# Optimized decoder for low-density parity check codes based on genetic algorithms

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**ABSTRACT**

Low-density parity check (LDPC) codes, are a family of error-correcting codes, their performances close to the Shannon limit make them very attractive solutions for digital communication systems. There are several algorithms for decoding LDPC codes that show great diversity in terms of performance related to error correction. Also, very recently, many research papers involved the genetic algorithm (GA) in coding theory, in particular, in the decoding linear block codes case, which has heavily contributed to reducing the bit error rate (BER). In this paper, an efficient method based on the GA is proposed and it is used to improve the power of correction in terms of BER and the frame error rate (FER) of LDPC codes. Subsequently, the proposed algorithm can independently decide the most suitable moment to stop the decoding process, moreover, it does not require channel information (CSI) making it adaptable for all types of channels with different noise or intensity. The simulations show that the proposed algorithm is more efficient in terms of BER compared to other LDPC code decoders.



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## 1. INTRODUCTION

Gallagher's initial publication in 1963 outlined an iterative decoding method for low-density parity check (LDPC) codes, demonstrating remarkable performance in terms of bit error rate (BER). This particular decoding technique, known as the sum-product algorithm (SPA), was introduced to estimate the probability associated with each message symbol [1]. Another highly effective example of soft decision decoding algorithms is the log-likelihood-ratio-based belief propagation (LLR BP) [2] which is, nevertheless, difficult to implement for sophisticated computations. As a reduction of the LLR BP method, [3] two sides of the min sum (MS) algorithm enable the implementation of soft decisions by replacing the tanh function with the minimal value at the expense of non-negligible performance loss. Several enhancements were proposed to close the disparity between both the BP algorithm and the MS approach [4]. Although the weighted BF (WBF) algorithm as well as the gradient descent BF (GDBF) have made significant progress over the soft decision decoding algorithm [5]–[9], but the gap between the two decoding methods is still there. To combine the advantages of the two procedures discussed above, the hybrid decision [10]–[13] has been proposed, which typically comprises two separate iterative serial decoding steps, if the first stage of the algorithm fails to discover the right decoded vector after a predetermined number of iterations, the algorithm will proceed to the second step until the number of iteration reaches its maximum value or the decoding is successful. Moreover, a decoding algorithm aiming for the best BER performance should work with knowledge of the channel parameters, sometimes known as channel side information (CSI) [14]. Several methods have been developed recently to avoid the need for CSI, among these methods we find the algorithm [15], which is based on the Euclidean distance and which performs better than the SPA whether it is on a Gaussian or Rayleigh noise channel. As shown in [16]–[18] genetic algorithm (GA) can be used as a decoding method that does not require CSI. Similar algorithms have been found in the literature to perform well as decoders for various coding schemes [19]–[22].

To achieve this, a novel decoding algorithm is introduced, exploiting GA for LDPC codes without the need for CSI. Notably, this proposed algorithm exhibits the capability to autonomously determine the optimal moment for concluding the decoding process, a distinctive feature setting it apart from existing algorithms in the literature, where decoder termination is typically governed by predefined parameters. Simulation results demonstrate the enhanced efficiency of the proposed algorithm in terms of BER and FER when compared to other LDPC code decoders. The structure of the paper unfolds as follows: section 2 provides a concise overview of LDPC codes and GA, while section 3 delves into the presentation of the proposed algorithm, along with simulation outcomes and discussions in section 4, and finally concluding the paper in section 5.

## 2. RELATED WORKS

### 2.1. LDPC codes

LDPC codes are high-performance codes that are able to correct a significant number of errors during the iterations. Suppose we have an LDPC code C, and we receive a sequence $(ri)$ $1 < i < n$ over a communication channel that is affected by additive white gaussian noise (AWGN). If the degree of the variable node $d_v$ and the degree of the check node $d_c$ are fixed, then the LDPC code is considered regular. Otherwise, if either of the degrees varies, the LDPC code is classified as an irregular code. Furthermore, the LDPC code is defined by a graph called a Tanner graph [12], it simply splits the 'M' control nodes and 'N' variable nodes into two sides. The LDPC code's parity check matrix H has a sparse structure, meaning it consists mostly of zeros with a small number of “1” s. This characteristic is evident from the code's name. The syndrome $s$ can be computed for any received vector “$r$”. It is defined as (1):

$$s = H^t x\, r^{\,hard} \tag{1}$$

The syndrome calculation allows us to check if the vector $r$ is a correct code word or not, consequently, if the syndrome equals zero, then the correct code word is “$r$”, otherwise the received vector $r$ contains errors. Principally, syndrome checking is a way to detect errors in received codewords [1]. The goal of the decoding method for a given block code is to discover the vector “$d$” which can be thought of as an estimation of the transmitter vector “$r$” and can meet the following conditions:

$$H^t * d = 0$$

$$d = r^{hard} \tag{2}$$

### 2.2. Genetic algorithms

The genetic algorithm (GA) represents a heuristic approach grounded in Charles Darwin's concept of natural evolution. It mirrors the process of natural selection, wherein the most well-adapted individuals are chosen for reproduction, giving rise to the subsequent generation. This algorithm proves valuable in addressing scenarios where the objective function lacks differentiability, displays discontinuity, and involves stochastic elements. Its probabilistic optimization method boasts inherent parallel processing capabilities and global searching functionalities [16], [23]. Commencing with an initial population shaped by the survival of the fittest principle, GA assigns each individual a fitness function indicative of its adaptability to the environment. Throughout the iterative process, individuals demonstrating robust adaptability persist, while those with weaker adaptability are systematically eliminated. Reproduction unfolds through natural selection, crossover, and mutation, leading to the creation of new individuals. The most compatible individuals are selected as parents for the ensuing generation via natural selection. During the crossover phase, segments of genetic material from two individuals are exchanged, generating novel individuals. Subsequently, chosen individuals undergo mutation, contributing to the emergence of a new generation.

The primary goals of genetic operations encompass maintaining the best individuals within the population, generating fresh individuals with unique traits, and enhancing the overall adaptability of the population. Through numerous iterations, the adaptability of individuals undergoes continuous refinement, culminating in the eventual attainment of an optimal solution [24]. Figure 1 depicts the flowchart illustrating the sequential steps of the GA.

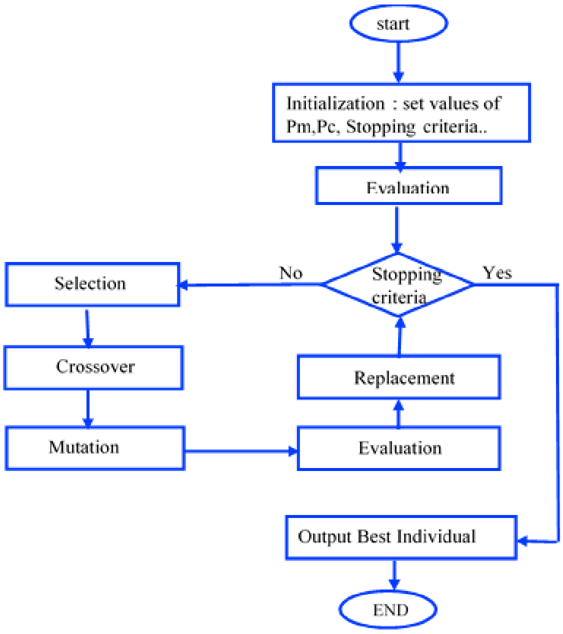


Figure 1. Flowchart of genetic algorithm

## 3. GENETIC ALGORITHM-BASED METHOD

In this part of the paper, a GA-based approach is introduced, employing a decoding strategy where an individual is represented as a series of numerical values ranging from 1 to the code's length (n). Furthermore, the various components of this proposed method function as explained in the following subsections. These elements of the algorithm include the fitness function, responsible for evaluating the fitness value of an individual.

### 3.1. Preliminaries and research method

The proposed method offers a decoding solution for the received vector without requiring any prior knowledge of channel information. Initially, a hard threshold is applied to the input vector, followed by the computation of the syndrome to assess the validity of the input vector as a code word. If the syndrome vector is non-zero, the GA decoding method is employed. This entire process is executed in parallel, highlighting efficiency and convergence towards the optimal decoding vector.

Let $c$ be the LDPC code, and $r_{i_{1<i<n}}$ the received vector over an AWGN Channel transmission, d is the hard decision of $r_{i_{1<i<n}}$ (3), and $c_x$ is the received vector $r_i$ transformed into [0,1] interval using hyperbolic tangent (4),

$$d = r^{hard} = \begin{cases} 1 & if\ r_i > 0 \\ 0 & otherwise \end{cases} \tag{3}$$

$$c_x = 0.5 * (1 + tanh\, r_i) \tag{4}$$

Firstly, we randomly generate $N_p$ (population size) vector ϵ [0,1] which will be the initial population $v_i$, and we define the vector $z_i$ as (5):

$$z_i = \begin{cases} 0 & if\ \ c_x < v_i \\ 1 & otherwise \end{cases} \tag{5}$$

The determination of optimal code-word (individuals) will rely on evaluating their fitness values through the fitness function, defined as (6):

$$Fitness = \sum_{i=1}^{m} S_i + \sum_{j=1}^{n} |z_i - c_x| \tag{6}$$

where $|z_i - c_x|$ is the distance between the individual vector and the received sequence and $S_i$ is the syndrome vector defined by (7).

$$S_i = z_i * H^T \tag{7}$$

### 3.2. The proposed method

In this approach, we utilized a fitness function based on established standards in the [18]. What sets our method apart is the algorithm's ability to autonomously determine the optimal moment to conclude the decoding process by the 'Limit counter' (which is chosen arbitrarily) which aims to ensure that it has explored the entire solution space. This distinct feature contrasts with other algorithms found in the literature, where decoder termination is often controlled by predefined parameters such as the number of generations. A detailed flowchart will be provided as shown in Figure 2, offering a comprehensive depiction of how the algorithm functions, with a clear representation of its inputs and outputs in Table 1.

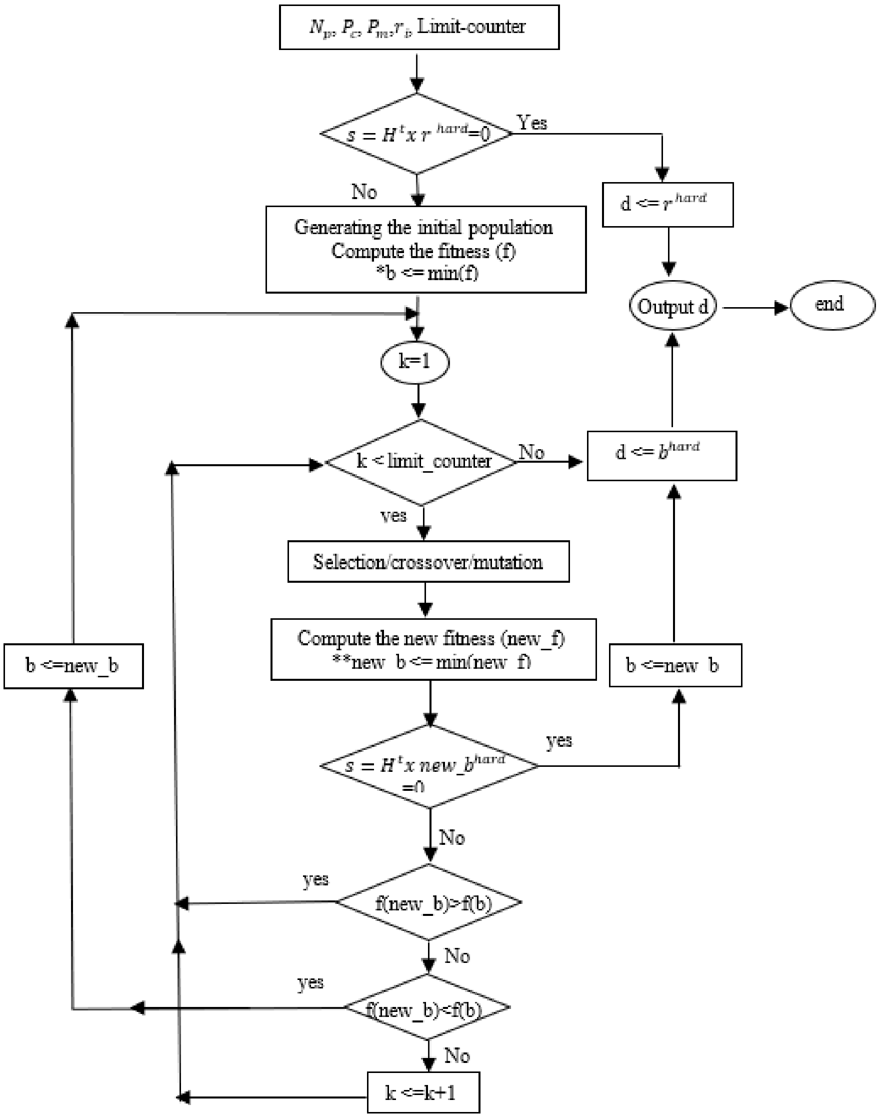


Figure 2. The proposed algorithm based on GA

Table 1. Input and output of the proposed algorithm

| | |
|---|---|
| Input | $r_i$ : the received codeword<br>$N_p$: initial population size<br>$P_c$: crossover probability rate<br>$P_m$: mutation probability rate<br>$Limit\_counter$: arbitrarily chosen parameters |
| Output | $d$: correct code-word |

Since our objective is to determine the individual (vector) with the least error, or ideally no error at all which is equivalent to the smallest fitness value, the fitness values must be classified into ascending order to choose the minimum value of the latter. This technique plays a crucial role in selecting and building individuals for the next generation through operators. By prioritizing the lowest fitness values, we increase the probability of selecting individuals leading to more efficient correction, thus improving the overall performance of the decoding process.

Since our goal is to find the vector that yields the minimum fitness value or $syndrome = 0$, the algorithm compares the vector (b) from the initial generation to the new vector (new_b) of the subsequent generation. If $f(new\_b) > f(b)$, we retain the vector $(b)$ and proceed to reproduce a new generation to search for a better result, specifically, the vector $(new\_b)$ with $f(new\_b) < f(b)$, in this case, the vector $(b)$ takes on the value of $(new\_b)$, and the reproduction process continues until exploring the entire solution space, aiming to achieve either $(s = 0)$ or $f(b) = f(new\_b)$, in this instance, the decoder repeats reproduction by incrementing $k$ if there is no change, to ensure that no new and better solution is present in the space. The decoding process stops when k reaches a predefined limit ($k = Limit\_counter$). However, if the decoder encounters $f(new\_b) < f(b)$, $k$ will be reset to 1, and the decoding process is repeated.

- $b$: is the vector or the individual that has the minimum value of fitness in the initial population.
- $new\_b$: is the vector or the individual that has the minimum value of fitness in the new population after selection, crossover, and mutation (it will be compared with b).

## 4. SIMULATION AND PERFORMANCE ANALYSIS

In this study, the BER and the FER are used as metrics to evaluate the performance or the correction power of the proposed decoding algorithm for a given noise level. Additionally, to the metric evaluations of the performance, the proposed algorithm must be compared with other ones that give good results in terms of BER and FER. The belief propagation (BP) and the normalized min sum (NMS) are chosen for the comparative study. Table 2 summarizes the used parameters in the simulations of the proposed algorithm coded in MATLAB. Two LDPC codes discussed below consist of code A: Gallager code (32,16) and code B: short the consultative committee for space data systems (CCSDS) code (32, 16) [25].

Table 2. Different parameters used in the simulations

| Designation | Parameters value |
|---|---|
| Population size (Np) | 500 |
| Crossover rate (Pc) | 70% |
| Mutation rate (Pm) | 1% |
| Limit counter | 5 |
| Channel | AWGN |
| Modulation | BPSK |
| LDPC regular code A&B | Gallager code N=32<br>CCSDS code N=32 |
| Type of selection | tournament |
| Type of crossover | 2 pts |
| Frame | 10000 |
| Max Iteration for NMS, BP | 6 |

Figure 3 presents the simulation results across various crossover rates, ranging from 50% to 90%. The performance of the proposed algorithm exhibits a decrease when the crossover rate $P_c$is set to 80%. However, upon closer examination of the graph, it becomes evident that alternative values of $P_c$ deliver favorable outcomes across different SNR settings. Notably, starting from an SNR of 4.5 dB, the proposed algorithm with $P_c$=70%, outperforms the other configurations. This observation prompts the selection of $P_c$=70% as the optimal choice for this contribution.

In Figure 4, we observe the simulation results that compare the performance of the algorithm across different population values, ranging from 100 to 500. The simulation reveals that the proposed algorithm exhibits improved decoding capabilities with larger population sizes. Consequently, the decision is made to select a population size of $N_p$=500 for this contribution. The rationale behind this choice lies in the understanding that a larger population size contributes to a higher diversity of individuals within the GA. This heightened diversity is instrumental in achieving a robust decoding performance. The larger pool of potential solutions afforded by a population size of 500 ensures that the GA explores a wide range of possibilities, thereby improving the overall efficacy of the proposed algorithm in correcting errors.

Figures 5 and 6 provide a comprehensive evaluation of the performance of the proposed algorithm applied to LDPC regular code A (16,32), with a focus on BER and FER compared to conventional algorithms such as BP and NMS both belonging to the soft decoding family. The results show a notable superiority of the suggested algorithm. Specifically, when considering BER values of $10^{-2}$ and $10^{-3}$, the proposed algorithm surpasses the others by a margin of 0.4 and 0.2 dB, respectively. These performance improvements suggest that the proposed algorithm is highly effective in error correction, outperforming established soft decoding algorithms in typical communication scenarios.

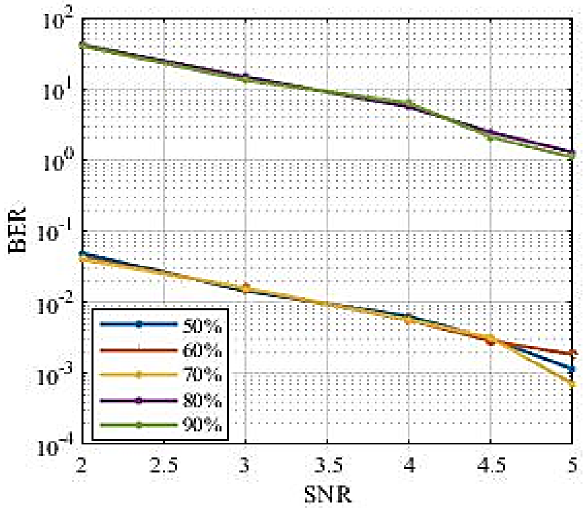


Figure 3. Comparison between different values of crossover rate Pc for LDPC code A (16,32)

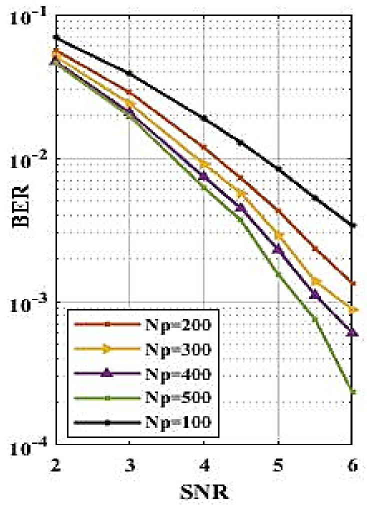


Figure 4. Comparison between different values of the population for LDPC code A (16,32)

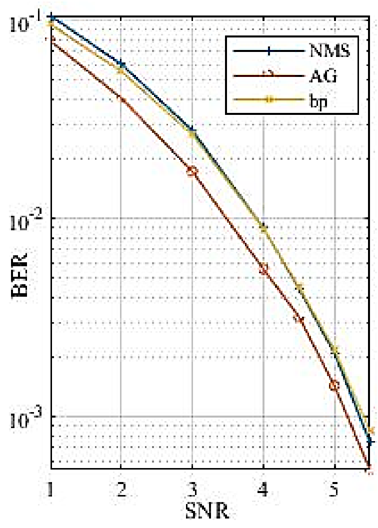


Figure 5. BER performance comparison of the proposed algorithm with BP and NMS for LDPC code A (16,32)

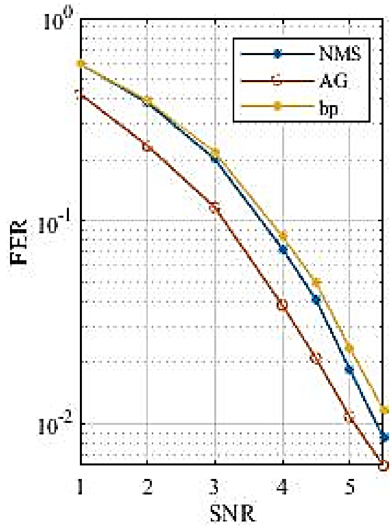


Figure 6. FER performance comparison of the proposed algorithm with BP and NMS for LDPC code A (16,32)

Figures 7 and 8 presents also the performance evaluation of the proposed algorithm for LDPC code B (16,32) in terms of BER and FER. The proposed method demonstrates consistently good results even when applied to a different LDPC code, specifically the one defined by the consultative committee for space data systems (CCSDS), distinct from the initial Gallagher code. With lower BER values, such as $10^{-3}$ and $10^{-4}$, the proposed algorithm consistently outperforms the traditional algorithms, BP and NMS, by a significant margin of 1 and 0.5 dB, respectively. This suggests that the proposed algorithm excels in error correction, showcasing its robustness and effectiveness across diverse LDPC codes.

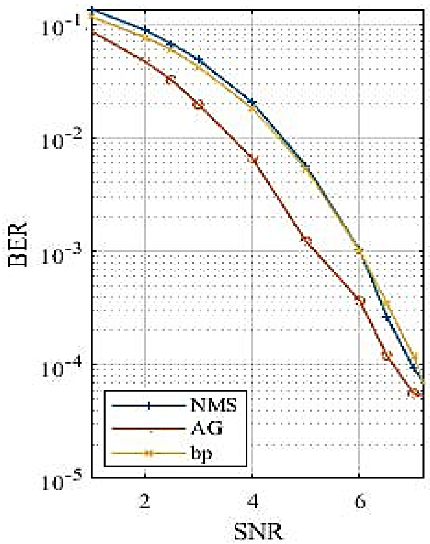


Figure 7. BER performance comparison of the proposed algorithm with BP and NMS for LDPC code B (16,32)

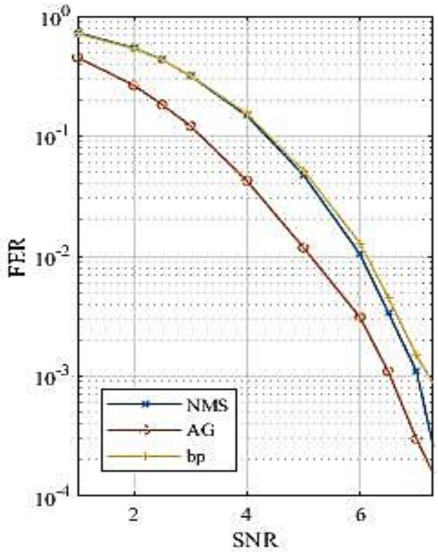


Figure 8. FER performance comparison of the proposed algorithm with BP and NMS for LDPC code B (16,32)

## 5. CONCLUSION

This paper proposes a new decoding approach based on the GA technique to enhance Low-Density Parity Check algorithm performance. GA is a handy approach since it can perform heuristic searches utilizing evolution-based convergence while traversing huge spaces at the same time. Additionally, the proposed decoder does not require any information on the channel which makes it adaptable for all types of channels with different types of noise or intensity, unlike other algorithms such as BP, NMS, and others. Moreover, the ability of the algorithm to autonomously determine the optimal moment to conclude the decoding process sets it apart from other algorithms found in the literature where the decoder stop is often controlled by predefined parameters. The simulations show that the proposed algorithm gives good results in terms of BER and FER compared to BP and NMS algorithms for different types of LDPC codes.

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