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RESEARCH ARTICLE

Joint data detection and channel estimation for coded and uncoded continuous phase modulation signals

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ABSTRACT

The performance of decision-directed approach for joint data detection and channel estimation for continuous phase modulation (CPM) signal is limited because of an inevitable decision delay, which results in a trade-off between data detection and channel estimation. In this paper, a novel hard output demodulation that solves the conflict requirement on the decision delay by predicting the channel coefficients over a given observation interval through a Kalman filter is proposed for uncoded CPM signal. The prediction guarantees high channel tracking capability and meanwhile maintains the accuracy of data detection. The proposed hard output demodulator is further extended to design a soft-input soft-output demodulator for serially concatenated CPM signal, which allows iterative processing. The convergence behavior of the proposed iterative receiver is presented. Simulation results show that the proposed demodulators provide improved performance in terms of bit error rate over some existing algorithms. Copyright © 2014 John Wiley & Sons, Ltd.

KEYWORDS

CPM; data detection; channel estimation; iterative receiver; SISO; concatenated systems

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1. INTRODUCTION

Bandwidth limitations have motivated considerable investigations into continuous phase modulation (CPM) techniques for communication systems [1]. Moreover, owing to the constant envelope property, nonlinear amplifiers can be used with CPM signals for cost saving without undesired effects on the shape of transmitted signals. Such properties are particularly attractive in mobile communications, which are bandlimited and need cost effectiveness. Therefore, CPM has been used in global system of mobile as well as in Bluetooth and 802.11 frequency-hopping spread spectrum wireless modems. Reliable data detection of CPM signals is challenging when they are transmitted over a flat fading channel. For example, when the receiver is moving at constant velocity, the channel can be considered as a Rayleigh flat fading channel. Joint data detection and channel estimation have been proposed to improve the system performance. One typical solution is a decision-directed (DD) approach that employs pilots for channel tracking during pilot transmission and uses the detected symbols (assumed to be correct) for channel estimation during payload transmission. Because the DD approach offers a better bandwidth efficiency than the pilot-only method [2] and

better performance and lower complexity than the blind estimation methods [3], it has attracted a large amount of research attention.

The DD approach has been used for joint data detection and channel estimation of orthogonal frequency-division multiplexing (OFDM) signals in [4]. Unlike with OFDM signals (in which instantaneous data decisions can be obtained), the demodulation of CPM signals entails a decision delay, which is the time delay between the present time and the time when the most recent decisions are made. This decision delay makes the application of the DD approach to CPM signals not as easy as its application to OFDM signals. The existing DD approaches to CPM demodulation fall into two categories: single estimation processing (SEP) [5] and per-survivor processing (PSP) [6]. Both of them are based on the use of Viterbi algorithm (VA) operating over a trellis diagram. In SEP algorithm [5], a decision delay is inevitable, and this results in poor tracking performance in fast-fading channels. Channel tracking in PSP [6] is operated for every state via the survivor branch on that state, which ensures high tracking capability. However, the selection of the survivor branch may not be accurate because of the zero decision delay. There exists a trade-off with respect to the decision delay. In

channel estimation part, increasing decision delay degrades channel tracking capability, whereas in data detection part, reducing it worsens the accuracy of the tentative decision, leading to potential divergence of the channel tracking trajectories. We address this DD problem in a different way. A Kalman filter (KF) that predicts the channel coefficients over a given observation interval is incorporated into the DD approach such that the effect of decision delay is greatly reduced. Compared with the PSP and SEP algorithms, the proposed algorithm guarantees the accuracy in data decisions and the ability of channel tracking simultaneously. Simulation results show that the proposed algorithm performs better than the previously mentioned benchmark algorithms.

For fading channels, even with the perfect knowledge of channel state information at the receiver, the performance may not satisfy communication requirements. As a solution, channel coding is introduced to protect the transmitted information sequences [7]. Because of the bandwidth efficiency of CPM signals, the serially concatenation of a convolutional encoder and a CPM modulator will not only have comparable performance to a modulator with serially concatenated convolutional codes but also achieves a better bandwidth efficiency. It is noted that Shannon limit performance can be achieved by an iterative receiver, which exchanges information between the demodulator and the decoder alternatively. In the literature, the design guideline for the encoder and the interleaver for serially concatenated CPM (SCCPM) signals with iterative detection has been analyzed in [8]. The problem of iterative detection when channel state information is perfectly known at the receiver has been addressed in [9]. Several pioneer works on SCCPM signals appear in [1,10,11].

Note that the proposed hard output demodulator as well as the PSP and SEP algorithms can only produce hard decisions, which are not suitable for an iterative receiver where soft information is needed for subsequent processing. Therefore, a family of adaptive soft-input soft-output (SISO) algorithms based on the PSP and SEP algorithms has been proposed in [10,12]. We denote them as PSP-based SISO and SEP-based SISO, respectively. It has been proven in [12] that the PSP-based SISO algorithm is better than the SEP-based SISO when channel variation is considerable. The PSP-based SISO consists of two categories: the SISO forward only (SISO-FO) and SISO forward backward (SISO-FB) algorithms. In [13], it has been shown that the PSP-based SISO-FO algorithm performs better than the SISO-FB algorithm for CPM signals. Another SISO demodulator has been addressed in [14] where the expectation-maximization (EM) algorithm is used to estimate the channel. The EM algorithm performs quite well in quasi-static channels, but its iterative nature for refining one parameter by multiple observations makes it difficult to be applied for time-varying channels [15]. Motivated by the performance improvement brought by SISO demodulators as analyzed earlier, the proposed hard output demodulator for uncoded CPM signals is then extended to a

SISO demodulator for SCCPM signals over an unknown time-varying flat fading channel.

The rest of this paper is organized as follows. Section 2 introduces CPM schemes and the channel model. Section 3 presents the hard output demodulator for uncoded CPM signals. Section 4 presents the SISO demodulator for SCCPM signals. Simulation results are presented in Section 5, and conclusions are drawn in Section 6.

2. PRELIMINARIES

2.1. CPM signal

The complex envelope of a CPM signal can be expressed as [16]

$$x(t) = \sqrt{2E/T} e^{j\phi(t,\mathbf{u})} \quad (1)$$

where $\mathbf{u}$ is the sequence of transmitted symbol u_i , E is the average signal energy per symbol, and T is the symbol duration. u_i can take any value within the set $\{\pm 1, \pm 3, \dots, \pm(M-1)\}$, and M is the alphabet size. The information-carrying phase of $x(t)$ between time nT and $(n+1)T$ is given by

$$\phi(t, \mathbf{u}) = \pi h \sum_{i=-\infty}^{n-L} u_i + 2\pi h \sum_{i=n-L+1}^n u_i q(t-iT) \quad (2)$$

where h is the modulation index, L is the CPM correlation length, and $q(t)$ is the phase response satisfying $q(0) = 0$ and $q(LT) = 1/2$. Express h as $h = k/p$ where k and p are mutually prime integers. As shown in [17], a tilted phase is introduced to make the phase trellis time invariant. The tilted phase signal is expressed as

$$\tilde{\phi}(t, \mathbf{u}) = \phi(t, \mathbf{u}) + \frac{\pi h(M-1)t}{T} \quad (3)$$

Define $\mathbf{a}$ as the sequence of modified data $a_i = (u_i + M - 1)/2$, $a_i \in \{0, 1, \dots, M-1\}$; the tilted phase can be expressed as

$$\begin{aligned} \tilde{\phi}(t, \mathbf{a}) = & 2\pi h \sum_{i=-\infty}^{n-L} a_i + 4\pi h \sum_{i=k-L+1}^n a_i q(t-(i-1)T) \\ & + \pi h W(t - (n-1)T) \end{aligned} \quad (4)$$

The first term of Equation (4) is called cumulative phase θ_n , and it has p possible values. The last term $W(\cdot)$ is independent of the data symbols. It is well known that the CPM modulator can be described by a finite-state machine [16]. The states at the n^{th} symbol interval can be represented as $s_n = [\theta_n, a_{n-1}, a_{n-2}, \dots, a_{n-L+1}]$, and the number of possible values of s_n is pM^{L-1} .

2.2. Channel model

In this paper, it is assumed that the communication channel condition is modeled as Rayleigh frequency flat fading.

The fading channel will cause a multiplicative distortion to the transmitted signal. The signal at the receiver is first down converted to baseband and sampled. For simplicity of presentation, symbol rate sampling is considered here, and its extension to multiple samples per symbol is straightforward. The received baseband signal can be represented as

$$r_n = h_n x_n + v_n \quad (5)$$

where h_n is the channel coefficient at time nT , v_n is the additive white Gaussian noise (AWGN) with covariance σ^2 , and x_n is the sampled CPM signal. A Jakes spectrum is assumed for the Rayleigh flat fading channel, and its corresponding autocorrelation function is $R_h[n] = J_0(2\pi f_d T n)$, where $f_d T$ is the normalized Doppler frequency and $J_0(\cdot)$ is the zeroth-order Bessel function of the first kind. Based on this autocorrelation function, the time-varying fading channel can be modeled as an auto-regressive (AR) process as [18]

$$\begin{aligned} \mathbf{h}_n &= \mathbf{B}\mathbf{h}_{n-1} + \mathbf{w}_n \\ &= \begin{bmatrix} b_1 & b_2 & \dots & b_{N-1} & b_N \\ 1 & 0 & \dots & 0 & 0 \\ 0 & 1 & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & 1 & 0 \end{bmatrix} \mathbf{h}_{n-1} + \begin{bmatrix} w_n \\ 0 \\ \vdots \\ \vdots \\ 0 \end{bmatrix} \end{aligned} \quad (6)$$

where $\mathbf{h}_n = [h_n, h_{n-1}, \dots, h_{n-N+1}]^T$ comprises the channel coefficients, N is the model order that corresponds to the required model accuracy, $\{b_1, b_2, \dots, b_N\}$ are the coefficients of the AR model, and w_n is an identically distributed zero-mean complex Gaussian random variable. The autocorrelation matrix of $\mathbf{w}_n$ is defined as $\mathbf{Q}_w$, which is a diagonal matrix with σ_w^2 as its first diagonal element and 0 as others. The entries of $\mathbf{B}$ and $\mathbf{Q}_w$ can be evaluated by solving the well-known Yule–Walker equation, which is given by

$$\mathbf{R}_h \mathbf{b} = \mathbf{r}_h \quad (7)$$

where $\mathbf{R}_h$ is the autocorrelation matrix of $\mathbf{h}_n$, $\mathbf{b} = [b_1, b_2, \dots, b_N]^T$, and $\mathbf{r}_h = [R_h[1], R_h[2], \dots, R_h[N]]^T$. The

inverse of $\mathbf{R}_h$ exists in most cases because $\mathbf{R}_h$ is usually positive definite. Thus, the AR model coefficients can be evaluated as $\mathbf{b} = \mathbf{R}_h^{-1} \mathbf{r}_h$. Given the estimated $\mathbf{b}$, σ_w^2 can be computed as $\sigma_w^2 = R_h[0] - \sum_{i=1}^N b_i R_h[i]$. Based on Equation (6), a KF will be designed in Section 3 for channel tracking.

3. THE PROPOSED HARD OUTPUT DEMODULATOR FOR UNCODED CPM

It is noted earlier that there exists a conflict requirement on the decision delay. In channel tracking part, a short decision delay is required, while in data detection part, a long decision delay is needed. The PSP and SEP algorithms cannot guarantee the accuracy of tentative decisions and the capability of channel tracking at the same time. Thus, we aim at solving this conflict. Figure 1 shows the flowchart of the proposed algorithm. Channel over a given observation interval is predicted via the modeling of the channel as an AR process. Then, a decision is made at the first symbol of the observation interval in the VA. The detected symbol is fed back for channel updating and the state updating for the detection of the next symbol. This prediction over an interval guarantees a high tracking capability and at the same time maintains the accuracy of the survivor path selection. The proposed algorithm consists of two parts: a truncated VA in Section 3.1 and a DD KF in Section 3.2. The selection of an important parameter for the proposed algorithm is discussed in Section 3.3.

3.1. Truncated Viterbi algorithm

Define three vectors in a block $\mathbf{a}_1^{N_b} = [a_1, a_2, \dots, a_{N_b}]$, $\mathbf{r}_1^{N_b} = [r_1, r_2, \dots, r_{N_b}]$, $\mathbf{h}_1^{N_b} = [h_1, h_2, \dots, h_{N_b}]$ where N_b is the block length, $\mathbf{a}_1^{N_b}$ and $\mathbf{r}_1^{N_b}$ represent the input data sequence at the transmitter and the received sequence at the receiver, and $\mathbf{h}_1^{N_b}$ is a vector of time-varying flat fading channel coefficients. If $\mathbf{h}_1^{N_b}$ is known, the maximum

Figure 1. Flowchart of the proposed hard output demodulator.

likelihood estimation of a_k based on the corresponding received sequence $\mathbf{r}_1^{N_b}$ can be evaluated as

$$\hat{a}_k = \arg \max_{\tilde{\mathbf{a}}_1^{N_b}, \tilde{a}_k} \Pr(\mathbf{r}_1^{N_b} | \tilde{\mathbf{a}}_1^{N_b}, \mathbf{h}_1^{N_b}) \quad (8)$$

where $\hat{a}_k$ represents the estimated a_k and $\tilde{\mathbf{a}}_1^{N_b}$ represents all the possible transmitted sequences of $\mathbf{a}_1^{N_b}$; $\tilde{\mathbf{a}}_1^{N_b} : \tilde{a}_k$ are possible transmitted sequences $\mathbf{a}_1^{N_b}$, which contain a_k at the k^{th} symbol. When $\mathbf{h}_1^{N_b}$ is unknown, one must evaluate the conditional probability density function over the probability density function of $\mathbf{h}_1^{N_b}$. However, this is not easy to perform. Another way is via the DD approach, which estimates the unknown parameter and then uses it in determining the probability. The decision criterion becomes

$$\hat{a}_k = \arg \max_{\tilde{\mathbf{a}}_1^{N_b}, \tilde{a}_k} \Pr(\mathbf{r}_1^{N_b} | \tilde{\mathbf{a}}_1^{N_b}, \hat{\mathbf{h}}_1^{N_b}) \quad (9)$$

where $\hat{\mathbf{h}}_1^{N_b}$ is the estimated channel coefficient. Because there are M^{N_b} possible sequences of $\tilde{\mathbf{a}}_1^{N_b}$, the computational burden for the direct evaluation of Equation (9) is relatively high, and the decision can only be made after the whole block has been received. In order to solve the problem of long decision delays, we use the fact that there is a high chance that the survivor up to time $(k + L_o - 1)$ will be the same as the one up to time k when the time spacing L_o is sufficiently large [16]. Therefore, for the k^{th} symbol decision, the decision criterion can be approximated as

$$\hat{a}_k = \arg \max_{\tilde{\mathbf{a}}_1^{k+L_o-1}, \tilde{a}_k} \Pr(\mathbf{r}_1^{k+L_o-1} | \tilde{\mathbf{a}}_1^{k+L_o-1}, \hat{\mathbf{h}}_1^{k+L_o-1}) \quad (10)$$

Note that in Equation (10), the k^{th} symbol decision is made during the trellis search up to time $(k + L_o - 1)$. This decision delay ensures the accuracy of symbol detection. Therefore, the previously detected sequence $\hat{\mathbf{a}}_1^{k-1} = [\hat{a}_1, \hat{a}_2, \dots, \hat{a}_{k-1}]$ is of high accuracy. Assume $\hat{\mathbf{a}}_1^{k-1}$ to be correct, and then, Equation (10) becomes

$$\hat{a}_k = \arg \max_{\tilde{\mathbf{a}}_k^{k+L_o-1}, \tilde{a}_k} \Pr(\mathbf{r}_k^{k+L_o-1} | \tilde{\mathbf{a}}_k^{k+L_o-1}, \hat{\mathbf{a}}_1^{k-1}, \hat{\mathbf{h}}_k^{k+L_o-1}) \quad (11)$$

Although the length of the possible sequence is shortened, the complexity of direct calculation of Equation (11) is still high. A truncated VA is resorted for efficient implementation. To make decision on a_k , the smallest state metric $\Gamma(s_{k+L_o-1})$ at time $(k + L_o - 1)$ needs to be found. In VA, the evaluation of $\Gamma(s_{k+L_o-1})$ can be splitted into two parts: one is the state metric at time $(k - 1)$, and the other one is the survivor branch increment from the k^{th} to the $(k + L_o - 1)^{th}$ instant.

$$\Gamma(s_{k+L_o-1}) = \Gamma(s_{k-1}) - \log(\Pr(\mathbf{r}_k^{k+L_o-1} | \tilde{\mathbf{a}}_k^{k+L_o-1}, \hat{\mathbf{h}}_k^{k+L_o-1})) \quad (12)$$

Let $s_{k-1}(\mathbf{a}_1^{k-1})$ denote the end state of the information sequence $\mathbf{a}_1^{k-1}$. As the previously detected sequence $\hat{\mathbf{a}}_1^{k-1}$ is assumed to be correct, the state metric that corresponds to the end state of $\hat{\mathbf{a}}_1^{k-1}$ is assigned 0, and for the other states at time $(k - 1)$, large values are assigned. In other words, we have that

$$\Gamma(s_{k-1}) = \begin{cases} 0 & s_{k-1} = s_{k-1}(\hat{\mathbf{a}}_1^{k-1}) \\ \text{Inf} & \text{otherwise} \end{cases} \quad (13)$$

For determining $\Pr(\mathbf{r}_k^{k+L_o-1} | \tilde{\mathbf{a}}_k^{k+L_o-1}, \hat{\mathbf{h}}_k^{k+L_o-1})$ in Equation (12), $\hat{\mathbf{h}}_k^{k+L_o-1}$ is essential to be known. A multi-step ahead Kalman prediction $\hat{\mathbf{h}}_k^{k+L_o-1} = [h_{k|k-1}, h_{k+1|k-1}, \dots, h_{k+L_o-1|k-1}]$ is used for its evaluation, where $h_{v|m}$ is the predicted channel coefficient at the v^{th} symbol time by the estimate at the m^{th} symbol time. Detailed description on the multi-step prediction will be introduced in Section 3.2. Given a known $\hat{\mathbf{h}}_k^{k+L_o-1}$, Equation (12) can be solved using the VA in which the evaluation of state metrics starts from the k^{th} symbol and ends at the $(k + L_o - 1)^{th}$ symbol. The survivor branch of each state is the branch with the smallest cumulative weight. The state metric is updated using the weight of the corresponding survivor branch. For $n = k, k + 1, \dots, k + L_o - 1$, we have that

$$\Gamma(s_n) = \arg \min_{s_{n-1} \in S_{n-1}(s_n)} (\Gamma(s_{n-1}) + \lambda(s_{n-1}, s_n)) \quad (14)$$

where $S_{n-1}(s_n)$ represents the set of states s_{n-1} in which there exist branches connecting state s_{n-1} to s_n . As the channel coefficients during the observation interval are obtained from Kalman prediction, we have

$$\lambda(s_{n-1}, s_n) = |r_n - h_{n|k-1} x(s_{n-1}, s_n)|^2 \quad (15)$$

where $|\cdot|$ denotes the Euclidean norm and $x(s_{n-1}, s_n)$ denotes the CPM signal connecting state s_{n-1} and s_n . Substituting Equations (13) and (15) into Equation (14), $\Gamma(s_{k+L_o-1})$ can be obtained. Let $\hat{a}_k^{k+L_o-1}(s_{k+L_o-1})$ denote the information sequence corresponding to the survivor path associated with the state s_{k+L_o-1} . We trace back from the state with the smallest state metric at time $(k + L_o - 1)$ along its survivor branch until time k . A decision is made on a_k , which causes the branch transition from time $(k - 1)$ to time k . In other words, $\hat{a}_k$ is selected as the first element of sequence

$$\hat{a}_k^{k+L_o-1} \left(\arg \min_{s_{k+L_o-1} \in S_{k+L_o-1}} \Gamma(s_{k+L_o-1}) \right).$$

3.2. Decision-directed Kalman filter

We have shown previously that for the k^{th} symbol decision, channel information $\hat{\mathbf{h}}_k^{k+L_o-1}$ is required to be known. Based on the AR model of the Rayleigh channel described

in Section 2.2, the state equation in Equation (6) can be iterated for L_o successive time intervals. The i^{th} channel prediction over the given observation interval can be obtained as

$$\mathbf{h}_{k+i|k-1} = \mathbf{B}^{i+1} \mathbf{h}_{k-1|k-1} + \sum_{n=0}^i \mathbf{B}^{i-n} \mathbf{w}_{k+n} \quad (16)$$

where $\mathbf{h}_{k+i|k-1} = [h_{k+i|k-1}, h_{k+i-1|k-1}, \dots, h_{k+i-N+1|k-1}]^T$, $0 \leq i \leq L_o - 1$. As a result, $\hat{\mathbf{h}}_k^{k+L_o-1} = [h_{k|k-1}, h_{k+1|k-1}, \dots, h_{k+L_o-1|k-1}]$. The second term of Equation (16) is the prediction error, and the corresponding error covariance can be expressed as

$$\mathbf{P}_{k+i|k-1} = \sum_{n=0}^i \mathbf{B}^{i-n} \mathbf{Q}_w (\mathbf{B}^{i-n})^H \quad (17)$$

After $\hat{\mathbf{h}}_k^{k+L_o-1}$ is obtained, $\hat{a}_k$ can be estimated via the aforementioned truncated VA algorithm. The estimated $\hat{a}_k$ is then used for channel updating at the k^{th} time. The CPM signal transmitted during the k^{th} symbol time can be uniquely determined by the detected symbol sequence $\hat{\mathbf{a}}_1^k$. Define a $1 \times N$ vector $\hat{\mathbf{x}}_k = [\hat{x}_k, 0, \dots, 0]$ where $\hat{x}_k$ is denoted as the regenerated CPM signal during the k^{th} symbol time; the KF updating equations can be represented as given by [4]

$$\mathbf{K}_k = \mathbf{P}_{k|k-1} \hat{\mathbf{x}}_k^T (\sigma^2 + \hat{\mathbf{x}}_k \mathbf{P}_{k|k-1} \hat{\mathbf{x}}_k^T)^{-1} \quad (18)$$

$$\mathbf{h}_{k|k} = \mathbf{h}_{k|k-1} + \mathbf{K}_k (r_k - \hat{\mathbf{x}}_k \mathbf{h}_{k|k-1}) \quad (19)$$

$$\mathbf{P}_{k|k} = (\mathbf{I} - \mathbf{K}_k \hat{\mathbf{x}}_k) \mathbf{P}_{k|k-1} \quad (20)$$

where $\mathbf{K}_k$ is the Kalman gain at the k^{th} symbol time. For the detection of symbol a_{k+1} , the detected $\hat{a}_k$ is substituted in Equation (13) for updating the state metric $\Gamma(s_k)$, and a prediction based on $\mathbf{h}_{k|k}$ is followed by a trellis search. These steps are iterated until the end of the received sequence.

3.3. The selection of observation interval

The length of the observation interval L_o in Equation (10) is an important parameter in the proposed scheme. If the channel information is known, the performance can be improved by increasing the value of L_o . However, in the proposed algorithm, longer observation interval will cause a larger channel prediction error. Therefore, there exists a trade-off that requires L_o to be suitably determined. Following the derivation in [19], an upper bound for the error probability $P_e(i)$ when the data-bearing signal $x_i(t)$ is detected in error, under a Rayleigh flat fading channel, can be derived as

$$P_e(i) \leq \sum_{k \neq i} \frac{1}{2} \left(1 - \sqrt{\frac{|x_i(t) - x_k(t)|^2 E_b/N_0}{1 + |x_i(t) - x_k(t)|^2 E_b/N_0}} \right) \quad (21)$$

where E_b/N_0 is the bit-energy-to-noise ratio (noise here is the additive noise in channel). When E_b/N_0 is reasonably high, it can be shown that the minimum distance $d_{\min} \triangleq \min_{i \neq k} \int (x_i(t) - x_k(t))^2 dt$ will dominate the detection error probability [20]. Let d_B represent the upper bound of $d_{\min}$. The bound would be attained if the observation interval is sufficiently long. At the receiver end, it is important to know the length of the observation interval required to achieve d_B ; let this observation interval be N_B . The minimum distance for some commonly used CPM schemes is listed later in the text. Minimum shift keying (MSK) signal achieves d_B when $N_B = 2$. The optimal modulation index for full response CPM with rectangular frequency pulse is $h = 0.715$, which gives $d_B = 2.43$ when $N_B = 3$. For CPM with raised cosine frequency pulse, $L=2$ and $h=0.5$, N_B is required to be 3 to attain $d_B = 2$ (which is equal to MSK). A method for the evaluation of d_B , $d_{\min}$, and N_B can be found in [16]. Because d_B is reached when $L_o = N_B$, further increase on L_o would not bring performance improvement in data detection part. Meanwhile, the increase on L_o would introduce more channel prediction error, which degrades the accuracy of data detection. Therefore, the observation interval should be selected at most as large as N_B .

4. THE PROPOSED SISO DEMODULATOR FOR SCCPM SYSTEM

As will be shown in Section 5, the previously proposed demodulator outperforms the two typically used DD algorithms (the PSP and SEP algorithms). The performance improvement is due to the fact that the proposed demodulator solves the problem of conflicting requirements on the decision delay. However, the proposed demodulator in Section 3 as well as the PSP and SEP algorithms can only produce hard outputs, which are not suitable for iterative processing. In the literature, the PSP and SEP algorithms have been extended to SISO algorithms called PSP-based SISO and SEP-based SISO, respectively. Here, the hard output demodulator developed in Section 3 is extended to a SISO demodulator, which mainly consists of two parts: a truncated BCJR algorithm and a DD KF. The convergence of the iterative receiver is analyzed, as well.

4.1. System description for SCCPM system

The block diagram of the transmitter and the receiver of an SCCPM system is depicted in Figure 2 [21]. The information bit sequence I_n is convolutionally encoded, then randomly interleaved, and finally CPM modulated. The proposed SISO demodulator acts not only as a CPM demodulator but also as a channel estimator. Its abilities of incorporating *a priori* symbol probability and outputting soft information make it suitable for iterative processing. In each iteration, the SISO demodulator takes the soft information $L_a(a_n)$ provided by the decoder from the pre-

Figure 2. Block diagram of transmitter and iterative receiver for SCCPM systems.

vious iteration as its *a priori* probability to perform joint data detection and channel estimation. The output of SISO demodulator is the log-likelihood ratio (LLR) of coded bit a_n , denoted as $L(a_n)$. The extrinsic LLRs $L_e(a_n) = L(a_n) - L_a(a_n)$ are then deinterleaved to obtain the LLRs of the coded bit sequence c_n , which are denoted as $L_a(c_n)$. At the end a SISO decoder, employing the BCJR algorithm outputs the estimated information symbol $\hat{I}_n$ and the LLRs of the coded sequence $L(c_n)$. Before passing to the next

where $\hat{a}_k$ and $\tilde{a}_k$ a_k , respectively. Applying Bayes' rule and total probability, Equation (22) becomes

$$\hat{a}_k = \arg \max_{\tilde{a}_k \in \{0,1,\dots,M-1\}} \sum_{\tilde{\mathbf{a}}_1^{N_b}, \tilde{\mathbf{a}}_k} \Pr(\mathbf{r}_1^{N_b} | \tilde{\mathbf{a}}_1^{N_b}, \mathbf{h}_1^{N_b}) \Pr(\tilde{\mathbf{a}}_1^{N_b}) \quad (23)$$

Similar to the approximation method adopted in Section 3.1, Equation (23) can be approximated as

$$\hat{a}_k = \arg \max_{\tilde{a}_k \in \{0,1,\dots,M-1\}} \sum_{\tilde{\mathbf{a}}_k^{k+L_o-1}} \Pr(\mathbf{r}_k^{k+L_o-1} | \tilde{\mathbf{a}}_k^{k+L_o-1}, \hat{\mathbf{a}}_1^{k-1}, \hat{\mathbf{h}}_k^{k+L_o-1}) \Pr(\tilde{\mathbf{a}}_k^{k+L_o-1}) \quad (24)$$

stage, $L_e(c_n) = L(c_n) - L_a(c_n)$ is evaluated, and $L_e(c_n)$ is interleaved to provide the updated *a priori* probability for the SISO demodulator in the next iteration [22]. By exchanging the soft information between the SISO demodulator and the SISO convolutional decoder, data detection is expected to be more accurate. Furthermore, the error covariance of the channel estimation, obtained by the proposed DD KF approach, is expected to decrease through iterations because of the increased accuracy of detected

Because the input of the CPM modulator is the output of the interleaver, the input symbols can be considered as independent such that

$$\Pr(\tilde{\mathbf{a}}_k^{k+L_o-1}) = \prod_{n=k}^{k+L_o-1} \Pr(a_n) \quad (25)$$

Followed by a recursive expansion, Equation (24) becomes

$$\hat{a}_k = \arg \max_{\tilde{a}_k \in \{0,1,\dots,M-1\}} \sum_{\tilde{\mathbf{a}}_k^{k+L_o-1}} \prod_{n=k}^{k+L_o-1} \Pr(r_n | \mathbf{r}_k^{n-1}, \tilde{\mathbf{a}}_k^n, \hat{\mathbf{a}}_1^{k-1}, \hat{\mathbf{h}}_k^n) \Pr(a_n) \quad (26)$$

data. Therefore, the performance of the whole system is improved.

4.2. The proposed SISO demodulator

Because of correlated fading and symbol dependence introduced by CPM modulation, the symbol-by-symbol maximum *a posteriori* probability detection of a_k in a block $\mathbf{a}_1^{N_b}$ under known $\mathbf{h}_1^{N_b}$ is [23]

$$\hat{a}_k = \arg \max_{\tilde{a}_k \in \{0,1,\dots,M-1\}} \Pr(\tilde{a}_k | \mathbf{r}_1^{N_b}, \mathbf{h}_1^{N_b}) \quad (22)$$

For simplicity of presentation, only binary transmission with $M = 2$ is considered here. When soft outputs are required for subsequent processing, $L(a_k)$ is evaluated as

$$L(a_k) = \frac{\sum_{\tilde{\mathbf{a}}_k^{k+L_o-1}, a_k=1} \prod_{n=k}^{k+L_o-1} \Pr(r_n | \mathbf{r}_k^{n-1}, \tilde{\mathbf{a}}_k^n, \hat{\mathbf{a}}_1^{k-1}, \hat{\mathbf{h}}_k^n) \Pr(a_n)}{\sum_{\tilde{\mathbf{a}}_k^{k+L_o-1}, a_k=0} \prod_{n=k}^{k+L_o-1} \Pr(r_n | \mathbf{r}_k^{n-1}, \tilde{\mathbf{a}}_k^n, \hat{\mathbf{a}}_1^{k-1}, \hat{\mathbf{h}}_k^n) \Pr(a_n)} \quad (27)$$

Direct evaluation of Equation (27) is prohibitively complex. Here, a truncated BCJR algorithm is used for efficient implementation. Following [24], it can be shown that

$$L(a_k) = \frac{\sum_{ST_1^k} \gamma(s_k \rightarrow s_{k+1}) \alpha(s_k) \beta(s_{k+1}) \Pr(a_k = 1)}{\sum_{ST_0^k} \gamma(s_k \rightarrow s_{k+1}) \alpha(s_k) \beta(s_{k+1}) \Pr(a_k = 0)} \quad (28)$$

where s_k is the state at k^{th} time, α and β are the forward and backward coefficients, and ST_1^k and ST_0^k are the branches connecting the state s_k to s_{k+1} associated with the input symbols 1 and 0, respectively. For the k^{th} symbol detection, $L(a_k)$ is evaluated under a truncated interval, which starts at the k^{th} symbol time and ends at the $(k + L_o - 1)^{th}$ symbol time. As the data decision is made at the first symbol of the observation interval, only an initialization is necessary when considering the evaluation of the forward coefficients for every truncated interval. This initialization can be easily obtained by means of the previously decided symbols. Let $\hat{s}_k(\hat{a}_1^{k-1})$ denote the state associated with the decided data sequence $\hat{a}_1^{k-1}$. Based on the approximation of Equation (26), we have $\alpha(s_k = \hat{s}_k(\hat{a}_1^{k-1})) = 1$, and for other states at the k^{th} symbol time, α will be equal to 0. The initialization $\beta(s_{k+L_o}) = 1$ is adopted for all possible states at the $(k + L_o)^{th}$ symbol time. The evaluation of α and β is based on γ . These two coefficients can be calculated recursively as [24]

$$\begin{aligned} \alpha(s_{k+1}) &= \sum_{s_n \in S} \gamma(s_k = s_n \rightarrow s_{k+1}) \alpha(s_k = s_n) \\ \beta(s_{k+1}) &= \sum_{s_n \in S} \gamma(s_k \rightarrow s_{k+1} = s_n) \beta(s_{k+1} = s_n) \end{aligned} \quad (29)$$

where S is the set of states at every symbol time.

Same as the hard output demodulator in Section 3, a multi-step Kalman prediction is used to evaluate the channel coefficients during the observation interval. Furthermore, the multi-step Kalman prediction can provide exact prediction error covariance $\mathbf{P}_{k|k-1}$, which can be used to obtain a more accurate $L(a_k)$. The channel estimation error is denoted as [25]

$$\Delta h_k = h_k - h_{k|k-1} \quad (30)$$

where h_k is the true value of the time-varying flat fading channel. Substituting Equation (30) into Equation (5) shows that an augmented noise component appears at the receiver, which is denoted as $m_k = \Delta h_k x_k + v_k$ [25]. It is noted that m_k is usually correlated and distributed as $p(m_k | v_k, \Delta h_k) \sim N(0, P_{v_k} + P_{\Delta h_k})$ where $N(e, c)$ denotes a complex Gaussian power density function with mean value of e and variance c . The value of $P_{\Delta h_k}$ is the first element of $\mathbf{P}_{k|k-1}$ in Equation (17). We can thus modify the truncated BCJR algorithm incorporating the channel estimation error as follows:

where $x(s_k \rightarrow s_{k+1})$ denotes the CPM signal associated with the state transition from s_k to s_{k+1} . With the estimated γ , α , and β , both the hard output $\hat{a}_k$ and the soft output $L(a_k)$ can be easily obtained by Equation (28). Soft output $L(a_k)$ is presented to the decoder for further processing, and the hard decision $\hat{a}_k$ is fed back for two purposes: one is for establishing the initial state for the next symbol decision in the truncated BCJR procedure, and the other is for regenerating the CPM signal during the k^{th} symbol time $\hat{x}_k$. Given a known $\hat{x}_k$, the KF updating equations given by Equations (18)–(20) can be used to evaluate $\mathbf{h}_{k|k}$. The soft information of the next symbol $L(a_{k+1})$ is then evaluated using the predicted channel and the predicted channel error covariance. These steps are iterated until the end of the received sequence.

4.3. Convergence analysis

In this section, the extrinsic information transfer (EXIT) chart is exploited to analyze the convergence behavior of the proposed iterative receiver. The EXIT chart uses mutual information (MI) for the convergence analysis of iterative receivers. MI between two variables x and y is defined as $I(x; y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{X,Y}(x, y) \log_2 \frac{f_{X|Y}(x|y)}{f_X(x)} dx dy$ [26]. The SISO demodulator and SISO convolutional decoder exchange information in each iteration, and the corresponding EXIT chart consists of two curves as shown in Figure 3. One curve is plotted for the SISO demodulator with MI $I_{a, \text{demodulator}} = I(L_a(a_n), a_n)$ as the horizontal axis and with MI $I_{e, \text{demodulator}} = I(L_e(a_n), a_n)$ as the vertical axis. The other one is plotted for the SISO decoder with MI $I_{a, \text{decoder}} = I(L_a(c_n), c_n)$ as the vertical axis and with MI $I_{e, \text{decoder}} = I(L_e(c_n), c_n)$ as the horizontal axis. Because the output LLR of the demodulator is the input of the decoder and the output LLR of the decoder is the input of the demodulator in the next iteration, the convergence behavior can be observed by stepping between these two curves of the EXIT chart. A wide tunnel between the two curves is preferred because it indicates a rapid convergence. When the two curves intersect, the MI will converge to the crossover point [27].

The proposed SISO demodulator performs joint data detection and channel estimation in the presence of a time-varying flat fading channel, and its EXIT charts are shown in Figure 3. According to Equations (28) and (31), the output LLRs $L(a_n)$ of the proposed SISO demodulator are evaluated using the estimated channel. Thus, the unavoidable channel estimation errors affect the extrinsic transfer function. From Equations (28) and (31), it can be concluded that under a specified data detection and channel estimation method, E_b/N_0 and the accuracy of channel estimates can quantify the output MI. Furthermore, the accuracy of channel estimates depends on E_b/N_0

$$\gamma(s_k \rightarrow s_{k+1}) = \exp\left(\frac{1}{2\sigma^2 + P_{\Delta h_k}} |r_k - h_{k|k-1} x(s_k \rightarrow s_{k+1})|^2\right) \quad (31)$$

Figure 3. EXIT chart for the proposed iterative receiver. Left: under different E_b/N_0 . Right: under different $f_d T$.

and $f_d T$. Therefore, the output MI of the proposed SISO demodulator can be characterized by

$$I_{e,demodulator} = G\left(I_{a,demodulator}, \frac{E_b}{N_0}, f_d T\right) \quad (32)$$

where $G(\cdot, \cdot, \cdot)$ indicates the correspondence relationship.

The left side of Figure 3 shows the effects of E_b/N_0 on the extrinsic transfer function of the proposed SISO demodulator at the fixed fading rate $f_d T = 0.01$. It is also interesting to note that for an AWGN channel, there exists a value of E_b/N_0 for which the demodulator–decoder trajectories just manage to sneak through a narrow tunnel [27]. Therefore, the bit error rate (BER) found for that E_b/N_0 converges to a very small value through iterations, and a turbo cliff (which is an abrupt decrease in BER) around that E_b/N_0 can be found. However, in the left side of Figure 3, such a bottleneck region is not seen. This implies that for the proposed SISO demodulator, a turbo cliff cannot be found in the BER curves. When $E_b/N_0 = 4$ dB, an intersection is observed at $I_{a,demodulator} = 0.5$. This indicates that as iterations proceed, MI increases and is eventually stuck at the intersection point. When $E_b/N_0 \geq 8$ dB, the BER can approach 0. The right side of Figure 3 shows the effects of the channel fading rate $f_d T$ on the extrinsic transfer function of the proposed SISO demodulator for a fixed $E_b/N_0 = 10$ dB. As the fading rate increases, the transfer function of the demodulator decreases. The reason is that a larger channel estimation error is expected for a higher $f_d T$, which causes the lowering of the transfer function.

5. SIMULATION RESULTS

Extensive simulations for CPM signals transmitted over a time-varying flat fading channel are performed to analyze the performance of the proposed demodulators. First, the proposed hard output demodulator in Section 3 is tested on an uncoded system and compared with the PSP and SEP algorithms. The selection of parameters, including the observation interval and frame length, is discussed. Second, the proposed SISO demodulator in Section 4 is tested

on an SCCPM system. The performance is compared with those of the PSP SISO and SEP SISO algorithms. The simulation results show that the proposed demodulators provide improved performance.

5.1. Performance evaluation in uncoded systems

5.1.1. Performance of the proposed algorithm in different fading rates.

Two types of CPM signals are used for simulation here: one is MSK, and another is partial response CPM with a raised cosine frequency response over two symbol intervals. A frame contains 30 symbols, of which three are pilot symbols. The sampling rate is eight samples per symbol, and the order of AR model for prediction is $N = 2$. The BER performance of the proposed demodulator in Section 3 with different normalized fading rate $f_d T$ is presented in Figure 4. The values of $f_d T$, 0.001, 0.01, and 0.05, are selected to represent slow, moderate, and fast fading channels, respectively. The performance of the VA endowed with the perfect channel state information (annotated as “Optimum”) is also plotted in this figure for comparison. As can be seen, BER will increase as $f_d T$ increases, but the performance is still acceptable even when $f_d T$ is as high as 0.05.

5.1.2. Effect of parameters.

The effect of the observation interval L_o on BER performance is investigated. A similar simulation setup as in subsection 5.1.1 is used, except that E_b/N_0 is fixed at 30 dB. For the sake of space, only MSK signal is considered. The guideline proposed in Section 3.3 suggests to choose $L_o \leq N_B$ ($N_B = 2$ for MSK signal). As shown in Figure 5, for different fading rates $f_d T$, the lowest BERs are all obtained when $L_o = 2$, which validates the proposed guideline.

The effect of the frame length on channel estimation is investigated, as well. $f_d T = 0.01$ and three different values of E_b/N_0 are used in the simulation. As shown in Figure 6, a low mean square error of channel estimation

Figure 4. BER performance provided by the proposed scheme. Left: for a full response CPM. Right: for a partial response CPM.

Figure 5. BER performance as a function of observation interval under $E_b/N_0 = 30$ with $f_d T = 0.001, 0.01$, and 0.05 .

Figure 7. BER performance provided by the PSP algorithm, the SEP algorithm, and the proposed algorithm.

Figure 6. Minimum mean square error of channel estimation versus frame length for $f_d T = 0.01$ ($E_b/N_0 = 10, 20$, and 30).

is obtained when frame length is in a middle range. If the frame length is too small, the channel tracking may not converge at the end of each frame. If the frame length is too large, the performance will degrade because of a

low insertion rate of pilot symbols. It is also observed that this middle region varies with E_b/N_0 . When E_b/N_0 is large (30 dB in Figure 6), this middle range would be quite wide, which therefore allows a lower pilot symbol insertion rate. This is because the chance for track divergence in such environment is lower than that in a low E_b/N_0 environment.

5.1.3. Reception technique comparison.

The proposed demodulator is compared with other algorithms in terms of BER performance. In the simulation, a frame contains 50 symbols, and the first two are pilots. The fading rate $f_d T = 0.01$, AR model order $N = 2$, and the observation interval of two symbol periods are adopted. Figure 7 depicts the performances curves of three algorithms: the SEP algorithm with a decision delay of 2, the PSP algorithm, and the proposed algorithm. The performance curve with known channel information is included for comparison, as well. As can be seen, the proposed algorithm provides improved performance. For example, it provides a 2.5-dB gain over the PSP algorithm and 3-dB gain over the SEP algorithm when $BER = 10^{-3}$.

Except the performance, the computation complexity is also a key aspect of an algorithm. For the three algorithms, the complexity is mainly contributed by the branch metric evaluation in the VA. For SEP and PSP algorithms, the computational complexity per symbol is $O(pM^L)$, while it is $O(L_o pM^L)$ for the proposed algorithm. L_o is usually a small integer for common CPM signals, for example, $L_o = 2$ for MSK signal and $L_o = 3$ for partial response CPM signal with a raised cosine frequency response over two symbol intervals. Therefore, the complexity of the proposed algorithm increases slightly with a relatively large performance gain.

5.2. Performance evaluation in SCCPM systems with iterative detection

In this subsection, the effectiveness of the proposed SISO demodulator proposed in Section 4 for SCCPM systems is evaluated. The selected convolutional encoder has a generator polynomial $[5, 7]_8$, a constraint length of 3, and a rate

of $1/2$. A random interleaver is used, and for simplicity, MSK is adopted.

5.2.1. The effects of interleaver size.

In Figure 8, the BER performance of the proposed receiver is shown against the number of iterations for different interleaver sizes ($N_t = 100, 640, 1600, 8000$, and $16,000$); the channel parameters are $f_d T = 0.01$ and $E_b/N_0 = 8$ dB. As can be seen, when the interleaver size is small (e.g., $N_t = 100$), the BER performance does not improve through iterations. As the interleaver size increases, the BER performance begins to improve with iterations. Thus, we can conclude that a sufficiently large interleaver size is an important requirement for the iterative receiver. Figure 9 shows the different requirements of the interleaver size for different fading rates. The BER curves are obtained after five iterations for $E_b/N_0 = 8$ dB. When the channel is slow fading (e.g., $f_d T = 0.001$), the BER curve lowers along with an increase of interleaver size. However, for a faster fading channel ($f_d T = 0.01$), when $N_t > 4000$, the performance does not improve. It can be concluded that the proposed iterative receiver with a slow time-varying channel needs a larger interleaver size than the one with a fast-fading channel. The reason is the following. The duration of a deep fade is long when the channel is slow fading, causing a long error burst at the output of the proposed SISO demodulator. Therefore, a large interleaver size is required to make these errors occur in a non-contiguous manner.

5.2.2. Performance of the proposed iterative receiver.

Figure 10 shows the BER performance provided by the proposed SISO demodulator with different numbers of iterations over flat fading channels with $f_d T = 0.001$ and $f_d T = 0.01$, respectively. The performance with known channel conditions is also included in these figures for comparison. The notation “ I_{te} ” refers to the number of iterations. The frame length is 32 symbols containing one pilot symbol for initialization. The AR model order is 1, and the observation interval is 2. The interleaver size N_t is 4096 in the left of Figure 10 while N_t is 2048 in the right of Figure 10. Several observations can be inferred from the figures. First of all, the largest performance gap in both figures occurs between the 0^{th} iteration and the 1^{st} iteration. Second, the performance can be improved through iterations. However, the performance improvement after the 5^{th} iteration is marginal. For this reason, performance curves beyond the 5^{th} iteration are not shown. Finally, the performance improvement via iterations is more significant when E_b/N_0 is high. When E_b/N_0 is low, the information fed back as *a priori* knowledge to the SISO demodulator is less reliable and hence does not improve the performance much.

Figure 11 shows the mean square error of channel estimates with different numbers of iterations. $f_d T = 0.001$ and 0.01 are considered. The settings of this figure are the same as those of Figure 10. In the proposed SISO

Figure 8. Effect of the interleaver size on iterative receiver.

Figure 9. Effect of the interleaver size for different fading rates ($f_d T = 0.01$ and $f_d T = 0.001$).

Figure 10. BER performance provided by the proposed iterative receiver. Left: over channel with $f_d T = 0.001$. Right: over channel with $f_d T = 0.01$.

Figure 11. Mean square error of channel estimates versus E_b/N_0 for a different number of iterations with $f_d T = 0.001$ and $f_d T = 0.01$.

Figure 12. Performance comparison among the proposed SISO demodulator, the PSP-based SISO-FO in [11], and the SEP-based SISO in [13].

demodulator, the detected data are assumed to be correct in channel tracking. As shown in Figure 10, through iter-

ations, the accuracy of data detection can be improved, and this will further refine the accuracy of the channel estimates. As expected, the mean square error of channel estimates reduces through iterations. It is interesting to note that the BER performance and the mean square error of channel estimates are consistent with each other. Figure 10 also shows that when $E_b/N_0 \leq 4$ dB, the BER curves do not change as the number of iterations increases. This also happens in Figure 11. Furthermore, the accuracy of channel estimation is inversely proportional to the channel fading rate $f_d T$.

5.2.3. Performance comparison.

As mentioned before, the PSP-based SISO-FO algorithm performs better than the SISO-FB algorithm [13]. So we only compare the proposed demodulator with PSP-based SISO-FO and SEP-based SISO algorithms. As can be seen from Figure 12, the proposed SISO demodulator provides a 0.8-dB gain over the PSP-based SISO algorithm and a 1.5-dB gain over SEP-based SISO algorithm at $BER = 10^{-3}$. Similar with the hard output demodulator proposed in Section 3, the computational complexity of the proposed SISO demodulator slightly increases to $O(L_{op}M^L)$ while the complexity of PSP-SISO and SEP-SISO is $O(pM^L)$.

6. CONCLUSIONS

In this paper, we first proposed a hard output demodulator that addressed the problem of joint data detection and channel estimation for uncoded CPM signals transmitted over time-varying flat fading channels. A multi-step channel prediction over a given observation interval guarantees zero decision delay and at the same time maintains the accuracy of the survivor path selection. Therefore, the proposed hard output demodulator is expected to achieve better performance than the PSP and SEP algorithms, and simulation results confirm this expectation. The effects of the selection of various parameters have also been investigated. The hard output demodulator was then extended to

a novel adaptive SISO demodulator for SCCPM signals. Because of its abilities of incorporating *a priori* symbol probabilities outputting soft decisions, the proposed SISO demodulator is well suited for an iterative receiver. The convergence behavior and the effects of the interleaver size have been analyzed. BER comparisons with existing algorithms have been presented to evidence the efficacy of the proposed algorithms.

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