remote sensing

Editorial

Editorial for the Special Issue “Advanced Techniques for Ground Penetrating Radar Imaging”

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1. Introduction

Ground Penetrating Radar (GPR) has become one of the key technologies in subsurface sensing and, in general, in Non-Destructive Testing (NDT), since it is able to detect both metallic and nonmetallic targets. Furthermore, it can also provide images from the underground, thus improving detection capabilities. GPR for NDT has been successfully introduced in a wide range of sectors, such as mining and geology (detection of cavities, mineral deposits), glaciology (measurement of ice thickness), civil engineering and civil works (detection of cracks and defects in infrastructure), archaeology, and security and defense (detection of buried landmines and Improvised Explosive Devices, IEDs).

Improvements in georeferring and positioning systems have enabled the introduction of Synthetic Aperture Radar (SAR) techniques in GPR, yielding GPR–SAR systems capable of providing high-resolution microwave images. In parallel, the radiofrequency front-end of GPR systems has been optimized in terms of compactness (e.g., smaller Tx/Rx antennas) and cost. These advances, combined with improvements in autonomous platforms, such as unmanned terrestrial and aerial vehicles, have fostered new fields of application for GPR, where fast and reliable detection capabilities are demanded. In addition, processing techniques have been improved, putting together advances in the field of inverse scattering and imaging and in the area of machine learning and artificial intelligence. As a result, novel and robust algorithms have been developed for noise and clutter reduction, automatic target recognition, and efficient processing of large sets of measurements to enable real-time imaging, among others.

This Special Issue comprises a set of contributions covering both hardware and software improvements for enhanced GPR imaging. The techniques described in these contributions have been successfully applied to a wide variety of areas, such as archaeology, landmine detection, snow thickness monitoring, and buried infrastructure location.

The scope of the Special Issue contributions can be classified into three main groups: High-resolution GPR systems [1–4], noise mitigation in GPR measurements [5,6], and GPR data processing enhancement [7–10].

2. High-Resolution GPR Systems

Contributions [1–4] introduce high-resolution GPR architectures for landmine and IEDs detection [1,2] snow thickness monitoring [3], and location of drainage pipes [4]. In general, compact Ultra-Wide-Band (UWB) radar modules working within the 150 MHz to 6 GHz are used, as this frequency band provides a good trade-off between range resolution and penetration depth.

Airborne-based GPR systems have become a research area of great interest due to their capability of contactless location and imaging of buried objects. This is especially desirable in the field of landmine and IED detection in order to minimize the risk of accidental detonation. An airborne Down-Looking GPR (DLGPR) architecture is presented in [1], proving the capability of conducting autonomous scanning with centimeter-level accuracy thanks to the use of Real Time Kinematics (RTK) and LIDAR sensors.

DLGPR systems provide good dynamic range thanks to the short distance between the radar and the ground, but at the expense of strong clutter coming from the air-ground interface. This limits the capacity of detecting shallow targets. Forward-Looking GPR (FLGPR) systems are able to minimize air-ground clutter. However, the dynamic range is greatly reduced with respect to DLGPR. Combination of FLGPR and DLGPR architectures yields a GPR system with reduced air-ground clutter, but without compromising the dynamic range. In [2] an experimental validation of a hybrid FLGPR-DLGPR architecture is presented. Practical implementation of the hybrid FLGPR-DLGPR has been made possible thanks to the use of transmitting and receiving radar modules working in the 3–5 GHz frequency band that use a wireless link for synchronization.

A GPR application devoted to measure the available water in snow cover is described in [3]. The radar module is implemented using a Software Defined Radio (SDR) and two UWB Vivaldi antennas. Measurements acquired in real conditions are processed by means of an approximated method derived from an electromagnetic model used to calculate the reflectance of snowpacks, proving the accuracy of the presented technique to retrieve the Snow Water Equivalent (SWE) parameter. Besides, a 120-GHz Frequency Modulated Continuous Wave (FMCW) radar is introduced to accurately measure the snow thickness.

An application of a GPR system to detect buried infrastructure is presented in [4]. In particular, the research focuses on tailoring the issue of multiple reflections that occur when two large targets are buried close to each other (two drainage pipes in this case). GPR-SAR processing is also applied together with ground removal resulting in improved along-track resolution of the images given by the GPR systems with respect to raw radargrams. In the post-processed images, the upper and lower bounds of the buried drainage pipes can be detected.

3. Noise Mitigation in GPR Measurements

Besides air-ground clutter, GPR measurements can be corrupted by different sources of noise. Different strategies have been proposed to mitigate the impact of noise in GPR measurements, thus improving detection capabilities. These strategies range from machine learning techniques [5] to spectral domain filtering approaches [6].

Aiming at improving the GPR image quality, [5] introduces a methodology to reduce random GPR noise. The technique presented by the authors is based on a neural network-based structure for denoising autoencoders (Convolutional Denoising AutoEncoders, CDAEs), introducing several improvements such as a dropout regularization layer, an atrous convolution layer, and a residual-connection structure. Validation of the method presented in [5] has been conducted using both simulation-based datasets and field measurements, proving that this technique not only reduces GPR noise, but also minimizes the degradation of the original waveform data.

Clutter can be partially mitigated by filtering the GPR measurements in the frequency domain. Sometimes, optimal choice of filter parameters must be selected based on a trial-and-error procedure. A new methodology is proposed in [6] to make filter parameterization easier, based on a Singular Value Decomposition (SVD) method applied in the two-dimensional spectral domain. The proposed filtering method has been validated using a three-dimensional GPR dataset, resulting in an increased geometric sharpness of GPR images.

4. GPR Data Processing Enhancement

Feature extraction from GPR data can be improved by means of advanced GPR processing techniques. On the one hand, processing methods are improved by accurate characterization of the measurement scenario. For example, if the composition of the soil is available, an accurate estimation of propagation velocity can be performed, thus improving GPR image focusing [1,7]. On the other hand, image processing techniques combined with machine learning approaches result in a more efficient detection of the features and targets of interest. The latter is of special interest when the surveyed volume is much greater than the targets and features, so visual inspection of the volume is extremely time-consuming and challenging. Besides, machine learning techniques have been also introduced to improve GPR image quality, e.g., by means of sidelobe suppression [9].

Two coherency functionals, the Complex Matched Coherency Measure, and the Complex Matched Analysis, are proposed in [7] to improve the Signal-to-Noise Ratio (SNR) of GPR data and to accurately retrieve the propagation velocity. Range migration algorithms are proved to perform better when considering a spatial-dependent propagation velocity rather than using a constant or only along-track estimation of propagation velocity.

Conventional GPR imaging is sensitive to changes in the measured amplitude of the signal, so resulting GPR images correspond to changes in the reflectivity. In attribute analysis, phase and frequency information is considered, resulting in GPR coherence maps. In [8] multi-trace attribute analysis is conducted to enhance GPR imaging, proving that, under certain conditions, improved data visualizations are achievable. The proposed GPR trace coherence imaging is applied to GPR data sets taken at archaeological sites, showing the capability to detect targets and features that conventional GPR imaging cannot resolve.

The presence of sidelobes in radar images may result in false detections or missed targets or features. A wide variety of techniques for sidelobe suppression has been proposed, ranging from windowing methods (e.g., Hamming window) to Convolutional Neural Network (CNN)-based techniques. The latter can be affected by the fact that the Point Spread Function (PSF) in the radar images can be sometimes spatially variant. A Spatial-Variant CNN (SV-CNN) with spatial-variant convolutional kernels is proposed in [9] to overcome this issue, proving its better performance compared to the conventional CNN in realistic scenarios.

Improvements in autonomous terrestrial and aerial systems have enabled fast scanning of large areas using GPR systems, where the resulting 3D data sets have to be processed automatically. Machine learning methods are quite efficient in properly identifying features and targets of interest, but at the expense of requiring a large number of data sets for training purposes. Ref. [10] introduces a machine learning framework based on wavelet scattering networks, which are functionally equivalent to CNN. The main goal is to detect the features corresponding to buried pipelines in GPR datasets. Results presented in [10] yield a classification accuracy greater than 95% in the presented examples.

5. Conclusions

Contributions of this Special Issue illustrate part of the advances in GPR technology for non-destructive inspection and imaging. The development of compact low-cost sensors has enabled the implementation of novel GPR architectures. Besides, recent advances in signal processing, machine learning, and data science, are being introduced in GPR data post-processing to improve feature extraction and automatic target recognition, even when dealing with larger GPR datasets. These machine learning techniques have also been applied for noise mitigation and artifact suppression in GPR measurements.

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