

Redesigning Ideological and Political Courses in the Digital Era with Computer Network Technology

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Abstract. In order to improve the effect of ideological and political curriculum design, this paper combines computer network technology (CNT) to conduct research on ideological and political curriculum design. The proposed evolved local synaptic plasticity rules (PA) allow different neurons within the reservoir to adopt different types and allow different parameters of the synaptic PA to be used to achieve local plasticity tuning of the reservoir connection weights. Moreover, the proposed local synaptic PA can effectively alleviate the synaptic interference problem in structural learning. In addition, this article also constructs a CNT based ideological and political curriculum system. The experimental research shows that the Digital Cultural Heritage-based ideological and political curriculum design system based on CNT proposed in this paper has a good effect.

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1 INTRODUCTION

The educating community should focus on sharing educating resources. By grasping the educating key points of body and soul building, select the ideological and political resources that are easy for college students (CS)to understand, rich in content, and diverse in forms to develop scientifically and systematically. This not only provides high-quality materials for deepening the "integration of five education", but also helps to broaden the learning horizons of CS and fully guarantee the quality of the ideological and political education.

Promoting the coordination of the process of educating people is an important step in the construction of a community of the ideological, and it is also a key path to highlight the advantages of the ideological. When building a community of the ideological and political education, it is necessary to make full use of practical educational resources to promote CS to obtain good spiritual experience and ideological edification in specific participation [6]. First, the community of the ideological and political education should be based on the "integration of five education" and actively follow the core principle of "student-oriented". Moreover, it should integrate the mental quality and growth needs of CS, design the ideological and political plans for educational courses in line with

different grades, and ensure the effective connection of the ideological and political practice [2]. Second, the community of the ideological and political education should be based on the multiple spatial advantages of the integration of internal and external education in CAU as a carrier to achieve an all-round collaborative linkage of educational practice. By grasping the practical requirements of ideology and politics, making full use of the process of practice, paying attention to the ideological and political construction and college student training [9]. Third, the education community should focus on "communication-deepening", and upgrade from knowledge learning and interactive sharing to understanding sublimation. It can promote the ideological and political construction of college in the form of a community of education, and focus on excavating the ideological and political elements contained in different practice environments. Moreover, by creating the ideological and political learning scene of practical exchange and interactive sharing for CS, it explores the ideological and political education ecology of practical experience and knowledge sharing [8-3].

This paper combines CNT to conduct research on the curriculum design of the ideological and political, and uses intelligent computer models to improve the effect of the ideological and political curriculum design[7-5].

2 INTELLIGENT PROCESSING TECHNOLOGY OF CURRICULUM DATA

2.1 Related Theory

The neural circuits of neurons and the synapses that connect them perform many of the complex information-processing tasks in the brain. Studies have shown that memories are primarily stored in synapses, and changes in their strength are regulated by synaptic plasticity mechanisms in the nervous system. The entire life course of synapses will be constantly changed, renewed and remodeled to meet the needs of body functions due to the influence of various internal and external factors. In a broad sense, synaptic plasticity mainly includes the plasticity of synaptic transmission, the plasticity of morphology and the plasticity of development[4].

Most of the existing synaptic plasticity learning rules can be regarded as the derivation and development of Hebbian rules, that is, the connection weights of the network are adjusted by the response states of pre- and post-synaptic neurons after being stimulated[10].

Formula (1) is the expression of the Hebbian learning rule:

$$\Delta W_{ii}(t) = \eta x_i(t) x_i(t)$$

However, since the Hebbian rule only describes how to increase the synaptic weight, it does not give a mathematical description of how the synaptic weight decays. Therefore, Hebbian learning rules are inherently unstable.

Based on the original Hebbian learning rule framework, more and more improved learning rules for synaptic plasticity have been proposed for the stable operation of the learning process. The first is that the learning rules based on the discharge rate mainly include Oja rules, anti-Oja rules and BCM rules. The second is the learning rule based on the discharge peak time represented by STDP. The third is the recently proposed plutonium ion-controlled plasticity and voltage-dependent plasticity, etc. These different types of PA are different perspectives on understanding and cognition of neural coding processes.

The Oja learning rule addresses the stability problem by normalizing the weights of all connections connected to the postsynaptic neuron j, namely:

$$\sqrt{\sum_{i=1}^{n} W_{ji}(t)^2} = 1$$

(2)

(1)

The expression of the learning rule after normalization is as follows:

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$$W_{ji}(t+1) = \frac{W_{ji}(t) + \eta x_i(t) x_j(t)}{\sqrt{\sum_{i=1}^{n} \left[W_{ji}(t) + \eta x_i(t) x_j(t) \right]^2}}$$
(3)

In the formula, the learning rate η is usually a small constant. When η tends to 0, formula (3) is expanded by a power series. Thus, the learning rule of synaptic plasticity with decay term is derived, that is, the Oja learning rule:

$$W_{ji}(t+1) = W_{ji}(t) + \Delta W_{ji}(t)$$
(4)

$$\Delta W_{ji}(t) = \eta x_j(t) \left[x_i(t) - x_j(t) W_{ji}(t) \right]$$
(5)

In the formula, $-x_j(t)^2 \Delta W_j(t)$ is the weight decay term. The anti-Oja learning rule is an inverse form of the Oja learning rule. The only difference between the two is how the weights are updated. The weight update formula of the anti-Oja learning rule is as follows:

$$W_{ji}(t+1) = W_{ji}(t) - \Delta W_{ji}(t)$$
(6)

The learned structure of the network during model training may be affected by synaptic interference present in consecutively input samples.

In the processing of pattern recognition tasks, the process of sequentially inputting samples into the network is accompanied by the continuous change of synaptic weights. In this process, new input samples can easily destroy the previously learned structure, which is called arithmetic formula. The main idea is to calculate the synaptic interference for the training samples of the corresponding

category in turn, and obtain the overall interference I^{sum} by averaging the synaptic interferences of all categories:

$$I_{t}^{class} = \frac{1}{N} \sum_{i=1}^{N} \left[\Delta W_{ti} \cdot \Delta W_{oi} < 0 \right] \left[\left| \Delta W_{ti} \right| < \left| \Delta W_{oi} \right| \cdot C_{n} \right]$$

$$I^{sum} = \sum_{t=1}^{C_{n}} \frac{I_{t}^{class}}{C_{n}}$$
(8)

Among them, ΔW_t represents the weight adjustment matrix of the current category, ΔW_o represents the average value of the weight adjustment matrix of all categories except the currently

learning mode, the subscript is the synaptic index, and N and C_n represent the number of synaptic connections and the number of categories, respectively.

Covariance Matrix Adaptation Evolution Strategy (CMA-ES) is a kind of random numerical optimization algorithm without derivative information. CMA-ES is often used to deal with nonlinear non-convex continuous optimization problems. The specific implementation steps of the CMA-ES algorithm mainly include initialization, selection, and reorganization.

1. Initialize

The algorithm parameters are initialized according to specific optimization tasks, including initial step size, covariance matrix, initial mean and so on. The initial population is generated according to the

initialization parameters. In the iterative process of the CMA-ES algorithm, the new population $\chi^{(g+1)}$ is generated by sampling:

$$x_{k}^{(g+1)} = m^{(g)} + \delta^{(g)} N(0, C^{(g)})$$
(9)

Among them, $x_k^{(g^{+1})}$ represents the k-th individual in the g+1 generation, $m^{(g)}$ is the mean of the g-th generation distribution, and $\delta^{(g)}$ is the step size of the g-th generation distribution. $N(0, C^{(g)})$ is a multidimensional normal distribution with mean 0 and covariance $C^{(g)}$, and the covariance matrix $C^{(g)}$ of the g-th generation distribution satisfies the following equation:

$$C^{(g)} = B^{(g)} \left(D^{(g)} \right)^2 \left(B^{(g)} \right)$$
(10)

In the formula, $B^{(g)}$ is an orthogonal matrix, and its column vector is the eigenvector of unit length of $C^{(g)}$. $D^{(g)}$ is a diagonal matrix whose diagonal elements are the square roots of the eigenvalues of $C^{(g)}$, corresponding to the column vectors of $B^{(g)}$.

2. Select

The CMA-ES algorithm uses (μ, λ) strategy to select individuals. That is, μ optimal individuals are selected from λ individuals to form a new optimal subgroup by sorting the fitness values of individuals, as shown in formula (11):

$$f\left(x_{l:\lambda}^{(g+1)}\right) \le f\left(x_{2\lambda\lambda}^{(g+1)}\right) \le \dots \le f\left(x_{\lambda:\lambda}^{(g+1)}\right) \tag{11}$$

Among them, $x_{i,\lambda}^{(g+1)}$ is the i-th optimal individual selected from λ individuals in the g+1 generation.

3. Reorganization

During the recombination process, the first μ optimal individuals of the g-th generation are used to update the strategy parameters of the algorithm, including the update of the step size, the covariance matrix and the mean parameter.

The update formula for the mean
$$m^{(g+1)}$$
 is as follows:

$$m^{(g+1)} = \sum_{i=1}^{\mu} w_i x_{i:\lambda}^{(g+1)}$$
(12)

In the formula,

$$\sum_{i=1}^{\mu} w_i = 1, w_1 \ge w_2 \ge \dots w_{\mu} \ge 0$$
(13)

The update formula of the covariance matrix $C^{(g+1)}$ is as follows:

$$C^{(g+1)} = (1 - c_{cov})C^{(g)} + \frac{c_{cov}}{\mu_{eff}}p_{s}^{(g+1)}(p_{s}^{(g+1)})^{T} + \frac{c_{cov}}{(\delta^{(g)})^{2}} \left(1 - \frac{1}{\mu_{eff}}\right)\sum_{i=1}^{\mu}w_{i}\left(\frac{x_{i:\lambda}^{(g+1)} - m^{(g)}}{\delta^{(g)}}\right)\left(\frac{x_{i:\lambda}^{(g+1)} - m^{(g)}}{\delta^{(g)}}\right)^{T}$$
(14)

In the formula,

$$u_{eff} = \left(\left(\sum_{i=1}^{\mu} w_i^2 \right) \right)^{-1}$$
(15)

In the formula, C_{cov} represents the learning rate parameter of the covariance matrix.

The update formula of evolution path P_s is as follows:

$$p_{s}^{(g+1)} = (1 - a_{s}) p_{s}^{(g)} + \sqrt{a_{s} (2 - a_{s}) u_{eff}} \frac{m^{(g+1)} - m^{(g)}}{\delta^{(g)}}$$
(16)

Among them, a_s is the learning factor, and the initial evolution path is 0.

The update formula of step size $\delta^{\scriptscriptstyle (g+I)}$ is as follows:

$$\delta^{(g+I)} = \delta^{(g)} exp\left(\frac{a_{\delta}}{d_{\delta}}\left(\frac{\left\|p_{\delta}^{(g+I)}\right\|}{E/N(0,I)/\ell} - I\right)\right)$$
(17)

The update formula of P_{δ} is as follows:

$$p_{\delta}^{(g+1)} = (1 - a_s) p_{\delta}^{(g)} + \sqrt{a_s (2 - a_s) \frac{x_t^{(g+1)} - m^{(g)}}{\delta^{(g)}}} (C^{(g)})^{1/2} \frac{m^{(g+1)} - m^{(g)}}{\delta^{(g)}}$$
(18)

According to the updated mean, covariance matrix and step size parameters, and through the formula population generation formula, individuals in a new generation of distribution are generated, so as to evolve generation by generation until the termination condition is reached.

2.2 Local Synaptic Plasticity Learning Rules

The PA adopted by the existing synaptic plasticity learning rules in the adjustment process of reservoir connection weights not only have the same learning mechanism but also the plasticity parameters are limited to a single global parameter. A single type of plasticity rule may fail to capture the essence of biological neuroplasticity, and it is also inflexible in practical applications, thereby failing to effectively improve the learning performance of the system. Based on this, this paper designs a local synaptic plasticity learning rule from the perspective of a single neuron, that is, different reservoir neurons can use different types of synaptic PA with different parameters to achieve local plasticity regulation of reservoir connection weights. A schematic diagram of the echostate network regulated by local synaptic PA is shown in Figure 1.

The whole process includes the following three steps:

Step 1: The algorithm passes in data through the input layer;

Step 2: The algorithm uses local synaptic PA to pre-train the connection weights inside the reservoir;

Step 3: The algorithm uses the least squares method to train the output layer weights.

In this section, we design two types of local synaptic PA, namely local Oja learning rules and local anti-Oja learning rules.

The local Oja learning rules are:

$$\Delta W_{ji}^{res}(t) = \eta_{j} x_{j}(t) \Big[x_{i}(t) - x_{j}(t) W_{ji}^{res}(t) \Big]$$
(19)

$$W_{ji}^{res}(t+1) = W_{ji}^{res}(t) + \Delta W_{ji}^{res}(t)$$
(20)

The local anti-Oja learning rules are:

$$\Delta W_{ji}^{res}(t) = \eta_j x_j(t) \Big[x_i(t) - x_j(t) W_{ji}^{res}(t) \Big]$$
(21)

$$W_{ji}^{res}(t+1) = W_{ji}^{res}(t) - \Delta W_{ji}^{res}(t)$$
(22)



Figure 1: Echo-state network regulated by local synaptic PA.

From the formula of the local synaptic plasticity learning rule, it can be seen that the only difference between the local synaptic plasticity learning rule and the global synaptic plasticity learning rule is that under the action of the local synaptic plasticity rule, different postsynaptic neurons j use

different learning rate parameters η_j .

In recent years, neuro evolution attempts to construct an evolutionary neural network through evolutionary algorithms, and the evolutionary optimization based on neural network is also a current research hotspot. In this work, we use the CMA-ES algorithm to evolve the learning rate parameter in the plasticity rule corresponding to each neuron. It should be pointed out that, from formula (20) and formula (22), we can see that the difference between the Oja rule and the anti-Oja rule is only the update formula of the synaptic weight. Based on this, we can further analyze whether the correlation or decorrelation corresponding to the Oja rule or the anti-Oja rule can help improve the learning performance.



Figure 2: The optimization process of the learning rate parameter of the cma-es algorithm for local synaptic plasticity.

The algorithm based on CMA-ES has unique advantages in dealing with nonlinear non-convex continuous optimization problems. Therefore, in this work, the CMA-ES algorithm is used to select

and optimize the learning rate parameter η_j corresponding to different postsynaptic neurons j in the reservoir. Then, the fitness value of each individual is calculated based on the fitness function, and then the parent population is selected by the fitness value. The above process is repeated until the termination condition is reached. The optimization process of the learning rate parameter of the CMAES algorithm for local synaptic plasticity is shown in Figure 2.

3 THE IDEOLOGICAL AND POLITICAL CURRICULUM DESIGN BASED ON BIG DATA TECHNOLOGY

They are design level, practice level and feedback level. Through such a framework system, there is a specific implementation path for the promotion of education curriculum ideology and politics. It not only grasps the key factor of teachers, gives full play to the enthusiasm, initiative and creativity of teachers, but also focuses on the main body of students, and guides students to be treated rigorously in education classes. Moreover, it implements the educational goal of "cultivating morality and cultivating people", and effectively realizes the connotative development of education. Figure 3 is the theoretical framework of the ideological and political courses.



Figure 3: The theoretical framework of the ideological and political courses.

By observing the process and functions of performance evaluation in the ideological and political construction of education courses, it is found that under certain conditions, the evaluation process and the teaching process, evaluation objectives and learning objectives, learning content and the ideological and political elements, and expected learning results and actual learning results can be combined with structural elements. Moreover, the evaluation process of negotiated construction and the teaching process of reverse design are unified by focusing on learning outcomes as a whole, as shown in Figure 4.





In order to promote the ideological and political development of college education courses (CEC), it is necessary to build a set of the ideological and political evaluation index systems for CEC that are consistent with the school's education teaching work. Moreover, it is necessary to supervise the ideological and political teaching of CEC from multiple perspectives and channels, and pay attention to the effectiveness of the ideological and political teaching in CEC. Figure 5 shows the ideological and political evaluation index system of CEC.



Figure 5: The ideological and political evaluation index system of CEC.

From a macro perspective, the moral, intellectual, aesthetic, labor and five education curriculum system based on cultivating morality and cultivating people has two major elements at the first level: The ideological and political courses and curriculum the ideological and political courses. The second level has four major elements from the perspective of curriculum ideology and politics: intellectual education and moral education, education and moral education, aesthetic education and moral education, and labor education and moral education (Figure 6).



Figure 6: Map of the ideological and political system of the curriculum.

Computer-Aided Design & Applications, 21(S16), 2024, 227-238 © 2024 U-turn Press LLC, <u>http://www.cad-journal.net</u> The co-creation and sharing mode of the ideological and political resources in CEC is supported by a stable and realistic basis, and has rich connotative elements. Its operation mechanism, supervision and evaluation, and support and guarantee all contain strong ideological and political education discipline characteristics and resource advantages (Figure 7).



Figure 7: Co-creation and sharing mode and operation mechanism of the ideological and political resources of CEC.

After constructing the above system model, the effect of the ideological and political curriculum design system based on CNT is verified, and its teaching effect is clustered, and the results shown in Figure 8 are obtained.



Figure 8: Clustering of the effect of the ideological and political curriculum design based on CNT.

Through the above research, it can be seen that the ideological and political riculum design system based on CNT proposed in this paper has good results.

4 CONCLUSION

The sharing and coordination of educational resources is an important support for the construction of the ideological and political education, and it is also the core support for breaking the barriers to sharing educational resources and broadening the learning horizons of CS. CAU should be guided by the sharing and coordination of the ideological and political resources, actively integrate into the new collaborative education environment, integrate and utilize various types and vivid forms of education resources, and jointly build an education system of morality. At the same time, it is necessary to provide continuous support for the high-quality construction of ideology and politics by comprehensively integrating educational resources and building a knowledge base shared by disciplines. In addition, under the guidance of the goal of comprehensive education, it is necessary to actively promote the close integration of ideology and politics through the exploration of the ideological and political resources hidden, and promote the development of the ideological and political education to a deep and effective level. This paper combines CNT to conduct research on the curriculum design of the ideological and political, and uses an intelligent computer model to improve the effect of the ideological and political curriculum design. The experimental research results show that the ideological and political curriculum design system based on CNT proposed in this paper has a good effect. Political courses in this manner, you can create a more engaging, interactive, and accessible learning environment that takes full advantage of computer network technology and the wealth of digital cultural heritage resources available.

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