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ENSEMBLE NOISE-AIDED BIT FLIPPING DECODING OF LOW-DENSITY PARITY-CHECK CODES

Mykola Shtompel[1], Oleksandr Shefer[2]

[1]Ukrainian State University of Railway Transport, Department of Transport Communication, Kharkiv, Ukraine, [2]National University "Yuri Kondratyuk Poltava Polytechnic", Department of Automation, Electronics and Telecommunications, Poltava, Ukraine

Abstract. *Moderate-length low-density parity-check codes are incorporated to increase the data transmission reliability and the energy gain in the next generation wireless communication systems. The paper proposes ensemble decoding based on reduced-complexity noise-aided gradient descent bit flipping algorithm. Block diagram and pseudocode of this approach were presented. The decoding by each constituent noise-aided bit flipping decoder is performed independently and in parallel mode. The ensemble size and the chosen noise scale values are key parameters of this decoding framework. The simulation results confirmed the efficiency of the proposed noise-aided ensemble decoder. It was shown that the increasing of ensemble size leads to improve the error performance. The average number of decoding iterations is acceptable in high signal-to-noise ratio region. The application of the presented decoding algorithm will improve the data transmission reliability under low-latency requirements in the next generation wireless technologies.*

Keywords: wireless communication systems, low-density parity-check codes, decoding, bit flipping

DEKODOWANIE Z WYKORZYSTANIEM SZUMU ZBIOROWEGO Z METODĄ INWERSJI BITÓW W KODACH Z NISKĄ GĘSTOŚCIĄ I KONTROLĄ PARZYSTOŚCI

Streszczenie. *W systemach komunikacji bezprzewodowej nowej generacji stosuje się kody LDPC o średniej długości w celu zwiększenia niezawodności transmisji danych i oszczędności energii. W niniejszym artykule zaproponowano dekodowanie zbiorcze oparte na algorytmie inwersji bitów metodą gradientowego spadku wspomaganego szumem o zmniejszonej złożoności. Przedstawiono schemat blokowy oraz pseudokod tego podejścia. Dekodowanie przez każdy składowy dekoder inwersji bitów wspomagany szumem odbywa się niezależnie i w trybie równoległym. Wielkość zespołu oraz wybrane wartości skali szumu są kluczowymi parametrami tej struktury dekodowania. Wyniki symulacji potwierdziły skuteczność proponowanego dekodera zespołowego wspomaganego szumem. Wykazano, że zwiększenie wielkości zespołu prowadzi do poprawy charakterystyki błędów. Średnia liczba iteracji dekodowania jest akceptowalna w obszarze wysokiego stosunku sygnału do szumu. Zastosowanie przedstawionego algorytmu dekodowania poprawi niezawodność transmisji danych przy wymaganiach dotyczących niskiego opóźnienia w technologiach bezprzewodowych nowej generacji.*

Słowa kluczowe: systemy komunikacji bezprzewodowej, kody z kontrolą parzystości o niskiej gęstości, dekodowanie, inwersja bitów

Introduction

The next generation wireless communication systems provide multiple new services, applications, and features. The enhanced mobile broadband, ultra-reliable low-latency communications and massive machine-type communications are the common use cases for fifth generation (5G) and sixth generation (6G) networks. The different services have unique requirements to reliability of data transmission, latency in the network devices, and communication channel capacity. To ensure the specified quality of service, the physical level of these wireless communication systems leverage advanced modulation schemes, digital signal processing methods, and channel coding technics. In particular, channel coding allows to achieve high reliability and energy efficiency of data transmission. The low-density parity-check (LDPC) codes play crucial role in the modern communication systems. For example, 5G technology incorporates these codes for physical downlink shared channel and physical uplink shared channel. The main advantages of LDPC codes are improved error-correction performance, reduced decoding complexity and latency, better energy efficiency, and support different data rates [6]. The belief propagation algorithm is a typical decoding approach for LDPC codes. This algorithm is a good choice for very long LDPC codes, but finite-length codes, which used in real communication systems, require more efficient decoding methods [5]. In the context of next generation wireless technologies, channel decoders must not only provide the necessary data transmission reliability, but also have high throughput and low latency.

Therefore, the development of decoding algorithms for LDPC codes which meet these requirements are an important direction in communication area. The problem of decoding for these codes under conditions of fading communication channel models, as well as in conjunction with advanced modulation techniques, is beyond the scope of this article.

1. Problem definition

Binary LDPC codes under soft-decision iterative belief propagation decoding do not perform well enough at short and moderate block lengths due to short cycles in the Tanner graph defined by parity-check matrix. Moreover, these algorithms have large computational complexity that restricts the decoder throughput which is a critical parameter of modern wireless communication systems [9, 10].

To decrease decoder latency while maintaining acceptable error-correction capability of the moderate-length LDPC codes, reduced-complexity bit flipping decoding algorithms have been developed. One famous class of these algorithms formulates decoding task as a gradient descent problem which resolved by the gradient descent bit flipping (GDBF) algorithms [13]. To avoid the well-known difficulty of these algorithms, which is being stuck in local maxima of an inversion function, the noisy GDBF (NGDBF) algorithm was proposed [11]. The feature of this algorithm is a random perturbation allowed to escape from undesirable local maxima. To increase the reliability of NGDBF decoding, the adjustment factor on the syndrome and adaptive inversion threshold were introduced [3]. The NGDBF algorithm requires Gaussian noise generators to work properly. In [8], they were replaced by special transformations of received signals to simplify the decoder design. Moreover, authors introduced tabu-list to reduce number of flipped bits during iterations and remove randomness at first iterations to improve the decoding convergence. The re-decoding procedure based on independent perturbations has been proposed to increase the NGDBF performance [12]. This approach can be interpreted as a sequential mechanism to combine multiple NGDBF decoders.

From the other side, the belief propagation list decoder for polar codes consists of multiple parallel decoders based on differently permuted factor graphs corresponded to modified parity-check matrices [4]. In [1], noise-aided version of belief propagation list algorithm that relies on adding artificial noise to each decoder was presented. In addition, the early detection and termination criteria check have been used to reduce decoding iterations. The great benefits of this parallel decoding mechanism are lower decoding latency compared to the sequential decoders and the achieving high throughput in technical implementation. In [2], this approach was adapted to quantum LDPC codes based on a two-bit flipping decoding to improve their error-floor performance under low-latency requirements. In [7], the authors proposed to interpreter a set of independent constituent parallel decoders as an ensemble decoder. The generalization and comparative study of different realizations of this parallel decoding framework for short LDPC codes have been presented.

It follows from the analysis carried out that to increase the error-correction performance of the moderate-length LDPC codes, ensemble decoding approach can be applied. In this work, the NGDBF algorithm is used in the constituent decoder to meet critical latency requirements of modern wireless communication systems.

2. Proposed decoding algorithm of LDPC codes

2.1. Notation

Let H is a parity-check matrix of a (n,k) binary LDPC code, where n is the codeword length, k is the message length. Then this code can be defined as $C \equiv \{\bar{c} \in \mathrm{GF}^n(2) : H\bar{c} = 0\}$, where $\bar{c} = (c_1, c_2, ..., c_n)$ denotes the binary codeword and $\mathrm{GF}^n(2)$ is the binary Galois field. Assumed that the codewords are transmitted by binary phase shift keying (BPSK) modulation through an additive white Gaussian noise (AWGN) communication channel. The equivalent bipolar code is $B \equiv \{\bar{b} \in \{-1,+1\}^n : H\bar{b} = m\}$, where $\bar{b} = (b_1, b_2, ..., b_n)$ is the bipolar codeword, $m = (n-k)$ is the number of check bits. After transmitting this codeword via AWGN channel, the received vector is $\bar{y} = \bar{b} + \bar{z}$, where $\bar{z}$ is a vector of independent and identically distributed Gaussian random variables with zero mean and variance $N_0/2$, N_0 is the noise spectral density. The decoder forms initial decision vector $\bar{x} = \mathrm{sign}(\bar{y})$, where $\bar{x} \in \{-1,+1\}^n$, and checks if $\bar{x} \in B$. The check condition is relied on evaluation bipolar syndrome components $s_i = \prod_{j \in N(i)} x_i$, $i \in [1,m]$, where $N(i) \equiv \{j : h_{ij} = 1\}$, $i \in [1,m]$, is the parity-check neighbourhoods, h_{ij} is the $(i,j)^{\mathrm{th}}$ element of the parity-check matrix H. The bit neighbourhoods, which used later in the decoding procedure, are defined in similar way as $M(j) \equiv \{i : h_{ij} = 1\}$, $j \in [1,n]$. The parity check for x_i is satisfied when its corresponding syndrome component is $s_i = +1$.

2.2. NGDBF algorithm

The maximum likelihood decoding of some linear block code, including LDPC code, is to search the decision vector $\bar{x}_{\mathrm{ML}}$ that has maximum correlation with the received vector $\bar{y}$:

$$\bar{x}_{\mathrm{ML}} = \underset{x \in B}{\mathrm{argmax}} \sum_{j=1}^{n} x_j y_j. \tag{1}$$

In fact, the task (1) is an objective function for optimization problem that can be solved by the gradient descent algorithm. However, the solution to this problem is difficult for moderate-length LDPC codes. To simplify finding the decision vector, it is advisable to introduce additional restrictions and represent the objective function as

$$f(x) = \sum_{j=1}^{n} x_j y_j + w \sum_{i=1}^{m} s_i + q_j, \tag{2}$$

where $w \in \mathrm{R}^+$ is a syndrome weight parameter, q_j is a Gaussian independent and identically distributed random variable with zero mean and variance $\sigma^2 = \eta^2 N_0 / 2$, $\eta \in (0,1]$ is a noise scale parameter.

In the modified objective function (2), the second term verifies that the decision vector is the valid codeword and the third term provides a low-complexity mechanism to escape from local maxima. Under provided constraints, the solution of (2) is also a solution to the maximum likelihood problem defined by (1).

By taking the partial derivative with respect to a symbol x_j, the local inversion function is equal to

$$E_j = x_j \frac{\partial f(x)}{\partial x_j} = x_j y_j + w \sum_{i \in M(j)} s_i + q_j. \tag{3}$$

Then the resulting iterative maximization algorithm for decoding LDPC codes consists of next steps on each iteration t.

Step 0. Initialize parity-check matrix H, vectors $\bar{y}$, $\bar{x}$, parameters w, η, λ, T, $\theta_j(t=0) = \theta$, $j \in [1,n]$, where $\theta \in \mathrm{R}^-$ is a global initial inversion threshold, λ is a global adaptation parameter, $\lambda \in (0,1)$, T is a maximum number of iterations.

Step 1. Evaluate bipolar syndrome components $s_i = \prod_{j \in N(i)} x_i$, $i \in [1,m]$. If $s_i = +1$ for all $i \in [1,m]$, the valid codeword is found, output $\bar{x}$ and stop. Otherwise, go to step 2.

Step 2. Compute inversion function (3) for each $j \in [1,n]$.

Step 3. Perform bit-flip operation for any decision vector component x_j if $E_j(t) < \theta_j(t)$. Otherwise, update $\theta_j(t+1) = \lambda \theta_j(t)$.

Step 4. Repeat steps 1 to 3 until a valid codeword is found or maximum number of iterations T is reached.

This algorithm is referred to as adaptive multi-bit noisy gradient descent bit flipping (AMNGDBF) [11]. The feature of this algorithm comes from using inversion function (3) taken into account the normal-distributed random value q_j with near equal to variance of real channel noise σ^2. To improve decoding performance, the concrete value of q_j should be obtained by optimizing noise scale parameter η. Besides, w, θ, and λ auxiliary parameters of AMNGDBF algorithm are code and communication channel dependent, so they should also be optimized to adjust error performance. It should be noted that this algorithm allows fully parallel implementation with only local arithmetic operations. From the other side, the AMNGDBF algorithm requires a channel noise estimator which leads to increase the computational complexity. The another drawback of this algorithm is possibility of bit flipping unintendedly due to the random added value q_j to the inversion function (3).

2.3. Noise-aided ensemble decoding algorithm

To improve performance of GDBF-like decoding of LDPC codes, the ensemble decoding framework is a visible choice. The main idea is to perform decoding in parallel by multiple constituent decoders. This allows to find possibly different decision vectors which used as codeword candidates. At the final step, the most possible decision vector as an estimated codeword based on some rule is chosen. In general, if the maximum likelihood rule is used, ensemble decoding helps to achieve near maximum likelihood performance. This approach leads to provide low latency, improve error-correction capability, and reduce error floor characteristic. Besides, the hardware implementation of this decoder with high throughput and limited control signal overhead is allowed [2].

The ensemble schemes for LDPC codes use algebraic code structure, artificial noise, scheduling procedures, and other mechanisms [7]. In this paper, noise-aided ensemble decoding framework based on described AMNGDBF algorithm is presented.

The proposed ensemble AMNGDBF (E-AMNGDBF) decoding framework, which is the set of AMNGDBF decoders, defined by

$$D_L = \{D_l : l \in [1, L]\}, \tag{4}$$

where D_l defines individual AMNGDBF decoder, L is the size of ensemble which equals to cardinality of the set. All L decoders work in parallel, so it can improve error correction within the allowed decoding time budget.

The proposed decoder uses multiple AMNGDBF decoders with set of different η_l values. By utilizing these different η_l, the set X of the different l decision vectors $\bar{x}_l$ can be obtained.

After generating l candidates, the E-AMNGDBF decoder uses the following rule to choose the final output:

$$x_D = \underset{x \in X}{\operatorname{argmax}} \sum_{j=1}^{n} x_{l,j} y_j. \tag{5}$$

The choice of the optimal η_l is a challenging task without existing mathematical proof. In this work, instead of using random η_l values, a fix value for each individual AMNGDBF decoder is used. It is known that the value of η_l is associated with the value of SNR and is a small impact in low SNR region. To adapt the decoder to different channel conditions the values for η_l were set in predefined optimized empirically range. This eliminates the need for a channel noise estimator and ensures the diversity of proposed decoder.

The general block diagram of the E-AMNGDBF decoder is given in Fig. 1.

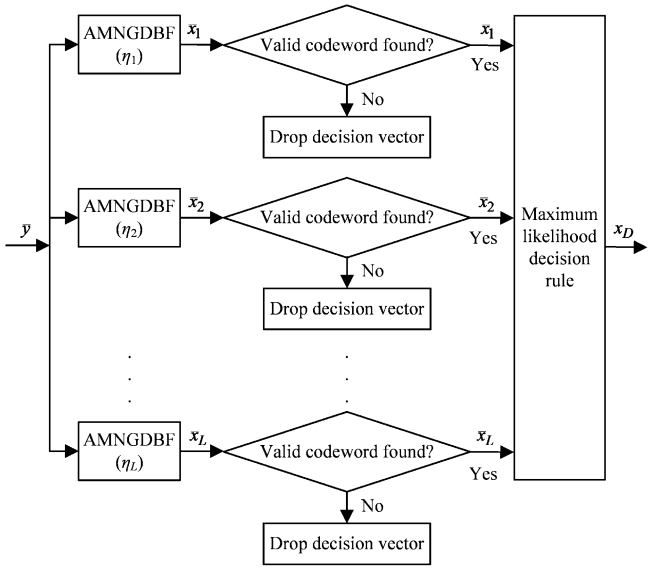

Fig. 1. Block diagram of the E-AMNGDBF decoder for LDPC codes

According to the block scheme from Fig. 1, the received vector are decoding by each individual AMNGDBF decoder with selected η_l value in parallel. After reaching stopping criteria, the E-AMNGDBF decoder selects the most probable candidate x_D as a final decision vector based on rule (5). In proposed decoder, only valid candidates $\bar{x}_l$, when its corresponding syndrome component is $s_i = +1$, are taken into account in the final decision process. As a result, greater ensemble gain and convergence behaviour are achieved.

According to [7], the ensemble recovery probability can be used to evaluate the potential ensemble gain:

$$\rho = \mathrm{P}(x_D = b \mid x_1 \neq b), \tag{6}$$

where x_1 is a decision vector of first individual AMNGDBF decoder.

If maximum likelihood errors are not considered, the probability (6) can be presented as a ratio between erroneous decoding probabilities ensemble of the ensemble decoder and constituent AMNGDBF decoder:

$$\rho \approx 1 - \frac{\mathrm{P}(x_D \neq b)}{\mathrm{P}(x_1 \neq b)}.$$

The pseudocode of the E-AMNGDBF decoding algorithm is presented in Fig. 2.

Algorithm: E-AMNGDBF decoding
Input: received vector $y = (y_1, y_2, \ldots, y_n)$
Output: estimated codeword $x_D = (x_1, x_2, \ldots, x_n)$
Parameters: noise scale parameters η_l,
size of ensemble L,
maximum number of iterations T,
syndrome weight parameter w,
global adaptation parameter λ,
global initial inversion threshold θ

for all $j = 1, \ldots, n$ **do** // Initialization
  $x_j = \mathrm{sign}(y_j)$
  $\theta_j = \theta$
end for

for all $l = 1, \ldots, L$ **do** // Iteration loop in parallel
  for all $t = 1, \ldots, T$ **do**
    for all $i = 1, \ldots, m$ **do**
      $s_i = \prod_{j \in N(i)} x_i$
    end for
    if $s_i = +1$, $\forall i$ **then** $\bar{x}_l$
    else
      for all $j = 1, \ldots, n$ **do**
        $E_j = x_j y_j + w \sum_{i \in M(j)} s_i + q_j$
        if $E_j < \theta_j$ **then** $x_j = -x_j$ **else** $\theta_j = \lambda\theta_j$ **end if**
      end for
    end if
  end for
  for all $i = 1, \ldots, m$ **do** // Codeword validation
    $s_i = \prod_{j \in N(i)} x_i$
  end for
  if $s_i = +1$, $\forall i$ **then** x_l
end for

for all $l = 1, \ldots, L$ **do** // Decision rule
  $\bar{x}_D = \underset{x \in X}{\operatorname{argmax}} \sum_{j=1}^{n} x_{l,j} y_j$
end for

Fig. 2. Pseudocode of the E-AMNGDBF decoding algorithm for LDPC codes

Based on the pseudocode from Fig. 2, the software implementation of the proposed decoding method of LDPC codes was developed to perform experimental research.

3. Experiments and results

The proposed E-AMNGDBF decoding algorithm was simulated on the AWGN channel with BPSK modulation using binary regular (1008, 504) LDPC code, which is commonly used as a benchmark for GDBF-like algorithms. The series of simulation were performed to identify the good-performing values for decoding parameters: the syndrome weight parameter is $w = 0.75$, the global adaptation parameter is $\lambda = 0.95$, the global initial inversion threshold $\theta = -0.9$. In each simulation, comparison results are provided for the decoding algorithms with maximum number of iterations $T = 100$. The number of decoders were set up as $L = \{4, 8, 16\}$. The noise scale parameters η_l were set up proportional to L in range from 0.5 to 0.95.

Simulation results for the E-AMNGDBF decoding algorithm with $L = \{4, 8, 16\}$ with corresponding values of η_l are shown in Fig. 3.

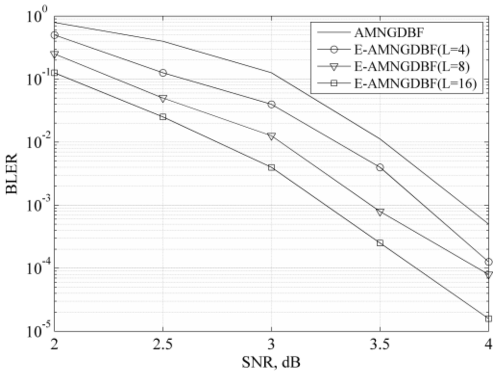

Fig. 3. Dependence of block error rate (BLER) on signal-to-noise ratio (SNR) for (1008, 504) LDPC code

It follows from Fig. 3 that the performance of the proposed decoding algorithm is higher than for pure AMNGDBF algorithm. For example, the energy gain, which is measured in dB, for the E-AMNGDBF decoding algorithm with $L = 4$ for the block error rate $BLER = 10^{-3}$ is 0.25 dB. Fig. 3 shows that the performance tends to improve with increasing size of ensemble around 0.3 dB for presented values L. The maximum achieved energy gain for proposed decoder amounts to 0.65 dB for $BLER = 10^{-3}$ when $L = 16$.

The average number of decoding iterations as a function of signal-to-noise ratio (SNR) for studied sizes of ensemble are presented in Fig. 4.

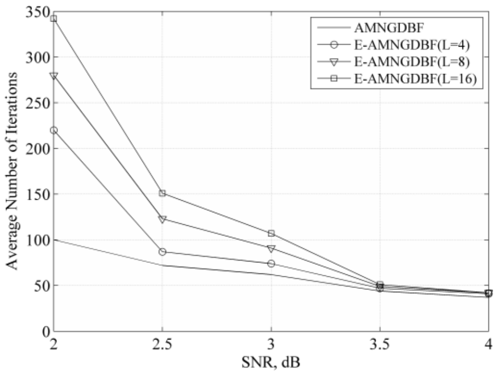

Fig. 4. Dependence of the average number of iterations on signal-to-noise ratio (SNR) for (1008, 504) LDPC code

It can be seen from the Fig. 4 that the average number of needed iterations for proposed ensemble decoder is much higher than for the pure AMNGDBF decoder in low SNR region, especially for large ensemble size L. However, after 3.5 dB no significant difference is observed. So it can be conducted that the E-AMNGDBF decoder is a good candidate for decoding in high SNR region when the requirements to latency is strong enough.

To confirm the possibility of applying the proposed decoding algorithm in modern communication systems, the simulation was performed for moderate-length quasi-cyclic (QC) LDPC codes as well. In particular, these codes are leveraged for physical shared channels in 5G technology. The two QC LDPC codes with the different lifting sizes Z generated using base graphs 2 (BG2) were investigated under the AWGN channel with BPSK modulation: binary (1024, 512) QC LDPC code, $Z = 64$; binary (2048, 1024) QC LDPC code, $Z = 104$.

Simulation results for the E-AMNGDBF decoding algorithm for both selected QC LDPC codes with $L = 16$ and $\eta_l = 0.9$ are demonstrated in Fig. 5.

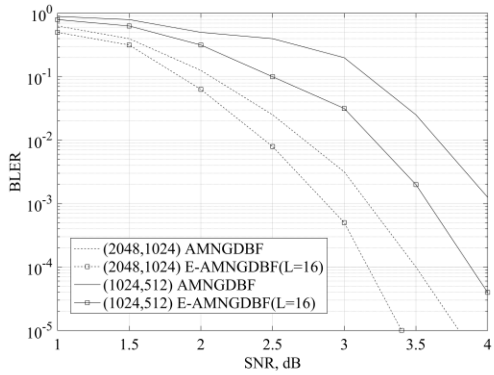

Fig. 5. Dependence of block error rate (BLER) on signal-to-noise ratio (SNR) for (1024, 512) and (2048, 1024) QC LDPC codes

The Fig. 5 shows that the proposed decoding algorithm outperforms pure AMNGDBF algorithm in terms of the energy gain about 0.4 dB for (1024, 512) QC LDPC code and 0.3 dB for (2048, 1024) QC LDPC code for $BLER = 10^{-3}$. Therefore, the increasing of codeword length of QC LDPC code tends to lower energy gain, but still can achieved. Besides, the decoder performance for (1024, 512) QC LDPC code is worse than for regular (1008, 504) LDPC code. This can be explained by the more complex and less regular structure of the parity-check matrix of QC LDPC codes.

The Fig. 6 shows the average number of decoding iterations of the E-AMNGDBF decoding algorithm with $L = 16$ for QC LDPC codes.

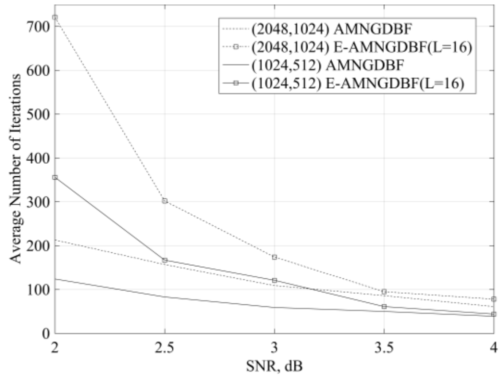

Fig. 6. Dependence of the average number of iterations on signal-to-noise ratio (SNR) for (1024, 512) and (2048, 1024) QC LDPC codes

It is clear from the Fig. 6 that the computational complexity of the presented ensemble decoder is increasing significantly for longer QC LDPC code in lower SNR range. Specifically, the average number of iterations is 1.9 times more for (1024, 512) QC LDPC code and 3.4 times more for (2048, 1024) QC LDPC code in case SNR 2 dB. Therefore, from a practical point of view the E-AMNGDBF decoder should be used in 5G scenarios when channel condition is good enough to prevent high latency.

4. Conclusion

The proposed ensemble decoding based on reduced-complexity noise-aided GDBF-like algorithm are potentially suitable for moderate-length LDPC codes incorporated in 5G communication systems. The decoding by each constituent noise-aided bit flipping decoder is performed independently and in parallel mode. The validation of each obtained decision vector is provided by syndrome component calculation. As a result, only valid candidate codewords are involved in the final decision process. The number of individual decoders, that determine the ensemble size, and the chosen noise scale values are key parameters of this ensemble decoding algorithm.

The simulation results for binary moderate-length regular and QC LDPC codes under the AWGN channel with BPSK modulation confirmed the efficiency of proposed noise-aided ensemble decoder. It was shown that the increasing of ensemble size leads to improve the error performance. Besides, the average number of decoding iterations is acceptable in high SNR region. Therefore, the obtained results confirm efficiency of the proposed approach for binary-input channels, but the future investigation should verify the applicability for higher-order quadrature amplitude and quadrature phase shift keying modulations used in 5G networks. Besides, the behavior of proposed decoder should be analyzed under the Rayleigh and Rician fading channel models, 5G tapped delay line and clustered delay line profiles, and other realistic wireless propagation conditions to determine the limitations of this approach by obtaining more BLER and computational complexity results for typical mobile conditions. It should be noted that the paper leverages the software implementation of the proposed ensemble decoder, its hardware implementation from latency and energy consumption perspective, as well as comparison with the standard min-sum or layered belief propagation decoders were not evaluated.

Thus, given the presented limitations, the presented ensemble decoding approach is a starting point for increasing the data transmission reliability under low-latency requirements in the next generation wireless technologies. In the future works it is planned to investigate the performance of noise-aided ensemble decoding in fading communication channels, joint decoding-equalization scheme for multi-level modulation techniques, and hardware implementation aspects.

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Prof. Mykola Shtompel
e-mail: shtompel.mykola@kart.edu.ua

Doctor of Technical Sciences, professor, professor of Transport Communication Department, Ukrainian State University of Railway Transport, Ukraine.
The research interests are related to the field of telecommunication and information technologies, signal processing and error-correcting codes.

http://orcid.org/0000-0003-3132-8335

Prof. Oleksandr Shefer
e-mail: itm.ovshefer@nupp.edu.ua

Doctor of Technical Sciences, professor, Head of the Department of Automation, Electronics and Telecommunications, National University "Yuri Kondratyuk Poltava Polytechnic", Ukraine.
The sphere of scientific interests is related to the field of electronic communications, information technologies and electric power engineering.

https://orcid.org/0000-0002-3415-349X