Robust Wiener filter-based time gating method for detection of shallowly buried objects

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Abstract
A robust method for ultra-wideband (UWB) imaging of buried shallow objects based on time gating, Wiener filtering, as well as constant false alarm rate (CFAR) is proposed. Moreover, it is demonstrated that Wiener filtering can be used as a clutter removal tool in UWB signal applications. Basically, the problem with time gating method is that the length of the timing window for unknown targets cannot be determined accurately in advance. In fact, it is a blind methodology and some targets can be missed due to a lack of pre-knowledge about their depth. Imprecise window length selection leads to missing some parts of the target signals along with the clutter, which in turn increases the missed detection rate. Herein, an algorithm to tackle this problem is proposed by using a Wiener filter along with CFAR as a primary detector of the target positions employing average similarity function imaging. The time gating method is then built on top of the information achieved for the window length selection from the primary detection. The combination of the two steps provides better detection of shallowly buried objects with less missed detection of targets, besides having fewer artefacts in comparison to other methods.

1 | INTRODUCTION

Buried objects identification (BOI) problem is usually encountered in detecting targets such as pipelines [1–3], landmines [4–6], cables [7,8], lost monuments [9,10] and mines [11]. Detection of buried objects with a shallow depth has been a hot topic in recent studies [6]. Notably, in some applications such as landmine detection, detection of all buried objects is a crucial task even at the cost of some artefacts [12].

Ultra-wideband (UWB) imaging is a versatile imaging method which is used in different fields of anomaly detection such as BOI [13–18], breast cancer imaging [19,20] and through wall imaging [21]. To accurately detect shallowly buried objects, proper cancellation of the reflected signals from the ground surface is needed. In BOI problems, the reflected signal from ground surface is usually much stronger than that from buried objects which makes shallow BOI difficult [19].

Researchers have proposed several methods to enhance clutter removal. Conventional methods such as mean subtraction and singular value decomposition (SVD) were proven not efficient for the detection of shallowly buried objects [13]. Non-negative matrix factorization is another discussed method in the literature [22–24]. However, it cannot be effectively applied on shallow BOI according to our experiments. Constant false alarm rate (CFAR) is another well-known method which could solve the problem. However, it needs a predeterimined threshold with respect to the noise and clutter model. In some applications, there is not enough information about the desired target. As a result, if the threshold is set on a high detection rate, it is expected that the method would encounter high false alarm rate, especially in landmine detection [25–27]. Principal component analysis (PCA) and zero-phase component analysis (ZCA) have been implemented as clutter and background removal methods in Refs. [28–30]. Nevertheless, their high artefact rates represent major drawbacks in average similarity function (ASF) imaging method. Coherence factor (CF)-based clutter mitigation is a method for surface clutter suppression, which is widely used in the literature [31–35], where CF leverages the received signals in an array antenna. Yet, it was shown to miss some targets in our experimental set-up. In UWB imaging, the reflected signals from different sources are almost separable. As a matter of fact, time gating method using a window in time domain to remove clutter can be more effective than other methods.
However, the problem of this method is that it is a blind methodology which can miss target easily. We have considered a primary detection part for better clutter cancellation by CFAR and Wiener filter. Wiener filter has been used in the literature for signal-to-noise (SNR) improvement. We proved that it can be used as a clutter removal toll in UWB signals due to the change of epsilon of targets with frequency [36].

Notably, there are several methods to reconstruct images from collected data. Back projection (BP) and reflected power methods are conventional compared with using ASF imaging [36]. Herein, ASF is implemented to reconstruct the images of buried objects and results of different methods of clutter cancellation are compared with each other according to the number of detected targets and artefacts. Another criterion measuring the effectiveness of the method is signal-to-clutter ratio (SCR) [37,38]. Since ASF imaging is less sensitive to power, we believe that SCR would not be an appropriate criterion for drawing a comparison between the proposed method and other existing methods.

Mainly, a new algorithm is presented for BOI based on time gating, Wiener filter and CFAR. The algorithm results show better efficiency in comparison to other methods. In Ref. [39], Wiener filter improved images as a noise reduction method. This method is used as a part of primary detection. The experimental data used are downloaded from the University of Georgia Tech website. The target placement scenario covers multiple buried objects.

The remaining parts of this paper are organized as follows. In Section 2, some of the conventional and new ground clutter removal methods are described. In Section 3, the simplified version of ASF to reconstruct images is described. In Section 4, the experimental set-up is explained and previously proposed methods to remove ground clutter are compared using the experimental data. Section 5 concludes the paper.

2 | CLUTTER CANCELLATION

The ground surface reflection is a very important problem in BOI. Different methods have been traditionally used to remove ground reflection. Wiener filter and CFAR are proposed herein for primary clutter cancellation in time gating method.

2.1 | Mean subtraction

Mean subtraction is the simplest method to eliminate ground surface reflection from data. The following describes this method:

\[
X'_{m,n} = X_{m,n} - \frac{1}{N \times M} \sum_{j=1}^{N} \sum_{i=1}^{M} x_{i,j}
\]  

(1)

where \(X'_{m,n}\) is the received signal in the location \((m,n)\), \(X_{m,n}\) is the modified version of \(X_{m,n}\) and \(N, M\) are the number of scan positions in \(x\) and \(y\) directions, respectively [13]. In Ref. [40], this method is stated to be the best one for eliminating ground surface reflection. However, the power of target signal can also decrease, and there are situations where there is no difference between clutter and target signals [41]. This means that ground surface clutter removal is not complete whenever the clutter variance is high. In addition, in this method, the target space must be sparse compared to the clutter. In the problem of pipeline and tunnel tracking, this method attenuates target signal, since in the mean signal, the target is also present and its behaviour is similar to that of clutter. In the shallowly buried object problem in which clutter must be eliminated completely [13], it is simply inefficient.

2.2 | Singular value decomposition

SVD removes ground surface reflection based on common singular vectors [15]. This method applies to received data in a line scan as described in the following:

\[
X_m = [x_{m,1}, x_{m,2}, \ldots, x_{m,N}]
\]

(2)

where \(X_m\) can be represented as follows [21]:

\[
X_m = \sum_{k=1}^{L} \sigma_k u_k v_k^H
\]

(3)

Here, \(H\) denotes conjugate transpose, \(\sigma_k\) is the \(k\)th singular value, \(u_k\) is the \(k\)th left singular vector, \(v_k\) is the \(k\)th right singular vector and \(L\) is the number of non-zero singular values. The first singular vectors of every sweep line project clutter signal are discarded in this method. But, in practice, in the decomposed data, the first singular vectors are not the same. It means that clutter and target signal are not separable completely [42]. After elimination of clutter singular vectors, \(X'_m\) is changed to the following:

\[
X'_{m} = \sum_{k=L+1}^{L} \sigma_k u_k v_k^H
\]

(4)

2.3 | Time gating

In UWB signal, the ground surface reflection is discriminated from buried object reflection in an appropriate time gate. The length of the time domain signal is related to the signal bandwidth. Minimum depth of target can be calculated as follows:

\[
R = \frac{c}{2B\sqrt{\varepsilon_r}}
\]

(5)

where \(c\) is light speed in free space, \(B\) is bandwidth of the signal and \(\varepsilon_r\) is permittivity. \(R\) describes minimum separable depth which is determined according to medium properties [36].
2.4 | Constant false alarm rate

CFAR is a robust method to detect anomalies in the presence of noise and clutter. The cell averaging CFAR (CA-CFAR) is a conventional method to detect anomalies and suppress the noise. According to the noise or clutter distribution and a specific false alarm, it determines a threshold to discriminate target from noise and/or clutter. In the near field imaging, the reflected signals from targets and ground clutter are of more level of power than the noise [13]. For simplifying the equations, the authors have assumed that the noise power is negligible.

In blind time gating method, the target, buried nearer than expected in terms of depth, could potentially be missed. In other words, the supposed window for removing specific depths can impact the reflected signals from targets partly or completely. For example, a rock located 1 cm deep is couldn’t be detected [36].

Herein, the authors have utilized the CA-CFAR method as a reliable one to detect all targets in the clutter. In the first step, we have considered the buried object detection as a sparse problem, that is, there is no target in most of positions [43], it seems that a CFAR method with sliding window, would effectively work.

Assuming that the signal model is an additive clutter with Gaussian distribution [36], the signal model is considered as follows:

\[ X = X_t + X_c \]  

where \( X_c \) and \( X_t \) are the reflected signal from clutter and target, respectively. There are two hypotheses as follows:

\[
\begin{cases}
H_0 : \text{no target present}, \\
H_1 : \text{target resen}.
\end{cases}
\]  

CA-CFAR picks some samples around the cell which is under the test, while excluding some nearer samples called the guard cells [44,45]. We have considered Weibull distribution as the representative of clutter, which provides better parameter estimation. Considering the mentioned assumptions, the joint probability function is

\[
f(x) = \left( \frac{C}{B} \right)^N \prod_{i=1}^{N} \left[ \frac{x_i}{B} \right]^{C-1} \left( \exp \left( \frac{x_i}{B} \right) \right)^C \]  

in which \( B \) can be calculated as follows:

\[
B = \left( \frac{1}{N} \sum_{i=1}^{N} X_i^C \right)^{\frac{1}{C}} \]  

Then, according to Equation (9), the detection threshold is as follows:

\[
T = \alpha \left( \frac{1}{N} \sum_{i=1}^{N} x_i^C \right)^{\frac{1}{C}}
\]  

where \( \alpha \) is a multiplier. Then, according to Equation (9), the detection threshold can be calculated. In this methodology, the false alarm rate is fixed. First, the relation between multiplier and the false alarm rate should be calculated. Then, the multiplier can be determined for a specific false alarm rate. When a test cell is larger than the specified threshold; whereas there is no target, it is regarded as a false alarm. Accordingly, the probability of false alarm is defined as follows:

\[
P_{fa} = \int_{0}^{\infty} P(TC > \text{Threshold}) f_{x(x)} \, dx \]  

Hence, \( P_{fa} \) is

\[
P_{fa} = \prod_{i=1}^{N} \exp \left( - \left( 1 + \left( \frac{\alpha^C}{N} \right) \right) y_i \right) \, dy_i
\]  

From this equation, the detection threshold for a specific false alarm rate is achievable.

2.5 | Non-negative matrix factorization

One of the most popular methods to analyse non-negative data is non-negative matrix factorization (NMF), which can be applied in a wide range of problems. The main idea behind this technique is to decompose a non-negative matrix to the product of two non-negative matrices [46,47]. The matrix \( M \) is the product of \( W \) and \( H \). They are as follows:

\[
M \in \mathbb{R}^{F \times T}, \\
W \in \mathbb{R}^{F \times M}, \\
H \in \mathbb{R}^{M \times T}.
\]  

This method can be applied to the magnitude or the spectrogram power of the received signals. In order to determine \( W \) and \( H \), a cost function is defined as follows:

\[
\mathbb{W}, \mathbb{H} = \text{argmin}_{W,H} D(M \mid WH) + \mu \| H \|
\]  

where \( D \) represents the cost function, which is meant to be minimized. The \( \beta \)-divergence, \( D_\beta \), is defined as follows:

\[
D_\beta(x \mid y) = \begin{cases} 
\frac{1}{\beta(\beta-1)} (x^\beta - y^\beta - \beta y^{\beta-1}(x-y)) & \text{if } \beta \in \mathbb{R} \setminus \{0,1\}, \\
\frac{x}{y} & \text{if } \beta = 1, \\
\frac{x}{y} - \log \frac{x}{y} - 1 & \text{if } \beta = 0,
\end{cases}
\]
where $\beta = 0$ yields Itakura–Saito (IS) distance, $\beta = 1$ yields the generalized Kullback–Leibler (KL) divergence, and $\beta = 2$ yields the Euclidean distance. Here, KL divergence is used as the cost function.

In Ref. [47], a simple algorithm is defined as follows to update $H$:

$$H \leftarrow H \otimes \frac{W^T (M \otimes \Lambda^{\beta-2})}{W^T \Lambda^{\beta-1}}$$

where $\Lambda = WH$.

After decomposition of $M$ to $H$ and $W$, $M_{\text{new}}$ will be reconstructed according to the following equations [46,47]. In fact, the first feature has been selected to reconstruct the signals:

$$M_{\text{new}} \in \mathbb{R}^{F \times T},$$
$$W_{\text{new}} \in \mathbb{R}^{F \times 1},$$
$$H_{\text{new}} \in \mathbb{R}^{1 \times T}.$$  

### 2.6 Zero-phase and principal component analysis

Due to the high similarity among the received signals in GPR—given a powerful clutter signal—a whitening method would improve the signal processing results. Based on the received signals, the mean and variance can be represented as follows:

$$E(x) = \mu = (\mu_1, \ldots, \mu_d)^T,$$
$$\text{var}(x) = \sigma^2.$$  

In the following, there are two conventional decomposition methods, according to which the ZCA and PCA can be defined:

$$\sigma^2 = uu^T,$$
$$\sigma^2 = V^{1/2} \Lambda V^{1/2}.$$  

The following term describes the formulation of PCA and ZCA [6,48,49]:

$$\left\{ \begin{array}{l}
\text{whitening matrix of PCA : } \sigma^{-1} \\
\text{whitening matrix of ZCA : } \Lambda^{-1/2} u^T.
\end{array} \right.$$  

### 2.7 Coherence factor (CF)-based clutter mitigation

The CF is a dimensionless quantity which is defined as the ratio of the coherent received power (reflected by fixed scatters) to the total incoherent power (produced by the ground clutter). It can be expressed as follows:

$$\text{CF}(q) = \frac{|\sum_{n=1}^{N_T} \sum_{m=1}^{N_R} w_{nm} \theta_{nm}(q)|^2}{\sum_{n=1}^{N_T} \sum_{m=1}^{N_R} |w_{nm} \theta_{nm}(q)|^2}.$$  

where $N_T$ and $N_R$ are the number of transmitters and receivers, respectively. For every pixel which is indicated by $q$, this correction factor should be calculated. According to this definition, it is clear that the CF varies from zero to unity. It assumes small values for low coherence image regions corresponding to ground surface clutter. As a result, the ground surface impact can be mitigated leading to an enhanced image, by a simple pixel-wise multiplication [32–35].

### 2.8 Wiener filter

Wiener filter is usually used to reduce the level of noise corrupting signals [12]. The additive noise is uncorrelated with the received signals from targets. In the UWB BOI problem for ground clutter reduction, the ground reflected signal is always present in the received data. The reflected signals from different targets are almost orthogonal in UWB imaging [36], thus, the signals can be assumed independent (due to the UWB nature, independence plus zero mean implies orthogonally [50]). To remove ground clutter reflection, the reflected signals from target and ground clutter are assumed to be orthogonal. The received signal is modelled as depicted in Figure 1. The reference signal for the Wiener filter is a ground reflected signal which is assumed to be the average of all of the obtained data.

The ground clutter can be suppressed to a good extent in the reflected signal from the environment by estimating $\tilde{H}$ and consequently differentiating between the clutter and the signal. The following formulation defines the operation of the system depicted in Figure 1:

$$T(n) = HX_c + X_t - \tilde{H}X_c,$$
$$E\{T^2(n)\} = E\{X_c^2(n)\} + E\{(H - \tilde{H})X_c(n)\}^2,$$  

where $X_c$ and $X_t$ are the transmitted and the target signals, respectively. $T$ is the residual signal after clutter suppression.
Mean of all signals as a clutter signal

\[ X_{\text{mean}} = \frac{1}{N^2} \sum_{m=1}^{N} \sum_{j=1}^{N} x_{i,j} \]

Every pixel which is more than absolute mean of all pixels considered as a primary target

\[ f(x) = \left( \frac{C}{B} \right)^N \prod_{l=1}^{N} \left[ \left( \frac{x_l}{B} \right)^{C-1} \exp\left(-\frac{x_l}{B}\right) \right]^C \]

The window length is determined based on two first sequential detected peaks. The first one is ground surface clutter and the second one is target.

\[ E_{m,n} = \frac{1}{N^2} \sum_{m=1}^{N} \sum_{j=1}^{N} \text{corr}(x_{i,j}, x_{m,n}) = \text{corr}(X_{\text{mean}}, X_{m,n}) \]

\[
\min \{ E \{ T^2(n) \} \} \equiv \min \{ H - \hat{H} \} \tag{23}
\]

This point can be fulfilled by the Wiener filter. Wiener filter coefficients can be calculated by minimizing the second moment of \( T \). More details on Wiener filter coefficients calculation are available in [16].

### 2.9 An algorithm based on Wiener filter and time gating and CFAR

Time gating method is a precise method for removing ground surface clutter, but the window length in this method is not determined in prior. For this reason, time gating window can remove target signal in addition to the clutter. The proposed method is based on using wiener filter for primary estimation of environment and buried objects after ground surface clutter removal. The time gating window length is determined according to the position of the estimated targets in the environment. The proposed algorithm is depicted in Figure 2. The clutter removal window length is determined by the midpoint between the two sequential peaks in the time domain signal. It is worth mentioning that peak detection is done based on CFAR method. When the test scene is an empty ground with no targets, the second peak is the side lobe of ground surface and this method removes ground clutter completely. In the case of buried objects, it is the target signal. Figure 3 shows the signal from two different positions where a target is present in one of them. The second peak is shown in Figure 3 is the
target signal. It is clear that ground clutter is about 10 dB stronger than the target signal. In two different positions, the reflected signals from ground surface are not aligned because of the slight fluctuation of the ground surface.

3 | SIGNAL-TO-CLUTTER RATIO

The SCR can be used as a metric to compare different methods quantitatively and it is calculated as:
TABLE 1 Properties of buried objects in experimental set-up [1]

| Target                  | Type     | Material | Dimensions (cm)          |
|-------------------------|----------|----------|--------------------------|
| Mine A                  | AT       | Plastic  | 22.2 (D), 9.2 (H)        |
| Mine B                  | AT       | Plastic  | 24 (D), 12 (H)           |
| Mine C                  | AT       | Plastic  | 31.2 (L), 27.5 (W), 11.3 (H) |
| Mine D                  | AP       | Plastic  | 9 (D), 4.5 (H)           |
| Mine E                  | AP       | Plastic  | 11.9 (L), 6.4 (W), 2 (H) |
| Mine F                  | AP       | Plastic  | 5.6 (D), 4 (H)           |
| Mine simulant           | AP       | Plastic  | 7.5 (D), 3.8 (H)         |
| Sphere                  | Buried clutter | Aluminium  | 5.1 (D)                 |
| Rock                    | Buried clutter | Rock  | 12 (L), 8 (W), 7.5 (H)   |
| Crushed can             | Buried clutter | Aluminium  | 8 (D), 3 (H)             |
| Cylinder                | Buried clutter | Nylon  | 15.5 (D), 7.6 (H)       |

Abbreviations: AT, anti-tank mine; AP, anti-personnel mine.

FIGURE 5 Results of conventional methods. (a) Mean subtraction, (b) SVD, (c) NMF, (d) CFAR. Red dash lines show non-detected objects, where targets are displayed by ‘T’ and artefacts displayed by ‘A’. CFAR, constant false alarm rate; NMF, negative matrix factorization; SVD, singular value decomposition.
FIGURE 6  Results of conventional methods. (a) ZCA, (b) PCA, (c) CF. Red dash lines show non-detected objects, where targets are displayed by ‘T’ and artifacts displayed by ‘A’. CF, Coherence factor; PCA, Principal component analysis; ZCA, zero-phase component analysis.

FIGURE 7  Results of the proposed methods. (a) Blind time gating. (b) Wiener filter. Some buried objects are not detectable in these scenarios. Red dash lines show not detected objects and targets are displayed by ‘T’ and artefacts displayed by ‘A’.
\[ E_{m,n} = \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} \text{corr}(x_{ij}, x_{m,n}) \]  

(27)

where \( E_{m,n} \) denotes the ASF for the location \((m,n)\) and \(X_{m,n}\) is the received signal in the location \((m,n)\). The above equation can be reduced to the following simpler one:

\[ E_{m,n} = \text{corr}(\text{avg}(x), x_{m,n}) \]  

(28)

5 | EXPERIMENTAL RESULTS

5.1 | Data acquisition

Experimental data have been collected in a lab at Georgia Tech University. The set-up is depicted in Figure 4a. The system consists of an array of similar antennas, including two transmitters and four receivers. Figure 4b shows the positional difference between the antennas (for more information refer to [12]). A vector network analyser and a 3-D positioner are used to scan the region. The area size is 120 × 120 cm with fix height and 2 cm scan step in x and y axes. The transmit signal bandwidth is 8 GHz with 20 MHz frequency step. Permittivity of soil is 4. Herein, we only consider the case T1R1 which deals with the signal transmitted by the first transmitter and received by the first receiver. Different scenarios for data collection are implemented. The utilized scenario is depicted in Figure 4c.

In Table 1, the relevant buried objects properties are mentioned. AT and AP are abbreviations for anti-tank and anti-personnel mines, respectively.

5.2 | Simulation results of different methods

Different methods mentioned in the previous sections are compared according to their results in the ASF images. In an ASF image, in any position with no buried object, the similarity value is maximized, and in positions with buried objects, the similarity value is minimized. As mentioned before, the area which is selected for image reconstruction is almost empty of buried objects. As a matter of fact, in the scenario used, the area is almost 85% empty.

Figures 5 and 6 depict the results of different conventional methods. For better observability, dynamic range has been maximized for every figure. Mean subtraction method has the worst result among other methods, since it misses the detection of several targets. Although SVD method—which results from removing the first sorted singular value, has few artefacts—it cannot detect some of the targets. NMF’s result is not satisfying at all, as most of the targets are not detectable and it results in a big artefact. After applying CFAR method, some targets cannot be detected which is a downside of this algorithm. CF algorithm also does not manage to detect some of the targets. In PCA and ZCA methods, although all targets are
detected, the methods suffer from excessive artefacts. The results of blind time gating and Wiener filtering methods are depicted in Figure 7, separately. All buried objects in the blind time gating method are identified except the rock in (33, 17) which is buried in 1 cm under the ground surface. The results also show that the Mine D in (45, −40), in the image is almost suppressed and is difficult to detect. Indeed, the window length of the blind time gating is not suitable and the buried target signal is suppressed. As it can be seen in Figure 7b, the Wiener filter method also can detect all buried objects except the one on the right side of Mine A which is buried in (0, −20). Furthermore, Wiener filter method has some artefacts as clear from Figure 7b. Although quite capable of detecting shallowly buried objects compared to other methods mentioned, time gating and Wiener filter methods have some drawbacks. For this reason, we have combined the two methods by first running the Wiener filter method and running the time gating method for which the window length is selected according to the results obtained by the primary detection which in-turn is based on the Wiener filter and CFAR. The results of this algorithm are shown in Figure 8. All buried objects are detected in this experimental scenario. However, some artefacts are still inevitable.

Another important factor is SCR outlined earlier. Table 2 compares the different methods from this point of view. It is clear that blind time gating method has desirable results in terms of SCR. Yet, the main problem with this method is its missed detection rate. The novel method proposed herein performs well from this aspect as well, in addition to being able to detect all targets with the lowest number of artefacts.

6 Conclusion

Different methods of ground clutter cancellation are compared against each other. Conventional methods have unsuitable results in the clutter cancellation of the shallowly buried object problem.

Finding all buried objects in the BOI problem is an important task, which is improved in this study in comparison to the literature. The proposed method is based on using a combination of Wiener filter, CFAR and time gating methods. The proposed combination leads to the best performance among the considered methods in terms of minimizing the number of missed detections and detected artefacts.

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| Method | SCR (dB) | Number of missed detections (max = 13) | Number of artefacts |
|--------|---------|--------------------------------------|---------------------|
| Mean subtraction | 3.23 | 13 | 5 |
| SVD | 2.65 | 3 | 3 |
| Blind time gating | 12.24 | 1 | 1 |
| CFAR | 8.32 | 3 | 5 |
| NMF | 4.76 | 11 | 1 |
| Coherence factor based clutter mitigation | 3.65 | 5 | 1 |
| ZCA | 10.76 | 0 | 11 |
| PCA | 10.96 | 0 | 9 |
| Primary wiener filter | 8.63 | 1 | 3 |
| The proposed method | 11.86 | 0 | 3 |

Abbreviations: CFAR, constant false alarm rate; NMF, negative matrix factorization; PCA, Principal component analysis; SVD, singular value decomposition; ZCA, zero-phase component analysis.
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