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Three-Dimensional Reconstruction of Water Leaks in Water Distribution Networks from Ground-Penetrating Radar Images by Exploring New Influencing Factors with Multi-Agent and Intelligent Data Analysis †

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Abstract: This paper promotes water distribution networks' (WDNs) sustainability and efficiency by integrating intelligent data analysis with ground-penetrating radar (GPR) to better interpret GPR images for detecting water leaks, favouring their asset assessment. This work uses GPR data from a laboratory setting to investigates the effects of various parameters on image interpretability across pipes. This methodology aims to advance the automation of leak and pipe identification, improving data interpretation and reducing dependency on human experts for leakage detection purposes. The findings suggest the possibility of uncovering new features enhancing GPR image interpretability, presented in 3D models.

Keywords: WDNs; GPR interpretation; 3D visualizations; water leakage; intelligent data analysis

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1. Introduction

Urban development hinges on the continuous availability of clean, safe, and cost-effective drinking water. The deterioration of water distribution network (WDN) infrastructure due to ageing and stress increases the production costs, leads to water loss, and affects both the quantity and quality of the water service [1]. In order to facilitate the (early) detection of water leaks, WDNs require the availability of reliable information from extensive monitoring programmes [2]. This work aims to promote WDNs' sustainability, resilience, and appropriate water resource management by improving the health asset assessment techniques [3]. This paper employs intelligent data analysis and a non-destructive method (in this case, ground-penetrating radar—GPR) to identify buried target objects like water leaks in GPR images, thus aiding WDN asset health assessments [4]. The selection of GPR in this paper is due to its easily deployed ability to detect diverse materials in a variety of environments [5]. However, the captured GPR images require considerable experience to analyze [6]. In this sense, this paper explores the feasibility of improving the interpretability of the information captured by GPR with the 3D reconstruction of the water leak event. This work uses GPR data captured under controlled laboratory conditions and analyses various GPR parameters—such as the capture velocity, the sample count, and the sampling intervals—to study their impact on image clarity. It also includes GPR images of pipes with different diameters (plastic pipes), water contents, and surrounding soil. The images undergo pre-processing with an agent race algorithm for feature extraction, followed by classification into clusters using a perceptron neural network [4]. Delaunay triangulation is then used to highlight areas of interest in the 2D images for 3D visualization creation. The ultimate goal of this works is to advance towards the automated identification of water

leaks (in particular, it focuses on early leak detection) and pipes, making data visualization easier through 3D visualizations and, thus, bettering the interpretability of the results.

2. Materials and Methods

This section describes the treatment of GPR data proposed in this work. The integrated method synthesizes the core elements from three distinct methodologies. Figure 1 presents the evaluated processes, from the capturing of GPR images to the generation of the 3D visualizations.

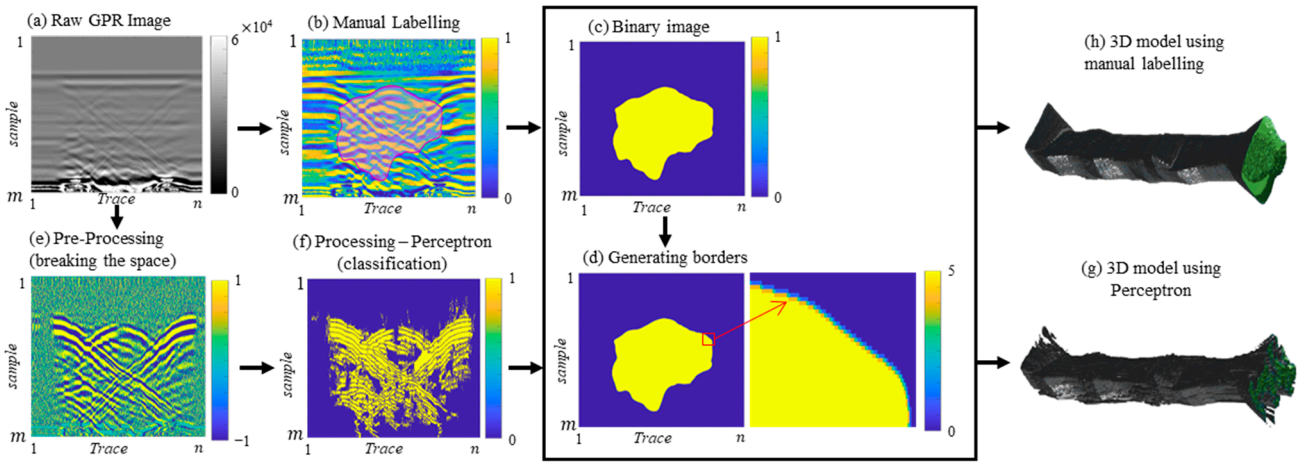


Figure 1. Outlines the methodology.

Raw GPR images. The process commences with the capturing of raw GPR images (Figure 1a), where electromagnetic waves emitted from a directional antenna are reflected upon encountering various materials. These reflections, with wave amplitudes denoting material interfaces, produce images that form a complex matrix [4,7], denoted in this paper as matrix A of size $m \times n$.

Manual labelling and categorisation. Following the capturing of the GPR images, each image is normalized by rows and manually labelled (Figure 1b) into three classes (denoted as matrix A_B: Class-1 for pipe images (Figure 1c), Class-2 for reflections from the left side of the tank, and Class-3 for reflections from the right side). It should be mentioned that the binary matrix for the perceptron-based pre-process (details below) corresponds to the comparison of the binary matrix resulting from this (Figure 1f) with the binary matrix of the image associated with Class-1 (Figure 1c). The categorisation aids in tailoring subsequent analytical processes to the characteristics of each class.

Bordering. The image borders are generated (Figure 1d) for the labelled data, reducing the interpolation time and enabling efficient 3D modelling (Figure 1g,h). The borders are generated by means of $B_{\mathrm{p},i,j} = (\left(\sum_{k=1}^{k=4} A_{\mathrm{B},cell_k}\right) + A_{\mathrm{B},i,j}\right)$, where $B_{\mathrm{p},i,j}$ represents the matrix with borders with $i = \{1,\ldots,m\}, j = \{1,\ldots,n\}$ and $cell = \{(i+1,j),(i,j-1),(i,j+1),(i-1,j)\}$ with $k = \{1,\ldots,4\}$.

Pre-processing—breaking the space. In this stage (Figure 1e), a game theory-based algorithm known as "agent race" [7] is used to break the complex image space into simpler, distinct groups by varying the directions of the agent track [4,8]. This pre-processing enhances feature detection by segregating noise, identifying horizontal lines, and discerning objects, thereby facilitating a clearer delineation of material boundaries.

Pre-processing—classification. Taking advantage of the space-breaking process, a perceptron neural network [4,8] (Figure 1f) is employed to clean the GPR data further. This step is essential for noise reduction and precise labelling, leading to clearer images for in-depth analysis [7,8]. Building upon the perceptron's foundation, in this work, additional inputs as range (ηs/total samples) and dimension (n) of the GPR image are applied (Perceptron 2) to refine and generate new interpretation perspectives.

Three-dimensional model generation. The culmination of the proposed method is the development of a series of 3D models (Figure 1g,h), which are constructed using tools like MATLAB's 3D Delaunay function and based on the images contained in the matrices B_p. These visualizations represent the spatial relationships and boundaries identified within the GPR data, offering a three-dimensional visual interpretation of subsurface structures.

This integrated approach encapsulates the evolution of GPR image analysis, from the initial capture to the final 3D modelling, by leveraging the strengths of individual methodologies and incorporating advancements in data processing techniques.

3. Case Studies, Analysis, and Results

Two cases of plastic pipes with cracks were used to reconstruct a leak according to the methodology proposed in this paper. Case 1 corresponds to data used by [2] for a water leak from a PVC pipe of a 100 mm diameter buried in sand with 22 profiles taken in both X and Y directions. Case 2 involved a polyethene pipe of a 24 mm diameter buried in pavement sand (in a wooden tank of 1 m × 1 m × 1 m) with 14 profiles, every 10 cm apart, taken in both X and Y directions. Both cases were tested in a laboratory setup and used a 1.5 GHz commercial GPR antenna and the same range 10 ηs/total samples. Figures 2 and 3 present, in their insets, the results of manual labelling (ideal case) and Perceptron 1 and Perceptron 2 for Cases 1 and 2, respectively.

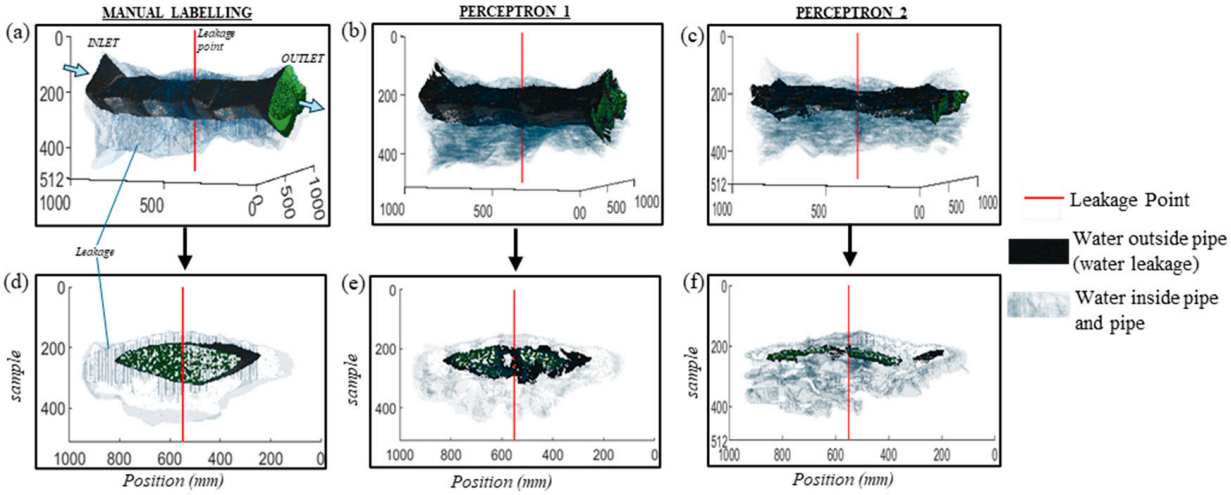


Figure 2. Case 1. (**a**–**c**) 3D reconstructions. (**d**–**f**) 2D cross-sections.

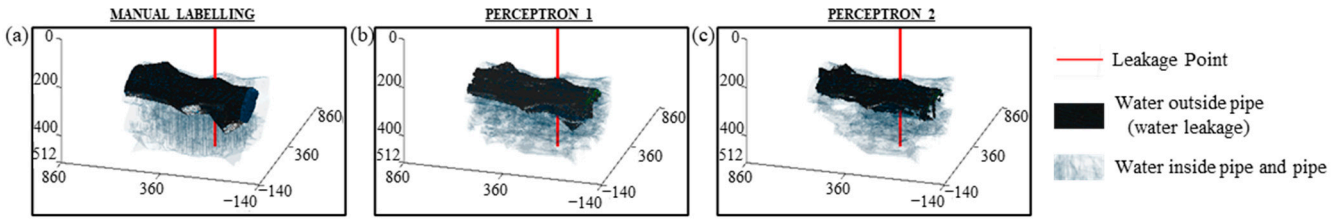


Figure 3. Case 2. (**a**–**c**) 3D reconstructions.

In Figure 2, the presence of leaking water is depicted in blue, encircling the pipe in all three of the proposed processes both in the 3D images and in the cross-sections. The result shows successful similarity between what is expected (Figure 2a) and what is predicted by Perceptron 1 (Figure 2b) and Perceptron 2 (Figure 2c). In Figure 2e, there are some gaps (compared to Figure 2d) that are due to the horizontal lines in the initial classification. In addition, it can be seen that Perceptron 2 focused its efforts on identifying the first reflection hyperbola. Therefore, we can see that only the top section of the pipe was generated (comparing Figure 2a with Figure 2e).

Figure 3a–c show that we applied the same techniques to a scenario involving a pipe with a reduced diameter. Despite the reduced size, our approach continued to accurately detect subsurface structures and leaks, showing similar precision to tests conducted on larger pipes. This demonstrates our method's flexibility in working effectively across different pipe sizes, maintaining its ability to accurately identify features in GPR data.

4. Conclusions

This work has explored various factors that may influence the interpretability of GPR images and employed a combination of feature extraction algorithms and neural network classifications. The results suggest the potential to significatively enhance GPR images' interpretability. The development and application of these methodologies not only streamline the identification of water leaks and pipe anomalies but also contribute to the reduction in expert dependency during the analysis process. The promising outcomes, showcased using detailed 3D visualizations, underline the effectiveness of integrating advanced data analysis techniques with GPR technology. This approach paves the way for more autonomous, accurate, and efficient assessments of WDN assets. This work marks an advancement in promoting WDN sustainability and efficiency by leveraging GPR data analysis through intelligent algorithms and 3D visualization techniques to facilitate health asset assessments of its infrastructure.

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Conflicts of Interest: The authors declare no conflicts of interest.

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