# CLUTTER REDUCTION AND OBJECT DETECTION IN SURFACE PENETRATING RADAR

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## ABSTRACT

This paper addresses the problem of detecting buried objects using a surface penetrating impulse radar. A big problem is that reflections from the ground surface will obscure the often much weaker target signal. The ground reflections and the target signal are modeled using a very simple model. This model is used to derive a detector based on a Likelihood Ratio Test, where unknown model parameters are estimated using a Maximum Likelihood approach. Even though the model is very simple, the detector is found to perform well. The detector is evaluated using real data from an impulse radar system. Both metallic and non-metallic buried objects can successfully be detected.

## INTRODUCTION

The particular application motivating this study is the detection of buried landmines. Landmines have traditionally been detected with metal detectors. However, nowadays landmines are made with very low metal content, or purely non-metallic. The impulse radar was suggested as a means to detect non-metallic buried objects. A problem in all surface penetrating radar systems is the clutter signal from the ground surface and from layers in the ground. The clutter from the ground surface is particularly disturbing when the goal is to detect shallowly buried objects like landmines. The weak signal from a target will be obscured by the much stronger signal from the surface. Since the signals have almost the same spectral properties and arrive almost at the same time, they are very difficult to separate from each other. In [1] the surface reflection is filtered out using a spatial moving average filter. After that, different detection algorithms are applied and evaluated. The problem of clutter suppression followed by detection of shallowly buried objects is also addressed in [2]. Instead of doing the detection procedure in two steps (clutter suppression followed by the actual detector), the present paper models the clutter and incorporates it in the detector. This means that no explicit prefiltering is done.

## SIGNAL MODEL

The impulse radar used for the present study transmits pulses of 0.3 ns length, with a pulse repetition frequency of 250 kHz. The pulse is transmitted using a broadband dipole antenna. The returned signal is received by an identical dipole antenna, perpendicular to the transmit antenna. This configuration with two crossed antennas is selected to minimize ground reflexes. The frequency range of the complete system is 0.3–3 GHz. The detector is planned to be used together with a classification algorithm. This means that if the detector makes a false detection, it might be rejected by the classifier as a false alarm. A very crude model for the returned signal is used throughout this paper. The assumptions made when modeling the signals are that the returned signals are mainly made up of specular reflexes. Another assumption is that there is only one object of interest present in the antenna lobe. Finally, it is assumed that the medium of propagation, i.e. the ground, is homogeneous and that the ground surface is relatively smooth. The geometry of the measurements is shown in Figure 1. The antenna is positioned just

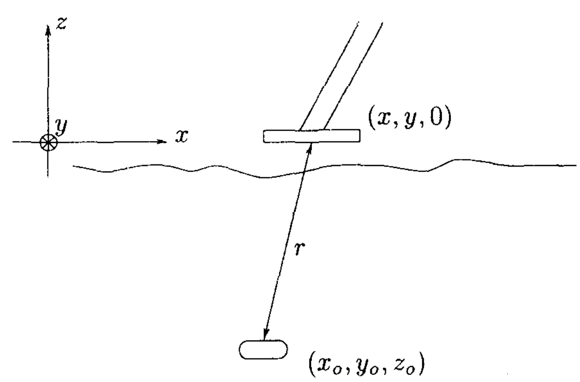


Figure 1: Geometry of measurements.

above the ground surface at $z = 0$. The object is positioned at $(x_o, y_o, z_o)$ and the distance between the antenna and the object is denoted $r$. With this measurement geometry and the above assumptions, the returned signals will consist of three parts. The first part is a clutter term that is the sum of antenna crosstalk and the return from the ground surface. Since the surface is assumed to be smooth, this first term will be slowly varying as a function of the spatial coordinates $(x, y)$. The second term is the return from the object. The distance, $r$, between the antenna and the object is a hyperbolic function in $x$ and $y$.

$$r = \sqrt{(x - x_o)^2 + (y - y_o)^2 + z_o^2} \tag{1}$$

For example, if the antenna is moved in the $y$ direction while $x$ is constant, a point target will produce a hyperbola characteristic for surface penetrating radar measurements. Such a scan, along a line, is called a B-scan to conform to the notation of [3]. The third term in the signal model is an additive noise. The noise term incorporates measurement noise and modelling errors. The noise is assumed to be Gaussian and temporally and spatially white. The signal model can thus be written as:

$$\mathbf{w} = \mathbf{b} + \mathbf{s} + \mathbf{e}, \tag{2}$$

where $\mathbf{w}$ is the measured signal, $\mathbf{b}$ is background clutter, $\mathbf{s}$ target signal and $\mathbf{e}$ is the noise. Note that $\mathbf{s}$ and $\mathbf{b}$ are modeled as unknown deterministic signals. The clutter signal, $\mathbf{b}$, could just as well be treated as the mean value of the noise, but here the terms are separated such that the noise is zero-mean. The current study is based on 4 measurement series of 13 B-scans each. Between each scan the antenna is moved 5 cm in the $x$-direction. The first scan is made 60 cm from the object and the last scan passes straight above the object. This type of measurements allows us to determine how close to the object the antenna must be to make a reliable detection.

## A Generalized Likelihood Ratio Detector

The detection problem can be formulated as a statistical hypothesis test, where the two hypotheses are

$H_0$: Measured signal is clutter plus noise only.
$\mathbf{w} = \mathbf{b} + \mathbf{e}$

$H_1$: Measured signal is clutter plus target signal plus noise.
$\mathbf{w} = \mathbf{b} + \mathbf{s} + \mathbf{e}$

A formulation of the test is to assume that hypothesis $H_0$ is true, and then test if this hypothesis can be rejected statistically. This is done by using a so called Likelihood Ratio Test, [4]. As will be noted later, the performance of the detector can be improved if several measurements are used in the test. Assume that $M$ measurements are made with no object present, then a subsequent measurement is to be tested. Stack the $M + 1$ measurements in a vector $\mathbf{x}$ and denote the noise covariance by $\boldsymbol{\Sigma} = E[\mathbf{e}\mathbf{e}^T]$. Under hypothesis $H_0$, $\mathbf{x}$ will be distributed as

$$\mathbf{x} = \begin{bmatrix} \mathbf{w}_1 \\ \mathbf{w}_2 \\ \vdots \\ \mathbf{w}_{M+1} \end{bmatrix} \in \mathcal{N}\left( \begin{bmatrix} \mathbf{b} \\ \mathbf{b} \\ \vdots \\ \mathbf{b} \end{bmatrix}, \mathbf{I} \otimes \boldsymbol{\Sigma} \right), \tag{3}$$

and under $H_1$

$$\mathbf{x} = \begin{bmatrix} \mathbf{w}_1 \\ \mathbf{w}_2 \\ \vdots \\ \mathbf{w}_{M+1} \end{bmatrix} \in \mathcal{N}\left( \begin{bmatrix} \mathbf{b} \\ \mathbf{b} \\ \vdots \\ \mathbf{b} + \mathbf{s} \end{bmatrix}, \mathbf{I} \otimes \boldsymbol{\Sigma} \right). \tag{4}$$

The likelihood ratio test is then

$$\Lambda' = \frac{p_{H_1}(\mathbf{x})}{p_{H_0}(\mathbf{x})}. \tag{5}$$

By taking the logarithm of the ratio it can instead be written as the difference between the negative log-likelihood functions.

$$\Lambda = \ell_{H_0}(\mathbf{x}) - \ell_{H_1}(\mathbf{x}) \tag{6}$$

Assuming $\boldsymbol{\Sigma} = \operatorname{diag}(\sigma_i)$, the log-likelihood function under $H_0$ is

$$\begin{aligned} \ell_{H_0}(\mathbf{x}; \{\sigma_i\}, \mathbf{b}) =& \frac{M+1}{2}(\log 2\pi + \sum_{i=1}^{N} \log \sigma_i) \\ &+ \frac{1}{2} \sum_{j=1}^{M+1} (\mathbf{w}_j - \mathbf{b})^T \boldsymbol{\Sigma}^{-1} (\mathbf{w}_j - \mathbf{b}) \\ =& \frac{M+1}{2}(\log 2\pi + \sum_{i=1}^{N} \log \sigma_i) \\ &+ \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{M+1} \frac{1}{\sigma_i} (w_{i,j} - b_i)^2, \end{aligned} \tag{7}$$

where $N$ is the number of samples in each measurement vector and the covariance matrix $\boldsymbol{\Sigma}$ is parameterized by its diagonal elements $\{\sigma_i\}$. This log-likelihood function depends on the unknown parameters $\{\sigma_i\}$ and $\mathbf{b}$. These unknown parameters can be replaced by their maximum likelihood (ML) estimates to obtain the concentrated log-likelihood function $\ell_{H_0}(\mathbf{x})$. To find the ML estimates of $\{\sigma_i\}$ and $\mathbf{b}$ we start by differentiating $\ell_{H_0}(\mathbf{x}; \{\sigma_i\}, \mathbf{b})$ with respect to $b_k$.

$$\frac{\partial \ell_{H_0}(\mathbf{x}; \{\sigma_i\}, \mathbf{b})}{\partial b_k} = \sum_{j=1}^{M+1} \frac{1}{\sigma_k} (w_{k,j} - b_k)(-1) = 0 \tag{8}$$

which gives

$$\hat{b}_k(\mathbf{x}|H_0) = \frac{1}{M+1} \sum_{j=1}^{M+1} w_{k,j}, \tag{9}$$

where the notation $\hat{b}_k(\mathbf{x}|H_0)$ means that this is the estimate of $b_k$ as a function of $\mathbf{x}$, assuming that hypothesis $H_0$ is true. This estimate of $\mathbf{b}$ is substituted into (7). The concentrated log-likelihood function $\ell_{H_0}(\mathbf{x};\{\sigma_i\})$ is then differentiated with respect to $\sigma_k$, and set to zero.

$$\frac{\partial \ell_{H_0}(\mathbf{x};\{\sigma_i\})}{\partial \sigma_k} = \frac{M+1}{2\sigma_k} - \sum_{j=1}^{M+1} \frac{1}{2\sigma_k^2}(w_{k,j} - \hat{b}_k(\mathbf{x}|H_0))^2 \tag{10}$$

$$\hat{\sigma}_k(\mathbf{x}|H_0) = \frac{1}{M+1}\sum_{j=1}^{M+1}(w_{k,j} - \hat{b}_k(\mathbf{x}|H_0))^2 \tag{11}$$

Here we see the advantage of using several measurements; both estimates above are improved when $M$ is increased. The concentrated log-likelihood function can now be written as

$$\ell_{H_0}(\mathbf{x}) = \frac{M+1}{2}\left(\log 2\pi + \sum_{i=1}^{N}\log\hat{\sigma}_i(\mathbf{x}|H_0) + \frac{N}{2}\right) \tag{12}$$

In the same fashion, the corresponding estimates under hypothesis $H_1$ can be derived.

$$\hat{b}_k(\mathbf{x}|H_1) = \frac{1}{M}\sum_{j=1}^{M} w_{k,j} \tag{13}$$

and

$$\hat{\sigma}_k(\mathbf{x}|H_1) = \frac{1}{M+1}\sum_{j=1}^{M}(w_{k,j} - \hat{b}_k(\mathbf{x}|H_1))^2 \tag{14}$$

Here we can also get an estimate of the target signal as

$$\hat{\mathbf{s}} = \mathbf{w}_{M+1} - \hat{\mathbf{b}}, \tag{15}$$

which is to be used for classification purposes. The concentrated log-likelihood function under $H_1$ thus has exactly the same form as the one under $H_0$, but with different estimates of $\{\sigma_k\}$ and $\mathbf{b}$.

$$\ell_{H_1}(\mathbf{x}) = \frac{M+1}{2}\left(\log 2\pi + \sum_{i=1}^{N}\log\hat{\sigma}_i(\mathbf{x}|H_1) + \frac{N}{2}\right) \tag{16}$$

The decision variable $\Lambda$ of the likelihood ratio test can now be written as

$$\begin{aligned}\Lambda &= \frac{M+1}{2}\left(\sum_{i=1}^{N}\log\hat{\sigma}_i(\mathbf{x}|H_0) - \sum_{i=1}^{N}\log\hat{\sigma}_i(\mathbf{x}|H_1)\right)\\ &= \frac{M+1}{2}\left(\sum_{i=1}^{N}\log(\hat{\sigma}_i(\mathbf{x}|H_0) - \log\hat{\sigma}_i(\mathbf{x}|H_1))\right)\end{aligned} \tag{17}$$

Under hypothesis $H_0$, the decision variable $\Lambda$ is $\chi^2(N)$-distributed. This distribution can be used to select the threshold $\lambda$ such that a good trade-off between false alarm rate and detection rate is obtained. In the present paper the threshold is selected ***ad hoc*** by inspection of detection plots.

## Results

The measurements are made in lines called B-scans, as mentioned earlier. The scans are made in the $y$-direction, with 2 cm spacing between measurement points. Each scan consists of 76 measurements. The first scan is made at a distance of 60 cm, in the $x$-direction, from the buried object. The antenna is then moved 5 cm closer to the object for each following scan such that scan number 13 passes straight above the object. The measurements are made in a sand box filled with dry sand. 4 different objects are used for this evaluation:

**A** A metal sphere. 20 cm diam.

**B** A metal cylinder. 30 cm diam., 5 cm high.

**C** A stone. Size and shape like a coconut.

**D** A plastic cylinder (mine dummy). 10 diam, 3 cm high.

The objects are buried with 10 cm distance between top of object and thesurface. The measurements in scan number 2 are used as the reference set to the detector, i.e., the measurements with no object present. For each measurement, the likelihood ratio in (17) is calculated. The measurements where $\Lambda$ exceeds a threshold $\lambda$ is marked with a white box in the following figures. The objects are located at coordinates $(150, 175)$, i.e., in the right, middle of the figures. Figure 2 shows the results for the two metallic objects (A and B). Both these objects are detected with essentially no false alarms. The shape of the detection patterns, i.e., like a half four-leaf clover, is a consequence of the crossed dipole antenna configuration. The detections for the non-metallic objects (C and D) are shown in Figure 3. These objects have dielectricity constants very close to that of the sand. This means that the objects give very weak returns, and thus are very difficult to detect. Despite this, they show up in the detection plots quite clearly. Only a few false detections are made. Note that the same detection threshold is used both for the metallic and non-metallic objects.

## Conclusions

In this paper a simple model for impulse radar measurements on buried objects is introduced. This model is the basis for the derivation of a detctor

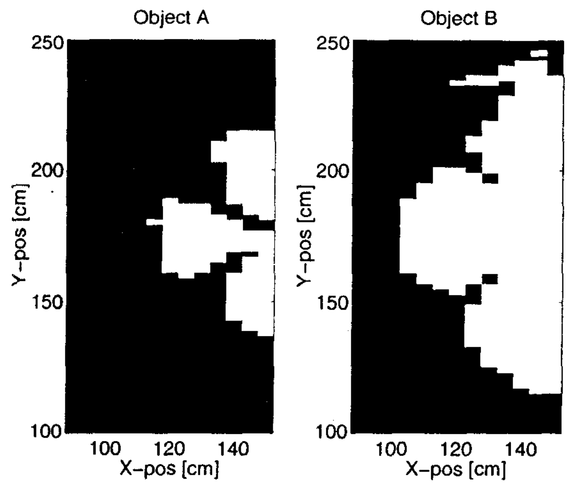


Figure 2: Detections for objects A and B.

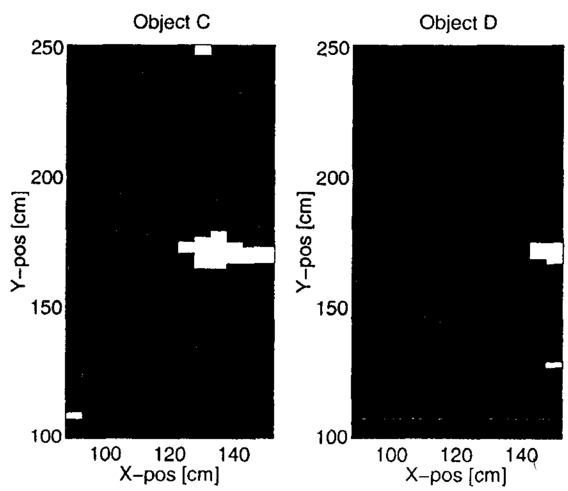


Figure 3: Detections for objects C and D.

based on a likelihood ratio test. The model parameters are estimated in a maximum likelihood sense. As opposed to earlier presented methods, the clutter suppression and detection is here performed in one step. The so derived detector is found to perform well on measured data. The results show that metallic objects can easily be detected using the impulse radar together with the here proposed detection algorithm. Perhaps more encouraging is that also non-metallic objects can be detected. The signal power returned from non-metallic objects is much lower than that of metallic objects, still the detections seems quite distinct. The amount of data used for this study is too small to draw any general conclusions, but the results at least indicate that the impulse radar might be a useful tool to detect buried non-metallic objects. Future work will be to investigate how sensitive this model and detector are to violations of the underlying assumptions. For example, how will an inhomogenous ground and a rough surface affect the results.

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