Experiments with Offline Visual Processing Modules for Learning Networks

Lian Qian
School of Physical Education
Nanjing University, Nanjing
Jiangsu, 210000, China
slxbr615765@163.com

ABSTRACT: *This article analyzes the visual processing module of table tennis using an offline learning network model. By training and learning a large amount of video data from table tennis matches, offline learning network models can automatically extract features from table tennis movements and accurately perform object detection, trajectory prediction, and action recognition. Unlike traditional visual processing methods, offline learning network models have higher accuracy and efficiency. Summarized the advantages and disadvantages of visual processing module analysis for table tennis based on an offline learning network model. Offline learning network models can automatically extract features, reduce manual intervention, and improve processing efficiency. At the same time, this model requires a large amount of training data and computing resources, resulting in high time and computational costs. In future research, offline learning network models can be further optimized to improve their processing speed and accuracy, providing more accurate and efficient visual aids for table tennis players.*

Keywords: Neural Network, Table Tennis Model, Robot, Optimal Batting

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1. Introduction

The development of humanoid robots began in the 1960s, and Japan is the most prominent. In 1973, Professor Kato Ichiro from Waseda University, known as "the father of the world robot", developed the earliest biped walking robot in the world(Isao Hayashi, Masanori Fujii [1]. From the initial slow static walking to the ASIMO, the Honda Corporation has produced the humanoid robot today. The humanoid robot has made a great breakthrough in the miniaturization and lightweight of the robot, which can reach 2.5 kilometers per hour and run 6 kilometres per hour [2]. At home, our country has done a lot of research on humanoid robots and achieved relevant results. "Pioneer", developed by the National University of Defense Technology as the first humanoid robot, achieved a significant breakthrough in humanoid robot technology for the first time [3]. Beijing Institute of Technology and the cooperation unit successfully developed "Hui Tong" 2 humanoid robots, height 1.63M, weight 63kg, with forward, backwards, turning, step up and other functions. For the first time in the world, the imitation of Taijiquan, sword and other complex human movements is a breakthrough in the complex motion design and control technology of humanoid robots, and the system function has reached the international advanced level [4]. The research work of humanoid robots is developing rapidly, showing the trend of personification, small size, lightweight and function diversification.

2. State of the Art

Since 1983, the table tennis robot has been researched. Many countries, such as Japan, Spain and the United States, have invested a large number of human and material resources to carry out specific research work [5]. In 2005, the American Rochester Institute adopted a robot manipulator with five degrees of freedom to design a robot capable of playing table tennis, and the actual moving speed reached about 0.64m/s. Just because the moment of inertia of its commercialized design is very large and the speed of moving is relatively slow, the actual table tennis cannot get the desired effect [6]. After a certain period, various types of robotic arms for hitting table tennis were developed at the Japanese Osaka University Laboratory of Miyazaki after summing up a series of studies and obtaining a playing table tennis robot control method that can hit the ball in the fixed time to hit the determined position above and be able to start a flight with people. The table tennis robot contains four degrees of freedom, two of which are horizontal linear motion and the other two are racket position determination [7]. TOPI3.0 humanoid robot made by TOSY of South Robotics Engineering Corporation played table tennis in 2009 at the International Robot Show in Tokyo, Japan. The robot, which is made of carbon fiber, is 1.82M high and has a mass of 120 kg. It has two cameras in the eye that can capture 200 frames per second; the actual machine strategy can achieve the recognition of table tennis and can analyze the ball's trajectory and select the corresponding hit way [8]. The University of Washington sports laboratory and the optimization algorithm design obtained the trembling robot arm. In this case, the period of the actual motion path of the high-speed camera facing the table tennis is the location tracking of Oms. And with the computer to expand real-time operation and control of the arm [9].

3. Methodology

3.1. Motion Parameter Learning

First, describe the visual predictive parameter algorithm based on Neural Networks in detail. The specific content of the work can be divided into two aspects. The kinematic inverse of the continuous model meal parameter is the first step, then building and learning networks. The first step of the kinematic inverse of the continuous model parameter belongs to the test of all kinds of trajectories. It obtains the closest data information to the actual trajectory [10]. The state equation of this part of the trajectory belongs to the important state information obtained after the first smoothing, just like the prediction point; the desktop produces the state before and after the collision. The inverse kinematic parameters of the continuous model have better applicability to the optimal state equation parameters of the trajectory and obtaining trajectory data by re-smoothing. Finally, by using the trajectory data of this part, the more accurate state parameter equation is derived, and as a parameter learning machine to train and test data, analysis of table tennis state and potential law between the parameters of the state equation of motion. Finally, by this rule, taking online positioning and input data into the filter, the parameters of the prediction equation of the track state are effectively estimated.

Then, we expand the Kinematic inverse of continuous model parameters. The key to the kinematic inverse of continuous model parameters is to input the position and speed information at the visual level and obtain the parameters of the motion equation matching with the trajectory by using the corresponding analysis. Using the equation of state, obtain the parameters of the continuous model and then transform them into discrete model parameters. It can be known that for the table tennis movement which is only affected by the first-order resistance, the equation of state is as follows.

Among them, k belongs to the drag coefficient, g is input in the vertical direction, a belongs to acceleration, v belongs to speed. *X, y, z* are in the direction of space, respectively. e is the parameter, S is the cross-sectional area.

$$c\begin{cases} V_x(t) = V_{x0}e^{-kt} \\ V_y(t) = V_{y0}e^{-kt} \\ V_z(t) = (V_{z0}e + \frac{g}{k})e^{-kt} - \frac{g}{k} \end{cases} \tag{1}$$

By equation $v_{xy}(t) = V_{xy}0e^{-kt}$, k can be obtained. And here, we introduce the position state to calculate the g value.

$$\begin{cases} S_x(t) = \int_0^t V_x(\tau)d\tau = \frac{V_{x0}}{k}(1-e^{-kt}) \\ S_y(t) = \int_0^t V_y(\tau)d\tau = \frac{V_{y0}}{k}(1-e^{-kt}) \\ S_z(t) = \int_0^t V_z(\tau)d\tau = \frac{V_{z0}+\frac{g}{k}}{k}(1-e^{-kt}) - \frac{g}{k}t \end{cases} \tag{2}$$

So we can push it:

$$\begin{aligned} S_z(t) &= \frac{V_{z0}+\frac{g}{k}}{k}(1-e^{-kt}) - \frac{g}{k}t \\ &= \frac{V_{z0}}{k}(1-e^{-kt}) + \frac{g}{k}(\frac{1-e^{-kt}}{k} - t) \end{aligned} \tag{3}$$

$$g = \frac{S_z(t) - V_{z0}(1-e^{-kt})}{(\frac{1-e^{-kt}}{k} - t)} \tag{4}$$

Then there are:

$$\begin{cases} a = S_z(t)k - V_{z0}c \\ b = (\frac{c}{k} - t) \\ c = (1-e^{-kt}) \end{cases} \tag{5}$$

Using the above calculation, the parameters matching the trajectory can be constructed. The performance of neural network fitting, generalization and network complexity are optimized using electromagnetism-like algorithms. Half of the data points are trained, and the rest are used to expand the test. The topology constructed by the network belongs to double-layer optimization. The lower layer adopts ROLS-Dopt (Regularized Orthogonal Least Squares > to construct an accurate parameter model. The upper layer adopts electromagnetism like algorithm to optimize the network performance, generalization performance and network complexity.

3.2. Parameter Correction and Algorithm Implementation

The algorithm proposed in this section combines electromagnetism-like mechanism algorithm (EM), and D-opt regularized orthogonal least square method (ROLS ten D-opt), design a self-optimizing two-level learning method for radial tomb (RBF) network to learn the key parameters of the table tennis flight and collision model. In a lower level, the ROLS+D-opt algorithm is used to design and build a lower-level RBF network model with good generalization performance based on specific parameter structure. The upper layer determines three key learning parameters in the establishment of subordinate networks: RBF (radial basis function width width); Zheng Bei ROLS algorithm, l coefficient (regularized parameter) and D-opt (D-optimality weight parameter) parameter optimization. By swarm intelligence optimization, after several generations of learning, a superior EM optimization method has obtained the optimal value of learning parameters and its decision network. The method of designing the network by the regularized orthogonal least squares algorithm is compared with the original network design method. We know that the RBF network structure model of the design complexity is lower, and the network of China's performance is more excellent. In the actual design process of the table tennis flight model, parameters, given the actual design of the network, must be effectively applied to online filtering; therefore, the network structure cannot be too complex and must have sufficient robustness. Combined with the previous discussion, the noise of table tennis track data in carrying out the parameter network is related to light angle, positioning error and other factors. We focus on constructing the network's ability to acquire data regularly, hoping that the training network will be suitable for the new sample and get the appropriate output. It does not belong to the simple sample mapping, that is, the generalization ability.

We analyze RBF network learning, RBF network design considering multiple inputs and single output three layers (m inputs, n hidden nodes, one output), and suppose that the basis width parameter of the radial basis function takes the same fixed value. At this point, the output of the network can be defined as.

$$\hat{y} = F_T(X) = \sum_{i=1}^{n} \theta_i \exp(-\|X - C_i\|^2 / \rho) \tag{6}$$

In this equation, $X = [x_1 ... x_m]^T$ is Input vector of network, θ_i is the weight coefficient of the I implicit node to the output, $C_i = [c_{1,i} ... c_{m,i}]^T$ is the data centers with first radial basis functions in the hidden layer, $\|.\|$ is two norms, ρ and is the base width of a function.

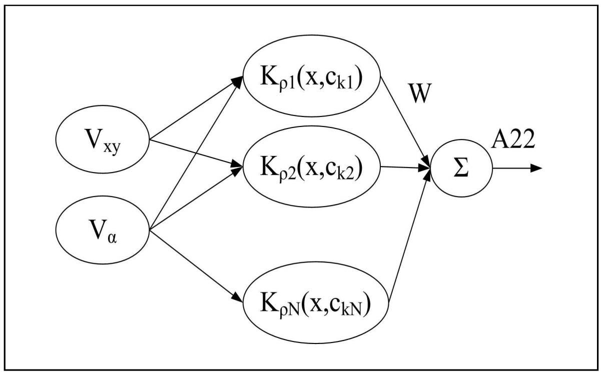

Figure 1. Updating model of filtering parameters

Figure 1 is a model for updating filter parameters. A motion parameter learning machine based on RBF (radial basis function) network is established here. The motion parameters of the network output as a graph with an example of the equation of flight motion equation of table tennis which needs to be modeled. The data analysis of the learning machine is the input of the tangential velocity and elevation of the initial state (prediction point), the parameters obtained from each trajectory are used as output training samples and Build a black box model. The parametric model is as accurate as possible through learning.

Our brief introduction to the EM algorithm and its application. The radial tomb function network based on the ROLS+D-optimality algorithm can be used as the basic algorithm for parameter learning. Electromagnetism-like Mechanism Algorithm (EM) is used to optimize the network in the optimization of the algorithm; the main purpose is to prevent the overfitting (overfitting) phenomenon and enhance the generalization performance of the network. EM algorithm is a global optimization algorithm with powerful search ability. the algorithm is simple, easy to implement, and the calculation is small. The algorithm's convergence has been proved and successfully applied in the topology and weight optimization of neural networks. The repulsive repulsion mechanism between charged particles in BIRBIL and FANG electromagnetic fields inspires its emergency. Imitating the mechanism of attraction and repulsion in the electromagnetic field, each solution is compared to a charged particle, then the search particle moves towards the optimal solution according to certain criteria[1]. For the EM algorithm, each particle represents a possible solution to the optimization problem; it has its position (position) and speed (velocity). Electromagnetism-like mechanism algorithm, that is, the EM algorithm, is a global optimization swarm intelligence optimization algorithm. The optimization problem of bounded variables has the following form:

$$\min f(x) \qquad s.t. \qquad x \in [l,u] \tag{7}$$

Among them, $[l,u] := \{x \in \Re^n | l_k \le x_k \le u_k, k = 1,...n\}$, u_k, and l_k is in the upper and lower bounds of K dimension variables. $F(x)$ as the fitness functions and expects to reach the minimum. The main steps of the EM algorithm can be divided into four stages: Initialization algorithm. Search local minimum in neighborhood. Calculate the total force of each particle. Particles move according to the magnitude and direction of force.

4. Result Analysis and Discussion

Table 1 is the collected initial data, obtained by target location without filtering (60 frames / sec camera frequency), 134 tracks in total.

	The ball is low in elevation	In the ball elevation angle	High elevation of ball outlet
Speed gear 1		28 tracks	13 tracks
Speed gear 2	1 tracks	26 tracks	
Speed gear 3	26 tracks	28 tracks	

Table 1. Test Data Collected By Grouping

The collected data are the most accurate and close to the trajectory information acquired by offline analysis and processing (filtering and fitting) for each trajectory. The above data is used for the training of the BF network.

In terms of application results, running and importing the neural network established by this system. In the previous chapter, as the physical model plates described, the most important parameters of the table tennis model are the vertical additional force input of gravity-buoyancy force and the air resistance caused by the flight speed. The parameters corresponding to the continuum model's two elements are *g* and *k*, respectively. In the discrete model, the absolute value of the y-axis state matrix (2,2) corresponding to the flight motion parameters can be adjusted to influence the air resistance. The absolute value of the z-axis input matrix can mainly adjust the influence of the synthesis force of gravity and buoyancy. Operating system software, the results shown in Figure 2 can be obtained by inputting a set of purchased track data.

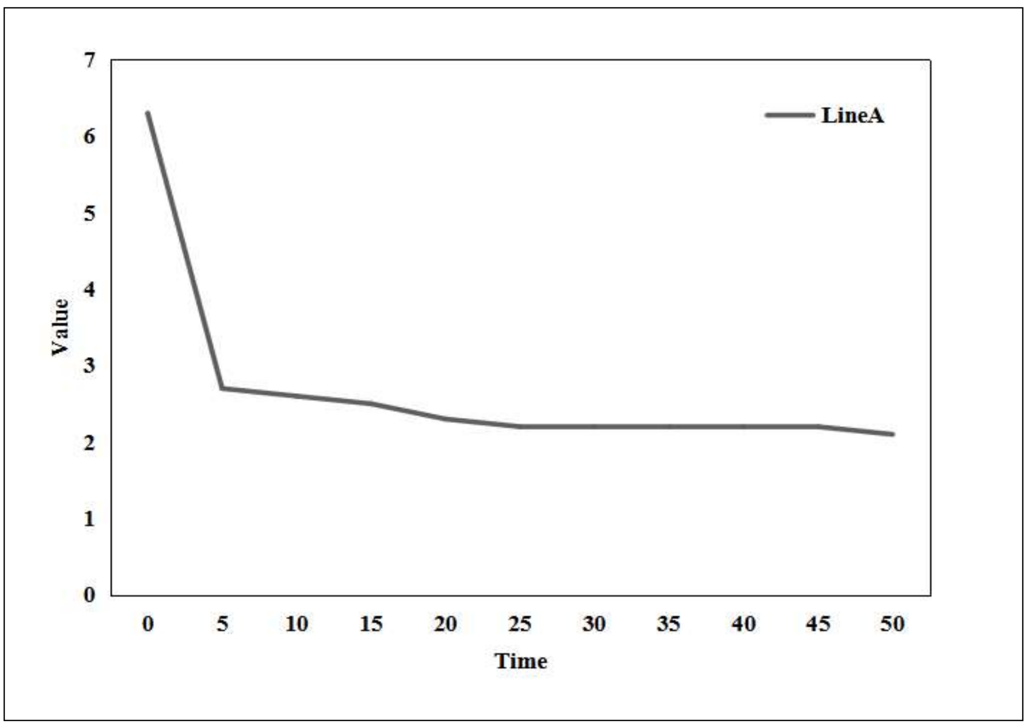

Figure 2. Convergence curve of *EM* optimization algorithm for *G* network with vertical additional force parameters

Figure 2 is the convergence curve of the optimization algorithm applied to the longitudinal additional force parameters. The lateral axis belongs to iteration times, the vertical axis belongs to construct the optimal neural network adaptation function returns the size. We know that the algorithm has a fast convergence speed in this application; after 20 generations, it can get relatively good results. The vertical additional force parameter g of gravity- buoyancy force is used to get the network output result through the test data. EM seeks convergence curves of the algorithm and network output results for test data. The fitting parameters which are relatively good in the whole range of the network are constructed and network output does not appear burr situation.result through the test data. EM seeks convergence curves of the algorithm and network output results for test data. The fitting parameters which are relatively good in the whole range of the network are constructed and network output does not appear burr situation.

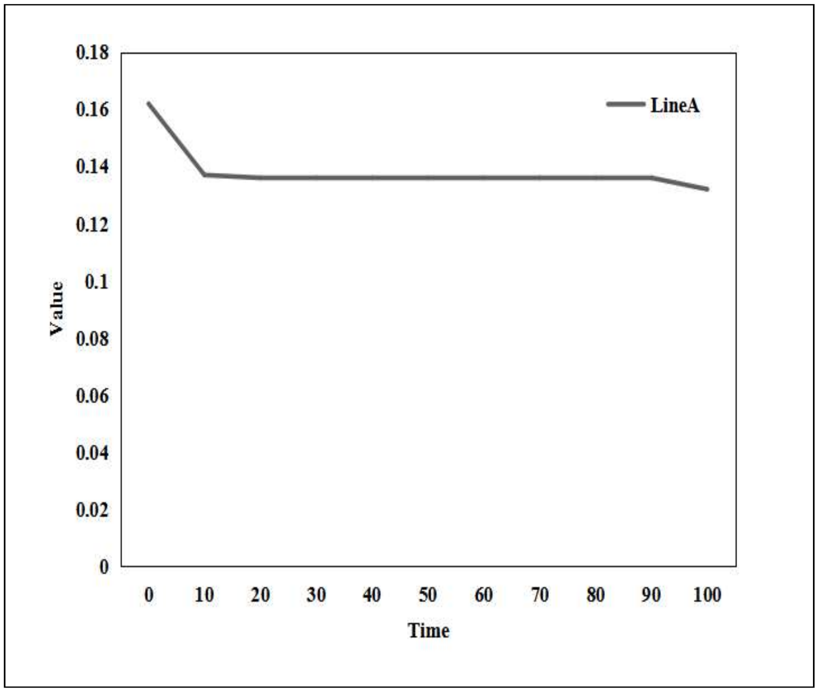

Figure 3. Convergence curve of K network EM optimization algorithm for table tennis direction resistance parameter

Figure 3 is the convergence curve of the EM optimization algorithm in the application of the resistance parameter in the motion direction. The lateral axis belongs to iteration times, the vertical axis belongs to construct the optimal neural network adaptation function returns the size. And also, the convergence speed of the algorithm in this application has achieved a satisfactory result after the first 20 generations. Table tennis movement direction of resistance parameter k is the network output result of the

	Calibration method of RBF network parameter model	**Linear trimming correction method**
Average value of absolute value of deviation measured by falling point	0.0277,0.0042,0.0001	0.0242,0.0043,0.0001
Point of arrival P prediction mean square deviation	0.2828,0.0292	0.3508,0.0304
Mean value of prediction deviation absolute value at fall point time	0.0018	0.0022
Fall point time T prediction deviation mean square deviation	4.58E-06	7.58E-06

Table 2. Comparison of Test Data Results

above test data set up by the proposed algorithm; it is also the convergence curve of EM optimization algorithm and the network output result of test data. The above parameters are the key parameters of the flight model of table tennis and it is also the model foundation of Kalman filtering and smoothing. After obtaining the parameters of the continuous model, it can discretise the model by a known frequency of drawing by 60 Hz.

We can learn from the test results, compared with the linear trimming correction method, the network model parameter correction method has significantly improved at the prediction accuracy and stability aspect. Specifically, there are several aspects of the content: Prediction of landing time, the network model calibration method has a very good effect than linear tuning correction method in general. Predicted fall point position, the mean deviation of the network parameter model calibration method is obviously larger than linear correction technique. The mean square error is better than the linear correction method, and more scientific and reasonable. Because the linear trimming correction method is oriented to the specific state trajectory, the manual setting method can be used to reduce the error effectively. But for all kinds of pitches, it is very sensitive to table tennis's angle, posture and speed change; its dependence on the overall system of the precision degree of pitch prediction is an important influencing factor. Network parameter search is greatly associated with data collection and can realize the large batch automatic acquisition; the concrete application is feasible in the project. This method can effectively improve efficiency and has relatively strong portability. Based on the above verification, we can find that the two-level learning method can be used to design the optimized RBF network in the global scope; in addition to the complexity of the structure is not high, and its generalization performance is very excellent, the key approach of the design of RBF network. By updating the set matrix of the online prediction program by learning the network characteristics, we can know that the neural network with excellent fitting correction is applied online.

The learning mechanism in the RBF network is a double-layer structure is introduced in this paper, combined with the electromagnetism-like mechanism algorithm and ROLS+D-optimality algorithm. Through the test, we get the method has the following innovative features: Compared with the generalization performance of the network and the original RBF network model, the former achieved significant enhancement because of the introduction of the regularized orthogonal least squares (ROLS) algorithm. The weak robustness caused by the possibility of the ill-conditioned network can be optimized by introducing the D-Optimality (D-opt) theory into the above method. The two-level learning model is designed based on the lower layer ROLS+D-optimality algorithm. The upper-class electromagnetism mechanism algorithm (EM) solves the problem that the network parameters of single-layer design cannot be set according to the model, making the algorithm perfect, and the algorithm improved further through the global optimal parameters search (network-based ROLS algorithm and width parameter regularization coefficient and D-opt parameter optimization) improve the network generalization performance, simplifying the network structure.

In total, in this paper, the network model of off-line learning is applied to the online filtering program of the visual processing module in the whole design project of the hit planning bureau, not only the integration of parameter object changes in different states of motion on a display and visual modeling, and more effective in real-time acquisition of table tennis in the data to improve forecasting accuracy.

5. Conclusion

Our country has done much research on humanoid robots and achieved relevant results. "Pioneer" developed by the National University of Defense Technology as the first humanoid robot, achieved a major breakthrough in humanoid robot technology for the first time, and the robot has been paid more and more attention in sports training. This paper introduces a two-layer network RBF learning mechanism, which combines an electromagnetism-like mechanism algorithm and ROLS algorithm and has innovative significance—proposing a new motion model construction and optimization algorithm based on intelligent learning training and parameter knowledge base based on multiple trajectories of table tennis. Introducing electromagnetism like mechanism algorithm (EM) and ROLS algorithm, we have designed a learning method with two levels structure to learn the key parameters of the table tennis model. Finally, it displayed through test, the network model of off-line learning is applied to the online filtering program of visual processing module on the whole project level, not only the integration of parameter object changes in different state of motion on a display and visual modeling, and more effective in real-time acquisition of table tennis in the data to improve forecasting accuracy.

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