Abstract

Direction-of-arrival (DOA) estimation is a process of determining the direction of electromagnetic sources from the output of a receiving sensor array. The approach has a wide range of applications in radar, astronomy, imaging, wireless communication, and other fields. Sparse linear arrays (SLAs) have gained popularity in this industry due to their increased degrees of freedom (DOF). Given a concept of difference co-array (DCA), the SLAs retain a $\mathcal{O}(N^2)$ long central uniform linear array (ULA) segment in their DCA, which increases their DOF and allows them to resolve $\mathcal{O}(N^2)$ uncorrelated sources with only N sensors. The classic ULA, on the other hand, can only estimate $N-1$ sources given N sensors. The conventional SLAs include minimum redundancy arrays (MRAs), nested arrays (NAs), and coprime arrays (CAs). These arrays, however, have shortcomings ranging from a lack of closed-form expression (MRAs) to incomplete difference co-array (CAs) and strong mutual coupling (NAs). Hence, this paper explores innovative sparse linear array design methodologies for sparse arrays with high DOF and low mutual coupling.

The key contribution of this dissertation is to offer new design approaches for SLAs. The first part of this dissertation introduces novel fundamental SLA designs including the extended nested array with multiple subarrays (ENAMS) and its extension, the flexible ENAMS (f-ENAMS). These SLAs offer improved DOF and high-resolution DOA estimation compared to existing ones. Besides, the trade-offs between robustness to mutual coupling (MC) and DOA estimation accuracy are also provided to demonstrate the effectiveness of the proposed array designs.

The second part of this dissertation introduces novel unified SLA configurations via the interelement spacing criterion (IES) with higher DOF and relatively reduced MC effect. The unified SLAs include the generalized ENAMS (GENAMS) and the enhanced sparse array via the maximum IES criterion (xMISC). The unified SLAs show improved DOF and high-resolution DOA estimation performance compared to state-of-the-art SLAs, even in mutual coupling scenarios. Furthermore, the paper develops a simulated annealing (SA)-assisted deep learning-based sparse array design method. The two-stage method leverages the SA algorithm to circumvent the computationally expensive stage of dataset notation, thereby alleviating overall computation time. Naturally, the paper concludes with remarks on future research directions.