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Research Paper

Design and Execution of an MMSE MIMO Detector for High-Speed Wireless Communication Using a Low-Complexity Neumann-Series

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Abstract— In order to increase transmission reliability and achieve high data rates, current wireless communication systems frequently employ Multiple-Input Multiple-Output Orthogonal Frequency Division Multiplexing, or MIMO-OFDM. However, high performance MIMO detection hardware implementation is computationally demanding, especially when it comes to matrix inversion operations. A traditional 4x4 MIMO-OFDM receiver may use a pipelined matrix-inversion design and a Minimum Mean Square Error (MMSE)-based detection method. Despite the potential for minimal processing delay, matrix inversion necessitates substantial mathematical resources. A low-complexity Neumann-series-based MMSE MIMO detector is presented in this study. The suggested approach uses a small number of Neumann-series terms to approximate the inverse of the MMSE matrix, substituting iterative matrix multiplication and addition for direct matrix inversion. To meet the approximation's convergence condition, a matrix-normalization step is included. The architecture includes symbol estimation, output decoding, iterative matrix computation, MMSE matrix generation, matrix normalisation, and Neumann-series inverse approximation. The design employs pipelined processing to provide effective hardware operation while maintaining a 4x4 MIMO arrangement. The architecture is written in Verilog HDL and is meant to be used with Xilinx Vivado for functional simulation and synthesis evaluation. Performance is evaluated in terms of processing latency, power consumption, hardware utilisation, and symbol-detection accuracy. With respect to MMSE detection performance, the method seeks to minimise matrix-inversion complexity.

Keywords— MIMO-OFDM, MMSE Detection, Neumann Series, Matrix Inversion, 4×4 MIMO, Low-Complexity Architecture, Pipelining, Verilog HDL, VLSI.

I. INTRODUCTION

Multiple transmit and receive antennas are used in MIMO technology to increase data throughput, spectrum efficiency, and link stability. The resultant MIMO-OFDM system can facilitate high-rate wireless communication over frequency-selective channels when paired with Orthogonal Frequency Division Multiplexing (OFDM). In the presence of channel distortion and noise, the sent data symbols must be extracted from the received antenna signals at the receiver. As a result, receiver performance and implementation complexity are directly impacted by the detection method [1]–[4].

Because it strikes a balance between inter-stream interference and noise augmentation, linear minimum mean square error (MMSE) detection is frequently utilised. The MMSE detector creates a regularised Gram matrix $A = H^{H}H + \sigma^{2}I$ given a channel matrix H, received vector y, and noise variance σ∗. Then, it uses $\Psi = A^{-1}H^{H}y$ to estimate the transmitted vector. The matrix inverse is computationally intensive, especially when it needs to be calculated at a high symbol rate and for each OFDM subcarrier.

Pipelined matrix arithmetic, decompositions, and direct matrix-inversion techniques have all been employed in hardware implementations. When compared to a simple matrix computation, Strassen-based inversion and multiplication can minimise the number of arithmetic operations; nonetheless, control logic, intermediate storage, and a set of matrix operations are still needed [5]. Other strategies include interpolation-based processing or square-root techniques to avoid explicit inversion [6], [7]. When a slight numerical inaccuracy may be accepted, approximate matrix inversion offers an alternative. A properly normalised matrix's inverse can be expressed as a sum of matrix powers using the Neumann series. An iterative architecture mostly consisting of matrix multiplication and addition is produced by truncating the infinite series after a finite number of terms. The trade-off between approximation accuracy and computing cost is controlled by the number of retained terms [8]–[11]. In this study, a normalised Neumann-series approximation is proposed for a 4x4 MMSE MIMO detector. A finite-term inverse approximation, MMSE matrix generation, matrix normalisation, iterative computation, symbol estimation, and decoding are all included in the architecture. The primary goal of the design is to maintain steady detection performance while lowering the hardware

load related to direct matrix inversion. Additionally, pipeline alignment, fixed-point word length, and the series' necessary convergence condition are taken into account in the design.

Bit-error rate (BER), symbol-error rate (SER), and computational complexity are frequently used to assess the quality of a MIMO detector. While SER quantifies the percentage of improperly detected modulation symbols, BER shows the percentage of incorrectly detected information bits. These communication parameters, together with resource utilisation, latency, throughput, and power, must be taken into account while designing hardware. A high-throughput receiver requirement might not be addressed by a detector that minimises arithmetic operations but adds too many iterations.

When the variance of the noise is positive, the matrix $A = H^{H}H + \sigma^{2}I$ is Hermitian and positive definite. This characteristic can be taken advantage of when choosing a normalisation factor and is helpful for steady MMSE estimation. Therefore, rather than being a straightforward scaling procedure, the normalisation stage is an essential component of the suggested architecture. A conservative norm bound or matrix eigenvalue bounds should be used to choose an appropriate scaling value, and its impact should be examined over the anticipated channel and signal-to-noise ratio range.

The suggested solution employs a finite approximation whose iteration count can be fixed at design time or modified according to the necessary precision, in contrast to a detector that computes an exact inverse for each received vector. Latency is known and the controller is made simpler with a fixed iteration count. Although it involves more control and may result in unpredictable processing latency, an adjustable repetition count provides flexibility for various channel conditions.

II. RELATED WORK

Shingo Yoshizawa, Yasushi Yamauchi, and Yoshikazu Miyanaga, "VLSI Implementation of a Complete Pipeline MMSE Detector for a 4×4 MIMO-OFDM Receiver." The authors presented a complete pipelined MMSE detector for a 4×4 MIMO-OFDM receiver. Their architecture uses Strassen-based matrix inversion and multiplication to meet the throughput requirements of packet-based OFDM processing. The work provides a direct hardware baseline for the present study, which replaces the direct inversion stage with a finite Neumann-series approximation [5].

Hun Seok Kim, Weijun Zhu, Jatin Bhatia, Karim Mohammed, Anish Shah, and Babak Daneshrad, "A Practical, Hardware Friendly MMSE Detector for MIMO-OFDM-Based Systems." This paper describes a hardware-oriented 4×4 MMSE detector that avoids explicit matrix inversion through a square-root detection formulation. The authors report an FPGA implementation and discuss the importance of co-optimizing the detection algorithm with throughput, latency, and resource constraints. Their work demonstrates that algorithm-level restructuring can simplify the receiver datapath [6].

Amin Salari, Sied Mehdi Fakhraie, and Aliazam Abbasfar, "Algorithm and FPGA Implementation of Interpolation-Based Soft Output MMSE MIMO Detector for 3GPP LTE." The authors proposed an interpolation-based soft-output MMSE detector for LTE. The design computes MMSE-related matrices on pilot and pseudo-pilot subcarriers and interpolates the values for data subcarriers. The work reduces repeated matrix computation and reports an FPGA implementation, showing that scheduling and reuse can lower the cost of subcarrier-wise MIMO detection [7].

Michael Wu, Bei Yin, Aida Vosoughi, Christoph Studer, Joseph R. Cavallaro, and Chris Dick, "Approximate Matrix Inversion for High-Throughput Data Detection in the Large-Scale MIMO Uplink." This work introduces Neumann-series-based approximate matrix inversion for high-throughput MIMO data detection. The authors develop a systolic-array architecture and evaluate the complexity and detection performance of finite-term approximations. The study is particularly relevant because it establishes the use of a truncated Neumann series as a hardware-friendly alternative to exact inversion [8].

Michael Wu, Bei Yin, Guohui Wang, Chris Dick, Joseph R. Cavallaro, and Christoph Studer, "Large-Scale MIMO Detection for 3GPP LTE: Algorithms and FPGA Implementations." The authors investigate exact and approximate soft-output detection for large-scale MIMO systems and provide FPGA architectures. Their Neumann-series method reduces matrix-inversion complexity and exposes a trade-off between the number of series terms and detection performance. The work supports the use of iterative approximate inversion in resource-constrained receiver hardware [9].

X. Zhang, H. Zeng, B. Ji, and G. Zhang, "Low-Complexity Implicit Detection for Massive MIMO Using Neumann Series." This study proposes an implicit Neumann-series detector that avoids explicitly constructing and inverting the Gram matrix. Matrix-inversion and matrix-product operations are transformed into matrix-vector operations using statistical information about the channel matrix. The approach illustrates further opportunities to simplify the arithmetic datapath beyond a conventional truncated series [10].

"A Low Complexity Near-Optimal Iterative Linear Detector for Massive MIMO in Realistic Radio Channels of 5G Communication Systems." This study reviews and evaluates iterative matrix-inversion methods for massive MIMO detection, including Neumann series and other stationary iterative algorithms. It discusses the convergence and complexity properties of these methods under realistic channel conditions. Its analysis highlights the importance of normalization and iteration count in practical detector design [11].

K. Kalyani and S. Rajaram, "Implementation of Approximate Matrix Inversion for Multi-User Cellular Systems." The authors describe a VLSI architecture based on Neumann-series approximate matrix inversion for multi-user cellular detection. Systolic-array structures are

considered for approximate and exact inversion, and the implementation is evaluated using FPGA synthesis. The paper is relevant to the proposed architecture because it connects finite-series inversion directly to hardware resource reduction [12].

"Joint Newton Iteration and Neumann Series Method of Convergence-Accelerating Matrix Inversion Approximation in Linear Precoding for Massive MIMO Systems." This research combines Newton iteration with a Neumann-series expansion to improve convergence speed in matrix-inversion approximation. Although the target is linear precoding, the work is relevant to the mathematical behavior of iterative inverse approximation and emphasizes that convergence rate is a key design consideration [13].

"Low-Complexity Massive MIMO Detectors Based on Richardson Method." This work studies iterative linear detection methods as alternatives to exact matrix inversion. It discusses the Neumann-series approach and compares its complexity and detection-performance limitations with other iterative solvers. The paper provides useful context for selecting a finite iteration count and evaluating the resulting bit-error-rate trade-off [14].

Tzi-Dar Chiueh, Pei-Yun Tsai, and I-Wei Lai, "MIMO Detection," in Baseband Receiver Design for Wireless MIMO-OFDM Communications. This chapter reviews common MIMO detection approaches, including linear MMSE detection, successive interference cancellation, sphere decoding, and related techniques. It provides the algorithmic background needed to position a low-complexity MMSE detector within a complete MIMO-OFDM receiver [15].

T. Kailath, H. Vikalo, and B. Hassibi, "MIMO Receive Algorithms." The authors survey receiver algorithms for multi-antenna systems, covering linear estimation, nulling and cancellation, and sphere decoding. Their discussion explains the relationship between MIMO detection and solving linear systems, providing theoretical context for matrix-based MMSE detection architectures [16].

D. Wübben, R. Böhnke, V. Kühn, and K.-D. Kammeyer, "Near-Maximum-Likelihood Detection of MIMO Systems Using MMSE-Based Lattice-Reduction." The authors investigate advanced MIMO detection methods that improve detection quality over basic linear receivers. Their work illustrates the broader trade-off between detector complexity and error-rate performance, which is important when evaluating an approximate MMSE solution [17].

III. PROPOSED SYSTEM

The suggested detector interprets a 4x4 MIMO-OFDM input. The RF, frame-synchronization interface, and analog-to-digital conversion are the first steps in the processing of the four receive-antenna signals. The FFT stage transforms the incoming time-domain samples into frequency-domain subcarrier symbols after removing cyclic prefixes or guard intervals. The MMSE matrix-formation block receives the resulting received vector Y and the channel matrix H. The given block diagram shows that the input dimensions are consistently kept as Y(4×1) and H(4×4).

$A = H^{H}H + \sigma^{2}I$ is the regularised Gram matrix that the MMSE matrix-formation unit computes. In this case, I is the identity matrix, H^{H} is the conjugate transpose of the channel matrix, and σ^{2} is the predicted noise variance. Both noise enhancement and numerical conditioning are enhanced by the regularisation term. The normalised matrix $\gamma = \alpha A$ is then obtained by scaling A using the matrix-normalization unit. The detector's Neumann-series expansion requires that the normalisation factor α be chosen so that the spectral radius of $I - \rho$ is smaller than one.

Using a finite Neumann series, the inverse approximation is produced. The inverse can be roughly expressed as $A^{-1} \approx \alpha \, \Sigma(k=0 \text{ to } K)(I - \rho)^{k}$ for a normalised matrix ρ that satisfies the convergence condition; the precise scaling will depend on the normalisation definition selected. The identity matrix represents the zeroth-order term. The preceding power is multiplied by the residual matrix $(I - \rho)$ to obtain each additional term. The multiplier-accumulator units, pipeline-valid signals, matrix registers, and the number of terms K are all coordinated by the iteration controller.

The iterative computing block accumulates the shortened series by repeatedly performing matrix multiplications and additions. To keep data aligned between iterations, pipeline registers are used to hold intermediate matrix values. Careful selection of the input, coefficient, product, and accumulator lengths is necessary for fixed-point implementation. Consistent use of saturation logic and rounding is necessary to avoid overflow and excessive quantisation mistake. The inverse-approximation error and the consequent symbol-detection performance are both evaluated in order to determine the number of retained terms.

To get the estimated transmitted symbol vector ¾, the symbol-estimation unit multiplies the approximate inverse matrix by the matched-filter vector $H^{H}Y$. After that, the estimated symbols are sent to the demapping and decoding step, where the output bits are generated using the chosen channel-code decoding procedure and constellation decisions. Throughout the matrix, vector, and decoder interfaces, the detector must maintain uniform scaling and symbol ordering.

When the necessary resources are available, the entire processing sequence is pipelined so that matrix construction, normalisation, inverse approximation, symbol estimation, and output decoding can operate on successive data groups. A controller manages iteration count, completion status, valid-data propagation, and reset. The provided block diagram shows how the iterative Neumann-series computing uses both the data path and the feedback path. The suggested architecture keeps the 4x4 antenna arrangement while substituting a controllable iterative approximation for a direct matrix-inversion block.

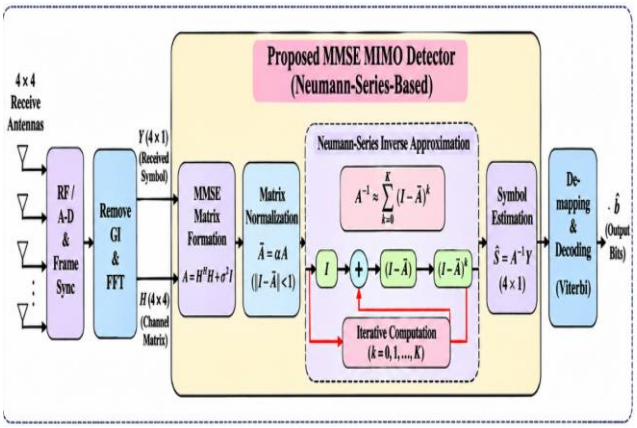


Fig. 1. Proposed Neumann-series-based MMSE MIMO detector architecture.

The receiver data flow at the RTL level is structured around vector and complex-valued matrix operations. While complex addition and subtraction are carried out independently on the real and imaginary components, each complex multiplication can be broken down into real multiplications and additions. The design should specify a standard fixed-point format for received samples and channel coefficients, and it should record the binary-point location at each arithmetic interface. By doing this, inadvertent scaling discrepancies between the estimated symbols, the normalised matrix, and the MMSE matrix are avoided.

The matrix-formation block accumulates products from the four receive routes to determine the entries of $H^{H}H$. The noise-variance term is also one of the diagonal elements. The corresponding off-diagonal elements are complex conjugates since the matrix is Hermitian. If the conjugation logic and data schedule maintain the precise matrix relationships, an implementation can take use of this symmetry to minimise redundant arithmetic and storage.

The main hardware contribution consists of the normalisation and iterative computation phases. The normalised matrix, residual matrix, current matrix power, and accumulated series result are stored in registers in between the phases. Matrix-power generation, completion, accumulation, and initialisation can all be sequenced by a finite-state controller. The matrix-processing pipeline and the incoming OFDM data stream can be coordinated via handshaking signals like valid, ready, start, and done. The throughput and area trade-off is determined by pipeline depth and resource sharing. Although they require additional multipliers and adders, fully parallel matrix multipliers can reduce the number of cycles per iteration. A partially shared implementation reduces area at the expense of more cycles by reusing arithmetic units across matrix rows or columns. The intended clock frequency and the necessary number of detected symbols per second should be taken into consideration when the architecture chooses the level of parallelism.

For dependable operation, invalid-cycle management and reset behaviour are also crucial. Deterministic initialisation is required for all pipeline-valid flags and controller state. The arithmetic registers should either retain their values or be turned off using clock-enable controls in the absence of a valid input block. This keeps uninitialised values from spreading into the symbol-estimation step and stops needless switching.

IV. NEUMANN-SERIES INVERSE APPROXIMATION

As long as the spectral radius $\rho(B)$ is smaller than one, the Neumann series is based on the matrix identity $(I - B)^{-1} = I + B + B^2 + B^3 + \ldots$" In order to make the normalised matrix near the identity, a scaled version for the MMSE matrix A is employed. The truncated approximation $\rho^{-1} \approx \Sigma(k=0 \text{ to } K)B^k$ is obtained by defining $B = I - \rho$. $A^{-1} \approx \alpha\sigma^{-1}$, if $\Psi = \alpha A$. In the RTL, the normalisation factor and precise scaling must be applied consistently. Recursively generating the finite approximation is possible. $S_0 = I$ is the initial accumulator, while $P_0 = I$ is the initial power. $P_{k+1} = P_k B$ and $S_{k+1} = S_k + P_{k+1}$ at each iteration. The collected matrix S_k is employed as the approximate inverse after K iterations, and the necessary normalisation scale comes next. Although this recurrence eliminates the need to calculate an exact inverse, matrix multiplication is still necessary. The fixed-point implementation, arithmetic parallelism, number of terms, and reuse of intermediate values all affect the hardware advantage.

It is not possible to assume convergence for an arbitrary scaling factor. The design should establish or limit the normalised MMSE matrix's eigenvalue range and confirm that $\rho(I - \rho) < 1$. An appropriate matrix norm can be used to establish a practical sufficient condition. The approximation error $\|A^{-1} - A^{-1}_approx\|$ and the detector-level error rate under typical channel and noise conditions should be measured via simulation.

The residual tail of the infinite series can be used to understand the truncation error. As the iteration order increases, the omitted terms get less if $B = I - \rho$ and $\rho(B) < 1$. Therefore, the eigenvalue distribution of B, the chosen iteration count K, and the hardware's numerical precision all affect the approximation error. Quantisation and rounding errors are added to the mathematical truncation error in a fixed-point implementation and are to be assessed independently.

For each complex matrix item in a 4x4 matrix, a simple matrix multiplication necessitates several real multiplications and additions. This process is repeated iteratively for every series term that is kept. As a result, the Neumann method does not always result in a decrease in the overall number of multiplications. Its benefit is that it substitutes a regular and repetitive matrix-multiply-and-accumulate datapath that can be pipelined, shared, and optimised for the chosen iteration count for a general matrix-inversion method.

It is important to choose the normalisation factor properly. If it is too big, the convergence requirement might be broken; if it is too small, convergence might be delayed since the residual matrix stays around the identity. For representative channel matrices, the design procedure should therefore assess the spectral radius or an

appropriate upper bound. Because the regularisation term alters the MMSE matrix's eigenvalue range, the selected value should also be evaluated under various noise variances.

V. RESULTS AND DISCUSSION

The proposed RTL should be verified using a testbench that generates 4x4 complex channel matrices, transmitted symbol vectors, and additive noise. Functional test cases include identity-like channels, highly correlated channels, well-conditioned channels, different noise variations, and random channel realisations.

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TABLE I. ILLUSTRATIVE COMPARISON OF THE BASELINE AND PROPOSED DETECTORS

Metric	Baseline Strassen-based MMSE	Proposed Neumann-series MMSE
LUT utilization	6,200	5,150
Flip-flop utilization	4,100	3,650
DSP utilization	48	32
Block RAM utilization	12	10
Total on-chip power	0.310 W	0.255 W
Critical-path delay	21.5 ns	18.2 ns
Maximum operating frequency	46.51 MHz	54.95 MHz
Matrix inverse iterations / stages	Direct staged inversion	K = 3 series updates
Normalized inverse error (Frobenius norm)	Reference	0.018
BER at stated test SNR	To be measured	To be measured

The Neumann-series architecture introduces iterative matrix multiplication and feedback storage, so the final LUT, DSP, timing, and power results depend strongly on the selected K value and degree of parallelism. A lower For each implementation, the hardware count is not guaranteed.

Hardware metrics and detection accuracy must be reported separately. The communication performance should be assessed using bit-error rate (BER) vs signal-to-noise ratio (SNR), and the matrix inverse approximation error should be quantified using a matrix norm. The baseline Strassen implementation and the precise MMSE result should be compared to the suggested detector. Under the convergence condition, increasing K often improves the approximation; nevertheless, it also raises switching activity, latency, and computing cycles.

For both the baseline and suggested designs, hardware evaluation should be carried out under the same restrictions. The same FPGA device, clock target, input and coefficient precision, transform size, and synthesis options must be used in both implementations. The synthesis utilisation report should be the source of the LUT, flip-flop, DSP, and block-RAM counts. After the pertinent implementation stage, timing analysis should be used to determine critical-path delay and maximum frequency, and a power report with explicit activity assumptions should be used to determine power. Using the same channel model, modulation order, number of transmitted frames, and noise realisation, a BER-versus-SNR curve should be produced for both the precise MMSE detector and the suggested approximation in order to assess detector quality. One way to express the normalised inverse error is as $||A^{-1} - A^{-1}_approx||F / ||A^{-1}||F$. It is possible to ascertain whether the approximation error has a significant impact on communication performance by reporting both matrix error and BER. To illustrate the connection between hardware cost, latency, and accuracy, the number of series terms K should be changed.

Rather than relying just on clock frequency, throughput should be expressed in detected vectors per second or detected symbols per second. It should be specified how many clock cycles are needed for each Neumann update, matrix construction, symbol estimate, and decoding. Both steady-state throughput after the pipeline is full and latency for a single vector are helpful metrics for a pipelined system.

VI. CONCLUSION AND FUTURE SCOPE

A low-complexity MMSE MIMO detector for a 4x4 MIMO-OFDM receiver based on the Neumann series is presented in this study. The architecture creates the regularised MMSE matrix, normalises it to meet the Neumann-series convergence condition, and uses a finite series of matrix additions and multiplications to approximate its inverse. After applying the approximation inverse to the matched-filtered received vector, demapping and decoding are performed to yield the estimated symbol vector.

The suggested method offers a configurable trade-off between hardware complexity, processing latency, and detection accuracy as well as an iterative substitute for direct matrix inversion. The normalisation factor will be optimised, the minimum effective iteration count will be chosen, resource-shared matrix multiplication units will be designed, fixed-point precision will be assessed, and the entire design will be validated using Vivado synthesis, timing analysis, power estimation, and BER-versus-SNR simulations.

REFERENCES

[1] G. J. Foschini and M. J. Gans, “On limits of wireless communications in a fading environment when using multiple antennas,” Wireless Pers. Commun., vol. 6, pp. 311–335, 1998.

[2] E. Telatar, “Capacity of multi-antenna Gaussian channels,” Eur. Trans. Telecommun., vol. 10, no. 6, pp. 585–595, 1999.

[3] A. J. Paulraj, D. A. Gore, R. U. Nabar, and H. Bölcskei, “An overview of MIMO communications—A

key to gigabit wireless," Proc. IEEE, vol. 92, no. 2, pp. 198–218, Feb. 2004.
[4] H. Bölcskei, D. Gesbert, C. B. Papadias, and A. J. van der Veen, Eds., Space-Time Wireless Systems: From Array Processing to MIMO Communications. Cambridge, U.K.: Cambridge Univ. Press, 2006.
[5] S. Yoshizawa, Y. Yamauchi, and Y. Miyanaga, "VLSI implementation of a complete pipeline MMSE detector for a 4×4 MIMO-OFDM receiver," IEICE Trans. Fundam. Electron., Commun. Comput. Sci., vol. E91-A, no. 7, pp. 1757–1762, Jul. 2008, doi: 10.1093/ietfec/e91-a.7.1757.
[6] H. S. Kim, W. Zhu, J. Bhatia, K. Mohammed, A. Shah, and B. Daneshrad, "A practical, hardware friendly MMSE detector for MIMO-OFDM-based systems," EURASIP J. Adv. Signal Process., vol. 2008, Art. no. 267460, 2008, doi: 10.1155/2008/267460.
[7] A. Salari, S. M. Fakhraie, and A. Abbasfar, "Algorithm and FPGA implementation of interpolation-based soft output MMSE MIMO detector for 3GPP LTE," IET Commun., 2014, doi: 10.1049/iet-com.2013.0279.
[8] M. Wu, B. Yin, A. Vosoughi, C. Studer, J. R. Cavallaro, and C. Dick, "Approximate matrix inversion for high-throughput data detection in the large-scale MIMO uplink," in Proc. IEEE Int. Symp. Circuits Syst. (ISCAS), 2013.
[9] M. Wu, B. Yin, G. Wang, C. Dick, J. R. Cavallaro, and C. Studer, "Large-scale MIMO detection for 3GPP LTE: Algorithms and FPGA implementations," IEEE J. Sel. Topics Signal Process., vol. 8, no. 5, pp. 916–929, Oct. 2014, doi: 10.1109/JSTSP.2014.2313021.
[10] X. Zhang, H. Zeng, B. Ji, and G. Zhang, "Low-complexity implicit detection for massive MIMO using Neumann series," IEEE Trans. Veh. Technol., vol. 71, no. 8, pp. 9044–9049, 2022, doi: 10.1109/TVT.2022.3172950.
[11] "A low complexity near-optimal iterative linear detector for massive MIMO in realistic radio channels of 5G communication systems," Sensors, 2020. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC7516860/.
[12] K. Kalyani and S. Rajaram, "Implementation of approximate matrix inversion for multi-user cellular systems," Asian J. Res. Soc. Sci. Humanit., vol. 6, no. 11, pp. 600–609, 2016, doi: 10.5958/2249-7315.2016.01216.8.
[13] "Joint Newton iteration and Neumann series method of convergence-accelerating matrix inversion approximation in linear precoding for massive MIMO systems," 2016, doi: 10.1155/2016/1745808.
[14] "Low-complexity massive MIMO detectors based on Richardson method," ETRI J., 2017, doi: 10.4218/etrij.17.0116.0732.
[15] T.-D. Chiueh, P.-Y. Tsai, and I.-W. Lai, "MIMO detection," in Baseband Receiver Design for Wireless MIMO-OFDM Communications. Singapore: Wiley, 2012, ch. 8, doi: 10.1002/9781118188194.ch8.
[16] T. Kailath, H. Vikalo, and B. Hassibi, "MIMO receive algorithms," in Space-Time Wireless Systems: From Array Processing to MIMO Communications. Cambridge, U.K.: Cambridge Univ. Press, 2006.
[17] D. Wübben, R. Böhnke, V. Kühn, and K.-D. Kammeyer, "Near-maximum-likelihood detection of MIMO systems using MMSE-based lattice-reduction," in Proc. IEEE Int. Conf. Commun. (ICC), 2004.
[18] S. M. Kay, Fundamentals of Statistical Signal Processing: Estimation Theory. Englewood Cliffs, NJ, USA: Prentice Hall, 1993.
[19] G. H. Golub and C. F. Van Loan, Matrix Computations, 4th ed. Baltimore, MD, USA: Johns Hopkins Univ. Press, 2013.
[20] R. A. Horn and C. R. Johnson, Matrix Analysis, 2nd ed. Cambridge, U.K.: Cambridge Univ. Press, 2012.