Electromagnetic Near-Field Scanning with a Spatially Sparse Sampling Strategy Utilizing Kriging-DMD

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

2024 IEEE 28th Workshop on Signal and Power Integrity (SPI) | 979-8-3503-8293-8/24/$31.00 ©2024 IEEE | DOI: 10.1109/SPI60975.2024.10539222

***Abstract*—This paper proposes a hybrid method for time-resolved electromagnetic near-field scanning, merging model-based (Gaussian processes regression model, a.k.a. Kriging method) and data-driven (dynamic mode decomposition) techniques. Specifically, Latin hypercube sampling enables spatially sparse measurements, followed by dynamic mode decomposition to analyze resulting sparse spatial-temporal data, extracting frequency information and sparse dynamic modes. The Kriging method is then employed for full-state reconstruction. The proposed approach is evaluated using crossed dipole antennas. Results indicate that, even with a spatial subsampling factor of 130, achieving a fully reconstructed field distribution suitable for engineering applications with frequency information extraction is feasible. This hybrid framework presents a promising avenue to enhance efficiency in electromagnetic near-field measurements, potentially finding applications across diverse electromagnetic measurement scenarios.**

***Index Terms*—Time-resolved electromagnetic near-field scanning, Kriging, spatially sparse sampling strategy, dynamic mode decomposition.**

I. Introduction

Electromagnetic near-field scanning (NFS) plays a vital role in antenna measurement and investigating electromagnetic interference (EMI) and compatibility (EMC) phenomena [1]. Despite its importance, obtaining the radiation distribution during this scanning process is time-consuming [2]. The traditional approach involves physically moving sensing probes to different positions, resulting in notably time-intensive data collection from numerous pixels [3], [4]. To overcome this challenge, various accelerated data acquisition methods have been developed, including such as compressed sensing [5], sequential sampling [2], Kriging method [6], and wide-mesh scanning [7]. These techniques primarily concentrate on obtaining sparsely sampled spatial data in the frequency domain to reconstruct global spatial distributions.

Recently, there has been a shift towards incorporating time-domain distribution measurements in electromagnetic NFS to enhance the analysis of transient electromagnetic phenomena [8], [9]. Unlike traditional frequency-domain measurements, time-resolved measurement involves acquiring electrical signals through high-speed oscilloscopes and deducing time-varying field signals [10], [11]. Effectively capturing time-varying near-field distributions requires simultaneous sampling of temporal and spatial dimensions, introducing complexities in fast NFS. In particular, tackling the time-consuming and costly aspects of time-resolved NFS is essential, which demands accessibility to all on-board locations and fast probe positioning.

This work proposes a novel hybrid framework named Kriging-DMD, integrating Gaussian processes regression (Kriging) and dynamic mode decomposition (DMD) for electromagnetic NFS. Specifically, we first employ the Latin hypercube sampling algorithm for sparse measurements in the spatial domain. Subsequently, DMD facilitates spatial-temporal decomposition analysis, extracting sparse dynamic modes and frequency information. Leveraging the Kriging method, we recover the full state of dynamic modes using sparse data from a small number of sampled points. Finally, Kriging-DMD offers the reconstruction of the raw near-field, enabling analysis of time-varying or transient signals.

II. Kriging-Dynamic Mode Decomposition

This section presents the proposed Kriging-DMD method for electromagnetic NFS. The method aims to provide a comprehensive representation of the electromagnetic field through a multi-step process:

Step 1): In the initial phase of spatial data collection through sparse measurement, Latin Hypercube Sampling (LHS) strategically samples the spatial distribution during NFS. LHS, derived from statistics and combinatorial mathematics, efficiently divides the multidimensional spatial scanning domain into equally spaced intervals along each dimension [12]. The advantage of LHS lies in its ability to maximize information gain while conserving resources [13]. By selectively choosing a subset of data points for measurement, LHS expedites the data collection process, proving to be an efficient technique for spatial analysis and modeling. In essence, sparse measurement involves selecting representative locations or sensor nodes for data collection, which are then used to reconstruct complete spatial data using the Kriging method.

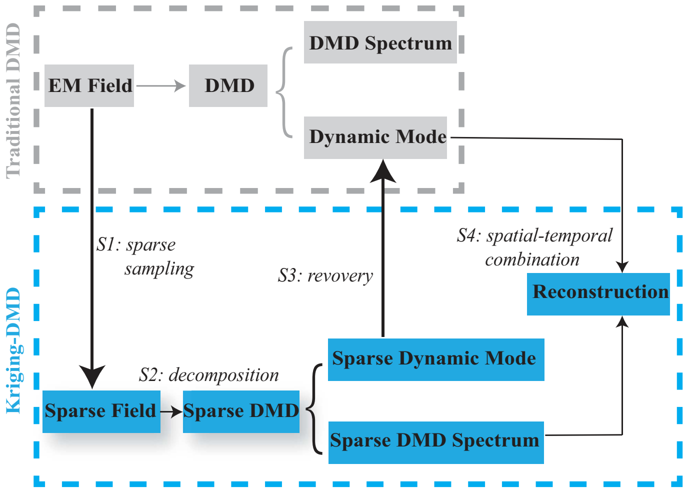

Fig. 1. Schematic of the proposed Kriging-dynamic mode decomposition for near-field scanning with sparse sampling in space domains.

Step 2): Then, the DMD is used to compute the sparse measured data. DMD is a technique used for modeling and analyzing the dynamics and extracting coherent structures from time-varying EM data [14], [15]. Notably, even in the context of sparse measured field data, the application of DMD remains feasible, which can be detailed as follows [16].

$$\boldsymbol{x}(t)=\sum_{i=1}^{I}\boldsymbol{m}_i\exp(\omega_i t)a_i=\sum_{i=1}^{I}\boldsymbol{m}_i\exp(\omega_i^{\text{real}}t+j\omega_i^{\text{imag}}t)a_i. \tag{1}$$

where the sparse field $\boldsymbol{x}(t)$ is expressed as a linear combination of dynamic modes $\boldsymbol{m}_i$ with associated frequency and damping factor information, denoted by $\omega_i=\omega_i^{\text{real}}+j\omega_i^{\text{imag}}$, and amplitude weights a_i. Through the LHS, the sparse measurement is obtained, which means that only a subset of the complete dataset is available. It is assumed that only K measured data sample are selected. Then, the EM radiated field is also with K dimension, i.e., $\mathbf{x}_t\in\mathbb{R}^K$ in (3). Similarly, due to sparse measurement, $\mathbf{m}_i\in\mathbb{R}^K$ in (3). Overall, when computing D-MD on sparse measured data, sparse spatial features, and their corresponding time-varying characteristics are also extracted.

Step 3): Next, the Kriging method is employed to facilitate the mapping of spatially sparse dynamic modes to their full-state counterparts. Illustratively, considering the i th dynamic mode, denoted as $\mathbf{m}_i$, the Kriging technique is applied to reconstruct data for additional spatial points, effecting a transition from the K-dimensional space to the full state residing in the Z-dimensional space, where Z signifies the dimensionality of the complete state. To be specific, the GPR model, denoted as $\mathbf{g}_K(\mathbf{r})$, takes the following form:

$$\mathbf{m}_i^Z(\mathbf{r})=\sum_{m=1}^{M}\beta_m h_m(\mathbf{r})+\sum_{k=1}^{K}\alpha_k\phi\left(\theta,\mathbf{r}_k,\mathbf{r}\right) \tag{2}$$

where the coefficients β_m and α_k are determined through estimation using a generalized least-squares procedure. The initial section of (2) corresponds to a linear regression with respect to the basis functions $h_m(\mathbf{r})$. Typically, these basis functions are chosen to be low-order polynomials or constants. The latter part of (2) signifies a localized deviation from the regression component, expressed as a sum of K shifted instances of the correlation function, each centered on an individual data sample. For each of the sparse dynamic modes, we establish an associated Kriging model, facilitating the recovery of the complete set of dynamic modes that constitute the entire state.

Step 4): Finally, the original full state spatial-temporal EM radiation field can be reconstructed. In particular, Kriging serves as a predictive tool for extrapolating values at unsampled points of each dynamic mode based on the information garnered from sampled points. Thus, the original full state EM radiation field can be expressed as follows.

$$\boldsymbol{x}^Z(t)=\sum_{i=1}^{I}\boldsymbol{m}_i^Z\exp(\omega_i t)a_i \tag{3}$$

The presented method underscores the significance of employing kriging for the estimation of missing data points across dynamic modes. This approach ensures the preservation of temporal sampling integrity, independent treatment of time and space dimensions, consistency in DMD spectrum characteristics, and, fundamentally, the reconstruction of the complete time-varying electromagnetic (EM) radiation field through the application of DMD-based analytical formulations. The schematic flow of the proposed Kriging-DMD framework is depicted in Figure 1.

III. Results

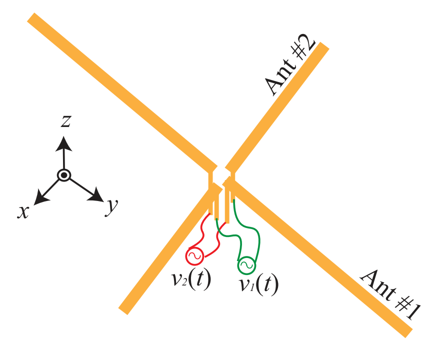

Fig. 2. Crossed dipole antenna with two different exciting signal

To validate the proposed method, we performed a simulation experiment employing a crossed dipole antenna configuration [17] depicted in Fig. 2. Both antennas are half-wave dipole antennas, with Antenna 1 operating at 2.4 GHz (wavelength $\lambda_1=0.125$ m) and Antenna 2 at 5 GHz ($\lambda_2=0.06$ m). Sinusoidal waves $v_1(t)$ and $v_2(t)$ at 2.4 GHz and 5 GHz, respectively, serve as excitations for Antenna 1 and Antenna 2.

In the spatial domain, the initial pixel count for sampling is 256×256. Through the application of the Kriging method, we select 500 pixels for subsequent reconstruction, resulting in a spatial sparse sampling factor of approximately 131.

The integration of temporal and spatial sparse sampling not only significantly diminishes data dimensionality but also elevates the overall efficiency of the data acquisition process. Subsequently, we scrutinize the data acquired through spatially sparse sampling utilizing the Kriging-DMD framework. The DMD spectrum derived from the Kriging-DMD analysis of spatially sparse sampled data is illustrated in Fig. 3 (b). For reference, we compute the DMD spectrum obtained through raw data analysis, as depicted in Fig. 3 (a). The outcomes manifest the successful extraction of two distinct frequency components, 2.4 GHz and 5.0 GHz, closely aligning with the actual scenario. This alignment underscores the Kriging-DMD method's proficiency in extracting frequency information using spatially sparse sampled data.

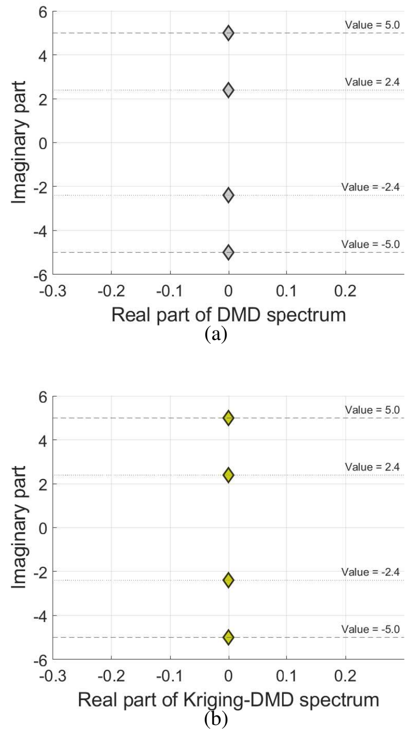

Fig. 3. The distribution of the eigenvalues obtained by the (a) traditional DMD in the analyze of global EM radiation and (b) Kriging-DMD in the analyze of sparse EM radiation.

Subsequently, Fig. 4 presents the reconstruction of sparse dynamic modes by the Kriging method alongside the original modes for direct comparison. Examining the 2.4 GHz dynamic mode as an illustrative case (Fig. 4 (c)), we observe good agreement between the reconstructed field data from 500 sampling points and the actual radiation mode illustrated in Fig. 4 (a). Comparable observations are made for the 5.0 GHz frequency, as evident in Fig. 4 (b) and (d). The Kriging-DMD method deduces spatial radiation patterns for each frequency based on spatially sparse sampled data. These findings underscore the method's proficiency in extracting crucial frequency information and elucidating associated spatial distributions.

Fig. 5 displays the initial spatial distribution of the electric field E_z and the corresponding reconstructions at 0.4 ns and 1

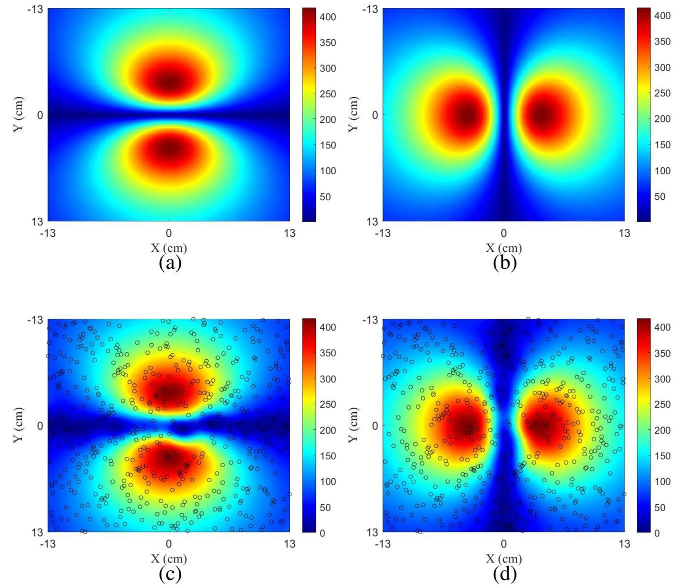

Fig. 4. (a) Initial distribution of the electromagnetic (EM) radiation field at 2.4 GHz. (b) Initial distribution of the electromagnetic (EM) radiation field at 5.0 GHz. (c) Kriging interpolation for the dynamic mode at 2.4 GHz (spatial sampling: 500). (d) Kriging interpolation for the dynamic mode at 5.0 GHz (spatial sampling: 500).

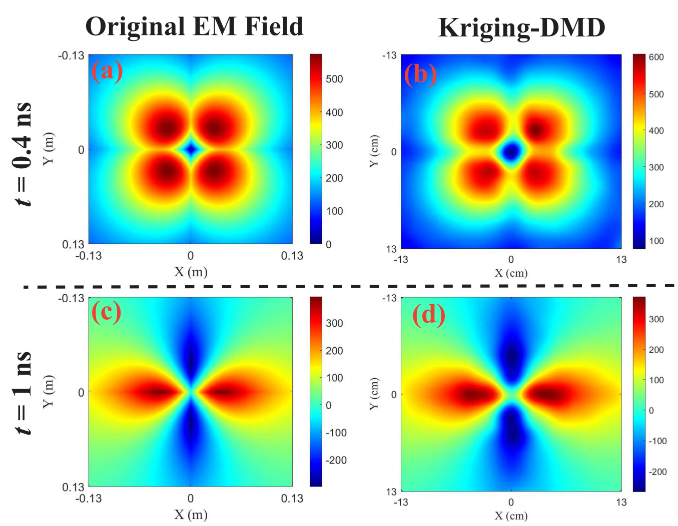

Fig. 5. Original spatial distribution of electric field E_z and reconstruction result of the spatial distribution of electric field E_z at 0.4 ns: (a) original radiated field with 256×256 pixels; (b) Krigin-DMD reconstruction with 500 pixels, at 1 ns: (c) original radiated field with 256×256 pixels; (d) Krigin-DMD reconstruction with 500 pixels.

ns. Specifically, Fig. 5 (a) and (c) exhibit the original radiated field at these time points with a resolution of 256×256 pixels. Additionally, Fig. 5 (b) and (d) plots the Kriging-DMD reconstruction results achieved with spatially sparse sampled data involving 500 spatial pixels. It can be clearly seen that Kriging-DMD can reconstruct the global EM signal with fewer spatial sampling points and provide frequency information and corresponding spatial distribution.

IV. Conclusion

In conclusion, we presented a hybrid framework, the Kriging-DMD method, for spatially sparse sampling in time-resolved electromagnetic NFS. The efficacy of this approach was verified through its successful application to crossed dipole antennas, encompassing two distinct dipole antenna configurations. Moreover, the proposed method could be useful for extension and applicability across diverse electromagnetic measurement settings.

Acknowledgment

This work is supported in part by the Research Grants Council of Hong Kong under Grant GRF 14210623 and in part by ITF Grant ITP/007/23LP.

References

[1] Y.-F. Shu, X.-C. Wei, R. Yang, and E.-X. Liu, "An iterative approach for emi source reconstruction based on phaseless and single-plane near-field scanning," *IEEE Trans. Electromagn. Compat.*, vol. 60, no. 4, pp. 937–944, 2017.

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

[4] 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.

[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] 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.

[7] 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.

[8] 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.

[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. 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.

[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] J. C. Helton and F. J. Davis, "Latin hypercube sampling and the propagation of uncertainty in analyses of complex systems," *Reliab. Eng. Syst. Saf.*, vol. 81, no. 1, pp. 23–69, 2003.

[13] W.-L. Loh, "On latin hypercube sampling," *Ann. Stat.*, vol. 24, no. 5, pp. 2058–2080, 1996.

[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] ——, "Spacetimefrequency characterization in electromagnetic near-field scanning: A data-driven approach," *IEEE Trans. Electromagn. Compat.*, pp. 1–9, 2023.

[16] ——, "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.

[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.