Improving the Total Variation De-noising algorithm in GPR noise reduction

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ABSTRACT

The existence of coherent and incoherent (random) noises in the Ground Penetrating Radar (GPR) signals which utilizes the high-frequency electromagnetic waves, is inevitable; therefore de-noising of the GPR data before performing any further analysis, is of great importance to increase the efficiency of the interpretations. In this paper, we apply the Total Variation De-noising (TVD) on the synthetic GPR data. The results point to the fact that the TVD method is effective in reducing the noise; however, because of the visibility of the staircase artifacts using TVD method, the GPR data is first transferred to the Empirical Mode Decomposition (EMD) framework and then the TVD method is applied on it. In final, the noise reduction using TVD is compared in time and EMD domains. The comparison of the outputs represents that the TVD-EMD algorithm preserves the event shapes, the signal forms and improves the continuity in the sections.

Keywords: De-noising, Ground Penetrating Radar (GPR), Empirical Mode Decomposition (EMD), Total Variation De-noising (TVD).

INTRODUCTION

Ground Penetrating Radar (GPR) is commonly used as a technique which employs the high-frequency electromagnetic waves from about 10 MHz to 2 GHz to image the shallow subsurface (Jol, 2008). In order to improve the resolution of the GPR signals and achieving the accurate prediction of the subsurface anomalies, some preliminary processes are necessary to be administrated to the data. Several studies have been carried out on GPR noise attenuation (Liu et al., 2017, Oskooi et al., 2015). In this paper, to estimate the true signal from noise, TVD method which is L1 norm dependent, is applied on synthetic GPR data. TVD is a nonlinear filtering in the time domain, introduced by (Rudin et al., 1992). This method has been generally applied in sparse signal processing as a penalty function in de-noising and the output is obtained by minimizing a non-differentiable cost function. The proposed TVD algorithm is derived using the maximization-minimization (MM) approach developed by (Figueiredo et al., 2006). During the resolution process, the MM algorithm monitors to minimize the difference between the observed and desired data and simultaneously applies the control parameter to the data (Pakmanesh et al., 2017). This method is applied in deconvolution, reconstruction and compressed sensing (Moghaddam et al., 2019). The GPR data set has a large bandwidth around the central frequency and noise exists on all frequencies. So to resolve this problem, the Empirical Mode Decomposition (EMD) method is used to extract the sub-signals. The EMD method is one of the non-stationary and nonlinear data processing techniques introduced by Huang et al. (1998) which is based on the decomposition of the energy associated with various intrinsic time scales of the signal ranging from high-frequency modes to lower ones called Intrinsic Mode Functions (IMFs). Each IMF includes different frequency components, which yields different geological and stratigraphic information. At each stage of the decomposition, the frequency decreases and in consequence, the number of extrema decreases too. In this work, TVD method is first applied on the GPR synthetic signals. Then, each noisy GPR signal in the de-noising procedure is adaptively decomposed into the IMFs by the sifting process in the EMD operator, and the TVD algorithm is applied to each IMFs. The purpose of applying Shifting process and splitting the GPR non-linear and non-stationary signals in to IMFs, is to get the nearly stationary and linear sub-signals by the statistical controls.

Application of suggested methods on simulated GPR signal

The received non-stationary signal of GPR system, y(t), which is usually contaminated by noises, can be expressed as follows (Oskooi et al., 2015):

$$y(t)=x(t)+w(t) \qquad (1)$$

Where x(t) is a main signal of the investigated object corrupted with noise w(t). The ultimate goal of de-noising is to get the y(t) as close as possible to x(t) by minimizing the effect of w(t). In total variation de-noising, it is assumed that the noisy data y(n) is of the form of (Selesnick, 2012):

$$Y(n)=x(n)+w(n) \qquad n=0,\ldots,N-1 \qquad (2)$$

In which x(n) is a piecewise constant signal and w(n) is white Gaussian noise. TVD estimates the signal x(n) by solving the optimization problem:

$$minimize \sum_{n=0}^{N-1}|y(n)-x(n)|^2+\lambda\sum_{n=1}^{N-1}|x(n)-x(n-1)| \qquad (3)$$

λ is a regularization parameter which controls the degree of smoothing. The matrix D is defined as:

$$D=\begin{bmatrix} -1 & 1 & & \\ & -1 & 1 & \\ & & & \\ & & -1 & 1 \end{bmatrix} \qquad (4)$$

The total variation of N-point signal x(n) is given by (Selsenick, 2012):

$$TV(x) := \|Dx\|_1 = \sum_{n=1}^{N-1}|x(n)-x(n-1)| \qquad (5)$$

In the above equation, Dx is the first-order difference of an N-point signal x where D is of size (N-1)*N. With above notation, TVD problem (3) is written compactly as (Selsenick, 2012):

$$argmin\{F(x)=\frac{1}{2}argmin\|y-x\|_2^2+\lambda\|Dx\|_1\} \qquad (6)$$

To solve the optimization problem of the equation (6), the MM algorithm which is well described in Selesnick (2012) is used.

In order to conduct a systematic search of applicability of the proposed methods on GPR signals, a synthetic model has been performed using full-wave solver of Maxwell's equations (GPRMax 2.0). The synthetic model chosen in this study as seen in Fig.1.a is considered to consist of three layers with different dielectric and conductivities, where the upper layer is made of concrete (t_1=1m, $\sigma_1=0.005\frac{s}{m}, \varepsilon_{r1}=6$), the middle layer of wet sandy soil (t_2=2m, $\sigma_2=0.0001\frac{s}{m}, \varepsilon_{r2}=25$) and the third layer is a saturated sandy soil (t_3=1m, $\sigma_3=0.07\frac{s}{m}, \varepsilon_{r3}=30$). To evaluate the performance of each method, the Gaussian noise was added to the data. Before any de-noising scheme, the SNR of the resulting noisy data is 3.71 (dB). We see in Fig. 1.b that the noise destroyed the data and the second reflector has completely disappeared. An example of an arbitrary traces of the synthetic data before and after adding noises has been shown in Fig. 2.a. The SNR calculated after using TVD is 9.4 (dB). As seen in Fig. 2.b, TVD has been able to reduce the effect of background noise from data and the second reflector is better visible. Increasing the amount of SNR confirms this fact too. However, the events with a lower amplitude have been more influenced as compared to the clean data from the de-noising process; on the other hand, the events with higher amplitude are less influenced. Also, the restoration of the border of the layers has not been performed well and the staircase artifacts are clearly visible which have produced a large number of unwanted events which is results from the implementation of filtering. Therefore in order to modify this method in GPR signal processing, EMD framework has been employed to extend the proposed algorithm and smoothing the riding and oscillatory GPR waves. The results of applying TVD-EMD on simulated GPR data have been shown in Fig. 2.b too. In order to compare two approaches, all input parameters have been considered equal. The primary advantages of the EMD method is extraction of the basis function from the GPR trace itself. The SNR calculated after applying TVD-EMD is 10.76 (dB).

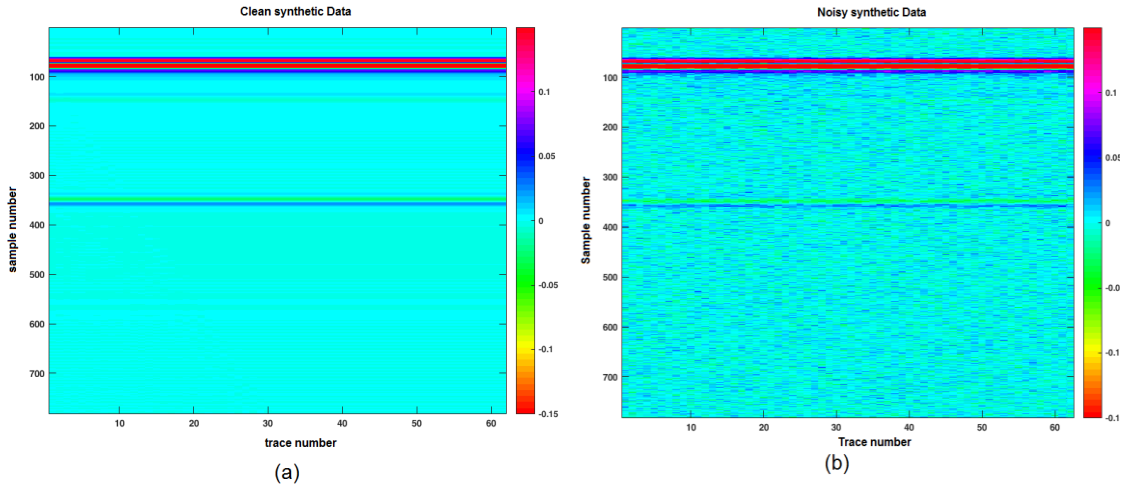

Figure 1.a: The synthetic GPR model and b: the synthetic model contaminated by white Gaussian noise.

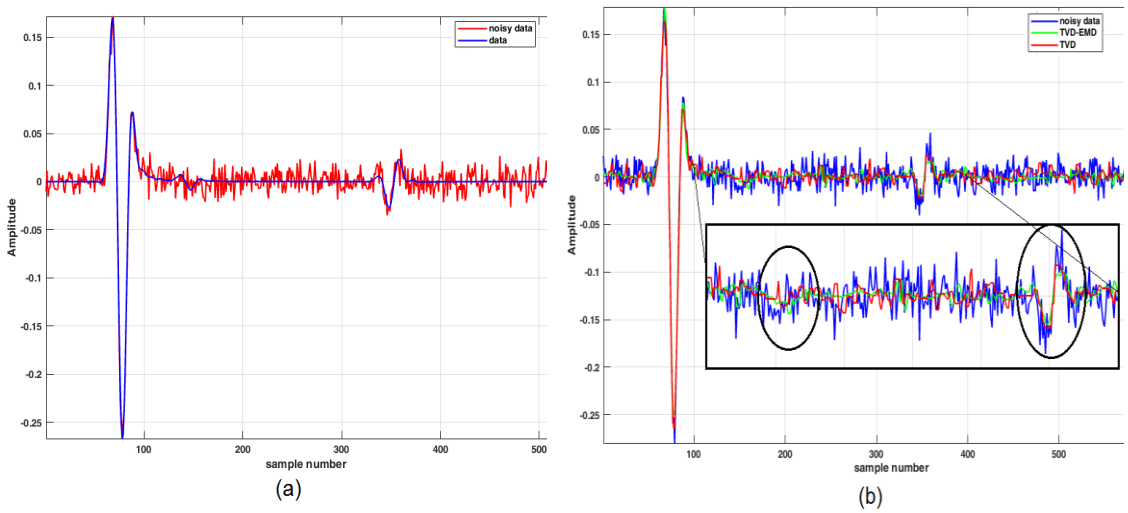

Figure 2.a: The second trace: clean data (blue color) and noisy data (red color) and b: De-noised synthetic second trace of GPR data after using TVD and TVD-EMD with λ=0.0066.

As seen in Fig. 2.b, TVD-EMD has been more effective than common TVD in attenuating the effect of background noise from data and restoration of the borders. The unwanted events have decreased significantly and also the decreasing of amplitudes the signal has been resolved compared to the TVD. While studying the power spectrum, it is possible to consider noise and signal elimination as a quantitative and qualitative fundamental challenge. Due to the proximity of the calculated SNR in the qualitative evaluation and quantitative assessment of the methods in de-noising and maintaining the signal, the power spectral densities of the noisy and de-noised data have been shown in Fig. 3. At lower frequencies, the two methods of TVD and TVD-EMD have almost the same decreasing trend and are not successful and noise has been added to the data. However, as the range of frequency increases, the trend of the TVD-EMD coincides with the true signal (red line) which indicates the power of maintaining the signal. Furthermore, at higher frequencies, the maximum noise reduction has been obtained with the TVD-EMD method.

CONCLUSIONS

This paper focuses on the reduction of the random noises of the GPR data by applying the TVD method based on the EMD framework. First, TVD method was applied to the synthetic data created from a three-layer model with different physical properties. By applying the TVD filter to the data, the SNR increased from 3.71(dB) to 9.4 (dB) which it can be concluded that the TVD method has an acceptable performance in de-noising of GPR signals. But, the implementation of TVD in the time domain creates artificial noises due to filtering. The trend of noise creation is the elongation of the events in line with the time axis and as a result, can cause negative effects on

the accuracy of detecting the real phenomena. However, by decomposition of each trace into a series of IMFs, and then applying the TVD on each IMFs, the de-noising process of GPR data is improved. We conclude that the TVD-EMD method preserves the events, keeps the signals, decreases the staircase events and enhances continuity in the sections. For better GPR signal de-noising, we plan to study of applying the Variational mode decomposition (VMD) because of the strong theory instead of EMD method.

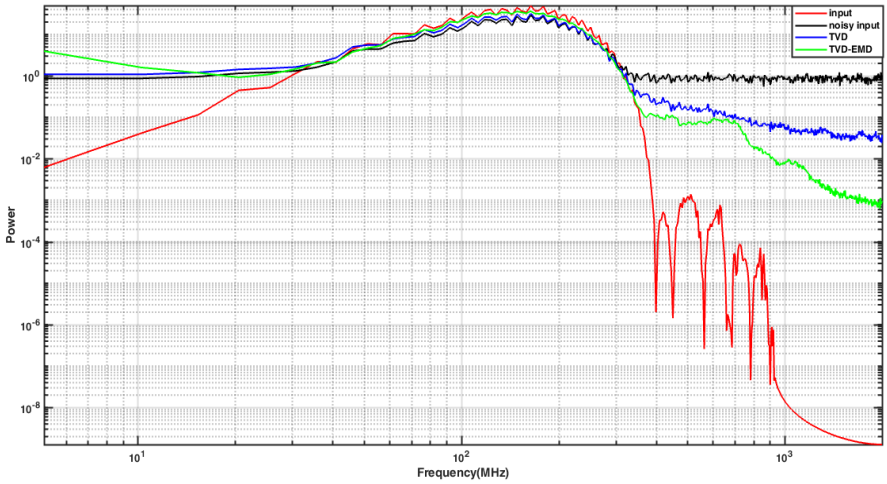

Figure 3. The power spectral densities of the noisy and de-noised data for TVD and TVD.

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