Table Tennis Trajectory Prediction Based on ELM Algorithm from System Perspective

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ABSTRACT: *This article validates and tests a table tennis trajectory prediction model based on a computer angle ELM algorithm. By comparing with actual competition results, it was found that the model has high accuracy and reliability in predicting the trajectory of table tennis. At the same time, the model can also provide athletes with more accurate competition strategies and suggestions based on different competition situations and opponent levels. Finally, this article summarizes table tennis trajectory prediction's application value and advantages based on a system perspective ELM algorithm. This algorithm provides athletes with more accurate competition strategies and suggestions and helps coaches better understand athletes' sports characteristics and levels, providing an important reference basis for training and competition. At the same time, this algorithm can be extended to other ball games, providing broader application value for athletes and coaches.*

Keywords: ELM Algorithm, Table Tennis, Trajectory, Prediction

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1. Introduction

Table tennis robot as a humanoid robot is an essential platform for studying robot vision and motion control. At home and abroad researchers of all ages in the current foreign countries for the study of table tennis robot has made progress gradually, our study is still relatively backward [1-2]. Table tennis robots have only 30 years of development history, belonging to the emerging field of robot development [3]. Table tennis robot refers to a typical real-time intelligent robot capable of playing ping-pong with human beings, perceiving the serving route and trajectory of competitive objects, making reasonable judgments and returning the ball strategy, and realizing flexible hitting. Researching ping pong robot systems involves a very wide range of fields. It integrates various fields of knowledge such as computer vision, artificial intelligence, automatic control, robot kinematics and computer graphics, and has particular research value and broad application prospects [4-5]. Table tennis is small in size and fast in flight, requiring table tennis robots to have continuous rapid response ability. It is required to complete the trajectory prediction of high-speed table tennis in a short period and make exact hits. This poses great requirements for table tennis robot control's real-time performance and accuracy [6]. Therefore, the development and widespread application of table tennis robots require effective prediction of table tennis trajectory. The ping-pong robot can be more timely and accurate under the premise of complete analysis of ball features.

2. State of the Art

Foreign research on table tennis robots began in the 1980s, the earliest developed table tennis machines. People are just a kind of table tennis ball machine. This robot has only the ability to serve but not the ability to fight back, mainly to replace the sparring until later developed into a new generation of ping pong robots [8]. There are some problems in the study of ping-pong robots. First, table tennis is a high-speed moving object with an average 30m / s speed. However, in the existing research, it is tough for the robot to respond quickly once the speed of the sphere exceeds 10 m / s. Second, for different types of balls, the existing system cannot judge, for example, up and down spin ball, left and right spin balls and so on, to return to the type of ball limitations, a single strike-back strategy [9]. According to the current research, most of the work of table tennis robots both at home and abroad focuses on the trajectory analysis of non-spherule ball, and a large number of trajectory prediction working is also carried out around this object. Spin-ball problem shelving is actually a lack of understanding of the spin-ball movement process. Related domestic research started relatively late. However, in recent years, the development of table tennis robots in our country has drawn much attention from all walks of life and has made great progress [10]. Therefore, this paper takes a table tennis robot as a platform to study the trajectory prediction of table tennis and the trajectory classification of a rotating ball.

3. Methodology

3.1. ELM Neural Network Trajectory Prediction Algorithm

Table tennis trajectory prediction is the basis of table tennis robot research; therefore, studying table tennis trajectory prediction is critical. In traditional artificial networks, implicit node parameters can be optimized and finally determined by some iterative algorithms many times. However, the steps brought by these algorithms will make the training process take a lot of time, which leads to an inefficient training process. To enhance the overall performance of neural networks, this paper presents the ELM algorithm (Extreme Learning Machine, ELM). ELM is a fast single hidden layer neural network training algorithm. Its characteristic is that the remote layer nodes' internal weights and offset values are randomly selected in training network parameters and do not need to be adjusted. The least-square solution obtains the external power, so the entire process does not require any iterative process, significantly reducing the network parameter adjustment time.

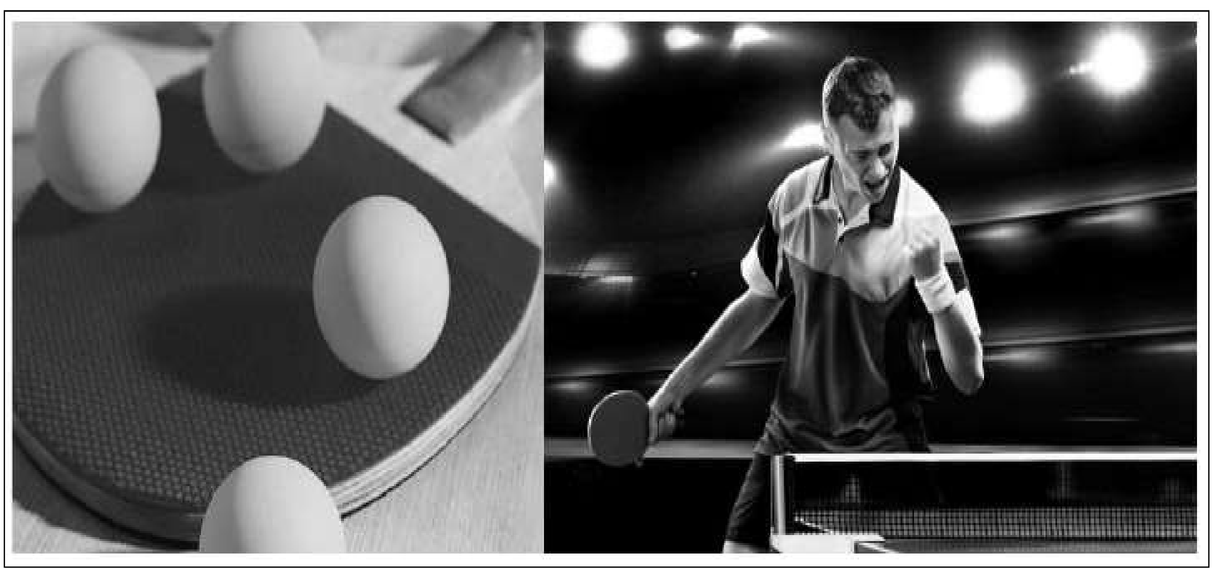

Figure 1. Table tennis track prediction research

ELM algorithm network structure is shown in Figure 2; from a structural point of view, ELM is a simple SLFN (hidden-layer feedforward neural network) but hidden layer feedforward neural network. The SLFN consists of three layers: input, hidden, and output. The hidden layer contains L hidden neurons. Under normal circumstances, L is much smaller than N.

ELM algorithm detailed working principle as shown below:

Assuming the training data sample (x, t), the output expression of a single hidden layer feedforward neural network of L hidden layer neurons is:

$$f_L(x) = \sum_{i=1}^{L} \beta_i G(\alpha_i, b_i, x) \tag{1}$$

As shown in Equation 1, where α_i, b_i are the parameters of the hidden layer nodes, β_i is the connection weight between the i^{th} hidden layer neuron and the output neuron, that is, an m-dimensional weight variable. $G(\alpha_i, b_i, x)$ Indicates that the i^{th} hidden layer corresponds to the hidden layer node output of the sample x. For additive hidden layer nodes, the expression of G is:

$$G(\alpha_i, b_i, x) = g(\alpha_i \times x + b_i) \tag{2}$$

Where g is the excitation function, and $\alpha_i \times X$ represents the inner product of the weight vector α_i and the sample x in R^n. For the hidden layer nodes of RBF type, $G(\alpha_i, b_i, x)$ expression is:

$$G(\alpha_i, b_i, x) = g(b_i \|x - a_i\|) \tag{3}$$

Among them, α_i, b_i represent the center and influence factor of the ith radial basis function node, respectively. The data sample contains N different data $\{(x_i, t_i)\}_{i=1}^{N} \subset R^n \times R^m$. Assuming a single hidden layer neural network with L hidden layer neurons, the N distinct data samples can be approached without error, that is,α_i, b_i, β_i and makes:

$$f_L(x_j) = \sum_{i=1}^{L} \beta_i G(\alpha_i, b_i, x_j) = t_j \tag{4}$$

This output function can also be expressed as:

$$H\beta = T \tag{5}$$

Among them: $H = \begin{bmatrix} h(x_1) \\ M \\ h(x_N) \end{bmatrix}$

H is the hidden layer output matrix, and the i^{th} column indicates the output of the i^{th} hidden layer neuron corresponding to input X_1, X_2, L, X_N. Under normal circumstances, the number of hidden layer nodes is much smaller than the number of training samples. Therefore, it is very difficult to construct a single hidden layer neural network with zero error approximation of N different data samples. Then, the problem of the weight vector there is no solution; that is, there is an error between the network output and the actual value. In this case, the above formula can be modified as:

$$H\beta = T + E \tag{6}$$

Among them, the definition of loss function is:

$$J = (H\beta - T)^T (H\beta - T) \tag{7}$$

The ELM training problem translates into solving the optimal weight vector to minimise the loss function value. That is to find the least square solution $\hat{\beta}$, so that:

$$\|H\hat{\beta} - T\| = min \|H\beta - T\| \tag{8}$$

Where ‖.‖ represents 2 norms, hidden layer output is H, if H is column full rank, find the best weight by using the second method:

$$\hat{\beta} = \text{argmin} \, \|H\beta - T\| \tag{9}$$

If H is not full rank, the singular value decomposition is used to solve the generalized inverse of H to calculate the optimal weight. ELM and BP use a gradient descent iteratively updating the weights between all layers differently; *ELM* does not adjust the SLFN input layer and hidden layer weights; these weights are set randomly (in practical applications, the experimental sample Is to be standardized, the hidden layer node parameters are generally randomly selected in the interval). ELM focus on the hidden layer to the output layer weight selection; the method used is least squares.

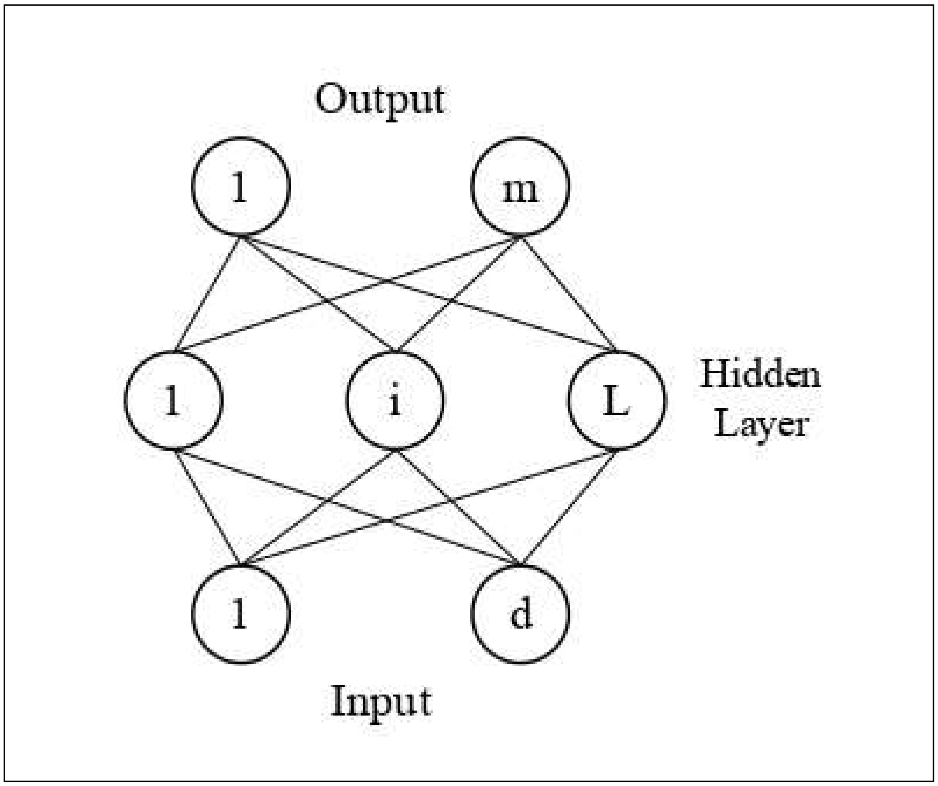

Figure 2. ELM architecture

In the prediction of table tennis, we generally select a large number of flight trajectory of table tennis as a sample to achieve neural network track prediction. Similarly, in the ELM model we give a complete table tennis flight trajectory as a source of training samples. Taking into account the need to meet the real-time requirements of table tennis robot, select 10 points to give the forecast results. That is, during the flight of a table tennis, the characteristic information of 30 points is collected, of which the characteristics of the first 10 points are input as samples and the features of the latter 20 points as output. Since a vector can express the characteristic information of each point, the input variable of the model is a 20-dimensional vector. The output variable of the model is the coordinate position and velocity of the last 20 points, which is the output vector T, and the inclusion speed is due to the appropriate attitude that needs to be considered when the ball returns from the ping-pong ball. The output vector T is a two-dimensional vector $T = (P, V)$. The experimental data in this paper come from the actual data of table tennis robots and human beings. There are 90 valid data groups; 70 of them are used as training samples of the ELM model, and 20 data groups are used as comparison data.

ELM algorithm prediction method: The current prediction method is mainly through the existing data analysis and processing, based on analysing the results of possible future data to be estimated. Its essence is to use the historical data to find the law and to model the future possible data by building a model. As the predicted data is sensitive to accuracy and noise, we usually use the variance to judge the prediction result. By assuming a time series in which the known data is X_n, X_{n+1}, L, X_{n+m} and the part to be predicted is data X_n, X_{n+1}, L, X_{n+m} at time $n+m+k$ ($k>0$), we actually predict the unknown data X_{m+n+k} based on the existing data. We think there is nonlinearity between them functions:

$$X_{m+n+k} = f\left(X_n, X_{n-1}, L, X_{n+m}\right) \tag{10}$$

Therefore, when we predict the data through the neural network model, our main task is to get the data we hope to predict by fitting the neural network method to a set of known data, namely the data prediction of $n+m+k(k>0)$ in the future.

1. Single-step Forecast

When the single-step prediction is $n+m+k$, $k>1$, all the known data are taken as the input of the network, and the obtained X_{n+m+k} prediction result is obtained. To put it simply, when we input a known sequence of X_n, X_{n+1}, L, X_{n+m} into the network, the result of the output is X_{m+n+1}, that is, the prediction result of the next moment. Continuing to incorporate into the known sequence as the input to the network, we can get the prediction for the next moment.

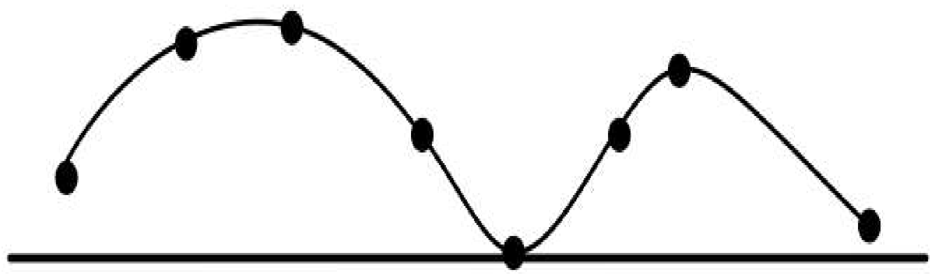

Figure 3. Table tennis track prediction vector diagram

2. Multi-step Prediction

Multi-step prediction is $n+m+k$ ($k>1$), all the known data as the network input, the resulting prediction $X_{n+1}, X_{n+2}, L, X_{n+m+1}$. However, this prediction method in the context of this article, the forecast results obtained generally deviate from the larger.

3. Scroll Forecast

The main method of rolling forecasting is to use the single-step forecast to get the network forecast value of the next moment, and then directly use the forecast value as the input of the network for the next forecast. For example, suppose that the known sequence is X_n, X_{n+1}, L, X_{n+m}. The predicted value of the next moment is X_{n+m+1}, and then X_{n+1}, L, X_{n+m+1} is used as the input of the network to predict of the next moment. At this moment, the predicted output x_{n+m+2} of the network is obtained, and then $X_{n+2}, X_{n+3}, L, X_{n+m+2}$ is taken as the input of the network to make another prediction of the time X_{n+m+3}; we can finally get the expected future time prediction sequence. The specific network input and output are shown in Table 1.

Steps	Input	Output
1	$x_n, x_{n+1}, \ldots, x_{n+m}$	X_{n+m+1}
2	$x_{n+1}, \ldots, x_{n+m+1}$	X_{n+m+2}
…	…	…
k	$X_{n+k+1}, \ldots, X_{n+k+m}$	$X_{n+m+\mathrm{k}}$

Table 1. Input and Output of Neural Network with Rolling Prediction Metho

Improved Analysis of ELM Algorithm: Because the success rate of ping-pong robot hitting depends on the accuracy of hitting robot and the preparation time of hitting, real-time is one of the most crucial characteristic attributes to be considered by table tennis robot. Because ELM algorithm is characterized by random selection of hidden layer node parameters (internal weights and offset values) in the process of determining network parameters, and network externalities are the least-squares solution obtained by minimizing the square loss function, thus greatly the adjustment time of the network parameters is reduced, so the training time of the original ELM algorithm is very short. ELM algorithm parameters in the training process, hidden layer node parameters are randomly determined, making the network training process is quite simple. But also because of hidden layer node parameters randomly selected, resulting in hidden layer does not have the ability to adjust. Therefore, when there are more neurons in the hidden layer, many hidden layer neurons do not have or have very few in the constructed single hidden layer network. Considering that without affecting the learning ability and predictive ability of the ELM algorithm under, optimize for hidden layers. According to the previous experimental results, we can see that due to the lack of data, the prediction accuracy of the ELM algorithm in the data environment is not high. We consider finding the hidden layer network parameters with good results by saving the loop algorithm, and saving the network parameters improves the purpose of the algorithm. ELM algorithm, the training part first passes the number of judgments to determine the type of algorithm excitation function, and then inputs the input variables to obtain the input weight matrix IW and the deviation matrix B, and finally combines with the excitation function to get the hidden layer weight matrix LW. We are looking for the LW that produces better results and saves the three matrices.

4. Result Analysis and Discussion

The ELM algorithm proposed above is applied to the experimental verification of table tennis trajectory prediction. The prediction results of *X, Y and Z* axes under the original ELM prediction algorithm are given below. Since the prediction of rolling motion Method. With the training of a large amount of data, the predicted result gets better gradually. Due to the limited data, the final error in the experiment is larger than other neural network models. However, the entire training session took 3.65 seconds. For table tennis robots, hit success rate depends on robot hit accuracy and hit preparation time, so real-time is one of the most crucial feature attributes of table tennis robots. Based on a large amount of data, the ELM algorithm Can achieve good prediction accuracy beyond good real-time.

To show the prediction accuracy of the ELM algorithm, the following table shows five sets of predicted and actual measured coordinates and their deviations. As can be seen from the table below, the ELM algorithm predicts that the maximum prediction error in the X-axis direction is 26.6 mm, the maximum prediction error in the Y-axis direction is 4.7 mm, the maximum prediction error in the Z-axis direction is 5 mm, Basic to meet the ping-pong robot in the hitting process accuracy requirements.

Index	Measured	Predicted	Errors
1	(6232,103.6,272.1)	(619.0,106.7,276.3)	(4.1,-3.1,-4.2)
2	(649,112.0,280.7)	(673.1,108.3,280.7)	(-24.2,3.7,0)
3	(673,114.1,292.4)	(665.1,117.7,291.9)	(7.8,-3.6,0.5)
4	(723.5,111.9,301.4)	(713.4,115.8,306.4)	(10,-3.9,-5)
5	(791.4,120.1,315.4)	(802.5,121.1,315.1)	(-11.1,-0.9,0.3)

Table 2. Predicted Trajectory Result Vs Practical Trajectory Results (ELM)

However, due to the small number of training samples, we consider adding an iteration to the parameter determination, thus increasing the ELM algorithm's time. In the experiment, because every time you predict the coordinates of a point needs to be a train, so each coordinate needs 5 times of network training. The *X* axis takes 20.1035s, the *Y* axis takes 18.2864s, the *Z* axis takes 7.539s and the average time spent on each axis is 15.3096s. The requirement of real-time performance of table tennis robot is fully satisfied. By saving the trained network, the weight matrix is directly called when predicting new data, and the coordinate of each point takes 0.006s.

In this experiment, choose 150 sets of table tennis track, spinless ball and spin ball each half. Among them, 40 groups of 75 non-spin balls are used for training, 35 are used for testing, and the spin-ball data is also the same. ELM algorithm training data and test data structure consistent with the previous section. The BP neural network training data structure and the ELM algorithm, the output data is designed to be 2-dimensional, using the binary representation of spin ball and non-spin ball trajectory type, including non-rotating ball with a vector $[0,1]^T$, spin ball with a vector $[1,0]^T$ said output, the target is shown in Table 3.

Types	**Vector**
With no rotation	$[0,1]^T$
Backspin	$[1,0]^T$

Table 3. The Output Vector Table

In this group of experiments, among the 70 groups of test data, 64 groups of data are consistent with the true values, with a correct rate of 91.4%. At run-time, the total run time of the ELM algorithm is 0.867889s.

Therefore, in summary, table tennis trajectory prediction based on ELM algorithm. First of all, a real man-machine docking experiment was done and a trajectory prediction Mat lab experiment based on ELM algorithm was designed. The experimental results show that the original ELM prediction model is not ideal for table tennis trajectory prediction. Thus, the ELM algorithm is improved, and the prediction effect is improved by saving the hidden layer weight matrix with good results and using it for the next trajectory prediction. At the same time, we verify the feasibility of improved ELM algorithm in trajectory prediction and its great advantage in real-time by improving the experimental data of ELM algorithm for predicting table tennis trajectory.

5. Conclusion

With the rapid development of sports, the traditional computer technology can no longer meet the demand of contemporary sports. The typical representative is the prediction of ball trajectories. Therefore, predicting sports ball trajectories based on the new computer technology becomes the hot point of current research. Based on this, ELM (Extreme Learning Machine) algorithm is put forward from the perspective of computer intelligent algorithm, which aims to study the prediction of table tennis trajectory and provide a scientific basis for the development of table tennis. The ELM algorithm is proposed and its prediction steps are analyzed. The mathematical model of trajectory motion prediction is established. At last, the experiment of multi-groups of ping-pong trajectories is taken as an actual case to verify the applicability of the ELM algorithm. The results show that: 1) ELM algorithm which can predict the trajectory of table tennis better. Therefore, it has good adaptability in the prediction of various ball trajectories in sports. 2) ELM algorithm-based trajectory prediction error is small, and the response speed, with high prediction accuracy, to meet the accuracy requirements of the system. In summary, the research in this paper provides a theoretical basis for sports ball trajectory prediction, which is of great significance.

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