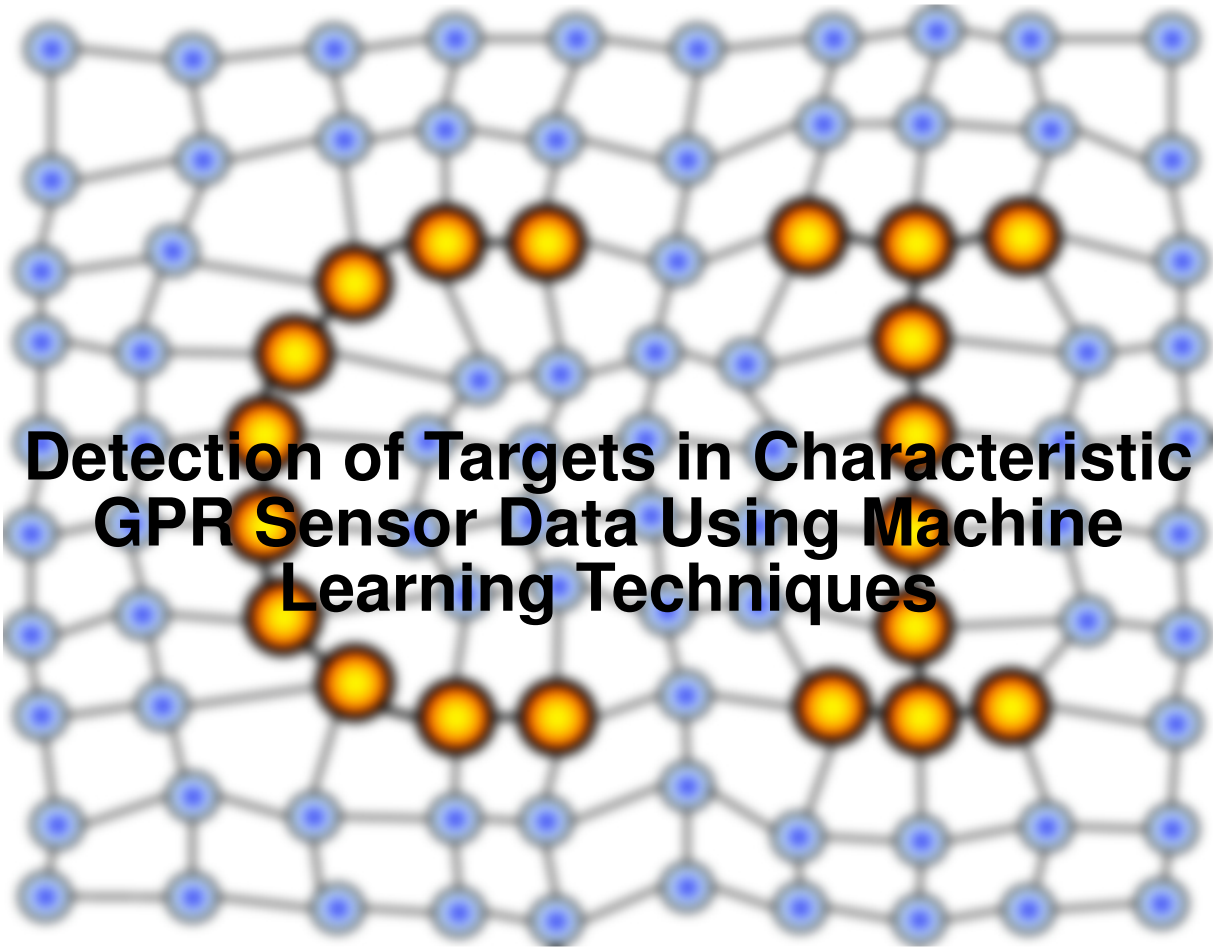
Machine Learning Reports



Detection of Targets in Characteristic GPR Sensor Data Using Machine Learning Techniques

Report 01/2013
Submitted: 25.06.2013
Published: 29.07.2013

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Abstract

Ground Penetrating Radar (GPR) is considered as one of the promising technologies to address the challenges of detecting buried threat objects, particularly in military applications. The aim of this research is to design a potential solution to the task of target detection and classification using GPR. This paper focuses on the first stage of this task which is target detection. Three approaches for automated target detection are presented; a probabilistic approach, an artificial neural network with direct data input, and an artificial neural network with frequency spaced features. These techniques are applied to a preliminary data set with promising results.

1 Introduction

Ground Penetrating Radar (GPR) technologies are widely used in defence applications such as detection of landmines, unexploded ordnance, and improvised explosive devices. GPR is considered as one of the promising technologies to address the challenges faced by operational teams in conflict situations. However, the success rate of the GPR systems are limited by sensing aspects of each individual solution, and tend to produce high false alarm rates [6].

Due to this limitation, automated target recognition techniques and algorithms are still being developed by research communities. For example, some of these techniques include filtering methods [15, 17], classification based techniques [4, 5, 13], and statistical and mathematical models for characterizing the GPR signatures [1, 8, 9, 10, 11, 12, 14]. Despite this, further research is still required particularly in the area of target discrimination.

The aim of this research is to design a potential solution to the task of detection and classification of targets using GPR data. This paper focuses on the first stage of this task which is target detection. Three approaches for automated target detection are presented; a probabilistic approach [3], an artificial neural network [7] with direct data input [16], and an artificial neural network with frequency spaced features [2]. The preliminary data set utilized in these investigations involved greyscale GPR images of real world targets deployed in operationally relevant scenarios. These images were taken using a vehicle mounted NIITEK GPR array.

This paper is arranged as follows: Section 2 describes the data set utilized in this research, and the pre-processing procedures performed prior to applying the target detection algorithms. Section 3 outlines the three target detection approaches implemented, the results produced, and the product of combining the outputs from each of the three methods. Finally, Section 4 summarizes the findings presented in this paper, and outlines directions for future research and improvement.

2 Data Set and Pre-processing

The preliminary data set utilized in these investigations was acquired using a vehicle mounted NIITEK GPR array. The data set itself consisted of greyscale image files depicting GPR signatures of real world targets deployed in operationally relevant scenarios. Each image had the following features:

- A cross-section of signal amplitudes (intensities) versus the down-track location of the GPR sensor head (horizontal axis) and the time delay/depth (vertical axis);
- Typical image size of approximately 800 x 200 pixels;
- The GPR signature of one target object.

Fig. 1 (Top) shows a typical sample image of the utilized data set, with the down-track position of the target object marked by two green arrows on the upper and lower edge.

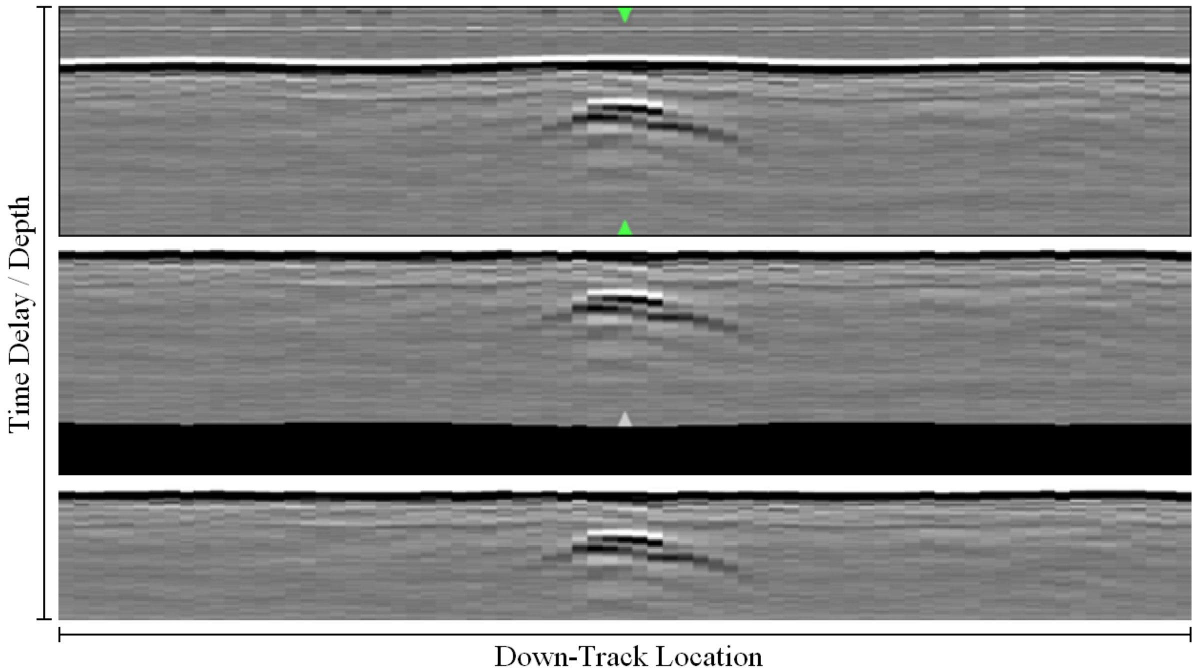

Figure 1: (Top) Typical sample image of the utilized data set (B-scan); (Middle) Sample image with basline correction applied; (Bottom) Pre-processed sample image.

A number of pre-processing procedures were performed to the data set prior to applying the automated target detection algorithms. Initially all images contained a small black frame. This frame was automatically removed to avoid possible interference with the automated image processing procedures.

In order to obtain a consistent upper reference in relation to the ground surface a baseline correction was performed (see Fig. 1 - Middle). This produced a straight line of the ground surface as the upper edge, which resulted in neighboring pixels in the down-track direction having approximately the same distance to the ground surface. This has positive effects because of the loss of signal strength with increasing distance from the ground surface (i.e. into the ground). Additional black pixels were also added at the lower edge when necessary.

In order to restrict the image size to relevant areas (e.g. without black areas at the bottom) and to speed up subsequent processing, all images were cropped to a particular vertical size of S_v pixels (counted from the top). This vertical size was an empirical value chosen based on all images of the given data set. Moreover, the green arrows were also removed after their position had been recorded to avoid possible interference with subsequent image processing procedures. Fig. 1 (Bottom) depicts the completed pre-processed sample image.

3 Automated Target Detection

In the presented research three different approaches of automated target detection were implemented and tested:

1. **Probabilistic approach**
   - Generation of a statistical ground model (without any target objects);
   - Detection of improbable grey values (anomaly detection) using the ground model.
2. **Artificial neural network with direct data input (with no extracted features)**
   - Utilization of a feed-forward neural net with the vertical scan lines (i.e. image pixel columns) as input vectors;
   - Training the neural net using image values corresponding to targets.
3. **Artificial neural network with frequency space features**
   - Analysis of the vertical scan lines in the frequency domain;
   - Perform classification again with supervised (or unsupervised) neural nets.

3.1 Probabilistic Approach

Generation of statistical ground model

For this approach, the starting point is the assumption that all pre-processed scans had at least c_v vertical scan lines on either end (leftmost c_{vl} and rightmost c_{vr} scan lines) that contained only bare soil. The term $n(c_{vl} + c_{vr})$, with n being the number of images in the data set, refers to the number of scan lines that were used to generate the statistical ground (i.e. soil) model. At each vertical depth a histogram over all samples is calculated as shown in Fig. 2. This information is then used to estimate an empirical distribution function of all grey values. In order to avoid probabilities of zero, it is assumed that each grey value is present at each depth at least once. To achieve this, the data matrix is initialized with ones instead of zeros.

The statistical ground model exhibits the following properties:

- At the ground surface the grey values are constantly or at least discretely distributed;

- At low depths (i.e. close to the surface) there exists a high variance in the grey values, if not a uniform distribution;
- At moderate depths a Gaussian distribution can be observed, and it appears as if the variance decreases with increasing depth;
- At maximum depth there lacks sufficient observations, thus uniform distribution is assumed.

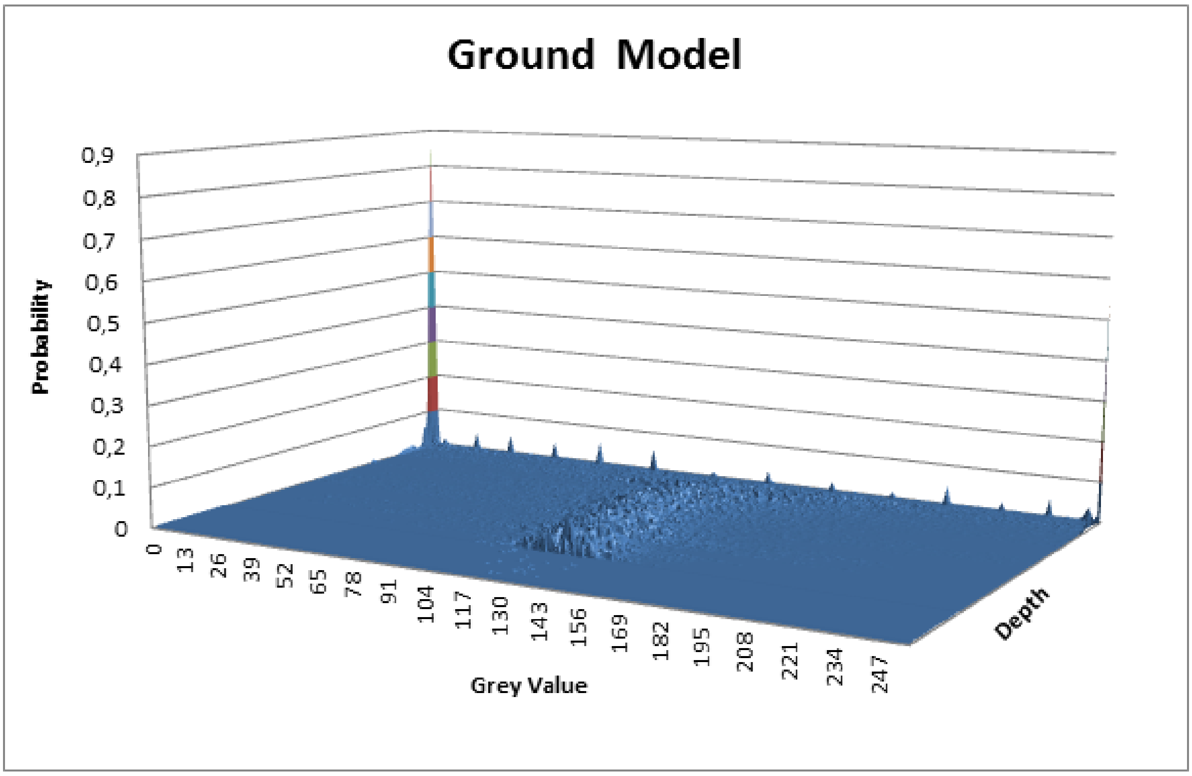

Figure 2: Empirically estimated ground model. The ground surface is located at the rear wall of the figure gaining depth forward-facing.

Classification of scan lines (Detection of Target Areas)

For the subsequent classification, the ground model is applied to all scan lines in the image with each image column processed separately. Based on its grey value, each individual pixel is assigned a probability that at the given depth a particular grey value is present (Bayesian approach). The resulting probability maps are then converted to images for analysis, and subsequent image segmentation is applied to isolate all areas containing particularly low probability values. By parameterizing this segmentation, further fine-tuning can be done to specify what ”low probability” actually means. Fig. 3 depicts the resulting probability maps for the pre-processed sample image previously shown in Fig. 1. In order to obtain a higher contrast in the images all probability values were multiplied by 2048. Implementing an automatically derived parameter (based on all probability values) might also be advantageous. Finally, a standard morphological operator (opening) is used to eliminate smaller isolated areas.

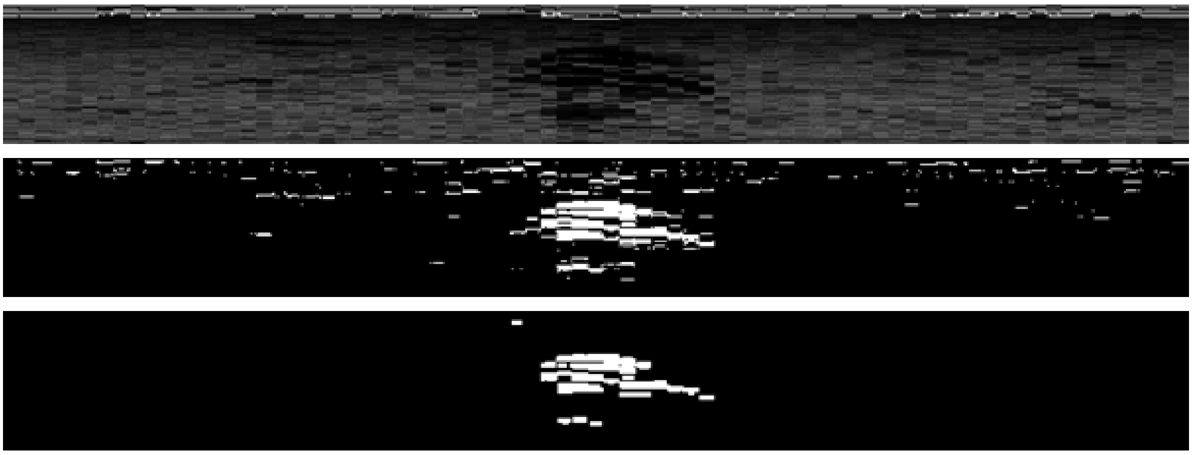

Figure 3: (Top) Example probability map for the probabilistic approach; (Middle) Binary probability map, threshold 5.0 used; (Bottom) Binary probability map after morphological operation *opening*.

3.2 Artificial neural network with direct data input (with no extracted features)

For this *supervised* approach an extended training data set is necessary which contains target objects together with additional background signals (c_{vl} and c_{vr} vertical lines on either end, see Section 3.1). As a preliminary assumption a range of $r = 20$ pixels around the marked target object positions is considered as the "positive area". This leads to $c_{vl} + c_{vr} + 2r$ scan lines containing target objects as an additional training data set. The scan line data (vectors of grey values) is directly used as training inputs into a supervised neural network [7]. Besides Multiple-Layer Perceptron networks that generally learn dividing rules between classes (in this case just two classes - target objects vs. background clutter) and typically offer a rather high discriminatory power, prototype based supervised networks (e.g. Radial Basis Function networks) or Support Vector Machines can also be applied. As commonly known, a well-chosen topology and training parameters can significantly improve the network's performance. Consequently, this step is subject to extensive parameter optimization in future work.

The data set is randomly divided into training and validation parts and a 5-fold cross validation is performed. The network output is the probability that the current input belongs to one of the two classes (target objects or background clutter). Again, this can be interpreted as an image by mapping the probability values (continuous range from 0.0 to 1.0) to the integer range of 0 to 255. Fig. 4 depicts the classification results for the pre-processed sample image previously shown in Fig. 1. Note that the white color implies high value.

3.3 Artificial neural network with frequency space features

This approach is based on the hypothesis that all periodic artifacts (target objects) show up as non-stochastically distributed frequencies. A Fast Fourier Transformation (FFT) [2] of each vertical scan line is performed as shown in Fig. 5, which shows the periodical artifacts caused by target objects that become clearly visible within the frequency domain. The first 39 elements (the first 40 elements without the mean value) are then used to train the neural network implemented in the previous approach (see Section 3.2). Fig. 6 depicts the classification results for the pre-processed sample image previously shown in Fig. 1.

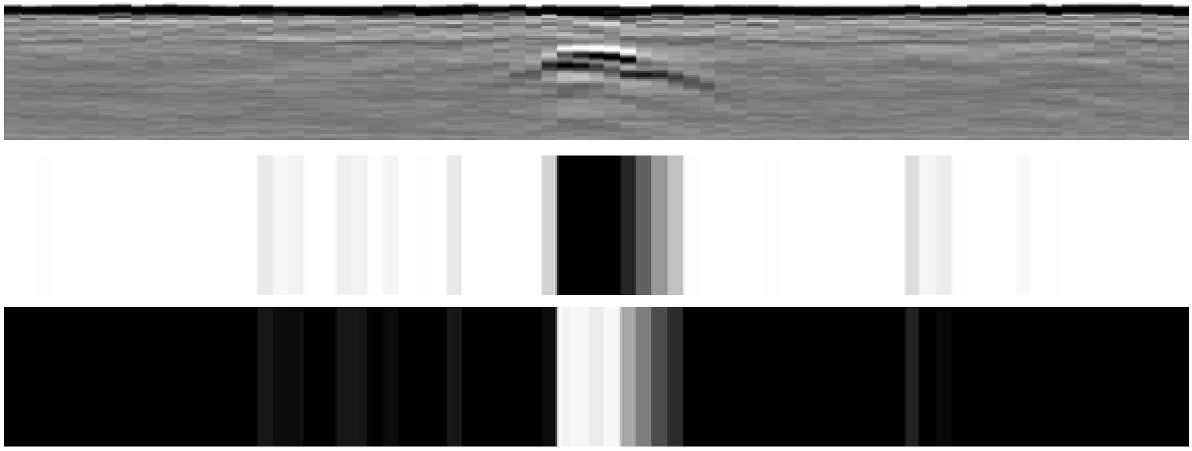

Figure 4: Example classification results for the neural network approach with direct data input: (Top) Pre-processed sample image; (Middle) Membership probability to class *background*; (Bottom) Membership probability to class *target object*.

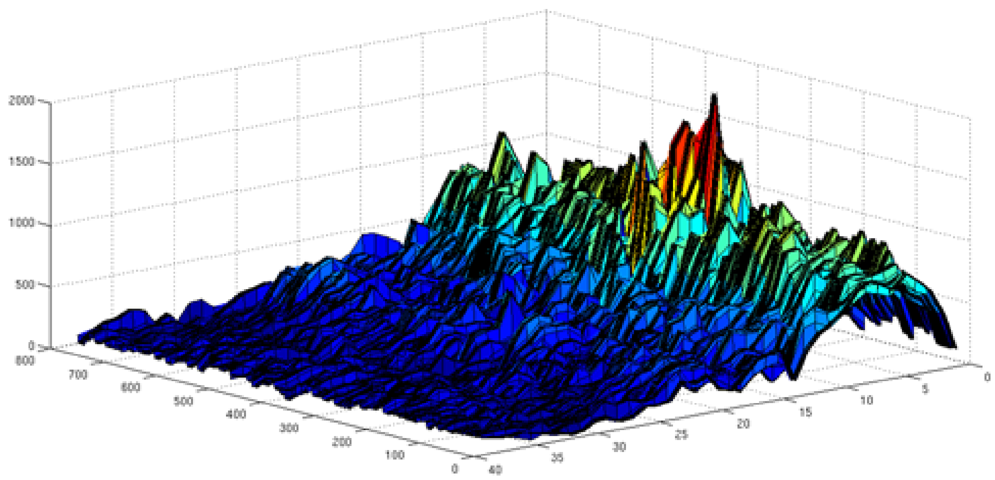

Figure 5: Example FFT for a pre-processed image.

3.4 Combination of individual results

The suggested three approaches are not considered as competitors but rather as complements of each other. As such, the results produced from all three methods are combined as shown in Fig. 7. This leads to a more robust detection compared to the individual detections produce by each method seperately.

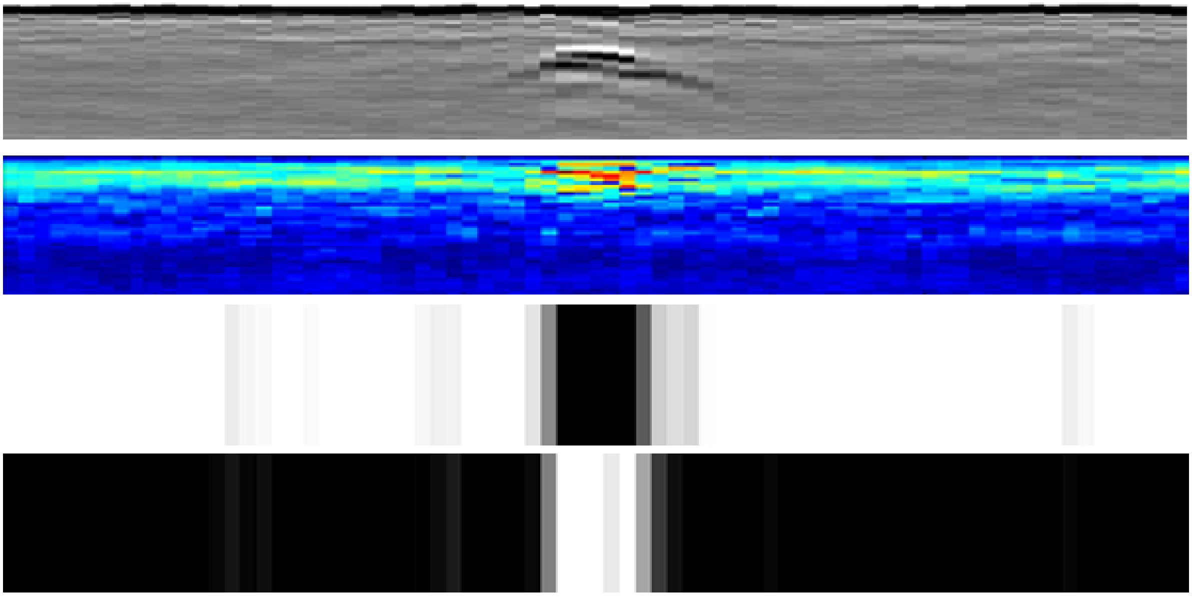

Figure 6: Example classification results for the neural network approach with frequency spaced features: (Top to Bottom) Pre-processed sample image; FFT image; Membership probability to class *background*; Membership probability to class *target object*).

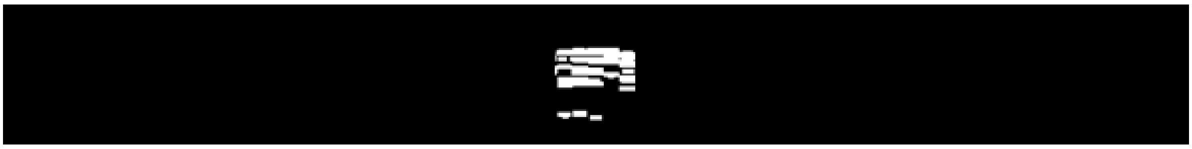

Figure 7: Combination of results from approaches presented in Section 3.1 to 3.3.

4 Conclusion and Further Work

This paper shows the first stage of a potential solution to the task of detection and classification of targets in characteristic GPR data. Three approaches were presented and used individually. The results produced by each method were promising, and it become evident that each approach had its own strengths and weaknesses. As a result, a combination of the results from these three approaches was performed, which showed a further significant improvement in the detection performance.

In terms of the required processing time, the most complex solution (FFT plus neural network) required approximately 150 ms to process almost 11,000 scan lines using MATLAB on a standard PC. This shows that real-time operation utilizing these approaches may be feasible. However, this is only an indicative observation as the processing speed strongly depends on the applied algorithms, utilized hardware and programming framework.

Despite the promising results, there are still a number of future research directions available, such as:

1. Algorithmic definition

    - Aggregated feature vector as network input;
    - Different neural network paradigms;

- Neighborhood relation between adjacent scan lines;
- Considering gradient images.

2. Parameter optimization of key modules of the processing pipeline
   - Network topology as well as training schemes and parameters;
   - Non-static thresholds.
3. Numerical optimization
   - Programming environment;
   - Parallel/Pipeline hardware.

Although the focus in this paper was on the detection of target objects, all the proposed concepts can be extended to classification of different target objects. To achieve this purpose, primarily an extended data set is needed that contains multiple samples of several different target objects. This would extend the current two-class problem to an n-class problem ($n-1$ classes of target objects plus one class for background). This is also the focus of future work.

5 Acknowledgements

The authors acknowledge funding provided by DSTO. Implementation was supported by Friedrich Melchert.

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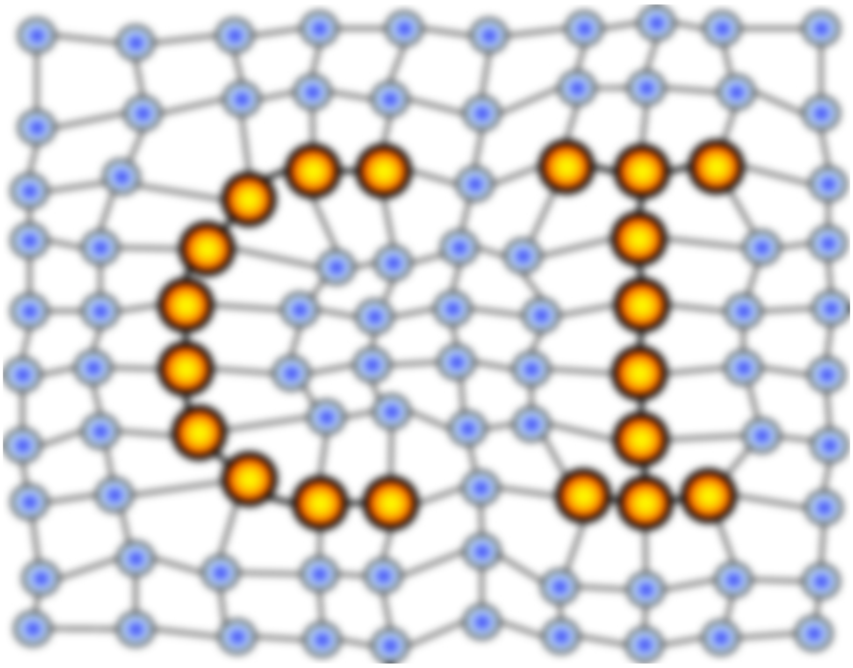

Impressum

Machine Learning Reports ISSN: 1865-3960

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▽ Acknowledgments
We would like to thank the reviewers for their time and patience.