Joint Equalization/Demodulation for Digital Data Storage on Photographic Film

Christoph Voges; Consultant; Braunschweig, Germany
Tim Fingscheidt; Technische Universität Braunschweig, Institute for Communications Technology (IfN); Braunschweig, Germany

Abstract

Data storage on photographic film has become a prospective alternative for long-term digital archiving. The storage capacity of such systems is strongly limited due to intersymbol interference (ISI) which can be significantly reduced by using equalization. This contribution presents two algorithms which jointly perform equalization and demodulation for data storage on film with non-linear, non-Gaussian, and amplitude-dependent characteristics. The performance of both approaches is investigated by means of simulations based on a realistic channel model.

1. Introduction

Long-term storage of digital data on photographic film materials, such as microfilm or cinematographic film, is a promising approach for archiving of digital data, especially due to the high stability of the medium itself. As an example, certain microfilms exhibit estimated lifetimes of up to 500 years (cf., e.g., [1]). A further advantage is that corresponding reading devices can be constructed in the future with acceptable effort [2].

In the past few years, this field of research has gained a high amount of attention and detailed introductions to this technology are provided in [3–5]. Recent publications deal, e.g., with error correction [3, 6, 7], signal and information processing [8], as well as storage of audio data [9]. A current focus of research is data storage on cinematographic film [2,10–12]. First approaches towards a channel model for data storage on film are described in [13] and a completely data-driven approach is presented in [14]. Although the underlying physical principles are difficult to model and the two-dimensional channel exhibits non-linear as well as non-Gaussian characteristics, the channel model presented in [14] allows realistic simulations. Due to the data-driven approach, this end-to-end channel model covers all system characteristics and models binary-modulated storage channels for photographic film with good preciseness. Also, a soft-output demodulator for digital data storage on photographic film is presented in [14].

For digital data storage on photographic film we encounter a two-dimensional storage channel whereby the maximum storage capacity is strongly limited due to intersymbol interference (ISI) [3,6]. In order to reduce the effects of ISI, it is highly reasonable to apply equalization. Two-dimensional equalization techniques have been widely investigated for page-oriented optical memories, such as holographic data storage systems (e.g., [15–17]). Also, two-dimensional equalization has been investigated for magnetic data storage, such as bit-patterned media (e.g., [18]). In this context, additive white Gaussian noise (AWGN) and linearity are often assumed and the equalizers may be highly adapted to the specific system properties. However, for digital data storage on photographic film materials we encounter non-Gaussian amplitude-dependent noise and non-linear channel characteristics [14].

In this paper, joint equalization/demodulation (JED) techniques are presented which are specifically suitable for the read-out of digital data from photographic film. The first algorithm (referred to as GED) is a JED which is based on Gaussian mixture models (GMMs) and provides soft outputs. As opposed to the soft demodulation approach presented in [14], it also evaluates the environment of each data point during the read-out process in order to reduce ISI. This *non-iterative* approach is fully data-driven, i.e., the parameters of the equalizer are obtained from a training process. The second algorithm is a variant of the decision feedback equalizer (DFE), which has been investigated in [15] for page-oriented optical memories. For each iteration step, this *iterative* approach calculates estimates of the received bits based on a known channel model and a set of preceding estimates. In [15] AWGN and a linear channel model are assumed. However, due to the non-linear and non-Gaussian characteristics, certain modifications are required in this context to adapt the DFE to the characteristics of photographic film. Therefore, a numerical noise-free channel model is obtained from the channel model suggested in [14] as a basis for the calculation of the updated estimates within each iteration step. The performance of both algorithms is investigated and also compared to the soft demodulator presented in [14], showing that the influence of ISI is reduced and thus higher storage capacity is gained.

This paper is organized as follows: The next section provides an overview on digital data storage on photographic film, including the write and read processes as well as a brief description of the channel model. Section 3 is about JED and introduces the GED as well as the DFE-based approach. A performance evaluation of the suggested algorithms is provided in Section 4 and the paper ends with a detailed set of conclusions (Section 5).

2. Data Storage on Photographic Film

The processing chain for storing digital data on photographic film is shown in Figure 1 and basically consists of the *write process*, the *photographic film* itself, as well as the *read process* (cf. also [14]). Aim of the write process is to store an input bit sequence $\mathbf{u} = \{u_n\}$ of length N (with input bits $u_n \in \{0,1\}$) on the medium film, such as microfilm (cf., e.g., [3]) or cinematographic film (cf., e.g., [2]). The read process serves to retrieve the digital data from the medium film and delivers an output bit sequence $\mathbf{v} = \{v_n\}$ of length N (with output bits $v_n \in \{0,1\}$). For the investigations in this paper, binary modulation is used according to the suggestions in [3,6]. The following subsection describes the read and write processes followed by a subsection dealing with the above-mentioned channel model.

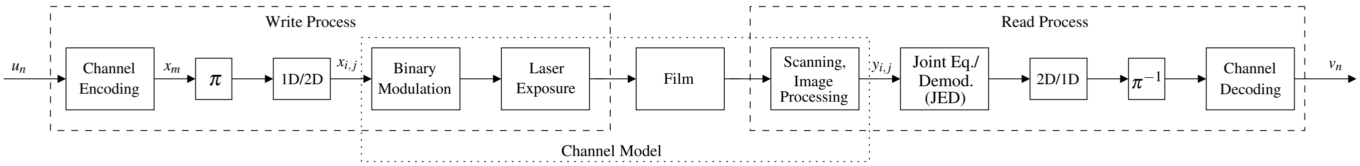

Figure 1. *The processing chain (cf. also [14]) for digital data storage on film using binary modulation and joint equalization/demodulation (JED).*

2.1 Read and Write Processes

The *write process* comprises channel encoding, interleaving (π), binary modulation, as well as laser exposure. At first, redundancy is added to the input bit sequence $\mathbf{u}$ leading to the encoded bit sequence $\mathbf{x} = \{x_m\}$, $x_m \in \{0,1\}$, of length $M > N$. Subsequent interleaving followed by a 1D/2D conversion results in the $I \times J$ matrix $\mathbf{X}$ as a two-dimensional structure with elements $x_{i,j} \in \{0,1\}$, $i = 1,2\ldots,I$, $j = 1,2,\ldots,J$, with i and j being the row and column indices of the data pattern. These bits are then binary modulated and finally exposed as data points on the photographic film by means of a laser film recorder. The simulations in this paper are based on the channel model parameters discussed in [14]. The *read process* involves scanning and image processing, joint equalization/demodulation (JED), 2D/1D conversion, deinterleaving (π^{-1}), as well as channel decoding. After scanning and image processing (cf., e.g., [8]), the normalized channel outputs $y_{i,j} \in [0,1]$ contained in the $I \times J$ matrix $\mathbf{Y}$ are available. These channel outputs subsequently serve as an input to the JED algorithms which produce either log-likelihood ratios (LLRs) $L_{i,j} \in \mathbb{R}$ contained in the $I \times J$ matrix $\mathbf{L}$ (for the GMM-based JED, referred to as GED) or estimated received bits $\hat{x}_{i,j}$ contained in $\hat{\mathbf{X}}$ (for the decision feedback equalizer, referred to as DFE). These values are translated into sequences $\{L_m\}$ or $\{\hat{x}_m\}$, respectively, of length M by means of a 2D/1D conversion and a deinterleaver (π^{-1}). A channel decoder (cf., e.g., [7]) finally delivers the output bit sequence $\mathbf{v} = \{v_n\}$ of length N.

2.2 Channel Model

The channel model suggested in [14] serves to generate simulated channel outputs $y_{i,j}$ according to the channel input bits $x_{i,j}$ (the scope of this model is defined in Figure 1 by the dotted box). For calculation of each simulated channel output $y_{i,j}$, the corresponding channel input bit $x_{i,j}$ as well as its eight vertical/horizontal and diagonal neighboring input bits $\mathbf{x}^{\square}_{i,j} = \{x_{i-1,j-1}, x_{i-1,j}, x_{i-1,j+1}, x_{i,j-1}, x_{i,j+1}, x_{i+1,j-1}, x_{i+1,j}, x_{i+1,j+1}\}$ are regarded. Thereby, it is assumed that the influence of further data points can be neglected.

As a basis for the channel simulation, the conditional probability density functions (PDFs) $\mathrm{p}(y|x_{i,j},\mathbf{x}^{\square}_{i,j})$ are employed as described in [14]. The simulated channel outputs $y_{i,j}$ are drawn as random samples according to

$$y_{i,j} \sim \mathrm{p}(y|x_{i,j},\mathbf{x}^{\square}_{i,j}) \,. \tag{1}$$

By assuming rotational symmetric data points, the PDF can also be expressed in terms of the number of exposed vertical/horizontal neighbors $\Phi_{i,j} = (x_{i-1,j} + x_{i,j-1} + x_{i,j+1} + x_{i+1,j}) \in \{0,1,2,3,4\}$ and the number of exposed diagonal neighbors $\Psi_{i,j} = (x_{i-1,j-1} + x_{i-1,j+1} + x_{i+1,j-1} + x_{i+1,j+1}) \in \{0,1,2,3,4\}$ as $\mathrm{p}(y|x_{i,j},\mathbf{x}^{\square}_{i,j}) = \mathrm{p}(y|x_{i,j},\Phi_{i,j},\Psi_{i,j})$.

Since the PDFs $\mathrm{p}(y|x,\Phi,\Psi)$ are not necessarily Gaussian[1], they are approximated by means of Gaussian mixture models (GMMs) [19] of orders K as

$$\mathrm{p}(y|x,\Phi,\Psi) \approx \sum_{k=1}^{K} \rho^{(k)}_{x,\Phi,\Psi} \cdot \mathcal{N}\left\{y^{(k)}; \mu^{(k)}_{x,\Phi,\Psi}, \left(\sigma^{(k)}_{x,\Phi,\Psi}\right)^2\right\} \tag{2}$$

with normal distributions $\mathcal{N}\left\{y^{(k)}; \mu^{(k)}_{x,\Phi,\Psi}, \left(\sigma^{(k)}_{x,\Phi,\Psi}\right)^2\right\}$, means $\mu^{(k)}_{x,\Phi,\Psi}$, variances $\left(\sigma^{(k)}_{x,\Phi,\Psi}\right)^2$, and weights $\rho^{(k)}_{x,\Phi,\Psi}$ $\left(\sum_{k=1}^{K} \rho^{(k)}_{x,\Phi,\Psi} = 1\right)$. These GMM parameters are obtained by means of a training process using the expectation maximization (EM) algorithm [20] and the training data originating from real film samples, i.e., pseudorandom data patterns with known bit constellations $x_{i,j}$.

3. Joint Equalization/Demodulation

In this section, two algorithms for JED are introduced: the GED (see Subsection 3.1) as well as the DFE-based approach (see Subsection 3.2).

3.1 GMM-based Equalization/Demodulation (GED)

For conventional soft demodulation, the LLRs are defined as

$$L_{i,j} = L(x|y) = \ln \frac{P(x=1|y)}{P(x=0|y)} = \ln \frac{\mathrm{p}(y|x=1) \cdot P(x=1)}{\mathrm{p}(y|x=0) \cdot P(x=0)} \tag{3}$$

with the natural logarithm $\ln(\cdot)$, the *a posteriori* probabilities $P(x=1|y)$ and $P(x=0|y)$, the conditional PDFs $\mathrm{p}(y|x=1)$ and $\mathrm{p}(y|x=0)$, and the *a priori* probabilities $P(x=1)$ and $P(x=0)$ (cf. [21,22]). Equal *a priori* probabilities $P(x=1) = P(x=0) = 0.5$ yield the simplification

$$L_{i,j} = L(x|y) = \ln \frac{\mathrm{p}(y|x=1)}{\mathrm{p}(y|x=0)} \quad . \tag{4}$$

Since for data storage on photographic film the PDFs $\mathrm{p}(y|x=1)$ and $\mathrm{p}(y|x=0)$ are typically non-Gaussian, a soft demodulator is suggested in [14] with the PDFs $\mathrm{p}(y|x=1)$ and $\mathrm{p}(y|x=0)$ being approximated by means of GMMs .

By extending the definition of y as

$$\mathbf{y} = \{y, \mathbf{y}^*\} \tag{5}$$

it is possible to also consider the channel outputs $\mathbf{y}^*$ of neighboring data points[2] in equations (4) and (5) leading to

$$L_{i,j} = L(x|\mathbf{y}) = \ln \frac{\mathrm{p}(\mathbf{y}|x=1)}{\mathrm{p}(\mathbf{y}|x=0)} \quad . \tag{6}$$

[1] In order to simplify the mathematical notation, the indices (i,j) are omitted here and – if reasonable – also in the remainder of the paper.

[2] In this paper, we focus on the next vertical/horizontal and diagonal neighboring data points for the neighborhood (i.e., $\mathbf{y}^*_{i,j} = \mathbf{y}^{\square}_{i,j}$). However, note that – depending on the amount of intersymbol interference – other definitions of $\mathbf{y}^*_{i,j}$ may be meaningful.

This actually implements a soft joint equalizer/demodulator (JED) which provides LLRs and simultaneously reduces ISI by performing equalization.

Similar to the framework of the channel model, the two PDFs $\mathrm{p}(\mathbf{y}|x)$ for $x=0$ and $x=1$ are approximated by means of GMMs (which are trained based on real data using the EM algorithm) as

$$\mathrm{p}(\mathbf{y}|x) \approx \sum_{q=1}^{Q} \rho_{x,q} \cdot \mathscr{N}(\mathbf{y}; \boldsymbol{\mu}_{x,q}, \boldsymbol{\Sigma}_{x,q}) \tag{7}$$

with orders Q and normal distributions $\mathscr{N}\{\mathbf{y}; \boldsymbol{\mu}_{x,q}, \boldsymbol{\Sigma}_{x,q}\}$. The GMM parameters are denoted as $\boldsymbol{\mu}_{x,q}$ (mean vector), $\boldsymbol{\Sigma}_{x,q}$ (full covariance matrix), and $\rho_{x,q}$ (weights) whereby $\sum_{q=1}^{Q} \rho_{x,q} = 1$.

3.2 Decision Feedback Equalizer (DFE)

The decision feedback equalizer (DFE) as described in [15] represents an iterative JED approach[3] which – in our context – basically works as follows:

1) Obtain the initial estimated received bits $\hat{x}_{i,j}^{(0)} \in \{0,1\}$ by comparing the channel outputs $y_{i,j} \in [0,1]$ to a fixed threshold.[4] This corresponds to a simple hard decision.
2) Calculate the new estimated received bits $\hat{x}_{i,j}^{(n)}$ from $\hat{x}_{i,j}^{(n-1)}$ and a known channel model at iteration step n).
3) Repeat step 2) for a desired number of iterations or until some predefined stop criterion is fulfilled.

In [15] a linear channel model based on a convolution with a two-dimensional impulse response and AWGN are assumed. As already mentioned above, this is not appropriate for digital data storage on film due to the underlying non-linear and non-Gaussian characteristics. Accordingly, a modification of step 2) is needed, which is described in the following.

In advance of steps 1)–3) and the above iterative procedure, for all 50 combinations $\{x_{i,j}, \Phi_{i,j}, \Psi_{i,j}\}$ we compute and store

$$\bar{y}(x, \Phi, \Psi) = \bar{y}_{i,j}(x_{i,j}, \Phi_{i,j}, \Psi_{i,j}) = E\{y_{i,j}|x_{i,j}, \Phi_{i,j}, \Psi_{i,j}\}, \tag{8}$$

which can be employed for arbitrary locations (i,j). Note that (8) reflects a deterministic noise-free channel model and can be computed, e.g., as mean values of the PDFs in (2).

The estimated bits $\hat{x}_{i,j}^{(n)}$ at step n) are calculated as

$$\hat{x}_{i,j}^{(n)} = \begin{cases} 0, & \text{if } |\bar{y}(x=0, \hat{\Phi}_{i,j}^{(n-1)}, \hat{\Psi}_{i,j}^{(n-1)}) - y_{i,j}| \\ & \quad < |\bar{y}(x=1, \hat{\Phi}_{i,j}^{(n-1)}, \hat{\Psi}_{i,j}^{(n-1)}) - y_{i,j}| \\ 1, & \text{else} \end{cases} \tag{9}$$

whereby the estimated number of exposed vertical and horizontal neighboring data points at iteration step n, $\hat{\Phi}_{i,j}^{(n-1)}$ and $\hat{\Psi}_{i,j}^{(n-1)}$, respectively, are obtained by evaluating $\hat{\mathbf{x}}_{i,j}^{\square(n-1)}$.

[3]This specific DFE-based approach is referred to as a JED in this context since it directly delivers estimated bits $\hat{x}_{i,j}^{(n)}$ for each iteration step n) and thus jointly performs equalization and hard-decision demodulation.

[4]This threshold is determined by means of an initial training process.

4. Performance Evaluation and Discussion

To evaluate the performance of the proposed JED algorithms, several simulations have been carried out. The bit error rate (BER) has been used to compare the GED with the DFE-based approach. Soft demodulation (SD) as described in [14] serves as a further reference. In the following section, details about the simulation setup are provided. The simulation results are discussed in Section 4.2.

4.1 Simulation Setup

The performance analysis is completely based on simulated data. Therefore, the model and the corresponding parameters from [14] have been employed. These parameters have been obtained from an analysis of test patterns exposed by the Arche laser recorder [9] at a grid space of $d = 6\,\mu$m.

Aside from the actual BER simulations, the equalizer GMMs (7) for the GED have been trained whereby each training process has been based on 25 data fields with 100×100 binary data points, i.e., 250,000 training bits in total. These trained GMMs have been used to generate estimated bits $\hat{x}_{i,j}$ from a different set of data fields (also 25 data fields with 100×100 binary data points) with known bit constellations $x_{i,j}$. Subsequently, the bit error rates p_e have been obtained as $p_e = E\{|x_{i,j} - \hat{x}_{i,j}|\}$ whereby $E\{\cdot\}$ denotes the expectation operator with $\hat{x}_{i,j}$ calculated from the sign of the LLRs:

$$\hat{x}_{i,j} = \begin{cases} 1, & \text{if } L_{i,j} < 0 \\ 0, & \text{else} \end{cases} . \tag{10}$$

4.2 Simulation Results and Discussion

The BERs for the JED algorithms can be observed in Table 1. For SD and GED, GMM orders $Q=1$ and $Q=2$ have been investigated. It is obvious on the first glance that compared to conventional soft demodulation, the GED is able to significantly improve the BER by more than one order of magnitude. Also, it can be observed that higher GMM orders Q do not lead to significant improvements of the BER.

However, when comparing the BER values at different GMM orders please be aware that the GMM order Q may possibly affect the quality of the LLR values. Also, the specific characteristics of the actually employed film material (or a variation of the system parameters) may also require larger values of Q. For SD, the BER at $Q=2$ is even slightly higher compared to the BER at $Q=1$. This can be explained by numerical effects during the training and the simulation processes. For a different set of training data – e.g., if an alternative exposure device is used – this may actually be vice versa. Note that in [14] the GMM orders Q have been selected in a way that the resulting GMMs reasonably approximate the measured PDFs.

Also, the BERs for the DFE detector are given in Table 1 for each iteration step n) from $n=0$ up to $n=5$. The BER for $n=0$ is obtained by means of thresholding within the initialization of the algorithm. As expected, this BER is approximately equal to the BER obtained by conventional soft demodulation for $Q=1$. Only two iteration steps are required to reduce the BER to values between around 0.05% and 0.06%.

Both algorithms show good results and are able to reduce the ISI and thus the BER. The DFE modified for the non-linear channel encountered in data storage on photographic film leads to significantly improved BERs that are even lower than the resulting BERs of the GED. However, it does not provide LLR values. Without such

Table 1: Bit error rates (in percent) for the investigated algorithms.

Iteration step *n*	0	1	2	3	4	5
SD ($Q = 1$)	1.17	*Algorithm is non-iterative*				
SD ($Q = 2$)	1.21					
GED ($Q = 1$)	0.104					
GED ($Q = 2$)	0.0904					
DFE	1.17	0.0824	0.0564	0.0544	0.0552	0.0544

soft information on the received bits, the decoding performance of state-of-the-art channel decoders would be surely suboptimal.

5. Conclusions

In this paper, joint equalization/demodulation (JED) algorithms for digital data storage on photographic film have been presented. Due to the underlying non-Gaussian and non-linear channel characteristics of such materials, advanced equalization techniques are required. Two approaches have been suggested: The GMM-based JED (GED) as well as a decision feedback equalizer (DFE). The performance of these JED approaches has been evaluated using the realistic channel model presented in [14].

It turns out from the simulations that the suggested JEDs perform significantly better compared to conventional soft demodulation (SD) since the bit error rate (BER) can be reduced by more than a magnitude. Regarding BER performance, the DFE outperforms the GED. However, the specific DFE-based approach investigated in this paper does not provide LLRs which are definitely required for high-performance channel decoding. A further advantage of the proposed GED is that it is non-iterative.

By employing JED, smaller grid spaces and thus increased storage capacities are possible. Also, the reduced BERs may allow to use channel codes with lower amounts of redundancy. Further research focuses on smaller grid spaces and different film materials (e.g., cinematographic film) although it is to be expected that higher orders of the equalizer GMMs may be required. In this context, also optimized forward error correction (FEC) decoding schemes will be investigated. The proposed JED algorithms provide universal data-driven approaches which may also be applied to other two-dimensional data storage technologies.

References

[1] Eastman Kodak Company, "KODAK IMAGELINK HQ, CS, CP and FS Microfilms, Camera Negative Microfilm Data Sheet," Rochester, NY, USA, 1998.

[2] C. Voges and J. Fröhlich, "Applications of Data Storage on Cinematographic Film for Long-Term Preservation of Digital Productions," *SMPTE Motion Imaging Journal* (reprint of contribution to IBC Conference 2011), vol. 121, no. 1, pp. 39–42, Jan./Feb. 2012.

[3] C. Voges and T. Fingscheidt, "Technology and Applications of Digital Data Storage on Microfilm," *Journal of Imaging Science and Technology (JIST)*, vol. 53, no. 6, pp. 060 505–1–060 505–8, Nov. 2009.

[4] C. Voges, "An Introduction to Long-Term Archiving of Digital Data on Film Material," in *Proc. of VDT International Convention*, Leipzig, Germany, Nov. 2010, pp. 243–249.

[5] F. Müller, P. Fornaro, L. Rosenthaler, and R. Gschwind, "PEVIAR: Digital Originals," *ACM Journal on Computing and Cultural Heritage*, vol. 3, no. 1, pp. 2:1–2:12, June 2010.

[6] C. Voges, V. Märgner, and T. Fingscheidt, "Digital Data Storage on Microfilm – Error Correction and Storage Capacity Issues," in *Proc. of IS&T Archiving Conference*, Bern, Switzerland, June 2008, pp. 212–215.

[7] F. Pflug, C. Voges, and T. Fingscheidt, "Performance Evaluation of Iterative Channel Codes for Digital Data Storage on Microfilm," in *Proc. of IEEE GLOBECOM*, Miami, FL, USA, Dec. 2010.

[8] C. Voges, V. Märgner, and T. Fingscheidt, "Digital Data Storage on Microfilm – The MILLENIUM Project: Signal and Information Processing," in *Proc. of IS&T Archiving Conference*, Arlington, VA, U.S.A, May 2009, pp. 187–191.

[9] A. Hofmann, W. J. Riedel, K. Sassenscheid, and C. J. Angersbach, "Archivelaser Project: Accurate Long-Term Storage of Analog Originals and Digital Data with Laser Technology on Color Preservation Microfilm," in *Proc. of IS&T Archiving Conference*, Washington, DC, USA, Apr. 2005, pp. 197–200.

[10] C. Voges and J. Fröhlich, "Long-Term Storage of Digital Data on Cinematographic Film," in *Proc. of IS&T Archiving Conference*, Salt Lake City, UT, USA, May 2011, pp. 158–161.

[11] C. Voges and J. Fröhlich, "The CineSave Project: Long-Term Preservation of Digital Production," in *Proc. of IS&T Archiving Conference*, Copenhagen, Denmark, June 2012, pp. 75–79.

[12] O. Plata and R. Bjerkestrand, "The ARCHIVATOR – A Solution for Long-Term Archiving of Digital Information," in *Proc. of IS&T Archiving Conference*, Copenhagen, Denmark, June 2012, pp. 71–74.

[13] A. Amir, F. Müller, P. Fornaro, R. Gschwind, J. Rosenthal, and L. Rosenthaler, "Towards a Channel Model for Microfilm," in *Proc. of IS&T Archiving Conference*, Bern, Switzerland, June 2008, pp. 207–211.

[14] C. Voges and T. Fingscheidt, "A Two-Dimensional Channel Model for Digital Data Storage on Microfilm," *IEEE Transactions on Communications*, vol. 59, no. 8, pp. 2046–2050, Aug. 2011.

[15] S. Nabavi and B. V. K. V. Kumar, "Iterative Decision Feedback Equalizer Detector for Holographic Data Storage Systems," *Proc. SPIE*, vol. 6282, no. 2, pp. 62 820T.1–62 820T.8, 2005.

[16] K. M. Chugg and X. Chen, "Two-Dimensional Equalization in Coherent and Incoherent Page-Oriented Optical Memory," *J. Opt. Soc. Am. A*, vol. 16, no. 3, pp. 549–562, Mar. 1999.

[17] M. A. Neifield, K. M. Chugg, and B. M. King, "Parallel Data Detection in Page-Oriented Optical Memory," *Opt. Lett.*, vol. 21, no. 18, pp. 1481–1483, Sept. 1996.

[18] S. Nabavi and B. V. K. V. Kumar, "Two-Dimensional Generalized Partial Response Equalizer for Bit-Patterned Media," in *Proc. IEEE International Conference on Communication (ICC)*, Glasgow, Scotland, June 2007, pp. 6249–6254.

[19] S. V. Vaseghi, *Advanced Digital Signal Processing and Noise Reduction*. Chichester, West Sussex, UK: Wiley, 4th ed., 2008.

[20] T. K. Moon, "The Expectation-Maximization Algorithm," *IEEE Signal Processing Magazine*, vol. 13, no. 6, pp. 47–60, Nov. 1996.

[21] B. Sklar, *Digital Communications*. Upper Saddle River, NJ, USA: Prentice Hall, Inc., 2nd ed., 2001.

[22] J. Hagenauer, "Source-Controlled Channel Decoding," *IEEE Transactions on Communications*, vol. 43, no. 9, pp. 2449–2457, Sept. 1995.

Author Biography

Christoph Voges studied electrical engineering at Technische Universität Braunschweig, Germany, and University of Southampton, U.K. He received a Dipl.-Ing. degree in 2005 and joined the Institute for Communications Technology in Braunschweig, Germany, as a research associate after graduating. Currently, he is working as a consultant in the field of digital archiving, especially "Bits on Film." Voges is a delegate at the ITG Technical Committee 3.4 "Film Technology," the AWV Working Committee 6.3 "Data and Storage Management," and the AWV Project Group 6.3.2 "Digital Archiving on Film." His specific research interest is digital data storage on film, including signal and image processing as well as error correction coding.

Tim Fingscheidt received the Dipl.-Ing. and the Dr.-Ing. degrees from RWTH Aachen University, Germany. From 1998 he worked with AT&T Labs, Florham Park, NJ, USA. In 1999 he joined Siemens AG (COM Mobile Devices) in Munich, Germany, from 2001 as team leader for Audio Applications. In 2005 he joined Siemens Corporate Technology in Munich, leading the company's speech technology development activities. Since 2006 he is Professor at the Institute for Communications Technology at Technische Universität Braunschweig, Germany. His research interests are speech and audio signal processing and pattern recognition.