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Recent progress in fault diagnosis of phased antenna arrays using excitation engineering

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***Abstract*—We review recent results in the area of fault diagnosis of phased antenna arrays. These results have distinguishing features that set them apart from related work, namely the use of a single, fixed measurement location, and the optimization of the excitations of the antenna elements of the array. We start with the relatively simple scenario of ignoring inter-element mutual coupling, and show how the element excitations can be optimized to reduce the mutual coherence of the sensing matrix. This leads to successful fault diagnosis with a reduced number of measurements. We then generalize this idea in two directions. In the first, we explore applications in the frequency domain by demonstrating online fault diagnosis in multi-carrier precoding systems. Here, a portion of the spectrum is used for fault diagnosis while the remaining continues to be used for wireless communication. In the second, we upgrade our technique for the case when inter-element mutual coupling is significant. By using two popular models that incorporate mutual coupling effects, we demonstrate efficient fault diagnosis also in this scenario. We expect these techniques to greatly simplify the task of fault diagnosis in modern wireless communication systems.**

I. Introduction

Phased antenna arrays are at the heart of modern wireless communication systems. They offer various functionalities such as beam forming and servicing multiple users purely by electronic control. Therefore, it is essential to come up with simple and efficient techniques to assess the health of these systems in a way that minimizes their downtime. In this work, we highlight recent advances in this area.

Most phased arrays operate in the linear regime, in that the relation between the measured electromagnetic field and the excitation current (or voltage) is linear. Further, a common (and reasonable) assumption is that the number of faults is very small as compared to the total number of elements. Combining these two ideas, i.e., that of a linear system with a sparse number of faults, it is natural to consider ideas from compressive sensing to address the problem of fault diagnosis [1]. However, compressive sensing requires the sensing matrix to satisfy certain mathematical properties, such as the restrictive isometry property (RIP), which is difficult to satisfy in the case of sensing matrices derived from phased array experiments. Indeed, early work tried to obtain "designer" sensing matrices by carefully choosing the receiver positions in space but keeping the array excitations as deterministic [2].

To make the measurement setup simpler, the next set of innovations kept the receiver location to be fixed in space while allowing the array excitations to be random [3]. However, these works did not optimize the sensing matrices to lower the number of required measurements. Instead of focussing on the RIP properties of the sensing matrix, parallel work explored the bounds on the mutual coherence of the sensing matrix to deliver performance guarantees on the compressive sensing problem [4].

We synthesized the above ideas into a new proposal for fault diagnosis in our first work, where a single fixed receiver collected the fields being radiated by an array with "designer" excitations [5]. Specifically, the excitations were optimized to reduce the mutual coherence of the sensing matrix, which directly led to a reduction in the number of measurements.

The above work focussed on measurements at a single frequency. However, most modern wireless communications systems such as massive MIMO systems use precoding techniques within a band of frequencies to achieve spatial multiplexing capabilities. If a part of the user-allocated band can be periodically used for fault diagnosis, it opens up the possibility of online fault diagnosis. In fact, each subcarrier frequency can be used as an independent measurement, thereby parallelizing the process of fault diagnosis. These ideas were formalized into a set of techniques that can be used by such multi-carrier precoding systems with different underlying precoding architectures [6].

Most contemporary work has ignored the presence of electromagnetic mutual coupling between the elements of the array. Since the relation between field measurements and element excitations is still linear, adapting the fault detection technique simply requires finding the correct system-matrix characterization. We successfully demonstrated fault diagnosis by using any of the two popular mutual coupling modeling approaches, namely the average embedded element pattern and a port-level coupling matrix approach [7]. The rest of the paper lays out the problem formalism and the solution strategies employed in the works discussed earlier [5]–[7].

II. Methods

A. Problem formulation

A measurement $y_j(\theta)$ at a location θ can be expressed as a linear combination of the antenna element excitations, x_i, weighed by a function characterizing the electromagnetic environment, $\alpha_i(\theta)$, and its fault state ρ_i ($= 0$ if faulty, $= 1$ if working correctly), i.e. $y_j(\theta) = \sum_{i=1}^{n} \alpha_i(\theta)\rho_i x_i = \alpha^T(\rho \cdot x) = x^T(\rho \cdot \alpha)$, where n is the number of elements in the array, and $(\cdot)$ signifies element wise multiplication. If the measurement location is kept fixed, and the excitations are varied for each measurement, then the m-length measurement vector, y, can be expressed as: $y = X(\rho \cdot \alpha)$, where each row of the matrix X corresponds to the element excitations for that measurement.

Assuming sparsity in the number of faults, and subtracting the measurements of the faulty array from that of a (reference) healthy array (i.e. $\rho = \mathbf{1}$, all ones) with the *same* excitations to obtain a differential set of measurements:

$$\tilde{y} = X\alpha \cdot (\mathbf{1} - \rho) = Xz \quad (1)$$

where z is a sparse vector, and a clear connection to the compressive sensing solution approach can be made.

B. Problem solution

Equation 1 forms the core approach of problem formulation for the works discussed in this paper. In particular,

1) In the vanilla approach [5], α comes from the array factor approach.
2) In the frequency domain approach [6], α comes as before (for each frequency) and several measurements are taken at various carrier frequencies to build a measurement scheme.
3) In the mutual coupling approach [7], α comes from either the average embedded element pattern approach [8] or the coupling matrix approach [9].

The central theme in these approaches is the optimization of the sensing matrix, X, to reduce the number of measurements required. In particular, we reduce the mutual coherence of the matrix, a quantity bounded between the Welch bound and unity; doing so directly translates to a reduction in the number of measurements [10]. An alternating projection algorithm helps attain this optimized matrix [11]. Having done so, the optimization problem to be solved is cast as $\min_z \|\tilde{y} - Xz\|_2 + \lambda\|z\|_p$,, where λ is a hyperparameter that is tuned empirically, and $p \in (0, 1)$ is the quasi-norm index, known to better promote sparse solutions than the traditional $1-$norm. The above problem is solved by means of an iteratively reweighted l1 (IRL1) minimization algorithm [12].

III. Results

Results for each of the cases discussed so far are summarized below:

1) In the vanilla single-frequency case when ignoring mutual coupling: When considering a 100-element linear array, we find that the number of measurements required to correctly identify the 1,5,10, and 15 faults are 9, 25, 63, and 79, respectively. We contrast this with the case where no optimization is done on the sensing matrix and the element excitations are chosen at random. Here we find that the number of measurements for 1 and 5 faults are 9 and 59, respectively, whereas the number exceeds the array size for 10 and 15 faults (and is therefore not practical).
2) In the case considering multiple frequencies: When considering a 64-element square array with half wavelength spacing, we find that the rate of successful recover to exceed 90% when considering up to 3 faults with 12 sub-carriers (with SNR 15 dB) and a fully connected RF precoder. When the sensing matrix is not optimized, this rate drops down to 70 % at 3 faults, all measured in a monte-carlo sense.
3) In the case incorporating mutual coupling: When considering a 49-element square array and 5 faults, we find that the performance of an algorithm that ignores mutual coupling versus one that doesn't, is comparable only with an inter-element spacing larger than 1.9λ. At lower spacings, we find that that the approach that ignores mutual coupling can take 50% or higher number of measurements. In fact, at the smallest spacing studied, 0.45λ, the approach ignoring mutual coupling fails to detect faults at all, pointing towards the importance of incorporating mutual coupling in fault diagnosis.

Other detailed results are available in the references. The results conclusively show the power of the paradigm of choosing a single measurement location and optimizing the element excitations for efficient fault diagnosis.

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