Signal Processing 122 (2016) 75–86

Contents lists available at ScienceDirect

Signal Processing

journal homepage: www.elsevier.com/locate/sigpro

Semi-blind joint phase tracking, parameter estimation and detection in the context of nonlinear channels with memory

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ARTICLE INFO

Article history:
Received 16 April 2015
Received in revised form
14 September 2015
Accepted 7 November 2015
Available online 30 November 2015

Keywords:
Carrier recovery
Nonlinear channel identification
Expectation–maximization (EM)
Pseudo maximum-likelihood estimation

ABSTRACT

We consider a transmission system, where the emitted symbols are subject to unknown nonlinear intersymbol interference. Several methods have been proposed in the literature to mitigate the degradation introduced by such channels. However, the problem of nonlinear channel identification in the presence of carrier phase noise has not been addressed previously.

In this paper, we derive an iterative receiver structure to detect the transmitted symbols, jointly with phase and channel estimation. At each iteration, the channel parameters are refined based on the expectation-maximization (EM) approach. Also, a pseudo maximum-likelihood (pseudo-ML) carrier recovery, operating in a decision-directed mode, re-estimates the time-varying phase at each iteration. The proposed technique is semi-blind, since a short training sequence is needed to initialize the phase and channel coefficients properly.

We show that the proposed scheme allows symbol detection performances close to the genie-aided detector with data-aided channel coefficient estimation. Moreover, a theoretical analysis of the residual phase error confirms that coherent detection in the presence of strong phase noise is achieved. Numerical simulations are presented for systems with severe nonlinear distortions, including satellite communications with nonlinear amplifiers and coherent optical fiber transmissions.

1. Introduction

Intersymbol interference (ISI) is a well-known phenomenon, which degrades the performances of digital communications by introducing memory in the channel in addition of noise. Existing compensation methods referred to as equalization, usually consider a linear channel model, whether in the time domain [1,2] or in the frequency domain [3,4].

However, a linear channel model is inadequate for many systems. Indeed, nonlinear ISI can originate either from nonlinear elements interacting with the channel filters (such as power amplifiers [5]) or from physical phenomena in the channel itself (such as distortions in magnetic recording channels [6] or the Kerr effect in optical fibers [7]). It follows that, even for standard linear modulations, practical communication systems often become nonlinear, either because of the nonideal characteristics of the transceiver devices or because of nonlinear physical phenomena in the transmission medium. In such applications, linear channel models would introduce mismodeling errors that would in turn lead to suboptimal

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http://dx.doi.org/10.1016/j.sigpro.2015.11.005
0165-1684/

equalization. Thus, in order mitigate the adverse effects of nonlinear channels properly, non-linearities need to be modeled explicitly. Several methods have been presented in the literature, including equalization based on maximum-likelihood sequence estimation (MLSE) using the Viterbi algorithm with cluster-based channel identification [8], symbol-by-symbol maximum *a posteriori* detection (MAP) using the forward–backward (FB) algorithm [9] with expectation-maximization (EM) channel estimation [10], Volterra series [11] with adaptive parameter identification, adaptive neural networks [12] and blind equalization with inverse nonlinearity estimation [13]. Recently, Markov Chain Monte Carlo (MCMC) techniques have also been applied [14,15], but they require prior knowledge on the form of the nonlinearity.

A fact often overlooked in most of the aforementioned methods, is that the nonlinear channel is assumed quasi-static in order to enable channel identification. However, this assumption is likely to break down in the presence of strong carrier-phase noise. A remedy to this common weakness is to perform a combined equalization and phase tracking/compensation procedure. In this paper, we propose several extensions of the EM approach in [10]. First, we introduce a real-domain baseband channel model for nonlinear ISI that is robust to modeling errors. To achieve this goal, we introduce a noise model whose real and imaginary part are correlated and have ISI state-dependent statistics. The motivation is to capture the joint effect of additive white Gaussian noise (AWGN) and residual nonlinear effects unmodeled or mis-modeled by the observation function. Secondly, we introduce an EM-based [16] iterative data detection and nonlinear channel parameter estimation procedure. In our version, the sequence of ISI states modeled by a Markov chain represent the *missing data*, while noisy channel outputs with ideal carrier phase compensation represent the *incomplete* data. At each iteration, the conditional likelihoods needed by the expectation step are easily computed using the FB algorithm applied to the ISI state Markov model, thus updated hard data decisions can be obtained as a by-product (see [9]). Thirdly, since ideal phase error compensation is impossible in practice, we use a carrier phase estimation algorithm to get a refined approximation of the *incomplete* data at each EM iteration. To achieve this goal, we derive a carrier recovery method based on the pseudo maximum-likelihood (pseudo-ML) approach that makes iterative use of hard decisions provided by the expectation step of EM.

Throughout the paper, bold letters indicate vectors and matrices, while $\mathbf{0}_{m\times n}$ is the $m \times n$ all-zero matrix. $\mathcal{N}(\mathbf{m},\mathbf{P})$ denotes a multivariate Gaussian distribution with mean $\mathbf{m}$ and covariance matrix $\mathbf{P}$. The i-th coordinate of a vector $\mathbf{x}$ is denoted by $\mathbf{x}(i)$, with $i \geq 0$.

This paper is organized as follows. Section 2 introduces the considered system model for nonlinear channels. Section 3 presents the proposed EM-based joint channel estimation and equalization approach, assuming ideal carrier phase compensation. The proposed decision-directed carrier phase estimation technique is derived in Section 4. Section 5 presents the proposed combined phase tracking, channel estimation and equalization scheme suitable for nonlinear channels in the presence of phase noise. In Section 6, a theoretical analysis of the performances of the proposed carrier phase estimation technique is provided. Finally, numerical results are given in Section 7 to illustrate the performances of the proposed technique for several realistic applications, where a nonlinear channel model is appropriate.

2. System model

We consider the transmission of K complex data symbols during each frame. Let d_k denote the complex symbol sent at the discrete time instant k. d_k is selected independently and with uniform distribution from an M-ary alphabet. The first N_t symbols correspond to training symbols known to the receiver. We consider a causal memory-L ISI channel, where the ISI state at instant k is defined as

$$\mathbf{x}_k = \begin{bmatrix} d_k \\ d_{k-1} \\ \vdots \\ d_{k-L} \end{bmatrix}. \tag{1}$$

We denote the possible values that the ISI states can take as $\mathbf{x}^i$, $i=0,\ldots,S-1$, where $S=M^{L+1}$. Obviously, $\mathbf{x}_k$ follows a first-order time-homogeneous Markov model of the form

$$\mathbf{x}_k = f(\mathbf{x}_{k-1}, d_k). \tag{2}$$

Let us now introduce the proposed nonlinear observation model in the absence of phase noise. The sampled complex baseband equivalent channel output received y_k, can be written in real form, for $0 \leq k \leq K-1$, as

$$\begin{bmatrix} \mathrm{Re}(y_k) \\ \mathrm{Im}(y_k) \end{bmatrix} = \begin{bmatrix} m^I(\mathbf{x}_k) \\ m^Q(\mathbf{x}_k) \end{bmatrix} + \begin{bmatrix} n_k^I \\ n_k^Q \end{bmatrix}, \tag{3}$$

where $m^I(.)$ (resp. $m^Q(.)$) is the expectation of the in-phase (resp. quadrature) component of the sampled channel output, conditional on $\mathbf{x}_k$. n_k^I (resp. n_k^Q) is the independent and identically distributed (i.i.d.) zero mean Gaussian noise affecting the in-phase (resp. quadrature) component. For the sake of robustness, we let the noise statistics dependent on the ISI state, in order to capture residual nonlinear effects not modeled by $m^I(.)$ and $m^Q(.)$. Compared with standard equalization strategies designed for non-data-dependent noise, it makes engineering sense to consider the simplest extension of the usual Gaussian noise model, by letting the covariance depend on the ISI state, i.e.,

$$\begin{bmatrix} n_k^I \\ n_k^Q \end{bmatrix} \Bigg| \mathbf{x}_k \sim \mathcal{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \mathbf{\Sigma}(\mathbf{x_k}) \right). \tag{4}$$

where the state-dependent noise covariance matrix has the form

$$\mathbf{\Sigma}(\mathbf{x}_k) = \begin{bmatrix} \sigma_I^2(\mathbf{x}_k) & \rho(\mathbf{x}_k)\sigma_I(\mathbf{x}_k)\sigma_Q(\mathbf{x}_k) \\ \rho(\mathbf{x}_k)\sigma_I(\mathbf{x}_k)\sigma_Q(\mathbf{x}_k) & \sigma_Q^2(\mathbf{x}_k) \end{bmatrix}. \tag{5}$$