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Low-complexity single-channel blind source separation

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Abstract

For the time-frequency overlapped signals, a low-complexity single-channel blind source separation (SBSS) algorithm is proposed in this paper. The algorithm does not only introduce the Gibbs sampling theory to separate the mixed signals, but also adopts the orthogonal triangle decomposition-M (QRD-M) to reduce the computational complexity. According to analysis and simulation results, we demonstrate that the separation performance of the proposed algorithm is similar to that of the per-survivor processing (PSP) algorithm, while its computational complexity is sharply reduced.

Keywords single-channel, separation, Gibbs sampling, QRD-M

1 Introduction

To improve the frequency spectrum efficiency and communication security, several novel communication schemes are proposed and applied, including full duplex, physical-layer network coding (PNC) and paired carrier multiple access (PCMA). In these schemes, the transmitter and receiver simultaneously transmit useful signals in the same frequency, which are mixed in the air, so the communication signal is the mixed signal. Besides, the electromagnetic environment is becoming more complex with the development of wireless communication, and the frequency interval between the systems becomes smaller, which will generate the mutual interference from different systems. Thus, the phenomenon that multiple time-frequency overlapping signals are simultaneously picked up by single receiver is becoming more prevalent. To recover the mixed signals, the blind source separation algorithm is required [1–2]. In some scenarios, only single channel is available. At this moment, the mixed signals must be recovered from single receiving signal by the SBSS algorithm [3–7], which has been a researching hotspot at present.

Though the SBSS is an ill-condition mathematical issue, it is still realizable because the sample number of the modulation signal is limited, and the realizable conditions are given in Ref. [3]. At present, the SBSS algorithms can be classified three categories, including the transform-domain filter [4], multi-dimensional mapping [5] and joint parameter estimation (JPE) [6–7]. In these algorithms, the separation performance of JPE is optimal, which mainly includes the particle filter (PF) and PSP algorithms. Compared with PF, the PSP does not only reduce the computational complexity, but also improves the separation performance, and it has been proved that the PSP is close to the theoretical threshold of the single-channel separation performance. While the modulation order of the mixed signal becomes more, the computational complexity of PSP is still exponentially increasing. Thus, the PSP is not suitable to separate the high-order mixed signal.

To solve the above problems, this paper proposes a novel SBSS algorithm. In the proposed algorithm, the Gibbs sampling theory is applied to separate the mixed signals, and the QRD-M decomposition algorithm is introduced to reduce the computational complexity. According to analysis and simulation results, we can conclude that the computational complexity of the proposed algorithm is much less than that of the existing

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SBSS algorithms, and the computational advantage becomes more outstanding with the increase of the modulation order. Besides, the performance of the proposed algorithm keeps good separation preference, which is similar to the PSP algorithm. That is, the proposed algorithm can provide excellent separation ability with acceptable complexity for practical application.

The rest of the paper is organized as follows. Sect. 2 describes the system model. Sect. 3 introduces the proposed algorithm and analyzes its computational complexity. The simulation results and the conclusion are discussed in Sects. 4 and 5, respectively.

2 System model

Now, the SBSS algorithms mainly focus on the mixed signal consisted of two modulation signals, so this paper chooses the mixed signal based on two multiple phase shift keying (MPSK) signals as analysis model, which can be expressed as

$$y(t) = x_1(t) + x_2(t) + v(t) \tag{1}$$

where $x_i(t)$ is the ith modulation signal. $v(t)$ is the Gaussian noise, and $x_1(t)$, $x_2(t)$ and $v(t)$ are mutually independent. $x_i(t)$ may be written as

$$x_i(t) = h_i \mathrm{e}^{\mathrm{j}(2\pi\Delta f_i t+\phi_i)} \sum_{n=-\infty}^{\infty} s_{i,n} g_i(t - nT_i + \tau_i) \tag{2}$$

where h_i is the channel gain. Δf_i is the frequency offset. ϕ_i is the phase. $s_{i,n}$ is the nth symbol of the ith signal. T_i is the symbol period. τ_i is the transmission delay. and $g_i(t)$ is the pulse response. $g_i(t)$ may be expressed as

$$g_i(t) = g_{\mathrm{t}}^i(t) \otimes g_{\mathrm{c}}^i(t) \otimes g_{\mathrm{r}}^i(t) \tag{3}$$

where $\otimes$ stands for convolution. $g_{\mathrm{t}}^i(t)$ is the shaping pulse. $g_{\mathrm{c}}^i(t)$ is the channel response. and $g_{\mathrm{r}}^i(t)$ is the matching filter. The symbol periods of two signals are supposed to be same in this paper and $T_1 = T_2 = T$. By oversampling, the discrete signal can be written as

$$y_k = h_1 \mathrm{e}^{\mathrm{j}(2\pi\Delta f_1 k\frac{T}{m}+\phi_1)} \sum_{n=-\infty}^{\infty} s_{1,\left\lceil \frac{n}{m} \right\rceil} g_1\left(k\frac{T}{m} - nT + \tau_1\right) + \\ h_2 \mathrm{e}^{\mathrm{j}(2\pi\Delta f_2 k\frac{T}{m}+\phi_2)} \sum_{n=-\infty}^{\infty} s_{2,\left\lceil \frac{n}{m} \right\rceil} g_2\left(k\frac{T}{m} - nT + \tau_2\right) + v\left(k\frac{T}{m}\right) \tag{4}$$

where m is the oversample rate. In general, $g_i(t)$ is equivalent to a raised cosine roll-off filter, whose effective time is limited in $[-LT, LT]$, where $L = 1,2,3$ is the length of the effective time. Then Eq. (4) can be rewritten as

$$y_k = h_1 \mathrm{e}^{\mathrm{j}(2\pi\Delta f_1 kT+\phi_1)} \sum_{n=-mL}^{mL} s_{1,\left\lceil \frac{n+k}{m} \right\rceil} g_1(-nT + \tau_1) + \\ h_2 \mathrm{e}^{\mathrm{j}(2\pi\Delta f_2 kT+\phi_2)} \sum_{n=-mL}^{mL} s_{2,\left\lceil \frac{n+k}{m} \right\rceil} g_2(-nT + \tau_2) + v_k \tag{5}$$

Without loss of generality, it is supposed that τ_1 is not equal to τ_2. Extracting from different starting time in Eq. (5), the

$$y_k^i = h_1 \mathrm{e}^{\mathrm{j}(2\pi\Delta f_1 kT+\phi_1)} \sum_{n=-L}^{L} s_{1,n+k} g_1(-nT + \tau_1 - \rho_i) + \\ h_2 \mathrm{e}^{\mathrm{j}(2\pi\Delta f_2 kT+\phi_2)} \sum_{n=-L}^{L} s_{2,n+k} g_2(-nT + \tau_2 - \rho_i) + v_k^i \tag{6}$$

where $\rho_i = u_i T$, $0 \leqslant u_i < m$, i is 1 or 2. The vector expression of Eq. (6) is expressed as

$$y_k^i = \boldsymbol{F}^{(i)} \boldsymbol{s}_k + v_k^i \tag{7}$$

where $\boldsymbol{F}^{(i)} = (h_1 \mathrm{e}^{\mathrm{j}(2\pi\Delta f_1 kT+\phi_1)}(g_1(LT+\tau_1-\rho_i), g_1((L-1)T+\tau_1-\rho_i), \ldots, g_1(-LT+\tau_1-\rho_i)), h_2 \mathrm{e}^{\mathrm{j}(2\pi\Delta f_2 kT+\phi_2)}(g_2(LT+\tau_2-\rho_i), g_2((L-1)T+\tau_2-\rho_i), \ldots, g_2(-LT+\tau_2-\rho_i)))$, $\boldsymbol{s}_k = [s_{1,k-L}\ s_{1,k-L+1}\ \cdots\ s_{1,k+L}\ s_{2,k-L}\ s_{1,k-L+1}\ \cdots\ s_{2,k+L}]^{\mathrm{T}}$.

3 Low-complexity SBSS algorithm

In the proposed SBSS algorithm, the Gibbs sampling theory is applied to separate the mixed signals by the joint conditional probability (JCP), and the QRD-M decomposition algorithm is introduced to reduce the computational complexity. The flow diagram is shown in Fig. 1.

In Fig. 1, the discrete receiving signals are acquired by oversampling and extracting, and the effective samples are determined by the QRD-M decomposition algorithm. Finally, the Gibbs separation algorithm is applied to renew the detected symbols. After multiple iterations, the estimation results are exported.

In Eq. (5), there are many signal parameters to be estimated, including h_i, Δf_i, ϕ_i, T and τ_i, which may be estimated by the blind estimation methods in Refs. [8–9], so these parameters are considered to be known in this paper.