Automatic Modulation Classification for Adaptive Wireless OFDM Systems

Lars Häring
Department of Communication Systems, University of Duisburg-Essen
Germany

1. Introduction

The flexible adaption of the transmission scheme to the current channel state becomes more and more a key issue in future communication systems. One efficient solution in multicarrier systems like Orthogonal Frequency Division Multiplexing (OFDM) has been proven to be adaptive modulation (AM) where the modulation scheme is selected on a subcarrier-basis or group of subcarriers. A lot of research has been carried out on AM or bit loading algorithms (Campello, 1998; Chow et al., 1995; Czylwik, 1996; Fischer & Huber, 1996; Hughes-Hartogs, 1987).

A basic disadvantage, however, is that the receiver requires the knowledge about the selection of the modulation schemes to decode the transmitted data. The conventional measure is to transmit the so-called bit allocation table (BAT) via a signaling channel.[1] This leads to a considerable reduction of the effective data rate. In contrast to wired communication links like the digital subscriber line (DSL) in which AM is already well-established, the time-variance of mobile radio channels usually necessiates a continuous and fast update of the BAT. Even sophisticated signaling schemes using state-dependent source coding of signaling bits reduce the throughput by $3 - 4\%$ for short packets (Chen et al., 2009). If the channel statistics are not known, the signaling overhead is significantly larger.

In order to lower the amount of the signaling overhead and to obtain more flexibility, the BAT can be automatically detected at the receiver side. Such automatic modulation classification (AMC) algorithms have already been explored intensively since several decades, primarily for military applications but not for civil radio communication systems. The classifiers can be categorized into two types: likelihood-based (Boiteau & Martret, 1998; Long et al., 1994; Polydoros & Kim, 1990; Sills, 1999; Wei & Mendel, 2000) and feature-based methods (Dobre et al., 2004; Hsue & Soliman, 1989; Nandi & Azzouz, 1998; Swami & Sadler, 2000). While likelihood-based approaches arise from a defined optimality criterion, feature-based methods are usually heuristically motivated using e. g. higher-order moments. On the other hand, likelihood algorithms tend to require a higher complexity. A comprehensive overview of existing AMC algorithms is given in (Dobre et al., 2007).

In this book chapter, we will highlight the classification of digital quadrature amplitude modulation (QAM) schemes in wireless adaptive OFDM systems using the likelihood principle (Edinger et al., 2007; Huang et al., 2007; Lampe, 2004). We particularly focus on

---

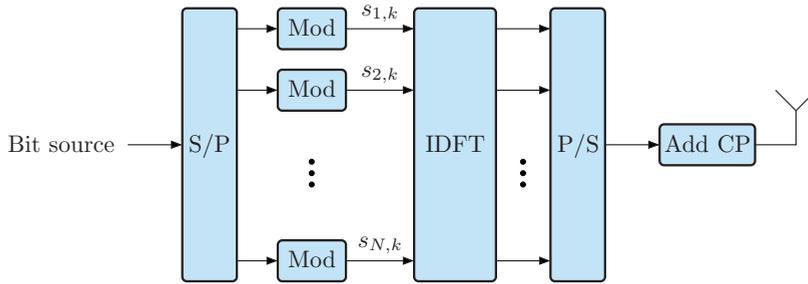[1] The BAT contains the information about the modulation schemes on each subcarrier.
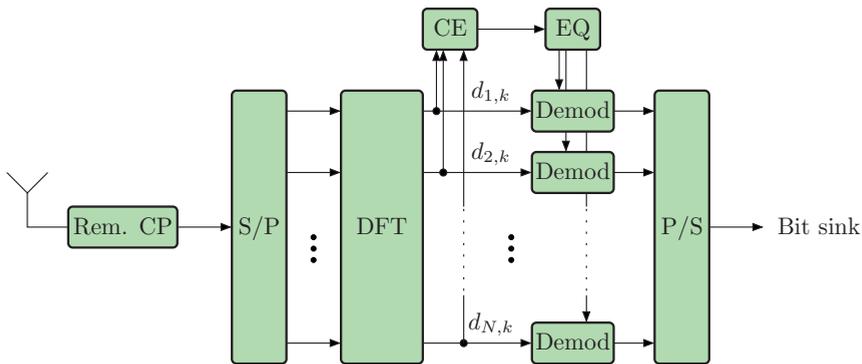
Fig. 1. Block diagram of an OFDM transmitter

Fig. 2. Block diagram of an OFDM receiver

time-division duplex (TDD) systems in which the channel can be regarded as reciprocal. In contrast to other research work, a lot of new constraints are taken into account. Namely, many parameters are known by the receiver that can be utilized to enhance the classification reliability (Häring et al., 2010a; Häring et al., 2010b; 2011).

2. System model

2.1 Signal model

In Fig. 1 and 2, the baseband models of an OFDM transmitter and receiver are depicted. In OFDM, information data are transmitted blockwise. A sequence of bits is split into blocks, fed to different subcarriers and modulated. For the k-th block, an inverse discrete Fourier transform (IDFT) of length N on the symbols of all carriers is carried out. Subsequently, in order to combat interblock interference, a cyclic prefix of sufficient length N_{g} is preceded before transmission via the frequency-selective radio channel.

At the receiver side, the cyclic prefix is removed. In order to decode in OFDM, a discrete Fourier transform (DFT) is carried out. In a perfectly synchronized OFDM system, the received symbol $d_{n,k}$ on the n-th subcarrier ($1 \leq n \leq N$) of the k-th OFDM block ($1 \leq k \leq K$)

can be modeled by

$$d_{n,k} = H_n \cdot s_{n,k} + v_{n,k} \,, \tag{1}$$

where $s_{n,k}$ and H_n denote the transmitted data symbol and the transfer function value on the n-th subcarrier of the k-th OFDM block, respectively. We consider a propagation scenario with slowly time-variant channels, typical for indoor communications. Thus the channel transfer function does not change significantly during one transmission frame, i. e. it holds: $H_{n,k} = H_n$. The additive white noise exhibits a complex Gaussian distribution: $v_{n,k} \sim \mathcal{CN}(0, \sigma_v^2)$. Due to the multicarrier principle, low-data rate signals are transmitted via flat-fading subchannels. This enables a simple frequency domain channel estimation (CE) and equalization (EQ) shown in Fig. 2.

In OFDM systems using adaptive modulation, symbols on different subcarriers can emanate from different symbol alphabets. Without loss of generality, we restrict ourselves to the digital modulation schemes with maximum bandwidth efficiencies 6 bit/symbol according to Table 1. In Fig. 3, the respective signal constellations are depicted.
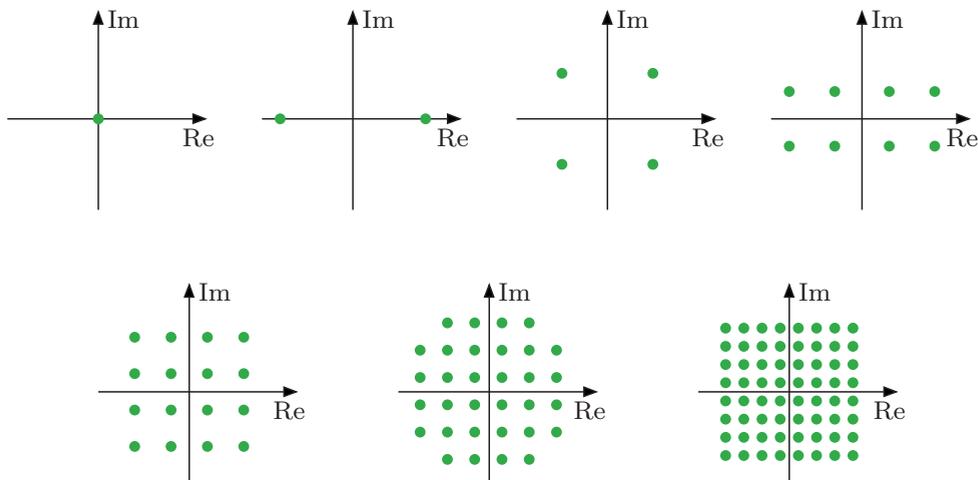

Fig. 3. QAM signal constellations: no modulation, BPSK, 4QAM, 8QAM, 16QAM, 32QAM, 64QAM

bandwidth efficiency [bit/symbol]	0	1	2	3	4	5	6
modulation type	null	BPSK	4QAM	8QAM	16QAM	32QAM	64QAM

Table 1. Considered digital modulation types

2.2 Adaptive modulation

Due to the frequency-selective nature of the radio propagation channel, some subcarriers exhibit good channel conditions whereas others suffer from a low signal-to-noise power ratio

(SNR). The overall system performance in terms of the raw bit-error ratio is dominated by the poor subcarriers.

The idea of adaptive modulation is to distribute the total amount of data bits among all subcarriers in an optimal way. If the subcarrier SNR is high, more bits than the average are loaded and higher-order modulation schemes are used. If the subcarrier SNR is low, less or even no bits are loaded such that the bit-error ratios on different subcarriers are evened out.

Using this principle, either the average bit-error ratio can be decreased at the same data rate or the data rate can be increased at the same target bit-error ratio. Since the knowledge about the data rate turns out to be an important feature of the AMC, the first approach with a fixed data rate is investigated here.

A huge amount of research on adaptive modulation algorithms has been carried out during the last twenty years (Campello, 1998; Chow et al., 1995; Czylwik, 1996; Fischer & Huber, 1996; Hughes-Hartogs, 1987). In the following, we focus on algorithms that utilize the bit metric:

$$b_n = \log_2 \left(1 + \frac{\gamma_n}{k \cdot \gamma} \right) \quad \text{s.t.} \quad \sum_{n=1}^{N} b_n = N_b \ , \tag{2}$$

where γ and γ_n denote the average signal-to-noise power ratio and the SNR of the n-th subcarrier. This bit metric b_n is motivated by the channel capacity formula which takes the SNR gap (Starr et al., 1999) into account. As an example of adaptive modulation, the magnitude of the channel transfer function $|H_n|$ in a typical indoor propagation scenario (dashed line) and the corresponding bandwidth efficiencies (solid line) are shown in Fig. 4. There are two challenges involved in the application of AM in practical systems:
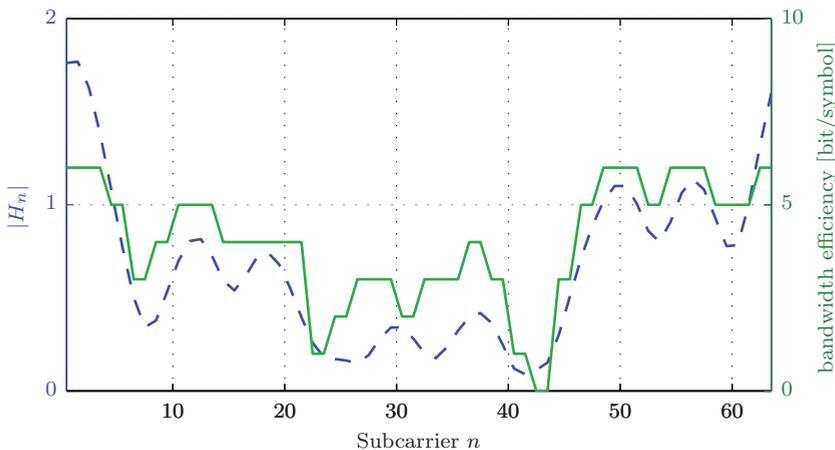

Fig. 4. Example of adaptive modulation

- *Channel knowledge at transmitter side*
  In order to be able to apply AM, the transmitter must know about the subcarrier SNRs. There are two ways to obtain this knowledge: 1) via feedback from the receiver or 2) using reciprocity in time-division duplex systems. Here, the focus is on TDD systems.

In our analysis, the channel transfer factors H_n are therefore obtained by a preamble-based channel estimation in the receive mode.

- *BAT knowledge at receiver side*
In order to be able to decode the transmitted information, the receiver must know about the bit allocation table which includes the assignment of modulation schemes to subcarriers. Either this information is transmitted via a signaling channel or it is automatically classified.
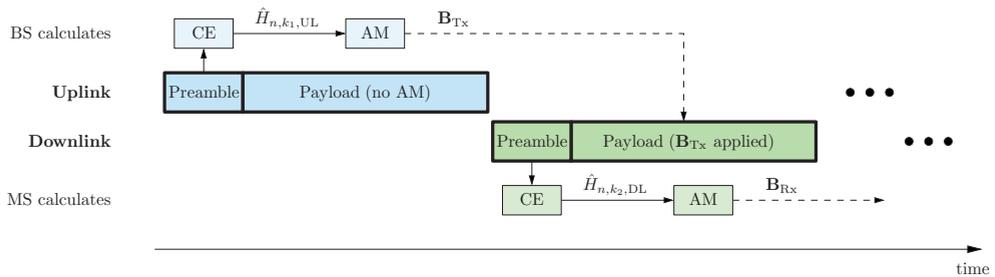
2.3 Problem formulation

Fig. 5. TDD system structure

Fig. 5 shows the signal flow at the initiation of adaptive modulation in downlink transmission of the considered time-division duplex system model:

1a) In the uplink (UL), the mobile station (MS) transmits a frame consisting of training information and payload. When establishing the link, the MS does not know the channel state. Hence, for the first frame transmitted, no AM can be applied.

b) Based on the received preamble, the base station (BS) estimates the channel $\hat{H}_{n,k_1,\mathrm{UL}}$ and calculates the optimal bit allocation table $\mathbf{B}_{\mathrm{Tx}}$ using an AM algorithm.

2a) In the downlink (DL), the BS transmits a frame composed of training symbols and payload according to $\mathbf{B}_{\mathrm{Tx}}$.

b) Based on the received preamble, the MS estimates the channel $\hat{H}_{n,k_2,\mathrm{DL}}$ and calculates the optimal bit allocation table $\mathbf{B}_{\mathrm{Rx}}$ using the same AM algorithm as the BS.

...

In order to decode the payload that has been sent by the base station, the mobile station requires the knowledge about $\mathbf{B}_{\mathrm{Tx}}$. Since we assume that the BAT information is not signaled, the receiver must *automatically* classify the modulation schemes on each subcarrier solely based upon the received signal. In this analysis it is shown that utilization of side information that is typically available in wireless communication systems can significantly boost the classification reliability. More specifically, the AMC algorithms can exploit:

- channel correlation in frequency direction (e. g. subcarrier grouping)
- channel correlation in time direction (fixed modulation order on subcarriers and/or subgroups for entire frame)

- channel reciprocity in TDD mode
- knowledge about overall data rate (total number of loaded bits)

3. Automatic modulation classifier

In this section, automatic modulation classifiers that are based on different levels of knowledge are introduced. Denote the group of M possible digital QAM schemes by ($1 \leq m \leq M$)

$$\mathcal{I}^{(m)} = \{S_1^{(m)}, S_2^{(m)}, \ldots, S_{L^{(m)}}^{(m)}\} , \tag{3}$$

where $L^{(m)}$ is the constellation size (number of constellation points) of the m-th modulation scheme and $S_i^{(m)}$ denote the complex constellation symbols.

After collecting the received symbols $\mathbf{d}_n^{\mathrm{T}} = [d_{n,1}, d_{n,2}, \ldots, d_{n,K}]$, where K is the data frame length, the following M hypotheses are tested for each subcarrier n:

$$\mathcal{H}_n^{(m)} \hat{=} \text{ the used modulation scheme of the received data symbols}$$
$$\mathbf{d}_n \text{ was } \mathcal{I}^{(m)} .$$

Based upon these symbols, the underlying modulation scheme is to be detected.
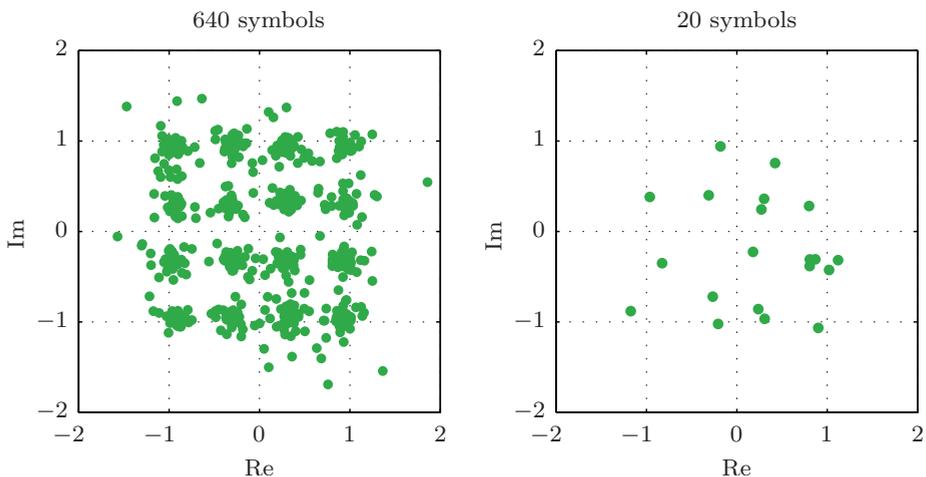

Fig. 6. Constellation diagrams of equalized 16QAM symbols at an average SNR of $\gamma = 20\,\mathrm{dB}$

As a motivating example, random signal constellations of received (and equalized) 16QAM symbols $d_{n,k}/\hat{H}_n$ at an average SNR of $\gamma = 20\,\mathrm{dB}$ are shown in Fig. 6. Whereas it seems obvious that the symbols emanate from a 16QAM scheme if a large number of symbols is available, it becomes much more difficult to classify the underlying modulation scheme if only a small number of symbols is available. Hence, the exploitation of additional information turns out to be a key aspect for a robust and reliable classification.

3.1 Maximum-likelihood (ML)

The maximum-likelihood (ML) approach chooses the hypothesis whose likelihood-function is maximum:

$$\hat{\mathcal{H}}_{n,\text{ML}} = \arg\max_{\mathcal{H}_n^{(m)}} p(\mathbf{d}_n|\mathcal{H}_n^{(m)}) \,. \tag{4}$$

The probability density function of the received symbols under the condition that the *m*-th modulation scheme was used (hypothesis $\mathcal{H}_n^{(m)}$) is

$$p(d_{n,k}|\mathcal{H}_n^{(m)}) = \sum_{i=1}^{L^{(m)}} p(d_{n,k}|S_i^{(m)}) \cdot p(S_i^{(m)}|\mathcal{I}^{(m)}) \,. \tag{5}$$

Each symbol within its constellation is equiprobable, i.e. $p(S_i^{(m)}|\mathcal{I}^{(m)}) = \frac{1}{L^{(m)}}$. Since v_n is assumed to be Gaussian distributed, it holds:

$$p(d_{n,k}|\mathcal{H}_n^{(m)}) = \frac{1}{L^{(m)}} \sum_{i=1}^{L^{(m)}} \frac{1}{\pi\sigma_v^2} \cdot \exp\left(-\frac{|d_{n,k} - H_n S_i^{(m)}|^2}{\sigma_v^2}\right) \,. \tag{6}$$

If symbols of different OFDM blocks $1 \le k \le K$ are statistically independent, the joint probability density function $p(\mathbf{d}_n|\mathcal{H}_n^{(m)})$ is given by:

$$p(\mathbf{d}_n|\mathcal{H}_n^{(m)}) = \prod_{k=1}^{K} p(d_{n,k}|\mathcal{H}_n^{(m)}) \,. \tag{7}$$

The log-likelihood function is:

$$\ln p(\mathbf{d}_n|\mathcal{H}_n^{(m)}) = \sum_{k=1}^{K} \ln p(d_{n,k}|\mathcal{H}_n^{(m)}) \tag{8}$$

$$= -K \cdot \ln L^{(m)} + c + \sum_{k=1}^{K} \ln\left(\sum_{i=1}^{L^{(m)}} \exp\left(-\gamma \cdot |d_{n,k} - H_n S_i^{(m)}|^2\right)\right) \tag{9}$$

with the average SNR $\gamma = \text{E}\{|S_i^{(m)}|^2\}/\sigma_v^2$ (= average symbol energy to noise spectral density E_S/N_0), $E_S = \text{E}\{|S_i^{(m)}|^2\} = 1$ and $\text{E}\{|H_n|^2\} = 1$. Neglecting irrelevant terms for the maximization, the ML-based classifier can be formulated as:

$$\hat{\mathcal{H}}_{n,\text{ML}} = \arg\max_{\mathcal{H}_n^{(m)}} J_{\text{ML}}(\mathbf{d}_n, \mathcal{H}_n^{(m)}) \quad \text{with}$$

$$J_{\text{ML}}(\mathbf{d}_n, \mathcal{H}_n^{(m)}) = \sum_{k=1}^{K} \ln\left(\sum_{i=1}^{L^{(m)}} \exp\left(-\gamma \cdot |d_{n,k} - H_n S_i^{(m)}|^2\right)\right) - K \cdot \ln L^{(m)} \,. \tag{10}$$

An example for the probability of correct classifications is given in Fig. 7. At the transmitter, the bandwidth efficiencies from 0 to 6 bit/symbol have been loaded by the AM algorithm in (Chow et al., 1995).
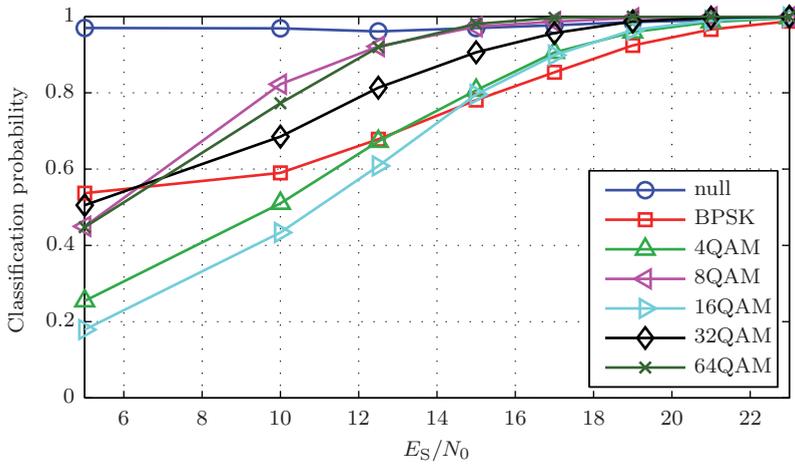
Fig. 7. Classification probability of the ML algorithm versus E_{S}/N_0, frame length $K = 10$

3.2 Maximum-a-posteriori (MAP)

One major drawback of the ML algorithm is that it cannot take into account that the hypotheses under test are not equally likely. Depending on the current channel status, however, some modulation schemes will be used more frequently than others. The ML algorithm is therefore not suitable for OFDM-based systems with adaptive modulation.

A first step to improve the performance is to maximize the a-posteriori probability $p(\mathcal{H}_n^{(m)}|\mathbf{d}_n)$ instead of $p(\mathbf{d}_n|\mathcal{H}_n^{(m)})$. The main difference can be seen by using the Bayes theorem:

$$p(\mathcal{H}_n^{(m)}|\mathbf{d}_n) = \frac{p(\mathbf{d}_n|\mathcal{H}_n^{(m)}) \cdot p(\mathcal{H}_n^{(m)})}{p(\mathbf{d}_n)} \ . \tag{11}$$

Since $p(\mathbf{d}_n)$ is irrelevant for the maximization of $p(\mathcal{H}_n^{(m)}|\mathbf{d}_n)$, the MAP classifier can be formulated as:

$$\hat{\mathcal{H}}_{n,\mathrm{MAP}} = \arg\max_{\mathcal{H}_n^{(m)}} J_{\mathrm{MAP}}(\mathbf{d}_n, \mathcal{H}_n^{(m)}) \quad \text{with} \tag{12}$$

$$J_{\mathrm{MAP}}(\mathbf{d}_n, \mathcal{H}_n^{(m)}) = \sum_{k=1}^{K} \ln\left(\sum_{i=1}^{L^{(m)}} \exp\left(-\gamma \cdot |d_{n,k} - H_n S_i^{(m)}|^2\right)\right) - K \cdot \ln L^{(m)} + \ln p(\mathcal{H}_n^{(m)}) \ .$$

The a-priori information about the occurence probabilities $p(\mathcal{H}_n^{(m)})$ is utilized.[2] But still, the MAP algorithm in its current form is not able to sufficiently consider the specific characteristics of adaptive modulation.

---

[2] If these probabilities are equal, i.e. it holds: $p(\mathcal{H}_n^{(m)}) = 1/M$, then the MAP approach reduces to the ML algorithm.

3.3 MAP algorithms exploiting channel reciprocity (MAP-R)

One key feature to increase the classification reliability is the utilization of channel reciprocity in TDD systems. Under ideal conditions (perfect channel reciprocity, channel time-invariance and channel state information (CSI)), the receiver can perfectly reconstruct the transmit BAT by applying the same AM algorithm based on the propagation channel in the receive direction. In that case, the bit allocation table $\mathbf{B}_{\text{Rx}}$ equals $\mathbf{B}_{\text{Tx}}$. To be more realistic, we assume that the channel is time-variant and CSI is taken from a data-aided channel estimation. This causes $\mathbf{B}_{\text{Tx}}$ and $\mathbf{B}_{\text{Rx}}$ to be different but still correlated.

Fig. 8 shows an illustrating example of the magnitudes of the channel transfer function at transmitter and receiver side and the corresponding BATs $\mathbf{B}_{\text{Tx}}$ and $\mathbf{B}_{\text{Rx}}$ at an SNR of $\gamma = 10\,\text{dB}$, a frame duration of $T_{\text{fr}} = 0.1\,\text{ms}$ and a Doppler frequency of $f_{\text{dop}} = 15\,\text{Hz}$. A typical preamble-based zero-forcing method to estimate the channels has been applied.
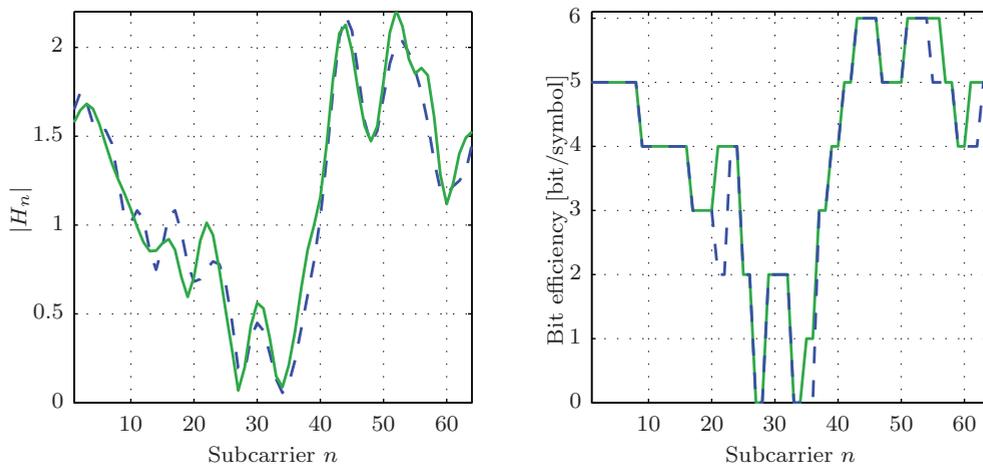

Fig. 8. Example channel transfer functions (left) and corresponding BATs (right) at transmitter (dashed lines) and receiver side (solid lines)

Both the channel transfer functions as well as the BATs differ for the transmitter and receiver, respectively. However, they are very similar which an AMC algorithm can take advantage of.

Two different concepts to benefit from this channel reciprocity are discussed now.

3.3.1 Receive bit allocation table (MAP-RQ)

Let $\hat{\mathcal{H}}_{n,\text{Rx}}$ be the modulation scheme for the n-th subcarrier in $\mathbf{B}_{\text{Rx}}$ which was computed by the AM algorithm. The method in (11) is extended by the knowledge about $\hat{\mathcal{H}}_{n,\text{Rx}}$. The modified approach which exploits channel reciprocity in terms of the quantized information $\hat{\mathcal{H}}_{n,\text{Rx}}$ can be written as:

$$\hat{\mathcal{H}}_{n,\text{MAP-RQ}} = \arg\max_{\mathcal{H}_n^{(m)}} p(\mathcal{H}_n^{(m)}|\mathbf{d}_n, \hat{\mathcal{H}}_{n,\text{Rx}}) \,. \tag{13}$$

By applying the Bayes theorem and then neglecting irrelevant terms, we obtain:

$$\hat{\mathcal{H}}_{n,\text{MAP}-\text{RQ}} = \arg\max_{\mathcal{H}_n^{(m)}} \frac{p(\mathbf{d}_n, \hat{\mathcal{H}}_{n,\text{Rx}}|\mathcal{H}_n^{(m)})\, p(\mathcal{H}_n^{(m)})}{p(\mathbf{d}_n, \hat{\mathcal{H}}_{n,\text{Rx}})} \tag{14}$$

$$= \arg\max_{\mathcal{H}_n^{(m)}} p(\mathbf{d}_n, \hat{\mathcal{H}}_{n,\text{Rx}}|\mathcal{H}_n^{(m)})\, p(\mathcal{H}_n^{(m)}) . \tag{15}$$

Since $p((A,B)|C) = p(A|(B,C)) \cdot p(B|C)$, it holds:

$$p((\mathbf{d}_n, \hat{\mathcal{H}}_{n,\text{Rx}})|\mathcal{H}_n^{(m)}) = p(\mathbf{d}_n|(\hat{\mathcal{H}}_{n,\text{Rx}}, \mathcal{H}_n^{(m)}))\, p(\hat{\mathcal{H}}_{n,\text{Rx}}|\mathcal{H}_n^{(m)}) . \tag{16}$$

The simplification $p(\mathbf{d}_n|(\hat{\mathcal{H}}_{n,\text{Rx}}, \mathcal{H}_n^{(m)})) \approx p(\mathbf{d}_n|\mathcal{H}_n^{(m)})$ turns out to be reasonable for increasing correlation between $\mathbf{B}_{\text{Tx}}$ and $\mathbf{B}_{\text{Rx}}$. We set:

$$\hat{\mathcal{H}}_{n,\text{MAP}-\text{RQ}} = \arg\max_{\mathcal{H}_n^{(m)}} \left\{ p(\mathbf{d}_n|\mathcal{H}_n^{(m)})\, p(\hat{\mathcal{H}}_{n,\text{Rx}}|\mathcal{H}_n^{(m)})\, p(\mathcal{H}_n^{(m)}) \right\} . \tag{17}$$

Taking the logarithm and using $p(\hat{\mathcal{H}}_{n,\text{Rx}}, \mathcal{H}_n^{(m)}) = p(\hat{\mathcal{H}}_{n,\text{Rx}}|\mathcal{H}_n^{(m)})p(\mathcal{H}_n^{(m)})$, the MAP classifier based on the receive BAT is:

$$\hat{\mathcal{H}}_{n,\text{MAP}-\text{RQ}} = \arg\max_{\mathcal{H}_n^{(m)}} J_{\text{MAP}-\text{RQ}}(\mathbf{d}_n, \mathcal{H}_n^{(m)}) \quad \text{with}$$

$$J_{\text{MAP}-\text{RQ}}(\mathbf{d}_n, \mathcal{H}_n^{(m)}) = \sum_{k=1}^{K} \ln\left(\sum_{i=1}^{L^{(m)}} \exp\left(-\gamma \cdot |d_{n,k} - H_n S_i^{(m)}|^2\right) \right) - K \cdot \ln L^{(m)}$$
$$+ \ln p(\hat{\mathcal{H}}_{n,\text{Rx}}, \mathcal{H}_n^{(m)}) . \tag{18}$$

The joint probability $p(\hat{\mathcal{H}}_{n,\text{Rx}}, \mathcal{H}_n^{(m)})$ could be numerically determined in advance and stored in look-up tables. Simulation results have shown that a coarse knowledge of these values is sufficient to achieve a significant performance improvement compared to the conventional ML algorithm. However, the probabilities $p(\hat{\mathcal{H}}_{n,\text{Rx}}, \mathcal{H}_n^{(m)})$ are usually not available in practice and, moreover, strongly depend on the transmission system and the propagation scenario. In order to overcome this disadvantage we present a heuristic approach to obtain these values. The classification performance is similar to the optimal one.

Approximation of joint probabilities

Suppose that $\hat{\mathcal{H}}_{n,\text{Rx}} = \mathcal{I}^{(\mu)}$ is the modulation scheme for the n-th subcarrier in $\mathbf{B}_{\text{Rx}}$. Due to the correlation between transmit and receive BAT, $\mathcal{I}^{(\mu)}$ is said to be more likely than the other $M-1$ possible modulation schemes. Consequently, we set

$$p(\hat{\mathcal{H}}_{n,\text{Rx}} = \mathcal{I}^{(\mu)}, \mathcal{H}_n^{(m)}) = \alpha \cdot \begin{cases} w & , \ m = \mu \\ \frac{1-w}{M-1} & , \ m \neq \mu \end{cases} \tag{19}$$

with $\frac{1}{M} \leq w \leq 1$. The proportional factor α is irrelevant for the metric maximization. The probabilities of all other hypotheses $m \neq \mu$ have been set equally to $\frac{1-w}{M-1}$. Further numerical investigations have shown that distributing the "residual" probability $1-w$ in a more sophisticated way does not lead to a significant advantage.

The optimal values of the weighting factors w depend on a multitude of effects: channel quality, channel estimation method, adaptive modulation algorithm etc. The more correlated

$\mathbf{B}_{Tx}$ and $\mathbf{B}_{Rx}$ are, the higher the value of w should be chosen. Unfortunately, the analytical search for the optimum seems to be intractable.

The simplicity of this heuristic approach appears attractive for a practical implementation. The receiver needs to calculate $\mathbf{B}_{Rx}$ anyway for the application of adaptive modulation in the next transmission frame.

A general drawback of using the BAT in order to exploit channel reciprocity is the quantization of bandwidth efficiencies.

3.3.2 Receive channel state information (MAP-RS)

An even better way to incorporate the channel correlation in transmit and receive direction into the AMC algorithm is described now. We assume that the AM algorithm at transmitter and receiver side is based upon bit loading according to the widely used criterion (Chow et al., 1995) for the estimated bandwidth efficiency:

$$\hat{b}_{n,\mathrm{Rx}} = \log_2 \left(1 + \frac{\gamma_n}{k \cdot \gamma} \right) = \log_2 \left(1 + \frac{|H_n|^2}{k} \right) \, , \tag{20}$$

in which k is adapted such that the target bit rate is achieved. The classification method that utilizes the *soft* channel information $\hat{b}_{n,\mathrm{Rx}}$ instead of the *hard* BAT information $\hat{\mathcal{H}}_{n,\mathrm{Rx}}$ can be formulated as:

$$\hat{\mathcal{H}}_{n,\mathrm{MAP-RS}} = \arg \max_{\mathcal{H}_n^{(m)}} \left\{ p(\mathcal{H}_n^{(m)} | \mathbf{d}_n, \hat{b}_{n,\mathrm{Rx}}) \right\} \, . \tag{21}$$

Following the same steps as in the previous section, the solution of (21) is:

$$\hat{\mathcal{H}}_{n,\mathrm{MAP-RS}} = \arg \max_{\mathcal{H}_n^{(m)}} J_{\mathrm{MAP-RS}}(\mathbf{d}_n, \mathcal{H}_n^{(m)}, \hat{b}_{n,\mathrm{Rx}}) \quad \text{with}$$

$$J_{\mathrm{MAP-RS}} = \sum_{k=1}^{K} \ln \left(\sum_{i=1}^{L^{(m)}} \exp \left(-\gamma \cdot |d_{n,k} - H_n S_i^{(m)}|^2 \right) \right) - K \cdot \ln L^{(m)}$$

$$+ \ln p(\hat{b}_{n,\mathrm{Rx}}, \mathcal{H}_n^{(m)}) \, . \tag{22}$$

Whereas the AMC algorithm based on the receive BAT in section 3.3.1 requires the knowledge about $p(\hat{\mathcal{H}}_{n,\mathrm{Rx}}, \mathcal{H}_n^{(m)})$, here the function $p(\hat{b}_{n,\mathrm{Rx}}, \mathcal{H}_n^{(m)})$ must be known. Fig. 9 depicts simulation examples of the joint probability density function $p(\hat{b}_{n,\mathrm{Rx}}, \mathcal{H}_n^{(m)})$ and the probabilities $p(\hat{\mathcal{H}}_{n,\mathrm{Rx}}, \mathcal{H}_n^{(m)})$.

Approximation of joint probability density functions

It is unrealistic to assume that the joint probabilities $p(\hat{b}_{n,\mathrm{Rx}}, \mathcal{H}_n^{(m)})$ are available in practical systems. Again, we find approximations based on a heuristic approach: Suppose that the AM algorithm at the receiver has computed $\hat{b}_{n,\mathrm{Rx}} = b_0$ for subcarrier n. Then it is obvious that those hypotheses which are "closer" to b_0 are more likely than others. We use the heuristic measure

$$p(\hat{b}_{n,\mathrm{Rx}} = b_0, \mathcal{H}_n^{(m)}) = \beta \cdot \exp \left(- \left(\frac{b(\mathcal{H}_n^{(m)}) - b_0}{\sqrt{2}\sigma} \right)^2 \right) \tag{23}$$
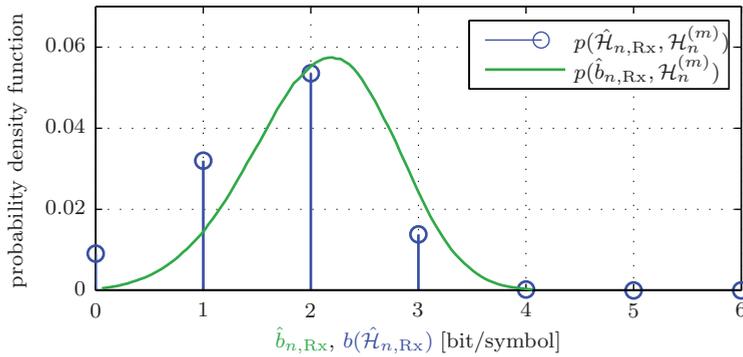
Fig. 9. Example of simulated probability density functions $p(\hat{b}_{n,\mathrm{Rx}}, \mathcal{H}_n^{(m)})$ and $p(\hat{\mathcal{H}}_{n,\mathrm{Rx}}, \mathcal{H}_n^{(m)})$ for $b(\mathcal{H}_n^{(m)}) = 2\,\mathrm{bit/symbol}$ and $\gamma = 10\,\mathrm{dB}$; the average bandwidth efficiency is $4\,\mathrm{bit/symbol}$

parameter	value
sampling period T	50 ns (20 MHz bandwidth)
FFT length N	64
cyclic prefix length N_{cp}	16
Channel model	(Medbo & Schramm, 1998) (indoor)
Delay spread τ_{ds}	100 ns
Doppler frequency f_{dop}	15 Hz (Jakes spectrum)

Table 2. Simulation set-up

thus assuming a Gaussian distributed deviation with the design parameter σ. Here, the operator $b(\mathcal{H})$ denotes the number of bits transmitted for hypothesis $\mathcal{H}$; β is a proportional factor that is irrelevant for the maximization.

The more correlated the channels at transmitter and receiver are, the smaller σ should be chosen. Due to the complex influence of the AM algorithm, it seems to be intractable to find the optimal value σ analytically.

However, compared to the quantized information that is used in the MAP-RQ algorithm, the MAP-RS method benefits from the more reliable soft information leading to a higher classification performance.

3.3.3 Discussion

In Fig. 10, the classification error probability $P_{\mathrm{ce}} = \mathrm{Pr}\{\hat{\mathbf{B}}_{\mathrm{Tx}} \neq \mathbf{B}_{\mathrm{Tx}}\}$ versus E_S/N_0 for various AMC methods is shown. If already one modulation scheme in $\mathbf{B}_{\mathrm{Tx}}$ is incorrectly classified, the whole packet would get lost. Throughout the entire contribution, the performance discussion is based upon a common simulation scenario: The main parameters concordant with a WLAN IEEE 802.11a/n system (IEEE, 2005) are summarized in Table 2. The bandwidth efficiencies, however, vary between $0 - 6\,\mathrm{bit/symbol}$. In average, $4\,\mathrm{bit/symbol}$ are loaded by the AM algorithm proposed in (Chow et al., 1995). Due to the fact that the subcarrier spacing is small compared to the channel coherence bandwidth, 2 neighbouring subcarriers are grouped without sacrificing significant system performance. The AMC algorithms utilize this
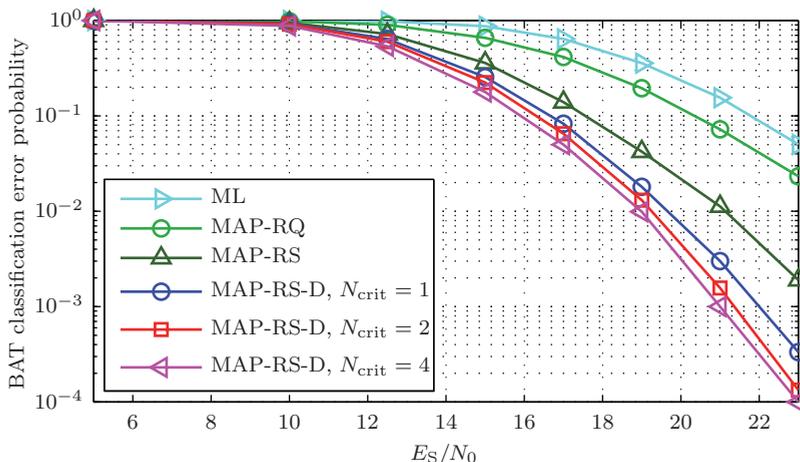
Fig. 10. BAT classification error probability P_{ce} of AMC algorithms versus E_S/N_0, frame length $K = 10$

subcarrier grouping by additively combining the corresponding metric values. A zero-forcing channel estimation is carried out on 2 training OFDM blocks with a total length of 160 samples. It is assumed that the receiver has perfect knowledge about the total data rate since this single information can be protected against errors well by suitable channel coding. The design parameters for the reciprocity-based classifiers are set to $w = 0.8$ and $\sigma = 0.3$.

First, we refer only to the ML algorithm (section 3.1) and the reciprocity-based methods MAP-RQ and MAP-RS: Due to the additional reciprocity information used, the reciprocity-based MAP algorithms outperform the classical ML algorithm significantly. With the soft information used in MAP-RS, the number of modulation classification errors can even be further reduced compared to MAP-RQ. Another step towards a higher reliability is to include even more side information in the modulation classification.

3.4 MAP-R algorithms exploiting the knowledge about the data rate (MAP-R-D)

In communication systems, the overall data rate is typically signaled to the receiver via a control channel. Therefore, we can incorporate the available information about the total number of transmitted bits N_b per OFDM block into the MAP-R algorithms.[3]

As an example, we describe the extension for the algorithm MAP-RS. The corresponding modifications in MAP-RQ are analogous. The scheme that jointly classifies the bandwidth efficiencies on all subcarriers can be formulated as:

$$\hat{\mathcal{H}}_{n,\text{joint}} = \arg \max_{\mathcal{H}_n^{(m)}} \left\{ p(\mathcal{H}_n^{(m)} | \mathbf{d}_n, \hat{b}_{n,\text{Rx}}) \right\} \quad , 1 \leq n \leq N,$$

$$\text{s.t.} \sum_{n=1}^{N} b(\mathcal{H}_n^{(m)}) = N_b . \tag{24}$$

---

[3] Note that the BAT is fixed for the entire transmission burst.

With the abbreviations

$$\vec{\mathcal{H}} = [\mathcal{H}_1^{(m)}, \ldots, \mathcal{H}_N^{(m)}] \tag{25}$$

$$\hat{\mathbf{b}}_{\text{Rx}} = [\hat{b}_{1,\text{Rx}}, \ldots, \hat{b}_{N,\text{Rx}}] \tag{26}$$

$$\hat{\vec{\mathcal{H}}}_{\text{joint}} = [\hat{\mathcal{H}}_{1,\text{joint}}, \ldots, \hat{\mathcal{H}}_{N,\text{joint}}] \tag{27}$$

$$\vec{\mathbf{d}} = [\mathbf{d}_1, \ldots, \mathbf{d}_N] \tag{28}$$

for the hypotheses under test, the bandwidth efficiencies computed at the receiver, the classified hypotheses and the collected received data symbols on all subcarriers, we reformulate (24):

$$\hat{\vec{\mathcal{H}}}_{\text{joint}} = \arg\max_{\vec{\mathcal{H}}} \left\{ p(\vec{\mathcal{H}}|\vec{\mathbf{d}}, \hat{\mathbf{b}}_{\text{Rx}}) \right\}$$

$$\text{s.t. } b(\vec{\mathcal{H}}) = N_{\text{b}} . \tag{29}$$

Since the modulation schemes and data symbols on different subcarriers are independent from each other, it holds:

$$p(\vec{\mathcal{H}}|\vec{\mathbf{d}}, \hat{\mathbf{b}}_{\text{Rx}}) \approx \prod_{n=1}^{N} p(\mathcal{H}_n^{(m)}|\mathbf{d}_n, \hat{b}_{n,\text{Rx}}) , \tag{30}$$

and hence:

$$\hat{\vec{\mathcal{H}}}_{\text{joint}} = \arg\max_{\vec{\mathcal{H}}} J_{\text{joint}}(\vec{\mathbf{d}}, \vec{\mathcal{H}}) \quad \text{s.t. } b(\vec{\mathcal{H}}) = N_{\text{b}} \quad \text{with} \tag{31}$$

$$J_{\text{joint}}(\vec{\mathbf{d}}, \vec{\mathcal{H}}) = \sum_{n=1}^{N} \left[\sum_{k=1}^{K} \ln\left(\sum_{i=1}^{L^{(m)}} \exp\left(-\gamma \cdot |d_{n,k} - H_n S_i^{(m)}|^2 \right) \right) - K \cdot \ln L^{(m)} \right.$$

$$\left. + \ln p(\hat{b}_{n,\text{Rx}}, \mathcal{H}_n^{(m)}) \right] . \tag{32}$$

The maximum search must be carried out over a set of all possible hypothesis *candidate combinations* $\vec{\mathcal{H}}$. Due to its high complexity, such a joint search is not feasible in practice. We investigate a trade-off between this joint algorithm and the subcarrier-independent methods instead.

First, we split the set of all subcarriers $\mathcal{S} = \{1, \ldots, N\}$ into two subsets:

- $\mathcal{S}_{\text{rel}} := \{n \,|\, \text{reliable decision}\}$ including subcarriers for which *reliable* decisions are possible, and

- $\mathcal{S}_{\text{crit}} := \{n \,|\, \text{critical decision}\} = \mathcal{S} \setminus \mathcal{S}_{\text{rel}}$ including subcarriers with *critical* decisions.

The number of elements in $\mathcal{S}_{\text{crit}}$ is denoted as N_{crit}. The distinction is based upon an ordering procedure according to the absolute distance between the largest and second largest metric value of the subcarrier-independent metrics (18) or (22), respectively. Subcarriers with the largest absolute distances are inserted in $\mathcal{S}_{\text{rel}}$; the remaining N_{crit} subcarriers are included in $\mathcal{S}_{\text{crit}}$. In other words, decisions are said to be critical if the two largest metric values are similar.

Surprisingly, ordering by subcarrier SNR values turns out to be unfavourable. Due to adaptive modulation in the considered OFDM systems, channel gains and modulation orders
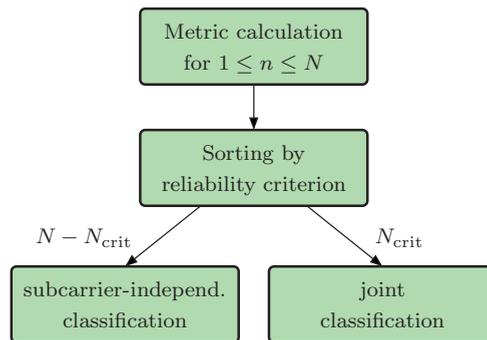
Fig. 11. Signal flow of joint algorithm

are mutually coupled – bandwidth efficiencies increase with increasing SNR. High-order modulation schemes like 64QAM are, however, more difficult to classify than low-order modulation schemes like BPSK.

The automatic modulation classification is performed for the two subsets in a different way:

- For set $\mathcal{S}_{\text{rel}}$, we apply the subcarrier-wise MAP-R algorithms described in section 3.3, e. g.:

$$\hat{\mathcal{H}}_{n,\text{MAP}-\text{RS}-\text{D}} = \arg\max_{\mathcal{H}_n^{(m)}} J_{\text{MAP}-\text{RS}}(\mathbf{d}_n, \mathcal{H}_n^{(m)}) \; \forall n \in \mathcal{S}_{\text{rel}} \, . \tag{33}$$

- For set $\mathcal{S}_{\text{crit}}$, we apply the joint MAP algorithm following (31):

$$\vec{\hat{\mathcal{H}}}_{\text{MAP}-\text{RS}-\text{D}} = \arg\max_{\vec{\mathcal{H}}_{\mathcal{S}_{\text{crit}}}} J_{\text{joint}}(\vec{\mathbf{d}}, \vec{\mathcal{H}}_{\mathcal{S}_{\text{crit}}}) \quad \text{s.t.} \; b(\vec{\mathcal{H}}_{\mathcal{S}_{\text{crit}}}) = N_{\text{b}} - b(\vec{\mathcal{H}}_{\mathcal{S}_{\text{rel}}}) \tag{34}$$

with $\vec{\mathcal{H}}_{\mathcal{S}_{\text{crit}}}$ and $\vec{\mathcal{H}}_{\mathcal{S}_{\text{rel}}}$ denoting the vectors that contain the hypotheses of all subcarriers in set $\mathcal{S}_{\text{crit}}$ and $\mathcal{S}_{\text{rel}}$, respectively.

The choice of the design parameter N_{crit} balances performance and complexity.

3.4.1 Discussion

We refer to Fig. 10 again. It shows, among others, the classification reliability of the MAP-RS-D algorithm for different values of N_{crit}. A significant increase of the reliability can be seen, independent of the value of N_{crit}. For $N_{\text{crit}} > 2$, the performance improvement saturates whereas the complexity grows rapidly. In numerous cases at high SNR, only very few decisions are ambiguous. By incorporating additional information, the reliability of these vague decisions can be considerably improved. Against the background of a practical design, small values of N_{crit} are an appropriate choice.

3.5 MAP algorithm with reduced complexity (MinMAP)

The complexity of all presented MAP methods is still rather high and may be prohibitive for real-time applications. In order to reduce the complexity, we take a closer look e. g. at the

classification metric (22) illustrated in Fig. 12 which is based on the expression

$$\sum_{k=1}^{K} \ln \left(\sum_{i=1}^{L^{(m)}} \exp\left(-\gamma \cdot |d_{n,k} - H_n S_i^{(m)}|^2\right) \right) - K \cdot \ln L^{(m)} + \ln p(\hat{b}_{n,\mathrm{Rx}}, \mathcal{H}_n^{(m)}) . \tag{35}$$

Both logarithmic and exponential functions in the metric are intensive operations which are
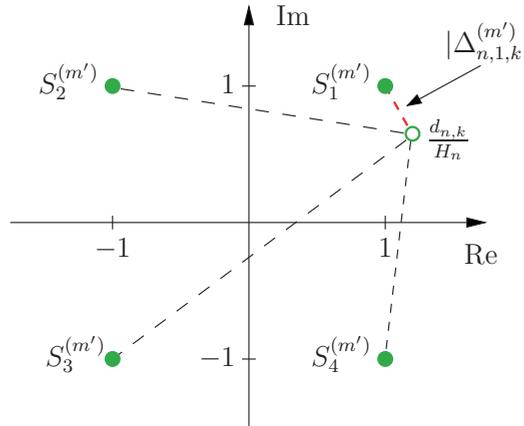

Fig. 12. Example of metric calculation for 4QAM transmission: Dominant contribution term $\exp(-\gamma_n |\Delta_{n,i,k}^{(m')}|^2)$ for fixed n and k arises from closest constellation point

not suitable for implementations in hardware structures. The metric evaluates weighted and squared distances $\Delta_{n,i,k}^{(m)}$

$$\gamma \cdot |d_{n,k} - H_n S_i^{(m)}|^2 = \gamma_n \cdot \left| \frac{d_{n,k}}{H_n} - S_i^{(m)} \right|^2 = \gamma_n \cdot |\Delta_{n,i,k}^{(m)}|^2 \tag{36}$$

between the received equalized symbol and all possible constellation symbols of the modulation scheme under test.

Let us consider the high SNR region obtaining a received equalized symbol $d_{n,k}/H_n$ located close to a possible constellation point. Thanks to the fast decrease of the exponential function for decreasing arguments, only the term $\exp\left(-\gamma_n \cdot \min\{|\Delta_{n,i,k}^{(m)}|^2\}\right)$ will significantly contribute to the inner sum in (22):

$$\sum_{i=1}^{L^{(m)}} \exp\left(-\gamma_n |\Delta_{n,i,k}^{(m)}|^2\right) \approx \max_{S_i^{(m)} \in \mathcal{I}^{(m)}} \left\{ \exp\left(-\gamma_n |\Delta_{n,i,k}^{(m)}|^2\right) \right\} \tag{37}$$

$$= \exp\left(- \min_{S_i^{(m)} \in \mathcal{I}^{(m)}} \left\{ \gamma_n |\Delta_{n,i,k}^{(m)}|^2 \right\} \right) . \tag{38}$$

The resulting simplified metric is denoted by MinMAP as the operations $\log(\cdot)$ and $\exp(\cdot)$ are replaced by a simple minimum search. As an example, the MinMAP-RS metric is:

$$\hat{\mathcal{H}}_{n,\text{MinMAP-RS}}^{(m)} = \underset{\mathcal{H}_n^{(m)}}{\arg\max}\, J_{\text{MinMAP-RS}}(\mathbf{d}_n, \mathcal{H}_n^{(m)}) \quad \text{with}$$

$$J_{\text{MinMAP-RS}} = \sum_{k=1}^{K} \ln\left(\exp\left(-\min\left\{\gamma_n |\Delta_{n,i,k}^{(m)}|^2\right\}\right)\right) - K \ln L^{(m)} + \ln p(\hat{b}_{n,\text{Rx}}, \mathcal{H}_n^{(m)})$$

$$= -\gamma_n \sum_{k=1}^{K} \min_{S_i^{(m)} \in \mathcal{I}^{(m)}} \left\{|\Delta_{n,i,k}^{(m)}|^2\right\} - K \ln L^{(m)} + \ln p(\hat{b}_{n,\text{Rx}}, \mathcal{H}_n^{(m)}) \,. \tag{39}$$

No exponential and almost no logarithm operations are needed in the classifier. This leads to an essentially decreased complexity. The algorithms MAP-RS-D, MAP-RQ and MAP-RQ-D are modified alike, i. e. denoted as MinMAP-RS-D, MinMAP-RQ and MinMAP-RQ-D.

Metric analysis for high SNR:

It will be shown that the error caused by the simplification (37) tends to zero (under mild conditions) if $\gamma \to \infty$. For simplicity reasons, we neglect all subcarrier, modulation and block indices. First, we analyze the sum:

$$\ln\left(\sum_{i=1}^{L} e^{-\gamma |\Delta_i|^2}\right) = \ln\left(e^{-\gamma |\Delta_1|^2} + e^{-\gamma |\Delta_2|^2} + \ldots + e^{-\gamma |\Delta_L|^2}\right) \,. \tag{40}$$

Here, we have sorted $|\Delta_i|$ in a ascending order with $|\Delta_1|$ being the minimum and $|\Delta_L|$ being the maximum distance. Now, let us define the error ε between the optimal MAP and the simplified MAP metrics ($K = 1$):

$$\varepsilon = \ln\left(\sum_{i=1}^{L} e^{-\gamma |\Delta_i|^2}\right) - \ln\left(e^{-\gamma |\Delta_1|^2}\right) \tag{41}$$

$$= \ln\left(\frac{\sum_{i=1}^{L} e^{-\gamma |\Delta_i|^2}}{e^{-\gamma |\Delta_1|^2}}\right) \tag{42}$$

$$= \ln\left(\sum_{i=1}^{L} e^{-\gamma(|\Delta_i|^2 - |\Delta_1|^2)}\right) \tag{43}$$

$$= \ln\left(1 + \sum_{i=2}^{L} e^{-\gamma(|\Delta_i|^2 - |\Delta_1|^2)}\right) \geq 0 \,. \tag{44}$$

Under the condition $|\Delta_i| \neq |\Delta_1|$ for $i \neq 1$, the error in the metric function for $\gamma \to \infty$ is:

$$\lim_{\gamma \to \infty} \varepsilon = \ln(1 + 0) = 0 \,, \tag{45}$$

since $|\Delta_i|^2 - |\Delta_1|^2 > 0 \ \ \forall \ \ 2 \leq i \leq L$. Numerical results have shown moderate deviations between the simplified and the optimal metrics already for practical SNR ranges.

Assume that the received equalized symbols converge to their constellation points for high SNR. Then e. g. the special case $|\Delta_2| = |\Delta_1|$ or $|\Delta_2| \approx |\Delta_1|$ that we excluded in our consideration so far can only occur if the hypothesis under test is incorrect. Since the neglect of terms in (37) lowers the metric value of this incorrect hypothesis, this condition can even have a favourable effect on the discrimination of the modulation schemes.
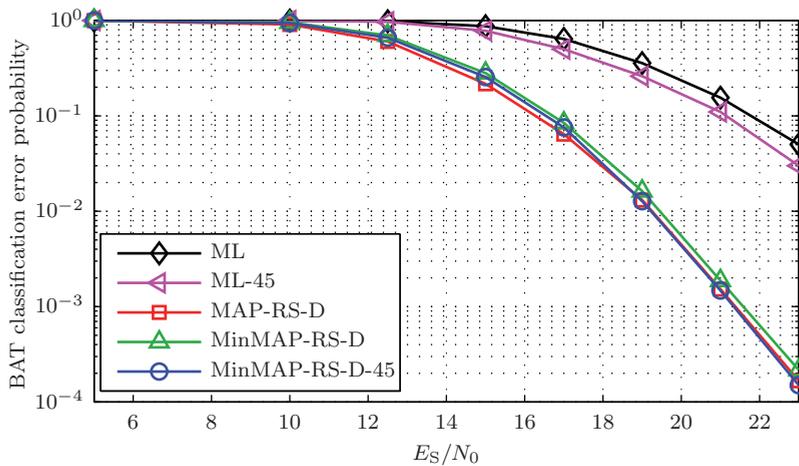
Fig. 13. BAT classification error probability P_{ce} of AMC algorithms versus E_S/N_0, frame length $K = 10$, $N_{crit} = 2$

An overview of the presented metrics is appended at the chapter end in Table 3.

3.5.1 Discussion

Fig. 13 shows the classification performance of the algorithm MAP-RS-D with and without the previously described metric simplification. It indicates that the influence of the metric simplification on the classification performance is minor. Only a small performance degradation is visible which will even decrease with increasing SNR. Obviously, the MinMAP-RS-D approach seems to be an proper tradeoff between performance and complexity.

3.6 QAM symbol rotation

Apart from the algorithm design of the receiver, also the transmitter can be factored into the modulation classification for performance improvements. A simple example is given here: Similar to pattern recognition, automatic classification becomes effective if the objects to discriminate are *as different as possible* and can therefore be easily separated.

However, especially the constellation sets of the higher-order modulation schemes are very *similar*. A large number of received symbols must be observed to judge safely from which set the symbols have been generated. As a first measure to achieve a better separation of the constellation sets we rotate all 16QAM symbols by 45° as shown in Fig. 14 (right). Note that the optimal constellation modifications would take the rotation of all modulation schemes into account.

3.6.1 Discussion

The algorithms using the constellation modification at the transmitter side are denoted as ML-45 and MinMAP-RS-D-45, respectively. A slight performance improvement due to the
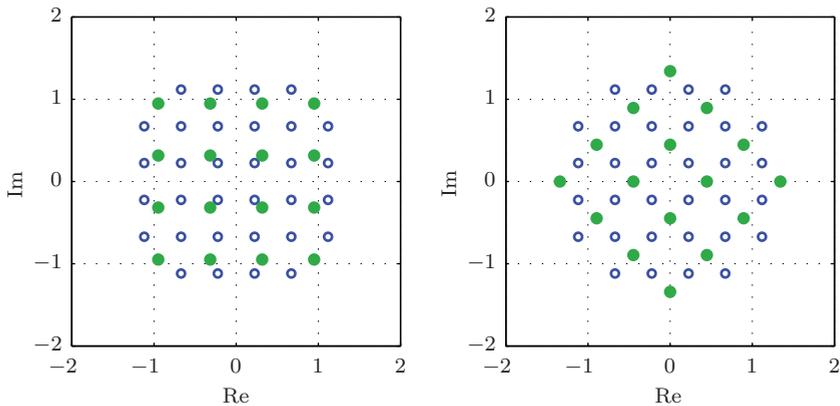
Fig. 14. Constellation diagrams of 32QAM and 16QAM (left) and 32QAM and rotated 16QAM (right)

symbol rotation by $45°$ can be seen in Fig. 13, especially in case of the ML algorithm. For the advanced techniques, the effect of the symbol rotation becomes less significant.

However, we expect further potential in jointly optimizing the adaptive modulation at the transmitter and the automatic modulation classification at the receiver side.

4. Overall system performance

Finally we analyze the overall system performance of a typical adaptive OFDM-based transmission system which applies AMC. We are primarily interested in the influence of errors caused by imperfect AMC on the packet error ratio (PER). A packet error is observed here if either the BAT or the payload data is detected erroneously. For these PER simulations, a hard-decision Viterbi algorithm decodes the information bits that have been encoded with a convolutional code of rate $R_C = 1/2$. Since each frame consists of 10 data OFDM blocks, the payload size amounts to 10 blocks $\cdot$ 64 subcarriers/block $\cdot$ 4 bit/subcarrier $\cdot$ $R_C = 1280$ bit $= 160$ bytes.

Fig. 15 depicts the PER versus E_S/N_0 for the following four scenarios:

- non-adaptive: The transmitter uses the same modulation scheme on all subcarriers.
- adaptive, ML: The transmitter applies AM; the receiver detects the transmit BAT automatically using the ML algorithm.
- adaptive, MinMAP-RS-D: The transmitter applies AM; the receiver detects the transmit BAT automatically using the MinMAP-RS-D algorithm.
- adaptive, BAT known: The transmitter applies AM; the receiver has perfect knowledge of $\mathbf{B}_{Tx}$ (reference).

For the frequency-selective indoor propagation channel considered here, the transmission system benefits significantly from adaptive modulation; the number of packet errors is lowest in the adaptive case with perfect knowledge of $\mathbf{B}_{Tx}$. Clearly, AMC degrades the system performance due to BAT classification errors. Whereas the degradation in case of the ML
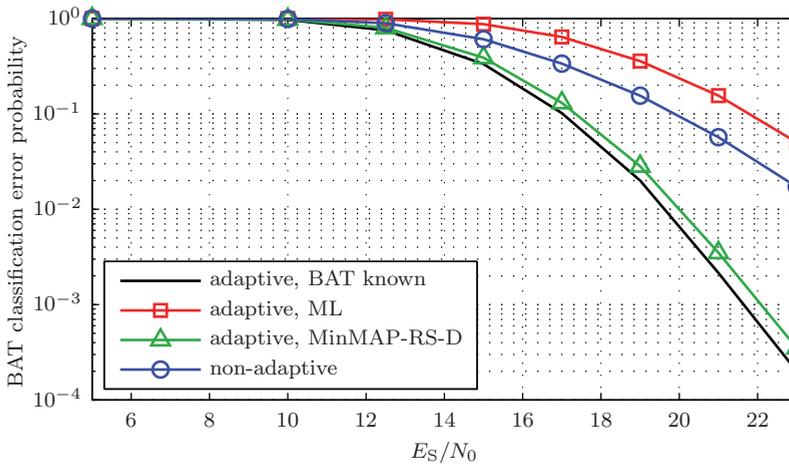
Fig. 15. BAT classification error probability P_{ce} of the MinMAP algorithm versus E_S/N_0, frame length $K = 10$, $N_{crit} = 2$

algorithm is considerable and even overcompensates the benefit from adaptive modulation, the overall PER with perfect knowledge and classified BAT according to MinMAP-RS-D is very similar. The longer the frames, the smaller the influence classification errors on the PER will be. On the one hand, AMC benefits from more symbols to average. On the other hand, payload detection errors will occur more frequently with increasing frame lengths.

By using the presented AMC approach, we can fully gain from adaptive modulation (at costs of a higher complexity) without loss in the effective data rate due to signaling of the BAT, also in wireless communication scenarios.

5. Summary

In this contribution, a framework of likelihood-based automatic modulation classification algorithms for wireless orthogonal frequency division duplex systems with adaptive modulation has been presented. Instead of signaling the bit allocation table to the receiver, the bit allocation table can be efficiently detected solely based upon the received signal and side information which is available in time-division duplex communication systems.

It has been shown that the well-known maximum-likelihood algorithm does not offer a sufficiently high classification reliability in typical wireless communication scenarios. Therefore, an improved maximum-a-posteriori technique has been presented that utilizes additional information, i.e. a fixed bit allocation table per frame, channel reciprocity in time-division duplex systems and the information about the overall data rate. A metric simplification is possible which reduces the computational burden considerably without sacrificing much performance.

By using these advanced classifiers, there is almost no performance loss in terms of the packet error ratio compared to the case with perfect knowledge of the bit allocation table. Due to the moderate computational complexity and high classification reliability even for short

packets, the application of automatic modulation classification can be an attractive alternative to conventional signaling schemes.

The automatic modulation classification could be even further improved if the transmitter and receiver signaling processing is considered jointly. A brief example has been given by rotating the symbols of the conventional 16QAM scheme. However, this sophisticated topic of a joint transmitter and receiver design will be part of future research.

Algorithm	Metric
ML	$\sum_{k=1}^{K} \ln\left(\sum_{i=1}^{L^{(m)}} \exp\left(-\gamma_n \cdot |\Delta_{n,i,k}^{(m)}|^2 \right) \right) - K \cdot \ln L^{(m)}$
MAP	$J_{\text{ML}}(\mathbf{d}_n, \mathcal{H}_n^{(m)}) + \ln\ p(\mathcal{H}_n^{(m)})$
MAP-RQ	$J_{\text{ML}}(\mathbf{d}_n, \mathcal{H}_n^{(m)}) + \ln\ p(\hat{\mathcal{H}}_{n,\text{Rx}}, \mathcal{H}_n^{(m)})$
MAP-RS	$J_{\text{ML}}(\mathbf{d}_n, \mathcal{H}_n^{(m)}) + \ln\ p(\hat{b}_{n,\text{Rx}}, \mathcal{H}_n^{(m)})$
MAP-RQ-D	two-step procedure in section 3.4 based on MAP-RQ
MAP-RS-D	two-step procedure in section 3.4 based on MAP-RS
MinMAP-RQ	$-\gamma_n \cdot \sum_{k=1}^{K} \min_{S_i^{(m)} \in \mathcal{I}^{(m)}} \left\{ |\Delta_{n,i,k}^{(m)}|^2 \right\} - K \ln L^{(m)} + \ln\ p(\hat{\mathcal{H}}_{n,\text{Rx}}, \mathcal{H}_n^{(m)})$
MinMAP-RS	$-\gamma_n \cdot \sum_{k=1}^{K} \min_{S_i^{(m)} \in \mathcal{I}^{(m)}} \left\{ |\Delta_{n,i,k}^{(m)}|^2 \right\} - K \ln L^{(m)} + \ln\ p(\hat{b}_{n,\text{Rx}}, \mathcal{H}_n^{(m)})$
MinMAP-RQ-D	two-step procedure in section 3.4 based on MinMAP-RQ
MinMAP-RS-D	two-step procedure in section 3.4 based on MinMAP-RS

Table 3. Metrics overview

6. References

Boiteau, D. & Martret, C. L. (1998). A generalized maximum likelihood framework for modulation classification, *Proc. of IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 2165–2168.

Campello, J. (1998). Optimal discrete bit loading for multicarrier modulation systems, *Proc. IEEE International Symposium on Information Theory*, p. 193.

Chen, Y., Häring, L. & Czylwik, A. (2009). Reduction of AM-induced signaling overhead in WLAN-based OFDM systems, *Proc. of the 14th International OFDM-Workshop (InOWo)*, Hamburg, Germany, pp. 30–34.

Chow, P., Cioffi, J. & Bingham, J. (1995). A practical discrete multitone transceiver loading algorithm for data transmission over spectrally shaped channels, *IEEE Transactions on Communications* 43(2/3/4): 773–775.

Czylwik, A. (1996). Adaptive OFDM for wideband radio channels, *Proc. of Global Telecommunications Conference GLOBECOM '96*, pp. 713–718.

Dobre, O. A., Abdi, A., Bar-Ness, Y. & Su, W. (2007). Survey of automatic modulation classification techniques: classical approaches and new trends, *IET Communications* 1(2): 137–156.

Dobre, O., Bar-Ness, Y. & Su, W. (2004). Robust QAM modulation classification algorithm using cyclic cumulants, *Proc. of IEEE Wireless Communication and Networking Conference (WCNC)*, Vol. 2, pp. 745–748 Vol.2.

Edinger, S., Gaida, M. & Fliege, N. J. (2007). Classification of QAM signals for multicarrier systems, *Proc. of the European Signal Processing Conference (EUSIPCO)*, pp. 227–230.

Fischer, R. F. H. & Huber, J. B. (1996). A new loading algorithm for discrete multitone transmission, *Proc. of IEEE Global Telecommunications Conference GLOBECOM'96*, pp. 724–728.

Häring, L., Chen, Y. & Czylwik, A. (2010a). Automatic modulation classification methods for wireless OFDM systems in TDD mode, *IEEE Trans. on Communications* (9): 2480 – 2485.

Häring, L., Chen, Y. & Czylwik, A. (2010b). Efficient modulation classification for adaptive wireless OFDM systems in TDD mode, *Proc. of the Wireless Communications and Networking Conference*, Sydney, Australia, pp. 1–6.

Häring, L., Chen, Y. & Czylwik, A. (2011). Utilizing side information in modulation classification for wireless OFDM systeme with adaptive modulation, *Proc. of the IEEE Vehicular Technology Conference 2011-Fall*, San Francisco, USA.

Hsue, S. Z. & Soliman, S. S. (1989). Automatic modulation recognition of digitally modulated signals, *Proc. of IEEE MILCOM*, pp. 645–649.

Huang, Q.-S., Peng, Q.-C. & Shao, H.-Z. (2007). Blind modulation classification algorithm for adaptive OFDM systems, *IEICE Trans. Commun.* E.90-B No. 2: 296–301.

Hughes-Hartogs, D. (1987). Ensemble modem structure for imperfect transmission media, *U.S. Patent 4,679,227* .

IEEE (2005). IEEE 802.11n, *Technical report*, http://grouper.ieee.org/groups/802/11.

Lampe, M. (2004). *Adaptive Techniques for Modulation and Channel Coding in OFDM Communication Systems*, PhD thesis.

Long, C., Chugg, K. & Polydoros, A. (1994). Further results in likelihood classification of QAM signals, *Proc. of IEEE MILCOM*, pp. 57–61.

Medbo, J. & Schramm, P. (1998). Channel models for HiperLAN/2 in different indoor scenarios, ETSI/BRAN document no. 3ERI085B.

Nandi, A. & Azzouz, E. (1998). Algorithms for automatic modulation recognition of communication signals, *IEEE Trans. on Communications* 46(4): 431–436.

Polydoros, A. & Kim, K. (1990). On the detection and classification of quadrature digital modulations in broad-band noise, *IEEE Trans. on Communications* 38(8): 1199–1211.

Sills, J. A. (1999). Maximum-likelihood modulation classification for PSK/QAM, *Proc. of IEEE MILCOM*, pp. 57–61.

Starr, T., Cioffi, J. M. & Silverman, P. J. (1999). *Understanding Digital Subscriber Line Technology*, Prentice Hall.

Swami, A. & Sadler, B. M. (2000). Hierarchical digital modulation classification using cumulants, *IEEE Trans. on Communications* 48: 416–429.

Wei, W. & Mendel, J. (2000). Maximum-likelihood classification for digital amplitude-phase modulations, *IEEE Trans. on Communications* 48(2): 189–193.
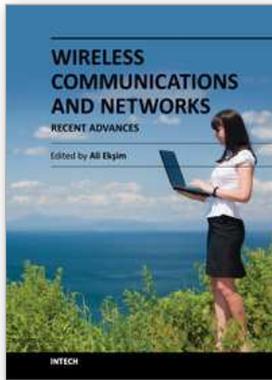
Wireless Communications and Networks - Recent Advances

Edited by Dr. Ali Eksim

This book will provide a comprehensive technical guide covering fundamentals, recent advances and open issues in wireless communications and networks to the readers. The objective of the book is to serve as a valuable reference for students, educators, scientists, faculty members, researchers, engineers and research strategists in these rapidly evolving fields and to encourage them to actively explore these broad, exciting and rapidly evolving research areas.

How to reference

In order to correctly reference this scholarly work, feel free to copy and paste the following:

Lars Häring (2012). Automatic Modulation Classification for Adaptive Wireless OFDM Systems, Wireless Communications and Networks - Recent Advances, Dr. Ali Eksim (Ed.), ISBN: 978-953-51-0189-5, InTech, Available from: http://www.intechopen.com/books/wireless-communications-and-networks-recent-advances/automatic-modulation-classification-for-adaptive-wireless-ofdm-systems

INTECH
open science | open minds