Prediction of Ball Placement Using Computer Simulation for Wheelchair Players in Table Tennis Singles

Ching-Hua Chiu¹, Chung-Shun Hung²*, Yi-Hung Ho², Tzai-Li Li³

¹Graduate Institute of Sports & Health Management, National Chung Hsing University, Taichung, Taiwan, 402, ROC
²Department of Bio-Industrial Mechatronics, National Chung Hsing University, Taichung, Taiwan, 402, ROC
³Department of Sports and Leisure Studies, National Dong Hwa University, Taiwan, 905, ROC

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Abstract

Because wheelchair table tennis players are physically limited by their handicap, they have to be trained efficiently for acquiring excellent skills and remarkable performance. Two integral skills they must possess are the control of ball placement and tactics of competition. To help such players, this study aimed to design a system which would be capable of predicting ball placement in table tennis singles. To this end, we have adopted the back-propagation neural network (BPNN), whose structure consisted of an input layer (48 input neurons), a hidden layer (30 hidden neurons), and an output layer (12 output neurons). The ball placement parameters were firstly converted into training samples of BPNN and then the learning algorithm of the BPNN was subsequently applied to the training samples. Finally, a recalling algorithm was used for predicting ball placement. The results showed that the mean square error of the learning algorithm of the BPNN was below the convergence standard of 0.25. In addition, the relative error between the predicted ball placement and the actual ball placement was smaller than 0.15%. The above two results demonstrated that the prediction module of this study would be able to precisely predict ball placement and may aid table tennis players to organise realistic table tennis tactics. Furthermore, this designed system could be developed into computer software, with which a player may analyse the typical ball placement patterns of a rival and thereby gain a distinct competitive edge.

Keywords: Neural network, Algorithm, Training sample

Introduction

In recent years Taiwanese teams of wheelchair table tennis have competed in many international contests with enthusiastic sponsorship from both government and civil departments. International Table Tennis Federation (ITTF) categorizes handicapped table tennis competitions into 10 classes according to players’ physical capacities. Classes 1 to 5 are for wheelchair players and classes 6 to 10 are for standing players. In the wheelchair classes, the coordination levels and the functions of player’s upper limbs are the criteria by which players are categorized. For winning a game, wheelchair players have to acquire two key skills which would be the command of controlling ball placements and the adequate employment of various tactics. However, only few studies have been conducted to inspect the ball placement in wheelchair table tennis up to now.

Similar to the bio-computation and information processing technique in biological neural network, the artificial neural network (ANN) is a system integrating a large number of connected artificial neurons [1]. The computing principles of ANN have been successfully applied in many fields such as the analysis of the clinic biomechanics [2] and the gait patterns to distinguish the different length of legs [3]. Additionally, the BPNN was adopted to carry out biomedical signal analysis [4-6].

Furthermore, ANN has also been applied in sports. For example, by means of ANN, researchers analysed and predicted the results of soccer games [7]. Chiu adopted the ANN algorithm to design a computing system to establish the offense and defence models and to predict the path of the shuttlecock in badminton singles [8]. ANN was also satisfactorily applied to identify and analyse the weight shift of legs during a golf swing [9]. In the study of Hambli et al. [10], ANN was combined with the finite element method in a virtual tennis environment. It was found that ANN could swiftly predict the reactions and feedback forces of tennis racquets. Wong [11-12] developed an artificial intelligence system which integrated image-processing techniques with identification capability of ANN to assist umpires to make a judgment in tennis competitions.

In table tennis competitions, quick reaction and adequate ability to control ball placements are two of the most important requirements for victory. With this designed computer simulation which may correctly predict the ball placement, a player may get familiar to an opponent’s ball path and habitual behaviour before the game, react more quickly during the
competition, and thus obtain substantial advantages to win. In view of the above-mentioned speculations, this study attempted to develop a prediction module of ball placements using the BPNN algorithm to obtain competitive advantages for wheelchair table tennis players in singles.

Materials and Methods

To establish the feasibility of predicting ball placements using the back-propagation neural network (BPNN), a number of different procedures were performed in the experiment.

BPNN

The BPNN consisted of three layers --- an input layer, a hidden layer, and an output layer (Fig. 1). The input layer contained 48 neurons \( x_j, j = 1,2,\ldots,48 \), the hidden layer comprised 30 neurons \( q_q, q = 1,2,\ldots,30 \), and the output layer comprised 12 neurons \( y_r, r = 1,2,\ldots,12 \). When using the learning algorithm of BPNN, the input value \( x_j \) and the target output \( y_r \) were needed to serve as training samples. To ensure that the learning algorithm of BPNN was effective, the mean square error function \( E \) was calculated to detect the convergence of the BPNN.

\[
E = \frac{1}{2} \left( \sum (d_r - y_r) \right)^2
\]

Input layers  
Hidden layers  
Output layers  

\[\begin{align*}
&x_1 \quad x_2 \quad x_3 \quad \ldots \quad x_{48} \\
&\quad q \quad q \quad q \quad \ldots \quad q \\
&y_1 \quad y_2 \quad y_3 \quad \ldots \quad y_{12}
\end{align*}\]

Figure 1. The Structure of BPNN

Training samples

The surface of the table was divided by a middle line into two sides (Fig. 2a). Each side was further divided into twelve squares of the same size. Each square was designated by the symbols \( Q_i \) and \( P_i \) (i = 1, …,12). The player on the left side was designated as Q, and the player on the right side as P. The scoring of player Q was elaborated here as an example. Player Q and player P competed in a single game (Fig. 2a): Player P hit the ball landed at position \( P_3 \) back to player Q landed at position \( Q_7 \), player Q returned it to player P at position \( P_5 \), player P again returned it to player Q at position \( Q_6 \), player Q returned it to position \( P_8 \), player P finally failed to return the ball back, and player Q won the point.

Ball placements \( P_3, Q_7, P_5, \) and \( Q_6 \) acted as parameters for the input vectors and ball placement \( P_8 \) acted as the parameter for the target output vectors. Therefore, the input vector of the BPNN could be assumed to be \( x_p = (P_1,\ldots,P_{12}, Q_1,\ldots,Q_{12}, P_1,\ldots,P_{12}, Q_1,\ldots,Q_{12}) \). If ball placements \( P_3, Q_7, P_8, \) and \( Q_6 \) were denoted by the number 1 and non ball-placements were denoted by the number 0, then the input vector could be written as \( x_p = (0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0) \). If ball placement \( P_8 \) was denoted by the number 1 and non ball-placements were denoted by the number 0, then the target output vector could be written as \( d_r = (0,0,0,0,0,0,0,1,0,0,0,0,0) \). The above model could be also applied to the situation in which player P won the point. The training samples could be obtained from the ball placements (Fig. 2b). In other words, the training samples were retrieved from the last five ball placements that determined whether player P or player Q won the point. These training samples were converted into the input vectors and target output vectors of the BPNN.

Subjects

Five female wheelchair table tennis players who represented Taiwan in the Paralympics Games were recruited as subjects in this study. These subjects were right-handed (mean age 37.2 ± 4.3 years; mean height 154.6 ± 3.0 cm; mean mass 49.2 ± 4.7 kg) and competed in the class 3 category. Players in this class have minimal limitation in the control of their upper limbs, but suffered from paraplegia that gives them no true trunk balance or rotation as well as severe paralysis of the lower limbs. They remain fixed against the back of the wheelchair unless they pull themselves forward with their non-racket arm. Each of the subjects has competed in the wheelchair table tennis tournaments for over five years.
Experimental setting and tools
A high-speed video camera (PULNIX6740GE) was used in the experiment. It recorded ball placements at a speed of 60 frames per second (Fig. 3). The camera recorded images at an angle of 15°, the lens was at a height of 2.9 m, and the horizontal distance between the lens and the center of the table was 10 m [14].

Data collection procedure
After a 15-min warm-up, one subject from class 3 competed against each of the other four subjects individually with a 10-min intermission in between (Fig. 2 & Fig. 4). The competition lasted for three days with twelve games each day. Therefore, there were a total of 36 games played. Data were collected only on the points from the hitting of five or more shots. Two hundreds and thirty six effective training samples were collected, of which 131 came from player Q’s scoring and 133 came from player P’s scoring.

Data analysis
To analyse the experimental data obtained in this study, the researchers firstly edited the learning algorithm and the recalling algorithm of the BPNN in computer programming language C++. The learning algorithm was applied to the collected training samples keyed into the computer programme. Next, the mean square error function $E$ was calculated in order to determine whether the learning algorithm of the BPNN converged. Finally, the recalling algorithm was adopted to explore whether the predicted ball placements corresponded to the actual ball placements. In this way, the feasibility of the prediction module designed in this study was confirmed.

Results and Discussion

Learning algorithm
Table 1. The predicted placements and the relative error for four scoring players

<table>
<thead>
<tr>
<th>BPNN output pairs</th>
<th>RE (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>A</td>
<td>0</td>
</tr>
<tr>
<td>B</td>
<td>0</td>
</tr>
<tr>
<td>C</td>
<td>0</td>
</tr>
<tr>
<td>D</td>
<td>.000</td>
</tr>
</tbody>
</table>

Relative Error (RE) = 100% ∗ [1-(BPNN output value)]/1

Table 2. The predicted placements and the relative error for four players losing a point

<table>
<thead>
<tr>
<th>BPNN output pairs</th>
<th>RE (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>a</td>
<td>.999</td>
</tr>
<tr>
<td>b</td>
<td>.037</td>
</tr>
<tr>
<td>c</td>
<td>0</td>
</tr>
<tr>
<td>d</td>
<td>0</td>
</tr>
</tbody>
</table>

Relative Error (RE) = 100% ∗ [1-(BPNN output value)]/1

Table 3. Distribution of the last ball placements for getting and losing a point

<table>
<thead>
<tr>
<th>Scoring (ball placement)</th>
<th>Distribution (%)</th>
<th>Losing a point (ball placement)</th>
<th>Distribution (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>P_1</td>
<td>2.29</td>
<td>Q_6</td>
<td>20.30</td>
</tr>
<tr>
<td>P_2</td>
<td>9.92</td>
<td>Q_7</td>
<td>11.27</td>
</tr>
<tr>
<td>P_3</td>
<td>21.40</td>
<td>Q_8</td>
<td>7.52</td>
</tr>
<tr>
<td>P_4</td>
<td>9.92</td>
<td>Q_9</td>
<td>9.02</td>
</tr>
<tr>
<td>P_5</td>
<td>6.87</td>
<td>Q_{10}</td>
<td>8.27</td>
</tr>
<tr>
<td>P_6</td>
<td>8.39</td>
<td>Q_{11}</td>
<td>13.53</td>
</tr>
<tr>
<td>P_7</td>
<td>13.74</td>
<td>Q_{12}</td>
<td>13.53</td>
</tr>
<tr>
<td>P_8</td>
<td>11.45</td>
<td>Q_{13}</td>
<td>11.28</td>
</tr>
<tr>
<td>P_9</td>
<td>3.82</td>
<td>Q_{14}</td>
<td>0.75</td>
</tr>
<tr>
<td>P_{10}</td>
<td>0.76</td>
<td>Q_{15}</td>
<td>2.26</td>
</tr>
<tr>
<td>P_{11}</td>
<td>6.10</td>
<td>Q_{16}</td>
<td>2.26</td>
</tr>
<tr>
<td>P_{12}</td>
<td>5.34</td>
<td>Q_{17}</td>
<td>0.01</td>
</tr>
</tbody>
</table>

The learning rate was a control parameter for adjusting the weighted values of the BPNN since it would be disadvantageous for the convergence of the BPNN if the learning rate was too large or too small. For example, when the learning rate is larger, the variation in weighted values of the BPNN would become larger, too, which would induce value oscillation and result in divergence.

Previous study showed that the learning rate could be modified by experimentation [8]. After conducting numerous tests on calculations with a computer program, the researchers of this study found that the learning algorithm was effective at the rate of 0.5. After running BPNN for 1,200 learning cycles, it was found that the mean square error $E$ between the predicted last ball placement and the actual last ball placement was 0.102 and 0.163 for player Q and P respectively, both of which were below the effectively convergent standard of 0.25 [8].

Prediction of ball placement

After the completion of learning and training of the BPNN, a comparison was made between the predicted ball placement and the actual ball placement through the values of relative error as an accuracy indicator of prediction (Chiu, 2003). Four examples for the last ball placement of winning a point were presented (Table 1, Fig. 5), and four examples for the last ball placement of losing a point were also elaborated (Table 2, Fig. 6).
The winning points’ routes of ball placement were detailed in Table 1 and Figure 5. It demonstrated that the relative error between the inferred input and the actual target output of the last ball placement was less than 0.15%, which indicated that the predicted placement of the fifth ball was almost the same as the actual ball placement. On the other hand, the losing points’ routes of ball placement were presented in Table 2 and Fig. 6. The relative error between inferred input and the actual target output of the last ball placement was also less than 0.15%. It has been proved that a smaller relative error contributes to better convergence of the network [15], and the better prediction of BPNN. Therefore, both the feasibility and utility of the BPNN prediction module were proved, paving the way for its application in training players in tactics and ball placement.

Distribution of last ball placements

The statistics on last ball placements in this study could be analysed to interpret players’ ball path and habitual behaviour via both winning and losing points’ ball placement (Table 3 and Fig. 7), which may further provide information to enhance efficiency of training. According to the statistics of the last ball placement in winning points of player Q, the distribution of both P1 and P7 accounted for 35.14% in player Q’s total shots (Table 3). Since the balls bouncing from P1 and P7 were near player P right-side body, it showed that player P was not good at forehand strokes near the body, whereas player Q was clever at placing the ball on P1 and P7 for winning. Contrariwise, based on the data on the last ball placement in losing points of player Q, the distribution of P1 accounted for 20.30% of player P’s total shots. The result indicated that player Q was not good at backhand strokes. From the above analysis, players may be aware of their strong points in offense as well as weaknesses in defence, by which they may improve their skills precisely.

In general, ball placements for both winning and losing points should be considered before running calculation and analysis through BPNN. The data on ball placement served as training samples for BPNN. With the learning algorithm, the weighted and biased values of BPNN were obtained. Subsequently the first four ball placements served as the input for running computer simulation and predicting the last ball placement, which was then compared with the actual ball placement (Fig. 5 & Fig. 6). The results of the present study showed that the relative error between the predicted placement and the actual placement was very small (Table 1 & Table 2). This finding confirmed that the BPNN offered excellent predicting capability, and can be effectively used to analyse the tactics and strategies in table tennis players [4]. In addition, the data on the distribution of the last ball placements (Table 3, Fig. 7) could be further incorporated with the BPNN prediction module to offer players information of predicted ball placements, which would be of great benefit to table tennis players in training and competitions.

Conclusion

This study aimed to develop a prediction module for ball placement in table tennis to assist wheelchair table tennis players. The actual ball placements in wheelchair table tennis singles games were converted into training samples for BPNN calculations. Through applying the learning algorithm of the BPNN, it was found that each mean square error reached the convergence standard correspondingly. The recalling algorithm was then adopted to calculate the relative error. It was found that each relative error between the target output, namely, the predicted ball placement, and the input value, which consisted of the actual ball placement, was less than 0.15%. This result confirms that the BPNN prediction module accurately predicts both ball placement and ball path. In the future, this model can be incorporated into a real-time system or combined with video science and technology to become a complete prediction and simulation system for table tennis. Consequently, the system will develop to become even more practical and versatile.

References


AUTHORS BIOGRAPHY

**Ching-Hua Chiu**

**Employment**
Prof., Graduate Institute of Sports and Health Management, National Chung Hsing University, Taiwan.

**Degree**
PhD

**Research interests**
Biomechanics and optimal control

**E-mail:** Chunggoodman@yahoo.com.tw

**Chung-Shun Hung**

**Employment**
Bio-industrial Mechatronics Engineering, National Chung Hsing University, Taiwan

**Degree**
PhD student

**Research interests**
Sports biomechanics, computer modeling

**E-mail:** hangcaso@gmail.com

**Yi-Hung Ho**

**Employment**
Bio-industrial Mechatronics Engineering, National Chung Hsing University, Taiwan

**Degree**
MSC student

**Research interests**
Sports biomechanics, computer modeling

**E-mail:** sasimihanhan@hotmail.com

**Tzai-Li Li**

**Employment**
Associate professor and director of PE Center, National Dong Hwa University, Taiwan

**Degree**
PhD

**Research interests**
Exercise Immunology

**E-mail:** leej@mail.ndhu.edu.tw