

# An Integrated Detection and Identification Methodology Applied to Ground-Penetrating Radar Data for Humanitarian Demining Applications

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*A mi padre, in memoriam, y a mi madre.  
A los hijos de Colombia, por un futuro libre de minas antipersonal.*

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# List of Abbreviations

|      |                                   |
|------|-----------------------------------|
| 1-D  | One-dimension                     |
| 2-D  | Two-dimensions                    |
| 3-D  | Three-dimensions                  |
| AP   | Antipersonnel                     |
| AT   | Antitank                          |
| BS   | Background subtraction            |
| CD   | Change detection                  |
| CM   | Center of mass                    |
| EM   | Electromagnetic                   |
| FA   | False alarm                       |
| FD   | Frequency domain                  |
| FDTD | Finite-difference time domain     |
| GPR  | Ground-penetrating radar          |
| IED  | Improvised explosive device       |
| MD   | Metal detector                    |
| MoM  | Method of moments                 |
| ROC  | Receiver operating characteristic |
| SAR  | Synthetic aperture radar          |
| SFCW | Stepped-frequency continuous-wave |
| SNR  | Signal-to-noise ratio             |
| STFT | Short-time Fourier transform      |
| SVD  | Singular value decomposition      |
| TD   | Time domain                       |
| TFD  | Time-frequency domain             |
| TDR  | Time domain reflectometry         |
| UWB  | Ultra-wide band                   |
| VNA  | Vector network analyzer           |
| WT   | Wavelet transform                 |
| WVD  | Wigner-Ville distribution         |



# Chapter 1

## Introduction

---

*The saddest aspect of life right now is that science gathers knowledge faster than society gathers wisdom.*

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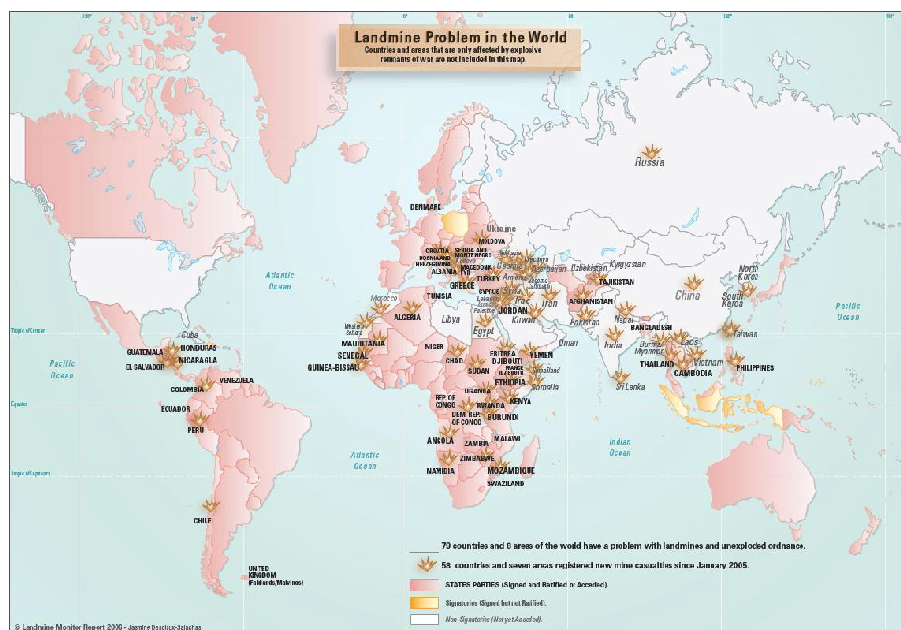
*Isaac Asimov*

### 1.1 Research Topic

#### 1.1.1 The Global Landmine Problem

Antipersonnel (AP) landmines are explosive devices which are normally buried below the surface and can be activated by contact or pressure of a small weight ( $\approx 20$  kg). Thus any person, including children, can become a victim. Landmines are placed fundamentally in supply centers and production fields, communication ways, etc., and therefore, they cause serious human, economic and sanitary damages [Goose, 1995].

AP landmines are manufactured from lasting materials such as plastic or metal, and are designed in different sizes and shapes. They have been used massively since they were invented. Since the beginning of World War II, 400 million of AP landmines have been buried in the ground of at least 70 countries. In the last 20 years, more than 65 million AP landmines have been placed, maiming or killing more than 20.000 civilians every year. The most contaminated regions by AP landmines are mainly underdeveloped countries (see Fig 1.1). Africa is the most mine-affected continent with approximately 37 million of these in at least 19 countries. There are at least 28 million of AP landmines in Afghanistan, Angola and Cambodia, where lives 85% of the world-wide victims of AP landmines. Eastern Europe also faces this problem, since more than 3 million landmines have been placed within the framework of



**Figure 1.1.** Distribution of the APM and UXO problem in the world (Map from Landmine Monitor Report 2006).

the conflict of ex-Yugoslavia. A similar situation is lived in Central and South America, with Colombia as the most affected country in the world in 2006 (more information can be found in *US Department of State* [1998], *GICHD* [2003] and *ICBL* [2006]).

**The Colombian Landmine Problem.** In Colombia, four decades of civil war have left more than 100 thousand AP landmines laid across 40% of the national territory. These mines caused 1110 victims in 2006, among which 35% were civilians [*ICBL*, 2006].

AP landmines used in Colombia are American and Belgian manufactured devices, as well as landmines manufactured by the Colombian Military Industry (INDUMIL). However, a considerable number is made in an artisan way by the guerrillas (e.g., FARC and ELN\*). Such low cost landmines are called *improvised explosive devices* (IEDs). Colombian Army used AP landmines to protect telecommunications areas and Military bases until 1999. Although the Colombian government ratified the Ottawa Convention in 2001, the guerrillas still place IEDs across the country.

The Explosive Devices Manipulation Unit (MARTE, in Spanish abbrevi-

\*Fuerzas Armadas Revolucionarias de Colombia - FARC, Ejército de Liberación Nacional - ELN





**Figure 1.2.** An example of classical demining operations in Croatia: deminers scan with metal detectors and trained dogs after the mechanical excavation.

ation) of the Military Forces is the most expert group in mine-clearing works in Colombia. They use classical demining procedures, namely, metal detector (MD). However, MDs do not reliably detect plastic, low-metallic landmines<sup>†</sup> in a post-conflict area contaminated by grenade fragments, cartridges, and other metallic materials buried premeditatedly to confuse the deminers. Besides the fact that some Colombian mine-affected areas contain ferruginous soils (*i.e.* with a high iron content) which adversely affects the sensibility of MDs, a significant amount of IEDs contains only plastic and other non-metallic elements. When demining is performed using MDs, all these factors increase the probability of having an accident<sup>‡</sup>.

### 1.1.2 Mine Action: Problems and Technologies

In general, demining consists in detecting and neutralizing landmines. Although many people are familiarized with military techniques to open breaches in mine-affected fields (tactical demining), the concept of humanitarian demining is different. In the first one, the basic rule is to open a passage through the minefield. AP landmines outside the footpath are ignored. For the humanitarian demining purposes, no misdetections are allowed, so that the civil use of the land can be recovered.

Nowadays, humanitarian demining procedures are carried out using MD, prodding sticks, trained dogs and/or mechanical demining equipment (see Fig. 1.2). However, development of demining technologies has not followed the fast development of landmines which are deadlier and more difficult to detect. AP landmines, which usually were made with significant amounts of metal

<sup>†</sup> A low-metallic AP landmine contains less than about 8 grams of iron or equivalent.

<sup>‡</sup> Information source: <http://www.derechoshumanos.gov.co/minas/>



**Figure 1.3.** Some of the objects found after demining operations in the M7753 minefield, Province of Siem Reap, Cambodia. In an area of ten thousand square meters, three AP landmines, four UXO (Unexploded Ordnance) and almost two thousand and six hundred metal fragments (bullets and cartridges) were found.

and, therefore, were relatively easy to locate, are elaborated with plastic and other non-metallic elements. Demining systems available today do not accurately detect plastic landmines with minimum metal content in a metal debris contaminated area. In Cambodia, for example, for each detected AP landmine, more than 500 inoffensive metallic debris such as grenade fragments and cartridges are located (results from the Cambodian mine-fields, see Fig. 1.3).

False alarm rate as well as misdetection of low and non-metal content AP landmines have made mine clearance operations dangerous, time consuming and expensive. Since the mid 90's, several research groups have been contributing in solving this world-wide problem by looking for potential techniques for demining applications [MacDonald *et al.*, 2003; Acheroy, 2007]. However, only a few are currently employed in real mine-affected areas. One of them is ground-penetrating radar (GPR), perhaps the most advanced new technology, which can detect both metallic and plastic mines in a variety of soils by non-invasive subsurface sensing [Bruschini *et al.*, 1998; Carin *et al.*, 1999; Gao *et al.*, 2000; Chen *et al.*, 2001; Scheers, 2001; Yarovoy *et al.*, 2002; Ho and Gader, 2002; Roth, 2004; Daniels, 2004; Sai and Ligthart, 2004; van



**Figure 1.4.** Explosive vapor detection using African rodents. Picture from APOPO.

*den Bosch*, 2006]. GPR sends a series of microwave pulses ranging from about 1 to 4GHz into the ground. It then looks for anomalies in the reflected signal which could indicate the presence of a landmine. GPR is currently employed in dual-sensor systems, which include MD, with the aim of reducing the false alarm rate of the MD. MDs can detect small metallic debris, bullets or cartridges. Due to the small reflection area of such objects, they are not detected by GPR. Therefore, in such systems, GPR is used as a confirmation sensor, after the MD detection.

Among other new demining methodologies applied to real mine-affected fields, trained rodents are achieving very good results. APOPO<sup>§</sup> is a Belgian NGO based in Mozambique that has developed such a technique for explosive vapor detection using African rodents (see Figure 1.4). Currently, this technique is applied to humanitarian demining and has proved to be very accurate and faster than other techniques that use human-made sensors. The National Institute for Demining in Mozambique, in collaboration with the GICHD (Geneva International Center for Humanitarian Demining), has conducted successful tests based on international standards on the sniffer rodents and their trainers. Since October 2004, a first detection capacity has been operationally deployed.

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<sup>§</sup>More information can be found in <http://www.apopo.org>



**Figure 1.5.** Dual-sensors in test fields: MINEHOUND<sup>TM</sup> (Left. Picture from ERA Tech.) and ALIS (Right. Picture from TOHOKU University).

### 1.1.3 Ground-Penetrating Radar for Landmine Detection

The application of GPR in humanitarian demining labors presents three major challenges: (1) development of affordable and practical GPR-based systems; (2) development of robust GPR signal processing techniques for landmine detection and identification; (3) development of accurate soil characterization techniques to evaluate soil properties effects and determine the performance of GPR-based systems under different conditions [Yarovoy, 2002; Rhebergen and Ralston, 2005; Lopera *et al.*, 2006a].

**GPR-based systems.** A variety of GPR-based systems have been developed for demining applications. GPR systems operate either in time domain or in frequency domain. Time-domain systems transmit a single discrete pulse of nanosecond duration or a pulse train frequency modulated waveform. Frequency-domain GPR are continuous wave systems in which the carrier frequency is changed either continuously or with a fixed step. Stepped-frequency continuous-wave (SFCW) radars have some advantages over the others, including wider dynamic range and better signal-to-noise ratio (SNR) [Nicolae *et al.*, 2003]. Besides the domain of operation, GPR may detect landmines using either monostatic, bistatic or array configuration of different antenna types. In this particular application, ultra-wide band (UWB) antennas

are required to achieve high depth resolution [Yarovoy *et al.*, 2003]. Vehicle-based systems generally use array antenna mode [Sato *et al.*, 2003] in combination with other sensors such as metal detectors [Chignell and Hatef, 2004]. Laboratory prototypes of UWB radar systems usually are built in bistatic mode [Scheers *et al.*, 2000; Yarovoy *et al.*, 2002], and such a configuration is adopted for hand-held GPR-based systems [Daniels *et al.*, 2004; Sato *et al.*, 2005]. For all these configurations, different types of antennas such as horn, loop, spiral, Vivaldi and combinations of them are used. An overview of their characteristics, advantages and drawbacks for demining applications can be found in Scheers [2001].

Latest developments on GPR-based systems for humanitarian demining are hand-held dual-sensors (*e.g.*, MINEHOUND<sup>TM</sup>, ALIS, HSTAMIDS). Such systems work with both MD and GPR, and they differ on the operating principle of GPR, the signal processing and the user interface. MINEHOUND<sup>TM</sup> has been developed by ERA Tech., U.K., in collaboration with Vallon GmbH, Germany. It combines a pulse induction MD and an impulse GPR (see Fig. 1.5). This dual-sensor transforms MD and GPR signals into two separated audio signals of different frequency of vibration and tone. MINEHOUND<sup>TM</sup> has been tested in different mine-affected countries including Afghanistan, Angola, Bosnia and Cambodia. It will be commercialized by Vallon in the next years [Daniels and Curtis, 2006].

ALIS (Advanced Landmine Imaging System) is a Japanese detector developed at the Tohoku University (see Fig. 1.5). It is equipped with a metal detector and a GPR, and it has a sensor tracking system, which makes possible to process the data afterwards, including migration. The hand-held version of ALIS uses a VNA (Vector Network Analyzer)-based GPR and a pulse induction MD. This dual-sensor has two different user interfaces: audio for MD signal and images for both MD and GPR signals. ALIS has been tested in mine-affected countries including Afghanistan, Cambodia, Croatia and Egypt. It will be commercialized in the next years [Sato *et al.*, 2007].

HSTAMIDS (Hand-held Standoff Mine Detection System) was originally a project sponsored by the Defense Advanced Research Projects Agency, DARPA, U.S., and has been produced afterwards by CyTerra Corp. (now L-3 Communications). It combines a pulse induction MD and a GPR based on a wide-band, stepped-frequency radar. HSTAMIDS indicates to the user whether metal is detected through an audio signal. A second sound, of a different frequency of vibration and tone, is the *aided target recognition*, which signifies that there is a metal detection and that GPR identifies other mine-like material. It is massively produced since 2006 for US Army operations in Iraq [Ritter, 2007].

**Software processing.** GPR operates by detecting contrasts on the electromagnetic (EM) properties in the soil-target medium, which allows it to locate even low- and non-metallic landmines. However, the GPR signal contains not only the response from a potential target, but also undesirable effects from antenna coupling, system ringing and soil reflections, which obscure the target response [Annan, 2002; Daniels, 2004]. These effects have to be filtered out from the signal to enhance landmine detection. Different techniques are used to reduce this clutter<sup>¶</sup> and to identify the buried object signal. By far the most applied clutter reduction techniques are average and moving average background subtraction (BS) [Daniels, 2004]. Other BS approaches include wavelet transform [Carevic, 1999] and system identification [Brooks *et al.*, 2000]. Once these techniques partially reduce the clutter, the next logical step is to detect the target. Among processing methods for the identification of the target signal, advanced algorithms for hyperbola detection [Milisavljevic, 2001; Zhu and Collins, 2005], convolutional models [Roth, 2004] and migration techniques [Scheers *et al.*, 2001; Takahashi, 2006] are applied. An overview of different signal processing techniques for landmine detection using GPR can be found in MacDonald *et al.* [2003] and Daniels [2004].

**Soil characterization and GPR performance estimation.** It is well known that the performance of GPR is influenced mainly by the dielectric permittivity, as it mainly governs EM wave propagation. Soil dielectric permittivity depends on a number of factors of which the most significant is the volumetric water content, which can vary considerably over time and space. Due to the resulting large tempo-spatial variability of the soil water content, it is therefore essential to characterize the soil dielectric permittivity at the local scale during the demining operation [Das *et al.*, 2001; van Dam *et al.*, 2005]. Due to the complexity of the problem, few studies have been conducted for evaluating in a systematic manner the effects of soil properties on the detection performance of GPR for demining applications [Miller *et al.*, 2004; Rhebergen *et al.*, 2004]. Besides, theoretical models such as finite-difference time domain (FDTD) and method of moments (MoM) has been used to simulate the EM wave propagation for different air-soil-target configurations with the aim of estimating GPR performances [Giannopoulos, 2002; Roth, 2004; van den Bosch, 2006].

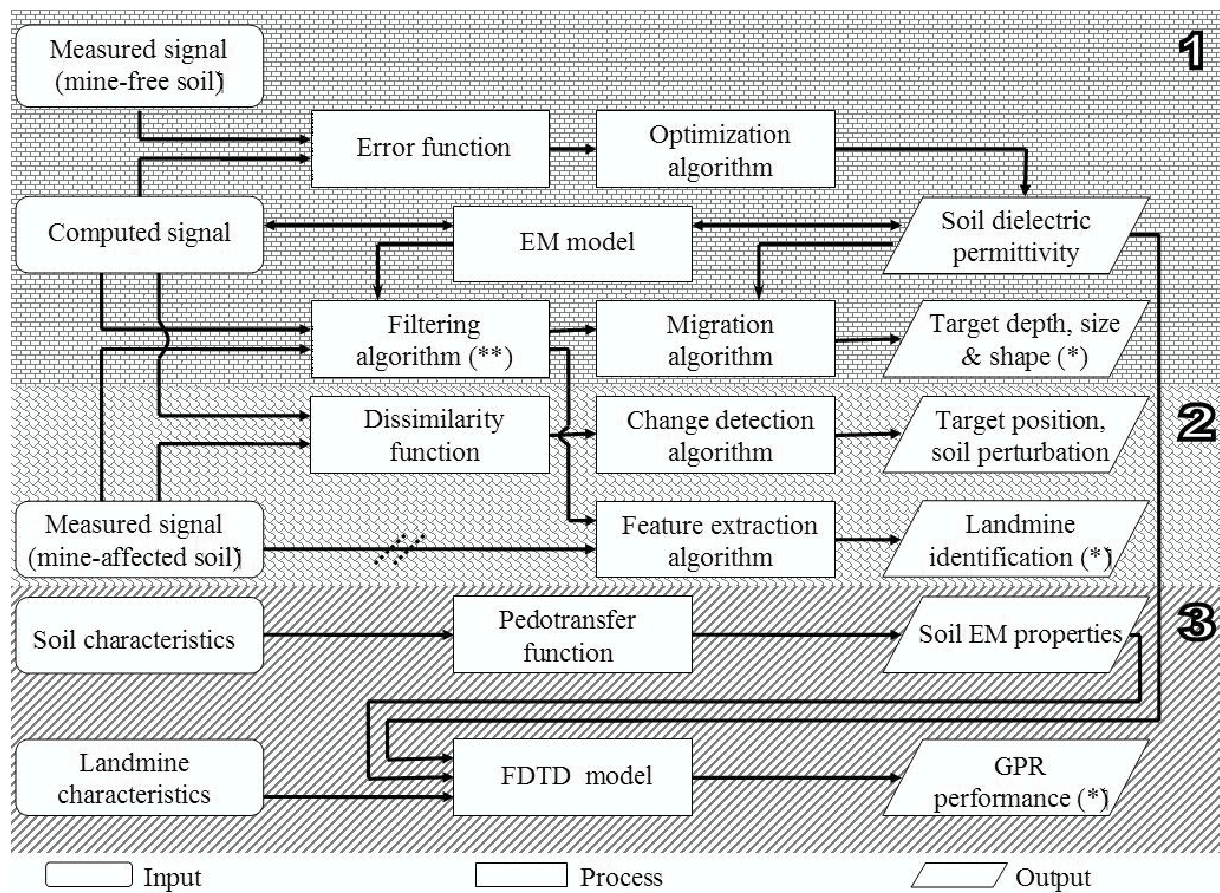
## 1.2 Project Objectives and Thesis Outline

GPR-based system development, signal processing and soil characterization are crucial steps for rendering GPR useful for humanitarian demining applica-

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<sup>¶</sup>In this thesis, all the reflections that do not originate from the target but from the background are called clutter.





**Figure 1.6.** Block diagram representing the proposed methodology for filtering GPR data, detecting buried objects and identifying AP landmines. (\*) End-user has to take a decision about the obtained results. (\*\*) Algorithm needs input from end-user.

tions. This thesis addresses these topics in an integrated approach aiming at improving GPR performance and efficiency.

Figure 1.6 represents the proposed approach in a flow chart on which this thesis is founded. It aims at extracting the maximum of information from GPR data that can be useful for landmine detection and identification<sup>||</sup> (Note that, for some output boxes, the end-user has to take a decision about the obtained results). In this framework, the special objectives outlining this thesis are related to each block section (1,2,3) in Fig. 1.6 as follows:

1. To filter out the soil surface reflection and major antenna effects from the GPR signal to enhance AP landmine detection. The predominant soil surface and antenna reflections can partly or totally hide or distort the response of the landmine. In Chapter 2, a new filtering approach is developed and validated under laboratory conditions. In particular, the antenna multiple reflections originating from the antenna itself and from the interaction between the antenna and the ground are removed using an EM model based on linear transfer functions. A computed Green's function accounting for the surface reflection is subtracted afterwards. The Green's function is derived from the estimated soil surface dielectric permittivity using full-wave inversion of the radar signal for a measurement taken in a local landmine-free area. Off-ground phase-shift migration is then performed to filter the effect of the antenna radiation pattern. We validate the approach in laboratory conditions for four differently detectable landmines embedded in a sandy soil. This approach is applied to data collected in mine-affected soils and results are presented in Chapter 3.
2. To reduce GPR false alarms produced by subsurface reflections and mine-like objects<sup>\*\*</sup>. Subsurface natural inhomogeneities can produce significant reflections which can be detected as alarms. In Chapter 4, a change detection methodology is proposed to reject these false alarms. For this, the computed Green's function derived from the estimated soil surface dielectric permittivity in Chapter 2 is used. A dissimilarity measure between this simulated signal and the radar signal from a mine-affected soil is applied to detect significant variations. The approach is validated in laboratory conditions and in mine-affected soils for different low-metallic AP landmines and low- and non-metallic IEDs.

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<sup>||</sup>In this thesis, *identification* is understood as the process of estimating whether a detected reflection is from a landmine.

<sup>\*\*</sup>The term *mine-like object*, or friendly object, describes a target whose size and shape resemble those of a landmine.



Mine-like objects, such as stones and metal debris, can also produce significant reflections which can be detected as alarms. In Chapter 5, relevant features are extracted in the time-frequency domain using the Wigner-Ville distribution (WVD). These features are used to distinguish landmines from mine-like objects. Radar data are collected over different types of soil and for different landmines and objects. The Wilk's lambda value is used as a criterion for optimal discrimination. Results show that time-frequency signatures from WVD contain valuable information, improving landmine identification and reducing the false alarm rate. They could also contribute to landmine classification<sup>††</sup>.

3. To analyze GPR detection performance. Landmine detection using GPR is limited by the effects of the soil EM properties on EM wave propagation. In Chapter 6, the effects of such properties on the detection performance of GPR are studied. We use soil properties, namely soil texture and EM parameters (measured or calculated using existing pedotransfer models) in a two-dimensional (2-D), FDTD modeling program in conjunction with the characteristics of AP landmines to calculate the buried target reflection. The soil/target medium is simulated considering different soil conditions and the performance of GPR can be analyzed. The approach is particularly applied to two soils selected among Colombian mine-affected areas, and several local IEDs and AP landmines are used as targets.

The resulting integrated approach shown in Fig 1.6 has been validated in laboratory and field conditions considering different scenarios, and some of the results have been used for improving the algorithms. Although the results seem to be very promising, some requirements for the application of the proposed approach are needed in practical conditions and are briefly addressed in Chapter 7. This chapter also reviews the contributions of this research and rises some questions about the perspectives and the future work.

### 1.3 Scientific Originality and Innovation

In this thesis, particular attention has been paid to the use of practical and affordable GPR-based systems for data collection, as well as the validation of the proposed approach in real mine-affected soils. The originality and innovation of the present study builds on the following:

---

<sup>††</sup>In this thesis, *classification* is understood as the process of determining (continue next page) the landmine type, *e.g.* M14, PMN-2. It is discussed in Chapter 5 but it is out of the scope of this thesis.



**Figure 1.7.** The GPR system emulated using the hand-held VNA connected to the horn antenna via a 50-Ohm N-type coaxial cable.

- Besides being practical and affordable, GPR-based systems for humanitarian demining demand other specific requirements such as large linear dynamic range, time and amplitude stability and high down-range resolution [Chignell *et al.*, 2000]. An original aspect of this thesis is the radar system used for data collection. It consists of a low-cost hand-held VNA connected to a high-directive monostatic horn antenna, thereby emulating a SFCW radar. The complete system can be seen in Fig. 1.7. It covers several of the requirements mentioned before. A more detailed description of the system can be found in Chapter 2.3. Additionally, some experiments were carried out using the MINEHOUND<sup>TM</sup> system under GPR mode. The MINEHOUND GPR has been developed specially for landmine detection, therefore it fulfills the specific requirements for demining applications (a description is given in Chapter 5.3).
- Currently, different signal processing techniques are applied for clutter subtraction or BS. An innovative aspect of this research is that it proposes a filtering method which, compared to traditional BS techniques, permits a better differentiation of the landmine and estimation of its depth and geometrical properties.

- Together with background clutter, false alarms are also an important issue for GPR. A novel approach is proposed in this thesis using a change detection methodology based on parameter estimation as well as a new feature extraction algorithm for landmine identification.
- Despite the considerable and growing efforts in hardware and software development, landmine detection using GPR is still limited by the effects of the soil EM properties on EM wave propagation. In this thesis, an innovative aspect is that methodologies for estimating the applicability and limitations of GPR-based systems are integrated to our signal processing approach.



## Chapter 2

# Filtering Soil Surface and Antenna Effects from GPR Data\*

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*All our science, measured against reality, is primitive and childlike - and yet it is the most precious thing we have.*

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*Albert Einstein*

In this chapter, we propose a novel approach to filter out the soil surface reflection and major antenna effects from 2-D off-ground monostatic GPR data (this approach is represented in Fig. 1.6, block section 1). We validate the methodology in laboratory conditions for four differently detectable landmines embedded in a sandy soil. The methodology proposed here is particularly beneficial for the detection of landmines in low-contrast conditions.

### 2.1 Introduction

Based on wave reflections produced by EM contrasts, GPR permits to image the subsurface [Davis and Annan, 1989] with a high spatial resolution. The interpretation of the reflected EM field may yield information on subsurface structural variations. In particular, it may provide useful information on the location and geometrical properties of buried metallic and non-metallic landmines [Bruschini et al., 1998; Scheers et al., 2000; van der Kruk et al., 2003; van den Bosch, 2006]. GPR may thus be used to reduce the false alarm rate in demining labors and may permit the detection of landmines which are not

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\*Adapted from Lopera O., Slob E., Milisavljević N. and Lambot S., Filtering soil surface and antenna effects from GPR data to enhance landmine detection. IEEE Transactions on Geoscience and Remote Sensing, vol 45, pp. 707-717, 2006.

detectable by the widely used metal detector. Yet, the extraction of the landmine response using GPR is complicated by a number of factors grouped under the term clutter, which can partly or totally hide or distort the response of the landmine. The main factors are: 1) the antenna effects producing multiple reflections and signal distortion; 2) the soil EM properties and their spatial distribution governing wave propagation velocity, attenuation, and soil reflections; 3) the EM contrast between the soil and the landmine determining the strength of the landmine response; 4) soil roughness yielding diffuse scattering. Therefore, there is a need to develop appropriate techniques for clutter reduction and landmine detection, which is quite challenging due to the complex EM phenomena occurring in the a priori unknown antenna-air-soil-mine system.

Many detection techniques based on different signal processing approaches have been developed and can be classified in two major groups: pattern matching and image-then-detect. Within the first category, anomaly detection methods based on fuzzy set theory and neural networks [Plett *et al.*, 1997; Yang and Bose, 2005], and rule-based discrimination and recursive hypothesis testing based on statistical signal processing [Gader *et al.*, 2001b; Xu *et al.*, 2002] are applied for landmine detection. Such techniques require extensive databases for training and calibration to differentiate successfully the clutter from the landmine signal. In the second category, detection techniques are employed on a subsurface image built from a full GPR scan (*e.g.*, B-scan, see Appendix A for its definition) after clutter reduction. They include advanced algorithms for hyperbola detection [Delbo *et al.*, 2000; Gader *et al.*, 2001a; Milisavljevic, 2001; Zhu and Collins, 2005], convolutional models [Scheers, 2001; Roth, 2004], and migration approaches [Scheers *et al.*, 2001; van der Kruk *et al.*, 2003], and their performance depends mainly on the data set quality and the preprocessing method used to subtract the background. Most of the applied clutter reduction techniques are based on surface and subsurface reflection removal. Average and moving average background subtraction (BS) [Groenenboom and Yarovoy, 2002; Roth *et al.*, 2003; Daniels, 2004] are often used to reduce this clutter. The quality of the BS generally depends on the width of the averaging window. Additionally, the estimated average will be affected by the presence of the target, and the subtraction may not be accurate. In [Brunzell, 1999], a least-square-based approach is proposed to remove ground noise coming from surface. Its performance depends heavily on the choice of the reference clutter. A parametric clutter suppression method is proposed in [Merwe and Gupta, 2000], which uses damped exponentials to model the variations of EM amplitudes and phases due to the subsurface inhomogeneity. However, this method requires precise knowledge about the target signal, which is not available in practice. In other clutter removal approaches, the filter design is based on clutter statistics [Zhan *et al.*, 1997; Dogaru and Carin, 1998; Brooks

*et al.*, 2000; *El-Shenawee and Rappaport*, 2002; *Ho and Gader*, 2002]. Finding a robust estimate of these statistics is however difficult and usually subject to strongly simplifying assumptions. New non-statistically-based approaches that extract the response of the landmine from the raw and generally noisy radar data, without deteriorating the information it contains, are essential for further supporting landmine detection using GPR.

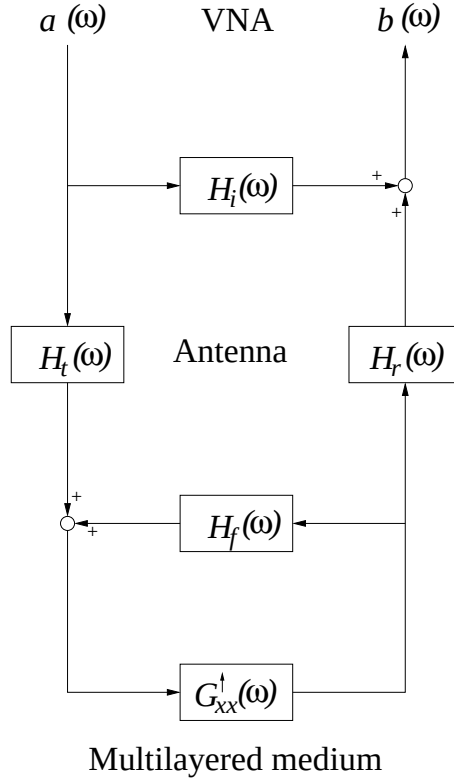
We propose here a physically-based approach for filtering out the soil surface reflection and major antenna effects from the GPR signal to enhance AP landmine detection [*Lopera et al.*, 2007c]. The GPR system consists of an UWB SFCW radar emulated using a VNA combined with a single emitting/receiving horn antenna used off the ground. The underlying processing method combines the frequency domain radar-antenna-multilayered medium model developed by *Lambot et al.* [2004] with time domain phase-shift migration. The antenna internal reflections and multiple reflections between the antenna and the ground as well as the related distortion effects are filtered out using frequency-dependent linear transfer functions. These functions also account for the antenna gain and wave propagation time, fixing time-zero at the antenna phase center. Subsequently, a calculated Green's function is subtracted from the GPR data. The Green's function is the solution of the three-dimensional (3-D) Maxwell's equations for wave propagating in multilayered media. In our case, this function accounts for wave propagation in air, including spherical divergence, and the surface reflection. The relative dielectric permittivity,  $\epsilon_r$ , of the soil surface used for the calculation of the Green's function is derived using full-wave inversion of the radar signal [*Lambot et al.*, 2005, 2006b] for a measurement taken in a local landmine-free area. The contribution of the electric conductivity,  $\sigma$ , to the surface reflection is assumed to be negligible. Finally, the effects of the antenna radiation pattern are filtered out in the time domain using the common Stolt's migration method [*Stolt*, 1978], which applies a Fourier transform to back-propagate the scalar wave equation, extended here for two media.

In this chapter, the filtering approach is validated in laboratory conditions for four differently detectable landmines embedded at different depths in homogeneous and non-homogeneous sandy soil.

## 2.2 GPR Signal Processing

### 2.2.1 Filtering Antenna Effects

**Mine-free soil.** Due to the variations of impedance between the antenna feeding point and the antenna phase center, multiple wave reflections inherently occur in the antenna and between the antenna and the soil. In common



**Figure 2.1.** The VNA-antenna-multilayered medium system modeled as linear transfer functions in series and in parallel (Figure from *Lambot et al. [2004]*). This diagram is represented by the *EM model* box in Fig. 1.6, block section 1.

off-ground GPR approaches, the antenna should be situated substantially far<sup>†</sup> from the ground to filter these effects in the time domain. However, in land-mine detection operations, the antenna should be situated relatively close to the ground to maximize the spatial resolution and SNR.

Recently, a new approach has been proposed by *Lambot et al. [2004]* for filtering major antenna effects. The method applies to SFCW radar systems operating off the ground in monostatic mode, *i.e.*, a single emitting and receiving antenna is used. Assuming that the distribution of the backscattered electric field measured by the antenna does not depend on the medium (air and subsurface layers), *i.e.*, only the amplitude and phase of the field change, the antenna can be modeled by linear transfer functions in series and in parallel, playing the role of global transmittances and reflectances, as it is shown in Fig. 2.1).

Accordingly, the following antenna equation holds and relates the quantity

<sup>†</sup> The distance (height) depends on the approach



measured by a VNA, namely,  $S_{11}(\omega)$ , to the ground response ( $G_{xx}^\uparrow(\omega)$ ):

$$S_{11}(\omega) = H_i(\omega) + \frac{H_t(\omega)H_r(\omega)G_{xx}^\uparrow(\omega)}{1 - H_f(\omega)G_{xx}^\uparrow(\omega)}, \quad (2.1)$$

where  $H_i(\omega)$ ,  $H_t(\omega)$ ,  $H_r(\omega)$  and  $H_f(\omega)$  are, respectively, the antenna return loss, the antenna transmitting and receiving transfer functions and the antenna feedback loss, that have to be determined, with  $\omega$  being the angular frequency. This antenna equation is expressed in the frequency domain and the transfer functions are frequency dependent complex quantities.

The return loss transfer function  $H_i(\omega)$  represents multiple wave reflections occurring into the antenna, due to the variations of impedance between the antenna feed point and the antenna aperture, which are independent of the medium.

Defining  $H(\omega) = H_t(\omega)H_r(\omega)$ , Eq. (2.1) can be written as

$$S_{11}(\omega) = H_i(\omega) + \frac{H(\omega)G_{xx}^\uparrow(\omega)}{1 - H_f(\omega)G_{xx}^\uparrow(\omega)}, \quad (2.2)$$

where  $H(\omega)$  accounts for the antenna gain and phase delay between the VNA calibration plane (the connection between the antenna feed point and the VNA cable) and the source and receiver virtual point (antenna phase center<sup>‡</sup>).

The feedback loss transfer function  $H_f(\omega)$  accounts for multiple wave reflections between the antenna and the subsurface.  $H_i(\omega)$  and  $H_f(\omega)$  act as global reflectances, and  $H(\omega)$  represents global transmittances.

Finally,  $G_{xx}^\uparrow(\omega)$  represents the air-soil system [Lambot *et al.*, 2004] and is defined by a Green's function, solution of the 3-D Maxwell's equations for electromagnetic waves propagating in horizontally multilayered media [Michalski and Mosig, 1997]. The emitting part of the antenna (horn) is approximated by an infinitesimal horizontal  $x$ -directed (second subscript  $x$  in  $G_{xx}^\uparrow(\omega)$ ) electric dipole (unit strength source) and the receiving part of the antenna is emulated by recording the  $x$ -directed component (first subscript  $x$  in  $G_{xx}^\uparrow(\omega)$ ) of the backscattered electric field (up arrow in  $G_{xx}^\uparrow(\omega)$ ). In the reminder of this thesis,  $G_{xx}^\uparrow(\omega)$  will be referred to as  $G(\omega)$ .

The antenna transfer function  $H_i$  can be determined from Eq. (2.2) using a measurement in free space ( $fs$ ) conditions, for which  $G(\omega) = 0$

$$H_i(\omega) = S_{11}^{fs}(\omega). \quad (2.3)$$

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<sup>‡</sup>In the far-field region of the antenna, the virtual source point represents the origin of the radiated field from which the spherical divergence is initiated, with the phase of the signal being equal at any point on the sphere.

The antenna transfer functions  $H(\omega)$  and  $H_f(\omega)$  are determined using measurements (e.g., two different heights  $a$ ,  $b$ ) above a planar metal sheet (considered as an infinite perfect electric conductor), for which  $G(\omega)$  is known accurately, and correspond therefore to a specific distribution of the measured electromagnetic field, referred here to as  $\mathcal{D}_r$

$$H_f(\omega) = \frac{\frac{S_{11}^b(\omega)}{G^b(\omega)} - \frac{S_{11}^a(\omega)}{G^a(\omega)}}{S_{11}^b(\omega) - S_{11}^a(\omega)}, \quad (2.4)$$

$$H(\omega) = \frac{S_{11}^a(\omega)}{G^a(\omega)} - S_{11}^a(\omega)H_f(\omega). \quad (2.5)$$

Once the antenna transfer functions  $H_i(\omega)$ ,  $H(\omega)$  and  $H_f(\omega)$  are known, they can be filtered out from the soil response using Eq. (2.2) as

$$G(\omega) = \frac{S_{11}(\omega) - H_i(\omega)}{S_{11}(\omega)H_f(\omega) - H_i(\omega)H_f(\omega) + H(\omega)}. \quad (2.6)$$

A conceptual requirement of this antenna model is to operate with the antenna sufficiently far from the ground. However, in order to minimize losses by spherical divergence in wave propagation, keep a high SNR, and ensure a high spatial resolution, it is essential to minimize the distance between the antenna and the ground, which is discussed next.

Consider the far-field of the antenna, or Fraunhofer region, which is commonly taken to be the radial distance from the antenna aperture as

$$R = \frac{2D^2}{\lambda}, \quad (2.7)$$

where  $D$  is the largest dimension of the transmitter at the phase center, and  $\lambda$  is the wavelength in free space. For an aperture antenna, the maximum dimension  $D$  is taken to be its diagonal. To make the Fraunhofer approximation of the point source valid, the antenna aperture should be situated at least at  $R$  from the soil surface. Equation (2.7) gives a theoretical and approximate indication and therefore, we have verified it by experiments. In *Lambot et al.* [2006a], laboratory experiments were carried out to characterize the transfer functions  $H_i(\omega)$ ,  $H(\omega)$  and  $H_f(\omega)$  of a horn antenna (the antenna used in this study) as a function of height to determine to which extend they are still correct when approaching the soil surface. From Eq. (2.7), the antenna should be placed at least at  $R=43$  cm (calculated considering the upper limit of the frequency range at 2.6 GHz, which is the limit used in this study). This means that the antenna aperture should be placed at least at 35.8 cm height<sup>§</sup>. For

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<sup>§</sup>The phase center, i.e., the virtual source and receiver point, of the antenna used in this study is located at 7.2 cm from the aperture inward the antenna (see [*Lambot et al.*, 2004]). The antenna aperture at the phase center is  $D=16$  cm.

the laboratory experiments in *Lambot et al.* [2006a], radar measurements were performed with the antenna aperture situated at 30 increasing heights  $h$  (from 1 cm to 28 cm) above a metal sheet ( $2 \times 2 \text{ m}^2$  area). Quite small errors have been observed on the transfer functions for  $h > 12$  cm. Below  $h \cong 12$  cm, these errors appear to be more significant, leading to important errors in the determination of the soil response  $G(\omega)$  for field applications. For this study, we consider that the independency of the received field distribution with respect to the medium holds (i.e, Eq. (2.6) holds) when the antenna aperture is at minimum  $h=12$  cm (antenna virtual source point at about 19 cm) in the frequency range 0.8-2.6 GHz.

**Mine-affected soil.** If the medium is the ground containing an inhomogeneity, such as a landmine, the distribution of the field received by the antenna will depend on the landmine and its relative position with respect to the antenna. Therefore, we cannot assume medium independency for the field distribution  $\mathcal{D}_r$  and Eq. (2.2) does not hold anymore. However, if we define  $\mathcal{D}_s$  as the unknown distribution of the field for a specific medium (consisting of the soil and the landmine) and using the superposition principle, we can write:

$$\mathcal{D}_s = \mathcal{D}_r + \mathcal{D}_d, \quad (2.8)$$

where the specific distribution of the landmine in the soil  $\mathcal{D}_d$  is also unknown. Consequently, Eq. (2.2) becomes:

$$S_{11,s}(\omega) = H_i(\omega) + \frac{H_r(\omega)G_r(\omega)}{1 - H_{f,r}(\omega)G_r(\omega)} + \frac{H_d(\omega)G_d(\omega)}{1 - H_{f,d}(\omega)G_d(\omega)}. \quad (2.9)$$

Here  $H_{\langle \cdot \rangle}(\omega)$  and  $H_{f,\langle \cdot \rangle}(\omega)$  are the antenna transfer functions corresponding to the field distribution  $\mathcal{D}_{\langle \cdot \rangle}$ , and  $G_{\langle \cdot \rangle}(\omega)$  is the component of the medium transfer function contributing to  $\mathcal{D}_{\langle \cdot \rangle}$ . Since  $H_d(\omega)$  and  $H_{f,d}(\omega)$  are unknown, Eq. (2.9) can be written as,

$$S_{11,s}(\omega) = H_i(\omega) + \frac{H_r(\omega)G_r(\omega)}{1 - H_{f,r}(\omega)G_r(\omega)} + f(G_d), \quad (2.10)$$

where  $f(G_d)$  is an unknown function. Then, the antenna effects related to the field distribution  $\mathcal{D}_r$  can be filtered out as follows:

$$\begin{aligned} G^*(\omega) &= \frac{S_{11,s}(\omega) - H_i(\omega)}{H_r(\omega) + S_{11,s}(\omega)H_{f,r}(\omega) - H_i(\omega)H_{f,r}(\omega)} \\ &= G_r(\omega) + f(G_d) \frac{1 - H_{f,r}(\omega)G_r(\omega)}{H_r(\omega) + S_{11,s}(\omega)H_{f,r}(\omega) - H_i(\omega)H_{f,r}(\omega)}, \end{aligned} \quad (2.11)$$

with  $G^*(\omega)$  being the data filtered from antenna effects. If  $G_d(\omega) = 0$ , as assumed in *Lambot et al.* [2004], then  $G^*(\omega) = G_r(\omega)$  and the antenna effects are theoretically completely filtered out. If  $G_r(\omega) = 0$ , then  $G^*(\omega) = S_{11,s}(\omega) - H_i(\omega)$  and the antenna effects are only partly removed.

For landmine detection applications, the contribution of the landmine to the measured signal  $S_{11,s}(\omega)$  is expected to be small compared to the contribution of the soil, because the landmine usually represents a small portion of the area illuminated by the antenna. This is particularly true for AP landmines while using the antenna off the ground. This contribution is further reduced when the antenna moves aside the landmine. As a result,  $G_r(\omega)$  is expected to be always significant and, therefore, Eq. (2.11) should still permit the removal of major antenna effects. When the landmine is just beneath the antenna, it may also contribute significantly to  $G_r(\omega)$  and thus improving antenna effect removal.

### 2.2.2 Filtering the Soil Surface Reflection

A major source of clutter contributing to obscure the response of the landmine is the surface reflection, which is always substantial due to the high impedance contrast between the air and the soil. The surface reflection may be removed from a full GPR transect by subtracting from all measurements a mean measurement or an one-dimensional (1-D) measurement (A-scan) performed over a landmine-free area (see Appendix A for the definition of A-scan). However, this requires that the surface electromagnetic properties have not varied over the transect, that all measurements have been performed with the antenna situated exactly at the same height above the ground and a flat ground surface. In practical demining applications, these requirements cannot be satisfied.

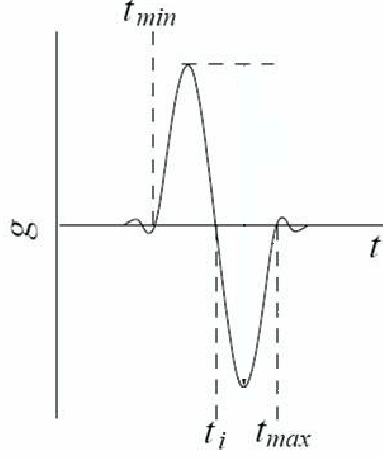
The new approach proposed in this study for filtering the soil surface reflection is to subtract from the radar signal, preliminarily filtered for antenna effects, a computed Green's function describing wave propagation with the antenna in air above a single interface (mine-free soil surface). To compute that Green's function, two parameters should be known: 1) the soil surface relative dielectric permittivity  $\varepsilon_r$ ; 2) the antenna height  $h$ . Note that the contribution of the electric conductivity  $\sigma$  to the surface reflection is assumed to be negligible, which is a valid assumption if  $\sigma < 0.1$  S/m (most soils).

In order to identify  $\varepsilon_r$  and  $h$ , we use full-wave inversion of the radar signal pre-filtered from antenna effects (Eq. (2.6)) and focused on the surface reflection in the time domain [Lambot *et al.*, 2005, 2006b]. In this case, parameter identification by inverse modeling is a non-linear optimization problem which consists in finding the parameter vector  $\mathbf{b} = [\varepsilon_r, h]$  so that an objective function  $\phi(\mathbf{b})$  is minimized. In the particular case where no prior information on the parameters is taken into account and assuming observation errors to be normally distributed, independent and homoscedastic, the maximum likelihood theory reduces to the classical least square problem.

The inversion problem<sup>¶</sup> is then formulated in the least-squares sense and

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<sup>¶</sup>The inversion problem is represented by the *EM model*, *Error function* and *Optimization*



**Figure 2.2.** Sketch of the windowed radar signal in the time domain after removing antenna effects (Figure from *Lambot et al.* [2006b]). Times  $t_{min}$  and  $t_{max}$  define the time window focused on the surface reflection on which inversion is performed and  $t_i$  is the time corresponding approximately to the surface interface in the space domain.

the objective function is accordingly defined as follows [*Lambot et al.*, 2004, 2005]:

$$\phi(\mathbf{b}) = (\mathbf{g}^* - \mathbf{g}')^T (\mathbf{g}^* - \mathbf{g}'). \quad (2.12)$$

Here

$$\mathbf{g}^* = g^*(t) \Big|_{t_{min}}^{t_{max}} \quad \text{and} \quad \mathbf{g}' = g'(t) \Big|_{t_{min}}^{t_{max}} \quad (2.13)$$

are the vectors containing, respectively, the observed and simulated time domain windowed Green's functions, i.e., the measured and modeled frequency domain Green's functions are first transformed in the time domain using the inverse Fourier transform  $F^{-1}$

$$g(t) = F^{-1}\{G(\omega)\} = \frac{1}{2\pi} \int e^{i\omega t} G(\omega) d\omega, \quad (2.14)$$

where  $t$  is time and  $i = \sqrt{-1}$ . Then, a time window is defined between  $t_{min}$  and  $t_{max}$  (see Fig. 2.2), focused on the surface reflection (note that, after applying Eq. (2.6), the real time-zero is fixed at the phase center of the antenna).

These vectors are arranged versus frequency. Since the Green's functions are complex quantities, the difference between observed and modeled data is expressed by the amplitude of the errors in the complex plane. Objective function (2.12) is two-dimensional (2-D) and its minimization can be performed using the local Nelder-Mead simplex algorithm [*Lagarias et al.*, 1998].

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algorithm boxes in Fig. 1.6, block section 1.

An initial guess for the antenna elevation  $h$  is derived from the root  $t_i$  of the signal between the positive and negative peaks of the surface reflection (see Fig. 2.2). The initial guess for the relative dielectric permittivity is arbitrary chosen in the range  $2.5 \leq \varepsilon_r \leq 20$ . This procedure leads always to the global minimum of the objective function [Lambot *et al.*, 2004, 2005, 2006b].

This approach has been validated and applied with success in laboratory and field conditions for identification of the soil relative dielectric permittivity ( $\varepsilon_r$ ) [Lambot *et al.*, 2004, 2005, 2006b]. Results are compared with the estimated  $\varepsilon_r$  from TDR (Time Domain Reflectometry) measurements and pedotransfer models such as Toop's equation [Toop *et al.*, 1980]. Figure 2.3 represents some of these results. The inversely estimated relative dielectric permittivity is illustrated as a function of nine different water content levels for a sand layer. Results are very consistent. A sensitivity analysis has been also handled in Lambot *et al.* [2004] in order to investigate the relation between the accuracy of the derived  $\varepsilon_r$  and the accuracy of the modeled Green's function. For this analysis, synthetic Green's function were generated for a given scenario, for which  $\varepsilon_r$  is known exactly. Then, errors were added to the synthetic data and inversions were performed afterwards to estimate back the original  $\varepsilon_r$ . Results have shown that relative errors between 0 and 3 on the simulated data can lead to absolute errors  $\Delta\varepsilon_r$  between 0 and 0.026, which, for our application, is negligible.

Once the soil surface dielectric permittivity is known, synthetic Green's functions  $G'(\omega)$  can be calculated for any radar measurement, whatever the antenna height, and subsequently subtracted from the corresponding pre-filtered radar data  $G^*(\omega)$  (Eq. (2.11)) as

$$R_{obj}(\omega) = G^*(\omega) - G'(\omega). \quad (2.15)$$

The obtained quantity,  $R_{obj}(\omega)$ , is considered as the response of the buried target<sup>||</sup>.

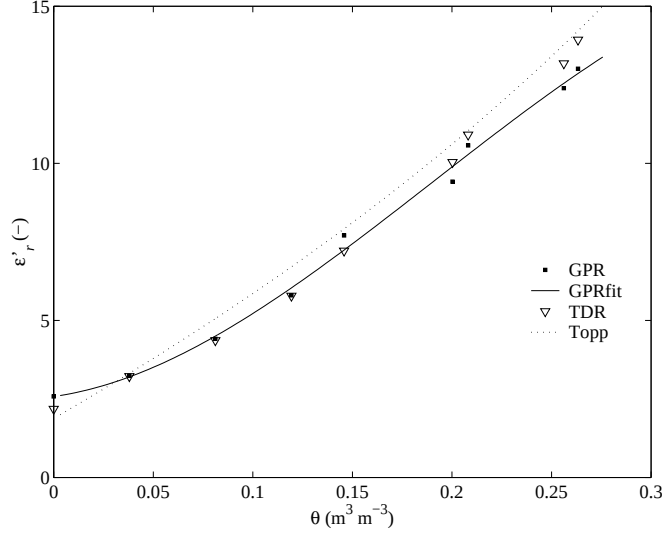
It is worth noting that the single measurement in a local mine-free area used to estimate the soil surface dielectric permittivity can be collected at any time in any surrounding, mine-free area, and therefore, the tempo-spatial variability of the soil properties can be partly taken into account to filter the surface reflection.

### 2.2.3 Focusing the Preprocessed Signal

The radar antenna transmits energy with a beamwidth pattern such that an object several centimeters away from the beam axis may be detected. As a result,

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<sup>||</sup>Equations (2.11) and (2.15) account for the *Filtering algorithm* box in Fig. 1.6, block section 1.



**Figure 2.3.** Estimated relative dielectric permittivity ( $\epsilon'_r$ ) for a sand layer as a function of its water content ( $\theta$ ). Square and triangular markers pertain, respectively, to GPR and TDR measurements, dotted line represents Topp's model, and solid line is a third-degree polynomial equation fitted to GPR measurements (Figure from *Lambot et al.* [2004]).

objects of finite dimensions appear as hyperbolic reflectors on the radar 2-D profiles, or B-scans (see Appendix B for more details about hyperbola formation). Migration techniques are used to reconstruct the reflecting structure present in the subsurface by focusing the reflections back into the true position of the object. Diffraction stacking method is quite used for shape reconstruction of subsurface objects [Takahashi, 2006]. However, some artifacts may appear in the migrated data when no target is present. This could be a problem in landmine detection since these artifacts could be considered as targets. A migration methodology by deconvolution is proposed in *Scheers et al.* [2001] for landmine detection. Since it applies to 3-D data and we are analyzing 2-D data, we have not considered it for this study. Another migration algorithm has been proposed in *van der Kruk et al.* [2003] for imaging subsurface objects. However, it applies to 3-D, multicomponent measurements using a bistatic radar, which is not the case in our study. We propose to adapt the phase-shift migration method to be applied to 2-D data from an off-ground monostatic radar. Phase-shift migration is based on a transformation from the frequency domain  $\omega$  to the wavenumber domain  $k$ . It was first applied for seismic imaging by Stolt in 1978 [Stolt, 1978]. The principle has been adopted for satellite SAR (Synthetic Aperture Radar) processing [Cafforio et al., 1991] and it has also been widely utilized for the image processing of GPR data [Yu et al., 1996].

| Type              | Metal content | Diameter (cm) | Height (cm) | Case material |
|-------------------|---------------|---------------|-------------|---------------|
| Antitank (AT)     | high          | 25            | 8           | Plastic       |
| PMN2 (AP)         | low           | 12.5          | 5.2         | Plastic       |
| M14 (AP)          | low           | 5.6           | 4.2         | Plastic       |
| SIM12 (ITOP - AP) | no            | 12            | 4           | Plastic       |

**Table 2.1.** Characteristics of the four landmines buried in the sand. The AT landmine is a surrogate of the 72MT, the PMN2 is a Russian AP landmine, the M14 is an American AP landmine and the SIM12 is a standard test target with a non-metallic fuze.

Consider the filtered signal  $r_{obj}(t)$  (Eq. (2.15) in the time domain) as a 2-D data set  $r(x, z, t)$  which satisfies the radar wave equation

$$\nabla^2 r(x, z, t) - \mu\epsilon \frac{\partial^2}{\partial t^2} r(x, z, t) = 0, \quad (2.16)$$

with  $x$  being the distance along the scanning axis,  $z$  the depth and  $\mu$  the magnetic permeability of free space.

Applying a Fourier transformation to Eq. (2.16) with respect to the time  $t$  and the spatial distance  $x$  results in

$$\frac{\partial^2}{\partial z^2} R(k_x, z, \omega) = \left( \frac{\omega^2}{v^2} - k_x^2 \right) R(k_x, z, \omega), \quad (2.17)$$

where  $v$  is the propagation velocity in the ground ( $v = c_0/\sqrt{\epsilon_r}$ , being  $c_0 = 3 \times 10^8 \text{ ms}^{-1}$  the speed of light in vacuum) and  $R(k_x, z, \omega)$  is the 2-D Fourier transform of  $r(x, z, t)$  defined as

$$R(k_x, z, \omega) = \int \int r(x, z, t) e^{-(ik_x x - \omega t)} dx dt. \quad (2.18)$$

The Fourier transformation along the  $x$  coordinate makes sense only if the propagation velocity does not vary in this direction. The method allows variations of the propagation velocity in the  $z$  direction.

Considering the wavenumber  $k$  ( $k = 2\pi/\lambda$ , with  $\lambda$  being the wavelength in the ground) as the vector sum of  $k_x$  and  $k_z$  for one-way propagation, we have:

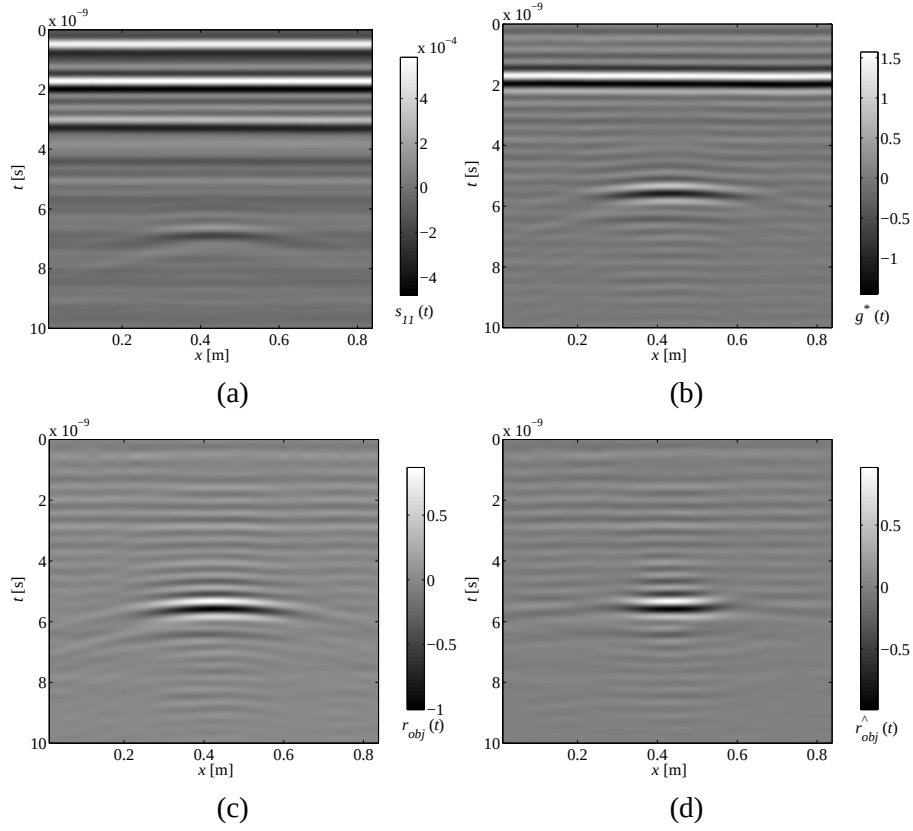
$$k = |\mathbf{k}| = \sqrt{k_x^2 + k_z^2} = \frac{\omega}{v}, \quad (2.19)$$

and by introducing  $k_z$  from Eq. (2.19) in Eq. (2.17), Eq. (2.17) has a general solution

$$R(k_x, z, \omega) = A e^{ik_z z} + B e^{-ik_z z}. \quad (2.20)$$

The constants A and B in Eq. (2.20) are found using the following two boundary conditions:





**Figure 2.4.** Time domain representation of radar measurements performed in a homogeneous sand ( $\varepsilon = 2.9$ ) for the AT landmine buried at 30 cm depth: (a) measured signal  $s_{11}(t)$ , (b) major antenna effects filtered from  $s_{11}(t)$ , (c) soil surface reflection filtered by removing synthetic Green's function from signal  $g^*(t)$  and (d) antenna radiation pattern effect filtered by migration.

- Assuming only upcoming waves,  $A=0$
- For  $z=0$ ,  $B = R(k_x, 0, \omega)$ .

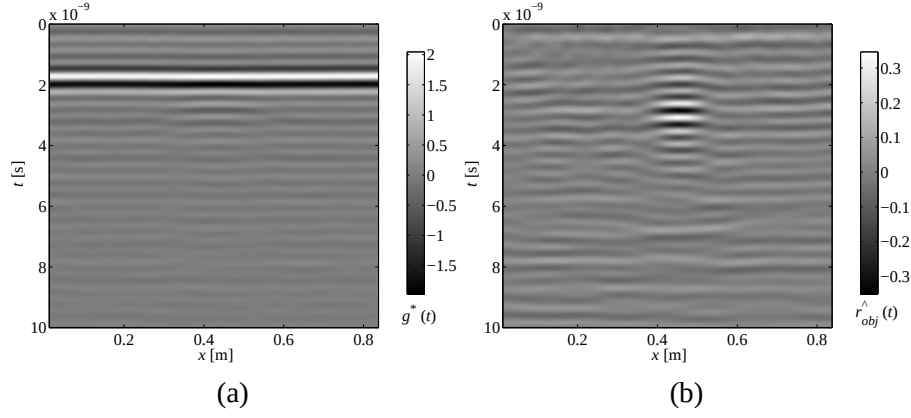
Finally, Eq. (2.20) becomes:

$$R(k_x, z, \omega) = R(k_x, 0, \omega)e^{-ik_z z}, \quad (2.21)$$

which represents the Fourier transform of the wave-front at depth  $z$ .

The migrated image will be the 2-D inverse Fourier transform of Eq. (2.21) at  $t=0$  as

$$\hat{r}(x, z) = \int \int R(k_x, 0, \omega) e^{-i(k_x x + k_z z)} dk_x d\omega|_{t=0}. \quad (2.22)$$



**Figure 2.5.** Time domain representation of radar measurements performed in a homogeneous sand ( $\varepsilon = 2.8$ ) for the PMN2 AP landmine buried at 10 cm (raw data not presented): (a) major antenna effects filtered from the measured signal  $s_{11}(t)$  and (b) antenna radiation pattern filtered by migration after removing synthetic Green's function from signal  $g^*(t)$ .

Equation (2.22) is the general representation of the phase-shift migration. In order to reduce the calculation time, a variant of the phase-shift migration developed by Stolt [Stolt, 1978] is applied. In the special case where  $v(z)$  is constant, Eq. (2.22) can be further developed by changing the variable  $d\omega$  to  $dk_z$  from Eq. (2.19) as

$$d\omega = \frac{k_z v^2}{\omega} dk_z. \quad (2.23)$$

Hence, Eq. (2.22) becomes:

$$\hat{r}(x, z) = v^2 \int \int \frac{k_z}{\omega} R(k_x, 0, \omega) e^{-i(k_x x + k_z z)} dk_x dk_z. \quad (2.24)$$

The implementation of Eq. (2.24)\*\* using the Fourier transform in depth direction is valid only for a constant propagation velocity case. However, there is a discontinuity at the air-ground interface due to the off-ground antenna configuration. Following the approach of Lopera *et al.* [Lopera *et al.*, 2005], migration is applied considering the antenna at  $\hat{h} = 0$  cm above the surface. This can be done by calculating the diffraction point  $x_d$  for all measurement points along the  $x$ -axis. Starting from Snell's law of refraction and assuming the air-ground interface flat, a system of three equations is obtained which can

\*\* Equation (2.24) accounts for the *Migration algorithm* box in Fig. 1.6, block section 1.

be solved iteratively:

$$x_d = z_0 \tan(\theta'), \quad (2.25a)$$

$$\theta' = \sin^{-1} \left( \frac{\sin(\theta)}{\sqrt{\varepsilon_r}} \right), \quad (2.25b)$$

$$\theta = \tan^{-1} \left( \frac{x - x_d}{h} \right), \quad (2.25c)$$

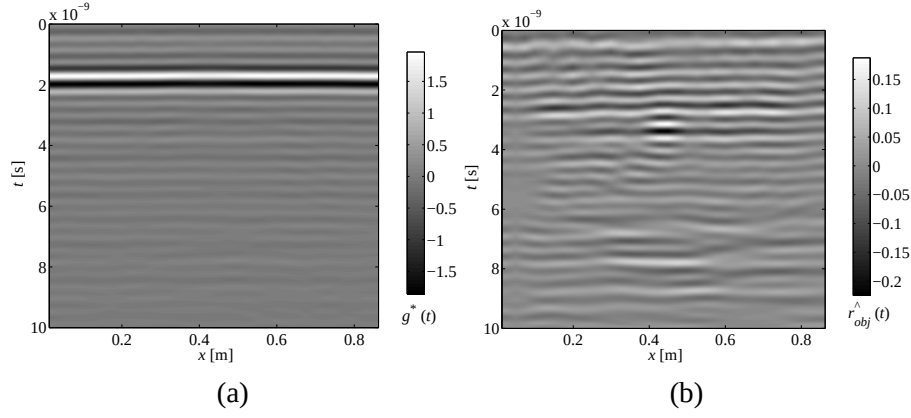
where  $\theta$  is the inference angle,  $\theta'$  is the refraction angle for the subsurface and  $z_0$  is the depth of the buried object (extracted from  $r_{obj}(t)$ ). The real position of the antenna  $x$  is thus considered at the diffraction point  $x_d$ , for  $\hat{h} = 0$  cm.

## 2.3 Experiment Description

Laboratory experiments were performed over a homogeneous sand at the test facilities of the TNO (The Hague, The Netherlands) and at the Catholic University of Louvain, UCL (Louvain-la-neuve, Belgium). The GPR system consists of an UWB SFCW radar that we emulate using a low-cost hand-held VNA connected to a monostatic horn antenna via a 50  $\Omega$  N-type coaxial cable. The VNA is composed of a spectral analyzer (FSH6, Rohde&Schwarz, Munich, Germany) equipped with a bridge and power divider (VSWR, Rohde&Schwarz, Munich, Germany) to enable vector measurements. The antenna we use for the measurements is a linear polarized double ridged broadband horn antenna (BBHA 9120A, Schwarzbeck Mess-Elektronik, Schönaue, Germany), whose dimensions are 22 cm length and  $14 \times 24$  cm<sup>2</sup> aperture area. For this application and from antenna characteristics, we can consider it as directive (3-dB beam width of 45° in the E-plane and 30° in the H-plane at 1 GHz and 27° in the E-plane and 22° in the H-plane at 2 GHz, operating in the 0.8-5.0 GHz frequency range). In this study, the measurements were performed in the range 0.8-2.6 GHz with a frequency step of 6 MHz.

Besides being practical and affordable, this SPCW radar covers several of the requirements mentioned in Chapter 1. It has a linear dynamic range of 60 dB, which allows to detect weak scatterers. Antenna ringing is accurately determined and taken in to account in the EM model described in the previous chapter. Therefore, it does not affect negatively the signal-to-noise ratio of the system. The effect of amplitude drift (that can be due to mechanical or temperature changes on the connection point or the antenna) is limited by a simple and accurate calibration procedure using a standard Open-Short-Match calibration kit, which can be repeated during the data acquisition process.

Radar measurements were performed over four different cylindrical landmines (antitank (AT), and AP), whose characteristics are described in Table



**Figure 2.6.** Time domain representation of radar measurements performed in a homogeneous sand ( $\varepsilon = 2.8$ ) for the M14 AP landmine buried at 12 cm (raw data not presented): (a) major antenna effects filtered from the measured signal  $s_{11}(t)$  and (b) antenna radiation pattern filtered by migration after removing  $g'(t)$  from signal  $g^*(t)$ .

2.1. They were placed horizontally, longest side up. The relative dielectric permittivity of the sand varied from 2.7 to 5.5, depending on the water content. To acquire 2-D data, the radar system was moved along the horizontal  $x$ -axis, crossing the center of the buried objects, using a scanning frame. Radar traces ( $S_{11}$ ) were recorded with a constant space step of 2 cm and 2.5 cm. The height of the antenna aperture above the sand was 20 cm (antenna phase center at 27 cm).

## 2.4 Results and Discussions

The whole signal processing approach described here is applied to 2-D data from four different landmines following the next five steps:

- Step 1: Filter out major antenna effects  $H_i$ ,  $H$  and  $H_f$ .
- Step 2: Retrieve the soil surface relative dielectric permittivity  $\varepsilon_r$  by full-wave inversion of a measured Green's function (prefiltered A-scan) from a mine-free area.
- Step 3: For each single acquisition (A-scan) of the B-scan, subtract its synthetic Green's function calculated after detection of the antenna height.
- Step 4: Normalize the antenna height and retrieve the landmine depth from the apex of the enhanced hyperbolic signature.
- Step 5: Focus the preprocessed 2-D data to identify the landmine shape.

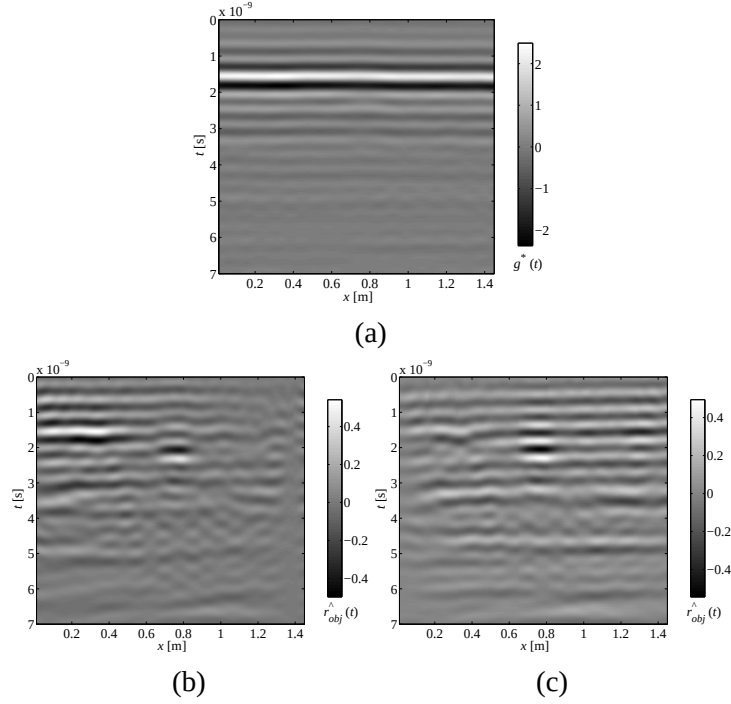
### 2.4.1 Antitank Landmine

Figure 2.4 represents the different filtering stages applied to the raw radar data for the AT landmine buried at a depth of 30 cm measured from the top. In Fig. 2.4(a), the 2-D raw radar data are presented in the time domain. Between about 0-2 ns, we can observe the multiple reflections occurring in the antenna. These reflections distort the signal for later times as well. At around 3.2 ns, the soil surface reflection is visible. Then a second order reflection occurring between the antenna and the soil surface comes at about 4.5 ns. Finally, the hyperbola originating from the AT landmine appears around 6.5 ns. The detection of this landmine in raw data is facilitated by its relatively large size, the strong electromagnetic contrast between the sand and the landmine, which contains metal, and by the low attenuation of the electromagnetic waves in the sand (the electric conductivity tends to zero).

Results of Step 1 are presented in Fig. 2.4(b). The true time zero corresponds now to the antenna phase center, situated at about 7 cm from the antenna aperture, inside the antenna, resulting in a time-shifting (Note that the soil reflection and hyperbola originating from the AT landmine is shifted in time). The multiple antenna reflections have vanished and the air-surface interface reflection is clearly distinguished, around 1.9 ns. This permits the accurate extraction of the antenna height. Then, the hyperbolic signature of the AT landmine is accentuated. The remaining oscillations visible in the B-scan could stem from the different hypothesis used in the model, mainly, (i) the far-field approximation, (ii) the virtual source and receiver point of the antenna which is assumed to be at a fixed position (actually, its position changes with frequency, the high frequencies being emitted nearer the feed point, and the low frequencies being emitted in the proportionally larger part of the antenna), (iii) the fact that only the  $x$ -component of the electric field is assumed to be measured and that only an  $x$ -directed current source is present. It could be also an artefact of the inverse Fourier transform applied to data taken in a limited frequency range. However, these oscillations do not represent a drawback for the detection and identification of AP landmines, as shown later in this document.

Step 2 permits to identify the sand surface dielectric permittivity,  $\varepsilon_r = 2.9$ . Results of Step 3 are shown in Fig. 2.4(c). The effect of the AT landmine ( $R_{obj}$ ) is isolated, which permits to differentiate the hyperbolic signature. Step 4 yields a landmine depth of 31.3 cm (real depth is 30 cm). The small (compared to the target size) error of 1.3 cm with respect to the real target depth can be explained by the fact that, for the migration, we are considering the AP landmine as a point reflector.

As the measurements are carried out using a scanning frame at a constant height, changes after shifting the antenna height are not noticeable.



**Figure 2.7.** Time domain representation of radar measurements performed in an inhomogeneous sand ( $3.9 < \epsilon < 5.5$ ) for the SIM12, with a non-metallic fuze, buried at 4 cm (raw data not presented): (a) major antenna effects filtered from the measured signal  $s_{11}(t)$ , (b) antenna radiation pattern filtered by migration after removing  $g_1'(t)$  from signal  $g^*(t)$  and (c) antenna radiation pattern filtered by migration after removing  $g_2'(t)$  from signal  $g^*(t)$ .

Finally, Step 5 permits to filter the antenna radiation pattern by focusing the object scattered data into their origin. The migrated data from Fig. 2.4(c) can be seen in Fig. 2.4(d). The shape of the AT landmine along the scanning axis becomes clear.

### 2.4.2 Antipersonnel Landmines

The same methodology is applied to two different AP landmines. Results for the PMN2 and M14 low-metallic AP landmines buried at a depth of 10 cm and 12 cm, measured from the top, can be seen in Fig. 2.5 and Fig. 2.6, respectively. In the raw radar data, the effect of the landmines is not visible (results not shown). After Step 1, the air-surface interface reflection appears around 1.9 ns. This strong return covers the reflection from the landmines. The hyperbolic signature can be hardly seen for the PMN2 AP landmine in Fig. 2.5(a), between 2 ns and 3 ns, and it cannot be seen at all for the M14 AP landmine, in Fig. 2.6 (a). The relative dielectric permittivity of the soil ( $\epsilon_r =$

2.8, identified by Step 2) is quite similar to those of the landmines, leading to low-contrast conditions. After Step 3, the hyperbolic signature is accentuated, and in Step 4 we find a burial depth of 10.45 cm (real depth is 10 cm) for the PMN2 AP landmine and 11.86 cm (real depth is 12 cm) for the M14 AP landmine. Small (with respect to the target size) errors of some millimeters are found for the estimated target depths, which can be explained from the assumption of a point reflector instead of a 3-D shape reflector.

Results of Step 5 are shown in Fig. 2.5 (b) and Fig. 2.6 (b), respectively. The shape of the landmines along the scanning axis is clearly distinguished. Despite their small size and low-contrast conditions, information about their position and form can be extracted from the processed data.

### 2.4.3 Inhomogeneous Soil

In the laboratory experiments presented above, the dielectric permittivity of the surface is assumed to be homogeneous. However, the soil is an inhomogeneous medium and therefore, its properties vary with position along surface and depth even for small-scales, *i.e.*, several centimeters, which is the range of study for landmine detection with GPR. In this context, the filtering approach is also applied in a sand whose  $\varepsilon_r$  varies horizontally, over a distance of 1.4 m. Results are shown in Fig. 2.7 for the SIM12 standard test target, with a non-metallic fuze, buried at the depth of 4 cm measured from the top. In the raw radar data, the effect of the landmine is not visible (results not shown). Results of Step 1 are presented in Fig. 2.7 (a), and the strong air-surface interface reflection appears at around 1.6 ns obscuring the hyperbolic signature of the landmine. Step 2 is applied to two local landmine-free areas and two different  $\varepsilon_r$  are retrieved:  $\varepsilon_{r,1} = 3.9$ ,  $\varepsilon_{r,2} = 5.5$ . After Step 3, the hyperbolic signature is accentuated, and in Step 4 we find a burial depth of 4.56 cm (preprocessing with  $\varepsilon_{r,1}$ ) and 3.84 cm (preprocessing with  $\varepsilon_{r,2}$ ). Note that the variation of the estimated values of  $\varepsilon_r$  ( $\Delta\varepsilon_r=1.6$ ) lead to small errors (some millimeters) on the estimation of the target depth, which could be also an effect of the point reflector assumption, as stated before for the AT landmine and the M14 and PMN-2 AP landmines.

Results after Step 5 are presented in Figs. 2.7 (b) and (c), respectively, where the shape of the target can be recognized. To deal with soil inhomogeneity, migration could be also performed using an average of the encountered  $\varepsilon_{r,1}$  and  $\varepsilon_{r,2}$ .

Since such a variation ( $\Delta\varepsilon_r=1.6$ ) on the estimated values of  $\varepsilon_r$  leads to a good approximation of the target depth and shape, the influence of small variations of  $\varepsilon_r$  due to the accuracy of the modeled Green's function is expected to be negligible.

Due to the inhomogeneous soil, the surface reflection persists in some ar-

eas, as can be seen in the first 50 cm along the scanning distance in Fig. 2.7 (b), and sparsely along the last 80 cm in Fig. 2.7 (c). However, its amplitude is weaker than that of the landmine reflection and the landmine shape can be distinguished in both filtered data. It is recommended to collect two or three different single radar measurements in local mine-free areas for comparing results when data is acquired under uncontrolled conditions.

The soil can be also vertically inhomogeneous (*e.g.*, layers in the subsurface). After radar data processing, these inhomogeneities are also accentuated, as can be seen in Fig. 2.5 (b) for layer reflections between 6 ns and 10 ns, as well as in Fig. 2.6 (b) between 2 ns and 3 ns and beneath 6 ns. In Fig. 2.7 (b) and (c), reflections beneath 3 ns correspond to the bottom of the sand layer (concrete). Nevertheless, the migration algorithm helps to identify the shape of the buried landmine and to differentiate from these inhomogeneities.

#### 2.4.4 A Comparison with BS by System Identification

The proposed approach to filter the soil surface reflection is compared to a system identification (SI) method described in Appendix C. For practical reasons, Steps 1 and 2 are first applied and Step 3 is replaced by SI. Note that in the case of applying SI without removing the antenna effects (Step 1), the burial depth of the landmine cannot be found and results would not be comparable. Additionally,  $\varepsilon_r$  (identified in Step 2) is necessary in the phase-shift migration algorithm. For the new Step 3, the same single acquisitions used to calculate  $\varepsilon_r$  by the proposed methodology are used here to derive the estimate of the *ground* signal (see Appendix C for its definition) for each B-scan. The pre-processed signal is then focused in Step 5 and results are given in Fig. 2.8, drawing a comparison. This figure presents only the single acquisition nearest to the center of the landmine after Step 1 and Step 5 (by the two methods) for the AT, PMN2 and M14 landmines. Results using the proposed methodology are given in the left column and results by SI are in the right column. Fig. 2.8 (a) clearly shows for the AT landmine how the SNR is extremely ameliorated after filtering. Results are less satisfactory in Fig. 2.8 (b), where the SI method leads to information loss on the amplitude of the AT landmine reflection. This drawback is critical in low-contrast conditions, as can be seen in Figs. 2.8 (d) and (f), for the PMN2 and M14 AP landmines, respectively. After applying SI, part of the information on the amplitude of the landmine reflection is lost, and the hyperbola signature is still obscured by the residual noise. This undesired effect does not occur after filtering the synthetic Green's function, as seen in Figs. 2.8 (c) and (e). Although the AP landmine responses are very weak (compared to the AT landmine response) and are intermingled with the surface reflection, the proposed methodology gives a better SNR. This improves migration results and, therefore, facilitates landmine detection and character-



ization. This is noticeable for the M14 AP landmine. The M14 is one of the smallest low-metallic AP landmines in the world (5.6 cm of diameter and 4.2 cm of height). Low-contrast conditions make its detection by GPR difficult. However, we demonstrate that information about the burial depth and shape from this small AP landmine can be extracted using the proposed methodology, under the controlled laboratory conditions.

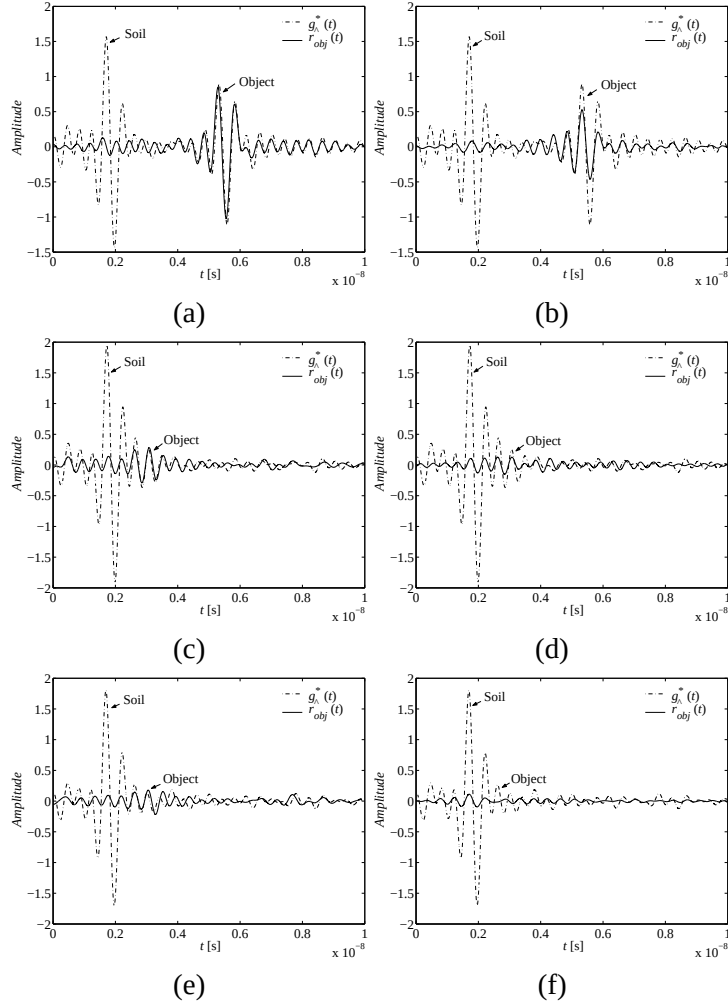
We draw the same parallel for the SM12 standard test target. Results using the proposed methodology are shown in the left column of Fig. 2.9 and results by SI are in the right column. As for the previous comparisons, this figure presents only the single acquisition nearest to the center of the landmine after Step 1 and Step 5. Results of filtering out the synthetic Green's functions, calculated using  $\varepsilon_{r,1}$  and  $\varepsilon_{r,2}$ , are presented in Figs. 2.9 (a) and (c), respectively. By applying the SI approach, the undesired reduction effect on the landmine reflection amplitude occurs after filtering out the estimate of the *ground* signal, which is calculated from the same single acquisition used to derive  $\varepsilon_{r,1}$  and  $\varepsilon_{r,2}$ . Results are given in Figs. 2.9 (b) and (d), respectively. These results emphasize how the SNR is improved using the proposed methodology. All results illustrate the appropriateness of the proposed approach for filtering the antenna and soil effects and enhancing the detection of landmines, even AP landmines in low-contrast conditions. The depth and shape are accurately retrieved and their sizes can be differentiated, from the largest one (the AT landmine) to the smallest one (the M14 AP landmine).

## 2.5 Conclusion

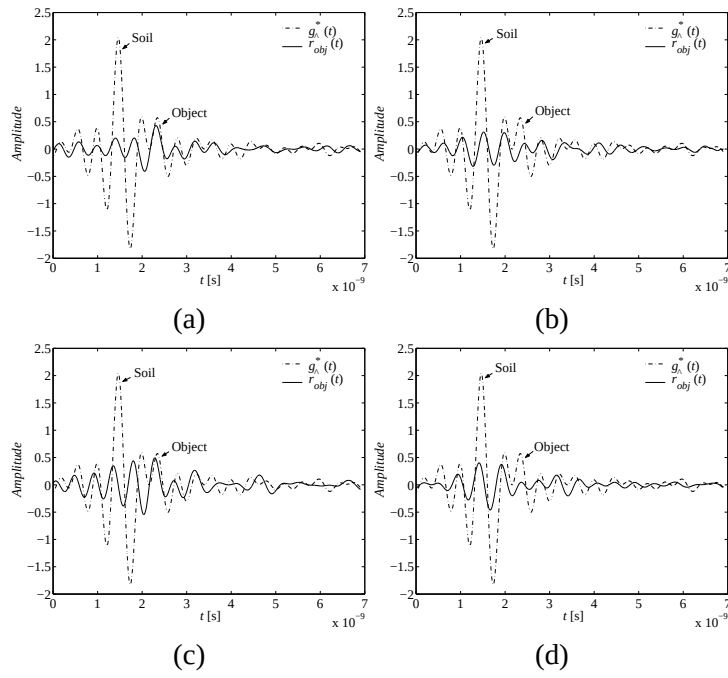
In this chapter, a new filtering approach for enhancing AP landmine detection using GPR is applied and validated under different conditions. The proposed physically-based methodology uses a recently developed radar-antenna-subsurface model in conjunction with phase-shift migration. Major antenna effects are removed using linear transfer functions. The strong air-surface interface reflection is eliminated by subtraction of simulated Green's functions. These functions are derived from the estimated  $\varepsilon_r$  of the soil surface using full-wave inversion of a single radar measurement in a local landmine-free area, and from the height  $h$  of the antenna. The influence of small variations of  $\varepsilon_r$  due to the accuracy of the modeled Green's function is expected to be negligible. The effect of the antenna radiation pattern is filtered out by focusing the scattered signals back to their point of origin. The radar-antenna-subsurface model used here allows removal of major antenna effects and soil surface reflection, resulting in a better SNR without losing information on the amplitude and shape of the landmine response. The latter is the dominant contributor in the clutter reduced radar data and therefore, it can be easily distinguished

using a migration algorithm. The whole methodology yields a set of parameters, namely,  $\varepsilon_r$  of soil, antenna height and landmine depth and shape. A comparison is drawn with a SI method and the proposed methodology shows promising results, even for low-contrast conditions and small landmines.

Natural inhomogeneities have to be considered in real soil conditions, where several single acquisitions in local landmine-free areas can be collected at any time. In the following chapter, this approach is applied on data acquired on real mine-affected soils, for different types of AP landmines.



**Figure 2.8.** Preprocessed radar signal  $g^*(t)$  and landmine response  $\hat{r}_{obj}(t)$  extracted by the two methodologies. Signals correspond to the single acquisition nearest the center of the landmine. Results using the proposed approach are in the left column and results by applying SI are in the right column, for: (a) & (b) the AT landmine, (c) & (d) the PMN2 AP landmine and (e) & (f) the M14 AP landmine.



**Figure 2.9.** Preprocessed radar signal  $g^*(t)$  and landmine response  $\hat{r}_{obj}(t)$  extracted by the two methodologies. Signals correspond to the single acquisition nearest the center of the SIM12 standard test target. Results using the proposed approach are in the left column and results by applying SI are in the right column. Two filters are used considering two single radar acquisitions in different local landmine-free areas (up:  $\varepsilon_{r,1} = 3.9$ , down:  $\varepsilon_{r,2} = 5.5$ ).

## Chapter 3

# Filtering GPR Data: Application to Real Mine-affected Soils\*

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*In theory, there is no difference between theory and practice. But, in practice, there is.*

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*Jan L.A. van de Snepsheut*

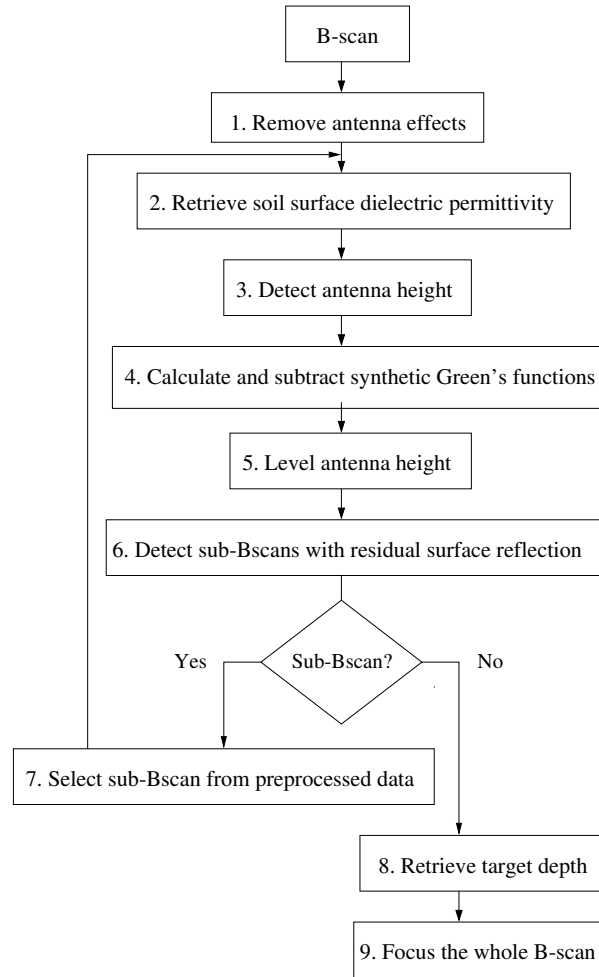
Recently, statistics of landmine victims ranked Colombia as the first most heavily mine-affected country in the world [ICBL, 2006]. The high rate of casualties is due to the amount of non-metallic IEDs buried in this country, which are very difficult to detect and cause accidents in demining activities with the traditional metal detector. Low and non-metallic devices are also the problem of other mine-affected countries. In this Chapter, the methodology developed in Chapter 2 is applied to these devices and Colombian mine-affected soils are considered for the data acquisition.

### 3.1 Introduction

In this chapter, we apply the proposed filtering approach of Chapter 2 to enhance the detection of shallowly buried AP landmines from data acquired in mine-affected soils [Lopera et al., 2007a]. Since measurements are carried out under non-controlled conditions, the algorithm is adapted to consider changes in  $\varepsilon_r$  due to natural inhomogeneities in the field soil. These changes in soil water distribution can add clutter to the GPR signal. A sub-process is added for subtracting this clutter and GPR data are filtered following the block diagram of Fig 3.1. Data are collected over two Colombian mine-affected soils and

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\*Adapted from Lopera O., Milisavljević N. and Lambot S., Clutter reduction in GPR measurements for detecting shallow buried landmines: a Colombian case study. Near Surface Geophysics, vol 5, pp. 73-80, 2007.

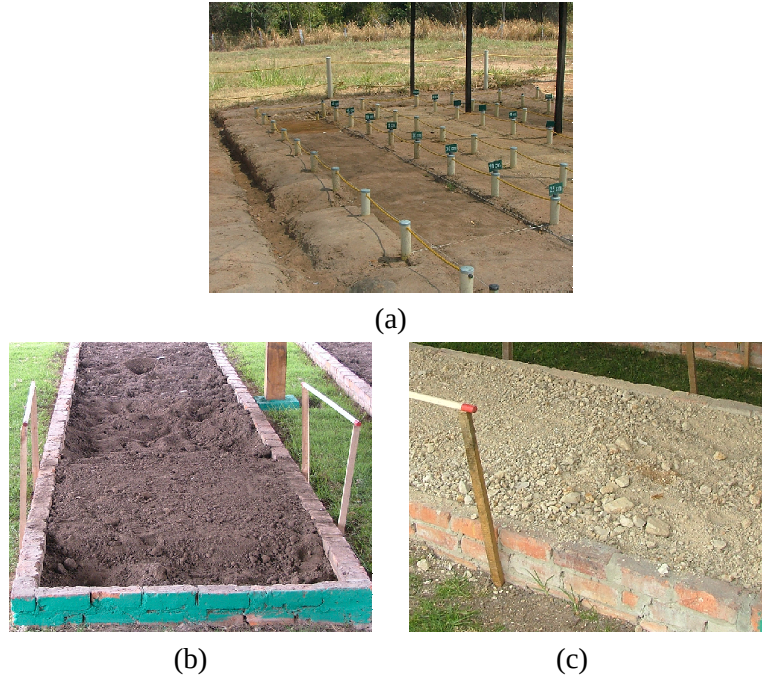


**Figure 3.1.** Block diagram representing the filtering methodology.

typical Colombian landmines such as M14 and low- and non-metallic IEDs are used. Results prove that the proposed technique effectively reduces clutter under non-controlled conditions and yields target features that are useful for detection of these landmines.

## 3.2 GPR Signal Processing

Steps 1 to 9 of Fig 3.1 are described below:



**Figure 3.2.** Outdoor test site: (a) silt loam soil, (b) loamy sand soil and (d) sandy clay soil.

### Step 1: Filtering Antenna Effects

Equation 2.11 is used to remove major antenna effects (see Section 2.2.1).

### Step 2: Calculating soil surface dielectric permittivity

The surface dielectric permittivity can be estimated by performing a single radar measurement in a local landmine-free area and using full-wave inversion of the radar signal, focused on the surface wave reflection in the time domain (see Section 2.2.2).

### Step 3: Calculating Antenna height

The antenna height can be derived directly from the radar measurements in the time domain, by identifying the surface reflection after applying Eq. (2.11).

### Step 4: Filtering Soil Surface Reflection

Soil surface reflection is filtered by subtracting from the preprocessed signal a computed Green's function describing wave propagation with the antenna in air above a single interface (soil surface). Synthetic Green's functions can

| Type  | Case material | Metal content | Diameter<br>(cm) | Width<br>(cm) | $\varepsilon_r$ |
|-------|---------------|---------------|------------------|---------------|-----------------|
| SIM12 | Plastic       | no            | 12               | 4             | 2.8             |
| M14   | Plastic       | low           | 5.6              | 4             | 3               |
| IED1  | PVC           | no            | 8                | 7             | 3.6             |
| IED2  | PVC           | low           | 12               | 8             | 3.6             |
| IED3  | PVC           | no            | 6                | 12            | 3.6             |
| IED4  | PVC           | low           | 6                | 12            | 3.6             |

**Table 3.1.** Characteristics of the local landmines buried in the lanes. The SIM12 is a standard test target, the M14 is an American AP landmine and the IEDs are improvised explosive devices with PVC case. The IEDs are generally used by the local guerrillas.  $\varepsilon_r$  is an approximative value.

be calculated for each radar measurement whatever the antenna height (see Section 2.2.2).

### Step 5: Leveling antenna height

The height of the antenna is equaled by shifting the single radar measurements in time and correcting the amplitude of the signal. This step facilitates the detection of residual surface reflection and of target depth.

### Step 6: Detecting Residual Surface Reflection

After Step 4, surface reflection can remain due to the inhomogeneity of the soil dielectric properties. If such a region is detected (confirmed by end-user), the algorithm proceeds to Step 7. If not, the algorithm proceeds to Step 8.

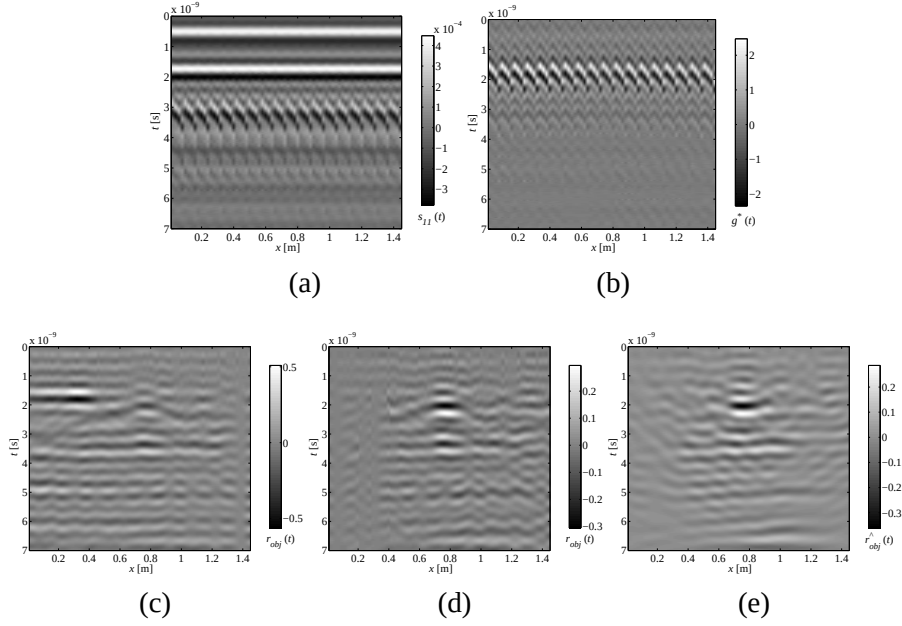
### Step 7: Selecting sub-Bscan from preprocessed data

If a sub-area is detected in Step 6, it is selected from the preprocessed data after filtering antenna effects. Steps 2 to 6 are repeated again over the selected subset. This sub-process is added to the original algorithm to deal with the soil surface inhomogeneity in field conditions. The single radar measurements corresponding to consecutive borders of sub-B-scans are merged to decrease high contrasts between two subsets.

### Step 8: Detecting Target Depth

In 2D GPR data, buried objects of finite dimensions appear as hyperbolic reflectors due to the beamwidth pattern of the radar antenna. Target depth is calculated at the apex of its hyperbolic signature (see Appendix B.).





**Figure 3.3.** Time domain representation of preliminary radar measurements performed in laboratory conditions (inhomogeneous sand,  $3.9 < \varepsilon < 5.5$ ). A plastic standard test target with a non-metallic fuze is buried at 4 cm of depth. The height of the antenna is intentionally increased and decreased: (a) measured signal  $s_{11}(t)$ , (b) major antenna effects filtered from  $s_{11}(t)$ , (c) soil surface reflection filtered by removing  $g_1'(t)$  from signal  $g^*(t)$ , (d) results of filtering  $g_2'(t)$  from the selected sub-Bscan, and (e) antenna radiation pattern effect filtered by migration.

### Step 9: Focusing the Preprocessed Data

Migration is performed following the approach proposed in Section 2.2.3.

## 3.3 Measurement Setup

### 3.3.1 Preliminary Experiment in Laboratory Conditions

The GPR system used for the measurements is the same GPR presented in Section 2.3. A preliminary experiment in laboratory conditions is carried out at the Catholic University of Louvain (Belgium), over a sand layer of 14 cm of thickness and  $1.5 \text{ m} \times 2 \text{ m}$  of surface area. Sand  $\varepsilon_r$  varies horizontally, between 3.9 and 5.5. A plastic standard test target with a non-metallic fuze was buried horizontally, longest side up, at 4 cm of depth measured from the top. It is referred to as SIM12 and its characteristics are presented in Table 3.1. To acquire 2-D data, the radar system was moved manually along the horizontal  $x$ -axis, crossing the center of the buried object, following a support frame. Radar

traces ( $S_{11}$ ) were recorded with a constant space step of 2 cm. The height of the antenna aperture above the sand was between 17 cm and 25 cm (antenna phase center at about 24-32 cm). It is increased and decreased intentionally to emulate changes in the sensor head position by a deminer during demining operations.

### 3.3.2 Outdoor Measurements

Outdoor measurements were performed over three typical Colombian mine-affected soils located in training lanes of Colombian Military Bases. Dimensions of the lanes are 3 m of depth and 1 m  $\times$  10 m of surface area, and contain different types of soil: silt loam ( $\epsilon_r = 4.1$ , measured at the time of the experiment), loamy sand ( $\epsilon_r = 4.4$ , measured at the time of the experiment) and sandy clay ( $\epsilon_r = 5.3$ , measured at the time of the experiment). Soil surfaces are almost flat and present some roughness, as can be seen in Fig. 3.2.

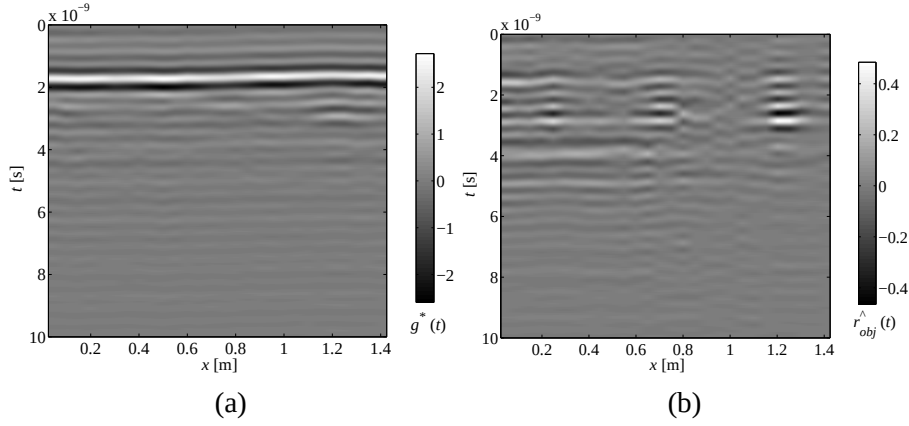
Radar measurements were carried out using local low- and non-metallic cylindrical devices (one AP landmine and four IEDs) as targets. In the remainder of this chapter, they are referred to as M14 (an American low-metallic AP landmine), IED1, IED2, IED3 and IED4 (IEDs with PVC case), of which characteristics are described in Table 3.1. They were placed horizontally with the side defining the diameter upper-most. To acquire 2-D data, the radar system was moved manually along the horizontal  $x$ -axis, crossing the center of the buried objects, following a support frame. Radar traces ( $S_{11}$ ) were recorded with a constant space step of 2 cm and 2.5 cm. The height of the antenna aperture above the sand was at about 17 cm (antenna phase center was at about 24 cm).

## 3.4 Results and Discussions

### 3.4.1 Preliminary Experiment in Laboratory Conditions

Figure 3.3 shows results of applying the whole methodology to data acquired under laboratory conditions. In Fig. 3.3(a), the 2-D raw radar data are presented in the time domain. Between about 0-2 ns, we can observe the multiple reflections occurring in the antenna. These reflections distort as well the signal for later times. Between about 3.0-3.5 ns the soil surface reflection is visible and we can observe the effect of varying the antenna height. Then a second order reflection occurring between the antenna and the soil surface comes at between about 4.2-4.7 ns.

Results after Step 1 are presented in Fig. 3.3(b). The true time zero corresponds now to the antenna phase center, situated at about 7 cm from the antenna aperture, inside the antenna. The multiple antenna reflections have



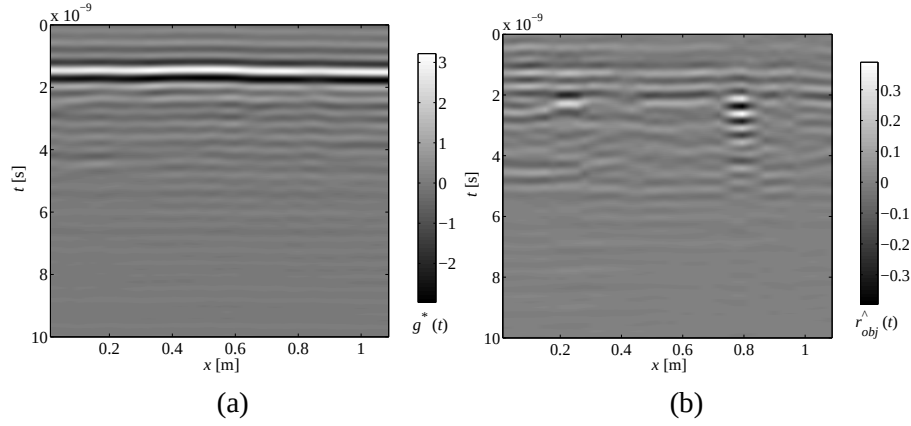
**Figure 3.4.** Time domain representation of radar measurements performed in the silt loam soil ( $\varepsilon = 4.1$ ) for the M14, IED1 and IED2, all buried at 5 cm (raw data not presented): (a) major antenna effects filtered from the measured signal  $s_{11}(t)$  and (b) results after applying the whole filtering approach.

vanished and the air-surface interface reflection is clearly distinguished, between about 1.3-1.8 ns. This permits the accurate extraction of the antenna height (Step 3). The remaining oscillations still visible in the B-scan between about 0-1.2 ns are an artefact of the inverse Fourier transform applied to data taken in a limited frequency range.

Step 2 enables us to identify a first sand surface dielectric permittivity,  $\varepsilon_{r,1} = 3.9$ . Results of Step 4 are shown in Fig. 3.3(c). The height of the antenna is leveled (Step 5) to show more clearly the hyperbolic signature of the landmine and residual surface reflection, the latter detected in Step 6. A second sand surface dielectric permittivity,  $\varepsilon_{r,2} = 5.5$ , is found from the sub-B-scan after performing again Step 2. No new residual surface reflection is found when repeating Steps 3 to 6. The effect of the standard test target ( $R_{obj}$ ) is isolated, which permits to differentiate the hyperbolic signature as can be seen in Fig. 3.3 (d).

In Step 8 we find accurately a burial depth of 4.56 cm (the real burial depth is 4 cm), and finally, Step 9 permits to filter the antenna radiation pattern by focusing the object scattered data into their origin. The migrated data from Fig. 3.3 (d) can be seen in Fig. 3.3 (e). The shape of the standard test target along the scanning axis becomes clear, and we can estimate a diameter of 14 cm, which is really close to the real value (12 cm).

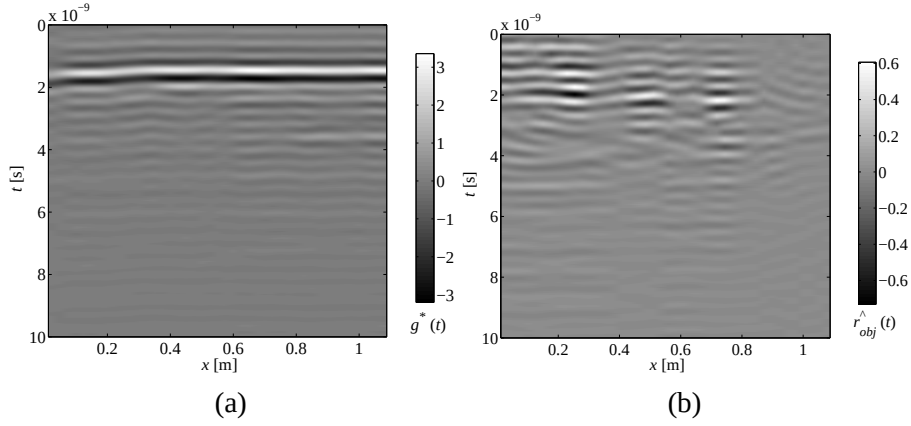
Other subsurface inhomogeneities are detected. In Fig. 3.3 (c,d,e), reflections below 3 ns correspond to the bottom of the sand layer (concrete). Nevertheless, the migration algorithm helps identifying the shape of the buried landmine and differentiating from these inhomogeneities.



**Figure 3.5.** Time domain representation of radar measurements performed in the loamy sand soil ( $\varepsilon = 4.4$ ) for the IED3 and IED4, buried at 5 cm (raw data not presented): (a) major antenna effects filtered from the measured signal  $s_{11}(t)$  and (b) results after applying the whole filtering approach.

### 3.4.2 Outdoor Measurements

The same methodology is applied to the measurements acquired in typical Colombian mine affected soils. Results for the silt loam soil are shown in Fig. 3.4. In this lane, M14, IED1 and IED2 are buried at 5 cm of depth, measured from the top, and their spatial locations are  $x = 20$  cm,  $x = 70$  cm and  $x = 120$  cm, respectively. In the raw radar data, the effect of the landmines is not visible (results not shown). After Step 1, the strong air-surface interface reflection appears around 1.5 ns. The hyperbolic signature can be hardly seen for the IED2 in Fig. 3.4(a), between 2.5 ns and 3.5 ns, and it cannot be seen at all for the M14 and IED1. This might be due to the dimensions of the IED2 and its air cavity, which are bigger than those of the M14 and IED1. Step 2 permits to identify a first soil surface dielectric permittivity,  $\varepsilon_{r,1} = 4.1$ . As the measurements were taken manually, small changes in the antenna height were detected in Step 3. After Step 5, no residual surface reflections were detected. In Step 8, we find a burial depth of 6.26 cm for the M14, 6.01 cm for the IED1 and 8.12 cm for the IED2. For the latter, the important difference between the real and the estimated depth value is possibly due to a bigger reflection coming from the layers inside the device instead of from its top. Results of Step 9 are shown in Fig. 3.4 (b). The shape of the landmines along the scanning axis is distinguished and we can differentiate their sizes, from the smallest one to the biggest one. It is worth noting that the M14 is one of the smallest low-metallic AP landmines in the world. In Chapter 2, promising results were achieved for this landmine under controlled low-contrast conditions (dry sand). Here we demonstrate that, under these outdoor conditions, information about the bur-



**Figure 3.6.** Time domain representation of radar measurements performed in the sandy clay soil ( $\varepsilon = 5.3$ ) for the IED3 and IED4, buried at 5 cm (raw data not presented): (a) major antenna effects filtered from the measured signal  $s_{11}(t)$  and (b) results after applying the whole filtering approach.

ial depth and shape from this small AP landmine can be also extracted by the proposed methodology.

The second outdoor experiment was done over the loamy sand soil. In this lane, the IED3 and IED4 are buried in at 5 cm of depth, measured from the top, and their spatial locations are  $x = 25$  cm and  $x = 75$  cm, respectively. Results of applying the proposed approach can be seen in Fig. 3.5. In the raw radar data, the effect of the landmines is not visible (results not shown). After Step 1, the strong air-surface interface reflection appears around 1.2 ns, as shown in Fig. 3.5 (a). No hyperbola can be distinguished. Step 2 permits to identify a first soil surface dielectric permittivity,  $\varepsilon_{r,1} = 4.4$ . As the measurements were taken manually, small changes in the antenna height were detected in Step 3. After Step 5, two sub-Bscans with residual surface reflections were detected. One of them is located along the first 35 cm of the B-scan and the other one is located between 45 cm and 70 cm, both with  $\varepsilon_{r,2} \approx 4.8$ . In Step 8, we find a burial depth of 5.83 cm for the IED3 and 6.03 cm for the IED4. Results of Step 9 are shown in Fig. 3.5 (b). The shape of the landmines along the scanning axis is distinguished.

The last outdoor experiment was done over the sandy clay soil. In this lane, the IED3 and IED4 are buried at 5 cm of depth, measured from the top, and their spatial locations are  $x = 25$  cm and  $x = 75$  cm, respectively. Results of applying the proposed approach are given in Fig. 3.6. In the raw radar data, the effect of the landmines is not visible (results not shown). After Step 1, the strong air-surface interface reflection appears around 1.2 ns, as can be seen in Fig. 3.6 (a). No hyperbola can be distinguished. Step 2 permits to identify a

first soil surface dielectric permittivity,  $\varepsilon_{r,1} = 5.3$ . As the measurements were taken manually, small changes in the antenna height were detected in Step 3. In Step 5, one sub-Bscan with residual surface reflection was detected. It is located along the first 30 cm of the B-scan with  $\varepsilon_{r,2} = 5.6$ . Steps 3 to 6 are repeated on this sub-Bscan. The high amount of stones with different sizes and shapes (see Fig. 3.2(d)) yields to less satisfactory results, as shown in the following. This makes burial depth extraction difficult for the IED3 located in this sub-Bscan. After Step 8, only the burial depth of IED4 is found accurately (5.64 cm). Results of Step 9 are shown in Fig. 3.5 (b). The shape of the IED4 is clearly distinguished. This is not the case of the IED3, due to the residual clutter along the first 30 cm of the B-scan. However, its shape is noticeable. Another inhomogeneity is detected, between 42.5 and 57.5 cm and at almost the same depth of the IEDs. After migration, its shape along the scanning axis is larger than that of the IEDs, and its form is still hyperbolic. Such false alarm is probably due to the presence of a subsurface layer with different water content. These effects are quite common in outdoor (non-controlled) conditions, where such false alarms can be found as explained in *Gorriti et al.* [2006] and *Sato et al.* [2007] for measurements performed using hand-held dual sensors in outdoor minefield trial sites. In the reminder of this document, these false alarms will be referred as *ghosts*.

An important effect can be observed on all these experiments. Soil surface reflection right above the landmine is not totally filtered out after Step 4. This effect is more noticeable in outdoor conditions than in laboratory, as can be seen in Figs. 3.3 (e), 3.4 (b) and 3.6 (b). This variation of the soil surface dielectric properties might be due to perturbation of the soil density, when the landmine is buried. In laboratory conditions, the test target had been buried one or two days before starting the measurements, therefore soil density perturbation is visible in the radar data. For the field measurements, the targets had been buried four months before. In this case, the variation of the soil surface dielectric properties might be also caused by perturbation of the soil hydrodynamics at the surface. Soil density, water flow and evapotranspiration can be affected by the presence of the landmine. A thorough study regarding these effects could bring a novel contribution to the detection of landmines using GPR.

Regarding the influence of soil characteristics, less satisfactory results were achieved in the sandy clay soil, where an IED was incorrectly detected and a false alarm was found. It is caused mainly by the presence of big stones and it seems there is no relation with the soil EM characteristics, since the other IED buried there was accurately detected. For the different types of soil, their surface moisture at the moment of the measurements was quite low, helping to an adequate performance of the GPR system. Measurements at different water content levels have to be carried out to well determine GPR performance

limits.

### 3.5 Conclusion

In this chapter, the filtering approach for enhancing AP landmine detection using GPR is applied and validated for measurements performed over typical Colombian mine-affected soils. The methodology applies to SFCW radar systems operating off the ground in monostatic mode, *i.e.*, a single emitting and receiving antenna is used. It has been adapted to inhomogeneities in the soil surface water content. The radar-antenna-subsurface model used here allows precise antenna effects and soil surface reflection removal, resulting in a better SNR. Therefore, the landmine response is the dominant contributor in the clutter reduced radar data and can be easily distinguished using a migration algorithm. As for the laboratory measurements, the whole methodology yields a set of parameters, namely,  $\varepsilon_r$  of soil, antenna height and landmine depth and shape.

Measurements are focused on real mine-affected soils in Colombia and on local explosive devices. Results show that the proposed technique could effectively reduce clutter and enhance landmine detection under non-controlled conditions. Although soil surface was not completely flat in any of the soils considered for the outdoor measurements, a deeper analysis regarding the robustness of the filtering approach with respect to soil roughness needs to be carried out.

A disadvantage of this approach is that natural inhomogeneities, as stones or subsurface layers, can be detected and considered as potential targets or false alarms. Many authors claim that this issue can be solved using dual-sensor systems, in combination with metal detector (MD). However, considering this particular case where non-metallic AP landmines are buried, reduction of GPR false alarm rate by MD cannot be carried out. A deeper study, containing a statistically relevant number of samples, needs to be addressed regarding probability of detection and false alarm rate. Since measurements in field conditions lead to the detection of soil density and hydrodynamics perturbation due to the presence of the buried landmine, this could be useful to reject some false alarms. This aspect is considered in the next chapter.





## Chapter 4

# Change Detection Algorithm for Landmine Localization\*

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*Rather than asking to search for a solution, ask your mind simply to remember it.*

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*Buddhist philosopher's trick.*

In this chapter, we propose a novel approach based on electromagnetic parameter estimation to localize buried objects by detecting substantial changes due to soil perturbation resulting from the presence of a buried object. This approach is represented in Fig. 1.6, block section 2. A dissimilarity measure between the simulated Green's function calculated in Chapter 2 and the radar signal from a mine-affected soil is used to detect significant variations. We validate the approach for different low-metallic AP landmines and low- and non-metallic IEDs buried in different soils, including typical mine-affected soils in Colombia. This new detection method permits an accurate localization of landmines and rejection of some false alarms.

### 4.1 Introduction

As shown in previous chapters, GPR can detect both low- and non-metallic AP landmines and IEDs and therefore, it could reduce the false alarm rate in demining achieved by MD. Yet, the detection performance of GPR largely depends on the dielectric contrast between the landmine and the soil surrounding it and, in the same way, GPR can also detect other dielectric contrasts such as significant changes in soil subsurface water content, stones or roots. These

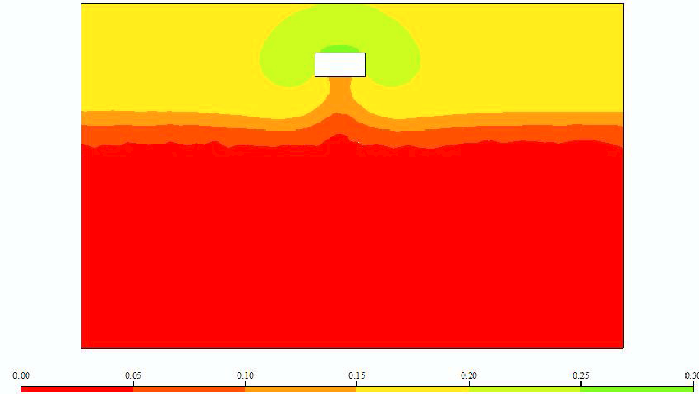
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\*Adapted from Lopera O., Milisavljević N., Macq B. and Lambot S., A Change Detection Algorithm Based on Soil Dielectric Permittivity Estimation from Frequency-domain GPR Data for Landmine Localization. IEEE Geoscience and Remote Sensing Letters. Submitted.

detections are considered as false alarms for the GPR [Gorriti *et al.*, 2006; Sato *et al.*, 2007]. Besides background subtraction algorithms, GPR signal processing has to focus on false alarm reduction.

Several authors have focused their research on the analysis of the effects of dielectric contrast and dielectric properties of the soil surrounding landmines on the performance of GPR for landmine detection. In some of these studies, electromagnetic (EM) models have been coupled to pedotransfer functions to simulate EM wave propagation in soil-mine mediums considering different types of landmines and changes on soil water content [Roth *et al.*, 2001; Miller *et al.*, 2004; Lopera and Milisavljevic, 2007]. Numerical, laboratory and in field results demonstrate how signal attenuation and dielectric contrast play an important role on GPR detection performance. In this respect, other studies have been focused on the integration of hydrological and EM models for modeling water content distribution around landmines after watering to use this information for enhancing landmine detection [Borchers *et al.*, 2000; Lensen *et al.*, 2001; Rhebergen and Ralston, 2005]. These integrated methodologies have been tested under laboratory and outdoor conditions and the analysis of the results showed differences on water content below and above the landmines with respect to a reference point in the surrounding soil. These differences are strengthened after precipitations events and change during drought periods. This is due to the obstruction generated by the landmine on the natural flow of water in a specific soil [Hendrickx *et al.*, 1999]. In Section 3.4.2, we notice that soil surface reflection right above the landmine is not totally filtered out after applying the proposed filtering methodology. These variations can be a result of changes on soil density and perturbation of soil hydrodynamics. In this chapter, a thorough analysis of these effects is presented and considered for landmines localization using a change detection approach.

Change detection has been the basis of some publications related to landmine detection using GPR [Brunzell, 1999; Ho and Gader, 2002; Xu *et al.*, 2002; Potin *et al.*, 2006]. These studies are based on the analysis of the target reflection and none of these contributions considers the hypothesis of detecting changes on soil surface properties (soil compactness and perturbation of soil hydrodynamics), due to the presence of a buried object, to localize landmines. In [Xu *et al.*, 2002], a change detection method based on energy detection is used to localize buried landmines on 2-D data. After clutter reduction, changes are detected in the spatial and time direction in order to find the landmines horizontal positions and their response times. Changes in both directions are detected thanks to a sequential probability ratio test. In [Potin *et al.*, 2006], an abrupt change detection algorithm is applied to GPR 2-D data. This methodology applies for the time domain where the signatures of shallowly buried landmines are very weak, which represents a difficulty for their detection under low-contrast conditions. In [Brunzell, 1999; Ho and Gader, 2002],



**Figure 4.1.** Vertical distribution of water content in a soil containing a mine-like object. In the graph, a vertical slide of the soil is represented. The soil subsurface corresponds to the big rectangle and the mine-like object corresponds to the white one. Soil surface is therefore the upper side of the big rectangle. Starting from dry conditions, the soil is subject to precipitation. Water content is expressed on a volumetric basis ( $\text{cm}^3/\text{cm}^3$ ). The more reddish the drier and the more greenish the wetter. The hydrodynamic simulation has been performed using the HYDRUS-2D code.

statistically-based change detection algorithms are applied. They consist in modeling the propagation of electromagnetic waves into an heterogeneous soil. However, GPR data are difficult to recreate accurately since real field conditions are far more complex than numerical modeling. These model-based statistical techniques are therefore of limited use.

We propose a change detection approach based on the estimation of the soil surface dielectric permittivity from GPR data in the frequency-domain for discerning AP landmines and, additionally, reject some false alarms [Lopera *et al.*, 2006b]. The Green's function is derived using full-wave inversion of the radar signal (Chapter 2) for a measurement taken in a local landmine-free area. A dissimilarity measure between the radar signal from a mine-affected area and the estimated soil response is calculated and significant variations are detected. This methodology has been tested on data collected using SFCW radar combined with a horn antenna (see Section 2.2.3) under laboratory and outdoor conditions. Laboratory measurements are carried out over a sand layer where a standard test target has been buried. Outdoor measurements were performed over typical Colombian mine-affected soils in which local devices (AP landmines and IEDs) are buried.

## 4.2 Change Detection Basis

In Section 3.4.2, we notice that soil surface reflection right above the landmine is not totally filtered out after applying the proposed filtering methodology. Since the latter is based on the estimation of the dielectric permittivity of soil, it is possible that these reflections remain after filtering due to changes on the soil surface dielectric properties right above the buried landmines. These variations can be due to soil perturbation after digging, even if the landmines lay after a long period (as shown later in this chapter). Another hypothesis is the obstruction caused by a landmine on the soil natural water flow and this effect can be illustrated by modeling the water propagation in a soil-landmine medium. Several mathematical and experimental studies have investigated water movement around stones and air-filled cavities in the soil [Bouwer and Rice, 1984; Hendrickx *et al.*, 1991; Fennemore and Warrick, 1997]. A landmine can be considered as a stone or air cavity, thus it can cause similar obstructions to water flow. Some authors have studied how an object (*e.g.*, landmine) in the subsurface can have an impact on the water distribution in its surroundings [Borchers *et al.*, 2000; Lensen *et al.*, 2001; Rhebergen and Ralston, 2005]. In these studies, simulations of water flow in a soil-mine medium are conducted using the HYDRUS-2D code [Šimunek *et al.*, 2007]. Analysis of numerical and experimental data has shown how the presence of a landmine may induce specific changes on the water content in the shallow subsurface around it, specially right below and above the landmine. When the mines are shallowly buried, this can create differences in the surface and could partially explain the results obtained in Section 3.4.2.

A preliminary study using HYDRUS-2D code is carried out and some results are given here. The HYDRUS-2D is a finite element model for accurate analysis of water flow in variably saturated porous media which has been developed at the Salinity Laboratory of the University of California. The physics behind this program is not considered here since it is out of the scope of this thesis. The reader is referred to Šimunek *et al.* [2007] and references therein for the theory details. The water flow depends on several factors such as soil texture, bulk density, organic matter content, water content among others. These parameters can be measured for a specific soil, some others are general for all types of soil. They are entered to the program in order to simulate the water transfer in the soil. This program has been validated by several studies and under different conditions<sup>†</sup>.

Figure 4.1 illustrates modeling results on how the presence of a landmine may induce specific water content patterns in both the surface and subsurface. In the graph, a vertical slide of the soil is represented. The soil subsurface

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<sup>†</sup>More information can be found in <http://www.envisci.ucr.edu/faculty/simunek.html>

| Type | Metal content | Diameter (cm) | Height (cm) | Case material |
|------|---------------|---------------|-------------|---------------|
| IED5 | No            | 5.5           | 12          | Glass         |
| IED6 | Low           | 5.5           | 12          | Glass         |

**Table 4.1.** Characteristics of two additional local IEDs buried in the Colombian mine-affected soils.

corresponds to the big rectangle and the mine-like object (simulated as a body with hydraulic conductivity of 0) corresponds to the white one. Soil surface is therefore the upper side of the big rectangle. In this simulated example, an initially dry soil is subject to precipitation. Water content is expressed on a volumetric basis ( $\text{cm}^3/\text{cm}^3$ ). The more reddish the drier and the more greenish the wetter. Since the landmine constitutes a non-conductive hydraulic body, it leads to an accumulation of water on its upper part, which may increase locally surface soil moisture<sup>‡</sup>.

These specific hydraulic conditions, in conjunction with the perturbation of soil compactness after digging, can create dielectric contrasts on the soil surface which can be favorable to the detection of the landmine, using subsurface imaging sensors such as GPR. However, these changes can be affected by the temporal variability of weather conditions such as precipitation and evaporation, the differences in soil hydraulic properties, surface roughness and vegetation, among other factors [Hendrickx *et al.*, 1999]. For instance, it has been demonstrated in [Borchers *et al.*, 2000; Lensen *et al.*, 2001; Rhebergen and Ralston, 2005] that watering can contribute to strengthen these changes, which can enhance (*e.g.*, by increasing dielectric contrast) or adversely affect (*e.g.*, by decreasing wave propagation velocity) GPR detection performance. Those factors are not taken into account here since they can be the subject of a complete study in their own. Nevertheless, we consider studying them thoroughly in further research.

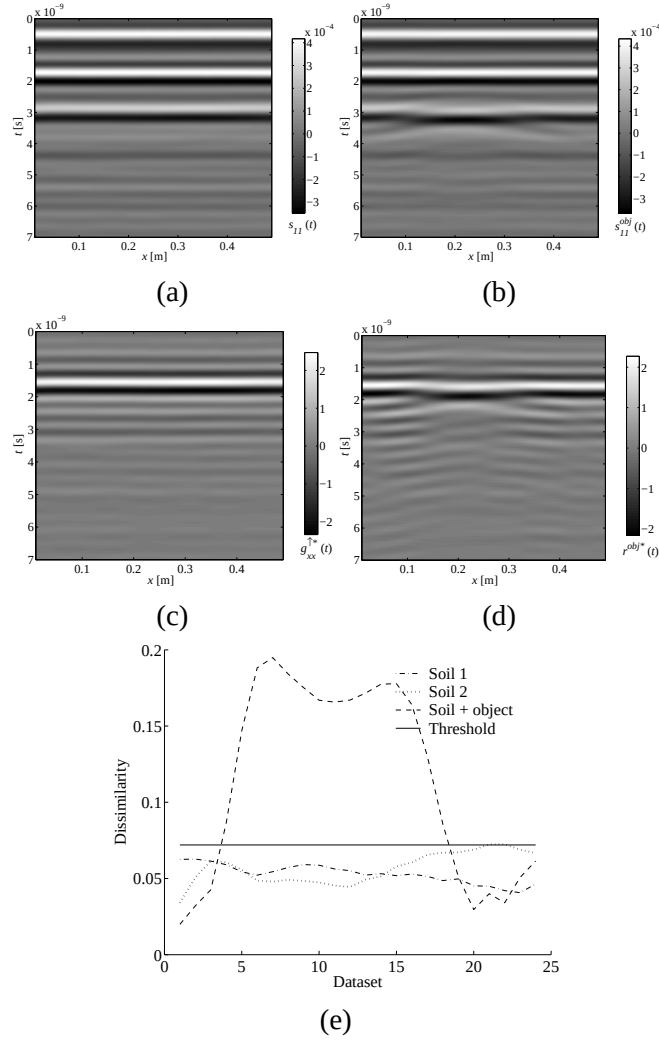
### 4.3 Change Detection Algorithm

The change detection algorithm developed here is based on measuring the differences between the surface reflections from a mine-affected area and the estimated soil response from a nearby mine-free area. After acquiring 2-D data from both areas using a SFCW radar, the changes are detected as follows.

Consider  $\mathbf{S}$  as the 2-D data set from a mine-free area, close to the mine-affected area,

$$\mathbf{S} = [S_{11,1} \cdots S_{11,K}], \quad (4.1)$$

<sup>‡</sup>A parallel phenomenon is also found in soil heat transfer and its corresponding effect is the basis of AP landmine detection using infrared cameras [Cremer, 2003].

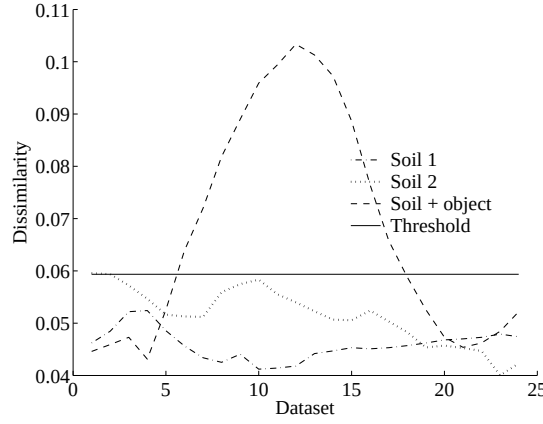


**Figure 4.2.** Change detection approach applied to a metallic cylinder buried at 4 cm: (a) and (b) measured signal  $s_{11}(t)$  and  $s_{11}^{obj}(t)$ , respectively, (c) and (d)  $h_i(t)$ ,  $h_f(t)$ ,  $h(t)$  are filtered from signal  $s_{11}(t)$  and  $s_{11}^{obj}(t)$ , respectively, (e) dissimilarity vector plotted for the reference data set (Soil 1), the tuning data set (Soil 2) and data set from the mine-affected area (Soil + object). Unit in dataset position is 2 cm.

where  $K$  is the number of consecutive single acquisitions, or A-scans. Using Eq. (2.2), the antenna characteristic transfer functions  $H_i$ ,  $H$  and  $H_f$  are filtered out from the signal  $S_{11,k}$  ( $k = 1, \dots, K$ ), resulting in a set of measured response functions

$$\mathbf{X}_a = [G^* \cdots G_K^*]. \quad (4.2)$$

Synthetic Green's functions are calculated for each  $G_k^*$  by full-wave inver-



**Figure 4.3.** Dissimilarity vectors from the data acquired in sandy soil for SIM12, buried at 5 cm depth and  $x = 25$  cm. After filtering  $h_i(t)$ ,  $h_f(t)$  and  $h(t)$  from signals  $s_{11}(t)$  and  $s_{11}^{obj}(t)$ , dissimilarity vectors are calculated and show the presence of a buried object for the *Soil + object* data set. Unit in *dataset* position is 2 cm.

sion (see Chapter 2). From the resulting set of  $K$  estimated signals, we selected the one which has the minimum error with respect to its observed signal,  $G'_l$  ( $l \in [1, \dots, K]$ ).

Let  $\mathbf{S}^{obj}$  be a 2-D data set from the mine-affected area,

$$\mathbf{S}^{obj} = [S_{11,1}^{obj} \dots S_{11,Q}^{obj}], \quad (4.3)$$

where  $Q$  is the number of consecutive single acquisitions. As for  $\mathbf{S}$ , the antenna characteristic transfer functions are filtered out using Eq. (2.11), and the resulting set of functions will be referred to as

$$\mathbf{X}_b = [G_1^{obj*} \dots G_Q^{obj*}]. \quad (4.4)$$

Defining the dissimilarity  $\mathbf{D}_b$  as a vector containing the difference of the signal focused on the soil surface reflection between the elements of  $\mathbf{X}_b$  in the time domain and  $g'_l$ ,

$$\mathbf{D} = [g_1^{obj*}|_{t_{min}}^{t_{max}} - g'_l \dots g_Q^{obj*}|_{t_{min}}^{t_{max}} - g'_l], \quad (4.5)$$

the change detection problem can be expressed as follows:

- no change occurs when  $D_{b,q} \leq \gamma$ ,
- a change occurs when  $D_{b,q} > \gamma$ ,

where

$$\gamma = \max(\mathbf{D}_a) + \kappa\sigma(\mathbf{D}_a) \quad (4.6)$$

is the threshold value,  $\mathbf{D}_a$  being the dissimilarity between the elements of  $\mathbf{X}_a$  and  $G'_l$ , and  $\sigma(\mathbf{D}_a)$  its standard deviation. The  $\kappa$  factor is calculated from an additional 2-D set of pre-filtered data from a nearby mine-free area,

$$\mathbf{X}_c = [G_1^{obj*} \dots G_Q^{obj*}], \quad (4.7)$$

by tuning Eq. (4.6) until no changes are detected, i.e., until  $D_{c,q} \leq \gamma$  for all  $q \in [1, \dots, Q]$ .

The algorithm<sup>§</sup> is first applied to GPR 2-D data, collected before for another purpose, from a PEC cylinder buried at 4 cm of depth in sandy soil ( $\varepsilon = 3.5$ ). This cylinder had been left buried for a few days and the soil was submitted to artificial watering. The GPR system used for the measurements is the same GPR presented in Section 2.3. Fig. 4.2 shows the results of the change detection approach. Raw data in the time domain are shown in Fig. 4.2 (a) and (b), representing the data sets  $\mathbf{S}$  and  $\mathbf{S}^{obj}$ , respectively. Due to the high electromagnetic contrast between the PEC cylinder and the soil, the hyperbolic signature of the object is easily distinguished. Note that multiple reflections distort the signal between about 0-2 ns. Data after filtering antenna effects (see Section 2.2.1) can be seen in Fig. 4.2 (c) and (d). Here, the strong air-surface interface reflection appears around 1.2 ns and the hyperbolic signature of the object is accentuated. The remaining oscillations visible in the B-scan are an artefact of the inverse Fourier transform applied to data taken in a limited frequency range. Dissimilarity vectors are plotted in Fig. 4.2 (e) and compared to a third vector from GPR 2-D data set acquired in a local area with no object. For each detection, a weight is then assigned by calculating the area  $\mathcal{A}$  of the dissimilarity function over the threshold value. The change detection (CD) output is:

- $\mathcal{A}$ , when a change occurs,
- 0, otherwise.

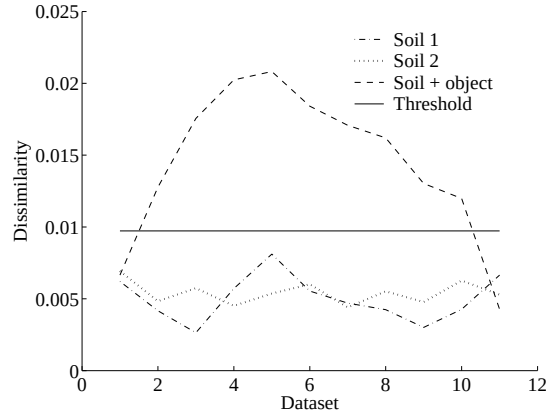
Additionally, the center of mass of the area  $\mathcal{A}$  of the dissimilarity function over the threshold value is used to calculate the position of the potential target.

For the PEC cylinder data, only one change is detected and its area is calculated as  $\mathcal{A} = 0.98$ . For this detection, its center of mass is calculated at *dataset* 11, which accurately localizes the PEC cylinder at  $x = 22$  cm (real value  $x = 20$  cm, error of 2 cm).

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<sup>§</sup>Dissimilarity and CD account for the Dissimilarity function and Change detection algorithm boxes in Fig. 1.6, block section 1.





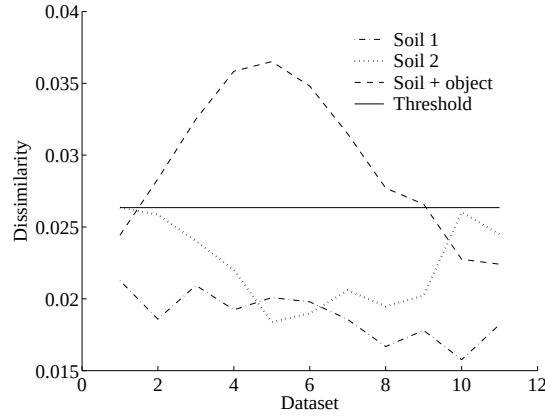
**Figure 4.4.** Dissimilarity vectors from the data acquired in sandy soil for the PMN2 landmine, buried at 10 cm depth and  $x = \text{cm}$ . After filtering  $h_i(t)$ ,  $h_f(t)$  and  $h(t)$  from signals  $s_{11}(t)$  and  $s_{11}^{obj}(t)$ , dissimilarity vectors are calculated and show the presence of a buried object for the *Soil + object* data set. Unit in *dataset* position is 2 cm.

## 4.4 Experiment Description

### 4.4.1 Laboratory measurements

Two experiments under laboratory conditions are carried out. The first one is carried out at the UCL, over the same sand layer of 14 cm thickness and  $1.5 \times 2 \text{ m}^2$  surface area of the laboratory experiments of Chapter 2, for the SIM12 target, with a non-metallic fuze, buried at 5 cm of depth measured from the top. After artificial watering, soil  $\varepsilon_r$  varies horizontally, between 3.9 and 5.5. To acquire 2-D data, the radar system was moved manually along the horizontal  $x$ -axis, crossing the center of the buried object, following a support frame. Radar traces ( $S_{11}$ ) were recorded with a constant space step of 2 cm. The height of the antenna aperture above the sand was about 17 cm (antenna phase center at about 24 cm).

The second laboratory experiment is carried out at the test facilities of TNO, The Hague, The Netherlands, over a sand layer of 3 m depth and  $1 \times 2.85 \text{ m}^2$  surface area. Two AP landmines, PMN2 and M14 are buried horizontally, the side designating the diameter up, at 10 cm depth. Their characteristics are listed in Table 2.1. Since several experiments including watering experiments have been carried out previously over this lane, changes on water content around landmines can be expected. Soil water content is not homogeneous and it varies from  $\varepsilon_r = 2.8$  and  $\varepsilon_r = 3.3$  (measured at the time of the experiment). To acquire 2-D data, the radar system was moved along the  $x$ -axis using a scanning frame, crossing the center of the buried object. Radar traces ( $S_{11}$ ) were recorded with a constant space step of 2 cm. The height of the antenna



**Figure 4.5.** Dissimilarity vectors from the data acquired in sandy soil for the M14 landmine, buried at 10 cm depth and  $x = \text{cm}$ . After filtering  $h_i(t)$ ,  $h_f(t)$  and  $h(t)$  from signals  $s_{11}(t)$  and  $s_{11}^{obj}(t)$ , dissimilarity vectors are calculated and show the presence of a buried object for the *Soil + object* data set. Unit in *dataset* position is 2 cm.

aperture above the sand was about 17 cm (antenna phase center at about 24 cm).

#### 4.4.2 Outdoor measurements

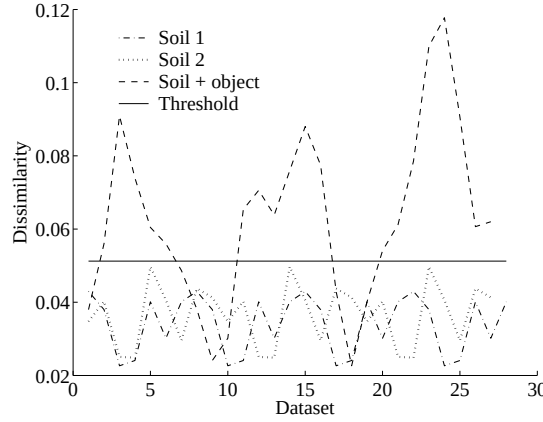
The same outdoor measurement setup and collected data sets from Section 3.3 are used here. Two additional targets, IED5 and IED6, of which characteristics are described in Table 5.2, are also used.

Note that mine-affected soils are located outdoor and landmines lay there for more than four months (at the moment of the measurements). Therefore, changes on water content around landmines after natural precipitation and evaporation events can be expected.

### 4.5 Results and Discussions

#### 4.5.1 Preliminary Experiments in Laboratory Conditions

In Fig. 4.3, results of applying the change detection approach for the SIM12 buried in sandy soil at 5 cm of depth and at 25 cm along the scanning axis are shown. After filtering out  $h_i(t)$ ,  $h_f(t)$  and  $h(t)$  from signals  $s_{11}(t)$  and  $s_{11}^{obj}(t)$ , dissimilarity vectors from the mine-free soil (*Soil 1*) and the mine-affected soil (*Soil + object*) are calculated and plotted in this figure. For a second GPR 2-D



**Figure 4.6.** Dissimilarity vectors from the data acquired in sandy clay loam soil for M14, IED1 and IED2, buried at 5 cm depth and  $x = 20$  cm,  $x = 70$  and  $x = 120$  cm, respectively. After filtering  $h_i(t)$ ,  $h_f(t)$  and  $h(t)$  from signals  $s_{11}(t)$  and  $s_{11}^{obj}(t)$ , dissimilarity vectors are calculated and show the presence of three buried objects for the *Soil + object* data set. Unit in dataset position is 2.5 cm.

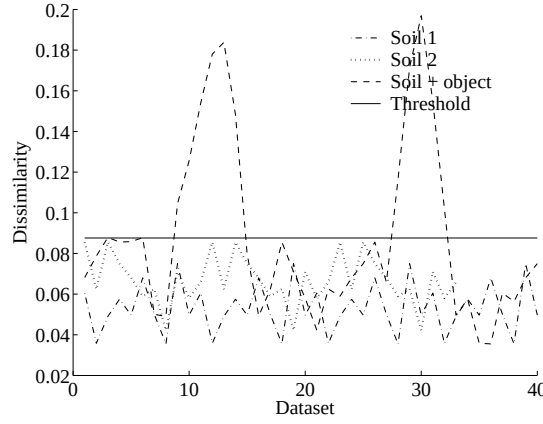
data set in a local mine-free area (*Soil 2*) no changes are detected<sup>¶</sup>. Results show only one change detected for the *Soil + object* data set, and its area and object position are calculated and listed in Table 4.2, accurately localizing the SIM12 at  $x = 24$  cm (error of 1 cm).

As for the PEC cylinder, the SIM12 has been buried a couple of days before taking the measurements. Therefore, detected changes can be mainly an effect of soil disturbance after digging, which produces a variation on the soil surface reflection due to different soil compactness.

In Fig. 4.4 and Fig. 4.5, results of applying the change detection approach for the PMN2 and M14 landmines, respectively, buried in sandy soil at 10 cm depth are shown. Spatial locations of these devices are  $x = 10$  cm. After filtering out  $h_i(t)$ ,  $h_f(t)$  and  $h(t)$  from signals  $s_{11}(t)$  and  $s_{11}^{obj}(t)$ , dissimilarity vectors from the mine-free soil (*Soil 1*) and the mine-affected soil (*Soil + object*) are calculated and plotted in these figures. For a second GPR 2-D data set in a local mine-free area (*Soil 2*) no changes are detected. Results show only one change detected for the *Soil + object* data set in each graph, and its area and object position are calculated and listed in Table 4.2, accurately localizing both PMN2 and M14 at  $x = 10$  cm.

These devices have been buried for more than three years and several ex-

<sup>¶</sup>Note that this soil corresponds to the left part of the scanned area in Fig. 3.3(b). This area has a higher moisture content and could be identified as a false alarm (if the residual surface reflection detection, or Step 6 in Chapter 3, is not performed). However, the change detection algorithm reject this inhomogeneity



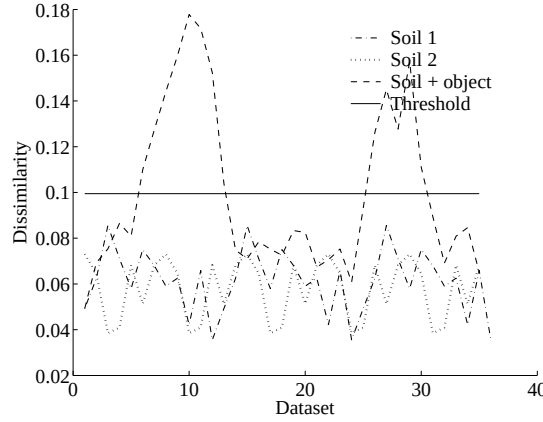
**Figure 4.7.** Dissimilarity vectors from the data acquired in sandy loam soil for IED3 and IED4, buried at 5 cm depth and  $x = 25$  cm and  $x = 75$  cm, respectively. After filtering  $h_i(t)$ ,  $h_f(t)$  and  $h(t)$  from signals  $s_{11}(t)$  and  $s_{11}^{obj}(t)$ , dissimilarity vectors are calculated and show the presence of two buried objects for the *Soil + object* data set. Unit in *dataset* position is 2.5 cm.

periments, including watering, have been carried out in this sand lane. Therefore, detected changes could be mainly more related to differences on the dielectric permittivity of the soil surface right above the landmines than to an effect of soil disturbance after digging.

#### 4.5.2 Outdoor Measurements

The same procedure is applied to radar data from local devices buried in typical mine-affected soils in Colombia. Results for the sandy clay loam soil are shown in Fig. 4.6. In this lane, the M14, IED1 and IED2 are buried at 5 cm of depth, measured from the top, and their spatial locations are  $x = 20$  cm,  $x = 70$  cm and  $x = 120$  cm, respectively. After filtering out  $h_i(t)$ ,  $h_f(t)$  and  $h(t)$  from signals  $s_{11}(t)$  and  $s_{11}^{obj}(t)$ , dissimilarity vectors from the mine-free soil (*Soil 1*) and the mine-affected soil (*Soil + object*) are calculated and plotted in Fig. 4.6. For a second GPR 2-D data set in a local mine-free area (*Soil 2*) no changes are detected. For convenience, dissimilarity vectors from *Soil 1* and *Soil 2*, are repeated four times since  $4 \times K \cong Q^{\parallel}$ . Results show three detected objects from the *Soil + object* data set. Their respective areas and positions are calculated and listed in Table 4.2, showing accurately the positions of the three devices at  $x = 20$  cm,  $x = 70$  cm and  $x = 120$  cm, respectively.

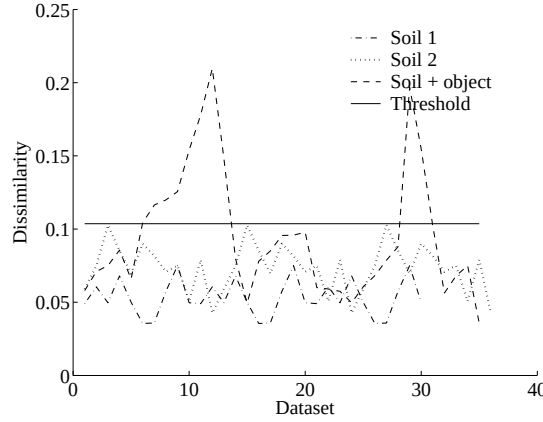
<sup>||</sup>Note that the length of the 2-D data set acquired over the mine-affected area is 150 cm. This does not mean that the length of the 2-D data set from the mine-free area has to be the same. For the latter, a small area is used and therefore, it has to be repeated some times in the graph for comparison.



**Figure 4.8.** Dissimilarity vectors from the data acquired in sandy loam soil for IED5 and IED6, buried at 5 cm depth and  $x = 25$  cm and  $x = 75$  cm, respectively. After filtering  $h_i(t)$ ,  $h_f(t)$  and  $h(t)$  from signals  $s_{11}(t)$  and  $s_{11}^{obj}(t)$ , dissimilarity vectors are calculated and show the presence of two buried objects for the *Soil + object* data set. Unit in *dataset* position is 2.5 cm.

The second outdoor experiment was performed over the sandy loam soil. In this lane, the IED3, IED4, IED5 and IED6 are buried in at 5 cm of depth, measured from the top, and their spatial locations are  $x = 25$  cm for IED3 and IED5 and  $x = 75$  cm for IED4 and IED6. After filtering out  $h_i(t)$ ,  $h_f(t)$  and  $h(t)$  from signals  $s_{11}(t)$  and  $s_{11}^{obj}(t)$ , dissimilarity vectors from the mine-free soil (*Soil 1*) and the mine-affected soil (*Soil + object*) are calculated and plotted in Fig. 4.7 (IED3 and IED4) and in Fig. 4.8 (IED5 and IED6). For each graph, a dissimilarity vector from a second GPR 2-D data set in a local mine-free area (*Soil 2*) is plotted and no changes are detected. Since  $K < Q$ , dissimilarity vectors from *Soil 1* and *Soil 2*, are repeated a few times. Only two changes are detected in the *Soil + object* data sets. The areas of all detected changes and their positions are calculated and given in Table 4.2, showing the position of IED3 at  $x = 27$  cm, with an error of 2 cm, the position of IED6 at  $x = 72.5$  cm, with an error of 2.5 cm, and accurately localizing IED4 and IED5 at  $x = 75$  cm and  $x = 25$  cm, respectively.

The last outdoor experiment was carried out over the sandy clay soil. In this lane, the IED3, IED4, IED5 and IED6 are buried in at 5 cm of depth, measured from the top, and their spatial locations are  $x = 25$  cm for IED3 and IED5 and  $x = 75$  cm for IED4 and IED6. After filtering out  $h_i(t)$ ,  $h_f(t)$  and  $h(t)$  from signals  $s_{11}(t)$  and  $s_{11}^{obj}(t)$ , dissimilarity vectors from the mine-free soil (*Soil 1*) and the mine-affected soil (*Soil + object*) are calculated and plotted in Fig. 4.9 (IED3 and IED4) and in Fig. 4.10 (IED5 and IED6). For each graph, a dissimilarity vector from a second GPR 2-D data set in a local mine-free area (*Soil 2*) is plotted and no changes are detected. Since  $K < Q$ ,



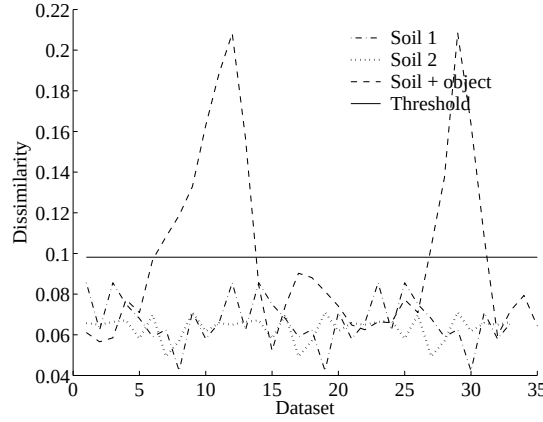
**Figure 4.9.** Dissimilarity vectors from the data acquired in sandy clay soil for IED3 and IED4, buried at 5 cm depth and  $x = 25$  cm and  $x = 75$  cm, respectively. After filtering  $h_i(t)$ ,  $h_f(t)$  and  $h(t)$  from signals  $s_{11}(t)$  and  $s_{11}^{obj}(t)$ , dissimilarity vectors are calculated and show the presence of two buried objects for the *Soil + object* data set. Unit in *dataset* position is 2.5 cm.

dissimilarity vectors from *Soil 1* and *Soil 2*, are repeated a few times. Only two changes are detected in the *Soil + object* data sets. Note that the region of the false alarm detected in Section 3.4.2, between  $x = 45$  cm and  $x = 60$  cm (*dataset* between 18 and 24 in Fig. 4.9), presents no detected changes. The areas of all detected changes and their positions are calculated and given in Table 4.2, accurately showing the positions of IED3, IED4 and IED6 at  $x = 25$  cm,  $x = 75$  cm and  $x = 25$  cm, respectively. Position of IED5 is located at  $x = 27$  cm, with an error of 2 cm.

It is worth noting that the choice of the 2-D data sets from local mine-free soil and their size  $K$  do not influence the results of the algorithm.

For the outdoor experiments, all devices have been buried for more than four months. As the training lanes are in open-air, detected changes can be related to both soil hydrodynamics perturbation and soil disturbance when digging (even after a long period). These produce a variation on the soil surface reflection above the landmine due to different soil moisture.

From Table 4.2, some relations can be derived. The value of the CD output will depend on the type of soil and also on the diameter and depth of the target. For targets in the sandy clay loam soil, their CD values are relatively low compared to the other soils, and the larger the diameter of the buried object, the higher its CD output. CD output for targets in the sand soil at TNO are the lowest values, but they are buried the deepest. For these landmines, the same effect is observed regarding the diameter: the larger the diameter the higher the CD output. Results from the sandy clay and the sandy loam soil are medium values (compared to the other results), quite similar. All these devices have



**Figure 4.10.** Dissimilarity vectors from the data acquired in sandy clay soil for IED5 and IED6, buried at 5 cm depth and  $x = 25$  cm and  $x = 75$  cm, respectively. After filtering  $h_i(t)$ ,  $h_f(t)$  and  $h(t)$  from signals  $s_{11}(t)$  and  $s_{11}^{obj}(t)$ , dissimilarity vectors are calculated and show the presence of two buried objects for the *Soil + object* data set. Unit in *dataset* position is 2.5 cm.

almost the same diameter and are buried at the same depth. The highest values are obtained for the experiments at the sand layer at UCL. These changes are mainly a result of the soil perturbation after digging, however, target diameters are among the highest.

### 4.5.3 Sensitivity analysis

In order to investigate the relation between the accuracy of the proposed change detection algorithm, we performed a sensitivity analysis. The threshold value is calculated from the synthetic Green's function  $G'_l$  from a mine-free area which has the minimum error with respect to its observed signal. Then we added errors (based on the accuracy of the modeled Green's function, see Section 2.2.2) to the synthetic data and applied the change detection algorithm again. For the reduced set of targets used here for the validation of the CD algorithm, this assumption leads to no misdetection (14 landmines out of 14 were detected) and no *ghosts* (no false alarms from no object were detected). An over or under estimation (as a consequence of small errors due to the accuracy of the modeled Green's function) of the threshold values calculated for the data sets analyzed in this chapter is negligible ( $|\Delta\gamma| \leq 0.006$ ) for the detection and false alarm rate. ROC\*\* (receiver operating characteristic) curves could be useful to determine the robustness of the proposed methodology, considering unexpected errors for which  $|\Delta\gamma| > 0.006$ . Since the number of

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\*\* ROC is a plot of the probability of detection versus false alarm rate as a function of the threshold setting on the output decision variable

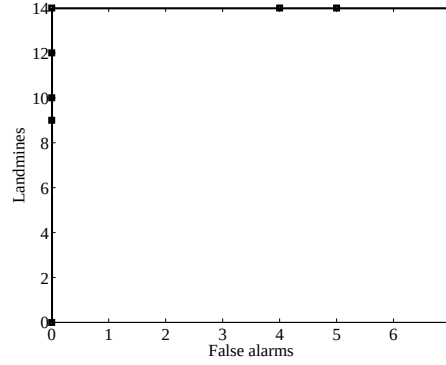
| Soil            | Target | CD output | Position (cm) |
|-----------------|--------|-----------|---------------|
| Sand, UCL       | PEC    | 0.989     | 22            |
|                 | SIM12  | 0.546     | 24            |
| Sand, TNO       | PMN2   | 0.099     | 10            |
|                 | M14    | 0.037     | 10            |
| Sandy clay loam | M14    | 0.095     | 20            |
|                 | IED1   | 0.108     | 70            |
|                 | IED2   | 0.301     | 120           |
| Sandy loam      | IED3   | 0.339     | 27            |
|                 | IED4   | 0.208     | 75            |
|                 | IED5   | 0.320     | 25            |
|                 | IED6   | 0.165     | 72.5          |
| Sandy clay      | IED3   | 0.367     | 25            |
|                 | IED4   | 0.155     | 75            |
|                 | IED5   | 0.431     | 27            |
|                 | IED6   | 0.287     | 75            |

**Table 4.2.** Results of applying the change detection (CD) algorithm. *CD output* is calculated as the area of the dissimilarity function over the threshold value,  $\mathcal{A}$ . *Position* is calculated from its center of mass.

landmines (14) and false alarms from friendly objects (0) used in this chapter is far from statistically high to perform such analysis, ROC is not considered here. However, an analysis in absolute values (number of detected landmines and of *ghosts*) is proposed as an alternative. For values of  $|\Delta\gamma| < 0.01$ , results remain the same (14 detected landmines, 0 *ghosts*). If  $\Delta\gamma \leq -0.01$ , all landmines are still detected but up to 7 *ghosts* could be found ( $\Delta\gamma \leq -0.10$ ). If  $\Delta\gamma$  is in  $[0.01, 0.03]$ , detected landmines drop to 12 and there are no *ghosts*. Five to six landmines are misdetected and no *ghosts* are found if  $\Delta\gamma$  is in  $]0.03, 0.11]$ . For values of  $\Delta\gamma > 0.11$ , the number of detected landmines fall to 0 but no *ghosts* are detected. These results are presented in Fig. 4.11.

The robustness of the proposed algorithm could be also affected by soils presenting very localized, small surface areas with a high variability in dielectric properties, such as those from a buried landmine, which could result in false alarms due to dissimilarity values larger than the threshold value. Mis-detection could occur when the threshold value is calculated from two mine-free areas with a high variability in dielectric properties, leading to a  $\gamma$  higher than the highest dissimilarity between the data from the mine-affected soil and  $G'_l$ . Although these two scenarios consider extreme soil conditions, it has to be taken into account for further analysis of the applicability and limitations of the proposed CD algorithm. This analysis will need more experiments carried out in many different real, outdoor conditions where these extreme soil





**Figure 4.11.** ROC analysis in absolute values (number of detected landmines versus number of false alarm), for the threshold  $\gamma$ .

conditions are naturally or artificially present.

## 4.6 Conclusion

In this chapter, a change detection algorithm based on parameter estimation is presented. The estimated properties of the soil from a single radar acquisition in a mine-free area are used to detect changes in the measured surface reflection due to buried objects. Compared to other change detection techniques, its performance is not related to the accurateness of a statistically-based model of the landmine and clutter signals. Since with this approach buried objects are detected but no information on their nature is given, the algorithms proposed in previous chapters can be easily integrated with this one for estimating target depth and geometrical properties.

The proposed methodology is tested under laboratory and outdoor conditions and gives promising results for localization of buried objects. Additionally, it could contribute to reduce false alarms produced by subsurface inhomogeneities. Other false alarms such as stones and large metal pieces (*e.g.*, grenade and bomb fragments), which are quite common in mine-affected fields, are not considered in this chapter. A methodology for distinguishing landmines from these false alarms is considered and is introduced in next chapter.

From the obtained CD values, the amplitude of the detected change could be related to the type of soil, landmine diameter and depth. However, to corroborate these relations, more data need to be collected and different mine-soil scenarios have to be taken into account.

Results also demonstrate how the presence of the object itself has an impact on the water distribution in its surroundings. Artificial irrigation can con-

tribute to create these changes and could thus facilitate landmine detection by the proposed approach. However, soil EM properties, which are mainly dependent on water content, govern wave propagation velocity and attenuation and therefore, watering can adversely affects GPR performance. A methodology for estimating the effects of watering on the performance of GPR is proposed in Chapter 6.

## Chapter 5

# Feature Extraction for Landmine Identification\*

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*It is common sense to take a method and try it. If it fails, admit it frankly and try another. But above all, try something.*

---

*Franklin D. Roosevelt*

In this chapter, the problem of detecting buried AP landmines is tackled in the broader context of target identification: determining relevant features, extracted from GPR signals, which can be used to identify landmines. These features are extracted in the time-frequency domain using the Wigner-Ville distribution (WVD) and the wavelet transform (WT). The Wilk's lambda value is used as a criterion for optimal discrimination. Results from the data collected for this application show that time-frequency signatures from WVD could contain more valuable information than the features extracted using WT.

### 5.1 Introduction

As stated before, GPR can contribute to locate buried objects such as metallic and non-metallic AP landmines and IEDs. Unfortunately, this technique can suffer false alarm rates as other reflectors (*e.g.*, stones, metal fragments, roots) can produce similar echoes. However, features extracted by analyzing the backscattering phenomena can be used to identify unknown targets. These features can be studied in either the time-domain (TD) or the frequency-domain (FD). TD analysis is usually the first and the most natural descriptor

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\*Adapted from Lopera O., Milisavljević N., Daniels D., Gauthier A. and Macq B., A time-frequency domain feature extraction algorithm for landmine identification from GPR data. Near Surface Geophysics. Accepted, Feb 2008.

of a signal we consider, as almost all physical signals are obtained by receivers recording variations with time. However, this analysis will not result in a good discrimination since TD features are influenced by external parameters such as target depth and position, or radar position. FD analysis essentially describes which frequencies are contained in the signal, as well as their corresponding amplitudes and phases, but it does not describe at which times these frequencies occur. We carried out TD and FD analysis, and concluded that 1-D solutions seem to be insufficient (results shown in Appendix D), thus we have to consider functions of both variables, time and frequency, i.e., time-frequency domain (TFD) transforms.

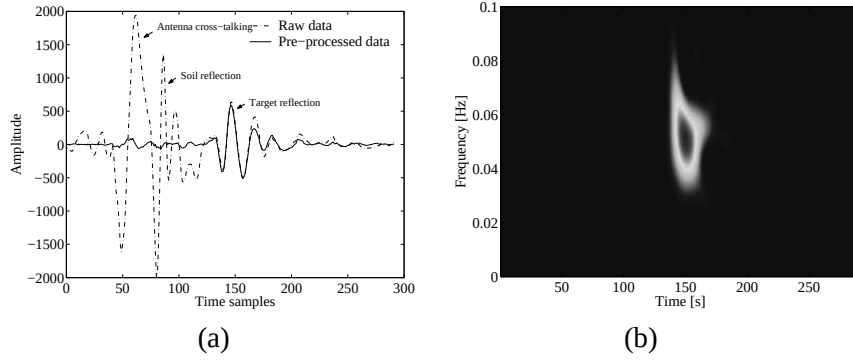
Time-frequency distributions, which are 2-D functions, can reveal the time-varying frequency content of 1-D signals [Marinovic and Eichmann, 1985]. One of these 2-D functions is the Wigner-Ville distribution (WVD), which is particularly important in the area of target recognition [Cohen, 1995]. In this chapter, we show how the interpretation of the WVD of a radar signal may provide useful information on the physical characteristics of buried AP landmines [Lopera *et al.*, 2007b]. Radar data are collected using two systems: the GPR system described in Section 2.3 and the MINEHOUND<sup>TM</sup> hand-held dual-sensor system on GPR mode. They will be referred as GPR1 and GPR2, respectively. We use two different GPRs with the aim of validating the proposed methodology for different data sets. It is out of the scope of this thesis to compare the performances of the two systems.

Data are acquired over different types of soil and for different landmines, IEDs and false alarms (FA). We draw a comparison with features extracted by the wavelet transform (WT), and the Wilk's lambda is used as a criterion for optimal discrimination. Finally, we demonstrate the effectiveness of the WVD in target classification and its potential in reducing FA rates.

## 5.2 Methodology

### 5.2.1 GPR Data and Pre-processing

In Fig. 5.1 (a), an example of a 1-D time signal, or A-scan, of an object buried in sandy soil is shown. This raw signal is represented by its amplitude as a function of time, and, since there is no pre-processing, three main components can be identified. For data collected using the GPR1, the first reflection can be related to antenna effects (see Section 2.2.1). In the case of the GPR2, it represents the direct wave or cross-talk, which corresponds to the part of the signal that travels directly from the transmitter antenna to the receiver antenna of the radar system. The second labeled peak corresponds to the air-soil interface reflection, while the third labeled peak is the target reflection. In this example, the buried object is an AT landmine, whose dimensions and metal content



**Figure 5.1.** Example of GPR2 data processing for an antitank landmine buried in sandy soil: (a) Raw and pre-processed data. In the raw data, three main components are identified. After SI, only the component of interest remains. (b) Results of applying the WVD to the pre-processed signal of (a).

make its reflection very easy to recognize. However, reflection from smaller targets such as AP landmines can be obscured by the two first components. For removing part of this unwanted echoes, the proposed filtering algorithm of Chapters 2 and 3 is applied to data collected using the GPR1. A simple SI algorithm based on the *auto-regressive moving average* (ARMA) [Lopera, 2004] is applied to remove part of these unwanted echoes (see Appendix C) for data acquired with the GPR2. The dotted line in Fig. 5.1 (a) represents raw data acquired with the GPR2 and results after SI are presented with the solid line. In the latter, only one component remains, which is the component of our interest (target reflection). Other techniques has been applied to filtering data from GPR2 [Daniels, 2004], and the SI is selected for its good performance<sup>†</sup>.

### 5.2.2 The Wigner-Ville Distribution

The WVD is an element of the time-frequency representations. Its main advantage with respect to other representations such as the short-time Fourier transform or spectrogram (see Appendix D) is a higher time resolution. The WVD of a 1-D signal  $s(t)$ ,  $WVD_s(t, f)$ , can be calculated as

$$WVD_s(t, f) = \int \tilde{s}\left(t + \frac{\tau}{2}\right) \tilde{s}^*\left(t - \frac{\tau}{2}\right) e^{-j2\pi f\tau} d\tau, \quad (5.1)$$

where

$$\tilde{s} = s(t) + j\hat{s}(t) \quad (5.2)$$

<sup>†</sup>The other applied techniques are not presented here since they are out of the scope of this study.

| Target       | Type       | Shape                    | Dimensions (cm)               | Metal content |
|--------------|------------|--------------------------|-------------------------------|---------------|
| C3A1         | Plastic AP | Irregular                | Diameter: 5.1,<br>Width: 9.0  | Low           |
| PFM          | Plastic AP | Irregular<br>(butterfly) | Width : 6.1,<br>Length: 12.0  | Low           |
| PMA          | Plastic AP | Rectangular              | Width: 15.2,<br>Length: 3.0   | Low           |
| VPMA-1       | Plastic AP | Rectangular              | Width: 14.0,<br>Length: 3.0   | Low           |
| VPMA-3       | Plastic AP | Cylindric                | Diameter: 10.3,<br>Width: 3.7 | Low           |
| Stone1       | FA         | Irregular                | Diameter: 12.0                | No            |
| Metallic can | FA         | Irregular                | Length: 12.0                  | High          |

**Table 5.1.** Some characteristics of the targets used in the measurement campaign at ERA.

is the analytic signal consisting of the real signal  $s(t)$  and its Hilbert transform [Cohen, 1995]

$$\hat{s}(t) = \frac{1}{\pi} \int \frac{s(\tau)}{1 - \tau} d\tau. \quad (5.3)$$

By replacing the analytic signal (5.2) in Eq. (5.1) and after some mathematical manipulations, Eq. (5.1) for a finite signal  $s(t)$  of duration  $T$  can be written as

$$\begin{aligned} WVD_s(t, f) = & 4 \left( \int_0^k s(t + \tau') s(t - \tau') \cos(4\pi f \tau') d\tau' + \right. \\ & \int_0^k \hat{s}(t + \tau') \hat{s}(t - \tau') \cos(4\pi f \tau') d\tau' - \\ & \int_0^k s(t + \tau') \hat{s}(t - \tau') \sin(4\pi f \tau') d\tau' - \\ & \left. \int_0^k s(t - \tau') \hat{s}(t + \tau') \sin(4\pi f \tau') d\tau' \right), \end{aligned} \quad (5.4)$$

where  $\tau' = \tau/2$  and  $k = \tau'$  if  $\tau' \leq T$  and  $k = T - \tau'$  if  $\tau' > T$ .

The WVD of the pre-processed signal of Fig. 5.1 (a) can be seen in Fig. 5.1 (b). At any time (frequency) point, the WVD represents the summed spectrum (correlation) of the signal power at this point and the cross-power of two signals parts, spaced symmetrically with respect to the current time point.

As the WVD is a 2-D representation (matrix) of a 1-D signal, this transform implies a given amount of redundancy. To address this issue, *Marinovic and Eichmann* [1985] suggested the Singular Value Decomposition (SVD), which is used here in conjunction with the concept of the center of mass (CM) to extract discriminant features [Roth *et al.*, 2001; van Kempen, 2006; Savelyev *et al.*, 2007].

### 5.2.3 Feature Extraction

SVD is intended for representing the WVD matrix  $\mathbf{W}_s$  with its singular values and singular vectors, which are unique for any matrix:

$$\mathbf{W}_s[m, n] = \mathbf{U}[m, m]\mathbf{\Sigma}[m, n]\mathbf{V}[n, n], \quad (5.5)$$

where the matrixes  $\mathbf{U}$  and  $\mathbf{V}$  contain the left-singular and right-singular vectors, respectively, and the matrix  $\mathbf{\Sigma}$  contains the singular values. Namely, any matrix can be decomposed into a number of singular triplets  $\{\mathbf{u}_k, \sigma_k, \mathbf{v}_k\}$ , with  $k = 1 \dots \min(M, N)$ , where each singular value  $\sigma_k$  can be treated as the square root of the corresponding triplet energy. Additionally, the rows and columns of  $\mathbf{W}_s$  represent, respectively, the distribution of the energy in time (related to the singular vectors  $\mathbf{v}_k$ ) and in frequency (related to the singular vectors  $\mathbf{u}_k$ ). Since the singular values and vectors are unique for any matrix, these triplets contain energy, time and frequency characteristics that can be discriminant. Therefore, we propose to use the CM (the center of mass is the strongest point in any distribution) of the singular vectors  $\mathbf{v}_k$  and  $\mathbf{u}_k$  as time and frequency features and the singular value  $\sigma_k$  as energy feature for each triplet  $\{\mathbf{u}_k, \sigma_k, \mathbf{v}_k\}$  as

$$\delta_{t,k} = \frac{1}{N} \sum_{n=1}^N n \mathbf{v}_k[n]^2, \quad (5.6a)$$

$$\delta_{f,k} = \frac{1}{M} \sum_{m=1}^M m \mathbf{u}_k[m]^2, \quad (5.6b)$$

$$\delta_e = \frac{\sigma_k}{\sum_k^{\min(M,N)} \sigma_k^2}, \quad (5.6c)$$

where  $\delta_{t/f}$  is the CM of the k-th right/left singular vector normalized to its length and  $\delta_e$  is the energy of the k-th singular triplet ( $\sigma_k$ ) normalized to the energy of the WVD.

After analyzing different triplets, we find that the following normalized features from the first triplet provide the best discriminant results:

$$\delta_t = \frac{1}{N} \sum_{n=1}^N n \mathbf{v}_1[n]^2, \quad (5.7a)$$

$$\delta_f = \frac{1}{M} \sum_{m=1}^M m \mathbf{u}_1[m]^2, \quad (5.7b)$$

$$\delta_e = \frac{\sigma_1}{\sum_{k=1}^{\min(M,N)} \sigma_k^2}, \quad (5.7c)$$

| Target          | Type  | Shape     | Dimensions (cm)              | Metal content |
|-----------------|-------|-----------|------------------------------|---------------|
| IED5            | PVC   | Cylindric | Diameter: 6.3<br>Width: 13.0 | No            |
| IED6            | PVC   | Cylindric | Diameter: 6.3<br>Width: 13.0 | Low           |
| IED7            | Glass | Cylindric | Diameter: 5.5<br>Width: 12.0 | No            |
| IED8            | Glass | Cylindric | Diameter: 5.5<br>Width: 12.0 | Low           |
| Stone2          | FA    | Irregular | Diameter: 8.0                | No            |
| Metallic debris | FA    | Irregular | Length: 6.0                  | High          |

**Table 5.2.** Some characteristics of the targets used in the measurement campaign in Colombia.

Since the right and left singular vectors are related, respectively, to the rows and columns of the WVD matrix,  $\delta_t$  and  $\delta_f$  can be referred, respectively, to the time and frequency representations of the signal. As the singular value  $\sigma_1$  can be treated as the square root of the corresponding triplet  $\{\mathbf{u}_1, \sigma_1, \mathbf{v}_1\}$  energy,  $\delta_e$  can be linked to the energy representation of the signal.

## 5.3 Experiment Setup

### 5.3.1 GPR-based Systems

Two GPR systems are used for the measurements. GPR1 is the GPR system presented in Section 2.3. GPR2 is the MINEHOUND hand-held dual-sensor. GPR2 combines the output from a pulse induction MD (the VALLON VHMD3.1) and an impulse GPR based on two spiral antennas and a central frequency of 1GHz. GPR2 has three modes of operation: (1) MD, (2) GPR, (3) MD+GPR, and it transforms MD and GPR signals into two separated audio signals of different frequency of vibration and tone. During a scanning, data (MD or GPR) can be separately logged in the electronic unit of the MINEHOUND and transmitted afterwards to a laptop via the serial port. For this study, only the GPR data are analyzed. Data format for the GPR system is 16 bit accuracy, 512 samples per A-scan in a time window of 19.2 ns, and 63 A-scans per second (one every  $\sim 15.9$  ms).

### 5.3.2 Outdoor Measurements

Two different measurement campaigns were carried out for the application of the proposed identification methodology. For the first campaign, two different lanes of the ERA test facility were selected for the measurements: sand and

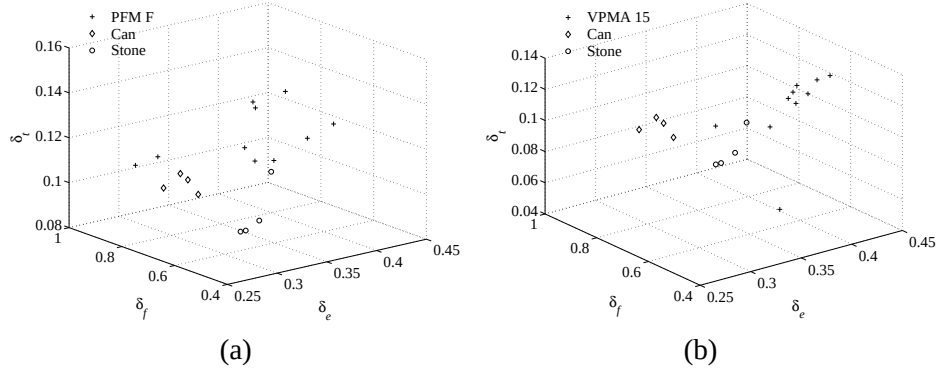




**Figure 5.2.** Scanning frame with the MINEHOUND unit over the ballast soil.

ballast (mix of sand and pebbles). No information about dielectric properties is available, however, their water content at the time of the experiment were 8% and 7.3%, respectively (dry soil). In these lanes, different targets are buried at different depths. Their characteristics are given in Table 5.1. AP landmines are buried from 0 to 15 cm depth, and FA are buried at 5 cm depth. They are placed horizontally with the side defining the diameter uppermost. For this campaign, data have been acquired using GPR2 only. The height of the GPR2 head above the soil was at about 3 cm. Data were recorded by moving the scanning frame over a scanning distance of 50 cm and crossing the center of the buried target (approximately).

The second campaign was performed over two typical Colombian mine-affected soils located in training lanes of Colombian Military Bases. These are two of the three lanes described in Section 3.3.2: loamy sand ( $\epsilon_r = 4.5$ , measured at the time of the experiment) and sandy clay ( $\epsilon_r = 5.0$ , measured at the time of the experiment). For this campaign, data have been acquired using both GPR1 and GPR2. Radar measurements were carried out using different targets including IEDs. Their characteristics are described in Table 5.2. IEDs are buried at two different depths: flush and 5 cm. FA are buried at 5 cm depth. They are placed horizontally with the side defining the diameter uppermost. For data acquisition, the GPR1 was moved manually along the horizontal  $x$ -axis, crossing the center of the buried target (approximately), following a support frame. The height of the antenna aperture above the soil was at about 15 cm (antenna phase center was at about 22 cm). Radar traces ( $S_{11}$ ) were recorded with a constant space step of 1 cm over a scanning distance of 35 cm. For the GPR2, data was acquired manually following a scanning



**Figure 5.3.** Extracted features from two low-metallic content AP landmines, PFM (Flush) and VPMA (15 cm)), and two false alarms, stone1 and metallic can. Data were acquired with GPR2.

distance of 30 cm and crossing the center of the buried target (approximately).

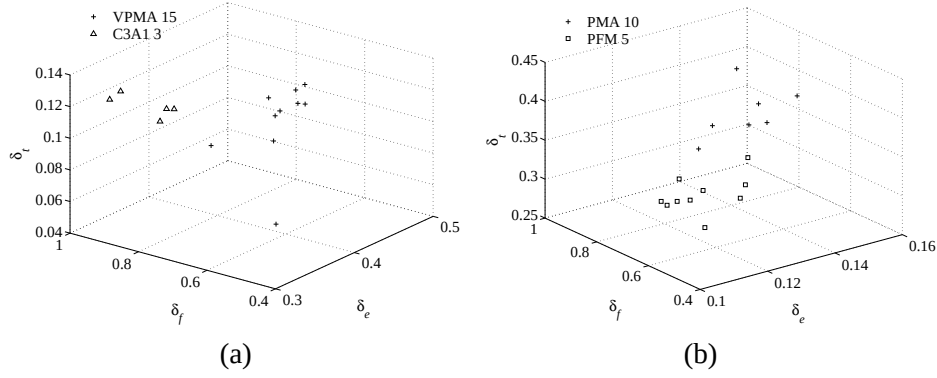
## 5.4 Results and discussion

We apply the pre-processing approaches presented in Section 5.2.1. From the pre-processed B-scan, the A-scan which maximizes an energy-based criterion is used in the feature extraction methodology.

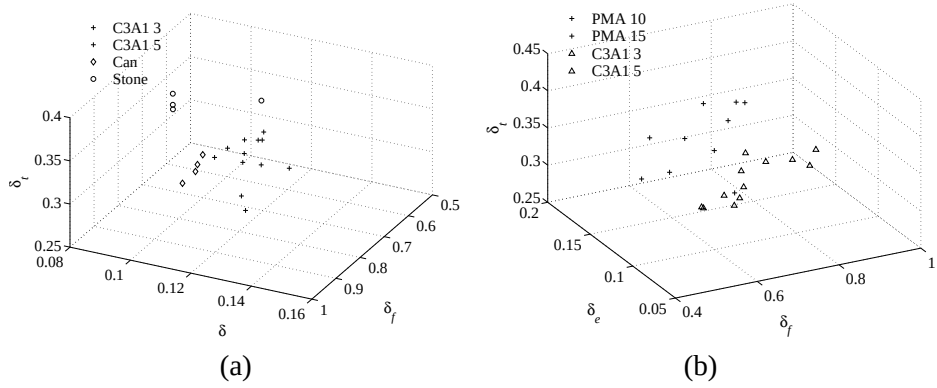
### 5.4.1 ERA Measurement Campaign

Fig. 5.3 shows the extracted features  $\delta_t$ ,  $\delta_f$  and  $\delta_e$  for two low-metallic content AP landmines, PFM and VPMA-1, and two FA, stone1 and metallic can. The PFM is buried flush, the VPMA-1 is buried at 15 cm of depth and the false alarms are buried at 5 cm of depth. Every object is represented by several points extracted from several pre-processed A-scans (which are extracted from different B-scans). The features of the AP landmines are well clustered and well separated from those of the metallic can and stone. The false alarms are clearly separated as well. Similar results have been obtained for the other targets, and they clearly show that the features are selected correctly and classification can be performed using the proposed methodology.

Classification between different AP landmines could be also obtained. Some results are presented in Figs. 5.4 (a) and (b), where the extracted features from two AP landmines with different shape are well separated. In these figures, two well defined clusters can be seen, which classify the points of the VPMA (rectangular shape) buried at 15 cm of depth out of those of the C3A1 (irregular shape) buried at 3 cm of depth, in Fig. 5.4 (a), and the points of the PMA (rectangular shape) buried at 10 cm of depth out of those of the PFM



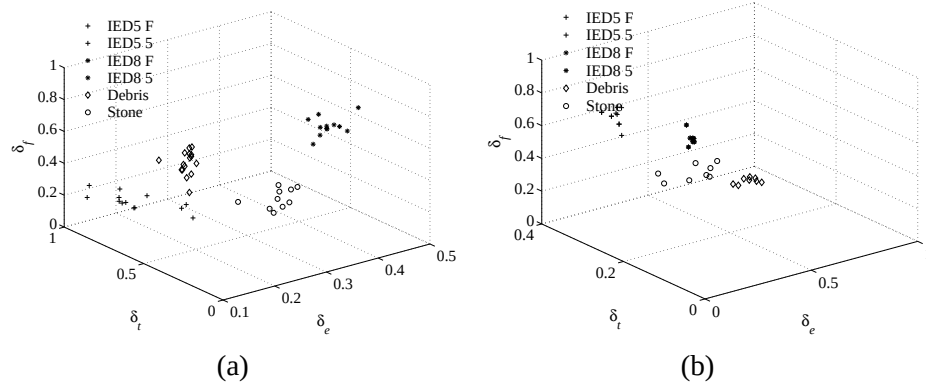
**Figure 5.4.** Extracted features from low-metallic content AP landmines with different shapes. Data were acquired with GPR2.



**Figure 5.5.** Extracted features from different targets: (a) the C3A1 buried at different depths and two false alarms, stone1 and metallic can, (b) the PMA and C3A1 at different depths. Data were acquired with GPR2.

(butterfly shape) buried at 5 cm of depth, in Fig. 5.4 (b). However, *classification*, as defined in Chapter 1, is not considered in this study but the obtained results could be deeply analyzed and validated in further research.

Results show that the extracted features could be independent of the target depth. In Fig. 5.5 (a) features extracted from the same AP landmine, C3A1, buried at different depths (3 cm and 5 cm) form a cluster which is well separated from the FA classes (can and stone). These features are also well differentiated from those of the PMA buried at 10 cm and 15 cm of depth, as can be seen in Fig. 5.5 (b).



**Figure 5.6.** Extracted features from the targets with no-metal content: (a) data acquired with GPR1, (b) data acquired with GPR2.

#### 5.4.2 Colombian Measurement Campaign

The same methodology is applied to the data collected in Colombia. Some results are shown in Fig. 5.6, for targets with no-metal content. Four classes are identified in each graph. All IEDs are well separated from the false alarms and a good classification between different IEDs is also obtained. Additionally, these data sets validate the independence of the extracted features with respect to depth. Targets from the same class at different depths are well clustered together, as can be seen for IED5 and IED8, in both graphs. Similar results were obtained for targets with low-metal content.

#### 5.4.3 A Comparison with Feature Extraction by Wavelet Transform

Feature extraction is also carried out based on WT (see Appendix D). Since it is not possible to visualize in a three-dimensional graph the four-dimensional feature clusters of the WT, the Wilk's lambda value [Krzanowski, 1988] is used to show the possibility of landmine discrimination in an explicit way. The Wilk's lambda value expresses how well feature vectors belonging to one class are clustered together, taking into account the between and within class distances. This value is always between zero and one, where *zero* means perfect class separation and *one* no class separation. Values under 0.5 express a good discrimination. Table 5.3 summarizes the Wilk's lambda values estimated for the two feature sets (WT and WVD) and for several couples of classes (mine, no-mine) for the data collected at ERA. For each mine class, the number of scenarios is defined by four different A-scans and two different depths which results in eight feature vectors. For each no-mine class, eight different A-scans at the same depth are considered. The WT provides a good

discriminant power for Cases 2, 3, 6 and 7. These cases correspond to the regular mines. Less satisfactory results are obtained for Cases 1, 4, 5 and 8, which correspond to irregular mines. The WVD provides a good discriminant power for all cylindrical, rectangular and irregular mines. This could indicate that the proposed features from WVD are implicitly related to the dielectric contrast, the geometrical properties and inner structure of the target.

| Cases            | WT     | WVD    |
|------------------|--------|--------|
| 1: PFM, can      | 0.2580 | 0,0307 |
| 2: PMA, can      | 0.1110 | 0,0191 |
| 3: VPMA3, can    | 0.0017 | 0,0181 |
| 4: C3A1, can     | 0.2761 | 0,0279 |
| 5: PFM, stone1   | 0.2591 | 0,0253 |
| 6: PMA, stone1   | 0.1219 | 0,0114 |
| 7: VPMA3, stone1 | 0.0047 | 0,0149 |
| 8: C3A1, stone1  | 0.3044 | 0,0190 |

**Table 5.3.** Wilk's lambda values from data collected at ERA.

Results of the Wilk's lambda value for data collected in Colombia are shown in Table 5.4. For each mine class, the number of scenarios is defined by four different A-scans and two different depths which results in eight feature vectors. For each no-mine class, eight different A-scans at the same depth are considered. Both the WT and the WVD provides very good discriminant power for all classes. However, values from the WVD approach are slightly better than those from the WT for these cylindrical no- and low-metallic IEDs. Since we are using a limited number of targets, these differences could not lead to a firm conclusion.

From the results presented in this chapter, 18 out of 18 landmines and 8 out of 8 FA are well identified by the WVD approach. Note that the approach is applied to pre-processed data, where unwanted reflections (antenna effects and soil reflection) are previously removed. Therefore, robustness of the proposed methodology depends on the robustness of the filtering algorithm applied to remove these components out of the raw signal. If part of these reflections remains after filtering, the energy of these remnants will be taken into account in the WVD, affecting the features extracted by the SVD approach. Remaining unwanted reflections due to the accuracy of the algorithms present in Chapter 2 (for filtering data from GPR1) and in Appendix C (for filtering data from GPR2<sup>‡</sup>) result in small errors in the extracted features (maximum  $\Delta\delta \simeq 10^{-3}$ ) that does not affect the identification of a landmine from a false

<sup>‡</sup>The accuracy of the estimated *ground* signal (see Appendix C) depends on the selected reference *ground* sample (*i.e.*, single radar measurement) in a nearby, landmine-free area.

alarm (maximum  $\Delta$ Wilk's-lambda-value  $\simeq 10^{-4}$ , i.e., 18 out of 18 landmines and 8 out of 8 FA are well identified). Consider an extreme case where the soil and antenna reflections completely remain after applying the filtering algorithms. This leads to Wilk's lambda values  $\simeq 1$  ( $\Delta$ Wilk's-lambda-value is in  $[0.6, 0.9]$ ), which means no class separation between mines and FA. This can be interpreted as

- 0 out of 18 landmines and 0 out of 8 FA are well identified, or
- 18 out of 18 landmines and 8 out of 8 FA are identified as landmines.

This is a normal expectation since the energy and time features are derived mainly from the remaining antenna and soil reflections, which are the same for all data sets. Therefore, the accuracy of the filtering algorithm for removing components of the signal that carry no useful information about the target is very important.

As for Chapter 4, this analysis is represented by a ROC curve in absolute values in Fig. 5.7.

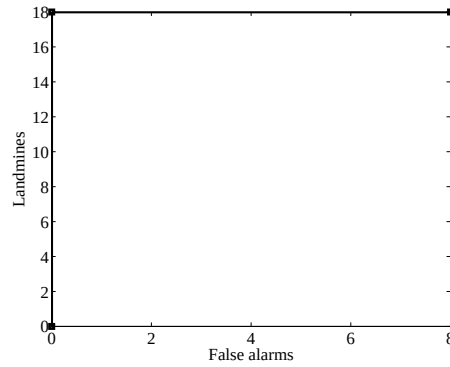
| Cases(*)                      | WT     | WVD    |
|-------------------------------|--------|--------|
| 1: IED5 <sub>m</sub> , debris | 0.0309 | 0,0214 |
| 2: IED5, debris               | 0.0130 | 0,0031 |
| 3: IED8 <sub>m</sub> , debris | 0.0505 | 0,0100 |
| 4: IED8, debris               | 0.0760 | 0,0101 |
| 5: IED5 <sub>m</sub> , stone2 | 0.0510 | 0,0138 |
| 6: IED5, stone2               | 0.0190 | 0,0200 |
| 7: IED8 <sub>m</sub> , stone2 | 0.0275 | 0,0093 |
| 8: IED8, stone2               | 0.0104 | 0,0090 |

**Table 5.4.** Wilk's lambda values from data collected in Colombia. (\*) Subscript *m* indicates low-metallic targets

## 5.5 Conclusion

A promising algorithm for feature extraction based in a time-frequency distribution is proposed in this chapter and is applied to the identification of AP landmines and IEDs from data acquired with different hand-held GPR systems and under different scenarios.

The methodology is based on the interpretation of the singular values and vectors of the WVD matrix of the radar signal after background subtraction. It is applied to different types of landmines (different shapes and sizes) buried at different depths. Two types of false alarms (stones and metal debris) are also



**Figure 5.7.** ROC analysis in absolute values (number of detected landmines versus number of false alarm) for the Wilk's-lambda-value.

considered. Discriminant time-frequency-energy features can be extracted, which are independent of the target depth and could be related to the dielectric contrast, the geometrical characteristics and internal structure of the targets. These features could be used to differentiate between an AP landmine and a false alarm, thus decreasing the false alarm rate.

Effects of soil roughness and signal attenuation due to increasing soil water content on the sensitivity of the proposed target identification methodology are currently carried out and will be considered in further work.





## Chapter 6

# Effects of soil properties on the GPR performance<sup>\*</sup>

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*I have not failed. I've just found 10,000 ways that won't work.*

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*Thomas A. Edison*

In this chapter, the influence of soil properties on landmine detection is analyzed in order to predict GPR performance. Accordingly, 2-D, EM finite-difference time-domain (FDTD) GPR model, coupled to pedotransfer functions, is used for calculating landmine signatures for different soil-target scenarios (this approach is represented in Fig. 1.6, block section 3). Besides, laboratory and field measurements are carried out over different types of soil subject to artificial changes on water content. Simulated and measured data illustrate how changes on soil water content can adversely affect or enhance landmine detection.

### 6.1 Introduction

It is well known that the detection performance of GPR is influenced by the EM properties of the soil [Das *et al.*, 2001; Rhebergen *et al.*, 2004; van Dam *et al.*, 2005; Miller *et al.*, 2004]. as well as by the target features [van der Kruk *et al.*, 2003; Daniels, 2004; Rhebergen and Ralston, 2005]. Due to the complex nature of the problem, most modeling and experimental efforts for determining GPR performances have focussed on the effect of one or few variables, mainly, soil water content [Miller *et al.*, 2004; Rhebergen *et al.*, 2004].

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<sup>\*</sup>Adapted from Lopera O. and Milisavljević N., Prediction of the effects of soil and target properties on the antipersonnel landmine detection performance of ground-penetrating radar: a Colombian case study. Journal of Applied Geophysics, vol 63, pp. 13-23, 2007.

The variation of soil water content can be useful for the detection and identification of landmines from GPR data since it could enhance the dielectric contrast between the landmine and the soil surrounding it. Additionally, natural precipitations or synthetic watering may induce specific water content patterns in both soil surface and subsurface in presence of a buried landmine which can be detected, as shown in Section 4.2. Yet, water content also contributes to EM signal attenuation and therefore it affects the detection performance of GPR.

Electromagnetic models can be used to predict the response from a landmine buried in a particular soil and to study the effects of the soil properties on landmine detection [Rhebergen *et al.*, 2004; Lopera and Milisavljevic, 2007]. In this chapter, a finite-difference time-domain (FDTD) modeling program [Giannopoulos, 2002] is used to show two of the major effects of soil properties on GPR performance: attenuation and contrast. Such effects are also illustrated through laboratory and field measurements.

## 6.2 Synthetic Data

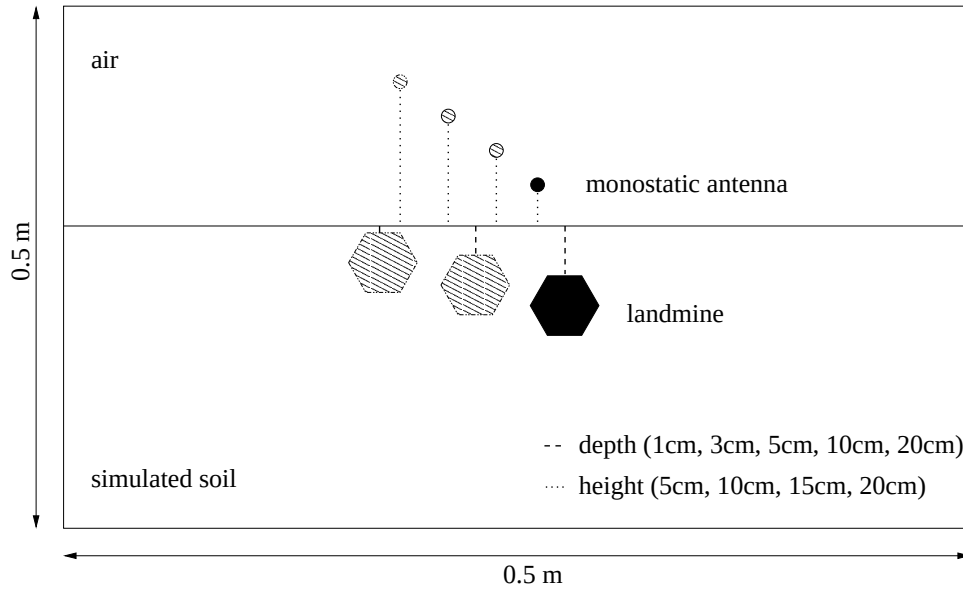
### 6.2.1 Finite-Difference Time-Domain Model

All electromagnetic phenomena, on a macroscopic scale, are described by Maxwell's equations. These are first-order partial differential equations that mathematically express the relationship between the fundamental EM field quantities and their dependence on their sources [Balanis, 1989] and on the EM properties of the medium. In order to simulate a GPR signal from a particular target embedded in the soil, these equations have to be solved subject to the geometry of the problem and its initial conditions. One of the available numerical programs for computing GPR wave propagation and signal properties is GPRMAX [Giannopoulos, 2002], which solves Maxwell's equations using the FDTD method [Taflöv, 1995]. FDTD techniques are based on discretizing both space and time using an orthogonal grid and solving the differential form of Maxwell's equations employing a second or fourth order approximation. An example of the numerical domain modeled with this tool is shown in Fig. 6.1.

For studying the effects of soil properties on landmine detection by GPR, specific radar-air-soil-target configurations are considered.

### 6.2.2 Target Characteristics

From the conventional AP landmines that can be found in the Colombian mine-affected fields, some low-metallic landmines are selected, and their features are summarized in Table 6.1. Their case material is plastic (polyethylene (PE), polypropylene (PP), polystyrene (PS), rubber or bakelite), and their main charge is a mixture of different chemical components (see Table 6.1). Their



**Figure 6.1.** Numerical domain used in the FDTD program.

dielectric constant  $\varepsilon_{tg}$  is calculated by averaging the case material dielectric constant and the main charge dielectric constant (values are taken from von Hippel [1995]).

| Target   | Geometry*<br>(cm)  | Material | Main charge** | $d$<br>(cm) | $\varepsilon_{tg}$<br>(-) |
|----------|--------------------|----------|---------------|-------------|---------------------------|
| M14      | D = 5.6<br>W = 4   | Plastic  | TETRYL        | 0~15        | 2.8                       |
| NR 409   | D = 8.2<br>W = 2.8 | Plastic  | TNT+AAP+RDX   | 0~15        | 3.1                       |
| MN-MAP-1 | D = 7.5<br>W = 7   | Plastic  | PETN+TNT+RDX  | 0~15        | 3.1                       |

**Table 6.1.** Summary of AP landmines features. The burial depth  $d$  is measured from the top of the mine. The dielectric values are an average of the dielectric constants of the case material and of the main charge - values taken from von Hippel [1995].

\* H = Height, D = Diameter, L = Length, W = Width.

\*\* AAP = atomized aluminum powder, PETN = pentaerythrite tetranitrate, RDX = cyclotrimethylene trinitramine, TETRYL = trinitrophenyl, TNT = trinitrotoluene.

Mine-affected areas are also contaminated with IEDs. These devices are fabricated in different forms, using different materials with a minimum or no metal content. Some of their characteristics are summarized in Table 6.2. The size and shape of the IEDs can vary from a small piece of PVC ( $\sim 10 \times 14 \text{ cm}^2$ )

| Shape       | Material      | Geometry*<br>(cm)                          | $d$<br>(cm) | $\varepsilon_{tg}$<br>(-) |
|-------------|---------------|--------------------------------------------|-------------|---------------------------|
| Cylindrical | Metal,        | W = 10 ~ 40,<br>D = 6 ~ 30                 | 0 ~ 50      | -                         |
|             | PVC,          | W = 10 ~ 17,<br>D = 8 ~ 14                 | 0 ~ 10      | 3.6                       |
|             | Glass,        | W = 12 ~ 15<br>D = 5 ~ 8                   | 0 ~ 10      | 3.5                       |
|             | Wood          | W = 20 ~ 30,<br>D = 7 ~ 10                 | 0 ~ 3       | 3.6 / 8.9                 |
| Rectangular | Wood          | H = 15 ~ 20,<br>L = 20 ~ 25<br>W = 20 ~ 25 | 0 ~ 20      | 3.6 / 8.9                 |
| Irregular   | Textile fiber | D = 15 ~ 25                                | 0 ~ 20      | 3.3                       |

**Table 6.2.** Summary of some IED characteristics. Plastic IEDs are made with polyvinylchloride or PVC. The textile fiber used for some IEDs is derived from the *fique* or *furcraea macrophylla* plant. The burial depth  $d$  is measured from the top of the object. The dielectric values are an average of the dielectric constants of the case material and of the main charge - values taken from von Hippel [1995]. Two values are provided for the wooden IEDs: dry and wet.

\* H = Height, D = Diameter, L = Length, W = Width.

to a large gas cylinder ( $\sim 25 \times 40 \text{ cm}^2$ ). Additionally, some IEDs are fabricated with textile fiber and therefore, their shape is irregular. Usually, different kinds of explosives are used in the fabrication of IEDs. The most popular, and powerful, is known as ANFO (ammonium nitrate and fuel oil), although BENCLO (sodium benzoate and potassium chlorate) is also used. Besides the explosive, some devices are filled with tar (byproduct of petroleum) or a mix of tar and grapeshot (*e.g.*, nails).

### 6.2.3 Soil Characteristics

Any type of soil can be considered for modeling EM wave propagation with GPRMAX. In this study, typical Colombian mine-affected soils are selected since they are of our interest. We focus on two ferruginous soils<sup>†</sup> from two highly mine-affected departments of Colombia, located within The Andes mountain chain: Santander and Antioquia. Some of their characteristics are previously measured in order to be used in the modeling program. They are classified as silt loam and loamy sand, respectively; their organic content is less than 1% and their Fe percentages are 5.2% and 8.8%, respectively. These soils are an issue for the detection of low-metallic AP landmines using MDs

<sup>†</sup> These soil are considered on Chapter 3 for the outdoor measurements.

[Toews and Sirovyak, 2003], due to their high magnetic susceptibility (MS,  $\chi$ ) and magnetic viscosity (or frequency-dependent MS,  $\chi_{FD}$ ) [Mullins, 1977]. In order to determine the effect of the iron components on the EM properties, the magnetic susceptibility of the selected soils was measured using a Barington MS2 dual-frequency sensor (0.46/4.6 KHz) [Dearing, 1994]. Results are published in Toews and Sirovyak [2003]. Several samples were taken from the upper 30 cm of the soil profile. Two measurements are obtained: the MS at low frequency ( $\chi_{LF}$ ) and the MS at high frequency ( $\chi_{HF}$ ). The frequency-dependent MS can therefore be expressed as a relative loss of susceptibility ( $\chi_{FD} = \chi_{LF} - \chi_{HF}$ ) [Dearing et al., 1996]. Results of these measurements and other available properties of both soils are summarized in Table 6.3.

| Class* | Sand (%) | Silt (%) | Clay (%) | $\rho_S$ (g/cm <sup>3</sup> ) | $\Theta_r$ (%) | $\Theta_s$ (%) | $\chi_{LF}$ (-) | $\chi_{HF}$ (-) | $\chi_{FD}$ (-) |
|--------|----------|----------|----------|-------------------------------|----------------|----------------|-----------------|-----------------|-----------------|
| SL     | 30.6     | 63       | 6.4      | 1.18                          | 4.4            | 38.9           | 307             | 304             | 2               |
| LS     | 72.1     | 26.9     | 1        | 1.3                           | 3.2            | 41             | 1080            | 1070            | 11              |

**Table 6.3.** Available properties of the two ferruginous soils. The residual water content ( $\Theta_r$ ) and the saturated water content ( $\Theta_s$ ) are calculated using the sand, silt and clay percentages and the bulk density ( $\rho_S$ ) [Schaap et al., 1998]. Several magnetic susceptibility measurements were made using a Barington dual frequency sensor. We have only included the average values.

\* Textural class: SL = Silt Loam, LS = Loamy Sand.

#### 6.2.4 Semi-Empirical Electromagnetic Model

In theory, principal factors influencing the detection performance of GPR are the EM properties of the soil, namely, relative dielectric permittivity,  $\varepsilon$ , effective conductivity,  $\sigma_{eff}$  and magnetic permeability,  $\mu$ . Although there are different approaches for modeling these properties, it is difficult to develop an opinion about the applicability of a method at a given environment because their success is dependent on the case study [Linde et al., 2006]. In general, these methodologies are based on a-priori information, i.e., different soil parameters previously measured which are introduced into a model. It is important to clarify that the available data for a mine-affected area are limited, due to the impossibility of taking measurements in situ as well as the lack of geophysical data bases from mine-affected, underdeveloped countries. Since it is not within the scope of this study to provide detailed descriptions of all these approaches, we briefly describe some of them which could be applied in this case study. For more information about different approaches, the reader is referred to reviews given by Mavko et al. [1998], Lesmes and Friedman [2005], and references therein.

Theoretical and empirical models of the electrical properties of the different components of the soil have been combined into semi-empirical models,

which can be used to predict electrical properties of field soils. For this study, we require a model for predicting  $\sigma_{eff}$  as well as both the real<sup>‡</sup> and imaginary parts of  $\varepsilon$  ( $\varepsilon = \varepsilon' - j\varepsilon''$ ) for a known frequency band and considering different moisture levels of a known soil type. In *Toop et al.* [1980], a semi-empirical model is proposed and relates the soil volumetric water content with  $\varepsilon$ . This approach is based on sandy soils and needs to be adjusted for each type of soil. This would require a calibrated formula for each environment, therefore we do not consider it here. Other semi-empirical models are based on mixing laws, such as the complex refracted index method (CRIM) [*Tinga et al.*, 1973]. In *Shutko and Reutov* [1982], it is demonstrated that CRIM gives a good approximation of  $\varepsilon$  for different soils in the range 1-10 GHz. However, it requires some parameters such as soil porosity which are not available in our case study. In *Peplinski et al.* [1995], a semi-empirical dielectric model based on pedotransfer functions [*Gupta and Larson*, 1979] is reported. This model relates the textural composition of the soil to electrical parameters and it covers the 0.3-1.3 GHz frequency range. The model provides frequency dependent expressions for the real and imaginary parts of the relative dielectric constant of a soil medium in terms of the fraction of sand particles  $S$ , the fraction of clay particles  $C$ , the volumetric water content  $\Theta$  and the bulk density of the soil  $\rho_S$ , all being available parameters. It is based on an earlier model for dielectric constants in the 1.4-18 GHz frequency range developed by *Dobson et al.* [1985]. The real part of the complex relative dielectric permittivity for the bulk soil is approximated as

$$\varepsilon' = \left[ 1 + \frac{\rho_S}{\rho_P} (\varepsilon_P^\varphi - 1) + \Theta^{\beta'} \varepsilon_{fw}^{\prime\varphi} - \Theta \right]^{\frac{1}{\varphi}} \quad (6.1)$$

in *Dobson et al.* [1985], and

$$\varepsilon' = 1.15 \left[ 1 + \frac{\rho_S}{\rho_P} (\varepsilon_P^\varphi - 1) + \Theta^{\beta'} \varepsilon_{fw}^{\prime\varphi} - \Theta \right]^{\frac{1}{\varphi}} - 0.68 \quad (6.2)$$

in *Peplinski et al.* [1995]. The imaginary part is derived as

$$\varepsilon'' = \left[ \Theta^{\beta''} \varepsilon_{fw}^{\prime\prime\varphi} \right]^\varphi, \quad (6.3)$$

where:

- $\rho_P = 2.66\text{g/cm}^3$  is a typical value,
- $\varepsilon_P = (1.01 + 0.44\rho_P)^2 - 0.062$  is the empirical model of the dielectric constant of the soil particles,

---

<sup>‡</sup>The real part of  $\varepsilon$ ,  $\varepsilon'$ , is the relative dielectric permittivity,  $\varepsilon_r$ , introduced in Chapter 2.

- $\beta' = 127.48 - 0.519S - 0.152C$  and  $\beta'' = 1.33797 - 0.603S - 0.166C$  are two frequency independent constants which join the soil type into the model,
- $\varphi = 0.65$  is empirically derived in *Dobson et al.* [1985] and *Peplinski et al.* [1995].

Furthermore, the frequency dependent variables  $\varepsilon'_{fw}$  and  $\varepsilon''_{fw}$  are the real and imaginary parts, respectively, of the dielectric constant for free water. The latter depends on the effective conductivity,  $\sigma_{eff}$ , which is derived in Dobson et al. (1985) as

$$\sigma_{eff} = 1.645 + 1.939\rho_S - 2.25622S + 1.594C, \quad (6.4)$$

and in Peplinski et al. (1995) as

$$\sigma_{eff} = 0.0467 + 0.2204\rho_S - 0.4111S + 0.6614C. \quad (6.5)$$

Once  $\varepsilon$  is approximated using the proposed semi-empirical models, other factors influencing the detection performance of GPR can be derived. They are the attenuation factor  $\alpha$  and the dielectric permeability contrast<sup>§</sup>  $\varepsilon_{contrast}$ . The attenuation factor  $\alpha$ , in dB, depends on the magnetic permeability of the soil,  $\mu = \mu_0 + \mu_0\chi_{FD}$  ( $\mu_0 = 4\pi * 10^{-7}$  H/m)<sup>¶</sup>, the complex permittivity of the soil and the angular frequency of the radar wave,  $\omega$ , [Reynolds, 1998]. It is derived from the equation

$$\alpha = \omega \sqrt{\frac{\mu\varepsilon_{eff}}{2} \left[ \sqrt{1 + \left(\frac{\varepsilon''}{\varepsilon'}\right)^2} - 1 \right]}, \quad (6.6)$$

where  $\varepsilon_{eff} = \varepsilon'\varepsilon_0$  is the effective permittivity of soil ( $\varepsilon_0 = 8.85 * 10^{-12}$  F/m) and the ratio between  $\varepsilon''$  and  $\varepsilon'$  is commonly referred to as the loss factor or loss tangent. This equation is only valid when  $\mu \leq 1$ , which is the case for both soils.

Assuming a plane wave vertically incident on the top of the target, the dielectric permeability contrast  $\varepsilon_{contrast}$  between the target and the background is calculated according to [Reynolds, 1998]:

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<sup>§</sup>GPR detect contrasts in EM properties, but reflections are mainly attributed to contrasts in permittivity [Reynolds, 1998]. Magnetic permeability contrast are rare in a natural environment but may occur with metal objects. Electric conductivity contrasts cause weak reflections in a natural environment. However, when the radar frequency is <100 MHz and when the conductivity is >5 mS/m (lossy soils), reflections at conductivity contrasts may become significant.

<sup>¶</sup>Note that the frequency-dependent MS have a negligible effect on the magnetic permeability ( $\mu \approx \mu_0$ ) for both soils.

$$\varepsilon_{contrast} = \frac{\sqrt{\varepsilon} - \sqrt{\varepsilon_{tg}}}{\sqrt{\varepsilon} + \sqrt{\varepsilon_{tg}}}, \quad (6.7)$$

where  $\varepsilon_{tg}$  is the dielectric permittivity of the target, whose imaginary part is considered equal to zero.

Since the strength of the buried target reflection depends on the wave penetration and the dissimilarity between soil and target permittivity,  $\alpha$  and  $\varepsilon_{contrast}$  have a direct impact on the SNR, as it is pointed out further in the following section.

### 6.2.5 Modeling Ground-Penetrating Radar

Firstly, a monostatic wide-band GPR is selected to avoid the direct wave between the transmitting and receiving antennas. This eliminates an important unwanted signal artefact that may obscure the other information in the signal. Secondly, the transmitting/receiving antenna is located over the soil surface at a maximal height of 20 cm. This value is a practical optimum that allows high antenna mobility without increasing the spreading loss. Finally, the choice of the bandwidth depends on the desired depth resolution and signal penetration. At frequencies above 1 GHz, depth penetration decreases dramatically [Daniels, 2004], whereas resolution increases. On top of this, one has to deal with rough surfaces and soil attenuation for shorter wavelengths [Sai and Ligthart, 2004]. The frequency range 0.8-2.8 GHz is selected because it is in the range of the GPR-based systems used in this thesis and in the range of most landmine GPR applications. Additionally, the size of the targets is larger than the wavelength of the propagating GPR wave (under the conditions considered here), therefore the target backscattering should be significant.

### 6.2.6 Results and Discussion

#### Estimation of the dielectric permittivity, attenuation and dielectric contrast

For frequencies ranging between 0.8 GHz and 2.8 GHz and for the two types of soil, the complex relative dielectric permittivity is approximated using Eqs. (6.1), (6.2), (6.3). Note that they depend on Eqs. (6.4) and (6.5). Different water content fractions are selected, which range between the residual water content,  $\Theta_r$ , and the saturated water content,  $\Theta_s$  (see Table 6.3). In Fig. 6.2, the estimated real and imaginary values of  $\varepsilon$  for the silt loam and loamy sand soil are shown as a function of the frequency (at 10% water content), and as a function of the water content (at 0.8 GHz and 2.5 GHz).

Considering the empirical model, different values of the real and imaginary parts of  $\varepsilon$  are found in Figs. 6.2 (a,b) for frequencies below and above 1.4 GHz,



and the same occurs at all different water content fractions. In practice, the dependence of the dielectric permittivity on the frequency should be a continuous function. For the estimated values, the maximum difference in  $\varepsilon$  is no more than 0.04. This value is lower than the error values found in *Peplinski et al.* [1995], after the linear adjustment introduced to correct the model reported in *Dobson et al.* [1985]. Additionally, similar errors on the estimated values of the real and imaginary parts of  $\varepsilon$  are observed in *Ponizovsky et al.* [1999] and *Yu et al.* [1999]. Since these studies compare experimental results with predictions based on other empirical models, one can state that such a difference should not represent a relevant error. Therefore, we can expect that this small gap on the representation of  $\varepsilon$  will have a slight impact on the simulations.

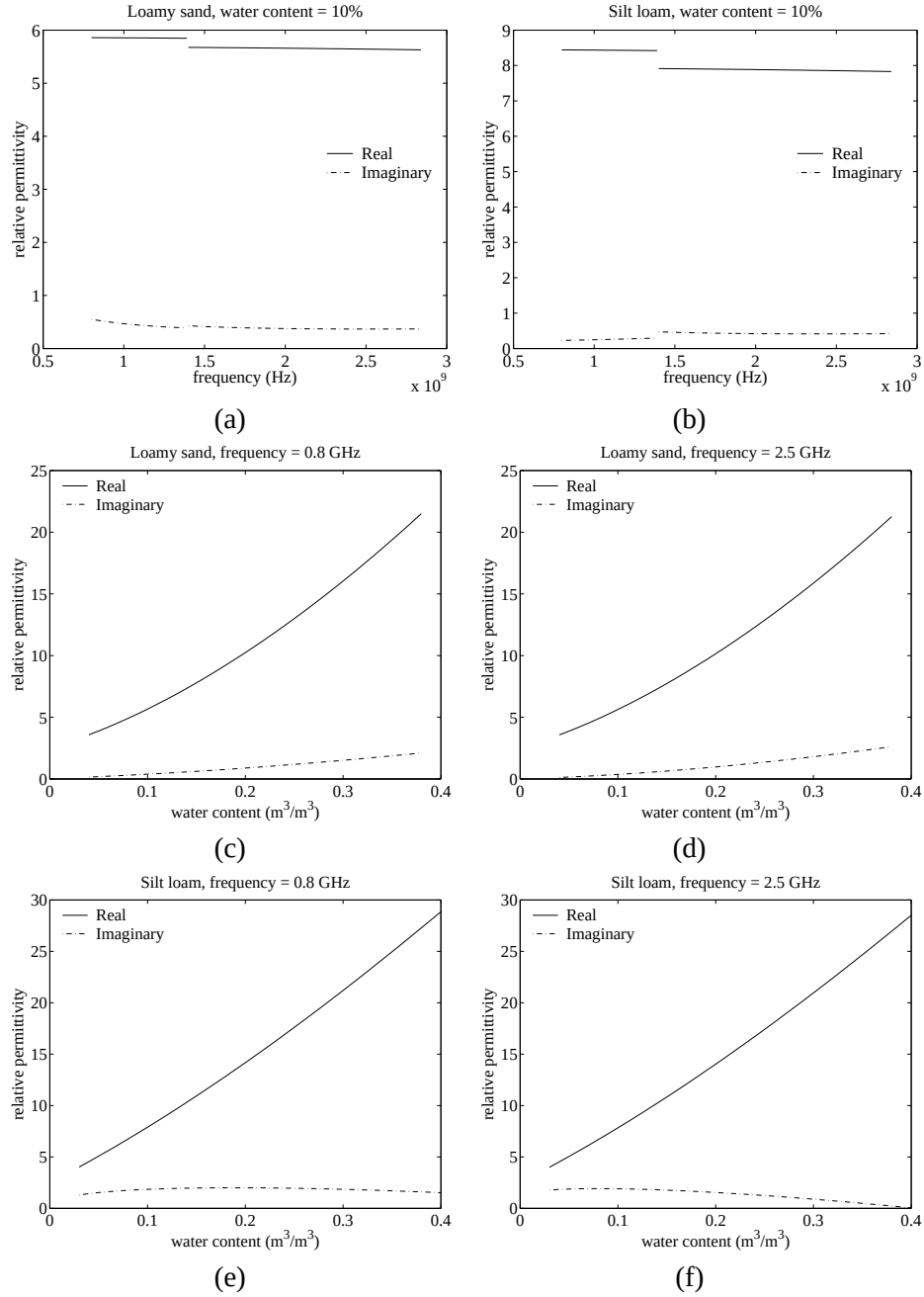
In Figs. 6.2 (c,d,e,f) one can observe that the real part of  $\varepsilon$  of both soils increases as the water content increases. Other interesting results are obtained for the imaginary part. It hardly increases in the loamy sand case, whereas it decreases in the silt loam case. Since  $\varepsilon''$  is related to losses (loss tangent), it has an important impact on the attenuation. For a specific frequency, the higher  $\varepsilon''$ , the more important the attenuation degree. This effect is illustrated by solving Eq. (6.6). In the loamy sand soil,  $\alpha$  increases as water content increases, whereas  $\alpha$  of the silt loam soil decreases as water content increases, and the same occurs at all frequencies.

The dielectric contrast is calculated for all different values of the target relative dielectric permittivity,  $\varepsilon_{tg}$  (see Tables 6.1 and 6.2), different water content fractions between the residual water content,  $\Theta_r$ , and the saturated water content,  $\Theta_s$ , as well as different frequencies between 0.8 GHz and 2.8 GHz. At all fractions of water content,  $\varepsilon_{contrast}$  for frequencies below 1.4 GHz is a little larger than  $\varepsilon_{contrast}$  for frequencies above 1.4 GHz, which is a logical expectation, considering the empirical formulae by [*Dobson et al.*, 1985] and [*Peplinski et al.*, 1995]. In accordance with Eq. (6.7),  $\varepsilon_{contrast}$  increases as water content increases, due to a larger difference between  $\varepsilon$  and  $\varepsilon_{tg}$ .

In Table 6.4, columns 3, 4 and 5 summarize  $\varepsilon'$ ,  $\alpha$  and  $\varepsilon_{contrast}$ , respectively, for three different water contents, 10%, 20% and 30%, at 1.8 GHz, and for three different  $\varepsilon_{tg}$  (or three different targets), 2.8 (*e.g.*, M14), 3.3 (*e.g.*, IED fabricated with textile fiber) and 3.6 (*e.g.*, IED fabricated with PVC).

### Numerical modeling of GPR

Simulations are carried out following different configurations of the numerical domain of Fig. 6.1. Firstly, eight types of target, with different shape and  $\varepsilon_{tg}$ , are represented at several depths, between 1 cm and 20 cm, measured from the top. Secondly, the transmitting/receiving point is placed at four different heights, between 5 cm and 20 cm. Additionally, three water contents are considered, between  $\Theta_r$  and  $\Theta_s$ , and the constitutive parameters ( $\mu$ ,  $\varepsilon'$



**Figure 6.2.** Examples of the complex relative dielectric permittivity calculated for both soils as a function of: (a,b) frequency, at 10% of water content, (c,d) water content, at 0.8 GHz, and (e,f) water content, at 2.5 GHz. Results of the silt loam soil are in the left column and those of the loamy sand soil are in the right column.

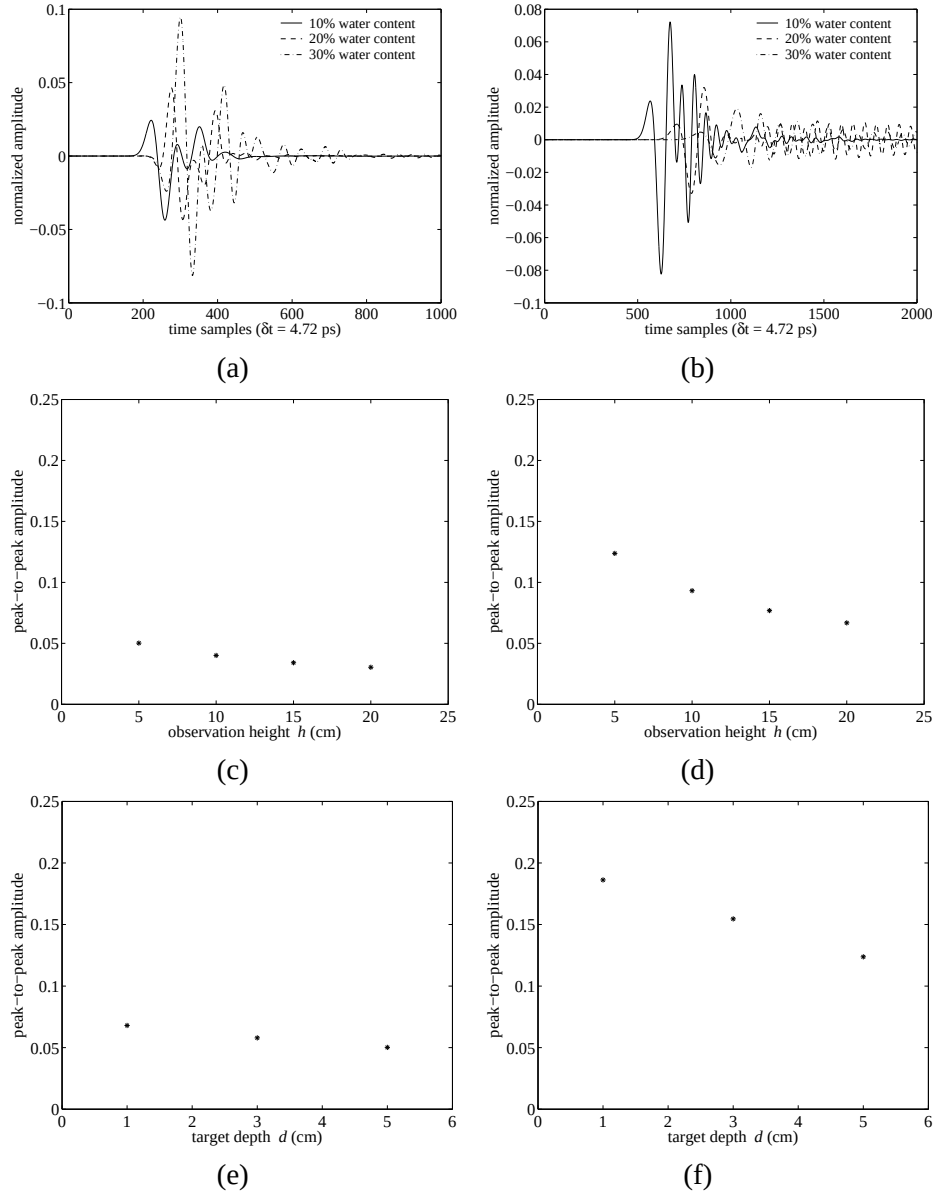
and  $\sigma_{eff}$ ) describing both soils at such moisture levels are introduced into the model. The combination of all these attributes leads to a great number of configurations. Although results are shown and discussed in this section for some of them, the observations stated below can be extended to all results.

Figs. 6.3 (a,b) represent the simulated GPR scans for a M14 AP landmine buried at 3 cm, measured from the top, in the silt loam and the loamy sand soil, respectively. The transmitting/receiving point is placed at 5 cm above the soil surface. It is excited using a Ricker wavelet (i.e., the second derivative of a Gaussian), which has a peak amplitude of 1.0 A and a central frequency of 1.8 GHz. In the silt loam soil, the amplitude of the numerical signal increases as soil water content increases, whereas it decreases as soil water content increases in the loamy sand soil. Therefore, the predicted effect of the attenuation factor using Eq. (6.6) is validated by the numerical simulations.

In Figs. 6.3 (c,d,e,f), the amplitude of the simulated target response for a M14 AP landmine buried in both soils (10% of water content) is shown as a function of the antenna height and target depth. In the silt loam soil, the signal amplitude barely decreases as target depth and antenna height increase, which is a consequence of the weak attenuation. In the loamy sand soil, the strong attenuation leads to a rapid decrease of the signal amplitude when the target depth and the antenna height increase.

Interesting observations can be made on the effect of  $\alpha$  and  $\varepsilon_{contrast}$  on the SNR for different fractions of water content. In the loamy sand soil, as the water content increases,  $\varepsilon_{contrast}$  increases. However,  $\alpha$  increases and, therefore the SNR decreases. This is not the case in the silt loam soil. For this soil, as the water content increases,  $\alpha$  decreases and  $\varepsilon_{contrast}$  increases, therefore the SNR increases. This effect is summarized in the three last columns of Table 6.4 for three targets: 1) M14, 2) IED fabricated with textile fiber, and 3) IED fabricated with PVC. They are located at a depth of 5 cm and the antenna is placed at 5 cm above the surface. From these results, we can observe that the target shape also influences the SNR. Irregular objects, such as target 2, will negatively affect the SNR, whereas larger, more regular objects, such as targets 1 and 3, will have a better SNR. As expected, the models show that the deeper the objects are buried and the higher the antennas are placed, the weaker the SNR.

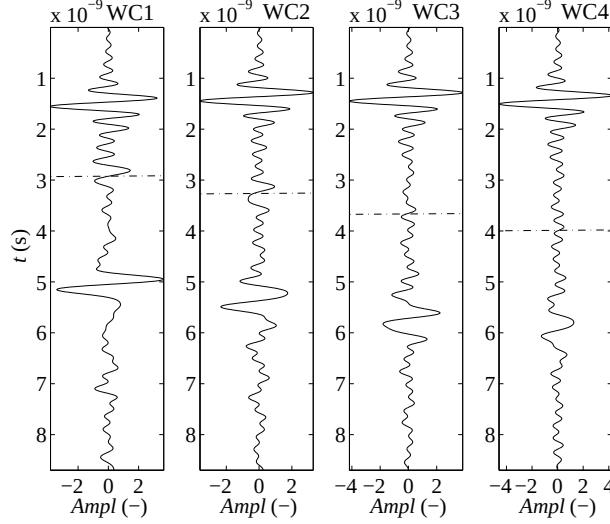
From the simulations one can state that deeper buried objects (e.g. 15 cm) will be hardly detected in both soils by a monostatic GPR working in the 0.8-2.8 GHz bandwidth, especially when the antenna is placed higher than 5 cm. Additionally, in the loamy sand soil, such GPR systems will perform better in dry conditions (e.g., water content  $\approx 10\%$ ), contrary to the silt loam soil. For the latter, the attenuation factor will become weaker as the soil water content increases and therefore, as the contrast between the soil and the target increases, the GPR will perform better in wet conditions (e.g., water



**Figure 6.3.** Representations of the simulated signal amplitude of a M14 AP landmine as a function of: (a,b) time and water content, at 1.8 GHz, (c,d) observation height, at 1.8 GHz and 10% of water content, and (e,f) target depth, at 1.8 GHz and 10% of water content. Results of the silt loam soil are in the left column and those of the loamy sand soil are in the right column.

| Soil       | WC<br>(%) | $\varepsilon'$<br>(-) | $\alpha$<br>(dB) | $\varepsilon_{contr1}$<br>(dB) | $\varepsilon_{contr2}$<br>(dB) | $\varepsilon_{contr3}$<br>(dB) | $SNR_1$<br>(dB) | $SNR_2$<br>(dB) | $SNR_3$<br>(dB) |
|------------|-----------|-----------------------|------------------|--------------------------------|--------------------------------|--------------------------------|-----------------|-----------------|-----------------|
| Silt loam  | 10        | 7.7                   | -14.5            | -15.1                          | -17.3                          | -18.8                          | -26             | -22.3           | -19.5           |
| Silt loam  | 20        | 14.1                  | -19              | -10                            | -11.1                          | -11.8                          | -23.7           | -24.9           | -21             |
| Silt loam  | 30        | 21.4                  | -21.8            | -7.7                           | -8.4                           | -8.9                           | -17.8           | -19.2           | -18.1           |
| Loamy sand | 10        | 5.7                   | -28.7            | -11.5                          | -12.9                          | -13.7                          | -16.1           | -18.1           | -14.9           |
| Loamy sand | 20        | 10.5                  | -25.8            | -8.2                           | -9                             | -9.5                           | -25.4           | -25.4           | -23.3           |
| Loamy sand | 30        | 16.5                  | -21.5            | -6.5                           | -7.2                           | -7.5                           | -30.3           | -32.2           | -31.2           |

**Table 6.4.** Results of the approximated values ( $\varepsilon'$ ,  $\alpha$  and  $\varepsilon_{contrast}$ ) for the two types of soil under three water content fractions and different targets (1: M14 AP mine, 2: textile fiber IED, 3: PVC IED). The SNR for the targets buried at 5 cm of depth, with the antenna placed at 5 cm above the soil surface, are also given.



**Figure 6.4.** Laboratory measurements representing the attenuation of the target signal for a metallic standard test target (SIM12) buried at 10 cm in a sandy soil which is subject to four different water contents.

content  $\approx 30\%$ ). Considering a smooth surface and a homogeneous soil, the backscattered signal from low-metallic AP landmines and non-metallic IEDs will have a higher SNR under these conditions than under other configurations. Rough surfaces and heterogeneous soils constitute an additional source of clutter, therefore the SNR is reduced. Following the recommendations in Yarovoy *et al.* [2003], and in addition to the GPR characteristics considered here, a high linear dynamic range GPR (*e.g.* -60dB) should be used for increasing the possibility of detecting a buried target where the backscattered signal is obscured by such additional clutter.

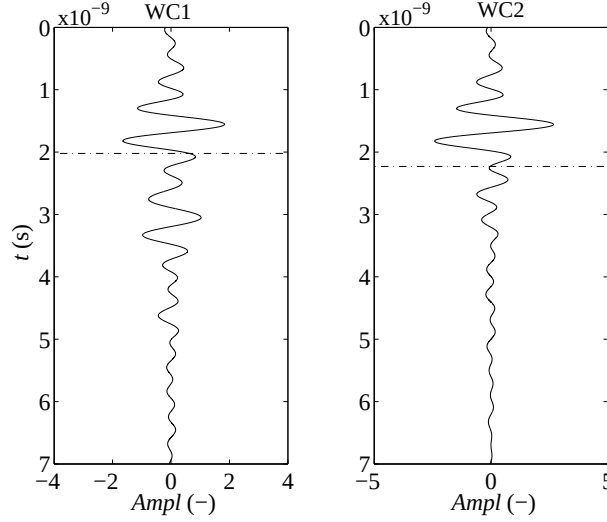
## 6.3 Experimental Data

### 6.3.1 Laboratory Measurements

Laboratory measurements were performed to represent the effects of contrast and attenuation on GPR performance. Due to the impossibility to recreate all the scenarios considered in the simulations, laboratory measurements were limited to a sand soil and one low-metallic target.

#### Measurement setup

Laboratory measurements were carried out at the Catholic University of



**Figure 6.5.** Laboratory measurements representing contrast between the dielectric properties of a non-metallic standard test target (SIM12) and the sandy soil surrounding it. The sandy soil is subject to two different water contents.

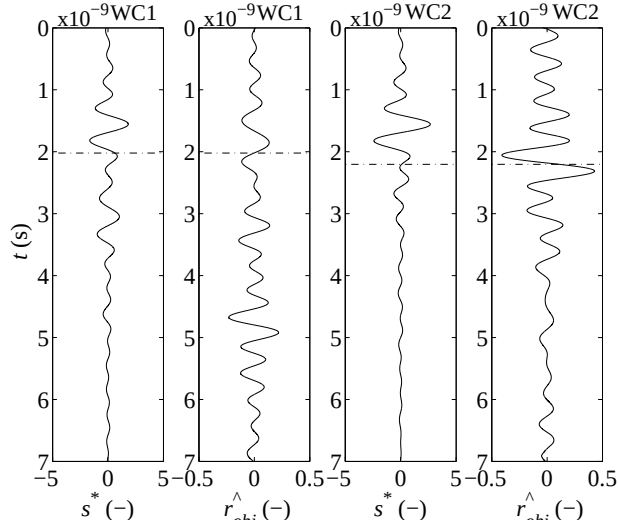
Louvain (Belgium) over sand soil. The GPR system used for the measurements is the same GPR presented in Section 2.3. A plastic standard test target (SIM12) with a low-metallic fuze was buried horizontally, longest side up, at different depths (its characteristics are listed in Table 3.1). The antenna was placed over the center of the target, using a support frame. Radar traces ( $S_{11}$ ) were recorded at 4 different heights between 15 cm and 18 cm (antenna phase center at about 22-25 cm).

Two different experiments were carried out. For illustrating the effect of the attenuation, the sand soil was subject to four different water contents (WC),  $WC11 \cong 0.07 \text{ m}^3 \cdot \text{m}^{-3}$ ,  $WC12 \cong 0.12 \text{ m}^3 \cdot \text{m}^{-3}$ ,  $WC13 \cong 0.15 \text{ m}^3 \cdot \text{m}^{-3}$  and  $WC14 \cong 0.21 \text{ m}^3 \cdot \text{m}^{-3}$ . The real part of the relative dielectric permittivity, measured using the approach presented in *Lambot et al.* [2004] (see Section 2.2.2), are:  $\epsilon'_{11} = 3.4$ ,  $\epsilon'_{12} = 5.4$ ,  $\epsilon'_{13} = 7.6$  and  $\epsilon'_{14} = 10.1$ , respectively.

For illustrating the effect of the dielectric contrast, the sand soil was subject to two different WC,  $WC21 \cong 0.0 \text{ m}^3 \cdot \text{m}^{-3}$  and  $WC22 \cong 0.07 \text{ m}^3 \cdot \text{m}^{-3}$  and their relative dielectric permittivity are:  $\epsilon'_{21} = 2.7$  and  $\epsilon'_{22} = 3.4$ .

### Results and discussion

In Fig. 6.4, the time-domain radar signal of SIM12 buried at 10 cm in a sandy soil subject to four different WCs (WC11, WC12, WC13 and WC14) is shown. These data have been pre-processed, *i.e.*, antenna effects are filtered

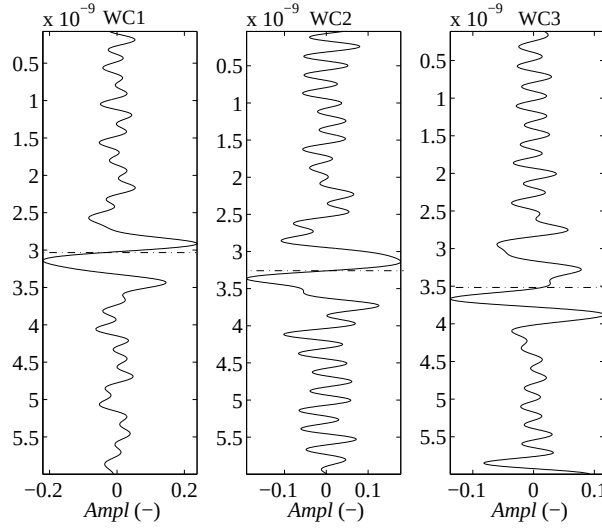


**Figure 6.6.** Time domain representation of the processed radar signal of Fig. 6.5. Due to a high dielectric contrast, target detection is easier in a sandy soil with WC2 than with WC1.

out using the methodology proposed in Section 2.2.1. The surface reflection is clearly identified between  $t=1.5$  ns and  $t=1.8$  ns. A metallic sheet is located at 25 cm of depth to control the boundary conditions, and its reflection can be seen beneath 6 ns. The response of the landmine is pointed out by the dotted line and the attenuation effect is clearly represented. For other antenna heights and target depths, results show the same tendency. We could then conclude that increasing water content will negatively affect the detection of SIM12-like landmines for a sandy soil.

Besides, dry soils could have a  $\varepsilon$  very close to that of the landmine, yielding low dielectric contrast conditions and, therefore, negatively affecting landmine detection by GPR. However, dielectric contrast can be enhanced by increasing the water content. Laboratory measurements were performed to represent such effect. In Fig. 6.5, the radar signal of SIM12 buried at 4 cm in a sand layer subject to two different WCs (WC21 and WC22) is shown. These data have been pre-processed, *i.e.*, antenna effects are filtered out using the methodology proposed in Section 2.2.1. The surface reflection is clearly identified between  $t=1.5$  ns and  $t=1.8$  ns. The sand layer width is 14 cm and at the bottom there is concrete and subsoil. Here, the  $\varepsilon'$  at WC21 is really close to that of the SIM12 ( $\varepsilon_{tg} \cong 2.8$ ). The water content is increased to WC22 ( $\varepsilon'_{22} = 3.5$ ) with the aim of increasing the dielectric contrast. The target response is pointed out by the dotted line, and the dielectric contrast is increased indeed. As the result is not clearly noticeable without subtracting the background, the signal processing





**Figure 6.7.** Time domain representation of the processed radar signal of IED5 buried at 5 cm depth in the loamy sand soil. Due to a high attenuation, target detection is easier in dry conditions.

approaches proposed in Sections 2.2.2 and 2.2.3 are applied to isolate the target signal and emphasize it.

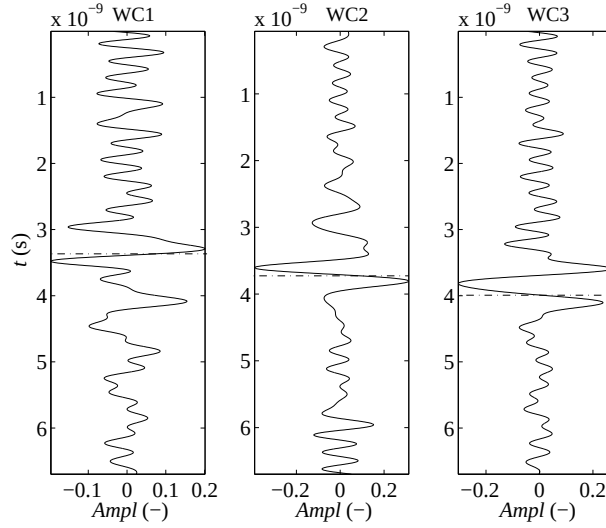
The effect of the increment on the dielectric contrast by increasing the soil water content can be now clearly seen in Fig. 6.6 for the processed target signal. Target reflection is pointed out by a dotted line. A larger target reflection appears after increasing the dielectric permittivity of the soil. The knowledge of this soil EM property could thus help to improve the GPR performance.

As expected, results show that the deeper the target and the higher the antenna, the weaker the target signal.

### 6.3.2 Outdoor measurements

#### Measurement setup

Outdoor measurements were performed to illustrate the effects of attenuation and contrast on the performance of the GPR system described in Section 2.3. Data were collected on the silt loam and loamy sand soils considered for the simulations. Due to the impossibility to recreate all the scenarios considered above, measurements were limited to two different IEDs (IED5 and IED6, described in Table 5.2) buried at two different depths. The antenna was placed over the center of the target, using a support frame. Radar traces ( $S_{11}$ ) were recorded at 4 different heights between 15 cm and 18 cm (antenna phase center at about 22-25 cm).



**Figure 6.8.** Time domain representation of the processed radar signal of IED5 buried at 5 cm depth in the silt loam soil. Due to a high contrast and small attenuation, target detection is enhanced in wet conditions.

Both soils were subject to three different WC,  $WC_{31} \cong 0.05 \text{ m}^3 \cdot \text{m}^{-3}$ ,  $WC_{32} \cong 0.15 \text{ m}^3 \cdot \text{m}^{-3}$ ,  $WC_{33} \cong 0.20 \text{ m}^3 \cdot \text{m}^{-3}$  for the loamy sand soil and  $WC_{41} \cong 0.07 \text{ m}^3 \cdot \text{m}^{-3}$ ,  $WC_{42} \cong 0.15 \text{ m}^3 \cdot \text{m}^{-3}$ ,  $WC_{43} \cong 0.20 \text{ m}^3 \cdot \text{m}^{-3}$  for the silt loam soil. The real part of the relative dielectric permittivity, estimated using the approach presented in *Lambot et al.* [2004] (see Section 2.2.2), are:  $\varepsilon'_{31} = 4.1$ ,  $\varepsilon'_{32} = 7.2$ ,  $\varepsilon'_{33} = 10.7$  and  $\varepsilon'_{41} = 6.2$ ,  $\varepsilon'_{42} = 12.1$ ,  $\varepsilon'_{43} = 14.6$ , respectively (note that the differences between these estimated values and those from the pedotransfer functions are quite small for both soils, varying from  $\Delta\varepsilon' = 0.2$  to  $\Delta\varepsilon' = 0.7$ , see estimated values in Table 6.4).

### Results and discussion

In Figs 6.7 and 6.8, time domain representations of the IED5 (buried at 5 cm depth) signal show the effects of increasing the soil water content for the silt loam soil and the loamy sand soil, respectively. Here, signal is presented after filtering antenna and soil effects following the approach proposed in Chapter 2. Results closely follow the prediction of the simulations. In the loamy sand soil, as the WC increases, the target signal is attenuated. And in the silt loam soil, the latter is enhanced, but already decreases for WC3. This can be an artifact of soil heterogeneity in real conditions. This factor is not taken into account in the simulations and can have an important effect on outdoor measurements.

The same was obtained for the IED6 and for different depths. As expected,

results also show that the deeper the objects and the higher the antenna, the weaker the target signal.

## 6.4 Conclusion

Different EM models can be used to analyze the effects of the soil properties on the detection performance of GPR. In this chapter, pedotransfer functions are coupled to a 2D EM FDTD model to study such effects, and laboratory and outdoor experiments are carried out to illustrate them. However, in real conditions there are other parameters, such as soil heterogeneity and surface roughness, that also negatively affect the GPR performance. These factors are not considered here and have different impact depending on the GPR system, type of soil and type of target. Therefore, GPR performance can not be completely predicted by the proposed approach, but it can be partially analyzed using EM modeling, soil characterization and soil dielectric permittivity measurements.



## Chapter 7

# Summary, Conclusions and Perspectives

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*O ser humano tem dois grandes problemas. O primeiro, saber quando começar.  
O segundo, saber quando parar.\**

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*Paulo Coelho*

The research results of this thesis demonstrate the possibility of enhancing landmine detection and identification under laboratory and outdoor, uncontrolled conditions by processing data acquired using a hand-held SFCW GPR. A number of new developments in GPR data processing were necessary to perform this type of target detection and identification, particularly the derivation of a physically-based approach that extracts the target response signal from the measured data, the integration of a physically-based change detection methodology for landmine localization, the development of a time-frequency-domain-based procedure for target identification and the design of a GPR performance estimation methodology. The proposed approach has been validated with success in laboratory and outdoor conditions and for different scenarios, including AP, low-metal content landmines and IEDs and real mine-affected soils. Results from the suggested algorithms have been compared with results achieved by published methodologies for landmine detection (where such publications exists). Additionally, part of the algorithms were applied for data collected using a commercial hand-held impulse-GPR-based system. This chapter summarizes the most important research results that have been achieved and formulates some conclusions. At the end of the chapter, some recommendations for future research are given.

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\*Traduction of the author: "The human being has two major problems. The first one, to know when to start. The second one, to know when to stop."

### **Physically-based approach for filtering out the soil surface reflection and major antenna effects**

One of the main scientific contributions of this thesis is the integration of a physically-based model with a migration approach for extracting the target response signal from the measured data by filtering out the soil surface reflection and major antenna effects. The method applies to SFCW radar systems operating off the ground in monostatic mode. Target response extraction procedure lends itself to in-field implementation, operates on a B-scan and proceeds in three stages, which are reviewed below.

In the first stage, major antenna effects from multiple wave reflections in the antenna are removed using frequency-dependent linear transfer functions which act as global reflectances and transmittances. These functions also account for the antenna gain and wave propagation time, fixing time-zero at the antenna phase center. The antenna transfer functions are determined using measurements above a planar metal sheet, playing the role of an infinite perfect electric conductor.

In the second stage of the target signal extraction, the soil surface reflection is considered and filtered by subtracting from the pre-processed radar signal a computed Green's function describing wave propagation with the antenna in air above a single interface (soil). To compute that Green's function, an inversion problem is formulated in the least-squares sense. Two main parameters are needed, dielectric permittivity and antenna height. A first approximation for the antenna height is directly derived from the radar measurements in the time domain, by identifying the surface reflection. The surface dielectric permittivity is estimated by performing a single radar measurement in a local landmine-free area and using full-wave inversion of the radar signal, focused on the surface wave reflection in the time domain.

In the third stage, the effect of the antenna radiation pattern is filtered out by focusing the scattered signals back to their point of origin for reconstructing the reflecting structure present in the subsurface and finding the true position of the target. Phase-shift migration is used and adapted to consider the discontinuity at the air-ground interface due to the off-ground antenna configuration. It was noticed that migration also contributed to reduce the clutter, acting as a BS method.

The research presented in this first part, and in particular in this thesis, focuses on laboratory and outdoor measurements. Results demonstrate that the algorithm minimize the unwanted signal components that carry no target information. It is also shown that it provides information about the shape, size and depth of the buried targets. Additionally, for particular cases where low-contrast conditions hampered the detection of landmines, the proposed algorithm demonstrates its appropriateness with respect to a traditional background

subtraction method by accurately detecting and characterizing the buried target.

Interestingly, it was found in both laboratory and outdoor conditions that the presence of a buried object creates a perturbation in the EM characteristics of the soil surrounding it. This effect is studied and resulted in an interesting methodology for landmine localization and false alarm partial reduction.

### **Parameter-estimation-based change detection methodology for landmine localization**

Changes in soil compactness as well as perturbation of soil hydrodynamics can create well defined patterns that, once detected, can be used to accurately determine the presence and position of a buried object. The newly developed change detection methodology makes use of a computed Green's function describing wave propagation with the antenna in air above a single interface (soil without target). Based on a dissimilarity measure between the computed and real signals, significant changes on the soil surface dielectric permittivity are detected, which correspond to soil disturbance due to the presence of a buried landmine. The proposed change detection approach can be implemented on real-time and operates on a B-scan.

This procedure could contribute to reduce false alarms caused by soil subsurface inhomogeneities. The filtering methodology reviewed before does not provide suppression of this kind of clutter. Since these inhomogeneities do not produce soil perturbation patterns on the soil surface like those of the landmines, this change detection approach can reject such false alarms.

The proposed procedure is validated in laboratory and outdoor conditions and shows promising results for landmine localization. Although the spatial position of the buried target is accurately found, a disadvantage of this technique is that no information about the nature of the target is given. The methodology was therefore easily integrated to the filtering procedure reviewed before, thus adding more information about the buried object.

Other interesting way for obtaining more information from GPR data for enhancing landmine detection and identification is feature extraction. This topic is considered also in this thesis with the aim of differentiating between a landmine and a friendly object and it is reviewed below.

### **Feature extraction for landmine identification**

Relevant features can be extracted from the scattering phenomena and can be used to identify unknown targets. These features are studied here in the time-frequency domain. The target identification procedure builds on a new time-frequency domain algorithm based on the Wigner-Ville distribution which is

coupled to the singular value decomposition theory to extract time and frequency representations from the WVD matrix using its singular vectors and singular values. The extracted time-frequency-energy features are used to identify the type of target (mine, no-mine).

This procedure can contribute to reduce false alarms from friendly objects such as stones or metal debris. Extracted features from A-scans could be related to the target size, shape and internal structure and therefore could provide information on the likely identity of a detected target.

This time-frequency concept is tested using data from two different hand-held GPR systems. Different types of landmines and IEDs are used and data are acquired over different soils under outdoor conditions. Results show that the proposed algorithm is able to differentiate between a landmine and a friendly object using three time-frequency-energy features. For the collected data, these features do not depend on the target depth. This methodology could be implemented on real-time and therefore is very attractive for potential use with hand-held demining GPR-based systems.

### **GPR performance estimation**

It is well known that soil water content governs EM wave propagation. Additionally, it is demonstrated by simulations that natural or artificial watering can contribute to increase dielectric contrast and to strengthen and to rise soil perturbation patterns, thus contributing to landmine detection and localization by both filtering and change detection methodologies proposed in this thesis. Therefore, an important aspect that has to be considered is the analysis of the effects of soil moisture and watering on signal attenuation for estimating the GPR performance.

Several models can be used to estimate the impact of the soil water content on the GPR detection performance. In this thesis, 2-D FDTD simulations are coupled to pedotransfer functions to study such effects and determine two of the most important parameters on GPR performance: impedance contrast and attenuation. Simulations are carried out for several types of AP landmines and IEDs and considering three different types of mine-affected soils. The numerical study is focused on the Colombian scenario, but its application can be extended to any type of target in any type of soil.

Experimental validation based on GPR data acquired with a hand-held GPR system at an outdoor test facility is carried out. Some of the modeled targets are buried at two different depths in the two types of soils considered for the simulations. Some differences are found between the numerical and the experimental results. However, the effects of impedance contrast and attenuation on the real measurements follow the predictions of those from the simulations. It is worth noting that soil roughness, soil inhomogeneity and



vegetation are not considered in the numerical study. Since they are important factors on the GPR performance, their absence can explain the differences between the synthetic and the real data.

### **Recommendations for future research**

In this study, we have tried to validate all the proposed algorithms under real mine-affected soils and using real, inactive, low-metallic AP landmines and IEDs. We notice that real field conditions are far more complex than numerical modeling and sand-based laboratory experiments. The development of GPR-based systems for landmine detection has arrived to a level on which outdoor experiments under more realistic scenarios are indispensable. Thorough analyses regarding dispersion due to soil roughness and vegetation are needed. Hence, further research should address the following problems:

- Analysis of sensitivity of the integrated methodology to ground surface roughness and patchy vegetation.
- Analysis of sensitivity of the identification procedure to tilted targets.
- Investigation of the minimum allowable signal-to-noise ratio for target detection and identification using the proposed procedures.

Although the obtained results for real mine-affected soils are quite promising, the proposed methodologies for landmine detection and identification still need to be validated under many different scenarios to state statistically relevant conclusions. This does not necessarily mean that the approach is not useful under real conditions, just that it is important to define under which circumstances it will be practicable and robust, especially if we want to implement this methodology for a real mine detection system. Dispersive effects from soil roughness and vegetation have an impact on the signal-to-noise ratio. In this respect, an important topic of future research should be the experimental estimation and validation of the minimum allowable SNR for which the target detection and identification procedure presented in this thesis will still produce useful results.

As a final remark, soil characterization is of fundamental importance to determine the GPR detection performance. The latter is a very important issue in demining applications. Soil EM properties, surface roughness and soil inhomogeneity represent the most important physical limitations of GPR target detection and identification. Future research should be towards the derivation of new EM models or the calibration of existing ones for estimating accurately soil attenuation and dielectric contrast, thus predicting GPR performance on the field.

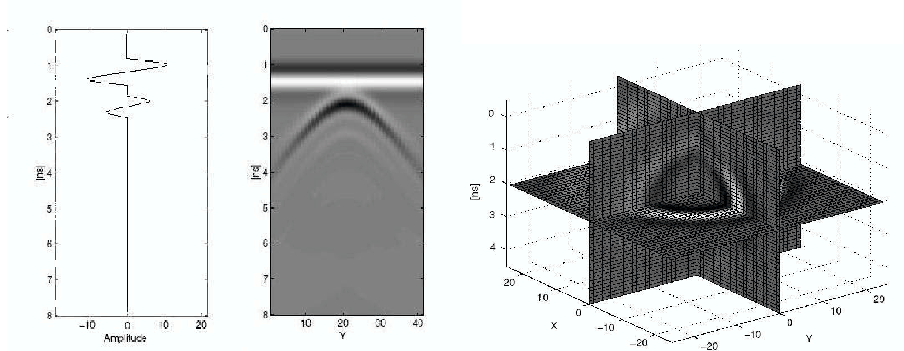
Data fusion, considering the features extracted by the proposed methodology in this thesis and other features from different sensors such as MD, should be included also in future research.

# Appendix

## A. Types of GPR data representation

The data recorded by a GPR are generally represented as a one, two or three dimensional data set, denominated by the acoustic terminology A, B and C-scans. Assuming the  $xy$ -plane as the ground surface plane,  $y$  axis as the line of data acquisition,  $z$  axis as the depth in the ground, and  $h$  the height of the antenna, the meaning of these scans are illustrated in Figure 7.1.

A single waveform recorded by GPR, with the antennas at a given position  $(x, y, h)$ , is referred to as an A-scan. In this data set, the time is the only variable, related to the depth  $z$  by the propagation velocity of the EM waves in the medium. When moving the GPR antennas along the  $y$  axis, we can gather a set of A-scans, which form a two dimensional data set, called B-scan. Finally, a C-scan is a three dimensional data set resulting from moving the antennas over a regular grid in the  $xy$ -plane.



**Figure 7.1.** An illustration of A, B and C-scans. The B-scan was simulated with GPRMAX2D ([Giannopoulos, 2002]) and the C-scan was created in MATLAB from the GPRMAX3D data.

## B. The hyperbola formation on the B-scan

In two-dimensional subsurface imaging, the wave reflected by a buried object provides a hyperbolic shape [Daniels, 2004]. This phenomenon is illustrated in Figure 7.2. If the buried object size is comparable to the wavelength of the GPR signal, we can consider the buried object as a scattering point [Arbel and Felsen, 1963]. For this assumption, and for a radar close to the ground (height  $h$  equal to zero) in monostatic mode of operation, the two-way-travel-time or time-of-flight (TOF) of the emitted wave is calculated by:

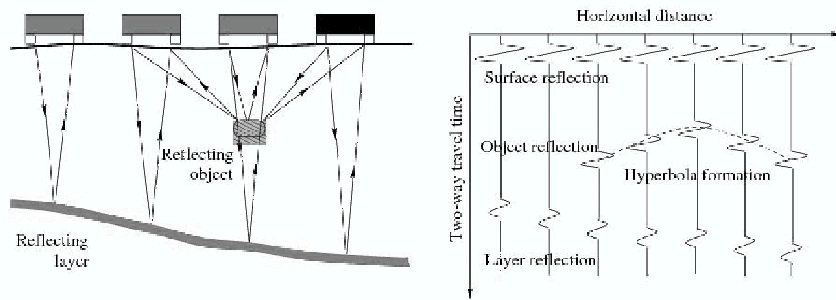
$$TOF = \frac{2(\sqrt{z_0^2 + y^2})}{v}, \quad (B.1)$$

where  $z_0$  corresponds to the depth of the buried object,  $y$  corresponds to the position of the antenna along the horizontal axis of the B-scan direction, and  $v$  the propagation velocity in a low losses non magnetic medium ( $v = c/\sqrt{\epsilon_r}$ , where  $c = 3 \cdot 10^8$  m/s is the velocity for the free space, and  $\epsilon_r$  is the real part of the relative dielectric permittivity  $\epsilon/\epsilon_0$ , with  $\epsilon_0 = 8.85419 \cdot 10^{-12}$  F/m).

By mathematical manipulations, we can write Eq. (B.1) in the form:

$$\frac{(TOF)^2}{(2z_0/v)^2} - \frac{(y)^2}{z_0^2} = 1. \quad (B.2)$$

Equation (B.2) represents a hyperbola with a vertex in the origin, a vertical axis, and an apex in  $2z_0/v$ . We can thus conclude that the shape of the hyperbola is function of the depth of the buried object  $z_o$ , and the propagation velocity in the medium above the object,  $v$ .



**Figure 7.2.** An illustration of the hyperbola formation in a B-scan.

## C. Background Subtraction by System Identification

SI methods are considerably promising for GPR signal processing [Brunzell, 1999]. The aim of these methods is to determine the object (*i.e.*, landmine) impulse response. Among all the system models used by SI to perform clutter suppression on GPR data, a convolutional model is used in this study to draw a comparison. This model was chosen for approaching to the radar-antenna-subsurface model used above. Accordingly, the preprocessed GPR data are considered as a convolution of the *ground* signal, which includes surface and subsurface effects, and the *object* signal, in the time domain. Then, the transfer function of this model  $G_s$  can be expressed in the frequency domain as

$$G^*(\omega) = G_s(\omega) = G_c(\omega)R_{obj}(\omega), \quad (C.1)$$

where  $G_c = Y_c/X_c$  is the *ground* transfer function and  $R_{obj} = Y_{obj}/X_{obj}$  is the *object* transfer function. The soil surface effect can be subtracted from radar measurements using the *auto-regressive moving average* to derive an estimate<sup>†</sup>  $\hat{G}_c$  of the *ground* signal

$$\hat{G}_c(z) = \frac{\hat{Y}_c(z)}{\hat{X}_c(z)}, \quad (C.2)$$

where  $z=e^{j\omega}$ . The estimate is derived in the z-domain from a reference *ground* sample (*i.e.*, single radar measurement) in a nearby, landmine-free area, assuming that the *object* and the *ground* processes are discrete samples of a continuous input-output process. The *object* signal  $R_{obj}$  is thus easily isolated subjecting the preprocessed radar signal  $G^*$  through the inverse *ground* filter, which is the reciprocal of (C.2).

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<sup>†</sup>From statistics conventions, " $\hat{\cdot}$ " refers to the estimate. This convention is adopted in this annex, however, in the primary part of this book, it means migration.

## D. Feature extraction by TD, FD and TFD transforms

### D.1. Time domain: Auto-correlation of target signatures

Auto-correlation is useful for finding repeating patterns in a signal, such as determining the presence of a periodic signal, or identifying the fundamental frequency of a signal which does not actually contain that frequency component, but implies it with many harmonic frequencies. Consider a signal  $s(t)$ , its auto-correlation  $C\{s(t)\}$  is defined as:

$$C\{s(t)\} = \int s(t + \tau)s^*(t)dt, \quad (D.1)$$

where  $s^*(t)$  is the complex conjugate of  $s(t)$ .

Fig. 7.3 shows the autocorrelation features for two different measurements of four objects. These features (number of oscillations, peak values, signal duration, ...) are very dissimilar between classes (different types of objects). However, they are strongly dependent on external parameters such as target depth and position, antenna height, possible surrounding scatters and soil properties. Due to these influences, direct auto-correlation will not result in good discriminative features. Other approaches must thus be applied.

### D.2. Frequency domain: Spectral analysis

Considering a signal  $s(t)$  as a group of variations recorded with time, its spectral response (using Fourier Transform  $F$ ) shows how much of  $s(t)$  lies within each given frequency over a range of frequencies

$$F\{s(t)\} = \int x(t)e^{i\omega t}dt, \quad (D.2)$$

In order to characterize the energy concentration in the spectral response as a potential discriminant, the peak frequency of the spectrum is plotted against its central frequency. Some results are illustrated in Fig. 7.4 for four AP landmines and two false alarms. This figure shows that all low-metallic targets have an energy concentration in the lower part of the spectrum, contrary to the metallic ones whose spectrums center the energy in a higher frequency range. However, discrimination between two different AP landmines or between a non-metallic object and an low-metallic one is not possible. Therefore, discriminative methodologies in both time and frequency domain are proposed next and in Chapter 5.

### D.3. Time-frequency domain

**D.3.1. The spectrogram based on the short-time Fourier transform** Since 1-D solutions seem to be insufficient, we can consider functions of both vari-

ables time and frequency. A simple way to characterize a signal simultaneously in both domains consists in distributing the energy of the signal along a time-frequency space. To apply such approach, we begin with the definition of the short-time Fourier transform (STFT), or short-time spectrum. In order to introduce time-dependency in the Fourier transform, a simple and intuitive solution consists in pre-windowing the signal  $s(t)$  around a particular time  $t$ , calculating its Fourier transform, and doing that for each time instant  $t$

$$STFT\{s(t)\} = \int s(t)\varpi(t - \tau)e^{-i\omega t}dt. \quad (D.3)$$

where  $\varpi(t)$  is the window function, a Gaussian function centered around zero.

To give rise to this energy time-frequency distribution, we consider the squared modulus of the STFT and we obtain a spectral energy density of the locally windowed signal  $s(t)$ . This define the spectrogram.

Fig. 7.5 shows the spectrogram calculated for two different measurements of PFM 0 cm ((a) and (b)) and two different measurements of PFM 5 cm ((c) and (d)). In Fig. 7.6, the same is done for PMA 0 cm ((a) and (b)) and PMA 5 cm ((c) and (d)). For each figure, the signal in the time-domain is presented in the upper side of the figure, its energy spectral density in the left side, and its spectrogram in the middle. In Fig. 7.7, the spectrogram is calculated for two different measurements of FA can ((a) and (b)) and two different measurements of FA stone ((c) and (d)). We can observe than high frequencies should dominate in the spectrogram of low-metallic objects (AP landmines), while the non-metallic target has a low frequency content and the metallic target shows a high peak just in between low and high frequencies. In a first analysis about position and peaks values of each distribution (image), no relevant information to be used in classification could be extracted from them. Cross-correlation between the spectrogram of low-metallic objects and the spectrogram of the metallic one is high (0.85 average). This is due to the poor resolution of the distribution (limited by the STFT), which leads to interference terms. We propose then to use another approach of the time-frequency domain analysis to get a better resolution.

**D.3.2. The wavelet transform** The WT is a specific type of TFD distribution and is characterized by the ability to segment the time-frequency plane into localized regions of interest.

Consider the Fourier transform of a signal  $s(t)$ ,

$$f(\omega) = \int_{-\infty}^{+\infty} s(t)e^{-j\omega t}dt. \quad (D.4)$$

The WT  $WT_s(\tau, a)$  replaces the sinusoidal kernel of the Fourier transform

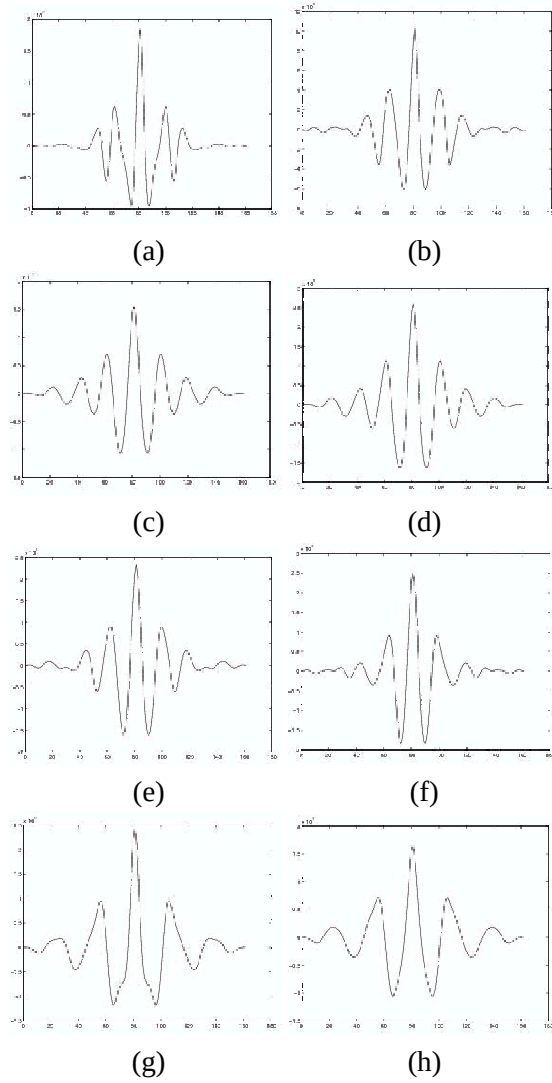
$e^{-j\omega t}$  with a scale and shift kernel  $|a|^{-1/2}\psi(\frac{t-\tau}{a})$ ,

$$WT_s(\tau, a) = |a|^{-1/2} \int_{-\infty}^{+\infty} s(t) \psi\left(\frac{t-\tau}{a}\right) dt, \quad (\text{D.5})$$

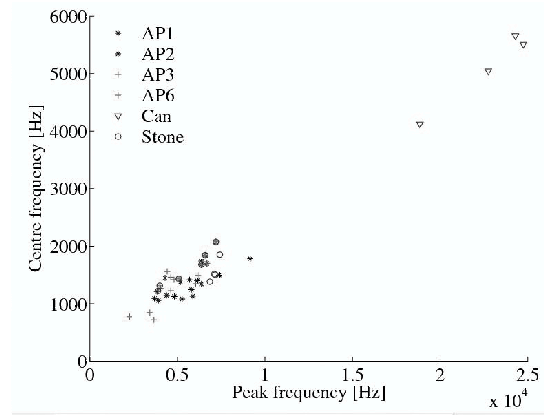
where  $\psi$  is the basic wavelet,  $\tau$  is the time shift of the wavelet and  $a$  the scale factor. An important point in the WT is the choice of the basic wavelet [Gaunard and Strifors, 1999]. Several basic wavelet have been applied and the Daubechies wavelet is selected since it has achieved the best results for this application.

Following the standard wavelet analysis, the first level approximation and detail coefficients are calculated for each A-scan. The detail coefficient is kept and the approximation is again decompose. This is continued until the third level, where both the detail and approximation coefficients are kept. Considering more than three levels results in redundant information. The estimated four coefficients are used as target features.

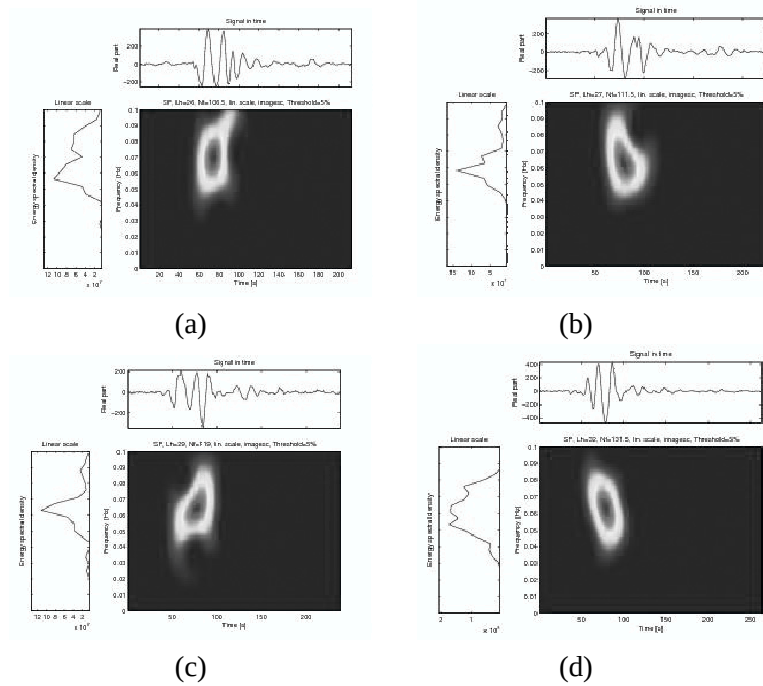




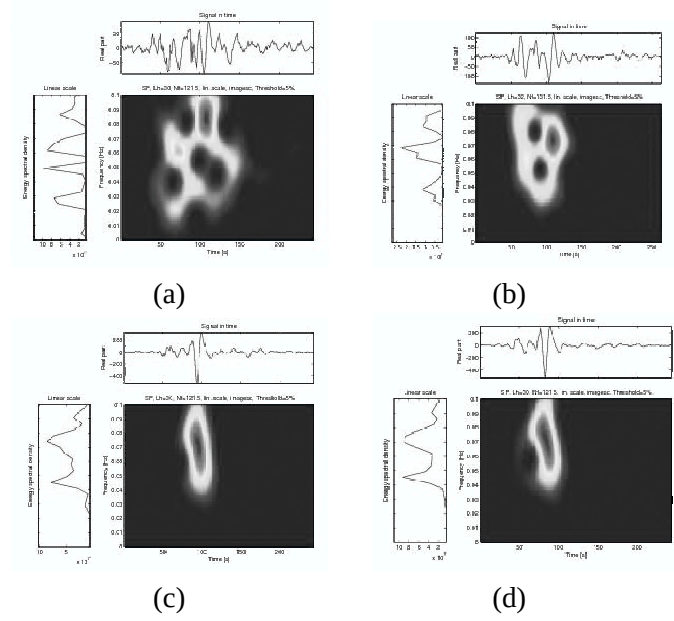
**Figure 7.3.** An example of auto-correlation features for two different measurements of various targets: (a) & (b) PFM at 0 cm, (c) & (d) PFM at 5 cm, (e) & (f) Metallic can, (g) & (h) Stone1



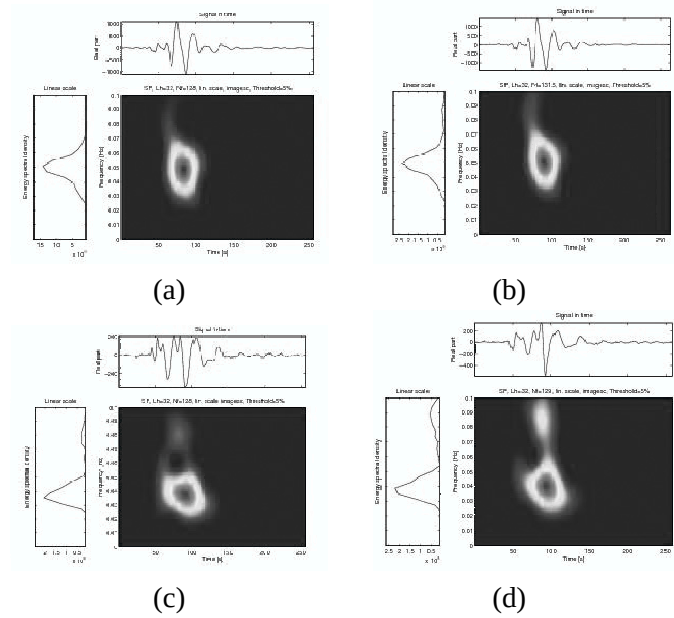
**Figure 7.4.** Frequency properties of various targets: AP1, AP2, AP3, AP6 are, respectively, PFM at 0 cm, PFM at 5 cm, PMA at 0 cm and PMA at 5 cm.



**Figure 7.5.** Spectrogram of two different measurements of various targets: (a) & (b) PFM at 0 cm, (a) & (b) PFM at 5 cm.



**Figure 7.6.** Spectrogram of two different measurements of various targets: (a) & (b) PMA at 0 cm, (a) & (b) PMA at 5 cm.



**Figure 7.7.** Spectrogram of two different measurements of various targets: (a) & (b) can, (a) & (b) stone1.



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*La vida no es la que uno vivió sino la que uno recuerda y como la recuerda <sup>‡</sup>...*

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*Gabriel García Márquez*

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<sup>‡</sup>Traduction of the author: "*Life is not what one lived, but what one remembers and how one remembers it...*"

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Olga Lucia Lopera  
*Brussels, 2008*

## List of Publications

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*Uno no es lo que es por lo que escribe, sino por lo que ha leído.*<sup>§</sup>

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*Jorge Luis Borges*

### DEA Thesis

1. **Lopera, O.**, Analysis and processing of two-dimensional data from ground-penetrating radar for Humanitarian Demining applications, June 2004.

### Journal Papers

1. **Lopera, O.** and N. Milisavljevic, Prediction of the effects of soil and target properties on the antipersonnel landmine detection performance of ground-penetrating radar: a Colombian case study, *Journal of Applied Geophysics*, Vol 63, pp 13-23, 2007.
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3. **Lopera, O.**, N. Milisavljevic and S. Lambot, Clutter Reduction in GPR Measurements for Detecting Shallowly Buried Landmines: a Colombian Case Study, *Near Surface Geophysics*, Vol 5, 73-80, 2007.
4. **Lopera, O.**, N. Milisavljevic, B. Macq and S. Lambot, A Change Detection Algorithm Based on Soil Dielectric Permittivity Estimation from Frequency-domain GPR Data for Landmine Localization, *IEEE Geoscience and Remote Sensing Letters*. Submitted, Oct 2007.
5. **Lopera, O.**, N. Milisavljevic, D. Daniels and B. Macq, A time-frequency domain feature extraction algorithm for landmine identification from GPR data. *Near Surface Geophysics*. Accepted, Feb. 2007.
6. **Lopera, O.**, N. Milisavljevic, J. Rhebergen, and S. Lambot, Analysis of the effect of soil properties on the detection performance of ground-penetrating radar: experimental and in field results. *Journal of Applied Geophysics*. Submitted, Dec 2007.

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<sup>§</sup>Traduction of the author: "One is not what one is for what one writes, but for what one has read."

### Conference papers

1. **Lopera, O.**, J. Rhebergen, E. Slob, N. Milisavljevic and S. Lambot, Analysis of the effect of watering on landmine detection. 12th International Conference on Ground Penetrating Radar 2008, Birmingham, U.K., July 2008.
2. Capineri, L., D. Daniels, P. Falorni, **O. Lopera**, C. G. Windsor, Estimation of Relative Permittivity of Shallow Soils by Using the Ground Penetrating Radar Response from Different Buried Targets. PIERS 2008, Hangzhou, China, March 2008.
3. **Lopera, O.**, N. Milisavljevic, D. Daniels and B. Macq, Time-frequency domain signature analysis of GPR data for landmine identification. International Workshop on Advanced GPR, Naples, Italy, June 2007.
4. **Lopera, O.**, N. Milisavljevic, B. Macq and S. Lambot, Change Detection Based on Parameter Estimation From Frequency-domain GPR Data for Demining Applications, in 11th International Conference on Ground Penetrating Radar, edited by Jeffrey J. Daniels and Chi-Chih Chen, 6 pages, on CD. Columbus, Ohio USA, 2006.
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7. **Lopera, O.**, B. Macq, N. Milisavljevic, and B. Scheers, Denoising and migration techniques for landmine identification from Ground-Penetrating Radar 2D data, in GRETSI 2005, edited by UCL, 6 pages, on CD. Louvain-la-neuve, Belgium, 2005.
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9. **Lopera, O.**, S. Lambot, I. van den Bosch, A. Gauthier, N. Milisavljevic, and B. Macq, A new signal processing approach for landmine signature extraction from Ground Penetrating Radar 2D data, in IV National Congress on Automation and Control ISBN 958 80 28396, edited by ACA, 6 pages, on CD. Bogota, Colombia, 2004.
10. **Lopera, O.**, N. Milisavljevic, B. Macq, I. van den Bosch, S. Lambot, and A. Gauthier, Analysis of segmentation techniques for landmine signature extraction from Ground Penetrating Radar 2D data, in II International IEEE Andean



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#### Conference abstracts

1. **Lopera, O.**, N. Milisavljevic, J. Rhebergen and S. Lambot. Analysis of the effect of target and soil properties on the detection performance of ground penetrating radar: experimental and in field results. IGARSS, Barcelona, Spain, July 2007.
2. **Lopera, O.**, I. van den Bosch, S. Lambot, N. Milisavljevic, and B. Macq, Simulation and analysis of landmine signatures from Ground Penetrating Radar 2D data, in International Symposium "Humanitarian Demining 2004", edited by HCR. Sibenik, Croatia, 2004.

## About the author



Olga Lucia Lopera Tellez was born in Bogota, Colombia, on October 12, 1978. In 2001, she obtained the Engineering degree in electrical engineering at the Faculty of Engineering of the Universidad de Los Andes (UA), Bogota, Colombia. There, she worked as researcher in two humanitarian demining projects until 2002. The topic of those projects was the analysis of data from ground-penetrating radar and metal detector for landmine detection.

In 2003, she started her PhD research programme founded by the Ministry of Defense of Belgium at the Signal and Image Centre of the Royal Military School (RMS), Brussels, Belgium, under the supervision of Prof. Marc Acheroy and within the BEMAT (Belgium Mine Action Technologies) project. Focusing on ground-penetrating radar for demining applications, she awarded a M.Sc. in Applied Sciences in 2004, at the Faculty of Applied Sciences of the Université catholique de Louvain (UCL), Belgium, under the supervision of Prof. Benoît Macq.

After her M.Sc., she continued her PhD project at both the UCL and RMS and in collaboration with the UA. Her project aims at developing detection and identification techniques of landmines and improvised explosive devices using ground penetrating radar for supporting demining activities. During her project, cooperation was established with the Escuela de Ingenieros Militares (Colombia), Department of Environmental Sciences and Land Use Planning at UCL, Department of Geotechnology, Delft University of Technology, (TUDelft, The Netherlands), as well as with the Physics and Electronics Laboratory of the Technische National Onderzoek (TNO), The Hague, The Netherlands.

She is currently working at the RMS as researcher and she participates to the working group on dual-sensors of the International Test and Evaluation Program (ITEP) for landmine detection and to the CEN (European Committee of Standardization) Workshop Agreement on soil characterization for metal detector and ground penetrating radar performance.

Her current research interests are radar imaging, target detection and target recognition.