Enhancing Near-Field Holographic Imaging with Predicted Object Position

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***Abstract*—In current near-field holographic imaging, a circular region is scanned using an array of transmitting and receiving antennas over a narrow frequency band. This makes the data acquisition system slow, complex, bulky, and costly. Reducing the number of receiver antennas and using a narrower frequency band can significantly reduce the cost and complexity of the data acquisition system. To do so, we propose a method that uses prior knowledge about the object position, obtained by applying a neural network algorithm, called convolutional neural network (CNN), to the scattered field responses. This prior knowledge is then used to add a new regularization term to the cost function that is minimized in near-field holography.**

I. Introduction

Holographic microwave imaging allows for fast and robust imaging of hidden objects. This imaging technique has been developed for far-field and near-field imaging applications [1]. In particular, the recently developed near-field holographic microwave imaging (NH-MWI) techniques have applications in the field of biomedical imaging and nondestructive testing (NDT).

NH-MWI offers certain benefits. Mainly, the product of the incident field and Green's function is obtained *a priori* as a point spread function (PSF). It is independent of radial wavenumber, making it capable of processing evanescent waves for enhanced resolution, can process forward and backscattered waves simultaneously, and perform two-dimensional (2D) and three-dimensional (3D) imaging using narrowband data with an array of antennas. This technique has been developed in rectangular and cylindrical imaging setups [1]-[3].

Over the years successful efforts have been made to reduce, the system cost, scanning time, and data acquisition complexity for NH-MWI. In [4], a low-cost and compact cylindrical system has been proposed for data acquisition using an array of receiver antennas performing mechanical scanning and collecting narrowband data. The depth biasing problem has been mitigated by standardizing the solution. Electrical scanning is used to expedite the data acquisition process at the cost of increased circuit complexity [5].

In this paper, we propose a method that uses prior knowledge about the object position, particularly, the predicted azimuthal position of the object under test (OUT). The received scattered field responses of an OUT located in a scanned circular region are provided as inputs to a neural network algorithm, called convolutional neural network (CNN). This prior knowledge is then used to add a regularization term to the involved system of equations in the spectral domain, in NH-MWI. We demonstrate that the proposed method can significantly reduce the number of receivers (RX) in the array while using single-frequency scanning which, in turn, reduces the data acquisition time, cost, and complexity.

II. Methodology

Fig. 1 illustrates the circular scanning setup used for acquiring the scattered field response $E^{SC}(\phi)$ at each azimuthal angle ϕ. For simplicity, we consider one-dimensional (1D), single-frequency imaging where the TX and RX antennas scan a full circle. In NH-MWI, the following system of equations can be obtained at each Fourier variable k_ϕ (as described in [5]):

$$\underline{\tilde{E}}^{SC} = \underline{\underline{\tilde{D}}}\,\underline{\tilde{F}} \tag{1}$$

where,

$$\underline{\tilde{E}}^{SC} = \begin{bmatrix} \tilde{E}_1^{SC} \\ \vdots \\ \tilde{E}_{N_A}^{SC} \end{bmatrix}, \underline{\underline{\tilde{D}}} = \begin{bmatrix} \underline{\underline{\tilde{D}}}_1 \\ \vdots \\ \underline{\underline{\tilde{D}}}_{N_A} \end{bmatrix}, \underline{\tilde{F}} = \begin{bmatrix} \tilde{f}_1(k_\phi) \\ \vdots \\ \tilde{f}_{N_r}(k_\phi) \end{bmatrix}, \tag{2}$$

$$\tilde{E}_{a_m}^{SC} = \begin{bmatrix} \tilde{E}_{a_m}^{SC}(k_\phi, \omega_1) \\ \vdots \\ \tilde{E}_{a_m}^{SC}(k_\phi, \omega_{N_\omega}) \end{bmatrix} \tag{3}$$

$$\underline{\underline{\tilde{D}}}_{a_m} = \begin{bmatrix} \tilde{E}_{1,a_m}^{SC,CO}(k_\phi, \omega_1) & \cdots & \tilde{E}_{N_r,a_m}^{SC,CO}(k_\phi, \omega_1) \\ \vdots & \ddots & \vdots \\ \tilde{E}_{1,a_m}^{SC,CO}(k_\phi, \omega_{N_\omega}) & \cdots & \tilde{E}_{N_r,a_m}^{SC,CO}(k_\phi, \omega_{N_\omega}) \end{bmatrix} \tag{4}$$

where $\tilde{E}_{a_m}^{SC}(k_\phi, \omega_n)$ and $\tilde{E}_{1,a_m}^{SC,CO}(k_\phi, \omega_n)$ are the Fourier transforms (FTs) of the scattered fields due to the OUT and calibration object, respectively, measured by a_m-th receiver ($a_m = 1, \dots, N_A$) at frequency ω_n ($n = 1, \dots, N_\omega$), and $\tilde{f}_i(k_\phi)$ ($i = 1, \dots, N_r$) is the FT of the contrast function of OUT over the i-th circle [5]. These systems of equations are solved at each k_ϕ to obtain $\underline{\tilde{F}}$ by calculating the product of Moore-Penrose pseudoinverse of $\underline{\underline{\tilde{D}}}$ with $\underline{\tilde{E}}^{SC}$. Then, inverse FT is applied to reconstruct 1D images $f_i(\phi)$, $i = 1, \dots, N_r$, as in [5].

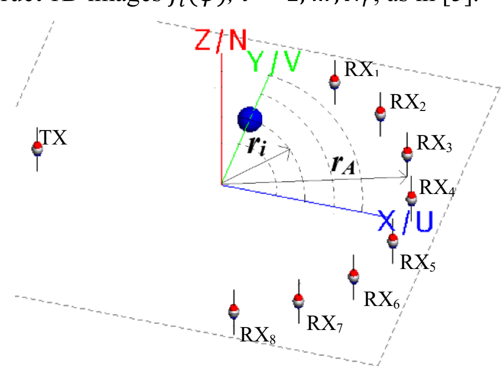

Figure 1. Scanning setup for NH-MWI.

For having prior knowledge about the azimuthal position of the object, the measured scattered fields $E^{SC}(\phi)$ for a range of various objects are used to train and validate a 1D CNN model which is later employed to predict the approximate azimuthal position of the object. A portion of the data is used for training and validation while testing is performed on the remaining data. Then, a regularization term is added to the system of equations in (1) that utilizes the predicted information for the azimuthal position of the OUT as well as the 1D images $f_i(\phi)$, reconstructed a priori, using NH-MWI [5]. Equation (5) shows the minimization problem when incorporating this prior knowledge to solve the original system of equations in (1):

$$min_{\underline{\tilde{F}}'} \left[\left\| \underline{\tilde{D}}\,\underline{\tilde{F}}' - \underline{\tilde{E}}^{SC} \right\|^2 + \alpha \left\| \frac{\tilde{F}'_{sum}}{M_{F_{sum}}} - \underline{\tilde{P}} \right\|^2 \right] \qquad (5)$$

where, $\underline{\tilde{P}}$ denotes the FT of a normalized square pulse, with a magnitude of 1 for the azimuthal segment containing the object predicted by the CNN model and zero elsewhere, $M_{F_{sum}}$ is the maximum of the sum of $|f_i(\phi)|$ obtained from NH-MWI over all imaged circles, $\underline{\tilde{F}}'$ denotes the vector containing the FTs of the contrast function of OUTs on the imaged circles ($f_i'(\phi)$), $\tilde{F}'_{sum}$ is the sum of the absolute values of the real parts of the components of $\underline{\tilde{F}}'$ vector and $\alpha \geq 0$ is the regularization parameter. To reconstruct the 1D images over all imaged circles, $|f_i'(\phi)|, i = 1, \ldots, N_r$, inverse FT is applied to the solutions. Finally, the normalized modulus of $f_i'(\phi)$, $|f_i'(\phi)|/M$, where M is the maximum of $|f_i'(\phi)|$ for all i, is plotted as an image for each imaged circle i. While the proposed methodology has been presented for 1D imaging at each radial position, extending that to 2D imaging at each radial position using the data collected and processed along the z-axis in addition to the ϕ is straight forward [5].

III. Results

Fig. 1, shows the FEKO model for an OUT which has relative permittivity (ε_r), conductivity (σ), azimuthal position (ϕ), and radial position (r). The background medium has a relative permittivity of 22.1 and conductivity of 0. Full-circle scanning of the OUT is performed using a transmitter and an array of 4 receivers at a distance of r_A = 60 mm and a frequency of 1.55 GHz. The OUT is located at $\phi = 90^0$ and r = 32 mm and has a relative permittivity of 55 and conductivity of 0. To perform deep learning, we use 1344 samples when varying the size, position, and properties of the object. A 1D CNN model is trained using 75 % samples and validated using 10 % samples. 15 % of the samples are used for testing. This model provides high accuracy for the prediction of OUT's azimuthal position. The minimization problem in (5) is solved using *fmincon* command in MATLAB to reconstruct 1D images of the OUT for all imaged circles, radii 24 mm, 32 mm, 40 mm, and 48 mm.

Fig. 2 shows the comparison between the 1D images over 4 imaged circles obtained when solving (1) [5] and when using the proposed method with a regularization term in (5). The 1D images in Fig. 2 are obtained by using data received by only four receivers, RX_3, RX_4, RX_5, and RX_6, and at a single frequency of 1.55 GHz. The proposed method shows significant improvement in reducing the level of spurious variations in the original NH-MWI due to insufficient data. Approximately, a reduction of 50% is observed in the level of background spurious variations. The modified NH-MWI provides images with smoother variations (due to the regularization term) which more reliably show the presence of the object on the correct imaged circle of radius 32 mm. Shadows with lower image values are observed on other imaged circles.

IV. Conclusion

A highly accurate deep learning model is first introduced to estimate the azimuthal location of the OUT in near-field microwave imaging. This prior knowledge is then used to formulate a regularization term in NH-MWI. By doing so, we have obtained satisfactory results with single-frequency scanning while employing a reduced number of antennas. This helps to cut down the imaging time, cost, and system complexity. While the performance of the proposed method has been demonstrated via 1D simulation results, this technique can be extended to 3D imaging.

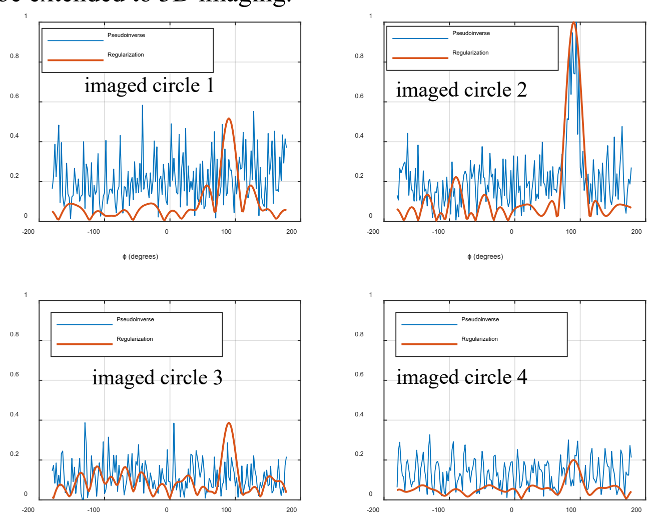

Figure 2. Comparison between conventional (pseudoinverse solution) and enhanced NH-MWI (regularized solution).

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References

[1] R. K. Amineh, N. K. Nikolova, and M. Ravan, *Real-Time Three-Dimensional Imaging of Dielectric Bodies Using Microwave/Millimeter Wave Holography*. Wiley & IEEE Press, 2019.

[2] R. K. Amineh, J. McCombe, A. Khalatpour, and N. K. Nikolova, "Microwave holography using point-spread functions measured with calibration objects," *IEEE Trans. on Inst. and Meas.*, vol. 64, no. 2, pp. 403–417, 2015.

[3] R. K. Amineh, M. Ravan, R. Sharma, and S. Baua, "Three-dimensional holographic imaging using single frequency microwave data," *Int. J. Antennas and Propag.*, vol. 2018, Jul. 2018, Art. no. 6542518.

[4] H. Wu, M. Ravan, and R. K. Amineh, "Holographic near-field microwave imaging with antenna arrays in a cylindrical setup," *IEEE Trans. Microw. Theory and Tech.*, vol. 69, no. 1, pp. 418-430, Jan. 2021

[5] H. Wu and R. K. Amineh, "A Low-Cost and Compact Three-Dimensional Microwave Holographic Imaging System," *Electronics*, vol. 8, no. 9, p. 1036, Sep. 2019, doi: 10.3390/electronics809103.