Performance Analysis of the Structured Irregular LDPC Coded MIMO-OFDM System with Iterative Channel Estimator

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Abstract— **In this paper, we evaluate the performance of the receiver employing an iterative RLS-based data detection and channel estimation for the structured irregular LDPC coded MIMO-OFDM system. Using the EXIT chart analysis, the performance of the detector with various approximate decoding algorithms is analyzed.**

I. Introduction

In recent years Low-Density Parity-Check (LDPC) codes [1] have gained a lot of attention with their capability to achieve near Shannon limit performance. Although LDPC codes of random construction allow for a high degree of parallelism, the randomness of the parity-check matrix makes it difficult to exploit in hardware. This disadvantage has lead to several approaches of designing structured irregular LDPC codes [2], [3], that are suitable for an efficient hardware implementation, yielding very high throughput. They are designed using different methods, but the basic idea is to partition the parity-check matrix into non-overlapping block rows and block columns. One such approach is to use a permutation matrix. Under this design method, one belief propagation algorithm [4] has been proposed, where an LDPC decoding iteration is broken into sub-iterations. During each sub-iteration updated log-likelihood ratios (LLRs) are computed for each of the non-overlapping block rows.

It is shown for single-carrier systems in [5] that an iterative minimum-mean square error (MMSE) equalizer combined with soft data detector lead to both better channel estimation and BER performance. Thus, iterative estimation/detection structures based on these latter methods may also yield better BER performance in OFDM systems with unknown channels. This paper presents a soft-RLS OFDM channel estimator and combines it with a recently proposed MIMO-OFDM soft-QRD-M data detector [6], [7] to develop a new semi-blind channel estimation and data detection algorithm.

The remainder of this paper is organized as follows. In Section II the structured LDPC code is described. In Section III, signal model is described. The proposed soft-RLS channel estimator is in Section IV. In Section V, the EXIT chart for the MIMO data detector is derived for the iterative LDPC coded MIMO-OFDM system. The simulation results are provided in Section VI, and conclusions follow in Section VII.

II. Structured Low-Density Parity-Check Codes

In this paper, we consider a baseband model for a received MIMO OFDM signal over a multipath fading channel. The notation used for the MIMO-OFDM system includes the following:

- N_f, N_t, N_r : number of multipaths and antennas in transmitter and receiver.
- K, N : number of subcarriers and OFDM data symbols in one packet.
- $T_g, T_d \stackrel{\triangle}{=} KT_s, T_s$: guard time interval, OFDM data symbol interval, and sampling time.
- $\mathbf{A}$, $\mathbf{a}$, $(\mathbf{A})_{l,m}$, $(\mathbf{a})_k$: a matrix, a vector, the (l,m) element of the matrix $\mathbf{A}$, and the k-th element of the vector $\mathbf{a}$.
- $\mathbf{\Lambda}(a_1, .., a_N)$: a diagonal matrix with $\{a_1, .., a_N\}$.

The symbols p, q, k, n are used as indices for the transmit antenna, receiver antenna, subcarrier, and OFDM data symbol respectively, with $1 \leq p \leq N_t$, $1 \leq q \leq N_r$, $1 \leq k \leq K$, $0 \leq n \leq N$.

LDPC codes can be constructed in many different ways. A completely random construction generally yields a very high performance LDPC codes, however they are not suitable for implementation. Some of the structured approaches yield a practical implementation, highly reconfigurable and high throughput LDPC code, with a slight performance degradation. While randomness is a desired property in the parity-check matrix, recently many researchers have shown that high performance LDPC codes can be constructed with a structured approach. One such approach is to build an irregular LDPC codes based on shifted permutation matrices [2], [3].

III. Signal Model for LDPC-MIMO-OFDM Systems

The coded bit stream is converted into N_t parallel data substreams by serial-to-parallel processing. One packet is composed of N OFDM data symbols where each of the data symbols is made up of K subcarriers. A guard time interval T_g is also included in each data symbol to eliminate ISI. The coded symbols $\{d_k^p(n)\}$ drive the p-th modulator, a K-point IFFT. The coded symbols $d_k^p(n)$ are chosen from a complex-valued finite alphabet, that is, $d_k^p(n) = g(b_{k,1}^p(n), \ldots, b_{k,Q}^p(n)) : \{-1,1\}^Q \to \mathsf{C}$, where $b_{k,j}^p \in \{-1,1\}$ is understood to implicitly map to $\{1,0\}$ if required for decoding. The n-th output of the p-th modulator is

$$\begin{aligned} s^p(t) &= s_D^p(t) p_D(t - T_d^g(n)), \\ s_D^p(t) &= \frac{1}{\sqrt{K}} \sum_{k=0}^{K-1} d_k^p(n) e^{j2\pi k(t - T_d^g(n))/T_d}. \end{aligned}$$

Here, $T_d^g \triangleq (T_g + T_d)$ and $p_D(t)$ is a pulse with finite support on $[0, T_d)$. The channel between the p-th transmit and q-th receiver antenna, $\{f_l^{p,q}(n)\}$, is modeled by a tapped delay line, such that the n-th received signal at the q-th antenna is $r^q(t) = \sum_{p=1}^{N_t} \sum_{l=0}^{N_f-1} f_l^{p,q}(n) s_D^p(t - lT_s) + n^q(t)$. It is assumed in the sequel that $N_f T_s < T_g$, a set of channels $\{f_l^{p,q}(n)\}$ is assumed to be constant over only one OFDM packet duration, and the receiver is assumed to be matched to the transmitted pulse. The additive noise $n^q(t)$ is circular white Gaussian with spectral density $2N_0$. The demodulator vector output of the n-th OFDM symbol after eliminating the guard interval is

$$\mathbf{y}^q(n) = [\mathbf{D}^1(n)\mathbf{C}^T, \ldots, \mathbf{D}^{N_t}(n)\mathbf{C}^T]\mathbf{f}^q(n) + \mathbf{z}^q(n), \quad (1)$$

where

$$\begin{aligned} y_k^q(n) &= \sum_{p=1}^{N_t} F_k^{p,q}(n) d_k^p(n) + z_k^q(n), \\ \mathbf{y}^q(n) &\triangleq \left[y_0^q(n), .., y_{K-1}^q(n)\right]^T, \\ \mathbf{D}^p(n) &\triangleq \mathbf{\Lambda}(d_0^p(n), .., d_{K-1}^p(n)), \mathbf{C} \triangleq [\mathbf{c}_0, .., \mathbf{c}_{K-1}], \\ \mathbf{c}_k &\triangleq [1, e^{-j2\pi k/K}, .., e^{-j2\pi k(N_f-1)/K}]^T, \\ \mathbf{f}^q(n) &\triangleq [\mathbf{f}^{1,q}(n)^T, .., \mathbf{f}^{N_t,q}(n)^T]^T, \\ \mathbf{f}^{p,q}(n) &\triangleq [f_0^{p,q}(n), .., f_{N_f-1}^{p,q}(n)]^T, F_k^{p,q}(n) \triangleq \mathbf{c}_k^T \mathbf{f}^{p,q}(n), \\ \mathbf{z}^q(n) &\sim \mathcal{N}(\mathbf{z}^q(n); \mathbf{0}, 2N_0/T_s \mathbf{I}_{K\times K}). \end{aligned} \quad (2)$$

IV. Soft-RLS Channel Estimator

For a received vector $\mathbf{y}_k(n) \triangleq [y_k^1(n), .., y_k^{N_r}(n)]^T$ on subcarrier k, the *a posteriori* probability (APP) for $b_{k,j}^p(n)$ is

$$L(b_{k,j}^p(n)) \triangleq \ln \frac{p(b_{k,j}^p(n) = 1|\mathbf{y}_k(n))}{p(b_{k,j}^p(n) = -1|\mathbf{y}_k(n))}. \quad (3)$$

The proposed soft-RLS estimator is driven by the soft decision $\bar{d}_k^p(n) \triangleq E[d_k^p(n)]$, where the expectation is with respect to the APP. Conditioned on the soft symbol decisions, the measurement vector used by the q-th soft-RLS estimator is

$$\mathbf{y}^q(n) = \mathbf{H}(\bar{\mathbf{D}}(n))\mathbf{f}^q(n) + \mathbf{H}(\tilde{\mathbf{D}}(n))\mathbf{f}^q(n) + \mathbf{z}^q(n). \quad (4)$$

In (4) $\tilde{\mathbf{D}}^p(n) = \mathbf{D}^p(n) - \bar{\mathbf{D}}^p(n)$, and

$$\begin{aligned} \mathbf{H}(\bar{\mathbf{D}}(n)) &\triangleq [\bar{\mathbf{D}}^1(n)\mathbf{C}^T, .., \bar{\mathbf{D}}^{N_t}(n)\mathbf{C}^T], \\ \bar{\mathbf{D}}^p(n) &\triangleq \mathbf{\Lambda}(\bar{d}_0^p(n), .., \bar{d}_{K-1}^p(n)). \end{aligned}$$

To develop the soft-RLS estimator, first rewrite the received vector signal using a composite noise vector including the data detection errors.

$$\mathbf{y}^q(n) = \mathbf{H}(\bar{\mathbf{D}}(n))\mathbf{f}^q(n) + \tilde{\mathbf{z}}^q(n), \quad (5)$$

where $\tilde{\mathbf{z}}^q(n) \triangleq \sum_{p=1}^{N_t} \tilde{\mathbf{D}}^p(n)\mathbf{C}^T\mathbf{f}^{p,q}(n) + \mathbf{z}^q(n)$. Considering the statistical property of $\tilde{\mathbf{z}}^q(n)$, we change the minimizing function applying an approach used in [8]. The soft-RLS algorithm is obtained by recursive minimization

$$\hat{\mathbf{f}}^q(n) = \arg\min_{\mathbf{f}^q(n)} \sum_{m=1}^{n} \beta^{n-l} (\delta^q(m))^H (\tilde{\mathbf{R}}^q(m))^{-1} \delta^q(m). \quad (6)$$

Here, $\delta^q(m) \triangleq \mathbf{y}^q(m) - \mathbf{H}(\bar{\mathbf{D}}(m))\mathbf{f}^q(n)$ and β is a forgetting factor. Denoting by $V(d_k^p(m))$ the variance of symbol $d_k^p(m)$ and by $\mathbf{e}_{k+1} \triangleq [\mathbf{0}_{1\times k}, 1, \mathbf{0}_{1\times(K-k-1)}]^T$, the covariance matrix [9] of $\tilde{\mathbf{z}}^q(m)$ will be $\tilde{\mathbf{R}}^q(m) = \tilde{\mathbf{R}}_f^q(m) + 2N_0/T_s\mathbf{I}$, where

$$\begin{aligned} \tilde{\mathbf{R}}_f^q(m) &\triangleq \sum_{p=1}^{N_t} \sum_{k=0}^{K-1} \mathbf{S}_{k+1}(\mathbf{f}^{p,q}(m)) V(d_k^p(m)) \mathbf{e}_{k+1}\mathbf{e}_{k+1}^T, \\ \mathbf{S}_k(\mathbf{f}^{p,q}(m)) &\triangleq \begin{bmatrix} \mathbf{0}_{1\times k-1} \\ (\mathbf{C}^T E[\mathbf{f}^{p,q}(m)\mathbf{f}^{p,q}(m)^H]\mathbf{C}^*)(l,:) \\ \mathbf{0}_{1\times K-k} \end{bmatrix}. \end{aligned}$$

With some computations, the following soft-RLS algorithm at the l-th receiver subiteration is obtained.

$$\begin{aligned} &\mathbf{P}^{q,l}(n)^{-1} = \\ &\quad \beta\mathbf{P}^{q,l}(n-1)^{-1} + \mathbf{H}(\bar{\mathbf{D}}^l(n))^H (\hat{\tilde{\mathbf{R}}}^{q,l}(n))^{-1} \mathbf{H}(\bar{\mathbf{D}}^l(n)), \\ &\hat{\mathbf{f}}^{q,l}(n) = \\ &\quad \hat{\mathbf{f}}^{q,l}(n-1) + \mathbf{P}^{q,l}(n)\mathbf{H}(\bar{\mathbf{D}}^l(n))^H (\hat{\tilde{\mathbf{R}}}^{q,l}(n))^{-1} \delta\mathbf{y}^{q,l}(n), \\ &\quad \delta\mathbf{y}^{q,l}(n) \triangleq \mathbf{y}^q(n) - \mathbf{H}(\bar{\mathbf{D}}^l(n))\hat{\mathbf{f}}^{q,l}(n-1). \end{aligned}$$

The matrix $\mathbf{P}^q(n)$ corresponds to the pseudocovariance. At receiver subiteration l, the iterative RLS algorithm approximates the unknown covariance $\hat{\tilde{\mathbf{R}}}_f^{q,l}(n)$ by incorporating a previous channel estimate and APP based soft decisions, that is,

$$\hat{\tilde{\mathbf{R}}}_f^{q,l}(n) \approx \sum_{p=1}^{N_t}\sum_{k=0}^{K-1} \mathbf{S}_{k+1}(\hat{\mathbf{f}}^{p,q,l}(n-1))V(d_k^{p,l}(n))\mathbf{e}_{k+1}\mathbf{e}_{k+1}^T.$$

V. EXIT Chart for the Iterative LDPC Coded MIMO-OFDM System

At receiver subiteration l, the soft-QRD-M algorithm [6], [7] is run on all subcarriers based on the following approximate measurement model derived from all N_r receive antennas:

$$\mathbf{y}_k(n) \approx \hat{\mathbf{F}}_k^l(n)\mathbf{d}_k(n) + \mathbf{z}_k(n), \tag{7}$$

where

$$\begin{aligned}(\hat{\mathbf{F}}_k^l(n))_{i,j} &\triangleq \mathbf{c}_k^T(\hat{\mathbf{f}}^{i,l}(n))_j, \mathbf{d}_k(n)\triangleq[d_k^1(n),..,d_k^{N_t}(n)]^T,\\ \mathbf{z}_k(n) &\sim \mathcal{N}(\mathbf{z}_k(n);\mathbf{0},2N_0/T_s\mathbf{I}_{N_r\times N_r}).\end{aligned} \tag{8}$$

Here, $\hat{\mathbf{F}}_k^l(n)$ represents estimated frequency responses of all $N_r \times N_t$ channels at frequency k and receiver subiteration l. The soft-QRD-M, with $N_r \geq N_t$, computes approximates APPs. The soft decisions at iteration l, $\bar{d}_k^{p,l}$ are obtained from the APPs using channel estimations $\hat{\mathbf{F}}_k^l(n)$, such that

$$\bar{d}_k^{p,l}(n) = g(\tanh(L^l(b_{k,1}^p(n))/2),..,\tanh(L^l(b_{k,Q}^p(n)/2))),$$

where

$$L^l(b_{k,j}^p(n)) \approx \ln\frac{p(\mathbf{y}_k(n)|\hat{\mathbf{F}}_k^l(n), b_{k,j}^p=1)}{p(\mathbf{y}_k(n)|\hat{\mathbf{F}}_k^l(n), b_{k,j}^p=-1)} + \lambda_2^l(b_{k,j}^p). \tag{9}$$

The prior APP $\lambda_2^l(b_{k,j}^p)$ is the extrinsic from the LDPC decoder. The extrinsic decoder information, denoted by $\lambda_2^l(b_{k,j}^p)$, becomes increasingly accurate as long as the SNR is above a threshold or the receiver subiteration proceeds. The LDPC decoder computes the APPs of the coded bits using the interleaved extrinsic bit information from the soft QRD-M, and then excludes *a priori* information to generate a new extrinsic as

$$\lambda_2^{\Pi^{-1},l}(b_{k,j}^p) = L_2^l(b_{k,j}^p) - \lambda_1^{\Pi^{-1},l}(b_{k,j}^p). \tag{10}$$

In (10), $\lambda_1^{\Pi^{-1},l}(b_{k,j}^p)$ is a deinterleaved $\lambda_1^l(b_{k,j}^p)$. On the next iteration, the soft-QRD-M uses the interleaved version of the *a priori* LLR, $\lambda_2^l(b_{k,j}^p)$. Specifically, the new APP from the decoder $\lambda_2^l(b_{k,j}^p)$ is added to the measurement LLR. Thus, the decoder extrinsic improves detector performance by providing more reliable data decisions.

A. LDPC Decoding Algorithms

In the conventional belief propagation algorithm or SPA [1], the extrinsic information is iteratively calculated from each check node to the participating bit nodes and from each bit node to check nodes. To speed up decoding process, a variation of the belief propagation algorithm, called the layered belief propagation algorithm, has been proposed in [10], where the extrinsic informations are updated after each layer is processed. The extrinsic information sent to the LDPC decoder is determined by the LLRs by

$$\lambda_1^l(b_{k,j}^p) = \hat{L}^l(b_{k,j}^p(n)) - \lambda_2^l(b_{k,j}^p), \tag{11}$$

where $\hat{L}^l(b_{k,j}^p(n))$ is an approximated LLRs and the *a priori* LLR of the coded bit $b_{k,j}^p(n)$ corresponds to the interleaved extrinsic information from the previous decoding iteration. To investigate the convergence behavior of the proposed iterative receiver structure with a different decoding algorithm, we use the EXIT chart analysis.

B. EXIT Chart Analysis

The EXIT chart analysis was originally developed in [11] to analyze iterative Turbo decoding performance without extensive BER simulations. Here, we apply a modified EXIT technique to evaluate the LDPC decoding/soft-QRD-M algorithm defined by iterations (10) and (11). The extrinsic information $I_E^m(b_{kj}^p)$ at the soft-QRD-M output will be plotted versus the a priori information $I_A^m(b_{k,j}^p)$ corresponding to the overall LDPC decoder extrinsic information. Compared to[11], we use simulations to generate the actual priors $\lambda_2(b)$ from the LDPC decoder, hence a Gaussian approximation is not required. Let $I_A(b_{k,j}^p) = I(\lambda_2(b_{k,j}^p); b_{k,j}^p)$ be the mutual information between the a priori information and bit $b^p(k,j)$. A Monte-Carlo simulation over N_e runs is used to estimate $I_A(b_{k,j}^p)$ as follows [7]
$\hat{I}_A(b_{k,j}^p) \approx \frac{1}{N_e}\sum_{l=1}^{N_e} I_{A,l}(b_{k,j}^p) = 1 + \frac{1}{N_e}\sum_{l=1}^{N_e}[\Delta_1^1 + \Delta_l^2]$,
where

$$\begin{aligned}\Delta_l^1 &\triangleq \frac{1}{1+\delta_l}\log_2(\frac{1}{1+\delta_l}), \Delta_l^2\triangleq\frac{\delta_l}{1+\delta_l}\log_2(\frac{\delta_l}{1+\delta_l}),\\ \delta_l &\triangleq \delta(l,p,k,j)\triangleq e^{\lambda_{2,l}(b_{k,j}^p)},\end{aligned} \tag{12}$$

where $\lambda_{2,l}(b_{k,j}^p)$ is the LDPC decoder output extrinsic LLR. Similarly, the mutual information between the soft-QRD-M output extrinsic LLRs $\lambda_1(b_{k,j}^p)$ and the information bit $b_{k,j}^p$, $I_E(b_{k,j}^p) = I(\lambda_2(b_{k,j}^p); b_{k,j}^p)$, is estimated. These Monte-Carlo estimates are consistent by the strong Law of Large Numbers for N_e independent trials, so $\hat{I}_A(b_{k,j}^p) \rightarrow I_A(b_{k,j}^p)$. The soft-QRD-M detector starts with zero *a priori* information, that is, $I_A^0(b_{k,j}^p) = 0$. On iteration m, the trajectory point is defined by $(\hat{I}_A^m(b_{k,j}^p), \hat{I}_E^m(b_{k,j}^p))$. We also have an estimate of $\hat{I}_E^m(b_{k,j}^p) = T(\hat{I}_A^m(b_{k,j}^p))$. The iterative detector/decoder evolves as long as $\hat{I}_E^{m+1}(b_{k,j}^p) > \hat{I}_E^m(b_{k,j}^p)$. Note that since the detector has no coding gain, the data detector extrinsic information $\hat{I}_E^m$ is typically less than unity.

However, at a sufficiently high SNR the LDPC decoder extrinsic information can reach unity.

VI. Simulation Results

The following parameters were used in the simulations.

- $K = 64$, $N_t = N_r = 4$, $N_H = 6144$, $K_H = 4608$.
- Fading channel powers, $N_f = 2$, $||\mathbf{f}^{p,q}(n)||^2 = \{0.5991, 0.4009\}, \ \forall p, q$.

The following seed matrix $\mathbf{H}_S$ in hexadecimal format [3] with $N_s = 128, p = 53$ is used to generate $\mathbf{H}$ matrix.

$$\mathbf{H}_S = [\mathbf{H}_{S,1}, \mathbf{H}_{S,2}]^T,$$

$$\mathbf{H}_{S,1}^T \triangleq \begin{bmatrix} \texttt{0x8013065040EF} \\ \texttt{0x006306D40A25} \\ \texttt{0x00C792C82502} \\ \texttt{0x018B61B04422} \\ \texttt{0x0303C2BD1020} \\ \texttt{0x060051D2D310} \end{bmatrix}, \mathbf{H}_{S,2}^T \triangleq \begin{bmatrix} \texttt{0x0C030A1B48B0} \\ \texttt{0x18031AF05028} \\ \texttt{0x30152AC0EC00} \\ \texttt{0x600806D64168} \\ \texttt{0xC00F2141C0A4} \\ \texttt{0x003282D06271} \end{bmatrix}.$$

The QPSK is used for a subcarrier modulation, and as a decoding algorithm belief-propagation (BP) and layered belief-propagation (L-BP) algorithms are used. Twelve LDPC iterations are used in these algorithms. Bit error rate (BER) performances of the detector employing a different decoding algorithm are shown in Figure 1. This figure shows that as detector-decoder iteration proceeds, the data detector works better. Compared to the BP algorithm, we have a better BER performance with the L-BP algorithm. If the number of detector-decoder iterations larger than two, the BER performance tends to be independent in mid-SNR ranges. We may observe a difference in higher SNR ranges. Compared to the ideal receiver, we have at most 1 [dB] SNR loss within three detector-channel estimator-decoder iterations. Figure 2 is the corresponding EXIT chart at a different SNR employing the proposed soft-RLS channel estimator. This figure shows that although there are BER differences between decoding algorithms, we cannot find corresponding noticeable differences in terms of the mutual information as SNR increases. Also, with only one or two detector-decoder iterations, the detector is usually trapped in a pinch-off region in higher SNRs. In lower SNRs, the L-BP algorithm leads to the pinch-off region faster than the BP algorithm.

VII. Conclusions

In this paper, we analyze the performance of the detector for the iterative LDPC coded MIMO-OFDM System. A structured irregular LDPC code is used in the proposed system with layered belief propagation algorithms.

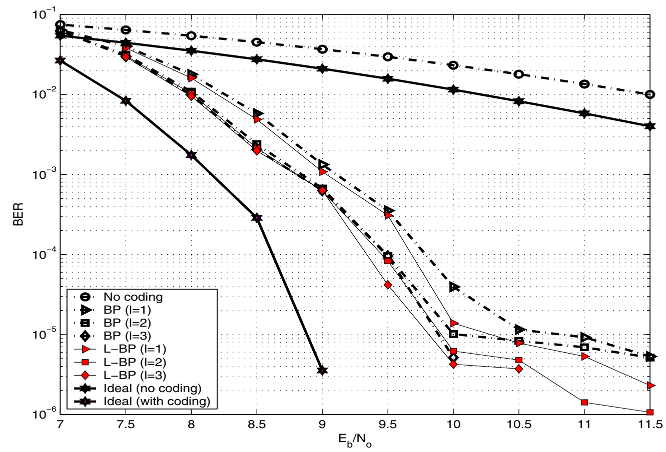

Fig. 1. BER Performance of the data detector in the iterative LDPC coded MIMO-OFDM System with BP and L-BP.

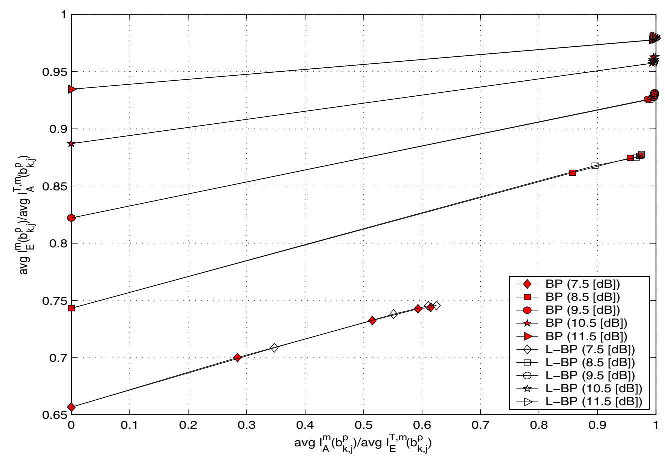

Fig. 2. EXIT Chart for the data detector employing a different decoding algorithm at a different SNR.

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