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An innovative Microwave Imaging Approach exploiting the Orthogonality Sampling Method for Physics-guided Deep-Learning

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In the last years, there is a growing interest in the integration of deep learning (DL) in microwave imaging (MWI) [1]. As well known, the performances of traditional inversion approaches are tamed by the non-linearity and the ill-posed of the underlying inverse scattering problem. This often leads to poor results or even false solutions, which are different from the ground truth that cannot be discriminated by the algorithm. The powerful computational tools offered by DL, which offer the capability of retrieving complex non-linear relationships between input and output, would allow to significantly enhance the performance of microwave imaging, possibly overcoming the drawbacks of traditional approaches. Such a perspective is particularly attractive in the field of medical MWI, wherein the availability of reliable, user-independent images is crucial to properly support the clinicians.

In this paper, we present an innovative framework to exploit DL to enhance microwave imaging (MWI) based on a combination of qualitative imaging [2] and convolutional neural networks (CNN). The main idea is to employ qualitative imaging as a physics-guided input for a CNN in charge of providing the final image. Qualitative imaging techniques are able to estimate the morphological properties of the targets (position, shape) by relying on the continuous map of an indicator function which attains large values where a target is located and low values elsewhere. Moreover, they are computationally inexpensive, hence particularly convenient for real-time applications.

In particular, the qualitative imaging herein adopted is the orthogonality sampling method (OSM) [3]. The indicator function of OSM estimates the shape of the unknown targets by simply testing the orthogonality between the farfield pattern and the Green's function in the far zone. As such, it does not require an explicit regularization and is therefore completely user-independent. Regarding the deep learning architecture, the selected CNN is an image-to-image fully convolutional neural network called U-Net [4]. This special type of CNN bestows additional features upon the continuous map retrieved by the OSM.

Two different implementations are explored in this work. In the first one, bestowing binary classification upon the combined framework, an MWI-DL architecture is designed to provide an objective estimate of the targets shape. In the second implementation, providing the framework with segmentation capabilities and exploiting the implicit relationship between the OSM indicator and the permittivity distribution [3], an MWI-DL architecture to automatically split the imaging domain into separated regions according to the present permittivities is devised.

Examples to assess the proposed framework in both canonical scenarios and applicative cases relevant to biomedical imaging will be presented at the conference.

References

[1] X. Chen, Z. Wei, M. Li, and P. Rocca, "A review of deep learning approaches for inverse scattering problems (invited review)," *Progress In Electromagnetics Research*, vol. 167, pp. 67–81, 2020.

[2] F. Cakoni and D. L. Colton, *A qualitative approach to inverse scattering theory*. Springer, 2014, vol. 767.

[3] M. T. Bevacqua, T. Isernia, R. Palmeri, M. N. Akinci, and L. Crocco, "Physical insight unveils new imaging capabilities of orthogonality sampling method," *IEEE Transactions on Antennas and Propagation*, vol. 68, no. 5, pp. 4014–4021, 2020.

[4] O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional networks for biomedical image segmentation," in *International Conference on Medical image computing and computer-assisted intervention*, Springer, 2015, pp. 234–241.