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Blind sequence detection using reservoir computing ☆

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ABSTRACT

The performance of *M*-ary quadrature amplitude modulation (QAM) can seriously be degraded by inter-symbol interference (ISI) as the number of levels increases. To mitigate ISI, blind sequence detection (BSD) has very important applications in data transmission systems, particularly where sending a training sequence is disruptive or costly. A new BSD approach of short data in QAM systems using reservoir computing (RC) is presented, together with the detailed theoretical derivation of the algorithm. Its convergence can be guaranteed within a short data packet and, therefore, it works in systems with a much shorter data record and faster time-varying channels. A RC network is constructed to solve the special issue of BSD, with reservoir weight matrix generated via the reduced QR decomposition from the view of receiving signal subspace instead of being selected randomly. The design methods of the activation function and readout function, the variation rule of initial vector which is changed by reservoir weight, and complexity of the proposed algorithm are described, respectively. The readout weight of the RC network is trained and updated by support vector regression (SVR) with a Gaussian insensitive loss function. The correctness and effectiveness of the new approach are verified by simulations, and some special simulation phenomena of the algorithm are discussed.

1. Introduction

Typical digital communication environments involve transmission of analog pulses over a dispersive medium, inevitably corrupting the received signal by inter-symbol interference (ISI) [1]. ISI is a limiting factor in many communication environments where it causes an irreducible degradation of bit error rate (BER) thus imposing an upper limit on data symbol rate. In addition, the limitations of spectrum allocation have renewed interest in the spectrally efficient quadrature amplitude modulation (QAM) format [2]. High-order QAM modulations (e.g., 64QAM, 128QAM) can increase the available data rate efficiently in a limited channel and spectral efficiency significantly, and it is essential for high-speed far-distance wireless communication. However, the performance of *M*-ary QAM can seriously be degraded by ISI as the number of levels increases. Compared with direct or simple modulation schemes, digital signal processing (DSP) techniques like pre-distortion and channel equalization could be used in high-order modulation systems, and helpful to enhance these systems tolerance. Simultaneously, high-order QAM modulations is still a challenge for high-speed communication due to its complexity and channel distortion [3].

To mitigate ISI, blind equalization has very important applications in data transmission systems, particularly in where sending a training sequence is disruptive or costly [4]. There exists two major blind equalization approaches: the first one estimates channel impulse response and uses an optimum method to recover the transmitted sequence and the second directly equalizes the channel to estimate the transmitted sequence without performing channel estimation. Both of these approaches have to seek a linear filter to minimize a criterion that measures the closeness of the filter output to a discrete-valued signal with the known alphabets. Simultaneously, high-order QAM systems entail a troublesome convergence of the algorithms, and a big data block is absolutely necessary to make these approaches work well.

Motivated by the aforementioned problems, it is therefore an important challenge to construct blind equalization for high-order QAM systems. A new BSD approach using RC [5] was proposed to

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Table 1
Notation conventions used in this paper.

Superscript T	Transpose of a matrix
Superscript *	Conjugate of a matrix
Superscript H	Conjugate transpose of a matrix
$diag(a_1, \cdots, a_n)$	Diagonal matrix with diagonal entries $a_1, \cdots$
z^{-1}	Unit-time delay
$range(\mathbf{X})$	The range of a linear transformation $\mathbf{X}$
$span\{\mathbf{x}_1, \cdots, \mathbf{x}_j\}$	Vector space of columns of $\mathbf{x}_1, \cdots, \mathbf{x}_j$
$E\{.\}$	Expectation operation
$\|\mathbf{x}\|_2^2$	Squared 2-norm defined by $\sqrt{\sum \|x_i\|^2}, i = 1, 2, \cdots$
$\nabla_{\mathbf{x}} J(\mathbf{x})$	Derivative of $J(\mathbf{x})$ with respect to the $\mathbf{x}$
$\mathbb{C}^{n\times m}$	The set of $n \times m$ matrices with complex entries
$\mathbb{R}^{n\times m}$	The set of $n \times m$ matrices with real entries
$x_{\mathcal{R}}$	The In-phase (Real) part of x
$x_{\mathcal{I}}$	The Quadrature-phase (Imaginary) part of x

remove ISI of QAM systems. RC is a framework for computation like a recurrent neural network (RNN) that allows for the black box modeling of dynamical systems. RC appeared as a generic name for designing a new research stream including mainly Echo State Networks (ESNs) [6] and Liquid State Machines (LSMs) [7]. Together they appeared under the umbrella term of RC: both approaches provide a reservoir with computational complexity that can be harnessed to solve a variety of nonlinear problems. These two methods built-in many highly challenging ideas which toward a new computational paradigm of neural networks, have quickly made RC become popular.

In this work, we focus the study on BSD using RC technique to remove ISI of QAM systems even if the training sequence is either too short or absent. It is noteworthy that the proposed approach could not be classified as one of the above two types of blind equalization techniques since it can estimate directly the input sequence without getting the equalizer coefficients and estimating channel impulse response at the receiver. In addition, the proposed approach guarantees a convergence within a short data packet, therefore, can work in systems with a much shorter data record and faster time-varying channels.

The rest of this paper is organized as follows. Section 2 presents the QAM and BSD problem formulation. Next, in Section 3, a new BSD approach along with the main theoretical results are described. A RC network is constructed to solve the special issue of BSD, with reservoir weight matrix generated via the reduced QR decomposition from the view of receiving signal subspace instead of selected randomly. And the variation rule of initial vector which is changed by reservoir weight is shown. Meantime, the activation function and readout function of this RC network are designed, respectively. In Section 4, the readout weight of the RC network is trained and updated by support vector regression (SVR) [8] with a Gaussian insensitive loss function and the complexity of the proposed algorithm is illustrated. In Section 5, simulation results are represented to verify the correctness and effectiveness of the new approach, and some special simulation phenomena of the algorithm are demonstrated, followed by conclusion and discussion in Section 6.

Throughout the paper, bold letters denote matrices or vectors, and the notation, shown in Table 1, is used.

2. QAM concept and BSD problem

QAM is widely used in many digital data radio and optical coherent communications. For domestic broadcast applications for example, high-order modulations (e.g., 64QAM) are often used in digital cable television and cable modem applications [11]. A variety of QAM are available and the most common one is M-QAM, $M = 4, 8, \cdots, 64$. By moving to higher-order constellations, it is possible to transmit more bits per symbol, which reduces bandwidth. However, the performance of QAM can seriously be degraded due to ISI as the number of levels increases. A typical BSD setup is depicted in Fig. 1 using a simple system diagram. The complex baseband model for a QAM data communication system consists of an unknown linear time-invariant channel $\{h\}$. The transmitter generates a sequence of complex-valued random input data $\{s_N\}$, each element of which belongs to a complex alphabet of QAM symbols. The data sequence $\{s_N\}$ is sent through a complex channel whose output x_N is observed by the receiver. The function of BSD at the receiver is to estimate the delayed version of original data $\{s_N\}$, $\{s_{N-k}\}$, from the received signal x_N (where k is bulk delay).

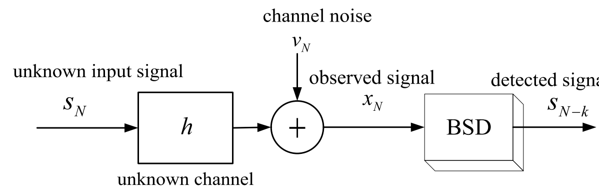

Fig. 1. Baseband communication system model.

This system identification scenario is a linear single-input multiple-output (SIMO) multichannel model which can always be treated as a collection of single-input single-output (SISO) models. It is well known that fractionally spaced samples of a single baseband received signal lead to a SIMO model. In order to simplify the presentation of the proposed sequence estimation method, without loss of generality, in a noise-free environment, a SIMO channel system whose i-th sub-channel output is

$$x_i(t) = \sum_{\tau=0}^{L_h-1} h_i(\tau)s(t-\tau) \tag{1}$$

where $s(t)$ is the QAM input signal and $h_i(\tau)$ is the i-th channel impulse response with length of L_h. Clearly, the column vector $\mathbf{x}(t)$ can be expressed as

$$\mathbf{x}(t) = \left[\mathbf{h}_1, \mathbf{h}_2, \cdots, \mathbf{h}_q\right]\mathbf{s}(t) \tag{2}$$

where $\mathbf{x}(t) \in \mathbb{C}^{q\times 1}$, q denotes the over-sample factor. And

$$\mathbf{h}_p = \left[h_p(0), h_p(1), \cdots, h_p(L_h-1)\right], p = 1, 2, \cdots, q \tag{3}$$

and

$$\mathbf{s}(t) = [s(t), s(t-1), \cdots, s(t-L_h+1)]^T \tag{4}$$

Thus the received data matrix can be formulated as

$$\mathbf{X} = \mathbf{S\Gamma} \tag{5}$$

where

$$\mathbf{S} = [\mathbf{s}_N(t), \mathbf{s}_N(t-1), \cdots, \mathbf{s}_N(t-L_h-L_w)] \in \mathbb{C}^{N\times(L_h+L_w+1)}, \tag{6}$$

and

$$\mathbf{s}_N(t) = [s(t), s(t-1), \cdots, s(t-N+1)]^T \tag{7}$$

is the transmitted signal matrix; N is the source signal length; and $\mathbf{\Gamma} = \left[\mathbf{H}_1, \mathbf{H}_2, \cdots, \mathbf{H}_q\right]$ with

$$\mathbf{H}_p = \begin{bmatrix} \mathbf{h}_p & 0 & \cdots & 0 \\ 0 & \mathbf{h}_p & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \mathbf{h}_p \end{bmatrix}, p = 1, 2, \cdots, q \tag{8}$$

where $\mathbf{H}_p \in \mathbb{C}^{(L_w+1)\times(L_h+L_w+1)}$.