DIP Paper Implementation
Topic: Ground Penetrating Radar

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1 Papers

1. W. Al-Nuaimy, Y. Huang, M. Nakhkash, M.T.C. Fang, V.T. Nguyen, A. Eriksen,"Automatic detection of buried utilities and solid objects with GPR using neural networks and pattern recognition",Journal of Applied Geophysics 43 (2000) 157–165

2. Minh-Tan Pham, Sébastien Lefévre,"Buried Object Detection From B-Scan Ground Penetrating Radar Data Using Faster-RCNN"

2 Introduction

Ground Penetrating Radar (GPR) has been widely used as a non-destructive tool for the investigation of the shallow subsurface, and is particularly useful in the detection and mapping of subsurface utilities and other solid objects. GPR displays are usually either manually scaled and interpreted, or stored and subsequently processed off-line.

As GPR is becoming more and more popular as a shallow subsurface mapping tool, the volume of raw data that must be analysed and interpreted is causing more of a challenge. There is thus a growing demand for automated subsurface mapping techniques that are both robust and rapid.

The proposed system employs a combination of neural network, signal and image processing techniques to provide a high-resolution image of the subsurface in near real-time facilitating straightforward data interpretation and providing accurate depth and azimuth location information.

3 Objective

The objective is to determine the location of the hyperbola in a radargram, as it corresponds to a target.

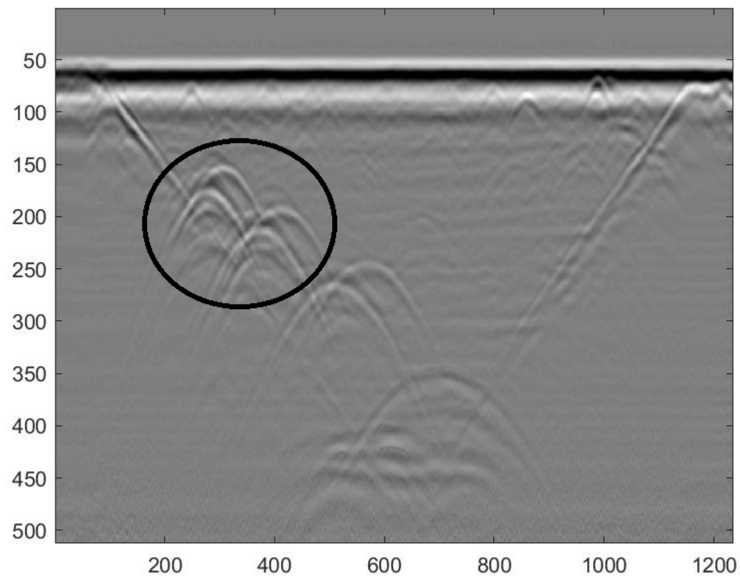


Figure 1: Detect the hyperbolas in the radargram

4 Proposed Method

The proposed system employs a combination of neural network, signal and image processing techniques. The main steps involved are:

1. Pre-processing
2. Feature Extraction
3. Neural Network Classification
4. Edge Detection
5. Pattern Recognition

5 Dataset Used

Dataset Used for implementation: TU1208 Open Database of Radargrams: The Dataset of the IFSTTAR Geophysical Test Site.

This is a wide dataset of ground penetrating radar (GPR) profiles recorded on a full-size geophysical test site, in Nantes (France). The geophysical test site was conceived to reproduce objects and obstacles commonly met in the urban subsurface, in a completely controlled environment; since the design phase, the site was especially adapted to the context of radar-based techniques.

- Number of radargrams in the dataset: 67
- Central Frequencies Used: 200 MHz to 900 MHz

6 Radargram Used

The following radargram image is used for the project.

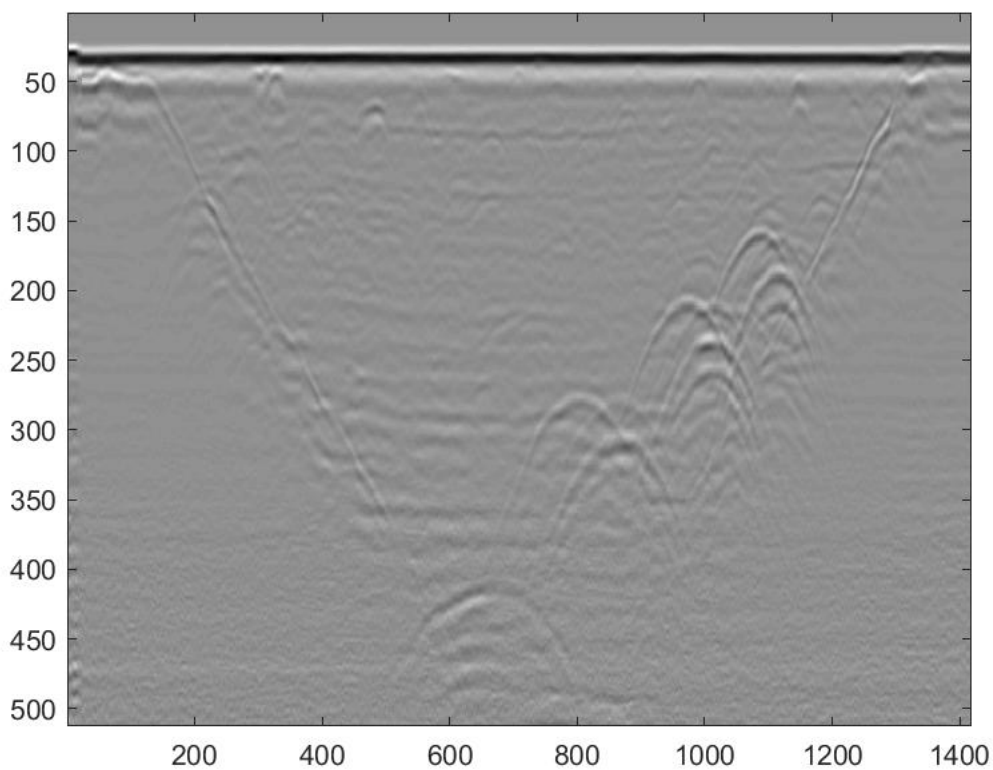


Figure 2: Radargram Used

7 Pre-processing

This involves background clutter removal and noise filtering.

Background clutter removal eliminates commonalities present in the data, such as the coupling pulse, surface reflection, and system ringing, and is achieved subtracting the ensemble mean of radargram with each row of pixel intensities across each strip.

High-frequency system noise, especially visible in the lower portion of the image is removed by rejecting frequencies beyond the frequency bandwidth of the radar, in the range of 2–2.5 times the antenna centre frequency.

7.1 Results

Following are the results of pre-processing

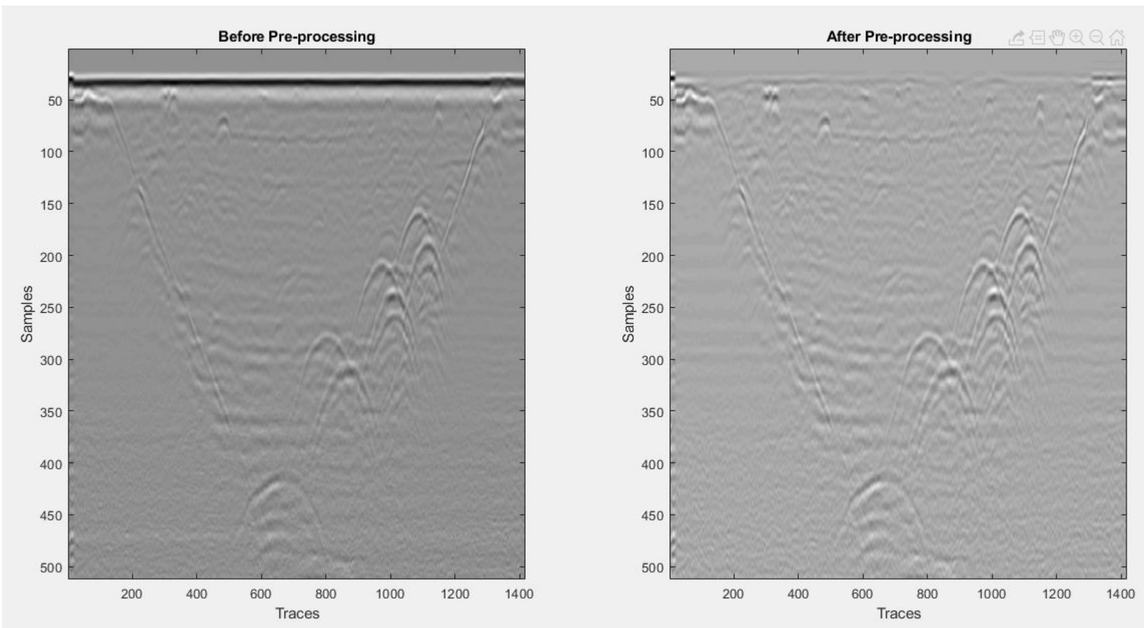


Figure 3: After pre-processing

8 Feature Extraction

Different representations of the time series data facilitate the pattern recognition task by extracting different features of the signal. Welch averaged overlapping periodograms of signal segments proved the most effective in discriminating and locating the required echo signals.

8.1 Results

Signal first subdivided into 8 segments of length N = 64. Then sectioned into K=2N/(M-1) = 7 subsets of length M=16 with 50 percent overlap.

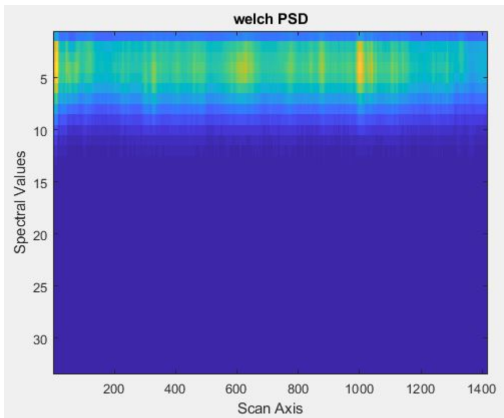


Figure 4: Welch PSD

9 Neural Network Classification

A Faster-RCNN framework for the detection of underground buried objects (i.e. hyperbola reflections) in B-scan ground penetrating radar (GPR) images. Following are the steps involved in this neural network classification:

- CNN is first pre-trained on the grayscale Cifar-10 database.
- The Faster-RCNN framework based on the pre-trained CNN is trained and fine-tuned on GPR data.
- Detection of regions in a radargram that has a hyperbola.

9.1 Results

Following are some images in the CIFAR-10 Data used for pre-training.


Figure 5: CIFAR-10 Data used for pre-training

Visualizing a layer in the pre-trained network

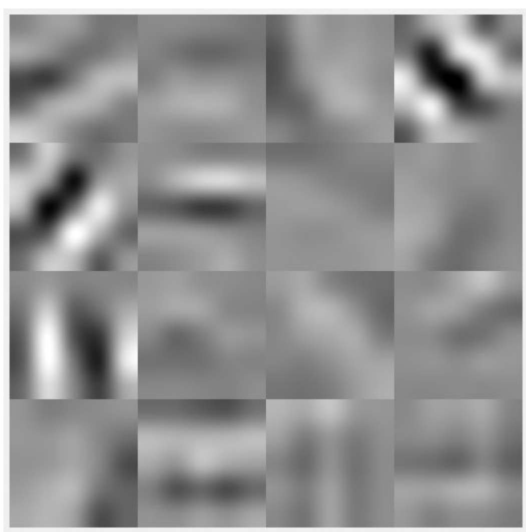


Figure 6: A netwrok layer after pre-training

Following is the detection results after training the pre-trained network on the radargram images

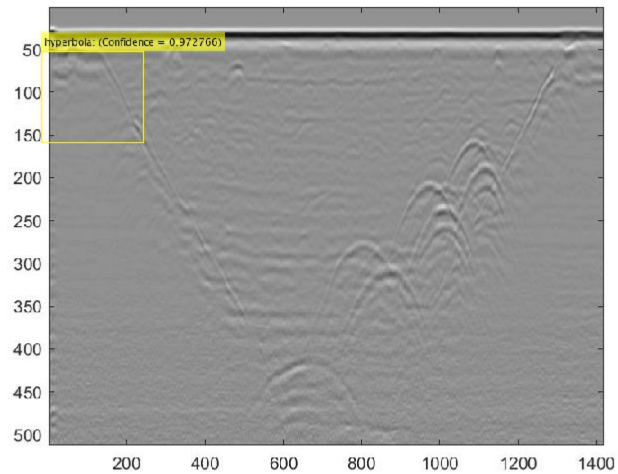


Figure 7: Detection Results

10 Edge Detection

This stage involves the detection of the outline or envelope of the main peaks of the reflected wave fronts. This is achieved by using a Canny edge detector.This results in a binary image representing the edges and leads to significant reduction in the amount of data to be processed.

10.1 Results

The results of edge detection are as follows:

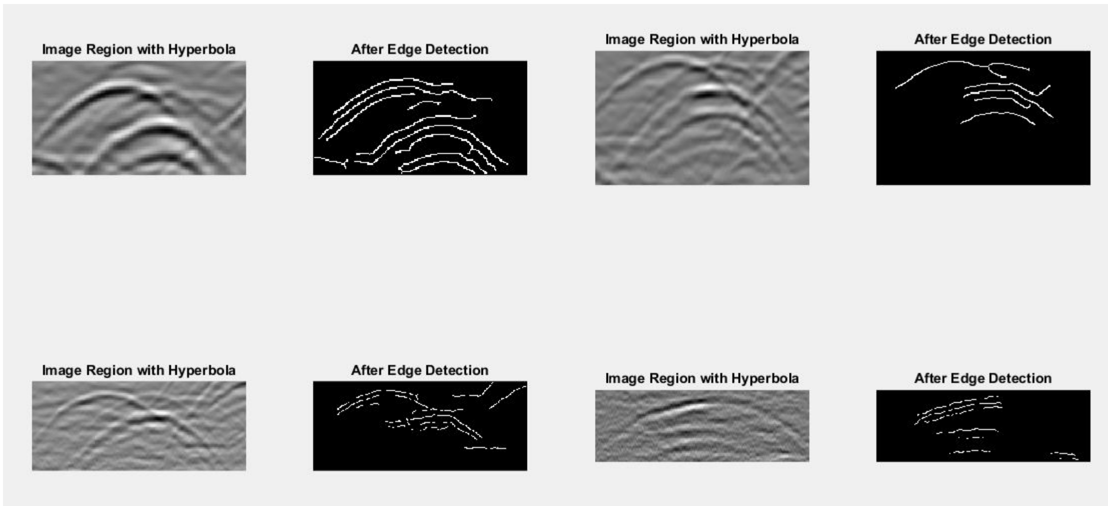


Figure 8: Edge Detection Results

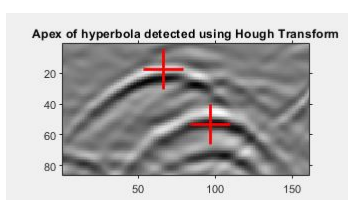
11 Pattern Recognition

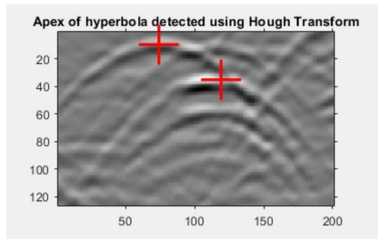
The Hough Transform is applied as a pattern recognition technique to locate and identify the hyperbolic anomaly. The Hough Transform (Illingworth and Kittler, 1988) is a well-tested method for detecting complex patterns of points in binary image data, and has been known to perform well in the presence of noise and occlusions.

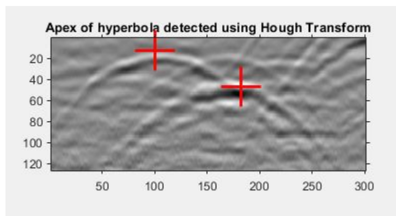
Using Hough transform we determine the peaks of each of the hyperbola that is present in the image. The peak corresponds to the location where a target is expected to exist.

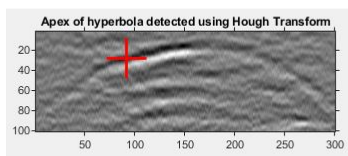
11.1 Results

Following are the results after using Hough Transform for detecting the hyperbolas and then finding the peaks.









12 Conclusion

Neural networks and pattern recognition techniques are combined to automatically produce a high resolution image of the shallow subsurface in a highly reduced computation time, suitable for on-site GPR mapping of utilities and other objects such as landmines.