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EBCODING & DECODING OF WIRELESS DATA USING LDPC CODES

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ABSTRACT

Low Density Parity Check (LDPC) codes gained considerable research attention in the recent years. Due to their powerful decoding performance, LDPC codes are increasingly deployed in communication standards. LDPC decoding algorithms are usually iterative in nature. They operate by exchanging messages between basic processing nodes. This work proposes a low complexity composite CDMA system based on MIMO (Multiple-Input-Multiple-Output) processing and LDPC codec based a CDMA system. Since the LDPC encoded sub-streams of reaching the mobile user are orthogonal to each other in space and time, the CDMA system performances (BER and SINR) can be improved much, but the multipath may ruin the orthogonally. To solve the problems, this work provides the algorithms of main function modules of transmitter and receivers, gives a simple method to test the girth of LDPC codes, and analyzes the performance of MIMO-LDPC CDMA systems theoretically and experimentally. All the simulation work is implemented in MATLAB R2013 using wireless communication and generalized MATLAB tool box. The simulation results show that the hybrid CDMA systems can have better performance than the conventional CDMA systems based on single transmitted antenna at a base station.

1. INTRODUCTION

Low-density parity check (LDPC) codes were first presented by Gallager in the early 1960s. It has been shown that these codes have remarkable performance that is very close to Shannon limit when using iterative decoding. They become strong competitors to turbo codes for error control for many digital communication systems [3] [5].

Low Density Parity Check (LDPC) codes gained considerable research attention in recent years. Due to their powerful decoding performance, LDPC codes are increasingly deployed in communication standards. The performance and cost of using LDPC codes are partly determined by the choice of decoding algorithm. LDPC decoding algorithms are usually iterative in nature. They operate by exchanging messages between basic processing nodes. Among the various decoding algorithms, the soft decision Belief Propagation (BP) algorithm and the approximate Min-Sum (MS) algorithm offer the best performance on the binary-input additive white Gaussian noise (AWGN) channel but these algorithms require a large number of arithmetic operations repeated over many iterations. These operations must be implemented with some degree of parallelism in order to support the throughput requirements of modern communication systems. As a result, LDPC decoders can be highly complex devices [1].

Many LDPC codes have been adopted as the standard codes for various communication systems, such as wireless, optical, satellite and deep space communications, digital video broadcast (DVB), multi-media broadcast (MMB), 10G BASE-T Ethernet, NASA's LANDSAT and other space missions. Bit error rate (frame error rate), throughout and complexity are usually used to evaluate performance of LDPC codes [6].

In most bit flipping algorithms, the symbol node updates are governed by an inversion function that estimates the reliability of received channel samples. [1].

A turbo encoder using serial concatenation of a convolution code or Low Density Parity Check (LDPC) code with a partial-response channel acting as the inner coder is shown in Fig. 1 [11]. The iterative decoder (Fig. 2) uses a combination of soft-input-soft-output (SISO) decoders separated by inter leavers, and the inverse. Author presents SISO decoder implementations that employ the MAP Algorithm (BCJR), Soft Output Viterbi Algorithm (SOVA), or the LDPC decoding algorithm. All systems considered in this work assume a partial response channel. The particular partial response target is not essential to the following discussion, and is used as an example because it presents a complexity equivalent to contemporary read channel detectors. The outer code is either a 16-state binary convolution code or an LDPC code, implementing a rate 8/9 coding.

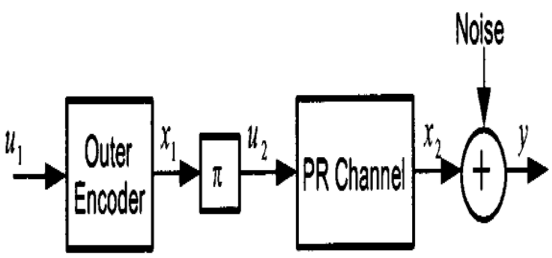

Fig.1. Serially concatenated turbo encoder with a convolution outer code [11].

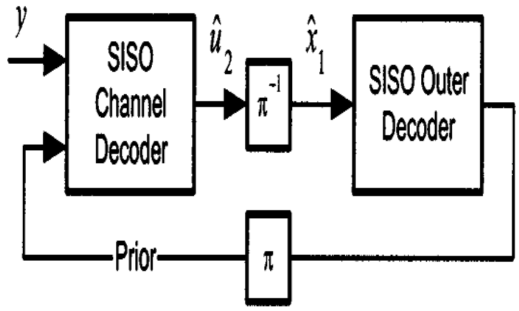

Fig.2. Iterative decoder using SISO decoders separated by inter leavers [11].

In order to achieve desired throughputs (above 1 Gbps) that are in line with current trends in magnetic recording systems, a fully unrolled and pipelined architecture is needed (Fig. 3). This results in a linear complexity increase with the number of iterations.

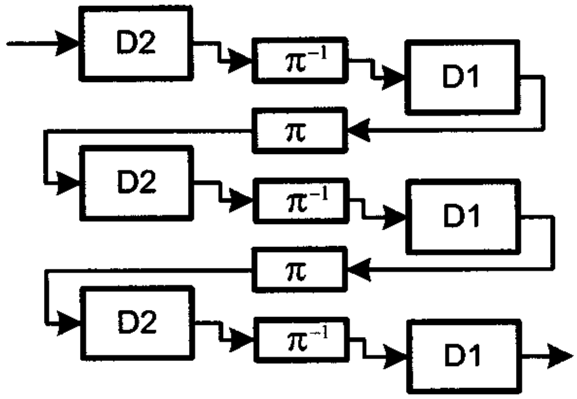

Fig.3. Pipelined decoder for serially concatenated turbo codes using outer decoder D1 and inner decoder D2 separated by inter leavers/de inter leavers, π/π^{-1} [11] .

CODING FOR DIGITAL DATA TRANSMISSION LOW-DENSITY PARITY-CHECK CODES

Coding for error correction is one of the many tools available for achieving reliable data transmission in communication systems. For a wide variety of channels, the Noisy Channel Coding Theorem [l2], of Information Theory proves that if properly coded information is transmitted at a rate below channel capacity, then the probability of decoding error can be made to approach zero exponentially with the code length. The theorem does not, however, relate the code length to the computation time or the equipment costs necessary to achieve this low error probability. The codes to be discussed here are special examples of parity-check codes.' The code words of a parity-check code are formed by combining a block of binary information digits with a block of check digits. Each check digit is the modulo2 sum[2] of a pre specified set of information digits. These formation rules for the check digits can be conveniently represented by a parity-check matrix, as in Fig. 4. This matrix represents a set of linear homogeneous modulo 2 equations called parity-check equations, and the set of code words is the set of solutions of these equations. Author call the set of digits contained in a parity check equation a parity-check set. For example, the first parity-check set in Fig. 4 is the set of digits (1, 2, 3, and 5). The use of parity-check codes makes coding (as distinguished from decoding) relatively simple to implement. Unfortunately, the decoding of parity-check codes is not inherently simple to implement, and thus Author must look for special classes of parity-check codes, such as described below, for which reasonable decoding procedures exist.

x_1	x_2	x_3	x_4	x_5	x_6	x_7
1	1	1	0	1	0	0
1	1	0	1	0	1	0
1	0	1	1	0	0	1

Fig.4 Example of parity check matrix [12].

LOW-DENSITY PARITY-CHECK CODES

Low-density parity-check codes are codes specified by a matrix containing mostly 0's and only a small number of 1's. In particular, an (n, j, k) low-density code is a code of block length n with a matrix like that of Fig. 5 where each column contains a small fixed number, j, of l's and each row contains a small fixed number, k, of 1's. Note that this type of matrix does not have the check digits appearing in diagonal form as in Fig. 4.

11110000000000000000
00001111000000000000
00000000111100000000
00000000000011110000
00000000000000001111
10001000100010000000
01000100010000001000
00100010000001000100
00010000001000100010
00000001000100010001
10000100000100000100   01000010001000010000
00100001000010000010
00010000100001001000
00001000010000100001

Fig.5 Example of a low density code matrix; N= 20, j= 3, k= 4 [12].

However, for coding purposes, the equations represented by these matrices can always be solved to give the check digits as explicit sums of information digits. These codes are not optimum in the somewhat artificial sense of minimizing probability of decoding error for a given block length, and it can be shown that the maximum rate at which these codes can be used is bounded below channel capacity. However, a very simple decoding scheme exists for low-density codes, and this compensates for their lack of optimality. It is simpler to analyze a whole ensemble of such codes because the statistics of an ensemble permit one to average over quantities that are not tractable in individual codes. From the ensemble behavior, one can make statistical statements about the properties of the member codes. Furthermore, one can with high probability find a code with these properties by random selection from the ensemble. In order to define an ensemble of (n, j, k) low-density codes, consider Fig. 2 again.

Note that the matrix is divided into j sub matrices, each containing a single 1 in each column. The first of these sub matrices contains all its l's in descending order; i.e., the i'th row contains l's in columns (i - 1) k + 1 to ik. The other sub matrices are merely column permutations of the first. Author define an ensemble of (l, j, k) codes as the ensemble resulting from random permutation of the columns of each of the bottom j - 1 sub matrices of a matrix such as fig. 2, with equal probability assigned to each permutation. There are two interesting results that can be proven using this ensemble, the first concerning the minimum distance of the member codes, and the second concerning the probability of decoding error. The minimum distance of a code is the number of positions in which the two nearest code words differ. Over the ensemble, the minimum distance of a member code is a random variable, and it can be shown [12] that the distribution function of this random variable can be over bounded by a function such as sketched in fig. 3.

2 DECODING

Two decoding schemes will be described here that appear to achieve a reasonable balance between complexity and probability of decoding error. The first is particularly simple but is applicable only to the BSC at rates far below channel capacity. The second scheme, which decodes directly from the a posteriori probabilities at the channel output, is more promising but can be understood more easily after the first scheme is described. In the first decoding scheme, the decoder computes all the parity checks and then changes any digit that is contained in more than some fixed number of unsatisfied parity-check equations [12].

Probabilistic Decoding

Assume that the code words from an (n, j, and k) code are used with equal probability on an arbitrary binary input channel. For any digit d, an iteration process will be derived that on the m^{th} iteration computes the probability that the transmitted digit in position d is a 1 conditional on the received symbols out to and including the m^{th} tier. Consider the ensemble of events in which the transmitted digits in the positions of d and the first tier are independent equi probable binary digits, and the probabilities of the received symbols in these positions are determined by the channel transition probabilities Pz(y). In this ensemble the probability of any event conditional on the event that the transmitted digits satisfy the j parity-check equations is the same as the probability of an event in the sub code described above. Thus, within this ensemble author want to find the probability that the transmitted digit in position d is a 1 conditional on the set of received symbols {y} and on the event X that the transmitted digits satisfy the j parity-check equations on digit d. Author write this as

$$P_r\,[x_d = 1 \mid \{y\}, S].$$

- Check if the degree constraint for the corresponding row is violated.
- Check if any cycles of length four will be formed.

If any of the above two conditions are violated, select and another random row and check again. Continue till a row is found which together with that column satisfies the above two constraints. Note that for the algorithm to be able to distribute ones properly the degree distribution equation should be satisfied.

$$M = N\,\frac{\Sigma dv}{\Sigma dc}$$

The decoder structure exactly resembles the decoder of a Repeat Accumulate code, only without the accumulator [2].

THE SPA AND MIN-SUM ALGORITHM

The main idea behind all belief propagation based algorithms is processing the received symbols iteratively in concatenated steps that can be seen over the Tanner graph as horizontal step followed by vertical step to improve the reliability of each decoded code symbol. The computed reliability measures of the code symbols at the end of any decoding iteration are used as inputs of the next iteration. This decoding iteration algorithm continues until a certain stopping criterion is satisfied. To illustrate this concept consider: the reliability of a decoded symbol is measured by a posteriori probability P (x_n |Y) for $1 \leq n \leq N$. Then the log-likelihood ratio LLR of each code bit is given by:

$$L(x_n) = \log\ P(x_{n=0} \mid Y) / P(x_{n=1} \mid Y)$$

During iteration, a message $r_{m\to n}$ is calculated in the horizontal step at each check node m and is passed to all variable nodes n if n ∈ ɲ {m}. Similarly each variable node n sends a message $q_{n\to m}$ in the vertical step to all check nodes m if m ∈ ɲ {n}. The codeword is denoted by X =[$x_1, x_2 \ldots\ldots x_n$] where x_n ∈ {0, 1} . The LLR values of the corresponding received vector are denoted by Y = [$y_1, y_2 \ldots\ldots\ldots\ldots y_n$]. In order to present SVS Min-Sum algorithm, Author need to review the required background theory of the SPA, Min-Sum, and Scaled Min-Sum and Variable Scaled Min-Sum algorithms. [3].

SUM-PRODUCT ALGORITHM (SPA)

The tanh-based SPA can be described in the following steps.

1) Initialization step

The initial values of the LLR can be obtained from the QAM demodulator output y_n. These initial values are used as $q_{n\to m}$, the first iteration's input message to the check node update step (Horizontal step).

2) Horizontal step

The horizontal step at a check node m is dedicated to process the messages which are coming from the variable nodes $q_{n\to m}$ to calculate the reply messages $r_{m\to n}$ for all n ∈ ɲ {m}. So for each check node m

$$r_{m\to n} = \Big[\prod_{n \in N(m)\backslash n} * \operatorname{sign}(q_{n\to m})\Big] \times 2\tanh^{-1}\Big[\prod_{n \in N(m)\backslash n} \times \tanh(|q_{n\to m}|)\Big]$$

3) Vertical step

The vertical step at a variable node n is dedicated to process the messages which are coming from the check nodes $r_{m\to n}$ to calculate the reply messages for

$q_{n\to m}$ all $m \in N\{n\}$. So for each variable node n compute:

$$q_{n\to m} = y_n + \sum_{m \in M(n)\backslash n} r_{m\to n}(x_n)$$

4) Decision step:

For each variable node, the LLR values are updated according to:

$$L(x_n) = y_n + \sum_{m \in M(n)} r_{m\to n}(x_n)$$

This approximation yields the Min-Sum algorithm [3] which is more implementation friendly.

MIN-SUM ALGORITHM

The Min-Sum algorithm follows the same steps as the tanh rule SPA. It is composed of the same steps with only single change in the calculation of the horizontal step which can be manipulated to be:

$$r_{m\to n} = \left[\prod_{n \in p(m)\backslash n} * \operatorname{sign}(q_{n\to m}) \right] \times \min_{n \in p(m)\backslash n} (|q_{n\to m}|)$$

The above algorithm is easier to implement as it gets rid of the tanh calculation. However, the approximation to the exponential calculations to the min (.) leads to some loss of performance compared to the tanh-based SPA algorithm.

PROPOSED METHODOLOGY

1. Initialization of some input parameters i.e. Number of rows and columns, number of cycles, number of 1s per column, input SNR values, number of iterations and number of frame for creating LDPC matrix.
2. Calculation of number of 1s per row &. Creation of LDPC matrix.
3. Declaration of a loop according to total SNR values & Generation of random data (0/1).
4. Generation of parity check vector bases on LDPC matrix h using sparse LU decomposition and random data.
5. Generation of new data by mixing of random data with parity check vector.
6. BPSK modulation of newly generated data & Generation of white Gaussian noise.
7. Addition of white Gaussian noise to modulated data.
8. Decoding of transmitted data according to updated LDPC matrix and number of iterations.
9. Calculation of bit error rate & average of BER
10. Plotting of the result between input SNR values at x axis and average BER at y axis.

EXPERIMENTAL RESULTS

All the simulation work has been implemented in MATLAB R2013a using wireless communication tool box and generalized MATLAB toolbox. A LDPC decoding algorithm in MIMO system with AWGN faded channel is proposed in this work. First, we have created a LDPC matrix with rate ½ i.e. number of rows is exactly half as compared to that of columns. Then, random data is generated and a parity check vector is generated in accordance with LDPC matrix and random data. After the generation of parity check vector a data is mixed with AWGN and has been sent to the transmitter. At transmitter end, decoding of the data is done using advanced log domain sum product algorithm. After that, a decoded data is compared with data mixed with parity check vector, so as to calculate bit error rate according to different input SNR values. Finally that rate is plotted w.r.t. input SNR and considered as an output performance parameter of proposed methodology. Figure 6 is a plot BER vs. SNR for proposed methodology. . At input SNR 0 dB BER is 0.0490 and decrease down to 0 dB at SNR 4 dB as shown in figure 7

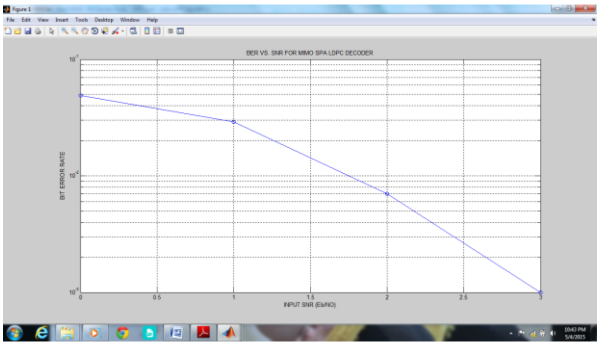

Fig.6 plot of BER vs. SNR

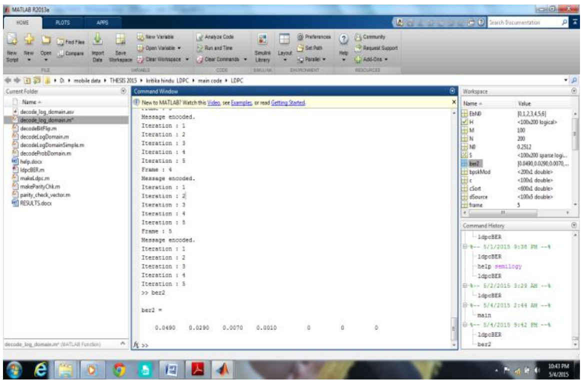

Fig.7. snapshot of MATLAB command window having different BER values at different SNR.

CONCLUSON & FUTURE SCOPE

Low Density Parity Check (LDPC) codes gained considerable research attention in the recent years. Due to their powerful decoding performance, LDPC codes are increasingly deployed in communication standards. LDPC decoding algorithms are usually iterative in nature. A LDPC decoding algorithm in MIMO system with AWGN faded channel is proposed in this work. First, we have created a LDPC matrix with rate ½ i.e. number of rows is exactly half as compared to that of columns. Finally the bit error rate is plotted w.r.t. input SNR and considered as an output performance parameter of proposed methodology. The simulation results show that the hybrid CDMA systems can have better performance than the conventional CDMA systems based on single transmitted antenna at a base station. In future work bit error rate can be further reduced & SNR can be improved.

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