In recent years, a significant research effort has been devoted to the study of ultra-wideband (UWB) communication systems. The basic principle behind ultra-wideband communication technology is that narrowband signals are transmitted over wide bandwidths and then received at far-field distances. This technique greatly simplifies the transmitter and receiver design. However, the transmitted bandwidth extends to the gigaHertz range. Any application of UWB technology must conform to the regulations imposed by the Federal Communications Commission (FCC) and enforced by the Federal Communications Commission (FCC). The FCC regulation [5] permits transmission of signals and wireless communications was first used in radar systems over thirty years ago [3].

The concept of ultra-wideband (UWB) communication systems was first proposed in [1]-[2]. The basic principle behind ultra-wideband systems [4] is that baseband pulses are transmitted over the channel [4]. The UWB concept was used to develop impulse radio, where baseband pulses are transmitted over the channel [4]. This technique greatly simplifies the transmitter and receiver design, however, the transmitted bandwidth extends to the gigaHertz range. Any application of UWB technology must conform to the regulations imposed by the Federal Communications Commission (FCC) and enforced by the Federal Communications Commission (FCC). The FCC regulation [5] permits transmission of signals and wireless communications was first used in radar systems over thirty years ago [3].

The UWB concept was used to develop impulse radio, where baseband pulses are transmitted over the channel [4]. This technique greatly simplifies the transmitter and receiver design. However, the transmitted bandwidth extends to the gigaHertz range. Any application of UWB technology must conform to the regulations imposed by the Federal Communications Commission (FCC) and enforced by the Federal Communications Commission (FCC). The FCC regulation [5] permits transmission of signals and wireless communications was first used in radar systems over thirty years ago [3].

In this paper, the error performance of error correcting codes is investigated in a UWB communication system and decision-feedback equalization (DFE) is considered. Coding is an alternative to the more complex and often impractical joint equalization and coding. A block diagram of the UWB system under consideration is shown in Fig. 1. The UWB communication system model used in this study is presented in Section II. The pulse-based UWB channel model is obtained between the input to the pulse shaping filter and the output of the matched filter. Section III considers the performance of suboptimal adaptive equalizers and decision-feedback equalization (DFE) is considered. Performance is measured using the reference UWB multipath channel model generated by the IEEE 802.15.3a standard [6].

The rest of the paper is organized as follows: In Section II, a UWB communication system model is presented. It is shown that an equivalent symbol-spread UWB channel model is obtained between the input to the pulse shaping filter and the output of the matched filter. Section III considers the performance of suboptimal adaptive equalizers and decision-feedback equalization (DFE) is considered. Performance is measured using the reference UWB multipath channel model generated by the IEEE 802.15.3a standard [6].

The rest of the paper is organized as follows: In Section II, a UWB communication system model is presented. It is shown that an equivalent symbol-spread UWB channel model is obtained between the input to the pulse shaping filter and the output of the matched filter. Section III considers the performance of suboptimal adaptive equalizers and decision-feedback equalization (DFE) is considered. Performance is measured using the reference UWB multipath channel model generated by the IEEE 802.15.3a standard [6].

The rest of the paper is organized as follows: In Section II, a UWB communication system model is presented. It is shown that an equivalent symbol-spread UWB channel model is obtained between the input to the pulse shaping filter and the output of the matched filter. Section III considers the performance of suboptimal adaptive equalizers and decision-feedback equalization (DFE) is considered. Performance is measured using the reference UWB multipath channel model generated by the IEEE 802.15.3a standard [6].
\[ s_n \in \{-1, +1\}. \] A wideband unit-energy real-valued pulse shape \( p(t) \) is employed such that the output of the transmit filter is given by

\[ s(t) = \sum_{n=-\infty}^{\infty} s_n p(t - nT). \] (1)

It is important to note that the pulse shape \( p(t) \) can be either a single UWB pulse or a sequence of UWB pulses (as in spread-spectrum systems) with good autocorrelation properties.

The UWB channel model employed in this work is fully compliant with that of the IEEE 802.15.3a group [7]. The model is based on a modified Saleh-Valenzuela model [8] with a lognormal distribution rather than a Rayleigh distribution for the multipath gain magnitudes. UWB channel models have been classified into four different modes: CM1 through CM4, with CM1 being a mild condition corresponding to short distances and line-of-sight and CM4 associated with extreme multipath conditions. To produce the results reported in this paper, a channel sampling time \( \tau = 0.02 \text{ ns} \) was used. The UWB channel impulse response (CIR) is given by

\[ h(t) = \sum_{\ell=0}^{L-1} \alpha_\ell \delta(t - \tau_\ell), \] (2)

where \( \alpha_\ell \) and \( \tau_\ell \) are the gain and delay of the \( \ell \)-th channel path, for \( \ell = 0, 1, \cdots, L - 1 \). The path delays can be expressed as multiples of the sampling time: \( \tau_\ell = m_\ell \tau_c \), where for \( 0 \leq \ell \leq L - 1 \), \( m_\ell \) is a positive integer and \( m_0 < m_1 < \cdots < m_{L-1} \). The delay spread of the channel is equal to \( \tau_{L-1} \).

It is assumed here that the noise process introduced at the receiver and denoted by \( N(t) \) is a zero-mean AWGN process with double-sided power spectral density \( N_0/2 \text{ W/Hz} \). Under this assumption, the output of the matched filter at \( t = mT \) can be expressed as

\[ Y_m = \sum_{\ell=0}^{L-1} \alpha_\ell \int_{(m-1)T}^{mT} s(t - \tau_\ell) p(t) \, dt + W \]

\[ = \sum_{n=-\infty}^{\infty} s_n \sum_{\ell=0}^{L-1} \alpha_\ell \int_{(m-1)T}^{mT} p(t - \tau_\ell - nT) p(t) \, dt + W \]
channel. Moreover, even with techniques such as a reduced-state trellises [11], complexity remains an exponential function of $J$. An alternative approach to reduce the complexity of the VE solution is the use of adaptive equalization techniques [12]-[14]. At the cost of a performance loss, the complexity of adaptive equalizers is a linear function of $J$. Consequently, it becomes of practical interest to study the performance of adaptive equalizers in UWB communications.

An adaptive equalizer needs to be trained, either by using a pilot sequence and estimating the channel to provide an initial setting of the coefficients [15], or by the use of a training sequence. For UWB applications, fast acquisition becomes important and channel estimation is the preferred method. In the simulation results presented below, we used a training sequence of 10000 symbols to initialize the equalizer. To provide a justification for this choice of training sequence length, Figs. 4 and 5 show the performance of 95-tap linear and nonlinear adaptive equalizers for an extreme multipath channel (CM4 type), respectively. Although the simulation results in this work are obtained using a training sequence, the results and conclusions can be extended to the case of channel estimation using pilot sequences [15].

A. Linear equalization

An adaptive linear equalizer (LE) is an FIR filter in which $M$ tap coefficients $\{w_m\}$ are updated in order to optimize a given cost function. Here, we use the mean square error (MSE) as the cost function. The coefficients are modified in order to minimize the MSE using the least mean square (LMS) algorithm, as follows. The output of the LE at time $t = nT$ is

$$c_n = \sum_{m=0}^{M-1} w_m Y_m. \tag{4}$$

Let the error sample be defined as $e_n = \hat{c}_n - c_n$, where $\hat{c}_n = \text{sgn}(c_n)$ is the output of the BPSK slicer in decision-directed mode and a known symbol in training (data-aided) mode. Then the coefficients are updated via

$$w_m(n + 1) = \mu w_m(n) + \Delta Y_n e_n, \tag{5}$$

where $\Delta$ is the step size and $\mu$ is the forgetting factor, $0 < \mu \leq 1$. Simulation results, not reported here, show that $\Delta = 0.00085$ and $\mu = 0.75$ are good choices.

Fig. 6 shows the performance of an LE with different numbers of taps $M$ over a UWB channel type CM1. From these results, it evident that the performance variation is relatively small, provided that the equalizer length $M$ is larger than the ISI length $J$ of the UWB channel. However, note that over an extreme multipath density channel (type CM4), Fig. 7 shows that performance may degrade considerably, not only in comparison to the CM1 channel, but also increasing as a function of $M$. 
B. Decision-feedback equalization

Decision-feedback equalizers for wideband communications have been studied extensively [15]-[21]. A brief overview of the fundamental idea is presented next. Let the error be defined as $e_n = \hat{c}_n - c_n$, where $\hat{c}_n$ is either the estimated symbol at the output of a BPSK slicer, $\hat{c}_n = \text{sgn}(c_n)$, or a known symbol in training (data-aided) mode. The output of the equalizer at time $t = nT$ is given by

$$c_n = \sum_{m=0}^{M-1} w_m Y_{n-m} + \sum_{\ell=1}^{M_f} v_m \hat{c}_{n-\ell},$$

(6)

and is based on the $M$ most recent matched filter outputs $\{Y_{n-m}, m = 0, 1, \cdots, M - 1\}$ and on the $M_f$ most recent decisions $\{\hat{c}_{n-\ell}, \ell = 1, 2, \cdots, M_f\}$ (or known symbols in training mode). The feedforward and feedback coefficients are updated via the LMS algorithm as follows:

$$w_m(n+1) = \mu w_m(n) + \Delta Y_n e_n$$

(7)

$$v_m(n+1) = \mu v_m(n) + \Delta Y_n e_n.$$ 

(8)

In the case of the pulse-based UWB communication system under consideration, the setting of the adaptive DFE parameters was studied based on computer simulations in [9], were it was found that the values $M = 63$, $M_f = 32$, $\Delta = 0.00085$ and $\mu = 0.75$ gave good performance across all UWB channel types CM1 through CM4.

A strong motivation for the need for channel coding, in the context of pulse-based UWB systems with adaptive equalization, can be obtained from the sensitivity of the performance of an adaptive DFE with respect to four different channel realizations of a CM4-type UWB channel, as illustrated in Fig. 8. The channel type CM4 models extreme multipath conditions in an indoor environment [7]. Two important observations can be made based on this result: (1) An irreducible error floor may appear due to the fact that DFE cannot completely remove the ISI; and (2) the signal-to-noise ratio (SNR) required to achieve a particular target bit error rate (BER) is expected to have a range of values of at least 3 dB. Similar studies [9] for the other UWB channel types, ranging from mild multipath conditions (CM1 type) to dense multipath conditions (CM3 type), show that the SNR variation grows with the multipath density or maximum delay spread, i.e., least variation for CM1 channels and most variation for CM4 channels.

A practical way to reduce the SNR variation in error performance of pulse-based UWB communication systems with adaptive equalization is by the use of powerful error correcting codes. This is the topic of the next section.

IV. CHANNEL CODING SCHEMES

In this section, a comparison of the error performances of various error correcting codes applied to a pulse-based BPSK
modulated UWB system with DFE is presented. In order to produce a meaningful comparison with the turbo product coding (TPC) scheme proposed in [9], the coding rate is set to \( R_c = 0.7 \). In particular, the following error correcting codes are investigated:

1. A TPC \((31, 26)^2\) code using two component binary Hamming \((31, 26, 3)\) codes
2. A regular low-density parity-check (LDPC) \((1057, 813)\) code with node degrees \( J = 3 \) and \( K = 13 \)
3. A concatenated code with an outer Reed-Solomon \((255, 239)\) code over \(GF(2^8)\) and an inner memory-6 rate-3/4 binary punctured convolutional code (PCC) based on a rate-1/2 convolutional encoder with generators, in octal notation, \((171, 133)\)
4. A binary-image \((889, 623)\) code obtained from a Reed-Solomon \((127, 89)\) code over \(GF(2^7)\)

The selection of these particular codes is based on practical considerations, which include availability and small latency. It is emphasized that no attempt was made to achieving performance close to capacity, but rather to obtaining a good performance with practical codes of relatively short lengths and similar rate. Regular LDPC codes are known to perform better than irregular LDPC codes at high SNR values (error floor region). However, irregular codes provide better performance at low SNR values (waterfall region). Here, a regular code is selected here mainly because it may be easier to encode and decode as its parity-check matrix and underlying Tanner graph have regular structure. The concatenated Reed-Solomon scheme serves as a reference. It has the same rate as the TPC scheme and constitutes a classical solution.

A. Turbo product coding with binary Hamming \((31, 26)\) codes

To improve upon the error performance of adaptive equalizers, a turbo product code (TPC) [23] was proposed and its error performance studied in [9]. This TPC is constructed from two component \((31, 26, 3)\) Hamming codes and has a coding rate \( R = (26/31)^2 = 0.7034 \). Henceforth, we refer to this code as TPC \((31, 26)^2\). Iterative soft-input soft-output (SISO) decoding with the Chase type-II algorithm [24] and four decoding iterations was employed. This channel coding approach is attractive from a practical perspective because of its very low complexity compared to other types of codes and decoding algorithms, while at the same time exhibiting turbolike error performance. It is interesting to note that a similar TPC scheme, using a shortened extended Hamming \((31, 25, 4)\) code, has been adopted in the IEEE 802.16 2004 standard for fixed broadband wireless communications [25].

1) Iterative decoding with Chase type-II algorithm: In the Chase type-II decoding algorithm, the equalizer outputs \( c_n \) are scored by their reliability values \( |c_n| \). A bit position \( n \) is said to be reliable if the value of \( |c_n| \) is high. Error patterns \( \bar{e} \) are constructed for those code positions with low reliability values. For each error pattern \( \bar{e} \), a noisy test vector \( \bar{r} = \bar{z} + \bar{e} \) is generated, where \( z_n = sgn(c_n) \) is the \( n \)-th component of the hard-decision received vector. The closest codeword \( \bar{v} \) to the test vector \( \bar{r} \) is determined via a hard-decision decoder. For a \((31, 26, 3)\) Hamming code, hard-decision decoding is extremely simple, using a combinatorial circuit to implement a syndrome look-up table. Moreover, since the minimum Hamming distance is equal to 3, Chase type-II algorithm reduces to Wagner decoding [26], whereby only one test vector is generated by simply complementing the bit in the least reliable position. This reduces decoding complexity dramatically, compared to that required for decoding extended Hamming codes. At each decoding iteration, soft-outputs are generated using the two closest codewords, \( \bar{v}_1 \) and \( \bar{v}_2 \), to \( \bar{z} \). In the event that these codewords are identical, the procedure suggested in [27] is used. In the simulations reported below, four iterations of decoding are performed as suggested by Pyndhia [23]. Increasing weights are used to modify the reliability correction factors when feeding back the extrinsic information in the iterative SISO decoder. This helps to speed up convergence of the decoding algorithm.

B. Regular LDPC \((1057, 813)\) code

This LDPC code was constructed by computer search [29]. In the context of LDPC coding, this is considered a very short code. Although in the low SNR region irregular LDPC codes are known to perform better, they require optimization of the node degree distribution. A regular code is selected here as it has the advantage that it is easier to encode and decode because of the regular structure of its parity-check matrix and underlying Tanner graph. The problem of designing good LDPC codes for applications in UWB systems (either in the waterfall region or in the error floor region) remains as a topic of future research interest.

A Tanner graph \( T \) a bipartite graph with two types of nodes: Variable nodes and check nodes [28]. \( T \) is obtained by regarding \( H \) as its incidence matrix. Each row of \( H \) specifies how variable nodes are connected to a check node. Conversely, each column of \( H \) specifies how check nodes are connected to a variable node. For the regular LDPC \((1057, 813)\) code, the Hamming weight of each column of \( H \) is \( J = 3 \) and each row of \( H \) has Hamming weight \( K = 13 \). The variable node degrees and check node degrees of the associated regular Tanner graph \( T \) are \( J = 3 \) and \( K = 13 \). Iterative belief-propagation (IBP) decoding can be applied to this graph [30].

1) IBP decoding: In IBP decoding, the received symbols from the channel (also known as channel log-likelihood ratio values) are used as initial metrics of the variable nodes. It is important to point out that in computing this initial metrics, the value of the variance \( \sigma_N^2 = N_0/2 \) of the underlying AWGN process samples needs to be known. The variable node metrics are then sent to check nodes in a top-down message-passing step and new metrics computed for the check nodes. An iteration is completed with a bottom-up message-passing step in which the check node metrics are sent back to the variable nodes. Details on IBP decoding and variations thereof can be found in [22]. In the simulation results reported in a later section, the maximum number of iterations is set to four. This is done for practical considerations of decoding latency. An increase in the number of iterations results in better...
and the PCC encoder.

D. Binary-image decoder.

Although the concatenation of the four coding schemes considered in this paper are summarized in Table I. Although the concatenated RS code scheme C is much longer than the other schemes, it is included as a reference because of its wide availability and also because of its rate which is practically the same as the TPC coding scheme.

C. Concatenated coding

A study of the performance of a standard concatenated code in the UWB communication system under consideration is of interest as it is widely available. This channel coding scheme is constructed by using an outer Reed-Solomon (RS) (255, 239) code over \( GF(2^8) \) and an inner rate-3/4 binary punctured convolutional code (PCC) which is based on the de-facto-standard memory-6 rate-1/2 convolutional encoder with generators \((171, 133)\).

The outputs of the matched filter are delivered to a conventional (“hard-output”) soft-decision Viterbi decoder processes to produce estimated sequences of bits in the inner PCC code. The Viterbi decoding (traceback) length is set to \( L = 112 \) bits. Block interleaving to depth 8 is used between the RS encoder and the PCC encoder.

The outer RS \((255, 239)\) code is based on the Galois field \( GF(2^8) \) with \( p(\alpha) = \alpha^8 + \alpha^4 + \alpha^3 + \alpha^2 + 1 \), has minimum Hamming distance equal to 17, and is capable of correcting, among many other combinations of errors, any single error burst of up to 57 bits. Decoding is accomplished as usual, following deinterleaving of the outputs of the Viterbi decoder andreassembling the 8-bit symbols, by using an errors-only decoder.

D. Binary-image \((889, 623)\) code

This binary code is constructed from a powerful Reed-Solomon \((127, 89, 39)\) code over \( GF(2^7) \) by expressing each element by its 7-bit vector representation in \( G(2)^7 \). The polynomial basis with \( p(\alpha) = \alpha^7 + \alpha^3 + 1 \) was used to obtain this vector. This code is capable of correcting numerous combinations of random errors and error bursts, including any combination of up to 19 random errors and any single error burst of up to 127 bits. At the receiver of this scheme, the outputs of the adaptive equalizer are passed through a BPSK demodulator to produce (hard) decisions that are fed to an errors-only decoder.

The parameters of the four coding schemes considered in this paper are summarized in Table I. Although the concatenated RS code scheme C is much longer than the other schemes, it is included as a reference because of its wide availability and also because of its rate which is practically the same as the TPC coding scheme.

V. SIMULATION RESULTS

In this section, simulation results are reported for all the channel coding schemes outlined in the previous section. For each UWB channel type, a total of 10 channel realizations and corresponding BER values over a range of SNR values were generated and the average BER evaluated. Each channel coding scheme is combined with a 95-tap adaptive decision feedback equalizer with the parameters given in section III-B.

Figures 9 and 10 show the performances of channel coding over UWB channel types CM3 and CM4, respectively. The case of the CM3 channel illustrates the presence of bad channel realizations that dominate the average. Over both types of channels, the binary-image \((889, 623)\) code suffers from a large number of nearest neighbor codewords at minimum Hamming distance and results in worse performance. Both LDPC and TPC codes achieve practically the same performance in the CM3 channel case. On the other hand, over a CM4 channel, best performance is obtained with the regular LDPC (1057, 813) code. In this case, both the TPC \((31, 26)^2\) and the concatenated coding schemes achieve practically the same performance and at a BER value of \(10^{-4}\) are at about 1 dB away from the LDPC code.

VI. CONCLUSIONS

Adaptive equalization and channel coding schemes applied to pulse-based UWB communication systems in short-range indoor environments have been studied. These offer low-complexity alternatives to joint coding and equalization. It has been shown that the performance of an adaptive DFE equalizer is very sensitive to channel conditions in an indoor environment. Simulation results have been presented of coding schemes combined with adaptive equalization to show that this sensitivity is effectively reduced. The TPC \((31, 26)^2\) code and the regular LDPC \((1057, 813)\) code presented in this

### TABLE I

<table>
<thead>
<tr>
<th>Scheme</th>
<th>Length</th>
<th>Dimension</th>
<th>Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>961</td>
<td>676</td>
<td>0.703</td>
</tr>
<tr>
<td>B</td>
<td>1057</td>
<td>813</td>
<td>0.769</td>
</tr>
<tr>
<td>C</td>
<td>255 - 4</td>
<td>239 - 3</td>
<td>0.703</td>
</tr>
<tr>
<td>D</td>
<td>889</td>
<td>623</td>
<td>0.701</td>
</tr>
</tbody>
</table>

Fig. 9. Error performance of channel coding over a CM3 channel.
paper are good candidates for applications in low-latency low-complexity UWB communication systems.

REFERENCES


[29] http://www.inference.phy.cam.ac.uk/mackay/CodesFiles.html


Robert H. Morelos-Zaragoza was born in Housma, Louisiana, U.S.A. He received the BSEE and MSEE degrees from the National Autonomous University of Mexico (UNAM) in 1985 and 1987, respectively, and the PhD degree in Electrical Engineering from the University of Hawaii at Manoa, in 1992. He was an Assistant Professor at Instituto Tecnológico y de Estudios Superiores de Monterrey (ITESM) of Mexico in 1992-1993. In 1993-1995, he held postdoctoral positions at Osaka University, Japan, and Nara Institute of Science and Technology, Japan. Dr. Morelos-Zaragoza was a research associate of Imai Laboratory of the University of Tokyo, from 1995 to 1997. During the period 1997-1999, he was a staff member of the Channel Coding Group of LSI Logic Corporation. In 1999-2002, he was a researcher at the Sony Computer Science Laboratories (Sony CSL) in Tokyo, Japan. Since 2002, he is with the Department of Electrical Engineering of San Jose State University. His current research interests include error correcting coding, software-defined cognitive radio and wireless communication system design. He is a senior member of IEEE and of Eta Kappa Nu.