EFFECTIVE NONLINEAR RECEIVERS FOR HIGH DENSITY OPTICAL RECORDING

L. AGAROSSI†, S. BELLINI††, and P. MIGLIORATI†††

SUMMARY The starting point of this paper is the definition of a nonlinear model of the read out process in high density optical discs. Under high density condition, the signal read out is not a linear process, and suffers also from cross talk. To cope with these problems, the identification of a suitable nonlinear model is required. A physical model based on the optical scalar theory is used to identify the kernels of a nonlinear model based on the Volterra series. Both analysis and simulations show that a second order bidimensional model accurately describes the read out process. Once equipped with the Volterra channel model, we evaluate the performance of various nonlinear receivers. First we consider Nonlinear Adaptive Volterra Equalization (NAVE). Simulations show that the performance of classical structures for linear channels is significantly affected by the nonlinear response. The nonlinear NAVE receiver can achieve better performance than Maximum Likelihood Sequence Estimator (MLSE), with lower complexity. An innovative Nonlinear Maximum Likelihood Sequence Estimator (NMLSE), based on the combination of MLSE and nonlinear Inter-Symbol Interference (ISI) cancellation, is presented. NMLSE offers significant advantages with respect to traditional MLSE, and performs better than traditional equalization for nonlinear channels (like NAVE). Finally, the paper deals with cancellation of cross talk from adjacent tracks. We propose and analyze an adaptive nonlinear cross talk canceller based on a three spot detection system. For the sake of simplicity, all the performance comparisons presented in this paper are based on the assumption that noise is Additive, White, and Gaussian (AWGN model).

key words: Nonlinear equalization, Optical recording, Volterra models, Compact disc, Cross talk.

1. Introduction

The information density on optical discs can be augmented either increasing the operating spatial frequency or decreasing the track pitch, i.e., the distance between adjacent tracks. In high density systems the read out signal is significantly affected by InterSymbol Interference (ISI) along the track that is being read, and by Cross Talk (XT), i.e., interference from adjacent tracks.

The recorded signal can be recovered only by a suitable channel equalizer. The definition of a realistic model of the read out system is therefore the first fundamental step. In case of high density recording the linear model, based on the Modulation Transfer Function (MTF) is no more realistic and a more complex one is required [1]. A good optical model was developed by Hopkins [2] using a scalar theory approach. This theory can be applied also to high density optical discs, even if pit dimensions of the order of one wavelength (in air) are involved, because light reflection is performed through a material with a refractive index that reduces the effective wavelength.

In our work an optical physical model has been implemented. This model has then been used to identify a nonlinear analytical model based on the Volterra series. The latter model has two great advantages: first, it allows to simulate the read out signal, for a given data sequence, much faster than the optical model does; second, and most important, it explicitly brings the dependence of the output on input data, and gives much more insight into possible equalization strategies.

The scalar theory, and also the experimental results, show that a second order nonlinear Volterra model is a good approximation of the read out process.

Using this channel model, equalizers designed for linear and nonlinear channels can be analyzed, and their performance and complexity can be compared. In previous works [3], [4] we considered linear adaptive Mean Square Error (MSE) equalization, adaptive Decision Feedback Equalization (DFE), Nonlinear Adaptive Volterra Equalization (NAVE), and Maximum Likelihood Sequence Estimation (MLSE), suggested by Ungerboeck for linear channels.

Here we present an innovative Nonlinear Maximum Likelihood Sequence Estimator (NMLSE), specifically designed for the optical channel. The proposed NMLSE receiver shows significant performance improvement with respect to other algorithms.

We analyze also possible simplifications of the above nonlinear receivers, and compare their performance and complexity. The complexity of NAVE can be reduced decreasing the number of either linear or nonlinear taps (or both). An NMLSE of reduced complexity can be obtained not only with fewer (linear and nonlinear) taps than required by a full implementation, but also decreasing the number of trellis states and the memory of the Viterbi detector.

The data density can also be increased reducing the track pitch, as long as cross talk is kept under control. We present a Cross Talk Canceller (XTC) based on a three spot detection system. In this architecture,
the information stored in the two adjacent tracks is estimated using classical (nonlinear) equalization algorithms. Then, an adaptive XT canceller cleans up the signal of the central track. Finally, the signal is processed with one of the nonlinear algorithms developed to combat nonlinear ISI, and final decisions are taken. The proposed XTC shows significant performance improvement with respect to a classical receiver without XT cancellation.

The performance comparisons presented in this paper are based on a two-dimensional Volterra model for the optical channel. For the sake of simplicity, we compare different receivers in presence of Additive White Gaussian Noise (AWGN).

The paper is organized as follows. Section 2 is devoted to the description of the procedure used to estimate the Volterra kernels, and shows some experimental results. Sections 3 and 4 introduce the proposed NMLSE and XTC. Simulation results for the receivers considered in this paper are presented and discussed in Section 5. Concluding remarks are given in the final section.

2. The Volterra model

In order to estimate the nonlinear characteristics of the optical disc, a mathematical model based on a Volterra series is considered [5]. The functional input output relationship \( y(t) = f[x(t)] \) is:

\[
y(t) = h_0 + \int h_1(\tau)x(t-\tau)d\tau + \int h_2(\tau_1,\tau_2)x(t-\tau_1)x(t-\tau_2)d\tau_1 d\tau_2 + \ldots \quad (1)
\]

The zero order term \( h_0 \) accounts for the response to a zero input. The first order kernel \( h_1(t) \) is simply the impulse response of a linear system. Higher order kernels can be viewed as higher order impulse responses, which characterize the various orders of nonlinearity of the system.

As discussed in [6], a second order Volterra model is expected to give an accurate analytical description of the read out process.

2.1 Calculation of Volterra kernels

Volterra kernels of second order systems can be evaluated probing the nonlinear system with pairs of impulses [7]. If we associate the amplitude 0 to lands, and 1 to pits, the test sequences consist of two short pits at appropriate locations.

In most cases, e.g. when we analyze the performance of an equalizer, we prefer to consider a “bipolar” input, namely \( \pm 1 \), instead of a polar one \((0,1)\). It is straightforward, however, to translate kernels from polar to bipolar representation of data. In the following, primes indicate “bipolar” kernels.

The kernel \( h_0 \) is the output when the input is identically equal to 0, that is when a mirror disc is used.

To evaluate the higher order kernels \( h_1 \) and \( h_2 \), a small pit of 30nm spatial width was chosen as a unitary impulse. Since the computation of the \( h_1 \) kernel is based on the knowledge of \( h_2 \), the latter is evaluated first.

When two impulses \( \delta(t-\tau_1) \) and \( \delta(t-\tau_2) \), are applied to a second order system, the output is [7]

\[
y_{12}(t) = h_0 + h_1(t-\tau_1) + h_1(t-\tau_2) + h_2(t-\tau_1, t-\tau_2) + 2h_2(t-\tau_1, t-\tau_2) \quad (2)
\]

while the response to an impulse in \( \tau_1 \) alone is

\[
y_1(t) = h_0 + h_1(t-\tau_1) + h_2(t-\tau_1, t-\tau_1) \quad (3)
\]

Likewise, the response to a single impulse in \( \tau_2 \) is

\[
y_2(t) = h_0 + h_1(t-\tau_2) + h_2(t-\tau_2, t-\tau_2) \quad (4)
\]

From the above equations we get the second order kernel

\[
h_2(t-\tau_1, t-\tau_2) = \frac{1}{2}(y_{12}(t) + h_0 - y_1(t) - y_2(t)) \quad (5)
\]

Finally, the first order kernel is given by

\[
h_1(t-\tau_1) = y_1(t) - h_0 - h_2(t-\tau_1, t-\tau_1) \quad (6)
\]

Note that \( \tau_1 = \tau_2 \) is not allowed, as this would require an impulse with amplitude 2, which has no physical meaning. Hence, \( h_2(\tau_1, \tau) \) is obtained by interpolation from the values of \( h_2(\tau_1, \tau_2) \) with \( \tau_1 \neq \tau_2 \). The “polar” Volterra kernels, without lens aberrations, are shown in Figs. 1 and 2. We considered the optical parameters of the Compact Disc Digital Audio (CDDA) system: the numerical aperture of the objective \( NA=0.45 \), the laser wavelength \( \lambda = 0.780 \mu m \), and the tangential velocity \( v = 1.25m/s \).

The equalization techniques to be discussed in this paper are adaptive. Hence, they are able to take care also of lens aberrations, and of other sources of ISI or XT, like e.g. nonlinear effects in disc recording.

The output signal coming from the physical optical model has been compared with the output of the nonlinear model based on Volterra series for an EFM (Eight to Fourteen Modulation) sequence input signal, and the CDDA standard’s parameters (the minimum pit or land length \( l = 0.9 \mu m \)). The input signal can be subdivided in small impulses of 30nm each. In the CDDA standard, however, pit and land lengths are multiple of 0.3 \( \mu m \), due to the Run Length Limited (RLL) code. Hence, we can also evaluate the first and second order response to rectangles this wide, and superpose them according to the data. The evaluation of the modified
kernels requires simply one- and two-dimensional discrete convolutions. The output signals obtained by the optical model and by the Volterra series are so similar that it is not possible to distinguish between them. This result confirms that the second order Volterra model agrees with the scalar Hopkins theory.

If we want to consider a bipolar input signal $x'(t)$ with -1 associated to lands and +1 to pits, we can express the corresponding polar signal as $x(t) = \frac{x'(t) + 1}{2}$. Substituting the above expression into (1) we easily obtain that the “bipolar” kernels are

$$h'_0 = h_0 + \frac{1}{2} \int h_1(\tau)d\tau + \frac{1}{4} \int \int h_2(\tau_1, \tau_2)d\tau_1 d\tau_2 (7)$$

$$h'_1(\tau) = \frac{1}{2} h_1(\tau) + \frac{1}{2} \int h_2(\tau, \tau)d\tau$$

$$h'_2(\tau_1, \tau_2) = \frac{1}{4} h_2(\tau_1, \tau_2)$$

It is noteworthy that part of the second order distortion is folded into the linear term $h'_1(t)$. Fig. 3 shows an example of the complete Volterra model’s output, compared to the contribution of the first order kernels $h_1(t)$ and $h'_1(t)$.

The contribution of the linear term alone is much closer to the physical model output if the bipolar approach is chosen. The amplitude of second order terms is clearly exaggerated by polar kernels. Since this conclusion holds for all the examples we worked out, in the following only bipolar kernels are considered. We used polar kernels only for identification purposes.

In presence of cross talk, we have a nonlinear system with many inputs and one output. Let $x_0(t)$ and $x_i(t)$ be the data stored on the central track, and on adjacent ones. Then, the output signal is

$$y(t) = h_0 + \sum_i \int h'_1(\tau)x_i(t-\tau)d\tau +$$

$$+ \sum_i \int \int h'_2(\tau_1, \tau_2)x_i(t-\tau_1)x_i(t-\tau_2)d\tau_1 d\tau_2 +$$

$$+ \sum_i \sum_{j \neq i} \int \int h''_2(\tau_1, \tau_2)x_i(t-\tau_1)x_j(t-\tau_2)d\tau_1 d\tau_2 (10)$$

where $h'_1(\tau)$ and $h'_2(\tau_1, \tau_2)$ ($i \neq 0$) represent linear and nonlinear XT due the $i$-th track alone, while $h''_2(\tau_1, \tau_2)$ ($j \neq i$) takes care of nonlinear combinations of data stored in different tracks. We have verified that in practice we need consider only XT terms due to the two adjacent tracks ($i, j = \pm 1$).

An appropriate kernel identification procedure of all the Volterra kernels was developed in previous works [6].

Simulations have shown that, even at the CDDA density, the contributions of second order terms are not
negligible [6].

Fig. 4 shows the Volterra output $y(t)$, along with the output without XT, and XT terms alone (arbitrarily shifted, to show them better). The data density along tracks is CDDA, and the track distance $d = 0.7 \mu m$ (instead of $d = 1.6 \mu m$). We see that at this density an exact representation of the read-out signal requires also cross talk kernels.

![Fig. 4](image)

**Fig. 4** Output signal (solid); Volterra’s output without XT (dotted); and XT terms (dashed).

3. The Proposed Nonlinear Receiver

With this receiver, we want to get rid of both linear and nonlinear ISI.

In this work we assume that noise is white, additive, and Gaussian. This AWGN model is not the most accurate one, but allows a simple comparison (i.e., ranking) of equalization techniques.

MLSE is the optimum strategy for linear channels, since decisions are based on the entire transmitted sequence [8]. However, MLSE shows a significant performance loss due to nonlinearity, if the channel is more realistically described by a second order Volterra model [4]. Also equalization strategies specifically studied for nonlinear channels, like NAVE [9] and NDFE [10], are not optimal solutions at high information densities, because they are based on a symbol by symbol approach.

On the other hand, the optimum sequence estimator for nonlinear channels [5] requires a bank of $L^M$ matched filters (where $M$ is the cardinality of the symbol alphabet and $L$ is the channel memory), followed by a modified Viterbi algorithm with metrics taking care of both linear and nonlinear terms. The complexity of this receiver is very high.

These considerations have triggered the idea of an innovative nonlinear receiver, based on NMLSE, described in the following subsections.

3.1 Metrics Computation for the Nonlinear Optical Channel

If $r(t)$ denotes the received signal, $n(t)$ the Gaussian noise, and $y(t)$ the nonlinear optical channel output, the received signal $r(t)$ can be expressed as

$$r(t) = y(t) + n(t)$$

(11)

The signal $y(t)$, which can be derived from Volterra kernels (Eq. 1), neglecting the zero-th order kernel $h_0$ can be rewritten in the form

$$y(t) = y_1(t) + y_2(t)$$

(12)

where $y_1(t)$ is the first order response and $y_2(t)$ is the second order response, i.e. the nonlinear contribution to the channel output.

Maximum likelihood sequence estimation requires that the likelihood function $\lambda$ be maximized with respect to all possible transmitted sequences. In presence of AWGN, $\lambda$ can be expressed as follows:

$$\lambda = \frac{2}{N_0} \int y(t)r(t)dt - \frac{1}{N_0} \int y^2(t)dt$$

(13)

Substituting Eqs. 11 and 12 in Eq. 13 we obtain the likelihood function in the case of the nonlinear optical channel, described by a second order Volterra kernel, namely

$$\lambda = \frac{2}{N_0} \int y_1(t)r(t)dt + \frac{2}{N_0} \int y_2(t)r(t)dt +$$

$$- \frac{1}{N_0} \int y_1^2(t)dt - \frac{1}{N_0} \int y_2^2(t)dt +$$

$$- \frac{2}{N_0} \int y_1(t)y_2(t)dt$$

(14)

Let us denote the five terms in Eq. 14 by $\alpha_1$, $\alpha_2$, $\beta_1$, $\beta_2$, $\beta_{12}$ respectively, i.e.,

$$\lambda = \alpha_1 + \alpha_2 + \beta_1 + \beta_2 + \beta_{12}$$

(15)

The terms $\alpha_1$ and $\beta_1$ in Eq. 15 are the same that would be required in the case of a linear channel, i.e., the cross-correlation between the received signal and the channel output, and the energy of the channel output [8]. The terms $\alpha_2$, $\beta_2$ and $\beta_{12}$ in Eq. 15, on the other hand, represent additional contributions due to nonlinearity. The term $\beta_2$, namely the energy of the second order distortion, is a fourth order contribution that can be neglected. The third order term $\beta_{12}$ is close to zero (on average) because the first and second order outputs $y_1(t)$ and $y_2(t)$ are uncorrelated. Then, the only relevant nonlinear term in Eq. 15 is $\alpha_2$, which takes into account the nonlinear ISI.

Hence, if we can remove nonlinear intersymbol interference before maximum likelihood sequence estimation, with appropriate equalization structures such as a Volterra equalizer, the metrics for the nonlinear optical channel is the same as that for linear channels.
3.2 Nonlinear MLSE

To realize an adaptive Maximum Likelihood Sequence Estimator, in the case of linear channels, we can make use of the combination of an adaptive Matched Filter (MF) and a cascaded Viterbi Detector (VD), as shown in [8]. To extend the MLSE structure to the nonlinear optical channel, we may add a Nonlinear Volterra Canceller (NLC), for nonlinear ISI suppression, to the adaptive MF. Then, the VD can make use of the ordinary expressions for metrics computation. The combination of the NLC, the adaptive MF and the VD leads to the proposed NMLSE [11].

The adaptive MF can be easily implemented by means of a transversal Finite Impulse Response (FIR) filter with $N$ taps $g_i$, whose output $z_n$ at the $n$-th iteration is expressed by

$$z_n = \sum_{i=1}^{N} g_i r_i$$

(16)

where $r_i$ are the samples of $r(t)$ spaced by $T$ seconds ($T$ is the channel bit duration). Using the steepest descent algorithm, the filter taps can be adaptively updated according to the equations [8]

$$g_i^{(n+1)} = g_i^{(n)} - \theta e_n r_i^{(n)}, \quad 1 \leq i \leq N$$

(17)

$$s_{l}^{(n+1)} = s_{l}^{(n)} + \phi (e_n a_{n-l} + e_n a_{n+l}), \quad 1 \leq l \leq M$$

(18)

where $s_{l}$, $|l| \leq M$, are the $M$ samples of the estimated autocorrelation of the linear part of the channel response, $a_{n}$ is the estimate of the transmitted bit $a_{n}$, $\theta$ and $\phi$ are the updating steps, and $e_{n}$ is the signal error defined as follows

$$e_n = z_n - \sum_{l=-M}^{+M} s_{l} a_{n-l}$$

(19)

For nonlinear intersymbol interference suppression, the samples $r_i$ are processed by a nonlinear combiner, whose outputs are all possible products of couples of samples $r_h r_k$, $1 \leq h \leq N$, $1 \leq k \leq N$. If $N$ is the number of linear taps of the adaptive MF, the combiner generates $N^2$ products $u_i$. Each combiner output is used as an input of a transversal FIR filter with $N^2$ taps $u_i$. The filter operates as an NLC, and its output $c_n$, at the $n$-th iteration, is given by

$$c_n = \sum_{i=1}^{N^2} w_i u_i$$

(20)

Using again the steepest descent algorithm for updating the NLC coefficients we get

$$w_i^{(n+1)} = w_i^{(n)} - \delta e_n u_{i}^{(n)}, \quad 1 \leq i \leq N^2$$

(21)

where $\delta$ is the algorithm updating step, and $\hat{e}_n$ is the signal error derived with the estimation delay $D$:

$$\hat{e}_n = c_n - \hat{a}_{n-D}$$

(22)

The NLC and the MF form a preliminary equalizer whose output $h_n$ is given by

$$h_n = c_n + z_n$$

(23)

Then, the signal $h_n$ is only affected by linear distortion, and can be processed by a VD the usual way.

Fig. 5 shows a simplified block diagram of the proposed NMLSE. In particular, updating of the adaptive matched filter coefficients, and of the autocorrelation estimator, is not shown.

Fig. 5 Simplified block diagram of the proposed NMLSE.

4. The Cross Talk Canceller

To take care also of cross talk, we adopt a multispot receiver, along with a cancellation algorithm [12].

Our receiver uses three spots, that read the main track and the two adjacent ones. Let the corresponding read-out signals be $r(t)$, $r_1(t)$, and $r_2(t)$, respectively. Note that $r_1(t)$ and $r_2(t)$ suffer from XT from two other neighboring tracks. We do not try to cancel these terms. The three read-out signals are also corrupted by additive Gaussian noise.

A simplified block diagram of the XT canceller is shown in Fig. 6. Note that all delays are understood. For instance, the estimates $\hat{a}_{1n}$ and $\hat{a}_{2n}$ of symbols stored in the adjacent tracks are produced with a delay equal to $(N - 1)/2$, where $N$ is the length of the two adaptive NAVEs, fed by the samples $r_{1n}$ and $r_{2n}$. Another delay is produced by the NAVE (or the NMLSE) that takes the final decisions $\hat{a}_{un}$. Hence, also the error signal used to update the coefficients of all the adaptive filters is delayed, and must be multiplied by delayed replicas of estimated data.
Linear combinations of the (nonlinearly) estimated data \( \hat{a}_{1n} \) and \( \hat{a}_{2n} \), obtained through two adaptive filters with \( N \) coefficients that try to reproduce the interference from neighboring tracks, are subtracted from the samples \( r_n \) of the main track. We have also analyzed more complex XT cancellers, taking into account also products of \( \hat{a}_{1n} \), \( \hat{a}_{2n} \) and of the (estimated) data along the central track. The improvement is negligible.

A third adaptive filter with \( M \) taps subtracts an estimate of ISI of the central track. We found that ISI cancellers eases the identification of the coefficients of the XT canceller.

![Fig. 6 Block diagram of the XT canceller.](image)

The coefficients \( g_{1i}, g_{2i}, i = 0, \ldots, N - 1 \) and \( h_i, i = 0, \ldots, M - 1 \) of the three filters are adaptively calculated, to minimize the mean-square error

\[
\begin{align*}
E &= E \left[ r_n - \sum_{i=0}^{N-1} g_{1i} \hat{a}_{1i} - \sum_{i=0}^{N-1} g_{2i} \hat{a}_{2i} + \\
&\quad - \sum_{i=0}^{M-1} h_i \hat{a}_{ui} \right]^2
\end{align*}
\]

(24)

Then, if we let

\[
\hat{\mathbf{a}} = \{\hat{a}_{10}, \ldots, \hat{a}_{1N-1}, \hat{a}_{20}, \ldots, \hat{a}_{2N-1}, \\
\hat{a}_{u0}, \ldots, \hat{a}_{uM-1}\}
\]

(25)

and

\[
\mathbf{z} = \{g_{10}, \ldots, g_{1N-1}, g_{20}, \ldots, g_{2N-1}, \\
h_0, \ldots, h_{M-1}\}
\]

(26)

the filter taps are updated by the stochastic gradient algorithm, namely

\[
\begin{align*}
\mathbf{z}^{k+1} &= \mathbf{z}^k - \delta_1 \sum_{i=0}^{N-1} g_{1i} \hat{a}_{1i} + \\
&\quad - \delta_2 \sum_{i=0}^{N-1} g_{2i} \hat{a}_{2i} - \delta_u \sum_{i=0}^{M-1} h_i \hat{a}_{ui} + r_n \hat{\mathbf{a}} \\
&\quad + \delta_0 \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} g_{1i} g_{2j} \hat{a}_{1i} \hat{a}_{2j}
\end{align*}
\]

(27)

Note that in the above equation delays are understood, as in Fig. 6. Finally, the estimated XT contributions of adjacent tracks are subtracted, and the symbols of the central track are obtained (by NAVE or NMLSE) from

\[
\tau_n = r_n - \sum_{i=0}^{N-1} g_{1i} \hat{a}_{1i} - \sum_{i=0}^{N-1} g_{2i} \hat{a}_{2i}
\]

(28)

5. Simulation results

In this Section we evaluate the performance of the receiver described above, considering the second order nonlinear Volterra model. In previous works, we evaluated also the performance of the same receivers neglecting second order contributions. We found that, even at the CDDA density, serious performance degradations due to second order terms are to be expected [4].

The optical parameters of the Compact Disc Digital Audio (CDDA) system have been assumed as a reference: the numerical aperture of the objective \( NA = 0.45 \), the laser wavelength \( \lambda = 0.780 \mu m \), and the tangential velocity \( v = 1.25 m/s \).

The simulations have been carried out with different information densities, obtained increasing the spatial frequency. For instance, 1.25xCDDA means that the spatial density is 1.25 times the CDDA density. The definition of the energy per information bit may be ambiguous, due to nonlinear terms. Hence, we adopt the following notation. We denote the peak to peak steady state system response as \( V_{pp} \). Then, if \( T \) is the symbol duration, a signal energy measure is expressed by \( E = T(V_{pp}/2)^2 \).

We have evaluated the bit error rate (BER) before the error correcting decoder (which is not considered in this analysis) as a function of the signal-to-noise ratio \( E/N_0 \), where \( N_0 \) is the one-sided power spectral density of noise.

5.1 NAVE

The use of channel equalization techniques proposed for nonlinear channels can offer significant performance improvements.

We consider the NAVE algorithm with \( N = 5 \) linear taps and \( N^2 = 25 \) nonlinear ones. Weights are updated according to the multiple step LMS algorithm, using \( \theta = 10^{-3} \) for linear taps and \( \rho = 10^{-6} \) for nonlinear ones. Fig. 7 shows the results.

If we reduce the complexity of NAVE, decreasing the number of nonlinear taps from 25 to 9, the SNR degradation is less than 0.5 dB, at BER \( = 10^{-3} \).

Among the algorithms proposed for linear channels, only MLSE obtains acceptable performance at 1.43xCDDA density. At this density NAVE achieves better performance than MLSE, with lower complexity. This confirms that we have to take care also of nonlinear ISI.
5.2 The proposed NMLSE

Fig. 8 shows the NMLSE performance versus $E/N_0$ for different information densities, ranging from the CDDA density to 1.67xCDDA.

NMLSE, which estimates the data sequence after canceling most second order terms, offers a significant improvement with respect to MLSE (see [4] for the performance of the latter). We can see that NMLSE performs also significantly better than symbol by symbol equalization designed for nonlinear channels (NAVE).

At the 1.43xCDDA density a full quality NMLSE would require about 19 linear taps, 25 nonlinear ones, and 512 trellis states. Simplifications can be obtained using a reduced number of linear and nonlinear taps of the preliminary equalizer, or a reduced number of trellis states, or a reduced path truncation length (i.e., memory) of the Viterbi algorithm.

For instance, a good combination of parameters for a practical NMLSE, having almost optimal performance at the 1.43xCDDA density, is shown in Table 1 (first column). The performance shown in Fig. 8 is obtained with this receiver. The second column of Table 1 gives a furtherly simplified version. The overall SNR loss of the latter version with respect to the full version turns out to be less than 1 dB, up to BER $= 10^{-5}$.

5.3 Cross Talk Canceller with NAVE (NAXTC)

In this receiver the estimated symbols $\hat{a}_1$ and $\hat{a}_2$ are obtained by two NAVE equalizers. Another NAVE equalizer is used to decide the useful symbols of the central track, after cross talk cancellation.

Table 1 Parameters of a practical NMLSE and of a simplified NMLSE (1.43xCDDA).

<table>
<thead>
<tr>
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<th>NMLSE</th>
<th>simpl. NMLSE</th>
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<td>linear taps</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>nonlinear taps</td>
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<td>11</td>
</tr>
<tr>
<td>number of states</td>
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<td>32</td>
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<tr>
<td>path truncation length</td>
<td>30</td>
<td>15</td>
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We considered NAVE algorithms with $N = 5$ linear taps and $N^2 = 25$ nonlinear ones. Weights are updated according to the LMS algorithm, with step size equal to $10^{-3}$ for linear taps, and $10^{-6}$ for nonlinear ones. Each cross talk canceller has $N = 5$ taps, updated according to the steepest descent algorithm with step size $10^{-3}$. Fig. 9 shows the performance of the complete cross talk canceller (NAXTC) at the CDDA density, with distance between adjacent tracks $d = 0.7 \mu m$. For comparison, also the performance of NAVE without XT, and without XT cancellation is shown. We can see that the
NAXTC almost completely eliminates the linear part of XT, but there is still room for some improvement by a second order XT canceller.

Fig. 10 shows the performance of NAXTC when the density is 1.43xCDDA. If we increase the density further, the NAXTC receiver fails, due to strong linear and nonlinear ISI. In this case, we need a more complex algorithm for the main track, like, e.g., the NMLSE.

5.4 Cross talk canceller with NMLSE (NMXTC)

Two NAVE equalizers estimate the symbols $\hat{a}_{1i}$ and $\hat{a}_{2i}$, as in NAXTC. However, after cross talk cancellation we use an NMLSE receiver for the main track. The NMLSE considered here has an adaptive matched filter with $N = 5$ linear taps and an NLC with $N^2 = 25$ nonlinear ones. Weights are updated according to the LMS algorithm, with step size equal to $10^{-3}$ for linear taps, and $10^{-5}$ for nonlinear ones. The decision delay, i.e., the trellis length that is kept in memory, is $L = 30$, and $S = 128$ trellis states are considered. The cross talk canceller is the same as in the previous case. Figs. 11 and 12 show the performance of NMXTC at densities CDDA and 1.43xCDDA, with distance between adjacent tracks $d = 0.7\mu m$. We can see that NMXTC gives good performance also at 1.43xCDDA. Further improvements require more trellis states, hence increased complexity. Part of the performance degradation at high densities is due to wrong decisions on adjacent tracks, hence to incomplete XT cancellation.

6. Conclusions

In this paper a nonlinear model for high density recording on optical discs has been presented. A model of the read out system based on optical scalar theory and second order Volterra series was developed. The simulation results show a significant nonlinear behavior of the read out signal. Using the nonlinear Volterra model, we have compared the performance of various equalization schemes for the high density optical channel. Specifically, we considered Nonlinear Adaptive Volterra Equalization (NAVE), and Maximum Likelihood Sequence Estimation (MLSE).

Among the equalization schemes conceived for linear channels, only MLSE offers acceptable performance, but is very complex. NAVE is a more appropriate solution, achieving better performance than MLSE (in particular at high SNR), with lower complexity. We also analyzed the NMLSE, an innovative nonlinear receiver that achieves better performance than traditional MLSE, which is the optimum receiver for linear channels. NMLSE outperforms also symbol by symbol equalization for nonlinear channels, like NAVE. The performance of NMLSE is close to optimum, with a reasonable computational complexity, and is the only viable solution at information densities higher than...
Considerable simplifications are possible, at the expense of small performance degradation. We can significantly reduce the number of linear and nonlinear taps of NAVE, with reasonable performance degradation. Also the complexity of NMLSE can be considerably reduced, with small SNR loss, reducing the number of linear and nonlinear taps of the preliminary equalizer, the number of trellis states, and the memory of the Viterbi detector.

Finally, cross talk cancellation algorithms based on a three spot detection system have been proposed and evaluated. Simulation results show the effectiveness of the proposed architecture, which is based on nonlinear detection of data on adjacent tracks, and linear cross talk cancellation, followed by nonlinear equalization (NAVE) or by NMLSE. The latter offers the best performance, at the cost of increased complexity. We have shown that, with a multipot detection system, the information density can be significantly increased in the tangential direction (by a factor of 1.43) and in the radial direction (by a factor 1.43/0.7=2.04), with reasonable computational complexity.

As a final remark, we observe that all the equalization techniques discussed in this paper are adaptive. Hence, they are able to take care not only of lens aberrations and of other impairments of the read out device, but also of other sources of distortion, like, e.g., nonlinear effects in disc recording.

References


