Optimizing Semiconductor Laser PIDNN Decoupling Control Base on CPSO

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Abstract. The coupling model of semiconductor laser is established for optical port components. The decoupling controller is designed by PIDNN, which enables the controller to response quickly and set parameter. The initial value of PID parameter is optimized by CPSO, and the appropriate initial value can make the system stable and reach expected value. CPSO can effectively prevent weight parameter search from falling into local optimal, and has a fast search speed.

1. Introduction
Semiconductor laser as an important light source of optical fiber communication system has been widely concerned by the academia and engineers. Because of its small size, light weight, high reliability, low voltage drive and other advantages, semiconductor lasers are also widely used in scientific research, medical and military fields[1]. Semiconductor lasers are very sensitive to operating temperature and driving current, and the output optical power will depend on the PN junction and driving current inside the laser. There is a serious coupling effect between junction temperature and output light power of semiconductor laser, that is, the increase of junction temperature will inevitably lead to the decrease of quantum efficiency, which will lead to the increase of threshold current and heat dissipation, thus further increase of temperature of semiconductor laser. The increase of temperature will inevitably increase of the kinetic energy of free electrons, which will lead to the increase of the optical absorption rate, which will further cause temperature rise. Only by dealing with the coupling effect between junction temperature and optical power well, the semiconductor laser can work properly[2,3].

In actual engineering, the semiconductor laser realizes temperature control by changing the operating current through the TEC control circuit, and the optical power of the semiconductor laser is mainly determined by the driving current of the laser [4-5], as shown in figure 1. The coupling relationship between junction temperature and output optical power of the laser is shown in the block diagram shown in figure2. TEC driving current is represented by $I_{TEC}(s)$, laser driving current is represented by $I_{LD}(s)$, junction temperature of laser is represented by $T(s)$, and output power is represented by $P(s)$. $C(s)$ represents the control module, which $C_1(s)$ controls junction temperature and $C_2(s)$ optical power. $G(s)$ represents the coupling relationship of semiconductor lasers, $G_{11}(s)$ and $G_{22}(s)$ respectively represent the transfer function between the driving current and the operating temperature of TEC, and the transfer function between the driving current and the output optical power of the laser. $G_{21}(s)$ and
respectively represents the transfer function of the coupling relation between the four control variables. The coupling relationship of semiconductor lasers represented by $G(s)$ is a multivariable nonlinear system with complexity and uncertainty [6], which is difficult to accurately model. Therefore, this paper attempts to use the PID neural network (PIDNN) without the control model as the controller, and adopts the initial weight of the Chaotic particle swarm optimization (CPSO) to ensure the convergence speed and accuracy of the PIDNN. CPSO has the advantages of simple architecture, fast convergence speed, global search ability, and prevention of getting into the local optimal solution. CPSO combined with PIDNN can effectively improve the convergence speed and accuracy [7-8].

2. Introduction to PIDNN Decoupling

2.1 PIDNN structure

In order to overcome the traditional PID controller parameters real-time tuning difficulties and improve the performance of the controller, at the end of the last century, a new control strategy PID controller combing with neural network appeared. The PID controller combined with neural network has three forms, including neural network tuning PID parameters, single neuron PID controller and PID neural network controller (PIDNN). The controller of communication laser is required to have quick command response. PIDNN structure is selected and the decoupling controller is designed considered its simple structure and quick parameters convergence. The structure of the controller is shown in figure 3. The nodes of the hidden layer in PIDNN correspond to proportional, integral and differential control respectively. There are $2n$ neurons in the input layer, and $n = 2$ in the laser controller[9]. The basic model structure of single PID (SPIDNN) is shown in figure 4.

The neuron input is

$$\begin{align*}
    net_{s1}(k) &= r_s(k), \\
    net_{s2}(k) &= y_s(k),
\end{align*}$$

(1)
where \( r_j(k) \) is the command of the system, \( y_j(k) \) is the system response quantity. The neuron input function of hidden layer is:

\[
\text{net}_{s_j}^i(k) = \sum_{l=1}^{3} w_{sij} x_{s_l}(k) .
\]

The proportional, integral and differential neuron forms of the discrete system are shown in equations (3),(4) and (5),

\[
\begin{align*}
\dot{u}_{s_j}(k) &= \text{net}_{s_j}(k), \\
\dot{u}_{s_j}(k) &= \dot{u}_{s_j}(k-1) + \text{net}_{s_j}(k), \\
\dot{u}_{s_j}(k) &= \dot{u}_{s_j}(k) - \text{net}_{s_j}(k-1),
\end{align*}
\]

where \( w_{sij} \) is the connection weight, \( x_{s_l}(k) \) is the output value of neurons in the input layer of each sub net, \( j \) is the neuron number of sub net hidden layer. The superscript " \( \cdot \) " indicates the hidden layer variable.

### 2.2 Neural network learning algorithm

The learning objective of generalized networks of PID neural networks and multivariable control objects is to minimize the output bias or error,

\[
J = \sum_{p=1}^{n} E_p = \frac{1}{m} \sum_{p=1}^{m} \sum_{k=1}^{n} \left[ r_p(k) - y_p(k) \right]^2 = \frac{1}{m} \sum_{p=1}^{m} \sum_{k=1}^{n} e^2_p(k),
\]

where, \( r_p(k) \) is the command of the system, \( y_p(k) \) is the output or response of the system, \( m \) is the number of sampling points per batch, and \( n \) is the number of controlled variables.

The weight iteration formula of PID neural network adjusted by gradient method is

\[
\begin{align*}
\dot{w}_{s_{jh}}(n_0 + 1) &= w_{s_{jh}}(n_0) - \eta_{s_{jh}} \frac{\partial J}{\partial w_{s_{jh}}}, \\
\dot{w}_{s_{jh}} &= \sum_{p=1}^{n} \frac{\partial J}{\partial w_{s_{jh}}} = \sum_{p=1}^{n} \frac{\partial E_p}{\partial w_{s_{jh}}} = \sum_{p=1}^{n} \frac{\partial y_p}{\partial w_{s_{jh}}} = \sum_{p=1}^{n} \frac{\partial x_h}{\partial w_{s_{jh}}} = \sum_{p=1}^{n} \frac{\partial \text{net}_h}{\partial w_{s_{jh}}},
\end{align*}
\]

and in which

\[
\begin{align*}
\frac{\partial y_p}{\partial v_h} &= \text{sgn} \left[ y_p(k+1) - y_p(k) \right], \\
\frac{\partial x_h}{\partial v_h} &= \text{sgn} \left[ x_h(k) - x_h(k-1) \right].
\end{align*}
\]

When we define

\[
\delta_{hp} = 2 [ r_p(k) - y_p(k) ] \text{sgn} \left[ y_p(k+1) - y_p(k) \right],
\]

thus, we get

\[
\frac{\partial J}{\partial w_{s_{jh}}} = \frac{1}{m} \sum_{p=1}^{n} \sum_{k=1}^{m} \delta_{hp} x_{s_l}(k).
\]

The weight iteration formula from hidden layer to output layer is

\[
\begin{align*}
\dot{w}_{s_{jh}}(n_0 + 1) &= w_{s_{jh}}(n_0) + \eta_{s_{jh}} \sum_{p=1}^{n} \sum_{k=1}^{m} \delta_{hp} x_{s_l}(k),
\end{align*}
\]

where, \( w_{s_{jh}} \) is the weight from the hidden layer to the output layer, \( \eta_{s_{jh}} \) is the learning step, \( x_{s_l}(k) \) is the output of neurons in the output layer, and \( h \) is the sequence number of neurons in the output layer \((h = 1, 2, \ldots, n)\).

In the same way, we can get the weight iteration formula from the input layer to the hidden layer:
\[ w_{sj}(n_0 + 1) = w_{sj}(n_0) + \eta_{sj} \sum_{p=1}^{n} \sum_{h=1}^{m} \delta_{sjh}(k)x_i(k) \]

and in which \[ \delta_{sjh} = \delta_{hp}w_{sjh} \text{sgn}\left(\frac{u_{sj}(k) - u_{sj}(k-1)}{\text{net}_{sj}(k) - \text{net}_{sj}(k-1)}\right) \]

When the learning step of PIDNN satisfy

\[
\left\{
\begin{array}{l}
0 < \eta < \frac{1}{\epsilon^2}, \\
\epsilon = -\frac{1}{2\sqrt{J \partial W}}
\end{array}
\right.
\]

the control system converges in the learning process, where \( W \) represents the connection weight of the neural network.

3. CPSO Optimizes Initial Weights

Reasonable selection of initial value of network weight can accelerate the speed of network learning and parameter convergence. A prominent advantage of PID neural network is that the initial value of connection weight is set according to the basic principle of PID control law. The initial value of network weight can be determined by using a large amount of existing experience data of PID control. Based on the initial value, the network can be trained, learned and adjusted to make the network learn quickly.

CPSO was selected to optimize the initial value of the weight, respectively determining the connection weights of proportional element, differential element and integral element from the input layer to the hidden layer, and the initial value of the network weight from the hidden layer to the output layer. Finally, the PIDNN is equivalent to several independent PID controllers through weight selection. The multi-output PIDNN becomes \( n \) independent sub networks, that is, \( n \) single-output PID neural networks, and the equivalent control law can be obtained as:

\[
v_s(k) = k_{ps}e_s(k) + k_{is}\sum_{i=1}^{k} e_s(i) + k_{ds}\left[e_s(k) - e_s(k-1)\right]
\]

Due to the nonlinear mapping characteristics, the PIDNN controller get the decoupling control ability. During training and learning, the controller itself does not know whether the task is decoupling or control. The controller only completes the mapping from system input to system output according to the requirements of the objective function. Therefore, according to the input and output of the system, the PIDNN can adjust the connection weight gradually according to the learning algorithm, so that the decoupling control performance of the system can reach the set point. Decoupling is the means and control is the end. PIDNN controller integrates decoupling and control and they complement each other and are closely related. Thus, PIDNN is used in the laser controller to simplify the design and realize the decoupling control.

Because of the strong linear characteristic of the laser parameters, the system can keep the parameters in a small range to get good output characteristics. Proper initial weights can stabilize the system quickly at the desired output value. By introducing chaotic mapping, the dynamic characteristics of the CPSO were revealed to be chaotic, so as to avoid the optimization falling into the local optimal solution. By adding chaos to the particle motion, the local search can be more refined. Common chaotic mappings include Logistic mapping, Lorenz mapping and Henon mapping[10]. The Logistic mapping was used in this paper, and the motion equation of particle swarm with chaos factor is shown in equation (15):

\[
v(k+1)_{id} = a_{id}v(k)_{id} + a_{r1}rand_{r1}(P_{bid} - P_{id}) + a_{r2}rand_{r2}(P_{gb} - P_{id})
\]

\[
P_{id}(k+1) = P_{id}(k) + v(k+1)_{id}
\]
Particle swarm consists of N particles, searching in d-dimensional space. The relation between velocity \(v(k)_i^d\) and position \(P_i^d(k)\) of particle i at time k is determined by equation (15). \(P_{bid}\) and \(P_{eb}\) respectively represent the optimal position experienced by a single particle and the optimal position experienced by all particles. \(a_1\), \(a_2\) and \(a_3\) are acceleration factor, \(rand_1\) and \(rand_2\) are random numbers with chaos effect. Limit the search scope around the global optimal point, and increase the search times within the limit range, we may get a refine point. The iterative mode of random numbers is carried out according to the Logistic mapping. The fitness function should be set for the evaluation of the population position. For the laser system, the fitness function with the output deviation of the controller as the main factor should be considered.

The control strategy flow of CPSO optimization is as follows:

Step1. Initializes population particles and positions, and performs chaotic mapping in preparation for particle swarm update.

Step2. Determine PIDNN weight by the particle swarm, thus controller parameters was determined and run the control system model.

Step3. Evaluate the system output and searcher for the optimal location. The chaotic map is used to update the particle swarm position.

Step4. Calculate the weights of the new positions and run the control system under the same conditions. Compare the system output and determine the update direction. At present, the global optimal point is searched in detail according to the chaotic map.

Step5. Terminate the search and determine the initial weight value when the control target is met. Otherwise, exit the search in the optimal location after setting the search time.

Step6. After the system starts to operate, monitor the output of the system in real time. When the output deviation exceeds the limit, enter Step3 for control.

4. Analysis of Examples

The coupling model of semiconductor laser was established according to literatures[3], and two control strategies, PIDNN controller and PIDNN controller with CPSO optimized initial value were used for test and simulation. Control goal of system temperature set at 25 °C, and the system output optical power set is 0.6 w. After several simulation calculations for different initial values, the typical experimental results are shown below. The system decoupling control output of the optimized PIDNN of CPSO is shown in figure 5 and 6, and the population search is shown in figure 7. In order to compare the optimization effect of CPSO, the PIDNN control effect without CPSO optimization under the same parameter condition was shown in figure 8, parameters are shown in table 1. The accelerating factor was set as \(a_1 = 1, a_2 = 2.1, a_3 = 2.05\), the evolutionary generation was 50, and the population size was 20.

Select the controlled object as \(G = \frac{K}{TS + 1} e^{-\tau}\), parameter references [3] are shown in table 2.

| Controller | Iterative Times | Temperature(C) | Power(w) |
|------------|----------------|----------------|----------|
|            |                | response | overshoot | minimum | response | overshoot | minimum |

Table 1. System Simulation Parameters.
| PIDNN | speed | error | speed | error |
|-------|-------|-------|-------|-------|
| 200   | 10    | 4%    | 8.991e-5 | 2%    | 0.082 |
| CPSO-PIDNN | 200 | 12 | 1% | 2.4425e-6 | 43 | 0 | 0.00061 |

| Table 2. Parameters of the Coupling G |
| Parameters | $G_1(s)$ | $G_2(s)$ | $G_3(s)$ | $G_2(s)$ |
| K | 11.25 | 7.29 | 0.61 | 1.89 |
| T | 131.23 | 149.71 | 175.13 | 60.61 |
| τ | 0.001 | 0.002 | 0.002 | 0.001 |

**Figure 5. Response of CPSO-PIDNN Controller**

**Figure 6. Error of PIDNN Controller**

**Figure 7. CPSO Adaptive Degree**

**Figure 8. Response of PIDNN Controller**

5. **Conclusion**

The results show that the PIDNN controller can decouple the laser system effectively. The introduction of CPSO did not significantly slow down the response speed of the system. In the case of disturbance, the response of the system with CPSO optimization was better, and it could effectively avoid the problem of falling into the local optimal point and output deviation in the process of neural network weight learning.
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References
[1] TIAN Yitong, WANG Haixing. High-precision Temperature control system for lasers[J]. Control and Instruments in Chemical Industry, 2017,44(3):267-270.
[2] ZHAO Bin, LI Hao. Temperature control of semi-conductor laser with PID parameter tuning[J]. Journal of Shenyang University of Technology, 2017,39(4):444-448.
[3] WU Wenfeng. Research on decoupling control of semiconductor laser based on DSP[D]. Nanchang Hangkong University, 2011.
[4] HAN Tuanjun, WEI Pingping, LI Gaofeng. Semiconductor laser temperature control system based on FPGA[J]. Laser Journal, 2018, 39(9): 47-50.
[5] LU Yan, ZHANG Yanrong, HU Xiaoli. Design of semiconductor laser temperature Control System Based on Fuzzy PID[J]. Machinery & Electronics, 2018, 36(6): 250-253.
[6] LOU Guohong, ZHANG Jianping. Improved particle swarm algorithm in the fiber laser decoupling control[J]. Laser Journal, 2018, 39(2): 64-67.
[7] LIU Jun. PID neural network decoupling control based on seeker optimization algorithm[J]. Industrial Instrumentation & Automation, 2015, (5): 97-100.
[8] HONG Yunguo. Simulation of greenhouse temperature and humidity decoupling control based on particle swarm algorithm optimized PIDNN[J]. Manufacturing Automation, 2013, 35(4): 124-126.
[9] SONG Shuiquan. Simulation of multivariable control systems based on improved PID Neural Network[J]. Electronic Science and Technology, 2016, 29(6): 26-28, 33.
[10] CHEN Shuaishuai, XIONG Zhixin, HU Mu-yi. Decoupling control of headbox with PIDNN based on particle swarm optimization[J]. China Pulp & Paper Industry, 2017, 38(6): 20-24.