MACHINE LEARNING BASED RADIATION SOURCE RECONSTRUCTION IN TERMS OF SPHERICAL WAVE EXPANSION COEFFICIENTS

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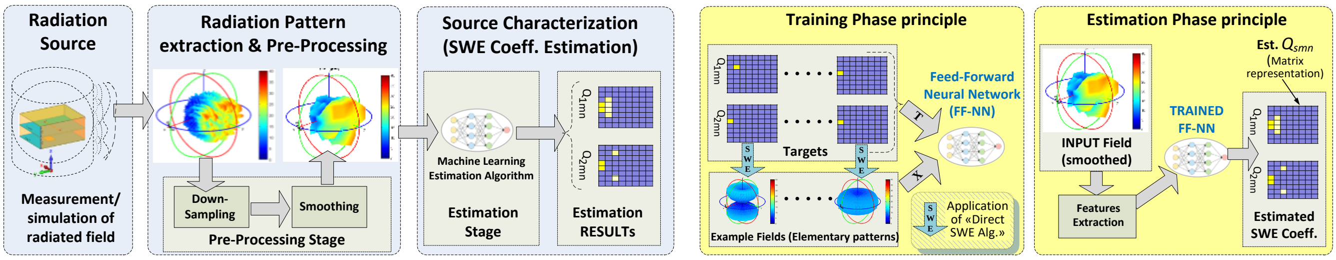
This memory collects the main details of the research activity developed by the research group in order to explore the possibilities offered by Artificial Intelligence techniques in the field of Source Reconstruction Methods (SRMs).

As well known, modern high-end electronic systems require accurate control of unwanted electromagnetic radiation. This work proposes a novel source reconstruction method based on the combined use of Spherical Wave Expansion theory and Machine Learning techniques. The proposed method aims to estimate the equivalent spherical wave expansion coefficients describing the radiation from a generic source starting from the knowledge of its field magnitude information only (measured or simulated).

The scope of this work is to provide a novel source reconstruction technique based on the proper training of a Machine Learning (ML) algorithm and capable to quickly characterize the radiation source in terms of its equivalent Spherical Wave Expansion (SWE) coefficients description [1]. The proposed method exploits the use of SWE theory to characterize the radiation source, differently from other approaches developed for similar applications [2]. The successful development of the proposed approach will bring several outcomes, such as the possibility of quickly deriving the source's equivalent SWE coefficients description starting only from the amplitude information of tangential field, thus, paving the path also to predictive capabilities [3]. Here the basic idea is to use the elementary field patterns, associated to proper sets of reference SWE coefficients, as inputs for the training stage of a ML method based on Neural Network algorithms, in this case a shallow Feed-Forward Neural Network (FF-NN). Once the FF-NN has been trained, the overall strategy accounts the collected tangential field components, from measurements or simulations. Specific features extracted from the E-field amplitude radiation pattern are given to the FF-NN, in order to estimate the representative equivalent SWE coefficients, i.e. the complex numbers Q_{smn} [1] appearing in (1). The overall basic structure of the proposed approach is depicted in the following Fig. 1, detailing both the training stage and the estimation stage of the method.



a) b)

Fig. 1. a) General sketch of the overall proposed ML-based method, b) training and estimation phases.

After the estimation stage, by using (1), it is possible to get the associated reconstructed E-field for comparison purposes.

$$\vec{E}(r,\theta,\phi) = \frac{k}{\sqrt{\eta}} \sum_{csmn} Q_{smn}^{(c)} \vec{F}_{smn}^{(c)}(r,\theta,\phi) \tag{1}$$

At this research development stage, the method has been proven to be effective for source reconstruction with low-order (N=2) SWE coefficients [4], by offering also good performance on a set of test case scenarios (in terms of both accuracy and computational burden) [5]. Some exemplary test cases are reported in the following Fig. 2, where a target test field has been generated starting from a set of given SWE coefficients, arbitrarily fixed. The test field has been compared versus the field reconstructed from the SWE coefficients estimated by the proposed ML approach. As can be seen the agreement is good and the estimation performance of SWE coefficients is satisfactory enough.

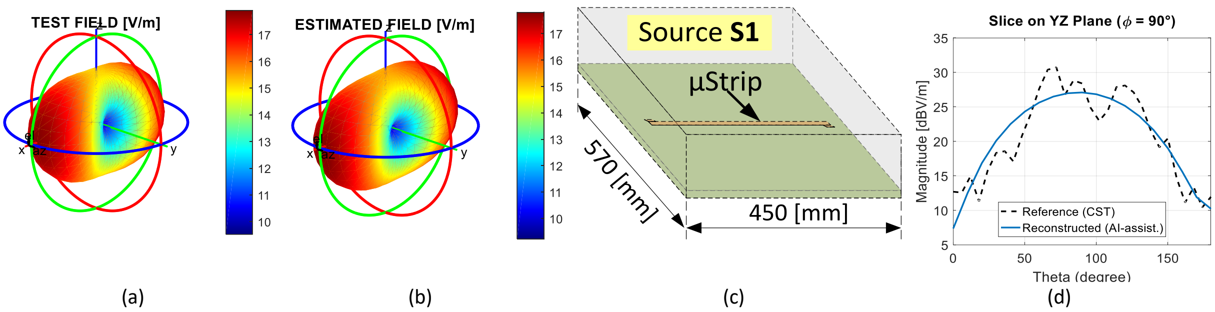


Fig. 2. SWE Coefficients estimation and field reconstruction for a sample test case (case #1): (a) Original test field; (b) Estimated/reconstructed field, and for test cases linked with server tray structures: (c) sample server tray structure; (d) Estimation/reconstruction performance.

Table I. Evaluated test scenarios and results for basic reference cases.

Test Case	**Preliminary SWE Coefficients estimation results**		
	Reference Coeffs	**Estimated Coeffs**	
#1	$Q1_{0,1}$= 0.8+j0; $Q1_{1,1}$= 0.9+j0.03; $Q1_{1,-1}$= 0.9+j0.03;	$Q1_{0,1}$= 0.74+j0.17; $Q1_{1,1}$= 0.81+j0.18; $Q1_{1,-1}$= 0.99+j0.06;	

The proposed approach has been also tested on simulation case studies [4] and by using proper measurement data [5], both linked with the radiation from test server tray units, showing good source reconstruction performance. In future studies the proposed approach will be targeted also to SWE coefficients of order greater than two (i.e. N=3 or more).

References

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