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Independent component analysis based digital signal processing in coherent optical fiber communication systems

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ABSTRACT

In this paper, channel equalization techniques for coherent optical fiber transmission systems based on independent component analysis (ICA) are reviewed. The principle of ICA for blind source separation is introduced. The ICA based channel equalization after both single-mode fiber and few-mode fiber transmission for single-carrier and orthogonal frequency division multiplexing (OFDM) modulation formats are investigated, respectively. The performance comparisons with conventional channel equalization techniques are discussed.

1. Introduction

Advanced channel equalization techniques are highly desired in current coherent optical fiber transmission systems. With the help of digital coherent receivers, many record transmission results have been made in single-mode fiber (SMF), including maximum capacity [1–3] and maximum capacity distance product [4]. Since then, it is difficult to further increase the channel capacity (or capacity distance product), if we continue to stay with the SMF platform. To overcome this bottleneck, space division multiplexing (SDM) over multi-core fiber (MCF) or few-mode fibers (FMF) is regarded as a promising solution to further improve the channel capacity in optical fiber transmission systems [5]. Since the optical signal is transmitted independently in the MCF [6–8], most channel equalization techniques are focused on the FMF transmission with multiple input multiple output (MIMO) digital signal processing (DSP) [9–11].

One of the key distinguishing features of a digital coherent receiver is its ability to compensate for transmission impairments in fiber, including chromatic dispersion, polarization mode dispersion (PMD), mode crosstalk and polarization rotations [12–14]. Since the channel compensation for chromatic dispersion is static, most channel equalization techniques mainly consider the dynamic channel equalization, where the time-varying effects are taken into account, such as PMD, mode crosstalk and polarization rotations.

In this paper, channel equalization techniques based on independent component analysis (ICA) are discussed in coherent optical fiber transmission systems [15–19]. The most two popular modulation formats, single-carrier and orthogonal frequency division multiplexing (OFDM) are considered in both SMF and FMF systems, respectively. The performance comparisons between ICA based channel equalizer and conventional channel equalizer are also discussed.
Notation: $(\cdot)^{\mathrm{T}}$ and $(\cdot)^{H}$ represent transpose and Hermitian operators, respectively. $\|\cdot\|_{\mathrm{F}}$ is the matrix Frobenius norm. $E\{\cdot\}$ represents expectation. Bold face letters denote vectors and matrices.

2. Principle of independent component analysis

ICA is a method for finding underlying factors or components from multidimensional statistical data. It is noted that the ICA is effective only when the components are both statistically independent and non-Gaussion. In this section, we will briefly introduce the basic concepts and principles of ICA for blind sources separation (BSS).

For example, in a cocktail party, people speak in the same room at different positions, so that Microphones at different positions will record a mixture of the original voice signals with slightly different weights. For simplicity, there are four amplitude source signals $s_1(t), s_2(t), s_3(\mathrm{t})$ and $s_4(t)$, and also four observed signals $x_1(t), x_2(t), x_3(t)$ and $x_4(t)$ at

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time point t. The $x_i(t)$ are the weighted sums of the $s_i(t)$, where the coefficients are denoted by a_{ij}:

$$\begin{aligned} \boldsymbol{x}_1(t) &= \boldsymbol{a}_{11}\boldsymbol{s}_1(t) + \boldsymbol{a}_{12}\boldsymbol{s}_2(t) + \boldsymbol{a}_{13}\boldsymbol{s}_3(t) + \boldsymbol{a}_{14}\boldsymbol{s}_4(t) \\ \boldsymbol{x}_2(t) &= \boldsymbol{a}_{21}\boldsymbol{s}_1(t) + \boldsymbol{a}_{22}\boldsymbol{s}_2(t) + \boldsymbol{a}_{23}\boldsymbol{s}_3(t) + \boldsymbol{a}_{24}\boldsymbol{s}_4(t) \\ \boldsymbol{x}_3(t) &= \boldsymbol{a}_{31}\boldsymbol{s}_1(t) + \boldsymbol{a}_{32}\boldsymbol{s}_2(t) + \boldsymbol{a}_{33}\boldsymbol{s}_3(t) + \boldsymbol{a}_{34}\boldsymbol{s}_4(t) \\ \boldsymbol{x}_4(t) &= \boldsymbol{a}_{41}\boldsymbol{s}_1(t) + \boldsymbol{a}_{42}\boldsymbol{s}_2(t) + \boldsymbol{a}_{43}\boldsymbol{s}_3(t) + \boldsymbol{a}_{44}\boldsymbol{s}_4(t) \end{aligned} \tag{1}$$

where a_{ij} are constant coefficients that represent the mixing weights. It is noted that the coefficients are available, only if all the properties of the physical mixing system are known, which is quite difficult in practical situation. As an illustration, the waveforms of the original source signals $s_i(t)$ are shown in Fig. 1(a). The four linear mixtures $x_i(t)$ are shown in Fig. 1(b), where the mixtures look like completely noise. The purpose is to find the original signals from the mixtures $x_i(t)$, which can be viewed as the BSS problem. Blind means that we know very little information of the original sources and mixing matrix.

A general idea to solve the BSS problem is to consider the statistical independence of the signals. In fact, if the signals are not Gaussian, the coefficients w_{ij} can be determined, where the recovered signals $y_i(t)$ can be expressed as:

$$\begin{aligned} \boldsymbol{y}_1(t) &= \boldsymbol{w}_{11}\boldsymbol{x}_1(t) + \boldsymbol{w}_{12}\boldsymbol{x}_2(t) + \boldsymbol{w}_{13}\boldsymbol{x}_3(t) + \boldsymbol{w}_{14}\boldsymbol{x}_4(t) \\ \boldsymbol{y}_2(t) &= \boldsymbol{w}_{21}\boldsymbol{x}_1(t) + \boldsymbol{w}_{22}\boldsymbol{s}_2(t) + \boldsymbol{w}_{23}\boldsymbol{x}_3(t) + \boldsymbol{w}_{24}\boldsymbol{x}_4(t) \\ \boldsymbol{y}_3(t) &= \boldsymbol{w}_{31}\boldsymbol{x}_1(t) + \boldsymbol{w}_{32}\boldsymbol{s}_2(t) + \boldsymbol{w}_{33}\boldsymbol{x}_3(t) + \boldsymbol{w}_{34}\boldsymbol{x}_4(t) \\ \boldsymbol{y}_4(t) &= \boldsymbol{w}_{41}\boldsymbol{x}_1(t) + \boldsymbol{w}_{42}\boldsymbol{s}_2(t) + \boldsymbol{w}_{43}\boldsymbol{x}_3(t) + \boldsymbol{w}_{44}\boldsymbol{x}_4(t) \end{aligned} \tag{2}$$

It is noted that if the recovered signals $y_i(t)$ are statistically independent, then they are assumed to be equal to the original source signals $s_i(t)$. Based on the statistical independence of the information, the recovered signals can be obtained as shown in Fig. 1(c). It can be seen that the observation information is noise-like signal, and the original source signals can be estimated by considering information on the independence only.

From Fig. 1, the problem of BSS can be viewed to find a linear representation where the components are statistically independent. Therefore, the ICA can be illustrated in matrix representation form. A set of independent components $(s_1(t), s_2(t), \ldots, s_n(t))$ as original source signals is given, where t is the sample index. The observations of random variables $(x_1(t), x_2(t), \ldots, x_n(t))$ are then generated as

$$\begin{bmatrix} x_1(t) \\ x_2(t) \\ \vdots \\ x_n(t) \end{bmatrix} = \mathbf{A} \begin{bmatrix} s_1(t) \\ s_2(t) \\ \vdots \\ s_n(t) \end{bmatrix} \tag{3}$$

where $\mathbf{A}$ is unknown matrix. ICA now consists of estimating both the matrix $\mathbf{A}$ and $s_i(t)$, when the observations $x_i(t)$ are given. The ICA can then be defined as: find a linear transformation given by a de-mixing matrix $\mathbf{W}$, so that the random variables $y_i(t)$ are as independent as possible, which are given by:

$$\begin{bmatrix} y_1(t) \\ y_2(t) \\ \vdots \\ y_n(t) \end{bmatrix} = \mathbf{W} \begin{bmatrix} x_1(t) \\ x_2(t) \\ \vdots \\ x_n(t) \end{bmatrix} \tag{4}$$

where the estimation of $\mathbf{W}$ can be regarded as the inverse of $\mathbf{A}$. For the DSP in optical fiber transmission systems, three assumptions are made to implement the ICA algorithms for channel equalization: (1) the independent components are assumed to be statistically independent; (2) the distribution of the independent components are non-Gaussian; (3) the mixing matrix $\mathbf{A}$ is a square matrix. It can be seen that the three assumptions can be easily satisfied in the coherent optical fiber transmission systems.

Generally, many ICA algorithms can be applied to achieve blind source separation. In this paper, complex maximum likelihood (CML) algorithm is chosen due to its easy implementation in the hardware, which is considered to be most practical in the real-time systems [20]. In the CML algorithm, the estimation of $\mathbf{W}$ after k-th iteration $\mathbf{W}_k$ can be expressed as

$$\mathbf{W}_k = \mathbf{W}_{k-1} + \mu\left[\mathbf{I} - \varphi(\mathbf{Y})\mathbf{Y}^H\right]\mathbf{W}_{k-1} \tag{5}$$

where μ is the step index, $\mathbf{I}$ is a $n \times n$ identity matrix, $\varphi(\mathbf{Y})$ is a nonlinear function for the matrix $\mathbf{Y}$ as $\varphi(\mathbf{Y}) = \tan h(\mathbf{Y})$ and $\mathbf{Y}$ is $\left[y_1(t), y_2(t) \cdots y_n(t)\right]^T$. The estimation of $\mathbf{W}$ can be obtained after many iterations until $\mathbf{W}_k$ converges. The performance of the ICA algorithms can be evaluated using inter-symbol interference (ISI) or the normalized Amari index [20], which is defined as

$$\begin{aligned} \mathrm{ISI} = \frac{1}{2 \times n \times (n-1)} &\left[\sum_{i=1}^{n}\left(\sum_{j=1}^{n}\frac{|p_{ij}|}{\max_k |p_{ik}|} - 1\right)\right. \\ &+ \left.\sum_{j=1}^{n}\left(\sum_{i=1}^{n}\frac{|p_{ij}|}{\max_k |p_{kj}|} - 1\right)\right] \end{aligned} \tag{6}$$

where p_{ij} is the element of the matrix $\mathbf{P} = \mathbf{WA}$. It is noted that lower value of ISI indicates better separation performances. The algorithm is not performing adequately if the value of ISI is larger than −20 dB. A simulation is conducted to verify the effectiveness of the chosen algorithm for source separation. In the simulation, 6 sequences are generated with 4 quadrature amplitude modulation (4QAM) format. The 6 sequences are then randomly mixed by a 6 × 6 complex-valued matrix $\mathbf{A}$. Additive white Gaussian noise is then added to the mixed sequences with signal-to-noise ratio (SNR) of 15 dB and 25 dB, respectively. According to Eq. (6), the ISI values with increasing number of samples and iterations are shown in Fig. 2(a) and (b), respectively. In the simulation, the number of samples (iterations) is fixed to study the effect of number of iterations (samples). From Fig. 2(a) and (b), lower value of ISI can be obtained with increasing number of samples and iterations.

3. Channel equalization in single-mode fiber systems

3.1. Single-carrier modulation format

In the context of optical communications, ICA is first considered for polarization demultiplexing applications in the single-carrier fiber transmission systems. To date, the most widely deployed channel equalizers for single-carrier format are based on the constant modulus algorithm (CMA) [12,13,21], where the equalizer is designed to minimize variations in the amplitudes of the received samples in blind mode. However, the CMA algorithm may cause the singularity problem of "converge to the same source" [21]. In [22], it has been demonstrated that ICA can solve the converge-to-the-same-source problem of CMA while maintaining similar polarization tracking capabilities. In [23], ICA is then used for blind demultiplexing of 16-QAM polarization multiplexed signals. In [24], ICA is proposed for arbitrary constellations with multiple amplitude levels. It is shown that ICA significantly outperforms CMA in terms of convergence rates. However, the choice of the initial matrix has great effect on the algorithm performance.

In the polarization demultiplexing techniques above, single-tap ICA algorithm is applied. Recently, channel equalization based on multi-tap ICA for single-carrier modulation format is proposed considering the channel polarization impairments induced by PMD and polarization dependent loss [25]. The error-rate performance of ICA is found to be comparable to that of CMA in the case of 4-QAM transmission, but exceeds it considerably in the case of 16-QAM. However, multi-tap ICA can only work in the condition of one sample per symbol, which is not suitable in the current real application scenario. Therefore, in the channel equalization of ICA, the research is mainly focus on the polarization demultiplexing and fast convergence.

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