

DETECTION AND CLASSIFICATION OF MULTIPLE SHALLOW-BURIED
TARGETS BY A GROUND PENETRATING RADAR

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ABSTRACT

DETECTION AND CLASSIFICATION OF MULTIPLE SHALLOW-BURIED TARGETS BY A GROUND PENETRATING RADAR

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In this thesis, detection and classification of conducting and/or dielectric objects of different sizes, shapes and burial depths are investigated based on numerically simulated ultra-wideband Ground Penetrating Radar (GPR) data for different soil properties in flat or rough surface conditions. One-dimensional A-scan time-domain signals, two-dimensional B-scan image data (in cross-track and/or down-track directions), as well as three-dimensional C-scan image GPR data are processed altogether in single target or multiple target problems.

The challenging scenario of extremely shallow-buried target detection is examined in detail paying special attention to undesired mutual coupling effects stemming from a collinear GPR antenna array. Signal processing algorithms used for the removal of direct coupling and ground-bounced signals are extensively studied and applied to various scenarios presented in the thesis on a comparative basis.

Detection and classification of buried objects in a complex multiple-target scenario are investigated in detail where the targets with quite dissimilar geometries and

different material compositions are placed very close to each other. Segmentation of energy maps is proposed and demonstrated to be useful to reveal the presence of low radar cross-section (RCS) targets that may be masked by closely located high RCS objects. For target classification, physics-based electromagnetic target features are extracted from the isolated A-Scan data by using the Page distribution (PD), a quadratic time-frequency distribution (TFD) technique. The method of principal component analysis (PCA) is implemented for feature fusion in the close vicinity of the detected target center to utilize multi-aspect electromagnetic scattered data for improved classification accuracy.

Keywords: Ground Penetrating Radar (GPR), Shallow-Buried GPR Target Detection, GPR Target Classification, Feature Extraction by Page Distribution in GPRs, Removal of Direct-Coupled and Ground-Bounced GPR Signals

ÖZ

YÜZEYE YAKIN GÖMÜLMÜŞ ÇOKLU HEDEFLERİN YER ALTI RADARI İLE TESPİTİ VE SINIFLANDIRILMASI

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Bu tezde, farklı toprak özellikleri ve toprak yüzeyindeki pürüzlülük şartlarında, aşağı bakan çok geniş bantlı Yer Altı Radarı (YAR) için elde edilmiş benzetim verileri kullanılarak, farklı büyüklüğe, şekle ve gömülüm derinliğine sahip iletken ve/veya dielektrik cisimlerin tespiti ve sınıflandırılması incelenmiştir. Tekli veya çoklu gömülü hedef problemlerinde, zamanın tek boyutlu fonksiyonu olan A-tarama sinyalleri, yanca veya ilerleme yönlerinde elde edilen iki-boyutlu B-tarama görüntüleme verileri ile üç-boyutlu C-tarama görüntüleme verileri hep birlikte işlenmiştir.

Yer yüzeyine çok yakın gömülen hedeflerin tespitine ilişkin zorlayıcı senaryolar, doğrusal diziliimli GPR anten dizinlerinden kaynaklanan istenmeyen sinyal bağlaşım etkilerini özellikle dikkate alarak, detaylı bir şekilde incelenmiştir. Doğrudan bağlaşan ve yer yüzeyinden sekerek bağlaşan sinyallerinin ayıklanması için kullanılan sinyal işleme algoritmaları derinliğine çalışılmış ve tezde verilen çeşitli senaryolara karşılaştırmalı bir şekilde uygulanmıştır.

Hedef geometrisi ve malzeme yapısı bakımından birbirinden oldukça farklı hedeflerin birbirine çok yakın konumlandırıldığı karmaşık bir gömülü hedef senaryosu için hedef tespiti ve sınıflandırma problemleri detaylıca incelenmiştir. Yakındaki yüksek radar kesit alanlı (RKA) cisimler tarafından maskelenen düşük RKA hedeflerin tespitinde, üç-boyutlu C-tarama verilerinden elde edilen enerji görüntüleme haritalarının bölütlenmesi yöntemi önerilmiştir. Hedeflerin tespit aşamasını takiben, tespit noktalarında izole edilen A-tarama sinyallerine ait fizik-tabanlı hedef öznitelikleri, ikinci dereeden bir zaman-frekans dönüşüm (ZFD) tekniği olan Page dağılımı kullanılarak elde edilmiştir. Birden fazla bakış açısında elektromanyetik saçınım verisi kullanarak hedef sınıflandırma doğruluğunu iyileştirmek için, hedefin tespit merkezine en yakın örnekleme noktalarında Esas Bileşenler Analizi (EBA) kullanılarak öznitelik füzyonu gerçekleştirilmiştir.

Anahtar Kelimeler: Yer Altı Radarı (YAR), YAR ile Sığ Gömülü Hedef Tespiti, YAR ile Hedef Sınıflandırılması, YAR’larda Page Dağılımı ile Öznitelik Çıkarma, Doğrudan Bağlaşan ve Yer Yüzeyinden Sekerek Bağlaşan YAR Sinyallerinin Ayıklanması



To my family

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LIST OF ABBREVIATIONS

ABBREVIATIONS

1D	One-Dimensional
2D	Two-Dimensional
3D	Three-Dimensional
CNR	Complex Natural Resonance
FDTD	Finite-Difference Time-Domain
FFT	Fast Fourier Transform
FFV	Fused Feature Vector
GPR	Ground Penetrating Radar
ICA	Independent Component Analysis
LTFV	Late-Time Feature Vector
PCA	Principal Component Analysis
PD	Page Distribution
PEC	Perfect Electric Conductor
RCS	Radar Cross Section
RX	Receiver
SEM	Singularity Expansion Method
SNR	Signal-to-Noise Ratio
TFR	Time-Frequency Representation
TX	Transmitter

UWB	Ultra-Wideband
WD	Wigner Distribution



CHAPTER 1

INTRODUCTION

Detection and classification of buried objects is a critical problem in many military and civilian applications [1-5]. In military areas, it is vital to identify various types of antipersonnel and anti-tank mines and different explosive objects, such as unexploded ordnances (UXO) and improvised explosive devices (IEDs) [6-10]. Use of metal detectors for the detection of mines and other explosives, which contain metal parts, dates back to the Second World War [11]. Although metal detectors (also known as electromagnetic induction sensors) are successful in recognizing buried metal targets, they are almost useless to detect objects with low-metal content such as small dielectric antipersonnel mines that have been widely used in real world. In these situations, broadband Ground Penetrating Radar (GPR) systems designed typically at microwave frequencies are used effectively to penetrate into soil to detect different types of explosive targets even if they have very low or even no metal content. Furthermore, GPR data provide detailed electromagnetic information which makes the estimation of targets' burial depths possible and can be further used for the non-intrusive characterization of detected targets [12-16].

Target detection and classification capabilities of modern GPRs are immensely enhanced by integrating various signal processing algorithms into the radar system. Use of proper techniques for the elimination of direct-coupled and ground-bounced signals as well as all kinds of clutter signals originating from the soil environment is essential in GPR target detection studies. In addition to signal processing and imaging algorithms needed for the target detection problem, advanced target classification techniques have also been developed using shape-based, image-based,

or physics-based target feature extraction techniques, to identify/classify buried targets [17].

Besides military applications, GPR systems are widely used in many other fields due to the penetration ability of electromagnetic waves into different media such as soil, walls, cement, asphalt etc., with high spatial resolution. With the support of integrated signal processing algorithms, the GPRs are not only fast to provide real-time sensor response with increased accuracy but they are also user friendly to be easily operated by people who are not radar experts. Archaeological studies, thru-the-wall operations, geophysics, vehicle localization, civil engineering, glaciology and even Mars explorations can be given as examples of areas where the GPR technology is utilized [18-25]. Furthermore, GPR systems offer non-destructive testing in many applications, allowing for the investigation of subsurface structures without the need for excavation or any other type of disturbances [26].

Despite its numerous advantages, GPR systems also present some inherent limitations. Certain materials, such as highly conductive substances like clay, saltwater, or metals, can impede GPR signals and limit their effectiveness. Also, the interpretation of GPR data may be extremely complex due to diverse factors influencing surface and reflections/scattering including soil heterogeneity, fluctuations in air-soil boundary, electromagnetic interactions between closely buried objects, random burial orientations of the targets, dynamical range regarding the burial depths of the objects as well as the geometry, size and the material composition of buried targets [27-29], [145-146].

Furthermore, Ground Penetrating Radars particularly suffer from severe performance limitations in detecting shallowly buried objects [30-31]. The directly coupled (DC) signals through air, and indirect-coupled ground-bounced (GB) signals (received after being reflected from the air/soil boundary) are common between the transmitter (TX) and receiver (RX) antennas of a GPR system. Self (within the same antenna channel) or mutual (across different antenna channels) coupling signals stemming from a GPR antenna array structure may overlap with the radar returns of

the targets which are buried very close to the soil boundary. Investigation of the effects of antenna arrays on the GPR detection performance is one of the topics emphasized in this thesis especially in the case of shallow-buried targets having low radar cross section (RCS) such as small dielectric antipersonnel mines having negligible metal content. In scenarios involving targets buried within a few centimeters below the air-soil interface, the targets are partially or even totally masked by these undesired coupling signals. It has been demonstrated as a novel study in this thesis that carefully chosen preprocessing algorithms should be used to reveal the presence of such camouflaged targets, and hence to improve the GPR detection accuracy in shallow-buried target problem in the presence of antenna arrays.

In this thesis, a comprehensive detection and classification approach has been developed for challenging GPR scenarios that include shallowly buried multiple targets located very close to each other. To the best of our knowledge, GPR detection/classification problems involving multiple shallow-buried targets in very close proximity have not been studied in depth in GPR literature, especially for the cases of inhomogeneous lossy soil with rough air-soil interfaces. Therefore, results of the thesis reported on such complex target identification scenarios are novel findings.

In order to detect targets with high accuracy and low false alarm rates in complex and challenging scenarios, the available GPR data need to be processed concurrently in alternative formats;

- one-dimensional (1D) *A-scan* time domain scattered signals recorded at each measurement spot,
- two-dimensional (2D) *B-scan* data recorded over a 2D domain formed by the time variable and a spatial distance variable either along the antenna array axis (cross-track) or along the sensor walking direction (down-track),
- three-dimensional (3D) *C-scan* data belonging to the overall volume scanned by the GPR in time, cross-track and down-track axes.

These different data formats provide significant information in complementary manner for improved target detection even in extremely challenging scenarios. Imaging information can be directly obtained from the B-scan and C-scan data. Two-dimensional slices of the C-scan data formed at certain depths, and especially energy heat maps obtained from the C-scan data provide quite valuable information for better visual interpretation of GPR outputs.

However, the GPR data in any of these data formats are usable for target detection only after certain preprocessing steps are implemented to remove possible types of cluttering signals such as the direct coupling terms, ground-bounced terms, rough surface effects and background clutter noise that stems from the inhomogeneous soil environment. In this thesis, a comprehensive study has been conducted to learn, apply, and compare different methodologies reported in GPR literature for the elimination of DC and ground bounce terms as well as the background clutter removal. It has been demonstrated that effectiveness of such preprocessing methods varies from one target detection scenario to another based upon the pertinent soil properties.

Once the detection process is completed, the next crucial step is the classification of the detected target [1-3], [32]. First of all, differentiation of false alarms from real threats is critical in many real-world missions. Secondly, if the detected object is believed to be a real threat, the choice of a proper method for its neutralization (i.e., deactivation) requires the knowledge of target properties. In this thesis, targets have been successfully classified even in the most challenging scenarios using a physics-based feature extraction and classifier design approach that was originally proposed and demonstrated for single target classification problems in unbounded dielectric media by Turhan-Sayan [33-34]. This approach has been successfully adapted to GPR problems for the first time in literature with a novel modification used to isolate the A-scan signals at the peak point of the detected target image. It is well known that characterization of a given target from its scattered electromagnetic data is a challenging task due to the strong dependence of data on aspect angle [33-38]. When a given target is investigated at different aspect angles using the unprocessed

scattered data, it can potentially be misidentified as a different target at some of these aspects. Similarly, different targets might be erroneously interpreted as being the same target at certain aspect angles due to the same reason of aspect dependency. To minimize the sensitivity of the GPR classifier on aspect variance, A-scan signals in the immediate neighborhood of the peak point of the target image are also used for target feature extraction. This novel process enables the utilization of multi-aspect electromagnetic scattered data in GPR target classifier design. As another novel contribution of the thesis, the Page distribution (PD), a quadratic (energetic) time-frequency representation (TFR) technique is used for target feature extraction in the GPR classifier design problem. In this work, the PD is implemented rather than the Wigner distribution (WD) which is used earlier in [33-34] due to the reduced nonlinear interference terms of PD in time and frequency [155]. Use of PD-based target feature extraction is successfully demonstrated for the GPR classifier design problem for the first time in literature in conjunction with a multi-aspect feature fusion approach based on Principal Component Analysis (PCA).

The approaches developed for subsurface target detection and classification have been applied to various GPR scenarios which consist of single or multiple targets with different material properties (conducting or dielectric materials), geometries, sizes and burial depths in varying soil conditions. Results of these GPR scenarios will be presented in the coming chapters with excellent detection/classification results.

Organization of the thesis is as follows:

In Chapter 2, fundamentals of the buried target identification problem will be discussed. First, the types and basic working principles of GPRs, then the basic physical concepts in GPR studies will be presented. Important concepts of electromagnetic wave propagation such as the propagation velocity and attenuation in a given low-loss soil environment will be revisited. Fundamentals of reflection and refraction phenomena at the discontinuities of the propagation medium (at the

air-soil interface and at the target-soil boundaries) are discussed with examples. In the rest of the section, fundamentals of down-looking GPR data simulation by the open-source software, gprMax is presented. This software solves electromagnetic wave propagation problems for GPR applications using the finite-difference time-domain (FDTD) method. Use of different signal processing algorithms for clutter elimination in simulated GPR data will be discussed in the last part of Chapter 2 with various realistic target detection scenarios.

Theory and applications of the novel physics-based GPR classifier design approach will be presented in detail in Chapter 3. Performance of a GPR classifier designed for conducting wire type targets will be demonstrated for perfect electric conductor (PEC) wires of two different thicknesses which are buried at different depths.

Applications of detection and classification approaches to GPR problems in shallow-buried multi-target scenarios will be presented in Chapter 4. The first part of this chapter is devoted to a detailed investigation of the antenna array effects on the detection accuracy of GPRs in the case of shallow-buried targets. Direct and indirect mutual coupling signals stemming from a collinear antenna array of Hertzian dipoles are simulated and their undesired impacts on the detection of conducting and dielectric targets are studied in depth. Then, a challenging multiple-targets scenario is defined with two PEC cylinders of different radii, a PEC wire and an air-filled void having a volume of a rectangular prism. All four targets are buried 3 cm below the air-ground boundary, and they are placed close to each other that results in strong electromagnetic interactions between the targets. Also employing different soil types and surface roughness parameters, targets have been successfully detected and classified in all these scenarios using the comprehensive detection and classification approaches proposed in this thesis.

The thesis is concluded in Chapter 5 with an overall discussion of the prominent results and suggestions for future work.

Appendix A presents the numerical verification of low-loss medium assumption made for soil media in GPR target detection/classification scenarios.

A sample input file used in gprMax simulations is presented and discussed in Appendix B.

Appendix C provides tables containing supplementary numerical data for the arrival times of the peak points of both self/mutual direct coupling signals and self/mutual ground-bounced coupling signals for the multi-channel GPR system discussed in Chapter 4. Tables of overall time spans for these clutter signals are also presented in this appendix.

Additional B-scan images obtained for the multi-target detection scenarios examined in Chapter 4.3 are given in Appendix D to provide further details.

Finally, various theoretical discussions about Page Distribution (PD) and Wigner Distribution (WD), in general, as well as the Time-Frequency Representations (TFRs), are given in Appendix E.



CHAPTER 2

BACKGROUND INFORMATION ON GPR SYSTEMS AND SUBSURFACE TARGET DETECTION

Fundamentals of a down-looking Ground Penetrating Radar (GPR) system problem will be discussed in this chapter including the basics of GPR operation, numerical simulation of GPR data and essential techniques for GPR signal preprocessing needed for accurate target detection.

2.1 Basics of GPR Systems and Electromagnetic Wave Propagation

In this section, a comprehensive overview will be provided regarding the fundamentals of Ground Penetrating Radar (GPR). Firstly, the general working principles and main types of GPRs will be discussed. Subsequently, behavior of electromagnetic wave propagation in the combined medium of air and soil will be summarized including the concepts of reflection, refraction, attenuation, and the estimation of burial depths of targets using the time-of-flight principle. These discussions are needed for a better understanding of the physics underlying subsurface sensing with GPRs and the fundamental principles behind the detection and classification techniques to be proposed and applied in the rest of the thesis.

2.1.1 Basic Principles of the Ground Penetrating Radar (GPR)

Ground Penetrating Radar (GPR) is a widely used electromagnetic sensor for subsurface sensing [1-3]. Detection and classification of targets buried in soil are perhaps the most well-known applications of GPRs where ultra-broad band

electromagnetic scattered data are collected and processed by advanced signal processing techniques for non-destructive target detection and classification. In today's world, GPR systems are widely used in many different fields due to the capability of electromagnetic waves to penetrate into media like soil, walls, cement, asphalt, etc., with high resolution leading to high accuracy in obscured object detection [145], [165]. In addition to common applications of GPRs such as demining or thru-the-wall operations, there are other fascinating implementations of GPRs such as the Mars Perseverance mission, where a GPR system is utilized to explore the subsurface of Mars [21], [39]. Additionally, GPRs have been instrumental in the examination of the Great Pyramid of Giza [40], Pompeii archaeological excavations [41], underground research at Stonehenge [42], and the El Salvador Lempa River Basin project [43]. These examples emphasize the importance of GPR applications in a diverse range of areas where subsurface sensing plays a crucial role.

There are two main approaches in GPR design; time-domain impulse radar design and continuous wave (CW) radar design [2], [13]. Although different studies are reported for continuous wave GPRs in literature [44-46], [149-150] such as the Frequency Modulated Continuous Wave (FMCW) GPR, Frequency Modulated Interrupted Continuous Wave (FMICW) GPR, and Noise Modulated Continuous Wave (NMCW) GPR, the Stepped-Frequency Continuous Wave (SFCW) radar is the most commonly used CW GPR design. In the SFCW radar approach, the GPR collects data in frequency domain at a sufficiently large number of equally-spaced sample frequencies within the required bandwidth. Then, the reflected/scattered time-domain signals are numerically synthesized using the inverse Fourier transformation technique together with proper frequency windowing and system calibration steps. SFCW type GPRs have the advantage of implementing larger bandwidth with the capability of controlling the spectral power density, higher mean power and lower noise figure in general [149-150]. In the impulse radar design approach [47-49] on the other hand, the GPR data reflected/scattered by the soil environment (with or without designated targets) are collected directly in time

domain in response to a narrow time-domain excitation pulse emitted by the GPR antenna(s). The effective frequency bandwidth of the GPR is inversely proportional to the pulse width. Time-domain impulse GPRs have better range resolution and simpler hardware design as compared to the CW GPRs. A significant portion of subsurface radars used in commercial markets, in military technologies, and in scientific research are impulse GPRs directly operating in time-domain.

All the GPR data generated and processed in this thesis are simulated by using the open-source software *gprMax* [54-55] that is based on the impulse radar type system modeling. Therefore, pulsed GPR (time-domain impulse radar) will be referred to as GPR in all future discussions in this work.

GPR systems basically consist of transmitter and receiver blocks, signal processing modules, and the display unit. In general, if the same antenna is used for both transmit and receive operations, the system is called a monostatic GPR. When the transmitter and receiver antennas are separate and placed at different locations, this system is called a bistatic GPR [1], [15]. Antenna arrays with multiple transmitter/receiver antenna channels are commonly employed in GPR applications [29-32] as the array operation provides fast and synchronous scanning of a large area of concern. In some circumstances, however, mutual coupling signals introduced by a multiple channel (array) antenna structure might lead to critical GPR detection errors as to be discussed in Chapter 4. In addition to the transmitter/receiver hardware modules, the signal processing blocks of the GPR systems are also indispensable. Strong DC leakage effects from a TX antenna to an RX antenna via air, and also the major reflections caused by the air-ground boundary (the ground-bounce (GB) phenomenon due to different relative permittivity values of the air and soil) are usually dominant enough to suppress the signals reflected/scattered from the buried targets. It is critical to eliminate these coupling effects so that the signals due to the target alone can be isolated as much as possible. This DC and GB elimination problem becomes extremely challenging for shallow-buried dielectric objects such as certain types of anti-personnel mines. This important problem will be investigated thoroughly in Chapter 4.

Another important point in GPR design is the trade-off between the penetration depth and spatial resolution. When operating at lower frequencies (higher wavelengths), electromagnetic waves emitted by the GPR experience lower attenuation rates in soil that results in higher penetration depths, but in the expense of poorer spatial resolution due to higher wavelength values. In other words, lower part of the GPR frequency spectrum is more suitable to detect deeply-buried larger size targets. The higher frequency part of the spectrum, on the other hand, is more useful to detect smaller-size targets (due to improved spatial resolution) buried at small or moderate depths (at higher frequencies, attenuation rate in soil increases leading to smaller penetration depths). The center frequency and bandwidth of a GPR system are fundamental design parameters which can be determined based upon the intended application if the geometrical and electrical properties of potential targets and properties of soil are known [1-2]. For instance, penetration depth is not a prime concern while detecting shallow-buried targets in a low-loss and almost homogeneous sandy soil. However, providing a reasonable penetration depth is important even in shallow-buried target applications as a precaution against occasional increases in attenuation that may happen, for example, in the case of a heterogeneous soil especially with increased moisture content. Practical GPRs are mostly ultra-wideband (UWB) systems having a bandwidth larger than three or four octaves. A UWB GPR spanning both low and high frequency spectra can be used effectively in diverse scenarios regarding the variations in target properties and burial depths. Using a GPR with a large system bandwidth is also beneficial for an improved target recognition capability because collecting GPR data over a larger bandwidth means the possibility of extracting more enhanced and diversified characteristic information about the detected target.

The main problem of this thesis is to detect and classify multiple shallow-buried targets which are placed in very close proximity so that electromagnetic interactions between buried objects bring additional complexity to detection and classification tasks. This problem is simulated for different types of soil ranging from a simpler case of homogeneous dry sand medium with flat air-soil interface to an extremely

complicated case of highly inhomogeneous soil with varying amounts of water/moisture content in the presence of a rough soil surface. In all scenarios to be presented in Chapter 4, the same target set is utilized with two PEC cylindrical disks of different radii, an air-filled rectangular prism-shaped void in soil and a PEC wire. In solving these challenging GPR problems, a Gaussian derivative type time-domain input pulse is simulated by gprMax. The center frequency of the spectrum for this excitation is chosen to be 6 GHz that is high enough to capture small details of the wire target with 2 mm radius. The half bandwidth at full maximum is about 9.7 GHz for this spectrum. Bandwidth becomes even wider for (-10 dB) bandwidth.

Figure 2.1 provides a simplified visual to give insight for the basic operating mechanism of a GPR. A narrow time pulse (having a broad bandwidth) emitted by the transmitting antenna(s) of the GPR experiences the reflection and refraction phenomena whenever there is an abrupt change in the refractive index of the propagation medium. Reflected pulses at the air-soil interface and at all possible interfaces between the soil and the buried objects are eventually collected by the receiving antenna(s) of the GPR with certain time delays. Presence of a buried object is indicated by the reception of a reflected pulse at a measurement spot. Arrival time of the reflected pulse is directly used to estimate the burial depth of a target or a clutter object within the soil using the expression

$$d = \frac{v_p T}{2} \quad (2.1)$$

where T is the total time elapsed in soil for two-way propagation and v_p is the phase velocity of the electromagnetic wave in the medium.

Propagation velocity of the radar pulse within the soil environment must be known to estimate this depth information correctly. Higher level properties of the targets can also be obtained from the received GPR data (containing specular reflections and scattered signals, in general) using advanced feature extraction techniques to be used for target recognition purposes.

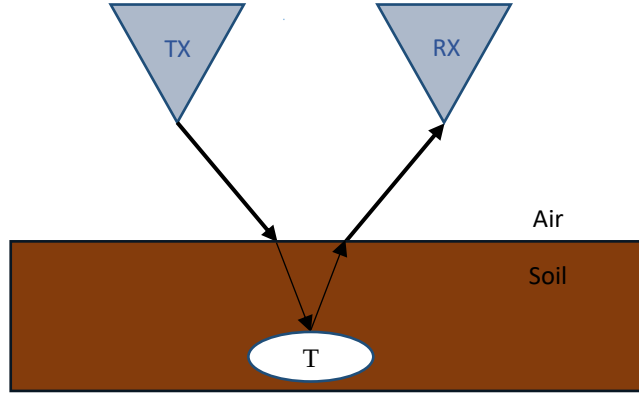


Figure 2.1 The basic working principle of the GPR with the transmitter/receiver (TX/RX) antennas and a buried target (T).

2.1.2 Basics of Electromagnetic Wave Propagation in a Lossy Medium

An arbitrary GPR scenario in a lossy soil medium can be modeled as a problem of electromagnetic wave propagation using Maxwell's equations. Time-domain Maxwell's equations are given as

$$\bar{\nabla} \times \bar{E}(\bar{r}, t) = -\frac{\partial \bar{B}(\bar{r}, t)}{\partial t} \quad (2.2.a)$$

$$\bar{\nabla} \times \bar{H}(\bar{r}, t) = \bar{J}(\bar{r}, t) + \frac{\partial \bar{D}(\bar{r}, t)}{\partial t} \quad (2.2.b)$$

$$\bar{\nabla} \cdot \bar{D}(\bar{r}, t) = \rho_v(\bar{r}, t) \quad (2.2.c)$$

$$\bar{\nabla} \cdot \bar{B}(\bar{r}, t) = 0 \quad (2.2.d)$$

in terms of $\bar{E}$ (electric field intensity vector), $\bar{D}$ (electric flux density vector), $\bar{H}$ (magnetic field intensity vector) and $\bar{B}$ (magnetic flux density vector), and the source terms $\bar{J}$ (true volume current density) and ρ_v (true volume charge density), which are all functions of both space coordinates and time.

For the assumption of a simple (linear, homogeneous and isotropic), source-free and lossy medium, the phasor domain expressions of Maxwell's equations become

$$\bar{\nabla} \times \bar{E}(\bar{r}) = -j\omega\mu\bar{H}(\bar{r}) \quad (2.3.a)$$

$$\bar{\nabla} \times \bar{H}(\bar{r}) = \sigma\bar{E}(\bar{r}) + j\omega\varepsilon\bar{E}(\bar{r}) \quad (2.3.b)$$

$$\bar{\nabla} \cdot \bar{E}(\bar{r}) = 0 \quad (2.3.c)$$

$$\bar{\nabla} \cdot \bar{H}(\bar{r}) = 0 \quad (2.3.d)$$

as the constitutive relations for such a medium are given as

$$\bar{D}(\bar{r}) = \varepsilon\bar{E}(\bar{r}) \quad (2.4.a)$$

$$\bar{B}(\bar{r}) = \mu\bar{H}(\bar{r}) \quad (2.4.b)$$

$$\bar{J}(\bar{r}) = \sigma\bar{E}(\bar{r}) \quad (2.4.c)$$

where ε, μ and σ are simple constants. All phasor domain variables depend on space coordinates only. Using Equations (2.3) and (2.4) the following second order partial differential equations

$$\nabla^2 \bar{E}(\bar{r}) - \gamma^2 \bar{E}(\bar{r}) = 0 \quad (2.5.a)$$

and

$$\nabla^2 \bar{H}(\bar{r}) - \gamma^2 \bar{H}(\bar{r}) = 0 \quad (2.5.b)$$

are obtained for $\bar{E}(\bar{r})$ and $\bar{H}(\bar{r})$ phasors with the complex valued propagation constant γ defined as

$$\gamma = \alpha + j\beta = \sqrt{j\omega\mu(\sigma + j\omega\varepsilon)} \quad (2.5.c)$$

where $\alpha = \text{Real}\{\gamma\}$ is the attenuation constant and $\beta = \text{Imag}\{\gamma\}$ is the phase constant.

In a general lossy medium, the propagation velocity (v_p), wavelength (λ) and skin depth (δ) are defined as

$$v_p = \frac{\omega}{\beta} \quad (2.6. a)$$

$$\lambda = \frac{2\pi}{\beta} \quad (2.6. b)$$

$$\delta = \frac{1}{\alpha} \quad (2.6. c)$$

Also, the complex valued intrinsic impedance of the lossy medium is computed from

$$\eta = \sqrt{\frac{j\omega\mu}{\sigma + j\omega\epsilon}} = \sqrt{\frac{\mu}{\epsilon}} \left(1 - \frac{j\sigma}{\omega\epsilon}\right)^{-1/2} \quad (2.6. d)$$

Loss tangent of the problem is defined as the magnitude of the ratio of the conduction current density to the displacement current density using the terms on the right-hand side of Equation (2.3.b) as

$$\text{Loss Tangent} = \frac{\sigma}{\omega\epsilon} \quad (2.7)$$

When the medium is a perfect (lossless) dielectric with $\sigma = 0$, the Loss Tangent becomes zero. When the displacement current density is much larger than the conduction current density, it means that the medium is a “good-dielectric” or a “low-loss dielectric” satisfying the condition $\sigma \ll \omega\epsilon$. Practically, if $\frac{\sigma}{\omega\epsilon} < 0.1$ as a rule of thumb, the medium can be accepted as a low-loss dielectric. In this case, applying the Binomial theorem to expressions of propagation constant (γ) and intrinsic impedance (η), it can be shown [50-52] that

$$\alpha \cong \frac{\sigma}{2} \sqrt{\frac{\mu}{\epsilon}} \quad (2.8. a)$$

$$\beta \cong \omega \sqrt{\mu\epsilon} \quad (2.8. b)$$

$$\eta \cong \sqrt{\frac{\mu}{\epsilon}} \left(1 + j \frac{\sigma}{2\omega\epsilon}\right) \quad (2.8. c)$$

In other words, the real part of the propagation constant and the imaginary part of the intrinsic impedance become very small in low-loss dielectric media. Also, the phase constant β becomes approximately the same as the wavenumber $k = \omega\sqrt{\mu\varepsilon}$ defined for a case of lossless dielectric of parameters (μ, ε) . Therefore, the expressions for the propagation (phase) velocity, wavelength and intrinsic impedance are approximately same for a low-loss dielectric and a perfect lossless dielectric as follows:

$$v_p = \frac{\omega}{\beta} \cong \frac{1}{\sqrt{\mu\varepsilon}} = \frac{1}{\sqrt{\varepsilon_0\varepsilon_r \mu_0\mu_r}} = \frac{c}{\sqrt{\varepsilon_r\mu_r}} \quad (2.9.a)$$

$$\lambda = \frac{2\pi}{\beta} \cong \frac{2\pi}{2\pi f \sqrt{\mu\varepsilon}} = \frac{v_p}{f} \quad (2.9.b)$$

$$\eta \cong \sqrt{\frac{\mu}{\varepsilon}} \quad (2.9.c)$$

where $c = 3 \times 10^8 \text{ m/s}$ is the velocity of light in vacuum.

The simulation software gprMax utilize the FDTD method to solve Maxwell's equations numerically for a given GPR scenario. Estimation of reflection and transmission coefficients at boundaries as well as propagation velocity and attenuation constant in a given medium are crucial for the accurate simulation and interpretation of GPR data. In this section, these basic topics will be outlined with relevant examples.

Firstly, the expression of propagation velocity and the computation of burial depth in a low-loss medium will be revisited briefly. It is well known that the phase velocity (or propagation velocity) of electromagnetic waves in air is approximately equal to the velocity of light in vacuum, $c = 3 \times 10^8 \text{ m/s}$. The phase velocity of an electromagnetic wave in a given lossless or low-loss medium with relative permittivity (ε_r) and relative permeability (μ_r) is already given in Equation (2.9.a).

Using the time-of-flight principle, burial depth (d) of a detected target measured from the air-soil boundary can be calculated using Equation (2.1) as $d = \frac{v_p T}{2}$. As a

simple example, A-scan signals are simulated using gprMax for a PEC wire of radius 2 mm and length $50\sqrt{2}$ cm that is buried at different depths in each simulation for $d = 1, 2, 3, 4, 5, 6$ cm in homogeneous dry sand (a low-loss dielectric medium) of parameters $\epsilon_r = 3$ and $\mu_r = 1$ with a flat air-soil boundary. Resulting A-scan waveforms (the x component of the time domain electric field) are simulated and plotted against time in Figure 2.2. In these six simulations, all parameters are kept the same except the burial depth for the sake of fair comparison. As the clutter elimination process was conducted prior to plotting these A-scan signals, each one of these curves represents the response waveform of the buried target only. It is observed in the simulation results of Fig. 2.2 that the difference between arrival times of the peak points of successive A-scan curves is $\Delta t \cong 0.119231$ ns corresponding to the successive difference in burial depth, which is $\Delta d = 1$ cm. This result is found in very good agreement with the theoretically expected value that is computed from Equation (2.1) as $\Delta t = 2 \times \frac{\Delta d}{\frac{c}{\sqrt{3}}} \cong 0.11547$ ns with only three percent error.

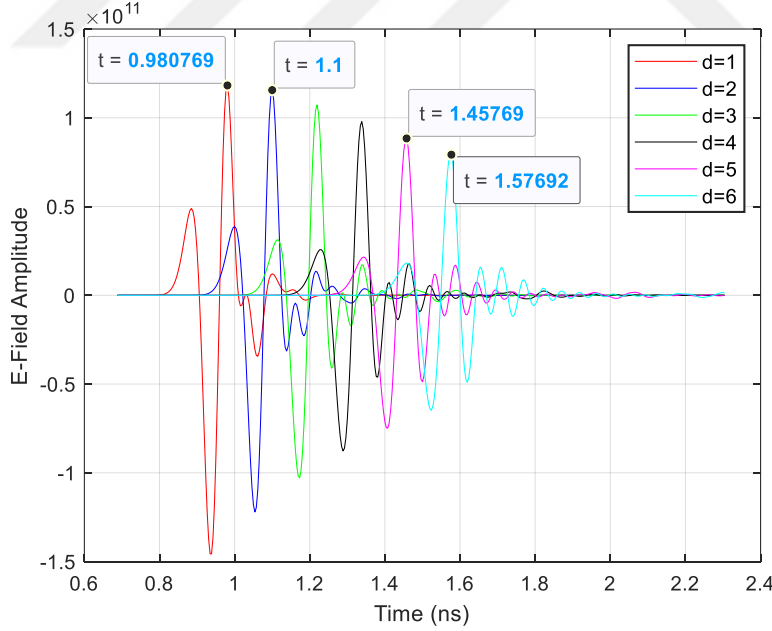


Figure 2.2 Simulated A-scan signals of the same PEC wire buried at different depths d (in cm) measured from the air-soil interface, in dry homogeneous sand of $\epsilon_r = 3$.

Reflection and transmission of electromagnetic waves at the surfaces of material discontinuities play a critical role in target detection with a GPR. Considering the general oblique incidence problem in phasor domain analysis for the reflection/refraction of plane waves at a planar boundary between two dielectric media, the reflection coefficient (Γ) and the transmission coefficient (T) for parallel and perpendicular polarizations (with respect to the incidence plane) are expressed by the set of well-known Fresnel Equations [50]. The normal incidence problem is the special case of the oblique incidence problem where the incidence angle is zero, i.e. the propagation vector of the incident wave hits the boundary perpendicularly. In this case, the expressions for Γ and T are simplified as

$$\Gamma = \frac{E_{reflected}}{E_{incident}} = \frac{\eta_2 - \eta_1}{\eta_2 + \eta_1} \quad (2.10.a)$$

and

$$T = \frac{E_{transmitted}}{E_{incident}} = \frac{2\eta_2}{\eta_2 + \eta_1} \quad (2.10.b)$$

where η_1 and η_2 are intrinsic impedances of the first and second media, respectively. When at least one of these media is lossy (with non-zero conductivity), Γ and T become both complex valued, in general. The expression for a complex valued intrinsic impedance in a lossy medium is already defined in Equation (2.6.d). Also, for a low-loss medium, the intrinsic impedance is shown to be real valued and equal to $\sqrt{\mu/\epsilon}$ in the approximate sense as shown in Equation (2.9.c).

In this thesis, GPR data have been simulated for various scenarios involving PEC or dielectric targets buried in different types of soil. All dielectric targets and types of soil used in these scenarios satisfy the low-loss medium condition as verified in Appendix A.

In gprMax simulations, the GPR data are computed using the general oblique incidence problems at the interfaces of air-soil and soil-target for given GPR scenarios. However, for the sake of simplifying the qualitative discussions, normal

incidence assumption has been used occasionally for the interpretation of simulation results in the thesis. This assumption may be justified as we have an antenna array placed only 10 cm above the air-soil surface, and small-size targets buried are very close to the air-soil boundary so that the obliquely incident waves see those targets at small incidence angles.

The expressions for reflection and transmission coefficients (under normal incidence assumption) given in Equations (2.10.a-b) can provide valuable clues about the relative permittivity of a buried object (assuming μ_r is equal to one) based on the phase relationship of the incident and reflected signals. The reflected signal may be in phase or out of phase with the incident signal based on the sign of the reflection coefficient. For example, a phase reversal (180 degrees phase shift) is observed always between the GPR excitation pulse (that travels from the air side) and the ground-bounced signal as the reflection coefficient computed at the air-soil interface is negative (due to the fact that soil's permittivity value is larger than the permittivity of air). Also, the direct-coupled pulse component and the ground-bounced pulse component of an A-scan signal are always out of phase by 180 degrees due to the same reason.

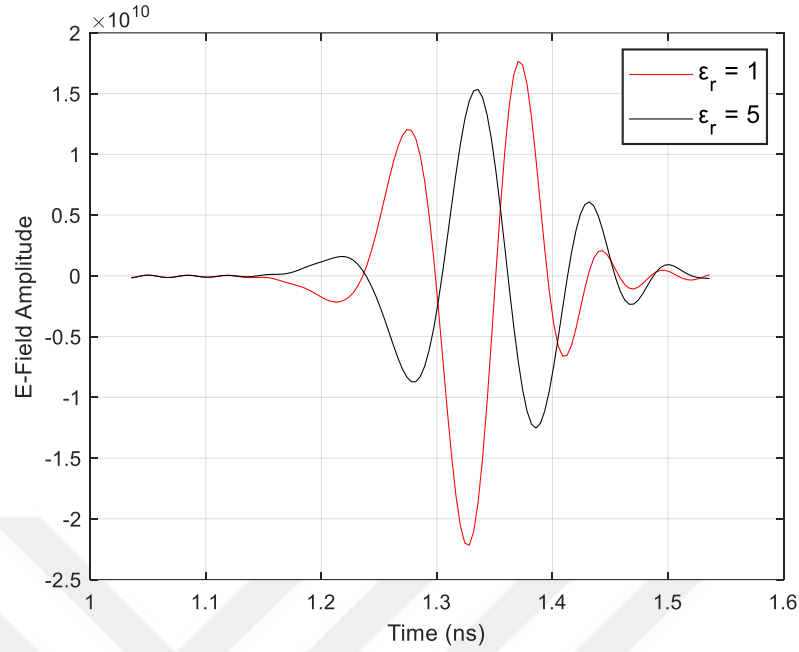


Figure 2.3 Simulated A-scan signals received from two different targets with different relative dielectric permittivity values buried in dry sand.

Another demonstration of this idea is presented in Figure 2.3 that shows the simulated A-scan signals received from two different targets; an air-filled void with ($\epsilon_r = 1$, $\mu_r = 1$) and a dense target with ($\epsilon_r = 5$, $\mu_r = 1$), both buried in dry sand with parameters ($\epsilon_r = 3$, $\mu_r = 1$). Sizes, shapes, and the burial depths of these two targets are the same. While the reflection coefficient computed at the sand-void boundary (incident pulse comes from soil) is positive, the reflection coefficient at the soil-dense target boundary is negative based on Equation (2.10.a) under the assumption of normal incidence problem. As a result, an approximate phase reversal relationship is observed between these two A-scan signals in Fig. 2.3. The phase reversal is not perfect due to the slightly oblique incident nature of the problem. Thanks to this approach, significant clues about the type and electrical properties of targets can be extracted from the A-scan GPR data.

The last concept to be discussed in this section is the attenuation of electromagnetic waves. In the GPR problem, attenuation in soil is a major concern as it significantly

limits the feasible depth that can be scanned for the presence of buried targets. As an example, Figure 2.2 presents six different A-scan signals returned by the same target buried at six different depths in sand. The amplitude of the A-scan signal received from the most shallowly buried target is the largest, while the amplitude of the A-scan signal belonging to the from the deepest buried target is the smallest. As the burial depth increases, the two-way propagation path length traversed in soil increases, leading to higher losses. After some critical depth, attenuation introduced by soil will reduce the amplitude of the signal to almost noise level making target detection impossible. There are numerous studies in literature examining the attenuation effects in GPR problems [53].

2.2 Detection of Buried Targets: From GPR Data Generation to Obtaining Accurate Detection Results

This section will describe the important steps of target detection process starting with the simulation of GPR data. The open-source software gprMax simulates GPR target detection scenarios to solve for the A-scan signals by using the Finite-Difference Time-Domain (FDTD) method. After explaining the basics of gprMax, details about possible GPR data formats; A-scan, B-scan and C-scan data types will be given. Next, clutter elimination methods will be discussed as they play a critical role to ease significant challenges in GPR problems. Specifically, the multi-step clutter elimination approach proposed in this thesis will be introduced and explained in detail. Finally, the suggested target detection approach will be applied to different GPR scenarios involving buried dielectric or PEC targets. This means that all stages of the detection process, ranging from data generation to obtaining accurate detection results, will be thoroughly discussed in this section.

2.2.1 Simulation of GPR Data Using the gprMax Software

The open-source software called '*gprMax*' [54-55] is used to simulate all the GPR scenarios studied in this thesis. It computes the GPR data by solving the Maxwell's equations using the FDTD method [54-55]. The groundbreaking series of works published by Maxwell between 1850 and 1870 established the foundations of electromagnetic wave propagation problem [56-57] and paved the way for the solution of electromagnetic fields even in extremely complex scenarios. The *gprMax* software makes use of the Yee's algorithm to solve Maxwell's equations for given GPR scenarios to obtain the corresponding A-scan signals, i.e., the electromagnetic response of the whole system composed of air, soil, buried objects in soil and the antenna system placed at a short distance above the air-soil boundary [58].

The first step in generating GPR data with the *gprMax* software is to create an input file. The ASCII text file, which can be prepared with any text editor or word-processing program, serves as the input file. For this file, the hash character (#) is used to denote the beginning of a command that will be run by the *gprMax* [55]. Properties of the transmitter and receiver antennas, details of the antenna array structure, geometrical and electrical parameters of buried targets, properties of the propagation media, locations of the antennas, air-ground boundary and the targets, discretization of the spatial domain with step sizes in the down-track and cross-track directions, temporal and spectral properties, and the type of the excitation pulse signal, are all specified in the input file. Many parameters such as humidity, material mixing ratio of the soil, and roughness of the air-soil boundary for chosen scenarios can be also specified easily within the *gprMax* software. The input file for one of the most significant scenarios studied in this thesis is given and explained in Appendix B. After the *gprMax* is run with the specified input file, the simulated output data are generated in HDF5 format that can be read by MATLAB [55]. Using the GPR data saved in MATLAB environment, necessary steps for detection and classification of targets are performed using the designated techniques and algorithms studied and/or developed in this thesis work.

As stated before, gprMax uses the FDTD approach to generate the GPR data. Finite-difference time-domain (FDTD) method, also known as Yee's method, is a numerical technique used to model computational electrodynamics by approximating solutions to a system of differential equations [59]. It falls under the category of grid-based differential numerical modeling methods. FDTD discretizes the time-dependent Maxwell's equations using central-difference approximations for space and time derivatives. The resulting finite-difference equations are solved iteratively, with electric field components computed at a certain time step and magnetic field components computed at the next time step. This process continues until the desired electromagnetic field behavior, whether transient or steady-state, is fully evolved. FDTD is a time-domain technique, and its advantages include its ability to cover a wide frequency range in a single simulation run and its natural treatment of nonlinear material properties. These advantages are crucial for GPR simulations. GPR, being a UWB radar, can be easily modeled with this method by using appropriate source signals such as Gaussian pulse, Gaussian derivative pulse, or Gaussian second derivative pulse. Additionally, linear or nonlinear dielectric or PEC materials can be easily modeled by using FDTD.

The FDTD method solves Maxwell's equations by discretizing both the spatial and temporal domains. The sizes of the spatial steps ($\Delta x, \Delta y, \Delta z$) and the temporal step (Δt) play a crucial role, as smaller steps lead to a more accurate representation of the problem. However, the sizes of these steps must be kept at feasible values considering the limitations on the computer memory and the overall computation time. It means the FDTD model is a discretized version of the actual problem and it must have a limited size. The fundamental component of this discretized FDTD grid is the Yee cell, named after Kane Yee, who pioneered the FDTD method [59].

Deciding the values of spatial discretization steps ($\Delta x, \Delta y, \Delta z$) and temporal discretization step (Δt) properly is vital for the performance of the FDTD simulations. Δt corresponds to the time elapsed in each iteration. If Δt is multiplied by the number of iterations, N , the total time window can be calculated. The Δt value

corresponds to the elapsed simulation time within the cell defined by $(\Delta x, \Delta y, \Delta z)$. As energy can never travel farther than one grid spacing in a single time step, these discretization steps cannot be determined independently of each other. The CFL (Courant, Freidrichs, and Lewy) condition describes the stability condition, which is one of the main constraints in determining the $(\Delta x, \Delta y, \Delta z, \text{ and } \Delta t)$ values. The CFL stability condition can be given as follows [60]:

$$\Delta t \leq \frac{1}{c \sqrt{\frac{1}{(\Delta x)^2} + \frac{1}{(\Delta y)^2} + \frac{1}{(\Delta z)^2}}} \quad (2.11)$$

Furthermore, if we assume spatial discretization is equal in all three dimensions as $\Delta l = \Delta x = \Delta y = \Delta z$, the CFL condition can be simplified and given in the following simple form:

$$\Delta t \leq \frac{\Delta l}{c\sqrt{3}} \quad (2.12)$$

In addition, there is a very important approach to determining spatial discretization for all dimensions. It is necessary to determine the spatial discretization based on the expected accuracy level from simulation results, the frequency content of the source pulse, and the target's geometrical dimensions, if we know. Obviously, all targets must be adequately resolved for successful identification. The rule for determining spatial discretization steps can be expressed as follows: "The discretization step should be at least ten times smaller than the smallest wavelength of the propagating electromagnetic fields." Its mathematical representation can be given as follows [58], [61]:

$$\forall (\Delta x, \Delta y, \Delta z) \in \mathbb{R}: \left(\Delta x \leq \frac{\lambda_s}{10} \right) \wedge \left(\Delta y \leq \frac{\lambda_s}{10} \right) \wedge \left(\Delta z \leq \frac{\lambda_s}{10} \right) \quad (2.13)$$

where λ_s corresponds to the smallest wavelength of the propagating electromagnetic field. When dealing with broadband signals, as in the GPR problem, the λ_s value may corresponds to the high-frequency end of the -3 dB effective bandwidth. If the center frequency is represented by f_c , this high-end frequency may roughly

correspond to a value between $1.5f_c$ and $2f_c$. A better estimate for λ_s can be chosen by examining the FFT of the time-domain source signal.

The resolution concept and the constraints on the step sizes are quite important in the GPR scenarios studied in this thesis as detection and classification of thin wires are parts of the multi-target GPR problems. For instance, one of the scenarios studied in the thesis aims to detect and classify PEC wires with 2 mm and 5 mm radii. The higher end of the excitation pulse's frequency spectrum should be chosen properly to ensure sufficient spatial resolution to be able to detect the details of the thinner wire with 2 mm radius. As mentioned before, spatial resolution gets better at lower wavelengths (i.e. at high frequencies), in general. In summary, two factors are taken into account in the selection of discretization steps for the gprMax simulations; spatial discretization requirement in the FDTD method, and the necessity of including higher frequencies in the source spectrum to provide enough resolution for very small size targets like thin wires.

Most of the GPR applications such as demining in military missions are real-time problems which require the completion of computations for target detection in the minimum possible duration of time. The memory space of the computers are also limited. Therefore, computational domains used for GPR simulations must be truncated. This truncation should be done at a reasonable distance from the sources and targets.

In gprMax, the Perfectly Matched Layer (PML) is applied for spatial truncation of the computational space [62]. The purpose of the PML is to absorb all electromagnetic waves coming onto the boundaries without reflecting them back to the computational domain. The computational domain should encompass all essential features of the model including the transmitting and receiving antennas, the media of propagation (air and soil) and the targets. If all sources and targets are positioned at least 15 cells away from the boundaries where PMLs are enforced in gprMax, the software will typically work effectively without any significant artificial reflections or any other undesired effects. As a matter of fact, gprMax utilizes

Complex Frequency Shifted (CFS) Perfectly Matched Layers (PMLs) [54-55], [147-148], which provide improved performance over traditional ABCs [63].

Figure 2.4 shows a typical simulation scenario for the gprMax, which emphasizes the use of PML type absorbing boundary regions for a limited computational domain containing the soil medium with a buried target in addition to the antenna system placed in air part of the domain [64].

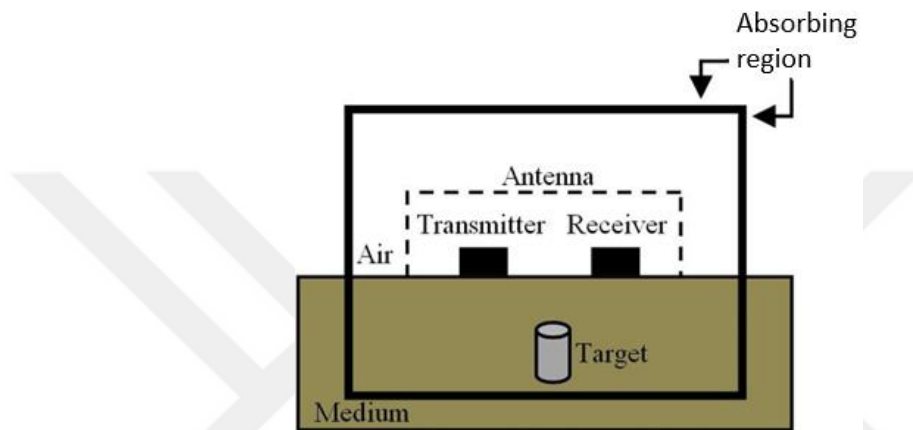


Figure 2.4 A basic simulation scenario constrained by the Perfectly Matched Layer (PML) type absorbing region.

2.2.2 Description of GPR Data Output Formats

This section will discuss the properties and usage of A-scan, B-scan, and C-scan type GPR output data which provide complementary information for target detection and imaging.

In order to detect targets with high accuracy and low false alarm rates in complex and challenging scenarios, available GPR data need to be processed concurrently in alternative formats;

- An *A-scan* signal is the basic output data of the GPR. It is a one-dimensional time-domain scattered signal collected by a receiving antenna at a measurement point in response to the excitation pulse(s) emitted by the

transmitting antenna(s) of the GPR system. In other words, it is the local system response signal dependent on the aspect angle and polarization as well. An A-scan signal implicitly contains all the transient electromagnetic information about the propagation media and the target(s) which are effective at the selected spatial location.

- *B-scan* data are the two-dimensional data composed of a collection of A-scan signals collected either along the antenna array axis (cross-track) or along the GPR walking direction (down-track). In other words, the B-scan data characterize the system over a 2D domain formed by the time variable and a spatial distance variable. B-scan data are commonly used in image processing-based target detection and classification techniques in the GPR literature [65-70] analyzing the hyperbolic-shaped target features. B-scan type data representation is also useful to detect the presence of some systematic sources of clutter such as the mutually coupled ground-bounced signals in GPRs having antenna arrays. Effects of such clutter signals are usually observed as horizontally oriented lines parallel to the cross-track or down-track axes (i.e. occurring at certain time instances) in B-scan images.
- *C-scan* data are three-dimensional data composed of the collection of A-scan signals recorded at the spatial sampling points of the terrain that is scanned along the cross-track and down-track axes simultaneously. The third dimension is described by the time variable that can be mapped to the depth variable using the propagation velocities in air and in soil. C-scan data provide the most complete representation for the GPR problem including the 3D images [2], [66]. Two-dimensional slices of the C-scan data formed at certain time/depth values, and especially energy heat maps computed from the C-scan data provide valuable information for better visual interpretation of GPR outputs. In summary, these different GPR data formats provide significant information in complementary manner for improved target detection even in the most challenging GPR scenarios.

Figure 2.5 describes the GPR data collection process. Using the transmitter and receiver antennas of an arrays, which are aligned in the cross-track direction, steps are taken in the down-track direction to scan the terrain of interest. The C-scan data collected in this process are saved in a 3D data matrix of size $(N \times I \times J)$ where the sampling index $i = 1, \dots, I$ is used for cross-track axis, $j = 1, \dots, J$ belongs to down-track axis, and $n = 1, \dots, N$ is used for the time axis. When the location is fixed over the terrain at some point P corresponding to spatial indices $(i, j) = (\tilde{i}, \tilde{j})$ at a chosen time index $n = \tilde{n}$, the corresponding depth $z = \tilde{z}$ can be computed by using different propagation velocity values of the radar wave in the air, soil and buried object (if there is any) portions of the vertical path under the point P .

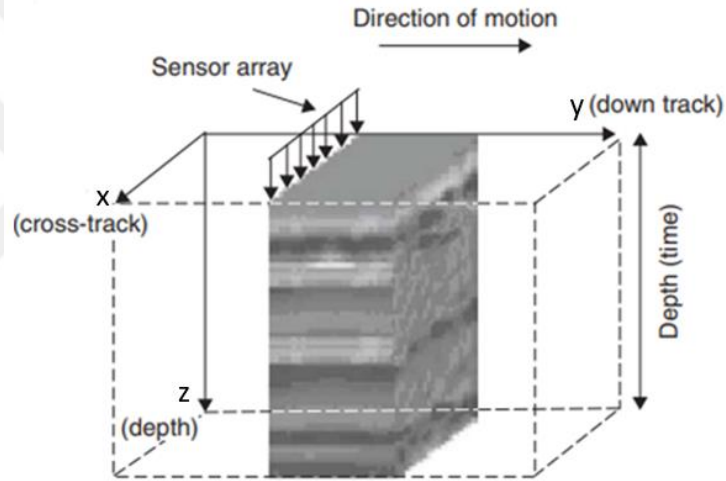


Figure 2.5 Collection of GPR data by a collinear antenna array.

As mentioned earlier, A-scan data provide important information about the presence of a target as well as its burial depth and electrical properties. Figure 2.6 illustrates A-scan data of a diagonally laid wire (with a radius of 2 mm) buried at 4 cm depth in sand. This A-scan signal is simulated using single antenna channel. The figure shows the self-direct coupling term arising from the interaction of transmitter and receiver antennas, ground-bounced reflection term due to the discontinuity at the air-ground boundary, and the reflection from the target. As can be seen from the figure, antenna direct coupling, and ground bounce effects can mask the response of the target or create false alarms. Minimizing these effects is vital for accurate GPR

detection. Figure 2.7 demonstrates the obtained signal after the “antenna calibration” process. This calibration step can usually be done mechanically in operational GPR systems by taking a reference measurement while the antennas are raised to look at the sky without sensing any ground boundaries or targets. Then, this reference measurement is subtracted from the usual down-looking GPR measurements to eliminate the effects of self or mutual direct coupling signals between the transmitter and receiver antennas of the GPR. The antenna calibration data can be simulated in gprMax for a scenario without any soil region defined (i.e., no boundaries due to the presence of soil or any targets) but the computational domain is just filled by air. After eliminating the highly dominant direct coupling signal components, the ground-bounced signal and target response become clearly observable although the strong ground-bounced term may still mask the target reflections especially in the case of low radar cross section (RCS) targets. As the conducting wire is a good reflector with a sufficiently high RCS, its GPR return is clearly seen in Fig. 2.7. If the relative permittivity of soil is known, the burial depth of the target can be successfully calculated using the time difference between the peak points of the ground-bounced and main target reflection signals detected in the A-scan signal. The burial depth of the wire (declared to be 4 cm in the simulation) target can be estimated accurately using the data in Fig. 2.7 using this simple approach.

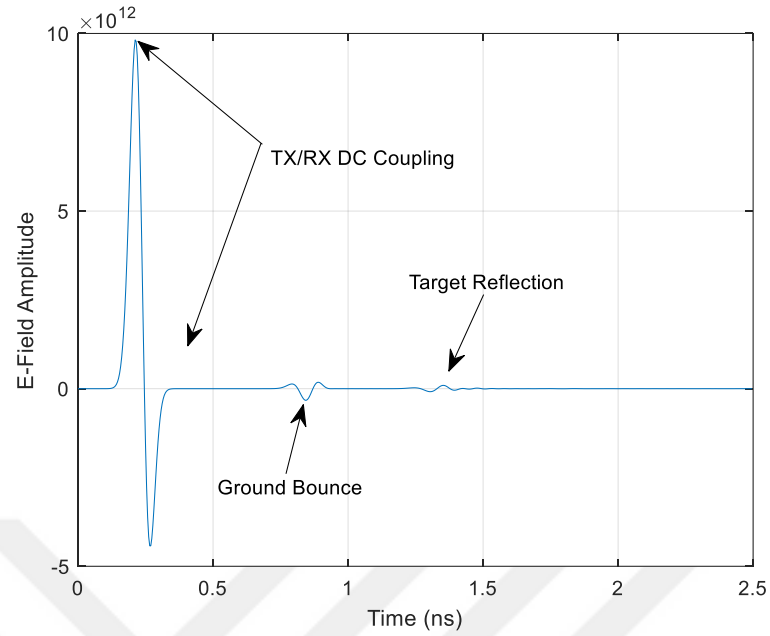


Figure 2.6 A-scan signal simulated for a PEC wire buried in sand at $d = 4$ cm using a single pair of transmitter/receiver antennas in simulation.

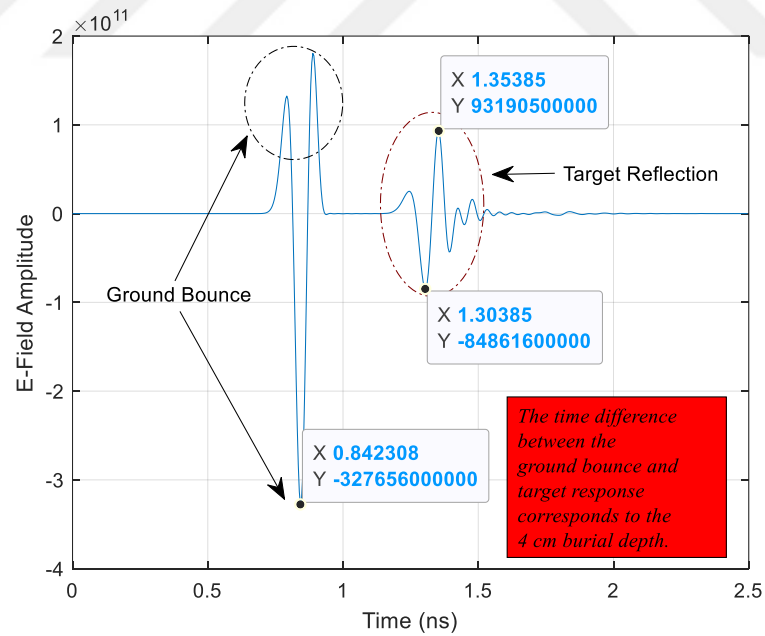


Figure 2.7 A-scan signal (shown above in Fig. 2.6) after the elimination of direct coupling term.

As another example, Figure 2.8 shows the A-scan data simulated for a PEC cylinder which is buried in sand in upright orientation such that its upper circular face is parallel to and 1 cm below the air-ground boundary. The radius of the cylinder is 3 cm, and its height is 2 cm. An 8-channel array of transmitter/receiver antennas is used for data collection in this scenario (details of these simulation scenarios will be given in later sections). The A-scan signal plotted on the left frame of Fig. 2.8 belongs to the target response only, which is obtained after the elimination of directly coupled (DC) and indirectly-coupled ground-bounced (GB) signal components. In this example, both self and mutual coupling terms resulting from the antenna array structure are removed from the original A-scan signal, which is plotted on the right-hand side frame of Fig. 2.8.

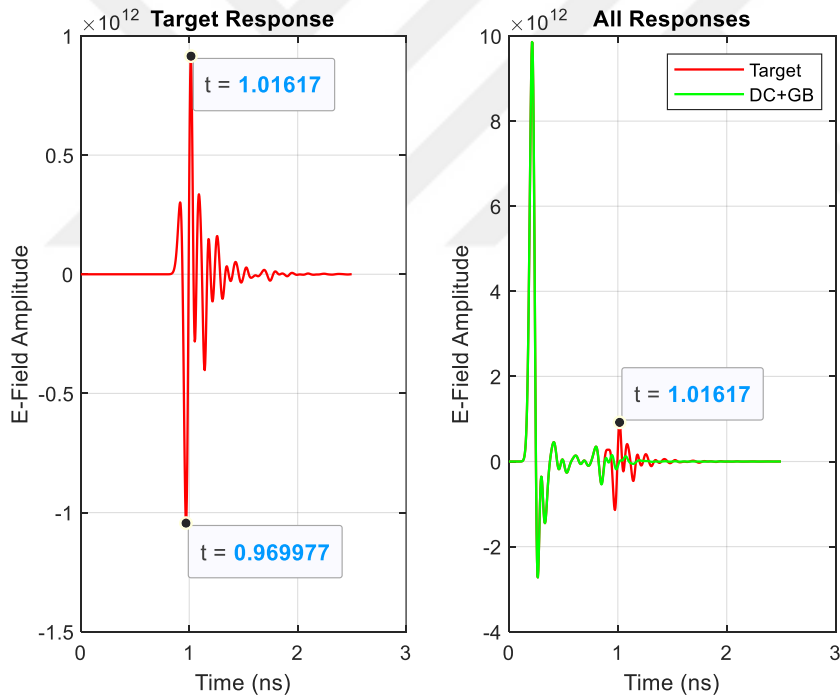


Figure 2.8 A-scan signal simulated for a PEC cylinder buried in sand using an antenna array (on the right) and the target response component of the A-scan signal obtained after the removal of DC and GB terms (on the left).

Figures 2.9 and 2.10 presents the B-scan images (plotted using the signal magnitudes for better contrast) showing the presence and location of the PEC cylinder. In Figure 2.9, the dark red-colored signal band corresponds to highly dominant self-direct coupling terms while the yellow and blue colored horizontal straight lines (parallel to and below the red lines) correspond to the mutual direct coupling and self/mutual ground-bounced signals. The concepts of self/mutual direct coupling and ground-bounced signals will be discussed in detail later in the thesis. The target's response is also detected and marked in the figure. The burial depth of 1 cm (used in the simulations) is also observed correctly in Figure 2.9. The preprocessed version of this B-scan image is given in Figure 2.10 where only the target response is shown as the clutter effects (DC and GB signal components) are eliminated by applying the mean subtraction method. The electromagnetic wave components returned by the target are much more clear, and the target is located with a much better precision in time versus down-track coordinate plane. These B-scan data are recorded under the TX/RX antenna pair seeing the target most directly along the cross-track direction. Original form of the preprocessed B-scan data (not the magnitude) are plotted in Figure 2.11 (after the removal of clutter terms) to examine the phase information of the main reflection as well as the second and third reflections from the top surface of the PEC cylinder.

In the rest of the thesis, absolute values of the B-scan images will be plotted whenever needed.

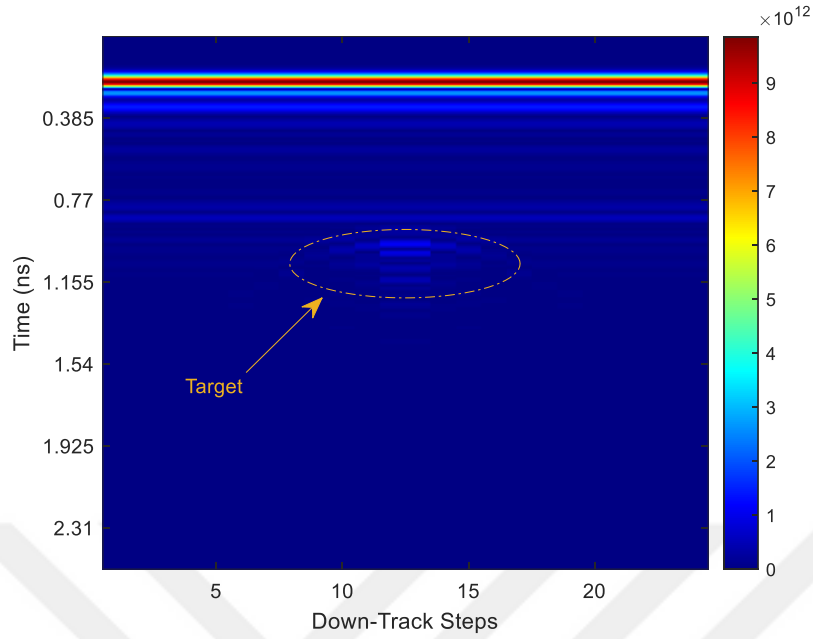


Figure 2.9 Magnitude of the B-scan image of the buried PEC cylinder having the self/mutual direct coupling, self/mutual ground-bounced, and target response terms.

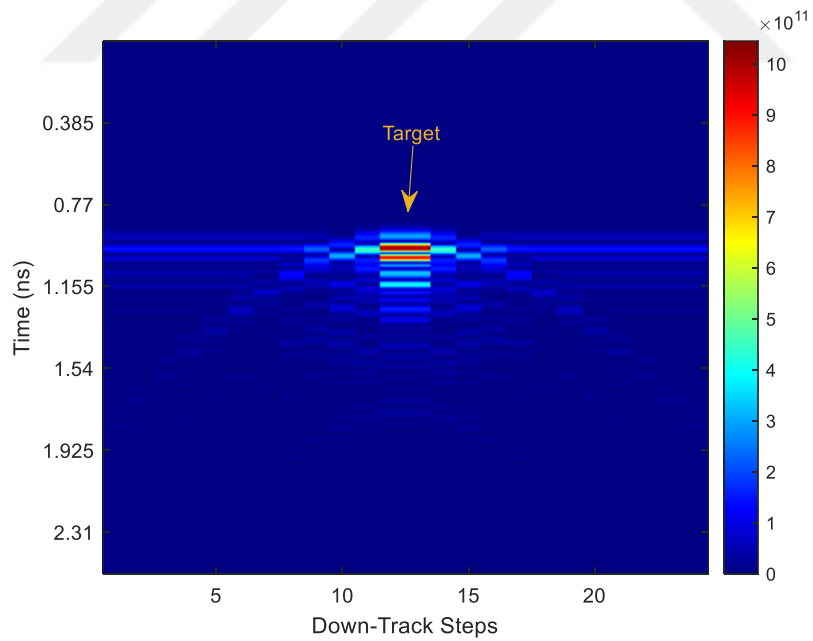


Figure 2.10 Magnitude of the B-scan image of the buried PEC cylinder after direct coupling and ground bounce removal, leaving only the target response behind.

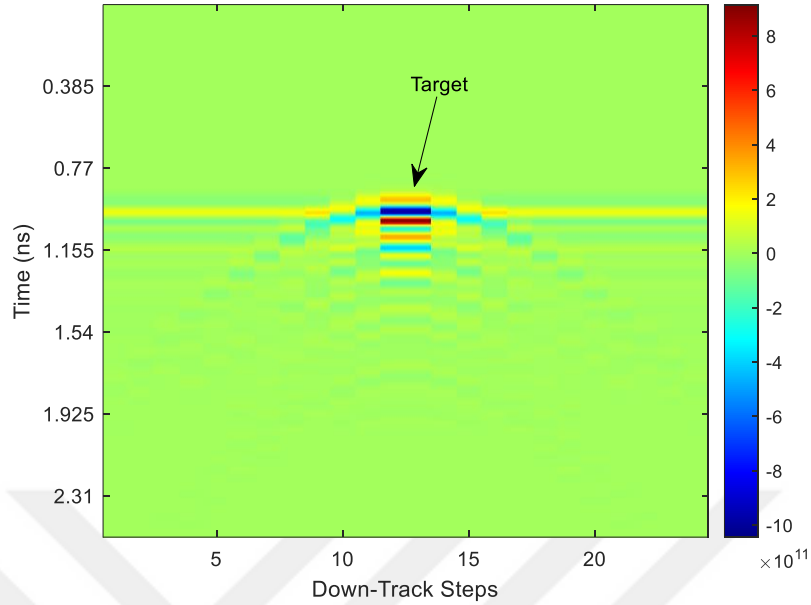


Figure 2.11 Original B-scan image (not the magnitude) of the buried PEC cylinder after the elimination of direct-coupled and ground-bounced terms (another version of Figure 2.10).

Finally, the C-scan slices are demonstrated at the depth corresponding to $t = 1.02$ ns, where the PEC cylinder's response takes its strongest value. Figure 2.12 shows the C-scan slice obtained from the original unprocessed C-scan data, while Figure 2.13 presents the same slice obtained from the preprocessed C-scan data (after applying the mean subtraction technique to eliminate DC and GB terms). At the time/depth index selected for slicing, the direct coupling and ground bounce effects are observed weakly as compared to the target response. Therefore, the target response is detected clearly in the C-scan slices of both Figure 2.12 and Figure 2.13, i.e. for both unprocessed and preprocessed data at the 13th down-track step of the 4th antenna pair. However, as can be seen in Figure 2.12, under the fifth antenna, there is a signal concentration which may create false alarms. Such phenomenon may be observed when operating with antenna arrays, especially in the case of shallow-buried and low RCS targets as to be discussed in detail in Chapter 4.

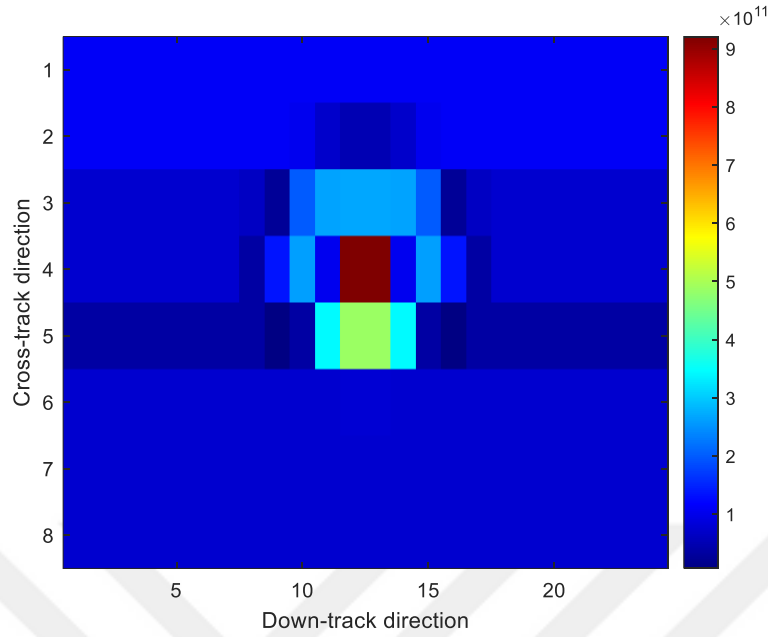


Figure 2.12 C-scan slice constructed at the constant depth index corresponding to time, $t = 1.02$ ns where the PEC cylinder is directly below the 4th TX/RX channel at the 13th down-track step.

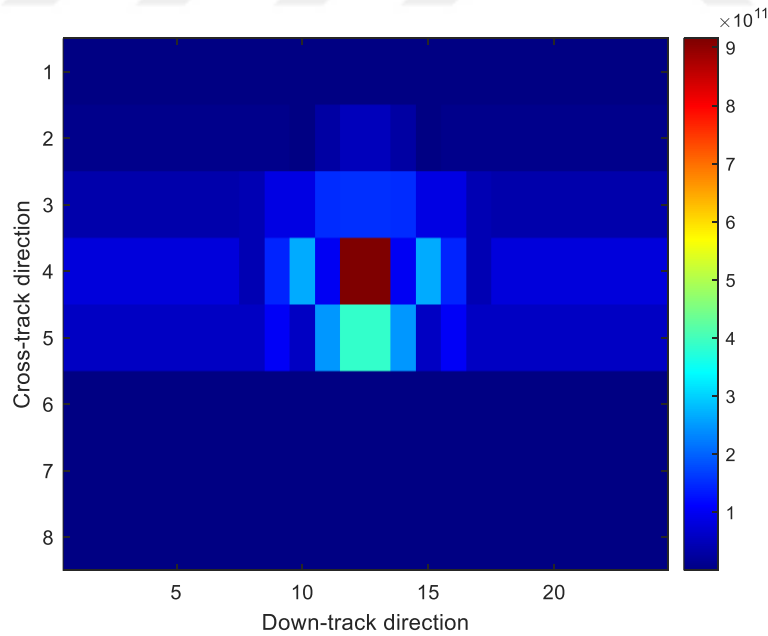


Figure 2.13 C-scan slice constructed for the case in Figure 2.12 using the preprocessed (clutter eliminated) GPR data.

2.2.3 Clutter Removal Techniques in GPR Applications

In general, the scattered signal measured by the receiver antenna (RX) of a GPR system has four main components, which are the direct coupling from the transmitter antenna (TX) to RX, ground-bounced reflections, response of the buried target(s), and undesired clutter signals caused by the random material compositions and moisture of the soil, surface roughness, rocks in the soil, man-made buried objects, and more, as summarized in Figure 2.14. Other than these main signal components, internal noise due to microwave components or imperfections of the GPR system as well as external noise picked up by the antennas from the surrounding region may be added to the GPR signals.

Mathematically, the signal $y(s, t)$ received by the RX, at time t and position s can be represented as

$$y(s, t) = x_T(s, t) + x_{GB}(s, t) + x_{DC}(s, t) + x_{IR}(s, t) \quad (2.14)$$

where $x_T(s, t)$ stands for the response of a buried target, $x_{GB}(s, t)$ corresponds to the ground bounce term, $x_{DC}(s, t)$ is the direct coupling signal originating from the TX/RX interaction through air, and $x_{IR}(s, t)$ corresponds to undesired signals caused by target/soil inhomogeneity, surface roughness, or unwanted buried particles that create clutter [71-72]. For successful target detection and classification, the response of a buried target must be clearly observable. Undesired clutter signals arising from direct coupling, ground bounce, and soil inhomogeneity and/or surface roughness can mask the target's presence or create false alarms. Therefore, effective elimination of clutter signals is crucial for the problem of GPR target detection.

In this section, well-known methods for background/clutter removal will be briefly discussed. Their use and performances in GPR target detection will be demonstrated in a comparative manner on common selected scenarios. In later chapters where target detection and classification problems are solved for inhomogeneous soil and rough surface cases, these background/clutter removal methods will be revisited with additional discussions and performance analyses.

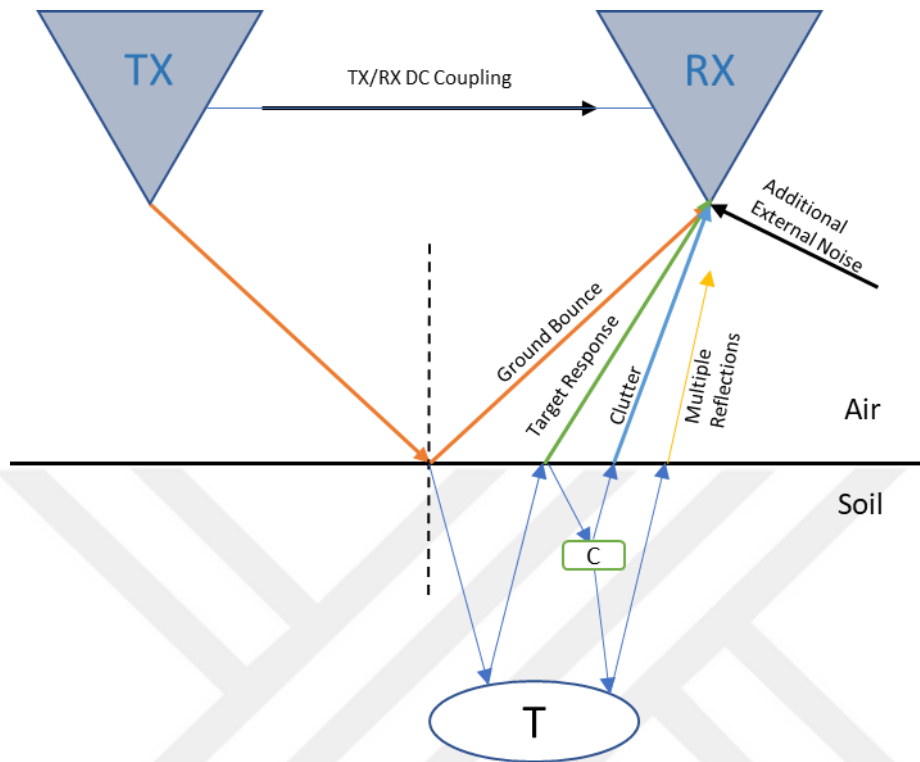


Figure 2.14 A basic single-channel GPR configuration model with main components of the received signal.

Self-DC signals resulting from the direct interaction of transmitter and receiver antennas of a given antenna channel may reach to extremely high amplitudes and mask other components of the received signal. In practice, various precautions are taken to isolate transmitter and receiver antennas from each other to minimize these self-DC terms but usually there are some leakages in DC signals that may be still strong enough to cause problems. Therefore, it is crucial to eliminate such direct-coupled signals. Statistical methods based on eigenvector decomposition and/or blind source separation (PCA, ICA, SVD, and more) do not work properly in the presence of highly dominant direct coupling signals. For this reason, especially for GPR scenarios with challenging soil/boundary conditions, a two-stage background/clutter removal approach is proposed in this thesis. First, the direct coupling effects are eliminated with simpler methods, then more advanced statistical

methods are applied to eliminate the remaining clutter terms. Five of the basic and simple methods are briefly described below as they are used frequently in GPR studies to eliminate the direct coupling (DC) effects [66], [73-74].

- *Antenna calibration:* In many practical applications, the calibration process is performed by operating the GPR system in a boundary-free area (raising the antenna array panel to “see” the unbounded sky) prior to the onset of terrain measurements. Hence, the collected calibration data will act as reference data containing system hardware effects and system-based direct coupling effects only. Next, these calibration data will be subtracted from all GPR data collected in regular measurement missions to eliminate unwanted directly coupled antenna interactions. It should be noted that the resulting signal after antenna calibration has the ground-bounced signals as the dominant terms.
- *Direct background removal (subtraction) method:* This method is frequently used in the GPR literature and in commercial applications [74-76]. At the beginning of the simulations/experiments, a reference data set of A-scan signals are collected from the vicinity of the test site with no buried test targets. Next, these data are extracted from the actual terrain measurements. Direct coupling, ground bounce, and other clutter types can be successfully eliminated with this method in those simpler cases with almost homogeneous soil and almost flat air-soil boundary. The disadvantages of this method are the performance limitations for challenging soil types and difficulties of data collection for no target case.
- *Time gating:* In the time gating technique, the initial portion of the A-scan data are cut at a proper index to exclude the direct coupling term (or both direct coupling and ground bounce terms if needed). This method is practical, fast and very easy to use as commonly mentioned in the GPR literature [77-79]. It can be used to remove the self-DC pulse in the A-scan signal but it may not be applied effectively to eliminate the time-extended mutual-DC terms (those terms may occur as an antenna array effect as to be discussed in Chapter 4). More importantly, in challenging scenarios involving rough surfaces or shallow-buried targets, time gating cannot remove the self and mutual ground-bounced terms

properly. In cases where the targets are shallowly buried, the target returns mostly overlap with strong ground-bounced signals in the time domain. Application of the time gating or adaptive time gating methods to remove the self and mutual indirect coupling terms (i.e. self or mutual ground-bounced reflections), may cause unintentional clipping of the shallow-buried target responses. False negative target detection errors or false alarms may be experienced in such applications.

- *Mean and median subtraction (removal) methods:* Mean and median subtraction techniques are among the most frequently utilized methods in the GPR literature to eliminate direct coupling and ground bounce clutters [74], [80-81]. Using these methods, direct coupling and ground bounce effects, can be successfully eliminated, enabling accurate target detection, especially in homogeneous soil cases. In more challenging soil scenarios, mean and median subtraction methods cannot completely eliminate the effects of soil inhomogeneity, soil moisture, and surface roughness. While working with more challenging soil types, the mean or median subtraction methods can be applied as the first step to eliminate the direct coupling and perhaps the main ground bounce effects. Then, in the second step, more advanced signal processing methods will be applied to eliminate the remaining clutter effects. It is advantageous to apply mean or median subtraction methods in the first step because they are fast, simple, and present good performance in GPR scenarios with almost homogeneous soil [74], [80-81]. Also, when using a GPR with an antenna array, these two methods become useful to effectively eliminate both the self and mutual direct coupling effects.

Suppose $\mathbf{X}$ denotes an unprocessed 3D GPR data with the size $(N \times I \times J)$ and $\mathbf{Y}$ corresponds to the output of mean or median subtraction algorithm having same size as $\mathbf{X}$. Let the indices $(n = 1, \dots, N, i = 1, \dots, I, j = 1, \dots, J)$ refer to samples along the time, cross-track and down-track axes, respectively. While applying mean/median subtraction method, the mean/median is calculated in the down-track direction for each time index and cross-track steps (antenna pair index in the arrays).

If we have a C-scan data matrix of size $(N \times I \times J)$, for each given index pair $(\bar{n}, \bar{i})$, the average (or median) of the corresponding 1D data is computed over the total of J elements along the down-track direction ($j = 1, \dots, J$). Repeating this for all possible $(\bar{n}, \bar{i})$ pairs, a new 2D matrix A having the dimensions $(N \times I)$ is obtained. Then, the mean value computed and saved at the entry $(\bar{n}, \bar{i})$ of the matrix A is subtracted from each element of the vector $X(\bar{n}, \bar{i}, j)$ along the down-track axis for $j = 1, \dots, J$. Mathematically speaking,

$$Y(\bar{n}, \bar{i}, j) = X(\bar{n}, \bar{i}, j) - \frac{1}{J} \sum_{j=1}^J X(\bar{n}, \bar{i}, j) = X(\bar{n}, \bar{i}, j) - A(\bar{n}, \bar{i}) \quad (2.15)$$

for all $j = 1, \dots, J$ and this operation is repeated for all possible $(\bar{n}, \bar{i})$ pairs for $\{\bar{n} \in [1, \dots, N] \cap \bar{i} \in [1, \dots, I]\}$.

If the same process is carried on with median calculations instead of mean calculations, the algorithm for the median subtraction method is obtained.

To summarize, either the mean subtraction or the median subtraction method can always be applied as the first step of clutter elimination. If the soil medium is almost homogeneous and the air-ground boundary is almost flat, this first step would be sufficient. However, for inhomogeneous and/or moist soil, and for rough surface conditions, additional more advanced, statistics-based clutter elimination methods are needed to remove the residual clutters from GPR data. The two-step (or if necessary, three-step) background clutter removal approach is summarized in the flowchart given in Figure 2.15. As indicated in this flowchart, methods such as PCA, ICA, SVD, Kalman Filter, and Matched Filter have been used in this thesis work with successful results in various target identification scenarios under challenging soil/boundary conditions with correct parameter optimizations. Mathematical details of these methods can be found in references [71-74], [80-92].

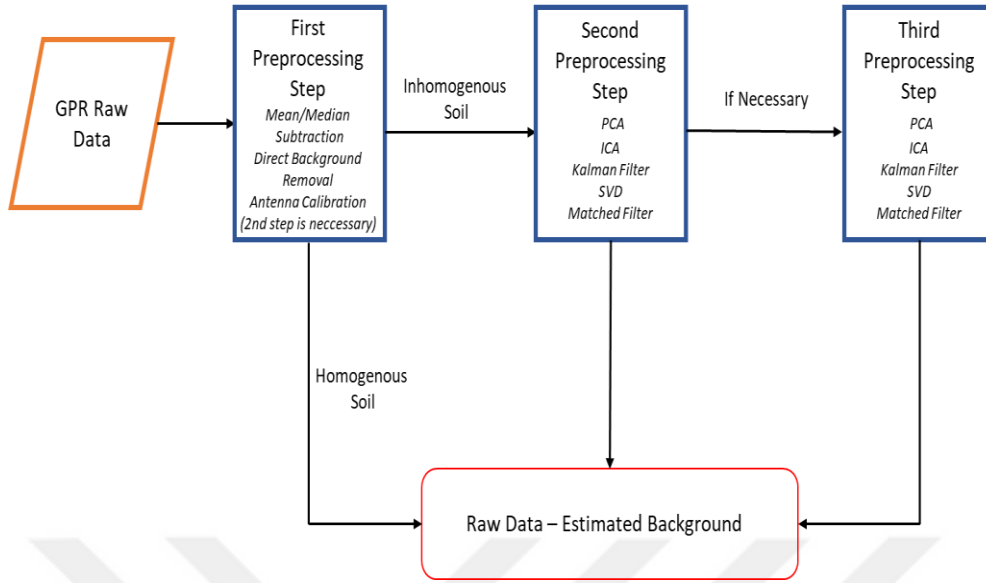


Figure 2.15 Flowchart of the proposed multi-step clutter elimination method

2.2.4 Detection of Buried Targets with GPR

As discussed so far, the comprehensive target detection process proposed in this thesis is composed of the following main steps; first the raw GPR data are obtained by simulations (or by measurements in real world) as the collection of A-scan signals, then the available data are processed by using multi-step clutter removal algorithms to eliminate all kinds of clutter effects as much as possible to sense the presence of buried target(s) more clearly. Finally, the overall processed GPR data are displayed and interpreted in the alternative formats of B-scan images, C-scan images (or slices) and energy heat maps as summarized in the block diagram shown in Figure 2.16 for target detection. As discussed earlier in Section 2.2.2, each one of these GPR data formats (A-scan, B-scan and C-scan data) give valuable information for the target detection process in a complementary manner providing the interpretation of the whole data set from different perspectives. Therefore, it is important to use all these tools together as needed to minimize the decision errors in GPR target detection.

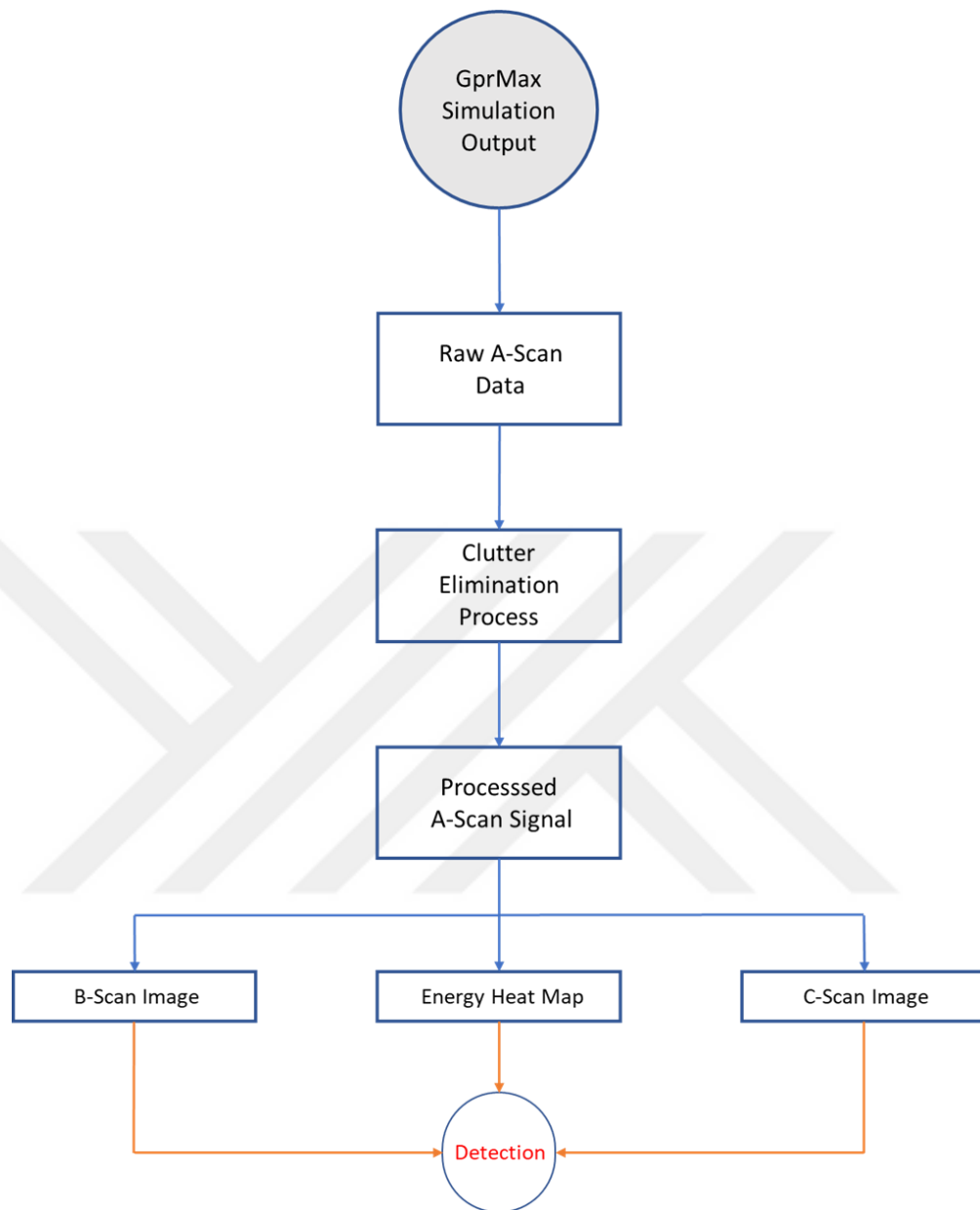


Figure 2.16 Block diagram containing the steps of the target detection approach proposed in this thesis.

An “energy heat map” is a two-dimensional contour plot representation of the C-scan data, which is generated over the cross-track versus down-track domain of size $(I \times J)$. Its matrix entries are the total energy values of A-scan signals, $E_{i,j}$ ’s, computed at spatial sampling points with indices (i,j) for $i = 1, \dots, I$ and $j = 1, \dots, J$. If the A-scan signal at the point (i,j) is denoted as $x_{i,j}(t)$ with the instantaneous power function $p_{x,ij}(t) = |x_{i,j}(t)|^2$, its total energy can be defined as

$$E_{i,j}(t) = \int_0^{T_0} p_{x,ij}(t) dt = \int_0^{T_0} |x_{i,j}(t)|^2 dt \quad (2.16)$$

where $[0, T_0]$ is the investigated time interval of the A-scan signal. Energy heat maps can be used effectively for target detection when they are constructed using the preprocessed GPR data with minimized clutter effects.

In the rest of this section, the proposed target detection approach is demonstrated using the problem scenario described in Figure 2.17 where two shallow-buried targets, T1 (a PEC cylindrical disk) and T2 (a dielectric cylindrical disk), are buried one at a time at a burial depth of 1 cm in dry sand whose relative permittivity is 3.5.

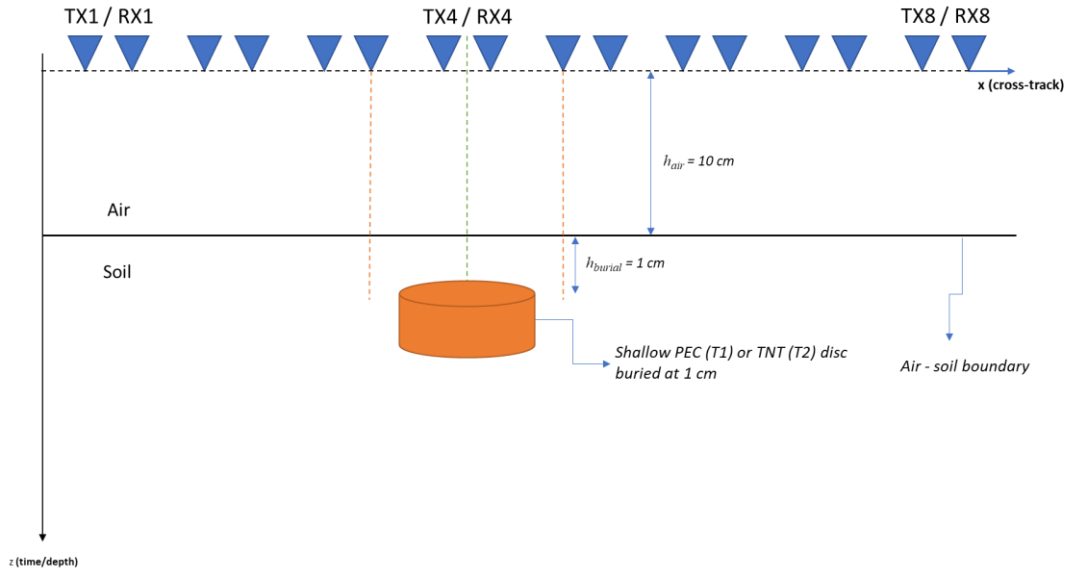


Figure 2.17 A shallow-buried target detection scenario using a down-looking GPR with an eight-channel antenna array.

Electrical parameters of the dielectric cylinder are $\varepsilon_r = 2.7$ and $\sigma = 0.01 \text{ S/m}$, simulating the material TNT (2,4,6-Trinitrotoluene) within the frequency bandwidth of the GPR. Targets T1 and T2 have exactly the same size with radii of 3 cm and heights of 2 cm. They are buried in upright orientation so that their circular faces are parallel to the air-soil boundary as shown in the figure.

This GPR scenario includes an eight-channel collinear antenna array with transmitter/receiver (TX_k/RX_k) pairs for $k = 1, \dots, 8$. All the antennas are chosen to be the basic omnidirectional Hertzian dipole type antenna elements. The distance between each transmitter and receiver antenna in a given channel is $a = 2 \text{ cm}$ while the period of the array is $b = 6 \text{ cm}$. Antennas are positioned 10 cm above the air-ground interface. As shown in Figure 2.17, the center of the cylindrical face of the targets (PEC or dielectric) is aligned with the midpoint of the fourth TX-RX antenna pair. Also, while the fourth receiver RX_4 is exactly above the target, the third receiver and fifth transmitter (RX_3 and TX_5) are close to the targets' side borders. In the down-track direction, the antennas sense the target directly at the 12th and 13th steps where the down-track step size is 2 cm. The scenario is planned for $J = 24$ steps to scan a length of 46 cm in down-track direction.

The *gprMax* simulations of this basic scenario are obtained first for the PEC target T1, then for the dielectric target T2. After the 3D GPR data are simulated, only the median subtraction technique is applied to data for both targets as the one-step clutter elimination process would be sufficient since the soil is homogeneous dry sand and the air-soil boundary is flat in this simpler scenario.

Processed (after clutter elimination) and unprocessed (raw) A-scan plots are given in Figure 2.18 for T1. Since T1 is a high RCS PEC target, its response (the red curve) is noticeable on the raw data despite the strong clutter contamination caused by DC and GB mechanisms (green curves). Details of the target response can be observed much more clearly after clutter elimination step by median subtraction.

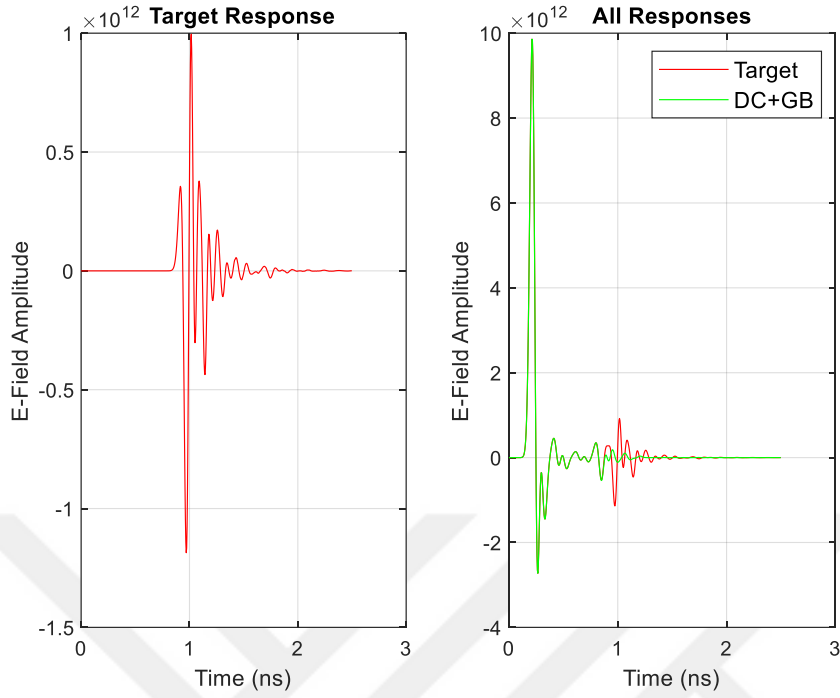


Figure 2.18 The A-scan signal simulated for the GPR target detection scenario given in Figure 2.17 with target T1 (PEC cylinder). Raw A-scan signal including DC and GB type clutter signals (on the right). The processed A-Scan signal having only the target response after clutter elimination (on the left).

The energy heat map obtained from the processed GPR data of this PEC cylinder is given in Figure 2.19. As mentioned above, the center of the buried target T1 is aligned with the fourth antenna pair along the cross-track and located in between the 12th and 13th steps along the down-track, as clearly seen in Figure 2.19. Since the antennas are omnidirectional and the target is a good reflector, the other receiving antennas on both sides of the 4th channel also capture the target returns. While the signals received by RX_3 and RX_5 are reasonably strong, they get weaker at farther distances at the locations of RX_2 and RX_6 . Similarly, the target T1 can be sensed over the down-track steps from 10 to 15 roughly, although the highest target energy is observed at the middle of this range.

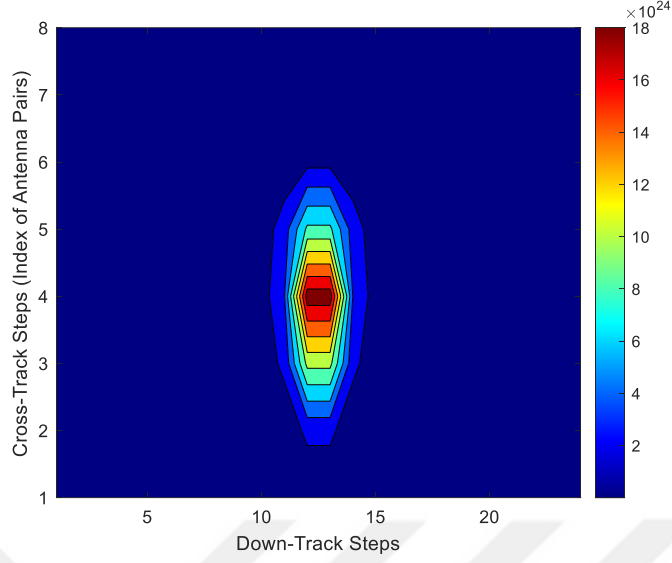


Figure 2.19 Energy heat map of the processed GPR data simulated for the target T1 (PEC cylinder) according to the scenario described in Figure 2.17.

Alternative perspectives are provided by the B-scan images for additional data interpretation as shown in Figure 2.20 and Figure 2.21. As the PEC cylinder is directly below the 4th antenna channel, the B-scan image is formed over the time versus down-track domain in Figure 2.20 by keeping the cross-track index constant at $i = 4$. Figure 2.20(a) displays the B-scan image for unprocessed data, showing the self-DC term as the earliest and the strongest clutter signal (horizontal signal band in dark red color), and the mutual-DC terms following it (weaker horizontal bands in light blue tones). Then, the self-GB term is seen shortly after 0.77 ns as a couple of darker blue horizontal bands followed by the mutual-GB terms (even weaker horizontal signal bands arriving after the self-GB terms, plotted in darker blue shades). These horizontally extending signal bands (occurring at certain time instances) in the B-scan images refer to systematic clutter signals due to self or mutual DC and GB effects, which are unrelated to the responses of the buried objects.

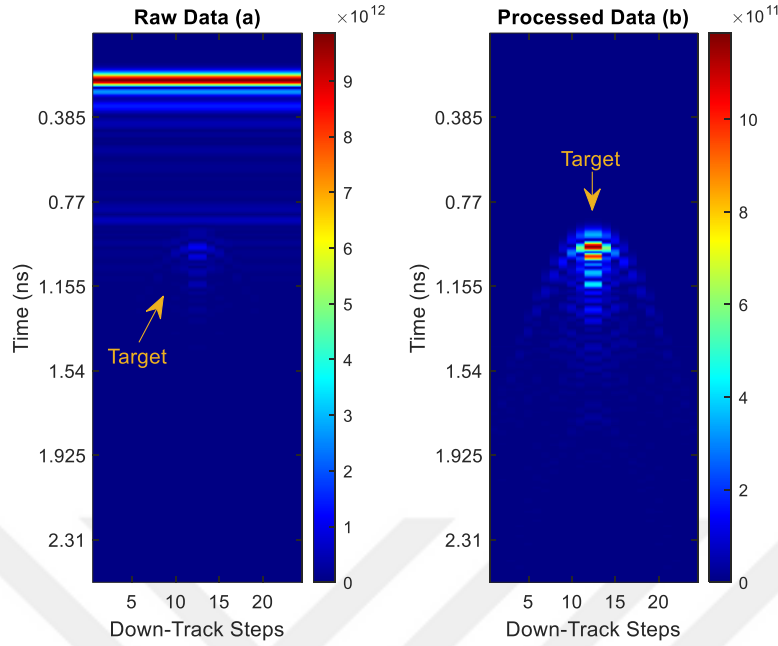


Figure 2.20 B-scan images of the buried PEC cylindrical target T1 at the fourth cross-track step (received by RX_4 of the array), for the (a) raw and (b) processed data.

Because of the masking effect of these strong clutter signals (especially due to highly dominating self-DC term), the main target reflection appears on the image very faintly as a hyperbolic curve followed by secondary much weaker curves due to multiple reflection signals. Those multiple reflections occur between the top surface of the PEC cylinder and the soil boundary. It is also seen that target returns are overlapping with mutual-GB terms that is well expected as T1 is a shallow-buried target, only 1 cm below the soil boundary. Figure 2.20(b), on the other hand, displays the processed B-scan data containing only the target response as all the clutter terms of the raw data are eliminated by the median subtraction method. The main hyperbolic curve as well as the multiple reflection-related terms indicating the presence of the target are very clear in Figure 2.20(b). The hyperbolic image pattern results from the fact that target is sensed at the down-track steps before the 12th step and after the 13th step also at weaker signal levels. Shapes of these hyperbolas are affected by various target properties and by the directivities of array antennas. For example, if the target has a large size, the corresponding hyperbola becomes wider

too with a flatter top as the target returns are received at more than one or two down-track steps. Also, the geometrical shapes and material properties of the targets may affect the slopes of the arms of the hyperbola. Directivity of GPR antennas affect the formation and shapes of these hyperbolic image features also. There is a large number of studies reported in GPR literature using B-scan images, especially the hyperbolic features, for target detection and classification [65-70], [93-94]. However, these approaches are prone to serious performance degradations when targets are buried at random orientations [146] or multiple targets are buried close to each other, or in the presence of heavy background clutter in soil etc.

The B-scan image of the same GPR data (for the PEC cylinder T1) is presented in Figure 2.21 over the time versus cross-track domain by keeping the down-track index constant at $j = 13$.

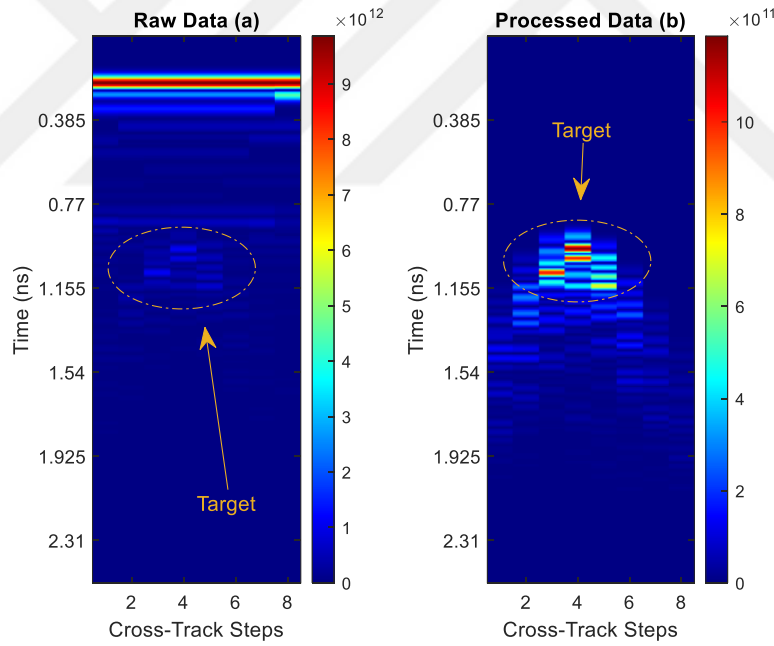


Figure 2.21 B-scan images of the buried PEC cylindrical target T1 at the 13th down-track step, for the (a) raw and (b) processed data.

Figure 2.21(a) shows the B-scan image for the raw data suffering from strong clutter signals of the type of DC and GB, and showing the target response quite weakly, as already discussed. However, Figure 2.21(b) displays the B-scan image of the processed data showing the target response much more clearly. The highest amplitude for the target return is observed at the 4th channel, under RX_4 as expected. Also, the receiver antenna RX_3 senses the target more strongly than RX_5 as the distance between RX_3 and the transmitter antenna TX_4 is shorter than the distance between RX_5 and TX_4 for the antenna array topology shown in Figure 2.17.

Lastly, Figure 2.22 presents C-scan slices obtained by cutting three-dimensional raw and processed data at a depth where the target is clearly visible (1 cm burial depth).

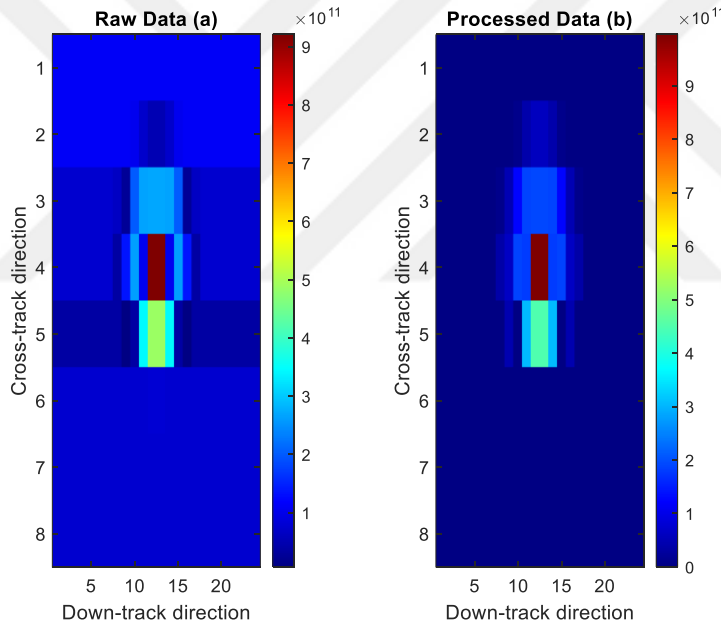


Figure 2.22 C-scan slices at the selected 1 cm depth (corresponding time) of the buried PEC cylinder, raw (a) and processed (b) data are used to create these slices.

Now, the A-scan plots, energy heat map, B-scan images, and C-scan slices generated from the GPR simulation data obtained for the dielectric target, T_2 (made of low-loss TNT) will be presented for raw and processed data in Figures 2.23 through Figure 2.28. Although, the GPR scenarios for PEC cylinder and for TNT cylinder

are completely identical except for the target type, their results turn out to be very different. First of all, the TNT cylinder T2 is a low RCS target so that the dominant coupling terms (DC and GB signals) mask the presence of T2 almost completely as seen in the right-hand side plot of Figure 2.23. The red curve representing the response of target T2 can be barely noticed as being completely overlapped by the self and mutual GB clutter signals. The target is completely hidden in the raw data based B-scan plots also in Figure 2.24(a) and Figure 2.25(a). The peak signal amplitude of T2 is about 15 times lower than the peak signal amplitude of the PEC target T1. Therefore, as opposed to the PEC target, it is extremely challenging to determine the existence of the dielectric target by using the raw A-scan data. Only after the removal of clutter signals by median subtraction method, the target response for T2 can be recovered as shown in the left-hand side plot in Figure 2.23. As discussed before, this scenario assumes a homogeneous sandy soil with a flat ground surface so that implementing the median subtraction algorithm alone removes the coupling type clutter terms from the GPR data and makes the target T2 visible.

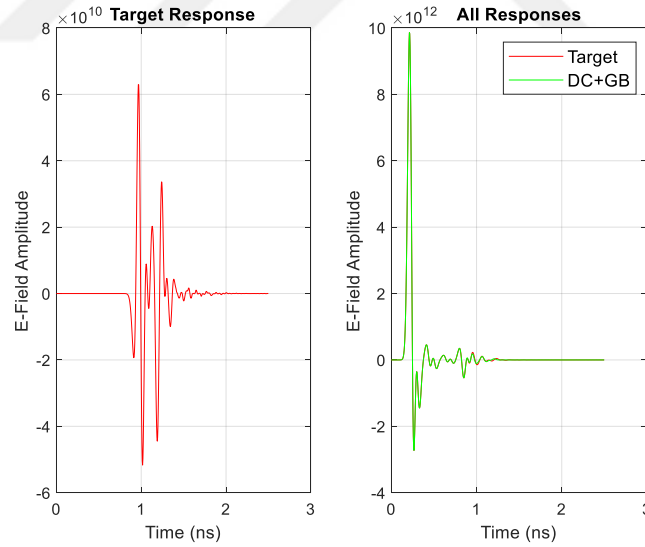


Figure 2.23 The A-scan signal simulated for the GPR target detection scenario given in Figure 2.17 with target T2 (dielectric-TNT cylinder). Raw A-scan signal including DC and GB type clutter signals (on the right). The processed A-Scan signal having only the target response after clutter elimination (on the left).

In this dielectric cylinder case, electromagnetic waves can penetrate into the target. Therefore, it is possible to locate the upper and lower faces of the cylinder in the B-scan images (obtained from processed data) shown in Figure 2.24(b) (plotted for $i = 4$, at the location of receiver antenna RX_4) and in Figure 2.25(b) (plotted for $j = 13$, at the 13th down-track step). This information is especially clear in Figure 2.24(b) where there are two different sets of hyperbolas corresponding to upper and lower faces of T2. The signal intensity at the center of the upper face-related hyperbola is much stronger as expected. An enlarged version of Figure 2.24(b) is given in Figure 2.26 showing the arrival times of the signals reflected from the upper and lower faces of the cylinder. The difference between these arrival times can be calculated from the figure as $(t_{lower} - t_{upper}) = (1.1932 \text{ ns} - 0.9738 \text{ ns}) = (0.2194 \text{ ns})$. Considering the round-trip time in the dielectric material with a relative dielectric permittivity of 2.7, the depth (i.e. the height of the TNT cylinder) can be calculated as

$$Depth = \frac{(Time\ difference)(c)}{2(\sqrt{\epsilon_r})} = \frac{(0.2194)(10^{-9})(3)(10^8)}{2\sqrt{2.7}} \approx 2 \text{ cm}$$

as expected.

Lastly, plots for the energy heat map (for the processed GPR data) and for the C-scan slices (for the raw and processed data) are given in Figure 2.27 and Figure 2.28 which supports the previous interpretations of GPR output data that there exists a target (T2) at the location specified by $i = 4$ (under the 4th antenna channel) and $j = 13$ (at about the 13th down-track step).

This shallow-buried dielectric target example demonstrates the critical importance of clutter removal process and the potential adverse effects of the signal coupling phenomena caused by the antenna arrays. These issues will be examined further in Chapter 4. As also demonstrated in this example, the B-scan images can provide additional information to extract certain target features that cannot be directly obtained from A-scan or C-scan data or from energy heat maps. Therefore, use of all data formats in a complementary manner is important in target detection problems.

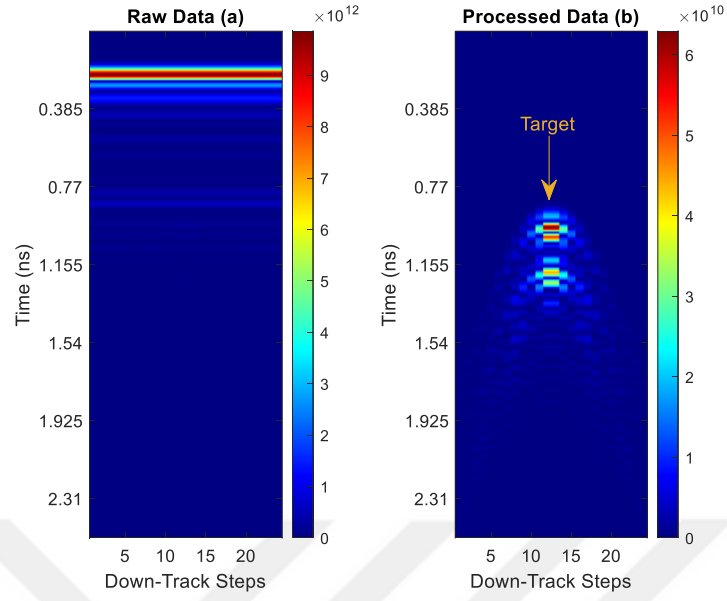


Figure 2.24 B-scan images of the buried cylindrical dielectric target at the 4th cross-track step (4th antenna pair in the array), for the (a) raw and (b) processed data.

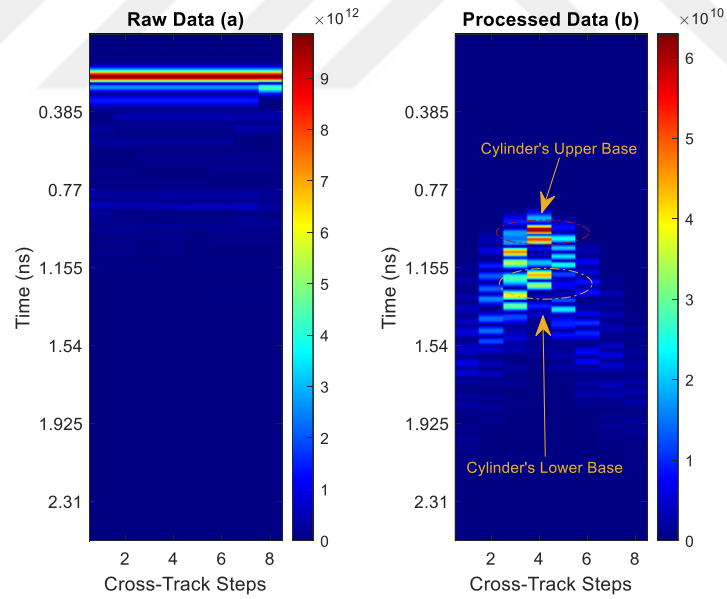


Figure 2.25 B-scan images of the buried cylindrical dielectric target at the 13th down-track step, for the (a) raw and (b) processed data.

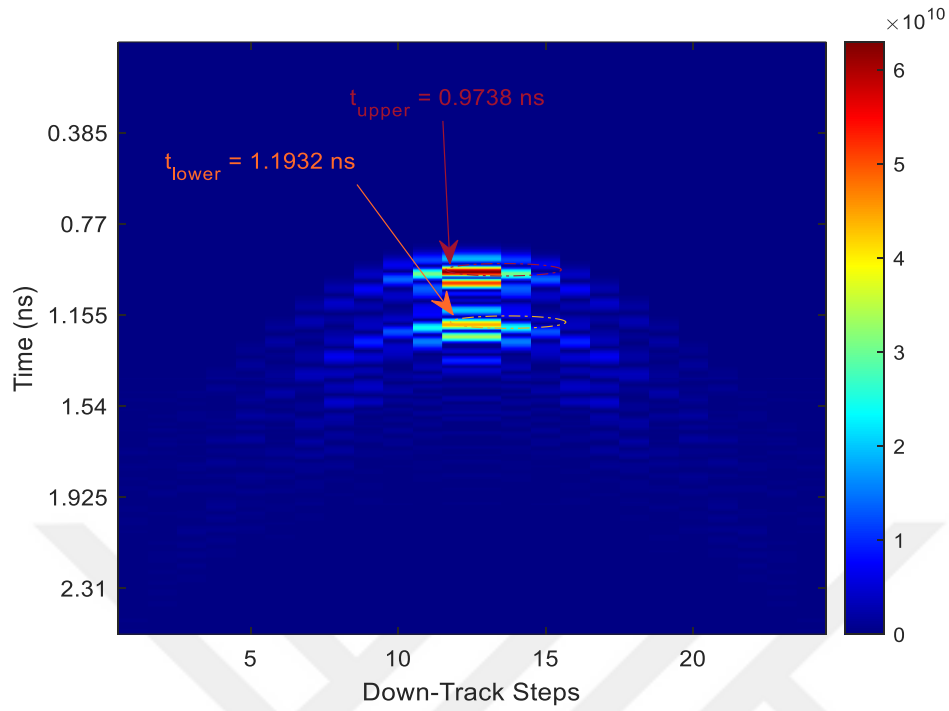


Figure 2.26 The enlarged version of the B-scan image of T2, showing the arrival times of the signals reflected from the upper and lower faces of the cylinder.

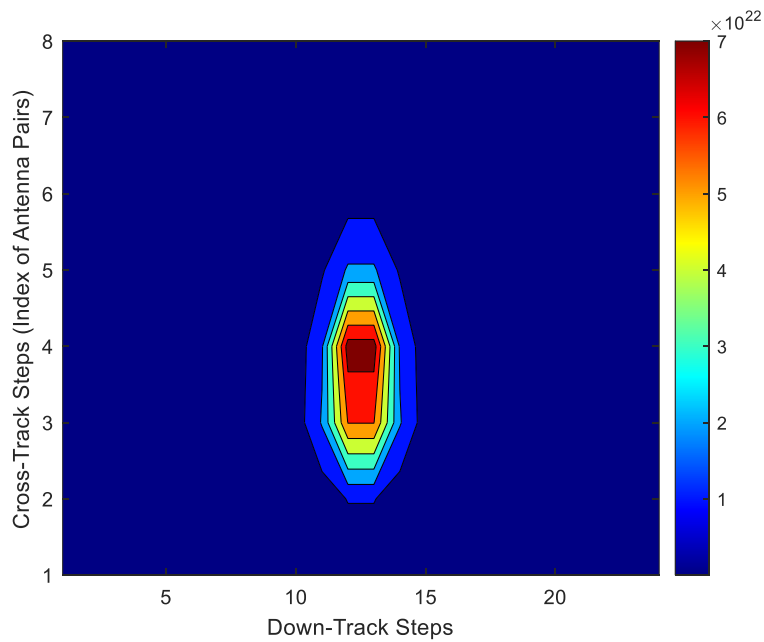


Figure 2.27 Energy heat map (using processed data) of the dielectric cylinder T2.

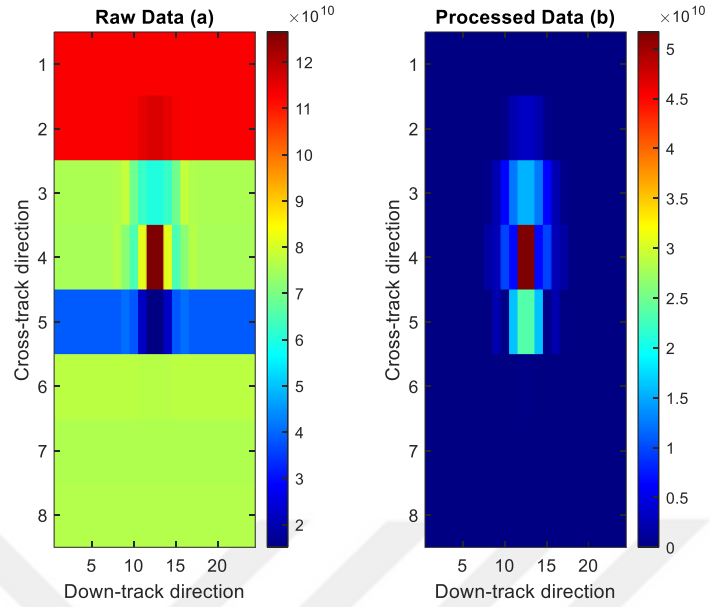


Figure 2.28 C-scan slices at the selected 1 cm depth (0.1247 ns in time) of the buried dielectric cylinder, (a) raw and (b) processed data, were used to create these slices.



CHAPTER 3

ELECTROMAGNETIC TARGET CLASSIFIER DESIGN FOR SHALLOW-BURIED TARGETS

3.1 Theory and Design Steps of the Proposed Classifier

In this chapter, theoretical background of a physics-based target classifier design technique [34] based on the Singularity Expansion Method (SEM), TFR-based feature extraction and PCA-based multi-aspect feature fusion will be presented. Adaptation of this technique to subsurface sensing problems will be introduced with novel modifications. Resulting target classifier design approach will be demonstrated for a GPR classifier library composed of thin PEC wire targets of different thicknesses which are buried in sand at different shallow depths.

3.1.1 Historical Background of the Proposed Classifier

As emphasized in previous chapters, detection and classification of buried targets pose significant challenges. When dealing with a GPR problem with or without buried targets, the only information we have is a collection of scattered signals (A-scan signals) representing the subsurface system as a whole. Important factors such as aspect angle, burial depth, soil composition, geometrical and electrical properties (permittivity, permeability, and conductivity) of the buried targets all remain unknown. Despite these inherent difficulties, the goal is to accurately detect and then classify buried objects in the presence of various clutter effects. This task can be accomplished by combining the LTI system modelling approach, concepts of electromagnetics and proper techniques of signal processing.

Even for airborne objects with minimal clutter effects, electromagnetic target classification is a challenging problem. The complexity arises not only from the

intricate scattering mechanisms but also due to the fact that these scattered signals are strongly dependent on the frequency, polarization, and aspect angle of the transmitted and received signals. The aspect dependency, in particular, makes the target recognition problem exceptionally challenging. Due to aspect dependency, a given target may be recognized as different targets when viewed at different aspect angles; or two different targets may be recognized as the same target at certain aspects. To achieve successful classification, we need to minimize the sensitivity of extracted target features to aspect variations. In addition, an effective classifier should exhibit high sensitivity to the target's size, shape, material composition, and electrical properties to distinguish it from other similar targets. A reliable classifier must satisfy both properties simultaneously [33-34]. For buried objects, target classification problem becomes much more challenging. Factors such as the reflection/refraction phenomena at the air-soil boundary, presence of fragments, rocks, or other undesired objects near the target of interest, variations in soil properties, differences in burial depths, and multiple reflections of all sorts taking place within the soil introduce further complexities, making the classification process exceptionally hard.

Various methods are available in literature for the classification of buried objects. Many studies have focused on target recognition and classification based on GPR images, particularly B-scan images, using techniques such as support vector machine (SVM) [95-97] and relevance vector machine (RVM) [98]. Generally, these methods extract features from the B-scan GPR images to train supervised learning algorithms. Other target classification approaches such as morphological image analysis and graph Laplacian regularization [99], gradient-based algorithms [100], and the Partial Least Squares Discriminant Analysis (PLS-DA) model [101] are also reported in literature. The main disadvantages of these methods are their limited interpretability, a large amount of data requirements, limited generalizations, computational cost and time consumption, sensitivity to noise and artifacts, and lack of fast real-time performance [102-105]. The minimum distance classifier, for instance, computes the Euclidean distance between the test and training patterns to classify objects, and

requires extensive processing load over a long run-time [106]. Furthermore, most of the present GPR classifiers may exhibit serious performance degradations in scenarios involving interactions among multiple targets. It is worth noting that a majority of studies reported in literature consider only a single buried target or multiple but remotely located targets in their experimental setups or simulation environments.

Convolutional Neural Network (CNN) type deep learning algorithms, have also become popular in recent years in GPR applications [107-109]. In contrast to the aforementioned classical methods, deep neural network-based classifiers eliminate the need for feature extraction by directly learning from the input data. However, CNN-based methods have a serious disadvantage of needing substantial amount of data for successful classifier training [110]. Collecting excessive amount of data in many real-world scenarios may be difficult or even impossible under harsh and risky conditions. It is beneficial to design classifiers that can achieve satisfactory performance with reasonable amount of training data.

A GPR classifier should possess the key features such as high accuracy, robustness, flexibility to handle several types of admissible targets (including finite-size conducting and/or dielectric targets with arbitrary geometries), and repeatability. It is an advantage for a classifier design if it needs only a small reference database constructed at only a few different aspects and low storage memory for target features while providing a high real-time decision speed. The physics-based classifier design technique to be implemented in this thesis achieves all of these desired characteristics. The concept of Complex Natural Resonance (CNR) frequencies and the Singularity Expansion Method (SEM) are powerful tools utilized in this approach. Use of advanced signal processing techniques such as Energetic Time-Frequency Representations (TFRs) and the PCA are also very effective to extract almost aspect independent target features from the GPR data.

In 1958, a groundbreaking research was published by E.M. Kennaugh and R.L. Cosgriff [111] who applied linear system theory to electromagnetic scattering

problems. Their pioneering work introduced the concept of impulse response for electromagnetic scatterers, which was a novel and significant advancement. This concept allowed for the analysis of electromagnetic scattering problems using principles of linear system theory, enabling a deeper understanding of the transient responses of targets. This breakthrough opened up new avenues for studying electromagnetic scattering phenomena and paved the way for further advancements in the field. Then, in the 1960s, Kennaugh and Moffatt proposed a linear time-invariant (LTI) lumped parameter system model for targets at low frequencies [112]. In 1970s, studies related to the complex natural resonance (CNR) phenomena associated with the linear system models of electromagnetic targets gained momentum [113-115]. In 1976, Baum formalized the use of complex natural resonances (CNRs) in the singularity expansion method (SEM) [116]. According to SEM, the scattered response of a target at late-time regime can be represented by a series expansion in terms of damped sinusoidal time functions formed by the complex conjugate pole pairs of the target's transfer function [116-120]. The most important point of the SEM is that the CNR frequencies are implicitly and strongly dependent on the target's geometrical and electrical properties such as its shape, size, permittivity, permeability and conductivity values but they do not depend on the aspect angle and polarization of the target response. Therefore, a target can be uniquely characterized by the collection of its CNR frequencies being independent of the aspect/polarization conditions. The residues of CNR frequencies and hence the electromagnetic scattered signals however are aspect and polarization dependent.

In literature, there are various studies using CNR frequencies directly or indirectly to classify buried targets. Performance of the methods in which target poles are extracted directly from the available scattered data is significantly degraded in noisy environments. For solving these problems, modified versions of Prony's algorithm [121] have been widely used. However, most of these algorithms still suffer from low SNR, clutter conditions, spurious poles, and multi-target interactions. Two new techniques, Backup Moving Prony's Method (BUMP) and Dominant Resonance

Omitting Prony's Method (DROP), have been developed to improve the drawbacks of the classical Prony's approach [122].

Instead of using the CNR frequencies directly for target recognition, Kennaugh proposed another target identification method based on the indirect utilization of target poles in 1981. The primary objective of this approach was to design a target-specific time-limited excitation signal known as the Kill pulse (K-pulse) [123]. The K-pulse technique was developed with the intention of eliminating target poles with the zeros of the K-pulse input and hence confining the temporal response of the target within a limited time window [124-125], [151-153]. The effectiveness of K-pulse (and the similar E-pulse) technique relies on prior knowledge about the duration of the K-pulse/E-pulse or the number of target poles excited within a specific frequency range. Estimating the number of excited target poles accurately based on the peaks in the frequency spectrum data is only viable when the target poles are well-separated in the spectral domain. This approach is insufficient when dealing with objects like a dielectric sphere, where the system poles are densely clustered together. A Genetic algorithm-based K-pulse design approach is reported in 2001 by Turhan-Sayan and Kuzuoglu [154] to estimate the unknown K-pulse duration during the K-pulse design for the first time in K-pulse/E-pulse literature. The CNR frequencies of a dielectric sphere are extracted with a very good accuracy from the Laplace transform of the designed K-pulse signal.

The research conducted in this thesis focuses on investigating multi-target GPR scenarios involving closely spaced buried targets near the air-ground interface. Rather than directly relying on the CNR frequencies of dielectric and PEC targets, indirect use of CNRs in the late-time region of scattered signals will be utilized to extract aspect-independent characteristic target features with minimized sensitivity to SNR ratio and to clutter noise that is caused by the soil medium.

Lastly, the use of Time-Frequency Representation (TFR) techniques in GPR target classification problems will be mentioned. Various classification methods exist in literature that involve obtaining TFR output matrices for scattered signals and

utilizing these matrices in conjunction with neural networks or machine learning techniques [126-127]. It has been observed that such methods encounter problems in distinguishing objects whose geometrical properties are very similar to each other, need too many inputs, have difficulties of working in real-time, and they run into performance degradation problems in challenging multi-target scenarios. Also, only PEC targets have been used for demonstrations in most of those articles, false alarms were encountered in discriminating dielectric targets. The target classification approach introduced in [163-164], on the other, combines the feature extraction techniques from TFRs with an unsupervised neural network method, and does not suffer from any of the drawbacks mentioned above. In addition to neural network/machine learning-based methods, there are also studies in which targets are classified by comparing the obtained TFR images [128]. TFRs provide detailed information about the A-scan type GPR data in time-frequency plane clarifying the importance of natural resonances in classification problems. For this reason, TFRs are used as the basic building block of the feature extraction method proposed in this thesis. Use of TFR outputs directly may work fine for simpler problems such as the one reported by Turhan-Sayan and Sayan [155] in 2002 where the matrix outputs of some linear TFRs (short-time Fourier transform (STFT) and Gabor transform) as well as quadratic TFRs (Wigner-Ville and Page transforms) are implemented for short- and long-term cycle detection in finance data. Although, a classification approach directly based on TFR output images may give a broad idea about target recognition, it certainly lacks sufficient accuracy and compactness in a complicated problem like GPR target recognition [146], [162].

The fundamentals of the classifier model proposed in this thesis are similar to the Wigner Distribution/PCA-Based classifier introduced by Turhan-Sayan in 2005 [34]. Turhan-Sayan's previous works in 2003 and 2005 [33-34] demonstrated successfully for dielectric targets placed in air even under very low signal-to-noise ratio (SNR) conditions. Additionally, theses and articles published as the follow-up research to [33-34] have validated the effectiveness of this method for conductor,

lossy dielectric and dielectric coated conductor objects of arbitrary shapes immersed in lossless or lossy unbounded media [37], [156-160].

This thesis will demonstrate that the TFR/PCA-based target classification technique works quite successfully in the classification and recognition of buried objects also after some novel modifications made in Turhan-Sayan's previous work [34]. The resulting modified TFR/PCA classifier design technique will be tested in a highly challenging GPR problem of shallow-buried multiple targets located in close proximity. Furthermore, effectiveness of the proposed technique has also been validated in this complicated scenario for inhomogeneous soil types and rough air-soil boundary conditions as to be demonstrated in Chapter 4. Unlike many other methods reported in the literature, the proposed classification approach is fast, repeatable, robust, and has an extremely high accuracy rate in challenging single or multiple target scenarios. Also, it operates successfully with very few features in the classifier library with a need for very small storage memory. It is also noteworthy to remind that unlike most of the other classifier design approaches, the classifier design method employed in this thesis provides a lot of physical insight as it combines the physics of the main electromagnetic scattering problem with linear system modelling concepts and advanced signal processing techniques.

3.1.2 Complex Natural Resonance (CNR) Frequencies and The Singularity Expansion Method (SEM)

The importance and historical background of the Complex Natural Resonance (CNR) concept and Singularity Expansion Method (SEM) have been discussed in detail in the previous section with the main conclusion that an isolated object with a finite size can be represented by a linear time-invariant (LTI) aspect-dependent system function. According to SEM, the aspect and polarization-dependent system function of a target can be expressed as follows in the complex frequency domain:

$$H(s, \Omega) = A(s, \Omega) + \sum_{n=1}^{\infty} \frac{R_n(s, \Omega)}{(s - s_n)(s - s_n^*)} \quad (3.1)$$

where $s = \sigma + j\omega$ is the complex frequency with $\omega = 2\pi f$, and the parameter Ω represents the aspect (in elevation and azimuth angles in spherical coordinates) and polarization dependency. The highly aspect/polarization dependent term $A(s, \Omega)$ is the forced component of the system transfer function which does not include any singularities and it is related to the early-time response of the buried target.

The system poles $(s_n, s_n^*) = (\sigma_n + j\omega_n, \sigma_n - j\omega_n)$ are the complex conjugate pole pairs (complex natural resonance frequencies) which are independent of aspect and polarization variations, but they are functions of geometrical and electrical properties of a target. Therefore, a target can be uniquely characterized by the complete set of complex system poles in an aspect and polarization independent manner and can be discriminated from the other targets. The term $R_n(s, \Omega)$, on the other hand, is the aspect and polarization-dependent residue for the n^{th} complex pole pair. Due to this fact, scattered signals themselves are highly dependent on the aspect/polarization conditions, and they cannot be used directly in target recognition problems.

According to the SEM Theory, the inverse Laplace transform of Equation (3.1) will give us the impulse response of the target which can be expressed as:

$$h(t, \Omega) = a(t, \Omega) + \sum_{n=1}^{\infty} b_n(\Omega) e^{-\sigma_n t} \cos(\omega_n t + \phi_n) \quad (3.2)$$

where the target response includes the superposition of sinusoidal damped oscillations which are caused by the poles of the system's transfer function. In other words, a successful target classifier can be designed if the information on the CNR frequencies (especially the dominant ones which are still effective in late-time regime) of the library targets are known.

In Equation (3.2), $a(t, \Omega)$ is the forced response component that exists only during the direct interaction of the excitation signal with the target. Hence it is effective only

at early times and it is a time-limited function. The duration of this interaction time between the incident wave and the target is approximately $T_L = T_P + T_D$, where T_P corresponds to the pulse duration of the incident electromagnetic wave and T_D is the time duration required for the incident wave to pass over the target completely. In late-time region, the aspect-dependent early-time response $a(t, \Omega)$ is zero and only the infinite sum of damped sinusoidal components remain as shown in Equation (3.2).

Due to differences in the attenuation constant (or damping coefficient) values, σ_n , these sinusoidal components decay at different rates. Only those related with the *dominant* CNR frequencies (with smaller attenuation constant values) can survive at sufficiently late-time windows. Target feature extraction algorithms, which focus on the CNR mechanism, typically utilize the direct or indirect use of such dominant poles within selected late-time regions.

As indicated before, the residues, $R_n(s, \Omega)$, are aspect angle and polarization-dependent terms. The dominant pole in one aspect angle may not be dominant for another aspect angle, as the residues can vary across different aspects. For this reason, the training data set of a target classifier must contain scattered signals (the A-scan signals in the GPR problem) in the late time regimes with sufficient aspect variation to capture an almost complete (indirect) information about most of the dominant CNR frequencies.

In GPR applications, a designated area is scanned using predetermined steps in both down-track and cross-track directions. As the antennas of the GPR “see” the buried target from different aspect angles while approaching to the target and then leaving the target during this two-dimensional scanning process, aspect-dependent GPR data can be collected. As mentioned earlier, determination of a proper late-time instant may be a difficult problem requiring different optimization techniques as mentioned in literature. However, since our method is based on feature extraction over an optimal late-time region determined by simple calculations, it does not require time-consuming optimization methods in the classifier design phase.

Figure 3.1 shows the A-scan data of a finite-size buried wire laid diagonally 2 cm below the air-soil boundary. The highly aspect-dependent early-time response coming directly from the buried target and late-time oscillations originating from the superposed damped sinusoids due to the CNR frequencies are visible in this figure. Figure 3.2 illustrates the zoomed-in version of the A-scan signal given in Figure 3.1 between the time indices 700th and 1296th that is a typical late-time region.



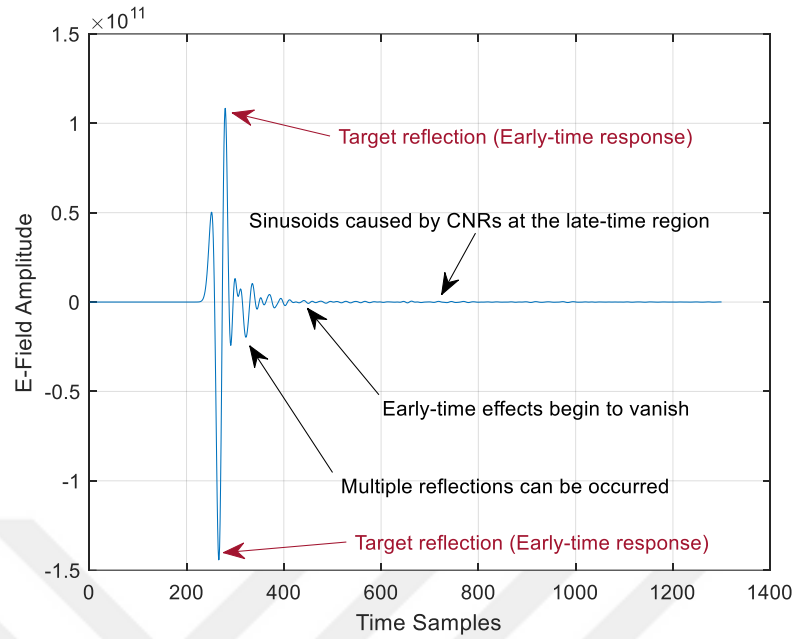


Figure 3.1 Processed A-scan data of the finite-size buried wire laid diagonally 2 cm below the air-soil boundary. Early-time and late-time regions are indicated.

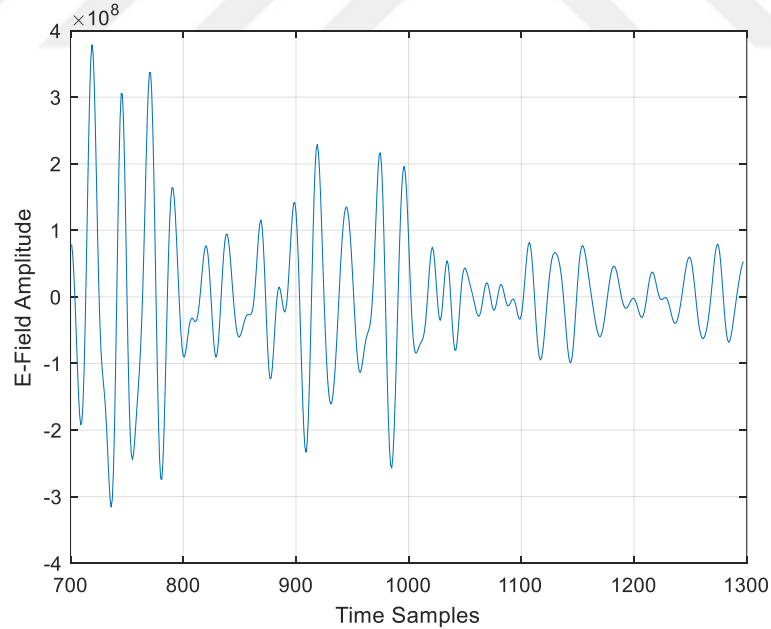


Figure 3.2 A zoomed-in version of the total A-scan signal in the late-time regions. This figure shows superposed sinusoids originating from the dominant system target poles.

3.1.3 Overview of the Design Steps of the Proposed Classifier

This section will briefly introduce the main steps of the proposed classifier design:

- Step 1: Firstly, 3D C-scan data will be collected. In this thesis, A-scan data for the investigated scenarios are obtained using the *gprMax* software, an FDTD-based open-source simulation program.
- Step 2: Following the applications of clutter removal algorithms, target location is detected from the processed GPR data.
- Step 3: A collection of A-scan time signals is isolated from the 3D GPR data at the peak target signal location (in the eye of the target image) and at a set of “closest points” to this center spot to obtain “training data” with some aspect variance. If the eye of target image is detected at the point $(\bar{l}, \bar{j})$ over the cross-track vs down-track domain, data at more additional points around that center location are used also for target feature extraction to provide less aspect-invariant information for better target characterization.
- Step 4: Each training A-scan signal is truncated to start with the very first reflections coming from the target along the time axis. This step is needed as the onset of arrival time (index) for the reflected/scattered signals from a target may vary across different aspect angles, burial depths, etc.
- Step 5: Each one of the isolated and truncated A-scan signals is also normalized as described in Turhan-Sayan’s previous work [33-34] such that its total energy will be equal to unity. This step is needed to compensate for varying attenuation effects for targets buried at different depths in soil.
- Step 6: Once the training database of A-scan signals for a target is ready, the auto-Page distribution (PD) of each A-scan signal is computed in the time versus frequency domain. PD is a quadratic (energetic) type of Time-Frequency Representation (TFR) that gives valuable information about the distribution of target’s total energy over the time-frequency domain. As it is a quadratic distribution, the output matrix of PD also contains undesired interference terms having no energy type physical meaning. However, PD

has a more favorable content of interference terms as compared to the widely used Wigner distribution (WD) especially in GPR problems [132], [146], [155], [162].

- Step 7: After obtaining the output matrix of the Page distribution for a normalized training A-scan signal, its Late Time Feature Vector (LTFV) will be computed over an optimally selected late-time interval as to be explained in more detail later in this section. This procedure is repeated for each A-scan signal belonging to a given target in the training database. The resulting LTFVs are late-time features implicitly dependent on target's CNR frequencies. Therefore, they have highly reduced aspect/polarization dependency and much better target-specific characterization as compared to the A-scan signal itself.

Step 8: To further reduce the aspect and polarization dependency of the extracted target features, the Principal Component Analysis (PCA) is used to fuse the aspect-specific LTFV features of a given target to obtain a single feature called *Fused Feature Vector* (FFV) that has sufficiently high correlation coefficients with each of the LTFVs. Hence, a single feature string, the FFV, characterizes a given target both accurately and compactly (with a very small need for storage memory) in the classifier testing database. This process is repeated for each target in the classifier library.

Step 9: In the testing phase, the LTFV feature extracted from the received test signal is compared to FFV features which are previously extracted for each possible target class and saved in the classifier's reference database. Correlation coefficients between the test target's LTFV and each one of these FFVs are computed. Then, the target is identified within the classifier's target library based on the largest correlation coefficient.

In addition to the classifier design steps outlined above, the A-scan graphs, B-scan images, and energy heat maps may also be helpful as auxiliary tools to enhance the accuracy of classifier especially in ambiguous cases.

Figure 3.3 illustrates a comprehensive flowchart that encompasses all the classification steps and auxiliary tools described in this section. The blue arrows represent the direct design steps of the classifier, while the orange arrows depict the beneficial auxiliary steps in the design of the classifier.

Figure 3.4 provides a zoomed-in version specifically focusing on the direct steps of the classifier design. It encompasses all the steps of the classifier design starting from the acquisition of A-scan data to the generation of Fused Feature Vector (FFV) data, which will be stored in the feature library.

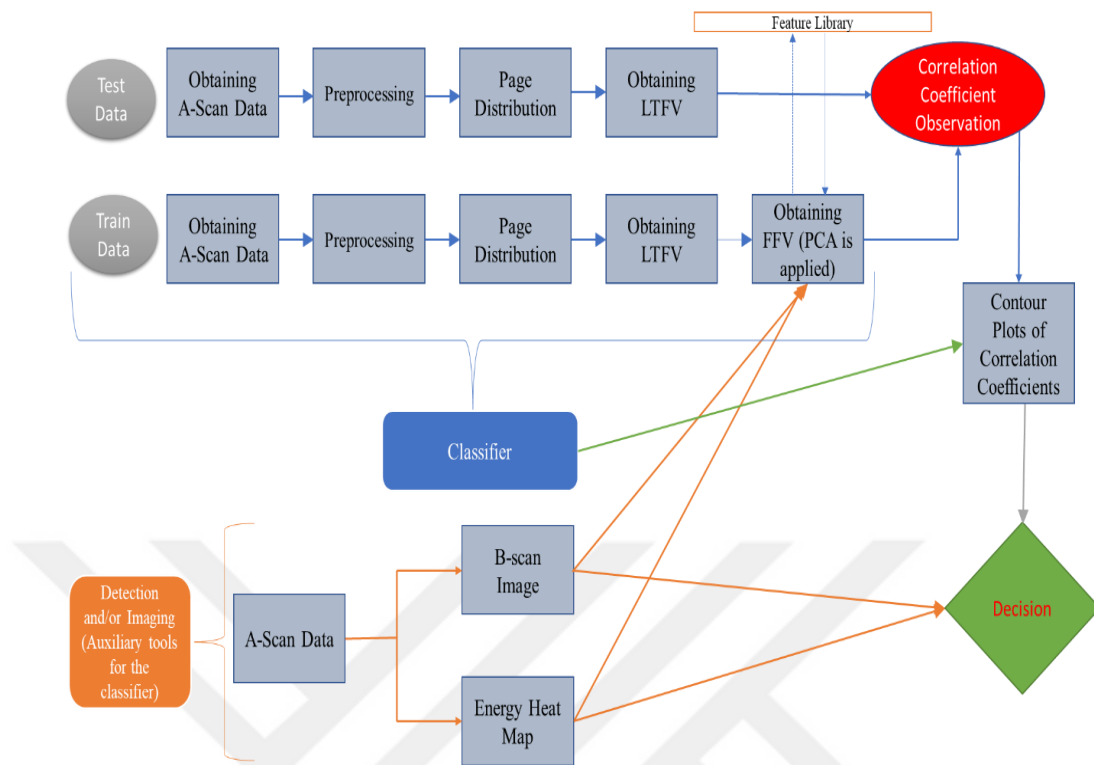


Figure 3.3 A comprehensive flow diagram that encompasses all the principal design steps and auxiliary tools for the proposed classifier.

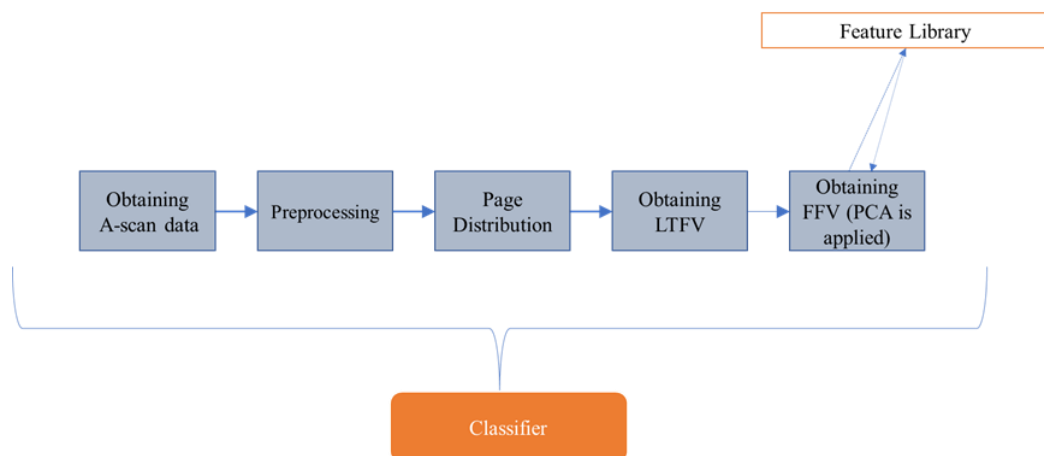


Figure 3.4 Classifier's principal design stages encompass all steps, from acquiring A-scan data to generating Fused Feature Vectors (FFVs).

3.1.4 Time-Frequency Representations (TFR) and Their Use in Target Feature Extraction Process

In this section, the basic concepts of Time-Frequency Representations will be outlined. Fundamentals of the TFRs, in general, and quadratic TFRs such as Wigner distribution (WD) and Page distribution (PD), in particular, are outlined in Appendix E. In this section, mathematical properties of Page distribution (PD) will be summarized emphasizing the reason why quadratic TFRs are used in the proposed GPR classifier design and why PD is chosen in particular to be used in this thesis.

As with many real-life problems, the GPR problem involves the processing of nonstationary transient signals, i.e., the A-scan signals in time domain. The use of classical Fourier Transformation (FT) approach is insufficient in such problems as it cannot describe the variation of the signal's spectral content over a given specific time window. Therefore, use of TFRs is crucial in studying nonstationary signals. As a matter of fact, in electromagnetic target recognition problems, quadratic TFRs are much more useful rather than the linear TFRs to interpret the energy distribution of a given nonstationary signals in the joint time-frequency domain in the approximate sense [33-34], [126-134].

Quadratic TFRs satisfying the time-frequency shift-invariance properties belong to Cohen's class. Wigner distribution (WD) is the main member of this class. Auto-WD of a time function $x(t)$ is defined as

$$W_x(t, f) = \int_{\tau} x\left(t + \frac{\tau}{2}\right) x^*\left(t - \frac{\tau}{2}\right) e^{-j2\pi f\tau} d\tau \quad (3.3)$$

where “*” represents complex conjugate operator.

The auto-WD is a real-valued transformation satisfying the *marginal properties* expressed as

$$\int_f T_x(t, f) df = p_x(t) = |x(t)|^2 \quad (3.4)$$

$$\int_t T_x(t, f) dt = P_x(f) = |X(f)|^2 \quad (3.5)$$

where $x(t)$ is the time-domain signal, and $X(f)$ is the Fourier Transform of $x(t)$. Furthermore, $p_x(t)$ and $P_x(f)$ denotes the instantaneous power and the spectral energy density of the signal, respectively. Provided that the marginal properties are satisfied, the total energy of the signal $x(t)$ can be obtained by summing up the TFR output at all times and frequencies as

$$E = \int_t \int_f T_x(t, f) dt df \quad (3.6)$$

In other words, the auto-WD has a loose but still very useful energy density interpretation within the constraints of the uncertainty principle [132] that does not allow the notion of energy density at a specific point in time-frequency domain with perfect resolutions in both time and frequency. The major drawback of the auto-WD is the presence of highly dominant and oscillatory interference terms (or cross-terms) resulting from its quadratic nature. Regarding the “energy interpretations” of the quadratic TFRs, these interference terms (which also assume negative values) are undesired and cause serious ambiguity in target recognition applications. As presented in [132], [135-136], [146], [155], [162] the Page distribution (PD) has a much better interference pattern as compared to the WD. Due to this important reason, the basic work in [34] is adapted by using PD instead of WD in this thesis for target feature extraction from transient GPR data.

The mathematical expression of the auto-PD of a time-domain signal $x(t)$ is defined as:

$$\begin{aligned}
PD_x(t, f) &= \frac{d}{dt} \left| \int_{-\infty}^t x(t') e^{-j2\pi f t'} dt' \right|^2 \\
&= 2\text{Re} \left\{ x^*(t) e^{j2\pi f t} \int_{-\infty}^t x(t') e^{-j2\pi f t'} dt' \right\}
\end{aligned} \tag{3.7}$$

As discussed before, strong oscillatory interference or cross-terms occur in PD outputs as well. It is impossible to get rid of these terms completely as they overlap with the auto-terms of the PD output. However, cutting at least the negative-valued parts of these cross-terms in a simple way as described in Equation (3.8) below was found helpful to extract much better target features in [33-34]. The same approach is also used in this thesis while using the PD outputs.

$$T_x(t, f) = \frac{T_x(t, f) + \text{abs}(T_x(t, f))}{2} \tag{3.8}$$

Given an A-scan signal $x(t)$ sampled at N points in time, the auto-PD output $PD_x(t, f)$ is originally computed as an $(N \times N)$ matrix in the joint time-frequency domain where the frequency axis extends over both negative and positive frequencies. Since the PD outputs are symmetric with respect to zero frequency along the frequency axis, they are saved and displayed in sizes $(N \times N/2)$ for only non-negative frequencies.

The raw A-scan signal plotted in Figure 3.1 is preprocessed to eliminate the DC and GB terms first, and after normalization, its PD is computed and plotted in Figure 3.5. The PD terms which are concentrated over a broad frequency range belongs to the “early-time response” of the wire extending roughly up to time index 400. This part of the PD pattern is mostly composed of specular reflections and multiple reflections between the target and the soil surface. The early and late time responses overlap for a while, then the late-time response of the wire becomes well-formed after the time index 650. In the rest of the late-time regime, it is clearly observed that there are energy bands extending horizontally (parallel to the time axis) at certain frequency values. These energy bands indicate the presence of natural resonances oscillating at the frequency values which correspond to the imaginary parts of complex resonance

frequencies. As expected, the dominant natural resonances with smaller damping coefficients (the real parts of the CNRs) survive longer in late-time windows. Figure 3.6 shows the zoomed-in PD result of the same signal between the time indices 1050 and 1150 to show details more clearly.

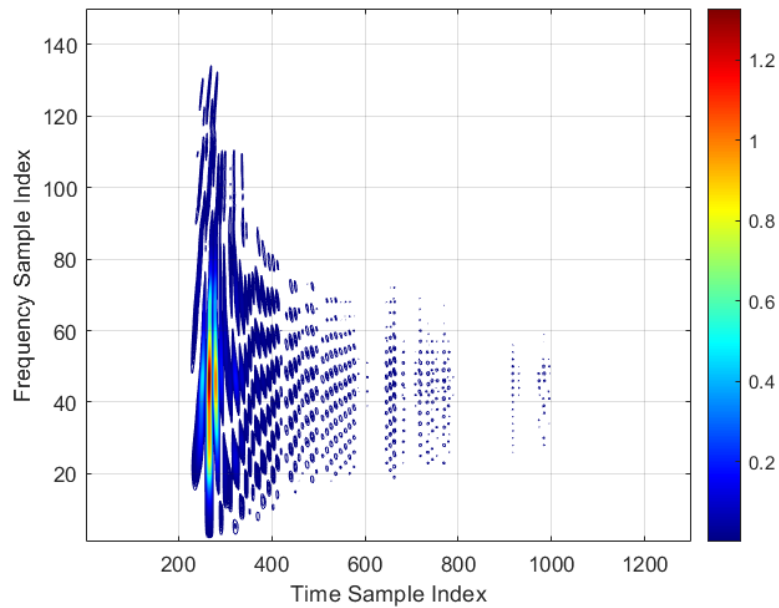


Figure 3.5 The auto-PD output of the buried wire's A-scan response given in Figure 3.1.

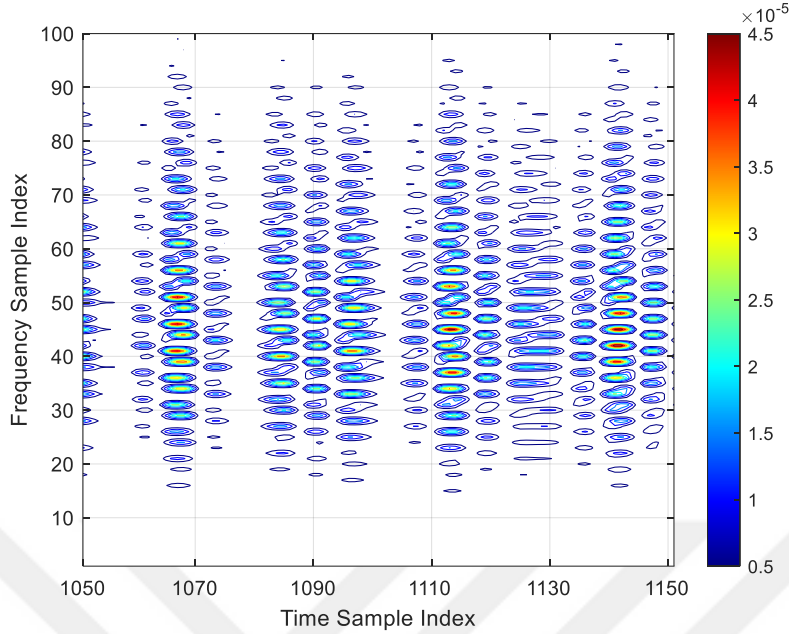


Figure 3.6 Zoomed-in version of Figure 3.5 over the discrete late-time region [1050-1150].

Finally, in this section, two GPR target classifiers are designed, and their target discrimination performances are compared on a fair basis keeping all the classifier design parameters the same except for using PD instead of WD for feature extraction. Use of PD type TFR is demonstrated to be superior based on the classification accuracy analyses presented below:

Computation of target features, the late-Time Feature Vectors (LTFVs) and the Fused Feature Vectors (FFVs) will be explained in detail in Section 3.1.5 and Section 3.1.6, respectively. The LTFVs are computed both for reference A-scan signals in the classifier design database for the tested A-scan signals at different spatial sampling points over the simulation terrain with different aspect angles. The FFVs, on the other hand, are computed as the fusion of training LTFVs. An FFV is a single highly aspect independent characteristic feature vector representing the associated target in the classifier library as to be given in full detail in the next two sections. The correlation coefficient matrix plotted in Figure 3.7 belongs to a 2-target classifier where the targets are two different thin PEC wires of the same length but different

radii of 2 mm and 5 mm. The GPR database of A-scan signals are simulated by gprMax for scenarios where targets are buried in sand at the same depths with exactly the same orientations one at a time.

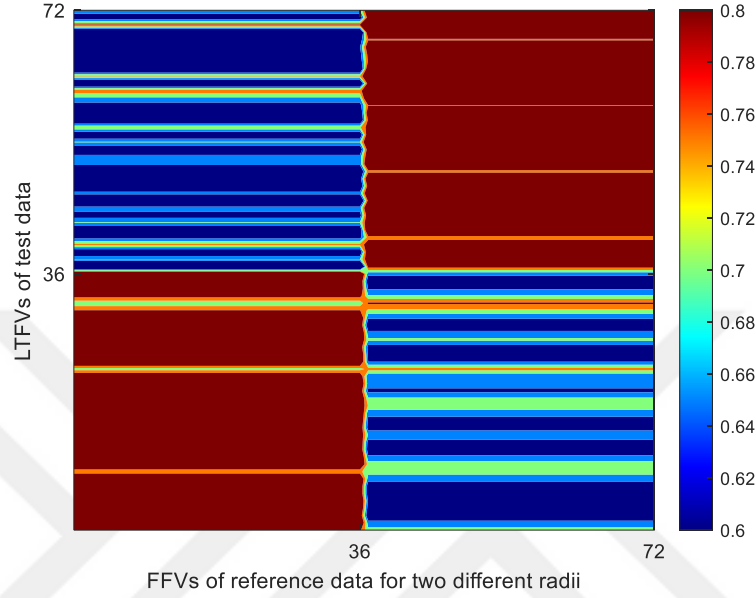


Figure 3.7 Contour plot of correlation coefficients between the LTFV and FFV features for two PEC wires with 2 mm and 5 mm radii; the WD is used as a TFR in classifier design.

In the design of this first classifier, the Wigner distribution (WD) is used as the TFR. In the second classifier, however, the Page distribution (PD) is implemented instead of WD. This is the only difference between the first and the second classifier designs. The correlation coefficient matrix of the second classifier is given in Figure 3.8. In these correlation coefficient matrices, the correlation coefficients of the tested LTFV vectors and the FFV vectors of each target are computed and plotted. On the vertical axis, a total of 72 LTFVs are used at different burial depths and at different aspects. The first set of 36 LTFVs (from index 1 to 36) belong to the first target (PEC wire with 2 mm radius) and the remaining 36 LTFVs (from index 37 to 72) belong to the second target (PEC wire with 5 mm radius). On the horizontal axis, on the other hand, the FFV of the first target is used first (repeated 36 times from index 1 to 36

to provide better visualization) and then the FFV of the second target is repeated 36 times also from index 37 to 72 for the same reason. The matching diagonal blocks in these correlation coefficient matrices are expected to assume high correlation coefficients while the mismatching off-diagonal blocks are assumed to have much lower correlation coefficients.

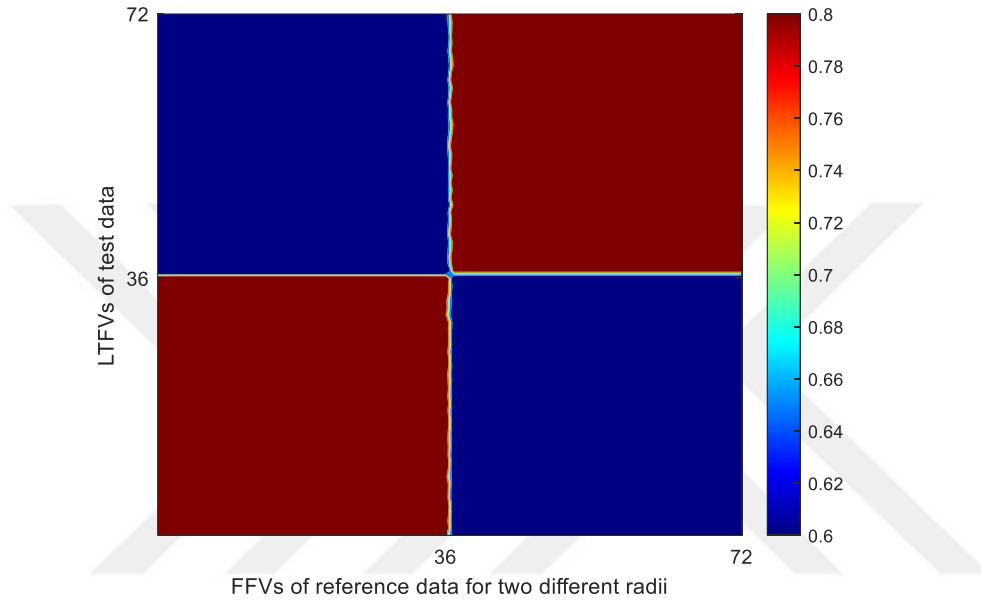


Figure 3.8 Contour plot of correlation coefficients between the LTFV and FFV features for two PEC wires with 2 mm and 5 mm radii; the PD is used as a TFR in classifier design.

As indicated by the color bars of Figure 3.7 and Figure 3.8, correlation coefficient values equal to or larger than 80 percent indicate the “definite matched target” case while correlation coefficient values equal to or less than 60 percent indicate the “definite mismatched target” case. There is a wide enough margin of 20 percent between these “pass and fail” thresholds.

When the classification results in Figure 3.7 and Figure 3.8 are compared, it is clearly seen that the PD-based classifier results presented in Figure 3.8 are perfect with 100 percent accuracy while the WD-based classifier results can reach about 85 percent accuracy.

3.1.5 Construction of Late-Time Energy Feature Vectors

The previous section describes generation of PD output matrices from the isolated normalized A-scan signals. However, as mentioned earlier, use of the PD output matrices directly does not have a strong discriminative power in target recognition problems. Instead, PD outputs need to be further processed to utilize late-time regime of the GPR A-scan signals to make indirect use of target's CNR frequencies for effective target feature extraction.

As mentioned in Section 3.1.3, for a given target, the reference A-scan database with sufficient aspect angle variation becomes ready after completing the first five steps of the classifier design. Then, PD output matrices of these A-scan signals calculated at the sixth step. The next step is the computation of a Late-Time Feature Vector (LTFV) from each non-negative valued PD matrix as follows: The total time span T_0 of the A-scan signal is divided into Q equal-length non-overlapping time bands. The spectral energy density at the sample frequency f_m for the time band q can be obtained by using marginal properties of the PD as

$$E_q(f_m) = \int_{(q-1)\Delta}^{q\Delta} PD_x(t, f_m) dt \quad \text{for } q = 1, 2, 3, \dots, Q \quad (3.9)$$

where $\Delta = T_0/Q$, $m = 1, 2, \dots, N/2$, and $f_m = \frac{(m-1)}{T_0}$

Then, for the time band q , the time-partitioned spectral energy density vector $\bar{E}_q$ can be defined as

$$\bar{E}_q = [E_q(f_1) \ E_q(f_2) \ \dots \ E_q(f_{N/2})] \quad (3.10)$$

Since the total time span is divided into Q bands, the overall time-partitioned spectral energy density vector $\bar{E}$ can be given in the form

$$\bar{E} = [\bar{E}_1 \ \bar{E}_2 \ \dots \ \bar{E}_Q] \quad (3.11)$$

which is of size $(1 \times (QN/2))$.

Obviously, using partitioned spectral energy density vector $\bar{E}$ instead of the positive half (with respect to frequency axis) of the PD output matrix, $PD_x(t, f)$, provides a dimensional reduction by the factor, N/Q . This dimensionality reduction leads to a faster running algorithm which is a highly desired property for real-time GPR problems.

Generally, two or at most three successive partitions of $\bar{E}$ in the late-time region will be selected to construct the corresponding Late-Time Feature Vectors (LTFVs) to catch the attenuation factor information of CNR frequencies. Assuming that the indices of the selected elements start from q^* , LTFVs will be generated by selecting the band q^* , $q^* + 1$ and perhaps $q^* + 2$. Turhan-Sayan's previous studies include detailed information on the selection steps of Q and q^* values [33-34]. In this thesis, the Q value will be chosen as 16 as suggested in [34] and the Correct Classification Factor (CCF) analysis will be conducted to select an optimal late-time starting band index, q^* . The mathematical expression of CCF can be given as

$$CCF(q^*) = \frac{1}{M_{tar}K^2} \sum_{i,j} r_{i,j}^{matched} - \frac{1}{(M_{tar}^2 - M_{tar})K^2} \sum_{i,j} r_{i,j}^{mismatched} \quad (3.12)$$

where M_{tar} is the number of candidate targets, K is the number of reference aspects, $r_{i,j}^{matched}$ is the correlation coefficient between any two features which belong to the same target, and $r_{i,j}^{mismatched}$ is the correlation coefficient between any two different features which belong to different candidate targets. In a good classifier, high correlation coefficients will be obtained for matched targets, while lower correlation coefficients will be observed for mismatched targets. Therefore, the CCF value is maximized for a good classifier. This CCF value is calculated for all bands, $q = 1, \dots, Q$ and plotted as a bar chart to decide the best index q^* and the optimal late-time band for the classifier design.

If the FFVs computed for each target is repeated L times and the number of LTFVs obtained as a result of the tests for each target is K , the total number of data for each LTFV-FFV combinations of a single target (it corresponds to the K^2 in Equation

(3.12) assuming $K = L$) can be given as $M_{data} = LK$. In such a case, the CCF expression of Equation 3.12 needs to be modified accordingly.

3.1.6 Multi-Aspect Feature Fusion by Principal Component Analysis

Although LTFVs are significantly aspect-independent as compared to A-scan type scattered signals, there is still room for improvement to extract target features with better aspect-independence. Using the Principal Component Analysis (PCA) method [137-138], the LTFVs computed for a given library target can be fused to obtain a single feature vector called *Fused Feature Vector* (FFV) which has typically very high correlations with all LTFVs, representing most of the feature information common to all aspects. Then, the target is represented in the classifier's testing database by this single feature vector for a simple, efficient and fast decision process. When the classifier is used for testing, LTFV of the tested A-scan signal is obtained using exactly the same steps used to extract the reference LTFVs. Then, the correlation coefficient of this tested LTFV with each one of target FFVs are computed. The highest correlation coefficient determines the identity of the tested target within the classifier library.

In the rest of this section, mathematical steps needed to obtain a FFV will be outlined by employing the Principal Component Analysis (PCA) method.

PCA method was invented in 1901 by Karl Pearson, [139] as an analogue of the principal axis theorem in mechanics. It is a well-known statistical method that has been used in various scientific research disciplines for data analysis and compression, redundancy and dimensionality reduction, feature extraction, clutter and noise reduction, anomaly detection, clustering, and classification [137-138], [87], [140]. Furthermore, many studies use PCA in GPR applications for clutter removal, target identification, and classification [34], [87], [140]. The purpose of using PCA in most of these studies is dimensionality reduction. However, in the TFR-PCA method used in this thesis, the most significant benefit of applying PCA

is the multi-aspect feature fusion as introduced in Turhan-Sayan's work [34] to obtain a simple significantly aspect-independent and compact target feature for each library target.

The basic steps of the PCA-based multi-aspect feature fusion technique can be summarized as follows [34]. Let's assume that we have K different LTFVs for each library target where the length of each LTFVs is $3N/2$ as 3 successive bands are used. Based on these assumptions, the real-valued feature matrix, F , can be obtained as shown in Equation 3.13 where $\bar{e}_k^T$ are the LTFVs of the target for $k = 1, \dots, K$ where each LTFV has the size $1 \times (3N/2)$.

$$F^T = [\bar{e}_1^T \ \bar{e}_2^T \ \dots \ \bar{e}_K^T] \quad (3.13)$$

where T denotes the transpose operator. The covariance matrix S_F of F^T is a symmetric, positive-definite matrix expressed as

$$S_F = \begin{bmatrix} s_1^2 & s_{1,2} & \dots & s_{1,K} \\ s_{2,1} & s_2^2 & \dots & s_{2,K} \\ \vdots & \ddots & \ddots & \vdots \\ s_{K,1} & s_{K,2} & \dots & s_K^2 \end{bmatrix} \quad (3.14)$$

where its off-diagonal entries $s_{i,j} = s_{j,i}$ correspond to the covariance between the LTFVs $\bar{e}_i$ and $\bar{e}_j$. Additionally, the diagonal entries s_i^2 demonstrate the variance of the feature vectors $\bar{e}_i$. The covariance matrix S_F can be transformed into a diagonal matrix Λ by using the similarity transformation,

$$\Lambda = U^T S_F U = \begin{bmatrix} \lambda_1 & 0 & \dots & 0 \\ 0 & \lambda_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \lambda_K \end{bmatrix} \quad (3.15)$$

where U is the modal matrix (it is a unitary matrix as $U^{-1} = U^T$). This unitary matrix U can be given as, $U = [u_1 \ u_2 \ \dots \ u_K]$ where each u_i shows the normalized eigenvectors corresponding to the eigenvalues λ_k for $k = 1, \dots, K$ of the covariance matrix. Because of that reason, calculating eigenvalues is the one of the most important steps of PCA algorithms. The eigenvalues λ_i can be obtained by solving

$\det(S_F - \lambda I) = 0$ where I the $K \times K$ identity matrix. Then, eigenvalues are ordered from the highest to the lowest such that, $\lambda_1 > \lambda_2 > \dots > \lambda_K$, and the corresponding eigenvectors t_i can be solved from:

$$[S_F - \lambda_i I]t_i = 0 \quad (3.16)$$

This equation gives us the eigenvectors for $i = 1, 2, \dots, K$. Finally, to construct the U matrix, these eigenvectors must be normalized for obtaining orthonormal eigenvectors. Mathematical expression of this normalization process is given below:

$$u_i = \frac{t_i}{\sqrt{t_i^T t_i}} = \frac{t_i}{|t_i|} \quad (3.17)$$

Then, the matrix Z which consists of a set of uncorrelated vectors $z_1, z_2, \dots, z_K$ can be given as:

$$Z = \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_K \end{bmatrix} = U^T \begin{bmatrix} \bar{e}_1 - \text{mean}(\bar{e}_1)I_N \\ \bar{e}_2 - \text{mean}(\bar{e}_2)I_N \\ \vdots \\ \bar{e}_K - \text{mean}(\bar{e}_K)I_N \end{bmatrix} \quad (3.18)$$

The transformed vectors, z_i s are the principal components of the feature matrix F . Mean of the elements z_i s are equal to zero. Furthermore, variance of each principal component is equal to λ_i .

The first principal component z_1 has the highest correlation coefficients with the original LTFVs. The reason of this phenomena is that the variance of the first principal component λ_1 is the dominant of all variations. It can be given as, $\lambda_1 / \sum_{k=1}^K \lambda_k$ is very close to 1. These explanations show that the leading principal component is usually used to represent the aspect-independent FFV of the target by neglecting the other principal components with sufficiently small variances. It is significantly useful property for our studies since our algorithms and methods work fast by considering this assumption. For all the classifier design scenarios studied in this thesis, first principal component turned out to be highly dominant. This assumption has been tested in all classifier designs and it has been observed that the

variance corresponding to the first principal component has a very high ratio to the total variation. The leading principal component z_1 describes most of the variations, and others are negligible. Therefore, in all scenarios which are investigated in this thesis, the first principal component term z_1 corresponds to the fused feature vector (FFV).

If necessary or preferred, the other principal components can be combined in a linear manner as seen in Equation 3.19 to create the FFVs of the targets.

$$FFV = \sum_{i=1}^K \bar{\lambda}_i z_i \quad (3.19)$$

where z_i corresponds to the i^{th} principal component, and $\bar{\lambda}_i$ corresponds to the weighting factor of the i^{th} principal component that is given by the ratio of the variance of the i^{th} principal component to the total variation. The weighting factor of $\bar{\lambda}_i$ is computed as

$$\bar{\lambda}_i = \frac{\lambda_i}{\sum_{i=1}^K \lambda_i} \quad (3.20)$$

It should be noted that the PCA algorithm can be easily implemented in MATLAB platform without writing a separate code based on the formulation steps above.

3.2 Design of GPR Classifiers for Shallowly Buried Perfect Electric Conductor (PEC) Wire Targets

In this section, the classifier design steps described in Section 3.1 will be applied to design a GPR classifier for thin PEC wires with two different radii (2 mm and 5 mm) shallowly buried at different depths (one at a time). By scanning a designated terrain in down-track and cross-track directions with a single pair of transmitter/receiver (TX/RX) antennas (omnidirectional Hertzian dipole antenna elements), scattered A-scan signals will be simulated in gprMax. This data will be used to design, verify,

and test the proposed GPR classifier. In addition, the robustness of the designed classifier will be tested under additive white Gaussian noise (AWGN).

3.2.1 Description of GPR Scenarios and Simulation Environment

In the GPR scenarios studied in this section, two finite length ($50\sqrt{2} \approx 70.71$ cm for each wire) PEC wires with radii 2 mm and 5 mm are buried in sandy soil at different shallow depths of $d = 1, 2, 3, 4, 5, 6$ cm. In each simulation, only a single wire is buried in the dry sandy soil that has $\epsilon_r = 3$ and $\sigma = 0.01$ S/m. The closest points of the cylindrical wires to the air-sand interface is 2.8 cm for the wire with 2 mm radius, and 2.5 cm for the wire with 5 mm radius, if the burial depth is 3 cm, for example. A single channel, x-polarized TX/RX antenna pair (separated by 2 cm) placed 10 cm above the soil boundary is used to scan the simulation domain.

Two main scenarios will be studied in this section.

In the first scenario, a single TX/RX antenna pair scans the buried wire in the down-track direction only taking a total of 11 steps with a step size of 2 cm. The wire is laid diagonally in the subsurface as described in Figure 3.9. That is to say, the center of the wire is positioned at ($x = 25$ cm, $y = 25$ cm). The TX of the antenna pair is located at $x = 24$ cm and the RX at $x = 26$ cm (in the cross-track direction). On the y-axis (down-track direction), the antennas scan the buried wire with the 2 cm step size from $y = 14$ cm to $y = 34$ cm. The red circles in Figure 3.9 indicate the TX/RX antennas. All details about targets and geometry are summarized in Table 3.1.

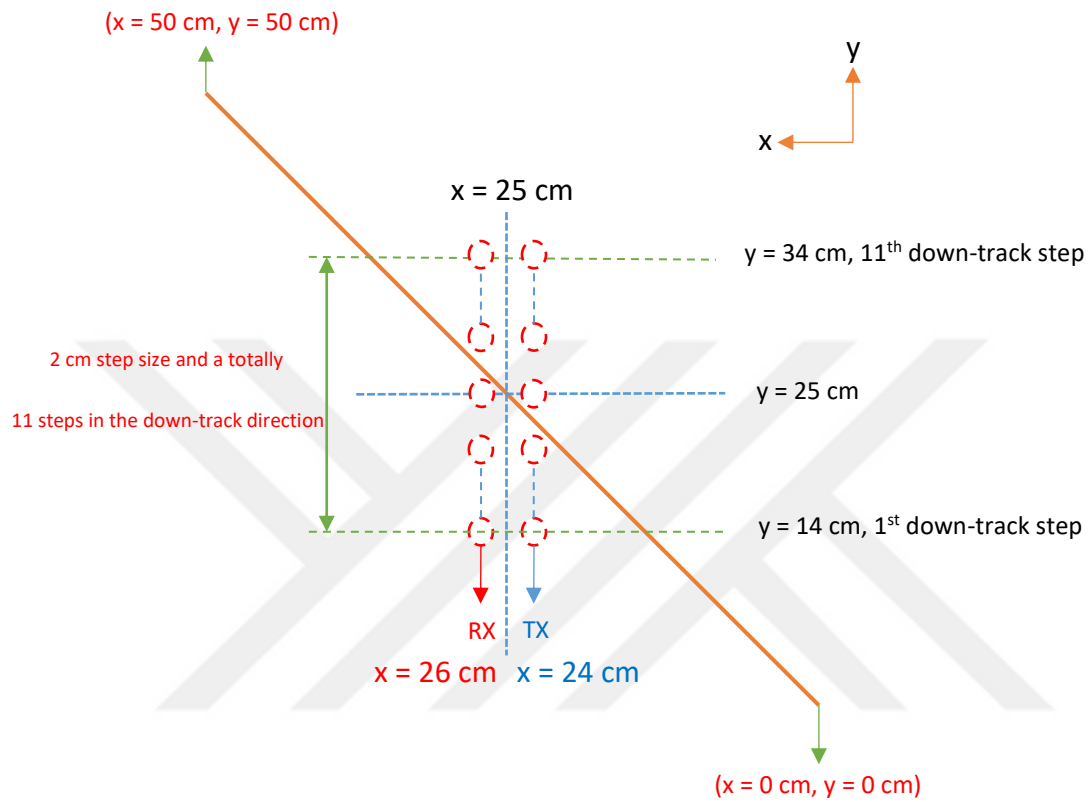


Figure 3.9 Geometry of the first GPR simulation scenario (Scenario 1) for PEC wire targets.

Table 3.1 Parameters of the simulation and the scenario

<i>Parameters</i>	<i>Explanation</i>
Target Type	2 and 5 mm radii PEC thin wires
Burial Depths of the Cylinders	1, 2, 3, 4, 5, and 6 cm
Length of the Cylinders	$50\sqrt{2}$ cm
Positioning of Cylinders in Geometry	Diagonally Laid from (0 cm, 0 cm) to (0.5 cm, 0.5 cm)
Height of Antennas from Air-Soil Interface	10 cm
Relative Dielectric Permittivity of the Sandy Soil	3
Electrical Conductivity of the Sandy Soil	0.01 S/m
Number of Steps	For Scenario 1, 11 down-track steps and for Scenario 2, 11 down-track and 11 cross-track steps
Scanning Step Size	2 cm in down-track and/or cross-track
Antenna Type	Hertzian Dipole
Polarization of the TX Antenna	Linearly polarized (x-direction)
Polarization of the RX Antenna	Linearly polarized (x-direction)
Utilized Input Waveform Type	Gaussian Derivative
Center Frequency of the Input Signal	6 GHz
Half-Power Bandwidth of the Input Signal	9.7 GHz
-10 dB Bandwidth of the Input Signal	16.2 GHz

Mathematical definition of the input signal emitted by the transmitting antenna is given in Equation 3.21. Not only in this section but in all simulations conducted in this thesis, the Gaussian Derivative (Gaussian Dot) waveform has been used. This waveform is commonly used as the excitation signal in GPR simulations due to its realistic band-pass nature. The mathematical expression of the Gaussian Dot waveform, the first derivative of the Gaussian signal, is given in as

$$W(t) = -2\zeta(t - \chi)e^{-\zeta(t-\chi)^2} \quad (3.21)$$

where $\zeta = 2\pi^2 f^2$, $\chi = \frac{1}{f}$ and f is the operating frequency.

As mentioned in the section on GPR data generation with GprMax and FDTD, an improved resolution is needed for the examination of thin wires. While the GprMax software is running, information is provided for the number of cells used to cover each target and the program warns the user if the spatial resolution is not sufficient. Considering such warnings, the center frequency of the spectral bandwidth for GPR input pulse is chosen to be 6 GHz for which the (-3 dB) bandwidth (half-power bandwidth) of the pulse is (1.9 GHz - 11.6 GHz), and (-10 dB) bandwidth (90 percent bandwidth) is (400 MHz - 16.6 GHz) approximately. Since the GPR problems of this thesis focus on shallowly buried target identification, increasing attenuation at higher frequencies does not create a significant problem. The time-domain plot for the input pulse is given in Figure 3.10 while the corresponding frequency spectrum (magnitude plot in dB scale) is shown in Figure 3.11.

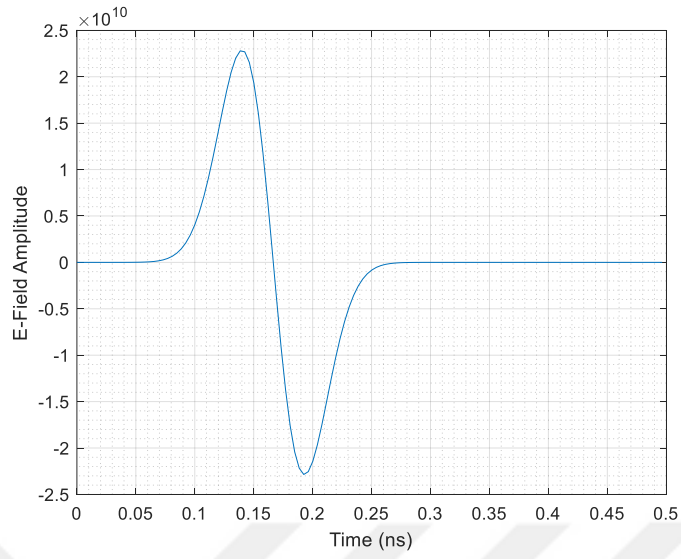


Figure 3.10 The input signal utilized in this thesis, time-domain Gaussian Derivative waveform.

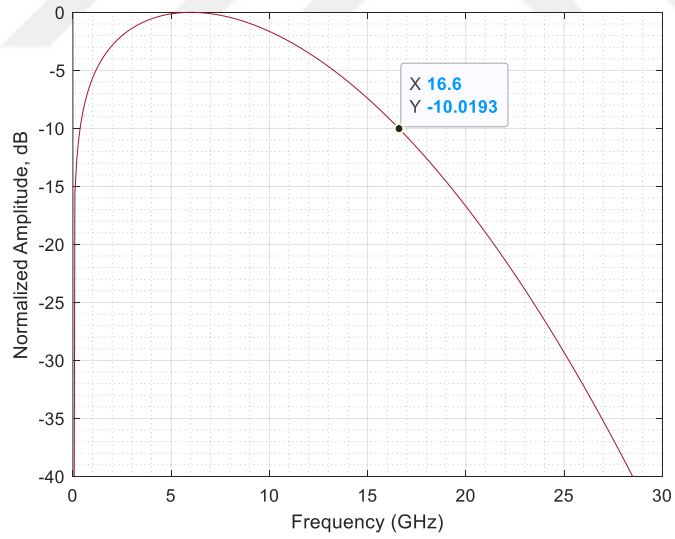


Figure 3.11 Magnitude of the Fourier transform (in dB scale) of the GPR input pulse shown in Figure 3.10.

In this thesis, all GPR data have been simulated using omnidirectional Hertzian dipole antenna elements.

In the second scenario, Scenario 2, to be studied in this section, the single antenna channel scans the target in down-track and cross-track directions as described in Figure 3.12. A total of 11 steps are taken both in down-track and cross-track directions. In this way, a GPR database with $11 \times 11 = 121$ A-scan signals are simulated for each buried PEC wire. All parameters are exactly the same in the Scenario 1 and Scenario 2 except the fact a two-dimensional scan is conducted in the second simulation scenario with a single antenna channel.

As shown in Figure 3.12 , the lower end of the PEC wire is located at ($x = 0$ cm, $y = 0$ cm), and the upper end is placed at ($x = 50$ cm, $y = 50$ cm). TX/RX antennas scan this wire by moving with 2 cm step sizes in both down-track and cross-track directions. The antenna pair moves from $y = 14$ cm to $y = 34$ cm along the down-track direction for each cross-track position while the transmitter antenna moves from $x = 14$ cm to $x = 34$ cm with 2 cm steps along the cross-track direction. As mentioned earlier, TX and RX antennas of the channel are aligned along the horizontal axis (x -axis, cross-track direction) with 2 cm separation.

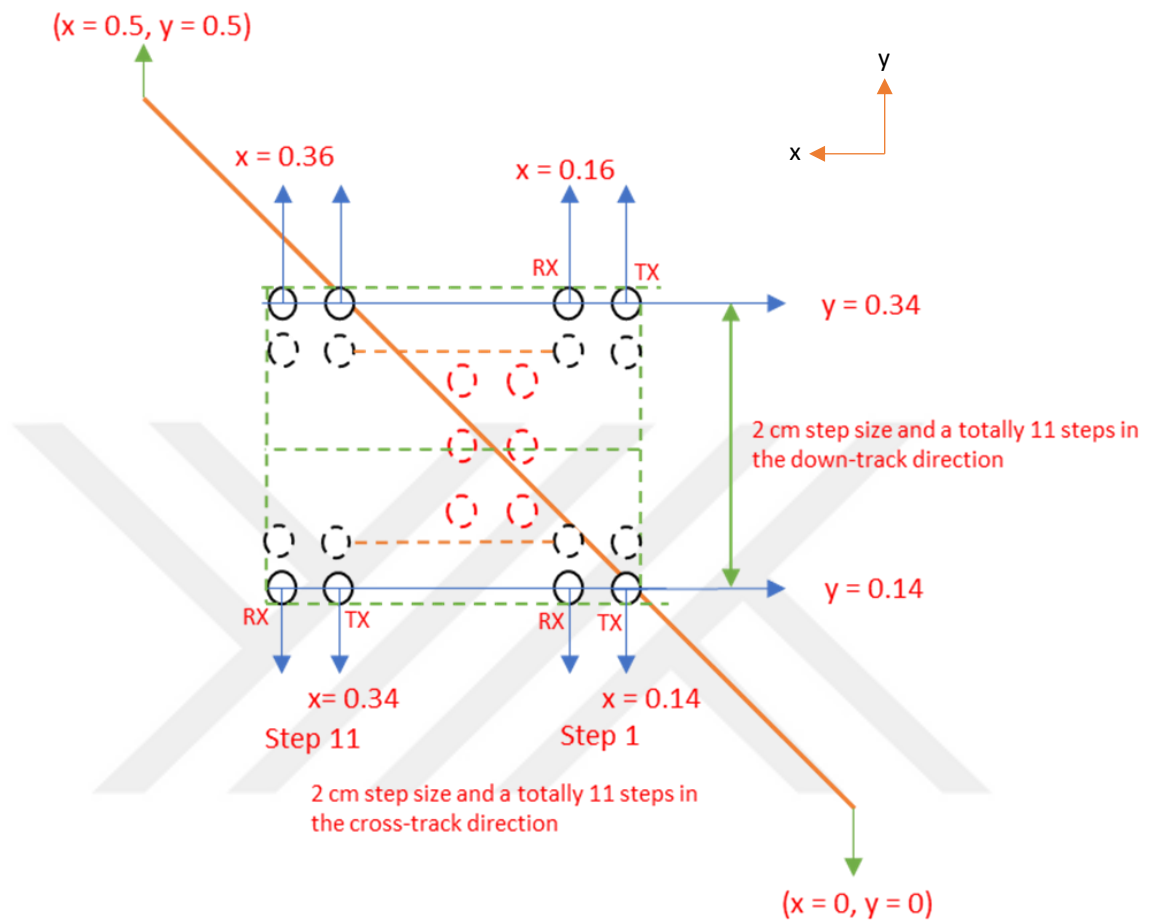


Figure 3.12 Geometry of the second GPR simulation scenario (Scenario 2) for PEC wire targets.

3.2.2 Parameter Selection of the Utilized Classifier

In Section 3.1.3, design steps of the proposed classifier are defined and described fully by flow diagrams. While designing a classifier, all the steps given in Figure 3.4 will be applied to the A-scan signals in the classifier reference database. In addition, final decisions can be made about the detection and classification of the targets with the comprehensive methodology given in Figure 3.3. When designing the classifier and following all the steps in Section 3.1.3, several parameters must be decided effectively.

One of the crucial steps is deciding on the optimal late-time partitions to create LTFVs. It means selecting optimal bands which represent the late-time response of the target effectively. As mentioned in the previous sections, the designed classifier uses the discriminative effect of the dominant target poles (Complex Natural Resonance (CNR) frequency) whose effects are implicitly provided in the late-time region of the target response. Detailed information about the indirect effects of system target poles, CNRs, LTFVs, and feature extraction mechanisms by using Page Distribution is given in the previous sections. As strongly emphasized, in this method, the partitioned energy density vectors are computed from the auto-PD matrices of scattered database signals with Q partition blocks. The total time span is divided into Q equally wide, non-overlapping time bands. As explained earlier, features will be obtained by selecting the proper bands within these bands that contain the most useful information on late-time target response and target system poles (CNR frequencies).

As in Turhan-Sayan's previous studies [33-34], the total number of bands, Q , is chosen as 16 in this thesis. In order to find the optimum Q value, different classifiers were designed by using the total number of bands 8, 16 and 32. The best classifier performance is obtained for $Q = 16$. In all the classifier design investigations conducted in this thesis, successful classification results are obtained when appropriate late-time bands are selected among 16 partitions. If the number of total bands selected is less than 16 (for example, 8), each band will contain twice more

terms and the time integrals taken over the time bands creates excessive smoothing leading to the loss of late-time signal characteristics and deteriorated classifier performance. If the Q value is selected more than 16 (for instance, $Q = 32$), it is observed that the performance of the classifier decreases due to an increase in aspect dependency leading to performance deterioration again. Therefore, the optimal value of Q is decided to be 16.

While selecting the onset of the appropriate late time bands, q^* , the scenario called as Scenario 1, which is described in Figure 3.9, will be investigated. First, CCF analysis will be performed for two different wires with different radii, 2 and 5 mm. These wires are buried at two different depths, 3 cm and 4 cm. Also, the targets have been scanned in the down-track direction only in Scenario 1. Six down-track steps have been used for the following investigation. In these steps, antennas are located near the center of the wire in the down-track direction ($y = 20\text{ cm}, y = 22\text{ cm}, \dots, y = 30\text{ cm}$ coordinates in the down-track direction). Therefore, CCF will be calculated for 12 different step-depth combinations for two targets altogether with $M_{tar} = 2$, $(M_{targ}^2 - M_{tar}) = 2$, $K = 12$ as follows:

$$CCF(q^*) = \frac{1}{(2)(144)} \sum_{i,j} r_{i,j}^{matched} - \frac{1}{(2)(144)} \sum_{i,j} r_{i,j}^{mismatched} \quad (3.22)$$

where $r_{i,j}^{matched}$ corresponds to the computed correlation coefficients for the matched case (same target), and $r_{i,j}^{mismatched}$ corresponds to the computed correlation coefficients for the mismatched case (different target). These correlation coefficient terms are obtained from the test and reference feature vectors for a band index q^* with the choice of a single, double, or triple successive bands design to compute the target features. The main goal to be achieved is to choose the design bands to obtain high correlation coefficients for matched targets and low correlation coefficients for mismatched targets. Also, the margin between the obtained correlation coefficients for matched and mismatched targets must be high enough to distinguish the different targets easily.

Initially, the CCF values were computed using only one band. Subsequently, the analysis was extended to examine cases where multiple bands were employed. Since I aim to design a classifier applicable to all scenarios and make the selected bands appropriate in all situations, more satisfactory results are expected to be obtained using more than one band. In particular, considering the presence of potential clutter signals that may persist in the late-time regions, multiple bands will be utilized to handle clutter effects better. Late-time target information can be characterized better in a longer time window while the undesired effects of clutters are minimized. By employing multiple bands, the impacts of dominant poles that endure for an extended duration can be more successfully observed.

After many investigations and analyses using the CCF concept and correlation coefficients, it was decided to use three bands. It means, $(q^*)^{th}$, $(q+1)^{th}$, and $(q+2)^{th}$ bands will be used to design of the classifier. When just one band is used, the CCF analysis results for each band are given in Figure 3.13. Furthermore, Figure 3.14 displays a bar chart illustrating the CCF results of this design, which incorporates the utilization of three bands. During the initial design phase of the classifier, many band alternatives were tried, and using the three partitions of the energy density vector, most accurate classification results were obtained. Considering the CCF values given in the figures, the bands to be used in the whole thesis process can be decided, and it will be confirmed that a successful band selection was made in all future scenarios. It should be noted that early-time effects i.e., reflections originating from the target including the secondary and multiple reflection effects are almost completely attenuated by the end of the fifth or at most sixth bands. The ideal bands to be used for the classifier design are observed to be the band $q^* = 8$ followed by $(q^* + 1) = 9$ and $(q^* + 2) = 10$. In other words, the partitioned time bands 8 to 10 are used as the late-time design period to create the features in this thesis work. Thanks to this band selection, the discriminative properties of the system target poles can be used effectively. It is also observed that aspect and polarization sensitivity is considerably reduced when LTFVs are created over these selected bands. At the same time, these bands are away from the low SNR

zone. In summary, with the optimal choice of $q^* = 8$ and using the bands 8, 9 and 10.

Figure 3.13 shows the CCF results when only one partition (band) is used. Also, Figure 3.14 shows the obtained CCF values when three bands (partitions of the partitioned energy density vectors) are used. Each q^* value in Figure 3.14 represents a set of bands that includes the corresponding q^* value and the two successive elements following it. For instance, $q^* = 8$ indicates the band consisting of partitions (bands) 8, 9, and 10 of the energy density vectors. The results obtained in Figure 3.13 and Figure 3.14 are consistent with each other, and successful classification results will be obtained in many different and challenging scenarios examined in this thesis using these three successive time bands. As mentioned before, in all studies in the continuation of this thesis, three successive time bands (8-10 bands) of the energy density vectors will be utilized to create features.

After this discussion, utilized LTFVs in this thesis can be given as follows:

$$LTFV\ Vector = [\bar{E}_8\ \bar{E}_9\ \bar{E}_{10}] \quad (3.23)$$

The terms $\bar{E}_8$, $\bar{E}_9$, and $\bar{E}_{10}$ can be calculated using the Equation (3.9) and Equation (3.10). Equation (3.23) is the modified version of the Equation (3.11) after selecting the appropriate late-time bands.

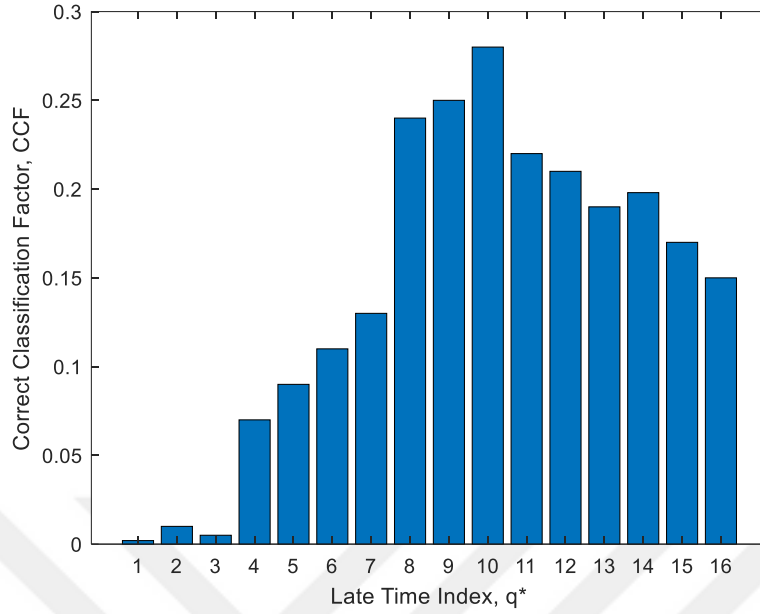


Figure 3.13 Correct Classification Factor (CCF) plotted against q^* to determine the optimal value q^* , just one band (partition) is used for this investigation.

As discussed in detail regarding classifier design, the test data consist of LTFVs, while the features to be stored in the library are FFVs derived by applying PCA to LTFVs. PCA technique is used for the generation of significantly aspect and polarization-independent features. As explained in Section 3.1.6, the PCA method is used for the purpose of multi-aspect feature fusion. In the same section, some assumptions about obtaining FFVs were mentioned. These assumptions will be proved mathematically with real scenarios. In addition, the CCF analyses will be repeated using the correlation coefficient values resulting from the comparison of the FFVs to be kept in the library and the testing LTFVs, then the assumption about the usage of principal components will be verified.

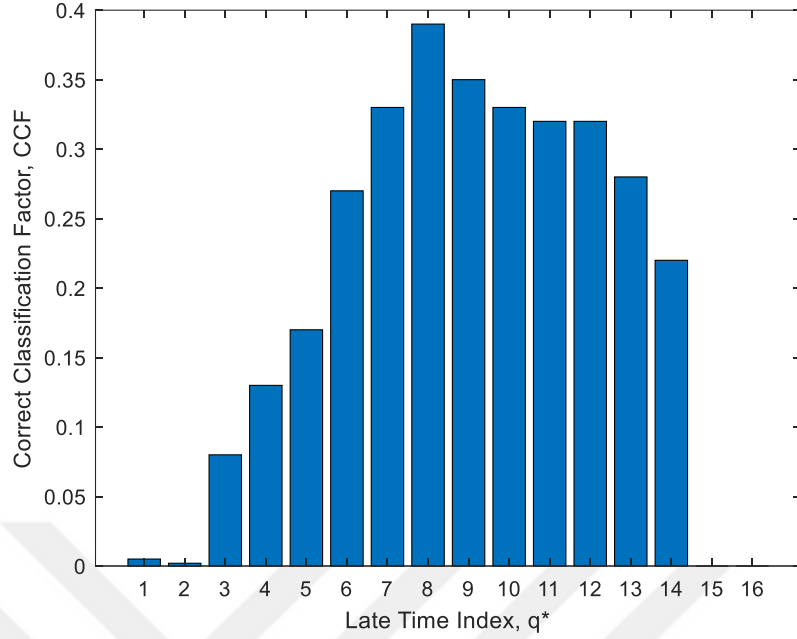


Figure 3.14 Correct Classification Factor (CCF) plotted against q^* to determine the optimal q^* , new bands were created using three partitions (q^* , $q^* + 1$, $q^* + 2$).

Successful classification results can be obtained by using a small number of reference features in our classifier. As mentioned in Section 3.1.6, FFVs reduce the aspect dependency of LTFVs. LTFVs belonging to several different steps and depths are fused by using the PCA technique, then FFVs are obtained. Since FFVs are robust against aspect and polarization variances, accomplished classification results can be obtained by using less number of reference features. In this example, only six reference features are used (instead of 12 features used in the previous case). The depth information will remain unchanged, but instead of six down-track steps, three steps will be utilized (specifically, $y = 20\text{ cm}$, $y = 24\text{ cm}$, $y = 28\text{ cm}$).

First, a feature matrix F will be obtained for six references, depths, and down-track steps combinations, according to Equation (3.13). The principal components $z_1, z_2, z_3, z_4, z_5, z_6$ of the matrix F are computed together with the related eigenvalues $\lambda_{\dots} (\dots = 1, 2, \dots, 6)$ where $\lambda_1 > \lambda_2 > \dots > \lambda_6$. By using obtained eigenvalues which are the variances of the corresponding principal components $z_1, z_2, \dots, z_6$, our claim can be proved. The leading principal component z_1 is the dominant principal

component to others if its variance λ_1 is much higher than the variances of other principal components.

The eigenvalues (variances of principal components), λ_i s and the percentage eigenvalues $100\bar{\lambda}_i$ for two different targets are given in Table 3.2.

It is seen that for both of the two targets, the variance of the first principal component z_1 , λ_1 , is dominant to others. This analysis proves that using only the first principal component is sufficient to generate reference features.

Table 3.2 Eigenvalues λ_i s and percentage eigenvalues $100\bar{\lambda}_i$ s of principal components for each target

Eigenvalues λ_i s for Each PEC Wire Target			Percentage Eigenvalues $100\bar{\lambda}_i$ s for Each PEC Wire Target		
Ordered Eigenvalues	2 mm radius wire (10^{-10})	5 mm radius wire (10^{-8})	Percentage Eigenvalues	2 mm radius wire	5 mm radius wire
λ_1	6.6476	1.4908	$\bar{\lambda}_1$	0.8167	0.8364
λ_2	1.2784	0.2052	$\bar{\lambda}_2$	0.1571	0.1151
λ_3	0.1388	0.0766	$\bar{\lambda}_3$	0.0171	0.0430
λ_4	0.0567	0.0069	$\bar{\lambda}_4$	0.070	0.0039
λ_5	0.0139	0.0028	$\bar{\lambda}_5$	0.0017	0.0016
λ_6	0.0037	8×10^{-35}	$\bar{\lambda}_6$	~ 0	~ 0

In addition to the analysis given in Table 3.2, our claim can be verified with the CCF calculation. Using (Equation 3.12), CCF can be calculated for this scenario. Since there are six depth/down-track steps combinations for reference FFVs and twelve depth/down-track steps combinations for LTFVs, the obtained CCF equation for this scenario can be given as follows:

$$CCF = \frac{1}{(2)(72)} \sum_{i,j} r_{i,j}^{matched} - \frac{1}{(2)(72)} \sum_{i,j} r_{i,j}^{mismatched} \quad (3.24)$$

In calculating CCF, different versions of FFVs will be used to make sure the usefulness of choosing FFV as equal to z_1 . Seven different alternatives of the FFV expressions will be used as:

$$FFV = \sum_{i=1}^6 \bar{\lambda}_i z_i \text{ and } FFV = z_i \quad \text{where } i = 1,2,3,4,5,6 \quad (3.25)$$

Table 3.3 shows the CCF values for 4 different versions of FFVs.

Table 3.3 CCF values for four different alternatives of FFVs based on different sets of principal components

Alternative fused feature vectors, z_{FFV}	$z_{FFV} = \sum_{i=1}^6 \bar{\lambda}_i z_i$	$z_{FFV} \cong z_1$	$z_{FFV} \cong z_2$	$z_{FFV} \cong z_3$
CCF	0.4006	0.4011	0.0911	0.0274

It is easily seen from Table 3.3 that the highest CCF value has been obtained when the first principal component z_1 is used to create FFVs of the investigated targets. Table 3.2 and Table 3.3 confirm our claim made in Section 3.1.6 that use of only the first principal component to create the FFVs is the right choice.

In this section, appropriate time band selection for generating LTFVs and assumptions for creating FFVs were examined in detail with real examples. The crucial observations and comparisons observed during classifier design will be explained in the following section, then the designed classifiers will be tested in many different scenarios.

3.3 Application of the Proposed Classifier to Basic Scenarios

Important design parameters such as $Q = 16$ and $q^* = 8$, and the length of the proposed classifier in the late-time region (3 successive bands: 8-9-10 are chosen) are determined so far in the previous sections. In this section, the implementation and performance testing for the classifier will be discussed.

First, the definition and explanation of different performance criteria for the proposed classifier will be discussed. Afterward, the performance analysis of the proposed classifier will be made for the two scenarios given in Figure 3.9 and Figure 3.12. In the last section, the designed classifier will be tested against noisy signals.

3.3.1 Parameter Selection of the Utilized Classifier

In this section, details will be given about the performance metrics of the utilized classifier. These performance metrics will be used in all applications presented in the thesis. The concept of CCF was mentioned in the previous sections, and a classifier design was obtained using this concept. CCF results are crucial to determine the optimal bands and for the overall design of GPR classifiers.

In addition to CCF results, the contour plots of correlation coefficients provide impressive visual interpretations about the performance of the classifier. Thanks to these figures, the matched and mismatched target blocks can be easily observed, and the unsuccessful target classification cases can be easily recognized. The unsuccessful classification cases breaking the expected pattern on a contour plot may be caused by false alarms or misclassification situations. Thus, the accuracy analysis of the classifier can be easily done with the help of these contour plots.

Furthermore, four performance metrics are going to be used in this thesis to compute correct decision rates of the classifiers as defined below:

- *Maximum reference match (MRM)*: The Maximum Reference Match (MRM) criterion identifies the reference signal/feature that has the strongest

correlation with the tested signal/feature. Then, the classifier assigns the target class associated with this reference as the final decision. MRM analysis can be easily performed with the help of contour plots of correlation coefficients.

- *Complete Class Match (CCM)*: Complete Class Match (CCM) looks for reference targets that have the highest correlation coefficient in all reference aspects with the test signal/feature. That is, if the correlation coefficient of the test feature is the highest with any target in all reference steps/depths/aspects, that test signal is matched with the target of that reference. As we use FFVs as the compact target features in the classifier reference database, the MRM and CCM criteria become the same for our classifier testing.
- *CCM – ψ %*: Complete class match with at least ψ percent contrast margin (CCM – ψ %) seeks to implement the CCM criterion while also adding a condition that ensures the maximum correlation coefficient for mismatched signals/features is at least ψ percent lower than the minimum correlation coefficient for matched signals/features. This additional requirement aims to decrease decision uncertainty and enhance the reliability of the classification process. In this thesis, CCM – ψ % criterion will be applied for different ψ values. For many studies, classifier performance will be examined for ψ is 5, 10, and 20.

The performances of classifiers will be examined using these methods. After the performance results are obtained, the correct decision rate percentages (R_{CD}) of the classifiers will be computed. The number of correctly classified test data according to a chosen performance metric gives the number of correct decisions, while the number of total test cases is given by the number of total decisions.

In that case, the correct decision rate (R_{CD}) can be expressed as follows:

$$R_{CD} = 100 \times (\text{number of correct decisions} / \text{number of total decisions}) \quad (3.26)$$

In addition to these methods, the accuracy concept will also be used frequently in examining classifier performance.

- *Accuracy*: Lower and upper limits of correlation coefficients are set for the “decision of matched target case” and for the “decision of mismatched target case”, respectively, between the LTFV feature of the test target and the FFV of each reference target. When the correlation coefficient between the test and reference data is higher than the matched criteria limit, our classifier says that we have a matched target, while the correlation coefficient between the test and reference data is lower than the mismatched criteria limit, our classifier says that we have a mismatched target. Thus, the number of true positive and true negative elements will be determined. The ratio of the total number of true positive and true negative test results to the total number of test cases (multiplied by 100) gives us the percentage accuracy value of the classifier. Establishing these upper and lower limits are crucial in the assessment of classifier performance. In all contour plots of correlation coefficients given in this thesis, the upper and lower limits will appear in the colorbar.

The mathematical expression of the classifier accuracy is given as follows:

$$Accuracy (\%) = \frac{(True\ Positive) + (True\ Negative)}{All\ Data} \times 100 \quad (3.27)$$

3.3.2 Overview of the Previous Trials of Classifier Design

In the previous sections, target features (LTFVs and eventually FFVs) are extracted to be used for target classification. In this section, to demonstrate the relative usefulness of these two types of target features, the A-scan reference signals themselves will be used directly in obtaining the correlation coefficient matrices in terms of correlation coefficients computed between the reference and testing datasets instead of comparing the extracted features for target classification.

In the previously defined Scenario 1 (described in Figure 3.9 of Section 3.2.1), thin PEC wires with two different radii (2 and 5 mm) are buried at six different depths (1, 2, 3, 4, 5, 6 cm). Buried targets were scanned with 11 steps in the down-track direction. In each scenario, only one target is buried in the soil. In this case, $(11 \text{ down-track steps}) \times (6 \text{ depths}) = 66$ reference A-scan signals are generated for one target. Therefore, 132 pieces of reference data are available in total for two targets.

In the first classification attempt, the late-time portions of the A-scan signals over the designated late time bands 8, 9 and 10 are isolated. Correlation coefficients within the set of 132 truncated A-scan signals are computed over the time range for all possible combinations of signal pairs. Figure 3.15 shows the contour plot of the computed correlation coefficients where the signals are ordered from 1 to 132 in both horizontal and vertical axes such that the first 66 signals belong to target 1 (2 mm radius wire) and last 66 signals belong to target 2 (5 mm radius wire). Therefore, in all contour plots given in this section, it is possible to define the diagonally located “matched target blocks” as

$$R_{H1} = \{(i, j) | i = 1, 2, \dots, 66 ; j = 1, 2, \dots, 66\}$$

for 2 mm radius wire (3.28a)

$$R_{H2} = \{(i, j) | i = 67, 68, \dots, 132 ; j = 67, 68, \dots, 132\}$$

for 5 mm radius wire (3.28b)

Contour plot elements other than these two diagonal blocks (taking place in the off-diagonal blocks) represent the mismatched target case. Also noted that scattered data of a given target are ordered with respect to their burial depth information within the 66-element data group such that the first 11 elements correspond to the data obtained from 1 cm depth data, the next 11 data from 2 cm depth case, and finally, elements 56 to 66 obtained from the wire buried in 6 cm. On the vertical axis, these signals are arranged in exactly the same order. In all the contour plots to be given in this section, the data are arranged in this specific order resulting in the matched target regions to be formed in the diagonal blocks R_{H1} and R_{H2} .

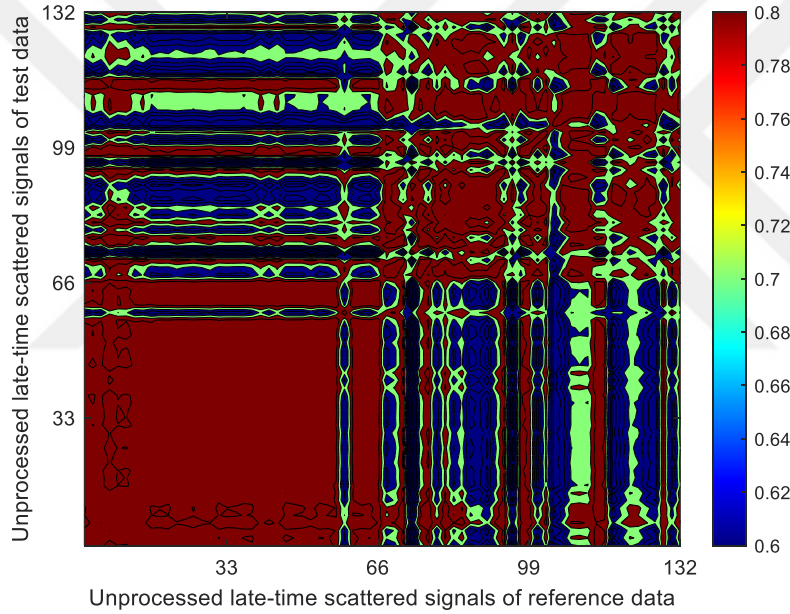


Figure 3.15 Contour plot of correlation coefficients computed for all possible pairs of test and reference data using the unprocessed late-time signals.

When Figure 3.15 is examined, many false alarms and misclassifications are noticed. Ideally, if the classification result were 100% correct, dark red color (corresponding to upper threshold of 0.8) was expected on the diagonal blocks for matched cases, and dark blue color blocks (corresponding to lower threshold of 0.6) should appear on the off-diagonal blocks for mismatched cases. Although four different blocks can be discriminated roughly in Figure 3.15, there are too many incorrect or ambiguous

results telling us that much better feature extraction in late-time region is needed. Detailed performance analysis for the correlation coefficient matrix seen in this contour plot will be given in Table 3.4.

In the second classification attempt, late-time features vectors (LTFVs) computed for each reference A-scan signals over the designated late time bands 8, 9 and 10 are used for the computation of correlation coefficients. The same ordering given in Equation 3.28 is used but LTFVs are used instead of A-scan signals in both axes of the generated contour plot (without using any PCA-based feature fusion). The resulting contour plot is presented in Figure 3.16 showing a much better formation of matched and mismatched target blocks. A contour plot of correlation coefficients for the investigation is given in Figure 3.16. Although there are some ambiguities within the matched blocks (greenish and blueish locations representing correlation coefficient values around 0.7), classification results within the mismatched blocks look very clear.

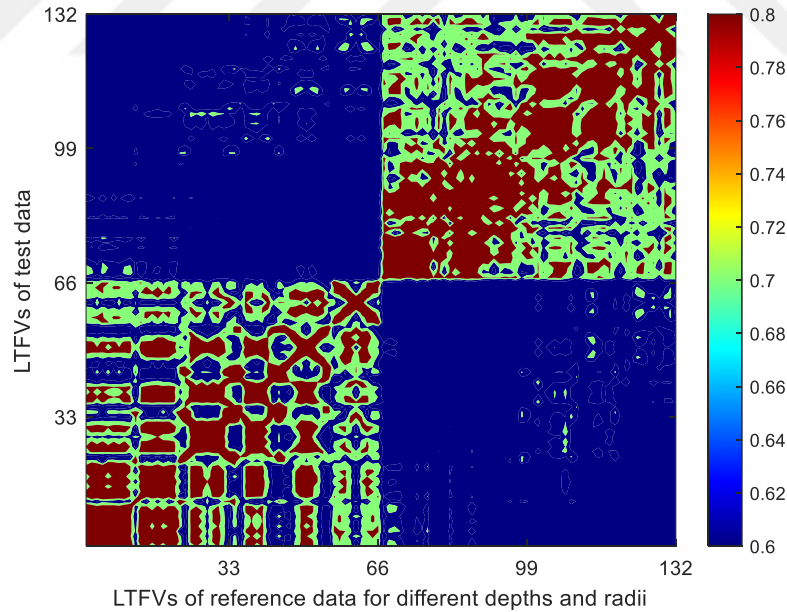


Figure 3.16 Contour plot of correlation coefficients computed for all possible pairs of test and reference LTFVs.

In other words, the classifier performance has improved considerably compared to the first attempt demonstrated in Figure 3.15. Detailed performance analyses of this second attempt will also be given in Table 3.4.

It is important to mention that by using LTFVs as both reference and test data, reasonable classification results can be obtained, and targets can be classified successfully for simple scenarios. However, false alarms and misclassification regions are still observed. In addition, it was observed that the performance of the classifier designed using only LTFVs decreased significantly for more challenging soil conditions, and in complicated multi-target scenarios.

Lastly, the relevant classification scenario was examined using the proposed classifier that makes use of FFV features (one FFV for each target) with the contour plot of correlation coefficients seen in Figure 3.17 with 100 percent accuracy with perfect 20 percent margin of discrimination between the matched and mismatched cases. In this contour plot, there are only two FFVs, one for each target but they are simply repeated 66 times each to make the correlation coefficient matrix a square matrix just like the others plotted in Figure 3.15 and Figure 3.16 to simplify the comparisons. There is a satisfactory margin between matched and mismatched regions. In this study, instead of selecting specific references to obtain FFVs, reference features are obtained for all step-depth combinations.

As a conclusion, the perfect result obtained by the use of FFV type aspect and depth invariant target features (seen in Figure 3.17) tell us that these two PEC wires with different thicknesses can be discriminated from each other even when they are buried at random depths ranging from 1 cm to 6 cm.

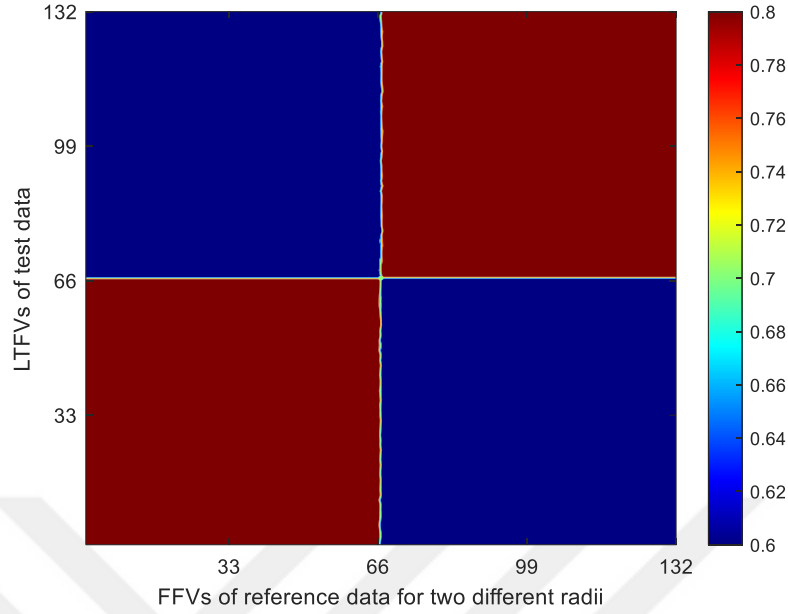


Figure 3.17 Contour plot of correlation coefficients computed for all possible pairs of test data and reference data using the testing LTFVs and reference fused feature vectors, FFVs.

Finally, in order to emphasize the importance of the selected bands in the classifier performance, a classification result obtained over a different late-time band will be given. Figure 3.18 shows the classification result (for LTFV-FFV comparison, the proposed method in this thesis) when the late-time band, 14-16 band, is used where the A-scan signals are attenuated to very small values being very sensitive to noise effects. The classification results seen in Figure 3.18 are poorer as compared to the results shown in Figure 3.17.

Performance comparison of the classifiers whose performance are shown in contour plots of Figure 3.15, Figure 3.16, Figure 3.17, and Figure 3.18 are summarized in Table 3.4 for different performance criteria.

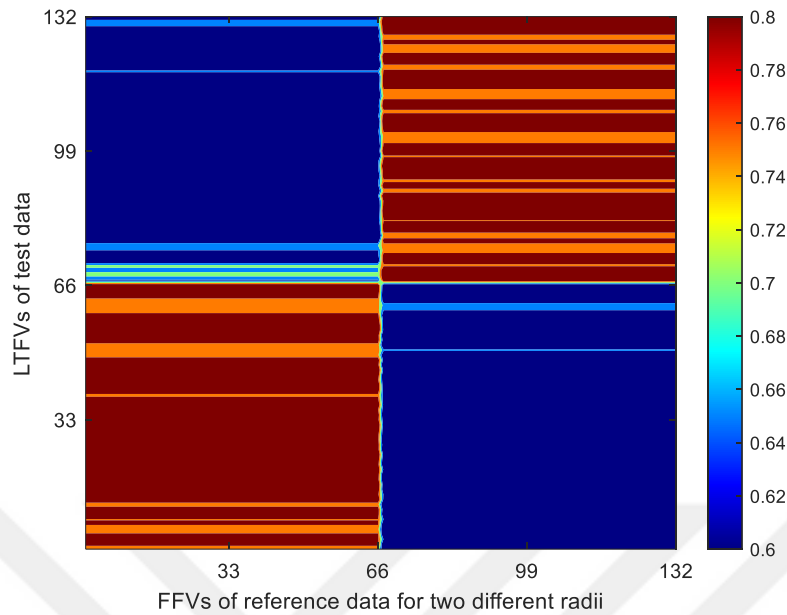


Figure 3.18 Contour plot of correlation coefficients computed for all possible pairs of LTFV-FFV comparisons using different band (14-16) from the selected one.

Table 3.4 Performance comparisons of different types of classifiers

	MRM	CCM	CCM 5	CCM 20	CCM 30	Accuracy for given limits
Scattered signal- based classifier (Figure 3.15)	88.6%	5.3%	0%	0%	0%	61.8%
LTFV-LTFV classifier (Figure 3.16)	98.3%	45.37%	37.9%	0%	0%	69.4%
LTFV-FFV classifier (Figure 3.17)	100%	100%	100%	100%	100%	100%
LTFV-FFV classifier with different bands (Figure 3.18)	100%	100%	100%	62.9%	51.5%	76.1%

3.3.3 Performance Analysis of the First Scenario

In this section, the classification results obtained for the Scenario 1 given in Figure 3.9 will be discussed. In the previous parts, LTFV-FFV pairs were obtained for all steps-depths combinations in this scenario. It has been observed that the classifier created by using all possible steps-depths combinations works with full success in all performance criteria. In this section, the whole data will be separated into two groups; the reference data to be used to design the FFV features of the classifier and the test data.

As mentioned before, data is collected for PEC thin wires buried at six different depths by running eleven steps in the down-track direction. There are two different wire targets with radii of 2 and 5 mm. Only a single wire is buried in each measurement. In other words, data is collected for $(2 \text{ different targets}) \times (6 \text{ different depths}) = (12 \text{ targets - depth combinations})$. This means 12 different simulations or measurements will be performed. Since there are 11 down-track steps in each measurement, there is a total of $(12) \times (11) = 132$ data pieces. 36 of them are reserved as reference data, and the remaining 96 as test data. In other words, one FFV will be created by applying PCA to 18 reference data for each target, and the same process will be done for the other target too. After creating two FFVs for two targets, LTFVs for 96 test data will also be generated, and correlation coefficient analysis will be performed.

Three depths were selected to obtain reference data for each target. The selected depths are 2, 4, and 6 cm. At the same time, FFVs were created by using six down-track steps at each depth. Considering the geometry given in Figure 3.9, selected down-track steps can be given in the down-track direction as, $(y = 18 \text{ cm}, y = 22 \text{ cm}, y = 26 \text{ cm}, y = 28 \text{ cm}, y = 30 \text{ cm}, y = 34 \text{ cm})$. These are the positions of the TX/RX antennas along the down-track direction.

The resulting data are assigned to axes of the contour plot in the following order: For each target, the data for the shallower depth is sorted by the down-track steps first.

By following this sequence, all data can be sorted systematically. Mathematically, this order can be given as follows. For any data array and/or feature type in each target, suppose that $F_{d,s}$ corresponds to any feature obtained from d^{th} depth and s^{th} down-track step. Obtained feature array F can be given as:

$$F = \{F_{1,1}, \dots, F_{1,11}, \dots, F_{d,1}, \dots, F_{d,s}, \dots, F_{d,11}, \dots, F_{6,1}, \dots, F_{6,11}\} \quad (3.29)$$

The contour plot of correlation coefficients obtained as a result of this scenario is given in Figure 3.19. In addition, the performance analysis using different criteria is given in Table 3.5.

In all contour plots where the 2- and 5-mm radii wires are examined, the FFV of the wire with a radius of 2 mm will be represented as W1, while the FFV of the wire with a radius of 5 mm will be represented as W2.

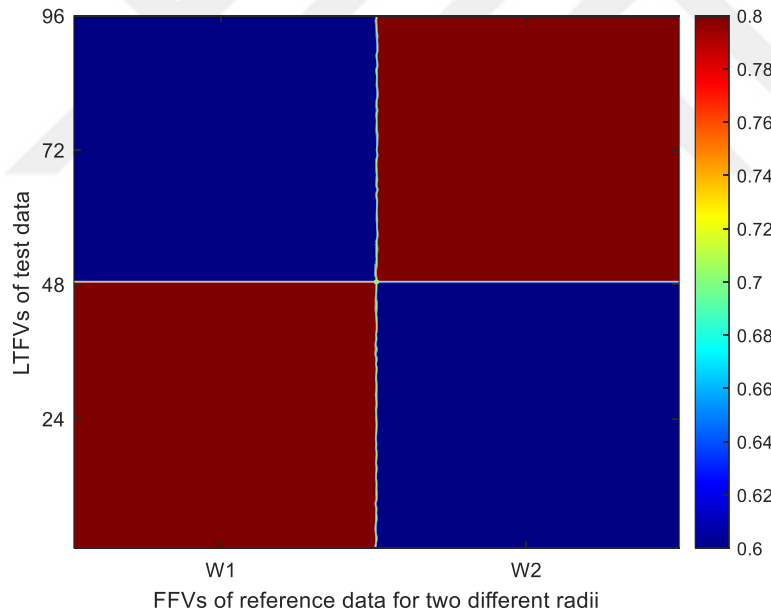


Figure 3.19 Contour plot of correlation coefficients for Scenario 1, 18 step-depth reference combinations used to create the corresponding single FFV for each target.

Furthermore, one more trial will be given. In this trial, while the number of reference data to be used for creating the FFV was decreased, the number of test data will be increased. While FFVs will be created with 6 data for each target (12 data will be used to create whole two FFVs), LTFVs will be generated with the remaining 120 data. Two depths were selected to generate FFVs. The selected depths are 3 and 5 cm. At the same time, FFVs were created using three down-track steps at each depth. Utilized down-track steps can be given as: ($y = 20\text{ cm}$, $y = 24\text{ cm}$, $y = 32\text{ cm}$).

The contour plot of correlation coefficients obtained as a result of this scenario are given in Figure 3.20. In addition, the performance analysis of this scenario using different criteria is given in Table 3.5.

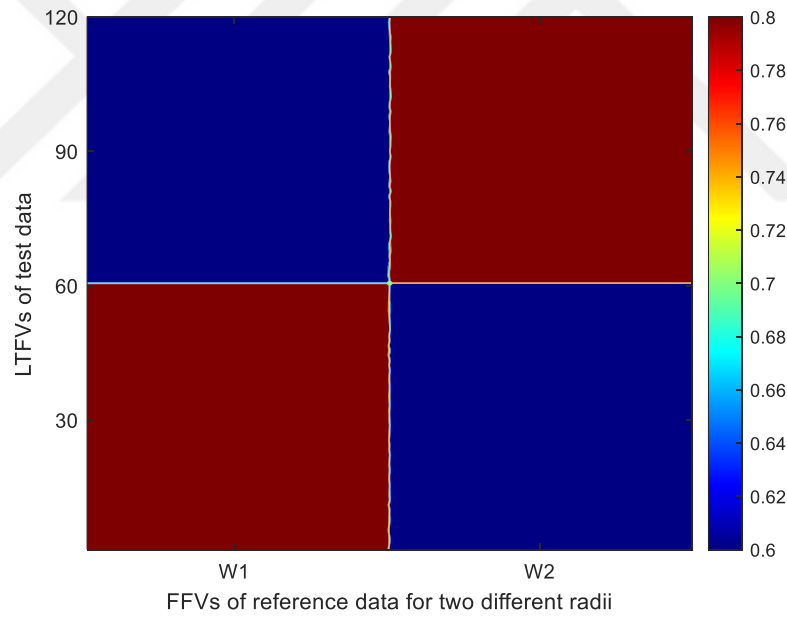


Figure 3.20 Contour plot of correlation coefficients for Scenario 1, 6 step-depth reference combinations used to create the corresponding single FFV for each target.

Table 3.5 Performance analysis (correct decision rates) of the utilized classifier in the Scenario 1

	MRM	CCM	CCM5	CCM20	CCM30	Accuracy for given limits
18 step-depth combinations used to create FFV for each target (Figure 3.19)	100%	100%	100%	100%	100%	100%
6 step-depth combinations used to create FFV for each target (Figure 3.20)	100%	100%	100%	100%	81%	100%

3.3.4 Performance Analysis of the Second Scenario

In this section, the performance of the classifier will be discussed for Scenario 2, given in Figure 3.12. Obtaining accurate classification results in Scenario 2 is harder than in Scenario 1 because it also includes cross-track steps, and data will be collected from a larger area. Therefore, the investigated wire target is scanned from various aspect angles while the RX antenna is capturing data even at distances where the signal level seriously diminishes. In this scenario, investigated wires are buried at four different depths (2, 3, 4, and 5 cm) and scanned with 11 down-track and 11 cross-track steps.

Therefore, there are a total $(4 \text{ depths}) \times (11 \text{ down-track steps}) \times (11 \text{ cross-track steps}) \times (2 \text{ targets}) = 968$ data will be collected. 128 of them will be used as reference data, and 840 of them will be used as test data.

Initially, FFVs will be created from the first four down-track and cross-track steps. That is, using all combinations of $(y = 14, y = 16, y = 18, \text{ and } y = 20) \text{ cm}$ down-track steps and $(x = 14, x = 16, x = 18, x = 20) \text{ cm}$ cross-track step pairs (all (x,y) combinational pairs of these coordinates) for two different targets at four distinct depths, 128 data will be used to generate reference features in this way. The remaining 840 data will be used as test data. This procedure is referred to as the *first trial of FFV selection* in this subsection.

The features in the contour plot of correlation coefficients are sorted in a similar manner to the previous section. For any data array and/or feature type in each target, suppose that $F_{n,i,j}$ corresponds to any feature obtained from n^{th} time/depth ($n = 1, \dots, N$), i^{th} cross-track step ($i = 1, \dots, I$), and j^{th} down-track step ($j = 1, \dots, J$). Obtained feature array F can be given as:

$$\begin{aligned}
 & \text{for } n = 1:N \\
 & \quad \text{for } i = 1:I \\
 & \quad \quad \text{for } j = 1:J \\
 & \quad \quad \quad \text{order } F_{n,i,j} \text{ where } F_{n,i,j} \text{ are the features} \\
 & \quad \quad \quad \text{end} \\
 & \quad \quad \text{end} \\
 & \quad \text{end}
 \end{aligned} \tag{3.30}$$

As can be seen in Figure 3.21, although the matched and mismatched blocks are well formed, a number of misclassified or ambiguous test results are also observed. It is observed that the performance of the classifier has decreased compared to the

previous trials. For this case, correct decision rates for different performance criteria are given in Table 3.6.

In order to solve this performance degradation problem, the following method will be developed. According to the approach given in Figure 3.3 and described in the relevant section (Step 3 of the given classifier design procedure), detection and classification processes support each other in a way that improves each other's performance. Proposed classification process can be carried out more successfully after deciding on the presence and locations of the targets using the approaches described in detail in Section 2.2.4. More accurate classification results were obtained with any test data when the reference features were created by selecting the measurement spots that were thought to contain more information about the target. For this reason, in the proposed classifier design approach, reference features will be extracted from peak target signal locations (in the eye of the target image) and neighbors of this point.

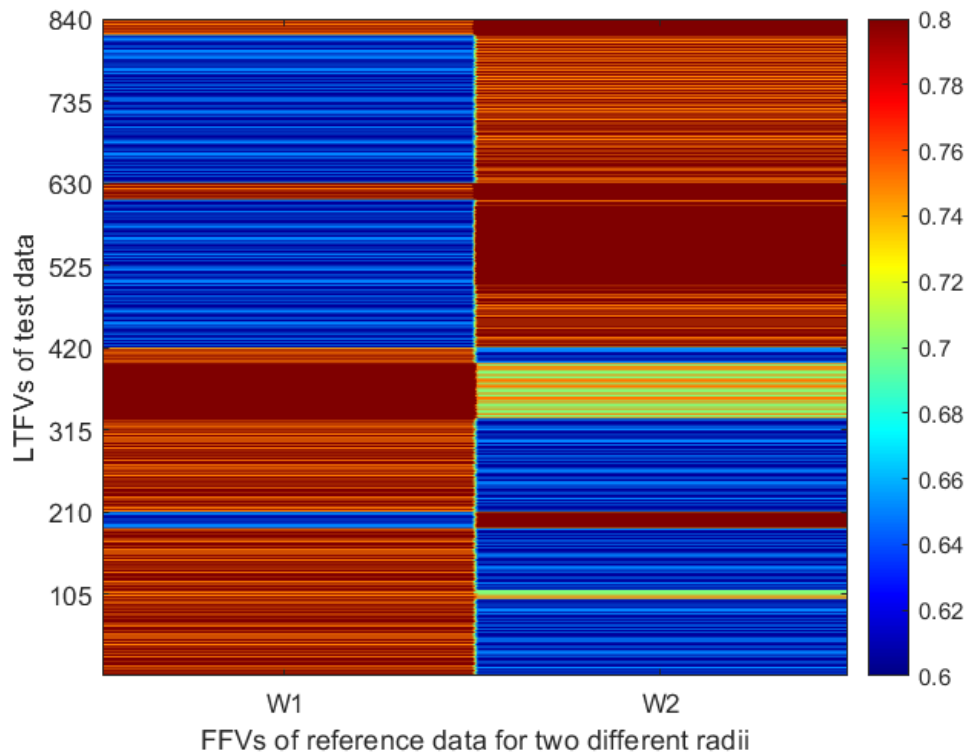


Figure 3.21 Contour plot of correlation coefficients for Scenario 2, with the first trial of FFV selection.

The energy heat map image of the examined buried wire (for example, for the wire buried at 3 cm) is shown in Figure 3.22. From this figure, better detection locations of the wire can be chosen, and the features can be generated from these points. To achieve this energy heat map, direct-coupled and ground-bounced clutter signals were eliminated. While obtaining the given figure, the direct background subtraction method was applied to eliminate these clutter/background signals. In addition, mean/median subtraction methods were also tried, and the same image and detection points were obtained as in Figure 3.22.

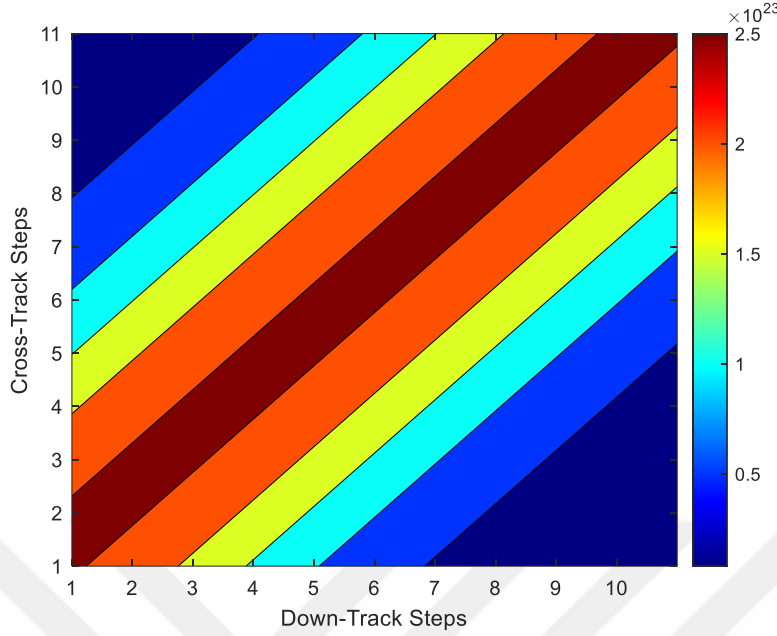


Figure 3.22 Energy heat map of the wire in Scenario 2

The highest energy line (darkest red line in the figure) observed in Figure 3.22 is exactly consistent with the geometrical location of the diagonally laid wire. While high energy densities continue both sides of the diagonal path; the energy decreases as we move away from the wire. By using four down-track and four cross-track steps around the center of the wire, the classifier can be successfully designed. Using the reference features obtained at points from down-track and cross-track steps in

$[(x, y) \in \{(22, 22), (22, 24), (22, 26), (22, 28), (24, 22), (24, 24), (24, 26), \dots$

$(24, 28), (26, 22), (26, 24), (26, 26), (26, 28), (28, 22), (28, 24), (28, 26), (28, 28)\}]$

cm, the FFVs will be obtained, and the classifier will be designed. Obtained contour plot of correlation coefficients for this approach (second trial of the FFV selection) is given in Figure 3.23.

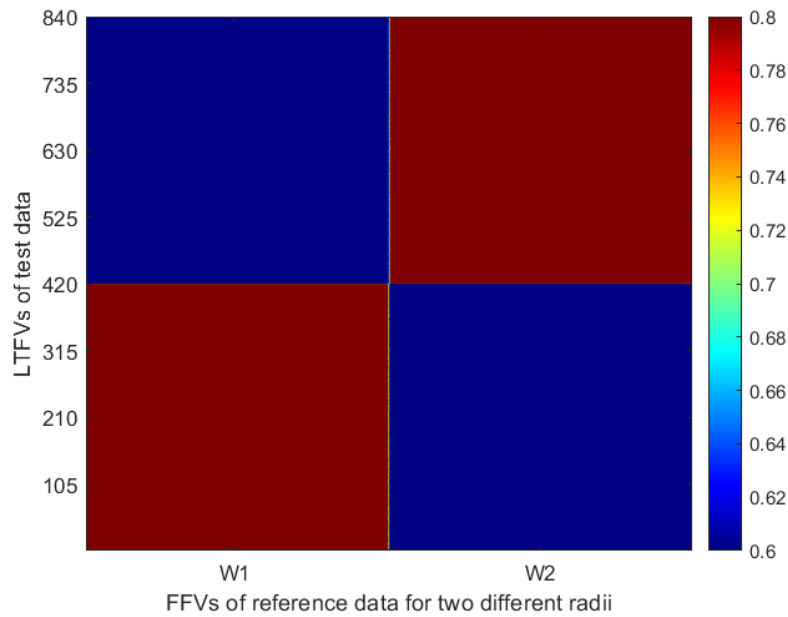


Figure 3.23 Contour plot of correlation coefficients for the Scenario 2, with the selected FFVs obtained from the locations where target is successfully detected (second trial of the FFV selection).

As can be seen from the figure, perfect classification results were obtained. There are no errors observed in the contour plot for the 0.6-0.8 correlation coefficient limits. Matched and mismatched areas are clearly formed without any ambiguity. Based on the performance criteria given in Table 3.6, it is observed that the classifier works quite successfully by using this approach as well. The approach of integrating detection and classification processes, as described in this section, will be employed extensively in the subsequent parts of the thesis. FFVs will be generated using data around the points where the target is successfully detected (from the eye of the target image and its close vicinity).

Table 3.6 Performance analysis of the utilized classifier in the second scenario

	MRM	CCM	CCM5	CCM20	CCM30	Accuracy for given limits
First trial of the FFV selection (Figure 3.21)	96%	96%	96%	81%	67%	83%
FFV selection by using detection mechanism, second trial (Figure 3.23)	100%	100%	100%	100%	88%	100%

3.3.5 Noise Performance of the Classifier

In this section, the noise performance of the designed classifier will be examined. For this purpose, a set of noisy test signals for the given scenario will be synthesized by adding white Gaussian noise (WGN) to the noise-free scattered time-domain A-scan signals, at the overall SNR level of 30, 20, 15, 10, 5, and 0 dB. This process was applied only to PEC wire with a radius of 5 mm and a burial depth of 4 cm.

Test LTFVs will be obtained using these synthesized noisy signals. Classifier performance analysis will be made by comparing these noisy test LTFVs, while the reference FFVs are obtained in the ideal environment and stored in the library. In this section, the investigated buried target is examined under Scenario 2. That is, the target is scanned with 11 down-track and 11 cross-track steps. So, 121 noisy LTFVs will be compared with the noise-free reference features.

It has also been mentioned in the previous sections that successful classification results can be obtained by using even a small number of reference features due to their significantly aspect, depth, and polarization-independent nature. Based on this information, 12 noise-free features are extracted from the library for each target $W1$ and $W2$ (2 mm and 5 mm radius PEC wires) and used in the classification design process to obtain FFVs. These features are selected from the region around that is the geometrical center of buried wires. In addition to three different depths (4, 5, and 6 cm), four down-track and cross-track steps combinations $[(x = 24, y = 24), (x = 24, y = 26), (x = 26, y = 24), (x = 26, y = 26)]$ cm] utilized for the FFV generation. Thus, LTFVs (obtained from noisy test signals) will be compared with the designed noise-free FFVs from the library, and the classifier performance analysis will be performed. Obtained features will be sorted in the contour plots as in Equation (3.30).

Examples of noisy A-scan signals with different SNR levels are given in Figure 3.24. White Gaussian noises are added to the entire signal, and since we are focusing on the late-time region of the signal, the effect of the added noises is strongly emphasized. The corresponding effective SNR levels over the selected late-time band (8-10 band) will be much lower than the overall SNR levels of the entire noisy signals.

In light of all these discussions, the classifier performance will be measured for the given scenario and using noisy test signals with different SNR levels. Furthermore, obtained accuracy values and correct decision rates using different performance criteria for all cases are given in Table 3.7. Figure 3.25 gives the obtained contour plots of correlation coefficients of all examined cases for scenarios generated from distinct LTFV testing features with different SNR levels, and noise-free reference FFVs.

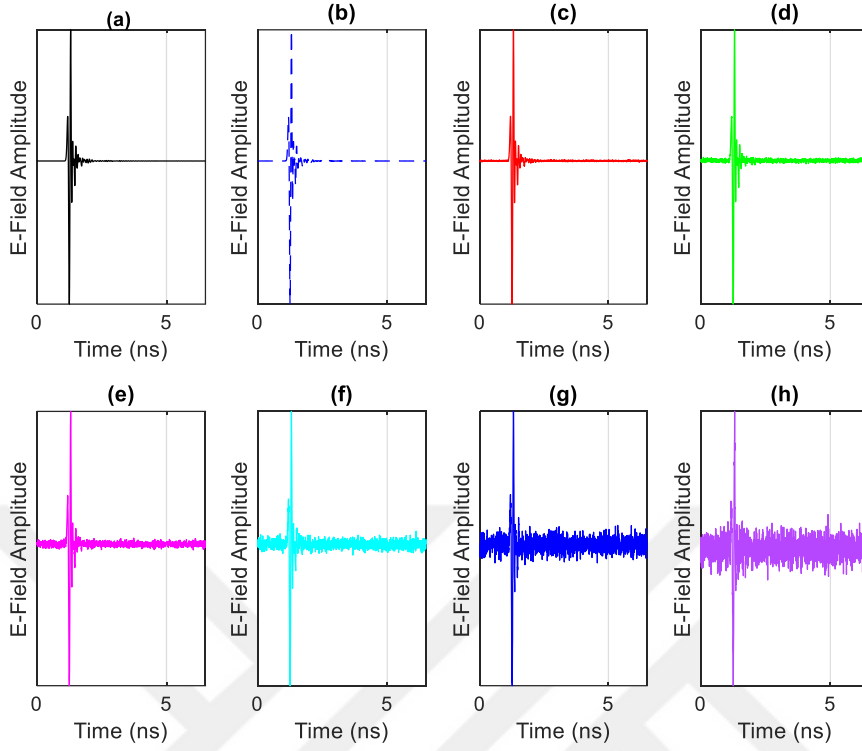


Figure 3.24 Noisy A-scan signals with (a) Infinite (b) 75 dB (c) 30 dB (d) 20 dB (e) 15 dB (f) 10 dB (g) 5 dB (h) 0 dB SNR levels for 5 mm radius PEC wires.

As can be interpreted from these investigations, while the classifier was working quite successfully with LTFVs obtained from signals whose SNR levels are *30 and 20 dB*, it started to deteriorate for signals whose SNR levels are *15 and 10 dB*, and many false alarms/misclassifications were observed for *SNR = 5 and 0 dB levels*. At these SNR levels of the time-domain signals, classifier performance was severely reduced. When examined in more detail, although the targets can be discriminated for *SNR = 15 and 10 dB* levels, false alarms and misclassifications were observed, albeit with a small amount, while false alarms/misclassifications were observed more frequently for signals whose *SNR = 5 and 0 dB*. In addition, at *SNR = 5 and 0 dB* levels, targets can be confused with each other and incorrectly classified for many different down-track and/or cross-track steps.

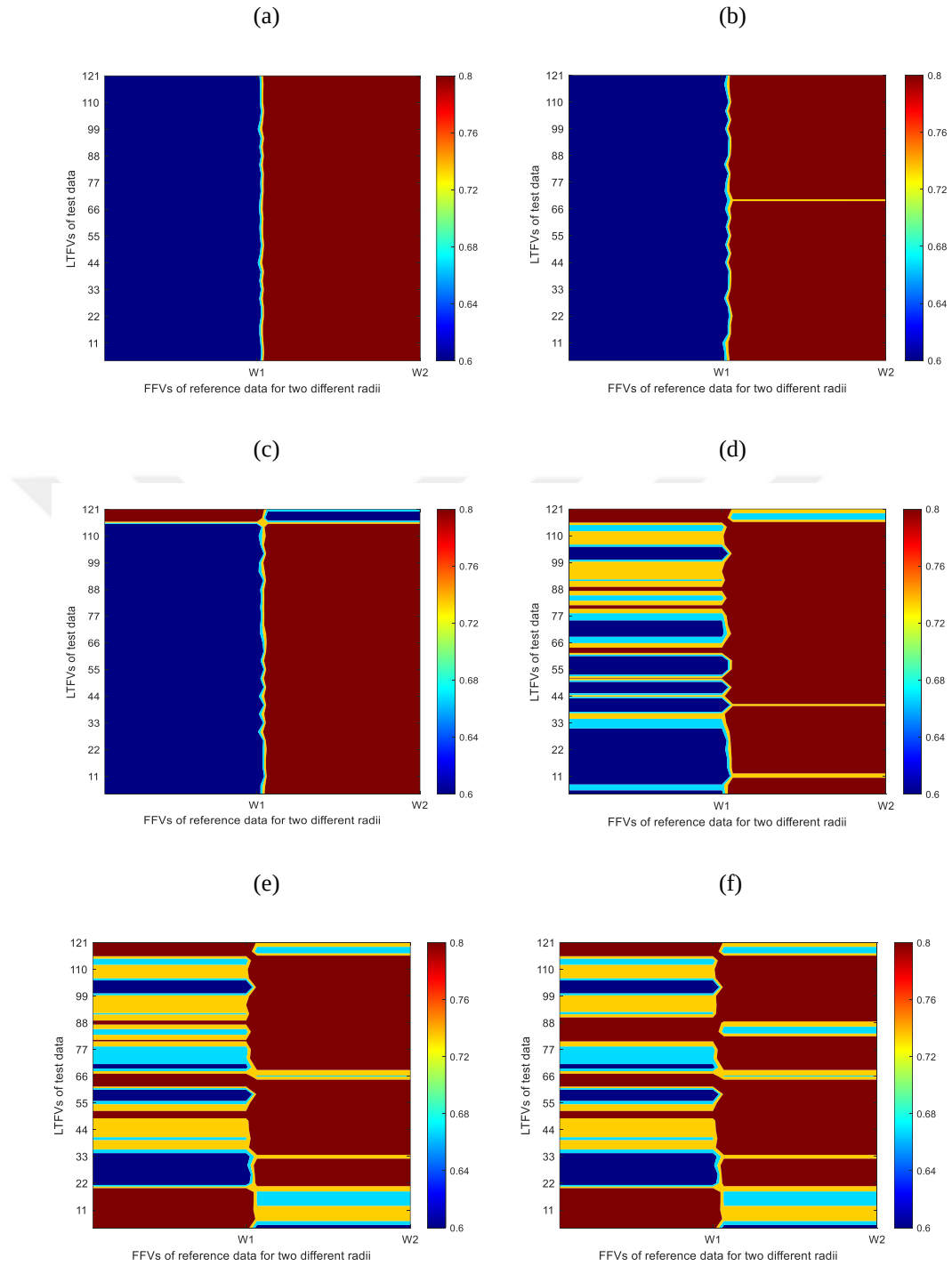


Figure 3.25 Contour plots of correlation coefficients for the given scenario, where the FFVs are obtained from noise-free signals, and LTFVs are obtained from noisy time domain signals with (a) 30 dB (b) 20 dB (c) 15 dB (d) 10 dB (e) 5 dB (f) 0 dB SNR levels.

An effective approach which has been suggested earlier in [157,164] is applied to our problem to improve the noise performance of our classifiers. Suppose the classifier is trained in a slightly noisy environment, meaning that the FFVs are generated using signals that contain certain levels of noise. In that case, the performance of the classifier in noisy test environments will improve significantly. In order to demonstrate this approach, the classifier was trained in a noisy environment. SNR levels of the time-domain signals have been equated to 30 dB and 20 dB levels, then FFVs have been obtained using these signals generated/collected in the slightly noisy environment. The classification process has been repeated using the new, slightly noisy FFVs. The FFVs obtained from signals whose SNR = 30 dB and the LTFVs obtained with the SNR = 10 dB and SNR = 15 dB signals will be compared and correlation coefficients will be obtained for these investigations. In addition, the FFVs obtained using the signals at the SNR = 20 dB level will also be compared with the LTFVs obtained from the signals whose SNR = 5 dB level, which is quite noisy. Contour plots of these three examinations are given in Figure 3.26. In addition, performance results are also included in Table 3.7.

As seen in Figure 3.26, classification performance improved significantly when the classifier is trained with slightly noisy signals. If reference features are obtained using signals with a 30 dB SNR level, a significant improvement in the classifier's performance is observed. Figure 3.27(c) shows that reference features generated using signals at 20 dB SNR levels and test features created using signals at 5 dB SNR levels give the desired correlation coefficient values at the specified limit. In this case, the classifier works with nearly one hundred percent success.

Although obtained results are so satisfactory for challenging noisy test features, the classifier performs poorly against the noise-free test features when noisy reference features are utilized. In this case, it is important to select reference features based on the noise levels of the environment/system that can be expected and to keep several alternative reference features in the system's feature library.

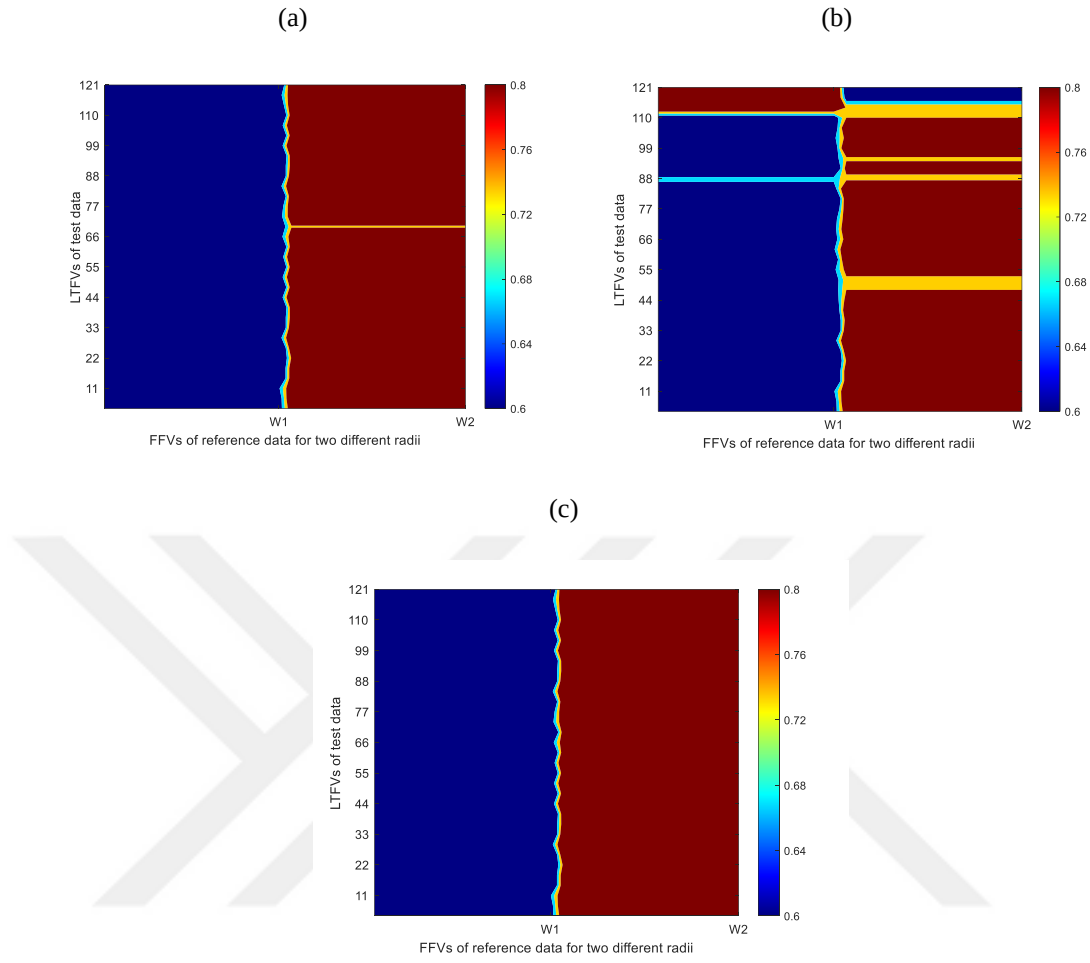


Figure 3.26 Contour plots of correlation coefficients for the given scenario, consist of FFVs obtained from noisy time-domain signals at (a) 30 dB (b) 30 dB (c) 20 dB SNR levels, and LTFVs obtained from noisy-time domain signals at (a) 15 dB (b) 10 dB (c) 5 dB SNR levels.

Table 3.7 Comparison of the noise performances of various GPR classifiers designed in Chapter 3

	MRM	CCM	CCM5	CCM10	CCM20	Accuracy for given limits
Classifier given in Figure 3.25 (a)	100%	100%	100%	100%	100%	100%
Classifier given in Figure 3.25 (b)	100%	100%	100%	100%	97.5%	98.7%
Classifier given in Figure 3.25 (c)	97.5%	97.5%	95.8%	93.4%	85.2%	93.4%
Classifier given in Figure 3.25 (d)	95.8%	95.8%	92.5%	87.6%	81%	64%
Classifier given in Figure 3.25 (e)	67%	67%	61%	55.3%	33%	40.5%
Classifier given in Figure 3.25 (f)	57.8%	57.8%	50.4%	46.3%	33%	37.6%
Classifier given in Figure 3.26 (a)	100%	100%	100%	100%	97.5%	98.3%
Classifier given in Figure 3.26 (b)	90%	90%	90%	90%	84.3%	86.7%
Classifier given in Figure 3.26 (c)	100%	100%	100%	100%	98.3%	100%

CHAPTER 4

DETECTION AND CLASSIFICATION OF SHALLOW-BURIED MULTIPLE TARGETS LOCATED IN CLOSE PROXIMITY

The main theme of this chapter is the detection and classification of multiple targets, which are located quite close to each other so that the electromagnetic interactions between the target responses highly complicate the GPR problem. The proposed detection and classification methods described in the previous chapters will be applied to such multi-target scenarios with some additional modifications. Modern GPR systems are designed almost always as multi-channel sensors integrated with antenna array structures. Before starting to examine the multi-target GPR problem, effects of using antenna arrays on target detection performance of GPRs will be investigated in the first section of this chapter.

4.1 Accuracy Issues in GPR Detection due to Antenna Array Effects

Design of multi-channel GPRs with antenna arrays of two or more transmitter/receiver antenna pairs have been common in both academia and industry [1-2], [141]. For the thin wire applications presented in the third chapter, a single channel antenna system was assumed in the gprMax simulations so that the whole search domain was scanned in both down-track and cross-track directions by a single pair of transmitter/receiver antennas. Such single-channel GPR designs may be feasible for portable hand-held devices, but they are obviously too slow while scanning a large area. Also, a systematic formation of 3D C-scan data with consistent spatial resolution may be difficult with a single-channel antenna system posing further problems in post-processing of GPR output data. Use of multi-channel GPR systems with antenna array panels is a necessity for most of the higher-level

subsurface sensing tasks. Accordingly, an 8-channel GPR using a collinear antenna array will be modeled in all gprMax scenarios to be studied in this chapter.

In certain applications such as the detection of shallow-buried low RCS targets, use of multi-channel GPRs may have adverse effects on the GPR's target detection performance due to direct (DC type) and indirect (GB type) mutual coupling effects introduced by the chosen antenna array structure. This important issue will be discussed in this section in detail.

4.1.1 Definition of Coupling Signals Between TX-RX Antennas for Multi-Channel GPRs

In this section, a down-looking GPR topology with a collinear antenna array will be modeled in gprMax with eight pairs of transmitter/receiver (TX/RX) antennas as shown in Figure 4.1. Omnidirectional, x-polarized Hertzian dipole antenna elements are used for both transmitter and receiver antennas in this 8-channel array to observe the effects of mutual coupling phenomena clearly.

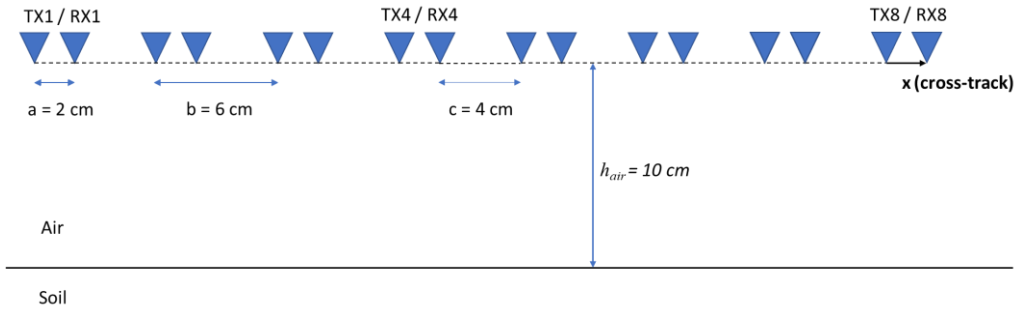


Figure 4.1 Collinear antenna array topology used in gprMax simulations.

As shown in the figure, the period of the array is $b = 6 \text{ cm}$ and the distance between the transmitter and receiver antennas in each channel is $a = 2 \text{ cm}$. The antenna array is placed $h = 10 \text{ cm}$ above the air-soil boundary, extending along the cross-track axis.

Fundamental types of coupling mechanisms encountered in such a multi-channel GPR (having an antenna array system) are summarized in Figure 4.2.

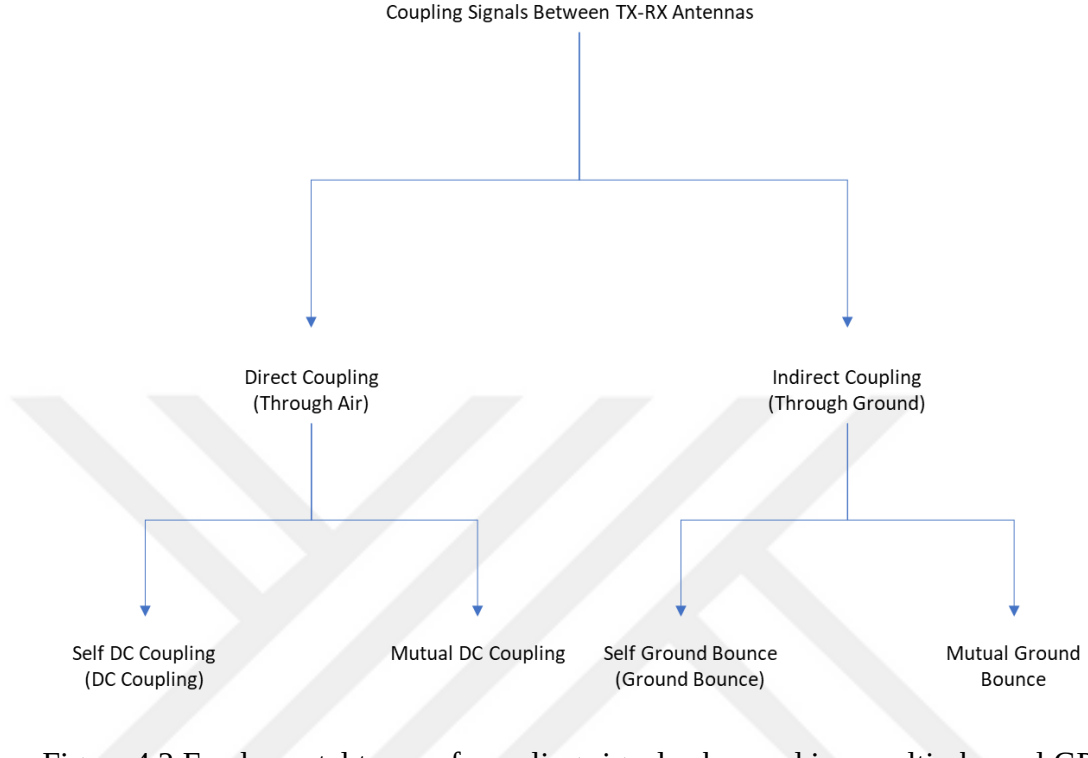


Figure 4.2 Fundamental types of coupling signals observed in a multi-channel GPR with an antenna array system.

The terminology used for the coupling types in this thesis is given below:

Self-Direct Coupling: It results from the coupling of excitation pulse radiated by a transmitting antenna TX_i to the receiving antenna RX_i while propagating in air within the same (i^{th}) channel of the array. The self-DC terms are observed both in single-channel and multiple-channel systems. As the distance between TX_i and RX_i is usually small in almost monostatic channels, the self-DC terms become very strong. In practical systems, various techniques are used to isolate transmitter and receiver antennas to minimize self-DC signals to protect the receiver from saturation. However, even a small amount of self-DC leakage may be strong enough to mask the presence of other signal components of an A-scan signal like the target return and even the ground-bounced signal.

Mutual-Direct Coupling: It results from the coupling of excitation pulse radiated by a transmitting antenna TX_i to a receiving antenna RX_j while propagating in air where $i \neq j$. Mutual-DC signals are observed in only multi-channel GPR systems with antenna arrays.

Self-Indirect Coupling: It can be also called *Self-Ground Bounce (Self-GB)* type coupling as it results from the coupling of excitation pulse radiated by a transmitting antenna TX_i to the receiving antenna RX_i within the same (i^{th}) channel after being reflected by the air-soil boundary. The self-GB terms are observed both in single-channel and multiple-channel systems. It is the second largest signal component (after the self-DC term) observed in A-scan data. Therefore, even if the self-DC term of an A-scan signal is eliminated, the remaining self-GB term can still mask the presence of a buried target unless the target is a large metallic object such as an anti-tank mine.

Mutual-Indirect Coupling: It can be also called *Mutual-Ground Bounce (Mutual-GB)* type coupling which results from the coupling of excitation pulse radiated by a transmitting antenna TX_i to a receiving antenna RX_j (where $i \neq j$) after being reflected by the air-soil boundary. Obviously, this type of coupling signals observed only in multi-channel GPR systems.

As expected, the strengths of mutual-DC and mutual-GB terms become smaller as the distance between the interacting channels gets longer. However, the antenna channels in close proximity can interact with each other quite strongly, leading to the formation of effective direct-coupled and ground-bounced signals with extended time durations. Especially, the effective ground-bounced signals may cause serious performance degradations in GPRs in the detection of shallow-buried targets with small RCS such as dielectric antipersonnel mines buried a few centimeters below the soil boundary. These discussions will be demonstrated in the next section using the shallow-buried target scenario described earlier in Figure 2.17 in Section 2.2.4.

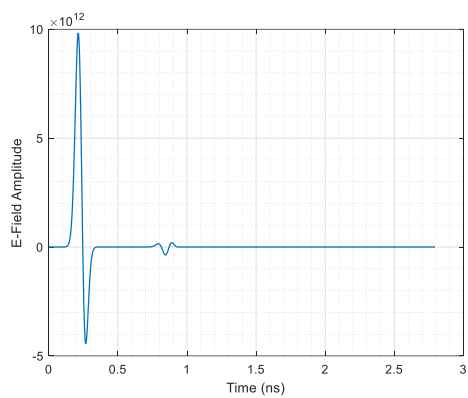
4.1.2 Investigation of the Self and Mutual Coupling Signals in the Presence of a GPR Antenna Array

In this section, a set of controlled simulations will be presented for the basic GPR scenario with an 8-channel collinear antenna array described in Figure 4.1 where the soil is homogeneous dry sand with a flat air-soil interface, and there is no object buried in sand. To isolate the individual self and mutual, DC and GB coupling terms caused by the given antenna topology, the transmitting antenna of only one channel, TX_{i^*} where $i^* \in \{i = 1, \dots, 8\}$ will be allowed to transmit the GPR pulse in a given simulation. In the meantime, all the channels are allowed to receive the resulting self/mutual DC/GB signals ($DC_{i^*,j}$ and $GB_{i^*,j}$) by their receiving antennas RX_j for $j = 1, \dots, 8$. This simulation is repeated for each transmitter antenna for $i = 1, \dots, 8$. Thus, the arrival times, amplitudes and phase characteristics of individual self or mutual coupling terms received at each GPR array receiver can be identified separately.

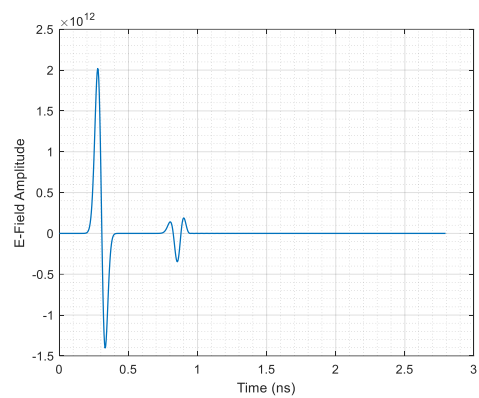
If all the channels were allowed to transmit simultaneously, the overall signal that would be received by a selected receiving antenna RX_{j^*} can be obtained by superposing the terms DC_{i,j^*} and GB_{i,j^*} for $i = 1, \dots, 8$.

Figure 4.3 illustrates the simulation scenario described above for the receiving antenna RX_1 of the GPR Channel-1 where each of the transmitting antennas is excited one at a time in this target-free problem. As expected, the strongest signal coupling is observed from TX_1 to RX_1 with the shortest delay time as these two antennas are separated from each other by only 2 cm. On the other hand, the weakest coupling signals with the longest delay time are due to TX_8 , that has the largest distance to RX_1 . Comparing Figure 4.3(a) and Figure 4.3(h), it is seen for example, that the mutual DC term due to the 8th channel's transmitter antenna is about 0.15 percent of the self-DC term of the first antenna channel. It should be also noted that the antenna coupling effects are investigated by these simulation results in a worst-case scenario under the assumption that no isolation measures are taken to minimize coupling effects between the omni-directional Hertzian dipole antenna elements.

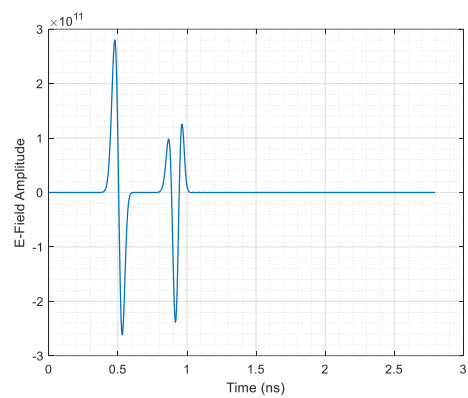
(a)



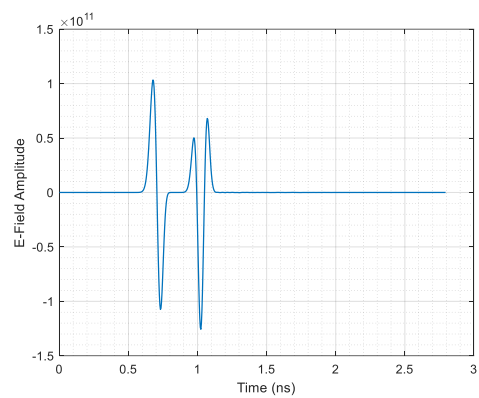
(b)



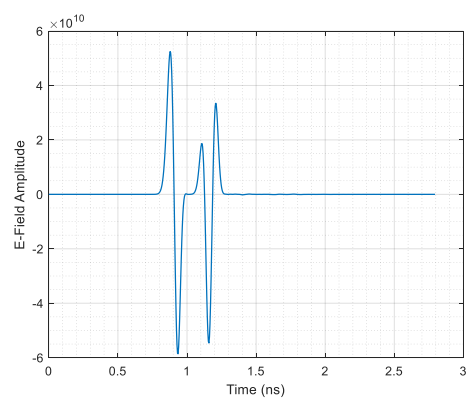
(c)



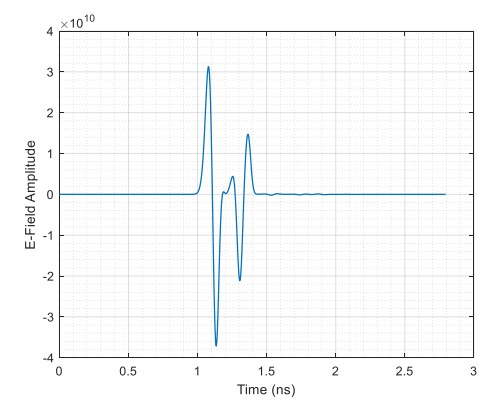
(d)



(e)



(f)



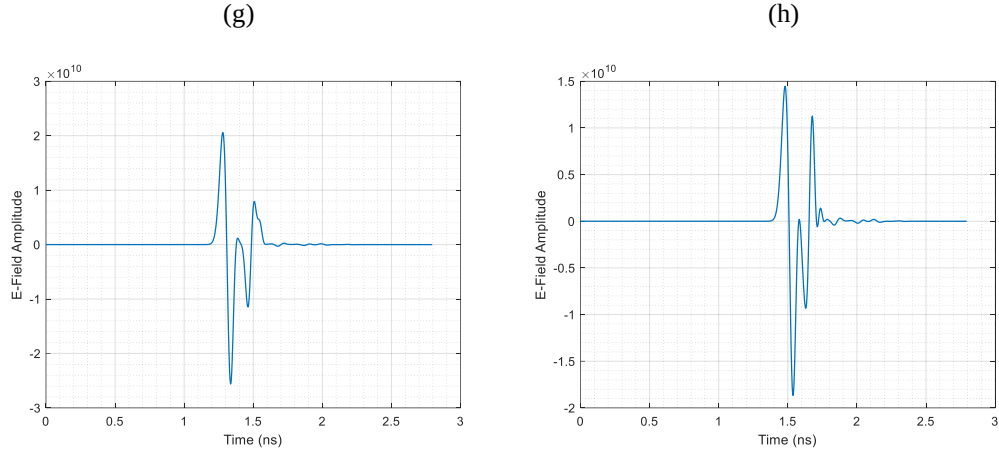


Figure 4.3 For target-free scenario, the observed self/mutual direct coupling and self/mutual ground bounce signals on the RX_1 antenna, originating from (a) TX_1 (b) TX_2 (c) TX_3 (d) TX_4 (e) TX_5 (f) TX_6 (g) TX_7 (h) TX_8 transmitting sources.

Figure 4.4 shows the superposition of the signal components given in Figure 4.3(a) through Figure 4.3(h), which is the total coupling signal to be received by the RX_1 if all of the channels transmit at the same time. Comparison of Figure 4.3(a) and Figure 4.4 clearly shows the effects of mutual coupling mechanisms due to the presence of this antenna array. The waveform and the effective time span of the received signal will be different at each receiver antenna of the array.

Arrival times of the peak points of self and mutual directly-coupled (DC) and ground-bounced (GB) signals are listed in Table C.1. and Table C.2, respectively, in Appendix C. Arrival times of ending points of self and mutual DC and GB signals are also listed in Table C.3 and Table C.4, respectively. Those ending points are important to know if a simple time-gating method is going to be used to remove DC and GB clutter components.

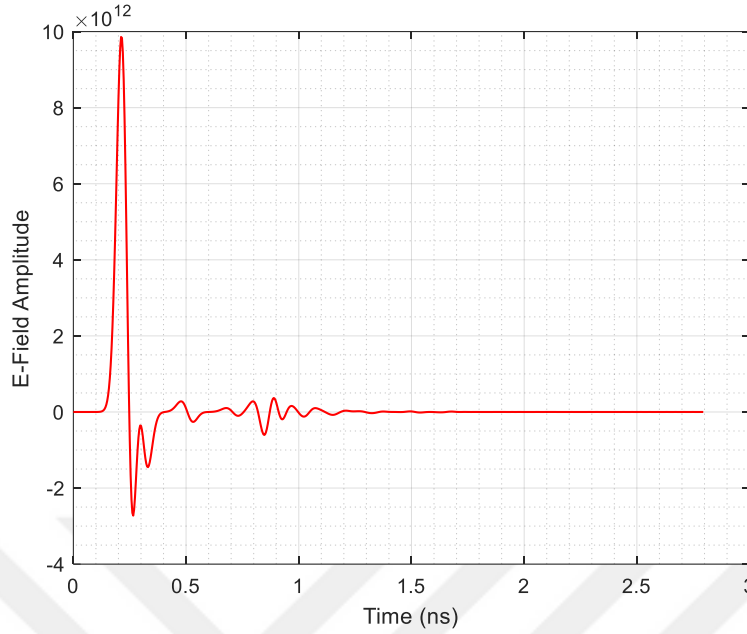


Figure 4.4 The total coupling signal, consisting of self/mutual direct coupling and self/mutual ground bounce signals observed in the RX_1 antenna, originates from all transmitter sources.

Assuming that the transmitter antenna TX_m emits the GPR pulse at the initial time $t = 0$, arrival times of the leading edges of direct-coupled and ground-bounced signals, at the receiver antenna RX_n can be computed as:

$$T_{DCS_{mn}} = \frac{\ell_{mn}}{c} \quad (4.1)$$

$$T_{GBS_{mn}} = \frac{h_{mn}}{c} \quad (4.2)$$

where the parameter ℓ_{mn} shows the line-of-sight distance in air between TX_m and RX_n in the array configuration shown in Figure 4.1. The parameter h_{mn} is the total path length of the ground-bounced signal in air from TX_m to RX_n such that the reflection from the air-soil boundary is experienced at the mid-point. The expressions for ℓ_{mn} and h_{mn} are given in Equations (4.3) and (4.4) as follows:

$$\ell_{mn} = \begin{cases} (6(n - m) + 2) \text{ cm} & \text{for } m < n \\ (6(m - n - 1) + 4) \text{ cm} & \text{for } m > n \\ 2 \text{ cm} & \text{for } m = n \end{cases} \quad (4.3)$$

and

$$h_{mn} = 2\sqrt{\left(\frac{\ell_{mn}}{2}\right)^2 + (h_{air})^2} \text{ cm} \quad (4.4)$$

For example, when examining the coupling effects observed in the 6th RX antenna due to the transmitted signal from the 2nd TX antenna, the distance parameters ℓ_{mn} and h_{mn} are computed as, $\ell_{26} = 26 \text{ cm}$ and $h_{26} \cong 32.8 \text{ cm}$.

Implementing Equations (4.1) through (4.4) and also using the pulse width information of the GPR input pulse (the Gaussian derivative signal defined by Equation (3.21)), the arrival times for the peak points or the ending points of DC or GB coupling components can be obtained being consistent with the gprMax simulation results.

4.1.3 The Effects of Collinear Antenna Arrays on the Multi-Channel GPR Detection Performance

Coupling signals between the TX-RX antennas, outlined in previous sections, significantly affect GPR detection performance. In particular, in the presence of shallowly buried low RCS dielectric targets, especially GB type direct and indirect coupling signals mask the target returns, or they simply create false alarms. If ground bounce signals are to be eliminated with time-gating-based methods, the target signatures are also removed leading to “false negative” type detection errors.

Time-gating is the simplest but perhaps one of the most common clutter elimination methods used in the literature [71-74]. In many scientific papers and research reports, time-gating or time-gating-based approaches have been used to eliminate

clutter/background signals. As described in Section 2.2.3, this method is based on clipping the raw data between user defined time indices.

Suppose we have a raw GPR C-scan data X of dimension (N, I, J) . The parameters N is the total number of time samples, I is the total number of cross-track sample points (at receiver antennas), and J is the total number of down-track steps. Let predefined clipping length is from time index 1 to N_c . If O represents the output matrix of the time-gating operation, its size becomes $(N - N_c, I, J)$. In the rest of this section, target detection examples with different N_c values will be demonstrated to show the disadvantages of using time-gating method in the case of shallow-buried target problems.

In single-channel GPRs, time-gating method works successfully, especially for deeply buried targets. By clipping the time-domain A-scan signals from the estimated ending index for the ground bounce component, the A-scan signals can be cleared of DC and GB type clutter terms, and a successful target detection becomes possible. However, this method can cause serious performance degradation, especially when working with shallowly buried targets. Also, as highlighted in this section, time extended DC, and especially, GB type coupling signals resulting from the multi-channel GPR structure make shallow-buried target detection almost impossible while using the time-gating method.

The GPR scenario given in Figure 2.17 will be used for the examples to be presented in the rest of this section. Investigations will be made for the dielectric target buried at 1 cm depth (T2 target for Figure 2.17 in Section 2.2.4). The time-gating method will be applied with different clipping indices to the simulated GPR data, and the resulting detection performance will be analyzed in each case by providing energy heat maps.

Firstly, for each receiver antenna, the early-time partitions of the A-scan signals will be clipped until a few indices after the peak of the self-ground bounce signals. This approach is frequently used in the implementation of time-gating method to remove DC terms as well as the peak of the ground bounce signal. In other words, clipping

the self-ground bounce signal is considered to be sufficient for eliminating clutters to successfully detect buried targets. Figure 4.5 shows the energy heat map for this GPR simulation where the clipping time index N_C is chosen to correspond to the time instant $T_C = 0.885$ ns which is right after the main peak of the self-GB pulse as seen in Figure 2.23 of Section 2.2.4.

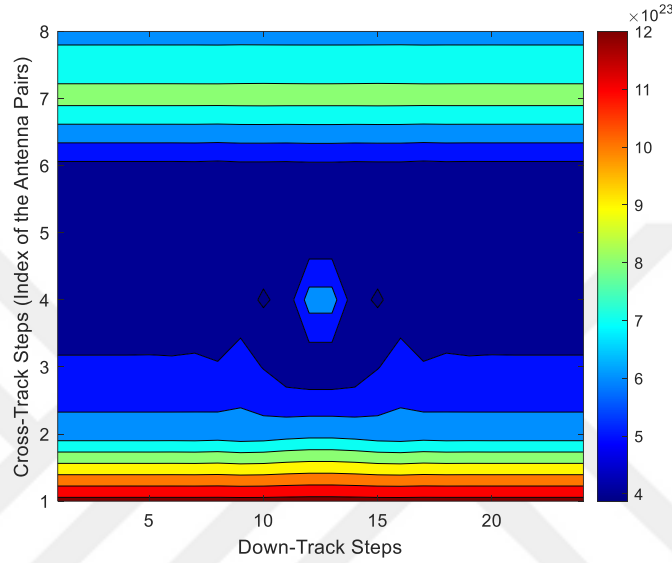


Figure 4.5 Energy heat map of the GPR simulation after applying the time-gating method, where all A-scan data are clipped up to $T_C = 0.885$ ns for clutter elimination.

In Figure 4.5, the target T2 (dielectric TNT disc) is barely noticed under the 4th channel at down-track steps 12 and 13 while having very strong false alarm signals under some GPR channels due to mutual ground-bounced coupling signals. The antenna channels 1, 2 and 7 (especially the 1st channel) are strongly affected by these undesired clutter signals. Clipping the GPR data in time until $T_C = 0.885$ ns clearly does not remove the mutual-GB components which may be stronger than the target return at some channels of the antenna array. If the self and mutual DC and GB clutters were properly removed from the GPR data (as presented in Section 2.2.4), the energy heat map of this problem would like as given in Figure 2.27 showing the presence and the location of the target T2 very clearly.

To support the present discussions, Figure 4.6 shows the B-scan image of the clipped GPR data. This image is obtained for the 13th down-track step showing the strong remainders of the mutual GB type coupling signals especially under channels 1,2,7, and 8. The tables C.1 through C.4 given in Appendix C also confirm these images and discussions.

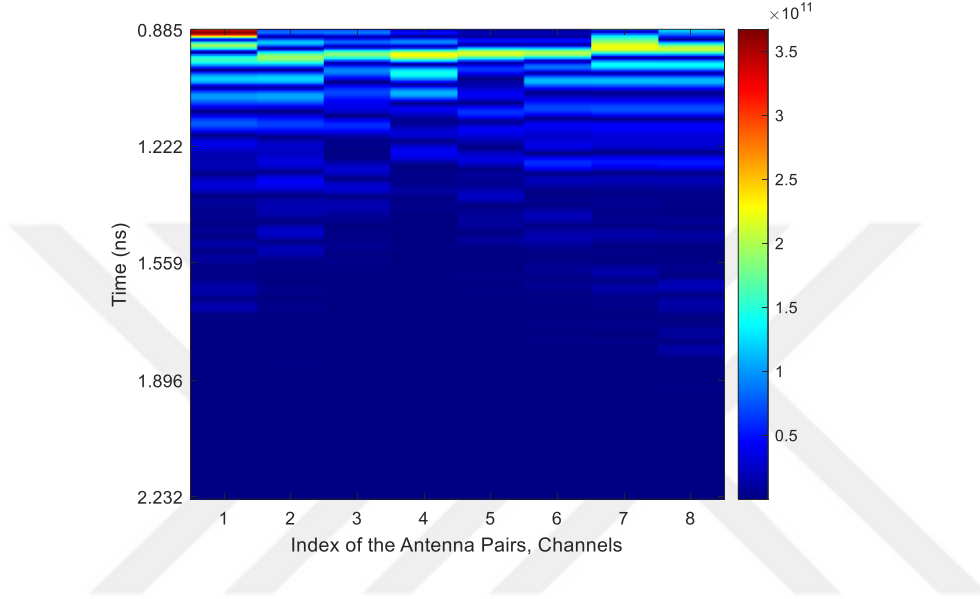


Figure 4.6 B-scan image of the buried dielectric target T2 after the time-gating process with $T_C = 0.885$ ns.

Next, in order to eliminate the coupling signals that create false alarms, a higher N_C value will be selected, corresponding to $T_C = 0.9622$ ns so that where the main (self) ground bounce signal is seriously attenuated and approximately ended. Figure 4.7 shows the resulting energy heat map after clipping the A-scan signal at this later time. Also, the first peak of the target's response is still preserved for this selection of T_C . As mentioned in Figure 2.26, peaks of the reflections arising from the upper and lower faces of the dielectric cylinder are both observed at time instances 0.9738 ns and 1.1932 ns.

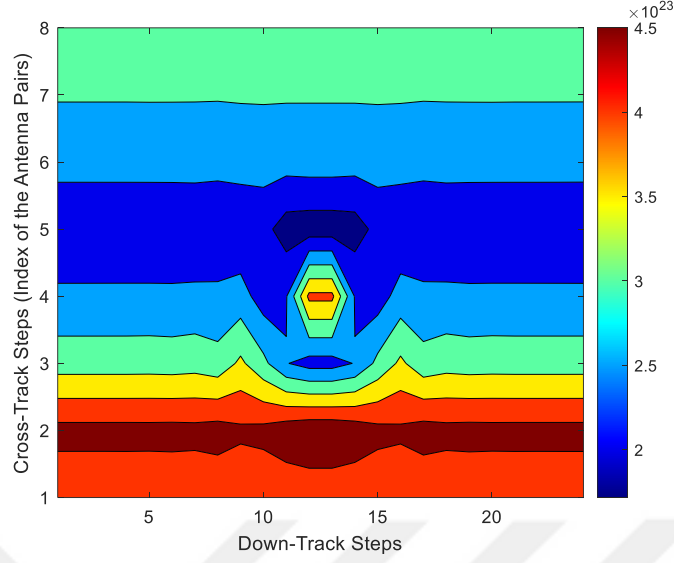
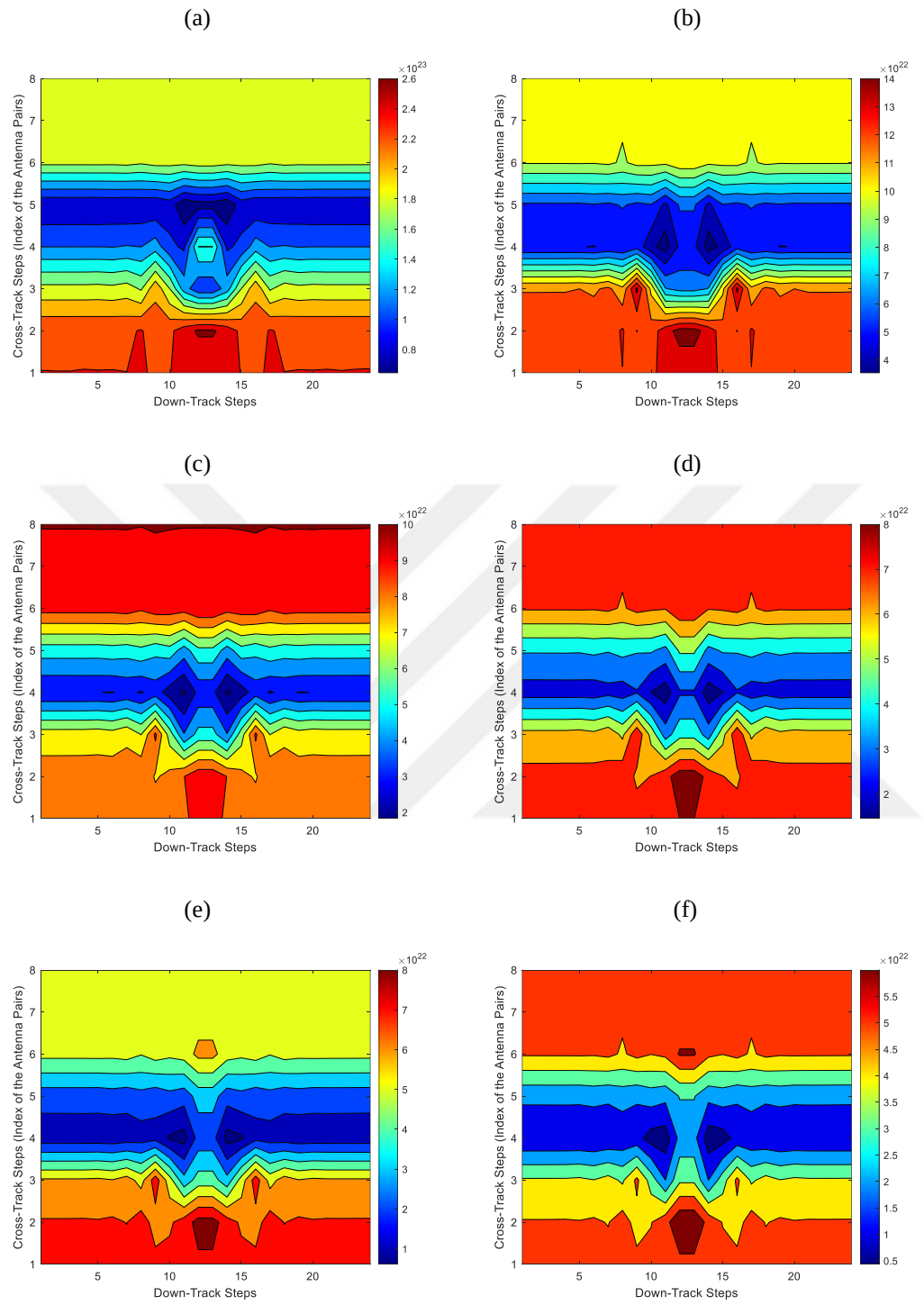


Figure 4.7 Energy heat map of the investigated scenario, for $T_C = 0.9622$ ns.

Although the target is more clearly visible in Figure 4.7, many false alarms and higher energy densities are also observed around the first, second, seventh, and eighth channels. Since the channels closer to the ends of the array receive mutual coupling signals later than the channels in the middle, the effect of the undesired coupling signals still continue.

Figure 4.8 shows the energy heat map images obtained by choosing different clipping times as T_C until the reflection from the target disappears. Undesired issues such as false alarms and masking of the original target continue throughout all investigations for these different T_C values. At the higher T_C values, the stronger response of the buried target is seriously attenuating, while coupling signals with higher amplitude reaching the antennas in the middle of the geometry are significantly eliminated. In addition to a certain amount of signal remaining from the target, new coupling signals that reach the first, second, seventh, and eighth channels at later times are also effective for higher T_C values.



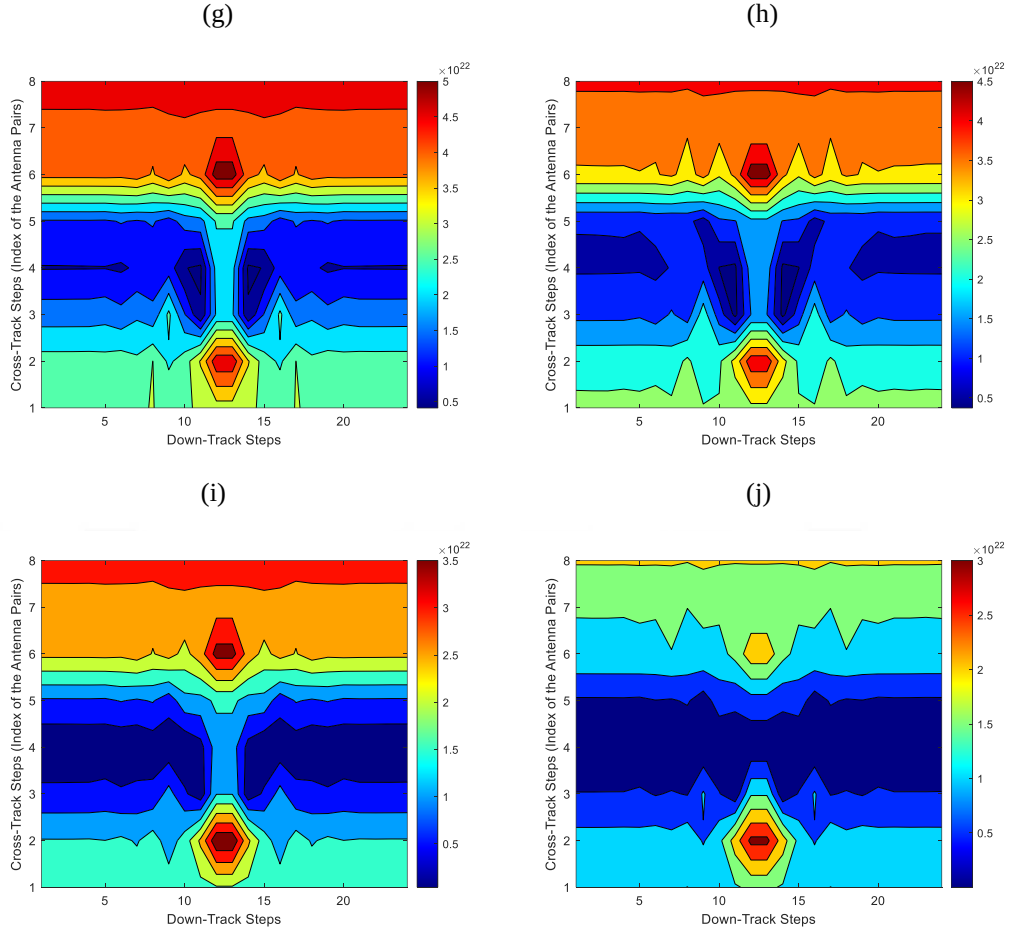


Figure 4.8 Energy heat map images of the buried dielectric cylindrical target in 1 cm depth when time-gating method is applied with different T_C values, $T_C =$ (a) 1.02 ns (b) 1.077 ns (c) 1.097 ns (d) 1.116 ns (e) 1.135 ns (f) 1.155 ns (g) 1.174 ns (h) 1.193 ns (i) 1.231 ns, and (j) 1.27 ns.

Figure 4.9 shows the A-scan signals observed at second, fourth, and sixth channels (under the thirteenth down-track step) for the value of $T_C = 1.27$ ns.

All these examinations can be repeated with cylindrical PEC target. The buried target will be changed for the same scenario, and the PEC target with the same geometry as the dielectric was buried 1 cm deep. Energy heat map of PEC target obtained for $T_C = 0.9622$ ns is given in Figure 4.10. As can be seen from the figure, the PEC target can be detected clearly, and false alarms are mostly suppressed because the response of the PEC target is dominant as compared to the mutual DC and GB signals.

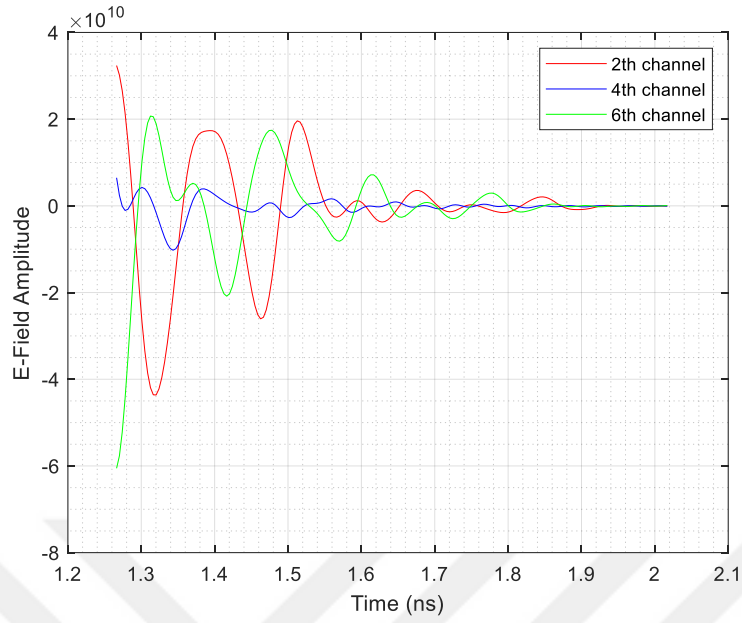


Figure 4.9 Comparison of the observed A-scan signals in the second, fourth, and sixth channels at the thirteenth down-track step for $T_C = 1.27$ ns for the dielectric cylindrical target, T_2 .

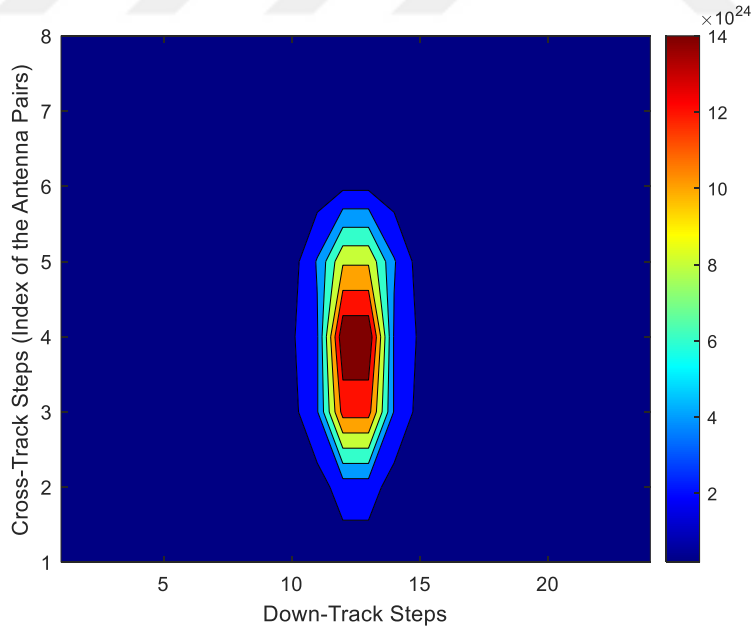


Figure 4.10 Energy heat map of the PEC cylinder for $T_C = 0.9622$ ns.

In light of all these discussions, when multi-channel GPR systems are used, the importance of coupling signals arising from the interaction between different channels should be studied carefully. Especially when working with shallow-buried low RCS dielectric targets, these coupling signals significantly reduce detection performance and create false alarms. In particular, time-gating and/or time-gating-based background removal techniques based on clipping the A-scan signals in the time domain will fail in such scenarios. As mentioned in Section 2.2.4, this type of undesired coupling signals can be eliminated by applying mean/median subtractions and/or using appropriate calibrations. The target response should be separated from coupling signals by applying appropriate background removal methods.

4.2 Description of the Main Multiple-Target Scenario

This section will present the main multiple-target GPR scenario describing each of the buried targets. Using the collinear Hertzian dipole antenna array given in Figure 4.1, the scenario consisting of four buried targets will be examined. The buried targets will be scanned with the antenna array, which consists of eight TX-RX pairs (channels), with 2 cm steps in the down-track direction. In these scenarios, a total of 24 down-track data will be collected from each channel. Upper faces of buried targets are 3 cm below the air-soil interface. Also, these targets are buried in sandy soil with flat air-soil boundary. The relative dielectric permittivity of sand is 3.5. In Section 4.5, more challenging soil conditions will be considered in simulations. In addition, these four targets are located in close proximity.

The first target $T1$ is a PEC wire with a radius of 5 mm. The wire is laid diagonally and connected to the larger PEC cylindrical target given in the scenario.

The second target $T2$ is a PEC cylindrical target. The large PEC cylinder is the farthest target from the initial position of the antenna array in the down-track direction. The radius of the $T2$ target (large PEC cylinder) is 4 cm, and the height is 3.8 cm. In addition, this target is buried in upright orientation so that its circular faces

are parallel to the air-soil boundary. The T1 wire is connected to the center point on the upper base of the T2. With this structure, it is desired to simulate a scenario similar an antipersonnel mine which is triggered by a conducting wire.

The third target T3 is the air-filled void having a volume of rectangular prism. Air-filled voids can be observed frequently in GPR studies and subsurface inspections. The top and bottom faces of this rectangular prism-shaped air-filled void are 9 cm x 6.4 cm rectangles. Also, the height of the T3 is 2 cm.

The last target T4 is a PEC cylinder similar to the T2. The radius of this cylinder is 3 cm, and its height is 2.8 cm. Also, this target is buried in upright orientation so that its circular faces are parallel to the air-soil boundary, similar to the T2.

All these four targets are positioned very close to each other in the GPR simulation. More detailed information about the investigated targets and scenarios will be given with figures and tables. Figure 4.12 shows the examined scenario. Many details about targets, antenna array, and geometry will be given in this figure. Additionally, Figure 4.11 is also the view of the geometry, which is obtained via the “ParaView” software. In Figure 4.11, only investigated targets are shown; soil and antenna array are not demonstrated. Using this figure, the topologies of the scenario and investigated targets can be understood more clearly. Furthermore, many details about the scenario and targets will be summarized in Table 4.1 and Table 4.2.

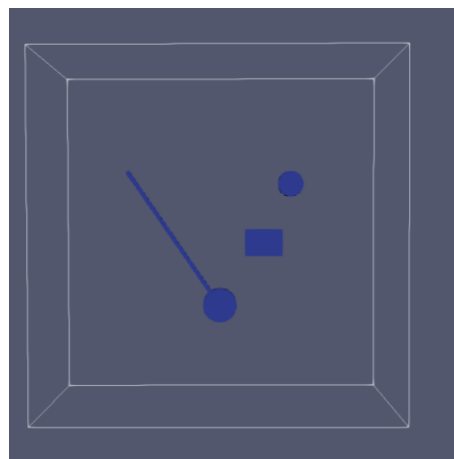


Figure 4.11 ParaView image of the main multiple-target scenario

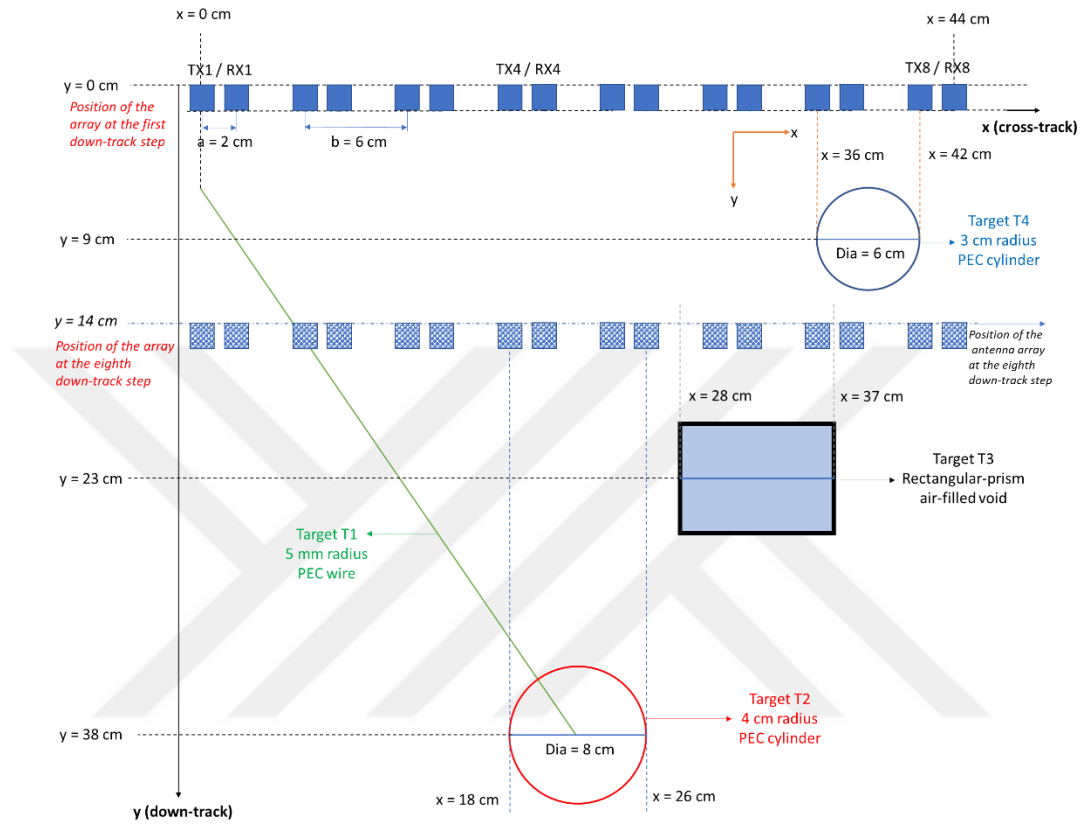


Figure 4.12 “Top view” of the geometrical sketch of the multiple-target GPR scenario.

Table 4.1 Parameters of the simulation and the scenario

<i>Parameters</i>	<i>Explanation</i>
Number of Targets	4
Number of Channels	8
Size of Down-Track Steps	2 cm
Height of Antennas from Air-Soil Interface	10 cm
Relative Dielectric Permittivity of the Soil	3.5
Electrical Conductivity of the Soil	0.01 S/m
Number of Steps	24 steps in the down-track direction
Utilized Antenna Type	Hertzian Dipole

Table 4.2 Utilized targets in the investigated multiple-target scenario

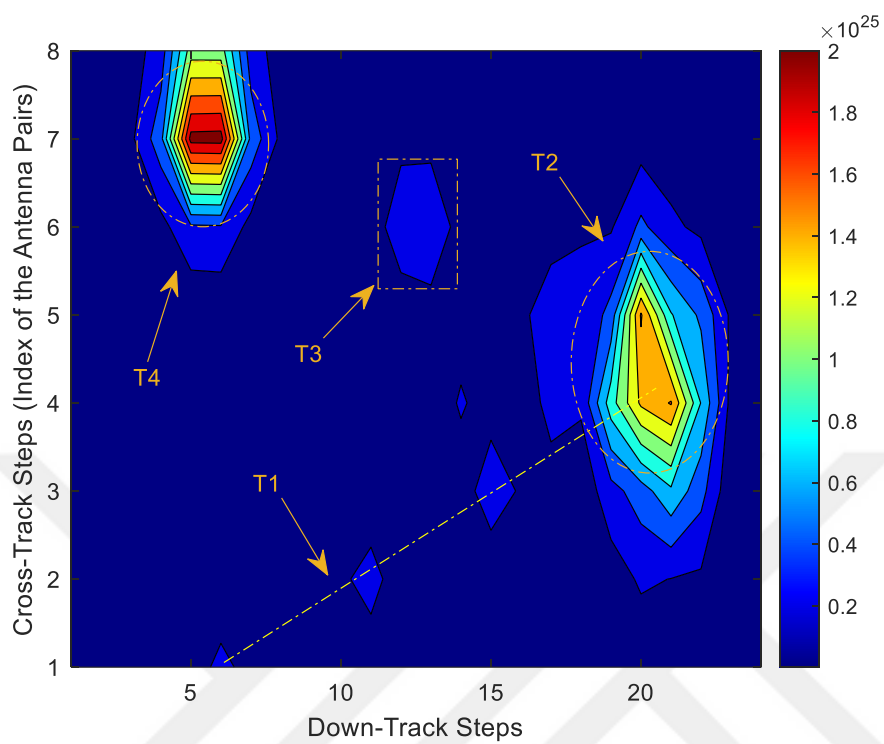
	T_1	T_2	T_3	T_4
Target Type	Cylindrical wire	Cylinder (Larger PEC Cylinder)	Rectangular prism air-filled void	Cylinder (Smaller PEC Cylinder)
Top and Bottom Faces' Dimensions	5 mm radius, diagonally laid (connected to the upper face of T_2)	4 cm radius, upright orientation	9 cm x 6.4 cm rectangles, top and bottom faces parallel to the air-soil boundary	3 cm radius, upright orientation
Height/Length	Diagonally laid, length is 38.8 cm	3.8 cm height	2 cm height	2.8 cm height
Burial Depth	3 cm	3 cm	3 cm	3 cm

4.3 Detection of Targets in the Multiple-Target GPR Scenario

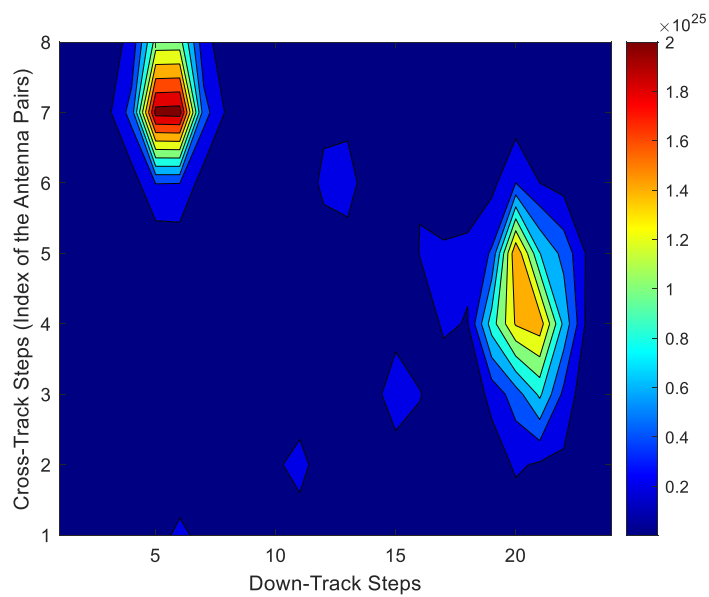
In this section, detection results for the main multiple-target scenario given in Figure 4.12 and described in Section 4.2 will be discussed. Using detection methods and approaches given in Section 2.2.4, four targets in the examined scenario will be detected successfully.

First, energy heat map images can be obtained to detect the presence and location of targets. Since the scenario studied in this subsection does not contain surface roughness, soil inhomogeneity or any other clutter effects, only the undesired DC and GB signals can be effectively eliminated with mean subtraction, median subtraction or direct background removal methods. Successful detection results are obtained using any of these three methods resulting in very similar energy heat map images. This section will present energy heat map images and detection results of clutter-free data generated by using the direct background removal method. For some applications, the results obtained with mean or median subtraction methods will be also presented to demonstrate the usefulness of all three methods as shown in Figure 4.13.

(a)



(b)



(c)

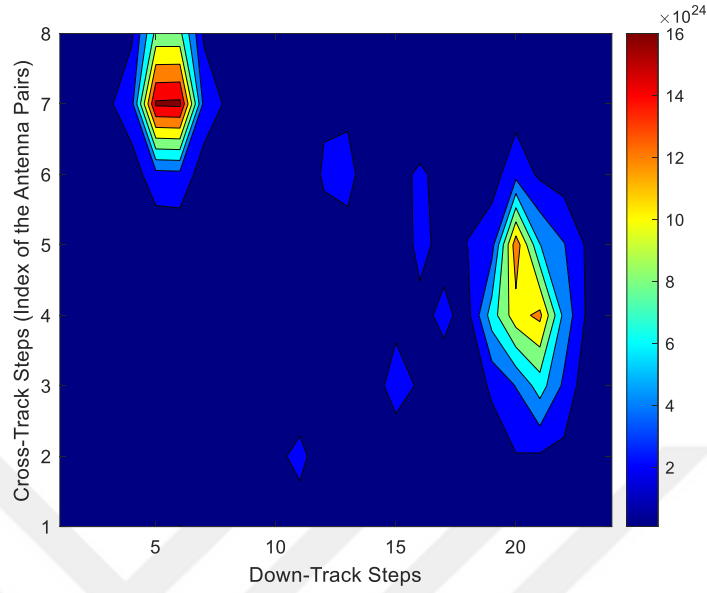


Figure 4.13 Energy heat map images of the multiple-target scenario obtained by using three different clutter elimination methods, (a) direct background removal method, (b) median subtraction method, (c) mean subtraction method.

As seen in Figure 4.13, all four targets can be detected successfully in all three cases. While the targets T2, T3, and T4 are observed at their expected locations, the shining points of T1, which is a 5 mm radius PEC wire, are clearly visible on these heat maps. The data points that clearly show the wire details are collected from locations where the antennas directly see the target with high energy levels.

When the image obtained after applying the direct background removal method to raw data in Figure 4.13(a) is examined, it is seen that the image of the larger PEC cylinder (T2) is located under the antenna channel 4, but it is also observed under the second, third, sixth, and seventh RX antennas which are not geometrically above the cylinder. This observation is expected since the antennas used in the array are omnidirectional Hertzian dipoles. There is a tiny glowing point that does not match with an anticipated target location in Figure 4.13(a) at the 14th down-track step under the 4th cross-track step. Energy localization at this point is due to the interaction of

targets T1 and T2, which are buried very close to each other. This interpretation will be verified in the next section using the designed PD and PCA-based classifier.

When the median subtraction technique is applied as shown in Figure 4.13(b) the resultant energy heat map image meets the expectations indicating the targets' locations exactly as described in the GPR scenario.

Various false alarms are observed when the mean subtraction technique is applied as presented in Figure 4.13(c). False alarms are essentially observed close to the larger PEC cylinder (T2). It is expected that the performance achieved in mean subtraction method will be slightly worse than the other two alternative methods. Especially when reflections from more than one target under the same channel (channels 5, 6, and 7 in our scenario) exist, performance of the mean subtraction method will be deteriorated. This phenomenon is expected by theory as mentioned in literature [71-74].

The numbers and locations of buried targets can be accurately detected using the energy heat maps. In Figure 4.13(a), the geometrical positions of the targets are also indicated with dashed lines.

Also, by dividing the energy heat map into smaller partitions, images of the low RCS targets (which are masked by stronger reflection originated from the higher RCS targets) can be observed more clearly. This approach is called *segmentation* and it is a simple but very useful novel application proposed in this thesis. Figure 4.14 shows the segmented view of the energy heat map given in Figure 4.13(a). Utilizing Figure 4.14, the geometry and continuity of the target T1 (PEC wire) can be clearly observed.

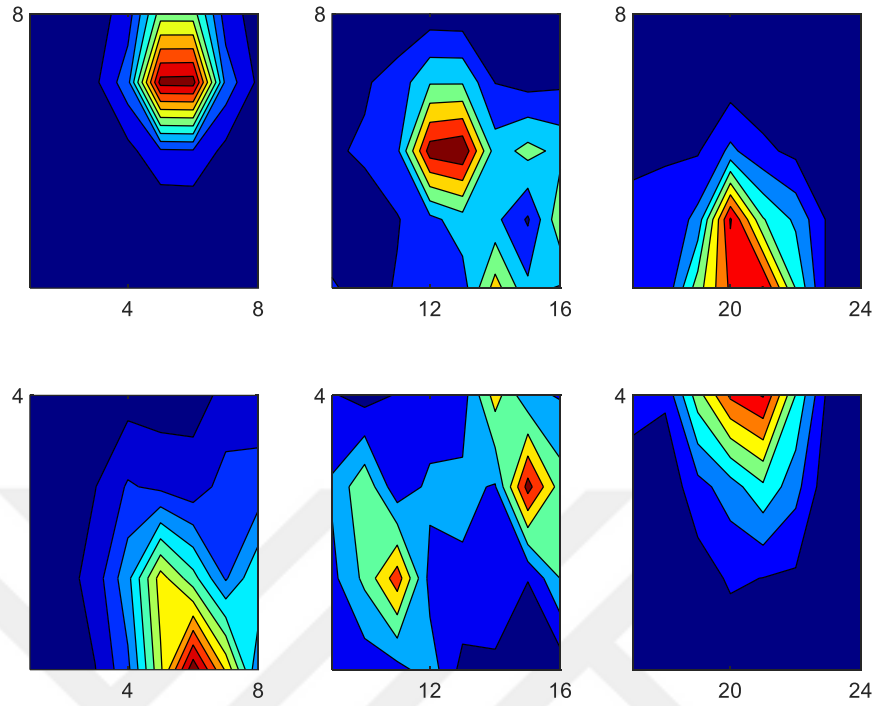


Figure 4.14 Segmented energy heat map image of the main multiple-target scenario

After obtaining important information about the presence and location of targets through the energy heat maps, these results can be further verified by using the related B-scan images. As an example, the B-scan image given in Figure 4.15 shows the presence and the location of the targets , T2, T3, and T4 under the 6th antenna channel over the time versus down-track domain. Similarly, Figure 4.16 reveals the presence of target T2 (the large PEC cylinder) as well as the path of the PEC wire (T1) clearly. The remaining B-scan images obtained under the other six antenna channels are presented in Appendix D. All these images are in perfect harmony with the results obtained from the energy heat maps and successfully show the presence and location of all four buried targets.

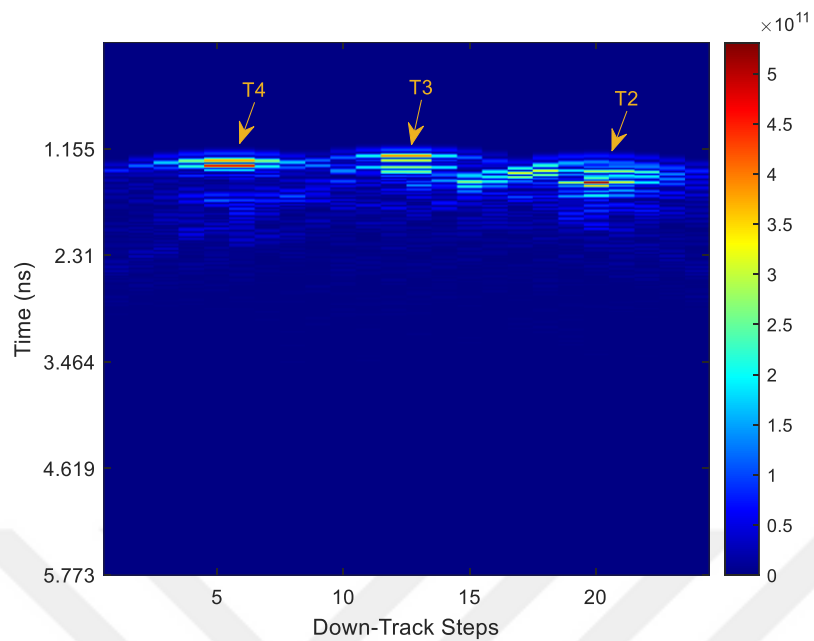


Figure 4.15 B-scan image of the main multiple-target scenario, obtained under the sixth channel.

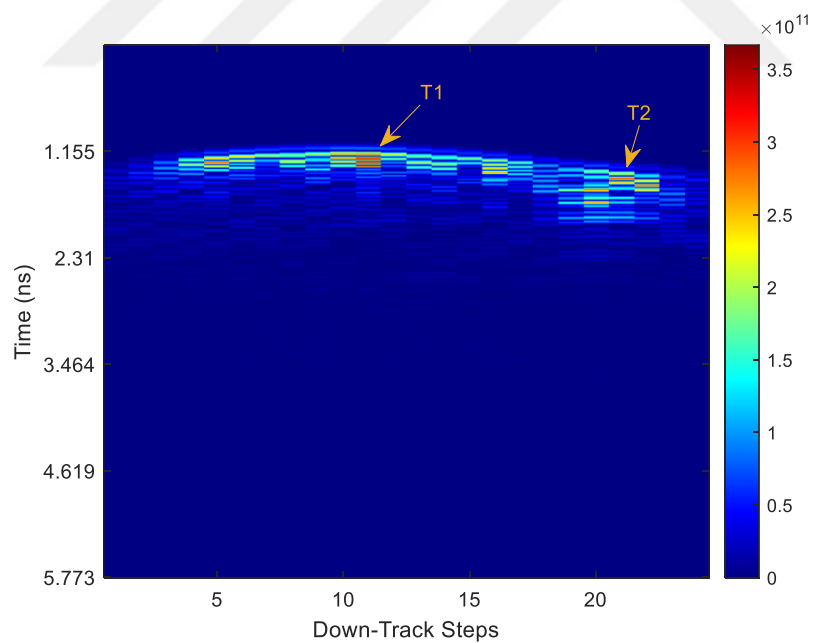


Figure 4.16 B-scan image of the main multiple-target scenario, obtained under the second channel.

Additionally, Figure 4.17 shows the C-scan slice obtained for the time instant of 1.232 ns which corresponds to the burial depth of 3 cm in sand.

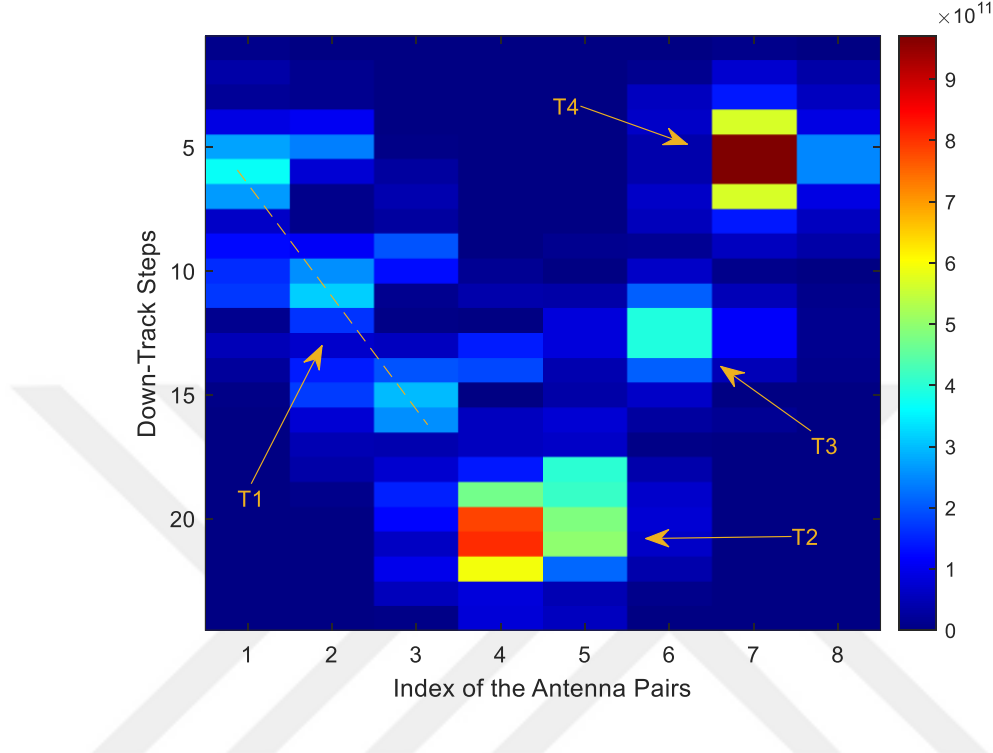


Figure 4.17 C-scan slice of the main multiple-target scenario, for $t = 1.232$ ns.

In summary, the target detection approach that makes use of the information provided by the B-scan, C-scan, and energy heat map images works successfully in the challenging multiple-target scenario examined in this section. On the other hand, certain false alarm points may be observed in these images which are mainly caused by the strong reflections from the PEC targets (especially T2) or by the electromagnetic interactions of targets with each other. The omnidirectional nature of the array antennas also contributes to the formation of such defect points.

4.4 Classification of Targets in the Multiple-Target GPR Scenario

In this section, a 4-target GPR classifier will be designed for the scenario defined in Figure 4.12, Table 4.1, and Table 4.2 where the targets are buried 3 cm below the flat air-soil boundary in a low-loss homogeneous sand. The main challenge in this scenario is the presence of four different shallow-buried targets located in close proximity.

Using the classifier design steps defined in Section 3.1.3 earlier, a multi-target classifier will be designed and tested as follows:

- i. First, a C-scan database is simulated for this multiple-target scenario with the 8-channel antenna array taking 24 steps in the down-track direction. Therefore, a total of 192 A-scan time strings are simulated at (8x24) spatial measurement points.
- ii. As the scenario assumes homogeneous low-loss sand with flat air-soil interface, there is no background clutter stemming from the soil medium but the only clutter that needs to be eliminated is due to self and mutual DC and GB signals. As discussed in the previous section by the help of Figure 4.13, use of a simple clutter removal approach can be applied to the simulated C-scan data for this purpose prior to target detection.
- iii. Picking the A-scan strings from the immediate neighborhood of the point of a target detection, the LTFV features of the target can be constructed. For the targets T2, T3 or T4, there is essentially one brightest energy point indicating the target location. Let this point be the “eye of the target image” that has the coordinates $(\bar{i}, \bar{j})$ over the cross-track versus the down-track domain. A-scan data at four closest points around this center location $\{(\bar{i} \mp 1, \bar{j}) \text{ and } (\bar{i}, \bar{j} \mp 1)\}$ are used for LTFV extraction providing sufficient aspect variation to the feature extraction process for better target characterization. For the PEC wire target T1, there are three bright points along the length of the wire with coordinates (1, 6), (2, 11) and (3, 15). To design the LTFV features of the PEC wire, 4 points with coordinates

$(2 \mp 1, 11)$ and $(2, 11 \mp 1)$ are used around the second eye of the target T1 at the point $(2, 11)$.

- iv. For a given target, after isolating the target returns from the A-scan signals at all these selected locations and normalizing their total energy to unity, the Page distribution (PD) of each isolated and normalized time signal is computed. As described in Section 3.2, four LTFV features are computed for each target over the time bands 8, 9 and 10 (with $Q = 16$).
- v. Then, for each target, a single characteristic feature vector FFV is computed using the PCA algorithm as explained in detail in Section 3.2.2. Repeating this feature fusion process for each target, the classifier's feature database is completed containing a total of four FFV features for each target $i = 1, \dots, 4$. It should be noted that those reference LTFV features are not the same as their FFV, but they are highly correlated with it. Therefore, those four LTFVs obtained for each target can still be used for the testing process later.
- vi. Finally, in the testing phase, the classifier is tested at a total of $8 \text{ antenna channels} \times 24 \text{ downtrack steps} = 192$ sample locations. At each one of these points, the testing LTFV vectors are computed from the corresponding A-scan data using the step (iv) explained above. Sixteen of these testing LTFV features are the same as those reference (or as also called training) LTFV vectors already computed and used in step (v) to compute the FFV features. The “eye of the target” points themselves have not been used in the classifier design before, so it is perfectly legitimate to include them in the testing LTFV database. At the remaining test locations, either the targets are not present or the omnidirectional array antennas can sense the target(s)'s scattered signals at some weak levels. Computation of testing LTFV features at all those 192 locations should be understood from this standpoint. Isolation of A-scan signals at no-target locations can be done by choosing a starting time index after all ground-bounced signals are effectively over. Prior to energy normalization, signal strengths of such no-target A-scan signals are expected to be very low as the soil medium becomes less and less

inhomogeneous. After energy normalization, the PD of these time domain signals are computed but naturally they do not contain any target CNR-related damped sinusoidal signal components (over the late-time classifier design band 8 to 10) as they mostly characterize the local soil environment instead of the targets. Figure 4.18 shows the matrix of correlation coefficients between the testing LTFVs, and the classifier's target features, FFVs. Order of features in the vertical and horizontal axes and the target definitions are given in Table 4.3.

- vii.** During a GPR mission, if there is a suspicious location over the terrain with increased energy localization (observed in B-scan or energy heat map images), the testing LTFV feature computed at that specific location needs to be tested against the FFV features (stored in the classifier's feature library) to identify the type of the detected target. This test is done by computing the correlation coefficient of the testing LTFV with each target's FFV and plotting them as simple bar charts as shown in Figure 4.19 (a) through (d) where the LTFV testing features for targets T1 through T4 are compared with the classifier's library FFVs. In these figures, at least 35 percent contrast is observed between the matched and the closest mismatched correlation coefficients. The matched correlation coefficients assume very high values around 95 percent, as expected. In such bar charts, the highest correlation coefficient refers to the target type. The testing LTFVs used in Figure 4.19 are created from the data points not used for the generation of FFVs but where targets are still detectable (at 10th down-track step under 2nd channel for T1, and at center detection points ($\bar{l}, \bar{j}$)s for the targets T2, T3 and T4).
- viii.** Normally, during a realistic GPR operation, the classification tests are conducted only at the points of "potential target detection". However, if a classification test is conducted at a "no-target" point for some reason, all of the correlation coefficients computed between the testing LTFV and the FFVs are expected to be close to each other assuming low values as demonstrated in Figure 4.20. The testing LTFV used in this figure is obtained

from the twenty-fourth down-track step of the eighth channel, where no targets are detected. As expected, the test feature is not highly correlated with any library FFV features, and the values of all four correlation coefficients are in the range from 0.3 to 0.5.

- ix.** As it is well known, occurrence of false alarms is totally undesirable in GPR measurements. They may occur due to clutter effects of different types, ranging from leftovers from the ground-bounce terms to background clutter stemming from soil inhomogeneity or surface roughness. Some objects such as rocks or man-made objects like metal pieces buried in soil may easily cause false alarms as well. Although, certain precautions are taken to minimize false alarm rates in GPR design, clarification of the sources of such false alarms are critical. This problem definitely calls for GPR classification tests. Figure 4.21 (a) through (c) demonstrate three different “false alarm” cases caused by the electromagnetic interaction between the closely located buried targets T2 (large PEC cylinder) and T1 (the PEC wire). This interpretation results from the observations that correlation coefficient values corresponding to the targets T2 and T1 are numerically close to each other. Although they are not very high, they are higher than both of those coefficients corresponding to targets T3 and T4.
- x.** As a final remark, the classifier design process outlined in this section could be started by the simulation of each library target buried in sand by itself, without having the other targets in the setup. Then, the simulation data computed for a given target can be used to synthesize its fused feature vector FFV following the basic steps summarized above. Then, the collection of FFVs computed individually for each library target would be used for testing a given multi-target scenario as described in this section. Obviously, this approach totally eliminates the close target interactions in the scattered signals during the extraction of training LTFV/FFV features. In this sense, it is an unbiased classifier design approach. However, in some GPR missions, the types of buried targets may not be known beforehand. As the GPR

continues to scan the terrain, data collected from the “potential target” locations can be used to construct the classifier library as an ongoing process while extracting the LTFT and FFV features in an unsupervised manner. In that respect, the reference LTFV/FFV extraction approach used in this thesis can be considered as a novel method for dynamical classifier design.

Table 4.3 Order of the test and classifier target features in the axes of the correlation coefficient matrix in Figure 4.18

LTFVs (Vertical Axis)		FFVs (Horizontal Axis)	
Indices Range	Channel Number	Indices Range	Target Type
1-24	Channel 1	0-T1	T1
25-48	Channel 2		(5 mm PEC Wire)
49-72	Channel 3	T1-T2	T2
73-96	Channel 4		(Larger PEC Cylinder)
97-120	Channel 5	T2-T3	T3
121-144	Channel 6		(Air-Filled Void)
145-168	Channel 7	T3-T4	T4
169-192	Channel 8		(Smaller PEC Cylinder)

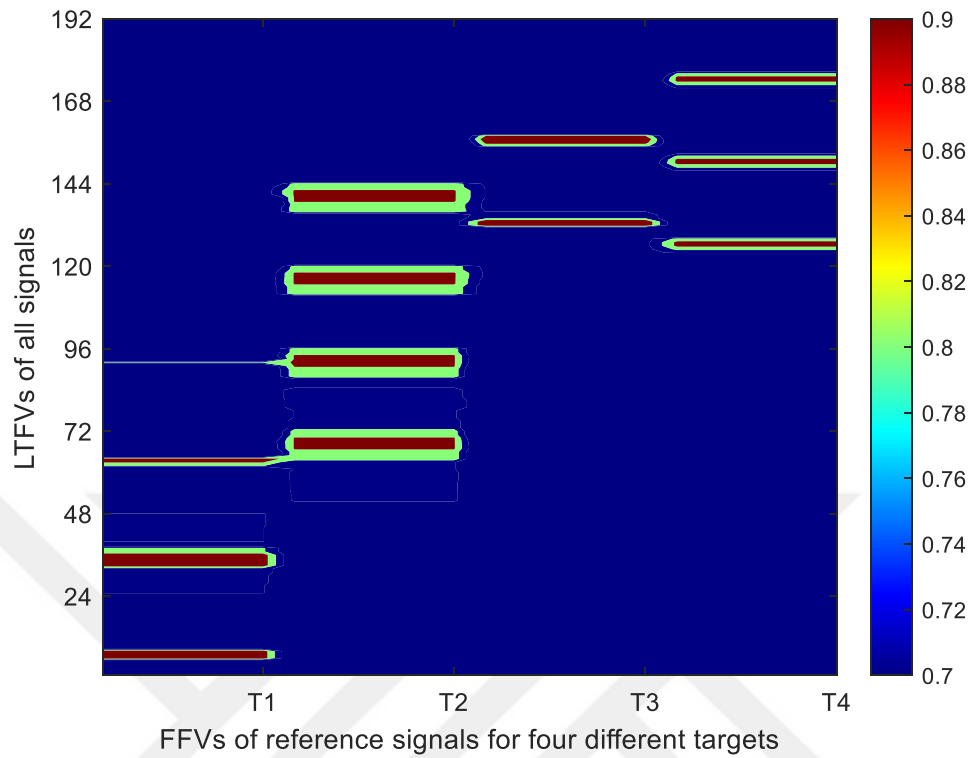


Figure 4.18 Contour plot of correlation coefficients computed between the testing LTFVs and the classifier library's FFV features for the multiple-target GPR scenario with four different targets, T1, T2, T3, and T4. Order of features in the vertical and horizontal axes and the target definitions are given in Table 4.3.

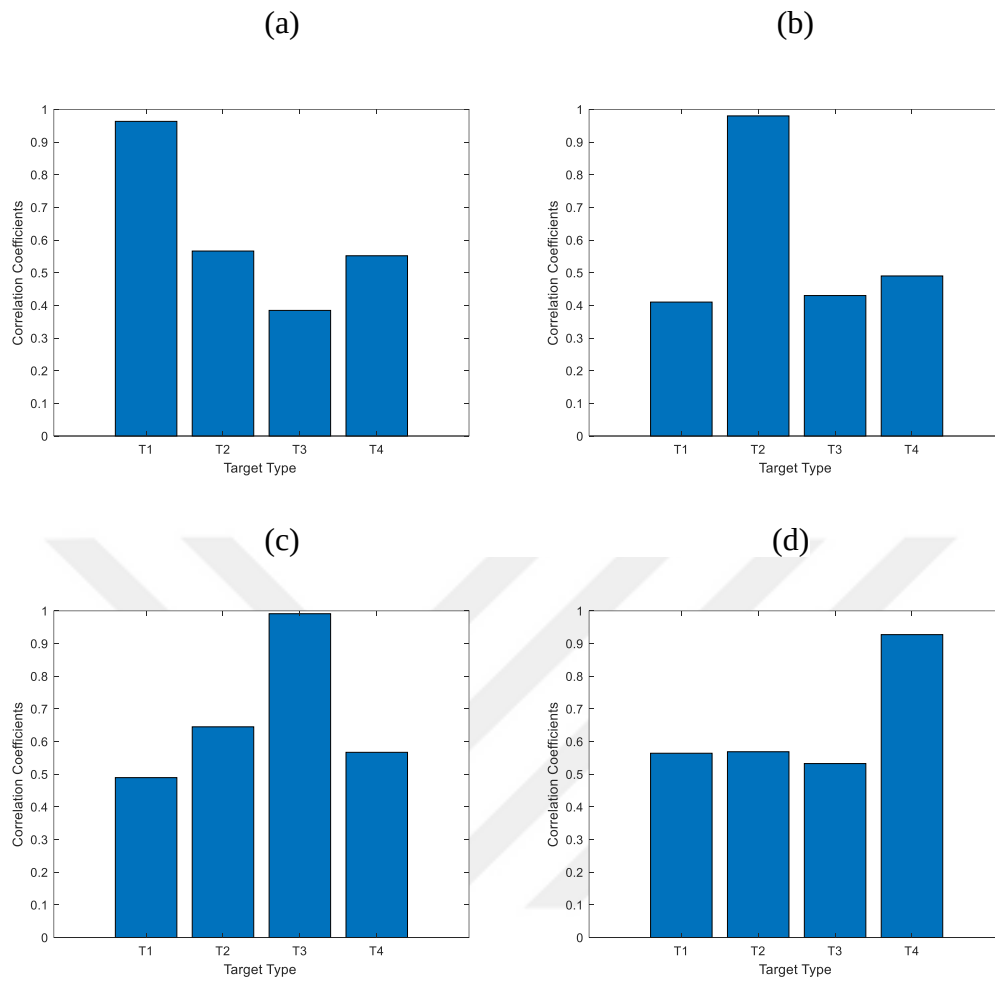


Figure 4.19 The classification of four different targets (a) T1, (b) T2, (c) T3, (d) T4

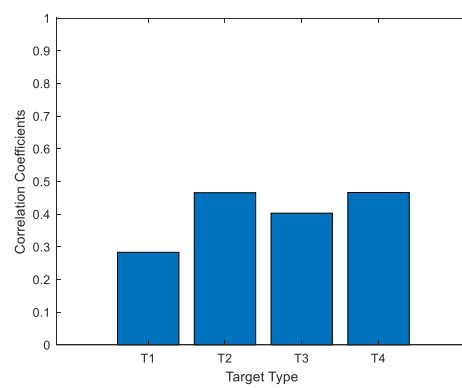


Figure 4.20 The bar chart of the obtained correlation coefficients from the comparison of FFVs with the LTFV generated from the no target case.

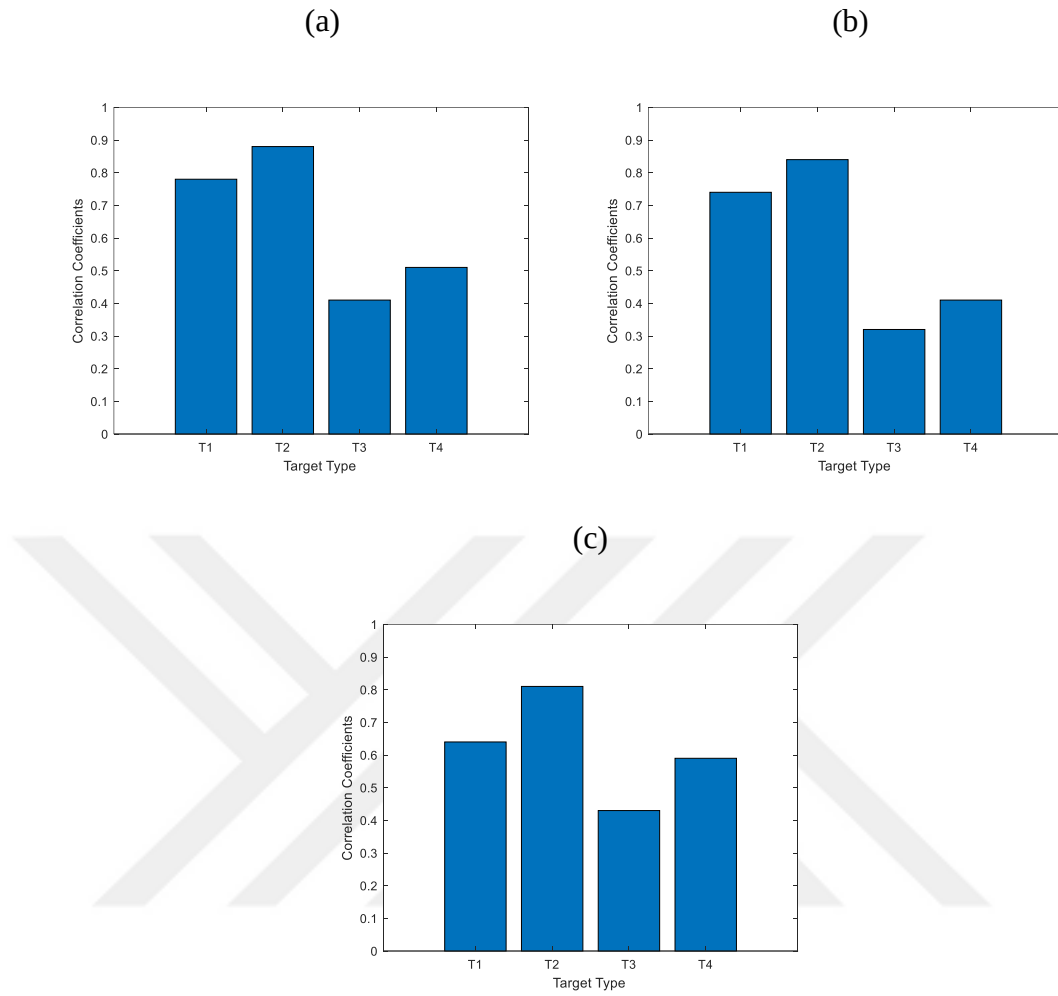


Figure 4.21 The bar charts of the obtained correlation coefficients for false alarm points, test features (observed false alarms in energy heat maps) obtained from (a) 14th down-track step under 4th channel for the direct background removal method's output, (b) 17th down-track step under 4th channel for the mean subtraction method's output, (c) 16th down-track step under 5th channel for the mean subtraction method's output.

At the last part of this section, Table 4.4 presents the effects of clutter removal methods in the performance of target classifier regarding its correct decision rate. Once the location of a target is detected, the A-scan test data (to be used for testing LTFV extraction) may be isolated either from the processed data (after the application of clutter removal techniques including the direct background removal, mean subtraction or median subtraction methods) or from the original unprocessed (raw) data. For each one of these cases, the classifier performance is assessed by comparing the resultant LTFVs by the FFVs obtained from the raw signals and stored in the library.

Table 4.4 Performance comparisons of the different type of classification processes

Criteria Data Type	CCM	CCM5	CCM10
LTFVs are obtained from raw data	100%	100%	100%
LTFVs are obtained from the result of the mean subtraction algorithm	98.9%	97.9%	95.8%
LTFVs are obtained from the result of the median subtraction algorithm	100%	100%	100%
LTFVs are obtained from the result of the direct background removal algorithm	98.9%	98.9%	98.9%

4.5 Performance Analysis of the Detection and Classification Approaches in Different Soil Conditions

In this section, the proposed detection and classification approaches will be tested in more challenging scenarios with different soil types and surface roughness conditions.

4.5.1 Description of the Scenario and Soil Types

In this section, the same scenario and targets as those used in Section 4.2 are employed with the only difference of the utilized soil type. During the analysis, 12 different soil types with varying material compositions and roughness values were used. As the representative of our studies with these different soil types, two of the most appropriate soil types are selected for use in the multi-target GPR scenario. . The first soil type (S1) to be examined is the moist soil, composed of different materials. This soil is modeled as an inhomogeneous soil with a sand fraction of 0.5, clay fraction of 0.5, and water fraction ranging from 0.01 to 0.2. Detailed explanations of these and more different parameters to describe various types of soils are given in the literature [54-55], [144].

In addition to this scenario, the second soil type (S2) is generated with the surface roughness of ± 1.5 cm to be added to the previously defined soil type. Working with the second soil S2 will pose additional challenges due to its inhomogeneity and surface roughness. Considering that the targets in the examined scenario are shallowly buried, the significance of soil properties should be emphasized. These two different soil types, S1 with only inhomogeneity and S2 with both inhomogeneity and roughness, will be employed to test the performance of the proposed clutter elimination, detection, and classification methods given in this thesis.

4.5.2 Signal Processing Methods Used for Clutter Elimination

In this part of the thesis, clutter elimination approaches will be discussed to eliminate undesired signals in different challenging scenarios containing inhomogeneity and/or roughness of the soil. When working with *S1* and *S2* soils, for successful target detection and classification, unwanted (cluttering) signals need to be eliminated as they mask reflections from shallow-buried targets, or they create false alarms. The response of the investigated target should be clearly observed and separated from undesired clutters. For this purpose, the approach described by the flowchart given in Figure 2.15 will be applied to raw (unprocessed) A-scan data.

First, by applying mean or median subtraction methods, direct coupling signals and an appreciable amount of ground bounce signals will be eliminated for all soil types. However, these methods are insufficient in challenging soil conditions, especially for *S2* with surface roughness. When working with challenging soil types with inhomogeneity and surface roughness, the second and maybe third steps of the clutter removal approach as mentioned in Figure 2.15 will be necessary.

Following the application of one of the simpler methods (mean/median subtraction in general) in the first step of the given clutter elimination approach to eliminate direct-coupled and ground-bounced signals, rest of the clutter signals can be successfully separated from the target's response using multivariate techniques such as PCA and ICA. In general, a raw (unprocessed) GPR signal X can be expressed as a mixture of clutter and target signals, $X = X_{target} + X_{clutter}$. The PCA method, for example, can be used to identify the principal components of the clutter and separate them from the desired subsurface signals. ICA is another multivariate analysis method that aims to separate a given signal into statistically independent components. Therefore, ICA can be used in GPR signal processing for clutter removal by decomposing the mixture of clutter and target signals into independent components. Different types of ICA algorithms can be utilized for this purpose. In this study, the FastICA [142], [161] algorithm is used. More detailed information

about the theory of PCA and ICA methods and their usage in various GPR studies is available in the literature [71-74], [137-138], [140-142], [161].

In addition to PCA and ICA techniques, unwanted clutter signals can be eliminated by other well-known approaches such as the Kalman filter and the matched filter. Optimization of filter parameters is the major challenge encountered when utilizing these types of filters. The Kalman Filter is a recursive filter that estimates the state of a dynamic system based on noisy measurements. It is commonly used in various fields, including signal processing and control systems [92]. In the context of GPR clutter elimination, the Kalman Filter can be employed to model the clutter as a dynamic process and estimate its state over time. By continuously updating the clutter model based on the received GPR measurements, the Kalman Filter can separate the clutter from the desired subsurface signals [92]. For the purpose of GPR clutter elimination, a matched filter can also be designed to match the characteristics of the clutter signals. By convolving the GPR data with the matched filter, the clutter can be enhanced and subsequently removed from the original signal, leaving behind the desired target-based information.

As discussed in Chapter 2, a multi-step clutter elimination process may be necessary to improve the GPR's detection performance especially in the case of challenging soil types with rough surfaces. In this thesis, the clutter elimination process have been conducted by using various alternative combinations of available clutter removal methods. For example, the median subtraction approach is applied as the first step to the raw A-scan data to eliminate the direct coupling and some parts of ground bounce signals. Afterward, the remaining clutter signals were removed by applying PCA and ICA techniques in succession. Methods such as the combination of PCA and ICA, which is called the PICA, or the combination of some filters with PCA, are encountered in the literature [143]. The success of all these approaches will be discussed in the next section.

4.5.3 Detection and Classification Performance in Different Soil Conditions

In this section, GPR detection and classification results under different soil conditions (soil *S1* and *S2*) will be discussed. As explained in Section 4.5.2, targets will be detected and classified for high-clutter soil types after applying a combination of different clutter elimination methods to the raw A-scan data.

First, results obtained for *S1* soil as a burial medium will be discussed. Obtained energy heat map images using different background removal approaches are given in Figure 4.22. The results show that a 2-step clutter removal process where the PCA method is applied after the direct coupling elimination method gives successful results. Also, a third method applied after PCA improves the detection performance slightly. The results obtained by using “*Median Subtraction + PICA (PCA + ICA)*” are almost perfect, about the same as the results obtained in the ideal case.

Then, the same processes will be applied to the other scenario, where targets are buried in *S2* soil which has not only inhomogeneity but also surface roughness. Energy heat map images Obtained for this scenario are given in Figure 4.23.

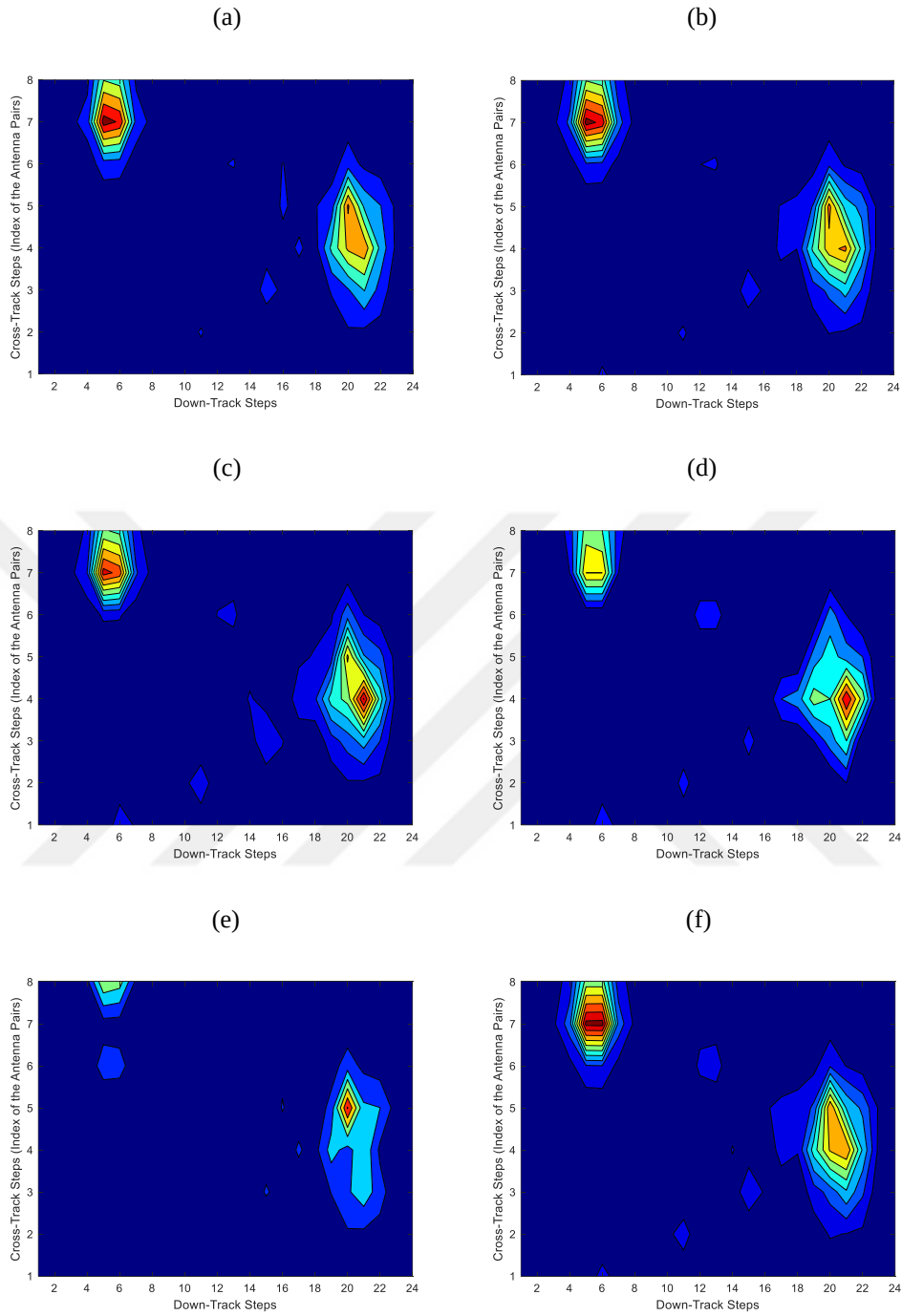


Figure 4.22 Energy heat map images after applying (a) mean subtraction, (b) median subtraction, (c) median subtraction + PCA, (d) median subtraction + PCA + Kalman filter, (e) median subtraction + ICA, (f) median subtraction + PICA, methods to simulated raw GPR data where targets are buried in *S1* soil.

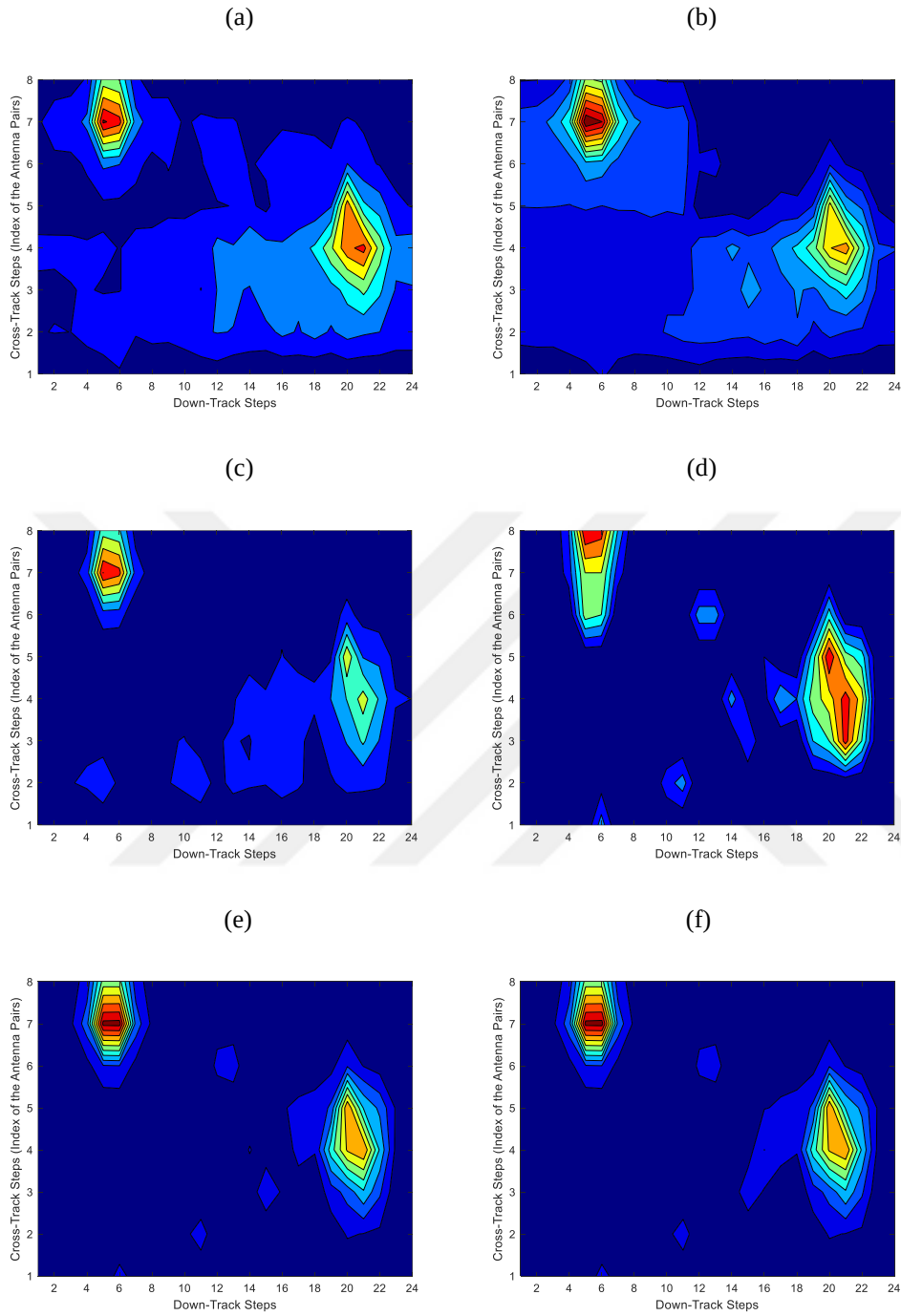


Figure 4.23 Energy heat map images after applying (a) mean subtraction, (b) median subtraction, (c) median subtraction + PCA, (d) median subtraction + ICA, (e) antenna calibration + ICA, (f) median subtraction + PICA, methods to simulated raw GPR data where targets are buried in S2 soil.

Based upon the results displayed in Figure 4.22 and 4.23, it is seen that ICA-based methods perform better in soil containing both inhomogeneity and roughness. The performance of the PCA method was markedly reduced for the GPR scenario with the soil type S2. For this scenario, the results obtained by using “*Median Subtraction + PICA (PCA + ICA)*” are very successful again similar to the case of S1 soil. The important observations made while applying the “*Median Subtraction + PICA (PCA + ICA)*” method for the S2 soil scenario are summarized below. The significance and success of each step of the overall method will be discussed using energy heat maps and B-scan images. The B-scan images obtained under the sixth channel showing the down-track versus time domain.

- In this approach, “*median subtraction*” method will be applied to the raw data in the first step. For S2 soil containing inhomogeneity and roughness, the energy heat map image obtained as a result of only median subtraction application to raw data is shown in Figure 4.23(b). It is obvious from the energy heat map image that this method could not successfully eliminate clutter signals. Furthermore, B-scan image for this case is given in Figure 4.24(b) while the B-scan image obtained from the unprocessed (raw) data is also shown in Figure 4.24(a) for comparison. Presence of strong clutter signals around the targets are clearly seen in Figure 4.24(b).
- In the second step, the PCA method is applied to the data matrix obtained after the median subtraction process. The energy heat map obtained as an output of this process is given in Figure 4.23(c), while the B-scan image is given in Figure 4.24(c). Although a certain amount of unwanted signals are eliminated according to the result of the first step of the process, the results obtained from this second step does not give successful detection results.
- In the third and the last step, ICA method is applied to the output of the 2nd step (median subtraction + PCA). Using this method, which is known as *PICA* in the literature [143], successful detection results are obtained even in the challenging scenarios with difficult soil types. Figure 4.23(f) gives the energy heat map image to show the results of the “*Median Subtraction +*

PICA (PCA + ICA)” method, while Figure 4.25 shows the B-scan image obtained for this case.



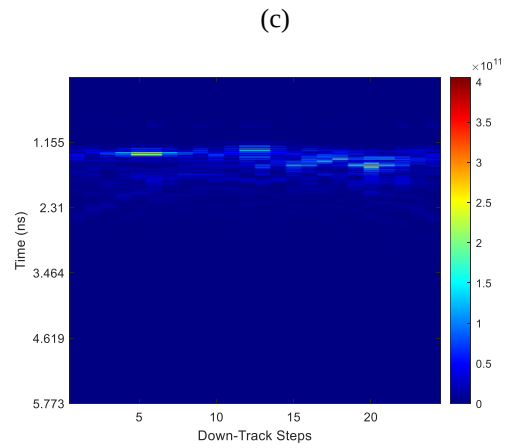
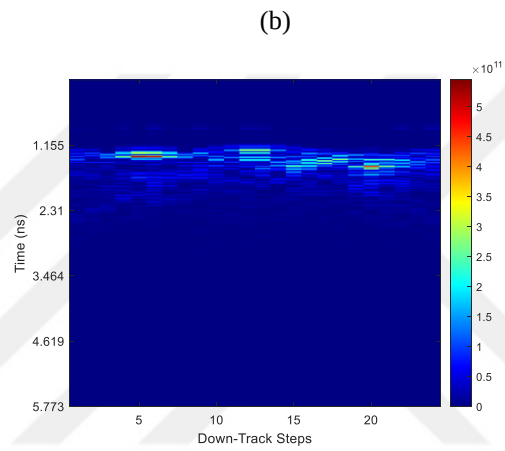
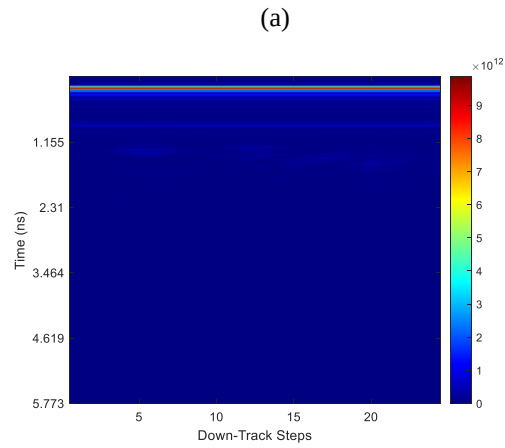


Figure 4.24 B-scan images obtained for the (a) initial raw data (zeroth step), (b) output of the median subtraction (first step), (c) output of the median subtraction + PCA (second step) in the “Median Subtraction + PICA” method. Results are shown for the sixth channel of the array for the *S2* soil scenario.

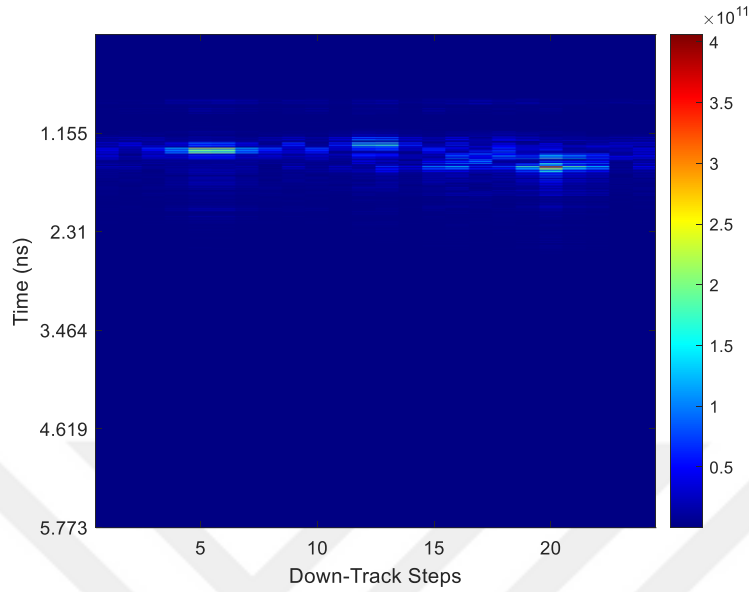


Figure 4.25 The B-scan image obtained as the final result of the “Median Subtraction + PICA” method (third step) under the sixth channel of the antenna array for the scenario using *S2* soil.

In order to deepen the discussions, the B-scan image obtained for the output of the “Median Subtraction + ICA” method is given also in Figure 4.26. This figure shows the significance of the PCA, (the second step) of the proposed “Median Subtraction + [PCA + ICA (PICA)]” method for a successful subsurface target detection in a challenging soil case. It is obvious that using the PICA approach is superior to the use of PCA or ICA methods individually for the investigated scenario under the *S2* soil condition.

Based on the results given in Figure 4.23, Figure 4.24, Figure 4.25 and Figure 4.26, the success, and the necessity of the “Median Subtraction + PICA” multi-step clutter elimination approach can be clearly understood. Similarly, when all different soil conditions are examined with these suggested methods, it is seen that the multi-step clutter elimination approach brings additional positive results and advantages in almost all GPR scenarios.

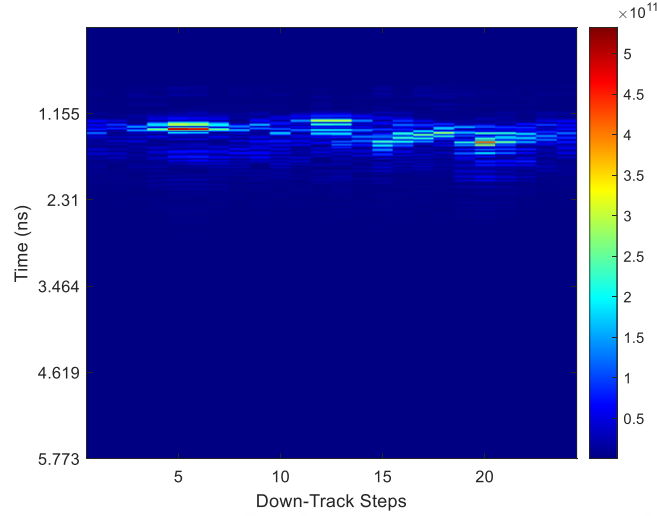


Figure 4.26 The B-scan image obtained as the result of the “Median Subtraction + ICA” method under the sixth channel of the antenna array for the scenario using S2 soil.

As stated in various clutter elimination studies in the literature, no method can be expected to work with the same level of success in all soil types and scenarios. The suitable clutter elimination method may vary for all different scenarios, soil types, and environmental properties. However, most of the unwanted clutter signals are shown to be successfully eliminated using the multi-step clutter removal methodology proposed in this thesis.

After the target detection process is completed satisfactorily, the target classification task will be performed for the four-target scenario in the most challenging S2 soil type using the outputs of two different methods; the “*Antenna Calibration + ICA*” method, and the “*Mean Subtraction + PCA*” method. For each method, the test features (extracted for the target T2 at the 21st down-track step under channel 4) will be compared with the reference FFVs stored in the classifier library. These reference FFV features of the classifier library were extracted previously for the four-target scenario in the homogeneous sandy soil with flat air-soil boundary case.

When the “*Antenna Calibration + ICA*” method is applied to this four-target scenario in S2 soil, all the targets are clearly detected. Therefore, the target T2 (investigated

in the present exercise) is also successfully classified for this same scenario. On the other hand, when the “Mean Subtraction + PCA” method is applied for clutter removal, the target T2 can be neither detected nor classified properly. This example shows that targets must be successfully detected first of all to obtain accurate classification results. In other words, In GPR missions, a successful detection is a prerequisite to a satisfactory target classification. It is well expected that performance of clutter elimination methods and hence the performance of target detection degrade as the heterogeneity of the soil medium and the roughness of the soil boundary increases. In such cases, the target classification task can still be completed successfully, although the correlation coefficient margins between the matched and mismatched target are reduced. On the other hand, if targets cannot be detected using appropriate signal processing techniques the classifier cannot work appropriately. An example to these discussions is given in Figure 4.27 that shows the classifier decision bar charts plotting the correlation coefficients between the testing LTFV (of the test target T2 extracted at the antenna channel 4 and down-track step 21) and the FFV features of the previously designed four-target classifier. Figure 4.27(a) is generated using test feature obtained after applying the “Antenna Calibration + ICA” methods to the raw data, and Figure 4.27(b) is created using test feature obtained after applying the “Mean Subtraction + PCA” methods to the raw data.

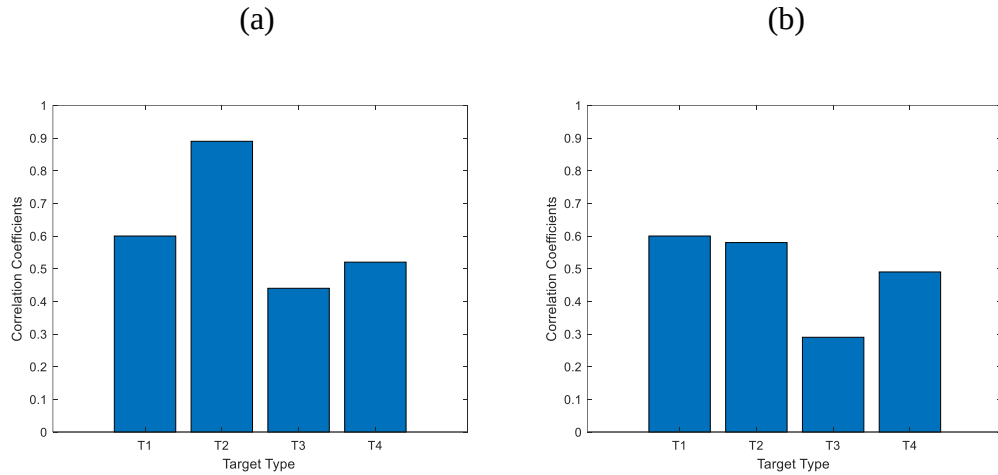


Figure 4.27 Classifier decision bar charts of correlation coefficients obtained after applying two different clutter removal methods, (a) Antenna Calibration + ICA (b) Mean Subtraction + PCA, to create the test features for the test target $T2$ buried in soil $S2$ at the location $(i, j) = (4, 21)$ in the cross-track versus down-track domain.

In addition to Figure 4.27, three different bar charts are also given in Figure 4.28, which show the correlation coefficients after applying the “Antenna Calibration + ICA” clutter elimination method to raw data for the classification targets $T1$, $T3$, and $T4$ at the “eye of target image” points $(\bar{i}, \bar{j})$ for each target in soil $S2$. Similar to Figure 4.27, obtained test features are compared with the reference FFVs of the target classifier stored in the library.

As further classification examples, Figure 4.29 and Figure 4.30 show the correlation coefficient values computed (against the FFVs of the classifier) for the targets $T1$ and $T3$ under three different soil conditions: the homogeneous sandy soil with flat surface (called ideal soil), inhomogeneous soil with flat surface ($S1$), and the inhomogeneous soil with rough surface ($S2$). FFVs are generated from the GPR scenario in ideal soil case. On the other hand, LTFVs were created from data, which are collected under relevant soil types; ideal soil, soil $S1$, and soil $S2$. These testing features are generated using processed (clutter-eliminated) time-domain A-scan signals. The “Median Subtraction + PICA” method is applied to all these data to for clutter removal.

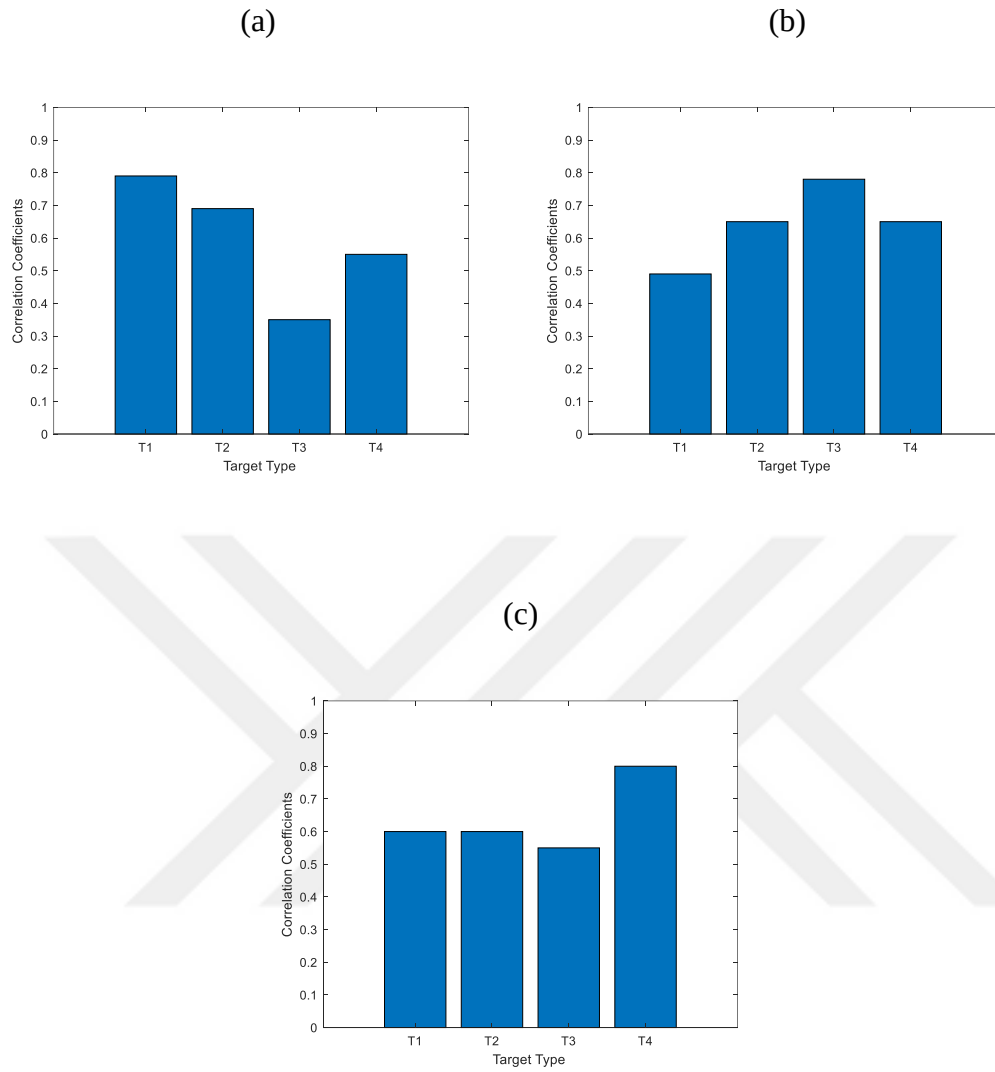


Figure 4.28 Classifier decision bar charts plotting the correlation coefficients between FFVs of the four-target classifier (designed previously for the homogeneous sandy soil with flat surface) and the testing LTFVs (obtained in soil S2 scenario) for the targets of (a) T1, (b) T3, (c) T4. Testing LTFVs are obtained after applying the “Antenna Calibration + ICA” clutter elimination method to raw GPR data.

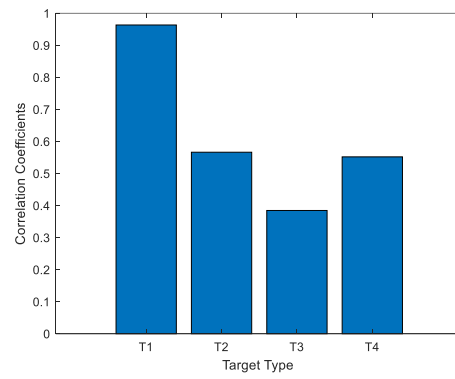
In addition to the examples given in this section, similar studies have been repeated for 12 different soil types mentioned earlier. As a result of these investigations about all these soil conditions and different clutter elimination methods, two basic conclusions have been reached regarding classifier performance:

- A GPR target classifier cannot be operated effectively unless the targets are detected properly. Successful target detection is a prerequisite for a successful target classifier.
- As the soil conditions become more difficult, more advanced multi-step clutter elimination methods are needed for satisfactory target detection.

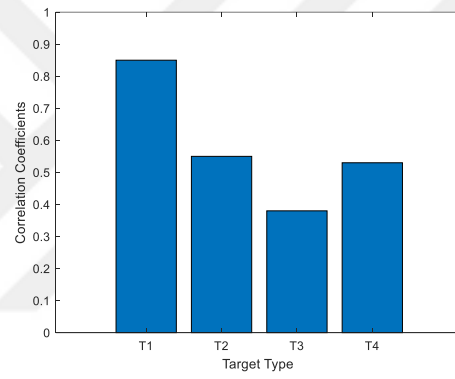
Even in the toughest soil conditions and very complex multi-target GPR scenarios, a well-designed classifier would have a chance to successfully identify targets if the targets were properly detected. The correlation coefficient values computed between the testing LTFV features and the classifier's FFV features have been carefully examined in challenging soil conditions during this thesis work. Although the margins between the correlation coefficient values for the matched and mismatched targets decrease as the soil type becomes more demanding, the test feature still shows the highest correlation with the FFV feature of the corresponding target. The change in correlation coefficient margins with the soil type in GPR classification is demonstrated in Figure 4.29 and Figure 4.30 for the targets T1 and T3, respectively, which are relatively lower RCS targets as compared to the high RCS targets T2 and T4 which are both PEC cylinders.

The bar charts in Figure 4.29 and Figure 4.30 are generated using features (test features, LTFVs) obtained from the processed A-scan signals given in Figure 4.31.

(a)



(b)



(c)

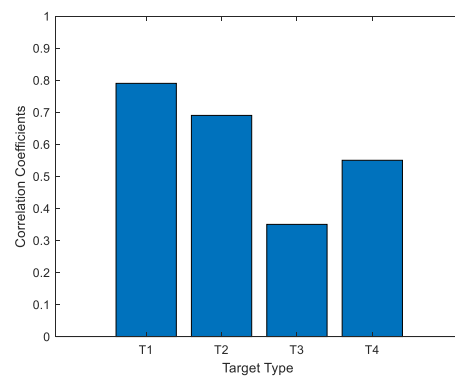
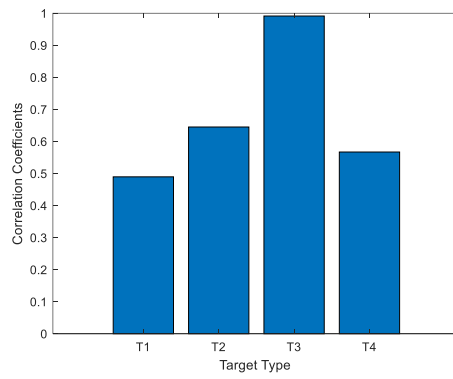
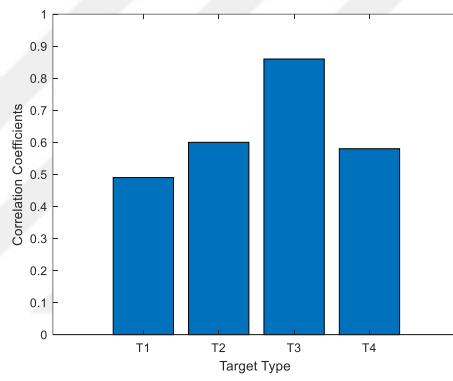


Figure 4.29 Classifier decision bar charts of correlation coefficients for target *T1*, the testing LTFVs of *T1* are obtained from processed GPR data simulated in (a) ideal soil, (b) soil *S1*, (c) soil *S2*.

(a)



(b)



(c)

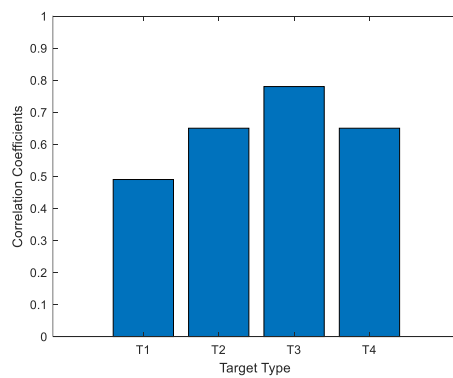


Figure 4.30 Classifier decision bar charts of correlation coefficients for target *T3*, the testing LTFVs of *T3* are obtained from processed GPR data simulated at (a) ideal soil, (b) soil *S1*, (c) soil *S2*.

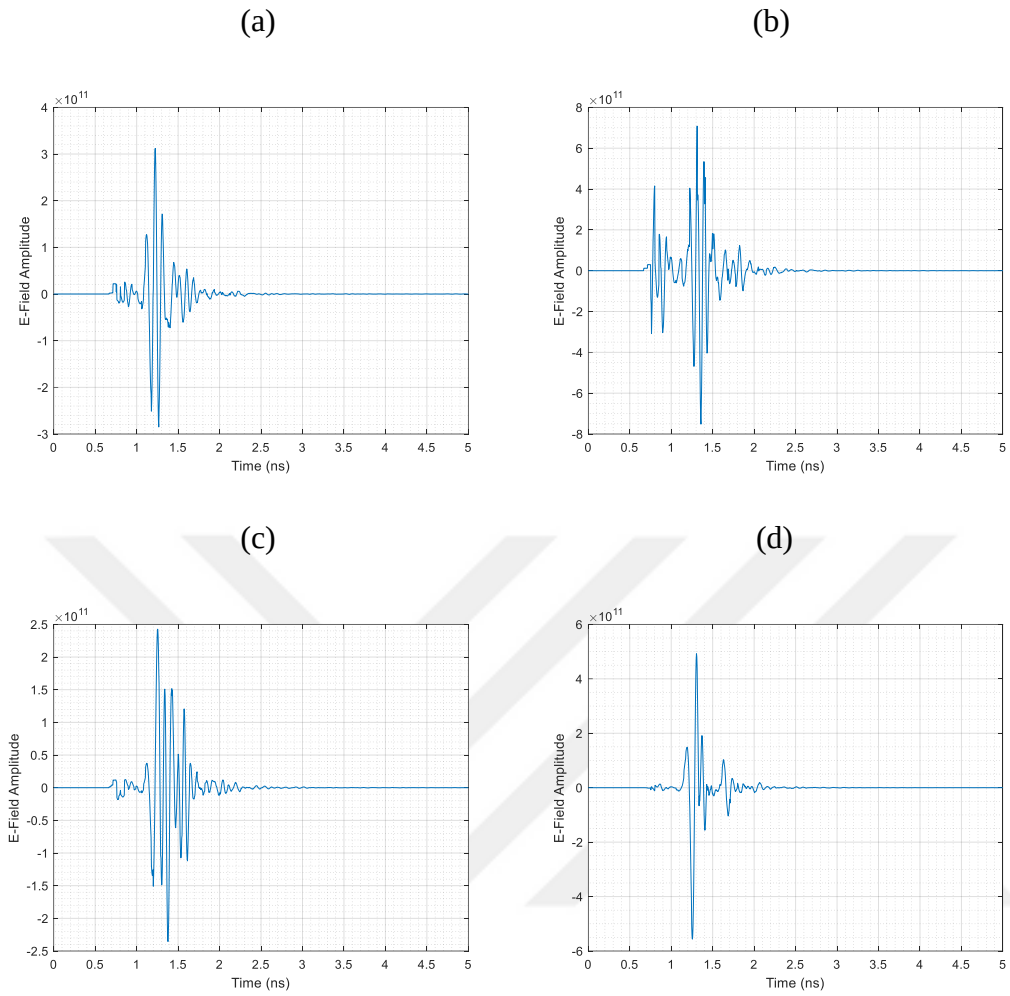


Figure 4.31 The processed A-scan data, ("Median Subtraction + PICA" clutter elimination method applied to raw data obtained from the scenario with S2 soil) for the targets (a) T1, (b) T2, (c) T3, (d) T4.

In this thesis, various clutter elimination methods have been applied to raw GPR data for the removal of DC type, GB type and background (in soil) type clutter components. It is well-known that GPRs are usually operated in real-time missions. Therefore, computation speed of the clutter elimination algorithms is a very critical issue for GPR systems.

All the computational processes for target detection and classification phases have been carried out on MATLAB with an Intel(R) Core(TM) i5-10210U CPU machine with 16 GB RAM. The elapsed time durations while applying each of the clutter removal algorithms in a standard four-target GPR scenario are given in Table 4.5 as a last piece of additional information.

Table 4.5 The elapsed times of applying utilized clutter elimination methods.

<i>Method</i>	<i>Elapsed Time</i>
Mean Subtraction	0.011 sec
Median Subtraction	0.025 sec
PCA	0.026 sec
ICA	0.113 sec
Kalman Filter	0.607 sec
Matched Filter	0.111 sec



CHAPTER 5

CONCLUSION

In this thesis, subsurface target detection and classification problems are studied in depth with broadband down-looking Ground Penetrating Radar (GPR) systems. Comprehensive approaches developed for detecting and classifying buried targets are applied to various GPR scenarios, consisting of single or multiple targets with different electrical and geometrical properties, burial depths, sizes, and more. The advantages and performance analyses of developed approaches for the detection and classification of objects are demonstrated throughout this thesis work.

First, the desired GPR scenarios are simulated with the FDTD-based GprMax open-source software, and a collection of raw time-domain signals (the A-scan signals) are obtained by scanning the designated area in down-track and cross-track directions. One-dimensional A-scan signals, two-dimensional B-scan images, and three-dimensional C-scan data are generated and used in a supportive manner to detect buried targets with high accuracy and low false alarm rates. In addition to these main data types, energy-heat map images and two-dimensional C-scan slices (at the constant depth) provide useful visual interpretations of GPR output data. On the other hand, any type of GPR data become useful only after clutter elimination process. This issue is particularly important for the detection of low RCS targets. The direct-coupled signals propagating through air, indirect-coupled ground bounce signals, as well as all kinds of clutter signals originating from the soil environment including undesired targets, must be eliminated appropriately to achieve satisfactory detection performance since all these clutter signals can mask the presence of the buried targets or they create false alarms. In this thesis, a comprehensive multi-step clutter elimination approach has been introduced by using different clutter removal methods given in the literature. In all the GPR scenarios examined in this thesis, this

approach is adhered to, and successful results are obtained for various challenging problems. After the clutter elimination process, the presence and location of targets are determined by examining A-scan data, B-scan images (in cross-track and/or down-track directions), C-scan slices, and energy-heat maps. Additionally, by interpreting these GPR data outputs, significant clues about the target properties (height, burial depths, comparison of ϵ_r values of targets) can be obtained from different simulations thanks to the physical concepts outlined in this thesis. PEC and dielectric cylindrical disks buried only 1 cm below the air-soil interface were successfully detected using the discussed approaches.

After the detection process, a novel GPR target classifier is designed in this work based on the indirect usage of the discriminative properties of CNR frequencies of the targets corresponding to the target's system transfer function poles. For different types of targets placed in unbounded air, a similar classifier design was proposed earlier by Turhan-Sayan [33,34] based on the SEM theory and using the Wigner distribution (WD) and the PCA technique. As a novel extension of this classifier design method, the combined use of Page Distribution (PD) and the Principal Component Analysis (PCA) is implemented to design a subsurface classifier in this thesis as a novel contribution to GPR literature. In addition to the use of PD instead of WD, some other novel modifications are also introduced to adapt the technique reported in [34] to the GPR target classification problem such as the isolation of target-related parts of the A-scan signals and the selection of multi-aspect GPR data in classifier feature extraction.

A novel PD-PCA-based classifier is designed to classify successfully two different PEC wires (identical wires except their radii) which are shallow-buried at different depths in soil (1, 2, 3, 4, 5, 6 cm burial depths). The accuracy and correct decision rates (especially for CCM, CCM-5%, and CCM-10% performance criteria) of the classifier for this GPR scenario are close to 100 percent.

After the design process and validations (using various shallow-buried single targets) of proposed detection and classification approaches, various shallow-buried multiple-target scenarios have been investigated. During the simulations, targets are

scanned with a multi-channel (8-channel in this work) GPR system. Due to the utilized collinear antenna array, mutual direct-coupled and ground-bounced signals are observed in addition to self-coupled signals. Significant effects of these mutual coupling signals on GPR target detection performance are investigated in depth. It has been shown that, due to these mutual coupling signals, false alarms may occur, and the presence of shallow-buried targets can be masked, especially for targets with low radar cross section (RCS), such as the dielectric disc used in our simulations.

Challenging multiple-target scenarios with two PEC cylinders of different radii, a PEC wire, and an air-filled void having a volume of a rectangular prism are investigated in detail where the targets are located very close to each other in a small investigation area of dimensions about 50 cm by 50 cm. In the first multiple-target scenario (homogeneous soil with flat surface), four different targets were successfully detected with a very small number of false alarms after applying a proper clutter elimination method (mean or median subtraction, or direct background removal method). Following the detection process, shallow-buried and closely located targets are classified with approximately a hundred percent accuracy. Reference features (FFVs) are generated using the GPR data selected at multiple points at the close neighborhood of the peak target signal locations (the eye of the target image) to minimize the aspect dependence of classifier features.

The task of detection and classification of shallow-buried targets in this four-closely located-targets scenario is made even more challenging by changing the soil medium from homogeneous to an inhomogeneous soil. In other words, the research is expanded to include soil types with varying material compositions, moisture levels, and surface roughness values. It has been observed that a classifier designed for the simple homogeneous soil case still works successfully in these harder cases provided that the targets can be properly detected prior to the classification phase. Using proper techniques of clutter elimination from the raw GPR data is the key point with utmost importance in the case of challenging soil problems. In this thesis, a multi-step clutter removal approach is proposed and demonstrated as a novel study. As a result of applying this multi-step clutter elimination approach, the targets can be

detected correctly even in the toughest soil conditions paving the way for successful target classification as well. Although the correlation coefficient margin between matched and mismatched targets decreases in the GPR classification problems having inhomogeneous soil with rough surfaces, all the targets can be successfully classified. Based upon the detection and classification simulation results, it has been concluded that successful target detection is a precondition for a satisfactory target classification in GPR studies.

The comprehensive approach for GPR target detection and classification proposed in this thesis has not been studied in the existing literature in depth, particularly for shallow-buried multiple-targets located in close proximity. In many research papers and theses in the literature, only a single buried target or multiple but remotely located targets have been examined. The investigated scenario in this thesis is quite challenging compared to the given examples in the literature because of strong electromagnetic interactions between closely located targets. Additionally, studying with shallow-buried targets is also challenging because of the self and mutual coupling signals (direct-coupled and ground-bounced signals) stemming from the GPR's antenna arrays. Detailed examination of the effects of a collinear antenna array on the detection performance of a GPR presents a unique and significant investigation. Furthermore, some other techniques such as the segmentation of energy heat maps add additional novel contributions to target detection studies in GPR literature.

Lastly, the physics-based GPR target classifier design proposed and demonstrated in this work is perhaps the fundamental novelty of this thesis. This classifier design method is introduced as a novel contribution to the subsurface electromagnetic target identification literature by us. A couple of manuscripts on this subject has been under preparation.

As the future work, it is planned to test the GPR target detection and classification algorithms developed in this thesis with experimental GPR data. Implementation of different broadband and more directive antenna types for GPR data simulation is

another task under planning. Use of different antenna array configurations for improved GPR detection performance will also be studied as a future work.





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APPENDICES

A. Verifying Low-Loss Medium Assumptions Made in GPR Scenarios

This section will present the verification of the low-loss assumption made for the materials used in this thesis. As mentioned in Section 2.1.2, if the loss tangent parameter that is formulized as $\frac{\sigma}{\omega\epsilon}$ is less than 0.1, the material medium of concern can be assumed as a low-loss medium at the given angular frequency $\omega = 2\pi f$. In Table A.1, the electrical conductivity, relative dielectric permittivity, and calculated loss tangent values of various targets and soils used in this thesis are given.

Table A.1 Electrical conductivity, relative dielectric permittivity, and loss tangent of the utilized materials

Material	Electrical Conductivity (S/m)	Relative Dielectric Permittivity	Loss Tangent at 1.9 GHz
TNT	0.01	2.7	0.035
Air	10^{-12}	1	$\sim 10^{-13}$
Sandy Soil	0.01	3.5	0.027
Soil S1	0.02	4.7	0.040
Soil S2	0.03	5.3	0.054

By using relative dielectric permittivity and electrical conductivity values and 1.9 GHz, which is the lowest frequency within the -3 dB bandwidth limits of the utilized input signal, all these materials successfully satisfy the low-loss condition. Since the low-loss condition is that the value of $\frac{\sigma}{\omega\epsilon}$ is less than 0.1, it will also be met for all frequencies within the bandwidth if this condition is met for 1.9 GHz, which is the most possible frequency to break this assumption. Therefore, the expressions for the low-loss condition can be used in all scenarios realized in this thesis.

B. An Example of gprMax Input File

To simulate a GPR scenario using gprMax, an input file containing all the required information must be provided. This input file is an ASCII text file that can be created using any text editor or word-processing program. Within the input file, the hash character (#) is reserved and serves as the indicator for the beginning of a command that will be executed by gprMax.

The input file given below as an example used to create multiple-target GPR scenarios with four targets and an eight-channel collinear antenna array. The full geometry of the system, spatial resolutions, antenna array structure, down-track step size, and target definitions are all given in this input file [54-55].

```
#domain: 0.8 0.8 0.5      %Size of the simulation domain
#dx_dy_dz: 0.002 0.002 0.002  % Spatial discretization in x,y,z directions
#time_window: 10e-9          % Total simulation time, 10 ns
#material: 1 0 1 0 air        % Definition of the air
#material: 3.5 0.01 1 0 sand  % Definition of the sand

#waveform: gaussiandot 1 6e9 my_wave  % Utilized waveform

#hertzian_dipole: x 0.180 0.610 0.350 my_wave  % Definiton of the TX1
#hertzian_dipole: x 0.240 0.610 0.350 my_wave  % Definiton of the TX2
#hertzian_dipole: x 0.300 0.610 0.350 my_wave  % Definiton of the TX3
#hertzian_dipole: x 0.360 0.610 0.350 my_wave  % Definiton of the TX4
#hertzian_dipole: x 0.420 0.610 0.350 my_wave  % Definiton of the TX5
#hertzian_dipole: x 0.480 0.610 0.350 my_wave  % Definiton of the TX6
#hertzian_dipole: x 0.540 0.610 0.350 my_wave  % Definiton of the TX7
#hertzian_dipole: x 0.600 0.610 0.350 my_wave  % Definiton of the TX8

#rx_array: 0.200 0.610 0.350 0.620 0.610 0.350 0.060 0 0  %Definition of the all RX Antennas

#rx_steps: 0 -0.02 0  % TX Step Size (2 cm step size in down-track direction)
#src_steps: 0 -0.02 0  % RX Step Size (2 cm step size in down-track direction)

#box: 0 0 0.250 0.800 0.800 0.500 air  % Layer of air above soil, antenna array in there
#box: 0 0 0 0.800 0.800 0.250 sand  % Definition of the sandy soil
#cylinder: 0.400 0.230 0.220 0.400 0.230 0.182 0.040 pec  %Definition of the target T2
#cylinder: 0.180 0.550 0.215 0.400 0.230 0.215 0.005 pec  % Definition of the wire, T1
#box: 0.460 0.348 0.200 0.550 0.412 0.220 hava  % Definition of the air cavity, T3
#cylinder: 0.570 0.520 0.220 0.570 0.520 0.192 0.030 pec  % Definition of the target T4
```

C. Observation Times of Coupling Signals in the Multi-Channel GPR

In this section, the tables mentioned in Section 4.1.2, the peak and approximate endpoints of the observed coupling signals, will be given in the time axis. Detailed information about self/mutual direct coupling and self/mutual ground bounce signals was given in Section 4.1.2. Using the results obtained from the simulation (for the case of only one transmitter being used, the simulations were repeated with each transmitter), the times of the peak and endpoints of the coupling signals were obtained. The following tables will give these time values for coupling signals from any transmitter and observed in any receiver. Each column in the tables corresponds to the transmitter data and each row to the receiver data. Cells, which are the intersection of rows and columns, indicate the index at which the direct coupling or ground bounce effects is observed in the A-scan signal of the corresponding receiver. For instance, the cell that is at the intersection of the 3rd TX antenna and 4th RX antenna corresponds to a DCS_{34} for direct coupling and GBS_{34} for ground bounce signal.

The approximate peak and endpoint times of direct coupling and ground bounce signals in nanoseconds are given in Tables C.1, C.2, C.3, and C.4.

Table C.1 Arrival times (in nanosecond) of peak points of self and mutual directly coupled (DC) type clutter signals

	TX 1	TX 2	TX 3	TX 4	TX 5	TX 6	TX 7	TX 8
RX 1	0.215	0.281	0.481	0.681	0.881	1.081	1.282	1.486
RX 2	0.416	0.215	0.281	0.481	0.681	0.881	1.081	1.282
RX3	0.616	0.416	0.215	0.281	0.481	0.681	0.881	1.081
RX 4	0.816	0.616	0.416	0.215	0.281	0.481	0.681	0.881
RX 5	1.016	0.816	0.616	0.416	0.215	0.281	0.481	0.681
RX 6	1.216	1.016	0.816	0.616	0.416	0.215	0.281	0.481
RX 7	1.416	1.216	1.016	0.816	0.616	0.416	0.215	0.281
RX 8	1.617	1.416	1.216	1.016	0.816	0.616	0.416	0.215

Table C.2 Arrival times (in nanosecond) of peak points of self and mutual ground-bounced (GB) coupling type clutter signals

	TX 1	TX 2	TX 3	TX 4	TX 5	TX 6	TX 7	TX 8
RX 1	0.847	0.858	0.920	1.028	1.162	1.308	1.466	1.632
RX 2	0.893	0.847	0.858	0.920	1.028	1.162	1.308	1.466
RX3	0.989	0.893	0.847	0.858	0.920	1.028	1.162	1.308
RX 4	1.112	0.989	0.893	0.847	0.858	0.920	1.028	1.162
RX 5	1.258	1.112	0.989	0.893	0.847	0.858	0.920	1.028
RX 6	1.413	1.258	1.112	0.989	0.893	0.847	0.858	0.920
RX 7	1.578	1.413	1.258	1.112	0.989	0.893	0.847	0.858
RX 8	1.751	1.578	1.413	1.258	1.112	0.989	0.893	0.847

Table C.3 Arrival times (in nanosecond) of ending points of self and mutual directly coupled (DC) type clutter signals

	TX 1	TX 2	TX 3	TX 4	TX 5	TX 6	TX 7	TX 8
RX 1	0.373	0.439	0.639	0.839	1.039	1.239	1.447	1.643
RX 2	0.573	0.373	0.439	0.639	0.839	1.039	1.239	1.447
RX3	0.773	0.573	0.373	0.439	0.639	0.839	1.039	1.239
RX 4	0.974	0.773	0.573	0.373	0.439	0.639	0.839	1.039
RX 5	1.174	0.974	0.773	0.573	0.373	0.439	0.639	0.839
RX 6	1.374	1.174	0.974	0.773	0.573	0.373	0.439	0.639
RX 7	1.574	1.374	1.174	0.974	0.773	0.573	0.373	0.439
RX 8	1.774	1.574	1.374	1.174	0.974	0.773	0.573	0.373

Table C.4 Arrival times (in nanosecond) of ending points of self and mutual ground-bounced (GB) coupling type clutter signals

	TX 1	TX 2	TX 3	TX 4	TX 5	TX 6	TX 7	TX 8
RX 1	1.005	1.016	1.078	1.185	1.320	1.466	1.624	1.790
RX 2	1.050	1.005	1.016	1.078	1.185	1.320	1.466	1.624
RX3	1.147	1.050	1.005	1.016	1.078	1.185	1.320	1.466
RX 4	1.270	1.147	1.050	1.005	1.016	1.078	1.185	1.320
RX 5	1.416	1.270	1.147	1.050	1.005	1.016	1.078	1.185
RX 6	1.570	1.416	1.270	1.147	1.050	1.005	1.016	1.078
RX 7	1.736	1.570	1.416	1.270	1.147	1.050	1.005	1.016
RX 8	1.909	1.736	1.570	1.416	1.270	1.147	1.050	1.005

D. B-Scan Images Under Different Channels in the Main Multiple-Target Scenario

In this section, for the scenario given in Section 4.3, B-scan images obtained under the remaining six channels that were not examined in the main thesis will be given. B-scan images given in Figure D.1 were obtained under Channels 1, 3, 4, 5, 7, and 8, respectively. The targets observed in all these images are in line with the expectations.

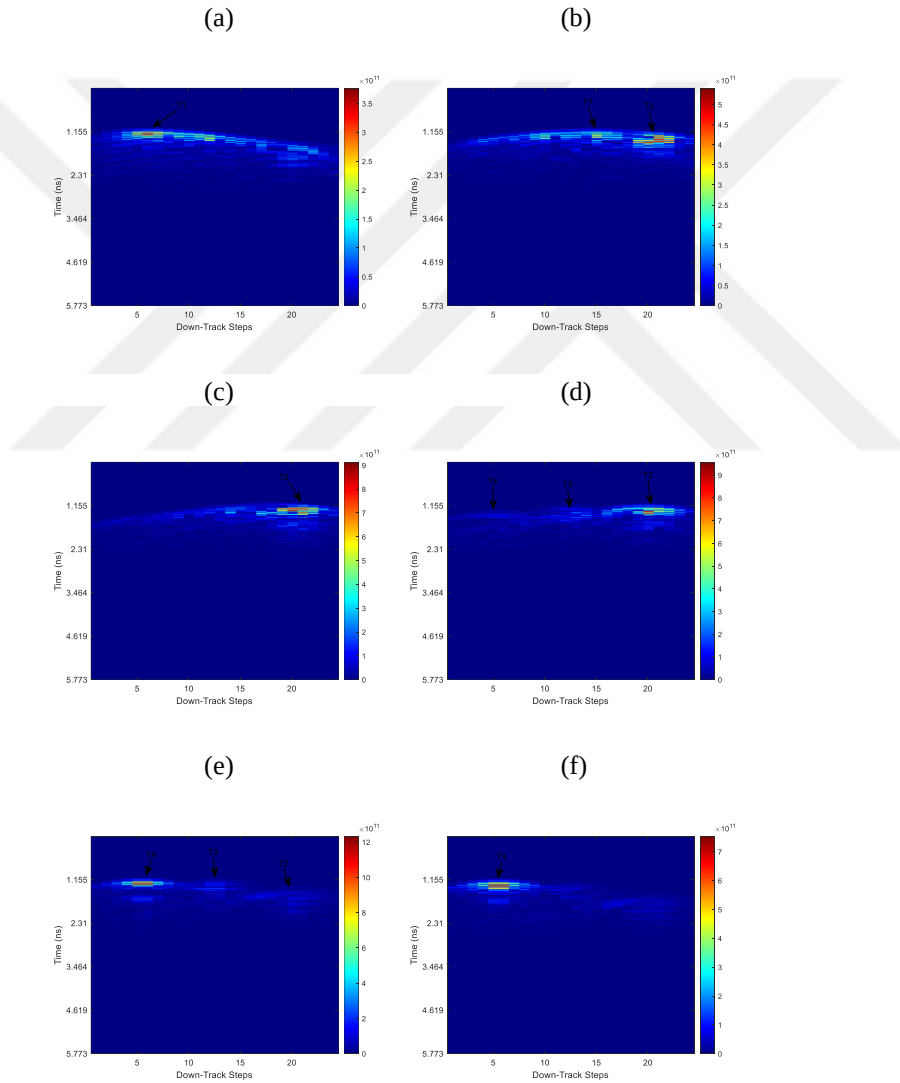


Figure D.1 B-scan images of the main multiple-target scenario under (a) Channel 1, (b) Channel 3, (c) Channel 4, (d) Channel 5, (e) Channel 7, (f) Channel 8.

E. An Overview of the Time-Frequency Representations (TFRs) with Special Emphasis on Quadratic TFRs Including the Wigner Distribution (WD) and the Page Distribution (PD)

Time-Frequency Representations (or as also called time-frequency distributions) are linear or quadratic transformations defined on joint (two-dimensional) time-frequency domain. TFRs are implemented in different fields such as electromagnetics, geophysics, biomedical, signal processing, communication, signal coding and decoding, especially for feature extraction and classification in recent years [128-131].

Linear TFRs frequently used in the literature are Short-Time Fourier Transform (STFT), Gabor transform (GT) and Wavelet Transform (WT). Mathematically, all linear TFRs must satisfy the superposition principle.

For given time functions $x_1(t)$ and $x_2(t)$ and for given arbitrary constants c_1 and c_2 , if $x(t) = c_1x_1(t) + c_2x_2(t)$, its cross-TFR $T_{x_1,x_2}(t, f)$ satisfies:

$$T_{x_1,x_2}(t, f) = c_1T_{x_1}(t, f) + c_2T_{x_2}(t, f) \quad (\text{E. 1})$$

where $T_{x_1}(t, f)$ and $T_{x_2}(t, f)$ correspond to linear TFRs of individual signals. When $x_1(t) = x_2(t)$, the resulting TFR is called auto-TFR.

In STFT, for example, the given time signal is multiplied by a sliding time window, and basically, the FT of the windowed function is computed to provide some localization in time. Thus, the local spectra over short time durations can be calculated. However, STFT suffers from a trade-off between time and frequency resolutions. Increasing the time resolution leads to a decrease in frequency resolution, and vice versa. This limitation can make it difficult to simultaneously capture fine-scale temporal and spectral features of a signal simultaneously. Also, parameter optimization like window length for STFT complicates and slows down the process in linear TFRs.

For quadratic Time-Frequency Representation $T_x(t, f)$, on the other hand, the quadratic TFR of the superposition of the individual signals $x_1(t)$ and $x_2(t)$, i.e. $x(t) = c_1x_1(t) + c_2x_2(t)$ leads to

$$T_x(t, f) = |c_1|^2 T_{x_1}(t, f) + |c_2|^2 T_{x_2}(t, f) + c_1 c_2^* T_{x_1, x_2}(t, f) + c_2 c_1^* T_{x_2, x_1}(t, f) \quad (\text{E.2})$$

where $T_{x_1}(t, f)$ and $T_{x_2}(t, f)$ are the auto-TFRs of the signals $x_1(t)$ and $x_2(t)$, respectively while $T_{x_1, x_2}(t, f)$ and $T_{x_2, x_1}(t, f)$ are the cross-TFR (or interference) terms representing the interaction of these two functions. This rule can be generalized for an N-component signal, $x(t) = \sum_{k=1}^N c_k x_k(t)$ for which the resulting quadratic TFR $T_{x_1, \dots, x_N}(t, f)$ will be composed of N auto-TFR terms and $(N)(N-1)/2$ interaction terms. If a given broadband GPR A-scan time-domain signal is considered to be the linear combination of N damped sinusoidal signals as modeled in the SEM theory, it is obvious that a huge number of cross-terms will result in a quadratic TFR of this A-scan signal in addition to the auto-TFR terms. The highly oscillatory cross-terms usually takes very large negative values as well as positive values. There are different methods [132] suggested in TFR literature for the elimination of these cross or interference terms.

There exist many types of quadratic TFRs defined in literature with an energetic representation. All time-frequency shift-invariant and quadratic TFRs are members of quadratic Cohen's class TFRs. The fundamental member of this class is the Wigner distribution (WD) and all other members of the Cohen's class derivable from the WD [132-134] through the convolution of a specific Kernel function with the WD of a given signal $x(t)$.

The auto-Wigner distribution of $x(t)$ is defined to be

$$W_x(t, f) = \int_{\tau} x\left(t + \frac{\tau}{2}\right) x^*\left(t - \frac{\tau}{2}\right) e^{-j2\pi f \tau} d\tau \quad (\text{E.3})$$

where the superscript (*) denotes complex conjugate operator. The Wigner distribution (WD) is advantageous for many studies because it has a good time-

frequency concentration and provides a lot of desired properties as discussed in detail in literature [132-134]. However, substantial interference terms pose a serious handicap for the practical use of WD. As it is well-known, there exists a general tradeoff between good time-frequency concentration and small interference terms. The interference terms (ITs) of the WD can be identified by their wild and oscillatory nature, and they seriously degrade WD's performance in many practical applications as they can overlap with auto terms. In practical applications of the WD, interference terms occur midway between each pair of signal components whether the auto WD overlap or not. For instance, if we investigate two signals that occur around time-frequency points (t_1, f_1) and (t_2, f_2) ; interference terms, t_{12} and f_{12} , will occur at the following points in time and frequency:

$$t_{12} = \frac{t_1 + t_2}{2} \quad (\text{E. 4})$$

and

$$f_{12} = \frac{f_1 + f_2}{2} \quad (\text{E. 5})$$

In the challenging GPR scenarios, there are many different signal components effective in time and also the signal bandwidth is very wide in frequency. Therefore, when the WD is applied to such A-scan signals, many interference terms occur reducing the target classification and detection performance. Therefore, the Page distribution (PD), which is an alternative quadratic TFR with reduced interference terms, is implemented for feature extraction in this thesis.