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GENETIC ALGORITHM FOR DECODING LINEAR CODES OVER AWGN AND FADING CHANNELS

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ABSTRACT

This paper introduces a decoder for binary linear codes based on Genetic Algorithm (GA) over the Gaussian and Rayleigh flat fading channel. The performances and compututional complexity of our decoder applied to BCH and convolutional codes are good compared to Chase-2 and Viterbi algorithm respectively. It show that our algorithm is less complex for linear block codes of large block length; furthermore it's performances can be improved by tuning the decoder's parameters, in particular the number of individuals by population and the number of generations

Keywords: *Block Code, Decoding, Methaheuristic, Genetic Algorithm, Neural Network*

1. INTRODUCTION

The current large development and deployment of wireless and digital communication encourages the research activities in the domain of error correcting codes. Codes are used to improve the reliability of data transmitted over communication channels susceptible to noise. Coding techniques create codewords by adding redundant information to the user information vectors. Decoding algorithms try to find the most likely transmitted codeword related to the received one as depicted in Fig.1.

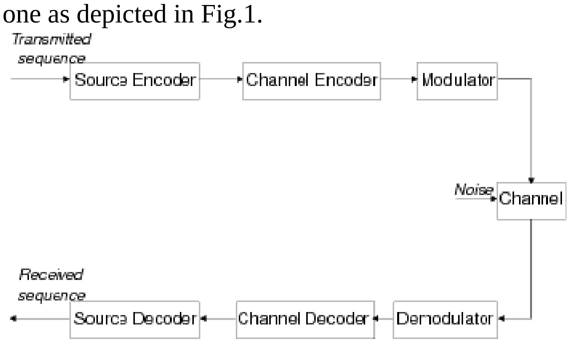

Fig. 1: Communication system model

Decoding algorithms are classified into two Categories: Hard decision and Soft decision algorithms. Hard decision algorithms work on a binary form of the received information. In contrast, soft decision algorithms work directly on the received symbols [1].

Soft-decision decoding is an NP-hard problem and was approached in different ways. Recently artificial intelligence techniques were introduced to solve this problem. Among the related works, the decoding of linear block codes using algorithm A* [9], genetic algorithms [10],[11] and neural networks [12].

Genetic Algorithms are search algorithms that were inspired by the mechanism of natural selection where stronger individuals are likely the winners in a competing environment. They combine survival of the fittest among string structures with a structured yet randomized information exchange to form a search algorithm with some of the innovative flair of human search. In each generation, a new set of artificial creatures (chromosomes) is created using bits and pieces of the fittest of the old [10],[13].

A artificial neural network, or supply feed forward neural network, is an interconnected group of artificial neurons that uses a mathematical model for information processing, based on the parallel architecture of animal brains [10].

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In this paper, we introduce two decoders based on genetic algorithms. The second decoder is improved by the use of neural networks. These decoders can be applied to any arbitrary binary linear code, in particular for codes with unknown algebraic decoder. In order to show the effectiveness of this decoder we applied it on some BCH and QR codes.

This paper is organized as follows. Section 2 describes the decoding of linear block codes based on genetic algorithms. The neural network enhanced the decoder will be presented in section 3. Section 4 reports the simulation results and discussions. Finally, Section 5 presents the conclusion and future trends.

2. THE FIRST DECODER

Let C denote a (n,k,d) binary linear code of generator matrix G, and let $(r_i)_{1\le i\le n}$ be the received sequence over a communication channel with noise variance $\sigma^2 = \frac{N_0}{2}$ where N_0 is noise power spectral density (W/Hz).

Let $(a_i)_{1\le i\le n}$ the fading amplitude vector associated in the case of fading channel

Let N_i, N_e and N_g denote respectively the population size, the number of elite members and the number of generations.

Let p_c and p_m be the crossover and the mutation rates.

2.1 Decoding Algorithm

The decoding based genetic algorithm is depicted on Fig 2. The steps of the decoder are as follows:

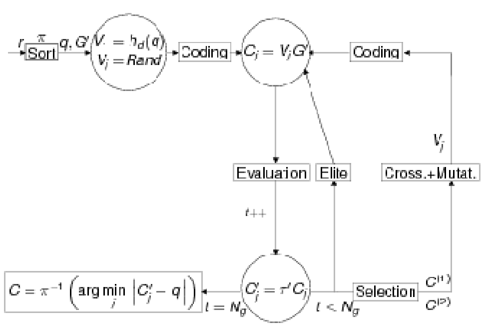

Fig. 2: Decoding of Linear Block Codes based genetic algorithm

Step 1. Sorting the sequence r (and the vector a in the case of fading channel) in descending order $(q = \pi r)$, such that the first k columns of the matrix $G' = \pi G$ are linearly independent :

$$\begin{cases} q_i = r_{p_i}, b_i = a_{p_i}, 1\le i\le n,\ p_i \in \{1,..,n\} \\ |q_1| \ge |q_2| \ge \quad \ge |q_n| \end{cases}$$

Step 2. Generate an *initial* population of N_i binary vectors of k bits:

2.1. The first member V_1 of this population is obtained by the quantization of the q:

$$V_{1i} = \begin{cases} 1 \text{if} q_i > 0 \\ 0 \text{otherwise} \end{cases}, i \le k$$

2.2. The other $N_i - 1$ members $(V_j)_{2\le j\le N_i}$ are uniformly-random generated.

2.3. Encoding the N_i members using the new matrix G' :

$$C_j = V_j G', \quad 1 \le j \le N_i \qquad (1)$$

Step 3. For i from 1 to N_g

3.1. The population is sorted in ascending order, $C_j' = \pi' C_j$, of member's fitness defined as the distance between the modulated individual $\overline{C}_j = 2C_j - 1$ and q:

$$f_j = \sum_{k=1}^{n} (\overline{C}_{jk} - q_k)^2, \quad 1 \le j \le N_i$$

To reduce the computational complexity of this expression, and since $\sum_{k=1}^{n} q_k^2$ is constant, and $\overline{C}_{jk}^2 = 1$, the fitness can be simplified as :

$$f_j = -\sum_{k=1}^{n} \overline{C}_{jk} q_k \qquad (2)$$

3.2. The first (elite) N_e best members of this generation are inserted in the next one.

3.3. The other $N_i - N_e$ members V_j of the next generation as generated as follows :

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a. Selection operation : Select pairs of individuals $(C^{'(1)}, C^{'(2)})$ use the following linear ranking method is

$$w_j = w_{\max} - \frac{2(j-1)(w_{\max}-1)}{N_i - 1},\ 1 \le j \le N_i$$

where w_j is the j th member weight and $w_{\max} = 1.1,$ is the the maximum weight associated to the first member.

b. Crossover operator : Create a new vector V_j *"child"* of k bits. Let *Rand* be a uniformly random value between 0 and 1 generated at each occurrence. The crossover operator is defined as follows :

If $Rand_1 < p_c$, then the i th bit of child $(V_j)_{N_e+1 \le j \le N_i}$ $(1 \le i \le k)$ is given by :

$$V_{ji} = \begin{cases} C_i^{'(1)} \text{if } C_i^{'(1)} = C_i^{'(2)} \\ \text{otherwise} \begin{cases} C_i^{'(1)} \text{if } Rand_2^{(i)} < p \\ C_i^{'(2)} \text{else} \end{cases} \end{cases} \quad (4)$$

where

$$p = \begin{cases} \dfrac{1}{1+e^{-I_i^{(s)}}} \text{if } C_i^{'(1)} = 1 \text{and} C_i^{'(2)} = 0 \\ \dfrac{e^{-I_i^{(s)}}}{1+e^{-I_i^{(s)}}} \text{if } C_i^{'(1)} = 0 \text{and} C_i^{'(2)} = 1 \end{cases} \quad (5)$$

and $I_i^{(s)}$ denote the systematic information of the i th symbol. :

$$I_i^{(s)} = \begin{cases} \dfrac{4q_j}{N_0} \text{AWGN channel} \\ \dfrac{4q_j b_j}{N_0} \text{fading channel} \end{cases} \quad (6)$$

For AWGN channel, $I_i^{(s)} = \dfrac{4q_j}{N_0}$.

It is clear that if the i th bit of the parent are different, then for greater positive value q_j, the function $\dfrac{1}{1+e^{-I_i^{(s)}}}$ converge to 1. Furthermore, the i th bit of child has a great probability to be 1.

Note that if $Rand_1 \ge p_c$:

$$V_j^{(3)} = \begin{cases} C^{'(1)} \text{ if } Rand < \dfrac{1}{2} \\ C^{'(2)} \text{ else} \end{cases} \quad (7)$$

c. Mutation operator :

If the crossover operation realized, the bits V_{ji} are *muted* with the mutation rate p_m :

$$V_{ji} \leftarrow 1 - V_{ji} \quad \text{if } Rand_3^{(i)} < p_m \quad (8)$$

3.4. Encoding the N_i members of the next generation using the new matrix G' :

Step 4. The best member from the last generation is returned as the decoder decision.

2.2 Computational complexity

In [6], it is shown that the computational complexity of the first algorithm is polynomial and is less than that of OSD and Chase-2 algorithm for great values of code block length. This make our first decoder more efficient in term of performance and complexity

3. SIMULATION RESULTS

The results correspond to simulations of a transmission system using a Additive White Gaussian Noise (AWGN) channel and BPSK modulation. Before studying the performance of DAG on the block codes, a preliminary step was to optimize p_c, p_m, N_g, N_i et $w_{\max}$. Expected the Fig. 3 and the Figures of RSC simulations, the performances of DAG were obtained for $p_c = 0.97,$ $p_m = 0.03,$ $N_g = 100,$ $N_i = 300$ et $N_e = 1$. Stopping the simulation corresponds to a minimum of 30 erroneous blocs. The performance is given in terms of BER as a function of Energy to Noise Ratio $\dfrac{E_b}{N_0}$.

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3.1 AWGN results

Effect of individuals number

The expansion of the overall number of individuals $N_g.N_i$, will generally expand the search space of code words closest to r, which improves the performance of the DAG. The Fig. 3 shows the effect of parameters N_i and N_g on DAG for $RQ(103,52,19)$ code. The gain curve associated with $N_g.N_i = 30000$ compared to that using 1000 individuals is $1.4dB$ at $BER = 10^{-4}$.

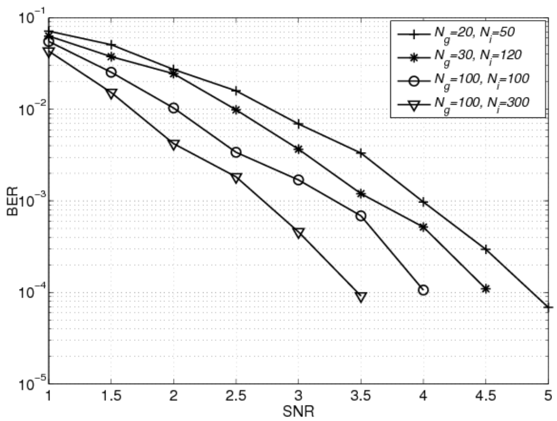

Fig. 3: Effect of the individuals and generations numbers on DAG applied to $RQ(103,52,19)$

Effect of code length

The Fig. 4 compares the DAG performances of five codes of rate ; $\frac{1}{2}$. Except the small code, all other codes have performance almost equal and this is possibly due to the parameters of DAG, in particular, the number of individuals chosen fixed for all codes. Indeed, when the code dimension k increases, this number covers a small percentage of the search space. Which may decrease the chances of finding the code word closest, especially for small $\frac{E_b}{N_0}$.

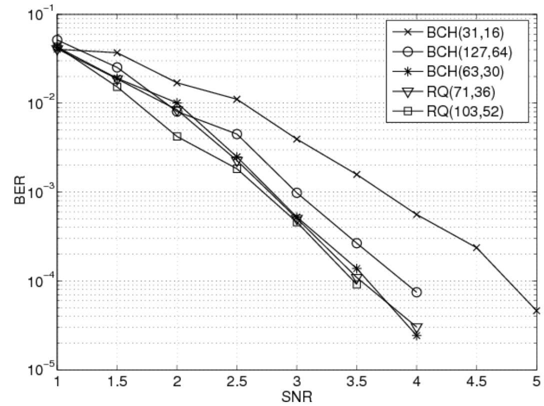

Fig. 4: Effect of length code on DAG

BCH(127,64,21) performance

The Fig. 5 compares the three decoding algorithms applied to the $BCH(127,64,21)$ code; it shows that the DAG is better than Chase-2 algorithm. Despite the large number of test sequences used by Chase-2 $(2^{10}$ sequences$)$, the DAG algorithm exceeds the performance level being less complex. . The gain of the decoder based on DAG over the $Chase\text{-}2$ at $BER = 2.10^{-5}$ is about $0.2dB$.

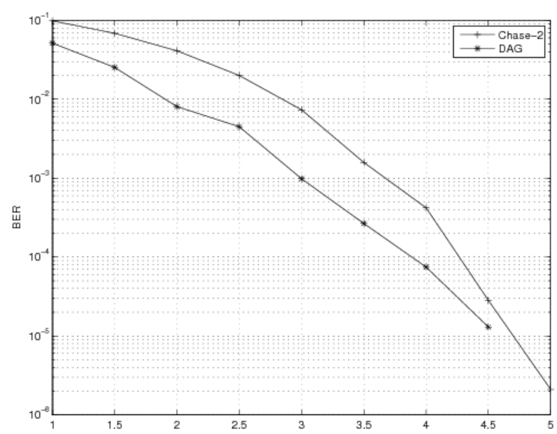

Fig. 5: Performances of DAG, Chase-2 for $BCH(127,64,21)$

RQ(71,36,11) performance

The fig. 6 shows that DAG reached almost OSD-3 for the $RQ(71,36,11)$ code. Increasing the individuals number $N_g.N_i$ would exceed the OSD-3 [6].

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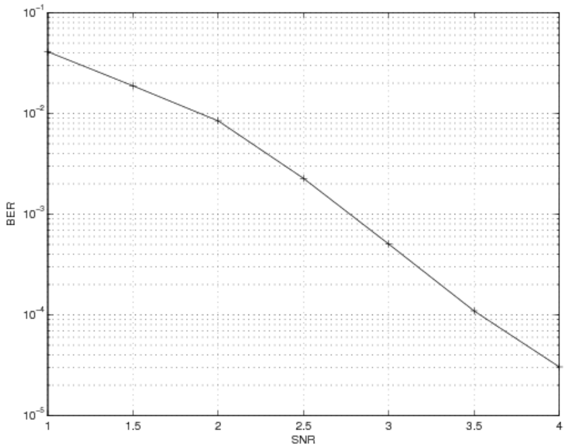

Fig. 6: Performances of DAG for $RQ(71,36,11)$

3.2 Rayleigh fading channel results

In this section, We present the performances of DAG for *BCH(63,30) over Rayleigh flat fading channel with BPSK modulation*. The Minimum number of transmitted bits is 10^7 and the minimum number of frames equal 40.

3.2.1 Optimal generations number

The Fig.7 shows the performances of our decoder applied in case of $p_c = 0.97$, $p_m = 0.03$ and $N_i = 100$. Taking into account the property of elitism and the possibility of reproduction of the same individuals from one generation to another, the number of code words treated in this first simulation is at most 2200. This represents a percentage of 0.0002 % of the total number of words in the code discussed. Thus, we have explored a small part of the search space, which however gave satisfactory results.

From the plotted curves, we see that the number of generations $N_g = 20$, the decoder corrects more errors on virtually the entire range of simulated SNRs..

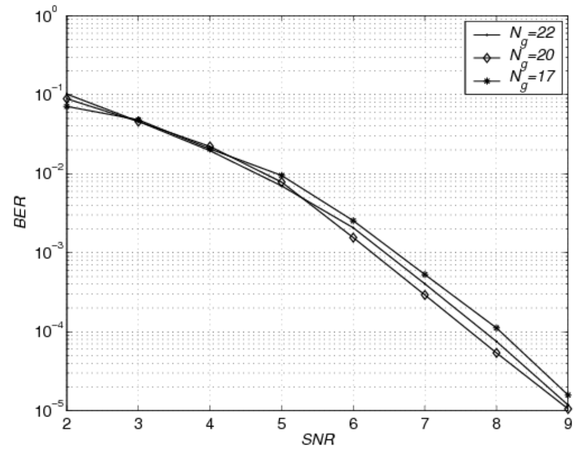

Fig. 7: Effect of generations number on decoder performances

3.2.2 optimal individuals number

The Fig. 8 presents the performance of the decoder based on GAs, applied to the BCH code studied in the case of $N_g = 20$, $p_c = 0.97$ and $p_m = 0.03$. We note that for large signal to noise ratios, performance is virtually the same for $N_i = 75,85$ et 90. Thus, the choice of $N_i = 75$ is justified because it reduces the time complexity of the decoder.

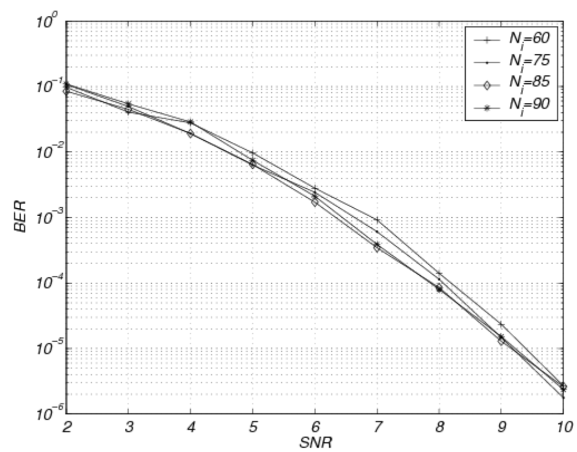

Fig. 8: Effect of individuals number on DAG performance

3.2.3 optimal crossover probability

The performances of DAG, in the case of $N_g = 20$, $N_i = 75$ and $p_m = 0.03$ is shown in Fig. 9. The curves plotted show that the

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performances are praticly the same over the range of SNRs used. the optimal valeur is aout $p_c = 0.99$. Nevertheless, the choice of this value (close to 1) slightly increases the complexity of operations that crossover and mutation will most likely be conducted.

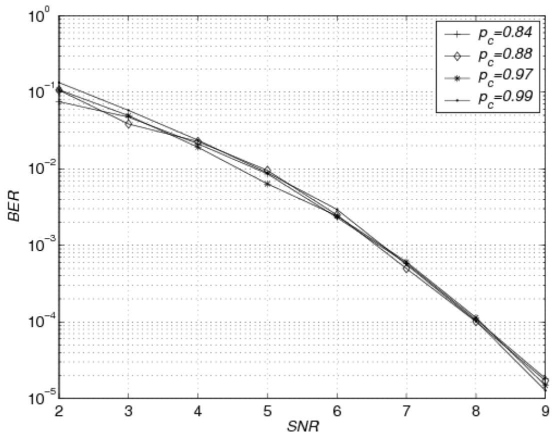

Fig. 9: Effect of crossover probability on DAG results

3.2.4 optimal mutation probability

The Fig.10 has studied the performance of the decoder in the case of $N_g = 20$, $N_i = 75$ and $p_c = 0.99$. It shows that the optimal value of the probability of mutation that contributes the most to éminiation noise is $p_m = 0.05$. Contrary to the probability of crossover, the choice of the probability of mutation has no influence on the complexity of the decoder.

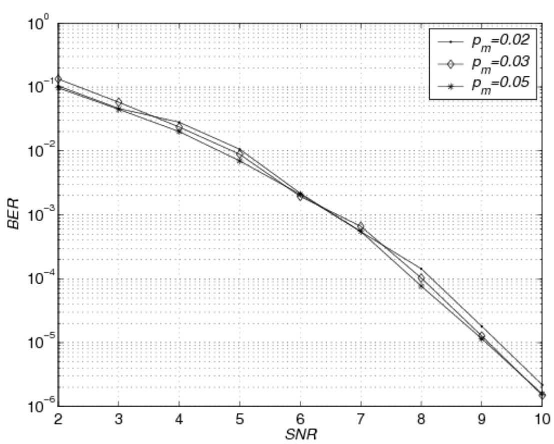

Fig. 10: Effect of mutation probability on DAG performance

3.2.5 Gain of the studied décoder

La Fig.11 compares the performance of the decoder studied with those given by the Berlekamp-Massey algorithm for channel with Rayleigh [19]. The two curves plotted show that has a higher gain at $9.6 \ dB$ for a $BER = 10^{-5}$. Moreover, the proposed agorithme have a little more complex than that of Berlekamp-Massey. Nevertheless, the result is found very satisfactory given the powers of existing machines.

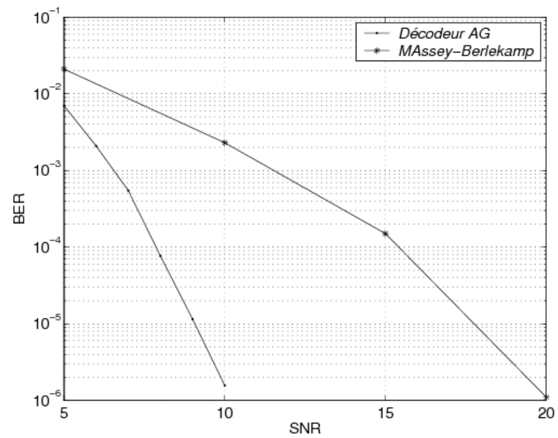

Fig. 11: Comparaison des performances du décodeur à base des AG avec celles de Massey-Berlekamp

4. CONCLUSION

In this paper, we have presented a decoder for binary block codes based on genetic algorithms that can be applied to any arbitrary binary code without needing knwledge of an algebraic decoder. Our results on BCH and RQ codes show the effectiveness of the decoding algorithm, in term of performance and complexity, over both Gaussian and Rayleigh plat fading channel. This work encourage the research in the field of methaheuristics for improving the performances and complexities of decoding algorithms.

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