Deep Learning Based Single-Channel Blind Separation of Co-frequency Modulated Signals

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Abstract. This paper presents our results in deep learning (DL) based single-channel blind separation (SCBS). Here, we propose a bidirectional recurrent neural network (BRNN) based separation method which can recover information bits directly from co-frequency modulated signals after end-to-end learning. Aiming at the real-time processing, a strategy of block processing is proposed, solving high error rate at the beginning and end of each block of data. Compared with the conventional PSP method, the proposed DL separation method achieves better BER performance in linear case and nonlinear distortion case with lower computational complexity. Simulation results further demonstrate the generalization ability and robustness of the proposed approach in terms of mismatching amplitude ratios.

Keywords: Single-channel blind separation (SCBS) · Deep learning (DL) · Bidirectional recurrent neural network (BRNN)

1 Introduction

Single-channel blind separation (SCBS) of co-frequency overlapping signals is vital in blind signal processing and widely applied in paired carrier multiple access (PCMA) noncooperative communication. Since the two signals completely overlap in the time-frequency domain and are similar in power, conventional multi-user detection algorithms such as successive interference cancellation (SIC) is difficult to apply to SCBS.

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During the last two decades, several approaches have been utilized for two signals with distinct symbol rates, different amplitudes, and different roll-off factors. Further, particle filter (PF) [10] and per-survivor processing (PSP) [11] algorithm were investigated for realistic scenarios. Although the performance of these algorithms is superior, their applications are limited due to the high complexity. PSP is a maximum likelihood sequence estimate (MLSE) based algorithm that requires traversal search for possible symbols, of which the modulation order and channel memory length cause an exponential increase in time complexity. Thus, it is not practical to implement PSP in the scenario with channel of large memory length. Currently, researches mainly focus on the complexity reduction and the joint separation and decoding algorithms.

In recent years, deep learning (DL) has shown its overwhelming privilege in computer vision, speech recognition and natural language processing. Based on artificial neural network (ANN) theory, DL is essentially a general function approximation with the ability to learn from large data set. DL has also shown great promise in complex scenarios of physical layer communication [7] such as channel decoding [1], channel modeling [12], signal detection [3,6] and end-to-end communication system [2]. SCBS can be modeled as a joint detection problem of two signals. Recurrent neural network (RNN) is appropriate for learning sequences and has achieved excellent performance in single-signal detection [3] because it can make full use of the correlation between symbols. However, it has not been well investigated in overlapped signal detection. Therefore, we conduct research on DL based SCBS.

In this article, we introduce a DL approach for SCBS, and a novel bidirectional recurrent neural network (BRNN) based separation network, called SepNet, is proposed. Its computational complexity does not increase exponentially with the channel memory length. Considering the inter-symbol correlation (such as ISI) caused by the memory channel, the search for symbols is avoided, which greatly reduces the computational complexity and thus achieves a compromise between performance and complexity. Our contributions in this paper are as follows. First, a separation network based on BGRU is designed. Then, aiming at the real-time processing of continuous received signals, a strategy of block processing is proposed, and high error rate at the beginning and the end of each block of data is solved. Finally, the performance and robustness of the algorithm are verified. Simulation results show that the proposed method performs better than the PSP algorithm with lower complexity.

The rest of this paper is structured as follows. In the next section, we describe the system architecture and signal model for single-channel received mixtures of two modulated signals. Section 3 shows the architecture of the proposed SepNet and training details. In Sect. 4, the simulation results and interpretations are presented and conclusions are drawn in Sect. 5.

2 System Architecture and Signal Model

2.1 System Architecture

The architecture of co-frequency modulated signals with DL based SCBS is illustrated in Fig. 1. The baseband system is similar to the conventional ones. At the transmitter, the source signals are first modulated from bit streams to symbol sequences. Second, the symbol sequences are upsampled and then passed through the pulse shaping filters to limit their bandwidth and reduce inter-symbol interference (ISI). After that, two source signals are transmitted through the channel with noise and hardware impairments such as nonlinear distortion. Then, at the receiver, overlapping signals pass the matched filter and are downsampled.

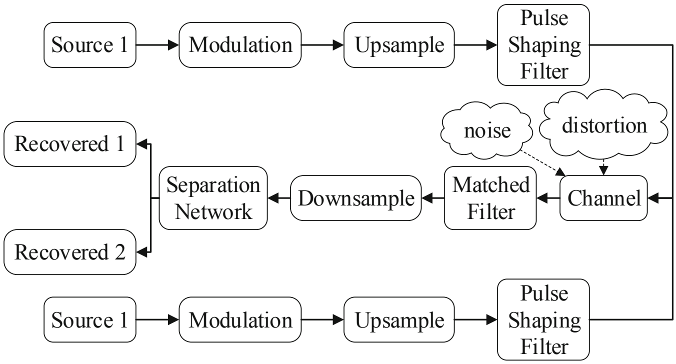

Fig. 1. The system architecture of DL based SCBS.

The SepNet should be trained with the labeled data to learn separation. After training stage, it takes the single-channel received data consisting of two overlapping signals as input, and then directly outputs two raw bit streams.

2.2 Signal Model

The received mixed signal model is described as follow. The baseband-equivalent single-channel received signal, which consists of two MPSK or MQAM signals, can be expressed as

$$y(t) = h_1 e^{j(\Delta\omega_1 t+\theta_1)} x_1(t) + h_2 e^{j(\Delta\omega_2 t+\theta_2)} x_2(t) + v(t), \tag{1}$$

where h_i denotes the amplitude of two modulated signals, $\Delta\omega_i$, θ_i, and $v(t)$ represent the carrier frequency offset, the initial phases, and additive white Gaussian noise (AWGN), respectively. The source signals $x_i(t)$ are defined as

$$x_i(t) = \sum_{n=-\infty}^{n=\infty} s_n^{(i)} g_i(t - nT + \tau_i), \tag{2}$$

where $s_n^{(i)}$ is nth symbol of two transmitted signals, which are independent and identically distributed (i.i.d.) random sequences; $g_i(t)$ is the pulse response of equivalent channel filters, which consist of shaping filters, channel filters and matched filters; T is the symbol period; $0 < \tau_i < T$ are the relative time delays between the two received modulated signals and the local clock reference.

Sampling the signals at symbol rate $1/T$, (1)–(2) can be rewritten respectively as

$$y_k = h_1 e^{j(\Delta\omega_1 kT+\theta_1)} x_k^{(1)} + h_2 e^{j(\Delta\omega_2 kT+\theta_2)} x_k^{(2)} + v_k, \quad (3)$$

$$x_k^{(i)} = \sum_{n=1-L_1}^{L_2} s_{k+n}^{(i)} g_i(-nT + \tau_k^{(i)}), \quad (4)$$

where $y_k = y(kT)$, $x_k^{(i)} = x_i(kT)$, $v_k = v(kT)$, $\tau_k^{(i)} = \tau_i(kT)$, and assuming that the pulse responses of the equivalent channel filters have finite duration from $(1-L_1)T$ to L_2T, $k = 0, 1..., K-1$ in a limited time.

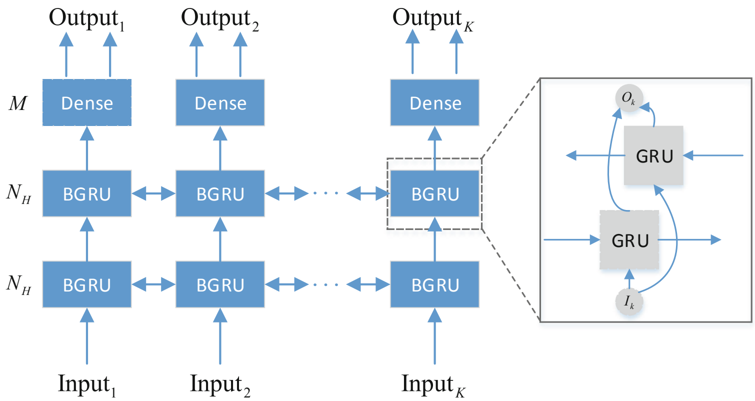

Fig. 2. The architecture of SepNet.

3 Separation Using Deep Learning

This section presents the SepNet for SCBS, and analyzes the motivation and necessity of the network structure design, while training details are specified afterwards.

3.1 Network Architecture

SCBS of co-frequency modulated signals is to detect the symbol sequences $s_{1:K}^{(i)} = \{s_1^{(i)}, s_2^{(i)}, ..., s_K^{(i)}\}$ from the set of received sampled points $y_{1:K} = \{y_1, y_2, ..., y_K\}$.

Symbol sequences detection can be treated as a classification problem in deep learning for each of the symbols $s_k^{(i)}$. For the sake of simplicity, QPSK is taken as an example, and other modulation methods can be analogized. A QPSK modulated symbol can be expressed as

$$s_k^{(i)} = \frac{1}{\sqrt{2}}(2b_{k,1}^{(i)} - 1) + j\frac{1}{\sqrt{2}}(2b_{k,2}^{(i)} - 1), \tag{5}$$

where $b_{k,1}^{(i)}$ and $b_{k,2}^{(i)}$ denote two bits of a symbol.

To make full use of the information between symbols, we intend to design the SepNet using BRNN architectures. It ensures that in the estimation of a symbol, future signal observations are taken into account, which overcomes the limitations of RNN.

Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are the most widely utilized unit structures in RNN, for solving long-term dependencies. GRU simplifies the structure of LSTM, making it easier to train and converge. In this work, we adopt the bidirectional GRU (BGRU) as the basic cell in the SepNet.

Figure 2 shows the structure of this network. It has two layers of BGRU, followed by a fully connected output layer. The BGRU is a combination of two GRUs. One of the GRUs is used for forward propagation and the other is used for backward propagation. At each time step, the output of two GRUs are concatenated as an output of the BGRU.

The activation function of the output layer is sigmoid $f_{Si}(a) = \frac{1}{1+e^{-a}}$ to force the output neurons to be in between zero and one, which can be interpreted as the probability of transmitting a bit equals one.

The amount of input node is 2 when the received signal is not oversampled. The number of hidden unit of BGRU is N_H, which is a hyper-parameter that can be adjusted. The amount of output node M depends on the modulation mode (e.g., for QPSK, the output number is 4 for 2 bits of two raw symbols).

The input of the SepNet is a noisy version of complex sequence of received signal, $y_1, y_2, ..., y_K$. At every time step, the real and imaginary part of a sampled symbol are concatenated as the input to the network:

$$\mathrm{Input_k} = \begin{bmatrix} \mathrm{Re}(y_k) \\ \mathrm{Im}(y_k) \end{bmatrix}, \tag{6}$$

The output is the concatenated estimated information bits $\hat{b}_{k,m}^{(i)}$ of two source signals:

$$\mathrm{Output}_k = \begin{bmatrix} \hat{b}_{k,1}^{(1)} \\ \hat{b}_{k,2}^{(1)} \\ \hat{b}_{k,1}^{(2)} \\ \hat{b}_{k,2}^{(2)} \end{bmatrix} = \begin{bmatrix} \mathrm{Pr}(b_{k,1}^{(1)} = 1 | y_{1:K}, \Theta) \\ \mathrm{Pr}(b_{k,2}^{(1)} = 1 | y_{1:K}, \Theta) \\ \mathrm{Pr}(b_{k,1}^{(2)} = 1 | y_{1:K}, \Theta) \\ \mathrm{Pr}(b_{k,2}^{(2)} = 1 | y_{1:K}, \Theta) \end{bmatrix}, \tag{7}$$

where Θ denotes the parameters in the SepNet, including weights and biases.

The decision bit $\tilde{b}_{k,m}^{(i)}$ is decided to be 0 or 1 according to whether $\hat{b}_{k,m}^{(i)}$ is greater than 0.5:

$$\tilde{b}_{k,m}^{(i)} = \begin{cases} 0 & 0 \leq \hat{b}_{k,m}^{(i)} < 0.5 \\ 1 & 0.5 < \hat{b}_{k,m}^{(i)} \leq 1 \end{cases} \tag{8}$$

and then bit error rate (BER) is calculated as a measurement of separation performance:

$$P_e = \frac{1}{4N} \sum_i \Pr(b_{k,m}^{(i)} \neq \tilde{b}_{k,m}^{(i)}), \tag{9}$$

In addition, the maximum time step of the network is fixed to $K_{max} = 80$ for the following reasons: First, the data stream arriving at the receiver is of arbitrary length and must be divided into blocks for real-time processing. Second, too many time steps will cause gradient disappearance, making it difficult to train the network.

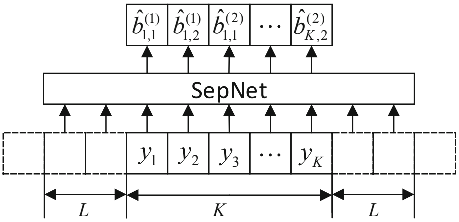

Fig. 3. Block processing method for received signal sequence.

However, since some of the information is not in this block, a large number of detection errors may occur for the symbol at the beginning and end of a block of data. To solve this problem, we divide the data stream into blocks and add L symbols to the beginning and end of each block of data as input to the network, as illustrated in Fig. 3, thereby improving the overall performance.

Algorithm 1. Proposed scheme

Input: Received signal sequence $y_{1:N} = \{y_1, y_2, ..., y_N\}$.

1: Divide the received overlapped signal sequence $y_{1:N}$ into $\lfloor \frac{N}{K} \rfloor$ blocks, each block $y_{jK:(j+1)K}$ contains K symbols.

2: **for** $j = 1 : \lfloor \frac{N}{K} \rfloor$ **do**

3: Add L symbols to the beginning and the end of each block to form a new block $y_{jK-L:(j+1)K+L}$.

4: Feed the new block $y_{jK-L:(j+1)K+L}$ to the SepNet and get the estimated sequences $\hat{b}_{jK:(j+1)K,m}^{(1)}$, $\hat{b}_{jK:(j+1)K,m}^{(2)}$.

5: By (8), we get the raw data bit sequences $\tilde{b}_{jK:(j+1)K,m}^{(1)}$ and $\tilde{b}_{jK:(j+1)K,m}^{(2)}$.

6: **end for**

Output: Reconsturcted raw data bit sequences $\tilde{b}_{1:N,m}^{(1)}$ and $\tilde{b}_{1:N,m}^{(2)}$.

The scheme of the proposed DL based separation is summarized in Algorithm 1.

3.2 Training Details

The goal of training stage is to minimize the distance between the detected symbols $\hat{s}_k^{(i)}$ and raw transmitted symbols $s_k^{(i)}$. Actually, as the output of our network is information bits, the objective function, or loss function is not related to the raw symbols $s_k^{(i)}$ but related to the transmitted data bits.

According to [4], there is a binary cross-entropy (CE) loss function suitable for this work, which is defined as

$$L_{CE} = \sum_{i,m,k} [b_{k,m}^{(i)} \log(\hat{b}_{k,m}^{(i)}) + (1 - b_{k,m}^{(i)}) \log(1 - \hat{b}_{k,m}^{(i)})], \tag{10}$$

where $\hat{b}_{k,m}^{(i)} \in [0, 1]$ and $b_{k,m}^{(i)} \in \{0, 1\}$ denote the output of the SepNet and the raw transmitted bit respectively, with k representing the symbol index and m being the mth bit in a symbol. It shows that in RNN, the loss function is defined as the sum of loss functions in all time steps.

The parameters Θ in the SepNet can be updated using the stochastic gradient descent (SGD) method:

$$\Theta \leftarrow \Theta - \alpha \frac{\partial L_{CE}}{\partial \Theta}, \tag{11}$$

where α is the learning rate, with initial values of 0.001 and decreases as the epochs increase. The gradient $\frac{\partial L_{CE}}{\partial \Theta}$ can be calculated by the use of back propagation through time (BPTT) approach [5].

Furthermore, a good initialization method is helpful for the convergence of the network and avoiding the gradient explosion and disappearance. Therefore, the Xavier method is adopted to initialize the network weights. To accelerate the training process and ease the gradient diffusion, batch normalization operation is added after the two BGRU unit layers.

4 Simulation Results

The target of our simulation is to demonstrate the performance of the DL methods for SCBS of co-frequency overlapping signals performs better than the conventional PSP method, and the model has the generalization ability to adapt to the amplitude shaking. For the sake of simplicity, we counted BER of two signals together instead of counting separately to characterize the performance of the different methods. In our simulation, root raised cosine filter was adopted as the shaping filter and matched filter. Its roll-off factor was set to be 0.35.

Labeled data is generated by simulation. For training set, According to (3)–(4)–(5), 8,000,000 symbols of received overlapped signal y_k and four corresponding raw data bits $b_{k,1}^{(1)}$, $b_{k,1}^{(2)}$, $b_{k,2}^{(1)}$, $b_{k,2}^{(2)}$ are randomly generated. The amount of

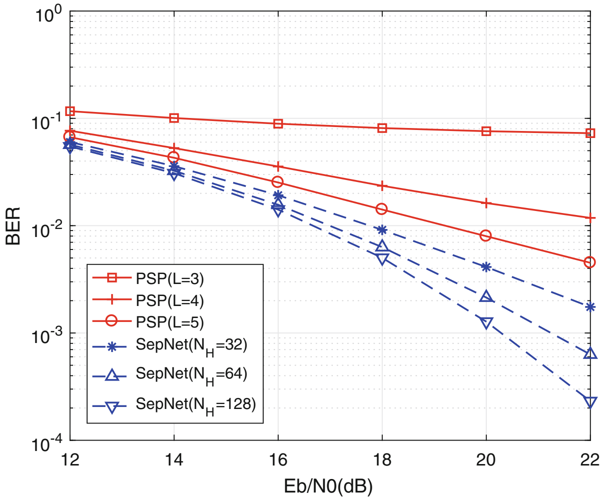

Fig. 4. BER of PSP and SepNet under the linear case.

testing set is $\frac{1}{10}$ of the training set, with other configurations remaining the same.

At first, we compare the BER performance of the conventional PSP method and the proposed SepNet method both in the linear case and the nonlinear case. Besides, we evaluate the BER performance of SepNet for different amplitude ratio, confirming the generalization ability of SepNet by its robustness in the mismatching amplitude ratio. Moreover, the effect of oversampling, training noise and the computational complexity is also discussed.

4.1 SepNet and PSP

Linear Case. The SepNet method is compared with the conventional PSP method for SCBS under the linear case, where the system is not affected by nonlinearity. In this case, we fix $\tau_1 = 0.4T$, $\tau_2 = 0.6T$, and $\Delta\omega_1 = \Delta\omega_2 = 0$, $\theta_1 = \theta_2 = 0$, $h_1 = h_2 = 1$, $L_1 = L_2 = 6$.

We compare the two algorithms at $L = 3, 4, 5$ and $N_H = 32, 64, 128$. As illustrated in Fig. 4 and Table 1, the performance of SepNet exceeds the PSP and the complexity is reduced. Compared with PSP ($L = 5$), SepNet ($N_H = 32$) has a performance gain of about 1 dB, while the computational complexity is only 0.058% of the former. As N_H increases, the separation performance of SepNet increases. It is because the network has a more powerful representation ability when the number of hidden unit increases. When the estimated L in the PSP is smaller than the actual channel memory length $L = L_1 + L_2 = 12$, the correlation between symbols is insufficient. Therefore, although the FLOPs of PSP ($L = 5$) is sufficiently high, the performance is still not ideal.

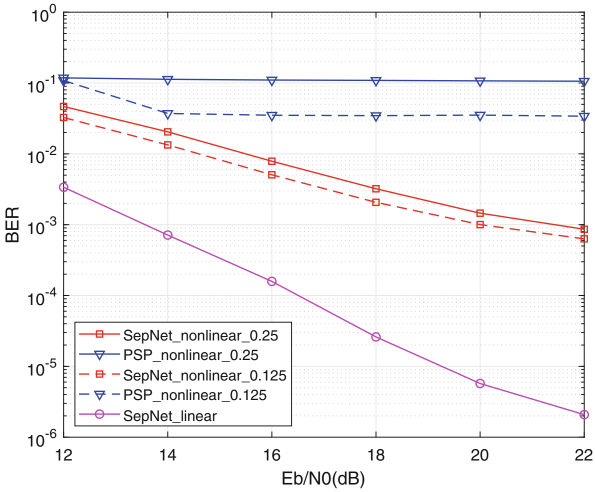

Fig. 5. BER of PSP and SepNet under the nonlinear case.

Nonlinear Case. To demonstrate the flexibility of separation network adaptable to non-ideal factors, nonlinear distortion is appended to the simulations. As indicated in [9], assuming that there are nonlinear amplifiers in the communication system, and the amplitude-to-amplitude (AM-AM) distortion is described by a third-order nonlinear function $f(x) = x - \beta_3|x|^2x$, where $\beta_3 = 0.25$ for travelling wave tube amplifiers (TWTA) and $\beta_3 = 0.125$ for solid-state amplifiers (SSA).

We compare the BER performance of the SepNet method and the PSP method under the nonlinear distortion. In this case, $\theta_1 = 0.2$, $\theta_2 = 0.5$, while other parameters are consistent with the setup of linear case. As shown in Fig. 5, the SepNet method significantly outperform the PSP method under the nonlinear distortion, which can be explained as nonlinear activation in the neural network introduces nonlinearity so as to realize nonlinear separation.

4.2 Performance Evaluation

Effect of Different Amplitude Ratios and Mismatching Robustness. Assuming that two signals overlapping in different amplitude ratios h_2/h_1 with other parameters are the same, correspondingly, the network is trained at different amplitude ratios. It can be seen in Fig. 6 that as the amplitude ratio decreases, the separation performance of the two signals is improved.

BER with amplitude ratio mismatching between training stage and testing stage is also illustrated in Fig. 6. The results are obtained by training the network under the amplitude ratio of $h_2/h_1 = 0.6$ while testing it under $h_2/h_1 = 0.8$ and $h_2/h_1 = 0.9$. The robustness of the SepNet, as indicated by the BER performance under the mismatched condition is close to that of matched condition, suggests that it has the generalization ability to avoid amplitude shaking.

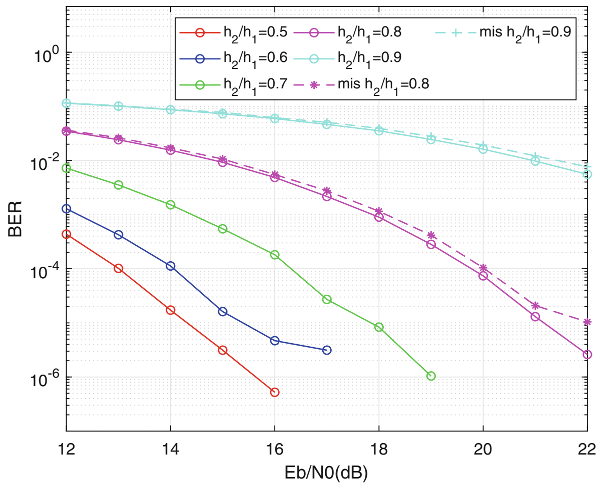

Fig. 6. BER of different amplitude ratios and amplitude ratios mismatching. Where mis $h_2/h_1 = 0.8$ and mis $h_2/h_1 = 0.9$ represent the performance of SepNet trained at the amplitude ratio of 0.6 whereas tested at 0.8, 0.9, respectively.

Effect of Oversampling and Training Noise. To investigate the effect of oversampling and training noise, we train and test the network under the same setup of the linear case except for oversampling and different training noise. It can be seen in Fig. 7 that the performance of two networks trained under AWGN ($E_b/N_0 = 12\,\text{dB}$) is better than that of no AWGN added to the training stage. According to [6], adding noise can make more training examples lie at the decision boundary to make full use of it. It shows that training with noise strengthens the generalization ability of the network and reduces the over-fitting of the training data, which improves the performance of separation.

In actual communication, the bandwidth of the modulated signal is larger than the symbol rate since the shaping filter is used. Therefore, when the complex signal is sampled at the symbol rate, the Nyquist sampling theorem is not satisfied, resulting in information loss. In other words, the oversampling method can compensate for the information loss caused by symbol rate sampling. Compared with the original network, the input of the network that processes the oversampled signal becomes p times the original input, that is, the number of input nodes becomes $2p$. As observed in Fig. 7, for the network trained under AWGN, the oversampled signal outperforms the signal without oversampled. However, for the network trained without AWGN, the performance of oversampled signal is worse than the signal without oversampled. This is because the input features of the oversampled signal are more complicated, but no AWGN is added, which makes the network difficult to converge.

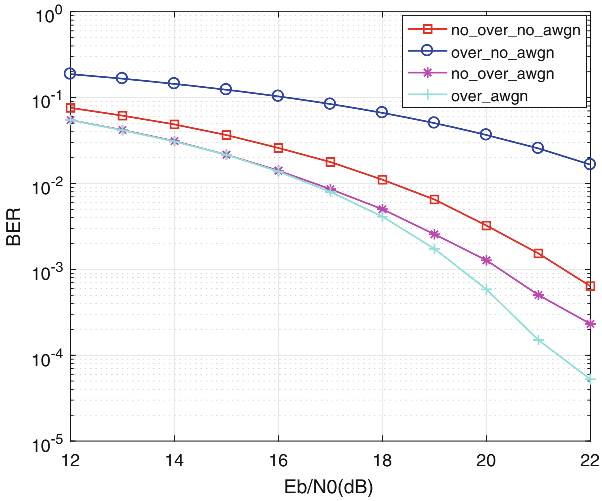

Fig. 7. BER of whether oversampled and whether added AWGN: (a) oversampled and not oversampled case marked as "_over" and "no_over" (b) added AWGN and not added AWGN case denoted as "_awgn" and "no_awgn".

Table 1. Computational complexities of SepNet and PSP

	Conditions	FLOPs
PSP	$L = 3$	106496
	$L = 4$	2228224
	$L = 5$	44040192
SepNet	$N_H = 32$	25344
	$N_H = 64$	99840
	$N_H = 128$	396288

4.3 Complexity Analysis

In Table 1, we compare the computational complexities of SepNet and PSP [2] in terms of the amount of floating-point multiplication-adds (FLOPs) to separate one QPSK symbol. Let M be the modulation level (eg. for QPSK, $M = 4$), and recall that L is the channel memory length. I_j and O_j denote the dimension of input and output of jth layer in SepNet, respectively.

The FLOPs of PSP can be expressed as $(8L + 2)M^{2L}$ for the number of states in trellis is $M^{2(L-1)}$ and each state has M^2 branches, while each branch metric needs $8L + 2$ real multiplication-adds [8]. For SepNet, the number of FLOPs is $\sum_j 6((I_j + O_j)O_j + O_j)$ as jth layer in BGRU has $6((I_j + O_j)O_j + O_j)$ network parameters and each parameter needs a real multiplication-adds [4]. It shows that FLOPs of PSP increase exponentially with L, whereas FLOPs of SepNet can be flexibly set. Therefore, SepNet is more efficient than PSP in computational complexity.

5 Conclusions

In this paper, we propose a novel BRNN based separation method SepNet for SCBS. The SepNet works in an end-to-end manner, which can recover information bits directly from overlapping signal. Besides, a strategy of block processing is proposed for real-time processing. Compared with the conventional PSP method, the SepNet achieves better BER performance in linear case and nonlinear distortion case with lower computational complexity. Moreover, the SepNet shows its generalization ability and robustness in the scenario of mismatching amplitude ratio. Future work can be extended to separate the overlapping signals with higher modulation level, and collect practical communication data to retrain and fine-tune the SepNet for practical deployment.

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