GPR Ground Bounce Removal Methods Based on Blind Source Separation

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Abstract—In this paper, the ground bounce (GB) removal methods based on Blind Source Separation (BSS) for land mine detection using ground penetrating radar (GPR) are investigated. These methods include an Independent Component Analysis (ICA) based method and Blind Instantaneous Signal Separation (BISS) based method. First, a modified ICA based method is presented. In this method, a fully automatic eigenimage based Independent Components (ICs) selection strategy combined with a non-homogeneous detector (NHD) is introduced. A BISS based method is also proposed for the GB removal. This method can be applied in various environments as ICA, but it has much fewer number of extracted components than ICA's, but has much fewer number of components to extract, therefore less computation load is required. Experimental results show that the proposed methods exhibit good performance.

1. Introduction

Downward looking GPR has been considered a viable technology for land mine detection [1]. For GPR with the antenna positioned very close to the ground surface, the reflections from the ground surface, i. e., the GB, are very strong and can much dominate the weak returns from shallowly buried plastic mines. Hence, one of the key challenges of using GPRs for landmine detection is to remove the GB as completely as possible without altering the landmine return.

The literature suggests a number of clutter (whose dominant contributor is GB) reduction methods, such as parametric system identification [2, 3], wavelet packet decomposition [4], subspace techniques [5, 6], and simple mean subtraction [7]. However, many of these fail to detect shallowly buried landmines, mostly because of the statistical nature of the clutter, e.g., the ground surface is not perfectly flat nor even relatively smooth. The other problem is that many of the methods use reference signals to estimate the signature of a landmine. These reference signals are used to remove signals based on how they relate to the reference. This will lead to improper target signal cancellation when the reference signals are selected inadequately. For subspace techniques, the GPR signals are decomposed into clutter and landmine signals by selecting principal components (PCs) and independent components (ICs) reasonably. These methods can be more robust and lead to the best results for GB removal. But automatic selection strategy for PCs and ICs is the key problem, and reduction for computational load is an attractive work.

In this paper, we present an NHD-based modified ICA algorithm with automatic selection strategy for PCs and ICs. To reduce the computational load, we also apply NHD to BISS to determine the number of components to be extracted.

2. Data Description

Consider a stepped frequency GPR system moving in the along-track direction. Let $x_p(\omega_n)$ denote the data collected at the pth scan for the nth stepped frequency, $b_p(\omega_n)$ denote ground bounce in $x_p(\omega_n)$, where $\mathbf{x}_p = [x_p(\omega_1)x_p(\omega_2)\cdots x_p(\omega_N)]^T$ is called A-scan data vector (for impulse GPR radar, this is the data vector expressed in the frequency domain), $\mathbf{b}_p = [b_p(\omega_1)b_p(\omega_2)\cdots b_p(\omega_N)]^T$ represents the ground bounce vector, and $\mathbf{X} = [x_1x_2\cdots x_p]$ represents the B-scan data matrix. As the mutual coupling of antennas can be removed by prior measurement or estimation, the received data vector at the pth scan can be simplified as

$$\mathbf{x}_p = \mathbf{r}_p + \mathbf{b}_p + \mathbf{e}_p \tag{1}$$

where $\mathbf{r}_p$ denotes reflected signal form target, and $\mathbf{e}_p$ denotes un-modeled noise. We also set up a sliding window for modified GLR-based HND [8], which is composed of a guard area of length N_1 and local area of length N_2 in the along-track direction[8, 9].

3. Modified ICA Based Method

3.1. Temporal ICA

The temporal ICA is one of the subspace techniques to remove GPR GB. The received signal is considered as the linear mixture of the independent components (ICs) [5, 6], and the GB is removed by reconstructing received signal with ICs corresponding to landmine target and target-like objects. ICA algorithm is processed in two steps. The first step is the pre-processing, which includes data centralization ($\mathbf{x}_{m,j} = \mathbf{x}_j - (1/P)\sum_{i=1}^{P}\mathbf{x}_i, j = 1 \sim P$) and whitening. The whitening is realized by PCA ($\mathbf{X}_m = [\mathbf{x}_{m,1}\cdots\mathbf{x}_{m,P}]$, $\mathbf{X}_1 = \mathbf{X}_m^T$, $\mathbf{Y} = \tilde{\mathbf{U}}^T\mathbf{X}_1$), where $\mathbf{y} = [y_1 y_2 \cdots y_{L_1}]^T$ is constructed by L_1 selected PCs, and $\mathbf{U}$ is the projection matrix for $\mathbf{X}_1$ projected in a subspace spanned by eigenvectors of L_1 selected PCs. Then, we consider $\mathbf{Y}$ as the input of ICA defined as

$$\mathbf{Y} = \mathbf{AS} = [\mathbf{a}_1\mathbf{a}_2\cdots\mathbf{a}_{L_1}][s_1 s_2\cdots s_{L_1}]^T = \sum_{i=1}^{L_1} a_i s_j^T \tag{2}$$

$$\mathbf{X}_1 = \tilde{\mathbf{U}}\mathbf{Y} = \tilde{\mathbf{U}}\mathbf{AS} = \mathbf{WS} = [\mathbf{w}_1\mathbf{w}_2\cdots\mathbf{w}_L]\mathbf{S} = \sum_{i=1}^{L_1}\mathbf{s}_i\mathbf{w}_i^T \tag{3}$$

where $\mathbf{W}$ is called matrix of eigenimages, and $\mathbf{S}$ is the ICs. After selecting K target and target-like ICs $s_{o,i} = s_j (i = \mathbf{1} \sim K,\ j = \mathbf{1} \sim L_1)$ and correspondent eigenimages $\mathbf{w}_{o,i} = \mathbf{w}_j (i = \mathbf{1} \sim K)$, the GB removal output is $\hat{\mathbf{X}}_I = \sum_{i=1}^{K}\mathbf{s}_{o,i}\mathbf{w}_{o,i}^T$. The key problem for ICA is how to select PCs for PCA and ICs for signal reconstruction.

3.2. PCs and ICs Selection Strategy

The PCs and ICs reflect the time-domain information and the eigenimages can be considered as the spatial steering vectors correspondent to them. The result of the NHD describes the buried position of the targets and target-like objects. So we can select PCs and ICs automatically according to the consistency between the eigenimage and the output of the modified GLR-based HND [8].

4. BISS Based Method

4.1. BISS

The ICA will be very computational demanding if the number of source signals is large [10–12]. After PCA, $L_1 \ll P$, but $L_1 \gg M$ (the number of targets and target-like objects). Obviously, ICA extracts much more signal the sources than that need by signal reconstructing. Fortunately, BISS overcomes somewhat this difficulty. The spirit of the BISS is to recover only a small subset of sources from a large number of sensor signals. For GB removal, if the number of targets and target-like objects is prior known, source signals not more than M are needed to be extracted.

Like the ICA, the first step of BISS is pre-processing. Then, the small subset of targets signals $\mathbf{S}_t$ is extracted from $\mathbf{Y}$ as

$$\mathbf{S}_t = \mathbf{HY} \tag{4}$$

where $\mathbf{H}$ is the separating matrix, and the GB removal output is

$$\hat{\mathbf{X}}_{\mathbf{BISS}} = \mathbf{W_t S_t} = \tilde{\mathbf{U}}\mathbf{H^T S_t} \tag{5}$$

The presented BISS algorithm is gradient-based algorithm that optimizes three different criteria: Maximum Likelihood (ML), Minimum Entropy (ME) and Cumulants based index. The algorithm based ML can be explicitly computed only when the sources densities are known. It needs to approximate the activation function for ME, although it is not necessary to know the source densities. The most robust approach is the cumulant-based algorithm, since it can be realized without approximations and not dependent on the density of sources [11].

4.2. Determination of M and Cumulant Order

There are two important parameters to be conformed for cumulant-based algorithm [13]: the number of extracted signals M and the order of the cumulant. Since the location of target, target-like object, and the homogeneity of GB can be detected by modified GLR based NHD, the value of M can be prior determined, and the order of cumulant should be chosen according to the statistical nature of GPR data.

5. Experiment Result

The GPR data is obtaied from Vrije Universiteit Brussel (VUB) [14]. The experiment was performed in wet clay mixed with small rocks. An area of $x = 50$ cm by $y = 196$ cm was scanned with a scanning step of 1 cm in each direction. There were irregularities with a maximum of 10 cm between the highest and the lowest point. The antenna head was placed at 5 cm above the highest point, and the scan was done horizontally. In

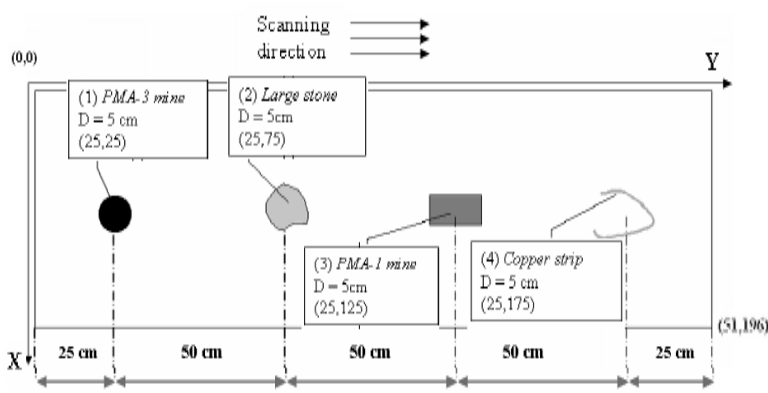

Figure 1: Distribution of buried objects.

the following examples, the target is a plastic anti-personal mine (PMA-1·PMA-3), big stone and curving U shape copper strip, the distribution of buried object is shown in Figure 1.

Figure 2 shows the output of the modified GLR base NHD. Using this result, the number and position of the targets (and target-like objects) can be determined.

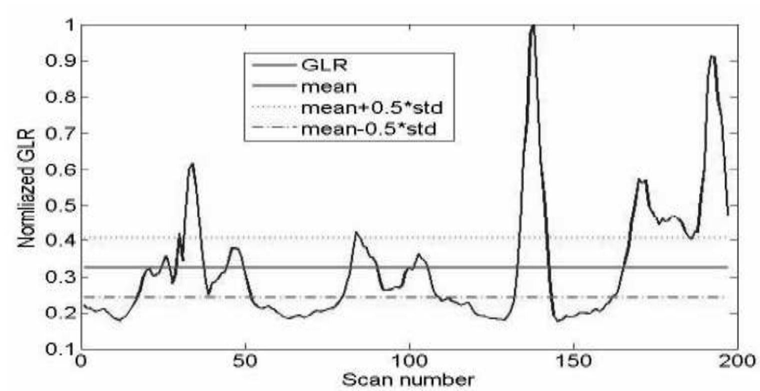

Figure 2: Output of normalized GLR.

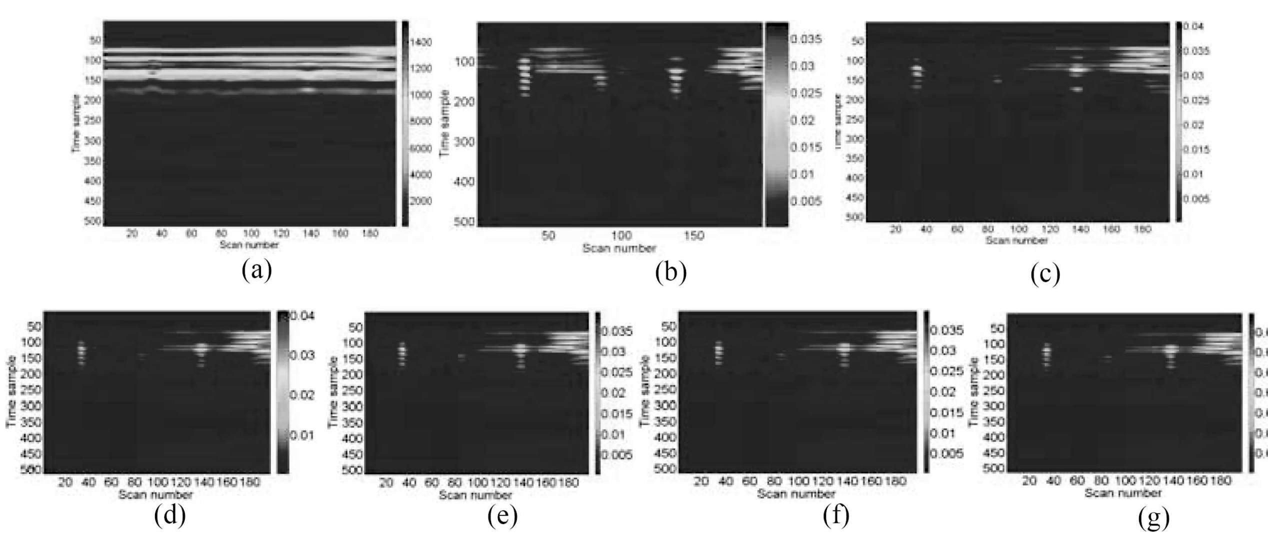

Figure 3: Comparison of ground bounce removal performances. (a) raw data, (b) ICA, (c) NHD based ICA, (d)BISS based 3rd order cumluant, (e) BISS based 4th order cumluant, (f) BISS based 3rd and 4th order cumluant, (g) BISS based 3rd, 4th, 5th, and 6th order cumluant.

The performance of the improved ICA and BISS based method are showed in the Figure 3. Figure 3(a) is the original received data of the GPR. It can be seen that the targets are obscured by the ground bounce. Figure 3(b) and Figure 3(c) show the results of ICA and NHD based ICA, respectively. Figure 3(d)∼(g) shows the results of BISS based cumluants with different orders. It can be seen that there are almost no difference among these four results, so the third order cumluant is enough.

5. Conclusion

In this paper, we present NHD-based ICs selection method. ICA can be realized automatically with this selection strategy. We also apply the BISS in the GB removal combined with NHD to determine the number of extracted signal sources. The experimental results show that these two methods have excellent performance in GB removal, and the BISS based method reduces the computational load greatly.

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