Journal of Southeast University (English Edition) Vol. 27, No. 3, pp. 244 – 247 Sept. 2011 ISSN 1003—7985

A new detector in EBPSK communication system

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Abstract: In order to raise the detection precision of the extended binary phase shift keying (EBPSK) receiver, a detector based on the improved particle swarm optimization algorithm (IMPSO) and the BP neural network is designed. First, the characteristics of EBPSK modulated signals and the special filtering mechanism of the impacting filter are demonstrated. Secondly, an improved particle swarm optimization algorithm based on the logistic chaos disturbance operator and the Cauchy mutation operator is proposed, and the EBPSK detector is designed by utilizing the IMPSO-BP neural network. Finally, the simulation of the EBPSK detector based on the MPSO-BP neural network is conducted and the result is compared with that of the adaptive threshold-based decision, the BP neural network, and the PSO-BP detector, respectively. Simulation results show that the detection performance of the EBPSK detector based on the IMPSO-BP neural network is better than those of the other three detectors.

Key words: extended binary phase shift keying; detector; impacting filter; logistic chaos disturbance; Cauchy mutation; adaptive threshold-based decision

doi: 10.3969/j.issn.1003 – 7985.2011.03.003

With the rapid development of information, the transmission rate of data becomes fast and the bandwidth of the communication system becomes wide. However, the spectrum efficiency has not been improved. How to use the limited spectrum resource more efficiently has great significance in the development of economy and society. The extend binary phase shift keying (EBPSK) modulation, which takes the advantages of the small-angle phase modulation and the variable hopping time to tighten the spectrum of the emission signal, is proposed [1-2]. The EBPSK not only covers the traditional BPSK modulation, but also includes the missing cycle modulation (MCM) [3], the pulse position phase reversal keying (3PRK) [4] and the pulse position phase shift keying (3PSK) [4] modulation methods in US patent. Ref. [5] studied the special filtering mechanism of the impacting filter and proposed the EBPSK detector model based on the BP neural network. However, due to the defect of the BP neural network in falling into local optimum easily, the performance of the EBPSK detector based on the BP neural network is limited. Refs. [6 – 7] proposed the particle swarm optimization algorithm (PSO) to train the BP neural network and demonstrated that the performance of the PSO-BP was better than that of the BP neural network in terms of stability, recognition rate, and training time.

In this paper, the EBPSK modulation and the impacting filter are introduced. Then, an improved particle swarm optimization algorithm (IMPSO) based on the logistic chaotic disturbance operator [8] and the Cauchy mutation operator [9] is proposed. Subsequently, the EBPSK detector based on the IMPSO-BP neural network is designed. Finally, the detection performance of the IMPSO-BP detector is compared with that of the adaptive threshold-based decision, the BP neural network and the PSO-BP detector.

1 EBPSK Modulation and Impacting Filter

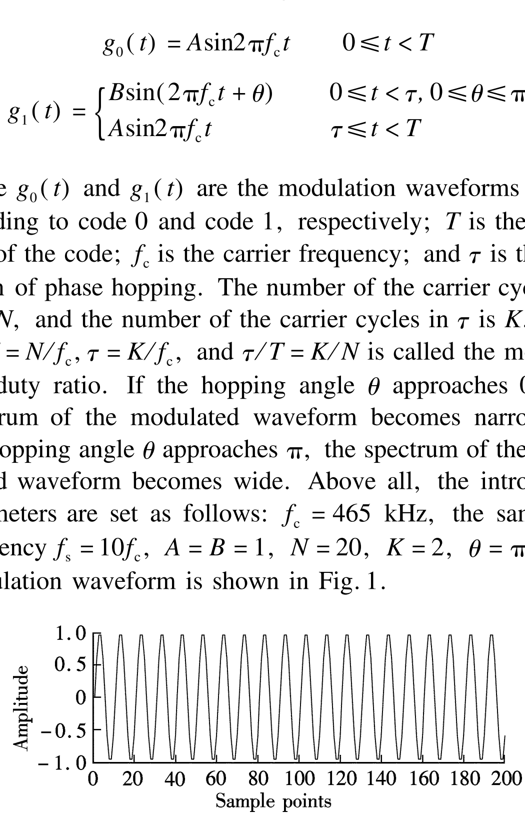
1.1 EBPSK modulation

EBPSK modulation is an asymmetric binary modulation method. EBPSK modulation signals are defined as follows:

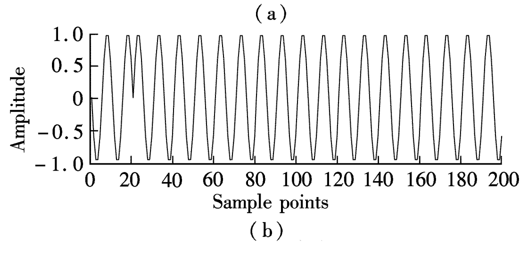
$$g_0(t) = A\sin 2\pi f_c t \qquad 0 \leqslant t < T$$

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

where $g_0(t)$ and $g_1(t)$ are the modulation waveforms corresponding to code 0 and code 1, respectively; T is the duration of the code; f_c is the carrier frequency; and τ is the duration of phase hopping. The number of the carrier cycles in T is N, and the number of the carrier cycles in τ is K. That is, $T = N/f_c$, $\tau = K/f_c$, and $\tau/T = K/N$ is called the modulation duty ratio. If the hopping angle θ approaches 0, the spectrum of the modulated waveform becomes narrow. If the hopping angle θ approaches π, the spectrum of the modulated waveform becomes wide. Above all, the introduced parameters are set as follows: $f_c = 465$ kHz, the sampling frequency $f_s = 10f_c$, $A = B = 1$, $N = 20$, $K = 2$, $\theta = \pi$. The modulation waveform is shown in Fig. 1.



(a)



(b)

Fig. 1 EBPSK modulation waveform. (a) Code 0; (b) Code 1

Received 2011-05-15.

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Foundation items: The National Natural Science Foundation of China (No. 60872075), the National High Technology Research and Development Program of China (863 Program) (No. 2008AA01Z227).

Citation: Jin Yi, Wu Lenan, Wang Jiwu, et al. A new detector in EBPSK communication system[J]. Journal of Southeast University (English Edition), 2011, 27(3): 244 – 247. [doi: 10.3969/j.issn.1003 – 7985.2011.03.003]

1.2 Impacting filter

The impacting filter is a special infinite impulse response (IIR) filter, with the feature of "notch-frequency selection" in an extremely narrow pass-band[10-11]. The mechanism of the impacting filter is given in Ref. [10]. At present, the impacting filter is designed by manual debugging. Here, we select the impacting filter formed by one pair of adjacent conjugate zeros and three pairs of adjacent conjugate poles, and its expression can be written as

$$H(z) = \sum_{i=0}^{2} b_i z^{-i} \Big/ \sum_{i=0}^{6} a_i z^{-i} \tag{1}$$

where

$$b_0 = 1,\ b_1 = -1.618\,092\,409\,933\,249$$
$$b_2 = 0.999\,900\,002\,500\,000\,44$$
$$a_0 = 1,\ a_1 = -4.562\,007\,492\,096\,165\,1$$
$$a_2 = 9.586\,283\,941\,681\,948\,3,\ a_3 = -11.566\,980\,661\,101\,638$$
$$a_4 = 8.452\,352\,883\,974\,324\,3,\ a_5 = -3.546\,714\,769\,300\,573\,2$$
$$a_6 = 0.685\,515\,443\,313\,960\,3$$

As shown in Fig. 2, when EBPSK signals pass the impacting filter, the phase hopping can be converted into the impacting of the amplitude. This paper just utilizes the significant waveform difference to design the best detector.

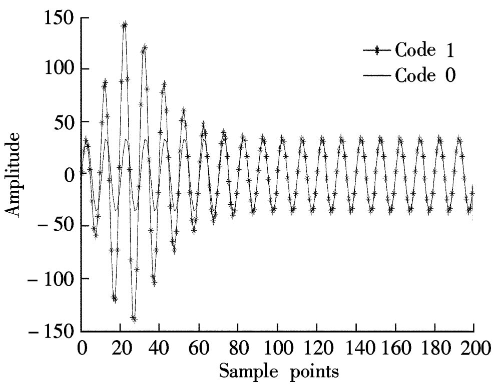

Fig. 2 EBPSK signal via the impacting filter

2 IMPSO-BP Detector

2.1 PSO algorithm

The PSO was proposed by Kennedy and Eberhart[12] in 1995, which has the advantages of a few parameters, simple structure and fast convergence velocity. After then, Shi and Eberhart[13] proposed the linear decline strategy of inertia weight to ensure that the PSO trends to a global search in the early stage and trends to a local search in the later stage. The updating formula of the inertia weight can be written as

$$\omega(t) = \omega_{\max} - \frac{(\omega_{\max} - \omega_{\min})t}{M} \tag{2}$$

where $\omega_{\max}$ and $\omega_{\min}$ denote the maximum and minimum of the inertia weight, respectively; t is the current iteration; and M is the maximum of iteration steps.

The PSO is based on the position-velocity model. The position of each particle is expressed as $\boldsymbol{x}_i = \{x_{i1}, x_{i2}, \dots, x_{iD}\}$, and the velocity is expressed as $\boldsymbol{v}_i = \{v_{i1}, v_{i2}, \dots, v_{iD}\}$, where D denotes the dimension of each particle. Each particle represents a feasible solution in the solution space, and its quality is determined by the fitness value. In the process of the search, each particle updates the position and velocity by tracking the historical optimum $\boldsymbol{P}_i = \{P_{i1}, P_{i2}, \dots, P_{iD}\}$ and the global optimum $\boldsymbol{P}_{\mathrm{g}} = \{P_{\mathrm{g}1}, P_{\mathrm{g}2}, \dots, P_{\mathrm{g}D}\}$ of the population until it meets the required precision or the maximum of iteration steps. Specific iteration formulae are as follows:

$$v'_{id} = \omega v_{id} + c_1 r_1 (P_{id} - x_{id}) + c_2 r_2 (P_{\mathrm{g}d} - x_{id}) \tag{3}$$

$$x'_{id} = x_{id} + v'_{id} \tag{4}$$

where $d \in [1, D]$; ω denotes the inertia weight; c_1 and c_2 are the learning factors; and r_1, r_2 are the random numbers between 0 and 1, respectively; $v_{id} \in [v_{\min}, v_{\max}]$.

2.2 IMPSO-BP neural network

Due to the limited global searching ability of the PSO, some improvements are introduced to enhance the global searching ability. The specific improvement strategies are as follows:

1) When the fitness value of a particle is less than the average fitness values of the population, the chaotic disturbance operator is imposed on the particles to increase local searching ability. Here, the logistic equation is used to generate a chaotic sequence. The specific expression is

$$x_{n+1} = \mu x_n (1 - x_n) \qquad n = 1, 2, 3, \dots \tag{5}$$

2) The Cauchy mutation operator is implemented on the particles whose fitness values are greater than the average fitness value of the population. The specific expression is

$$x_i = x_i + \eta\sigma \tag{6}$$

where η is the amplitude parameter of disturbance, and σ is a random variable which meets the Cauchy distribution. Although improvement strategies are conducted on the updated particles, the steps of the PSO algorithm remain unchanged. The training process of the IMPSO-BP neural network is shown in Fig. 3.

2.3 IMPSO-BP detector

When the modulation waveforms pass the impacting filter, there is a significant difference between code 0 and code 1. Code 1 has impacting feature, but code 0 does not, as shown in Fig. 2. The EBPSK detector based on the IMPSO-BP neural network is shown in Fig. 4.

3 Simulation

3.1 Simulation parameters

In the simulation, parameter settings include three parts:

1) EBPSK communication system The communication channel is AWGN channel, the dimension of the input vector of the BP neural network is 40, the number of the training samples is 3 000, and the number of the testing samples is 10^6.

2) Neural network The number of neurons in the input layer, the hidden layer and the output layer are 40, 3 and 1, respectively.

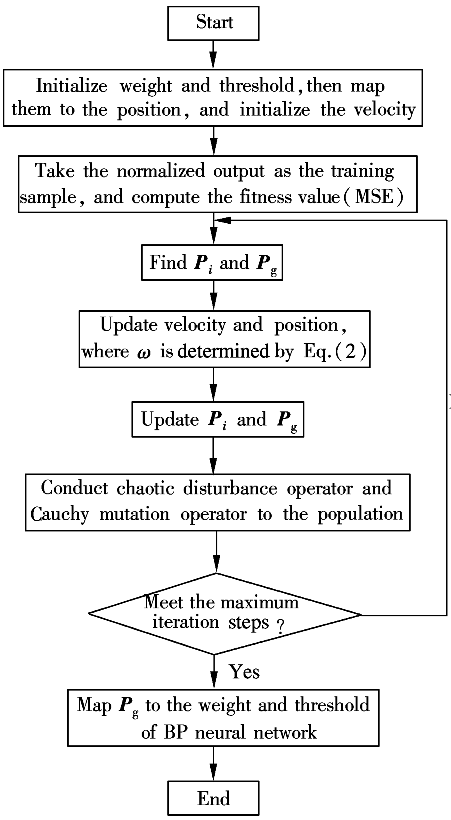

Fig. 3 Training process of IMPSO-BP neural network

3) IMPSO algorithm The population size is 100; the dimension of the particle is 127; c_1 and c_2 are 1.496 2; and the chaos control parameter μ is 0.4. Every dimension of the particle position and velocity belongs to $[-1, 1]$ and $[-0.5, 0.5]$, respectively; $\omega_{\max} = 0.95$, $\omega_{\min} = 0.4$. The maximum iteration number is 50.

3.2 Simulation results

On the condition of parameter settings given in section 3.1, simulation of the IMPSO-BP detector is implemented. In order to compare the detection performance, simulations of the adaptive threshold-based decision, the BP neural network and the PSO-BP detector are also implemented. As shown in Fig. 5, we can clearly see that: 1) When the SNR is higher than -2.3 dB, the PSO-BP detector has a better performance than the BP neural network; 2) When the SNR is lower than -0.8 dB, the PSO-BP detector has worse performance than the adaptive threshold decision; 3) The IMPSO-BP detector has the best detection performance of all, and it can derive the SNR enhancement of 0.5 dB compared with the adaptive threshold decision (BER is 10^{-4}). The results demonstrate that the global searching ability of the PSO is limited, while the proposed IMPSO has a better global searching ability.

3.3 Performance analysis

The three major factors affecting the IMPSO-BP detector are the dimension of the input vector, the number of training samples, and the selected SNR during the training period. When the dimension of the input vector is 40 and the SNR during the training period is -1 dB, the curves of the BER vs. different training samples are shown in Fig. 6(a). It can be seen that the more the training samples, the lower the BER. When the number of the training samples is 3 000 and the SNR during the training period is -1 dB, the curves of the BER vs. different dimensions of the input vector are shown in Fig. 6(b). It can be seen that compared with the dimensions of the input vector of 40 and 60, the BER is better when the dimension is 50. When the dimension of the input vector is 40 and the number of the training samples is 3 000, we obtain the curves of the BER vs. different SNRs during the training period as shown in Fig. 6(c). It can be seen that when the SNR during the training period is the median of the SNR range, the generation ability is the strongest, and the BER performance is the best.

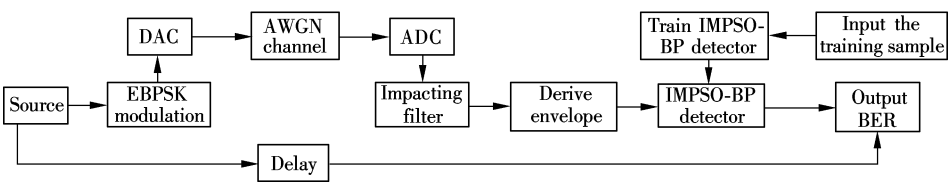

Fig. 4 IMPSO-BP detector in EBPSK communication system

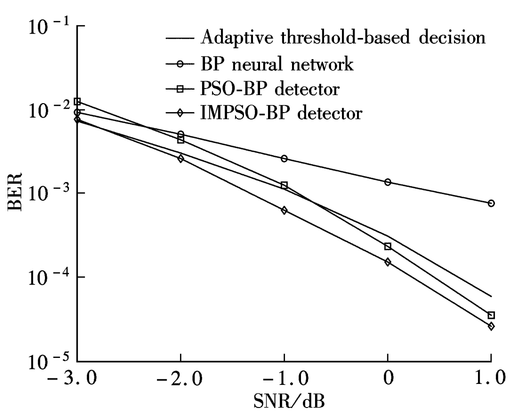

Fig. 5 BER comparison of different detectors

4 Conclusion

This paper proposes an IMPSO algorithm based on the logistic chaos disturbance operator and the Cauchy mutation operator, and designs the EBPSK detector based on the IMPSO-BP neural network. The BER performance of the IMPSO-BP detector is compared with three other detectors by simulation. Simulation results show that: 1) The detection performance of the IMPSO-BP is better than that of the adaptive threshold-based decision, the BP neural network, and the PSO-BP, which verifies that the IMPSO has better global searching ability than the PSO; 2) The main factors affecting the IMPSO-BP detector are the dimension of the input vector, the number of training samples, and the selected

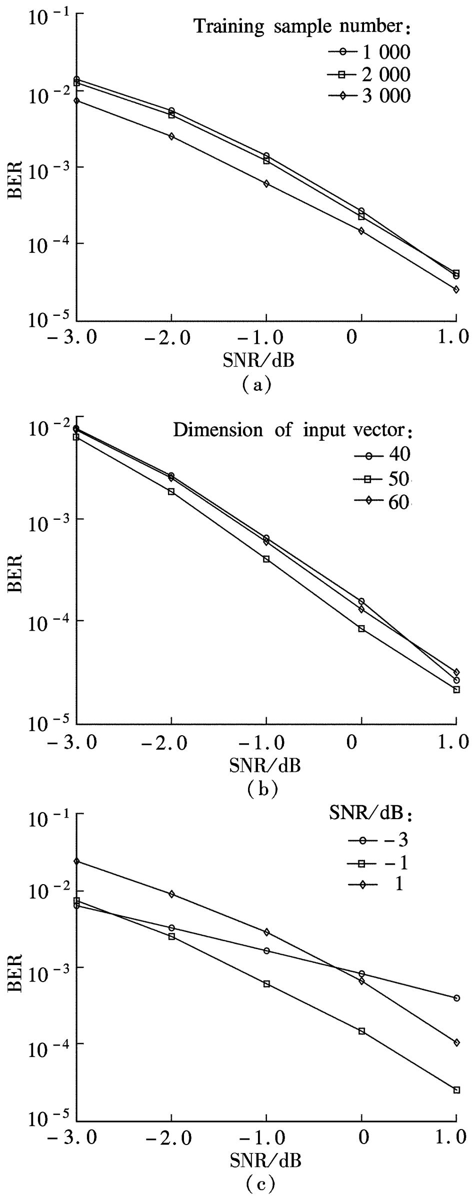

Fig. 6 BER comparison under different conditions. (a) BER vs. different training sample numbers; (b) BER vs. different dimensions of input vector; (c) BER vs. different training SNRs

training SNR. Meanwhile, how to select the input vector reasonably is the future research direction.

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一种新的 EBPSK 通信系统检测器

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摘要:为了提高扩展的二元相移键控(EBPSK)接收机的检测精度,设计了一种基于改进粒子群算法(IMPSO)和BP 神经网络的 EBPSK 检测器. 首先,阐述了 EBPSK 调制特征及冲击滤波器的特殊滤波机理. 然后,提出了基于 logistic 混沌扰动和 Cauchy 变异的改进粒子群算法,并利用 IMPSO-BP 神经网络设计了 EBPSK 检测器模型. 最后,对 IMPSO-BP 检测器进行了仿真,并分别与自适应门限判决、BP 神经网络和 PSO-BP 检测器进行了对比. 仿真结果表明:基于 IMPSO-BP 神经网络的 EBPSK 检测器检测效果要明显好于其他 3 种检测器.

关键词:扩展的二元相移键控;检测器;冲击滤波器; logistic 混沌扰动;Cauchy 变异;自适应门限判决
中图分类号:TN919.72