

# Real-time Buried Object Detection Using LMMSE Estimation

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**Abstract**— We present the application of linear minimum mean square error (LMMSE) estimation to GPR data for achieving buried object detection. Without employing any empirical assumptions, nonstationary form of Wiener-Hopf equations is applied to GPR signals to estimate the next sample in normal conditions. A large deviation from this estimation indicates the presence of a buried object. The technique is causal, which allows it to be used in real-time applications. Our approach is theoretically optimal in linear minimum mean square error sense, and it is also validated with the tests that are carried out on a comprehensive data set of GPR signals.

## I. INTRODUCTION

Nonintrusive detection of buried objects appeals great interest among scientists. Among many available methods, ground penetrating radar (GPR) has become especially popular. GPR has a wide spectrum of application areas, some of which include archaeological investigations, building condition assessment, forensic investigations, detection of buried mines, road condition survey and pipe detection [1].

There are two basic factors, by means of which GPR has gained its reputation. First, GPR is capable of sensing both metallic and nonmetallic objects as it is sensitive to all three characteristics of the scanned area, which are, electric permittivity, electric conductivity and magnetic permeability. Moreover, GPR can survey an area before the sensor moves past over it. This is extremely beneficial in detection of dangerous objects, such as buried landmines [2]. A simplistic GPR block diagram is provided in Fig. 1, where antenna coupling, ground bounce and target signature are shown.

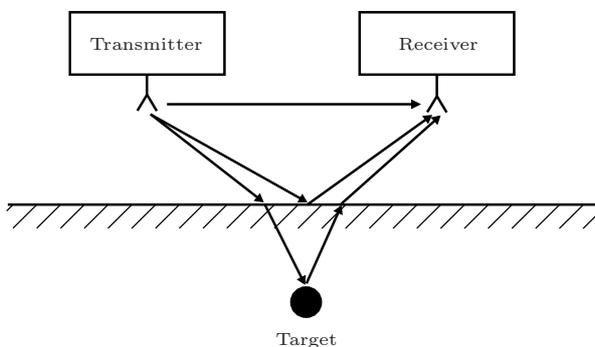


Fig. 1. Main structure of the GPR system

In this study, we propose to use time domain linear minimum mean square error (LMMSE) estimation in the buried object detection problem. Actually, this implementation turns out to be a Wiener filter, without the stationarity assumption of the signals. LMMSE estimation is vastly exploited in the communications society, however, to the best of our knowledge, it is not used in the buried object detection problem using GPR yet. In [3], baseband Wiener processing is applied to laser induced acoustic scanner data, by assuming a multipath model for the received signal. In [4], Wiener filter is used to detect changes in synthetic aperture radar images. Neither of these studies deals with GPR data. Our technique depends on estimating the next sample in the GPR signal using the optimal LMMSE estimator. This estimator corresponds to a causal FIR filter, which allows the method to be applied in real-time applications. After estimating the next sample, the sample is gathered and compared with its estimation. A large deviation from the estimated value signifies an anomaly at the inspected zone.

This paper is structured as follows. Section II discusses the problem formulation and presents the proposed method. Section III gives the results of applying the technique to an extensive GPR data set, which is collected using a GPR sensor developed at The Scientific and Technological Research Council of Turkey (TÜBİTAK). Conclusion is drawn in Section IV, which finalizes our discussion.

## II. PROBLEM FORMULATION AND ALGORITHM

### A. Data Representation

A GPR B-scan is represented as an ensemble of A-scans. Let a B-scan be composed of  $r$  A-scans, each of which contains  $q$  samples. We model this B-scan as  $r$  realizations of  $q$  random sequences. In other words, each depth bin forms a random sequence.

For representing each random sequence, we utilize the fact that, clutter signatures are similar among themselves, however, they exhibit a high degree of discrepancy from buried object signatures. In other words, in the absence of a buried object, GPR signals vary slowly. Hence, clutter samples can be represented as a linear combination of previous samples. This assumption is used in quite a few of previous studies (e.g. [5], [6]). Under this assumption, the linear combination model can be shown as