



Machine Learning for analysis of GPR images and electromagnetic diagnostics

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The aim of this work is to exploit Machine Learning (ML) for the analysis of Ground Penetrating Radar images. In particular, the objective is to apply a scaled-down version of DenseNet [1] architecture with a multipurpose approach to extract from b-scan images of buried cylinders: the cylinder radius, the cylinder length, the depth with respect to the ground, and the relative permittivity of the cylinder and of the medium in which the cylinder is immersed. The cylinders have an infinite length or have a length much greater than the diameter. The main feature of the network chosen in order to extract those features is that each layer is connected to all subsequent layers, through the concatenation of the feature maps. Indeed, traditional convolutional networks, composed of L layers, present L connections, one for each layer, while DenseNet presents $L(L+1)/2$ direct connections. The DenseNet network has many advantages: it reduces the problem of the evanescent gradient, strengthens the propagation of features, encourages the reuse of parameters and substantially reduces the number of parameters. The Georadar (or Ground Penetrating Radar, GPR) images are obtained through the GprMax[2] software simulation tool, combining the relative dielectric constant of the medium and of the cylinder, radius, the length and depth of the cylinder.

The input images, of initial size 3453×1772 pixels, are resized to 32×32 pixels, in order to speed up the training phase. For the purpose of extracting the features of the images, MSE loss function is used. Since the data set is small, the k -fold cross validation is performed by dividing the data set into 10 parts. Therefore 10% of the data constitutes the validation set and the remaining part is chosen as a training set. The training of the network is performed by varying opportunely the learning rate.

The study has shown interesting results in terms of the ability of the scaled-down version of DenseNet in classifying b-scan images, despite a small data set. In future studies we will complete the characterization of the behavior for the network chosen on simulated images, we will start considering realistic GPR images to validate the dataset.

References

- [1] Huang, G., Liu, Z., Van Der Maaten, L. and Weinberger, K.Q., "Densely connected convolutional networks," *Proceedings of the IEEE conference on computer vision and pattern recognition*, 4700-4707, Honolulu, USA, July 2017.
- [2] Warren C., Giannopoulos A., and Giannakis I., "gprMax: Open source software to simulate electromagnetic wave propagation for ground penetrating radar," *Computer Physics Comm.*, Vol. 209, 163-170, 2016.