

PERFORMANCE OF BUTTERWORTH FILTER IN DENOISING GROUND PENETRATING RADAR SIGNALS OVER HETEROGENEOUS EARTH MEDIUM

Idi, B. Y.

Department of Physics, Federal University Dutse, Jigawa state, Nigeria.
belyus2000@gmail.com

ABSTRACT

One of the major challenges of Ground Penetrating Radar (GPR), as a near surface nondestructive geophysical survey tool is the relatively low signal to noise ratio (SNR) of its output. This is partly caused by the existence of low frequency signals associated with electrostatic and inductive fields near the transmitting and receiving antennas. Getting rid of this low frequency noise is a subject of intensive research in signal processing. In this work, the spectral characteristic of a raw GPR signal is analyzed using Fast Fourier Transform (FFT) with the aim of studying the frequency characteristics of the noise. Appropriate Butterworth filter was designed and used to attenuate the noise component of the spectrum. The performance of the designed filter was evaluated by comparative analysis of the SNR and Normalized Root Mean Square Error (NRMSE) of the pre and post processed signals. The filter enhanced SNR value from 0.0146 dB to 5.2296 dB while the NRMSE was successfully reduced from 0.1941 to 0.0861. The results show that the designed Butterworth filter greatly denoised the signal and enhanced the SNR. The processing technique could therefore be used to enhance target detection and characterization.

Keywords: Ground Penetrating Radar, Fourier Transform, Butterworth filter, signal-to-noise ratio; Normalized Root Mean Square Error, Peak Signal-to-Noise Ratio.

1 INTRODUCTION

Ground Penetrating Radar is a near-surface subsurface survey tool designed primarily for the location of objects or interfaces buried shallowly beneath the earth surfaces. The technique is very effective and efficient in gathering information about subsurface soil and near surface geologic formations. It records continuous graphic profiles of the subsurface interfaces with a high degree of accuracy. The technique is particularly found to be successful in detecting subsurface geologic structures[1], buried archeological remains [2], subsurface fracture zones and cavities [3] etc.

Radar probing technique is based on the principles of conventional radio transmission and detection where back-scattered energy from an incident target are detected and interpreted to determine physical, electrical and geometrical properties of the target. In GPR, transmitting and receiving antennas are used to scan the surface where natural or man-made anomalous features or artifacts are buried within the

shallow subsurface. GPR signal frequency is typically within a range of 100 to 9000MHz [4].

The transmitted signals are scattered or reflected by a change in impedance of the subsurface anomaly as they travel through the material medium. The back-scatter is received by the receiving antenna normally fixed in the same geometry with the transmitter so that they are moved together over the surface. The reflected transient electromagnetic waves received by the receiving antenna can be analyzed to detect electrical and geometrical properties of the subsurface discontinuity through the changes in the vertical electrical properties notably electrical conductivity, dielectric permittivity and signal amplitude.

GPR signal is however characterized by low signal-to-noise ratio (SNR) mainly due to ultra-wide bandwidth nature of the receiving antenna and high degree of subsurface discontinuity. In many situations, the noise level is so high to the extent that the required information is obscured, making it undetectable. For any useful information to be detectable, the received power must be in excess of the noise level in the receiver [5]. Thus the accuracy of information derivable from the raw GPR signal depends on the effectiveness of the signal processing technique adopted.

There are several GPR radar signal processing algorithms, broadly categorized into basic, dealing with noise and clutter reduction and enhancement of SNR and advanced processing, which is user biased, depending on the kind of information required [6]. SNR enhancement is of fundamental relevance since it determines the detectability or absurdness of the target anomaly. Various algorithms for denoising GPR data and enhancement of its SNR were developed in recent times mainly associated with the various developed processing software. Two commonly identified algorithms are: empirical mode decomposition [7], which involves the application of time domain spline curve fitting operator, and discrete wavelet transform and the Multilayer Perceptron (MLP) neural network model developed by [8] where the MLP was used to filter the data from the random noise after identifying it with the training algorithm. It is however observed that the machine is not effectively able to preserve amplitudes of the signal [8].

This work is aimed at developing an appropriate filter for denoising raw GPR data which can effectively preserve the signal amplitudes thereby minimizing the lost of useful information. The work involves analysis of the spectral characteristic of A-scanned raw GPR signals using Fast Fourier Transform (FFT) in order to observe the frequency characteristics of the noise. This is used to determine the appropriate filter parameters needed to cutoff the noise component of the data. Frequency-domain band pass Butterworth filter was developed and used to denoise the data. The goal of the work is evaluate the performance of the developed Butterworth filter in denoising GPR data acquired in a heterogeneous (noise source) medium.

2 METHOD AND MATERIALS

2.1 Theoretical framework

Even though GPR backscatter are received as a continuous signal within a specific time window, computer processing of the signal require its digitization from a continuous to a set of finite discrete-time samples. This is necessary for processing in a digital computer. Digitization can be achieved by sampling the continuous signal $x(t)$ at an equal interval with appropriate sampling frequency that will enable complete reconstruction of the signal with minimum loss of information. A time series function like GPR signal can be decomposed into its frequency domain using Fourier Transform (FT). FT of a function of time is a complex-valued function of frequency whose absolute value represents the amount of that frequency present in the original function, and whose complex argument is the phase offset of the basic sinusoid in that frequency. The transformed function is called the frequency domain representation of the original signal.

The algorithm is mathematically given as

$$F(\omega) = \int_{-\infty}^{\infty} f(x)e^{-2\pi ix\omega} dx \dots\dots\dots (1)$$

Where $F(\omega)$ is the FT of a continuous function $f(x)$, that is the amount of the function represented by frequency ω . This reveals the frequency content of the continuous function (or signal) and therefore enables the signal's spectra to be viewed and analyzed.

For many functions of practical interest, an operation that reverses this, the Inverse Fourier Transformation (IFF), also called Fourier synthesis of a frequency domain representation, combines the contributions of all the different frequencies to recover the original function of time. Its inverse operation reverts the frequency space to physical time space given by

$$f(x) = \int_{-\infty}^{\infty} F(\omega)e^{2\pi ix\omega} d\omega \dots\dots\dots (2)$$

Thus a time series discrete data such as GPR A-scan can be represented by the Discrete Fourier Transform (DFT) as

$$F_{\omega} = \frac{1}{N} \sum_{\omega=0}^{N-1} f_n e^{-2\pi in\omega/N} \dots\dots\dots (3)$$

With its inverse as

$$f_n = \frac{1}{N} \sum_{\omega=0}^{N-1} F_{\omega} e^{2\pi in\omega/N} \dots\dots\dots (4)$$

Where N is evenly spaced real data. For complete reconstruction of the signal, sampling must be done based on Shannon's sampling theorem which require that the sampling frequency must be greater than twice the highest frequency component of the sampled signal [9].

Filters are generally applied to signals in frequency domain in order to remove the unwanted component of the spectrum. An ideal temporal filter is characterized by frequency dependent impulse response $H(\omega)$ defined by the ratio of the filter's output to its input in frequency domain. Ideally, the frequency components of the input that fall into the stopband (cutoff) are completely eliminated while the components within the

pass band are passed without any modification. While ideal filter is hardly realizable, a good approximation of it is the Butterworth filter with a frequency response given by [10] as

$$H(\omega) = \frac{1}{\sqrt{1+(\frac{\omega}{\omega_c})^{2N}}} \dots\dots\dots (5)$$

Where N is the order of the filter and ω_c is the cutoff frequency. The degree of attenuation of signals within the cut-off band increases with increase in the order of the filter.

The performance of the filter was evaluated by computing SNR, Normalized Root Mean Square Error (NRMSE) and Peak Signal-to-Noise Ratio (PSNR). SNR is the measure of the ratio of meaningful information of a signal to its background noise. It is normally expressed as the ratio of the square of amplitudes (signal power) of the signal to that of the noise. SNR is the measure of the level of the desired signal to the level of background noise. It is defined as the ratio of signal power to the noise power, expressed in decibels [11] as

$$SNR(dB) = \frac{\sum_k^N [r(k)]^2}{\sum_k^N [f(k)_i - r(k)_i]^2} \dots\dots\dots (6)$$

Where $f(k)$ is the amplitude of the raw data at a given scale level from k to N and $r(k)$ is the corresponding amplitude of the de-noised signal. SNR of a signals vary from $-\infty$ (pure noise without desired signal) to $+\infty$ (pure desired noise-free signal). An SNR value of 0dB indicates that the signal and the noise are of equal level. Thus a ratio higher than 1:1 (greater than 0 dB) indicates more signal than noise while a negative value indicates more noise than signal.

NRMSE is a dimensionless equivalent of Root Mean Square Error (RMSE). It is the measure of the difference between the processed and the preprocessed (raw) signals. The NRMSE between a raw signal $r(k)$ and its corresponding processed signal $f(k)$ is given by

$$NRMSE = \frac{RMSE}{f(k)_{max} - f(k)_{min}} \dots\dots\dots (7)$$

Where $RMSE = \sqrt{\frac{f(k)_i - r(k)_i}{N}}$

Its significance is similar to Signal-to-Noise Ratio (SNR) except that it takes into accounts distortion and interference coming from several sources such as multipath, high tension cable etc. A good denoising filter reduces NRMSE value. Another important validation parameter is the Peak Signal-to-Noise Ratio (PSNR) which measures the purity of the output signal. It is defined as the ratio of the maximum possible power of a signal to the power of the corrupting noise that affects its quality [12]. PSNR is computed using the equation

$$PSNR(dB) = 20 \log_{10} \frac{f(k)_{max}}{\sqrt{MSE}} \dots\dots\dots (8)$$

2.2 Data acquisition and processing

GPR radar acquisition system (IDS DAD fast wave radar) was used to scan a 10m long profile over a moist clay soil with a shallowly buried PVC pipe at a radar

central frequency of 200MHz. A common offset single fold reflection profiling was used. The scanning was repeated at different strike angles in order to obtain the profile that best strike the buried pipe normal to the scanning axis. The pipe is imaged in the 2-D radargram (B-scan) as a point reflector and thus spread out a hyperbola. The data was visualized using Reflex2D visualization and processing software [13]. The 2-D radargram that best meet this condition is shown in Fig. 1.

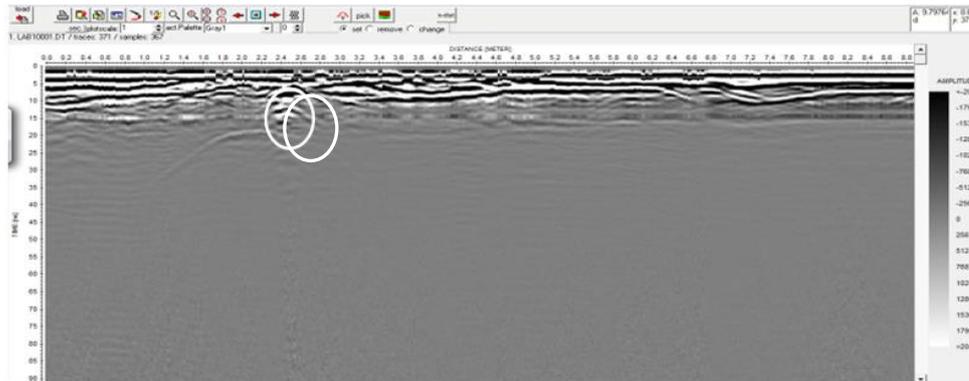


Figure 1. Two dimension radar image obtained. The hyperbolic image of the target pipe is shown (cycled).

The first strong arrival within the range of 5-15ns is the reflection from the ground surface and therefore has nothing to do with the subsurface. This effect was removed from the image using subtract DC-shift of the processing software.

To study the characteristics of the noise, a 1-D (A-scan) plot of the data was acquired across the centre of the hyperbola. The acquired A-scan plot was digitized at a constant time interval of 0.5ns using Plot Digitizer. Figure 2 is the plot of the digitized signal which show slow amplitude signal between 15 to about 50ns time.

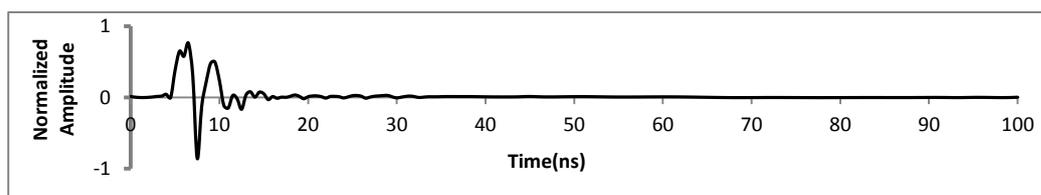


Figure 2. Digitized A-scan of the acquired raw data above the position of the target

This coincides with position of the expected response of the target of interest. The fact that the response at the expected position is not uniquely localized clearly indicates that it is masked with unwanted noise. DFT was used to generate the frequency-domain spectra of the signal. The frequency-domain spectrum (Figure 3) displays power spectra of the signal with respect to the various frequency components.

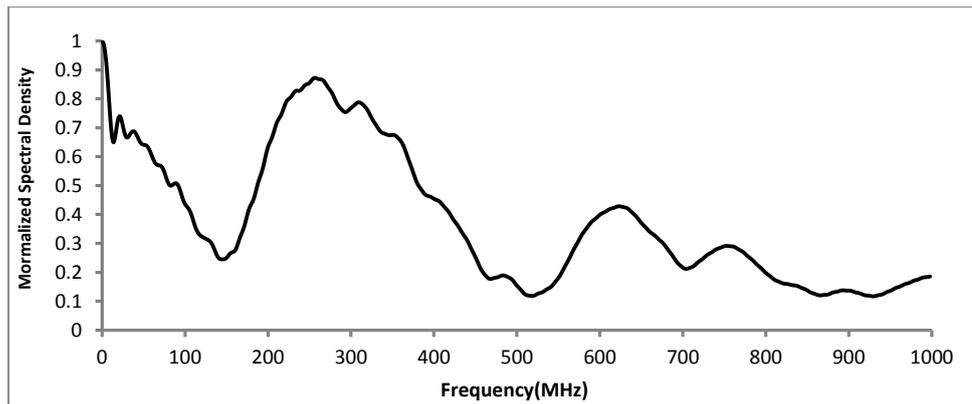


Figure 3. Power spectra of the digitized raw data

It could be observed that bulk amount of the signal's components lies within 100-400MHz bandwidth. Significant amount of power is however observable at a frequency above 500MHz especially around 600MHz. With the peak of the spectrum roughly at 200MHz, a half power bandwidth is considered as the main signal bandwidth from which desired components of the signal is available. Half power frequency is the frequency at which the spectral power reduces to $1/\sqrt{2}$ of its peak value. This corresponds to a frequency band of 150-340MHz. Thus the required signals may be unmasked by attenuating frequencies below and above this range.

Butterworth filter was designed using the Filter Design and Analysis Tool (FDA Tool) toolbox in MATLAB with the goal of narrowing down the pass region of the signal to the specified half power bandwidth. The designed filter parameters are given in Table 1. Figure 4 is the window snapshot of the designed filter showing the filter frequency response curve. The response curve shows how signals below and above the passband are attenuated at -80dB and 80dB rates respectively. The signals within the passband were however passed without modification.

Table 1. Designed Filter Parameters

<i>Filter parameter</i>	<i>Value</i>
Filter order	10
Pass attenuation	1 dB
Stop attenuation	80dB
Sampling frequency	1000MHz
First stop	100MHz
First pass	150 MHz
Second pass	340 MHz
Second stop	400 MHz

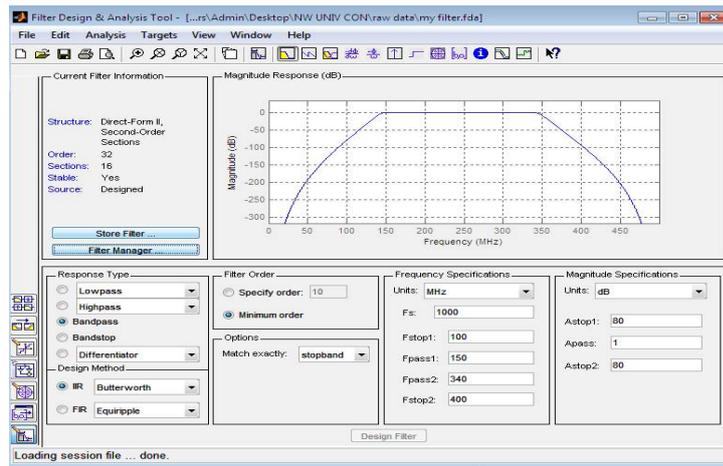


Figure 4. GUI interface of the designed filter showing the parameters and the filter response curve

The frequency-domain spectral data obtained from the FFT was applied as an input on the designed filter. The output also in frequency domain was back-Fourier transformed into time domain. To evaluate the performance of the filter, a noise-free model of the A-scan GPR response for a buried PVC pipe in a wet clay subsurface was simulated using GPRSim.net simulation software based on the model parameters shown in Table 2. The model parameters were obtained from literature values of the physical properties of the materials involved [14, 15].

Table 2. Simulation model parameters

	PVC pipe	Wet soil
Mean Relative Dielectric permittivity	3.3	22.5
Mean Electrical conductivity	0.00000008 Sm ⁻¹	0.55 Sm ⁻¹
Pipe depth	0.67m	

The simulated data which is considered noise-free (Fig. 5), was used to estimate the noise level of the acquired raw data. Comparison of the noise level between the simulated noise-free signal and that of raw data was done in terms of three validation parameters namely Signal-to-Noise Ratio (SNR), Normalized Root Mean Square Error (NRMSE) and Peak Signal-to-Noise Ratio (PSNR). A similar analysis was done in respect of the raw and the processed (filtered) signals. The noise levels were analyzed to ascertain the effectiveness of the filter in noise reduction.

3 RESULTS AND DISCUSSION

Visual observation of the simulated model, the raw and processed responses (Figures 2, 5, and 7 respectively) clearly showed similarity between the three, but greater contrast is discernible between the raw and the noise-free model. Figure 6 is a plot of the power spectra of the filtered signal. It could be observed that the masked response in Figure 2 is clearly more identifiable in the processed signal (Figure 7). It is also more uniquely localized as a pulse within a relatively shorter duration of 20-30ns.

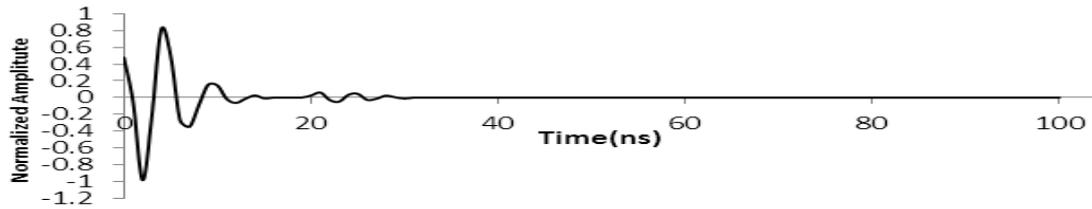


Figure 5. Results of 1-D radar modeling using a 200 MHz frequency

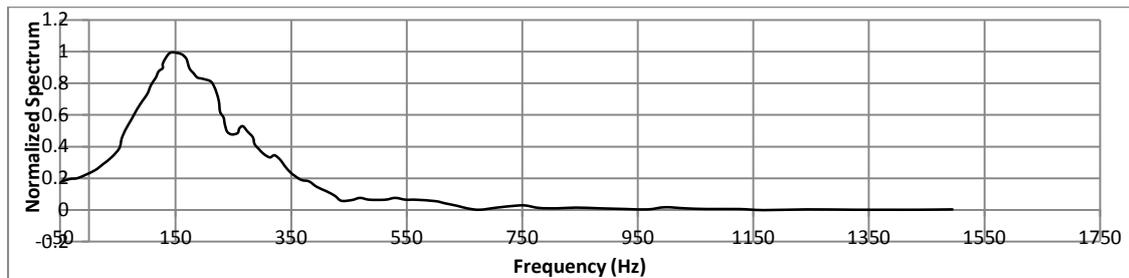


Figure 6. Frequency-domain power spectra of filtered signal

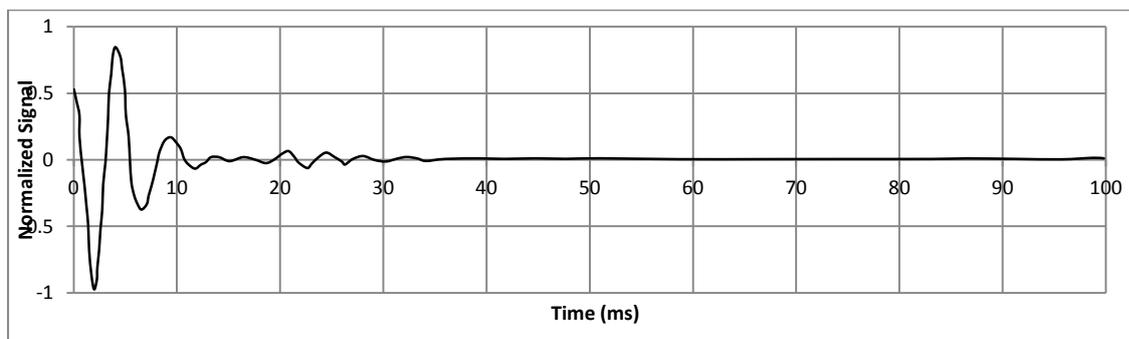


Figure 7. Processed (filtered) signal

The three validation parameters used quantitatively to evaluate the filter performance of the signal were computed in respect of the two pairs of the signals in order to validate the performance of the designed filter.

The simulated model signal is compared with the preprocessed data in order to estimate the noise level of the later. The model signal is also compared with the filtered (processed) in order estimate the noise level of the filtered signal. Comparison of the noise levels of the raw and processed data all with respect to the noise-free model validates the effectiveness of the filter in denoising the signal. Thus in each case, the aforementioned validation parameters were computed. Table 3 gives the results of the computed validation parameters.

Table 3. Computed validation parameters

	<i>Raw signal</i>	<i>Processed signal</i>
SNR	0.0146dB	5.2296dB
MSE	0.1223	0.0241
NRMSE	0.1941	0.0861
PSNR	9.1257dB	16.1798dB

It could be observed from the results that with an SNR value of 0.0146dB, signal and noise are almost at the same energy level in the raw data. It will be very difficult to extract useful information from the signal at this situation without enhancement. Considering the increase in the SNR level after filtering however, it could be concluded that the designed filter is very effective in denoising the signal. The MSE and NRMSE values were also less with respect to the processed data compared to that of the raw data. These are indication of significant reduction in the error level of the processed signal compare to the raw signal. The processed signal's PSNR value of 16.1798dB recorded against a value of 9.1257dB with respect to the preprocessed signal also indicates that the purity of the processed signal is significantly higher than that of the raw signal. These results therefore validate the effectiveness of the designed Butterworth filter in denosing radar signal within the given frequency range. The precision with which the target-scattered pulse appear also implies that processing the signal with the designed filter will results into precise determination of the depth of the target, estimation of the dielectric permittivity and moisture content of the overburden soil with higher level of accuracy.

4 CONCLUSION

In this work, a bandpass Butterworth filter was designed and used to filter an A-scanned GPR data with the aim of validating the performance of the filter in denoising ultra-wide band EM signals. Computed validation parameters showed that the processed signal has greater SNR and PSNR values of 5.2296 dB and 16.1798 dB respectively compared to the raw signal's 0.0146 dB and 9.1257 dB, indicating relatively higher value of signal compared to noise levels and higher signal purity. Least values of MSE and NRMSE were also recorded with respect to the processed signal compared to that of the raw signal. This is also an indication of lesser error value and higher level of accuracy in respect of the processed signal. It is therefore evidently established that the designed filter is significantly effective in denoising ultra-wide band signals such as GPR. It can therefore be used as a preprocessing tool in near surface geophysical explorations such as moisture content estimation, dielectric permittivity determination, and buried pipe detection with reasonably higher level of accuracy.

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