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A Novel Blind Detection Algorithm Based on Adjustable Parameters Activation Function Hopfield Neural Network

Shaowei Chen

School of Electronic Science and Engineering
Nanjing University Of Posts And Telecommunications
66 XinMofan Road,Gulou District,Nanjing 210000, P.R.China
15062201378@163.com

Shujuan Yu, Zhimin Zhang and Yun Zhang

School of Electronic Science and Engineering
Nanjing University Of Posts And Telecommunications
66 XinMofan Road,Nanjing 210000, P.R.China
yusj@njupt.edu.cn;17805005530@163.com;y021001@njupt.edu.cn

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Abstract. *Aiming at the shortcomings of the traditional blind detection algorithm, we focus on the flexibility of the activation function. This paper presents an adjustable parameters activation function, which not only showed greater flexibility and nonlinear properties by regulating the steepness, position and mapping range, but improved the performance of the Hopfield Neural Network(HNN) blind detection algorithm. The simulation results demonstrate that the novel algorithm can reduce the error rate significantly and speed up the convergence of HNN on the condition of low signal-noise ratio(SNR) and complex large data environment. Thereby the novel activation function improves the performance of blind detection algorithm.*

Keywords: Blind detection algorithm, HNN, Activation function, Adjustable parameters

1. **Introduction.** Blind equalization and blind detection technology have been gradually maturing since 1980. Under the condition of without training sequence, blind detection technology merely rely on the received sequence to detect the transmitted signals. Combined with the advantages of low computational complexity, requiring short data and suitable for containing the common zero channel [1], now using HNN for blind detection algorithm have certain researches [2-7]. In general, a great many algorithms gained good performance and convergence by ameliorating sigmoid function. Di Fen proposed a new activation function [8], which showed a strong anti-interference ability and robustness at low SNR and complex large data environment. Reference [9] noted that using arctangent function as the activation function of the network compared with traditional sigmoid function, the convergence rate of BP neural network accelerated 3 to 10 times. Subsequently, an adjustable parameter activation function proposed has greatly improved the convergence speed of BP neural network [10-12].

Inspired by the reference [11], firstly this paper studies the continuous HNN blind algorithm detection algorithm, then on the basis of the original algorithm, we introduce an adjustable parameters activation function into the HNN blind detection algorithm. The simulation results illustrate that the novel activation function has greatly improved the performance of blind detection algorithm.

2. Blind detection algorithm based improved HNN.

2.1. The construction of a Hopfield neural network model. According to reference [12], a single neuron block diagram of HNN as shown in figure 1:

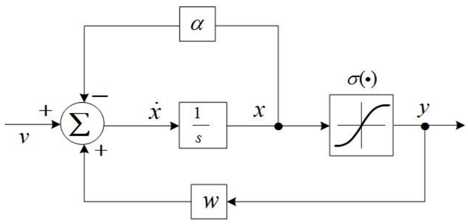

FIGURE 1. A single neuron block diagram of HNN.

From figure 1, a single neuron dynamic equation of HNN can be written as the following form:

$$\frac{dx\left(t\right)}{dt}=-\alpha x\left(t\right)+\omega y\left(t\right)+v \tag{1}$$

$$y\left(t\right)=\sigma\left(x\left(t\right)\right) \tag{2}$$

where, x is the state of neurons, y is the output of the neuron, w is the connection weights, v is bias, α is the recession coefficient, $\sigma\left(\cdot\right)$ is the activation function.

2.2. A novel activation function is proposed. Usually, in order to solve the poor anti-noise performance and slow convergence rate, inspired by the reference [11], we introduce an adjustable parameters activation function to blind detection algorithm:

$$\sigma(x(t))=\frac{A}{1+e^{Bx(t)+C}}+D, AB>0 \tag{3}$$

where, B is steepness factor, the greater B, the more steep curve of the sigmoid function; C and D are the location parameter of the sigmoid function, C adjusting the horizontal position, D adjusting the vertical position; A is a mapping interval factor. In order to guarantee $\sigma'(t)>0$, $AB>0$. So, given appropriate parameter values, the novel sigmoid function can show rich nonlinear ability, such as the hyperbolic tangent function can be expressed by proposed sigmoid function.

Improved activation function has the following main advantages: (1)the new improved activation function expresses stronger nonlinear mapping ability by regulating the steepness, position and mapping range of the activation function. (2)the improved activation function can ensure fast convergence when the absolute value of the input neurons is bigger. (3)adjusting the parameter C can make the value of derivative near zero smaller than the traditional sigmoid activation function. Therefore, at the point of near zero, the improved activation function has lower sensitivity of the neuron input values and stronger anti-interference ability.

2.3. **Stability proofs of improved HNN.** To judge the stability of improved HNN, the general method is using the law of Lyapounov and derivative Lyapounov, etc. According to the reference [13], this paper energy function can be expressed as:

$$E(t) = -\frac{1}{2}\sigma^T(t)w\sigma(t) + \alpha\int_0^{y(t)}\sigma^{-1}(\eta)d\eta - vy(t) \tag{4}$$

$$\begin{aligned}\frac{dE(t)}{dt} &= -w\sigma(t)\frac{dy}{dt} + \alpha\sigma^{-1}(y)\frac{dy}{dt} - v\frac{dy}{dt}\\ &= -\frac{dy}{dt}(-\alpha\sigma^{-1}(y) + wy + v)\\ &= -\frac{dy}{dt}\frac{dx}{dt}\end{aligned} \tag{5}$$

For the new sigmoid function, when $AB > 0$, $\sigma'(t) > 0$, $\frac{dy}{dt} = \sigma'(x)\frac{dx}{dt}$, so $\frac{dE(t)}{dt} = -\sigma'(x)(\frac{dx}{dt})^2 \leq 0$. Based on Lyapounov stability theorem, the network energy function is stable because of network energy value decreased during the iteration operation.

3. **The configuration of weight matrix of the novel blind detection algorithm based on HNN.** According to the reference [12,13], in case of ignoring noise, SIMO(Single-Input Multi-Output) receiving signal equation and blind processing equation in a digital communication system are as follows:

$$\begin{aligned}(x(n))_{q\times1} &= [h(0), h(1), \ldots h(M)](s(n))_{(M+L+1)\times1}\\ &= \sum_{k=0}^{M}(h(k))_{q\times1}s(n-k)\end{aligned} \tag{6}$$

$$x_N = s_N \cdot {\tau_L}^{\mathrm{T}} \tag{7}$$

Where, q is over-sampling factor, M is the channel order, L is equalizer coefficients, $[\mathrm{h}(0), \mathrm{h}(1), \ldots \mathrm{h}]$ is impulse response of communication channel, $(x_N)_{N\times(L+1)q}$ is receiving data matrix, $(s_N)_{N\times(L+M+1)}$ is sending signal matrix. $(\tau_L)_{(L+1)q\times(L+M+1)}$ is block Toeplitz matrix:

$$\tau_L = \begin{bmatrix} h(0) & h(1) & \cdots & h(M) & 0_{q\times1} & \cdots & 0_{q\times1}\\ 0_{q\times1} & h(0) & \cdots & \cdots & h(M) & \ddots & \vdots\\ \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & 0_{q\times1}\\ 0_{q\times1} & \cdots & 0_{q\times1} & h(0) & \cdots & \cdots & h(M)\end{bmatrix}_{(L+1)q\times(M+L+1)} \tag{8}$$

The equation (7) shows that, while τ is column full rank matrix, there must be $Q = u_c u_c^H$, with $Qs_N(k-d) = 0$. Where, u_c is Unitary array of the SVD. $x_N = [u, u_c] \cdot \begin{bmatrix} d\\ 0\end{bmatrix} \cdot v^T$, $u_c \in C^{N\times(N-(L+M+1))}$. Thus, we can construct cost function and the optimization problem as follows:

$$J(\tilde{s}_N) = \varepsilon_N^T\varepsilon_N = \tilde{s}_N^T Q\tilde{s}_N \tag{9}$$

$$\hat{s} = \arg\min(J) \tag{10}$$

Obviously, the problem of signal restoration can be transformed into the quadratic function optimization problems as shown in equation (9). For the use of HNN to solve the blind detection problem of equation (9), we can make a network connection matrix as follows:

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

The Q is supplementary projection operator, the point when s(k) = s(k+1) is the equilibrium point of HNN, at this time, s(k) = f(s(k)-Qs(k)) meet the requirements of cost function. So, the neural network weight matrix as above configuration can put the BPSK (Binary Phase Shift Keying and Binary Phase Shift Keying) signal blind detection problem into a HNN energy function of the minimum problem, we can ensure the stable convergence point of HNN is the needed sending signal.

4. **Simulation experiment.** Simulation environment: the sending signal is BPSK signal, the channel noise is additive white Gaussian noise. All the simulation parameters are set as follows: each simulation result comes out through 100 times Monte Carlo experiments. According to reference practice [16], the point whose error rate is zero in simulation experiments is set 10^{-5} in order to be convenient for plotting. According to a large number of simulation results, the selection of simulation parameters: $A = 2, B = -4, C = 0.2, D = -1$.

Experiment 1: we fix the data length of sending signal N=100, choose the synthesis channel with fixed weight and time delay containing no zero. we compare the error performance of improved HNN blind algorithm with traditional HNN blind detection algorithm [8] and Variable Step Hopfield neural network (VSHNN) blind detection algorithm [13]. Recording the convergence time of these three algorithms are as shown in table 1, the error performance of three blind detection algorithms are shown in figure 2.

Table 1. the convergence time comparison of two algorithms.

Algorithm type	HNN	VSHNN	Improved HNN
Convergence time(Unit Second)	36.7980	32.8180	33.0360

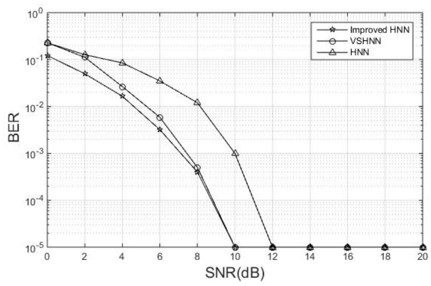

Figure 2. The error performance comparison of three algorithms.

From table 1 and figure 2, the average bit error rate (BER) of traditional HNN decrease to 0 when SNR=12, the average BER of improved HNN and VSHNN decrease to 0 when SNR=10, but the speed of the novel algorithm faster than VSHNN, which illustrate the error performance of the blind detection algorithm based on adjustable parameters activation function HNN is superior to traditional HNN and VSHNN. The convergence time of improved HNN is also less than traditional HNN, but a little longer than VSHNN.

Experiment 2: using two different classical channels, channel one: the synthesis channel with fixed weight and time delay containing one common zero. Channel two: Zhi Di channel [17]. we also compare the error performance of improved HNN blind algorithm with traditional HNN blind detection algorithm [8] and VSHNN blind detection algorithm [13], as showed in figure 3 and figure 4.

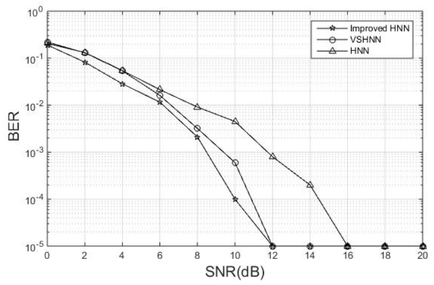

Figure 3. In one common zero channel, the error performance comparison of three algorithms.

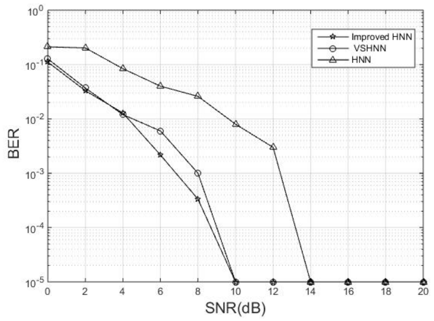

Figure 4. In Zhi Di channel, the error performance comparison of three algorithms.

Figure 3 and Figure 4 show that the three blind detection algorithms based on adjustable parameters activation function HNN, VSHNN and traditional HNN are all suitable for the above two classic channels, and has a certain universal properties. It also illustrates the blind detection algorithm is a good way to solve the problem of channel containing zero, but the error performance of the improved HNN is the best among the three algorithms.

5. **Conclusion.** In this paper, we have introduced an adjustable parameters activation function into HNN blind detection algorithm and chosen suitable activation function of the algorithm by adjusting the four parameters. Under the same conditions, the proposed algorithm showed the better error performance and convergence than traditional HNN and VSHNN, suitable for low SNR and complex large amount of data environments, laid a certain foundation for further study of blind detection algorithm in high speed and complex environments.

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