A Three-Dimensional Feature Vector for Identification of Buried Landmines Using GPR Data

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Abstract

Identification of shallowly buried landmines using ground penetrating radar (GPR) data is studied. Three kinds of features for target identification are proposed: (a) time interval between two pulses reflected from top and bottom sides of the objects, (b) normalized waveform correlation, and (c) dispersion of arrival time of target responses. Since the identification considered here is reduced to a classification problem of a desired target and other clutter objects, a support vector machine (SVM) is employed as a classifier. In order to evaluate the identification performance, we carry out a Monte Carlo simulation using dataset generated by a two-dimensional finite difference time domain (FDTD) method. The results show that good identification performance is obtained, and thus we can confirm that the proposed features are useful for discrimination of landmines from confusing clutter objects.

1. INTRODUCTION

Detection of small and shallowly buried landmines is a very challenging problem. Compared with the metal detector that is widely used for landmine detection, a ground penetrating radar (GPR) based approach would appear to offer many advantages, particularly for the detection of plastic landmines with little or no metal content [1]. However, reliability of the GPR system applied to detection of shallowly buried landmines is not sufficient because the GPR also receives returns from other subsurface objects such as rocks, tree roots, or metal fragments in the ground, which yields high levels of false alarms. Accordingly, development of highly reliable algorithms for target detection and identification that are applied to GPR data is highly desired [2]-[11].

In general, a process of landmine detection is divided into two steps. The first step is the find stage, where all the various types of buried objects are located. The second stage, the identification stage, then differentiates landmines from stones and other objects using reference data prepared through prior experiments and/or simulations. In this research, we consider the identification stage. Thus, we assume that the location of a buried object is already known, but that it has not yet been identified.

In the process of target identification, it is required to discriminate between targets and clutter objects using features extracted from GPR data and reference data. In general, the selection of the features plays a key part in target identification because the identification performance strongly depends on the features. Thus, we propose here three kinds of features for target identification: a time interval between two pulses reflected from top and bottom sides of the objects [12], a normalized waveform correlation [11], and a dispersion of arrival time of target responses [11]. Since the identification considered here is reduced to a classification problem of a desired target and other clutter objects, a support vector machine (SVM) [13] is employed as a classifier. In order to evaluate the identification performance, we carry out a Monte Carlo simulation using dataset generated by a two-dimensional finite difference time domain (FDTD) method. The results show that good identification performance is obtained, and thus we can confirm that the proposed features are useful for discrimination of landmines from confusing clutter objects.

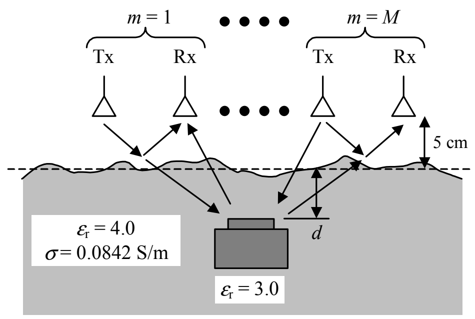


Fig. 1 Schematic of a GPR measurement system

2. FEATURES FOR TARGET IDENTIFICATION

Figure 1 shows a typical configuration of the GPR measurement system for identification of shallowly buried landmines under rough ground surface. The GPR measurements are made at multiple observation points above the rough ground surface using transmitting and receiving antenna pairs. Since the classification performance strongly depends on the features as mentioned in the Introduction, we employ here a three-dimensional feature vector whose elements are, time interval between two pulses reflected from top and bottom sides of the objects, normalized waveform correlation, and dispersion of arrival time of target responses. Since these features are detailed in References [11] and [12], we briefly explain about them in the following sub-sections.

A. Time Interval Associated with Target Thickness

First, we roughly estimate a time resolution that is required in detecting object thickness from GPR data. Let us consider electromagnetic pulse reflection from a dielectric landmine-like object of thickness *d* as shown in Fig. 2. Time interval between two pulses reflected from top and bottom sides of the object is expressed as

$$T = (2d / c_0)\sqrt{\varepsilon_r} \tag{1}$$

where ε_r is the relative permittivity and c_0 is the speed of light in free space. Change of the thickness Δd leads to the following time difference:

$$\Delta T = (2\Delta d / c_0)\sqrt{\varepsilon_r} \tag{2}$$

Since a relative permittivity of trinitrotoluene (TNT) is about $\varepsilon_r = 3.0$ [7], it can easily be found that the difference of the thickness $\Delta d = 1.0\,\mathrm{cm}$ corresponds to the time difference $\Delta T = 0.12$ ns. This indicates that if the detection ability of the time difference is less than 0.12ns, then we can distinguish two objects that are more than 1.0cm different in thickness. Thus, we can expect that good identification performance will be achieved by employing the time interval *T* as one of the features.

B. Normalized Waveform Correlation

Next, we introduce a concept of a matched filter that is commonly utilized for detecting a deterministic and known

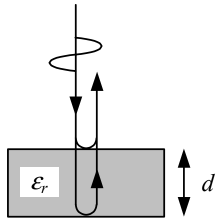


Fig. 2 Electromagnetic pulse reflection from a landmine-like object of thickness *d*.

target signature included in signals with noise contamination. As mentioned in the Introduction, we assume that the location of the buried object is known, and target data, prepared through prior experiments and/or simulations, is available as reference data. Thus, we use the known target signature $s_m(t)$ at position *m* as a template for target feature extraction. We define the following normalized correlation $C_m(t)$ between the measured GPR signal $x_m(t)$ and the template $s_m(t)$ as a measure of waveform similarity,

$$C_m(t) = \frac{1}{\| \hat{x}_m \| \| s_m \|} \int x_m(\tau) s_m(\tau - t) d\tau \tag{3}$$

$$C_m^{\max} = \max_t C_m(t), \tag{4}$$

$$t_m^{\max} = \arg\max_t C_m(t) \tag{5}$$

where $\hat{x}_m$ is the truncated part of $x_m(t)$ within the region of support $s_m(\tau - t)$. Note that the template $s_m(t)$ is simply the target signature from the desired landmine, and it does not include ground surface reflection (the ground surface reflection can be reduced using the procedure described in [11]). Thus, if the measured GPR signal x_m includes the target signature s_m, then the maximum correlation $C_m^{\max}$ becomes close to unity at $t = t_m^{\max}$, which corresponds to the signal arrival time. In order to reduce the effect of ground surface reflection, we employ a mean value of the maximum correlation $C_m^{\max}$ defined by

$$\overline{C}^{\max} = \frac{1}{M} \sum_{m=1}^{M} C_m^{\max} \tag{6}$$

as the second feature for target identification.

C. Dispersion of Arrival Time of Target Responses

Next, we define a difference of signal arrival time T_m between x_m and s_m as follows:

$$T_m = t_m^{\max} - t_m^{arr} \tag{7}$$

where t_m^{arr} is a known arrival time of the signature s_m. If the signal, x_m, includes the target signature, s_m, then the deviation of the arrival time, $t_m^{\max}$, does not vary significantly when the observation point, *m,* changes. We can therefore expect that variance of T_m is a good feature for target identification. We accordingly employ the variance of T_m defined by

$$V_T = \frac{1}{M} \sum_{m=1}^{M} (T_m - \overline{T}_m)^2 \tag{8}$$

as the third feature for target identification.

3. PERFORMANCE EVALUATION

In Section 2, we have proposed three-dimensional feature vector for identification of buried landmines. It becomes, however, difficult to identify shallowly buried landmines under rough ground surface, because ground surface clutters caused by surface roughness and target/surface interaction effects make significant contributions to measured target signals. Furthermore, low contrast in relative permittivity of the buried target and its surrounding soil makes the target signals weak and obscure. Thus, in order to examine the ability of this feature vector to identify the landmines when it is applied to realistic GPR data, we perform Monte Carlo simulations using a dataset that includes various GPR data samples generated by a two-dimensional FDTD method with a PML absorbing boundary condition.

A. Simulation Models

The landmine model (target) and three kinds of confusing objects (clutter objects) are tabulated in Table 1. Rectangular object has the same size as the landmine model except for its height, and randomly deformed circular and elliptic cylinders have various shapes. Relative permittivity of them is $\varepsilon_r = 3.0$. The depths of the landmine as well as that of the confusing objects are varied between 2.0 cm and 6.0 cm. The number of each sample is 500. Surface roughness with Gaussian distributed height and slope is realized using the method proposed by Thorsos [14]. Figure 3 shows one of the realizations of surface roughness that we used for the present numerical simulations; for this case the root mean square (RMS) height and the correlation length of the surface roughness are set to be both 1.0cm. In our simulations we assume the surrounding dry soil with a relative dielectric constant of $\varepsilon_r = 4.0$ and conductivity $\sigma = 0.0842$ [S/m] is non-dispersive. As the incident pulse, we use a monocycle pulse excited by Gaussian current whose parameters are chosen such that the incident pulse has most of its energy in the frequency band between 1GHz and 5GHz.

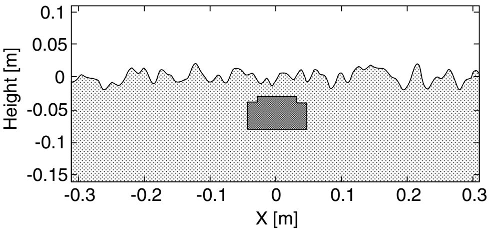


Fig. 3 One of the realizations of the rough ground surfaces used for the numerical simulations. The root mean square (RMS) height and the correlation length of the surface roughness are both 1.0 cm.

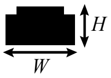
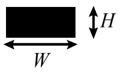
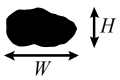
B. Classification Using SVM

In this research, we employ a support vector machine (SVM) as a classifier. The SVM is a novel type of learning machine and represents a very promising tool for solving pattern classification. The classification procedure using the SVM consists of two stages, training and testing stages. In the first stage, we train the SVM using the training dataset. Training the SVM means mapping of the training data into a higher-dimensional feature space, and finding the optimal hyperplane that separates hyper feature space into two classes. In the testing stage, unknown testing data samples are presented to the SVM and categorize them into two classes (target and clutter objects). In our simulation, we divided 500 data samples into 300 and 200 samples for training and testing, respectively (see Table 1). As the kernel function, we use the Gaussian kernel.

C. Performance Evaluation

In order to check the identification performance, we employ receiver operating characteristic (ROC) curve that has been

Table 1 Landmine model (target) and three kinds of confusing objects (rectangular objects and randomly deformed circular and elliptic cylinders)

<table>
<tr><th>Type</th><th colspan="2">Shape</th><th>Size</th><th>ε_r</th><th>Depth d (cm)</th><th>Number of samples</th></tr>
<tr><td>Landmine model (target)</td><td colspan="2"></td><td>W = 6cm (top), 9cm (bottom)
H = 5cm = 1cm (top) + 4cm (bottom)</td><td>3.0</td><td rowspan="4">2.0
3.0
4.0
5.0
6.0</td><td>Training: 300
Testing: 200</td></tr>
<tr><td rowspan="3">(a) Rectangular object.
Randomly deformed
(b) circular and
(c) elliptic cylinders
(confusing objects)</td><td>(a)</td><td></td><td>W = 9cm,
H = 4cm</td><td rowspan="3">3.0</td><td>Training: 300
Testing: 200</td></tr>
<tr><td>(b)</td><td></td><td>Mean size of deformed circular cylinders
D = 5cm</td><td>Training: 300
Testing: 200</td></tr>
<tr><td>(c)</td><td></td><td>Mean size of deformed elliptic cylinders
(W, H) = (9cm, 5cm)</td><td>Training: 300
Testing: 200</td></tr>
</table>

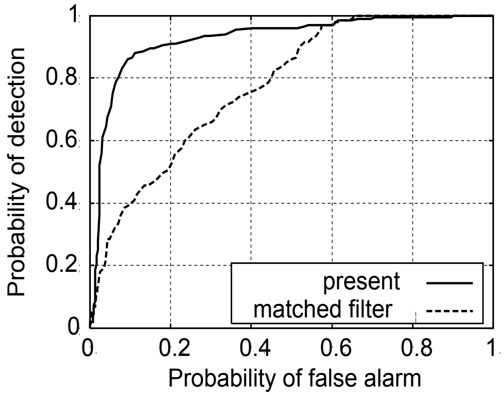


Fig 4. ROC curves plotted for the present 3D feature vector and the simple wave correlation (matched filter)

widely used in evaluating performances of radar and sonar systems [15]. Before showing the results of performance evaluation, we briefly explain about the ROC curve. The ROC curve, that is a plot of the probability of detection (P_d) versus the probability of false alarm (P_f), is obtained by varying the detection threshold. P_d is calculated by taking the ratio of the number of detected targets to the total number of targets, where P_f is calculated by taking the ratio of the number of target declarations that are not true targets to the total number of false alarms. When we plot the ROC curve with P_f value as x-axis and P_d as y-axis, the ROC curve connects the top right point ($P_d = P_f = 1$) to bottom left point ($P_d = P_f = 0$) of the ROC space (see Fig. 4 as an example). When we adjust the threshold so as to get higher P_d value, P_f value increases at the same time due to a trade-off between detection rate and false alarm rate. Since a high detection rate with low false alarm rate, that is a desired property of the detector, corresponds to upper-left region in ROC space, the detector whose ROC curve is closer to the upper left corner has better performance.

Figure 4 shows the ROC curves for testing dataset when the rme-height and correlation length are both 1.0cm. The solid line indicates the result of the SVM classifier with 3D feature vector, and the dashed line indicates the result of the matched filter detector that uses only the feature $\overline{C}^{\max}$. By comparing these two curves, we can see that the performance of the SVM classifier with 3D feature vector proposed here is significantly improved. This is due to the fact that the feature based on the time interval associated with target thickness is utilized effectively. From these results, we can confirm that the proposed 3D feature vector gives good performance for identification of buried landmines.

4. Conclusions

We have proposed the 3D feature vector for identification of shallowly buried landmines using GPR data, and have evaluated its identification performance. Three features are, a time interval between two pulses reflected from top and bottom sides of the objects, a normalized waveform correlation, and a dispersion of arrival time of target responses. In order to evaluate the identification performance, we have carried out a Monte Carlo simulation using dataset generated by a 2D-FDTD method. As the classifier, we employ the SVM with the Gaussian kernel. The results show that good identification performance is obtained, and thus we can confirm that the proposed 3D feature vector is useful for discrimination of landmines from confusing clutter objects.

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