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Maximum Likelihood Estimation of Trellis Encoder and Modulator Transition Utilizing HMM for Adaptive Channel Coding and Modulation Technique

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SUMMARY In order to achieve adaptive channel coding and adaptive modulation, the main causes of degradation to system performance are the decoder selection error and modulator estimation error. The utilization of supplementary information, in an estimation system utilizing channel estimation results, blind modulation estimation, and blind encoder estimation using several decoders information and encoder transitions have been considered to overcome these two problems. There are however many issues in these methods, such as the channel estimation difference between transmitter and receiver, computational complexity and the assumption of perfect Channel State Information (CSI). Our proposal, on the other hand, decreases decoder and demodulator selection error using a Hidden-Markov Model (HMM). In order to estimate the switching patterns of the encoder and modulator, our proposed system selects the maximum likelihood encoder and modulator transition patterns using both encoder and modulator transition probability based on the HMM obtained by CSI and also Decoder and Demodulator Selection Error probabilities. Therefore, the decoder and demodulation results can be achieved efficiently without any restraint on the pattern of switching encoder and modulation.

key words: *hidden-Markov model, maximum likelihood encoder and modulator transition, decoder and demodulator selection error*

1. Introduction

Recently, there has been a growing amount of research into mobile communications, especially adaptive algorithms that can achieve optimal system constructions considering time and/or geographic environmental problems as well as an adaptive algorithm that adjusts the constructions in order to satisfy users needs. One of the research topics, which has attracted much attention, is adaptive channel coding and the adaptive modulation scheme [1]. The aim of this research is to alter encoders or modulators in order to achieve the desired performance.

On the other hand, to change the encoders and modulators, it is necessary to design a pattern for transmitter and receiver. Therefore, along with the problem that poor decoding performance occurs due to error in selection of decoders and demodulators, the sequence synchronization problem that occurs due to the utilization of several decoders with different coding rates or different modulation orders is also a crucial problem.

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In order to solve these problems, there are two main methods [2]–[6]. One is to add supplemental information at the transmitter to indicate which encoder and modulation scheme are being used, the other is to estimate which encoder and modulation scheme are used at the receiver using the decoder and demodulator results. In the first case, in order to prevent error in the supplementary information, error correction codes with high quality are needed. However, longer redundancy causes lower transmission rates, and this rate becomes even lower when the encoder and modulator are changed frequently. Additionally, one can consider using pilot symbols to choose encoder and modulator, however, this method requires perfect channel estimation, or a non appropriate decoder and demodulator can be selected. On the other hand, in the latter case, the minimum distance between encoders determines encoder estimation accuracy. Just as with the minimum distance between codewords, the longer the distance, the better the performance. Due to the limited choices of encoder, it is hard to change the estimation accuracy adaptively. Moreover, modulation estimation accuracy depends on the distance between any two of the constellation points.

In addition, the encoding method considering a finite state machine utilizing the fading channel model has also been studied [7]. However, this method cannot accommodate all the channel models. It means that it is not clear whether the proposed method of limiting the encoder transition by FSM is appropriate to support estimation of dynamic channels. To solve this problem, Ref. [7] extended the layered encoder transition scheme which selects several encoder transitions of FSMs that can adapt to changes in the channel condition. However this method is not realistic because this has to predict a change of channel condition over a long period to select the optimum encoder switching several FSMs, each with different encoder transitions. In order to solve this problem, we focus on the HMM. Our proposal can adapt to changes in the channel condition and also select the optimum encoder and modulator by using prediction of channel condition in switching timing. Fading channel-modeling schemes using HMM have been recently widely studied [8], [9] which can accurately model the fading channel and also estimate the parameters of HMM by using the Baum-Welch algorithm for a time varying channel. We propose a scheme using this kind of channel modeling to encode and modulate. Our proposals performance deteriorates

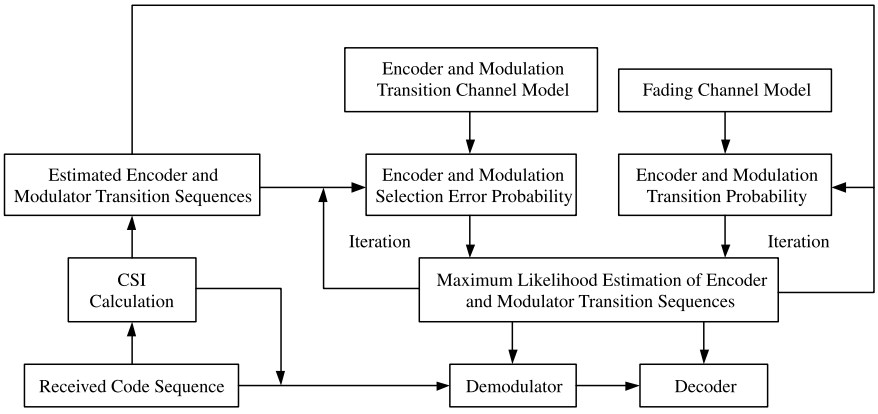

Fig. 1 System model.

when the channel estimations at transmitter and receiver are different, or if the estimation of encoder and modulator at the receiver is invalid. Consequently, we additionally add an algorithm to our proposal to reduce decoder and demodulator selection errors using the HMM.

In more detail, our proposed system selects the maximum likelihood encoder and modulator transition by using both encoder and modulator transition probabilities, based on the HMM obtained using CSI and Decoder and Demodulator Selection Error probabilities. We use the Expectation-Maximization (EM) algorithm [10] as a maximum likelihood algorithm, and this proposal can be realistically achieved with reasonable computational complexity relying only on the number of trellis states, which differs from the conventional system. Compared with a conventional finite state machine scheme whose transition pattern and encoder or modulator switching pattern have a one to one correspondence, the proposed HMM scheme whose transition pattern is probabilistically determined is more efficient in a fading channel. Therefore, the decoder and demodulation results can be achieved efficiently without any restraint on the pattern of encoder and modulator switching.

This paper is organized as follows. In Sect. 2, considering our proposed adaptive coding and modulation scheme under HMM, we show the encoder and modulator switching estimation schemes with maximum likelihood in more detail. In Sect. 3, the performance of the proposed system using computer simulations is shown. Finally, we conclude this paper in Sect. 4.

2. Adaptive Coding and Modulation Scheme Using HMM

2.1 System Model

The transmit sequence is shown in Fig. 2. We assume a TDD system with L frames, and each frame consists of d transmit bits plus p pilot symbols for channel estimation. According to the channel estimation result, the appropriate encoder and modulator are selected for the information sequence. Notice that the channel model is HMM. Figure 1 shows the proposed system block diagram. Figure 3 shows the flowchart of our proposed system.

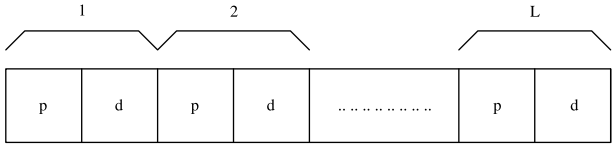

Fig. 2 Frame structure of received data for fading channel.

In Fig. 3, we assume a fading channel with Rayleigh-distributed amplitude fading and no phase coherence, which is equivalent to independent Gaussian amplitude fading on both the in-phase and quadrature components of the transmitted symbols. We use the EM-based receiver [11] to obtain the optimum sequence estimation and channel parameters to estimate encoder and modulator. The EM algorithm is a broadly applicable approach to the iterative computation of maximum likelihood estimates, useful in a variety of incomplete-data problems [12], [13]. On each iteration of the EM algorithm, there are two steps called the expectation step (E-step) and the maximization step (M-step). One of the reasons for its attractiveness is that it provides a numerical method for obtaining maximum likelihood estimates that might not be readily available otherwise. For the sequence estimation problem studied in this paper, the algorithm converges surprisingly quickly and has an efficient implementation that makes it of practical as well as theoretical interest.

Figure 2 illustrates the received data for $T = p + d$ and $U = pL$. In setting the initial fading estimate, the algorithm uses the fact that the symbols in positions $1, (T+1), \cdots, (U-1)T + 1$ are known. An initial fading estimate is then easily obtained by summing the data in each of the U known bit positions and dividing by U.

$$a_0 = \frac{1}{U} \sum_{k=0}^{U-1} r_k T + 1. \tag{1}$$

Further, the maximization step of the algorithm needs only be performed over the $U(T-1)$ modulated bits, and since these bits are randomly chosen, maximizing over the set of length $U(T-1)$ bit sequences is equivalent to making

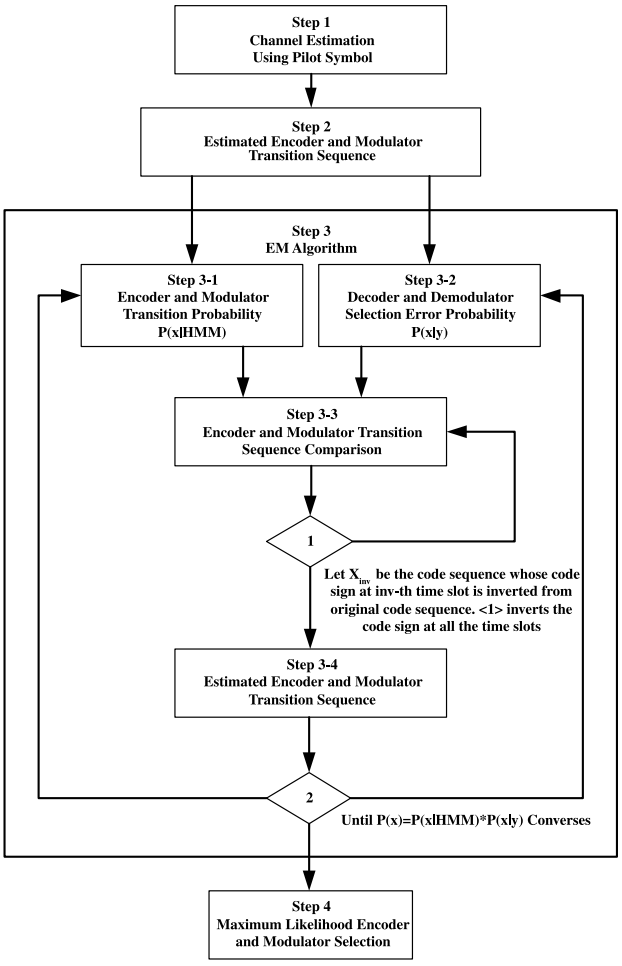

Fig. 3 Flowchart of our proposed system.

symbol-by-symbol decisions on each bit. Seq^{i+1} is the sequence where components are easily obtained through

$$Seq_k^{i+1} = sgn[\Re(r_k^{\dagger} a_i)] \tag{2}$$

where $sgn(\cdot)$ is the signum function, i is number of iteration and † denotes conjugated transpose. For the nonbinary case, the above symbol-by-symbol estimator is replaced by

$$Seq_k^{i+1} = \arg\max_{Seq_k} \Re(r_k^{\dagger} Seq_k a_i). \tag{3}$$

After estimating the channel with the p received pilot symbols in Step 1, the result is used to estimate the encoder and modulator as well as the received sequence compensation. The encoder and modulator can be selected to meet performance with lower than desired BER depending on the change in estimated SNR by using Seq in (3) which is obtained by EM algorithm receiver. With the selected encoder and modulator in Step 2, the encoder and modulator switching pattern is constructed to obtain a switching pattern probability using the BCJR algorithm in Step 3-1. Additionally, the probability of decoder and demodulator selection errors is extracted using CSI and selected encoder and modulator in Step 3-2. With these two probabilities, iterative maximum likelihood estimation is implemented to find a more appropriate encoder and modulator switching pattern in Step 3-3 and 3-4.

2.2 Definition of Maximum Likelihood Estimation of Encoder and Modulator Switching Patterns

This section describes how to define the maximum likelihood encoder and modulator selection, Step 4. When HMM is used as a probabilistic model for the encoder and modulator switching pattern, this model has the possibility to derive the conditional probability $P(\hat{x}|HMM)$ (Step 3-1) using the BCJR algorithm, where $\hat{x} = (x_1, x_2, \cdots, x_t, \cdots x_{time})$ represents the switching pattern sequence. Defining $P(\hat{x}|\hat{y})$ (Step 3-2) as the conditional probability that the estimated switching pattern $\hat{y}$ at the receiver provides a value close to $\hat{x}$, $P(\hat{x}|\hat{y})$ can be derived from CSI or decoder and demodulator selection errors based on the selected encoder and modulator. Moreover, to find the optimum sequence $\hat{x}$ from both of these probabilities leads to a maximum likelihood estimation of the encoder and modulator switching pattern.

2.3 Extraction of the Probability of Encoder and Modulator Switching Pattern

The conditional probability $P(\hat{x}|HMM)$ of encoder and modulator switching pattern sequence $\hat{x}$ when using the HMM can be easily derived by the BCJR algorithm due to the utilization of the HMM model. Notice that we use the normalized BCJR algorithm that considers the underflow problem. Let us define the forward metric as $\alpha_t(s)$, and the backward metric as $\beta_t(s)$, where $t = (1, 2, \cdots, time)$. Assume the channel condition is the same as the HMM, the transition probability from state s to state $\acute{s}$ is $p_{s\acute{s}}$, and according to this transition, $p_{s\acute{s}}(x_t)$ represents the probability when selected encoder and modulator pattern is transformed to be a code x_t. Note that there are N_s states, where N=$(1, \cdots, s, \acute{s}, \cdots, N_s)$. $\alpha_t(s)$ and $\beta_t(s)$ are given by (4) and (5), and calculated recursively.

$$\alpha_t(\acute{s}) = \sum_{s=1}^{N_s} \alpha_{t-1}(s) p_{s\acute{s}} p_{s\acute{s}}(x_t) \tag{4}$$

$$\beta_t(\acute{s}) = \sum_{s=1}^{N_s} \beta_{t+1}(s) p_{s\acute{s}} p_{s\acute{s}}(x_{t+1}) \tag{5}$$

The initial values are $\alpha_1(N) = (\pi_1, \pi_2, \cdots, \pi_{N_s})$, where $\sum_{s=1}^{N_s} \pi_s = 1$ and $\beta_{time}(N) = 1$, respectively, and due to the necessity of normalization, (6) and (7) are used.

$$\bar{\alpha}_t(\acute{s}) = \frac{1}{\sum_{\acute{s}=1}^{N_s} \alpha_t(\acute{s})} \alpha_t(\acute{s}) \tag{6}$$

$$\bar{\beta}_t(\acute{s}) = \frac{1}{\sum_{\acute{s}=1}^{N_s} \beta_t(\acute{s})} \beta_t(\acute{s}) \tag{7}$$

Then $P(\hat{x}|HMM)$ is given by (8).

$$P(\hat{x}|HMM) = \sum_{s=1}^{N_s} \alpha_{t-1}(s) \cdot \sum_{\acute{s}=1}^{N_s} \beta_t(s) \cdot \sum_{s=1}^{N_s} \sum_{\acute{s}=1}^{N_s} \bar{\alpha}_{t-1}(s) p_{s\acute{s}} p_{s\acute{s}}(x_t) \bar{\beta}_t(\acute{s}) \quad (8)$$

2.4 Extraction of Decoder and Demodulator Selection Error Probability

Define $P(\hat{x}|\hat{y})$ as the probability of sequence $\hat{x}$ when the received encoder and modulator switching pattern sequence is $\hat{y}$. $P(\hat{x}|\hat{y})$ belongs to a binary symmetric channel, and given by,

$$P(\hat{x}|\hat{y}) = p^d(1-p)^{n-d} \quad (9)$$

where p represents the decoder or demodulator selection error, d is the number of these errors and also can be described as the hamming distance between $\hat{x}$ and $\hat{y}$. n is the length of encoder and modulator switching pattern sequence.

2.5 Maximum Likelihood Estimation Scheme for Encoder and Modulator Selection

We focus our attention on seeking a sequence $\hat{x}$ that maximizes both $P(\hat{x}|HMM)$ and $P(\hat{x}|\hat{y})$. We adopt the EM algorithm for our proposal. Step 3 in Fig. 3 indicates this algorithm. Define $\hat{x}^i = (x_1^i, x_2^i, \cdots, x_t^i, \cdots, x_{time}^i)$ as the sequence of estimated encoder or modulator switching pattern in i-th iteration. In the E-step, $P(\bar{x}_{inv}^i)$ is derived by multiplying $P(\bar{x}_{inv}^i|HMM)$ by $P(\bar{x}_{inv}^i|\hat{y})$. Let $\bar{x}_{inv}^i$ ($inv = 1, \cdots, time$) be the code sequence whose code sign at inv-th time slot is inverted from the original code sequence constructed from encoder and modulator, and substitute this into (10) to obtain t sequences and thus t probabilities of $P(\bar{x}_{inv}^i)$. In the M-step, each of the t probabilities, $P(\bar{x}_{inv}^i)$, is compared to the original sequence $P(\hat{x}^i)$, and we invert the code sign at all the time slots whose probability $P(\bar{x}_{inv}^i)$ is larger than the original sequence probability $P(\hat{x}^i)$, thus obtain one sequence $P(\hat{x}^{i+1})$. (11) indicates the M-step algorithm, where T represents the transpose. In the next iteration, $P(\bar{x}_{inv}^{i+1}|HMM)$ and $P(\bar{x}_{inv}^{i+1}|\hat{y})$ are extracted again using (8) and (9), and then substituted into (10) and (11). After several iterations the convergence of $P(\hat{x}^{i+1})$, $\hat{x}^{i+1}$ is considered to be the maximum likelihood encoder and modulator selections.

$$P(\bar{x}_{inv}^i) = P(\bar{x}_{inv}^i|HMM) \cdot P(\bar{x}_{inv}^i|\hat{y}) \quad (10)$$

$$P(\hat{x}^{i+1}) = (P(x_1^{i+1}), P(x_2^{i+1}), \cdots, P(x_{time}^{i+1})) = \begin{pmatrix} \arg\max(P(\bar{x}_1^i), P(\hat{x}^i)), \\ \arg\max(P(\bar{x}_2^i), P(\hat{x}^i)), \\ \vdots \\ \arg\max(P(\bar{x}_{inv}^i), P(\hat{x}^i)) \end{pmatrix}^T \quad (11)$$

3. Computer Evaluation

We show the reduction of decoder and demodulator selection errors in order to clarify the effectiveness of our proposal.

3.1 Prerequisite

Assuming that the fading channels are defined by HMM, and AWGN channels. The transition probability $p_{s\acute{s}}$ from state s to $\acute{s}$, and the probability $p_{s\acute{s}}(x_t)$ that $p_{s\acute{s}}$ transforms the encoder and modulator selected based on this probability to x_t, are considered to be given. Moreover, the synchronization at the receiver is considered to be perfect. The information data is encoded by the encoder selected based on CSI information obtained by EM based receiver, and the encoded data $a_i (i = 1, 2, \cdots, n)$ is obtained. Notice that the code lengths are the same even if the code rates or the error correction probabilities are different. The same number of symbols is transmitted for any modulation scheme in each packet. The timing for switching the modulation scheme is determined by synchronizing the packet length of BPSK. Therefore, the modulation scheme is switched by the length of packet which is one frame with BPSK, two frames with QPSK, three frames with 8PSK, and four frames with 16QAM.

3.2 Evaluation of Reduction of Selection Errors

Table 1 shows the simulation parameters. The fading channels rely on the HMM, and the state of the HMM is 2. Figure 4 shows the trellis diagram and state transition of HMM. The probability $p_{s\acute{s}}$ and $p_{s\acute{s}}(x_t)$, and the code sequence x_t are described in the previous subsection and are defined as in Table 2. We describe CM1, CM2, CM3 and CM4 as quasi-static fading channel models whose characteristics are different to each other. These channel models still stay constant over more than two packets. In CM1, channel state changes slowly, therefore the system selects the same modulator for long term. On the other hand, in CM2, channel state changes faster than CM1; therefore, channel condition changes randomly compared to CM1. CM3 is defined as a bad channel condition where system almost always transmits with BPSK. In CM4, channel condition between sate s and $\acute{s}$ is defined to almost be the same and each channel selects the almost same number of modulations between BPSK and QPSK randomly. These channel models cover

Table 1 Simulation parameters.

Information Length	50
Codeword Length	100
Coding Rate	0.5
Pilot Symbol	10
Modulation	BPSK QPSK
Frame Length	110 (BPSK) 55 (QPSK)
Packet Length	110 Symbols
Encoder and Modulator Switching Sequence Length	25 49, 100
Iteration of EM	1-6

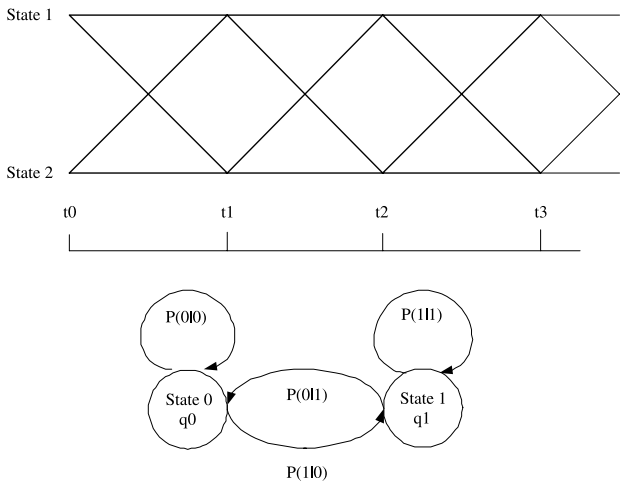

Fig. 4 Trellis diagram and state transition of HMM.

Table 2 Channel model and its parameters.

	CM1	CM2	CM3	CM4
p_{00}	$1-p_{01}$	$1-p_{01}$	$1-p_{01}$	$1-p_{01}$
p_{01}	0.06	0.5	0.06	0.06
p_{10}	0.017	0.5	0.017	0.017
p_{11}	$1-p_{10}$	$1-p_{10}$	$1-p_{10}$	$1-p_{10}$
$p_{00}(0)$	0.01	0.01	0.999	0.6
$p_{01}(0)$	0.5	0.5	0.9	0.4
$p_{10}(0)$	0.01	0.01	0.999	0.6
$p_{11}(0)$	0.5	0.5	0.9	0.4
BPSK	26.55%	25.5%	94.74%	49.57%
QPSK	73.45%	74.5%	5.26%	50.43%

both worst and better cases therefore we can show that proposed method can accommodate all the channel models by using these four typical channel models. In the EM based receiver, note that channel estimation error occurs which causes demodulator estimation error at Step 1 and 2 in Fig. 3 on the receiver side. Note that 0 represents BPSK modulation scheme, 01 indicates that the modulation scheme is changed from BPSK to QPSK. Considering the combination of encoder and modulator according to the HMM states, for simplicity, BPSK and QPSK are used here, the modulation scheme is changed relying on the CNR estimated by CSI. The threshold of switching modulation scheme pattern is shown in Table 3. In this case, we desire a BER of less than 10^{-4}. The value 10^{-4} is chosen in order to determine the threshold of switching modulation scheme pattern. This threshold should be decided considering the demodulator selection error, i.e., when this demodulator selection error is constant for all the channel models, the threshold is also constant. Let the information data length be 50 bits, the code rate be $R = 0.5$. Therefore, using a convolutional (7, 5) code, the number of encoded bits is 100. The uncoded pilot symbols with bit length 10 are added to each packet, and transmitted using BPSK. The encoder and modulator switching sequence $\hat{x}(x_1, x_2, \cdots, x_{time})$ lengths are considered to be 25, 49, and 100. The number of iterations of the EM algorithm is from 1 to 6.

Table 3 Threshold for adaptive modulation scheme.

BPSK - QPSK
Es/No=7 (dB)

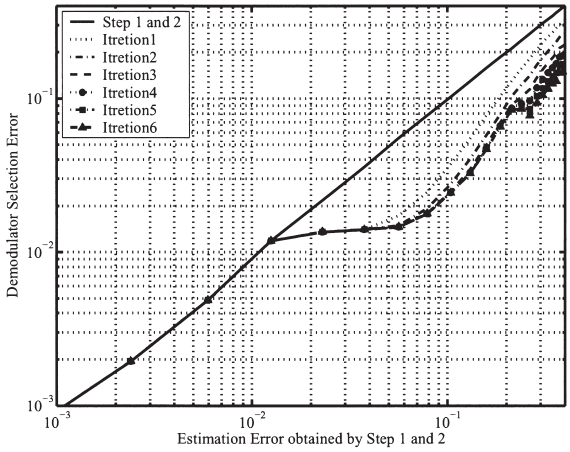

Fig. 5 Demodulator selection error in case switching sequence length is 25.

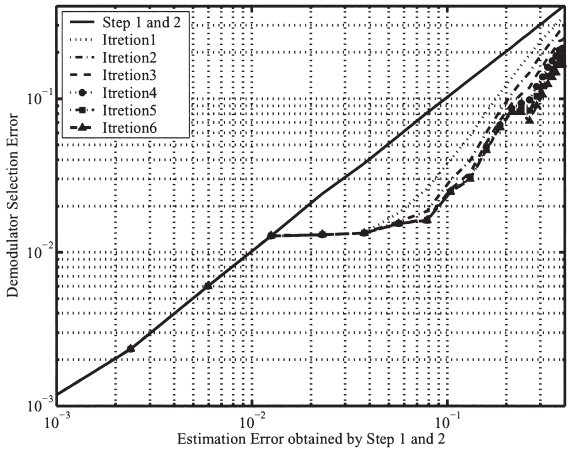

Fig. 6 Demodulator selection error in case switching sequence length is 49.

Figures 5–8 show computational evaluation for demodulator selection error considering CM1 channel model compared with estimation error at Step 1 and 2 in Fig. 3. In Figs. 5–7, it is seen that the system converges at less than the 6-th iteration with the EM algorithm. The complexity of proposed system considers $6n$ sequences, while the maximum likelihood estimation system selecting all the combinations of any sequence considers 2^n sequences to estimate the most probable sequence. Therefore, the proposed system is effective when $n \geq 5$. Additionally, as far as time permits, the longer the sequence length is, the lower the decoder and demodulator selection errors are. Moreover, we can see an error floor at around 10^{-2}, this means that there is a limitation to reduce the modulation selection error by using proposal method.

Compared with estimation error at Step 1 and 2 in

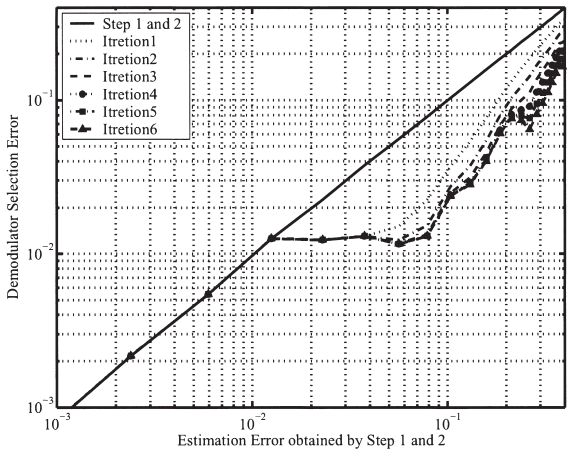

Fig. 7 Demodulator selection error in case switching sequence length is 100.

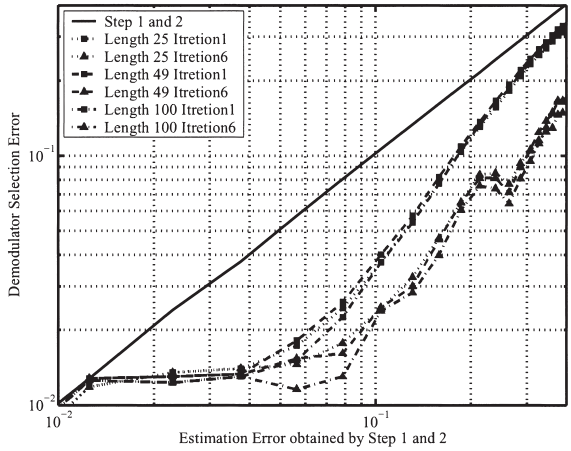

Fig. 8 Demodulator selection error compared with switching sequence length.

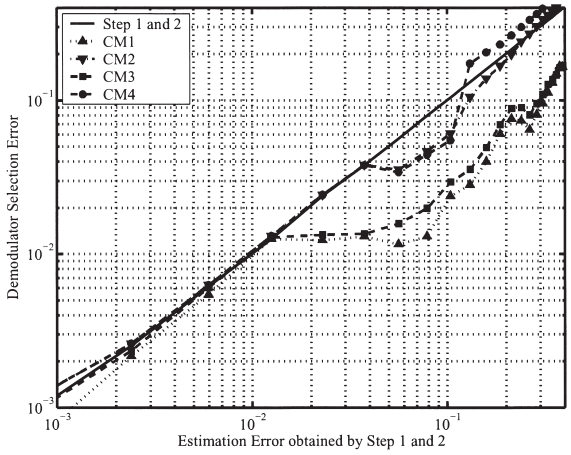

Fig. 9 Demodulator selection error considering channel models of CM1-CM4.

Fig. 3, Fig. 9 shows demodulator selection error considering CM1-CM4 channel models. Note that the number of iterations of the EM algorithm is 6. It is seen that the performance using CM1-CM4 achieves lower demodulation selection error compared with estimation error at Step 1 and 2. Moreover, we can see that the performance of CM1 and CM3 channel model achieves lower demodulation selection error than that of using CM2 and CM4. It means that system considering both CM2 and CM4 channel model selects BPSK and QPSK randomly and this characteristic is hard to distinguish bad state 0 from good state 1 of the HMM in (8). In terms of the threshold of switching modulation pattern described above, due to the difference of demodulator selection error according to the channel models in Fig. 9, we decide this threshold to achieve a BER less than 10^{-4} in order to show our proposed scheme is effective even though it is in the worst case. We utilize this threshold to change the modulation scheme in transmitter and estimate the modulation scheme in receiver to obtain the demodulator estimation error such as Fig. 9. As a result, it is proved that our proposed scheme is effective in any channel model. The details are shown below. In proposed system, we assume that the modulation scheme changes between BPSK and QPSK considering CM1 and CM3 channel models in Fig. 9. In this case, we can see that the proposed system achieves the BER of less than $2 \cdot 10^{-2}$ when the estimation error is from 10^{-1} to $2 \cdot 10^{-2}$ obtained by Step 1 and 2. On the other hand, when we assume the same modulation switching pattern for CM2 and CM4 channel models is used as that for CM1 and CM3 in Fig. 9, it is seen that the proposed system also achieves the BER of less than 10^{-1} when the estimation error is from 10^{-1} to $4 \cdot 10^{-2}$ obtained by Step 1 and 2. Moreover, in the future work, we shall concentrate on reducing the error floor of our proposed system to meet lower BER.

4. Conclusion

In this paper, a reduction of decoder and demodulator selection errors scheme is proposed using HMM as an elemental technology to achieve adaptive channel coding and modulation schemes. Based on channel estimation results, the proposal estimates the sequences such as encoder or decoder switching pattern at the transmit side using the probabilities of decoder and demodulator selection errors that are obtained by the switching pattern and channel information. Especially, we proposed a maximum likelihood estimation scheme in order to estimate the most likely switching patterns by EM algorithm, and then evaluated the performances by computer simulations. Comparing to the scheme only considering channel estimation results, the proposed scheme achieves better performance, and the computational complexity to search the encoder and modulator switching pattern sequence is lowered from 2^n to $6n$, which is effective when $n \geq 5$. In the future, we will investigate the balance of pilot symbols and information bits, and also the number of encoder or modulator switching pattern sequences that are needed to estimate HMM at the receiver.

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