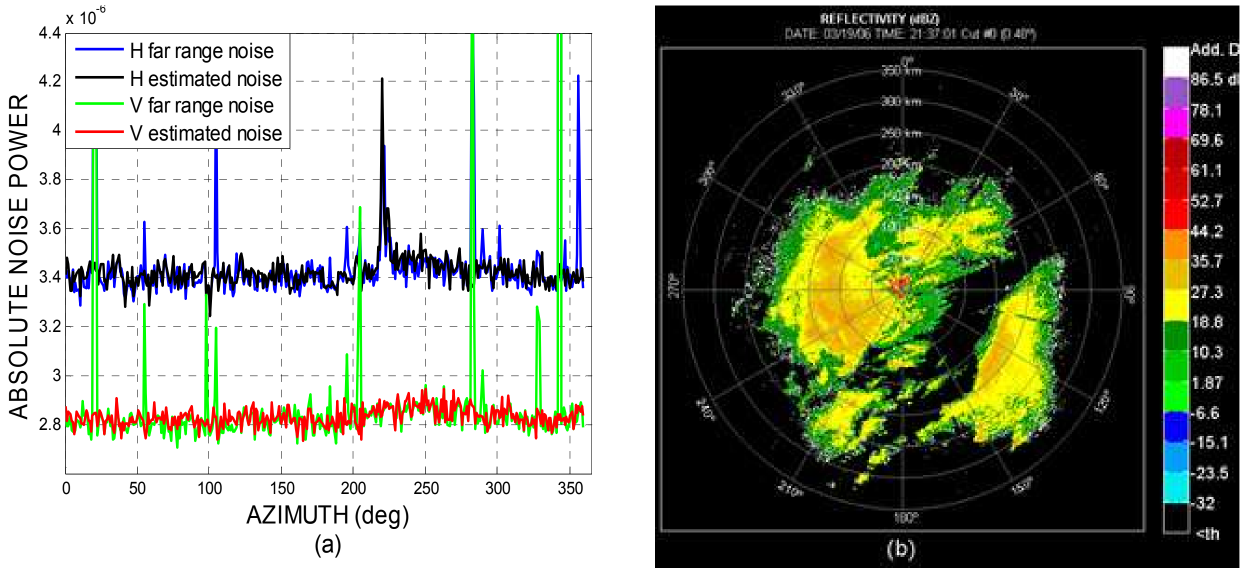

FIG. 5. (a) Noise estimates compared to the far range noise. (b) Reflectivity field with additional detections, resulting from the use of the noise estimation algorithm, highlighted in white.

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References

Doviak, R. J., and D. S. Zrnić, 1993: *Doppler radar and weather observations*. Academic Press, 562 pp.

Hildebrand P. H., and R. S. Sekhon, 1974: Objective Determination of the Noise Level in Doppler Spectra, *Journal of Applied Meteorology*, **13**, 808-811.

Ivić I. R., and S. M. Torres, 2009: Using Signal Coherency to Improve Detection on Weather Radars, *34th Conference on Radar Meteorology*, Williamsburg, VA, AMS.

Ivić I. R., D. S. Zrnić, and T. Yu, 2009: Use of Coherency to Improve Signal Detection in Dual-Polarization Weather Radars, *Journal of Atmospheric and Oceanic Technology*, **26**, 2474-2487.

Urkowitz H., and J. D. Nespor, 1992: Obtaining Spectral Moments by Discrete Fourier Transform with Noise Removal in Radar Meteorology, *Int. Geoscience and Remote Sensing Symp.,* Houston, TX, IGARSS, 125–127.

Siggia A. D., and R.E. Passarelli, 2004: Gaussian Model Adaptive Processing (GMAP) for Improved Ground Clutter Cancellation and Moment Calculation, *ERAD 2004*, Visby, Sweden, 67-73.

Appendix A

In this appendix, we derive the rank ordered statistics power estimator which is used in the last step of the algorithm. If n independent samples that are exponentially distributed with mean power N are arranged in ascending order this results in a distribution function that can be associated with each Y_i (i is the position in the ascending vector) viewed as random variable of the form

$$\begin{aligned} f_{Y_i}(y) &= \frac{n!}{(i-1)!(n-i)!}\left[1-e^{-y/N}\right]^{i-1} e^{-y/N(n-i)}\frac{1}{N}e^{-y/N} \\ &= \frac{1}{N}\frac{n!}{(i-1)!(n-i)!}\sum_{j=0}^{i-1}\frac{(i-1)!}{j!(i-1-j)!}(-1)^{(i-1-j)}e^{-y/N(i-1-j)}e^{-y/N(n-i+1)} \\ &= \frac{n(n-1)\cdots(n-i+1)}{N}\sum_{j=0}^{i-1}\frac{(-1)^{(i-1-j)}}{j!(i-1-j)!}e^{-y/N(n-j)}. \end{aligned} \tag{A.1}$$

The maximum likelihood value at each position in the ascending array can be obtained from the following expression:

$$\begin{aligned} \frac{df_{Y_i}(y)}{dy} &= \frac{1}{N}\frac{n!}{(i-1)!(n-i)!}\left(\frac{(i-1)}{N}\left[1-e^{-y/N}\right]^{i-2} e^{-y/N(n-i+2)} - \frac{n-i+1}{N}\left[1-e^{-y/N}\right]^{i-1} e^{-y/N(n-i+1)}\right) \\ &= \frac{1}{N^2}\frac{n!}{(i-1)!(n-i)!}\left[1-e^{-y/N}\right]^{i-2} e^{-y/N(n-i+1)}\left((n-i+1)+ne^{-y/N}\right). \end{aligned} \tag{A.2}$$

Setting the previous expression to 0, one can solve for N as :

$$\frac{df_{Y_i}(y)}{dy} = 0 \Rightarrow y = N\ln\left(\frac{n}{n-i+1}\right). \tag{A.3}$$

Having an array of ascending powers values, the mean power can be found as one that minimizes the mean square error between the measured powers and the maximum likelihood values. That is,

$$\begin{aligned} R^2 &= \sum_{i=0}^{n-1}\left(y_i - N\ln\left(\frac{n}{n-i+1}\right)\right)^2, \\ \frac{\partial R^2}{\partial N} &= -2\sum_{i=0}^{n-1}\left(y_i - N\ln\left(\frac{n}{n-i+1}\right)\right)\ln\left(\frac{n}{n-i+1}\right) \\ &= -2\sum_{i=0}^{n-1} y_i \ln\left(\frac{n}{n-i+1}\right) + 2\sum_{i=0}^{n-1} N\ln^2\left(\frac{n}{n-i+1}\right) \\ &= 0. \end{aligned} \tag{A.4}$$

So, the mean power can be estimated as

$$\hat{N} = \frac{\sum_{i=0}^{n-1} y_i \ln\left(\frac{n}{n-i+1}\right)}{\sum_{i=0}^{n-1}\ln^2\left(\frac{n}{n-i+1}\right)}. \tag{A.5}$$