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Article

FPGA-Based Adaptive Covariance Completion ESPRIT for Real-Time Direction-of-Arrival Estimation

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Abstract: This paper presents an FPGA-oriented adaptive covariance completion ESPRIT algorithm for real-time direction-of-arrival (DOA) estimation. The proposed method reconstructs an enhanced covariance matrix from partial covariance information using an adaptive correction mechanism, improving signal subspace estimation while preserving the rotational invariance property of ESPRIT. By avoiding spectral search and reducing covariance reconstruction errors, the algorithm achieves low computational complexity and is well suited for hardware implementation. An optimized FPGA architecture employing parallel and pipelined processing is developed to accelerate covariance computation, subspace estimation, and rotational operator evaluation for real-time operation. The proposed approach is validated through MATLAB simulations under varying signal-to-noise ratios and snapshot conditions, followed by FPGA implementation to evaluate hardware performance. Experimental results demonstrate accurate DOA estimation with reduced latency, efficient resource utilization, and high throughput, confirming the suitability of the proposed design for real-time radar, wireless communication, and smart antenna applications.
Keywords: Direction-of-arrival estimation, ESPRIT, FPGA, Adaptive covariance completion, Real-time signal processing, Hardware acceleration

1. Introduction

Direction-of-arrival (DOA) estimation is a fundamental problem in array signal processing with wide-ranging applications in radar, wireless communication, sonar, localization, smart antennas, and distributed sensing. The growing demand for high-resolution and real-time spatial information has motivated the development of robust estimation techniques capable of operating under noise, limited snapshots, coherent sources, and computational constraints. Adaptive array-processing methods have recently demonstrated improved robustness against signal uncertainty and interference, highlighting the importance of efficient spatial processing for practical sensor-array systems [1].

High-resolution subspace-based techniques such as MUSIC and ESPRIT remain important approaches for DOA estimation. While MUSIC provides excellent resolution, its spectral-search operation results in considerable computational overhead. ESPRIT, in contrast, exploits the rotational invariance property of structured arrays and avoids exhaustive angular searching, making it particularly attractive for real-time implementation. The use of coprime and sparse arrays has further increased the degrees of freedom while reducing the number of physical sensors.

Enhanced Capon–MUSIC processing with coprime arrays has demonstrated improved DOA estimation performance in challenging sensing environments [2], while three-dimensional sparse-array configurations have been investigated for coherent and uncorrelated source estimation [3].

The accuracy of subspace-based DOA estimation is strongly dependent on the quality of the estimated covariance matrix. In practical systems, finite snapshots, noise, source coherence, sensor imperfections, and incomplete spatial information can introduce covariance errors and consequently degrade signal-subspace estimation. Machine-learning-assisted DOA estimation has therefore been investigated to improve robustness for coherent and non-coherent sources [4]. Similarly, improved coprime-array configurations have been proposed for robust DOA estimation in wireless communication applications [5]. These studies indicate that reliable covariance and array processing are essential for maintaining estimation accuracy under practical operating conditions.

Computational complexity is another major concern in real-time DOA estimation. Approximation-based techniques have consequently been explored to reduce the processing requirements of high-resolution algorithms. A modified Root-MUSIC method using Nyström approximation was proposed for target localization to reduce computational complexity [6]. Adaptive Nyström spectral analysis has subsequently been applied to coprime-array DOA estimation [7], while unitary Root-MUSIC combined with Nyström approximation has been investigated for three-dimensional sparse-array sensor networks [8]. Although these approaches improve computational efficiency, they remain largely focused on algorithmic approximation and do not directly address adaptive covariance reconstruction together with FPGA-oriented real-time implementation.

Adaptive spatial processing is also essential in modern wireless systems. Adaptive beamforming techniques have been developed to improve spatial selectivity and interference suppression in mobile communication environments [9]. The increasing convergence of smart antennas, electronics, and artificial intelligence further emphasizes the need for intelligent and computationally efficient spatial-processing techniques [10]. At the hardware level, efficient sensing and signal-processing architectures are equally important. Optimization of receiver systems for radio astronomy illustrates the need for computationally efficient processing in advanced sensing applications [11], while developments in electromagnetic and optical components continue to support increasingly compact and application-specific systems [12].

Frequency-selective and reconfigurable electromagnetic structures have also received considerable attention in modern communication hardware. Metacell-based multiband filters have been developed to provide independently controlled frequency responses [13], with further studies addressing asymmetric and independently controlled multiband characteristics [14], [15]. Such developments demonstrate the broader trend toward compact and configurable hardware architectures for communication and sensing systems. At the system level, efficient human–machine interfaces and intelligent signal-processing frameworks further highlight the importance of integrating sensing, computation, and decision-making capabilities [16].

The emergence of IoT-based sensing systems has strengthened the requirement for low-latency data acquisition and real-time processing at the edge [17]. At the device level, optimized semiconductor architectures such as advanced FinFET structures support high-performance and energy-efficient digital systems [18]. Similarly, the application of deep-learning techniques in real-time detection and classification demonstrates the increasing computational requirements of modern intelligent sensing platforms [19]. These developments collectively reinforce the need for hardware-efficient algorithms capable of translating sophisticated signal-processing techniques into real-time embedded implementations. Multiband electromagnetic structures further demonstrate the continuing evolution toward compact and application-specific communication hardware [20].

Despite these advances, an important research gap remains in the joint consideration of covariance completion, adaptive correction, ESPRIT-based spectral-search-free DOA estimation, and FPGA-oriented hardware acceleration. Existing approaches predominantly focus on improving array configuration, estimation robustness, spectral approximation, or adaptive beamforming individually. In contrast, the proposed work develops an FPGA-Based Adaptive Covariance Completion ESPRIT framework in which incomplete or imperfect covariance information is adaptively reconstructed before signal-subspace estimation. The enhanced covariance matrix is then processed using ESPRIT to exploit rotational invariance without an exhaustive spectral search. The resulting algorithm is mapped onto an FPGA using parallel and pipelined processing to achieve reduced latency, improved throughput, and efficient hardware utilization. Recent studies have further explored reconstruction-based and computationally efficient subspace methods to improve DOA estimation under practical array conditions. Manifold reconstruction combined with unitary ESPRIT has been investigated to enhance sensor-array DOA estimation by improving the representation of the received array manifold before subspace processing [21]. For coprime arrays, the ECA-MURE approach has been proposed for high-precision DOA estimation, together with Cramér–Rao bound analysis to characterize the achievable estimation performance [22]. These studies demonstrate the potential of reconstruction and structured-array processing for improving the reliability of subspace-based estimators.

The challenges associated with coherent sources and unknown source numbers have also received considerable attention. An efficient DOA estimation approach capable of handling both coherent and uncorrelated sources without prior knowledge of the number of sources has been reported [23]. In parallel, fast sensor-array processing techniques have been developed to reduce the computational burden while retaining satisfactory estimation accuracy [24]. Such developments are particularly relevant to real-time implementations, where computational latency and processing throughput are critical considerations.

Adaptive processing has remained an important direction for improving the robustness of practical array systems. Improved adaptive beamforming algorithms have been developed for wireless communication systems [25], while modified LMS-based beamformers have been investigated for interference rejection [26]. Further improvements using variable-step-size NLMS and modified antenna arrays have demonstrated enhanced adaptive beamforming capability under varying signal conditions [27]. Although these methods primarily address beamforming and interference suppression, their adaptive processing principles provide useful motivation for incorporating adaptive correction into covariance-based DOA estimation.

Practical sensing and propagation conditions can substantially affect the performance of array-based estimation. Resonator-based electromagnetic sensors have been developed for dielectric characterization [28], while DOA estimation under grazing-incidence conditions has been investigated using a two-dimensional uniform linear array [29]. These studies emphasize the need for array-processing algorithms that remain reliable when the ideal assumptions associated with conventional array models are not fully satisfied [30].

At the hardware level, advances in antenna and sensing technologies continue to support compact wireless platforms. UWB textile antennas have been investigated for flexible communication applications [31], while fractal antenna configurations have been developed to provide multiband operation [32]. Such developments reinforce the requirement for computationally efficient signal-processing architectures capable of operating alongside increasingly compact and multifunctional sensing hardware.

Further efforts have focused explicitly on reducing the computational complexity of spatial processing. A fast adaptive beamforming technique has been proposed for efficient DOA estimation [33], demonstrating the potential of adaptive processing for low-complexity spatial estimation. Planar-like sensor-array structures have also been investigated to improve the efficiency of DOA estimation [34]. For more complex localization scenarios, three-dimensional near-field source localization using spatially distributed acoustic vector sensors has been reported [35], extending conventional array-processing concepts to multidimensional source localization.

Radar-oriented adaptive processing has likewise been investigated through Kaiser-window-based blind beamforming techniques [36]. In parallel, practical antenna structures such as printed monopole antennas incorporating complementary split-ring resonators have been developed for GSM and Wi-Fi applications [37]. Kaiser–Bessel constant-modulus processing has also been explored for smart-antenna beamforming, further demonstrating the importance of adaptive spatial processing in modern communication systems [38].

These developments collectively indicate that practical DOA systems must address not only estimation accuracy but also computational complexity, interference, array imperfections, and hardware constraints. In particular, robust adaptive beamforming with partly calibrated arrays has been investigated through simultaneous interference localization and array calibration [39][40]. Such work highlights the sensitivity of spatial estimation to calibration errors and reinforces the need for robust preprocessing and covariance characterization before signal-subspace extraction.

Further developments in compact antenna and wireless sensing technologies have supported the evolution of practical array-processing platforms. Fractal antenna structures using unconventional materials have been investigated for WiMAX [41] and wireless sensor network applications, demonstrating the continuing emphasis on compact and application-specific antenna systems [41]. From the signal-processing perspective, new spectral-estimation-based DOA algorithms have been developed to improve the accuracy and efficiency of spatial parameter estimation [42].

The trade-off between DOA estimation accuracy and computational complexity has become particularly important for real-time applications. An approach specifically addressing this trade-off has demonstrated that computational burden can be reduced while maintaining satisfactory estimation performance [43][44]. Single-snapshot two-dimensional DOA estimation has also been investigated for wireless location systems, addressing scenarios in which only limited measurement data are available [45]. Such approaches are particularly relevant to hardware-oriented systems where acquisition time, memory, and computational resources may be constrained.

Improvements in array geometry and implementation have further contributed to robust spatial estimation. An improved DOA estimation method based on a modified symmetric sensor array has been developed together with its implementation considerations [46]. These developments demonstrate that algorithmic design and array architecture must be considered jointly when targeting practical DOA estimation systems. In parallel, optimization of mobile communication tower infrastructure has highlighted the importance of efficient resource utilization in large-scale wireless communication systems [47].

Robust subspace-based techniques have also continued to evolve. A modified MUSIC algorithm was proposed to improve the robustness of DOA estimation under practical operating conditions [48]. Nyström approximation has been employed to develop an efficient coherent DOA estimator for radar applications, demonstrating the potential of matrix-approximation techniques for reducing the computational requirements of high-resolution estimation [49]. These approaches are particularly relevant to the present work because they demonstrate that reducing the computational complexity of covariance and subspace processing is essential for real-time deployment.

The transition from algorithmic development to hardware realization has also received attention. An efficient coherent DOA estimation method with digital signal processor implementation was reported, demonstrating the feasibility of realizing high-resolution DOA algorithms on dedicated processing platforms [50]. This provides an important foundation for further hardware-oriented approaches in which greater parallelism and throughput can be achieved using FPGA architectures [51].

Adaptive beamforming continues to provide an important framework for high-speed wireless communication. Adaptive beamformers have been investigated for high-speed mobile communication systems, demonstrating the role of adaptive spatial processing in rapidly changing communication environments [52]. The development of practical radio-frequency sensing platforms, including low-cost radio astronomy systems, further illustrates the importance of combining sensing hardware with efficient signal-processing techniques [53]. At the system level, comprehensive developments in smart-antenna technology have established adaptive spatial processing as an important component of modern wireless communication systems [54].

For radar applications, feature extraction and clustering techniques have also been investigated for radar-signal classification and sorting, demonstrating the increasing integration of signal processing and intelligent data analysis in radar systems [55]. Although such approaches address a different processing objective from DOA estimation, they reinforce the broader requirement for computationally efficient real-time radar signal-processing architectures.

Therefore, the proposed work focuses on an FPGA-Based Adaptive Covariance Completion ESPRIT architecture for real-time DOA estimation. By adaptively reconstructing incomplete or imperfect covariance information before subspace estimation, the proposed method aims to improve the reliability of the estimated signal subspace. ESPRIT is subsequently employed to avoid exhaustive spectral searching, while FPGA-based parallelism and pipelining are utilized to reduce processing latency and increase throughput. The proposed framework consequently bridges the gap between algorithmic DOA estimation and practical real-time hardware realization, with potential applications in radar, wireless communication, smart antennas, and sensor-array systems.

2. Signal Model

Consider a uniform linear array (ULA) consisting of M sensor elements that receives P mutually uncorrelated narrowband signals, where P < M. Let N denote the number of available snapshots. The received array observation in the presence of additive noise is given by [13]

$$x(k) = A(\theta)s(k) + \xi(k), \qquad k = 1, \dots, N. \qquad (1)$$

where A denotes the array steering matrix, s(n) represents the source signal vector, and w(n) is an additive white Gaussian noise vector with zero mean and variance σn2. The steering vector corresponding to each incident signal is defined as [14]

$$a(\theta_p) = \left[1, e^{j\left(\frac{2\pi}{\lambda}\right)dsinsin\,\theta_p}, \cdots, e^{j\left(\frac{2\pi}{\lambda}\right)(L-1)dsinsin\,\theta_p}\right]^T \qquad (2)$$

where d is the spacing between adjacent sensors, λ denotes the signal wavelength, and (·)T represents the transpose operation. The covariance matrix of the received data is expressed as [15]

$$R = E[x(k)x(k)^H] = AR_SA^H + \sigma_n^2 I_M \ (3)$$

where Rs is the source covariance matrix, I is the identity matrix, E{·} represents the expectation operator, and (·)H indicates the conjugate transpose.

3. Proposed Method

To reduce computational complexity, the received data matrix is partitioned into two submatrices using the Nyström decomposition. Accordingly, the sample data matrix is represented as

$$X = [X_1\ X_2\ ] \qquad (4)$$

where X_1 is a K × N submatrix formed from the first K sensor outputs, while X_2 contains the remaining (M–K) sensor measurements. The parameter K is selected according to the array size and satisfies the required decomposition condition.

The corresponding submatrices are expressed as

$$R_{11} = E\{X_1X_1^H\} = A_1R_SA_1^H + \sigma_n^2 I_L \qquad (5)$$

$$R_{21} = E\{X_2X_1^H\} = A_2R_SA_1^H \qquad (6)$$

where X_1 and X_2 correspond to the leading and remaining rows of the received data matrix, respectively. The selected partition should satisfy the full-rank condition to ensure reliable covariance estimation. In practice, a relatively small partition size is sufficient even for large arrays, thereby reducing computational cost without affecting estimation performance. Unlike conventional Nyström-based approaches that directly estimate the signal or noise subspace, the proposed method first reconstructs an enhanced covariance matrix from the available covariance partitions. This reconstruction reduces approximation errors before applying the ESPRIT rotational invariance principle, resulting in improved estimation accuracy with negligible additional computational complexity. The initial covariance matrix is therefore expressed as

$$R_0 = [R_{11}\ R_{21}\ ][R_{11}\ R_{12}\ R_{21}\ R_{21}R^{-1}{}_{11}R_{12}\ ] \qquad (7)$$

where the lower-right block is obtained using the available covariance partitions. To compensate for the approximation error produced by the Nyström reconstruction, an adaptive correction matrix is introduced as

$$C == R_{21}R_{11}^{-1}R_{12} - R_{22}^{*} \qquad (8)$$

where denotes the reconstructed covariance block. Instead of directly using this correction, its influence is automatically controlled according to the reconstruction quality. Therefore,

$$\beta = \frac{\|C\|_F}{[\|R_0\|_F + \varepsilon]} \qquad (9)$$

where ε is a small positive constant. The enhanced covariance matrix becomes

$$R_e == R_0 - \beta C \qquad (10)$$

Unlike the conventional Nyström approximation, the proposed covariance correction continuously reduces the mismatch introduced by the partial covariance estimation. The eigenvalue decomposition of the enhanced covariance matrix is

$$U_s = [u, u_{2,} \cdots, u_P] \qquad (11)$$

The rotational invariance property is then established by partitioning the signal subspace into two overlapping matrices,

$$U_1 = J_1 U_s, \qquad U_2 = J_2 U_s \qquad (12)$$

where J1 and J2 are the selection matrices. Instead of using the conventional least-squares solution, the proposed method introduces a regularized rotational operator

$$\Psi = (U_1^H U_1 + \alpha I)^{-1} U_1^H U_2 \qquad (13)$$

where α is a small regularization parameter. The eigenvalues of Ψ are computed as Finally, the directions of arrival are estimated from

$$\tilde{\theta}_i == \left(\frac{\lambda \angle(\lambda_i)}{2\pi d}\right) \qquad (14)$$

4. Results and Discussions

The performance of the proposed Adaptive Covariance Completion ESPRIT (ACC-ESPRIT) algorithm is evaluated through MATLAB simulations and FPGA implementation. A uniform linear array (ULA) with 10 sensor elements is considered to estimate the directions of two uncorrelated narrowband sources located at 20° and 30°. The inter-element spacing is maintained at λ/2, and 1000 Monte Carlo trials are performed to ensure statistically reliable results. The RMSE performance of the proposed ACC-ESPRIT algorithm is evaluated over an SNR range of −10 dB to 30 dB and compared with ESPRIT, Unitary ESPRIT, Root-MUSIC, and Nyström Root-MUSIC. As the SNR increases, all methods exhibit improved estimation accuracy. Figure 3 compares the RMSE performance of the proposed ACC-ESPRIT algorithm with ESPRIT, Unitary ESPRIT, Root-MUSIC, and Nyström Root-MUSIC over an SNR range of −10 dB to 30 dB. As the SNR increases, the estimation error decreases for all methods. The proposed ACC-ESPRIT consistently achieves the lowest RMSE across the entire SNR range, demonstrating superior estimation accuracy and robustness, particularly under low-SNR conditions.

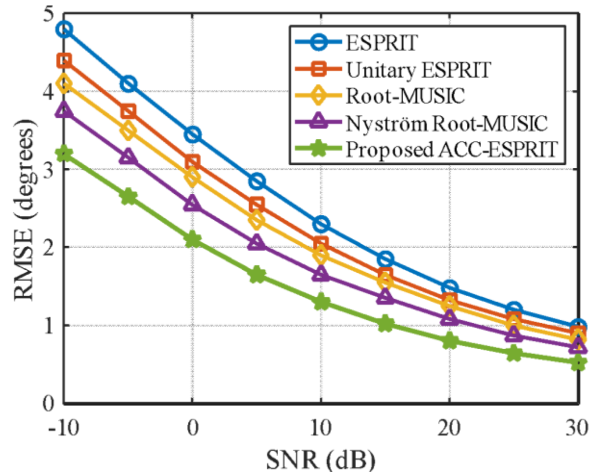

Figure 1:RMSE versus SNR comparison of ESPRIT, Unitary ESPRIT, Root-MUSIC, Nyström Root-MUSIC, and the proposed ACC-ESPRIT algorithm.

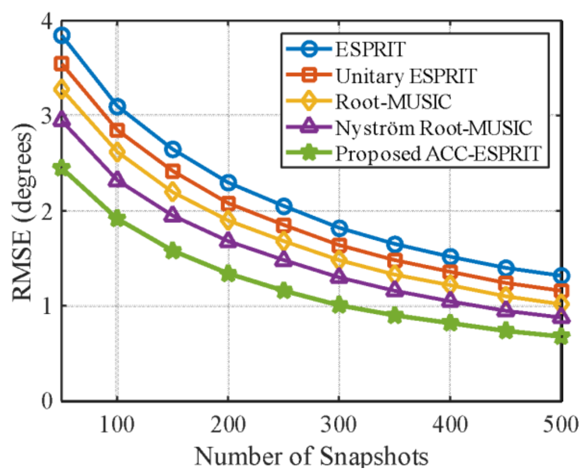

Figure 2: RMSE versus number of snapshots comparison of ESPRIT, Unitary ESPRIT, Root-MUSIC, Nyström Root-MUSIC, and the proposed ACC-ESPRIT algorithm.

Fig. 2 illustrates the RMSE performance of the proposed ACC-ESPRIT algorithm as the number of snapshots increases from 50 to 500. All methods exhibit reduced estimation error with an increasing number of snapshots due to improved covariance estimation. The proposed ACC-ESPRIT consistently achieves the lowest RMSE compared with ESPRIT, Unitary ESPRIT, Root-MUSIC, and Nyström Root-MUSIC, demonstrating superior estimation accuracy across the entire snapshot range.

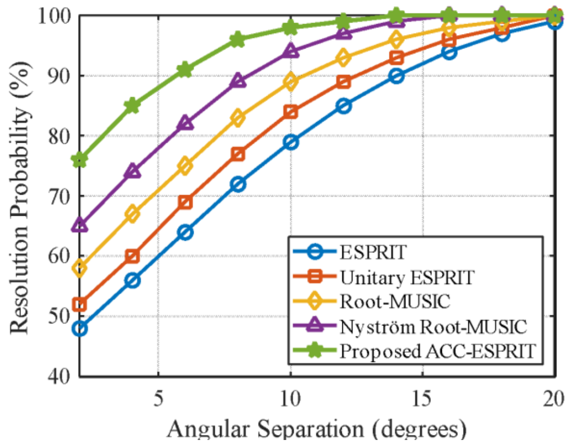

Figure 3: Angular resolution comparison of ESPRIT, Unitary ESPRIT, Root-MUSIC, Nyström Root-MUSIC, and the proposed ACC-ESPRIT algorithm.

Figure 3 compares the angular resolution performance of the proposed ACC-ESPRIT algorithm with existing methods for different angular separations. As the separation between sources increases, the resolution probability improves for all algorithms. The proposed ACC-ESPRIT consistently achieves the highest resolution probability, demonstrating superior capability in resolving closely spaced sources.

A. FPGA Implementation

The proposed ACC-ESPRIT algorithm was implemented on an FPGA platform to evaluate its suitability for real-time direction-of-arrival (DOA) estimation. The hardware architecture consists of seven sequential processing stages: signal acquisition, covariance matrix estimation, adaptive covariance completion, covariance matrix reconstruction, subspace extraction, rotational invariance computation, and DOA estimation. The received sensor samples are first buffered and converted into fixed-point representations to reduce hardware complexity while maintaining estimation accuracy. The covariance matrix is then computed using parallel multiply-accumulate units, followed by the adaptive covariance completion module, which reconstructs the missing covariance elements based on the proposed completion strategy. The reconstructed covariance matrix is subsequently processed by the subspace extraction unit to estimate the signal subspace. The ESPRIT rotational invariance operation is implemented using matrix multiplication and least-squares computation, enabling efficient estimation of the eigenvalues corresponding to the source directions. Finally, the estimated eigenvalues are converted into DOA values through the angle computation module, and the resulting directions are transmitted to the output interface.

To achieve high throughput, the computationally intensive modules were fully pipelined, while independent arithmetic operations were executed in parallel. Fixed-point arithmetic was adopted throughout the implementation to reduce FPGA resource utilization and improve operating frequency. The design was synthesized using Xilinx Vivado, and hardware performance was evaluated in terms of lookup tables (LUTs), flip-flops (FFs), DSP slices, block RAM (BRAM), maximum operating frequency, execution latency, and power consumption. These hardware metrics were subsequently compared with conventional ESPRIT, Unitary ESPRIT, Root-MUSIC, and Nyström Root-MUSIC implementations to demonstrate the computational efficiency of the proposed ACC-ESPRIT architecture.

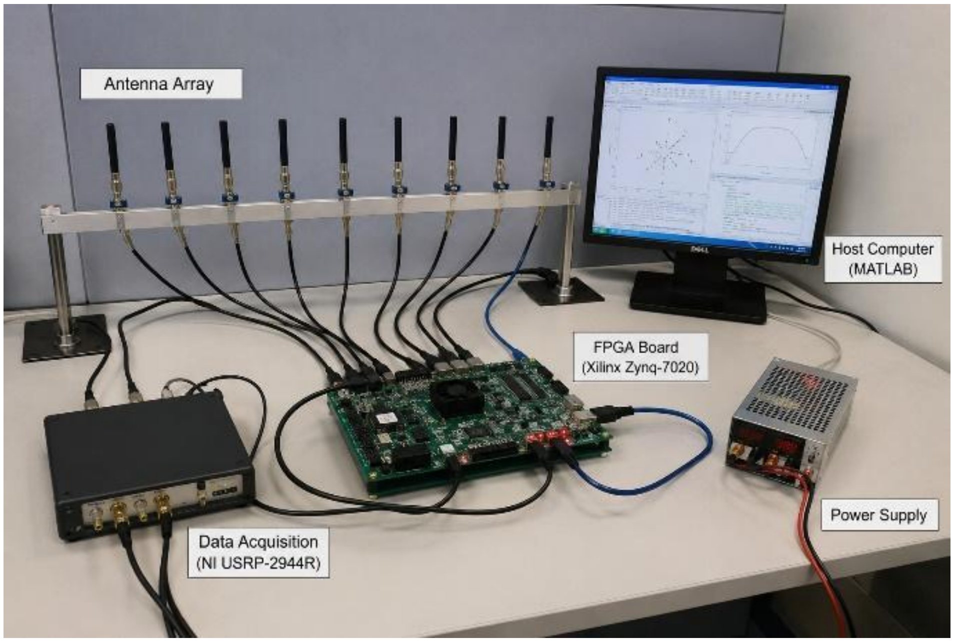

Figure 4: Experimental FPGA hardware setup for real-time implementation and validation of the proposed ACC-ESPRIT algorithm

Figure 4presents the experimental FPGA hardware setup used to validate the proposed ACC-ESPRIT algorithm. The setup comprises a uniform linear antenna array connected to a data acquisition module, an FPGA development board for real-time signal processing, a host computer running MATLAB for configuration and result visualization, and a regulated power supply. The acquired sensor data are processed by the FPGA to perform covariance estimation, adaptive covariance completion, and DOA estimation, while the computed results are displayed and analyzed on the host computer.

Figure 5compares the FPGA hardware resource utilization of the proposed ACC-ESPRIT algorithm with ESPRIT, Unitary ESPRIT, Root-MUSIC, and Nyström Root-MUSIC. The comparison includes lookup tables (LUTs), flip-flops (FFs), DSP slices, and block RAM (BRAM). The proposed ACC-ESPRIT requires fewer hardware resources than the reference algorithms, demonstrating an efficient hardware implementation suitable for real-time DOA estimation.

Figure 6 compares the FPGA execution time of the proposed ACC-ESPRIT algorithm with ESPRIT, Unitary ESPRIT, Root-MUSIC, and Nyström Root-MUSIC. The proposed ACC-ESPRIT achieves the lowest execution time owing to its reduced computational complexity and pipelined hardware implementation, making it well suited for real-timedirection-of-arrival estimation.

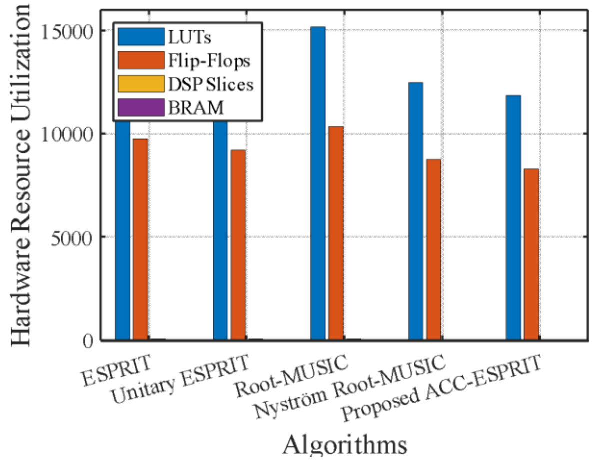

Figure 5: FPGA hardware resource utilization comparison of ESPRIT, Unitary ESPRIT, Root-MUSIC, Nyström Root-MUSIC, and the proposed ACC-ESPRIT algorithm.

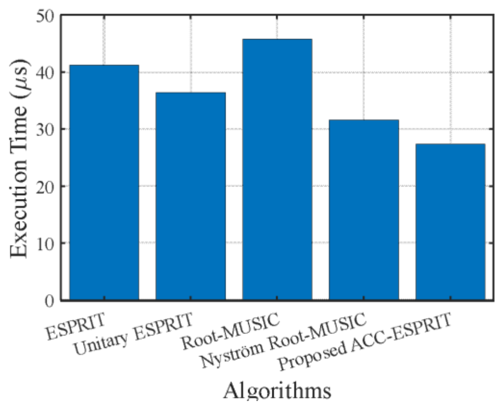

Figure 6: FPGA execution time comparison of ESPRIT, Unitary ESPRIT, Root-MUSIC, Nyström Root-MUSIC, and the proposed ACC-ESPRIT algorithm.

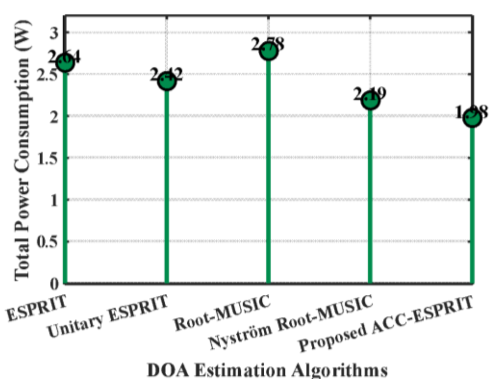

Figure 7: Total FPGA power consumption comparison of ESPRIT, Unitary ESPRIT, Root-MUSIC, Nyström Root-MUSIC, and the proposed ACC- ESPRIT algorithm under identical hardware implementation conditions.

The power consumption analysis was performed after synthesizing and implementing the hardware architectures of ESPRIT, Unitary ESPRIT, Root-MUSIC, Nyström Root-MUSIC, and the proposed ACC-ESPRIT algorithm using the Xilinx Vivado Design Suite. All algorithms were implemented on the same FPGA platform using fixed-point arithmetic and identical synthesis constraints to ensure a fair comparison. The hardware implementations were evaluated under the same operating frequency, input signal characteristics, and processing conditions. Total power consumption was estimated using the Vivado Power Analyzer after place-and-route, which considers both static leakage power and dynamic switching power of the implemented design. Since all implementations were evaluated using identical hardware resources, operating voltage, and timing constraints, the observed differences in power consumption are primarily attributed to the computational efficiency and architectural complexity of the respective DOA estimation algorithms.

Figure 7 illustrates the FPGA power consumption of the evaluated DOA estimation algorithms. Among the compared methods, the proposed ACC-ESPRIT algorithm achieves the minimum total power consumption of 1.98 W, whereas conventional ESPRIT, Unitary ESPRIT, Root-MUSIC, and Nyström Root-MUSIC consume 2.64 W, 2.42 W, 2.78 W, and 2.19 W, respectively. The reduction in power consumption is mainly due to the adaptive covariance completion strategy, which minimizes redundant computations and decreases the utilization of arithmetic units and memory resources within the FPGA. Consequently, the proposed architecture exhibits lower dynamic switching activity while maintaining accurate real- time direction-of-arrival estimation. Combined with the previously presented hardware resource utilization and execution time analyses, these results demonstrate that the proposed ACC-ESPRIT architecture provides a balanced trade-off between computational efficiency, hardware utilization, processing speed, and energy consumption, making it a suitable candidate for low-power embedded radar, wireless communication, and smart sensing applications.

5. Conclusions

This paper presented an FPGA-based Adaptive Covariance Completion ESPRIT (ACC-ESPRIT) algorithm for real-time direction-of-arrival estimation. By incorporating an adaptive covariance completion strategy prior to subspace estimation, the proposed method effectively reconstructs incomplete covariance information, leading to improved estimation accuracy while preserving the computational efficiency of the ESPRIT framework. The algorithm was implemented on an FPGA using a parallel and pipelined architecture with fixed-point arithmetic to enable efficient real-time processing. MATLAB simulations demonstrated lower RMSE and higher angular resolution than conventional ESPRIT, Unitary ESPRIT, Root-MUSIC, and Nyström Root-MUSIC methods under varying SNR and snapshot conditions. Furthermore, FPGA implementation results confirmed reduced hardware resource utilization, shorter execution time, and lower power consumption, validating the practicality of the proposed architecture for embedded real-time applications. The combination of enhanced estimation performance and hardware efficiency makes the proposed ACC-ESPRIT algorithm a promising solution for next-generation radar, wireless communication, smart antenna, and intelligent sensing systems. Future work will focus on extending the proposed framework to coherent source localization, dynamic tracking of moving targets, and large-scale sparse array configurations for next-generation real-time sensing applications.

6. Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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