DOI: 10.14529/jsfi260209

Supercomputer-Aided Space-Time Processing Methods for MIMO Radars in Advanced Airborne Earth Remote Sensing Systems

Vladimir S. Verba[1], *Vyacheslav A. Miheev*[1], *Viktor A. Plushchev*[1], *Andrey A. Chernienko*[1,2]

This paper addresses the problem of escalating computational complexity arising from the transition from classical Active Electronically Scanned Arrays to fully-fledged Multiple-Input Multiple-Output (MIMO) radars for airborne Earth remote sensing (ERS) systems. It is shown that the formation of a virtual aperture increases the number of virtual channels to 10^5–10^6, making classical adaptive processing methods based on direct access to covariance matrices of dimension NN impossible for existing onboard computers. Modifications of the MUSIC and ESBM (Estimation of Signal Parameters via Beamspace Mapping) algorithms have been developed. These algorithms are adapted to operate with sparse covariance matrices, which makes it possible to radically reduce the amount of stored and processed data. Based on the proposed methods, a pipelined processing architecture has been developed and implemented on hybrid CPU+FPGA computers, providing latency compatible with real-time requirements for detection tasks in air-ground and air-sea circuits. The results obtained pave the way for the creation of next-generation airborne radar systems with unprecedented spatial resolution and high noise immunity.

Keywords: MIMO radar, supercomputer processing methods, reduced-rank algorithms.

Introduction

The evolution of airborne Earth remote sensing (ERS) systems over the past decades has been characterized by a consistent transition from mechanically scanned antenna systems to Active Electronically Scanned Arrays (AESAs) and, more recently, to multiple-input multiple-output (MIMO) radars. While classic AESAs have provided significant advances in scanning speed and beamforming flexibility, they have nevertheless reached the physical limit of their resolution with a fixed aperture.

In contrast, MIMO radars open up fundamentally new possibilities for airborne ERS systems. Creating a virtual aperture equivalent to the product of the number of transmitting and receiving elements, they enable a substantial increase in angular resolution without increasing the physical size of the antenna system [3, 4]. In MIMO radars, each channel emits orthogonal (independent) signals. This method implies a virtual receive antenna array whose size is equal to the product of the number of transmitting and receiving channels. This approach significantly improves angular resolution and the accuracy of reflected signal with the same physical antenna size, suppressing fluctuating signals and increasing the probability of detecting small and maneuvering objects [7, 8].

As in many areas of radar, a significant increase in the tactical and technical characteristics of a MIMO radar requires a significant increase in computing resources. As in many areas of radar, a significant increase in the tactical and technical characteristics of a MIMO radar requires a significant increase in computing resources. The transition to full-fledged MIMO radars raises a fundamental problem related to the "curse of dimensionality." Indeed, the formation of a virtual aperture (Virtual Array) leads to the fact that the number of virtual receiving channels reaches

[1]JSC "Vega Radio Engineering Corporation", Russian Federation
[2]JSC "New Start", Russian Federation

the value of $N_{rx} \times N_{tx}$, where N_{rx}, N_{tx} are the number of receiving and transmitting elements, respectively. In promising remote sensing complexes, the number of virtual channels reaches 10^5.

Classical Space-Time Adaptive Processing (STAP) algorithms, which form a space-time filter to protect against interference, the parameters of which adapt depending on the motion parameters of the radar carrier and the interference environment, require computational costs of the order of $O(N^3)$ for an $N \times N$ correlation matrix, which at $N \approx 10^5$, it makes them physically unrealizable on existing onboard computers.

At the same time, the tasks of detecting small objects: unmanned aerial vehicles of a small class, submarine periscopes or hypersonic missiles, impose strict requirements on processing latency [1, 2]. The acceptable processing window for detecting small objects is units-tens of milliseconds. Thus, there is a "computational gap" between the potential capabilities of MIMO radars and the actual performance of existing onboard computing systems.

A number of approaches to reducing the computational complexity of STAP algorithms have been proposed in the literature. Rank reduction methods such as multichannel Wiener filtering (MWF) and auxiliary channel filter (ACS) can reduce the effective dimension of the processing space by projecting onto a subspace of a smaller dimension. Knowledge-Aided (KA) methods use a priori information about terrain and interference conditions to reduce the size of the training sample.

However, as the number of virtual channels grows to 10^5, the performance of these methods decreases significantly: the required subspace size is still too large, and the gain in computational complexity is insufficient to achieve real-time mode. In addition, classical spectral estimation algorithms (MUSIC, ESPRIT) in their traditional formulation also face insurmountable computational difficulties when processing such a high dimension [5, 6].

This article aims to overcome the described computational gap by synthesizing new algorithmic and architectural solutions. The main hypothesis is the transition to a heterogeneous computing architecture of the onboard supercomputer core, combining general-purpose central processors (CPUs) and field-programmable gate array (FPGAs).

This work is divided as follows: Section 2 discusses the basics of the method used to reduce computational complexity. Section 3 describes the detection algorithm in detail. The architecture of the onboard computer suitable for the proposed algorithm is presented in Section 4. Possible applications and practical value of the algorithm and the computer architecture presented is discussed in Conclusion.

1. Matematical Signal Model and Computational Complexity

1.1. Geometry of Shooting in MIMO Radars

Let us consider an aviation complex for remote sensing of the Earth (remote sensing), equipped with a MIMO radar. In general, the system configuration can be monostatic, when the transmitting and receiving antenna arrays are placed on the same aircraft, or bistatic, in which the transmitter and receiver are separated into different carrier. For the sake of certainty, the monostatic configuration, characteristic of most promising aviation complexes, is further considered, however, the results obtained can be generalized to the bistatic case.

Let the transmitting antenna array contain N_{tx} radiating elements, and the receiving antenna contain Nrx receiving channels. With time or code separation of signals, each of the N_{tx} transmitters emits an orthogonal (or quasi-orthogonal) signal. Figure 1 shows the geometry of the MIMO radar survey. After consistent filtering, a virtual aperture is formed at the receiving point, the number of channels of which is equal to the product $N_v = N_{tx} \cdot N_{rx}$. The vector $v \in C^{N_v}$ is the result of convolution of the transmitting and receiving antenna patterns and contains all information about the angular position of objects.

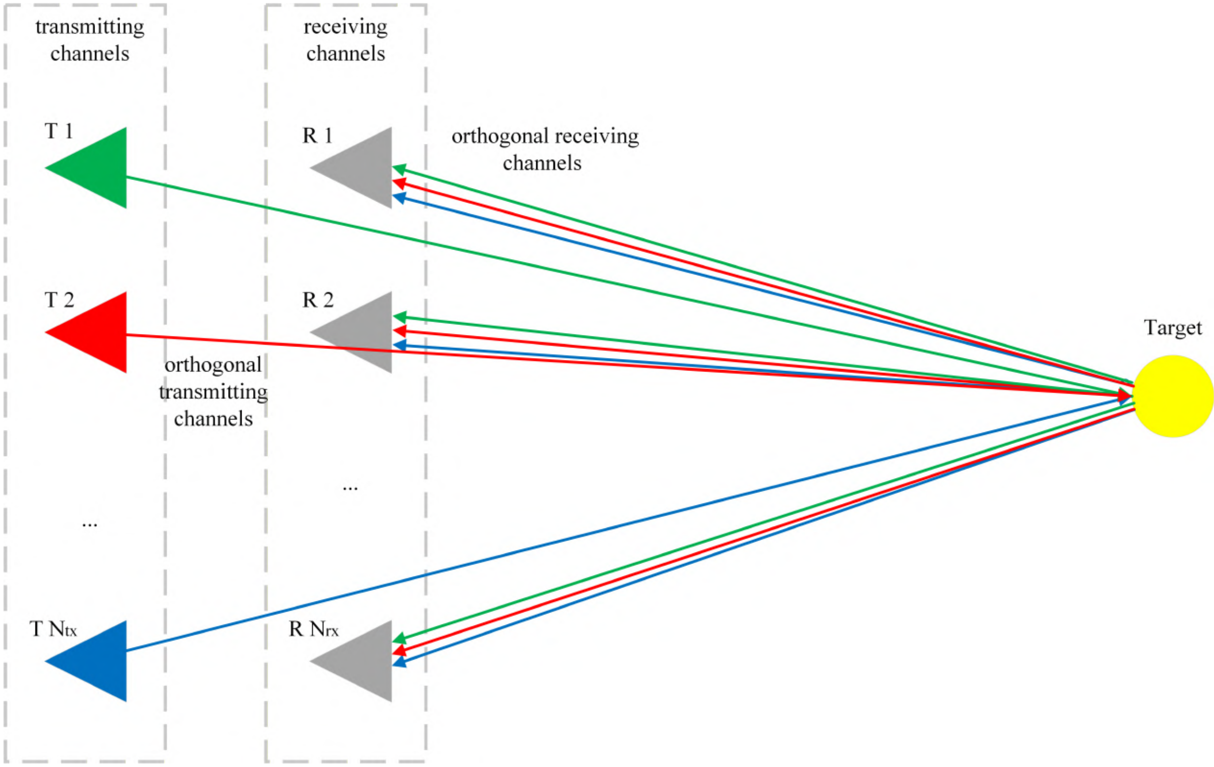

Figure 1. Principle of operation of the MIMO radar

The moving carrier of ERS is characterized by the presence of a Doppler frequency shift due to both the movement of the carrier itself by the possible movement of targets. Let M transmitting pulses with a repetition period of T be processed in a coherent packet. The space-time domain vector of the signal is formed as a result of the Kronecker product of the time and space vectors. The synthesized MIMO covariance matrix (signals from all virtual channels for the entire observation time) makes it possible to consider joint space-time processing as a single task of estimating signal parameters in the dimensional space $N_v \times M$.

1.2. Model of the Signal and Interference Environment for MIMO Radars

In MIMO radars, the received signal is represented as a superposition of reflections from target objects, passive interference from the underlying surface, and active noise interference. Passive interference (reflections from the ground, water surface, urban buildings) is characterized by high space and time correlation and dominates in terms of energy. Active noise interference is created by special electronic warfare equipment and can have both broadband and narrowband structures.

Let $x \in C^{N_v M}$ denote the space-time vector of the received signal samples, where N_v is the number of virtual channels, M is the number of transmitted pulses in a coherent packet. The vector x can be represented as:

$$x = x_s + x_i + x_n, \tag{1}$$

where x_s is the component of the signal reflected from the object, x_i is the component of passive and active interference, and x_n is the component of the receiving channels noise.

The covariance matrix of the received signal is defined as $R = E[xx^H]$, where $E[\cdot]$ is the expectation operator, $(\cdot)^H$ is the Hermitian conjugation. In practice, R is unknown and must be estimated from a training sample:

$$\hat{R} = \frac{1}{L} \sum_{l=1}^{L} x_l x_l^H, \tag{2}$$

where x_l are independent implementations.

For R to be non-degenerate and there to be an inverse matrix, it is necessary that $L \geq 2 \cdot NM$.

1.3. Computational Complexity of the Classical Space-Time Processing Approach

The classical approach to STAP involves solving the optimal filtering problem using a weight vector w that minimizes the output power of interference with a fixed response to the target signal. The optimal weight vector is determined by the expression:

$$w_{opt} = \mu R^{-1} s, \tag{3}$$

where μ is a normalization multiplier that provides $w_{opt}^H s = 1$, s is the "true" reflected signal that we expect to receive from the target in the direction we are interested in. The key computational problem is the need to calculate the inverse covariance matrix R^{-1} with dimension $NM \times NM$.

The computational complexity of solving the inverse of an R^{-1} matrix with dimension $NM \times NM$ by the Gaussian or LU decomposition method is $O((NM)^3)$ arithmetic operations. For promising MIMO radars with N_v on the order of 10^4 virtual channels and M on the order of 100–500 pulses per packet, the NM product can reach 5×10^6.

When using classical space-time processing algorithms to find the inverse R^{-1} covariance matrix with a dimension of $5 \times 10^6 \times 5 \times 10^6$, the computational complexity will be about $O(10^{20})$ floating-point operations, which is physically impossible even on modern supercomputers with a capacity of about 10^{18} operations per second.

As for the required amount of RAM, a preliminary estimate shows that to store only the R matrix, the required minimum amount of memory should be $(NM)^2 \times 16\ bytes = 5 \times 10^{14}\ bytes$ (approximately 500 TB). It is impossible to store a matrix of this size in RAM on board existing and promising ERS.

The classical approach to space-time processing becomes inapplicable when switching to full-fledged MIMO radars with a high-dimensional virtual aperture. This fact forms a fundamental limitation, the overcoming of which requires the development of fundamentally new algorithmic and architectural solutions proposed in the following sections of this work.

1.4. Problem Statement and Initial Data

Suppose there is a MIMO radar with N_{rx} receiving and N_{tx} transmitting channels forming a virtual aperture of dimension $N_v = N_{tx} \cdot N_{rx}$. A coherent packet contains M pulses, so that the space-time vector of the signal has dimension $NM = N_v M$. The received signal is a superposition of reflections from K targets, passive interference, and noise:

$$x(t) = \sum_{k=1}^{K} \alpha_k a(\theta_k, \varphi_k) \otimes b(f_{d,k}) + x_i(t) + x_n(t), \tag{4}$$

where α_k is complex amplitude reflections from the k-th target, $a(\theta_k, \varphi_k) \in C^{N_v}$ is a vector of the reflected signal in the spatial basis (depends on the azimuth φ_k and elevation θ_k), $b(f_{d,k})$ is a vector of the reflected signal in a temporal basis (depends on the Doppler frequency $f_{d,k}$), $\otimes$ is a work of Kronecker, $x_i(t)$ is the interference component of the reflected signal and $x_n(t)$ is the noise component of the reflected signal.

It is necessary to develop an algorithm for estimating the angular coordinates (θ_k, φ_k) and the Doppler frequency $f_{d,k}$ of all objects K with minimal computational effort and high resolution. To achieve this goal, we will decompose the task. Since calculations based on the covariance matrix are necessary in the framework of space-time adaptive signal processing, it is impossible to solve the problem in this form. At the first stage, it is necessary to reduce the dimension of the covariance matrix. At the second stage, the azimuth, elevation angle, and Doppler frequency are estimated.

2. The Dimensionality Reduction Method

The central problem formulated in the previous sections is that the dimension of the space-time vector of the NM signal for promising MIMO radars reaches values of the order of 10^6, which makes classical processing methods computationally unrealizable. This section proposes several complementary approaches to reducing the effective dimension of the, based on the use of sparse representations, adaptive rank reduction methods, and coherent restoration of the covariance structure.

The first stage is the projection of the initial space-time vector x into the space of rays of a smaller dimension $Q \ll NM$. At the second stage, the projection matrix is optimized. At the third stage, the signal is projected into a smaller dimensional space.

2.1. Projection Matrix Formation

The projection matrix $B \in C^{NM \times Q}$ is formed based on a priori information about the expected directions of arrival of the signal. In general, the pillars B are a set of signal vectors corresponding to the Q reference directions:

$$B = [\tilde{a}(\theta_1, \varphi_1) \otimes \tilde{b}(f_{d,1}), \tilde{a}(\theta_2, \varphi_2) \otimes \tilde{b}(f_{d,2}), ..., \tilde{a}(\theta_Q, \varphi_Q) \otimes \tilde{b}(f_{d,Q})], \tag{5}$$

where $\tilde{a}(\theta_q, \varphi_q)$ is the approximation of the reflected signal in the space basis, $\tilde{b}(f_{d,q})$ is the approximation of the reflected signal in the time (frequence) basis.

2.2. Projection Matrix Optimization

The KAC-JIOAF (Knowledge-Aided Constrained Joint Iterative Optimization Framework for Adaptive Filters) optimization procedure [6] is used to minimize information loss. The problem is formulated as an optimization with confines:

$$\min_{B,W} \|B^H R B - W W^H\|_F^2 + \lambda \|B\|_* + \mu \|W - W_0\|_F^2, \tag{6}$$

where R is the covariance matrix of the initial reflected signal, W is the matrix of weights of the adaptive filter, W_0 is the initial approximation obtained from a priori data, $\|\cdot\|_F$ is the Frobenius norm, $\|\cdot\|_*$ is the nuclear norm providing a low-rank solution and λ, μ are the regularization parameters.

Since optimization is performed using two parameters, the search for a solution is carried out iteratively:

Step 1 (fixing B, optimizing W):

$$W_{t+1} = \frac{(B_t^H R B_t W_t + \mu W_0)}{(B_t^H R B_t + \mu I)}, \tag{7}$$

where I is the identity matrix.

Step 2 (fixing W, optimizing B):

$$B_{t+1} = \arg\min_{B} \|B^H R B - W_{t+1} W_{t+1}^H\|_F^2 + \lambda \|B\|_*. \tag{8}$$

The solution of the second stage is performed by the algorithm of proximal gradient descent with soft threshold processing of singular values.

2.3. Projecting a Signal into a Smaller Space

After the optimal matrix B_{opt} is found, the projection of the signal is performed:

$$y = B_{opt}^H x \tag{9}$$

and the projection of the reduction in the dimension of the covariance matrix:

$$R_y = B_{opt}^H R B_{opt}. \tag{10}$$

At the same time, the dimension of the processing space is reduced from NM to Q, where Q is selected in the range from 100 to 1000, depending on the complexity of the scene.

3. Estimation of Target Parameters in Space-Time Signal Processing

At the next stage of processing, an adapted version of the MUltiple SIgnal Classification algorithm (MUSIC) is applied to the projected covariance matrix R_y [7, 9, 10], which is based on the decomposition of the covariance matrix $R \in C^{N_v M}$ into signal and noise subspaces.

3.1. Decomposition into Signal and Noise Subspaces

Decomposing the matrix into eigenvectors:

$$R_y = U_y \Lambda_y U_y^H, \tag{11}$$

where $U_y = [u_1, u_2, ..., u_Q]$ – the matrix of eigenvectors, $\Lambda_y = diag(\lambda_1, \lambda_2, ..., \lambda_Q)$ is a diagonal matrix of eigenvalues, ordered in descending order $\lambda_1 \geq \lambda_2 \geq ... \geq \lambda_Q$.

The number of objects $\hat{K}$ is estimated using the minimum description length criterion:

$$U_s = [u_1, u_2, ..., u_{\hat{K}}]. \tag{12}$$

The noise subspace is formed from the remaining vectors:

$$U_n = [u_{\hat{K}+1}, u_{\hat{K}+2}, ..., u_Q]. \tag{13}$$

3.2. Projection of Reflected Signals into the Ray Space

For each potential direction (θ, φ) and the Doppler frequency f_d, the original reflected signal is projected into the ray space:

$$c(\theta, \phi, f_d) = B_{opt}^H (a(\theta, \varphi) \otimes b(f_d)). \tag{14}$$

3.3. Calculation of Parameter Estimates

To calculate the estimates parameters using the MUSIC algorithm, a pseudospectrum in the ray space is calculated:

$$P_{MUSIC}(\theta, \varphi, f_d) = \frac{1}{\|U_n^H c(\theta, \varphi, f_d)\|^2} = \frac{1}{c(\theta, \varphi, f_d)^H U_n U_n^H c(\theta, \varphi, f_d)}. \tag{15}$$

The peaks of the pseudospectrum correspond to estimates of the parameters of the objects:

$$\hat{\theta}_k, \hat{\varphi}_k, \hat{f}_{d,k} = \arg \max_{\theta, \varphi, f_d} \hat{P}_{MUSIC}(\theta, \varphi, f_d), \ k = 1, 1, ..., \hat{K}. \tag{16}$$

The proposed hybrid algorithm of MUSIC with a reduction in the dimension of the covariance matrix is an effective solution to the problem of space-time processing of MIMO radar signals for remote sensing aircraft systems, providing an optimal compromise between computational complexity and accuracy of estimates of the parameters of detected objects.

3.4. Analysis of the Computational Complexity of the Proposed Hybrid Algorithm and the Capabilities of onboard Computing Systems

Table 1 presents a comparative analysis of the computational complexity of the classical MUSIC method and the proposed hybrid method.

Table 1. Comparison of computational complexity of classical MUSIC and hybrid method

Stage / Method	Classical MUSIC	Proposed hybrid method
Formation of the covariance matrix	$O((NM)^2L) \approx 10^{12}$	$O(Q^2L) \approx 10^8$
Calculation of eigenvectors of the covariance matrix	$O((NM)^3) \approx 10^{18}$	$O(Q^3) \approx 10^9$
Calculation of the pseudospectrum (per object)	$O(NM) \approx 10^6$	$O(Q) \approx 10^3$
Iterative optimization of KAC JIOAF	-	$O(T \cdot Q^3) \approx 10^{10}$
Overall difficulty	10^{18}	10^9

Table 1 shows that the computational complexity of the proposed algorithm is 8 orders of magnitude less than the classical MUSIC algorithm, which allows it to be implemented in modern and promising remote sensing systems.

Considering that the accumulation time of 1 coherent packet is 10 microseconds, the onboard computing system must be able to process the received signals before the next packet arrives (pipelining). Thus, the minimum performance of the onboard computing system should be at least 10^{10} operations/ 0.01s = 10^{12} operations/s. Taking into account the fact that for accurate calculations it is necessary to use the double precision data type (double 64), the number of operations should be an order of magnitude greater. Thus, in order to perform pipelining using the proposed hybrid method, the onboard computing system performance should be at least 10^{13}–10^{14} operations per second (10–100 TFLOPs).

onboard computing systems are characterized by severe performance, power consumption, and size limitations. The high computational complexity of classical MUSIC makes it inapplicable in such conditions. The hybrid method, on the contrary, has a number of properties that make it promising for implementation in onboard computing systems:

- reduced load on central processing unit (CPU);
- the possibility of parallelism;
- adaptability to resources;
- compatible with hardware accelerators.

Thus, the hybrid method is not only significantly superior to classical MUSIC in computational efficiency, but also optimally meets the requirements for signal processing algorithms in onboard computing systems.

4. Architecture of the Onboard Supercomputer

Overcoming the "computational gap" formulated in Section 2 requires not only the development of new dimensionality reduction algorithms but also the creation of a specialized computing architecture capable of implementing these algorithms in real time under severe restrictions on weight, energy consumption, and vibration loads typical of remote sensing aircraft systems. This section proposes the architecture of an onboard supercomputer core based on the principles of heterogeneity, pipelining, and specialized computing coprocessors.

4.1. The Principle of Heterogeneity: Separation of Computing Load

The classical approach to implementing radar algorithms on a universal central processing unit (CPUs) does not provide the required performance when processing MIMO signals. An alternative is to use a heterogeneous computing architecture that combines different types of computing devices, each of which is optimal for its class of tasks. In the proposed architecture, the computing load is distributed as follows. FPGAs are assigned tasks that require high bandwidth and deterministic low latency: pre-filtering, compressed range sampling, fast Fourier transform (FFT) in range and Doppler frequency, as well as primary signal detection. FPGAs provide hardware parallel processing of the data stream coming from analog-to-digital converters (ADCs), which allows for pipelining with minimal latency.

Multicore processors (CPUs) and graphics processing units (GPUs) are tasked with adaptive processing and spectral analysis, requiring high computational complexity and flexibility of algorithms. Such tasks include: estimation and access to low-dimensional covariance matrices, implementation of MUSIC and KAC-JIOAF algorithms, space-time adaptive processing, as well as post-processing (trajectory filtering, targets classification). For performing sequential and control operations CPUs are efficient, while GPUs provide massively parallel processing of matrix operations typical for spectral analysis.

4.2. Pipelining Calculations: Cascading Processing

A key requirement for an onboard remote sensing system is to ensure continuous processing of radar data in real time. The traditional processing model "assemble frame – process – output result" leads to unacceptable latency due to waiting for the completion of the full processing cycle of the previous frame. To eliminate this disadvantage, a pipeline (cascade) data processing architecture is proposed. Figure 2 shows the structural and functional diagram of an onboard supercomputer.

The structural and functional scheme of the mentioned supercomputer consists of 5 main modules. In module 1, the received reflected signals are digitized, transferred to a zero intermediate frequency, and accumulated to increase the signal-to-noise ratio and reduce data flow. The main computing unit in module 1 are FPGAs with buffer memory and ADC boards. In module 2, a space-time vector of reflected signals is formed, the initial covariance matrix R is estimated, and a fast Fourier transform is performed along the time coordinate. The main computing unit of module 2 are FPGAs.

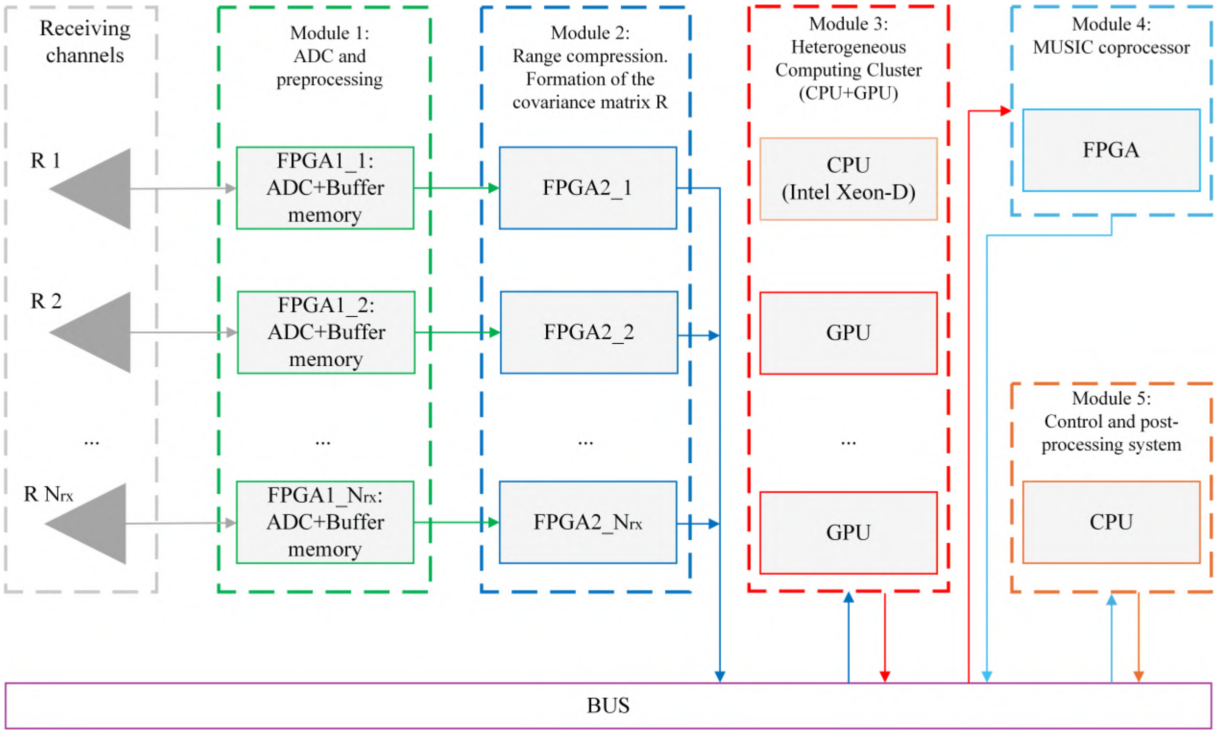

Figure 2. Structural and functional diagram of an onboard supercomputer

Module 3 (heterogeneous computing cluster) implements iterative optimization of KAC-JIOAF for calculating the $\mathbf{B}_{\mathbf{opt}}$ projection matrix and the subsequent eigenvalue decomposition of the projected covariance matrix $\mathbf{R}_{\mathbf{y}}$ of dimension $Q \times Q$. The heterogeneous computing cluster includes an Intel Xeon-D multi-core processor and graphics processors based on video cards. The central processor performs the KAC-JIOAF iterative optimization control, the formation $\mathbf{B}_{\mathbf{opt}}$ of the projection matrix, and the process stop. Graphics processors perform parallel matrix multiplication.

Module 4 consists of a specialized FPGA computer that performs calculations to find the MUSIC pseudospectrum for the entire grid of directions.

The final stages of processing are performed: filtering of trajectories, iterative refinement of estimates. A central processor is used for these purposes. In addition, modules 3, 4 and 5 are connected by a high-speed bus (bandwidth up to 10 Gbit/s per line), which ensures end-to-end pipelining of processing and a delay of no more than 5 ms per coherent packet. The proposed architecture fully covers the computational needs of the proposed hybrid algorithm and ensures its operation in real time under the conditions of severe weight and size limitations of the airborne remote sensing system.

Conclusions

As a result of the conducted research, it was possible to successfully solve the problem of computational gap in signal processing in MIMO radars for remote sensing aircraft systems. The developed hybrid algorithm demonstrates an impressive reduction in computational complexity by more than 10^8 times compared to the classical MUSIC method.

The practical significance of the work is confirmed by the possibility of implementing real-time signal processing with limited computing resources. The developed approach ensures robustness to small data samples and a high level of compatibility with onboard computing systems.

The prospects of the proposed solution are determined by the possibility of computing parallelism, adaptability to computing system resources, and compatibility with hardware accelerators. It is especially important to maintain high-quality signal processing while significantly reducing the computing load. The practical implementation of the developed algorithms opens up wide possibilities for use in modern aviation complexes. This includes real-time signal processing, improved direction finding accuracy, operation in high-noise environments, reduced power consumption of onboard equipment, and scalability of the solution for various classes of onboard systems.

Thus, the conducted research has made it possible to create an innovative method for processing space-time signals, which can be successfully applied in promising aviation complexes for remote sensing of the Earth. The developed algorithms and architecture of the computing core ensure an optimal balance between computational efficiency and signal processing quality, which makes them suitable for practical use in conditions of severe limitations of onboard systems.

References

1. Bashly, P.N., Denisenko, V.G., Mishchenko, S.E., Shatsky, V.V.: Angular super-resolution MUSIC algorithms based on the NIPALS and Jacobi methods. Antennas (6), 6–14 (2025). https://doi.org/10.18127/j03209601-202506-01

2. Fa, R., Rodrigo, C.: Knowledge-based, low-rank STAP for MIMO radar, based on collaborative iterative optimization of adaptive filters with multiple constraints. In: ICASSP. pp. 2762–2765 (2010)

3. Gupta, P., Kar, S.P.: MUSIC and an improved musical algorithm for estimating the direction of arrival. In: IEEE. pp. 0757–0761 (2015). https://doi.org/10.1109/ICCSP.2015.7322593

4. Lee, J., Stoica, P.: MIMO radar signal processing. Wiley, Hoboken, New Jersey (2008)

5. Lee, J., Strutoy, P.: Transmission diversity in MIMO radar: a look at the radiation pattern. IEEE Signal Processing Letters 13(6), 369–372 (2006)

6. Mohanna, M., Rabeh, M.L., Zier, E.M., Hekala, S.: Optimization of a musical algorithm for estimating the angle of arrival of a signal in wireless communication. NRIAG Journal of Astronomy and Geophysics 2(1), 116–124 (2013). https://doi.org/10.1016/j.nrjag.2013.06.014

7. Strutka, P., Lee, J.: On the identifiability of parameters in MIMO radar. IEEE Transactions on Signal Processing 55(1), 123–134 (2007)

8. Verba, V.S.: Multipurpose tracking in multi-position radar systems. Radio Engineering and Electronics 64(9), 902–909 (2019)

9. Verba, V.S.: Problems of intercepting priority air targets. Information and measurement control systems 17(1), 55–64 (2019)

10. Wang, H., Lee, J.: Space-time coding for MIMO radar. IEEE Transactions on Aerospace and Electronic Systems 45(2), 621–635 (2009)