2024 IEEE International Symposium on Electromagnetic Compatibility, Signal & Power Integrity (EMC+SIPI) | 979-8-3503-6039-4/24/$31.00 ©2024 IEEE | DOI: 10.1109/EMCSIPI49824.2024.10705494

A Hybrid Algorithm to Dual Sparse Sampling Measurement in Time-Resolved Electromagnetic Near-Field Scanning

Yanming Zhang
Dept. of Electronic Engineering
Chinese University of Hong Kong
Shatin, NT, Hong Kong
ymzhang@cuhk.edu.hk

Steven Gao
Dept. of Electronic Engineering
Chinese University of Hong Kong
Shatin, NT, Hong Kong
scgao@ee.cuhk.edu.hk

Lijun Jiang
Dept. of Electrical and Computer Engineering
Missouri University of Science and Technology
Rolla, MO, USA
ljf82@mst.edu

***Abstract*—Time-resolved electromagnetic near-field scanning is vital for antenna measurement and addressing complex electromagnetic interference and compatibility issues. However, the swift acquisition of high-resolution spatiotemporal data remains challenging due to physical constraints, such as moving the probe position and allowing sufficient time for sampling. This paper introduces a novel hybrid approach that combines Kriging for sparse spatial measurement, compressed sensing (CS) for sparse temporal sampling, and dynamic mode decomposition (DMD) for a comprehensive analysis of dual-sparse sampling electromagnetic near-field data. CS optimizes sparse sampling in the time domain, capitalizing on the inherent sparsity within electromagnetic radiated signals, resulting in reliable representation of time-domain signals and reducing the required time samples. Latin hypercube sampling guides the probe position, facilitating sparse measurement in the space domain. DMD extracts meaningful insights from the resulting sparse spatiotemporal data, producing sparse dynamic modes and temporal evolution information. Subsequently, Kriging is employed to infer missing spatial measurements for each sparse dynamic mode. Finally, the entire spatiotemporal signals are reconstructed based on interpolated dynamic modes and temporal evolution information. Validation of the proposed method is demonstrated with an example using crossed dipole antennas as the device under test. The Kriging-CS-DMD framework effectively reconstructs electromagnetic fields with precision while concurrently reducing the measurement workload in both the time and space domains. This methodology holds promise for various applications, including space-time-modulated electronic devices.**

***Index Terms*—Time-resolved electromagnetic near-field scanning, compressed sensing, Kriging, dynamic mode decomposition.**

I. Introduction

Electromagnetic near-field scanning is crucial for antenna measurement and investigating electromagnetic interference (EMI) and compatibility (EMC) phenomena [1]. However, obtaining radiation distribution in this scanning process remains time-consuming [2]. The traditional approach involves physically moving sensing probes to different positions during near-field scanning, making data collection from numerous pixels notably time-intensive [3], [4]. To address this challenge, accelerated data acquisition methods have been developed, such as sequential sampling [2], compressed sensing [5], equilateral-triangular-spaced samples [6], Kriging method [7], and wide-mesh scanning [8]. These methods primarily focus on spatially sparse sampling in the frequency domain to reconstruct global spatial distributions.

Recently, there has been an introduction of time-domain distribution measurements in electromagnetic near-field scanning to enhance the analysis of transient electromagnetic phenomena [9], [10]. Unlike traditional frequency-domain measurements, this approach involves acquiring electrical signals through high-speed oscilloscopes and deducing time-varying field signals through basic computational processes [11], [12]. Herein, effectively capturing time-varying near-field distributions requires simultaneous sampling of both temporal and spatial dimensions, introducing complexities in high-speed near-field scanning. Accurate characterization of transient electromagnetic phenomena necessitates synchronization and coordination of temporal and spatial sampling methodologies.

In this study, we introduce a novel hybrid method named Kriging-CS-DMD to effectively tackle the challenges associated with temporal and spatial sampling in near-field scanning. Our approach combines Kriging, compressed sensing (CS), and dynamic mode decomposition (DMD). Specifically, we leverage CS to attain temporal sparsity in data acquisition, and Latin hypercube sampling enables spatial sparse sampling. The resulting spatiotemporal dual-sparse data undergoes DMD analysis, allowing the extraction of sparse dynamic modes and corresponding frequency information. Subsequently, we apply the Kriging method to recover the full dynamic modes from the sparse dynamic modes. Finally, our hybrid approach reconstructs the original spatiotemporal field distributions based on the full dynamic modes and corresponding frequency information.

II. Kriging-Compressed Sensing-Dynamic Mode Decomposition

Fig. 1 outlines the proposed Kriging-CS-DMD method for electromagnetic near-field scanning, specifically addressing situations with sparse spatial and temporal sampling. The

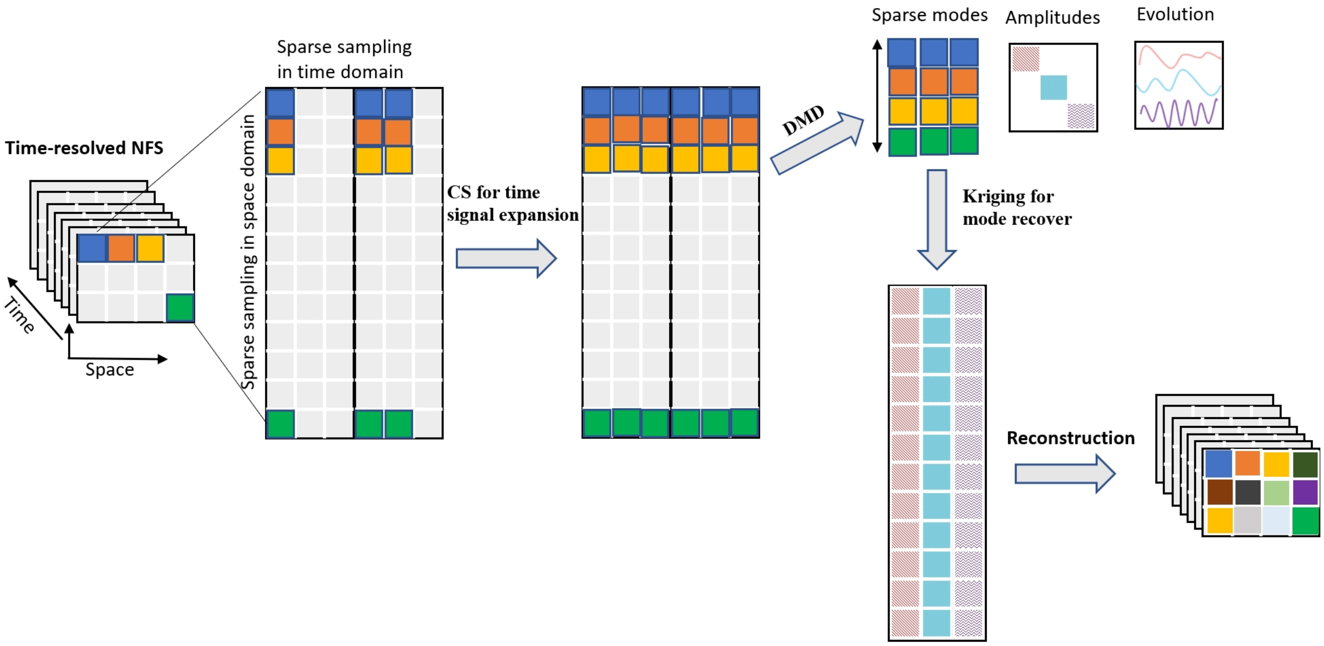


Fig. 1. Schematic of the proposed Kriging-compressed sensing-dynamic mode decomposition for near-field scanning with dual sparse sampling in both time and space domains.

method aims to provide a comprehensive representation of the electromagnetic field through a multi-step process:

Step 1): The initial phase of the process commences with sparse sampling, a technique that meticulously gathers a limited set of spatial data points, represented by Z, alongside discrete samples in time, denoted as n. This selection of spatial points is strategically executed using the Latin Hypercube Sampling (LHS) method, a statistical approach designed to ensure a comprehensive and uniformly distributed representation of the multidimensional parameter space. Concurrently, temporal samples are acquired at these spatial locations in a randomized manner. This deliberate methodology results in the formation of sparse spatiotemporal data, symbolically represented as $\mathbf{Q}_Z^n \in \mathbb{R}^{Z\times n}$. The essence of this step lies in its ability to efficiently capture critical points in space and time with minimal data, setting a robust foundation for subsequent analysis efforts.

Step 2): To enhance temporal resolution, compressed sensing matching pursuit [13] is used, increasing the number of time samples (n) by generating m contiguous time samples at each of the Z spatial points. The result is a denser and more informative temporal dataset, denoted as $\mathbf{Q}_Z^m \in \mathbb{R}^{Z\times m}$.

Step 3): The dataset $\mathbf{Q}_Z^m$ with $Z \times m$ data points undergoes DMD analysis, extracting sparse dynamic modes and corresponding frequency information. DMD models $\mathbf{Q}_Z^m$ as [14]–[16]

$$\mathbf{q}_Z(t) = \sum_{l=1}^{L} \mathbf{x}_l \exp(\eta_l t)\alpha_l = \sum_{l=1}^{L} \mathbf{x}_l \exp(\eta_l^{\text{real}} t + j\eta_l^{\text{imag}} t)\alpha_l. \tag{1}$$

where $\mathbf{q}_Z(t)$ represents the time-varying state in the sparse spatial domain.

Step 4): The Kriging method is then applied to recover complete global dynamic modes from the sparse dynamic modes. Specifically, it is employed to extrapolate the information obtained from a limited number of spatial dimensions (Z) to a fully realized spatial domain encompassing R dimensions. This is achieved by transforming the sparse dynamic modes represented by $\mathbf{x}_l \in \mathbb{R}^Z$ into comprehensive global dynamic modes, denoted as $\mathbf{x}_l^{Kri} \in \mathbb{R}^R$. As a result, Kriging not only fills in the gaps within the sparse dataset but does so in a manner that is statistically optimized based on the spatial distribution of the known data points.

Step 5): The recovered $\mathbf{x}_l^{Kri}$ replaces $\mathbf{x}_l$ in (1), modeling the entire spatial-temporal radiated fields as

$$\begin{aligned} \mathbf{q}_R(t) &= \sum_{l=1}^{L} \mathbf{x}_l^{Kri} \exp(\eta_l t)\alpha_l \\ &= \sum_{l=1}^{L} \mathbf{x}_l^{Kri} \exp(\eta_l^{\text{real}} t + j\eta_l^{\text{imag}} t)\alpha_l. \end{aligned} \tag{2}$$

The Kriging-CS-DMD approach constructs a data-driven model for time-resolved near-field scanning based on doubly sparse data. This enables the reconstruction of entire distributions, the identification of frequency components, and the determination of corresponding spatial distributions. The method proves valuable for gaining insights into time-varying electromagnetic field behavior, especially in scenarios with limited and sparse sampling in both spatial and temporal dimensions.

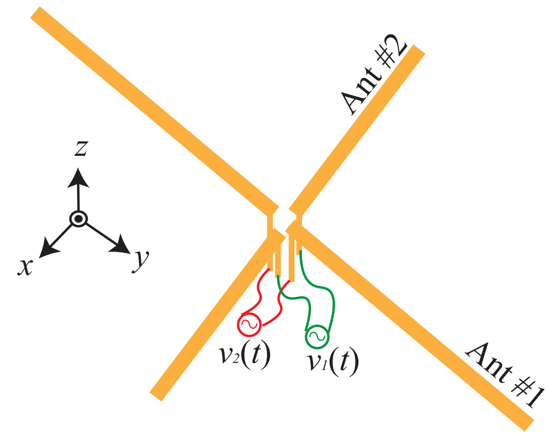


Fig. 2. Crossed dipole antenna with two different exciting signal

III. Results

To validate the proposed method, we conducted a simulation experiment using a crossed dipole antenna configuration [17] as the DUT, visually depicted in Fig. 2. Both antennas are designed as half-wave dipole antennas. Antenna 1 operates at the 2.4 GHz frequency band with $\lambda_1 = 0.125$ m, while Antenna 2 is tailored for the 5 GHz frequency band ($\lambda_2 = 0.06$ m). Sinusoidal waves $v_1(t)$ and $v_2(t)$, operating at 2.4 GHz and 5 GHz, respectively, are used to excite Antenna 1 and Antenna 2.

Herein, we first illustrate sparse sampling in the time domain, starting with an initial sampling of 1000 data points. Through the application of Compressed Sensing (CS), this quantity is efficiently reduced to 128 data points, resulting in a temporal sparse sampling factor of approximately 7.8 times. Simultaneously, in the spatial domain, the original pixel count for sampling is 256×256. By employing the Kriging method, we select 500 pixels for subsequent reconstruction, leading to a spatial sparse sampling factor of approximately 131. The combination of temporal and spatial sparse sampling not only significantly reduces data dimensionality but also enhances the overall efficiency of the data acquisition process.

Next, we analyze data acquired through dual sparse sampling using the Kriging-CS-DMD framework. The DMD spectrum obtained through Kriging-CS-DMD analysis of doubly sparse sampled data is depicted in Fig. 3 (b). For comparison, we also calculate the DMD spectrum obtained via original data analysis, shown in Fig. 3 (a). The results show successful extraction of two distinct frequency components, 2.4 GHz and 5.0 GHz, aligning closely with the actual scenario. This concordance underscores the Kriging-CS-DMD method's ability to extract frequency information using temporally and spatially doubly sparse sampled data.

Furthermore, Fig. 4 visualizes the corresponding dynamic modes alongside the representation of the original modes for comparison. Taking the 2.4 GHz dynamic mode as an example (Fig. 4 (b)), we observe consistency between the reconstructed field data based on 500 sampling points and the actual radiation mode shown in Fig. 4 (a). Similar findings are observed for the 5.0 GHz frequency, as depicted in Fig. 4 (c) and (d). The Kriging-CS-DMD method effectively derives spatial radiation patterns for each frequency based on temporally and spatially doubly sparse sampled data. These results highlight the method's efficacy in extracting essential frequency information and elucidating associated spatial distributions.

Fig. 5 presents the original spatial distribution of the electric field E_z and the corresponding reconstruction results at three distinct time points: 2 ns, 4 ns, and 5 ns. Fig. 5 (a), (c), and (e) depict the original radiated field at these time instances with a resolution of 256×256 pixels. Fig. 5 (b), (d), and (f) show the Kriging-CS-DMD reconstruction results achieved with temporally and spatially doubly sparse sampled data, involving 128 temporal points and 500 spatial pixels. The proposed approach is implemented by MATLAB R2022b, the information of the adopted workstation is Intel(R) Xeon(R) Gold 5222 @3.80GH 64GB, and the execution time is 6.89s. The comparison between original and reconstructed fields demonstrates the effectiveness of the Kriging-CS-DMD approach in capturing the dynamic evolution of the electric field over time with reduced data points.

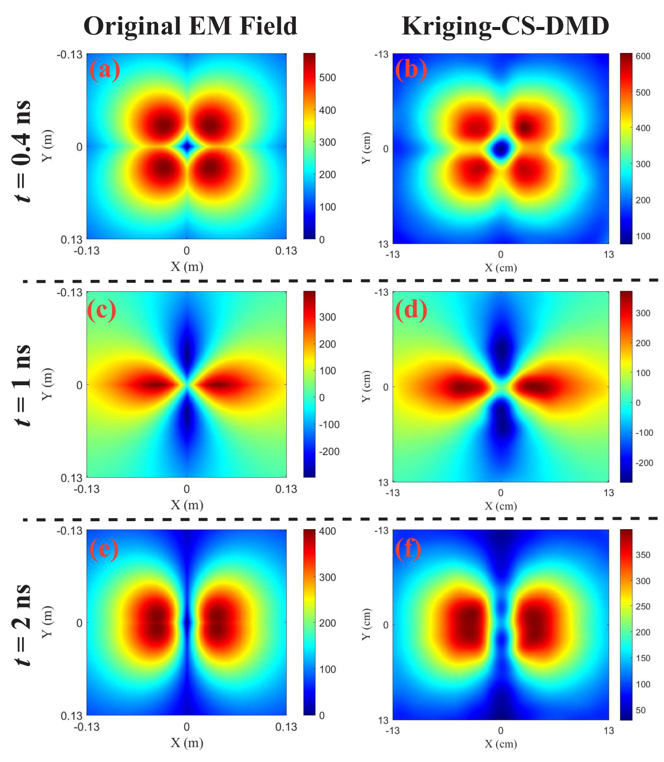
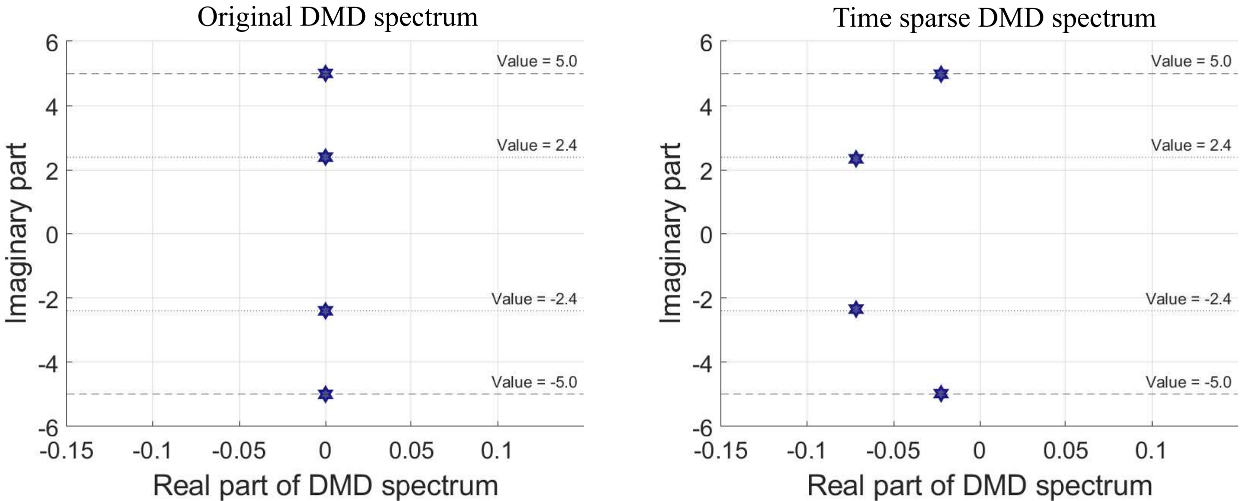
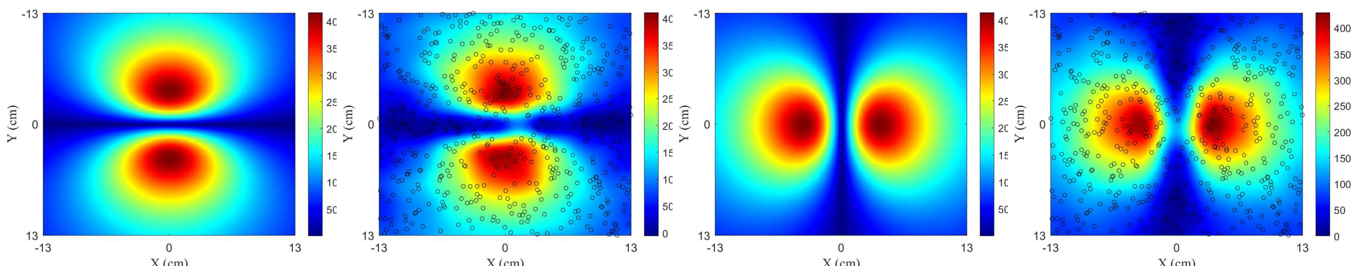


Fig. 5. Original Spatial Distribution of Electric Field E_z and Reconstruction Results at Different Time Points: (a) Original Radiated Field (256×256 pixels) at 2 ns; (b) Kriging-CS-DMD Reconstruction with Temporally and Spatially Doubly Sparse Sampled Data (128 temporal points and 500 spatial pixels) at 2 ns; (c) Original Radiated Field (256×256 pixels) at 4 ns; (d) Kriging-CS-DMD Reconstruction with Temporally and Spatially Doubly Sparse Sampled Data (128 temporal points and 500 spatial pixels) at 4 ns; (e) Original Radiated Field (256×256 pixels) at 5 ns; (f) Kriging-CS-DMD Reconstruction with Temporally and Spatially Doubly Sparse Sampled Data (128 temporal points and 500 spatial pixels) at 5 ns.



(a) (b)

Fig. 3. (a) The DMD spectrum acquired through the utilization of DMD for the analysis of the original dataset. (b) The DMD spectrum obtained by employing the Kriging-CS-DMD for the analysis of spatial-temporal dual sparse data.



(a) (b) (c) (d)

Fig. 4. (a) Original radiated filed distribution at 2.4 GHz. (b) 2.4 GHz mode extracted by Kriging-CS-DMD method. (a) Original radiated filed distribution at 5.0 GHz. (b) 5.0 GHz mode extracted by Kriging-CS-DMD method.

IV. Conclusion

In summary, we presented the Kriging-CS-DMD approach to overcome the challenges posed by dual temporal and spatial sampling in near-field scanning. Our method optimizes data acquisition by employing Kriging for spatial sparse sampling and compressed sensing for achieving temporal sparsity, preserving data fidelity. The application of dynamic mode decomposition to the resulting spatiotemporal dual-sparse data enables the extraction of valuable insights, encompassing frequency information and global spatial distributions for each frequency. Our numerical case study effectively demonstrated the method's efficiency and accuracy in reconstructing electromagnetic fields while simultaneously reducing measurement overhead. The versatility of this methodology makes it applicable in various scenarios, especially in space-time-modulated electronic devices.

Acknowledgment

This work is supported in part by Chinese University of Hong Kong Startup Fund under Grant 4937123, Grant 4937124, Grant 14223422 and Grant 14201923, in part by the Research Grants Council of Hong Kong under Grant GRF 14210623, in part by ITF Grant ITP/007/23LP, in part by AoE/E-101/23-N, and in part by AoE/E-603/18.

References

[1] J. Fan, "Near-field scanning for em emission characterization," *IEEE Electromagnetic Compatibility Magazine*, vol. 4, no. 3, pp. 67–73, 2015.

[2] S. Serpaud, A. Boyer, S. Ben-Dhia, and F. Coccetti, "Fast and accurate near-field measurement method using sequential spatial adaptive sampling (SSAS) algorithm," *IEEE Trans. Electromagn. Compat.*, vol. 63, no. 3, pp. 858–869, 2020.

[3] K.-L. Chen, Y. Guo, J. Wang, and X. Yang, "Contactless islanding detection method using electric field sensors," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–13, 2020.

[4] F. R. Varela, B. G. Iragüen, and M. Sierra-Castaner, "Application of nonuniform FFT to spherical near-field antenna measurements," *IEEE Trans. Antennas Propag.*, vol. 68, no. 11, pp. 7571–7579, 2020.

[5] M. Azadifar, H. Karami, F. Rachidi, and M. Rubinstein, "A compressive sensing framework for emi source localization using a metalens structure: Localization beyond the diffraction limit," *IEEE Trans. Electromagn. Compat.*, vol. 64, no. 1, pp. 58–65, 2020.

[6] M. H. Francis, "Aperture-sampling requirements [and reply]," *IEEE Antennas Propag. Mag.*, vol. 39, no. 5, pp. 76–81, 1997.

[7] D. Deschrijver, F. Vanhee, D. Pissoort, and T. Dhaene, "Automated near-field scanning algorithm for the EMC analysis of electronic devices," *IEEE Trans. Electromagn. Compat.*, vol. 54, no. 3, pp. 502–510, 2012.

[8] F. DAgostino, I. De Colibus, F. Ferrara, C. Gennarelli, R. Guerriero, M. Migliozzi *et al.*, “Far-field pattern reconstruction from near-field data collected via a nonconventional plane-rectangular scanning: experimental testing,” *Int. J. Antennas Propag.*, vol. 2014, 2014.
[9] J. Li, J. Zhou, S. Yong, Y. Liu, and V. Khilkevich, “Automatic sparse esm scan using gaussian process regression,” in *2020 IEEE International Symposium on Electromagnetic Compatibility and Signal/Power Integrity (EMCSI)*, 2020, pp. 671–675.
[10] Y. Liu and B. Ravelo, “Fully time-domain scanning of em near-field radiated by rf circuits,” *Prog. Electromagn. Res. B*, vol. 57, pp. 21–46, 2014.
[11] S. Hedia, B. Zitouna, J. B. H. Slama, and L. Pichon, “Electromagnetic time reversal in the near field: Characterization of transient disturbances in power electronics,” *IEEE Trans. Electromagn. Compat.*, vol. 62, no. 5, pp. 1869–1878, 2020.
[12] Y. Xie, X. Yang, P. Su, Y. He, and Y. Qiu, “A microwave time domain reflectometry technique combining the wavelet decomposition analysis and artificial neural network for detection of defects in dielectric structures,” *IEEE Trans. Instrum. Meas.*, vol. 71, pp. 1–11, 2022.
[13] D. Needell and J. A. Tropp, “Cosamp: Iterative signal recovery from incomplete and inaccurate samples,” *Appl. Comput. Harmon. Anal.*, vol. 26, no. 3, pp. 301–321, 2009.
[14] Y. Zhang and L. Jiang, “A novel data-driven analysis method for electromagnetic radiations based on dynamic mode decomposition,” *IEEE Trans. Electromagn. Compat.*, vol. 62, no. 4, pp. 1443–1450, 2020.
[15] ——, “A novel data-driven analysis method for nonlinear electromagnetic radiations based on dynamic mode decomposition,” in *2019 IEEE International Symposium on Electromagnetic Compatibility, Signal & Power Integrity (EMC+SIPI)*, 2019, pp. 527–531.
[16] ——, “Spacetimefrequency characterization in electromagnetic near-field scanning: A data-driven approach,” *IEEE Trans. Electromagn. Compat.*, pp. 1–9, 2023.
[17] S. X. Ta, I. Park, and R. W. Ziolkowski, “Crossed dipole antennas: A review,” *IEEE Antennas Propag. Mag.*, vol. 57, no. 5, pp. 107–122, 2015.