Clutter Distributions for Tomographic Image Standardization in Ground-Penetrating Radar

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Abstract—Multistatic ground-penetrating radar (GPR) signals can be imaged tomographically to produce 3-D distributions of image intensities. In the absence of objects of interest, these intensities can be considered to be estimates of clutter. These clutter intensities spatially vary over several orders of magnitude and vary across different arrays, which makes a direct comparison of these raw intensities difficult. However, by gathering statistics on these intensities and their spatial variation, a variety of metrics can be determined. In this study, the clutter distribution is found to fit better to a two-parameter Weibull distribution than Gaussian or log-normal distributions. Based on the spatial variation of the two Weibull parameters, scale and shape, more information may be gleaned from these data. How well the GPR array is illuminating various parts of the ground, in depth and cross track, may be determined from the spatial variation of the Weibull scale parameter, which may in turn be used to estimate an effective attenuation coefficient in the soil. The transition in depth from clutter- to noise-limited conditions (which is one possible definition of GPR penetration depth) can be estimated from the spatial variation of the Weibull shape parameter. Finally, the underlying clutter distributions also provide an opportunity to standardize image intensities to determine when a statistically significant deviation from background (clutter) has occurred, which is convenient for buried threat detection algorithm development that needs to be robust across multiple different arrays.

Index Terms—Clutter, ground-penetrating radar (GPR), landmine detection, tomography, Weibull distribution.

I. INTRODUCTION

GROUND-PENETRATING radar (GPR) allows for buried object detection, such as landmines or utility pipes. GPR can be used to detect spatial changes in dielectric permittivity, meaning that both metallic and nonmetallic objects are detectable. In the system used for this study, a vehicle-mounted multistatic radar array takes time-series measurements, which are used to form 3-D images in real time. In the absence of buried objects, the images are not empty, but rather contain clutter, where the word “clutter” is used here to denote random volumetric scattering associated with spatial variations in soil permittivity—in other words, homogeneous scattering associated with soil composition and structure, as opposed to scattering associated with discrete buried objects such as rocks or man-made objects. The amplitudes of those clutter voxels are then statistically analyzed to determine their deviation from the background. This study discusses the statistics of those clutter voxels, including empirical fits to probability distribution functions (PDFs) and spatial variations of the distributions’ parameters, and how standardization can be performed on image voxels to improve buried object visibility.

A. Clutter Statistics

Most literature involving the fitting of clutter amplitudes or intensities to PDFs is associated with monostatic radars looking at weather-, land-, or sea-based clutter, with the latter receiving the most attention. A variety of clutter distributions are considered. These include one-parameter distributions, such as the zero-mean Gaussian model [1], [2], which was an adequate model for thermal noise, and the Rayleigh distribution for amplitudes [3] (or chi-squared distribution for intensities [4]), which was found to be suitable for high-grazing angle radar turns. A number of two-parameter distributions have been proposed for handling low-grazing angle returns, including the log-normal distribution [3], the Weibull distribution [5], [6], the Rice distribution for amplitudes [7] (or noncentral chi-squared distribution for intensities [4]), the heavy-tailed Rayleigh distribution [8], and the $K$-distribution [9]–[11] and similar generalizations [12]. For additional flexibility, more parameters may be added, such as with the six-parameter generalized compound distribution [13], which contains within it numerous special cases, including the generalized gamma distribution, the hypergeometric distribution, and all of the other one- and two-parameter systems named here. The overview provided here is far from complete, as there have been several decades of research into radar clutter modeling [14]. It is also noted that some of these distributions have physical interpretations for their parameters, while others
are simply empirical fits. In this study, for simplicity, only the two-parameter log-normal and Weibull distributions are considered. Some physical interpretation of the shape and scale parameters is provided, but the parameters are fundamentally an empirical fit. This is in agreement with the claim by Shnidman [4] that the Weibull and log-normal distributions are used because “they produce a reasonable fit to measured clutter densities, rather than any underlying physical argument.”

There are other investigations into clutter associated with GPR, including physical modeling of soil scattering [15], a graphical method to determine the goodness of fit for different clutter probability distributions [16], and a study on the relationships between complex permittivity and the observed signal-to-clutter ratios [17]. These studies all utilize statistics gathered on time-series data directly, whereas the study here utilizes GPR imaging data, formed from an application of computed tomography on the measured time-series data.

While the GPR system utilized for this study is downward-looking, many characteristics are shared with forward-looking GPR systems. Computed tomography images associated with forward-looking GPR are detailed in [18]–[20]. Several studies [21]–[23] use electromagnetic simulations to study the effects of clutter originating from rough surface scattering and present methods to reduce that type of clutter. A detailed study by Liao and Dogaru [24] showed the quantitative effect of rough surface scattering and determined that scattering amplitudes are well-described by $K$-distributions or Rayleigh distributions at low surface roughness. Another forward-looking GPR imaging study [19] found that clutter amplitudes follow a truncated Rayleigh distribution and targets follow a three-component Gaussian mixture model. In this study, clutter intensities are empirically found to be well-described by log-normal and Weibull distributions instead (see Section II-A).

### B. Multistatic Tomographic Imaging for GPR

Many commercially available GPR systems operate in a bistatic or multimonostatic configuration, where only one transmitter and one receiver are active at a time. In the vehicle-based system [25] used for this study, a multistatic array is used, where only one transmitter (Tx) is active at a time, but all receivers (Rxs) are taking measurements, as shown in Fig. 1. The array used here has $N = 16$ transmitters and an equivalent number of receivers located at approximately the same position in cross track and are separated by a small distance in down track. After cycling through all 16 transmitters, $16^2 = 256$ time-series measurements are stored, representing one frame. This is an increase in the amount of received data by a factor of 16 when compared to a monomostatic configuration. These additional measurements, and their associated spatial diversity, permit improved signal-to-noise ratios compared to a monomostatic system.

Each of the frame’s time series is preprocessed to remove the coupling pulse, radio interference, and the reflection from the ground, leaving only the radar returns from subsurface features, such as buried objects or volumetric scattering (clutter). Note that imperfect removal of the surface reflection would also lead to clutter, but this study does not distinguish between origins of clutter (i.e., surface roughness or volumetric scattering). The preprocessed time series serve as inputs to a plane-to-plane backpropagation algorithm [26], which leverages temporal and spatial Fourier transforms to focus on the received signal amplitudes to a uniformly spaced spatial grid. The focused tomographic image serves as the data utilized for this study, as well as the input to detection and classification algorithms [25], [27]. The spatial convention used here is shown in Fig. 2, along with a photograph of the vehicle with the GPR array mounted to the front of the vehicle. The array is nominally 30 cm above the surface.

In the construction of the images used in this study, not all of the 256 time series are utilized. Visualizing the time series as a $16 \times 16$ matrix of time series, if only the diagonal were used, this would be comparable to a monomostatic array. We found empirically that utilizing matrix elements within four rows or columns of the diagonal gave better imaging performance. In other words, using the language mentioned in [27], the multistatic degree is set to four (where a multistatic degree of zero corresponds to the monomostatic case). This choice is primarily limited by the beamwidth of the antenna,
the along-track direction, 2.4 m (128 voxels) in the cross-track direction, and 0.9 m (46 voxels) in the depth direction. A total of 189 runs were used in this study, representing 45 billion individual voxels or approximately 150 km (or 90 acres) of imagery. Due to the spatial sparseness of objects that were intentionally buried in these lanes, the overwhelming majority of this tomographic image data can be considered to be measurements of the background or clutter. Thus, for purposes of gathering statistics on the clutter, the first and second moments of the distributions are not expected to be influenced by the presence of buried objects, as these represent less than 1% of the image volume. While these buried objects have little effect on the first and second moments of the distribution, they may cause deviations from the anticipated distribution for image amplitudes above the 99th percentile—see discussion in Section II-D.

D. Methodology Overview

For clarity, we summarize the processing steps applied to the recorded data that serve as the input data for the analyses given in the remaining sections of this article in the following.

1) Fully multistatic (16 × 16) time series are recorded every 2 cm.
2) The coupling pulse is removed from the time series.
3) The surface reflection is found and subtracted from the time series.
4) The time series are realigned to a nominal height of 10 cm above the surface.
5) Plane-to-plane backpropagation is performed on these time series.
6) The image is formed through the summation across a range of frequencies (given by the bandwidth) and a range of transmitter/receiver pairs (given by the multistatic degree).
7) Image magnitudes are stored as a function of depth, cross track, and along track.
8) Repeat steps 1)–7) for each of 189 runs.

In Section II, these image magnitudes are fit to probability distributions. In Section III, physical interpretations of the probability distribution parameters are provided. In Section IV, these image magnitudes are standardized to suppress clutter and accentuate buried targets, and Section V provides the conclusions drawn from this study.

II. PROBABILITY DISTRIBUTIONS

A. PDF and CDF Definitions

The data described in Section I-D are fit to two distributions, the log-normal and Weibull distribution. Their definitions are given in the following:

\[
P_{\text{Lognormal}}(X = x | \mu, \sigma) = \frac{1}{\sqrt{2\pi}\sigma^2} \exp\left(-\frac{(\ln x - \mu)^2}{2\sigma^2}\right) \tag{1}
\]

\[
P_{\text{Weibull}}(X = x | \lambda, \kappa) = \kappa \left(\frac{x}{\lambda}\right)^{\kappa-1} \exp\left(-\left(\frac{x}{\lambda}\right)^{\kappa}\right) \tag{2}
\]

Thus, \(\mu\) and \(\lambda\) can be seen as “scale” parameters, whereas \(\sigma\) and \(\kappa\) can be seen as “shape” parameters. \(X\) is the random variable containing the clutter amplitudes, and \(x\) is the

with a wider beamwidth supporting a higher multistatic degree. Given that the receivers are spaced at 15 cm and the nominal array height above the ground is 30 cm, a multistatic degree of four is equivalent to using surface reflections of 45° or less. The antenna used in this study has an approximate half-width half-maximum beamwidth of 20°–25°, which means the far off-diagonal elements receive approximately 12 dB less power (or 25% of the amplitude) as the monostatic (diagonal) elements receive.

Since the backpropagation algorithm operates in the frequency domain, only certain frequencies (100 MHz–3.5 GHz) are imaged in this study. The synthetic aperture radar (SAR) algorithm detailed by Chambers et al. [25] was turned off for this study so that magnitude trends in depth could be assessed without the additional complication of along-track summations that vary in depth. The images that are created are 2.4 m (128 pixels) in cross track \((x)\), 90 cm (46 pixels) in depth \((z)\), and a variable number of frames along track \((y)\), with a frame spacing of 2 cm. In depth, the first 10 cm correspond to the air gap with a refractive index of 1. The remaining 80 cm correspond to the soil, with an assumed refractive index of 2.0.

C. Data Set Overview

In this study, the data from only one array are used. Specifically, a resistively loaded V-dipole (RLVD) antenna is used (shown in Fig. 3), along with its monostatic pulse shape for ground reflections. The center frequency of the pulse is approximately 500 MHz, though all frequencies between 100 MHz and 3.5 GHz are utilized in the plane-to-plane backpropagation imaging algorithm. The same antenna is used for transmission and receiving, meaning that there are 32 antennas inside the array shown in Fig. 2(b). The 16 receiving antennas are spaced 15 cm apart in the cross-track direction for a physical array aperture of 2.25 m. The 16 transmitting antennas have the same spacing and are offset from the row of receivers by 26.5 cm in the along-track direction. Due to the antenna beamwidth, the imaging aperture of the array is found empirically to be approximately 2.4 m.

The data used here were taken across two campaigns (separated by one year) to a southwestern United States GPR testing location. A total of 12 lanes at this location were imaged by this array, representing approximately 9.3 km (or 5.5 acres) of unique Earth. Each run (a single pass over a single lane) is comprised of thousands of frames—on average, 40,000 frames per run. Each frame represents 2 cm (1 voxel) in depth, the first 10 cm correspond to the soil, with an assumed refractive index of 2.0.
corresponding dummy variable. The cumulative distribution function of each function is given by

\[
\text{CDF}_{\text{Lognormal}}(X = x | \mu, \sigma) = \frac{1}{2} \left(1 + \text{erf}\left(\frac{\ln x - \mu}{\sqrt{2\sigma}}\right)\right)
\]

(3)

\[
\text{CDF}_{\text{Weibull}}(X = x | \lambda, \kappa) = 1 - \exp\left(-\left(\frac{x}{\lambda}\right)^\kappa\right).
\]

(4)

**B. Distribution Parameter Estimates**

To estimate log-normal distribution parameters, the following equations are used, where \(E(\cdot)\) represents an expected value:

\[
\mu = E(\ln X)
\]

(5)

\[
\sigma = \sqrt{E((\ln X)^2) - (E(\ln X))^2}.
\]

(6)

To estimate the Weibull distribution parameters, the first and second moments of the clutter amplitude data, \(E(X)\) and \(E(X^2)\), can be used

\[
\frac{\Gamma(1 + \frac{1}{\lambda})}{\Gamma(1 + \frac{1}{\lambda})^2} = \frac{E(X^2)}{E(X)^2}
\]

(7)

\[
\lambda = \frac{E(X)}{\Gamma(1 + \frac{1}{\lambda})}.
\]

(8)

In (7), it is not possible to analytically evaluate \(\kappa\) directly; however, the function on the left is well behaved, so a simple numerical interpolation scheme is sufficient to determine \(\kappa\), given the right-hand side ratio of moments.

For some intuition for the data set, a histogram of the voxel magnitudes for all 45 billion voxels is given in Fig. 4. Note that this is a log–log plot. On a linear vertical axis, the distribution would simply appear bell-curve shaped and could be interpreted to be a Gaussian distribution (that is, a log-normal distribution since the horizontal axis is logarithmic). However, a log-normal distribution would give a symmetric parabola on a log–log plot, and it is clear to see in Fig. 4 that the distribution is skewed right, with the left tail decidedly linear, not parabolic. This is in good agreement with a Weibull distribution, where in the \(X \ll \lambda\) limit, the distribution should appear linear on a log–log plot. The right tail is where buried objects exist, and it is not obvious from this plot where the transition from buried object to clutter occurs. Of course, as with any detection problem, these distributions overlap. However, due to the low prevalence of buried objects, only the extreme right edge of the plot would be contaminated with buried objects. The additional structure to the plot beyond a magnitude of \(\sim 10^8\) is likely due to the strong spatial relationship that the scale parameter has with space or, in particular, depth.

For the purposes of evaluating the two fit parameters for both distributions, each of runs, cross-track, and depth positions is treated as statistically independent of each other. In other words, there are 1.1 million different shape and scale parameters for both distributions (189 runs \(\times 128\) cross-track positions \(\times 46\) depth positions = \(\sim 1.1\) million). A histogram of these four parameters is given in Fig. 5.
Fig. 5. Histogram of best-fit parameters for the log-normal distribution [(a) \( \mu \) and (b) \( \sigma \)] and the Weibull distribution [(c) \( \log(\lambda) \) and (d) \( \kappa \)].

This plot can be generated for all 1.1 million data sets [one for each of the runs, and \((x, z)\) positions]. To avoid plotting 1.1 million lines, instead, the mean (solid colored lines), the \( \pm 1 \) standard deviation (dark-shaded regions), and the maximum/minimum (light-shaded regions) are shown. The closer the lines and the shaded regions are to the black diagonal line, the better the fit. If the shaded regions fall above the black line, this means that the observed distribution has a fatter tail than the proposed distribution. Similarly, falling below the black line means that the observed distribution has a thinner tail than the proposed distribution. In addition, to quantify the goodness of fit, the Kolmogorov–Smirnov (KS) statistic is generated, which is effectively a measure of the largest difference between the empirical CDF and the test distribution’s CDF for any quantile [28], where a smaller KS statistic implies a better fit to the proposed distribution.

These Q-Q plots support the following conclusions.

1) The observed clutter distributions have consistently fatter tails on the left (low clutter magnitudes) than would be expected for a log-normal distribution.

2) The observed clutter distribution has thinner tails on the left (low clutter magnitudes) than would be expected for a Weibull distribution, but the match is quantitatively better than that of the log-normal distribution.

3) Both plots show significant deviations above the 99% CDF. However, this is where buried objects are expected to reside, and therefore, a mismatch in that region is not surprising, as image magnitudes for buried objects would be expected to follow a different distribution than for clutter and would likely be strongly dependent on the buried objects’ scattering physics.

4) The average KS statistic (averaged over each run and each cross-track and depth position) for the Weibull distribution (0.0312) is about half the value of the KS statistic using the log-normal distribution (0.0555), which implies that a Weibull distribution is a better fit to the data than log-normal distribution.

In addition, it can be seen qualitatively that the Weibull plot in Fig. 7(a) is closer to linear (particularly below the 99th percentile) than the log-normal plot in Fig. 7(b), which has a consistent curve away from the black line. For all of these reasons, it is claimed that the Weibull PDF is a better fit to the observed distribution than the log-normal PDF. Though it is also important to point out that for the middle (which represents \( \sim 80\% \) of the observed distribution), both distributions fit reasonably well. Only at the more extreme values in the left tail are deviations appreciable.

III. PARAMETER INTERPRETATIONS

This section considers the spatial variation of the distribution parameters given in the previous section. More specifically, it delineates what the spatial variation means in physical terms about either the array or the environment.

A. Attenuation Coefficient

A plot of the mean linear amplitude as a function of depth is given in Fig. 8. The linear amplitude is averaged across all runs (weighted by the number of frames in a run) and then averaged in cross track.
Theoretically, this plot of power versus depth would give amplitudes near the noise floor above the surface and then would decay linearly with increasing depth until returning to the noise floor. Roughly, the trend does hold but only approximately so. Above the surface, the amplitudes here are likely above the would-be noise floor, as this part of the image corresponds to early arrival times, which is where the coupling pulse dominates the signal. Imperfect removal of the coupling pulse can lead to higher amplitudes in this air-gap region.

The first 20 cm of soil shows an unexpected peak in amplitude. The most likely culprit for this is imperfect removal of the ground bounce, the removal of which is known to be difficult on nonflat ground, as well as the imperfectly impulsive source waveform (see Fig. 3, which shows some ringing after the main pulse). However, from about 20 to 50 cm in depth, the plot is roughly linear, with a best-fit slope of 24 dB/m, which can be considered to be an indirect measurement of the attenuation coefficient. This estimate ignores other forms of losses, such as spherical spreading, or the beam pattern of the antennas, so 24 dB/m could be considered an upper bound on the attenuation coefficient. Nonetheless, this value is reasonable, given the frequency content of the pulse and the geology of the test location (a hot desert region whose soil type is primarily loamy sand, containing 2% or less of silt or clay).

C. Transition From Clutter Limited to Noise Limited

Consider a plot of the average Weibull shape parameter as a function of depth, as shown in Fig. 10. A value of $\kappa = 1$ corresponds to an exponential distribution, whereas a value of $\kappa = 2$ corresponds to a Rayleigh distribution. A Rayleigh distribution is interesting because this would be the distribution that one would anticipate for the magnitude of a complex number whose real and imaginary parts are zero-mean Gaussian distributed. The expectation is that noise, i.e., thermal noise, would produce this zero-mean Gaussian distribution for the real and imaginary parts, leading to $\kappa = 2$ for the best-fit Weibull distribution. Thus, for deeper voxels, the best-fit Weibull distribution is getting closer to a Rayleigh distribution, which would be the noise-limited case. However, it is not possible to claim the exact depth at which the voxel magnitudes are no longer clutter-limited, but instead noise-limited. For example, $\kappa = 1.9$ might truly still be clutter-limited, though it cannot be confirmed without conducting simulations or more detailed analyses of this data. However, if one uses a nominal cutoff of $\kappa = 1.5$ (being halfway
between the extreme cases of a Rayleigh distribution and an exponential distribution), then a penetration depth of approximately 35 cm can be estimated. Note that this does not mean targets that cannot be detected deeper than this depth. What it does suggest is that a more powerful transmitter (or lower noise receiver) would likely push this transition point deeper. Or, alternatively, if the region of interest is no deeper than 35 cm, a more powerful transmitter would not be expected to improve the performance.

Fig. 7. Modified Q-Q plot that allows the determination of which distribution fits the data best, with (a) Log-normal distribution and (b) Weibull distribution. The black diagonal line is the line of perfect match between the empirical and theoretical distributions. The blue/red lines indicate the average Q-Q plot across all runs and \((x, z)\) positions. The dark-shaded regions represent ±1 standard deviation across all runs and \((x, z)\) positions. The light-shaded regions represent the maximum and minimum values observed. Note that the plots are shown with linear sampling in the \(Z\)-score equivalent axes, labeled across the top and right, though the corresponding CDF percentages are labeled on the left and bottom axes.

Fig. 8. Average power, in decibels (dB), averaged cross track, versus depth, in centimeters. The decibel scale is relative—no milliwatt reference is implied in this figure. The red dashed line is a line of best fit between 20 and 50 cm of depth, which has a slope of approximately 24 dB/m, which can be interpreted as an indirect measure of the attenuation coefficient for this soil.

Fig. 9. Average power versus cross-track, averaged across runs, and in depth.

IV. GPR IMAGE STANDARDIZATION

Given knowledge of the underlying clutter distributions and their spatial variation, this information can be used to transform voxel magnitudes from their raw values into another value, which more accurately reflects their deviation from the background. To do this, the CDF for each voxel can be estimated based on the underlying distribution. Plotting CDFs directly, however, is inconvenient, as the most interesting data points would occur in the range between 0.9 and 1.0. However, calculating a \(Z\)-score on logarithmic data allows brightness values to be compared more intuitively, on a “linear” axis, much like the rescaled axes in Fig. 7. This transformed image is termed the “standardized logarithmic intensity” image or SLI image. This is the motivation behind image standardization—the exact implementation of which is considered in Section IV-A.

A. SLI Definition

Consider the raw tomographic image output \(R(x, y, z)\). The SLI image output is given by

\[
\text{SLI}(x, y, z) = \log \frac{R(x, y, z) - \mu(x, z)}{\sigma_{\text{avg}}} + f_{\text{airgap}}(z). \quad (9)
\]
In this form, it is more easily seen that SLI images are simply logarithms of the normalized image, which is then rescaled by an exponent of $1/\sigma_{\text{avg}}$. Thus, even though SLI is named a standardized image and its definition certainly resembles a standardization process, it can also be thought of as substantively equivalent to a normalized image, due to the use of a constant $\sigma_{\text{avg}}$ as opposed to a spatially varying one. In addition, keeping $\sigma$ constant means that only $\mu(x, z)$ can amplify or attenuate data, not $\sigma$ as well.

Also, it should be noted that the SLI definition utilizes magnitudes, not intensities, though its name contains the word “intensity.” However, due to the logarithm, using true intensities (proportional to magnitude-squared) would produce $\mu$ and $\sigma$ that are a factor of two larger, and therefore, the standardization equation would cancel out this effect.

B. Standardized Images of Targets

Four example targets are selected to illustrate the utility of image standardization. In Fig. 11, four pairs of images are shown. On the left are raw images, shown after a logarithm is applied, i.e., $\log(R(x, y, z))$, and on the right are SLI($x, y, z$) images, standardized according to Section IV-A. In all four raw image plots, the raw color scale is defined to be between 13 (dark blue) and 16 (dark red). In all four standardized image plots, the SLI color scale is set to be between 0.5 (dark blue) and 2.5 (dark red). Since the images are fundamentally 3-D volumes, a max projection across each of the three axes is used to display these cubes. Recall that $x$ (cross-track) is the 240-cm-long dimension, $y$ (along-track) is the 300-cm-long dimension, and $z$ (depth) is the 90-cm-long dimension. The upper dark blue region seen in the $x$–$z$ and $y$–$z$ plots show the air gap, where the region is made darker blue than expected due to the use of $f_{\text{airgap}}(z)$ in the SLI definition.

For these targets, the standardized images are generally superior when detecting buried objects, as the target can technically be seen in the raw images in all four cases, but the presence of shallow clutter tends to obscure them (here, “shallow” refers to depths of a few wavelengths). By standardizing with respect to the underlying clutter distribution, only voxels with anomalously high magnitudes are accentuated, with the rest being suppressed. These four images illustrate that standardization is generally positive for improving the contrast between clutter and targets, which is convenient for the development of an automated detection algorithm. The target in the first row is fairly typical, in which the target and the suppression of shallow clutter to reveal a slightly deeper target [see Fig. 11(h)].

While these figures show an improvement in contrast with standardization, note that this apparent improvement in contrast is primarily associated with compensating for the spatial variation of the clutter distribution. Standardization by itself does not increase intrinsic contrast, and it simply measures
Fig. 11. (a), (c), (e), and (g) Raw images and (b), (d), (f), and (h) standardized images for four different targets: a circular plastic-encased landmine (first row), a large, square, plastic landmine seen at the edge of the array (second row), a deep large, metallic target (third row), and a shallow plastic-encased circular landmine surrounded by bright clutter (fourth row).

contrast in a way that can be easily compared with other regions of the image or with other systems.

Standardizing in this way relies upon the underlying clutter distribution being unimodal for a given \((x, z)\) row, with well-defined means and variances. The unimodal requirement is typically satisfied unless there are significant along-track variations in the environment that could lead to multimodal distributions. The means and variances of multimodal distributions are less mneaningful for standardization and could present challenges. However, if multimodal distribution occurred due to the background environment changing discontinuously (i.e., the vehicle abruptly transitioned from soil to concrete),
the running mean and variance calculation could be reset based on some threshold. Other than this, only pathological clutter distributions, such as the Cauchy–Lorentz distribution whose variance is undefined, would present difficulties for this method of standardization. In the authors’ experience, this methodology to standardize GPR images was found to be robust across a variety of testing locations and GPR imaging settings.

V. CONCLUSION
This study supports the following three conclusions.

1) The underlying clutter magnitude distribution in GPR imagery is modeled well by a Weibull distribution rather than a log-normal distribution. This suggests that clutter magnitudes in GPR imagery follow similar distributions as sea clutter gathered from SARs.

2) The Weibull shape parameter can be used to estimate the transition in depth from clutter-limited to noise-limited. In this study, objects at a depth of 35 cm or less are unlikely to be improved by a more powerful transmitter, whereas deeper objects could benefit from a more powerful transmitter.

3) Image standardization that appropriately compensates for attenuation and finite antenna beamwidths leads to images with significantly improved clutter-to-target contrast and allows for a more fair comparison between targets seen at the edge of the array, deep targets, and shallow targets surrounded by bright clutter.

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