Adaptive IA-TCNN Multiuser Detector Based on Simulated Annealing of Optimization

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Abstract

In this paper, the action of annealing function in optimal process was researched. The sensibility of self-feedback connection weights was analyzed. The multiuser adaptive detector IA-TCNN based on simulated annealing of optimization is proposed.

A new simulated annealing transiently chaotic network was applied to the CDMA multiuser detection technique. The IA-TCNN has powerful capability to escape from into the local minima. The simulation results show that the adaptive IA-TCNN multiuser detector based on simulated annealing is more effective than the existing neural network multiuser detectors.

1. Introduction

Transiently Chaotic Neural Networks (TCNN) [1] were studied by Chen and Aihara and were introduced a parameter into CNN to harness chaotic dynamics to prevent the network from being trapped into local minima, and obtain a near-optimal solution. By autonomously decreasing the parameter, the chaotic dynamics are gradually vanishes, and the neural networks approach the HNN, which assure a convergence to a stable equilibrium solution.

Sergio Verdu has proposed the optimal MUD [2] and has proved that his algorithm deals with the minimization of a quadratic form. However, its complexity is on the order of $O(2^k)$ for $k$ active users.
To avoid the complexity of implementing this algorithm, several suboptimal linear and nonlinear solutions have been proposed such as MMSE detector, Successive Interference Cancellation (SIC) detector, Parallel Interference Cancellation (PIC) detector, Multistage detector and based on the TCNN detector. In recent years, when the algorithm of neural network is studied deeply, Kechriotis et al[3] proposed a Hopfield net based approach to the MUD problem. Their network finds a local minimum of the associated energy Lyapunov function.

Recently, the most of neural networks were used to solve the routes to near optimality. They were based on Hopfield Neural Network and then were added a self-feedback, which creates more efficient chaotic dynamics to the network. The dynamics of networks depend deeply on the self-feedback character $z_i(t)$ which is similar to the temperature of simulated annealing and is very important to network optimization and converge quickly. To solve the problem, some scholars proposed some modified methods and have made good progress[4][5]. This paper analyzes a simulated annealing function of optimization about self-feedback connection weights $z_i(t)$. With the strategy, the improved network can make good use of chaotic dynamics and converge quickly. Through applying it to the CDMA multiuser detector, a multiuser detector for adaptive transiently chaotic neural network (A-TCNN) based on simulated annealing of optimization is proposed.

2. Adaptive Transiently Chaotic Neural Networks (A-TCNN)

2.1 Transiently Chaotic Neural Networks

TCNN equation can be written in the following form:

$$v_i(n) = \tanh(\varepsilon * u_i(t)) \quad (1)$$

$$u_i(n+1) = ku_i(n) + \alpha(-\frac{\partial E}{\partial u_i}) - z_i(n) * [v_i(n) - I_i] \quad (2)$$

$$-\frac{\partial E}{\partial v_i} = \sum_{j=1}^{n} w_{ij} v_j + I_i \quad (3)$$

$$z_i(n+1) = (1-\beta)z_i(n) \quad (4)$$

where, $v_i(n)$ is output of neuron $i$, $u_i(n)$ is internal state of neuron $i$, $z_i(n)$ is self-feedback connection weight of neuron $i$, $w_{ij}$ is connection weight from neuron $j$ to neuron $i$ ($w_{ij} = w_{ji}$, $w_{ii} = 0$), $I_i$ is input parameter of neuron $i$, $I_0$ is positive parameter, $\varepsilon$ is sharpness parameter for outputs, $k$ is damping factor of nerve membrane ($0 \leq k \leq 1$), $\alpha$ is damping factor of time-dependent term ($0 \leq \beta \leq 1$), $\alpha$ is positive scaling parameter for inputs.

2.2 Adaptive Transiently Chaotic Neural Networks

In [6] adaptive transiently chaotic neural network has been proposed. It adjusts $\alpha$ according to the change of the energy function and adds relational expression to the model of TCNN:

$$\alpha(t+1) = f(\alpha(t)) \quad (5)$$
where, $f()$ is changing rule of $\alpha$. $f()$ can be described concretely to the comparison between energy function $E_1$ which is obtained by every iterating and energy function $E_2$ which is obtained by the last iterating:

1. If $\gamma_2 > 1$, $\alpha(t + 1) = \gamma_1 \alpha(t)$, $\gamma_1 \in (0, 1)$;
2. If $E_1 > E_2$ and $E_1 < \eta E_2$ (The ratio $\eta$ has been given), $\alpha(t + 1) = \alpha(t)$;
3. If $E_1 > \eta E_2$, $\alpha(t + 1) = \gamma_2 \alpha(t)$, $\gamma_2 > 1$.

The simulation results in [6] show that A-TCNN possesses the better performance in convergence and accuracy. Then it is used in CDMA multiuser detector, the results is also ideal.

3. Analysis Of Simulated Annealing Strategy

For understanding the running mechanism of above-mentioned network, we can analyze the chaotic dynamics of the network in one-dimensional TCNN. The model of it can be described in terms of scalar variables as follows:

$$
\begin{align*}
\dot{v}_i(n) &= \tanh(\varepsilon * u_i(t)) \\
u_i(n + 1) &= ku_i(n) - z_i(n) \left[ v_i(n) - I_v \right] \\
z_i(n + 1) &= (1 - \beta) z_i(n)
\end{align*}
$$

(6)

In Ref.[4], the author gives an annealing function of subsection exponent (7) in stead of (4) in network model:

$$
z_i(t + 1) = \begin{cases} 
(1 - \beta_1) z_i(t), & z_i(t) > z_i(0)/2 \\
(1 - \beta_2) z_i(t), & \text{其它}
\end{cases}
$$

(7)

If $z_i(t)$ is larger and $\beta$ is smaller, traversal searching can be carried on in extensive extents. The algorithm can not be trapped into local minima, and obtain a near-optimal solution. So we can use a large exponential damping to converge quickly.

By autonomously decreasing the parameter, the chaotic dynamics are gradually vanishes. The end of converging quickly to the global-minimum is ideal, but is disrurbed by self-feedback. Above-mentioned (7) can not solve the problem, so in Ref.[5], an improved method is proposed to aim at (7): when the outputs of the network balance to a stable value, $z_i(t)$ must be set to 0 to eliminate perturbation.

The function (8) can describe the improved optimization strategy:

$$
z_i(t + 1) = \begin{cases} 
(1 - \beta_1) z_i(t), & \text{if } z_i(t) > z_i(0)/2 \\
(1 - \beta_2) z_i(t), & \text{if } z_i(t) \leq z_i(0)/2 \\
0, & \text{and } |x_i(t + 1) - x_i(t)| > \delta \\
& \text{and } |x_i(t + 1) - x_i(t)| < \delta
\end{cases}
$$

(8)

where, $\beta_1$ and $\beta_2$ are constants, $\beta_1 < \beta_2$, $\delta$ is a positive value which is small enough (generally is $10^{-3}$ order of magnitude).

(4) in TCNN model is replaced by (8). Then one-dimensional TCNN (6) is considered, and the parameters are as follows: $k = 0.9$, $\beta_1 = 0.02$, $\beta_2 = 0.1$, $I_v = 0.65$, $\gamma(0) = 0$, $z(0) = 3$, $\varepsilon = 5$. 
Fig. 1 Outputs of single neuron

Fig. 1 (a) (b) show the evolution graph of output $v_i(t)$ of single neuron with iterations $N$. And they separately base on exponential annealing strategy and optimal strategy (8). By contrasting them, the last strategy can accelerate the search speed and guarantee the assurance of the veracity of the optimal arithmetic.

4. A Multiuser Detector For Adaptive Tcnn Based On Simulated Annealing Of Optimization (IA-TCNN MUD)

In the synchronous case, the estimate which is produced by the Optimal Multiuser Detector (OMD) of the information vector transmitted at the discrete-time instants can be obtained by solving the following problem:

$$\hat{b}_{OMD} = \arg \min_{b \in \mathbb{R}^K} \left(-y^T b + \frac{1}{2} b^T H b\right)$$

(9)

where, $y = [y_1, y_2, \ldots, y_K]^T$ is the outputs of the matched filter, $b = [b_1, b_2, \ldots, b_K]^T$ is the vector containing information bits of the users, $H \in \mathbb{R}^{K \times K}$ is the signal correlation matrix with elements $h_{k\ell} = \int s_k(t)s_\ell(t) \, dt$.

(9) can be rewritten as:
\[
\hat{b}_{\text{OMD}} = \arg \min_{b \in \mathbb{R}^K} \left(-y^T b + \frac{1}{2} b^T Hb\right) \\
= \arg \min_{b \in \mathbb{R}^K} \left(-y^T b + \frac{1}{2} b^T (H - E) b + \frac{1}{2} b^T E b\right) \\
= \arg \min_{b \in \mathbb{R}^K} \left(-y^T b + \frac{1}{2} b^T (H - E) b\right)
\]

(10)

where, \(E = \text{diag}\{e_1, e_2, \cdots, e_{22}\}\) is a diagonal matrix with element \(e_i = h_i = \int s_i(t) \, dt, i = 1, 2, \cdots, K\), \(\frac{1}{2} b^T E b\) as a constant can be omitted in (10).

The TCNN energy function is very similar to that of HNN, can be written as:

\[
E(v) = \frac{1}{2} v^T Wv - I^T v
\]

(11)

Therefore, the OMD objective function can be directly translated into the energy function of a TCNN Neural Network as follows:

\[
\begin{align*}
W &= -(H - E) \\
I &= y \\
v &= b
\end{align*}
\]

(12)

According to the TCNN model, the iterative process of the network can be updated as follows:

\[
u(n+1) = ku(n) + \alpha \left( \sum_{j=1}^{K} w_j v_j + I \right) - z(n) \left[ v(n) - I_0 \right]
\]

(13)

Now through substituting (13) to the improved TCNN which is described by Equations (1) ~ (3), (5) and (8), a multiuser detector for adaptive TCNN based on simulated annealing of optimization (IA-TCNN) can be obtained.

The spreading sequence assigned to the users are derived from Gold Sequences with length \(L = 31\). Then, we can simulate the HNN, TCNN, TCNN based on simulated annealing of optimization (I-TCNN) and adaptive TCNN based on simulated annealing of optimization (IA-TCNN) multiuser detector, and compare their performance.

In the simulation, a sixteen-user synchronous CDMA system was considered. Fig.2 shows the results of comparison of the algorithm with HNN, TCNN, I-TCNN and IA-TCNN multiuser detector. With the SNR becoming large, the BER of all the detectors descend quickly, but the IA-TCNN MUD outperformed the others.
Fig. 2 Average BER versus SNR

Fig. 2 shows that the average BER of every MUD change with the near-far ratio (Energy ratio $E_i/E_1$) when $SNR = 10dB$. From the figure, the ability of IA-TCNN to combat near-far effect outperforms the others.

Fig. 3 Average BER versus $E_i/E_1$

Fig. 3 shows that the average BER of every MUD change with the near-far ratio (Energy ratio $E_i/E_1$) when $SNR = 10dB$. From the figure, the ability of IA-TCNN to combat near-far effect outperforms the others.

Fig. 4 SIR comparison of different number of user in IA-TCNN MUD

Fig. 4 shows that SIR of IA-TCNN MUD is usually high. And when the number of user change from 5 to 15, SIR descends 3dB every time. It indicates that IA-TCNN MUD has powerful ability to suppress the multiple access interference (MAI).
5. Conclusions

In this paper, the sensibility of $z(t)$ is analyzed in dynamics of TCNN model. Through researching the action of annealing function in optimal process, a multiuser detector for adaptive TCNN based on simulated annealing of optimization is proposed. The improved network can escape from local optimum and converge quickly. The simulated results show that the performance of IA-TCNN is more effective than the other ones of neural network.

References