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A METHOD FOR DETECTING SHALLOWLY BURIED LANDMINES USING GPR SIGNATURES

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1. Introduction

Detection of small and shallowly buried landmines is an important and difficult problem. As compared with a metal detector that is widely used for landmine detection, ground-penetrating radar (GPR) [1] seems to offer the promise of this problem, especially for detection of plastic landmines with little or no metal content [2][3]. However, the GPR performs inadequately due to the ground clutter because returns from the shallowly buried landmines and that from ground surface overlap in time. Furthermore, the GPR also receives returns from other subsurface objects such as rocks, tree roots, or metal fragments in the ground, which leads to high levels of false alarms.

In this study, we present a method for detecting shallowly buried landmines under rough ground surface using sequential GPR data. First, we remove a strong coherent component of ground surface reflection from sequential GPR data using correlation between the GPR signal and deformed incident pulse. After the removal, we extract three kinds of target features related to wave correlation, energy ratio, and signal arrival time from the residual signals. Since this detection problem is reduced to a binary hypothesis test (H_1 : landmine, H_0 : no landmine), we employ here a classical detection theory based on likelihood ratio test [4]. In order to check the detection performance, the Monte Carlo simulation is carried out for data generated by the two-dimensional finite-difference time domain (2D-FDTD) method. The results are shown in the form of receiver operating characteristics (ROC) curves [4], which quantify the probability of detection as a function of the false alarm rate (FAR). The results show that this method gives better performance than the matched filter detector.

2. Ground Clutter Reduction

Figure 1 shows a typical configuration of the GPR measurement system for detecting shallowly buried landmines. The GPR measurements are made at multiple observation points above the rough ground surface using transmitting and receiving antenna pairs. The transmitting antenna sends out a short duration pulse and the receiving antenna samples the returned signal that includes target response together with reflection from the rough ground surface. Because the ground surface reflection is very strong compared to the response from plastic landmines, a pre-processing step of ground clutter removal from the GPR signals is required. However, complete removal of the ground clutter from the GPR signals is impossible. Therefore, we simply reduce the ground clutter contribution by subtracting dominant coherent component of ground surface reflection. Since the coherent component is a reflection from a flat ground surface without any buried target under it, we can approximately express it in terms of the Fresnel reflection coefficients $R(\omega)$ and incident pulse $q(t)$. Taking into account of this fact, we decompose the GPR signal $p_m(t)$ measured at the observation point m (m = 1,2,..., M) into a dominant coherent term and a residual term as follows:

$$p_m(t) = R_m q_{\tau,a}(t) + r_m(t), \qquad R_m = \max_{\tau,\, a} < p_m, q_{\tau,a} >, \qquad m = 1, 2, \ldots, M \tag{1}$$

where $q_{\tau,a}(t) = q((t-\tau)/a)$ is the scaled and shifted incident pulse, R_m is a constant that corresponds to the reflection coefficient of the flat ground surface, and $r_m(t)$ is the residual term that includes reflection from the target and *incoherent* component of the reflection from the rough ground surface

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(and also additive noise). Since the coefficient R_m can be estimated by maximizing the inner product $< p_m, q_{\tau,a} >$ with respect to scale and shift parameters (τ, a), the residual term $r_m(t)$ is obtained by subtracting $R_m q_{\tau,a}(t)$ from the signal $p_m(t)$. Note that, in Eq.(1), the coefficient R_m is assumed to be a constant because an effect of dispersion of soil on the surface reflection is relatively small at the frequency band used here.

3. Target Features

The next step is an extraction of target features from the residual component $r_m(t)$. Here, we introduce the concept of matched filter that is commonly utilized for the detection of the known target signature in noise/clutter. In our problem, although the target signature from the landmine is deterministic and known, its amplitude and arrival time are unknown. Therefore, we define the following normalized correlation $C_m(t)$ as a measure of waveform similarity,

$$C_m(t) = \frac{< r_m(\tau),\ s_m(\tau+t) >}{\| \hat{r}_m \| \, \| s_m \|}, \qquad C_m^{\max} = \max_t C(t), \qquad t_m^{\max} = \arg\max_t C(t) \tag{2}$$

where $s_m(t)$ is a known target signature (template) at position m, $\hat{r}_m(t)$ is a truncated part of $r_m(t)$ within the region of support $s_m(\tau+t)$. Note that this normalized correlation $C_m(t)$ becomes close to unity when r_m has a similar part with s_m. Therefore, if the pre-processed signal r_m includes the target signature s_m, then the maximum correlation $C_m^{\max}$ becomes close to unity at $t_m^{\max}$ that corresponds to the signal arrival time. Furthermore, we define an energy ratio E_m and a difference of signal arrival time T_m between r_m and s_m as follows:

$$E_m = \| \hat{r}_m \|^2 / \| s_m \|^2, \qquad T_m = t_m^{\max} - t_m^{arr} \tag{3}$$

where t_m^{arr} is an arrival time of s_m. Since deviations of these values become small when the signal r_m includes the target signature s_m, we can expect that variances of E_m and T_m are good features for target detection. Therefore, we define three-dimensional feature vector υ whose elements are given by

$$\overline{C^{\max}} = \frac{1}{M} \sum_{m=1}^{M} C_m^{\max}, \qquad V_E = \sum_{m=1}^{M} (E_m - \overline{E}_m)^2, \qquad V_T = \sum_{m=1}^{M} (T_m - \overline{T}_m)^2 \tag{4}$$

where $\overline{C^{\max}}$ is the mean value of the maximum correlation $C_m^{\max}$, V_E and V_T are the variance of E_m and T_m, respectively.

4. Detection Algorithm

Since the detection problem treated here corresponds to a binary hypothesis test (H_1: landmine, H_0: no landmine), we employ a classical detection theory based on likelihood ratio test [4]. Assume that $p(H_1 | \upsilon)$ and $p(H_0 | \upsilon)$ represent the probabilities of hypotheses H_1 and H_0, respectively, given the feature vector υ. The likelihood ratio test is described as follows:

$$\lambda = \frac{p(H_1 | \upsilon)}{p(H_0 | \upsilon)} \quad \begin{cases} > \gamma & : H_1 \\ < \gamma & : H_0 \end{cases} \tag{5}$$

where γ is a threshold. Given a set of feature vectors υ, variation of the threshold γ yields a variation in the probability of detection (P_d) and the probability of false alarm (P_f). In order to evaluate the performance of this detector, we use the receiver operating characteristic (ROC) curve that is a plot of the P_d versus P_f. The PDFs of Eq.(5) can be estimated using training data. The simplest approximation of the PDFs is the multivariate Gaussian distribution. However, we employ here Gaussian mixture models (GMMs) to approximate them because the PDFs are non-Gaussian distributions. The GMM approach assumes that the PDF can be modeled as a weighted sum of component densities and given by the following equation

$$p(H_1 \mid \upsilon) = \sum_{i=1}^{L} \alpha_i N(\upsilon; \boldsymbol{\mu}_i, \Sigma_i), \qquad \sum_{i=1}^{L} \alpha_i = 1 \quad \text{and} \quad \alpha_i \geq 1 \tag{6}$$

$\;\;\;\;\;\;\;0$

where $N(\upsilon; \boldsymbol{\mu}_i, \Sigma_i)$ are multi-variate Gaussian functions with mean vector $\boldsymbol{\mu}_i$ and covariance matrix Σ_i, and α_i are mixture weights. These parameters can be estimated by using the method of maximum likelihood estimation.

5. Numerical simulation and discussions

The detection performance is evaluated through the Monte Carlo simulation. The 2D-FDTD method with PML absorbing boundary condition is employed for data generation. The geometry and dimensions of the model used here is shown in Fig.1. The landmine model and confusing objects are shown in Table 1. These objects are composed of homogeneous, lossless dielectric with various dielectric constants. The depths of the target and confusing objects are varied between 2.0cm and 4.0cm. The surface roughness with Gaussian distributed height and slope is realized using the method proposed by Thorsos [5]. For simplicity, we assume the surrounding dry soil with relative dielectric constant of $\varepsilon_r = 6.0$ is non-dispersive and lossless $\sigma = 0$. The input pulse is excited by Gaussian current, which parameters are chosen such that the incident field has most of its energy in the frequency band between 1GHz and 5GHz. The transmitting and receiving antennas located 8cm apart and 5cm above the ground surface are used for data collection (see Fig. 1). The number of observation points is seven ($M = 7$) and a distance between them is 2cm.

Figure 2 shows ROC curves for data with and without coherent component of ground clutter. The RMS height and correlation length of surface roughness are both 1.0cm. This result indicates that the detection performance is improved by reducing the coherent component of the ground clutter. Next, we check the effect of surface roughness on the detection performance. Figure 3 shows ROC curves for two different kinds of surface roughness. For comparison, results of a classical matched filter detector using one point data at $m = 4$ are also shown with dashed line. As we expected, the detection performance becomes worse as the surface roughness increases. However, the present detector gives better performance than the classical matched filter detector.

6. Conclusions

We have presented a method for detecting shallowly buried landmines using sequential GPR data. After removing the strong coherent component of ground surface reflection from the GPR data, we have extracted three kinds of target features from the residual signal. Performance evaluation has been done using simulated GPR data and the result has been given in terms of ROC curves. The result shows that good performance is obtained in spite of simple three-dimensional feature vector.

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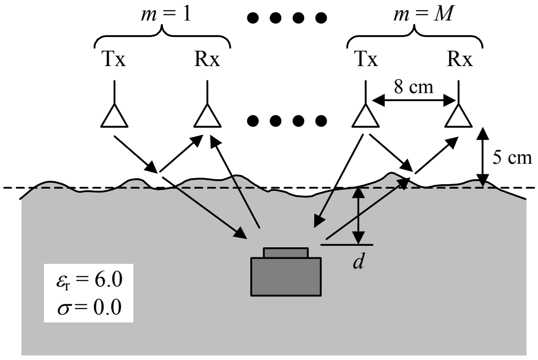


Fig. 1. GPR measurement system. The transmitting and receiving antennas located 8cm apart and 5cm above the ground surface are used for data collection. The number of observation points is M.

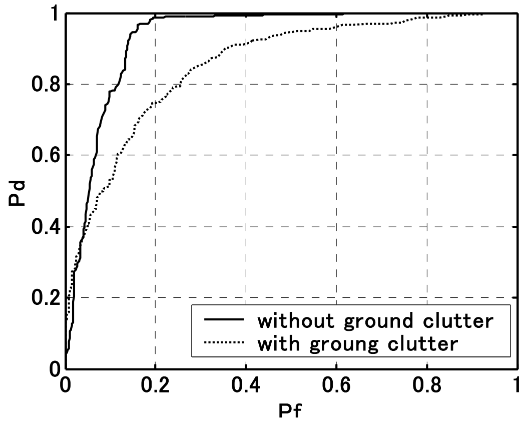
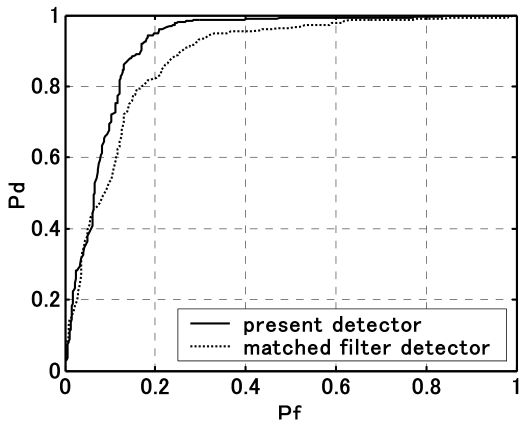
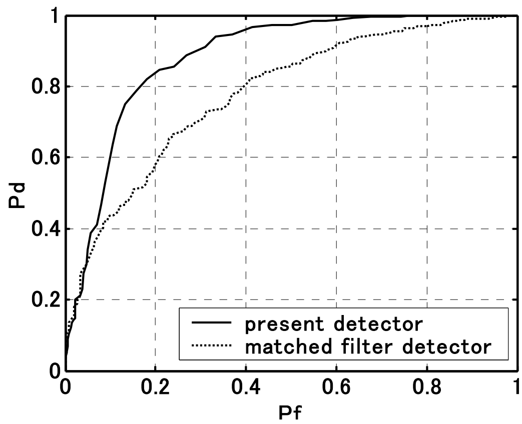


Fig.2. ROC curves for data with and without coherent component of ground clutter. The RMS height and correlation length of surface roughness are both 1.0cm.



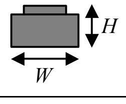
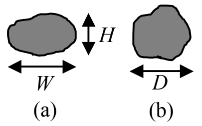
(a) RMS height: 1.0cm, correlation length: 1.5cm.



(b) RMS height: 1.5cm, correlation length: 1.5cm.

Fig.3. ROC curves for different kinds of ground surfaces. (a) RMS height: 1.0cm, correlation length: 1.5cm. (b) RMS height: 1.5cm, correlation length: 1.5cm. Dashed line indicates the result of a classical matched filter detector.

Table 1. Landmine model (target) and confusing objects used for Mote Carlo simulation.

Type	Shape	Size		ε_r	Depth d	Number of total samples
Landmine model (target)		W = 6cm (top), 9cm (bottom) H = 5cm = 1cm (top) + 4cm (bottom)		3.0	2.0cm 2.5cm 3.0cm 3.5cm 4.0cm	Training: 500 Testing: 500
Randomly deformed elliptic and circular cylinders		(a)	Mean size of deformed elliptic cylinders (W, H) = (9cm, 5cm) and (11cm, 6cm)	3.0 4.0 5.0 7.0 9.0		Training: 500 Testing: 500
		(b)	Mean diameter of deformed circular cylinders D = 3cm, 5cm, 7cm, 9cm, 11cm			