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Blind Signal Detection Using Complex Transiently Chaotic Hopfield Neural Network

Yun Zhang
College of Electronic and Optical Engineering & College of Microelectronics
Nanjing University Of Posts And Telecommunications
No.9 WenYuan Road,Qixia District,Nanjing 210000,Jiangsu Province, P.R.China
y021001@njupt.edu.cn

Zhimin Zhang, Ying Liang and Shujuan Yu
College of Electronic and Optical Engineering & College of Microelectronics
Nanjing University Of Posts And Telecommunications
No.9 WenYuan Road,Qixia District,Nanjing 210000,Jiangsu Province, P.R.China
17805005530@163.com;501964307@qq.com;yusj@njupt.edu.cn

Li Wang
College of Electrical Engineering and Control Science
Nanjing Tech University
No.30 Pukou South Road, Pukou District, Nanjing 210000,Jiangsu Province, P.R.China
shenjienj@163.com

Yan Zhang
Shandong University of Finance and Economics
No.40 Shungeng Road,Shizhong District,Jinan 250002,Shandong Province, P.R.China
zhangyan@binghamton.edu

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Abstract. *For blind MPSK signals detection, the performance of CHNN-APHM (Complex Hopfield Neural Network with Amplitude-phase-type Hard Multistate activation function) algorithm is better than the classical second-order statistical algorithm, but it is easy to fall into local optimum. In order to overcome this shortcoming, improve the algorithms* anti-noise performance and reduce the shortest data volume, this paper introduced the chaotic neural network algorithm, and proposed CTCNN-APHM (Complex transiently chaotic Hopfield Neural Network with Amplitude-Phase-type- Hard-Multistate-activation-function) algorithm. Simulation results show satisfactory performance in detecting MPSK signals blindly, it has better anti-noise performance and greatly shortens the required minimum data length.*

Keywords: MPSK; blind detection; Hopfield neural network; chaotic neural network

1. Introduction.

There are two typical research directions to solve ISI(Inter-Symbol Interference) and ICI(Inter-Channel Interference) and get channel acquisition of communication systems.The first one is training-based approach,such as the widely used adaptive equalization algorithm, in which way the transmission of each frame is divided into two phases, the training and the data transmission, first,obtained the channel information by known training sequences and then transmitted the normal data. This method of obtaining channel state information without blindness consumes a large amount of system resources due to the pre-training in the first phase and eventually occupies part of the system capacity. The other one is the blind detection scheme,the receiver estimates the channel and the detection data without prior knowledge of the signal from the transmitter, the scheme can effectively make up for the shortcomings of the previous scheme.Blind equalization techniques can achieve signal detection by using the characteristics of the received signal sequence. That can improve the capacity and reliability of the communication system. It has many advantages, which can not only greatly reduce the additional overhead of sending training sequences can also work in the case of unknown data modulation and coding.

Blind detection algorithm for BPSK signals has been studied for many years. Compared with binary digital modulation, the multi-band digital modulation has a higher information transmission rate at the same symbol transmission rate, which can meet the requirements of high-speed data transmission.The MPSK is a multi-ary modulation of the signal,which has more advantages than the BPSK. But the blind detection technology for MPSK signal is more complex than for BPSK signal. MPSK signal is highly sensitive to nonlinear distortion which causes spectral spreading, ISI and constellation warping. The CHNN-APHM algorithm is proposed to detect MPSK signals blindly [1], and the performance has been significantly improved compared with the traditional SOS (second-order statistics) algorithm. However, as with other intelligent algorithms, the CHNN-APHM algorithm is easy to fall into the local optimal value [2]. In view of the above problems, the general solution is to choose a different starting point when the algorithm falls into the local optimal value [3]. In recent years, the study of chaotic neural networks has attracted numerous scholars attention [4-8]. In the context of non-blind signals detection, the literature [4,5,6] points out that the transiently chaotic neural network algorithm can avoid getting into the local optimum, and has great effects.

In this paper, for improving the performance of blind MPSK signal detection algorithm, we introduced the chaotic neural network to construct the CTCNN-APHM algorithm. The application of chaotic neural network has alleviated the drawbacks of getting into local optimization, and the new algorithm can get the desired result with shorter data length and lower SNR(Signal to Noise Ratio). Taking the 8PSK as an example, the experimental results prove this conclusion.

2. Blind MPSK Signal Detection Based on Discrete Phase Multi - level Complex Chaotic Neural Network.

2.1. Blind signal detection models.

The following discussion is based on the SIMO (Single-Input Multi-output) system. The discrete time model of SIMO channels output vector is usually given by [11]:

$$\mathbf{x}(\mathrm{k}) = \mathbf{h}(\mathrm{z})\mathbf{s}(\mathrm{k}) + \mathbf{v}(\mathrm{k}) = \sum_{\mathrm{j}=0}^{\mathrm{M}} \mathbf{h}(\mathrm{j})\mathrm{s}(\mathrm{k}-\mathrm{j}) + \mathbf{v}(\mathrm{k}) = \mathbf{H}_{\mathrm{q}}\mathbf{s}_{\mathrm{M}+1}(\mathrm{k}) + \mathbf{v}(\mathrm{k}) \tag{1}$$

where the input sequence vector $\mathbf{s}_{\mathrm{M}+1}(\mathrm{k}) = [\mathrm{s}(\mathrm{k}), \cdots, \mathrm{s}(\mathrm{k}-\mathrm{M})]^T$, $\mathbf{x}(\mathrm{k}) = [\mathrm{x}_1(\mathrm{k}), \cdots, \mathrm{x}_{\mathrm{q}}(\mathrm{k})]^T$ is received signal sequence,q is the oversampling factor; the impulse response of the channel is $\mathbf{h}(\mathrm{z}) = \sum_{\mathrm{j}=0}^{\mathrm{M}} \mathbf{h}(\mathrm{j})\mathrm{z}^{-\mathrm{j}}$, and $\mathbf{H}_{\mathrm{q}} = [\mathbf{h}(0), \cdots, \mathbf{h}(\mathrm{M})]$ where $\mathrm{M} = \max\{\mathrm{M}_i|\mathrm{i} = 1, \cdots, \mathrm{q}\}$,$\mathrm{M}_i$ is the order of theith subchannel;

The transmitted and received signals are both MPSK signals, and the polar form of the signals are as follows:$\{\mathrm{e}^{-i(\mathrm{K}-1)\theta_s}, \mathrm{e}^{-i(\mathrm{K}-3)\theta_s}, \cdots, \mathrm{e}^{i(\mathrm{K}-3)\theta_s}, \mathrm{e}^{i(\mathrm{K}-1)\theta_s}\}$,where $\theta_s = {}^{\pi}\!/_{\mathrm{K}}, \mathrm{K} = 2, 4, 8, 16, \cdots$ .When setting $\mathrm{K} = 8$,the signal is 8PSK signal, and $\mathrm{s}(\mathrm{k}) \in \{\mathrm{e}^{i\frac{\pi}{8}\mathrm{k}_0}|\mathrm{k}_0 =$

$-7, -5, -3, -1, 1, 3, 5, 7\}$ [12]. 8PSK signal constellation distribution is shown in Figure 1:

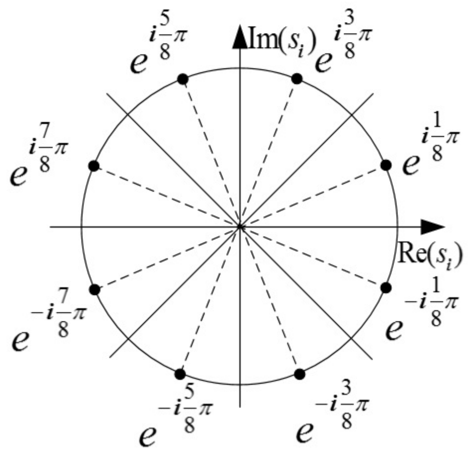


FIGURE 1. 8PSK signal constellation distribution

Receiving additive noise $\mathbf{v}(\mathrm{k}) = [\mathrm{v}_1(\mathrm{k}), \cdots, \mathrm{v}_\mathrm{q}(\mathrm{k})]^T$. The signal $\mathbf{s}$ and $\mathbf{v}$ are independent of each other.

If we ignore the noise, eq. (1) can be expressed as eq.(2).

$$\mathbf{X_N} = \mathbf{S\Gamma^T} \tag{2}$$

$\mathbf{S} = [\mathbf{s}_{L+M}(k), \cdots, \mathbf{s}_{L+M}(k+N-1)]^T = [\mathbf{s}_N(k), \cdots, \mathbf{s}_N(k-M-L)]_{N\times(L+M+1)}$ is input signal matrix, the L is the equalizer coefficient [11].

$$\mathbf{\Gamma} = \mathbf{\Gamma}_\mathrm{L}(\mathrm{h_j}) = \begin{bmatrix} \mathbf{h}(0) & \mathbf{h}(1) & \cdots & \mathbf{h}(\mathrm{M}) & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{h}(0) & \mathbf{h}(1) & \cdots & \mathbf{h}(\mathrm{M}) & \ddots & \vdots \\ \vdots & \ddots & & & \ddots & & \mathbf{0} \\ \mathbf{0} & \cdots & \mathbf{0} & \mathbf{h}(0) & \mathbf{h}(1) & \cdots & \mathbf{h}(\mathrm{M}) \end{bmatrix}_{\mathrm{q(L+1)\times(M+L+1)}}$$

$\mathbf{\Gamma}$ is block Toeplitz matrix which constituted by $h_j, j = 0, 1, \cdots, M$;The $(\mathbf{X}_N)_{N\times(L+1)q} = [x_L(k), \cdots, x_L(k+N-1)]^T$ is received signal matrix. If $\mathbf{\Gamma}$ is full rank, there will be $\mathbf{X}_N = [\mathbf{U}, \mathbf{U}_c] \cdot \begin{bmatrix} \mathbf{D} \\ 0 \end{bmatrix} \cdot \mathbf{V}^T$, $\mathbf{Q} = \mathbf{U}_c\mathbf{U}_c^H$ and $\mathbf{Q}\mathbf{s}_\mathrm{N}(\mathrm{k}-\mathrm{d}) = 0$ .The matrix $\mathbf{U}_c$ is obtained from the singular value decomposition of the received signal matrix.

Then we can write the cost function [11]:

$$J_0 = \mathbf{s}_N^\mathrm{T}(k-d)\mathbf{Q}\mathbf{s}_N(k-d) = \mathbf{s}^H\mathbf{Q}\mathbf{s} \tag{3}$$

$$\hat{\mathbf{s}} = \arg\min\{J_0\} \tag{4}$$

The $\hat{\mathbf{s}}$ is the detected signal. Getting the minimum value of J_0 is a quadratic function optimization problem which contains constraints. We need to solve the optimize problem of Eq. (4). The CHNN-APHM algorithm proposed in literature [1] is a much better option than traditional ways , but it still requires a large number of data and easy to fall into the local optimal. So it has space for improvement.Using artificial neural network to solve the problem of blind detection has great advantages.So this direction is of great research value,and this paper would introduce the TCNN , propose the CTCNN-APHM algorithm to solve this problem.

2.2. **Constructing the Complex transiently chaotic Hopfield Neural Network with Amplitude-Phase-type-Hard-Multistate-activation-function.** Compared with the general Hopfield neural network, the transient chaotic neural network has the ability of global search, and makes the neural network jump out of the local optimal solution through fine search to find the global optimal solution. The idea has been successfully used in blind detection of BPSK signals, but it has not been applied to the problem of blind detection of MPSK signals.In accordance with the thought of literature [14], Combined with MPSK signal blind detection we proposed the CTCNN-APHM algorithm. The dynamic equation of the model as follows:

$$y_i(t+1) = ky_i(t)+\alpha[\sum_{j=1}^{n} w_{ij}x_j(t)] - \lambda z_i(t)x_i(t) \tag{5}$$

$$\theta_{\mathrm{y}}= \mathrm{angle}(\mathrm{y_i(t)}) \tag{6}$$

$$\theta_x = \sigma(\theta_y) \tag{7}$$

$$\mathrm{x_i(t)} = \mathrm{e}^{\mathrm{i}\theta_{\mathrm{x}}} = \cos\theta_{\mathrm{x}} + \mathrm{i}\sin\theta_{\mathrm{x}} \tag{8}$$

$$z_i(t+1)= (1-\beta)z_i(t) \tag{9}$$

where eq. (5) is the dynamic equation of the network. The phase angle was gotten by eq.(6), eq.(7) is the phase activation function, eq. (8) is the Euler angle formula. The eq. (6) to eq.(8) is the activation function of the network. The eq.(9) is the annealing function. The connection weight between the neuron i and j is w_{ij} , the α is the coupling factor, the k is the neurons attenuation factor,the β is the simulated annealing parameters, the $z_i\,(t)$ is the self-feedback.

Eq. (9) is an annealing term of the CTCNN-APHM algorithm. There are many annealing strategies, and we choose the traditional linear annealing strategy in this algorithm. The idea comes from the annealing algorithm, due to space limitations, the algorithm does not do in-depth introduction here. The choice of annealing strategy is critical, which guarantees the fine search capabilities of the algorithm. The characteristic of the linear annealing strategy adopted by eq. (9) is that the speed of getting smaller is slower, so that the algorithm can get the global optimal solution.

No matter in associative memory or in the blind signal detection, when dealing with the signal of "constant mode and different phase" ,the activation function of the Hopfield neural network always being the discrete phase activation function, this is the specific meaning of eq. (8), the following will give the specific expression which is shown in eq. (10).

$$\theta_{\mathrm{x}}=\sigma(\theta_{\mathrm{y}}) = \begin{cases} (\mathrm{K}-1)\theta_{\mathrm{s}} & (\mathrm{K}-2)\theta_{\mathrm{s}} \le \theta_{\mathrm{y}} < \mathrm{K}\theta_{\mathrm{s}} \\ \vdots & \vdots \\ 3\theta_{\mathrm{s}} & 2\theta_{\mathrm{s}} \le \theta_{\mathrm{y}} < 4\theta_{\mathrm{s}} \\ \theta_{\mathrm{s}} & 0 \le \theta_{\mathrm{y}} < 2\theta_{\mathrm{s}} \\ -\theta_{\mathrm{s}} & -2\theta_{\mathrm{s}} \le \theta_{\mathrm{y}} < 0 \\ -3\theta_{\mathrm{s}} & -4\theta_{\mathrm{s}} \le \theta_{\mathrm{y}} < -2\theta_{\mathrm{s}} \\ \vdots & \vdots \\ -(\mathrm{K}-1)\theta_{\mathrm{s}} & -\mathrm{K}\theta_{\mathrm{s}} \le \theta_{\mathrm{y}} < -(\mathrm{K}-2)\theta_{\mathrm{s}} \end{cases} \tag{10}$$

where $\theta_{\mathrm{s}} = \frac{\pi}{\mathrm{K}}$, K is the total number of element's type. We take the 8PSK constellation signals as an example. Setting $\mathrm{K} = 8$.

We keep the modulus of the complex signal unchanged, and both the input and the output of the activation function are argument.This activation function has the following characteristics [12]: (1) The input of the activation function is the " phase ", and the definition range is $[-\pi, \pi)$. (2) For 8PSK constellation signal, the output of the activation function is $y_i(t) \in \{e^{i\frac{\pi}{8}k_0} | k_0 = -7, -5, -3, -1, 1, 3, 5, 7\}$. (3) The geometric meaning of the activation function is: the output of the activation function is the phase angle of the midpoint of the sector for this sectors input. For example, the output is $\frac{\pi}{8}$ for the input phase angle in the sector $[0, \frac{2}{8}\pi)$. According to the dynamic equation, the CTCNN-APHM algorithms model diagram is shown in Figure 2.

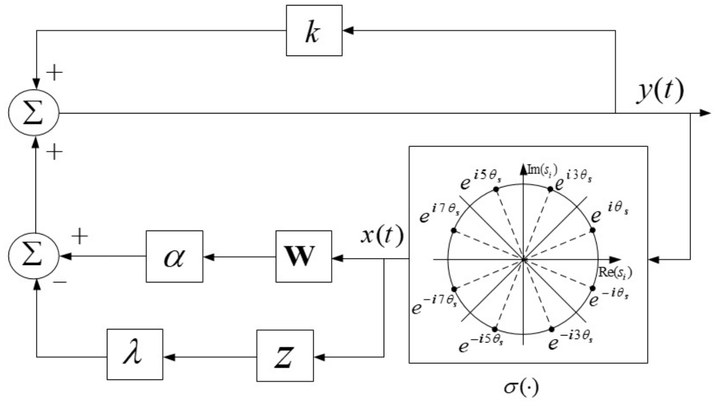


FIGURE 2. CTCNN-APHM model

As is shown in Figure 2.The $x(t)$ is the input. The $y(t)$, which is the $x(t)$ multiplied by the weight matrix plus other items,is the input of activation function. The output of the activation function as input $x(t)$ again. The loop will stopped until the input and output of the activation function are equal.At this point we will get the result of blind detection.

3. **Weight Matrix Configuration of Blind Detection Algorithm for Discrete Multi-level Complex Value Chaotic Neural Network.** The transient chaotic neural network is an extension of Hopfield neural networks, so their form of weight matrix is the same.By using CTCNN-APHM to solve eq.(4), the synaptic matrix of the network is designed as follows: [1]

$$\mathbf{W} = \mathbf{I} - \mathbf{Q} \tag{11}$$

where $\mathbf{Q} = \mathbf{U}_c\mathbf{U}_c^H$, and $\mathbf{I}$ is the identity matrix. Then we have the energy function as follows:

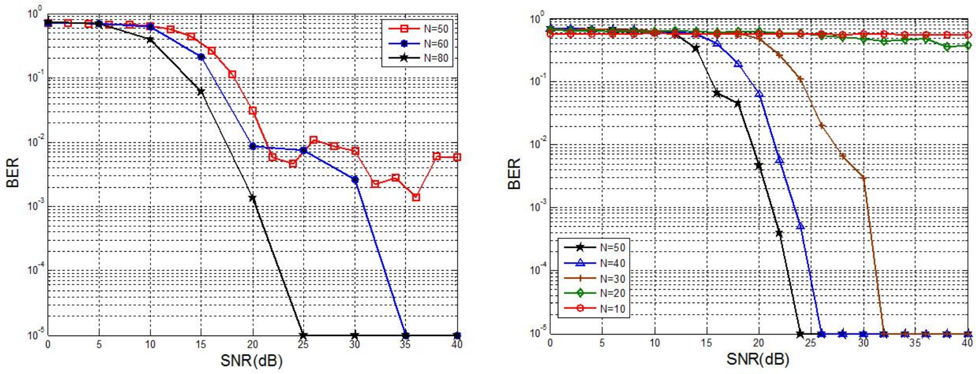
$$\begin{aligned} \mathrm{E}(k) &= -\tfrac{1}{2}\mathbf{x}^H(k)\mathbf{W}\mathbf{x}(k)+\tfrac{\lambda}{2}\sum_{i=1}^{N} z_i\,(k)x_i{}^*\,(k)\,x_i\,(k) \\ &= -\tfrac{1}{2}\mathbf{x}^H(k)(\mathbf{I}-\mathbf{Q})\mathbf{x}(k)+\tfrac{\lambda}{2}\sum_{i=1}^{N} z_i\,(k) \end{aligned} \tag{12}$$

When $\mathbf{x}$ is stable equilibrium point of the energy function, there will be $\mathbf{x}(\mathrm{k}+1) = \mathbf{x}(\mathrm{k})$ .That means $\mathbf{x}$ is transmitted signals should be detected and the solution of optimizing problem eq. (4).

4. **Simulation.** In this part, simulation results are presented to illustrate the quantitative performance of the algorithm. The matlab R2014a serves as the experimental tool. The input signal is 8PSK. The model of a two ray multi-path channel [14,15] is $h(t) = \sum_{j=1}^{2} (w_j(h(\alpha_0, t-\tau_j)))$ .The $h(\alpha_0, t-\tau_j)$ is roll-off factor,setting α_0= 0.1.The τ_j is delay factor,which is randomly raised cosine impulse response.The w_j is randomly weight coefficient.The noise is Gaussian white noise, the oversampling factor $q = 3$ .The multipath of signal propagation is 2. The results are averaged over 100 Monte

Carlo simulations. While bit error rate (BER) equals 0, we set the BER=10^{-5} .We set $k = 0.2, \alpha = 0.7, \beta = 0.0000012, z_i(0) = 0.12, \lambda = 1$.

Experiment 1: The channel is random channel with varying delay and weight .Acquiring the BER of CHNN-APHM algorithm and CTCNN-APHM algorithm under different data lengths, respectively. Analyzing the affect of data length to algorithms performance. The experimental results are shown in Figure 3: From Fig. 3, we can know the CTCNN-



(a) CHNN-APHM algorithm with different data length

(b) CTCNN-APHM algorithm with different data length

FIGURE 3

APHM algorithm can get stable detection result when the data length is 40, but the CHNN-APHM algorithm needs N = 80 at least. The experimental results show that the CTCNN-APHM algorithm requires shorter data length, then the algorithms time complexity of is reduced and the algorithm runs faster.

Experiment 2:The signal length of 8PSK is 100. Under the random channel with varying delay and weight ,getting the BER of CHNN-APHM algorithm and CTCNN-APHM algorithm in different SNR. The simulation results are presented in Fig.4. The average

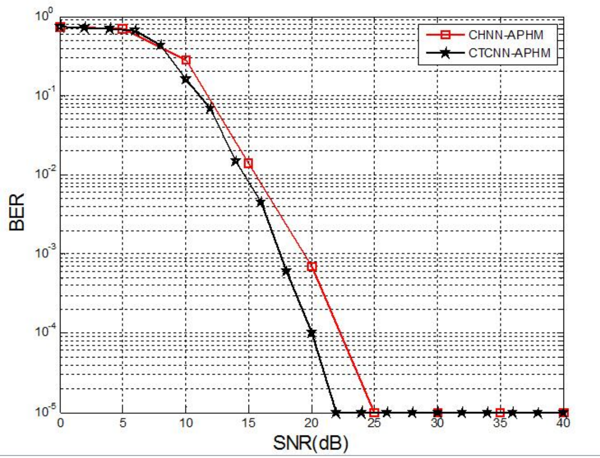
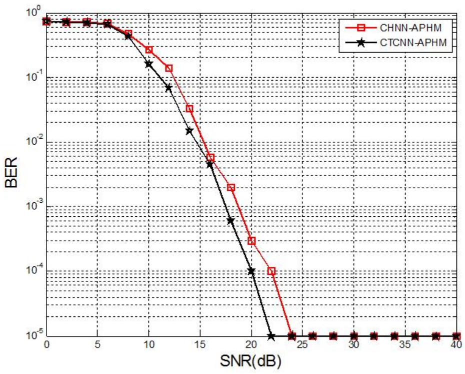


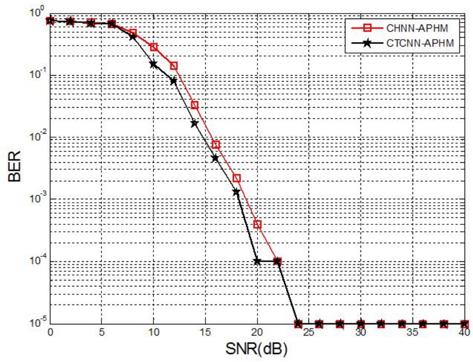
FIGURE 4. CHNN-APHM algorithm and CTCNN-APHM algorithm under random channel

BER of CTCNN-APHM algorithm is reduced to 0 when the SNR is 22dB. However the CHNN-APHM algorithms average BER is 0 when the SNR is 25dB.So the new algorithm has better anti-noise performance.

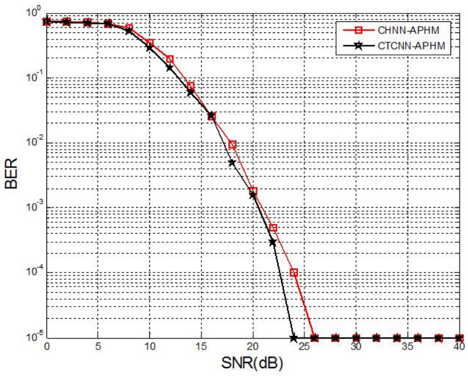
Experiment 3: Setting the length of 8PSK signal is 100.Getting the BER and SNRs relation curve of CHNN-APHM algorithm and CTCNN-APHM algorithm, respectively, in the following four channel environments. CH1: channel without common zeros, whose delay and weight are constant; CH2: channel with one common zero, whose delay and weight are constant; CH3: channel with two common zeros, whose delay and the weight are constant; CH4: the Zhi Di channel, where $delay = [0, 1/3]$, and the power factor $\mathbf{W} = [1, -0.7]$. The experimental results are shown in Figure 5. From Fig. 5(a) ,in



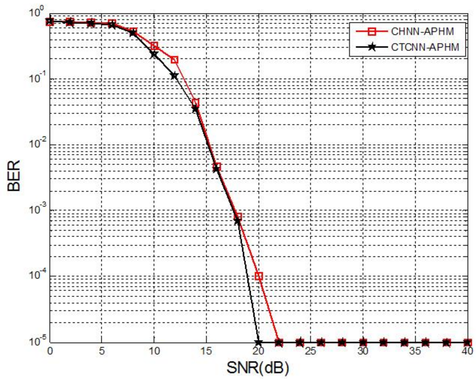
(a) CHNN-APHM algorithm with different data length



(b) CTCNN-APHM algorithm with different data length



(c) CHNN-APHM algorithm with different data length



(d) CTCNN-APHM algorithm with different data length

FIGURE 5

channel CH1, when the BER of is 0, the CHNN-APHM algorithms SNR is 24dB, and the CTCNN-APHM algorithms SNR is 22dB; From Fig. 5(b) ,in channel CH2, we can see that the CHNN-APHM algorithm and the CTCNN-APHM algorithms BER is 0 when the SNR is 24dB. But the curve of CTCNN-APHM algorithm is lower than the CHNN-APHM algorithms, so the CTCNN-APHM algorithm is slightly better. From Fig. 5 (c), in channel CH3, when the BER of 0, the CHNN-APHM algorithms SNR is 26dB, and the CTCNN-APHM algorithms SNR is 24dB. From Fig. 5 (d), in channel CH4, when the BER is 0, the CHNN-APHM algorithms SNR is 22dB, and the CTCNN-APHM algorithms SNR is 20dB. So new algorithm has applicability. Its anti-noise performance is better than CHNN-APHM algorithm in above channels.

5. **Conclusion.** This paper focuses on avoiding getting into the local optimum and reducing the required data length of blind MPSK signals detection algorithm. According to the idea of the chaotic neural network, this paper proposed the CTCNN-APHM algorithm of MPSK signal ,the first application of TCNN to the blind detection of MPSK signals,

which has better anti-interference performance than the traditional SOS algorithm and the CHNN-APHM algorithm, and given the structure and the dynamic equation. Setting 8PSK signals as an example. The experimental results indicate the new algorithm can avoid getting into the local optimum, has better anti-noise performance. This advantage is shown in the random synthesis channel, the Zhi Di channel and the channel without common zeros, with one or two common zero. The shortest required data length of the CTCNN-APHM algorithm is only half of the CHNN-APHM algorithms. So the new algorithm is more suitable for fewer data and high-speed communication environment,it is more applicable.If this algorithm replaces the existing non-blind adaptive equalization algorithm, it will greatly improve the efficiency and accuracy of the communication system.

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