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Particle swarm optimization in the LTE system for symbol detection

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This study suggests various ways to improve the performance of mobile terminals at fast speeds, cheap cost, and low power consumption. Indeed, higher rates imply more problematic transmission channels, making receivers' jobs more onerous. We're interested in solving the classic problem of detecting a linear mixture of Gaussian noise for LTE telecommunication systems from a noisy observation of an input signal mixed with a known matrix representing the channel's behavior; we're looking for the vector that minimizes the Euclidean distance between the noisy output and the noiseless one. The frequency diversity of LTE systems is very high. In this context, we look at the performance of traditional equalizers (ML, ZF, MMSE) in the first part. In the second section, we offer PSO (Particular Swarm Optimization), a detection method with near-optimal performance in terms of bit error rate BER 10^{-3} for SNR of 16 dB, which is extremely close to ML.

Keywords: long-term evolution, maximum likelihood, zero forcing, minimal mean square error, particular swarm optimization, bit error rate, signal-to-noise ratio.

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Introduction

The communications industry is currently at a critical juncture in its development. Technologies performance has improved as a result of their shrinking. Wireless and mobile communication are major obstacles. Several generations have passed, each with the goal of increasing speed and capacity while maintaining a high level of service quality. Prior to the eventual acceptance of digital modulation, the wireless world went through an analogue phase. Throughput can be enhanced by simultaneously delivering distinct streams of data on different transmit antennas but at the same carrier frequency (LTE system) by using multiple antennas at both the transmitter and receiver. Furthermore, OFDM (orthogonal frequency division multiplexing) has the potential to improve spectral efficiency. The combination of both LTE's throughput increase and OFDM's resistance against frequency-selective fading produced by severe multipath scattering and narrowband interference is seen as a promising foundation for future high-speed data transfer. As a result, the task at hand is to develop an LTE system that is both efficient and simple [1]. Symbol detection is necessary for coherent demodulation in these systems, but LTE detection is a computationally intensive and time-consuming task. As a result, a number of techniques for detecting symbols have been developed, including maximum likelihood (ML), zero forcing (ZF), and minimal mean square error (MMSE). Although ZF and MMSE are simple and quick to implement, they perform poorly in rapid fading and time-varying settings. In these circumstances, the ML method outperforms all others [2]. However, the fundamental disadvantage of machine learning is its tremendous computational complexity. It scans each subcarrier's candidate symbol vector and computes the Euclidean distance between received and actual symbols in all conceivable transmission combinations. Furthermore, as the number of transmitter and receiver antennas increases, the search space rises exponentially, increasing the computing complexity [3]. In this research, we examine and compare several detection methods, and we propose a heuristic approach called PSO to minimize the search space of ML detectors while also lowering computing complexity.

1. Problem formulation

We'll go through an LTE system briefly before getting into signal detection. The LTE system is illustrated in Fig. 1 as a simplified block diagram. N_{tx} transmit and N_{rx} receive antennas, n OFDM symbols, and K subcarriers are used in this system.

The modulation type is used to convert the data stream onto complex symbols. The symbol vector that is conveyed is written as follows:

$$S(n,k) = \left[S_1(n,k), \dots, S_{N_{tx}}(n,k)\right]^T, \quad k = 0 \dots 1.$$

The symbol $S_i(n,k)$ is sent on the n^{th} symbol, the k^{th} subcarrier, and the i^{th} antenna. Transpose operation is represented by the letter T. Symbol vectors are converted into OFDM symbols using the inverse fast Fourier transform (IFFT).

$$S_n[m] = \frac{1}{\sqrt{k_{N_{tx}}}} \sum_{k=0}^{1} S[n,k] e^{j2\pi m/k}, \quad m = 0 \dots k.$$

We use cyclic prefix (CP) to remove inter symbol interference (ISI) before feeding signal vectors via the i^{th} transmitter antenna. At the q^{th} receiver antenna, the CP is eliminated from the signal vector, and the fast Fourier transform (FFT) is used.

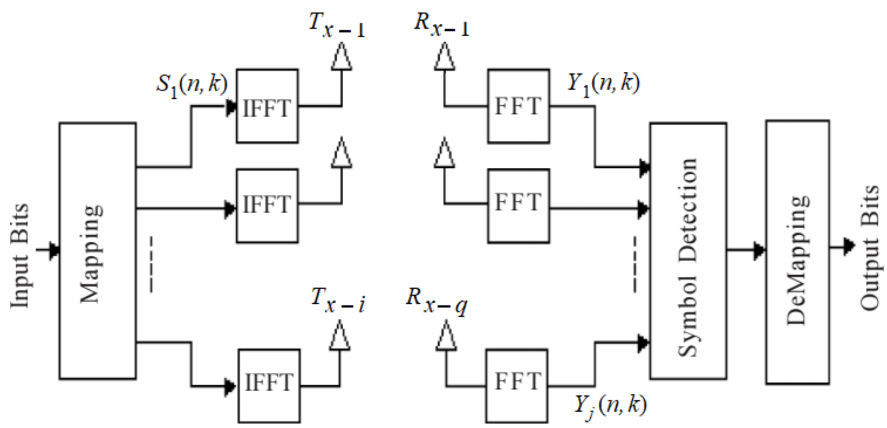

Fig. 1. Block diagram of MIMO-OFDM system

The signal vector received can then be written as

$$Y_q[n,k] = \sum_{i=1}^{N_{tx}} H_i[n,k] S_i[n,k] + W_q[n,k],$$

$W_q[n,k]$ is additive white Gaussian noise, while $H_i[n,k]$ is a channel impulse response vector.

The goal is to distinguish N_{tx} transmitted symbols S from a set of N_{rx} observed symbols Y that have gone over a non-ideal communication channel H, which is commonly described as a linear system followed by an AWGN W [4].

2. Performance of ZF, MMSE, and ML Equalizers in LTE

We investigate BER evaluation based on SNR while changing the type of Equalizer, mapping technique, and antenna count.

2.1. The effect of Equalizer type on BER fluctuation as measured by SNR

We utilise simulated QAM-4 modulation for the LTE system with 64 subcarriers and 16 the length of the Cyclic prefix to compare the characteristic BER according to the SNR for MMSE, ZF, and ML Equalizer. Figure 2 depicts the outcome of this comparison.

The performance of symbol detectors in LTE systems is demonstrated in Fig. 2 as a function of bit error rate (BER) and signal-to-noise ratio (SNR). The ML method outperforms the ZF and MMSE algorithms, as can be demonstrated. All M N_{tx} feasible combinations of transmitted symbols must be searched in order to get the best ML detection solution. When a result, as the transmitter antenna gets bigger, the computational complexity grows.

2.2. For a ZF, MMSE, and ML Equalizer, the effect of method modulation on BER variation according to SNR

For LTE systems, we assume the channel is multi-journey, with 64 subcarriers and 16 cyclic prefix length. Figures 3 and 4 show the performance of the ZF and MMSE Equalizers in terms of BER while employing QAM-4 modulation, QAM-16, QAM-64, and ML detectors

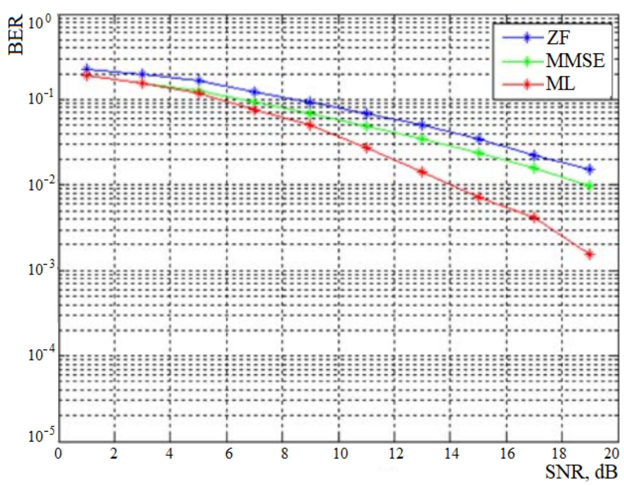

Fig. 2. For LTE systems with QAM-4 modulation, BER according to SNR for ZF, MMSE, and ML detectors utilizing Rayleigh canal

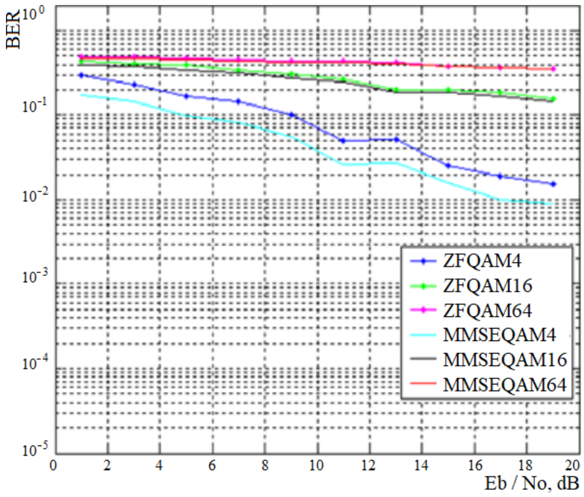

Fig. 3. For LTE systems, BER according to SNR for ZF modulations QAM-4, QAM-16, QAM-64, and MMSE Equalizer

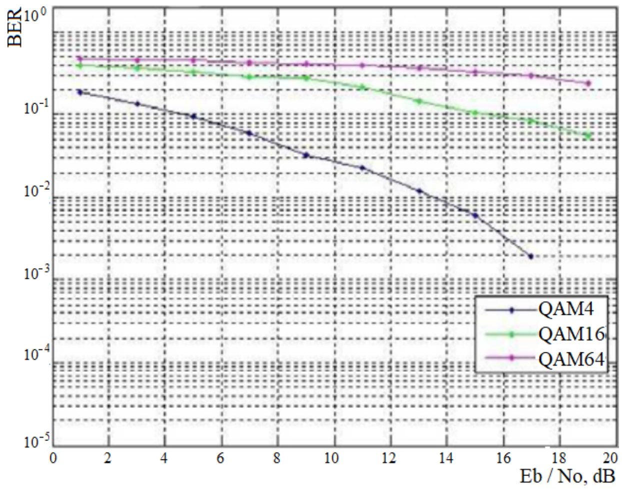

Fig. 4. For LTE system, BER corresponds to SNR for QAM-4, QAM-16, and QAM-64 modulations of the ML detector

under the same simulation conditions. As the number of possible states in the constellation diagram grows from QAM-4 to QAM-64, the principle of worth precinct observed becomes more and more complicated when sweeping the entire diagram. The larger the number of states, the greater the probability of a binary mistake.

2.3. The effect of antennas count on BER fluctuation as a function of SNR

To examine the typical BER according to SNR for different numbers of antenna, we utilize QAM-4 modulation with 64 subcarriers and 16 the length of the Cyclic prefix for LTE system simulation (Fig. 5). In comparison to Fig. 2, we can see that the system's performance is proportional to the number of antennas because the channel capacity grows as the number of antennas grows.

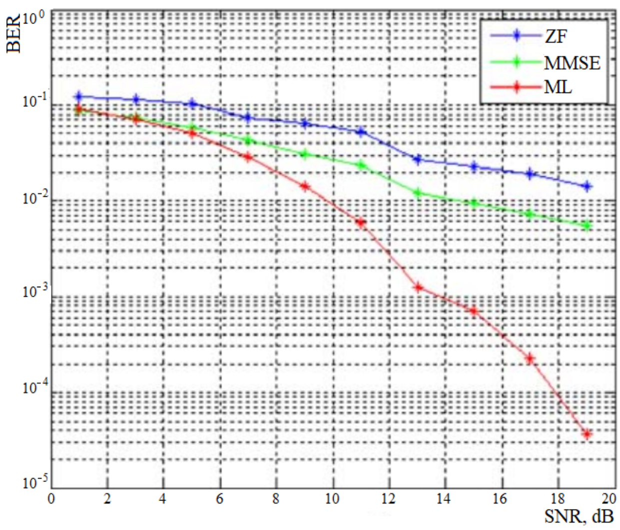

Fig. 5. For ZF, MMSE, and ML detectors employing QAM-4 modulation and LTE systems, BER according to SNR

3. Using particle swarm optimization meta-heuristics to recognize symbols in LTE system

The channel receives symbols from a known finite alphabet of size M, $v = \{x_1, \ldots, x_M\}$. From the provided data, the detector selects one of $M^{N_{tx}}$ potential transmitted symbol vectors. The maximum likelihood detector always produces an optimal solution, assuming that the symbol vectors $x \in V_{N_{tx}}$ are equiprobable:

$$X = \arg\max_{x \in V_{nx}} P\Big(y \text{ is observed} \Big| x \text{ was sent}\Big).$$

The ML detection issue can be described as the reduction of the squared Euclidean distance to a target vector y across a N_{tx} dimensional finite discrete search set, assuming the additive noise w is white and Gaussian.

$$X = \arg\min_{x \in V_{N_{tx}}} ||y - Hx||^2. \tag{1}$$

All $M_{N_{tx}}$ or $2^{bN_{tx}}$ symbol combinations must be examined using the best ML detection scheme (b is the number of bits per symbol).

The problem can be solved by counting all of the potential x and finding the one that results in the lowest value, as shown in (1). When a result, as the constellation size M and number of transmitters N_{tx} grow, the computational complexity grows exponentially. We introduce PSO-assisted LTE symbol detectors, which treat the LTE symbol detection problem as a combinatorial optimization problem and iteratively estimate the near optimal solution with computing cost lower than that of ML.

3.1. Particle swarm optimization

A swarm is made up of many particles (possible solutions) that move (fly) over the viable solution space in order to find the best solution, which can be encoded as binary strings or real-valued vectors. The particles can interact with each other in a particular neighbourhood and navigate a search space in which a quality metric, fitness, can be assessed. Over the course of iterations, the particles cooperate and compete with one another. Each particle's coordinates reflect a feasible solution for which two vectors, position X_i and velocity V_i, have been assigned (Fig. 6).

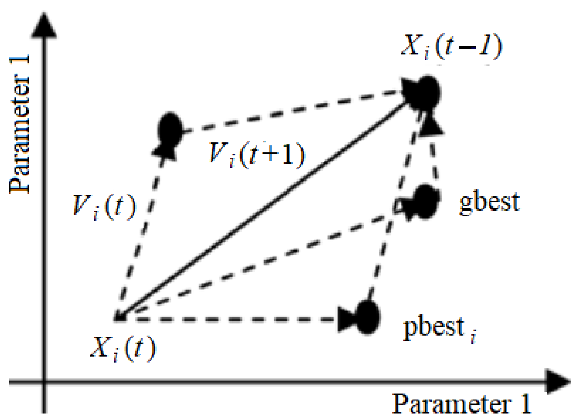

Fig. 6. Vector representation of PSO model

Each particle goes through an iterative adaptation process to two types of major information: individual learning and cultural transmission, which means that the procedure accelerates particles at each time step towards their personal best (best value recorded by each particle) and the position of the most recent global best point (best position returned form the swarm).

The PSO technique has a basic mathematical model with only two model equations and fewer parameters to change [5]. This is one of its most appealing features.

3.2. PSO-LTE detection algorithm

The definition of a fitness function, which connects the optimization algorithm to the real-world problem, is a key step in putting PSO into practice. Each optimization issue has a different fitness function. The fitness function produces a fitness value that can be set to the current position when using the particle's coordinates. If the value is higher than the value at each particle's personal best (pbest) or the swarm's global best (gbest), previous locations are overwritten. According to the relative positions of pbest and gbest, the particle's velocity changes. The particle simply advances to the next spot once the velocity has been computed. This method is then repeated for each particle until the maximum number of iterations has been reached.

The following is a description of the suggested MIMO detection technique, which is based on the Conventional continuous PSO [6] (Fig. 7).

1. Using the initial solution guess, set the particle size (swarm) to zero. Set the parameters of the algorithm.
2. Using (1) is used to determine the fitness of each particle:

$$f = ||y - H_x||^2.$$

The solution's fitness is measured by the minimum Euclidean distance between symbols. Find the population's global best performance, gbest_{id}, that indicates the shortest Euclidean distance. For each bit, keep track of your personal best pbest_{id} and its prior values.

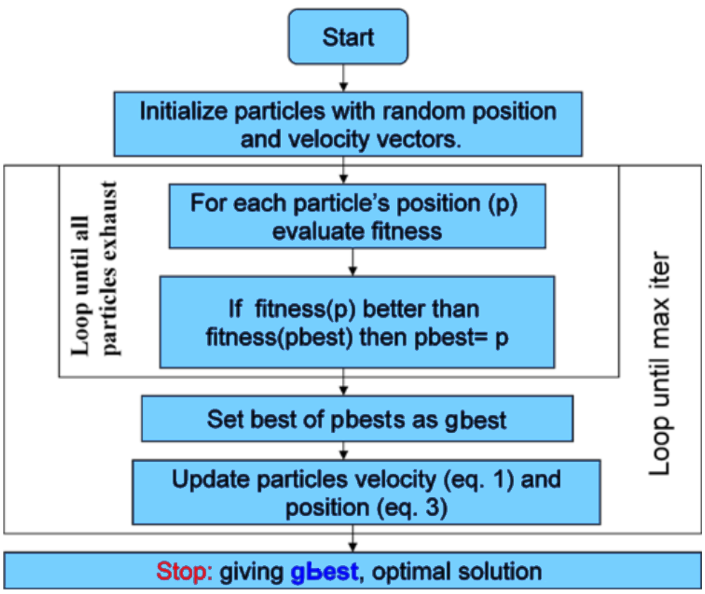

Fig. 7. Flow chart depicting the PSO algorithm

3. The following PSO velocity update equation is used to compute each particle's velocity:

$$V_{id}(k) = V_{id}(k-1) + \varphi_1 \mathrm{rand}[\mathrm{pbest}_{id} - x_{id}(k-1)] + \varphi_2 \mathrm{rand}_2[\mathrm{gbest}_{id} - x_{id}(k-1)]. \quad (2)$$

4. The following PSO velocity update equation is used to update particle position:

$$x_{id}(k) = x_{id}(k-1) + V_{id}(k).$$

5. Repeat step 2 until you've completed the maximum amount of repeats. The number of iterations is denoted by the letter k. For efficient performance, an optimal number of iterations is tuned. Iteratively fine-tuning the answer [7].

3.3. Simulation results

The algorithms' performance was evaluated using systems with a 10 MHz bandwidth and 16 QAM modulation for varied antenna sizes across the channel. Tables 1 and 2 contain the PSO system and channel parameters, respectively. With 64 subcarriers, CP length of 16, BPSK modulation, and LTE systems, we compare the performance of ZF, MMSE, ML, and PSO detectors. Figure 8 compares the performance of the ZF, MMSE, ML, and PSO detectors against the ML for a 2×2 2-QAM LTE system in terms of BER vs Eb/No. PSO outperforms ZF and MMSE algorithms, and its BER performance is comparable to that of ML detectors. At a 17 dB SNR value, for example, the BER difference between PSO and ZF is greater than (10 to power 1). However, a significant reduction in ML complexity is obtained, as detailed in the following part. Table 3 also contains the parameters of the proposed PSO algorithms with GA and BSA for symbol detection. Figure 8 depicts a comparison of the proposed method's results with those of other detectors for a PSO system with a two-antenna array.

Although the ML approach has the best performance (as shown in Fig. 8), increasing the size of the transmitter and receiver antennas renders this algorithm unworkable in terms of complexity. Furthermore, the suggested PSO method outperforms both standard and heuristic techniques in terms of BER values. The PSO algorithm outperforms the worst-performing ZF by 14 dB and the BSA by 2 dB at 10^{-1} BER. Additionally, for a 20 dB

T a b l e 1. LTE-PSO system parameters

Parameter	Value
Bandwidth	10 MHz
Number of subcarriers	64
Number of user	2
Power allocation factor	$0.75 \ldots 0.25$
Modulation	16 QAM

T a b l e 2. Channel parameters

Path	1	2	3	4	5	6
Delay spread, μs	0	0.3	1.0	1.6	5.0	6.6
Average power, dB	-2.5	0	-3	-5	-2	-4

T a b l e 3. Heuristic algorithm parameters

BSO	PSO	GA
Number of population 30 Step size amplification 3 RND generation interval $(0-1)$ Mix rate 1	Swarm size 30 Max velocity 20 Inertia factor $0.9 \ldots 0.4$ Learning factor 2	Number of population 30 Crossover rate 0.8 Mutation rate 0.5

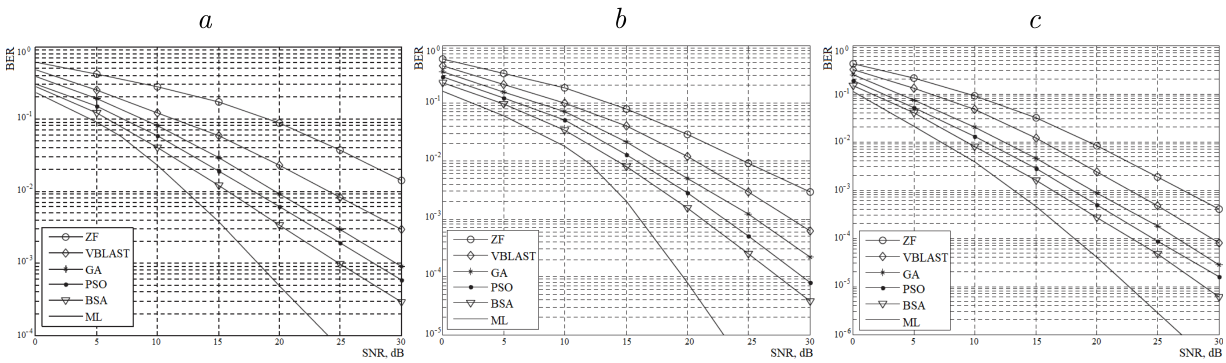

Fig. 8. BER according to SNR for ZF, VBLAST, ML, GA, BSA and PSO detector for 2×2 (*a*), 4×4 (*b*), and 8×8 (*c*) LTE

signal to noise ratio (SNR), the difference between PSO and VBLAST is roughly 10^{-1}. Figure 8, *b* shows the suggested detector's BER performance for systems with four antennas. BER = 102 GA requires 18 and 16.5 dB for BSA, and 14 dB for PSO, as shown in Fig. 3. Moreover, the proposal's needed SNR value is lower than the other techniques for lower BER values.

Finally, when comparing the performance of the algorithms for the system with 8×8 antennas in Fig. 8, *c*, we can see that our proposal improves detection capability not only for small antenna arrays but also for larger antenna arrays. According to Fig. 8, *c*, the PSO method requires more than 21 dB of SNR to achieve BER = 103, whereas the BSA and GA algorithms require around 23.5 and 26 dB of SNR to achieve BER = 103, respectively. All of the figures show that our concept provides significant SNR gains over other detectors.

3.4. Computational complexity theoretical evaluation

The computational complexity of the disclosed PSO-MIMO detector is investigated in this paper, and a theoretical formulation for computational complexity is established. The method is also compared to the traditional ML optimum detection method. We aim to give a reasonable estimate of complexity in terms of the number of complex multiplications because the hardware cost of each algorithm is implementation specific. Table 4 contains the detector complexity comparative analysis in terms of the number of multiplications.

In terms of N_{tx}, N_{rx} and constellation size M, the computational complexity is calculated. As can be seen from (1), the ML detector requires MN_{tx} multiplications for matrix multiplication and $MN_{tx}N_{rx}$ multiplications for square operations [8]. As a result, the difficulty of machine learning increases.

$$\varepsilon_{\mathrm{ML}} = N_{rx}(N_{tx}+1)MN_{tx}.$$

T a b l e 4. Computational complexity analysis of detectors

Detector	2×2 LTE	4×4 LTE	8×8 LTE
ML	1536	1 320 720	$309{\cdot}10^9$
ZF	48	384	3072
VBLAST	70	712	8864
BSA	1440	5400	23 760
PSO	1800	6480	29 700
GA	1980	7560	31 680

First fitness of each particle in population N_P is computed for the proposed detector using (1). The complexity of multiplication for PSO is a measure of how difficult it is to multiply a number becomes

$$\varepsilon_{\mathrm{PSO}} = N_P(N_{tx}N_{rx}).$$

Pheromone updates and velocity updates in PSO both necessitate extra multiplications every iteration (2). $W = 1$ are assumed to reduce some complexity. As a result, the level of difficulty rises

$$\varepsilon_{\mathrm{PSO}} = N_P(N_{tx}N_{rx} + \mu_{vel}).$$

To get to the near-optimal BER performance, this technique is done N_{itr} times. Therefore,

$$\varepsilon_{\mathrm{PSO}} = N_P(N_{tx}N_{rx} + \mu_{vel})N_{itr}.$$

With N_{tx} and M, ML's complexity grows exponentially. In MIMO systems with multiple transmitters, this gain is much greater with higher-order modulation methods. Because it is based solely on the amount of complex multiplications, this complexity estimate is only meaningful in the order of magnitude sense. For the LTE system [7], the aforementioned complexity is calculated by sub carrier.

Conclusion

Global research in the field of digital communications without son has advanced significantly in recent years. The development of new systems attempts to transmit digital data at higher bandwidths and provide service to a larger number of people. Following a discussion of the fundamental principles of digital transmission and the exposure characteristics of the linear model of the wireless channel, examples of systems studied in the literature and depicted as linear radio channels are given, followed by a discussion of detection techniques under optimal sub optimal most popular. These sensors do not make a trade-off between performance and complexity; for example, simple linear detectors perform poorly compared to maximum likelihood detectors, which have a significantly higher computational complexity. The results demonstrate that ML is the best detector, albeit with a large search space and significant processing complexity. As a result, we proposed the PSO method for lowering it. Particle detection swarm PSO approach yields encouraging results.

References

[1] **Khare A., Saxena M., Mandloi V.S.** Performance analysis of V-blast based MIMO-OFDM system with various detection techniques. International Journal of Engineering and Advanced Technology (IJEAT). 2011; 1(2):64–67. ISSN:2249-8958. Available at: `https://www.ijeat.org/wp-content/uploads/papers/v1i2/B0135111211.pdf`.

[2] **Kiessling M., Speidel J.** Analytical performance of MIMO zero-forcing receivers in correlated Rayleigh fading environments. Proceedings of the IEEE Workshop on Signal Processing Advances in Wireless Communication. Rome, Italy; 2003: 383–387.

[3] **Jiang M., Akthman J., Guo F., Hanzo L.** Iterative joint channel and symbol detection for multiuser MIMO-OFDM. Proceedings of the IEEE Vehicular Technology Conference. Melbourne, Australia; 2006: 63–72.

[4] **Liang Y.M., Luo H.W., Huang J.G.** RLS channel estimation with adaptive forgetting factor in space time coded MIMO-OFDM systems. Journal of Zhejiang University Science. 2006; (7):507–515.

[5] **Kennedy J., Eberhart R.C.** Swarm intelligence. San-Francisco: Morgan Kaufman Publisher; 2001: 541. Available at: `https://www.scirp.org/reference/referencespapers.aspx?referenceid=1304666`.

[6] **Khan A.A., Bashir S., Naeem M., Shah S.I.** Optimized detection in multi-antenna system using particle swarm algorithm. Third International Conference on Intelligent Systems. Prague, Czech Republic; 2006: 113–121.

[7] **Khan A.A., Bashir S., Naeem M., Shah S.I., Li X.** Symbol detection in spatial multiplexing system using particle swarm optimization meta-heuristics. International Journal of Communication Systems. 2008; 21(12):1239–1257.

[8] **Khan A.A., Naeem M., Shah S.I.** A particle swarm algorithm for symbols detection in wideband spatial multiplexing systems. Proceedings of the Annual Conference on Genetic and Evolutionary Computation. London, England; 2007: 77–84.

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ИНФОРМАЦИОННЫЕ ТЕХНОЛОГИИ

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Оптимизация роя частиц в системе LTE для обнаружения символов

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Аннотация

Предложены различные способы повышения производительности мобильных терминалов за счет высоких скоростей, низких стоимости и энергопотребления. Действительно, более высокие скорости подразумевают более проблемные каналы передачи, что делает работу приемников более обременительной. Нас интересует решение классической задачи обнаружения линейной смеси гауссовых шумов для телекоммуникационных систем LTE по зашумленному наблюдению входного сигнала, смешанного с известной матрицей, представляющей поведение канала. Требуется найти вектор, который минимизирует евклидово расстояние между зашумленным выходом и бесшумным. Частотное разнообразие систем LTE очень велико. В этом контексте рассмотрена производительность традиционных эквалайзеров (ML, ZF, MMSE), предложен PSO (Particular Swarm Optimization) — метод обнаружения с почти оптимальной производительностью с точки зрения частоты ошибок по битам BER 10^{-3} для SNR 16 дБ.

Ключевые слова: долговременная эволюция, максимальное правдоподобие, нулевой форсинг, минимальная среднеквадратическая ошибка, рой частиц, частота битовых ошибок, отношение сигнал — шум.

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