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Faster-than-Nyquist rate communication via convolutional neural networks-based demodulators

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Abstract: A demodulator based on convolutional neural networks (CNNs) is proposed to demodulate bipolar extended binary phase shifting keying (EBPSK) signals transmitted at a faster-than-Nyquist (FTN) rate, solving the problem of severe inter symbol interference (ISI) caused by FTN rate signals. With the characteristics of local connectivity, pooling and weight sharing, a six-layer CNNs structure is used to demodulate and eliminate ISI. The results show that with the symbol rate of 1.07 kBd, the bandwidth of the band-pass filter (BPF) in a transmitter of 1 kHz and the changing number of carrier cycles in a symbol $K=5, 10, 15, 28$, the overall bit error ratio (BER) performance of CNNs with single-symbol decision is superior to that with a double-symbol united-decision. In addition, the BER performance of single-symbol decision is approximately 0.5 dB better than that of the coherent demodulator while K equals the total number of carrier circles in a symbol, i.e., $K=N=28$. With the symbol rate of 1.07 kBd, the bandwidth of BPF in a transmitter of 500 Hz and $K=5, 10, 15, 28$, the overall BER performance of CNNs with double-symbol united-decision is superior to those with single-symbol decision. Moreover, the double-symbol united-decision method is approximately 0.5 to 1.5 dB better than that of the coherent demodulator while $K=N=28$. The demodulators based on CNNs successfully solve the serious ISI problems generated during the transmission of FTN rate bipolar EBPSK signals, which is beneficial for the improvement of spectrum efficiency.

Key words: bipolar extended binary phase shifting keying (EBPSK); convolutional neural networks (CNNs); faster-than-Nyquist (FTN) rate; double-symbol united-decision

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With the rapid development of information technology, many wireless broadband access technologies, such as WiMAX, 3G and HSDPA[1−3], have been widely used, and the radio spectrum has become the most essential source for all countries. Hence, it will be advantageous to transmit data symbols with a faster-than-Nyquist (FTN) rate. However, since the improvement of spectrum efficiency via FTN rate transmission is always accompanied with severe inter-symbol interference (ISI), selecting a suitable demodulator for the FTN rate receiver is a very important challenge.

The current method of solving the demodulation problem of FTN rate signals mainly consists of two steps: using channel equalization and inverse filtering to eliminate ISI, then adopting regular methods, such as coherent demodulation or integral decision of amplitude. From the aspect of the frequency domain, adopting the method of channel equalization and inverse filtering to eliminate ISI is like using an equivalent band-stop filter (for carrier modulation signal) or a high-pass filter (for baseband signal) to compensate for the high-frequency component of the receiving signal. This inevitably increases the out-of-band noise and therefore results in the deterioration of the signal to noise ratio (SNR) before demodulation.

The convolutional neural network (CNN) is a type of artificial neural network (ANN), which has been successfully applied to image recognition, computer vision and speech recognition[4−6]. In the application of image recognition, the input for CNN is the image pixels without any pre-processing, which avoids the complex procedures of feature extraction and data reconstruction[7]. These achievements inspire us to try CNNs for the demodulation of FTN signals.

Bipolar extended binary phase shifting keying (bipolar EBPSK) is proposed as an energy efficient version of EBPSK, which is a type of spectral efficient modulation method[8]. This paper, therefore, proposes a novel CNN demodulator for faster-than-Nyquist rate signals, which directly operates on the input sampling sequence of bipolar EBPSK signals. Since the popular BPSK modulation is also a special category of bipolar EBPSK modulations, it will ensure the universality of our method.

1 Bipolar EBPSK Modulation System and Faster-than-Nyquist Rate Communication

1.1 Bipolar EBPSK modulation system

EBPSK, as a type of asymmetric modulation with high spectrum efficiency, is defined as[9]

$$g_0(t)=\begin{cases}A_1\sin 2\pi f_c t & 0\leqslant t\leqslant\tau\\ A_2\sin 2\pi f_c t & \tau<t<T\end{cases}$$

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$$g_1(t)=\begin{cases}B\sin(2\pi f_c t+\theta) & 0\leqslant t<\tau, 0\leqslant\theta\leqslant\pi\\ A_2\sin 2\pi f_c t & \tau\leqslant t<T\end{cases} \tag{1}$$

where A_1, A_2 and B are the amplitudes; θ is the modulating angle; T denotes the symbol duration; f_c is the carrier frequency; $g_0(t)$ and $g_1(t)$ represent the modulated signals for transmission "0" and "1", respectively. The number of carrier cycles in a symbol is $N=Tf_c$, which is chosen according to both the size of the CNN specific kernel and the number of CNN layers. $\tau=K/f_c$ denotes the duration of the phase changing with $K\leqslant N$ carrier cycles.

For convenience in the following analyses, by setting $\theta=\pi$, $\omega_c=2\pi f_c$, $A_1=B=A$ and $A_2=0$, the bipolar EBPSK as a simple version of the EBPSK can be obtained as[10]

$$s_0(t)=\begin{cases}A\sin\omega_c t & 0\leqslant t\leqslant\tau\\ 0 & \tau<t<T\end{cases}$$

$$s_1(t)=\begin{cases}-A\sin\omega_c t & 0\leqslant t\leqslant\tau\\ 0 & \tau<t<T\end{cases} \tag{2}$$

Bipolar EBPSK signals can degenerate into classical BPSK signals by setting $\tau=T$.

1.2 Faster-than-Nyquist communication

According to the first Nyquist criterion[11], for the ideal low-pass channel with the bandwidth of W, the symbol transmission rate must be less than $2W$ Bd, where $2W$ Bd is defined as the Nyquist rate. For the ideal band pass channel, the corresponding Nyquist rate is W Bd.

For faster-than-Nyquist rate communication, the symbol transmission rate is faster than $2W$ Bd, where the bandwidth of the low-pass channel is just W. With the same symbol rate, FTN communication can improve the spectrum efficiency directly. Additionally, the noise figure can be reduced, and the sensitivity of the receiver is increased. The existing method for demodulating ISI symbols in FTN communication deteriorates the signal to noise ratio (SNR). Therefore, finding a novel demodulator for FTN communication is important for enhancing both the spectrum and power efficiency.

2 Convolutional Neural Networks

CNN as a type of ANNs is characterized by the local connectivity, pooling (subsampling) and weight sharing[12]. Instead of using the fully connected hidden layers in traditional ANNs[13], a special network structure with several pairs of convolution and pooling layers is introduced in CNN. In the convolution layer, the local perceptive field (convolutional kernel) is adopted to connect the layers locally. Then, the input data feature can be extracted and the number of weights can be deduced. During the weight sharing, all the neuron nodes convolve within the same convolutional kernel in the feature map, and the feature diversity is realized by various kernels. The pooling (subsampling) layer can reduce the computational complexity and keep the original features. Finally, all the inputs are combined in the fully connected layers, and the classification and output results are generated[14].

Since CNN is highly capable of self-learning and self-adapting, it is relatively simple to classify the new data with the pre-trained CNN. The feature extraction and the data reconstruction in the traditional classification methods can also be avoided[15]. These properties above allow CNN to demodulate the bipolar EBPSK signals with serious ISI.

3 EBPSK Demodulation Based on CNN

3.1 System model

In the traditional EBPSK systems, the demodulation methods based on the pattern recognition, such as ANN and support vector machine (SVM), are inaccurate and time consuming[16], where the features are extracted manually from the hidden input layers. Therefore, we exploit the CNN feasibility in the bipolar EBPSK system for the FTN rate communications, and the system model is shown in Fig. 1, where the FTN rate system is realized by reducing the bandwidth of the modulated signals. The first band-pass filter (BPF) causes ISI and the second BPF in the receiver can reduce the noise from the band.

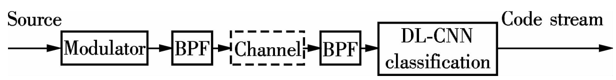


Fig. 1 System model of bipolar EBPSK system using CNNs for FTN rate communication

3.2 Multi-symbol united-decision

For the bipolar EBPSK signals at the receiver, severe ISI is caused by the narrow bandwidth of both the first BPF and the channel, and the condition of statistical independence cannot be satisfied in the classic demodulator. Thus, in the consideration of the above situation, the multi-symbol united-decision for CNNs classification is proposed in this paper. The input of CNN is the sampling of n symbols after BPF, and the output of CNN is the code block of those n symbols.

1) When $n=1$, the traditional single-symbol independent detection can be performed.

2) When $n=2$, the input is the waveform sampling of the adjacent two symbols, and the output is one of the four code blocks: "1 1", "1 0", "0 1", "0 0".

4 Experiments and Results

4.1 Experimental setup

1) Pre-training and design of CNNs

Using CNNs to classify the new input data, the connecting weight coefficients between the internal neuron nodes must be first trained. The noise is added during the processes of pre-training for practical considerations. In this paper, CNN consists of two convolution layers, two pooling layers, one input layer and one output layer. The size of convolutional kernel is set to be 5. For both performance and efficiency considerations, the number of iterations is set to be 10.

2) Design of bipolar EBPSK system

In bipolar EBPSK modulation, the carrier frequency is $f_c = 30$ kHz; the sampling frequency is $f_s = 300$ kHz; the number of carrier cycles in a symbol is $N = 28$; and K takes the value of 5, 10, 15, 28, respectively. The bandwidth of BPF in the transmitting end takes 1 000 and 500 Hz, respectively, and the symbol rate of this system is about 1.07 kBd.

For each value of K, the bit error ratio (BER) performances of both the CNN double-symbol decision and single-symbol decision are given. When $K = 28$, the bipolar EBPSK degenerates into the classic BPSK, and we compare the BER performance of CNNs demodulation with coherent demodulation in the additive white Gaussian noise (AWGN) channel. The training SNR for CNNs is −15 dB.

4.2 Results

When the bandwidth of BPF in the transmitter is $W =$ 1 kHz, and $K = 5, 10, 15, 28$, the BER performance comparisons are given in Fig. 2, where the overall performance of CNNs with single-symbol decision outperforms the double-symbol decision. When $K = N = 28$, the single-symbol decision is about 0.5 dB better than the coherent demodulator.

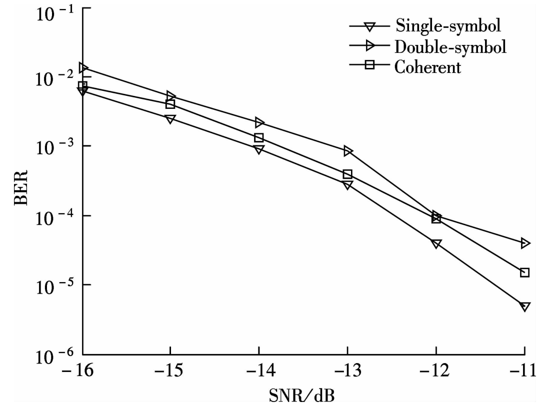
The similar comparisons for $W = 500$ Hz are given in Fig. 3, where the overall performance of CNNs with double-symbol decision is superior to those with single-symbol decision, and when $K = N = 28$, the double-symbol decision method is about 0.5 to 1.5 dB better than the coherent demodulator.

The simulation results shown in Fig. 4 are the comparisons of CNN demodulation performance with different values of the modulation parameter K.

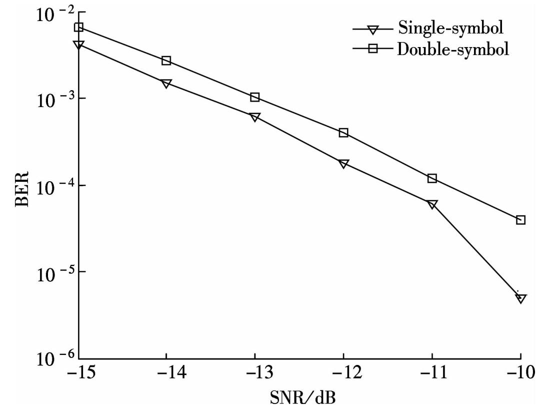
Fig. 4(a) shows that when $W = 1$ kHz, the BER performance of CNN with single-symbol decision is improved with the increase in K. However, Fig. 4(b) demonstrates that when $W = 500$ Hz, the critical condition of the FTN rate is satisfied for CNN with double-symbol decision, and the signals with $K < N$ are better than that with $K = N$. This means that in the FTN rate and using multi-symbol CNN discrimination, the energy efficiency of bipolar EBPSK modulations is superior to the classical BPSK modulation.

5 Conclusion

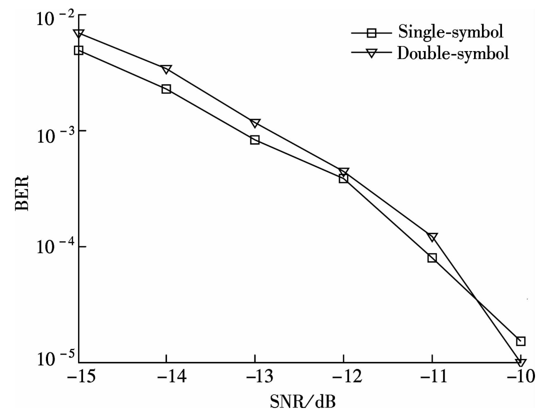
A novel demodulator based on CNNs for faster-than-Nyquist rate communication is proposed in this paper. The multi-symbol CNN discriminator is used to demodu-



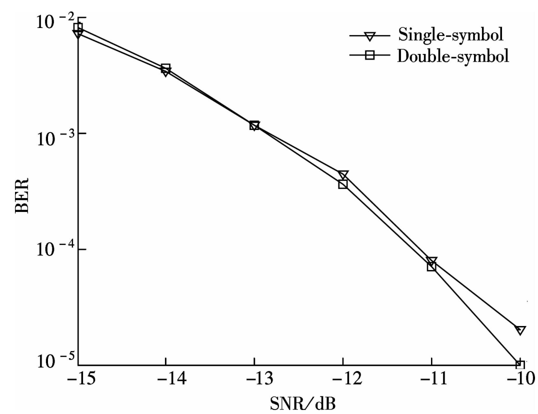
(a)



(b)



(c)



(d)

Fig. 2 BER performance of demodulators via single/double-symbol CNN and coherent detection when $W = 1$ kHz. (a) $K = 28$; (b) $K = 15$; (c) $K = 10$; (d) $K = 5$

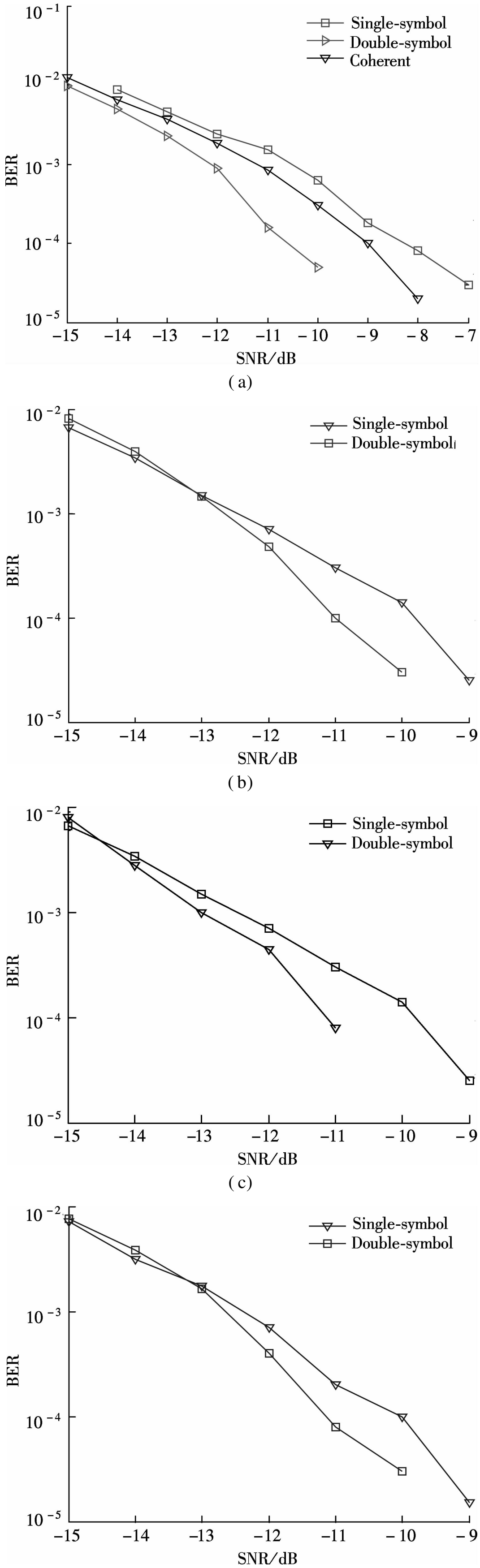


Fig. 3 BER performance of demodulators via single/double-symbol CNN and coherent detection when $W = 500$ Hz. (a) $K = 28$; (b) $K = 15$; (c) $K = 10$; (d) $K = 5$

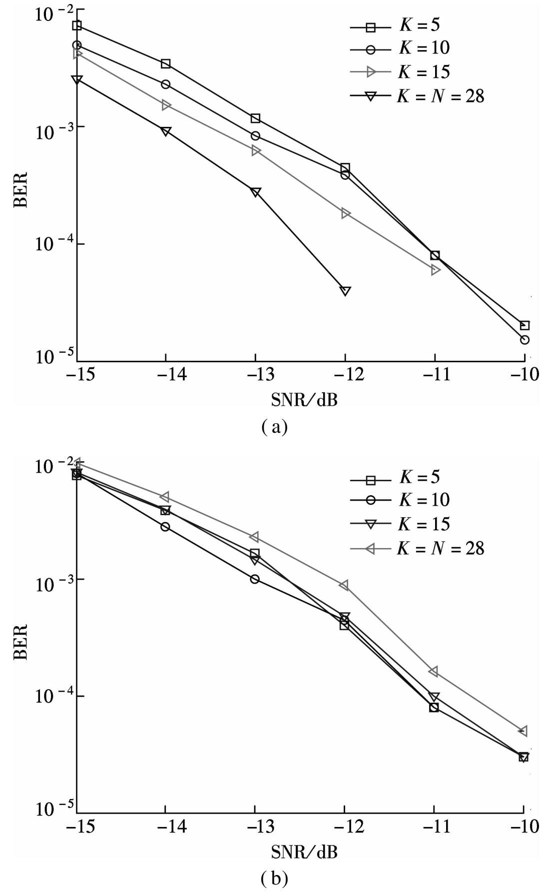


Fig. 4 Comparison of CNN demodulator with different values of K. (a) $W = 1$ kHz, single-symbol CNN decision; (b) $W = 500$ Hz, double-symbol CNN decision

late the binary signal, and generalization to M-ary (where $M > 2$) modulated signals still needs implementation. The results demonstrate that the proposed CNN classification methods are suitable for the demodulation of the FTN rate communication systems.

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基于 CNN 解调器的超奈奎斯特速率通信

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摘要:针对超奈奎斯特速率传输信号在传输过程中产生的严重码间干扰问题,提出了一种基于卷积神经网络(CNN)的解调器,对双极性扩展的二进制相移键控(bipolar EBPSK)超奈奎斯特速率信号进行解调.利用卷积神经网络局部感受野、池化和权值共享的特点,提出了一种具有6层结构的卷积神经网络来解调扩展的二进制相移键控调制信号并消除码间干扰.实验结果表明:当码率为1.07 kBd、发送端带宽限制为1 kHz,且一个码元中跳变载波周期数 $K=5,10,15,28$ 时,CNN单码元判决方法误码率性能总体优于CNN双码元联合判决方法;当 K 等于码元载波周期总数 N,即 $K=N=28$ 时,CNN单码元判决误码率方法优于相干解调约0.5 dB;当码率为1.07 kBd、发送端带宽限制为500 Hz,且 $K=5,10,15,28$ 时,CNN双码元联合判决方法优于CNN码元判决方法;当 $K=N=28$ 时,CNN双码元判决方法优于相干解调约0.5~1.5 dB.基于CNN的解调器成功地解决了由超奈奎斯特速率双极性传输信号产生的严重码间干扰问题,有利于频谱利用率的提高.

关键词:双极性 EBPSK;卷积神经网络;超奈奎斯特速率;双码元联合判决

中图分类号:TN911.3