International Journal of Hybrid Information Technology
Vol.8, No.12 (2015), pp. 181-190
http://dx.doi.org/10.14257/ijhit.2015.8.12.12

Prediction of Basketball Players' behavior based on Radial Basis Function Neural Network

Shengbo Liao[1], Deming Zhang[2] and Haitao Yang[3,*]

[1]*Beijing Jiaotong University, Beijing 100000, china*
[2]*Heilongjiang University of Chinese Medicine, Harbin 150000, China*
[3]*Beijing University of Technology, Beijing 100000, china*
daliao168@tom.com

Abstract

An approach based on online RBFNN is proposed to predict the ball-carrier's behavior shooting, passing and dribbling in basketball matches. In order to describe the factors affecting the behavior of ball carrier, artificial potential field (APF)-based player information is introduced to model the court situation of all players after tracking and vision range determination, then a feature vector is formed as the input of the online RBF neural network. The behavior prediction of the ball carrier is solved by the online RBF neural network based on GIRAN learning algorithm. Compared with the offline RBF neural network, the online neural network can adjust both structure and parameters to basketball matches, thus the prediction accuracy is improved to some extent.

Keywords: *behavior prediction, player tracking, online RBF neural network, players' behavior*

1. Introduction

At present, video-based moving body analyses mostly refer to the cognition of motion behaviors, fewer about the prediction of behaviors. Duarte Duque [1], *et al.*, proposed the abnormal behavior prediction method based on N-ARYTREES classifier; then, they introduced dynamic oriented graph [2] which is of better real-time and stronger adaption for abnormal behavior prediction. In real applications, human behavior prediction is more meaningful than motion behavior recognition, such as in safety-sensitive places like bank, airport, government building. If the intelligent monitoring system can foresee criminal behaviors of the suspect and send alarms promptly to securities, it's possible to prevent the occurrence of crimes and also reduce the investment of manpower, material resources and financial resources. In the sport trainings like basketball and football, if the data can be acquired about competitions by excellent teams, a discriminator can be tailored to predict behaviors of the ball controller [3]. Then, the device is used on players of poor behaviors. Based on the comparison of behavior decisions given by the device and the actual behaviors made by the player with the ball, the goal of helping player trainings can be achieved [4-5].

In basketball match, the ball holder can choose three behaviors: shooting, throwing and dribbling. Basketball match is a team sport. In it, the player with the ball's choice of one of the three behaviors is affected jointly by various factors, *e.g.*, the role (forward, center forward, rear guard) in the competition, the distance away from the basketry of opponent team, position of both his other four members and rivals [6-7]. So the behavior prediction of the player with ball can be regarded as a highly non-linear, multi-factor concurrent and complicated process with randomness and uncertainties. Such complication determines the difficulty in creating mathematical model. Characteristic of

* Corresponding Author

ISSN: 1738-9968 IJHIT

self-organizing, self-learning, adaption and non-linearity, artificial neural network can deal with laws that are hardly resolved, fit for nonlinear system modeling. In numerous artificial neural networks, radius base radial basis function (RBF) neural network has merits like, simple structure, fast learning, good fitness accuracy, strong generalization ability and not easily falling into local minimum. It has been widely applied in function approximation, classification, as well as time sequence prediction. Hence in the paper, we choose RBF neural network as prediction model, considering the ball holder's behaviors as a three-class problem with many factors as input. Firstly, we utilize the player information quantity based on artificial potential field to create the model about positions of players in the court [8], forming a feature vector which describes situations in visual field behavior decisions of the player with ball. By using it as well-trained radius base neural network input, we can further forecast behaviors of the baller holder as per the classification results. When the predicted result is throwing a ball, we can thus predict behaviors of the receiver.

2. Player Information Amount based on Artificial Potential Field

2.1. Artificial Potential Field

Artificial potential field was raised by Khatib in 1986. It was originally a common method which was used to guide motion robots to avoid from online collision [9]. Its basic idea is to simplify robot, obstacles and target as one point, and to regard robot's movements as what's happening in abstract artificial stress field, that is, to build in environments the artificial potential field on which target position gravitational field and obstacle surrounding repulsive field can co-work, searching the descending direction of potential function to find a collision-free path. Target points cause gravity to moving robot but obstacles cause repulsive forces to robot. The outcome is robot is forced to move from "potential peak" to "potential valley". The combined force of gravity and repulsive force, as accelerative force, controls robot's motion direction and calculates its position. Let q the position of moving object and q_{goal} the position of target; then the artificial potential field in the position of the moving object can be expressed as:

$$U_{APF}(q) = U_{att}(q) + U_{rep}(q) \tag{1}$$

Attraction potential is generally defined as a parabolic function:

$$U_{att}(q) = \frac{1}{2} k_{att} \rho^{2}_{goal}(q) \tag{2}$$

The attractive potential energy is differentiable, the attractiveness of the general definition for the negative gradient attractive potential energy is expressed as:

$$F_{att} = -\Delta U_{att}(q) = -k_{att} \rho_{goal}(q) \Delta \rho_{goal}(q) = -k_{att}(q - q_{goal}) \tag{3}$$

2.2. Player Information Quantity based on Artificial Potential Field

To describe the assignment of players in the court, we use artificial potential field mentioned above to create a model and propose the player information quantity based on artificial potential field. In the match, players in the controlling side can be one with the ball and a few others without it. Set the position X of Player i at time t. Then its artificial potential field at the time can be expressed like:

$$U^{t}_{APF-i}(x) = U^{t}_{att-i}(x) + U^{t}_{rep-i}(x) \tag{4}$$

In the formula (4), the meaning of $U^{t}_{rep-i}(x)$ and the 2.1 section are same meaning, $U^{t}_{att-i}(x)$ is defined as:

$$U^{t}_{att-i}(x) = \frac{1}{2} k_{att} \frac{1}{\rho^{2}_{goal}(x)} \tag{5}$$

Here, P is one parameter in the repulsive potential $U^{t}_{rep-i}(x)$ of opposing players around against players i. If it's a fixed threshold over ρ_0, then counter-players won't have impacts on the player i. Besides, when several opposing players surround player i, the repulsive potential he is bearing equals to the cumulative repulsive potential of them.

It's stressed that: in expression (5), parameter k_{att}, k_{rep} has lots of practical significances to describe the information amount of players. Parameter k_{att} is a positive value, representing scoring ability of player. For different roles of the offensive players, the scoring ability is varying and hence k_{att} is not similar, with forward stronger than center forward, who is better than rear guard. But k_{rep} is a negative value, indicating the defensive ability of rivals. For different roles of the offensive players, the defensive capability is varied and $|k_{rep}|$ is not the same, with rear guard stronger than center forward, who is better than forward.

Since it's impossible to judge directly from match video frames the role of players (forward, back guard etc.), we introduce a method which automatically updates parameter k_{att} and k_{rep} according to the times of player tackling and shooting:

In the learning period, initialize shooting capability value $\{k_{rep-A_i}, k_{rep-B_i}\}_{i=1...,5}$ and tackling capability value $\{k_{rep-A_i}, k_{rep-B_i}\}_{i=1...,5}$ of both 10 players to α and β ; at this moment, assume the ability of each player is equal. As the match goes on, when team B's player B_i steals successfully the ball from a's player, refresh the tackling ability value of player B_i through the following equation:

$$k_{rep-B_i} = k_{rep-B_i} + \gamma, \eta_d \le k_{rep-B_i} \le \theta_d \tag{6}$$

If it is not successful, then

$$k_{rep-B_i} = k_{rep-B_i} - \gamma, \eta_d \le k_{rep-B_i} \le \theta_d \tag{7}$$

Similarly, when the J player successfully grab the ball and not the ball, respectively according to the update:

$$k_{rep-_{Ai}} = k_{rep-A_i} + \gamma, \eta_d \le k_{rep-A_i} \le \theta_d \tag{8}$$

$$k_{rep-A_i} = k_{rep-A_i} - \gamma, \eta_d \le k_{rep-A_i} \le \theta_d \tag{9}$$

In the game, players got score, according to the type of the shooting ability for real-time updates

$$k_{att-carrier} = k_{att-carrier} + \tau, \eta_a \le k_{att-carrier} \le \theta_a \tag{10}$$

$$k_{att-carrier} = k_{att-carrier} - \tau, \eta_a \le k_{att-carrier} \le \theta_a \tag{11}$$

3. Behavior Prediction of the Player by Online RBFNN based on GIRAN

It's all known that in the basketball contest, behavior decision of the ball holder at some time point is the coordination result of many factors. Using computer to predict the decisions of player is a complicated process of high nonlinearity. Moreover, in the game, player's decision may change for being affected by, such as waning of remaining time, substitute of player. Therefore, the training of the proposed prediction neural network should sustain with the progress of the competition. Here we adopt one online approach to train the neural network. When in the game, the neural network gives wrong prediction, we use the actual decision as training sample and input to the neural network for real-time modification of network structure parameter. Next we'll introduce the topological structure of radius base neural network and elaborate online training algorithm based on GIRAN.

3.1. RBF Neural Network

3.1.1. Topology of RBF Neural Network. The structure of Radial Basis Function Neural Network (*i.e.,* RBFNN) is presented in Figure 1. From it, we can know it's a typical forward neural network, consisted of three layers. Nodes in the input layer is to transfer signals to hidden level, in which nodes are composed of radius base functions; nodes in output layer are generally simple linear functions. In RBF gal, the conversion from input layer to the hidden is nonlinear. The hidden layer performs nonlinear transformation of input vectors. But the conversion from hidden layer to the input is linear, *i.e.,* output of network equal to the summation of linear weights of hidden node outputs.

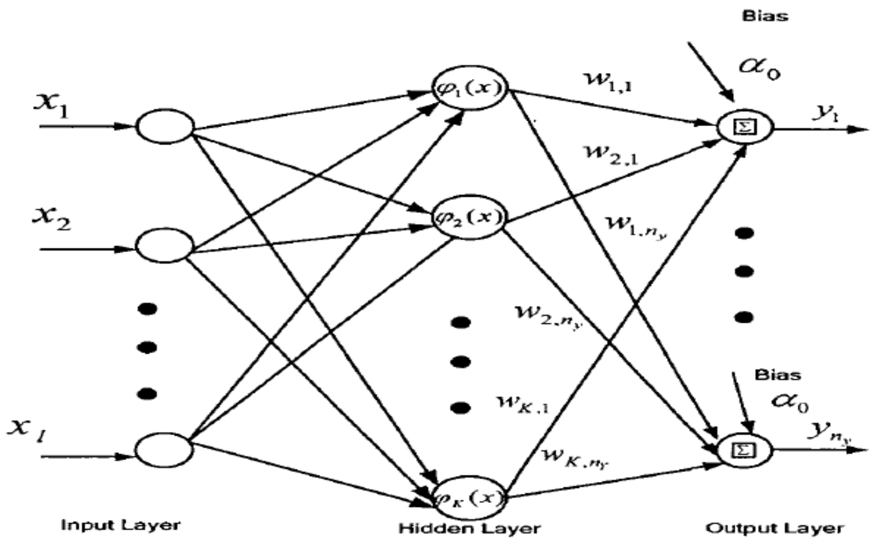


Figure 1. The Basic Structure of RBF Neural Network

The hidden layer radial basis functions used to have the following several kinds of forms:

1 Multi-Quadrics functions:

$$\varphi(r) = (r^2 + b^2)^{1/2}, b > 0, r \in R$$

2 Inverse Multi-Quadrics functions:

$$\varphi(r) = \frac{1}{(r^2 + b^2)^{1/2}}, b > 0, r \in R$$

3 Gauss functions:

$$\varphi(r) = \exp(-\frac{r^2}{2\sigma^2}), \sigma > 0, r \in R$$

In this paper, RBFNN is used in the hidden layer of Gauss as a function of radial basis function, the specific forms of representation for:

$$\varphi_k(x) = \exp(-\|x - c_k\|^2 / \sigma_k^2), k = 1, 2, .., K \tag{12}$$

3.1.2. RBF Neural Network Learning Algorithm. From the structure of RBF neural network, it's learnt that constructing and training one RBFNN is a process determining the number k of hidden neurons, center c and width σ of each hidden RBF, as well as the link weight from hidden layer to the output, so as to complete required mapping from input to output. Regarding RBFNN, its network performance depends on selection strategy of hidden neurons and renewal process of link weights from hidden layer to output level.

In terms of the time when parameter modification happens, RBF neural network learning algorithm can be divided into offline learning way (*i.e.,* batch method) and online learning way (*i.e.,* serial order learning or sequential learning).

1 Offline Learning Way

What's trained by the method is a RBF network of determinate structure, which means fetching center from the distribution pattern of training sample space and the network structure is determined once the center is chosen. When data mode changes, the network can't make any change, even though it can change network features by adjusting weights, which however is not fundamental and is limited in the adjustment range; particularly when one sample never learns, the network will lose recognition ability. Thus, this method's fitness ability is not strong enough for time-varying system.

2 Online Learning Way

The above method can only adjust network parameters after all training samples are made to have one complete learning (*i.e.,* one epoch). The learning process of it is one epoch after another till network parameters are stable and the mean output errors in the whole training set are converged to one minimum value; by then, the learning ends. When online learning method is employed, each training sample goes to the network. After calculation, they make adjustments of network parameters.

3.2. Prediction of Ball Player

When the predictor output pass, it can further predict the ball players. As a player, in general, he will find within the field of view is the most favorable conditions for the team. In the process of looking for the ball team, not only to consider the ball players are more score advantage, but also need to consider the ball between the team and the player with the ball away. The greater the distance, then pass the ball more easily mistake or destroyed by each other. The smaller the distance, the possibility of success is passed the ball more. Therefore, for the player with the ball within the field of view of K teammates, the definition of team mate i on the pitch for favorable degree:

$$\varpi_i = w_1 \times U_{APF_i} + w_2 \times \frac{1}{d_{ci}^2}, w_1 + w_2 = 1 \tag{13}$$

4. Experimental Analysis and Results

To validate the effectiveness of the proposed prediction method, we test on PC with Intel Core2, T6500, RAM 4G, realizing by VC++6.0 and OpenCV. The experiment includes two steps: training of neural network and predicting behaviors of ball carrier. First of all, to create RBF network, we collect NBA regular season and playoff game videos of totally 654 sessions from the year 2008 to 2014 as original training data, at 25fps. Teams joining the game have similar strength. For videos of each session, we sum up shooting and stealing of every player as to decide the shooting ability k_{att} and tackling ability k_{rep} of them each. As per the real situation, we make the initial value of k_{att} and k_{rep} respectively 10 and 3; the upper limit θ_d and lower limit η_d of tackling ability respectively 5 and 1; the upper limit θ_d and lower limit η_d of shooting capability respectively 25 and 1; γ and τ both as 1.

After the ability of players in each session is set, it shown in Figure1and Figure2, we program to calculate automatically the triple $(U^t_{APF_i}, d^t_{carrier-i}, P^t_i)_{i=A1,\ldots,A5}$ which describes player's field information at the time of behavior decision, where $U^t_{APF_i}$ means the artificial potential field information quantity of the ith player at T; $d^t_{carrier-i}$ is the distance between the ith player and the ball holder at t; P^t_i is court coordinate of the ith player at t. Then, we use triples of all its team members in sight of the ball controller to constitute feature vector $fv^t = (U^t_{APF\,carrier}, P^t_{carrier}, U^t_{APF_{Ai}}, d^t_{carrier-Ai}, P^t_{Ai})^T_{i=1,\ldots,S}$, where S stands for the number of team players in sight of the ball carrier at t; and we mark the actual behavior of the carrier as t^t_{ij}, in which, i represents the behavior decision of the player who carries the ball for the j-th time in the video labeled j. After implementing calculation of feature vector fv^t_{ij} of all 654-session videos, we get an eigenvector set $S = \{(fv^t_{ij}, t^t_{ij}) \mid i = 1,\ldots 654,\ j = n_1,\ldots,n_i\}$ totaling 25363, where n_i means the total number of behavior decisions of the ball holder in i-th session match. Finally, we use elements in the set as training sample of RBFNN. To compare the prediction accuracy between traditional offline RBFNN and online RBFNN based on GIRAN, we apply separately orthogonal least square (OLS) and supervised learning LMS algorithm to train offline RBFNN, and use GIRAN algorithm to train online RBFNN.

To determine the weight w_1 and w_2 in (13). Let $ratio = w_1 / w_2$, for different ratios we compare the relationship of $ratio$ and prediction precision, as seen in Figure 1. In it, right precision ratio is $\sum_{i=1}^{N} (\tau^i_{shooting} + \tau^i_{passing} + \tau^i_{dribbling}) / 3N$, $\tau^i_{shooting}, \tau^i_{passing}, \tau^i_{dribbling}$ indicates the percentage of predicting correctly the shooting, passing and dribbling; N is total number of tested videos. From the picture, we know that the ratio is 2.6, the prediction precision is the highest. So in the experiment, we set w_1 and w_2 as 0.72 and 0.28.

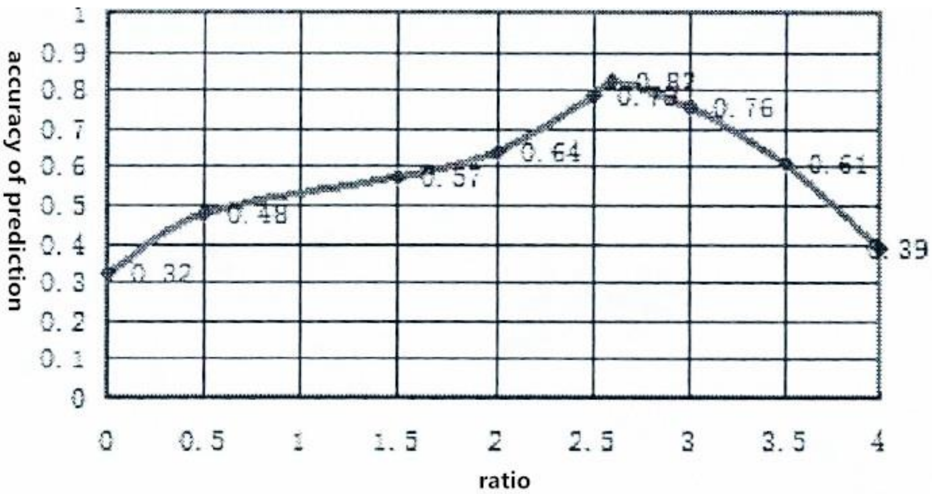


Figure 1. The Relationship between Ratio and the Correct Rate Curve

In the testing stage, we chose 10 sessions of football match videos at 25fps. The overall quality of teams joining the game is basically equal to those in the trained videos. For lens shift in videos, we cut manually videos to numerous single shots. Then, we analyze each single shot. See Table 1 for specific data about behavior prediction by two neural networks of the ball holders in 10 matches. See Table 2-Table 3.

Table 1. Predicting the Behavior of Experimental Data Description

	Shooting lens number	Passing lens number	Dribbling lens number
Screening1	41	49	28
Screening2	45	52	33
Screening3	38	46	39
Screening4	47	50	36
Screening5	37	52	31
Screening6	48	45	40
Screening7	44	33	41
Screening8	53	58	30
Screening9	51	63	29
Screening10	46	58	37

Table 2. The Prediction Results of Traditional RBFNN

	Shooting	Passing	Dribbling
Screening1	83%	74%	89%
Screening2	79%	68%	82%
Screening3	81%	70%	85%
Screening4	77%	69%	82%
Screening5	82%	73%	87%
Screening6	85%	77%	91%
Screening7	80%	70%	83%
Screening8	81%	68%	84%
Screening9	82%	71%	85%
Screening10	84%	76%	90%
Average correct rate	81.4%	71.6%	85.8%

From Table 2 and Table 3, for both the traditional RBF neural network and GIRAN-based online neural network, the accuracy ratio of predicting shooting and dribbling are on average above 80%, with lower ratios of predicting passing the ball. That is because when we were estimating the throwing prediction accuracy, we considered predicting accurately ball passing, and also foreseeing accurately one team member to receive the ball. From the two Tables, we learnt that GIRAN-based neural network has higher prediction accuracy ratio than the traditional RBFNN for various behaviors. That's mainly because GIRAN learning algorithm's online updating function can make structural adjustment accordingly with the ongoing game. The method has stronger generalization ability. Besides, GIRAN learning algorithm incorporates hidden neuron's deletion strategy. Its network structure is simpler than the traditional RBFNN, with fewer hidden neurons and thus running time shortened to satisfy better the requirement of real-time.

However, wrong judgments were found in experimental results after analysis. That can be explained from the following aspects:

(1) In the game, the ball carrier's choice of behaviors is not only decided by some non-contingent factors and caused by some accidental factors (like physical power, any wound), and certain randomness;

(2) Being restricted to some tactical plays and not better teamwork. Due to such influences, misjudgments were made to some extent.

Table 3. The Prediction Results of Online RBFNN

	Shooting	Passing	Dribbling
Screening1	87%	79%	94%
Screening2	84%	75%	87%
Screening3	87%	76%	91%
Screening4	82%	74%	88%
Screening5	88%	79%	94%
Screening6	90%	84%	96%
Screening7	86%	78%	91%
Screening8	87%	75%	89%
Screening9	88%	75%	92%
Screening10	71%	82%	94%
Average correct rate	85%	77.7%	91.6%

5. Conclusion

This paper presents a method to predict the basketball video player behavior type. First, the player with the ball tracking vision determined results, Based on the amount of players information artificial potential field for the player with the ball in the view of the players on the field at the modeling, to form a feature vector describing the competition scene. In order to make the artificial potential field on the position of the player's model is more accurate. The Homo-graphy matrix by extracting four pitch mark line of the intersection of the image coordinates and the world coordinates of the court to complete mapping image coordinates to the coordinates of the golf players. To reduce the influence of the camera perspective projection transformation. Finally, the ball players' online of RBF neural network predicted behavior based on the GIRAN learning algorithm. Because the neural network has better generalization ability, it can adjust the network parameters with the corresponding game development, experiment results show that the prediction accuracy is better than the traditional RBF neural network.

Acknowledgment

This work was supported by The Fundamental Research Funds for the Central Universities. No. HEUCF151601.

References

[1] D. Duque, H. Santos and P. Cortez, “Nary trees classifier”, Proceedings of the 3rdInternational Conference on Informatics in Control, Automation and Robotics, Setubal, Portugal: INSTICC, **(2006)**, pp. 457-460.

[2] D. Duque, H. Santos and P. Cortez, “Prediction of abnormal behaviors for intelligent video surveillance systems”, Proceedings of the 2007 IEEE Symposium on Computational Intelligence and Data Mining, Honolulu, Hawaii, USA: IEEE, **(2007)**, pp. 362-367.

[3] W. Qian and X. Limin, “Tan is the player with the ball, The predicted behavior of basketball video game”, Chinese Journal of image and graphics, vol. 04, **(2012)**, pp. 560-567.

[4] L. Jianwu and J. Yuming, “Application of improved ant colony algorithm for ball controlling player behavior in the virtual human football decision”, Microelectronics & computer, vol. 07, **(2009)**, pp. 176-179.

[5] D. Liang and J. Yuming, “Study on the decision algorithm of offensive players' behavior football game”, Computer engineering and design, vol. 15, **(2009)**, pp. 3641-3644.

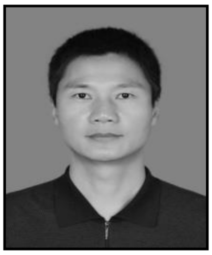
[6] W. Junjie, “Research on technology, characteristics of basketball tactics the pick and roll”, Wuhan Sports Institute, **(2012)**.

[7] W. Gang, C. Mubin, L. Fuhong and Z. Shumei, “Study on the strategy of pass Robocup simulation game”, Computer engineering and science, vol. 10, **(2007)**, pp. 101-104.

[8] Z. Hui, “Analysis and research of modern basketball aggressive defense tactics characteristics”, Hebei Normal University, **(2007)**.

[9] O. Khatib, “Real-time obstacle avoidance for manipulators and mobile robots”, The International Journal of Robotics Research, vol. 5, no. 1, **(1986)**, pp. 90- 98.

Author



ShengBo Liao, he received his B.S degree from Beijing Sport University, and received his M.S degree from Beijing Sport University. He is an associate professor in Beijing Jiaotong University. His research interests include Physical education and training.