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A Measurement Mode Selection Method for Computational Microwave Imaging

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Abstract—This paper introduces a novel method for selecting useful measurement modes in computational microwave imaging (CMI) systems utilizing metasurface antennas. With the aim of improving the computational efficiency without compromising the imaging quality, a regional average correlation matrix (RACM) that can evaluate the quality of measurement modes based on an area-specific analysis of the near-field distributions is firstly proposed. Building upon the RACM, an algorithm known as the contribution matrix sorting (CMS) is subsequently developed to filter useful measurement modes based on their contributions to the CMI. By implementing this selection method, the paper demonstrates the potential for significantly improving the CMI computation efficiency. The effectiveness of this approach is validated through full-wave simulations in CST Microwave Studio, showing that the quality of reconstructed images can be maintained even when the number of measurement modes is reduced by as much as 76%. This work presents a significant step forward in the practical application of metasurface-based CMI systems, offering a method to tackle the challenges of computational efficiency while ensuring high-quality imaging outcomes.

Index Terms—Microwave imaging, computational imaging, measurement modes, correlation, metasurface.

I. INTRODUCTION

MICROWAVE imaging offers a significant potential in a wide range of applications, including medical diagnostics, security screening, non-destructive testing, and through-wall imaging [1]–[4]. Traditional microwave imaging systems primarily use variants of raster-scan-based solutions, exhibiting limitations in key system metrics, such as slow data acquisition and increased hardware complexity. To overcome these challenges, computational microwave imaging (CMI) has been proposed [5]–[8]. The CMI is a technique that uses sequences of low-correlated radiation patterns (or modes), typically generated by coded-apertures (realized by metasurfaces), to capture and extract the scene information. In this context, two types of antennas, the frequency-diverse metasurface antenna (FDMA) and the dynamic metasurface antenna (DMA) demonstrate significant potential for the implementation of CMI systems. In an FDMA modality, the scene information is encoded onto a set of measurement modes and sampled by stepping through several frequency points across the operating frequency band [9]–[14]. Contrary to the frequency-diverse method, the metamaterial elements of a DMA can modulate the measurement modes by adjusting their own resonances using electronic components (PIN or a varactor diode) [15]–[21]. However, both the FDMA and DMA face the problem of redundant measurement modes, which results in high computational costs in the post-processing stage of the CMI.

To address this challenge, a method using the principal component analysis (PCA) technique to optimize the sensing matrix was proposed in [22]. This method utilizes the singular value decomposition (SVD) to filter out the parts with smaller contributions in the sensing matrix, thereby truncating its size and improving the efficiency of CMI. Nevertheless, this method can only assess whether the measurement modes are of high quality or not, without providing detailed information on which specific measurement mode is useful. Consequently, this letter presents a new method that can effectively select useful measurement modes while maintaining imaging quality and significantly improving the post-processing efficiency. In particular, we demonstrate that using the proposed technique, the number of measurement modes can be reduced by 76% without sacrificing the fidelity of the reconstructed images.

II. METASURFACE-BASED COMPUTATIONAL MICROWAVE IMAGING

In this paper, we consider a CMI system consisting of a metasurface-based transmitter (Tx) radiating quasi-random radiation patterns and an array of waveguide probe antennas as a receiver (Rx) as depicted in Fig. 1. Adopting the first Born approximation [23], the back-scattered signal from the
scene, \( g \), is correlated to the sensing matrix, \( H \), and the scene reflectivity \( f \) as follows [24]:

\[
g_{M \times 1} = H_{M \times N} f_{N \times 1} + n_{M \times 1}. \tag{1}
\]

In (1), \( M \) denotes the total number of measurement modes and \( N \) is the number of pixels into which the imaging scene is discretized. For the work presented in this paper, \( M = 656 \) and \( N = 961 \). The entire collection of measurements is succinctly represented using a matrix notation as follows [24]:

\[
\begin{bmatrix}
  g_1 \\
  g_2 \\
  \vdots \\
  g_i \\
  \vdots \\
  g_M
\end{bmatrix} =
\begin{bmatrix}
  E_{Tx11} \cdot E_{Rx11} & \cdots & E_{Tx1j} \cdot E_{Rx1j} \\
  \vdots & \ddots & \vdots \\
  E_{Tx11} \cdot E_{Rx11} & \cdots & E_{Txij} \cdot E_{Rxij}
\end{bmatrix}
\begin{bmatrix}
  f_1 \\
  f_2 \\
  \vdots \\
  f_j \\
  \vdots \\
  f_N
\end{bmatrix} + n_{M \times 1}, \tag{2}
\]

where the sensing matrix \( H \) is the dot product of the radiated fields generated by Tx and Rx, \( H = E_{Tx} \cdot E_{Rx} \), \( i = 1 \rightarrow M \) and \( j = 1 \rightarrow N \), respectively [25]. \( n \) denotes the system noise [26]. To estimate the reflectivity of the scene, \( f_{est} \), computational reconstruction algorithms, such as the least-squares (LS) algorithm, can be used [27]:

\[
f_{est} = \arg \min_f \| g - H f \|_2^2. \tag{3}
\]

The quantity and quality of measurement modes are important factors, and they govern the quality of the reconstructed images [28]. Consequently, to reconstruct high-fidelity images of targets located in the scene, a larger number of measurement modes are needed. Accordingly, the size of the sensing matrix \( H \) will also increase greatly, posing a significant pressure on the post-processing stage of CMI.

III. MEASUREMENT MODES ANALYSIS AND SELECTION METHODS

The correlation coefficient matrix (CCM) is a well-known tool for evaluating the ability of CMI-based metasurface antennas to generate quasi-random spatial-orthogonal measurement modes [28], [29]. In this section, we begin with the definition of the proposed regional average correlation matrix (RACM). Subsequently, based on the RACM technique, a contribution matrix sorting (CMS) algorithm is developed for the selection of measurement modes carrying higher information content [30], [31].

A. Regional average correlation matrix

The CCM typically provides the overall correlations of measurement modes but lacks information on the correlation within a specific region of measurement modes. Therefore, a new approach, RACM, is proposed to estimate the antenna’s imaging potential by analyzing specific regions of its near-field. RACM employs a three-step process to perform a detailed analysis of the measurement modes. As shown in Fig. 2(a), the measurement modes are firstly discretized into several sub-pixels of same size. Then, as depicted in Fig. 2(b), the CCMs of all measurement modes located at different sub-pixels are calculated. Finally, the RACM is obtained by calculating the CCM average of the corresponding sub-pixels, as shown in Fig. 2(c).

To verify the effectiveness of the proposed RACM, CMI simulations with a metallic square patch placed at different positions are conducted, and the reconstructed results are presented in Fig. 3. According to the RACM shown in Fig. 2(c), the average correlation coefficient of the upper region is relatively high. Based on this, we anticipate that positioning the target in Position 2 of the imaging scene [See
Fig. 4. Measurement modes selection method flow chart.

Fig. 5. Two alternative situations (a) and (b) examples of high-quality modes, (c) low average correlation coefficient but redundant mode, and (d) high average CC but carries the unique information mode.

Fig. 6. A simplified example to explain the selection method; (a) CMS of the modes, (b) Filtered modes matrix, (c) rank table of occurrence frequency, and (d) selected mode group.

B. Contribution matrix sorting

In CMI, measurement modes with low correlation coefficients are expected to provide more information about the imaged scene [32], [33]. Here, we propose a CMS algorithm to select measurement modes with lower correlation coefficients (i.e., higher information-carrying capacity). The flow chart of the proposed technique is depicted in Fig. 4. We sort individual sub-pixels based on their values on the RACM of this measurement mode group. The number inside each sub-pixel indicates the ranking of the average correlation coefficients for the sub-pixel of this measurement mode within this group of measurement modes. We refer to this metric as the contribution index. A more forward contribution index suggests a reduced correlation coefficient, and thus, is desirable for CMI. In this context, RACM can evaluate the performance of measurement modes in a specified spatial region while CMS can further evaluate the contribution of a single measurement mode in a specific region.

It is important to note that the CMS is not flawless. In certain cases, the sub-pixel correlation may not align with the global correlation of the measurement modes, and the accuracy of the useful measurement mode selection may be affected by two specific situations. As shown in Fig. 5, assuming that there are four measurement modes and each of them are divided into nine sub-pixels, the highlighted (black-coloured) sub-pixels represent the low-correlated parts. It is evident that the first two measurement modes possess lower correlation properties and exhibit distinct information from each other. The third measurement mode also exhibits the low-correlation characteristic, but the information it carries is redundant due to the overlap with the first two. When using a large number of quasi-random measurement modes in CMI, there is a higher likelihood of encountering measurement modes that may appear to be of high quality but actually contain redundant information. This can significantly increase the computational complexity of the post-processing layer. Additionally, the fourth measurement mode has three fewer low-correlated parts than the others, but it provides valuable information that the other modes do not offer. Thus, it is crucial to avoid filtering out measurement modes that may appear to be of poor quality but actually carry critical information. In order to address this challenge, a six-step selection process as illustrated in Fig. 6 is developed. To explain the selection process, a simple example is presented here. Assuming 10 randomly generated $3 \times 3$ matrices, and considering that they correspond to 10 measurement modes:

Step 1: Calculate the CMS of this group of measurement modes. This process is depicted in Fig. 6(a).

Step 2: Based on the actual situation, set a contribution index threshold as a selection criterion. In this example, only the measurement modes with a contribution index of less than 4 in each sub-pixel are kept.

Step 3: Starting from the first sub-pixel of the CMS, the measurement mode whose contribution index is within the threshold is selected and recorded at the same position. This step requires traversing every sub-pixel, as shown in Fig. 6(b).

Step 4: Sort all measurement modes across sub-pixels by frequency of occurrence, as shown in Fig. 6(c).

Step 5: Starting with the measurement mode that occurs most frequently, check whether this mode exists in all sub-pixels. If it does, note down the measurement mode for that
area and move on to the next one. If it does not, move on to the measurement mode with the second-highest frequency, and so on, until all sub-pixels have recorded a measurement mode, as depicted in Fig. 6(d).

**Step 6:** Extract all measurement modes recorded in the matrix obtained in the previous step to form a new measurement mode group.

The proposed selection method ensures that each sub-pixel has measurement modes within the threshold, guaranteeing the imaging quality. On the other hand, measurement modes with information redundancy in the same sub-pixel are eliminated. Therefore, after the selection process, the CMI system can achieve comparable imaging quality while using a reduced number of measurement modes, thus reducing the computational burden.

**IV. SIMULATION RESULT**

The CMI experiments based on full-wave simulations are conducted using CST Microwave Studio. Following the above studies, we perform contrast imaging simulations using a set of measurement modes generated by the frequency-diverse reflection metasurface antenna (FDRMA) presented in [34]. The FDRMA produces 41 measurement modes within the frequency range of 18-22 GHz, resulting in \( M = 41 \times 16 = 656 \) given that the CMI setup in Fig. 1 consists of 16 Rx elements. The scan range covers an area of \( 0.42 \text{ m} \times 0.42 \text{ m} \). The imaging scene size is \( 0.3 \text{ m} \times 0.3 \text{ m} \), and the imaging distance is \( 0.2 \text{ m} \). The imaging target of this study is an H-shaped patch located in the centre of the imaged scene. The longitudinal metal strip is \( 0.09 \text{ m} \) in height and \( 0.02 \text{ m} \) in width, and the transverse metal strip is \( 0.03 \text{ m} \) in height and \( 0.07 \text{ m} \) in width. In the CMI experiment, we reduced the dimension of the sensing matrix to 51% and 24% of the original, respectively. This reduction is done using three methods: First, on a random basis; second, using the PCA technique; and third, using the proposed selection method. Figs. 7(a) and 7(d) show the imaging results of randomly selected measurement mode groups. Figs. 7(b) and 7(e) present the imaging results obtained through the PCA technique, while Figs. 7(c) and 7(f) demonstrate the reconstruction results using the proposed framework. A comparison between the reconstructed images using these three methods reveals a significant difference. The images reconstructed after the dimension reduction of the sensing matrix using the measurement modes selected by the proposed method are of better quality. To put this observation into context, with respect to the benchmark scenario, we compare the random selection and the proposed selection methods in terms of the normalized mean square error (NMSE) [35] and the required post-processing time as shown in Fig. 8. Despite a 76% reduction in measurement modes, the imaging results achieved using the proposed selection method maintain small errors with an NMSE of around 0.13. Additionally, the time taken for post-processing has been reduced by around 71% compared to the original duration. As a result, it can be concluded that the proposed measurement mode selection method can greatly reduce the overall number of measurement modes while preserving the quality of the reconstructed images. The qualitative and quantitative analyses demonstrate that the proposed method can effectively filter out redundant measurement modes and retain valuable information in each region, which significantly improves the post-processing efficiency.

**V. CONCLUSION**

In this paper, we introduced a method based on RACM and CMS techniques to characterize and select the measurement modes of metasurface antenna-based CMI systems. The analysis of imaging results using NMSE shows that even with a reduction of measurement modes up to 76%, the imaging accuracy remains intact, with an NMSE value of 0.13. This reduction in measurement modes also reduces the post-processing time, resulting in a time-saving of up to 71%. This method not only optimizes computational efficiency but also ensures that the quality of imaging outcomes remains uncompromised, offering an effective solution for the practical application of CMI systems.
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