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## ► To cite this version:

R. Jaufer, C. Heinkele, N. Loubat, David Guilbert, Amine Ihamouten. Deep convolutional neural network for estimation of depth and radius from GPR raw signals. NSG2021 2nd Conference on Geophysics for Infrastructure Planning, Monitoring and BIM, Aug 2021, Bordeaux, France. pp.1-5, 10.3997/2214-4609.202120222 . hal-03653514

**HAL Id: hal-03653514**

**<https://hal.science/hal-03653514>**

Submitted on 30 Sep 2022

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## Deep convolutional neural network for estimation of depth and radius from GPR raw signals

R. Jaufer 1 C. Heinkele 2 N. Loubat David Guilbert 1 A. Ihamouten

### Introduction

There are 5 major underground utility networks in France (telecoms, electricity, gas, water and heat), and each network has different physical properties, among them depth and radius. Precise location and identification of such networks became a critical point in terms of preventing accidents during any excavations. There are limited amount of research work found in the field of ground penetrating radar (GPR) focused on detection and localization of these utility networks. The major part of these studies deals with hyperbola detection and parameters estimation, using physical models by inversion or supervised machine learning techniques.

There are varieties of classification or regression machine learning methods that exist like decision trees, Bayesian classification, k-means, etc... For example, the SVM (Support Vector Machine) is widely used and consists of determining a boundary between two classes by maximizing the distance between them using characteristic elements (Smola & Schölkopf 2004). All methods are based on a prior extraction of features from the data in order to reduce the dimension of the problem. However, identification of the correct local features still remains a challenge. Deep learning approaches brought great attention due to its proven ability to automatically extract features from the input data in order to perform classification or regression precisely and rigorously in various fields. Faster-RCNN and Yolo models has been found in literature for detection of utility pipe's in two steps: a proposal of region of interest followed by detection of hyperbolas in these regions. However, the deep learning was rarely evaluated as a regression model for the estimation of geometrical parameters such as depth and radius of the buried pipes.

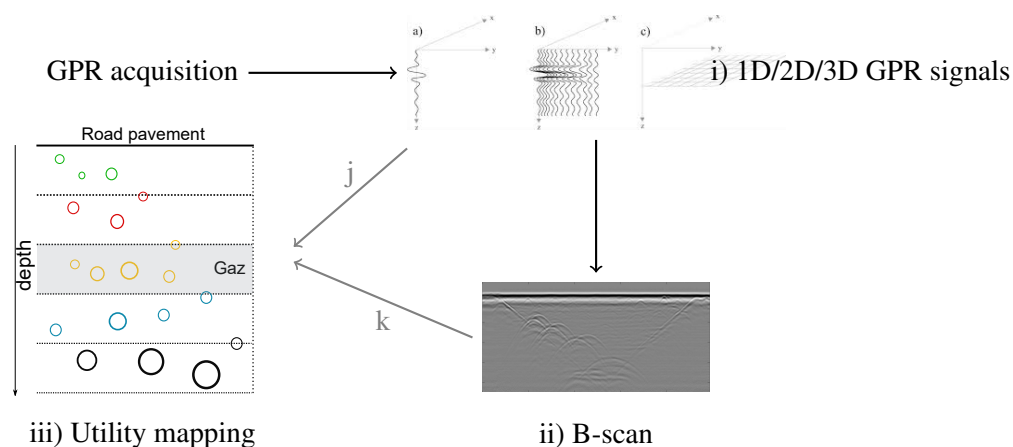


Figure 1: Diagram reminding the different type of raw data. j) corresponds to signal processing methods based on signal analysis. k) corresponds to methods based on images built from the 2D signal.

Most of machine learning methods for GPR are based on an analysis of B-scans pictures ((ii) on figure 1). As a supervised learning, the annotation is done on these pictures and the algorithms of detection, classification or regression relying on pixels. The objective of this research work is to evaluate the ability of a deep learning method such as Deep Convolutional Neural Network (DCNN) applied to GPR 2D raw signals instead of pictures. It is still an electromagnetic non-destructive technique, and its goal is also the estimation of the physical and geometrical characteristics of buried cylindrical pipes.

According to recent norms, each utility network type is assigned with a standard depth range to avoid overlapping between networks. In this context, among these five buried networks, we decided to focus on gas networks for this study ((iii) on figure 1), because the gas network is standardized : it has to be buried at depths between 0.7 and 1 m with the radius classes of 63, 110, 200 or 250 mm, according to AFNOR French Standard NP P98-331 (AFNOR Février 2005). In our work, the approach is parametrized and validated only using numerical data at this stage. The main reason is the lack of labeled experimental data at this project progress step. Hence, synthetic GPR data (A-scans and B-scans

with various configurations) generated using the Finite Difference Time Domain (FDTD) gprMax 2D model (Warren et al. 2016).

Contrary to the proposed method, existing similar works use resized processed images instead of raw signal. In such a case, the signal's dynamic information is lost by rescaling the signal amplitude to a certain color scale. Furthermore, many authors used different pre-processing steps on the data to improve the readability of the hyperbola and remove noise and clutter. In some cases, thresholding and filtering functions were applied to differentiate the target (hyperbola) from the background. However, the pre-processing steps require rescaling of the image and it causes the loss of information. To overcome this challenges, raw B-scans have been utilised in this study. Thus, the complex and sequential GPR signal pre-processing steps can be avoided in the localisation of the buried pipes.

### Methodology and implementation

The proposed parameter estimation models based on multi classification Deep Convolutional Neural Network (DCNN) have been numerically validated on subsurface raw GPR images (B-scans).

In order to generate the synthetic GPR raw B-scans, simple homogeneous dispersivness noiseless gprMax 2D model is used (Warren et al. 2016) with the configuration stated in the Table 1.

Configuration	Values
Pulse type and center frequency	Ricker, 1.5 GHz
Antenna off-set, type and height	Zero-offset, hertzian dipole, 0.5 cm
Medium's relative permittivity	3 - 6
Medium's conductivity	$1 \times 10^{-5}$ S/m
Acquisition step size	5 cm
Pipe's depth	0.7 m - 1 m
Pipe's radius	53 mm, 110 mm, 200 mm, 250 mm

Table 1: gprMax 2D configurations for synthetic GPR data modelling

gprMax is an open source simulation software developed in python environment for forward modelling of GPR that uses Finite Difference Time Domain (FDTD) to simulate EM wave propagation solving Maxwell's equations (Warren et al. 2016). The Fig. 2 illustrates a ground truth geometry and raw B-scan obtained from gprMax.

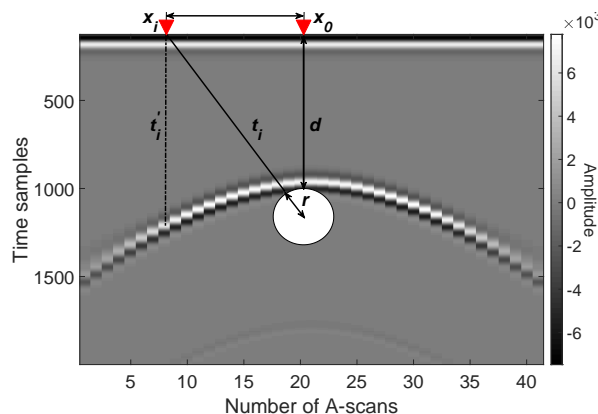


Figure 2: Example of a synthetic B-scan modeled in gprMax, and a ground truth of metallic pipe at  $d$ : depth,  $r$ : radius,  $x_i$ : horizontal positions of zero-offset ground coupled GPR,  $t_i$ : travel time of the pulse

Since the proposed model adopts supervised learning approach, each B-scan was labeled with its designed parameter values. In terms of radius estimation, the radii of the gas networks are highly stan-

standardized and classified into different radius classes. So that, a multi classification model was deployed by assigning a class label (for each B-scan) for each radius class. The number of classes is defined in advance according to the expected results, here the 4 radius classes of the pipes such as 63, 110, 200 and 250mm. In the meantime, the depth estimation is considered as regression problem with depth range between 0.7 and 1m. The labeled 1725 B-scans dataset got splitted into two sets such as training and testing. Which then allows learning to be carried out on 894 training B-scans dataset and validated on 430 B-scans with the training : validation ratio of 67% : 33%. The method is then tested on the 401 B-scans that has not been used for training. In the proposed deep convolutional neural networks, the first few steps consist of extracting the features through the process of convolution and max pooling. The process extracts unique features from the input data (raw B-scan) while reducing the dimension and flattens the features to a vector appropriate for the fully connected ANN as shown in Fig. 3. By contrast, in previous works the authors extract the local features through series of signal pre-processing steps (Jaufer et al. 2020).

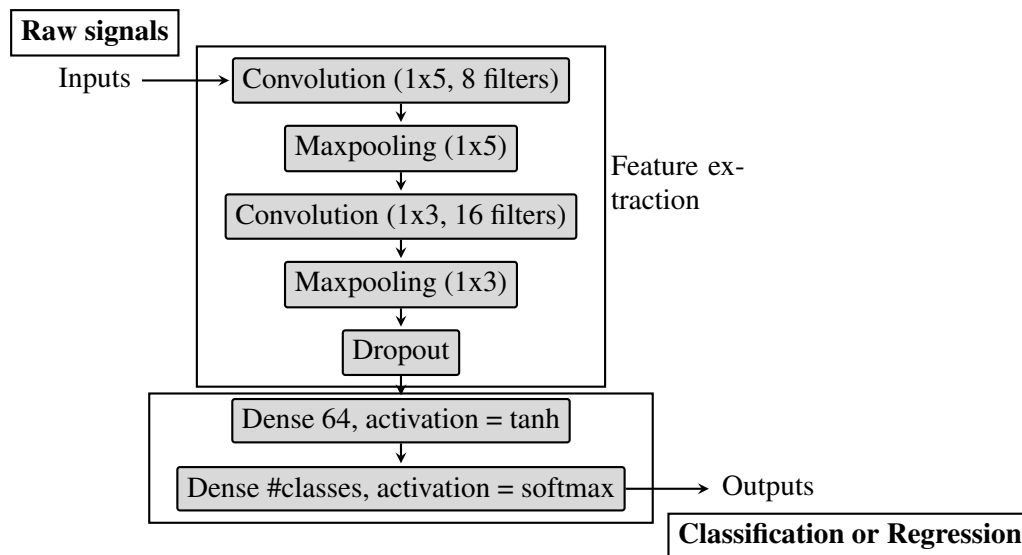


Figure 3: The CNN architecture proposed to perform classification on radius or regression on depth.

This feature extraction and dimension reduction step is performed directly by the convolutional layers without any advanced processing.

## Results and discussion

A DCNN multiclass classification model and a DCNN regression model were trained separately for the inversion of radius and depth respectively. Then, each model was deployed to perform the prediction out of test B-scan datasets. Hence, its ground truth labeled values are compared with the model prediction. Whereas, the Fig. 4a presents the confusion matrix of the radius estimation using proposed multiclass classification model.

According to confusion matrix in Fig. 4a, target class represents the actual values, while output class represents model predicted values. Classes 0,1,2 and 3 indicate radius classes 63, 110, 200 and 250 mm respectively. In 398 out of 401 (99.2 %) cases, radius classes were correctly predicted by the trained model while only in 3 out of 401 instances, the false alarms were observed. Among the false alarms, the misclassification was only one class away from the actual value in two instances. Likewise, the proposed DCNN based regression model was evaluated for the inversion of depth as seen on Fig. 4b, and the model provided mean square error of 0.21 % on 200 B-scan samples of test data within the depth range from 0.7 to 1 m. The predicted depth values were well fitting with its ground truth. Furthermore, detail parametric study was conducted but not included in this paper.

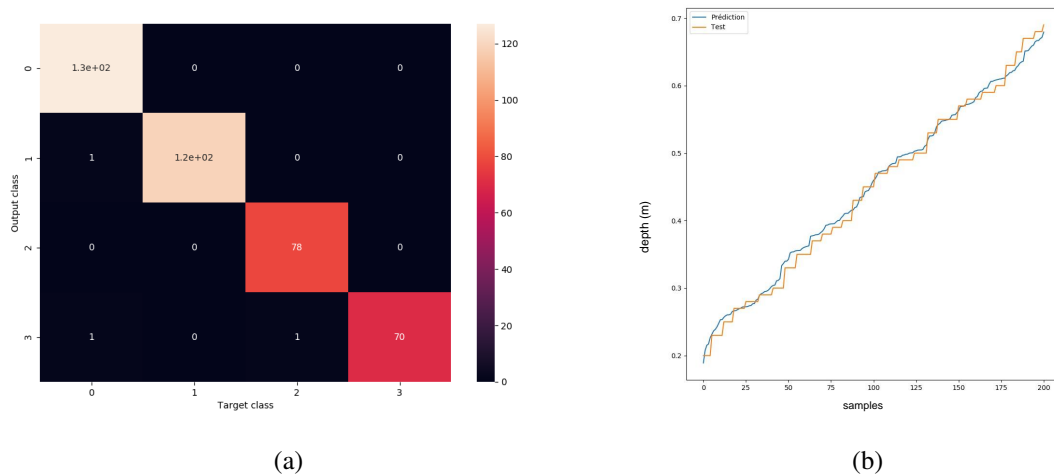


Figure 4: a) Confusion matrix of radius estimation, whereas classes 0,1,2 and 3 indicate radius classes 63, 110, 200 and 250 mm respectively; b) The depth regression test results of 200 samples between 0.7 and 1 m.

## Conclusions

The work carried out consists of creating a database of annotated "raw" B-scans to demonstrate the feasibility of a deep learning algorithms for determining the depth and diameter of buried gas pipes using multiclassification and regression approach. The methods show very encouraging results, both in classification for diameter and regression for depth. Though the research work has focused on gas pipes due to its standardized radius and depth range, the method can be also adapted to all types of underground utility networks. At this stage, due to lack of field data, the model has been numerically validated. In the mean time, the numerically trained model can be potentially used along with experimental data if the antenna and pulse wavelets are modeled precisely. However, firstly the authors propose to perform the experimental validation on real data coming from home made and commercial GPRs. In fact, this would require an annotation tool and a lot more training data to be generated to develop the corresponding neural networks. Furthermore, the current analysis remains in 2D B-scans, so it would also be interesting to evaluate the model's performance on raw C-scans. Hence, the algorithm will computationally heavier.

## Acknowledgements

The present work is based on the intership of Nathan Loubat.

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