URSI GASS 2020, Rome, Italy, 29 August - 5 September 2020

Imaging of a micro-structure: binary contrast source inversion and convolutional neural networks

P. Ran*(1), Y. Qin(1)(2), D. Lesselier(1), and M. Serhir(3)
(1) Université Paris-Saclay, CNRS, CentraleSupélec, Laboratoire des signaux et systèmes, 91190, Gif-sur-Yvette, France
(2) Université Paris-Saclay, ENS Paris-Saclay, CNRS, Systèmes et Applications des Technologies de l'Information et de l'Energie, 94235, Cachan, France
(3) Université Paris-Saclay, CentraleSupélec, CNRS, Laboratoire de Génie Electrique et Electronique de Paris, 91192, Gif-sur-Yvette, France

Time-harmonic transverse-magnetic electromagnetic imaging of a grid-like, finite set of circular cylindrical dielectric rods placed in air with sub-wavelength distances between adjacent rods and sub-wavelength diameters. The need of achieving super-resolution in the resulting micro-structure, reaching far beyond the Rayleigh criterion, is quite demanding. In addition, the fields scattered by the micro-structure are observed in the far-field, precluding any resolution from collecting near-field data. Comprehensive analyses of imaging, including issues of resolution in general, are in particular discussed in reference works [1, 2].

A peculiar imaging case is focused onto herein: all rods have same permittivity, but some may be missing (with no information on number and location), the aim being to detect them in the now damaged micro-structure. Two methods are developed to that effect. One is building upon the well-known iterative contrast source inversion (CSI), going back to [3], now enforcing a binary contrast (binary CSI). It yields maps of the micro-structure whenever damaged, i.e., missing rods show up as several sets of zero-contrast pixels differing from the non-zero ones of the existing rods, with the limit that computational time of the solution might become quite high while large relative dielectric contrasts may lead to poor results (that will be the case if those 3 or higher). The other is within a machine learning framework and uses convolutional neural networks (CNN) to perform the imaging, e.g., [4]. Such CNN (tailored to the binary case here) contain three main parts: the convolutional layers, batch normalization layer, rectified linear function and the max-pooling as first part; full-connected layers as the second part; and the deconvolutional layers with the sigmoid function as the third part. Such CNN can achieve a fast mapping from the scattered fields to the distribution of dielectric contrasts in the region of interest (properly pixelized), with changes as a function of the chosen priors, and in contrast to CSI, capability to perform for contrasts even larger than 5.

After a sketch of the developed solutions, illustrations will be proposed from comprehensive numerical simulations in a number of configurations of interest, this seen in terms of organization of the micro-structure itself, discrete frequencies of observation, data acquisition and data noise. Due attention will be given to CNN training, to make sure that no inverse crime is committed, even if priors should not be underestimated in the present-day analyses.

To conclude, an experiment in an anechoic chamber has been completed on two well-designed dielectric micro-structure prototypes (with missing rods in them), with the additional complexity that the antennas employed are 3-D, even if the rods are long enough to fit the 2-D aforementioned hypothesis, in addition to calibration issues (a total field is collected, not a scattered one). Beyond feeding the acquired data to the aforementioned CNN, the main challenge is how to combine simulations and experiments, for example, via Generative Adversarial Networks.

References

[1] H. Ammari, J. Garnier, W. Jing, H. Kang, M. Lim, K. Sølna, and H. Wang, *Mathematical and Statistical Methods for Multistatic Imaging*, Springer, Berlin, 2013.

[2] X. Chen, *Computational Methods for Electromagnetic Inverse Scattering*, 1st Edition, Wiley-IEEE Press, Singapore, 2018.

[3] P. M. van den Berg and R. E. Kleinman, "A contrast source inversion method," *Inverse Probl.*, Vol. 13, pp. 1607-1620, 1997.

[4] Z. Wei and X. Chen, "Deep-Learning schemes for full-wave nonlinear inverse scattering problems," *IEEE Trans. Geosci. Remote Sens.*, Vol. 57, no. 4, 1849-1860, 2019.