Low-Complexity Iteration Control for MIMO-BICM Systems

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***Abstract*—Air bandwidth is a precious resource for wireless communication. Multiple-antenna (MIMO) systems enable an increase in channel capacity without increasing the air bandwidth. An iterative demapping and decoding at the receiver improves the communications performance remarkably. However, MIMO demapping and channel decoding have a high computational complexity. Energy consumption, latency and throughput of a hardware implementation strongly depend on the number of iterations. Iteration control techniques are very efficient to reduce the average number of iterations thus increasing decoder throughput and reducing energy consumption and average decoding latency.**

To the best of our knowledge, we present the first analysis of iteration control in MIMO bit interleaved coded modulation systems. We introduce a novel stopping metric for iteration control, which outperforms existing stopping metrics for middle and high signal-to-noise ratios. Additionally, we analyze state-of-the-art stopping metrics with respect to their algorithmic complexity in due consideration of a later hardware implementation.

I. Introduction

Wireless services are driven by the rising demand to provide high-speed data transmissions (several 100 Mbit/s) anytime and everywhere. A common way to increase the throughput and the system capacity is to increase the transmission bandwidth. The available frequency space for wireless transmission is naturally limited and already occupied by different services. Multiple-input multiple-output (MIMO) antenna systems can overcome this problem by increasing the channel capacity without increasing the bandwidth, e.g., the LTE standard already includes a MIMO transmission mode [1].

The receiver of a MIMO system consists of a MIMO detector, which recovers the transmitted bits from all receive antennas. After that a channel decoder corrects corrupted bits to provide a certain quality of service. The communications performance of the receiver can be remarkably improved by introducing an iterative decoding between the MIMO detector and the channel decoder [2] [3].

However, this iterative improvement comes at a cost as energy consumption, latency and throughput of the receiver are directly related to the number of iterations. Instead of using a fixed number of iterations, an iteration control exploits the dynamics of the channel and adapts the number of iterations accordingly. This way, latency and energy consumption are considerably reduced and throughput is increased. The implementation of stopping conditions causes an energy and area overhead. Therefore, the complexity of stopping metrics has to be low to avoid that the benefits of iteration control are counterbalanced by its implementation cost.

A. Related Work

Iteration control methods have been extensively studied for the decoding of iterative channel codes like e.g. turbo codes or low-density parity-check (LDPC) codes. It was shown that iteration control is the most efficient technique for energy saving in a turbo decoder system without sacrificing communications performance [4]. Common iteration control metrics are based on either the sign bits [5] [6] or the extrinsic or a posteriori values [5] [7] [8] at the output of the channel decoder. Some of them can be implemented with a very low complexity [9] [10]. For systematic codes in high signal-to-noise ratio (SNR) ranges, it is even possible to avoid decoding completely by detecting valid codewords at the entry of the channel decoder [11]. A more theoretical approach was chosen in [7], where Hagenauer et al. use the cross-entropy between different iterations for iteration control. However, all those works restrict iteration control to the field of channel decoding.

In the context of MIMO bit interleaved coded modulation (BICM) systems, Zimmermann et al. [12] use an estimate of the information content at the entry of the turbo decoder to reduce the overall number of iterations of the inner channel decoder. However, this technique is not able to reduce the number of iterations between MIMO detection and channel decoding.

B. New Contributions

In contrast to the afore mentioned work, we aim at reducing the number of iterations between MIMO detector and channel decoder and not the iterations within the channel decoder. To the best of our knowledge, this is the first paper analyzing iteration control for MIMO-BICM systems.

We introduce a novel stopping metric for iteration control and compare it with several state-of-the-art stopping metrics. We present the first analysis for these stopping metrics for iterative demapping and decoding in a MIMO-BICM system regarding

- their impact on communications performance,

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- their ability to reduce the number of iterations and thereby influencing throughput, latency and energy consumption of a hardware implementation,
- and their algorithmic complexity.

All presented simulation results are obtained with low-complexity algorithms where all values have been quantized. The choice of the algorithms was determined by their suitability for a later hardware implementation.

The rest of this paper is structured as follows. Section II introduces the analyzed communications system and basic receiver algorithms. An overview on iteration control techniques is given in III. Furthermore, a new stopping metric based on mutual information is presented. Its algorithmic complexity is compared to several state-of-the-art metrics. Simulation results on communications performance and reduction of iterations are discussed in IV. Finally, the paper is concluded in V.

II. System Model

In this paper, we focus on a bit interleaved coded modulation (BICM) scheme like shown in Fig. 1. The source generates a random infoword $\boldsymbol{u}$ of length K_c, which is encoded by the channel encoder. The interleaved codeword $\boldsymbol{X}^N$ consists of N_c bits, which are grouped into N subblocks $\boldsymbol{x}_n$.

$$\boldsymbol{X}^N = (\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_n, \ldots, \boldsymbol{x}_N) \tag{1}$$

Each subblock $\boldsymbol{x}_n$ consists of Q coded bits.

$$\boldsymbol{x}_n = (x_{1,n}, x_{2,n}, \ldots, x_{q,n}, \ldots, x_{Q,n}),\ x_{q,n} \in \{-1, +1\} \tag{2}$$

Each subblock $\boldsymbol{x}_n$ is mapped directly to a complex symbol s chosen from a 2^Q-ary QAM modulation scheme. M_T symbols are combined in one transmission vector $\boldsymbol{s}_t$.

$$\boldsymbol{s}_t = (s_{1,t}, s_{2,t}, \ldots, s_{m,t}, \ldots, s_{M_T,t}) \tag{3}$$

The whole modulated sequence is represented by

$$\boldsymbol{S}^T = (\boldsymbol{s}_1, \boldsymbol{s}_2, \ldots, \boldsymbol{s}_t, \ldots, \boldsymbol{s}_T) \tag{4}$$

$T = \lceil N/M_T \rceil$ time slots are needed to transmit all symbols of one codeword. The transmission of vector $\boldsymbol{s}_t$ in time step t is modeled by

$$\boldsymbol{y}_t = \boldsymbol{H}_t \cdot \boldsymbol{s}_t + \boldsymbol{n}_t \tag{5}$$

with $\boldsymbol{H}_t$ the channel matrix of dimension $M_T \times M_R$ and $\boldsymbol{n}_t$ the noise vector of dimension M_R whose entries are zero-mean and unit variance Gaussian variables. The elements of $\boldsymbol{H}_t$ are modeled as independent, complex, zero-mean, Gaussian random variables. Real and imaginary parts are independent variables each with variance $\sigma^2 = N_0/2$. All received vectors $\boldsymbol{y}_t$ are gathered in the matrix $\boldsymbol{Y}^T$

$$\boldsymbol{Y}^T = (\boldsymbol{y}_1, \boldsymbol{y}_2, \ldots, \boldsymbol{y}_t, \ldots, \boldsymbol{y}_T) \tag{6}$$

with

$$\boldsymbol{y}_t = (y_{1,t}, y_{2,t}, \ldots, y_{m,t}, \ldots, y_{M_R,t}) \tag{7}$$

It is assumed that $\boldsymbol{H}_t$ is perfectly known by the MIMO detector and that symmetric antenna constellations are employed with $M_T = M_R = M$.

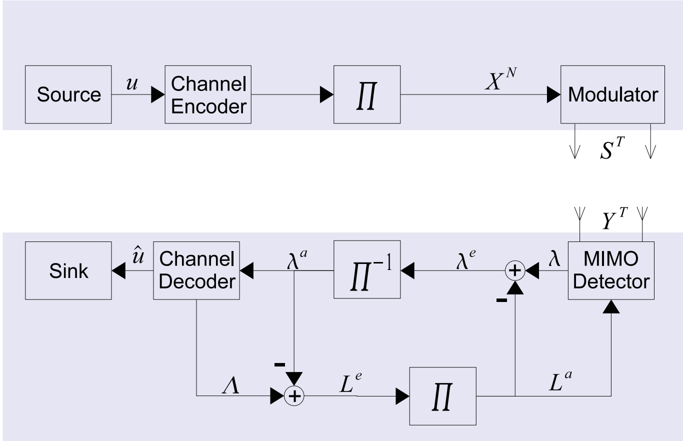

Fig. 1. MIMO bit interleaved coded modulation system model

The decoding process is iterative between MIMO detector and channel decoder. They iteratively exchange probability information of the codeword. The soft-input soft-output MIMO detector determines the likelihood of the bits for each received vector $\boldsymbol{y}_t$ using the a-priori information $\boldsymbol{L}^a$ from the channel decoder. Thus, T MIMO detections are needed to process a whole codeword. The MIMO detector works on one received vector $\boldsymbol{y}_t$ at a time. For ease of notation, the time indices of $\boldsymbol{y}$, $\boldsymbol{H}$ and $\boldsymbol{s}$ are dropped. $x_{q,m}$ denotes the qth bit of the mth symbol in $\boldsymbol{s}$. For iterative detection and decoding the MIMO detector computes logarithmic likelihood values (LLRs) on each bit

$$\lambda(x_{q,m}) = \log \frac{P(x_{q,m} = +1|\boldsymbol{y})}{P(x_{q,m} = -1|\boldsymbol{y})} \tag{8}$$

The likelihood that a specific vector $\boldsymbol{s}$ has been sent is measured by the metric $d(\boldsymbol{s})$.

$$d(\boldsymbol{s}) = \frac{1}{N_0} \left\| \boldsymbol{y} - \boldsymbol{H}\boldsymbol{s} \right\|^2 - \frac{1}{2} \sum_{q,m} x_{q,m} L^a(x_{q,m}) \tag{9}$$

Small metrics $d(\boldsymbol{s})$ relate to a high probability of $\boldsymbol{s}$ being sent. Equation (8) can then be calculated by the Max-Log-Map approximation [2].

$$\lambda(x_{q,m}) = \min_{\boldsymbol{s}|x_{q,m}=-1} d(\boldsymbol{s}) - \min_{\boldsymbol{s}|x_{q,m}=+1} d(\boldsymbol{s}) \tag{10}$$

Only the extrinsic information $\lambda^e = \lambda - L^a$ is passed on to the channel decoder.

The channel decoder works on the whole codeword at the same time. The channel decoder uses the interleaved a-priori information $\boldsymbol{\lambda}^a$ from the MIMO detector for the calculation of the estimated information bit sequence $\hat{\boldsymbol{u}}$ and the a-posteriori LLRs Λ of the codeword. The extrinsic information $L^e = \Lambda - \lambda^a$ is returned to the MIMO detector.

III. Low-Complexity Stopping Metrics

An iteration control typically monitors exchanged values in an iterative system and checks stopping conditions to detect convergence of processed block. The iterative process is stopped as early as possible to minimize decoding costs in terms of energy and throughput.

Stopping metrics can be based on the input or the output values of the channel decoder. In this paper, we concentrate on metrics at the output of the channel decoder (see Fig. 3). A stopping metric C_{it} is calculated after each iteration it. It serves as an estimate of the convergence state of decoding. C_{it} can either increase or decrease for a converging block. If a stopping condition is true, decoding is stopped. Stopping conditions can be formulated using the stopping metric C_{it} in two ways:

- direct comparison of C_{it} to a threshold
$$C_{it} \leq \theta_{min1}$$
$$C_{it} > \theta_{max1}$$
- taking the metric C_{it-1} of the previous iteration into account (thus a minimum of two iterations is necessary)
$$C_{it} - C_{it-1} \leq \theta_{min2}$$
$$C_{it} - C_{it-1} > \theta_{max2}$$

The crucial point for all stopping conditions is the choice of the thresholds θ since they allow a trade-off between decoding complexity (number of iterations) and decoding performance (frame error rate (FER)).

For ease of notation, we reduce the notation of the LLR values to $L^{it}(x_k)$ for the introduction of the metrics. it stands for the iteration in which the LLRs have been generated and k for the bit position within the codeword. In the following paragraphs, we analyze different metrics C_{it}.

A. State-of-the-art stopping metrics

1) Sign-Change Ratio (SCR_{it}) [6]: This metric keeps track of the sign changes of the output values between two iterations. The number of changes is divided by the number of considered values to obtain a ratio that is independent of the block length. If decoding has converged, no changes will occur. However, if the block is not converging many sign bits will change after each iteration.

2) Re-Encoding [11]: For this metric, estimates of systematic **and** parity bits have to be available. The decoded systematic bits are re-encoded and the resulting codeword is compared to the codeword estimate at the decoder output. The number of differences Δ_{it} is zero if a valid codeword has been found. It is high in the case of non-convergence.

3) Mean-Reliability [9]: Many state-of-the-art stopping metrics try to estimate the information content of the output LLRs by simple functions. The mean of the absolute values of the LLRs μ_{it} is one of those measures, which can be calculated with very low complexity.

$$\mu_{it} = \frac{1}{N_c} \sum_{k=1}^{N_c} \left| L^{it}(x_k) \right| \tag{11}$$

The mean reliability can be seen as an estimation of the mutual information [12]. There are other metrics based on LLR values (Minimum-Reliability, Sum-Reliability [9]) with similar complexity. Our simulations have shown that their performance is similar or worse than the performance of Mean-Reliability. Thus, they are not considered in the following analysis.

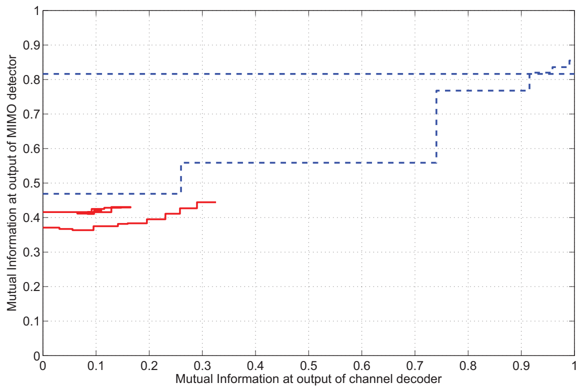

Fig. 2. EXIT chart showing the typical behavior of decodable (dashed lines) and non-decodable (solid lines) blocks during iterative detection and decoding of the analyzed MIMO-BICM system

4) Channel Capacity: Shannon's theorem [13] states that reliable communication is only possible for transmission rates smaller or equal to the channel capacity. The channel capacity C of a MIMO Rayleigh fading channel is according to Telatar [14]

$$C = \log_2 \det \left(\boldsymbol{I}_{M_T} + \frac{E_S/N_0}{M_T} \boldsymbol{H}\boldsymbol{H}^H \right) \tag{12}$$

where $\boldsymbol{I}_{M_T}$ is an identity matrix of size M_T and $\boldsymbol{H}^H$ is the Hermitian transpose of the channel matrix. The channel capacity can be used to detect non-decodable blocks. If the capacity is too low, decoding is not started at all.

5) Magic Genie: We additionally introduce Magic Genie as an exact lower bound for all other stopping conditions. It stops blocks as soon as they are correctly decoded. If a block cannot be decoded within the maximum number of iterations, Magic Genie does not even start decoding. Thus, Magic Genie has no false alarms and uses the minimum number of iterations possible.

B. Novel Stopping Criterion: Mutual Information

The convergence behavior of iterative systems composed of soft-input soft-output decoders is often studied by means of extrinsic information transfer charts (EXIT charts) [15]. EXIT charts based on mutual information have been shown to predict the decoding behavior very exactly [15]. Another advantage is that the mutual information is practically unaffected by clipping of values [15]. This is especially important for a hardware implementation where LLR values constantly have to be clipped to fit in a given bit width.

Figure 2 shows several exemplary block trajectories for the considered MIMO-BICM system (compare Fig. 1). One trajectory is generated by measuring the mutual information of the extrinsic information $\boldsymbol{\lambda}^e$ after the MIMO detector and the extrinsic information $\boldsymbol{L}^e$ after the channel decoder for each iteration. A mutual information of 1 relates to a fully corrected block. It is observed that even for high SNR and high a priori knowledge the output of the MIMO detector does not reach a mutual information of 1. Therefore, it is concluded that decoding can only be stopped after the channel decoder.

Moreover, decodable (dashed lines) and non-decodable blocks (solid lines) show very different characteristics in the EXIT chart. Therefore, we propose a new stopping metric M_{it} for iteration control based on mutual information of the extrinsic information $\boldsymbol{L}^e$ after the channel decoder.

The exact calculation of the mutual information between the original bit sequence $\boldsymbol{X}$ and $\boldsymbol{L}^e$ involves tracking the conditioned probability density function of the LLR values $\boldsymbol{L}^e$ [15]. This relates to a high complexity in a hardware implementation. However, in [16], it was shown that the mutual information can be calculated only based on the LLR values of one iteration.

$$M_{it} = \frac{1}{N_c} \sum_{k=1}^{N_c} \left\{ \frac{1}{1+e^{L^{it}(x_k)}} \cdot \log_2 \left(\frac{2}{1+e^{L^{it}(x_k)}} \right) + \frac{1}{1+e^{-L^{it}(x_k)}} \cdot \log_2 \left(\frac{2}{1+e^{-L^{it}(x_k)}} \right) \right\} \quad (13)$$

This equation is exact when Log-APP decoders are used. As we use Max-Log-Map decoders, a small inaccuracy can be expected but M_{it} is still a very good indicator for the convergence behavior of a block. Equation (13) includes a division by N_c. Divisions have a very high implementation cost in hardware compared to additions or comparisons. Instead of using M_{it} as stopping metric we use $N_c \cdot M_{it}$, which avoids this division.

To the best of our knowledge, this is the first time that mutual information is used for iteration control.

C. Complexity Analysis

The calculation and evaluation of stopping metrics naturally introduces an overhead in the receiver decoding complexity. It has to be ensured that this overhead is low to avoid that the benefits of iteration control are counterbalanced by its implementation cost.

The SCR metric compares all signs of the coded bits (XOR) and counts (ADD) the number of differences. The Mean-Reliability is calculated by adding all the LLR values of the coded bits. A convolutional encoder is needed for the Re-Encoding metric, which consists of single bit XOR operations. The re-encoded bits are compared to the decoded bits (XOR) and the number of differences is counted (ADD). The mutual information metric seems to have a higher complexity due to the term in the sum of (13). However, the values of $L^{it}(x_k)$ are quantized with 6 bits and the term is an even function of $L^{it}(x_k)$. Therefore, it can be stored in a Look Up Table (LUT) with only 32 entries.

Table I shows the algorithmic complexity for each of the analyzed stopping metrics normalized on one information bit and one iteration. As a comparison, the complexity for one iteration of the convolutional decoder normalized on one information bit is given. (The complexity of the convolutional decoder is determined by the operations needed in one trellis step.) It can be seen that all metrics have a very low complexity compared to the channel decoder. The calculation of the channel capacity has a higher complexity than the other metrics. However, part of the computations are already done in the preprocessing for the MIMO detection and the additional complexity is low.

Stopping metrics	Operations per information bit and iteration
Sign-Change Ratio	2x XOR, 2x ADD
Mean-Reliability	2x ADD
Re-Encoding	6x XOR, 2x XOR, 2x ADD
Mutual information	2x LUT, 2x ADD
Convolutional Decoder	398x ADD , 266x COMPARE

TABLE I
ALGORITHMIC COMPLEXITY FOR DIFFERENT STOPPING METRICS

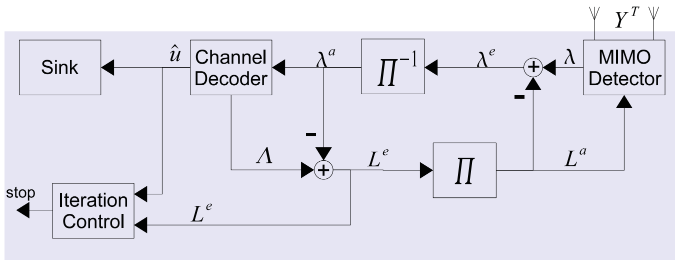

Fig. 3. Iterative MIMO-BICM receiver including iteration control based on channel decoder outputs

IV. SIMULATION RESULTS

The design space for MIMO-BICM systems is huge. Therefore, a feasible simulation setup was defined which is shown in Table II. It is assumed that the channel stays constant during the transmission of one codeword (quasi-static channel). As channel code, a convolutional code is chosen, which is used in many communication standards like e.g. WiMax [17]. However, the presented stopping metrics are not specific for convolutional codes and, with adapted thresholds, they can also be applied to other soft-output channel decoders like e.g. turbo codes or LDPC codes. The iterative process can only be stopped after the channel decoder (compare Section III-B). Therefore, all stopping metrics are evaluated on the outputs of the channel decoder (see Figure 3).

For any efficient hardware implementation, an algorithm with low computational complexity is mandatory. This decrease in complexity always comes with a certain degradation in communications performance.

- A sphere decoder is selected which considerably reduces the exponential algorithmic complexity of MIMO detection. For ML detection, the sphere decoder provides the optimal solution. However, for iterative detection and decoding, a soft-input soft-output sphere decoder is mandatory [2] [3] which is not optimal due to the Max-Log-Map approximation [2].
- MIMO detector and channel decoder both use quantized values in their calculations. Real and imaginary part of the channel matrix $\boldsymbol{H}$ and the received values $\boldsymbol{y}$ are quantized with 12 bits each. The exchanged likelihood values are represented by 6 bits. This quantization was chosen because it is a good trade-off between communications performance and implementation complexity.

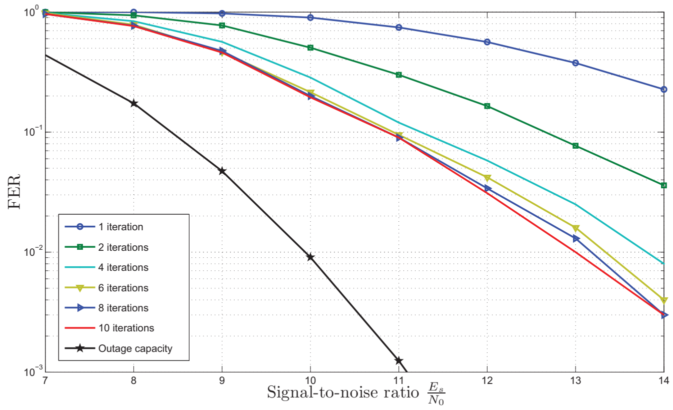

Fig. 4. Frame error rate versus signal-to-noise ratio for different number of iterations

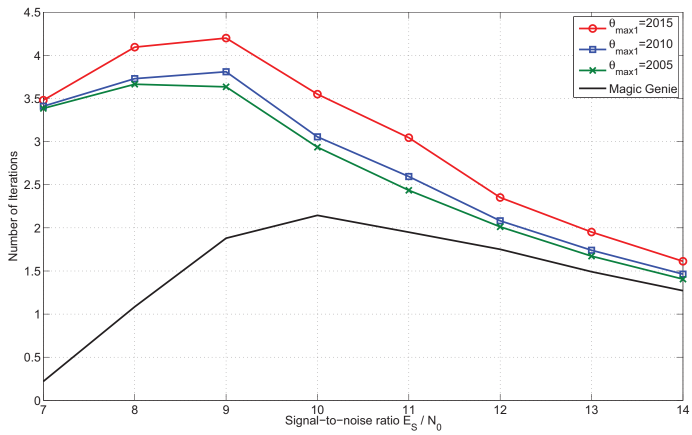

Fig. 5. Average number of iterations for variation of threshold θ_{max1} for mutual information metric

Modulation	16-QAM
Antenna constellation	4×4
Convolutional code polynomials	135_8, 163_8
System code rate	$\frac{1}{2}$
Block length	2016 bits
Max. number of iterations	10

TABLE II
SIMULATION PARAMETERS

Fig. 4 shows the communications performance for the iterative decoding of quantized sphere decoder and channel decoder. Compared to the communications performance of the unconstrained MIMO detection and floating point accuracy, the loss is smaller than 0.2 dB.

All stopping conditions presented in section III need thresholds $\theta_{min/max}$ in order to decide if a block is further processed or not. The choice of these thresholds is always a trade-off between decoding complexity (number of iterations) and decoding performance (FER). Figure 5 demonstrates this trade-off for the mutual information metric $N_c \cdot M_{it}$. M_{it} can only take on values between 0 and 1. Therefore, the stopping metric $N_c \cdot M_{it}$ can never be larger than 2016. In the block trajectories of Fig. 2, correctly decoded blocks have a mutual information of 1. Due to the approximation of the mutual information (Eq. (13)) and the influence of quantization, this value is not always reached for correctly decoded blocks. The threshold θ_{max1} is varied between the values 2005 and 2015 while the threshold $\theta_{min2} = 0$ stays constant. Table III shows the degradations in communications performance evaluated at FER 1%, which result from the different choices of θ_{max1} in Fig. 5.

Next, we will analyze and compare the performance of different stopping conditions. The thresholds (see Table IV) have been chosen such that the loss in communications performance induced by the iteration control is less than 0.1 dB. For the analyzed system 8 bits are transmitted per channel use. Yet the threshold θ_{min1} for the channel capacity is set to 9.5 which means that more blocks are stopped. The communications performance in Fig. 4 is more than $2dB$ from the outage capacity. Therefore, the threshold can be chosen higher without loss of communications performance.

θ_{max1}	2005	2010	2015
Loss in dB	0.4	0.2	0.05

TABLE III
LOSS OF COMMUNICATIONS PERFORMANCE FOR VARIATION OF THRESHOLD θ_{max1}

Fig. 6 shows the average number of iterations resulting from each stopping condition. Magic Genie serves as a lower bound. For low signal-to-noise ratios (SNR) many blocks cannot be decoded correctly (compare Fig. 4). Therefore, Magic Genie needs on average less than one iteration. For high SNR, more than 80% of the blocks are corrected after the second iteration and the number of iterations needed on average is between 1 and 2 only. However, in the middle SNR region, several iterations are often needed to correct a received block and thus the maximum iterations are in this SNR region.

Except for the stopping condition based on the channel capacity, all analyzed stopping metrics show the same behavior as Magic Genie. They are able to effectively reduce the average number of iterations. Re-Encoding shows very good performance for high SNRs. As Mean-Reliability is an approximation of Mutual Information, they show very similar behavior. The newly presented Mutual Information metric outperforms all state-of-the-art metrics for middle and high SNRs.

The channel capacity is a good means to detect undecodable blocks in the low SNR regime. However, it cannot reduce the number of iterations for decodable blocks. A combination of channel capacity and mutual information would result in a low complexity over the whole SNR range.

To illustrate the efficiency of the presented iteration control two vertical lines are inserted in Fig. 6 at the SNR points for which an FER of 10% respectively 1% is achieved. For mutual information and a target FER of 1% less than 2 iterations are needed on average. The gain of decoding time can be used either to directly speed up the decoder or to save energy, which is of high importance in mobile devices.

Stopping metric C_{it}	θ_{min1}	θ_{max1}	θ_{min2}	θ_{max2}
Sign-change Ratio SCR_{it}	0	40%	-	-
Re-Encoding Δ_{it}	0	600	-	-
Mutual Information $N_c \cdot M_{it}$	-	2013	0	-
Mean-Reliability μ_{it}	-	30	-0.25	-
Channel Capacity C	9.5	-	-	-

TABLE IV
THRESHOLDS FOR DIFFERENT STOPPING METRICS

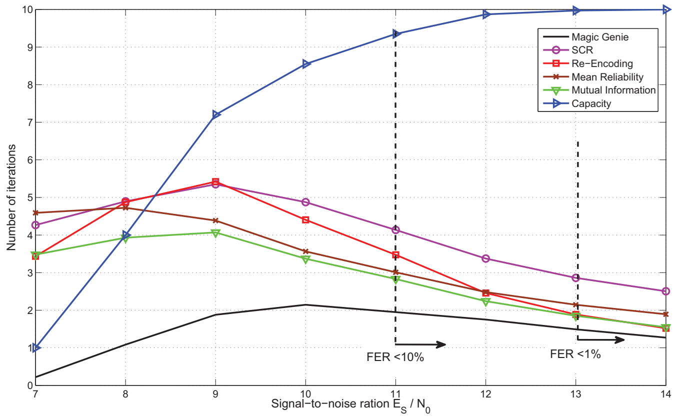

Fig. 6. Average number of iterations of different iteration control metrics versus signal-to-noise ratio

V. Conclusions

MIMO-BICM systems are a promising candidate for high data rate transmission on wireless channels. Their excellent performance is achieved by iterative decoding between MIMO detection and channel decoder, which comes along with high implementation costs in terms of throughput and energy.

To the best of our knowledge, we presented the first analysis of iteration control for MIMO-BICM systems. We have shown that low-complexity stopping metrics can effectively reduce the number of iterations between MIMO detector and channel decoder without decreasing the communications performance. Thereby, iteration control is an effective means to increase throughput or reduce the energy consumption of the receiver. The newly presented low-complexity stopping metric on Mutual Information outperforms existing stopping metrics for middle and high SNRs.

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