A Classified Normalized BP-Based Algorithm with 2-Dimensional Correction for LDPC Codes

Zhou Zhong, Shuming Guo, Xiangyang Xu, and Huiqing Bai
National Digital Switching System Engineering & Technological Research Center
Zhengzhou 450002, Henan, China
Email: zhongzhoundsc@gmail.com; guoshuming@ndsc.com.cn; xxy@ndsc.com.cn; bhq@ndsc.com.cn

Abstract—A BP-based algorithm with 2-dimensional classified normalized correction is developed to reduce the complexity and improve the performance of decoding algorithm for the low density parity check (LDPC) codes. The algorithm first utilizes classification according to the absolute values of incoming messages in check nodes. Then it uses 2-dimensional normalization to correct the minimum and sub-minimum values. The 2-dimensional normalized factors can be calculated respectively by using probability and statistic theory in the initialization step. Simulation results illustrate that the proposed algorithm achieves better performance in bit error ratio (BER) and average iteration number than normalized BP-based algorithm in the high signal noise ratio (SNR) region, i.e., it can achieve 0.4 dB SNR gain and reduce 20% number of iterations at BER= 10^{-5} , whose complexity is also much less than that of belief propagation (BP) algorithm. It is concluded that the proposed algorithm offers better tradeoff between performance and complexity.

Index Terms—channel coding theory, density evolution, Iterative decoding algorithm

I. INTRODUCTION

Low density parity check (LDPC) codes were first proposed [1] by Gallager in the 1960s, and later rediscovered by MacKay and Neal, which have been of great academic interest recently due to their capacity approaching performance and flexibly parallelizable hardware architectures of decoder. These two advantages have significantly contributed to LDPC codes being the most promising channel coding candidates for the next generation wireless digital communication system, such as DVB-S.2, IEEE 802.16e, IEEE 802.11n, etc.

The iterative belief propagation (BP) is a general algorithm for decoding both the regular and irregular LDPC codes by a message passing strategy which is computing log-likelihood ratio (LLR) values between check and variable nodes in Tanner graph (TG) [2]. Theoretically speaking, when the TG corresponding to the parity check matrix of a specific code is cycle free, the decision message of each variable node obtained will converge to a posteriori probability (APP) after iterative decoding. Unfortunately, due to short cycles in the TG, the likelihood messages passed through the edges between check and variable nodes are statistically dependent. Therefore, it is no longer an optimal decoding algorithm for short and moderate lengths codes with girth=4 or girth=6.

The simplifications and approximations of the BP algorithm are attractive for hardware implementations due to the complexity reduction without sacrificing much of performance. Some approximate algorithms have been discussed in [3]-[6]. Fossorier presented the min-sum approximation algorithm which is also referred to as the BP-based algorithm [3]. The BP-based algorithm in its original form is treated as a generalization of the Viterbi algorithm of iterative decoding of code realizations on general graphs. Compared with the BP algorithm, though the decoding complexity in implementation is greatly reduced, the performance loss almost reaches to 0.5–l dB. In [4], Chen used density evolution (DE) which calculates the probability distributions of infinite long codes to analyze the performance of the offset and normalized BP-based (OBP-based and NBP-based) algorithms. These two improved algorithms were regarded as better approximations to the BP algorithm than the original BP-based algorithm. But they show error-correcting performance degradation for some irregular degree distributions.

In this paper, we compare the likelihood message values in check nodes delivered by the BP algorithm and the BP-based algorithm respectively, and propose a 2-dimensional normalized BP-based decoding algorithm using the classified correction. Unlike the single correction factor adopted in the NBP-based algorithms, the two different correction factors would be employed. We derive a set of formulas to determine these factors theoretically, and show both the error-correcting performance and the average number of decoding iterations for some LDPC codes with different row weights.

The rest of the paper is organized as follows. We construct an error-correcting model with LDPC codes and analyze performance loss of several decoding approximation algorithms in Section II. Then we present the 2-dimensional classified normalized BP-based

Manuscript received April 19, 2013; revised May 15, 2013.
This work supported in part by the National Science and Technology Major Project of China (GrantNo.2011ZX03006-003) and National High Technology Research and Development Program of China (GrantNo.2011AA010604).
Corresponding author email: zhongzhoundsc@gmail.com
doi:10.12720/jcm.8.5.315-321

decoding algorithm in Section III. Some simulation results are provided for both small and large weights of the LDPC codes to illustrate the performance of the proposed algorithm in Section IV. Finally, we present conclusions in Section V.

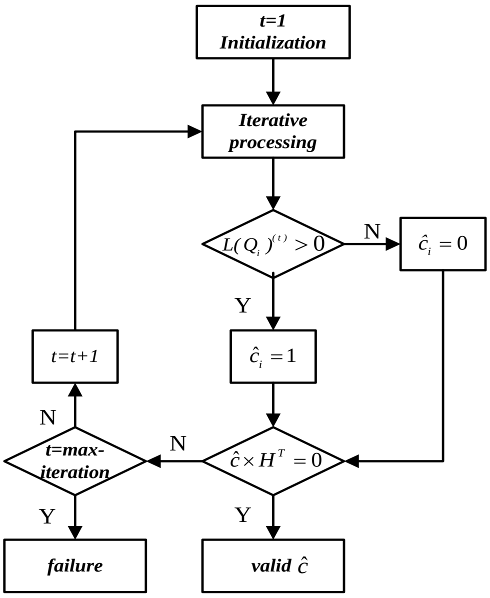

Figure 1. The flow chart of the BP decoding in error-correcting model.

II. Revew of Error -Correcting Model and Some Decoding Algorithms

In this section, we build an error-correcting model with LDPC codes to illustrate how dose the general LDPC decoder works. We assume the parity check matrix H is a $M \times N$ sparse matrix. The two parameters d_c and d_v represent row weights and column weights of H, respectively. We also assume that the information sequence $m = (m_1, m_2, \cdots, m_N)$ is coded as $c = (c_1, c_2, \cdots, c_N)$ by H and then modulated by the binary phase shift keying (BPSK) as $s = (s_1, s_2, \cdots, s_N)$, according to $s_i = 2c_i - 1$, $i = 1, 2, \cdots, N$ at the transmitter. At the receiver, the received value can be described as $y_i = s_i + n_i$, where n_i is a Gaussian random variable with zero mean and variance σ^2.

We define several notations for ease of later use as follows.

$L(r_{ji})$: the LLR message in check node j which is to be sent to the variable node i.

$L(q_{ij})$: the LLR message in variable node i which is to be sent to the check node j.

$L(Q_i)$: the posteriori value computed at the end of each iteration, which is about to participate in hard decision of bit i.

$R(j)\backslash i$: the set of all variable nodes connected to check node j with variable node i excluded.

$C(i)\backslash j$: the set of all check nodes connected to variable node i with check node j excluded.

The BP algorithm can be divided into four steps in Fig. 1:

- Initialization:

$$L(P_i) = \ln \frac{P(c_i = 1 \mid y_i)}{P(c_i = 0 \mid y_i)} = 2y_i / \sigma^2. \tag{1}$$

- Iterative processing:

1) Horizontal step:

$$L(r_{ji}) = 2\tanh^{-1}\left\{ \prod_{i' \in R(j)\backslash i} \tanh\left[\frac{1}{2} L(q_{i'j})\right] \right\}. \tag{2}$$

2) Vertical step:

$$L(q_{ij}) = L(P_i) + \sum_{j' \in C(i)\backslash j} L(r_{j'i}). \tag{3}$$

- Hard decision:

$$L(Q_i) = L(P_i) + \sum_{j \in C(i)} L(r_{ji}). \tag{4}$$

$$\hat{c}_i = \begin{cases} 1 & L(Q_i) > 0, \\ 0 & L(Q_i) < 0. \end{cases} \tag{5}$$

If the decode iterations are less than the maximum number we set and $\hat{c} \cdot H^T = 0$, then $\hat{c}$ is regarded as a successful decoded word. Otherwise, the decoding procedure breaks and it will restart from the step 1). The worst case is that the decoding iterations gets ahead of the maximum iterations and still keeps $\hat{c} \cdot H^T \neq 0$, it will terminate decoding and assert with failure.

It had been proved that the BP algorithm could achieve good error-correcting performance, but the difficulty in hardware implementation is that the function of $\tanh^{-1}$ and $\tanh$ are too complex to be calculated. For the sake of simplifying the functions above, the BP-based algorithm is proposed to makes an ingenious approximation in message updating step of the check nodes.

First, we define $L(q_{i'j}) = \phi_{i'j} \cdot \beta_{i'j}$, where $\phi_{i'j} = sign(L(q_{i'j}))$ and $\beta_{i'j} = |L(q_{i'j})|$, then simplify (2) in the horizontal step as follows.

$$\hat{L}(r_{ji}) = \left(\prod_{i' \in R(j)\backslash i} \phi_{i'j}\right) \cdot \min_{i' \in R(j)\backslash i} (\beta_{i'j}). \tag{6}$$

For a certain pair of i, j, denote L_1, L_2 as the value computed by (2) and (6) respectively. It can be proved that the sign of L_1 is the same with that of L_2, but $|L_2| > |L_1|$ [4], which means the output message values have the same sign but different amplitudes for the same incoming extrinsic LLR values in check nodes. In other words, the reliability which calculated by the BP-based algorithm is overestimated.

For the sake of recouping the accuracy loss of $|L_2|$ in approximation, the NBP-based as a kind of modified algorithm has been proposed to make use of the same correction to all of the LLR messages in check nodes by (7). The normalized parameter α is optimized according to DE which calculates the distributions of decoding probability messages for the infinite length codes. It can provide near the BP algorithm error-correcting performance. Besides, the less computational complexity is more suitable for hardware implementation.

$$L(r_{ji}) = (\prod_{i' \in R(j)\backslash i} \phi_{i'j}) \cdot \frac{1}{\alpha} \min_{i' \in R(j)\backslash i} (\beta_{i'j}). \tag{7}$$

III. A 2-Dimensional Classified Normalized BP-Based Algorithm

Through the analysis of the NBP-Based algorithm above, we can use normalization to get more accurate soft values from L_2. A normalized factor α which is greater than 1 is divided. But, from the principle of the horizontal step, not all the LLR values of the variable nodes participate in updating the LLR value of check nodes *j*, which implies that, in BP-based algorithm when updating the LLR of this check node and sending it to which connect to the variable nodes without minimum magnitude in TG graph, the minimum of β_{ij} is chosen. Otherwise, the sub-minimum one is involved.

Since the NBP-based algorithm adopts only one fixed normalized factor to decrease the overestimated magnitudes of all the incoming messages, in essence, the updated LLR messages are not only related to the minimum magnitude but also the sub-minimum one (denoted as $Y_{\min 1}^{d_c}$ and $Y_{\min 2}^{d_c}$ respectively). The performance loss would be arisen. Hence, it is desirable to find a solution to improve the accuracy in the NBP-Based algorithm with a tolerable computational cost, and hopefully, more accurate values could help improving the performance.

In order to derive two theoretical 2-dimensional normalization factors, we denote d_c as check node degree in the TG, $\{Y_1, Y_2, \ldots, Y_{d_c}\}$ are the absolute values of the incoming LLR messages $\{L(P_{1j}), L(P_{2j}), \ldots, L(P_{d_c j})\}$ in check nodes j. Obviously, they are independent identically distri-buted (i.i.d) random variables. Then, $Y_{\min 1}^{d_c}$ and $Y_{\min 2}^{d_c}$ can be obtained by classifying according to the amplitude of $\{Y_1, Y_2, \ldots, Y_{d_c}\}$. Our purpose is to calculate the two normalized correction factors for $Y_{\min 1}^{d_c}$ and $Y_{\min 2}^{d_c}$ according to (8) and (9). It can be modeled as calculating the mean of order statistics for incoming LLR messages in check nodes.

$$\alpha_1 = \frac{E(Y_{\min 1}^{d_c})}{E(|L_1|)}. \tag{8}$$

$$\alpha_2 = \frac{E(Y_{\min 2}^{d_c})}{E(|L_1|)}. \tag{9}$$

First, we calculate the mean of the $|L_1|$ statistically based on (10) in the BP algorithm.

$$E(|L_1|) = E\left(\left| \ln \frac{1 - \prod_{i=1}^{d_c-1} \frac{1-\exp(L(q_{ij}))}{1+\exp(L(q_{ij}))}}{1 + \prod_{i=1}^{d_c-1} \frac{1-\exp(L(q_{ij}))}{1+\exp(L(q_{ij}))}} \right| \right). \tag{10}$$

Using Taylor's series, we have (11), where $m_k = [E(\tanh(\beta_{ij}/2)^k)]^{d_c-1}$. The first few terms of (11) are good enough to give an estimation of (10).

$$E(|L_1|) = 2(m_1 + m_3/3 + m_5/5 + \ldots\ldots). \tag{11}$$

Then, we calculate the mean of the $|L_2|$ by (12) to obtain $E(Y_{\min 1}^{d_c-1})$, where $\mu = 4/N_0$, $\sigma^2 = 8/N_0$, $Q(x) = (1/\sqrt{2\pi})\int_x^\infty e^{-x^2/2} dx$.

$$\begin{aligned} E(Y_{\min 1}^{d_c-1}) &= E(|L_2|) \\ &= \int_0^\infty \left[\int_y^\infty f_{Y_1}(y_1) dy_1 \right]^{d_c-1} dy \\ &= \int_0^\mu \left[1 - Q(\frac{\mu-y}{\sigma}) + Q(\frac{\mu+y}{\sigma}) \right]^{d_c-1} dy \\ &+ \int_\mu^\infty \left[Q(\frac{y-\mu}{\sigma}) + Q(\frac{y+\mu}{\sigma}) \right]^{d_c-1} dy \\ &\approx \int_0^\mu \left[1 - Q(\frac{\mu-y}{\sigma}) + Q(\frac{\mu+y}{\sigma}) \right]^{d_c-1} dy. \end{aligned} \tag{12}$$

So that $E(Y_{\min 1}^{d_c})$ can be calculated as follows:

$$\begin{aligned} E(Y_{\min 1}^{d_c}) &= \int_0^\infty \left[\int_y^\infty f_{Y_1}(y_1) dy_1 \right]^{d_c} dy \\ &= \int_0^\infty \left[1 - F_y(y) \right]^{d_c} dy \\ &\approx \int_0^\mu \left[1 - Q(\frac{\mu-y}{\sigma}) + Q(\frac{\mu+y}{\sigma}) \right]^{d_c} dy. \end{aligned} \tag{13}$$

To obtain the mean of the sub-minimum magnitude of incoming LLR message, let $a = y, b = y + \varepsilon, \varepsilon \to 0^+$, the properties of the order statistics are used in (14) and (15).

$$\begin{aligned} &\Pr(a < Y_{\min 2}^{d_c} \le b) \\ &= \frac{d_c!}{(d_c-2)!} F_Y(a)(1-F_Y(b))^{d_c-2}(F_Y(b) - F_Y(a)). \end{aligned} \tag{14}$$

$$
\begin{aligned}
f_{Y_{\min 2}^{d_c}}(y) &= \lim_{\varepsilon \to 0^+} \frac{F_Y(b) - F_Y(a)}{b-a} \\
&= \lim_{\varepsilon \to 0^+} \frac{\frac{d_c!}{(d_c-2)!} F_Y(y)(1-F_Y(y+\varepsilon))^{d_c-2}(F_Y(y+\varepsilon)-F_Y(y))}{\varepsilon} \\
&= d_c(d_c-1)F_Y(y)(1-F_Y(y))^{d_c-2} f_Y(y).
\end{aligned} \tag{15}
$$

Finally, $E(Y_{\min 2}^{d_c})$ can be described as follows:

$$
\begin{aligned}
E(Y_{\min 2}^{d_c}) &= \int_0^{\infty} y d_c(d_c-1)F_Y(y)(1-F_Y(y))^{d_c-2} f_Y(y)dy \\
&= d_c(d_c-1)\int_0^{\infty} y\left[(1-F_Y(y))^{d_c-2} - (1-F_Y(y))^{d_c-1}\right] dF_Y(y) \\
&= d_c\int_0^{\infty}(1-F_Y(y))^{d_c-1}dy - (d_c-1)\int_0^{\infty}(1-F_Y(y))^{d_c}dy.
\end{aligned} \tag{16}
$$

According to the analysis above, we have α_1 and α_2 already and propose the 2-dimensional classified normalized BP-based (CNBP-based) algorithm as follows.

1) Keep the initialization unchangeable and adopt the same principle to update $L(q_{ij})$ in vertical step.
2) Calculate the final sign of $L(r_{ji})$ as $\prod_{i' \in R(j)\backslash i} \phi_{i'j}$ by multiplying all the input LLR signs and obtain $Y_{\min 1}^{d_c}$, $Y_{\min 2}^{d_c}$ by comparing with all the input LLR magnitudes. Record the location of $Y_{\min 1}^{d_c}$ in the TG as k.
3) Correct $Y_{\min 1}^{d_c}$ and $Y_{\min 2}^{d_c}$ respectively by 2-dimensional different correction factors based on (8), (9).
4) The final sign in 2) and the corrected magnitudes in 3) compose the new output messages in check nodes together, which can be described as (17).

$$
L(r_{ji}) = \begin{cases} \left(\prod_{i' \in R(j)\backslash i} \phi_{i'j}\right) \cdot \dfrac{Y_{\min 1}^{d_c}}{\alpha_1} & i' \neq k, \\[2ex] \left(\prod_{i' \in R(j)\backslash i} \phi_{i'j}\right) \cdot \dfrac{Y_{\min 2}^{d_c}}{\alpha_2} & i' = k. \end{cases} \tag{17}
$$

It can be seen that the probability density function (pdf) of $L(q_{ij})$ depends on signal noise ratio (SNR) and code rate from (3) and (6). So in the CNBP-based algorithm, the best choice of the classified normalized factors, α_1 and α_2, can be obtained by referring to the specific SNR which the best α is corresponding to, because the α in NBP-based algorithm is calculated by DE.

IV. SIMULATION RESULTS

We denote α is the single correction factor in NBP-based algorithm and α_1, α_2 are the correction factors of $Y_{\min 1}^{d_c}$, $Y_{\min 2}^{d_c}$ respectively in CNBP-based algorithm. Fig. 2 and Fig. 3 depict the numerical values of α_1 and α_2 we obtained by analysis in section III for some LDPC codes with row weights $d_c = 6$ and $d_c = 32$. We take the first five terms of (11) into account for an estimation of (10). It can be observed that the values of correction factors decrease when the row weights of the parity check matrix increase. All the correction factor values increased with the SNR gradually converge to a constant. In addition, the values of α_1 and α_2 in proposed algorithm are actually different from that of single correction factor α in NBP-based algorithm at the same SNR during the decoding process. It indicates that compared to the NBP-Based algorithm which uses single correction, the CNBP-based algorithm classifies the minimum and sub-minimum absolute values according to the incoming messages in check nodes and utilizes 2-dimensional different normalization for correction is more rational.

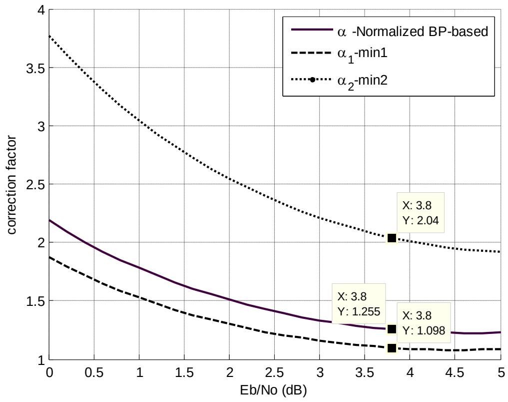

Figure 2. Correction factors obtained by analysis for $d_c = 6, R = 0.5$ LDPC codes

Simulation results are presented for the CNBP-based algorithm and some other decoding algorithms discussed in Section II. First, we consider a small row weights regular LDPC code with $d_c = 6$. The length of this code is 504 whose code rate is 0.5 [5]. We transmit 10^5 frames random 0, 1 codeword with the BPSK modulation over an additive white Gaussian noise (AWGN) channel and set maximum of 100 decoding iterations for each frame. We choose normalization factor of 1.25 by means of DE in [4], [6] and choose $\alpha_1 = 2.04$, $\alpha_2 = 1.09$ according to the numerical results in Fig. 2 for classified correction. Fig. 4 shows the statistical bit error ratio (BER) versus SNR of different algorithms.

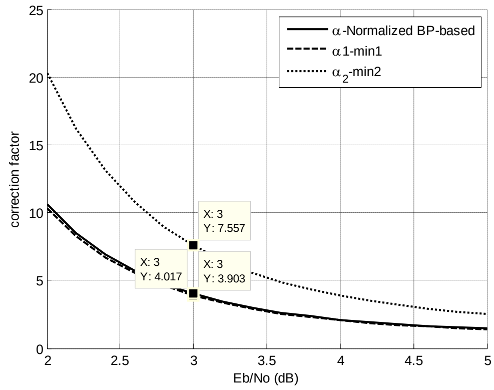

Figure 3. Correction factors obtained by analysis for $d_c = 32, R = 0.76$ LDPC codes

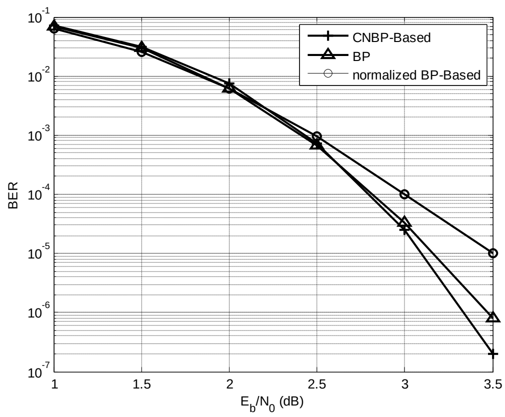

Figure 4. Decoding performance of (504, 252) LDPC code with different algorithms.

Due to the reliability overestimation of the extrinsic LLR message magnitudes and inaccurate correction with a single factor, the error-correcting performance of NBP-based decoding algorithm is the worst. It is about 0.3dB gap between the BP and the NBP-based algorithms at BER= 10^{-5} . Furthermore, in the CNBP-based decoding algorithm, we make use of 2-dimensional correction factors for $Y_{\min 1}^{d_c}$ and $Y_{\min 2}^{d_c}$, respectively. We can see also at BER= 10^{-5}, about 0.4dB coding gain to the NBP-based algorithms can be achieved by the CNBP-based algorithm. It should be emphasized that since the girth g=4 exists in the TG of this code, the BP algorithm is not the optimal, but the CNBP-based algorithm can counteract the feedback values in the TG with cycles. Hence, it even slightly outperforms the BP algorithm at higher SNR in Fig. 4.

Then we take the large row weights $d_c = 32$ LDPC code into account. The code rate of the (1023, 781) LDPC code is 0.76. For the NBP-based decoding algorithm, with the single correction factor $\alpha = 4$ derived in [4] and [7], the bit error performance gap between the BP algorithm increases to 0.5dB in Fig.5. The CNBP-based algorithm also outperforms the NBP-based algorithm about 0.4dB, and its performance is only less than 0.1dB away from the BP algorithm.

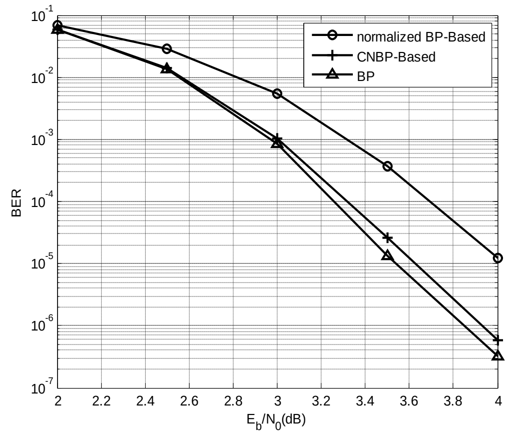

Figure 5. Decoding performance of (1023, 781) LDPC code with different algorithms.

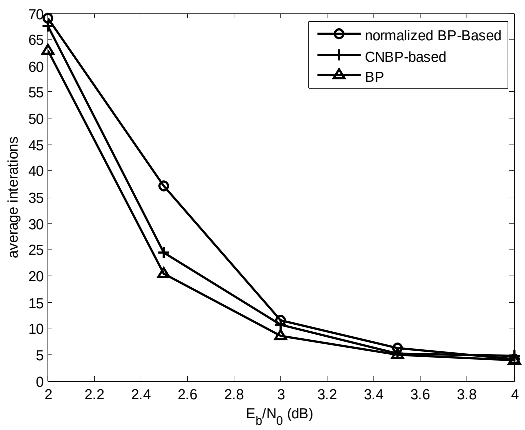

Figure 6. Average iterations of (504, 252) LDPC code with different algorithms.

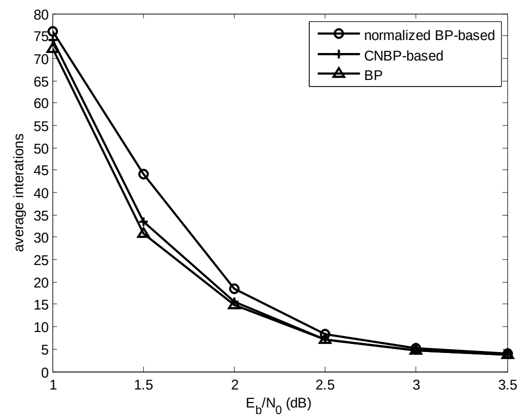

Figure 7. Average iterations of (1023, 781) LDPC code with different algorithms.

Fig. 6 and Fig. 7 show the average decoding iteration number with different algorithms which determine the decoder throughput. The CNBP-based algorithm decreases nearly 20% average iterations of the NBP-based algorithm due to the comparatively accurate correction, and almost as the same as the BP algorithm with the SNR increase. Therefore, the CNBP-based decoder throughput could be larger. Table I lists the computational complexity of three algorithms in a single decoding iteration. In each iteration, the division number in CNBP-based algorithm is twice over the NBP-based algorithm due to 2-dimensional classified normalization, but the multiplicative operations in both algorithms no longer exist. In general, the proposed algorithm is slightly more complicated than NBP-based algorithm, but much less than the BP algorithm.

TABLE I: COMPUTATIONAL COMPLEXITY IN A SINGLE ITERATION

Decoding Algorithm	Multiplication	Division	Addition
BP	$11Nd_c - 6(N+M)$	$N(d_c+1)$	$N(3d_c+1)$
Normailized BP-based	0	Nd_c	$N(4d_c-3)$ $+M(\log_2 d_c+2)$
CNBP-based	0	$2Nd_c$	$N(4d_c-3)$ $+M(\log_2 d_c+2)$

V. CONCLUSION

In this paper, we have analyzed and compared the soft values delivered by the BP algorithm and the BP-based algorithm, then assert the degradation of the NBP-based algorithm due to the inaccurate correction. Both the minimum and the sub-minimum LLR magnitudes in check nodes participate in the message updating. In order to compensate performance loss caused by single correction, we propose to use order statistics analysis method and utilize 2-dimensional classified correction for improving accuracy. Simulation results show the 2-dimensional correction can decrease number of decoding iterations to increase the decoding throughput. For both small and large row weights LDPC codes, it can get even slightly better error-correcting performance than the BP algorithm at high SNR with much less computational complexity. The main idea of the proposed algorithm can also be used in APP-based algorithm [8] with some new architecture [9]-[12] for larger decoding throughput.

REFERENCES

[1] R. G. Gallager, “Low-density parity check codes,” *IEEE Trans. Inform Theory*, vol. 8, pp. 21-28, January 1962.

[2] E. Eleftheriou, T. Mittelholzer, and A. Dholakia, “Reduced cpmplexity decoding algorithm for low density parity check codes,” *IEEE Electronic Letters*, vol. 37, pp. 102-104, January 2001.

[3] M. P. C. Fossorier, M. Mihaljevic, and H. Imai, “Reduced complexity iterative decoding of low-density parity check codes based on belief propagation,” *IEEE Transactions on Communications*, vol. 47, pp. 673-680, May 1999.

[4] J. Chen and M. P. C. Fossorier, “Density evolution for BP-based decoding algorithms of LDPC codes and their quantized versions,” in *Proc. IEEE Global Telecommunications Conference*, Taipei, Taiwan, 2002, pp. 1378-1382.

[5] S. L. Howard, C. Schlegel, and V. C. Gaudet, “A Degree matched check node approximation for LDPC decoding,” in *Proc. IEEE Intl. Sym. Inf. Theory*, Adelaide, AU, 2005, pp. 1131-1135.

[6] M. Martalo, G. Ferrari, A. Abrardo, M. Franceschini, and R. Raheli, “Density evolution-based analysis and design of LDPC codes with a priori information,” in *Proc. Information Theory and Applications Workshop*, San Diego, CA, 2010, pp. 1-9.

[7] I. Sason and B. Shuval, “On universal LDPC code ensembles over memoryless symmetric channels,” *IEEE Transactions on Information Theory*, vol. 57, pp. 5182-5202, August 2011.

[8] X. R. Wang, Y. Zhang, and J. L. Chen, “Modified APP-based decoding algorithm for low-density parity check codes,” in *Proc. IEEE 7th International Conference on Wireless Communications, Networking and Mobile Computing*, Shenzhen, China, 2011, pp. 1-4.

[9] Y. Sun, G. H. Wang, and J. R. Cavallaro, “Multi-layer parallel decoding algorithm and VLSI architecture for quasi-cyclic LDPC codes,” in *Proc. IEEE International Symposium on Circuits and Systems*, Rio de Janeiro, Brazil, 2011, pp. 1776-1779.

[10] A. R. R. Abolfazli and Y. R. Shayan, "New multi-dimensional mapping for MIMO-BICM-ID systems," *Journal of Communications*, vol. 6, pp. 232-239, May 2011.

[11] V. K. K. Srinivasan, C. K. Singh, and P. T. Balsara, “A generic scalable architecture for min-sum/offset-min-sum unit for irregular/regular LDPC decoder,” *IEEE Transactions on Very Large Scale Integration Systems*, vol. 18, pp. 1372-1376, September 2010.

[12] G. Thiagarajan and C. R. Murthy, “Trellis coded block codes: Design and applications,” *Journal of Communications*, vol. 7, pp. 73-85, January 2012.

Zhou Zhong received his B.E. and M.S. degrees in 2005 and 2008 respectively, from the Department of Communication Engineering, Zhengzhou Information and Science Institute. Currently, he is a Ph.D. candidate at the National Digital Switching System Engineering & Technological Research Center. His research interests lie in the field of coding theory, signal processing and physical layer security in wireless communication.

Shuming Guo received his B.E., M.S. and Ph.D. degrees in 1998, 2002 and 2008 respectively, from the Department of Communication Engineering, Zhengzhou Information and Science Institute. Currently, he is an associate professor and member of National Digital Switching System Engineering & Technological Research Center. His main research interests focus on channel estimation, signal processing and coding techniques in wireless communication.

Xiangyang Xu received his B.E. degree in 2005, from the Department of Communication Engineering, Zhengzhou Information and Science Institute. Currently, he is an intermediate engineer and member of National Digital Switching System Engineering & Technological Research Center. His general research interests include statistical signal processing and communication systems design.

HuiQing Bai was born in Henan, China, in 1988. She has received her B.Sc.degree in Electron and Information Engineering from Zhengzhou Information and Science Institute. She is currently a M.A.Sc. candidate at National Digital Switching System Engineering & Technological Research Center. Her research interests are mobile communication, physical layer security and channel coding.

