ITERATIVE DEMODULATION ALGORITHM BASED ON GRADIENT SEARCH METHOD FOR MU-MIMO SYSTEMS WITH LARGE ANTENNA ARRAYS

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This paper proposes and examines an iterative demodulation algorithm based on the optimized gradient method (OGM2) for high-dimensional multi-user MIMO (MU-MIMO) systems, taking into account the spatial correlation of fading. The classic MMSE algorithm, which is effective for small antenna configurations, becomes inapplicable in Massive MU-MIMO systems due to its high computational complexity. The proposed iterative approach provides a significant reduction in computational costs while maintaining acceptable noise immunity in conditions close to those of real communication channels. The simulation results are given for the MU-MIMO system with antenna configurations 128x128, 256x256, and 512x512 for 4 and 8 users at the level of spatial correlation of fading equal to 0.2. It is shown that the proposed algorithm provides a reduction in computational complexity by 2-8 times compared to the traditional MMSE algorithm with losses in noise immunity not more than 0.1-0.2 dB in systems with turbo coding at the level *FER* = 10^{-2}. The results demonstrate the robustness of the algorithm to spatial correlation, which confirms its practical applicability in real MIMO systems.

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Introduction

Modern and future wireless communication systems impose increasingly stringent requirements on data rates and quality of service for a large number of simultaneously active users. Multi-user transmission with many transmit and many receive antennas (MU-MIMO, Multi-User Multiple-Input Multiple-Output) is one of the key solutions for meeting these goals, enabling a base station to serve multiple users simultaneously on the same time-frequency resources [1, 2].

The transition to Massive MU-MIMO systems, where the base station is equipped with hundreds of antennas, opens up new opportunities for increasing throughput [3, 4]. However, the practical implementation of such systems faces serious computational challenges, especially at the stage of demodulating the received signals. The classical linear MMSE (Minimum Mean Square Error) algorithm, widely used in small-scale MIMO systems, requires inversion of large-dimension matrices, which leads to computational complexity on the order of $O\left(L^3\right)$, where L – Is the number of antennas [5, 6].

An important factor that distinguishes real communication channels from idealized models is the presence of spatial correlation between antenna elements. Ignoring spatial correlation when developing and analyzing demodulation algorithms can lead to an inaccurate assessment of their actual effectiveness.

The aim of this work is to study the applicability of the proposed OGM2-based iterative demodulation algorithm for high-dimensional MU-MIMO systems taking into account spatial correlation of the fading. This will allow evaluating the algorithm's performance under conditions as close as possible to real communication channels and confirming its practical relevance for modern wireless communication systems.

1 MU-MIMO system model

Figure 1 shows the block diagram of an MU-MIMO system in the uplink[1],. Let us denote by L the total number of transmit antennas (the sum of the antennas of all users), and by K – the number of receive antennas at the base station.

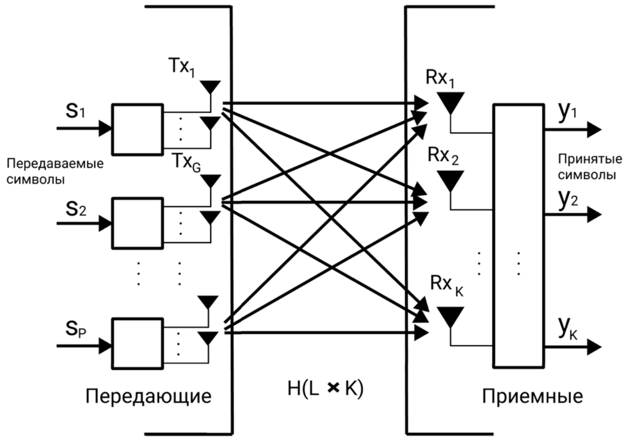

Fig. 1. Block diagram of the MU-MIMO system.

In the considered configuration, P users simultaneously transmit data to a base station equipped with K receive antennas; each user is equipped with G transmit antennas. For example, the $\mathrm{Tx}_1,\ldots,\mathrm{Tx}_G$ antennas transmit the complex information symbols $s_i(1)$ of the first user to the $\mathrm{Rx}_1,\ldots,\mathrm{Rx}_K$ antennas. The signals received at the $\mathrm{Rx}_1,\ldots,\mathrm{Rx}_K$ antennas are denoted by $y_1,\ldots,y_K$. The transmit antennas of all P users simultaneously send complex information symbols to the base station. Each receive antenna of the base station receives signals from all $L = P \cdot G$ transmit antennas of all users [7].

The MU-MIMO channel model in vector-matrix form is given by:

$$\mathbf{y} = \sum_{p=1}^{P} \mathbf{H}_p \mathbf{s}_p + \mathbf{n} \tag{1}$$

In expression (1) the following notations are used:

- $s_i(p)$, $i = 1,2,\ldots G$, – is the complex symbol transmitted by the i -th antenna of the p -th user;
- $\mathbf{s}_p = [s_1(p),\ldots s_i(p),\ldots,s_G(p)]^{\mathrm{T}}$, $p = 1,2,\ldots P$ - is the complex column vector of transmitted information symbols of the p -th user with dimensions $\mathrm{G}\times 1$;
- $\mathbf{y} = [y_1,\ldots,y_K]^{\mathrm{T}}$ – s the complex column vector of the signal received at the base station with dimensions $\mathrm{K}\times 1$.
- $\mathbf{n} = [n_1,\ldots,n_K]^{\mathrm{T}}$ – is the complex column vector of additive white Gaussian noise (AWGN) with dimensions $\mathrm{K}\times 1$, whose elements are uncorrelated and each has zero mean and variance $2\sigma_n^2$;
- $\mathbf{H}_p$ - is the complex channel matrix of the p -th user with dimensions $\mathrm{K}\times \mathrm{G}$.

Expression (1) can be written in vector-matrix form by combining the channel matrices of all users into a single block matrix and the vectors of transmitted symbols into a single column vector:

$$\mathbf{y} = [\mathbf{H}_1 \quad \mathbf{H}_2 \quad \ldots \quad \mathbf{H}_P] \cdot \begin{bmatrix} \mathbf{s}_1 \\ \mathbf{s}_2 \\ \vdots \\ \mathbf{s}_P \end{bmatrix} + \mathbf{n} \cdot \tag{2}$$

By denoting the combined channel matrix as $\mathbf{H} = \left[\mathbf{H}_1 \quad \mathbf{H}_2 \quad \ldots \quad \mathbf{H}_P\right]$ of dimensions $\mathrm{K}\times \mathrm{L}$ and the combined vector of transmitted symbols as $\mathbf{s} = [\mathbf{s}_1^T \quad \mathbf{s}_2^T \quad \ldots \quad \mathbf{s}_P^T]^{\mathrm{T}}$ of dimensions $\mathrm{L}\times 1$, the following model of a multi-user MIMO system is obtained, which is formally similar to the model of a single-user MIMO system:

$$\mathbf{y} = \mathbf{H}\mathbf{s} + \mathbf{n}\,. \tag{1}$$

Thus, the demodulation problem in a MU-MIMO system can be reduced to the demodulation problem in an equivalent single-user MIMO system with a channel matrix of dimensions $\mathrm{K}\times \mathrm{L}$. This makes it possible to apply demodulation algorithms originally developed for single-user MIMO systems.

[1] On this line, the base station receives signals from many users.

2 Algorithm MMSE

A large number of different demodulation methods are known for model (1). Among them, a class of linear algorithms can be distinguished, which have significantly lower computational complexity compared to nonlinear optimal detection methods [3, 5].

The MMSE demodulation algorithm is a linear algorithm that is optimal according to the minimum mean square error criterion between the transmitted information symbols and their estimates at the receiver side. The MMSE algorithm performs linear processing of the received vector $\mathbf{y}$ in order to obtain an estimate $\hat{\mathbf{s}}^{MMSE}$ of the transmitted information symbol vector $\mathbf{s}$. The obtained estimate $\hat{\mathbf{s}}^{MMSE}$ generally does not belong to the set of possible symbols $\mathbf{\Theta}$ which is determined by the modulation scheme. Therefore, an additional nonlinear transformation of the estimate is required in order to map the obtained values to the nearest valid constellation symbols [8, 9].

The MMSE algorithm calculates the estimate $\hat{\mathbf{s}}^{MMSE}$ as follows [5]:

$$\hat{\mathbf{s}}^{\text{MMSE}} = \left(\mathbf{H}'\mathbf{H} + 2\sigma_n^2\mathbf{1}\right)^{-1}\mathbf{H}'\mathbf{y}\,, \tag{4}$$

where $\mathbf{1}$ – is the identity matrix of dimensions $\text{L}\times\text{L}$.

It should be noted that the calculation of the estimate $\hat{\mathbf{s}}^{MMSE}$ according to expression (4) requires a significant number of arithmetic operations, with computational complexity on the order of ($O\left(L^3\right)$ for $L = K$). For a large number of transmit and receive antennas, which is typical for high-dimensional MIMO (Massive MIMO) systems, the computational complexity of the MMSE algorithm becomes excessively high. This significantly complicates or even prevents its practical implementation in such systems.

3 Iterative demodulation algorithm

Let us now consider approximate linear iterative demodulation methods. In this case, it is necessary to optimize a scalar function $f(\mathbf{s})$, hat depends on the vector of complex information symbols $\mathbf{s}$. As such a function $f(\mathbf{s})$ we choose the following quadratic form. Let us turn to approximate linear iterative demodulation methods:

$$f(\mathbf{s}) = \left\|\mathbf{y} - \mathbf{H}\mathbf{s}\right\|^2 + 2\sigma_n^2\cdot\left\|\mathbf{s}\right\|^2 \quad , \tag{5}$$

where $\|\ldots\|$ – denotes the Euclidean norm of a vector.

Let us now find the minimum of function (5). Due to its quadratic form, this function has a unique minimum, which can be found by setting its gradient equal to zero. Then, taking expression (5) into account, we obtain:

$$\begin{aligned} grad\left(f(\mathbf{s})\right) &= \frac{df(\mathbf{s})}{d\mathbf{s}} = 2\cdot\left(\mathbf{H}'\mathbf{H} + 2\sigma_n^2\cdot\mathbf{1}\right)\cdot\mathbf{s} - 2\cdot\mathbf{y} = \\ &= 2\cdot\left(\mathbf{H}'\cdot(\mathbf{H}\cdot\mathbf{s}) + 2\sigma_n^2\cdot\mathbf{s}\right) - 2\cdot\mathbf{y} = 0 \end{aligned} \tag{6}$$

By solving equation (6) with respect to the unknown vector $\mathbf{s}$, the following estimate of $\hat{\mathbf{s}}$ is obtained:

$$\hat{\mathbf{s}} = \left(\mathbf{H}'\mathbf{H} + 2\sigma_n^2\mathbf{1}\right)^{-1}\mathbf{H}'\mathbf{y}\,. \tag{7}$$

Comparing expressions (4) and (7), it can be seen that the exact solution of the minimization problem for the quadratic function $f(\mathbf{s})$ leads to the MMSE estimate given in (4). As noted earlier, due to the high computational complexity of calculating the exact MMSE estimate in systems with a large number of transmit and receive antennas, direct implementation of expression (4) becomes difficult or even impractical [5, 9].

Therefore, it is reasonable to avoid the exact solution in (4) and instead use approximate iterative methods to minimize the function $f(\mathbf{s})$. A large number of iterative optimization methods are known for solving such problems [10-12]. Among the most widely used methods are:

- the Heavy Ball Method, which introduces a momentum term and uses gradient information from previous iterations in order to accelerate convergence [13];
- the Momentum Method, which forms an exponentially weighted moving average of past gradients [14];
- Nesterov's Accelerated Gradient method, which provides an optimal convergence rate for smooth convex optimization problems 11];
- the Fast Iterative Shrinkage-Thresholding Algorithm (FISTA), which demonstrates high convergence speed in large-scale optimization problems [15];
- the Conjugate Gradient Method, which also provides high convergence speed in cases where the eigenvalues of the system matrix have a small spread [16];
- quasi-Newton methods, such as the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm, which approximate the Hessian matrix of second derivatives [17, 18].

One of the most efficient iterative optimization methods is the OGM2 method (Optimized Gradient Method 2) [11].

The OGM2 algorithm is an improved version of accelerated gradient descent designed for minimizing convex functions. Compared with the conventional gradient descent method, OGM2 provides a higher convergence rate, allowing the solution to be obtained in a smaller number of iterations.

The algorithm belongs to the class of first-order optimization methods, since it uses only gradient information and does not require computation of second derivatives or inversion of large matrices. As a result, OGM2 has relatively low computational complexity and is well suited for high-dimensional problems.

In massive MU-MIMO signal demodulation problems, the use of OGM2 is particularly effective because the computational complexity of conventional methods such as MMSE increases significantly with the number of antennas. In contrast, OGM2 is implemented as a sequence of iterative matrix-vector multiplication operations, which reduces computational complexity and improves the efficiency of hardware implementation.

The operation of the proposed demodulation algorithm based on the OGM2 method includes the following steps:

Initial conditions: $\mathbf{s}_0 = \mathbf{0}$ – is the initial value of the vector $\mathbf{s}$; L_0 – is the algorithm parameter corresponding to the Lipschitz constant of the function $f(\mathbf{s})$) [19]; I – is the total number of iterations of the algorithm; $i = 0$ – is the initial value of the current iteration index i; $\theta_0 = 1$ – is the initial value of the acceleration parameter.

1. alculation of the gradient of the function $f(\mathbf{s})$ at the current point $\mathbf{s}_i$:

$$grad\left(f\left(\mathbf{s}_i\right)\right) == 2\cdot\left(\mathbf{H}'\cdot\mathbf{H}+2\sigma_n^2\cdot\mathbf{1}\right)\cdot\mathbf{s}_{i-1}-2\cdot\mathbf{H}'\cdot\mathbf{y}\ . \qquad (8)$$

2. alculation of the Lipschitz constant:

$$L_0 = 8\cdot\left(\|\mathbf{H}\|_F^2 + 5\cdot 2\sigma_n^2\right), \qquad (9)$$

where $\|\mathbf{H}\|_F$ – is the Frobenius norm of the matrix $\mathbf{H}$ [20].

3. Calc lation of the temporary (intermediate) point:

$$\mathbf{y}_{i+1} = \mathbf{s}_i - \frac{1}{L_0} grad\left(f\left(\mathbf{s}_i\right)\right). \qquad (10)$$

4. Update of the acceleration pa meter θ_{i+1} :

$$\theta_{i+1} = \frac{1+\sqrt{1+6\theta_i^2}}{2}, i = 0;\dots I-1 \qquad (11)$$

5. orrection using a weighted sum of gradients (i.e., with accumulation of gradients from all previous iterations):

$$\mathbf{z}_{i+1} = \mathbf{s}_i - \alpha\cdot\frac{1}{L_0}\sum_{k=0}^{i}\theta_k grad\left(f\left(\mathbf{s}_k\right)\right) \qquad (12)$$

where α – is a tunable algorithm parameter whose value is determined experimentally during simulation depending on the antenna configuration dimensions of the MIMO system.

6. Calculation of the estimate at the next point. This estimate is determined as a weighted sum of $\mathbf{y}_{i+1}$ and $\mathbf{z}_{i+1}$:

$$\mathbf{s}_{i+1} = \left(1-\frac{1}{\theta_{i+1}}\right)\mathbf{y}_{i+1} + \frac{1}{\theta_{i+1}}\mathbf{z}_{i+1} \qquad . \qquad (13)$$

7. $i = i+1$.

Steps 1–7 are repeated for all values of $i = 1\dots I$, As a result, an estimate $\hat{\mathbf{s}}$ of the complex information symbol vector $\mathbf{s}$ is obtained at the output:

$$\hat{\mathbf{s}} = \mathbf{s}_I\ . \qquad (14)$$

8. Next, the decoding parameter D is calculated:

$$D = 0.22\cdot\left(1+4.3\cdot 2\sigma_n^2\right)\cdot 2\sigma_n^2\ . \qquad (15)$$

9. Decoding, i.e., obtaining the vector of estimated transmitted bits $\hat{\mathbf{b}}$, is then performed using a soft-input turbo decoder.

$$\hat{\mathbf{b}} = \boldsymbol{\varphi}\left(\hat{\mathbf{s}}, D\right), \qquad (16)$$

where $\boldsymbol{\varphi}(\dots)$ - is the function describing the turbo decoding algorithm.

The proposed demodulation algorithm differs from the original OGM2 algorithm in the specific computation of the Lipschitz constant L_0 according to expression (9), the computation of the decoding parameter D according to expression (15), and the introduction of the tunable parameter α . During simulation, the optimal values of parameter α , providing the best convergence performance of the algorithm, were determined. For the 128×128 antenna configuration, the parameter value is $\alpha = 38$, while for the 256×256 and 512×512 antenna configurations, the optimal value is $\alpha = 40$.

The demodulation algorithm described by expressions (8)…(16), achieves accelerated convergence due to the additional correction introduced by expression (12) for $\mathbf{z}_{i+1}$, which takes into account the gradients accumulated during previous iterations. This modification considers the contribution of all previous gradients, thereby improving the convergence rate of the algorithm.

4 Computational complexity analysis

Let us compare the computational complexity of the proposed demodulation algorithm (expressions (8)…(16), hereinafter referred to as OGM2) and the conventional MMSE algorithm (4). Computational complexity is understood as the number of elementary arithmetic operations (multiplications and additions) required to execute the corresponding algorithm. In digital signal processing systems, computational complexity directly determines the hardware resource requirements, power consumption, and data processing latency. The main computational operations in demodulation algorithms for MU-MIMO systems are:

- matrix-vector multiplication with computational complexity $O(KL)$;
- multiplication of two matrices with computational complexity $O\left(K^2L\right)$;
- inversion of an $L\times L$ matrix with computational complexity $O\left(L^3\right)$.

The conventional MMSE algorithm (4) requires inversion of an $L\times L$ matrix, which results in a cubic dependence of the number of operations on the system dimension. In contrast, the proposed iterative OGM2-based algorithm performs only matrix-vector operations at each iteration, completely avoiding matrix inversion. Even when several tens of iterations are performed, the total computational complexity remains significantly lower.

Table 1 presents the results of computational complexity analysis for the OGM2 algorithm (8)…(16) and the MMSE algorithm (4) for antenna configurations of 128×128, 256×256 and 512×512. It is assumed that the number of transmit and receive antennas is equal, i.e., $K = L$.

Table 1

Computational complexity of the OGM2 and MMSE algorithms

Number of iterations	32	-
	Algorithm OGM2	MMSE
Number of multiplications	$I(8L^2+16L+10)+4L^2+2L$	$4L^3+6L^2-L$
Number of multiplications for $L=128$ antennas	4,323,952	8,486,784
Number of multiplications for $L=256$ antennas	17,171,264	67,501,824
Number of multiplications for $L=512$ antennas	68,420,928	538,443,264
Number of additions	$I(8L^2+8L+5)+2L(2L-$	$4L^3+3L^2-3L$

Number of additions for 128 antennas	4,291,712	8,437,376
Number of additions for 256 antennas	17,104,544	67,304,704
Number of additions for 512 antennas	68,287,648	537,655,808
Total number of operations for 128 antennas	8,615,664	16,924,289
Total number of operations for 256 antennas	34,275,808	134,806,528
Total number of operations for 512 antennas	136,708,576	1,076,099,072

On Fig. 2 a graphical representation of the computational complexity is shown.

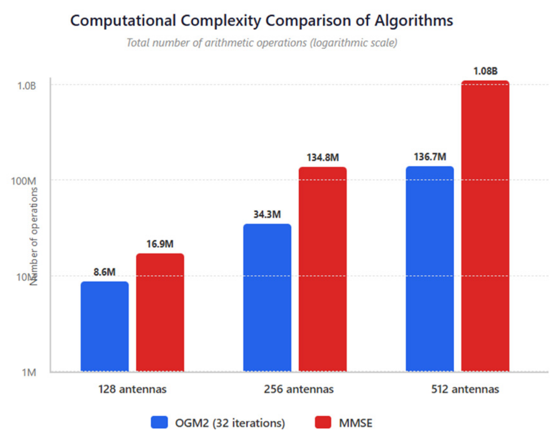

Fig. 2. Diagram of computational complexity for the OGM2 and MMSE algorithms for 128, 256, and 512 antennas.

Based on the results presented in Table 1 and Fig. 2, it can be concluded that the proposed iterative OGM2-based demodulation algorithm, described by expressions (8)…(16) exhibits high computational efficiency.

For a MU-MIMO system with a 128×128 antenna configuration, the proposed OGM2 algorithm requires 8,615,664 arithmetic operations when 32 iterations are performed. For the same configuration, the MMSE algorithm requires 16,924,289 operations. Thus, the use of OGM2 reduces computational complexity by approximately a factor of 2. This indicates that even for medium-scale systems, the iterative approach provides a noticeable reduction in computational cost while maintaining the required demodulation accuracy.

For a system with a 256×256 configuration, the difference between the two algorithms becomes even more pronounced. The OGM2 algorithm requires 34,275,808 arithmetic operations, whereas the MMSE implementation requires 134,806,528 operations. In this case, the reduction in computational complexity reaches approximately 3.9 times. This result shows that the growth in complexity of the OGM2 algorithm is significantly slower compared to MMSE, for which computational costs increase sharply due to the need for matrix inversion operations of large dimension.

The most significant advantage is observed for a MU-MIMO system with a 512×512. configuration. In this case, the OGM2 algorithm requires 136,708,576 arithmetic operations, while the MMSE algorithm requires 1,076,099,072 operations. Consequently, the reduction in computational complexity is approximately 7.9 times. This confirms the high scalability of the proposed iterative method and its effectiveness for use in large-scale massive MU-MIMO systems.

It should be noted that the advantage in computational complexity becomes more pronounced as the MU-MIMO system dimensionality increases. This is due to the fact that the MMSE algorithm requires matrix inversion, which leads to significant computational costs of order $O\left(L^3\right)$, whereas OGM2 has a substantially lower complexity of $O\left(L^2 I\right)$. Consequently, the proposed iterative demodulation algorithm significantly reduces the computational burden compared to the conventional MMSE approach, making it practical for large-scale MU-MIMO systems.

5 Turbo coding

Turbo coding is applied in the considered MIMO system to improve the noise immunity of data transmission and to reduce the probability of errors in signal reception. The use of turbo codes enables high transmission reliability even at low signal-to-noise ratio (SNR) values, which is especially important for multi-user MU-MIMO systems with a large number of transmit and receive antennas. Thanks to iterative decoding, turbo codes achieve performance close to the theoretical Shannon limit and are therefore widely used in modern digital communication systems.

Structurally, the turbo encoder consists of a parallel connection of two systematic convolutional encoders, between which an interleaver is used [21, 22]. The input to the turbo encoder is a vector of information bits, which is simultaneously fed:

- into the first systematic convolutional encoder;
- into the second convolutional encoder through an interleaver.

The first encoder processes the original bit sequence without changing its order and generates systematic and parity bits. In the second branch, the sequence is first permuted by the interleaver, which changes the ordering of bits according to a predefined rule. After that, the permuted sequence is passed to the second convolutional encoder. The use of the interleaver helps to remove correlation between errors and improves the efficiency of iterative decoding, since both encoders operate on different representations of the same message.

At the output, a stream of encoded bits is formed. To control redundancy, puncturing is applied in order to achieve the required code rate [23]. Decoding is performed using an iterative method with two MAP decoders exchanging a posteriori information [24].

6 Spatial correlation of fading

Let $\mathbf{H}_w$ – denote the uncorrelated Rayleigh fading MIMO channel matrix of dimensions $L \times K$, consisting of complex, independent Gaussian random variables with zero mean and identical variances. Let $\mathbf{H}$ – denote the correlated MIMO channel matrix, also of dimensions $L \times K$.

The following Kronecker model of a correlated MIMO channel is well known [25]:

$$\mathbf{H} = \mathbf{R}_r^{1/2}\mathbf{H}_w\mathbf{R}_t^{1/2}, \tag{17}$$

where $\mathbf{R}_t$ – is the transmit correlation matrix of dimensions $L \times L$; $\mathbf{R}_r$ – is the receive correlation matrix of dimensions $K \times K$. The matrices $\mathbf{R}_t$ and $\mathbf{R}_r$ are positive definite Hermitian matrices with ones on the main diagonal.

For the sake of simplification, it is assumed that the correlation matrices $\mathbf{R}_t$ and $\mathbf{R}_r$ are tridiagonal matrices [3]:

$$\mathbf{R}_t = \begin{bmatrix} 1 & p_t & 0 & \cdots & 0 \\ p_t & 1 & p_t & \cdots & \vdots \\ 0 & p_t & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & p_t \\ 0 & \cdots & 0 & p_t & 1 \end{bmatrix}; \quad \mathbf{R}_r = \begin{bmatrix} 1 & p_r & 0 & \cdots & 0 \\ p_r & 1 & p_r & \cdots & \vdots \\ 0 & p_r & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & p_r \\ 0 & \cdots & 0 & p_r & 1 \end{bmatrix}; \quad (18)$$

The values of the correlation coefficients p_t and p_r can be selected to represent different types of channels.

It should be noted that in the presence of spatially correlated fading in the MU-MIMO model (1) the channel matrix $\mathbf{H}_p$ of each user can be generated using the Kronecker model (17).

7 Simulation results

Statistical simulations were carried out to investigate the noise immunity of the MU-MIMO system using the conventional MMSE demodulation algorithm (4) and the proposed OGM2 algorithm (8)…(16). The simulation conditions are as follows:

- Antenna configurations: – 128×128, 256×256 and 512×512.
- Number of iterations in the OGM2 algorithm – 32.
- Number of experiments – 2500.
- Spatial fading correlation coefficients at the transmitter and receiver sides – $p_t = p_r = 0.2$.
- Modulation scheme – QAM-16.
- Demodulation algorithms – MMSE и OGM2.
- Number of users – 4.
- Constraint length –4.
- Generator polynomials – (13,15) in octal notation.
- Frame length – 128 бит.
- Code rate – 1/2.

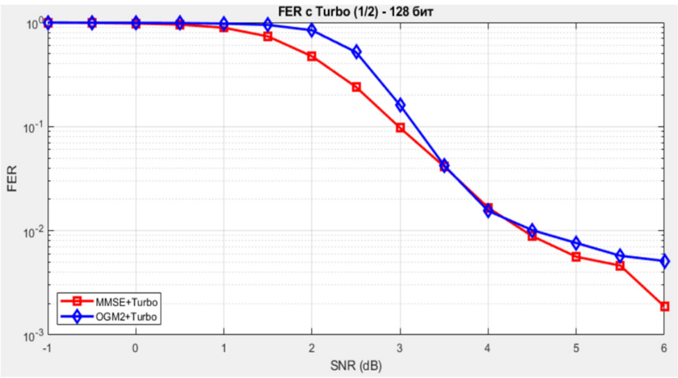

Fig. 3. Performance characteristics of the MU-MIMO system for 4 users with a 128×128 antenna configuration.

Let us consider the noise immunity characteristics of the MU-MIMO system using the conventional MMSE algorithm and the proposed iterative OGM2-based demodulation algorithm. The comparison is performed using two key performance metrics: the Bit Error Rate (BER), defined as the ratio of incorrectly received bits to the total number of received bits, and the Frame Error Rate (FER), which characterizes the proportion of frames containing at least one erroneously received bit. Both metrics are analyzed as functions of the Signal-to-Noise Ratio (SNR).

Figure 3 shows the dependence of the frame error rate (FER with turbo coding) on the signal-to-noise ratio for a MU-MIMO system with a 128×128 antenna configuration, using the MMSE and OGM2 algorithms for 4 users. As can be seen from Fig. 3, the performance loss of the OGM2 algorithm in terms of noise immunity at $FER = 10^{-2}$ is only about 0.1 dB.

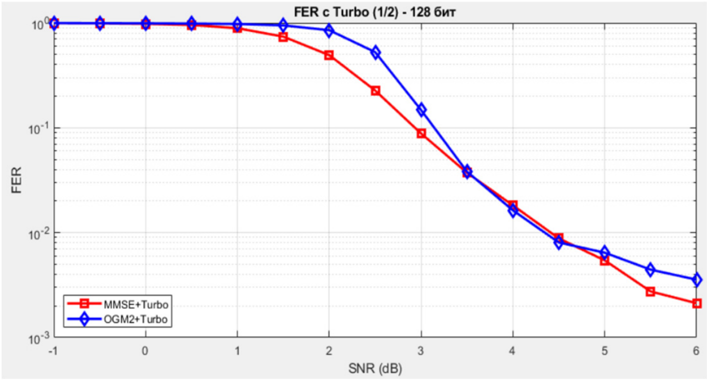

Fig. 4. Performance characteristics of the MU-MIMO system for 8 users with a 128×128 antenna configuration.

Figure 4 presents similar dependencies for 8 users. It can be observed that the noise-robustness loss of the OGM2 algorithm at $FER = 10^{-2}$ is negligible (practically zero).

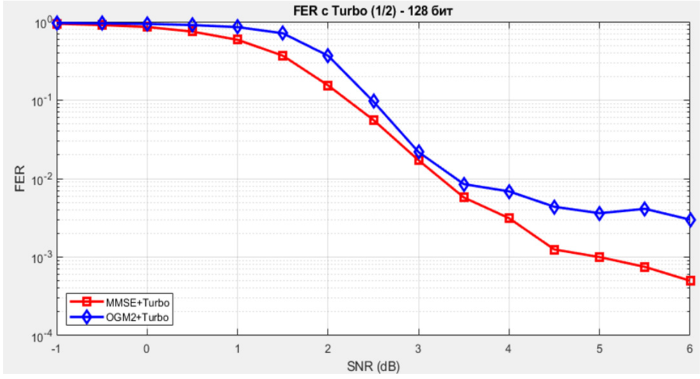

Fig. 5. Performance characteristics of the MU-MIMO system for 4 users with a 256×256 antenna configuration.

Figure 5 shows the dependence of the frame error rate (FER with turbo coding) on the signal-to-noise ratio for a MU-MIMO system with a 256×256 antenna configuration using the MMSE and OGM2 algorithms for 4 users. From the graph, it can be seen that the noise-robustness loss of the OGM2 algorithm at $FER = 10^{-2}$ is approximately 0.2 dB.

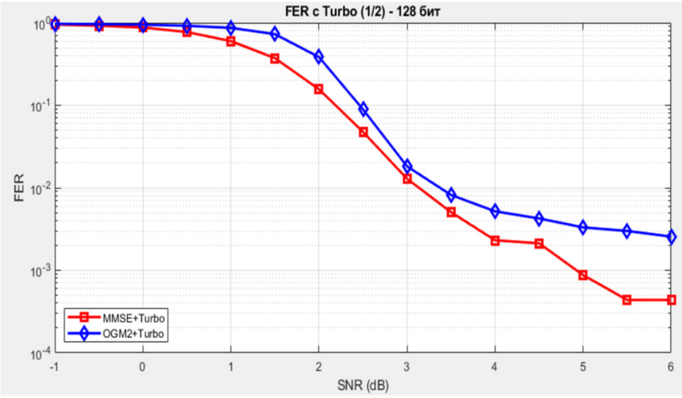

Fig. 6. Performance characteristics of the MU-MIMO system for 8 users with a 256×256 antenna configuration.

Figure 6 presents similar results for 8 users. It can be seen that the noise-robustness loss of the OGM2 algorithm at $FER = 10^{-2}$ is also about 0.2 dB.

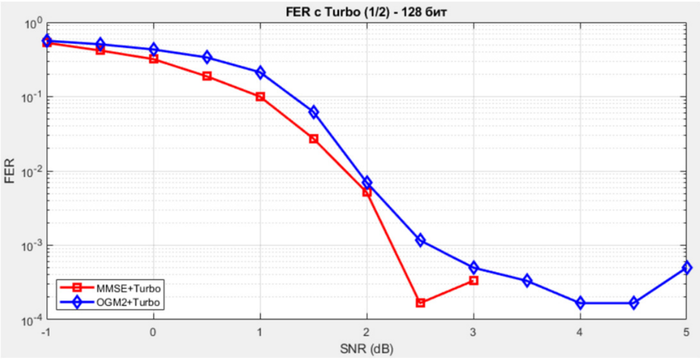

Fig. 7. Performance characteristics of the MU-MIMO system for 4 users with a 512×512 antenna configuration.

Figure 7 shows the dependence of the frame error rate (FER with turbo coding) on the signal-to-noise ratio for a MU-MIMO system with a 512×512 antenna configuration using the MMSE and OGM2 algorithms for 4 users. From the graph, it can be seen that the noise-robustness loss of the OGM2 algorithm at $FER = 10^{-2}$ is also approximately 0.2 dB.

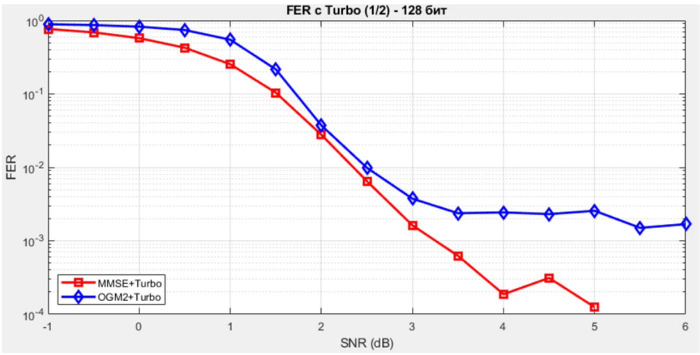

Fig. 8. Performance characteristics of the MU-MIMO system for 8 users with a 512×512 antenna configuration.

Figure 8 presents similar results for 8 users. It can be observed that the noise-robustness loss of the OGM2 algorithm at $FER = 10^{-2}$ is also about 0.2 dB.

8 Conclusions

Based on the conducted statistical simulation of a high-dimensional MU-MIMO system with various antenna configurations and numbers of users, using the proposed linear iterative demodulation algorithm based on OGM2, the following conclusions can be drawn.

1. **Reduction of computational complexity.**The proposed OGM2-based demodulation algorithm demonstrates a significant advantage in computational complexity compared to the conventional MMSE algorithm. For a MU-MIMO system with a 128×128 antenna configuration, the gain is approximately 2.0 times; for a 256×256 – configuration, about 3.9 times; and for a 512×512 – configuration, up to 7.9 times. The obtained results show that the efficiency of the OGM2 algorithm increases with the system dimensionality. This makes the proposed algorithm promising for application in Massive MU-MIMO systems, where the use of the conventional MMSE detector becomes challenging due to high computational load and hardware implementation complexity.

2. **Acceptable degradation in noise immunity.** The simulation results show that the proposed iterative algorithm introduces only a minor loss in noise immunity compared to the optimal MMSE algorithm when turbo coding is employed. For different system configurations and numbers of users, the energy loss at $FER = 10^{-2}$ s approximately in the range of (0.1-0.2) dB, which can be considered an acceptable trade-off for a significant reduction in computational complexity of 2 to 8 times. In some cases, for example in the 128×128 configuration with 8 users, the difference between OGM2 and MMSE is practically negligible, further confirming the high efficiency of the proposed approach.

3. **Robustness under spatially correlated fading.** The simulation results obtained for a spatial correlation level of $p_{\mathrm{t}} = p_{\mathrm{r}} = 0.2$ demonstrate that the proposed algorithm maintains stable performance under correlated fading conditions typical of real wireless channels. This confirms the applicability of the algorithm not only in idealized channel models with independent fading, but also in more realistic MU-MIMO operating scenarios. Therefore, the algorithm can be effectively used in practical wireless communication systems.

4. **Performance under different numbers of users.**The analysis of simulation results for different numbers of users (4 and 8 users) shows that the proposed algorithm maintains high efficiency even as the number of simultaneously served users increases. This indicates good robustness against inter-user interference and confirms its suitability for multi-user systems with high traffic density.

5. **Scalability with system dimensionality.**The results obtained for MIMO systems with 128×128, 256×256 и 512×512 antenna configurations confirm that the computational gain of the proposed algorithm relative to MMSE increases with system dimensionality. This property is particularly important for future Massive MU-MIMO systems, where a further increase in the number of base station antennas is expected. Thus, the OGM2 algorithm demonstrates good scalability and is capable of efficient operation in large-scale systems.

Based on the obtained results, the use of the proposed iterative OGM2-based demodulation algorithm is well justified for high-dimensional multi-user MU-MIMO systems. The algorithm provides an effective trade-off between computational complexity and noise immunity while maintaining robust performance under realistic conditions with spatial fading correlation and inter-user interference.

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ИТЕРАЦИОННЫЙ АЛГОРИТМ ДЕМОДУЛЯЦИИ НА ОСНОВЕ МЕТОДА ГРАДИЕНТНОГО ПОИСКА ДЛЯ СИСТЕМ MU-MIMO С БОЛЬШИМ ЧИСЛОМ АНТЕНН

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Аннотация

В данной работе предлагается и исследуется итерационный алгоритм демодуляции на основе оптимизированного градиентного метода (OGM2) для многопользовательских систем MIMO (MU-MIMO) высокой размерности с учетом пространственной корреляции замираний. Классический алгоритм MMSE, эффективный для малых антенных конфигураций, становится неприменимым в системах Massive MU-MIMO из-за высокой вычислительной сложности. Предлагаемый итерационный подход обеспечивает значительное снижение вычислительных затрат при сохранении приемлемой помехоустойчивости в условиях, приближенных к условиям реальных каналов связи. Приводятся результаты имитационного моделирования для системы MU-MIMO с конфигурациями антенн 128x128, 256x256 и 512x512 для 4 и 8 пользователей при уровне пространственной корреляции замираний, равном 0.2. Показано, что предлагаемый алгоритм обеспечивает снижение вычислительной сложности в 2-8 раз по сравнению с традиционным алгоритмом MMSE при потерях в помехоустойчивости не более 0.1-0.2 дБ в системах с турбокодированием на уровне $FER = 10^{-2}$. Результаты демонстрируют устойчивость алгоритма к пространственной корреляции, что подтверждает его практическую применимость в реальных системах MIMO.

Ключевые слова: *MU-MIMO, Massive MIMO, MMSE, OGM2, пространственная корреляция, помехоустойчивость, вычислительная сложность, турбокод, QAM*

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