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RESEARCH ARTICLE

Enhancing Physical Education: A Dynamic Fuzzy Neural Network-Based Information Processing System Design

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ABSTRACT With the advent of digital intelligent education, educational resources are expanding. In the realm of physical education, data encompassing students' physical fitness test results, sports performance, and health status stand as pivotal pillars for the assessment of teaching. Consequently, this manuscript conceives a dynamic fuzzy neural network-based system for processing physical education information. Primarily, this work introduces compensatory fuzzy neurons into the Dynamic Fuzzy Neural Network (DFNN) and advances the creation of a Generalized Dynamic Fuzzy Neural Network (GDFNN). Furthermore, the GDFNN is seamlessly integrated with the Reinforcement Learning (RL) method to devise a neural network inverse controller equipped with online learning capability, employing the temporal difference learning method within RL. The empirical findings demonstrate that the enhanced generalized dynamic fuzzy neural network attains impressive results, yielding 0.0025, 0.2668, and 0.9356 on the root mean square error, standard root mean square error, and homogeneity coefficient, respectively. These outcomes are juxtaposed with those of eight contemporary algorithms, including the RBF method, BP algorithm, and other prevalent feedforward neural network algorithms. The root mean square error (RMSE), standard Root Mean Square Error (RRMSE), and Equality Coefficient (EQU) performance metrics register an augmentation of 9%, 11.1%, and 6.7%, respectively. This enhancement signifies a substantial boost in predictive efficiency, thereby effectively advancing the intelligent development of the information processing system for physical education.

INDEX TERMS Dynamic fuzzy neural network, compensated fuzzy neurons, neural network, reinforcement learning, information processing.

I. INTRODUCTION

In the face of physical education data, encompassing students' physical fitness test results, sports performance, and health status, the effective and expeditious utilization of this data for the assessment and processing of physical education data has emerged as a formidable challenge for governments and individuals worldwide. Traditional information processing systems for sports instruction typically employ predictive modeling algorithms to first analyze and scrutinize teaching data. Subsequently, these systems deploy trained predictive models to forecast changes in data over future intervals, striving to achieve maximum alignment with actual data [1]. The prediction of students' physical fitness and related information serves as a crucial foundation for the development of rational and accurate individualized sports training regimens for students and instructional plans for teachers. Given the highly nonlinear, time-varying, and inherently stochastic nature of statistical data in physical education, these characteristics pose significant hurdles in forecasting data trends. In the long term, data flows remain unpredictable, while in the short term, predictability is attainable. Enhancing short-term data flow prediction accuracy and laying the groundwork for precise future data forecasts at

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specific time points constitute pivotal focal points in this research.

Neural networks [2] prove to be potent tools for data prediction due to their profound nonlinear processing capabilities, distributed processing proficiency, and robust learning and adaptability. Fuzzy logic [3] can amalgamate human empirical knowledge into fuzzy rules, thus conferring abstract attributes upon intricate research subjects. Consequently, the integration of neural network techniques with fuzzy logic theory embodies the fusion of nonlinear processing capacity and fuzzy logic's if-then rule framework.

Nevertheless, in existing Fuzzy Neural Networks (FNN), the model parameters are universally subject to adaptive adjustment and optimization [4]. Since fuzzy rules within the fuzzy system emanate from the designer's knowledge and expertise, determining the number of fuzzy rules remains challenging, making it arduous to identify an optimal set of rules within the complex system's input and output data. Hence, the FNN approach encounters impediments in accurately ascertaining the ideal number of fuzzy rules and the most favorable fuzzy rules. To address these issues, scholars have introduced the Dynamic Fuzzy Neural Network (DFNN) [5]. The network structure of DFNN evolves organically through the gradual expansion of fuzzy rules during the learning process. This characteristic imparts formidable nonlinear prediction capabilities and the ability to autonomously determine the number of fuzzy rules. This sets DFNN in stark contrast with conventional FNN, not only in terms of network structure but also in its aptitude for parameter learning.

Nonetheless, it's imperative to acknowledge that training the DFNN model necessitates the optimization of both the neural network and fuzzy rules, thereby rendering the training process more intricate and demanding in terms of computational resources and time [6]. Furthermore, owing to the black-box nature of the learning process in DFNN, it results in limited comprehensibility of the fuzzy rules generated by DFNN. Moreover, manual adjustments and optimization of factors such as affiliation functions [7] and weights in DFNN's fuzzy rules expose the system to potential redundancy and overlap in rule generation and deletion frequency.

Consequently, in this study, the approach employs the Generalized Dynamic Fuzzy Neural Network (GDFNN) and Reinforcement Learning (RL) to construct a physical education data evaluation system. The primary contributions of this work are outlined as follows:

- Enhancement of DFNN: The second layer's structure in DFNN has been refined by assigning an affiliation function to each neuron within the second affiliation function layer. Consequently, each input variable in the second layer boasts multiple affiliation functions to realize performance enhancement.
- Introduction of Compensating Fuzzy Neurons and RL: Positive and negative fuzzy neurons are ingeniously combined to create compensating fuzzy neurons, and RL is integrated to enhance the model's robustness.
- Performance Enhancement: The improved GDFNN achieves remarkable results with RMSE, RRMSE, and CU registering values of 0.0025, 0.2668, and 0.9356, marking a substantial advancement when compared to prevailing mainstream methodologies.

This paper encompasses an examination of prior research on DFNN and RL in Section II. Section III delineates the construction of the GDFNN in this study, coupled with RL learning, to facilitate the evaluation of instructional information. Section IV is dedicated to presenting experimental results and a discourse on the scheme's performance. Finally, Section V offers a concluding summary.

II. RELATED WORKS

A. DFNN

Over the past two decades, theoretical and applied research in fuzzy logic has furnished a mathematical framework for emulating the cognitive reasoning process, thereby finding widespread application in diverse domains such as modeling and control. Numerous studies have demonstrated that the supervised learning functionality of neural networks can assist conventional fuzzy inference systems in establishing an objective method for formulating fuzzy rules and adapting fuzzy inference to potential changes.

Consequently, researchers have proposed a multitude of fuzzy neural networks, each characterized by distinct structures and training methodologies, including but not limited to neural network-based fuzzy logic control systems [8], intelligent control paradigms rooted in approximate reasoning [9], adaptive neural network-based fuzzy inference systems [10], fuzzy rule-based neural networks [11], fuzzy neural networks [4], and fuzzy adaptive learning control networks [12]. All of these fuzzy neural networks are typically trained using gradient descent feedback learning, which, however, tends to engender local optima and results in sluggish training speeds. Consequently, to identify a more rational approach for designing fuzzy inference systems, research endeavors have progressively turned to the study of DFNN.

DFNN stands out for its distinctive feature of gradually shaping the network structure through continuous adjustments during training, eliminating the need for prior manual configuration. Within the realm of DFNN research, the literature [13] introduced a network structure and training method for DFNN based on radial basis functions. It introduced novel concepts such as "hierarchical learning," "self-organized structure," and "pruning techniques," all of which diverge from the traditional BP learning algorithm. These concepts have set DFNN apart from the conventional BP learning algorithm. In another study [14], an enhanced DFNN and its learning algorithm were proposed, inheriting the strengths of the DFNN algorithm while incorporating the use of self-organizing mapping for neuron tuning, particularly well-suited for real-time applications due to its noise elimination capabilities. Literature [15] introduced a DFNN where the fuzzy rules adapt to input data changes. Furthermore, literature [16] applied DFNN to traffic flow prediction, employing a chaotic phase space reconstruction method to determine network inputs and outputs, thereby advancing theoretical exploration and experimental analysis in traffic flow prediction.

To enhance DFNN performance, literature [17] replaced the RBF function in DFNN with an elliptic basis function, expanding the network's dimensionality to enable adaptive adjustment of each rule's width. This led to the development of the GDFNN learning algorithm. In another instance [18], a fuzzy neural network was integrated with RL to transform the discrete output of Q-learning into continuous output, with the network dynamically adapting its parameters based on reward values, thereby accelerating network training. Literature [19] leveraged GDFNN in optimizing the lane-changing strategy for autonomous driving, introducing a self-learning optimization method within GDFNN to predict lane-changing frequency.

Furthermore, in a different domain, literature [20] combined fuzzy reasoning techniques with robust logical reasoning and neural networks to propose a short-term inbound passenger flow prediction method based on GDFNN. These noteworthy applications of GDFNN across diverse fields have garnered extensive attention within the academic community.

B. RL

RL [21] has remained a focal point of research ever since the inception of the artificial intelligence concept. RL constitutes a computational paradigm in which intelligent entities strive to maximize cumulative rewards while interacting with intricate environments. In the realm of RL, literature [22] advances the Monte Carlo method by introducing a time-difference algorithm. This innovative approach, as opposed to waiting until the conclusion of a full round to assess all traversed states, estimates them incrementally at each step. Building upon the time-difference algorithm, literature [23] introduces the classical Q-learning algorithm. This algorithm appraises the environmental states and the actions taken by the intelligent agent at every step of each round, assigning rewards and thereby completing the training of the intelligent agent's decision-making process.

Furthermore, literature [24] conducts analysis and comparison of RL and evolutionary strategies, assessing their merits and demerits in terms of scalability, exploratory capabilities, adaptability to dynamic environments, and multiagent learning. In a complementary effort, literature [25] introduces contemporary techniques for amalgamating evolutionary computation into RL. It categorizes and scrutinizes these integration methods in the context of hyper-parameter optimization, strategy exploration, meta-reinforcement learning, and multi-objective reinforcement learning. Moreover, in the literature [26], the utilization of Gaussian processes is proposed to model the payoff function with parameters, leading to the development of a reinforcement learning algorithm. This approach assumes that the payoff function adheres to the conditions of regularity, Lipschitz continuity, and bounded behavior.

Conversely, in literature [27], the reachability of Markov decision processes is harnessed to introduce the SafeMDP safe exploration method atop SafeOpt. This method addresses deterministic finite Markov decision process problems. It's worth noting that in both SafeOpt and SafeMDP, the payoff function is presumed to be known in advance and time-invariant. In practical scenarios, however, the payoff function is typically not known in advance and tends to change over time. In light of this, literature [28] incorporates temporal and spatial information into the kernel function by employing spatio-temporal Gaussian processes to model the return function with parameters. Literature [29] adopts a system transformation using a barrier function, enforces state constraints, and reformulates the original problem as an unconstrained optimization challenge. This results in the proposition of a secure reinforcement learning algorithm based on an actor-critic architecture. The approach leverages empirical playback techniques to seek an optimal secure controller in an online manner, ensuring both optimality and stability. In contrast, literature [30] integrates a microscopically robust control barrier function into a model-based reinforcement learning framework.

Despite the effectiveness of RL in converging towards optimal policies, it grapples with the issue of dimensionality catastrophe as data dimensions increase. Moreover, it encounters challenges related to stability, robustness, and local optimization in real-world scenarios characterized by complex operational tasks. These challenges arise from the difficulty of obtaining training data online and the presence of continuity between behaviors.

III. METHODS

The sports teaching information processing system presented in this study primarily relies on DFNN to facilitate system-wide information processing. It achieves this by enhancing GDFNN and incorporating compensated fuzzy neurons into DFNN, thereby enhancing the system's data processing efficiency, as shown in Figure 1. Furthermore, the process of physical education information processing entails establishing dynamic fuzzy rules, promoting more user-friendly data sequence predictions. RL is harnessed to appraise the value function of states and actions, assessing the quality of the choices made by the intelligent agent in its current state. This information is then used to formulate an inverse controller for the coordination system endowed with online evaluation and correction capabilities. This approach results in a sports teaching information processing system characterized by high efficiency and stability.

A. GDFNN

In this paper, GDFNN is improved on the DFNN, and its structure is shown in Figure 2:

In this neural network, the initial layer serves as the input layer, with each neuron in this layer directly linked to each

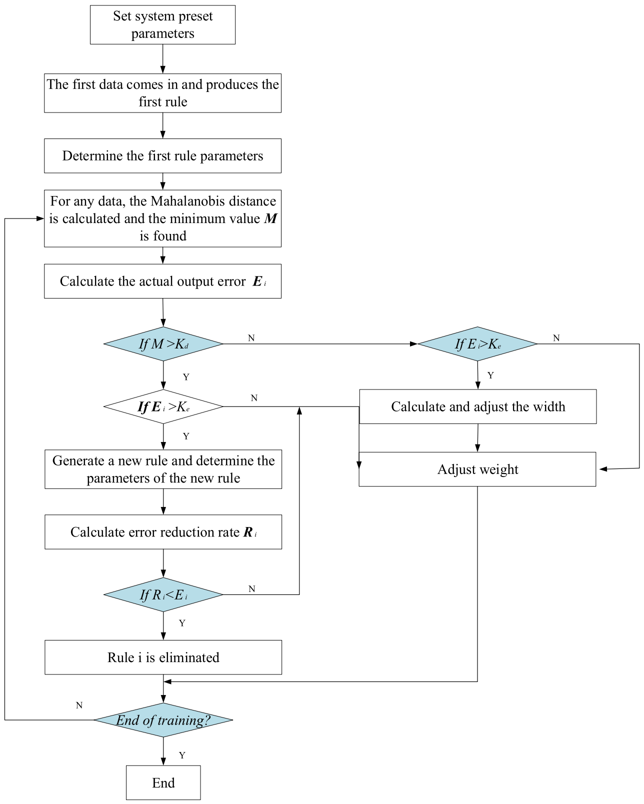

FIGURE 1. Flow chart of the proposed model.

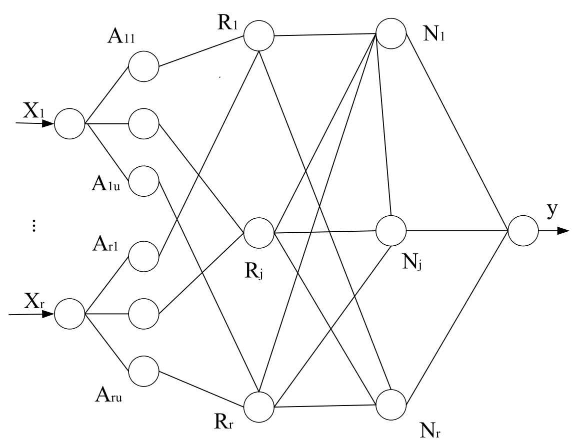

FIGURE 2. The structure of GDFNN.

component of the input vector. The subsequent layer functions as the affiliation function layer, where each neuron corresponds to an affiliation function. Notably, each input variable in the second layer encompasses multiple affiliation functions:

$$\lambda_{ij}(x_i) = e^{-(x_i-c_{ij})^2/\sigma_{ij}^2} \tag{1}$$

In Equation (1), $i = 1, \ldots, r, j = 1, .., u$, where r is the number of input variables and u represents the total number of rules. $\lambda_{i,j}$, $c_{i,j}$ are the center of the j-th affiliation function and the width of the j th affiliation function of x_i, respectively.

Each neuron in the third layer represents the IF-part of a possible rule, where the output of the j-th rule R_j is:

$$\varphi_j = e^{-\sum_{i=1}^{r}\frac{(x_i-c_{ij})^2}{\sigma_{ij}^2}} \tag{2}$$

According to the definition of the Mahalanobis distance, Equation (3) can be obtained:

$$md(j) = \sqrt{(X - C_i)^T \sum\nolimits_j^{-1} (X - C_j)} \tag{3}$$

where $X = (x_j, \ldots, x_r)^T$, $C_j = (c_{1j}, c_{2j}, \ldots, c_{rj})$, and

$$\sum\nolimits_j^{-1} = \begin{bmatrix} \frac{1}{\sigma_{1j}^2} & 0 & \cdots & 0 \\ 0 & \frac{1}{\sigma_{2j}^2} & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & \cdots & 0 & \frac{1}{\sigma_{rj}^2} \end{bmatrix} \tag{4}$$

Combining Equations (2) and (3), Formula (5) can be obtained as follows.

$$\varphi_j = e^{-md^2(j)} \tag{5}$$

The fourth layer is normalizing the output of the third layer and the output of the j-th neuron N_j is:

$$\psi_j = \frac{\varphi_j}{\sum_{k=1}^{u}\varphi_k}, j = 1, 2, 3, \ldots, u \tag{6}$$

The fifth layer is the output layer and the output of each neuron is:

$$y(X) = \sum_{k=1}^{u} \omega_k \cdot \psi_k \tag{7}$$

where y is the output of the variable and ω_k is the result parameter or the concatenation right of the kth rule, i.e..

$$\omega_k = a_{k0} + a_{k1}x_1 + \ldots + a_{kr}x_r \tag{8}$$

Based on the above equation, we can get the expression between the output y about the input X:

$$y(X) = \frac{\sum_{i=1}^{u}[(a_{k0} + a_{k1}x_1 + \ldots + a_{kr}x_r) \cdot e^{-||X-C_i||^2/\sigma_i^2}]}{\sum_{i=1}^{u} e^{-||X-C_i||^2/\sigma_i^2}} \tag{9}$$

For the output y, traditional fuzzy neurons use an extreme decision for the input. Positive fuzzy neurons or negative fuzzy neurons are generally used, as shown in Figure 3. (a) is a positive fuzzy neuron that maps the input x_i $(i = 1, 2, \ldots, n)$ to the best output y, i.e., $y = O(x_1, \ldots, x_n) = \max(x_1, \ldots, x_n)$, which in turn formulates an optimistic decision for the best case scenario. (b) is a message neuron that maps the input x_i $(i = 1, 2, \ldots, n)$ to the worst output y, i.e., $y = P(x_1, \ldots, x_n) = \min(x_1, \ldots, x_n)$,

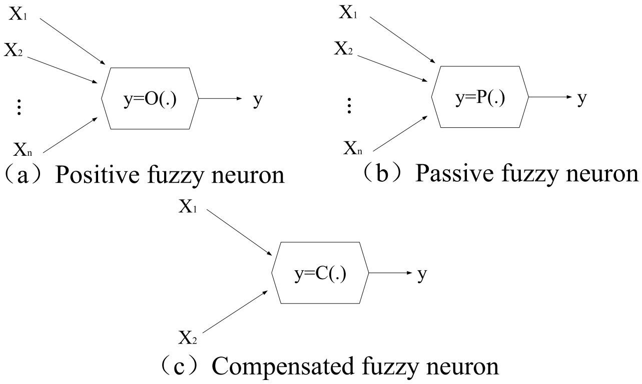

FIGURE 3. Input and output of fuzzy neurons.

which in turn formulates a conservative decision for the worst case scenario.

Both of the above scenarios should result in biased final outputs for the best and worst decisions in practical applications. For this reason, we improve the decision-making by combining positive fuzzy neurons and negative fuzzy neurons to form a compensated fuzzy neuron that maps the best and worst inputs to the compensated output y and develops a relative compromise decision for the best and worst input cases as shown in the (c) in Figure 2, at which point $C(x_1, x_2) = x_1^{1-\nu} x_2^{\nu}$, and ν is the degree of compensation, $0 < \nu < 1$.

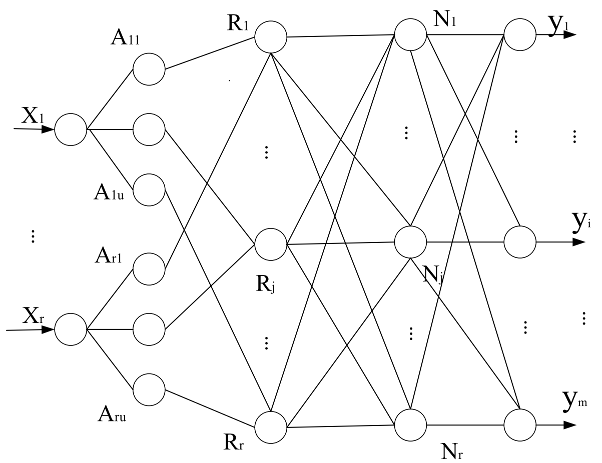

FIGURE 4. GDFNN structure of dynamic compensation fuzzy neural network.

Upon the introduction of compensatory fuzzy neurons, the structure of the GDFNN, with dynamic compensatory fuzzy neural networks, is depicted in Figure 4. It is evident from the diagram that the five-layer structure of the dynamic compensatory fuzzy neural network in GDFNN closely resembles the GDFNN model. The notable alteration occurs in the fourth layer, where compensatory fuzzy neural elements are introduced. In this transformation, the normalization layer is replaced by a compensatory operational layer. This modification enhances the system's fault tolerance and contributes to its overall stability.

B. FUZZY RULES

Define the systematic error based on the data observed in the system, and let t_k be the desired output with respect to the input when the systematic error is:

$$||e_k|| = ||t_k - y_k|| \tag{10}$$

When $||e_k|| \geq k_e$, we add a new fuzzy rule, where k_e is constantly changing in the continuous learning in the dynamic neural network with the change criterion:

$$k_e = \begin{cases} e_{\max}, 1 < k < n/3 \\ \max[e_{\max} \cdot \beta^k, e_{\min}], n/3 \leq k \leq 2n/3 \\ e_{\min}, 2n/3 < k < n \end{cases} \tag{11}$$

In Equation (11), $e_{\min}$ is the minimum error, $e_{\max}$ is the maximum error, k represents the number of samples that have been learned, and $\beta = \left(\frac{e_{\min}}{e_{\max}}\right)^{3/n}, 0 < \beta < 1$ is the attenuation coefficient.

According to the first fuzzy rule established, a new affiliation function is next assigned to the elements of the input sample of the GDFNN based on the Euclidean distance. Also, for a new sample X_k, the Gaussian width is constantly corrected. The closest rule to the sample is found by calculating the Marginal distance between the sample and the center of the affiliation function of all rules. If both $||e_k|| > k$ and $md_{k,\min} \leq k_d$ are satisfied, then yX_k can be decomposed into the corresponding one-dimensional variable $x_i\ (i = 1, 2, \ldots, r)$. The width of the closest affiliation function to this variable σ_{ij} can be corrected according to Equation (12):

$$\sigma_{ij,new} = \alpha \cdot \sigma_{ij,old} \tag{12}$$

where

$$\alpha = \begin{cases} 1/[1 + k_w(B_{ij} - 1/r)^2], & B_{ij} < 1/r \\ 1, & B_{ij} \geq 1/r, \end{cases} \quad k_w$$

is the width decay rate. Equation (12) shows that if the significance of the i-th input variable falls below the average importance of all input variables in the j-th rule, it is advisable to decrease the width of the affiliation function corresponding to that variable within the j-th rule.

In the case of GDFNN, researchers and scholars primarily employ the least squares method to determine its resultant parameters. While the least squares method is globally optimal, its accuracy diminishes as the sample size grows. Hence, this paper introduces Linear Least Squares (LLS) with recursive regression least squares to segment the resultant parameters. This enhancement renders GDFNN more flexible and adaptive in comparison to DFNN. Despite the increased complexity of the training method, GDFNN entails fewer preset training parameters. Furthermore, the fuzzy rules derived from this algorithm exhibit improved comprehensibility.

C. RL-GDFNN

To assess the physical education information processing system constructed on the foundation of DFNN, this section introduces Reinforcement Learning (RL) into the system. It combines RL's state value evaluation with the proposed formulation of student learning plans in the physical education information processing system under the precision of the GDFNN model. This approach allows for the assessment of the quality of choices made by the intelligent agent in the current state by estimating the value function of both the state and the action. Moreover, it designs an inverse controller for the coordination system equipped with online evaluation and correction capabilities.

Upon analysis, it becomes evident that for a system that remains incompletely understood, such as the physical education teaching information processing system that we have developed, the system should leverage past experiences to forecast future behavior. This involves predicting aspects like students' training plans in the future and teachers' instructional plans based on student fitness data. Learning to predict stands out as the most fundamental and widely applicable RL algorithm for this purpose. The key advantage of learning to predict lies in its unsupervised nature, as it relies on training samples derived from a real-time sequence of data rather than pre-existing teacher signals.

Given the non-deterministic nature of the time-sequenced information stored and recorded in physical education, the use of temporal difference learning, serving as an incremental online learning algorithm, becomes pertinent. This approach entails estimating the value of the state before execution based on the value of the new state at the end of each time step as the system progresses through a sequence. This is accomplished without waiting for the final output to be generated and then adjusting the values of all states simultaneously. Therefore, at the moment t+1, it is possible to immediately form a goal and generate the appropriate update values using the observed r_{t+1} and estimated $V(s_{t+1})$. The computation process is as follows:

$$V(s_t) = V(s_t) + \alpha[r_{t+1} + \gamma V(s_{t+1}) - V(s_t)] \tag{13}$$

Further, we can obtain the time-differentiated signal $TD(t)$ based on introducing this formula into GDFNN:

$$TD(t) = r_{t+1} + \gamma V(x_{t+1}) - V(x_t) \tag{14}$$

where $V(x_t)$ is the state value of GDFNN at time t and r is the reinforcement signal. An estimation of the state value can be made based on the time-differential deviation, and the performance of the GDFNN can be evaluated as:

$$En = \frac{\sum_{t=k}^{t=k+T} TD(t)}{T} \tag{15}$$

IV. EXPERIMENTS AND ANALYSIS

In this section, we will conduct a simulation experiment focusing on the Mackey-Glass chaotic time series. We will employ the DFNN method within the fuzzy neural network [5], the RBF method in the feedforward neural network [31], and the BP algorithm [32], along with its five enhanced variants. We aim to compare and analyze the experimental outcomes of each method.

Subsequently, we perform an ablation experiment on the proposed model to assess the impact of compensated fuzzy neurons and RL on the model. This will enable us to explore the effectiveness of the GDFNN method, which introduces compensated fuzzy neurons and reinforcement learning in the context of information processing within physical education for time series data prediction.

A. EXPERIMENTAL INDICATORS

In the evaluation of the modeling system, our primary focus is on assessing the predictive performance of GDFNN. A high predictive performance indicates its suitability for application in a physical education information processing system, enabling the alignment of teaching and training plans with the data collected from students. Given the diversity of predictive evaluation metrics available and their broad applicability across various domains, this paper employs the following predictive evaluation measures: RMSE, NRMSE, and EQU. RMSE represents the average deviation of actual values from predicted values. NRMSE quantifies the correlation between the average deviation of actual values and predicted values. EQU gauges the proximity of the actual data curve to the predicted curve.

RMSE is calculated as:

$$E_{rmse} = \sqrt{\tfrac{1}{S-1} \textstyle\sum_{t=1}^{s} [y'(t) - y(t)]^2} \tag{16}$$

NRMSE is calculated as:

$$E_{nrmse} = \sqrt{\tfrac{1}{(S-1)\sigma^2} \textstyle\sum_{t=1}^{s} [y'(t) - y(t)]^2} \tag{17}$$

where σ is the standardized variance. From the perspective of the definition domain, it can be seen that E_{nrmse} it is greater than or equal to zero. When E_{nrmse} is closer to 0, it indicates that the prediction effect is better. On the contrary, the prediction effect becomes worse gradually.

NRMSE is calculated as:

$$E_{equ} = 1 - \frac{\sqrt{\sum_{t=1}^{s} [y'(t) - y(t)]^2}}{\sqrt{\sum_{t=1}^{s} y^2(t)} + \sqrt{\sum_{t=1}^{s} y'^2(t)}} \tag{18}$$

In Equation (18), $0 < E_{equ} \leq 1$. If the closer the actual data curve is to the predicted result curve, the closer E_{equ} is to 1, indicating that the prediction effect is better. On the contrary, the prediction effect is not good.

B. PARAMETER SETTING

In this paper, the Gaussian function is employed in the second affiliation function layer of the GDFNN network structure. The specific values for σ (sigma) and μ (mu) for the Gaussian function are determined through experimental procedures. As the fuzzy rules of GDFNN evolve in response to incoming data, the structure of GDFNN is not pre-defined in the absence of data. It adapts and forms as data becomes available. When the first observation data (x_1, t_1) is input, this observation data is regarded as the first fuzzy rule of GDFNN, which is $c_1 = x_1, \sigma_1 = \sigma_0 = 0.98$.

From the premise parameter allocation principle of fuzzy rule generation criterion $c_i = x_i, \sigma_i = k \times d_{\min}$ is obtained, where k is the overlap factor and $d_{\min}$ is the minimum length of the input space. In the comparison and ablation experiments k = 1.2 and $d_{\min} = 0.25$. In the premise parameter adjustment strategy, when new data comes, there is no need to add new fuzzy rules, but only need to adjust the center as well as the width of the Gaussian function in the affiliation function layer. For $||e_i|| > k_e, d_{\min} \leq \sigma_k^{i-1}$, the Gaussian function unit needs to be adjusted, and the adjustment method is $\sigma_k^i = 1.1 \times \sigma_k^{i-1}$.

The setting of each initial parameter in the GDFNN and comparison experiments is that $d_{\min} = 0.2, \gamma = 0.977, \beta = 0.9, e_{\max} = 1.1, e_{\min} = 0.02, k = 1.2, \eta = 6$. In the experiments, 1000 samples between 118 ≤ t ≤ 1117 are selected as the prediction experimental data. Among them, the first 500 points are used for training and the last 500 points are used for testing.

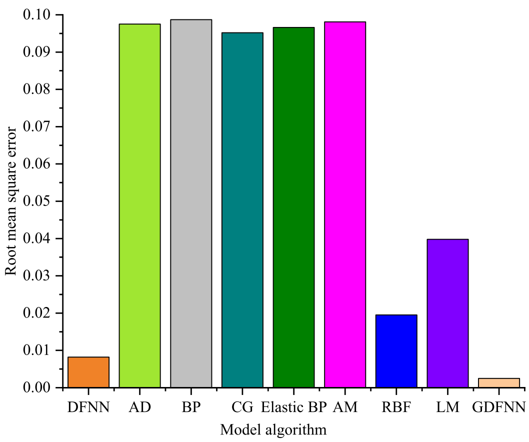

FIGURE 5. Comparison of RMSE among different models.

C. MODEL COMPARSION

For assessing the model's performance, five improvement algorithms for the BP algorithm are considered: the additional momentum improvement algorithm [31] (abbreviated as AM), the adaptive tuning parameter improvement algorithm [33] (abbreviated as AD), the elastic BP algorithm [34], the conjugate gradient improvement algorithm [35] (abbreviated as CG), and the LM improvement algorithm [36]. In this paper, eight methods are employed as comparison approaches for prediction experiments to evaluate the effectiveness of GDFNN methods in prediction.

The results, as depicted in Figure 5, demonstrate that the mean square error for the BP algorithm within the feedforward neural network method is 0.0987. In contrast, the mean square error scores for the improved algorithms incorporating additional momentum, adaptively adjusted parameters, the elastic BP algorithm, conjugate gradient, and LM are 0.0981, 0.0975, 0.0966, 0.0952, and 0.0398, respectively. The optimized BP neural network with these improved algorithms exhibits higher prediction accuracy compared to the traditional BP neural network.

Moreover, the prediction effectiveness of the RBF method and the GDFNN method is relatively superior. The mean square error for the RBF method is 0.0195, while for the GDFNN method proposed in this paper, it is 0.0025. Notably, GDFNN significantly outperforms RBF. Although GDFNN's generalization performance may be slightly less favorable than that of the RBF method in practical applications, this does not substantially affect GDFNN's overall prediction capability.

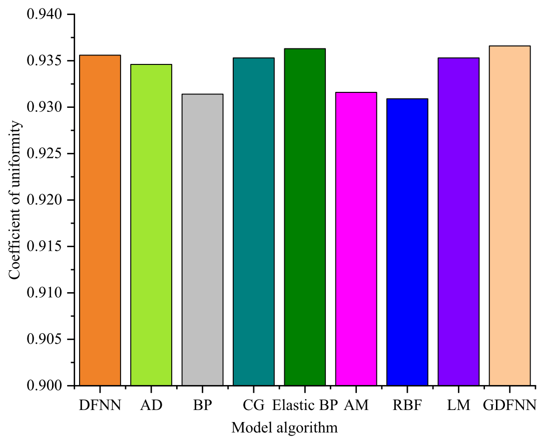

FIGURE 6. Comparison of uniformity among different models.

Then, we compare the uniformity and NRMSE of the various algorithms. As indicated in Figure 6, among the feedforward neural networks, the LM algorithm exhibits the most favorable prediction performance. However, once again, the dynamic fuzzy neural network method surpasses the feedforward neural network method in terms of prediction quality.

Upon comprehensive analysis, it can be deduced that both the GDFNN method and the DFNN method deliver commendable prediction performance, achieving equality coefficients of 0.9356 and 0.9366, respectively. While the DFNN's prediction performance may be slightly less effective than that of the GDFNN in practical applications, this difference is not significant enough to substantially impact overall prediction capability.

However, in the context of a system like the sports teaching information processing system, which handles time-sequenced data characterized by uncertainty, the more uncertain the data, the better the compensatory role of the GDFNN algorithm's fuzzy neurons. This leads to the performance of DFNN being gradually overshadowed by that of GDFNN.

To further validate the comparative performance of the algorithms, as shown in Figure 7, it's evident that the numerical changes in the regularized root mean square error of

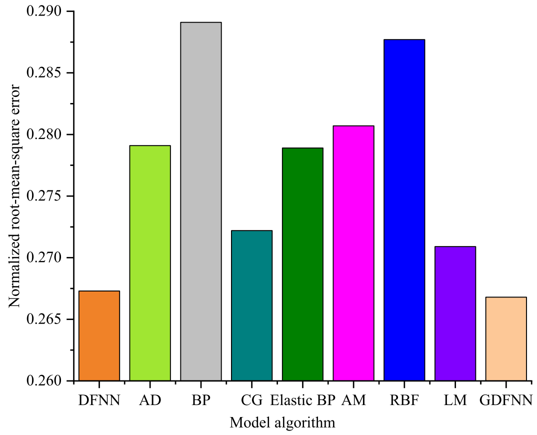

FIGURE 7. Comparison of NRMSE among different models.

the algorithms closely mirror the variations in their equality coefficients. Once again, both the GDFNN method and the DFNN method exhibit superior performance, with their regularized root mean square errors reaching 0.2668 and 0.2673, respectively. In contrast, the RBF method registers the highest regularized root mean square error, reaching 0.2877.

This demonstrates that while GDFNN may have weaker generalization abilities, its superior regularized root mean square error enables it to be effectively utilized in the physical education information processing system.

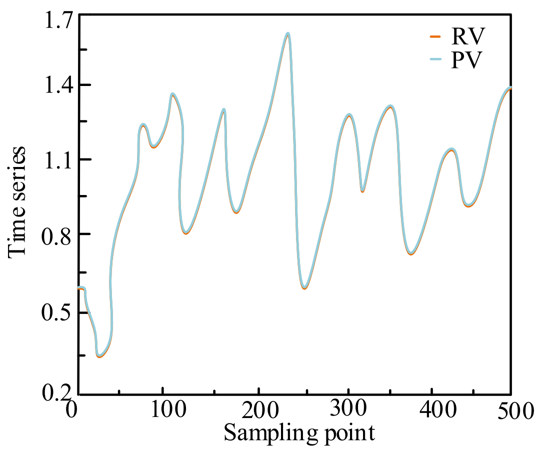

FIGURE 8. Predictive results of GDFNN.

D. ABLATION EXPERIMENTS

The prediction results for the Mackey-Glass chaotic time series are presented in Figure 8, with the horizontal axis representing the sampling data and the vertical axis denoting the real values (RV) and predicted values (PV) of the time series. As depicted in Fig. 6, the RV and PV of the time series align nearly perfectly at various sampling points, with errors not exceeding 0.03. Furthermore, when the sampling points fall within the range of 150 to 400, the error remains below 0.01.

These findings illustrate that the predicted values produced by the proposed GDFNN closely match the desired output values, demonstrating exceptional generalization performance.

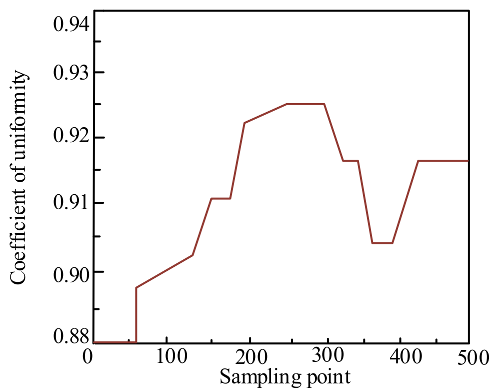

FIGURE 9. The uniformity of GDFNN (with no compensates fuzzy neurons and RL).

To assess the performance enhancement achieved by the GDFNN algorithm, ablation experiments were conducted based on the previous experiments. These experiments compared GDFNN without the addition of compensating fuzzy neurons and reinforcement learning, GDFNN with only compensating neurons, and GDFNN with only reinforcement learning. The graph depicting the equality coefficient of GDFNN without compensating fuzzy neurons and reinforcement learning is displayed in Figure 9. The equality coefficient initially increases, then decreases as the number of sampling points rises and ultimately stabilizes. At this point, the equality coefficient reaches a maximum of 0.9251, and after stabilization, it rests at 0.9189, which is evidently suboptimal.

Subsequently, the GDFNN was modified by introducing compensating fuzzy neurons and RL. The results obtained are presented in Figure 10. In Figure 10, (a) illustrates the performance after adding compensating neurons, while (b) demonstrates the outcome after introducing only reinforcement learning. It is clear that the incorporation of compensating fuzzy neurons or reinforcement learning significantly enhances the performance of GDFNN, with the equality coefficient essentially maintaining a value of 0.9339.

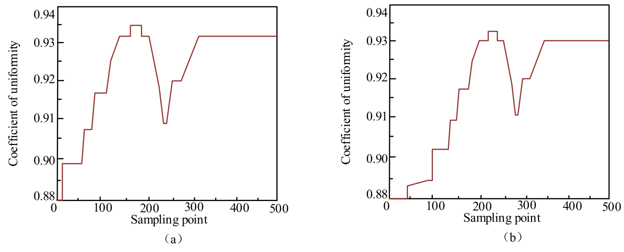

FIGURE 10. Add the equality coefficient of GDFNN that compensates fuzzy neurons or reinforcement learning.

E. DISCUSSION

Based on the experimental results, the Generalized Dynamic Fuzzy Neural Network designed in this paper combines the strengths of fuzzy logic and neural networks. Our scheme achieves remarkable performance metrics, with RMSE, RRMSE, and EQU reaching 0.0025, 0.2668, and 0.9356, respectively. When compared to eight algorithms, such as the RBF method and BP algorithm commonly used in contemporary feedforward neural networks, our scheme outperforms them with improvements of 9%, 11.1%, and 6.7% in terms of RRMSE and EQU performance metrics, respectively.

Additionally, the results from simulation experiments on the Mackey-Glass chaotic time series underscore the superiority of this algorithm. The Real Values (RV) and Predicted Values (PV) of the time series at each sampling point closely align, with an error of no more than 0.03. Given that data related to students' physical fitness and other factors often exhibit characteristics of chaotic time series, the GDFNN model's affiliation function and fuzzy rules effectively process the input information in the physical education information processing system. This leads to accurate output results, facilitating the efficient analysis and processing of physical education information. This, in turn, assists teachers in gaining a better understanding of students' physical education skills and areas needing improvement.

Furthermore, the GDFNN model constructed in this paper offers the advantages of online learning and hierarchical learning. The model can continuously adapt and optimize according to new data, making it well-suited for the dynamic nature of sports teaching information. To sum up, the DFNN-based physical education information processing system effectively enhances teaching quality and students' learning efficiency. Through this intelligent system, teachers can gain a more accurate understanding of each student's learning status and predict their future progress. This enables the customization of teaching plans and strategies, offering valuable insights for ongoing instruction. The system holds great significance and practical value in improving the quality of physical education teaching.

V. CONCLUSION

The GDFNN designed in this paper harnesses the advantages of both fuzzy logic and neural networks. The performance metrics of RMSE, NRMSE, and EQU in our scheme reach impressive values of 0.0025, 0.2668, and 0.9356, respectively. In comparison to eight well-known feedforward neural network algorithms, including the RBF method and BP algorithm, our scheme exhibits an improvement in RMSE, RRMSE, and EQU by 9%, 11.1%, and 6.7%, respectively.

Furthermore, the simulation results for the Mackey-Glass chaotic time series highlight the superior performance of the proposed algorithm. At each sampling point, the RV and PV of the time series align perfectly with an error of less than 0.03. Since data such as students' physical fitness often exhibit characteristics of chaotic time series, the GDFNN model effectively processes input information using membership functions and fuzzy rules within the physical education information processing system. This results in accurate output data and efficient processing and analysis of physical education information, aiding teachers in gaining a better understanding of students' physical skill levels and areas requiring improvement. Additionally, the GDFNN model developed in this paper possesses features of online learning and hierarchical learning, enabling continuous adjustment and optimization of the model with new data to adapt to evolving physical education information.

In conclusion, the physical education information processing system based on DFNN effectively enhances teaching quality and students' learning efficiency. Through this intelligent system, teachers can gain a more accurate understanding of each student's learning status, predict their future progress, and customize teaching plans and strategies accordingly. This system provides a valuable reference for ongoing teaching, holding significant importance and application value in improving and enhancing the quality of physical education.

CONFLICTS OF INTEREST

The authors declares that there are no conflicts of interest.

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