Wavelet Packets for GPR Detection of Non-Metallic Anti-Personnel Land Mines Based on Higher-Order-Statistic

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Abstract— An algorithm is described for the detection of non-metallic anti-personnel (AP) land mines by using ground penetrating radar (GPR). The algorithm combines two powerful tools: the wavelet packet analysis and higher-order-statistics (HOS). The use of both techniques makes detection of shallowly anti-personnel land mines objects possible which obscured by the return from air-soil interface.

The experimental data sources include 1GHz pulse GPR data, and 1GHz to 4GHz stepped-frequency GPR data, from laboratory measurements.

Index Terms— Clutter, GPR, Landmine, HOS, Wavelet Packet.

I. INTRODUCTION

GPR senses electrical inhomogeneities caused by a dielectric contrast [1]. One key problem is how to extract the mines scattered signals from the received data when the contrast is very weak (i.e. when GPR used for detecting non-metallic anti-personnel (plastic) landmine in the presence of soil) implying that the landmine GPR signal is very small [2]. The largest contrast typically exists between the air and the soil and therefore GPR is typically characterized by a very large "ground bounce". If a landmine is buried at a shallow depth, then the GPR, which is used to detect and localize AP mines, will lead to several problems especially if the surface of the soil is rough or the soil is inhomogeneous. Unfortunately, this technology can suffer false alarm rates as high as that of metal detectors. Thus, it is clear that signal processing of the GPR data is needed in order to extract useful information for the target. Signal-processing algorithms, which filter out clutter signals and select objects to be declared as mines, is considered the most critical part of the GPR system. There are two distinct types of GPR: Time-domain and frequency domain. Time domain or impulse GPR transmits discrete pulses of nanosecond duration and digitizes the returns at GHz sample rates. Frequency domain GPR systems transmit single frequencies either uniquely, as a series of frequency steps, or as a chirp. The amplitude and the phase of the returned signal are measured, and the resulting data is converted back to the time domain [3].

In the last twenty years, the wavelet analysis [4] and the higher-order statistics [5] have been among the most successful tools in the field of signal processing. The two techniques, here, are combined together and then have been applied to GPR data to show how such a combination can improve the GPR detection.

In our work, the wavelet packet transform has been used to remove the clutter from GPR data. This has been done by thresholding the wavelet-packet-transform coefficients of the received GPR data. The threshold level selection is based on the higher-order statistics of the coefficients. Using a threshold that is based on higher-order statistics has proved to be more efficient than the conventional way of wavelet thresholding. By combining the wavelet packet and higher-order statistics a correct detection can be achieved.

II. GPR MEASUREMENTS

Two types of data have been used in this work. The first data has been acquired with a bistatic-stepped frequency GPR system at IESK, Magdeburg University, Germany. The system consists of a network analyzer (Rohde & Schwarz), which is connected to a computer (a PC type Pentium 4). A wooden box with dimensions 1.1 x 1.1 x 1.1 m has been used. The internal sides are covered by absorption material and it is filled with sand of 0.5 m depth. The

chirp z-transform has been used to transform frequency domain to time domain. The measurement grid covers the area bounded by x = 27-76 cm and y= 39-89 cm with distance between the measurements of 1 cm in both x and y directions.

The transmitting and receiving antennas are mounted on the 2D scanning system. The measurements form a two dimensional matrix, referred to as a B-scan. Column vector of the B-scan matrix (image) is called an A-scan and it represents the data. At each individual point on the basic surface of the soil and extending it down, the antenna is used to collect this A-scan data.

An example of A-scans in the presence and absence of a landmine are displayed in Fig. 1.

The radar system operates in the frequency range of 1 GHz to 4 GHz and the number of the samples is 1024 for each A-scan.

The second GPR data has been provided by the DeTeC laboratory of the "Ecole polytechnique fédérale de Lausanne" (Suisse) [6] The data was acquired by a monostatic impulse GPR system. A 1GHz antenna is used. A series of measurements were taken, each measurement form a B-Scan. Each B-
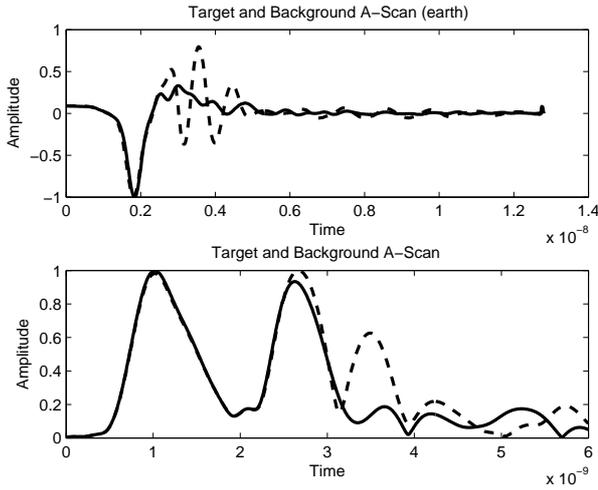
Fig. 1. A scans in the presence (dashed) and absence (solid) of a mine, DeTeC and IESK data, respectively.

Scan is composed of 98 A-Scan, and each A-Scan is composed of 512 samples.

In both case the PMN anti-personal landmine is used.

III. WAVELET

Time-frequency representations are used to distribute the energy of a signal in the time-frequency plane; in such away that relevant information can be extracted to make a good detection. The results generally depend on the method used as a time-frequency representation. The wavelet transforms are pretty the same as Fourier transforms except they have different bases.

The wavelet transform is capable of providing both time and frequency localization simultaneously while Fourier transform can only provide frequency representations.

The Short Time Fourier Transform (STFT) can provide a time-frequency representation of the signal. However, STFT does not have inverse. In other word; the original signal cannot be reconstructed from the time-frequency map.

For GPR, we need data cleaning to remove clutter, and data transformation to convert the data into suitable form. So we can transform the data into wavelet domain, and choose some significant wavelet coefficients. The chosen coefficients are based on their higher order statistics.

Assume that the observed data $x(n)$ is given by:

$$x(n) = t(n) + e(n) \tag{1}$$

Contains the target signal $t(n)$, and the clutter signal $e(n)$, with $n = 1, 2, ..., N$.

The two-dimensional wavelet transform gives the two-dimensional wavelet packet coefficients in the form

$$WP_{j,s}^x(i) = WP_{j,s}^t(i) + WP_{j,s}^e(i) \tag{2}$$

where $WP_{j,s}^x(i)$, $WP_{j,s}^t(i)$ and $WP_{j,s}^e(i)$ are the wavelet packet coefficients of x, t, and e respectively, $j = 1, 2, ..., J$ is the number of decomposition levels, $s = 1, 2, ..., 2j$ is the number of scales, $i = 1, 2, ..., M$, where $M = N/2j$ and N is the length of the signal.
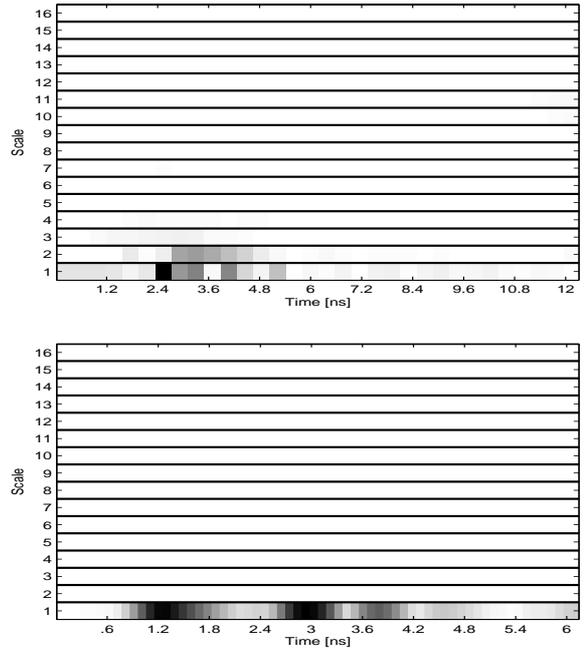
Fig. 2. The wavelet packet of DeTeC and IESK data, respectively.

The target signal, can be extracted, by thresholding the wavelet-packet-transform coefficients, which is based on the higher-order statistics.

IV. HIGHER ORDER STATISTIC

Dealing with non-Gaussian random processes, the notions of higher order moments, cumulants, and their polyspectra called higher order statistics are of paramount importance in statistical signal processing.

If $x(n), n = 0, \pm1, \pm2, \pm3, ..$ is a real stationary discrete-time signal and its moments up to order p exist, then its pth-order moment function is given by

$$m_p(\tau_1, \tau_2, ..., \tau_{p-1}) = E\{x(n)x(n+\tau_1)....x(n+\tau_{p-1})\} \tag{3}$$

and depends only on the time differences $\tau_1, \tau_2, ..., \tau_{p-1}$ $\tau_i = 0, \pm1, \pm2, \pm3, ...,$ for all i. Here $E\{.\}$ denotes statistical expectation and for a deterministic signal, it is replaced by a time summation over all time samples (for energy signals) or time averaging (for power signals). If in addition the signal has zero mean, then its cumulant functions (up to order three) are given by
second-order cumulant:

$$C_2(\tau_1) = m_2(\tau_1)$$

third-order cumulant:

$$C_3(\tau_1, \tau_2) = m_3(\tau_1, \tau_2)$$

By setting all the lags to zero in the above cumulant expressions, we obtain the variance and skewness respectively, Variance:

$$\gamma_2 = C_2(0) = E\{x^2(n)\}$$

Skewness:

$$\gamma_3 = C_3(0,0) = E\{x^3(n)\}$$

When estimating higher-order statistics from finite data records, the variance of the estimators is reduced by normalizing the input data to have a unity variance, prior to computing the estimators.

Equivalently, the third order statistics are normalized by the appropriate powers of the data variance, thus we define the Normalized skewness:

$$S = \frac{C_3(0,0)}{[C_2(0)]^{1.5}} = \frac{E\{x^3(n)\}}{[E\{x^2(n)\}]^{1.5}} \qquad (4)$$

V. PROCEDURE OF DE-NOISING AND PERFORMANCE

For the purpose of detection, the idea is to transform the data by wavelet and keep only target coefficients, which allows one to get rid of the greatest part of the disturbing noise. This classical technique is called de-noising and consists of setting to zero all the wavelet coefficients whose magnitude is below an appropriate threshold.

We have assumed that the received data consists of two parts; noise, and target signals as in(1).

In this work, the noise $e(n)$ is assumed to be white Gaussian stationary noise. By applying the Gaussian test to the wavelet coefficients, All Guassian coefficients are set to zero.

A. Gaussian test

In the Gaussian test the noise is assumed to be white Gaussian, and the noise and the target signals are stochastically independent.

The skewness of the received data (x) can be written as [5]

$$S(x) = S(b) + S(t) \qquad (5)$$

Where $S(b)$ and $S(t)$ are the skewness of the clutter and target signals, respectively.

We also assume that some of the wavelet coefficients of the received data belong to the target signal, and some of it belong to the noise signal. So we have target, and noise coefficients. The problem now, how can we separate the target coefficients. Instead, determination of the wavelet coefficients of the noise by checking its Gaussianity using the higher-order statistics. When the noise is white stationary, the coefficients remain white stationary.

Our candidate is the skewness, which is the normalized version of the third-order cumulant.

The Gaussian process has a skewness value that equals zero. To perform a de-noising procedure on the wavelet coefficients, all Gaussian coefficients are set to be zero. The test we present here is based on the normalized third order cumulant, skewness (4), which has been computed by the method of moments. In this method, while fitting a probability distribution to a sample, the parameters are estimated by equating the sample moments to those of the theoretical moments of the distribution. Even though this method is conceptually simple, and the computations are straight-forward, it is found that the numerical values of the sample moments can be very different from those of the population from which the sample has been drawn, especially when the sample size is small and/or the skewness of the sample is considerable [7].

In our work we have a limited number of data sample, so we are not able to obtain an exact value of the skewness. Instead of that we have an estimate value using sample averages. The estimation of the skewness can be calculated as:

$$\hat{S} = \frac{1}{N} \sum_{N=1}^{N} \left(\frac{x_i - \hat{\mu}}{\hat{\sigma}} \right)^3, \qquad (6)$$

where $\hat{\mu} = \frac{1}{N} \sum_{N=1}^{N} x_i$ and $\hat{\sigma} = \frac{1}{N} \sum_{N=1}^{N} (x_i - \hat{\mu})$

The estimated value of the skewness is allowed to exist in a confidence interval. Normally, the confidence interval is calculated when the probability density function is known. On the other hand, the probability density function of the third-order cumulant of a Gaussian sequence is not known analytically.

A partial solution to this problem is to use the Bienayme-chebyshev inequality, which makes it possible to frame our estimates for the estimator and is expressed as [8]:

$$Prob\left(|\hat{S} - E(\hat{S})| \le a\sqrt{var(\hat{S})} \right) \ge 1 - \frac{1}{a^2}$$

A fixed confidence percentage corresponds to a value of the factor $a = 1/\sqrt{1-\alpha}$, where α is the authorized confidence percentage value.

Now, the skewness estimator varies between

$$\pm \frac{1}{\sqrt{1-\alpha}} \sqrt{var(\hat{S})}, \qquad (7)$$

The variance of the skewness is [9]

$$var(\hat{S}) = \frac{1}{n} \left\{ \frac{\mu_6}{\mu_2^3} - 6\beta_2 + 9 + \frac{\beta_1}{4}(9\beta_2 + 35) - \frac{3\mu_5\mu_3}{\mu_2^4} \right\} \qquad (8)$$

where μ is the central moment, $\beta_1 = \mu_3^2/\mu_2^3$ and $\beta_2 = \mu_4/\mu_2^2$

In the case where the n coefficients $WP_{j,s}^{e}(i)$ are white and Gaussian, the variance of the third-order cumulant is evaluated as [9]

$$var(\hat{S}) = 6\sigma^6/n$$

where σ^2 is the variance of the n noise. The variance of skewness estimator (for σ=1) is

$$var(\hat{S}) = 6/n \qquad (9)$$

The simple test for Gaussianity measure is that the skewness varies between

$$\pm \frac{1}{\sqrt{1-\alpha}} \sqrt{6/n} \qquad (10)$$

The skewness has been framed with 90 % of confidence by the following inequality:

$$-\frac{3}{10}\sqrt{\frac{6}{n}} \le \hat{S} \le \frac{3}{10}\sqrt{\frac{6}{n}} \qquad (11)$$

B. Clutter Removal

The Gaussian test algorithm has been applied to remove the noise from GPR data. The steps of the algorithm are

1) Compute the wavelet packet coefficients of the received data $WP_{j,s}^{x}(i)$ at level j, scale $s = 1, 2, ..., 2j$.
2) Estimate the skewness for the wavelet packet coefficents of each scale using (6).
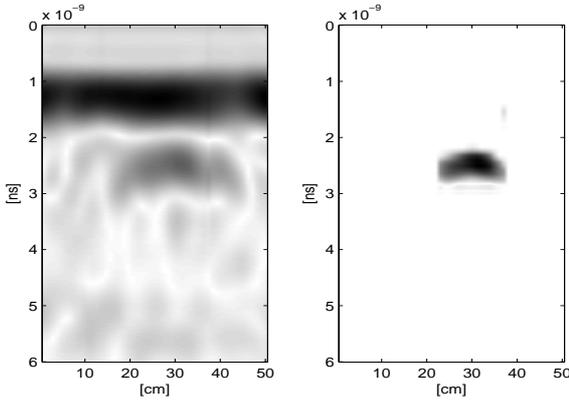
Fig. 3. B-Scan for IESK data before and after applied the Gaussianity test algorithm, respectively.
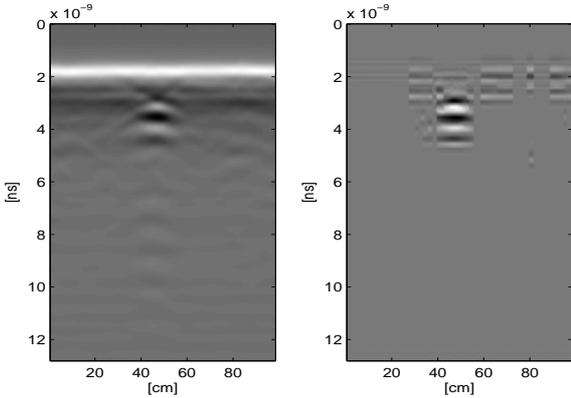
Fig. 4. B-Scan for DeTeC data before and after applied the Gaussianity test algorithm, respectively.

3) Compare the skewness of the wavelet packet coefficients with interval value (10).
4) All the coefficients, which have skewness value in this interval, have been removed.
5) For the remaining non-Gaussian coefficients a hard threshold has been applied to further improve the SNR. The threshold value is calculated using the following relation:

$$\delta_S = \bar{\sigma}_s \sqrt{2log(N)} \qquad (12)$$

where $\bar{\sigma} = median(|WP_{j,s}^t|)/0.6745$

6) Reconstruct the target signal from the remaining coefficients.

VI. RESULTS

The skewness algorithm test consists of two parts has been applied to both DeTeC and IESK GPR data.

The first part of the algorithm is to remove the Gaussian noise, and the second part is used for further improvement in SNR if necessary.

The threshold value is calculated using confidence percentage value $\alpha = 90\%$ by using equations 11. The Daube-chies wavelet has been used of order 4 and number of levels J=3. The B-Scan of the data and the result of applying the algorithm are depicted in Fig.3 and Fig.4.

The effect of the algorithm for clutter reduction have been investigated. The area under Receiver Operating Characteristic
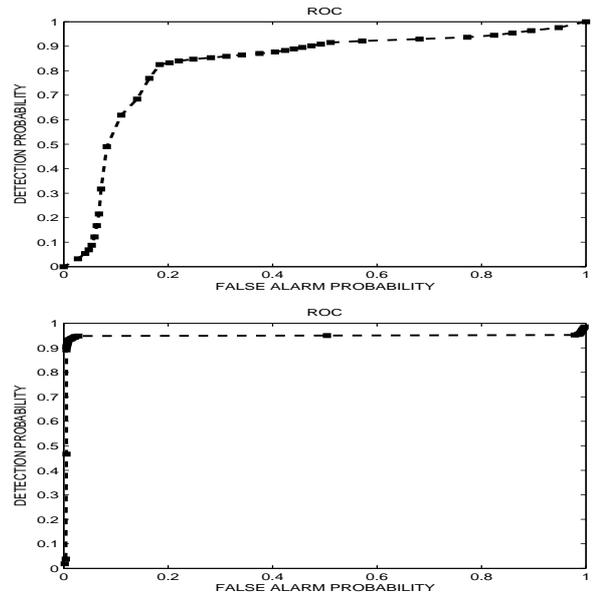
Fig. 5. ROC curve before and after applied Gaussian test, respectively.

curve is used. Fig.5 show the ROC curves before and after applied the algorithm, respectively. The images (Fig.3 and Fig.4) and ROC curves (Fig. 5) show that the detection is improved. The surface reflection and the reflection within the earth have been almost removed.

VII. CONCLUSION

The main purpose of this communication was the study of skewness test of GPR data.

An algorithm for denoising GPR data has been described. The algorithm combines two powerful tools, the wavelet packet transform and the higher order statistics. Most of the clutter has been removed, where the clutter has been assumed to be white Gaussian noise. The algorithm gives good result, which proves its validity.

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