Hindawi
Security and Communication Networks
Volume 2023, Article ID 9878632, 1 page
https://doi.org/10.1155/2023/9878632

Retraction

Retracted: Optimization of Artificial Intelligence Model for Badminton Teaching and Training with Wireless Network Support

Security and Communication Networks

Received 8 August 2023; Accepted 8 August 2023; Published 9 August 2023

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] S. Zhang, W. Zhang, and J. Liu, "Optimization of Artificial Intelligence Model for Badminton Teaching and Training with Wireless Network Support," *Security and Communication Networks*, vol. 2022, Article ID 8925907, 6 pages, 2022.

Hindawi
Security and Communication Networks
Volume 2022, Article ID 8925907, 6 pages
https://doi.org/10.1155/2022/8925907

Research Article

Optimization of Artificial Intelligence Model for Badminton Teaching and Training with Wireless Network Support

Sheng Zhang ,[1] Wen Zhang,[2] and Junmao Liu[3]

[1]*School of Sports, Central South University of Forestry and Technology, Changsha 410000, Hunan, China*
[2]*School of Sports, Hunan University of Finance and Economics, Changsha 410000, Hunan, China*
[3]*Translator, Hunan Deutz Power Ltd, Co., Changsha 410000, Hunan, China*

Correspondence should be addressed to Sheng Zhang; t20142228@csuft.edu.cn

Received 22 March 2022; Revised 23 April 2022; Accepted 28 April 2022; Published 6 June 2022

Academic Editor: Muhammad Arif

With the rapid development of the Internet of Things and artificial intelligence, the society gradually moves into the era of intelligence, and the research results and intelligent products based on wireless networks come into being. Machine learning algorithms are used to classify and recognize badminton strokes in this research, and a badminton technical feature statistics and pace training system are built on this foundation. By exploring the model characteristics and algorithm training method of the Hidden Markov Model (HMM), this paper proposes a model algorithm with an improved HMM training method for recognizing ten common badminton strokes, including serve, forehand rub, backhand rub, and forehand lunge. Serve, forehand rub, backhand rub, forehand flutter, forehand push, backhand push, forehand pick, backhand pick, and forehand loft are among the 10 typical badminton strokes identified by the algorithm. Our technique can distinguish ten common ball-striking movements in real-time, according to the testing.

1. Introduction

In the 21st century, machine learning has been applied in various fields, such as the powerful real-time speech recognition technology of KDDI, the top go level of Alpha Go of Google, and the intelligent news recommendation system of today's headlines, which are all products of the rapid development of machine learning [1, 2].

At present, the application of artificial intelligence in badminton, both in depth and breadth, is very limited. Badminton training is still mostly one-on-one or one-to-many manual instruction, and the player's own level of improvement relies heavily on the professional level of the coach and the player's technical level of strengths and weaknesses without a more detailed quantitative analysis of the standard, so for the player. Therefore, there is a lack of targeted training for players to develop their individual strengths and compensate for their weaknesses [3–5]. Reference [6] uses K-nearest neighbor and decision tree algorithms to recognize Ping-Pong batting actions; references [7, 8] identify four common sports, including badminton, Ping-Pong, volleyball, and soccer, by analyzing the inertial signals collected by the sensors; references [9, 10] classify and recognize several common batting actions by four inertial sensors worn on the two wrists, waist, and right ankle of the athletes.

The arrangements of the paper are as follows: Section 2 describes the related work. Section 3 introduces the various badminton mathematical models. Section 4 analyzes the different HMM algorithm. Section 5 discusses the different testing effective procedures. Section 6 concludes the article.

2. Related Work

Here, the human daily behavioral action recognition is discussed. They distinguish daily behavioral activities. They define sports action recognition and training.

2.1. Human Daily Behavioral Action Recognition. Action recognition of human behavior mainly uses inertial sensors such as gyroscope and accelerometer to perform algorithm classification and pattern recognition of daily behavioral actions such as standing, walking, running, and lying down [11–13]. Reference [14] distinguishes daily behavioral activities such as walking upstairs and downstairs, running, sitting, and standing by obtaining data information from five inertial sensors worn at different locations on the body. Reference [15] classifies and recognizes five types of human actions such as walking, sitting, lying down, running, and standing using deep convolutional neural networks, and achieves a recognition rate of 0. 9126 on the actitraker open-source database. References [16, 17] recognize daily complex behaviors of the human body by arranging various smart sensors indoors, and the improved algorithm has a high recognition rate [18]. The accuracy of reference [19] was investigated through several experiments.

2.2. Sports Action Recognition and Training. For human daily sports, such as badminton, table tennis, tennis, soccer, and other activities with high complexity, the wearable acceleration sensors are mainly used to collect data and action classification. Reference [20] designs a set of human wearable sensor system that can be used to measure players' breathing, ECG, and EMG signals, etc. In real-time, during badminton matches, identify the four movements of players such as running, walking, sitting, and standing on the court, and monitor and analyze the real-time status of players during matches and training: in reference [21], by obtaining data from the built-in inertial sensors on the game pad to identify several user's hitting stance, such as serve and forehand and backhand swing shots. Reference [22] uses the sensors on the user's arm to identify the important motions in the tennis game and uses the synchronized timestamps between the sensors and the captured match videos to label and index the key events and exciting moments in the tennis game; References [10, 23] explore the dependence of ball speed on the two parameters of acceleration and stroke sound during the snap by acquiring the acceleration and sound sensor data on the badminton racket, and through these dependencies to predict the ball speed, so as to achieve the effect of assisting training instruction. Reference [24] used the optimized apriori association rule algorithm to mine the sample data in multiple dimensions and realized the personalized training for specific players.

3. Paper Badminton Mathematical Model

We start from the analysis of the badminton trajectory model and the player catching process. Firstly, we analyze the factors affecting badminton motion through the badminton motion model, and through these factors, we initially determine the required degrees of freedom for the badminton robot hitting mechanism. Then we analyze the badminton player's catching action and flow, determine the overall structural division of the badminton robot, and the required functions through the analysis of the badminton player's catching action, and finally design the corresponding control scheme according to the functions.

3.1. Stroke Motion Model. Flat shot, flat high ball, and flat long ball are the most popular badminton shots, and they differ in terms of hitting force, hitting angle, and height. A specific striking strategy can be achieved by controlling different hitting forces and angles. Because badminton air kinematics is more complicated and there are more factors affecting the motion, creating a seamless motion model is difficult, hence this research assumes that the badminton motion state is optimal. Treating badminton as a mass point, the badminton stroke type is determined by four parameters: stroke height H_O, stroke elevation angle β, stroke horizontal angle α, and stroke velocity V, without considering its mass and external influencing factors.

The equations of motion of the simplified model of badminton aerodynamics can be found as

$$\begin{cases} y(t) = \dfrac{m}{C_x}\left(V_e + V_i\right)\left(1 - e^{-C_y/mt}\right) - V_e t + H_0, \\ \\ x(t) = \dfrac{V_i V_e}{C_x}\left(1 - e^{-C_x/mt}\right), \end{cases} \tag{1}$$

where V_i and V_e are the badminton exit velocity and final drop velocity, C_x and C_y are the air drag coefficient and lift coefficient, respectively, and m is the badminton mass.

The initial coordinates A_0, the coordinates A_1 of the highest point, and the coordinates A_2 of the landing point during the movement of badminton are found, respectively, and the variation factors of each coordinate point are studied.

Assuming $t = t_0 = 0$, the initial coordinates of the moment the badminton is struck are $A_0 = (0, H_0)$.

Assuming that the badminton of type $t = t_1$ reaches the highest point of the parabola, we have

$$y'(t) = \frac{C_y}{C_x}\left(V_e + V_i\right)e^{-C_y/mt} - V_e = 0. \tag{2}$$

It is obtained that

$$t_1 = \frac{m}{C_y}\ln\frac{Cy\left(V_e + V_i\right)}{C_x V_e}. \tag{3}$$

Assuming that the badminton's hit out instant time is Δt, this moment badminton movement can be approximated as a straight line, and then at this time, the elevation angle of the badminton can be expressed as

$$\beta = \arctan\frac{y(\Delta t) - H}{x(\Delta t)}. \tag{4}$$

Assuming that the badminton landing time point $t = t_2$, the landing coordinates are $A_1 = \left(x(t_2)\sin\alpha, x(t_2)\cos\alpha\right)$.

To sum up, the trajectory of badminton is related to four parameters: the speed of the ball, the horizontal angle of the ball, the elevation angle of the ball, and the height of the ball. By controlling these four parameters of badminton, the trajectory of badminton can be predicted.

4. HMM Algorithm

This section discusses the HMM principle and defines the improved HMM-based badminton action recognition. The stroke actions can be modeled.

4.1. HMM Principle. Assume that $\lambda = (A, B, \pi)$ are learned by the above conditions. Considering the observation sequence data as observation data 0 and the state sequence data as unobservable hidden data I, then we have the following equation:

$$P(O|\lambda) = \sum_{I} P(O|I, \lambda) P(I|\lambda). \tag{5}$$

Its parameter learning can be implemented by the EM algorithm.

Step E of the EM algorithm: find the Q function $Q(\lambda, \lambda)$,

$$Q(\lambda, \bar{\lambda}) = \sum_{I}^{\bar{\sum}} \log. \tag{6}$$

where $\bar{\lambda}$ is the current estimate of the model parameters and λ is the maximized model parameters. The function $Q(\lambda, \lambda)$ can then be rewritten as

$$Q(\lambda, \bar{\lambda}) = \sum_{I}^{\sum_{i_1}^{-} \sum_{I}^{\sum^{-}} \sum_{I}^{\sum} \left(\sum_{t=1}^{T} \sum_{i_1 (O_t)} \log() \right) \left(\sum_{t=1}^{T-1} \sum_{i_t i t+1} \log() \right)} \log. \tag{7}$$

To find the parameter π_i, the first term of equation (7) can be written as the following equation:

$$\sum_{I}^{\sum_{i_o}^{-} \sum_{i=1}^{N} \sum_{i} \left(o, i_1 = i | \bar{\lambda}\right) \log} \log. \tag{8}$$

Noting that π_i satisfies the constraint $\sum_{i=1}^{N} \pi_i = 1$, using the Lagrange multiplier method, write the Lagrangian function as follows:

$$\sum_{I}^{\sum_{i=1}^{N} \sum_{i} \sum_{i=1}^{N} \sum_{i} \left(o, i_1 = i | \bar{\lambda}\right) \left(\sum_{i=1}^{N} \pi_i - 1\right)} \log. \tag{9}$$

By taking the partial derivative and making the result 0, we obtain

$$\frac{\partial}{\partial \pi_i} \left[\sum_{i=1}^{N \sum_{i} \left(o, i_1 = i | \bar{\lambda}\right) \left(\sum_{i=1}^{N} \pi_i - 1\right)} \log \right]. \tag{10}$$

Thus, we find π_i

$$\pi_i = \frac{P\left(O, i_1 = i | \bar{\lambda}\right)}{P(O|\bar{\lambda})}. \tag{11}$$

To find the parameter A, the second term of equation (3.16) can be written as

$$\sum_{I}^{\bar{\sum} \sum_{i=1}^{N} \sum_{ij} \left(o, i_t = i, i_{t+1} = j | \bar{\lambda}\right) \sum_{j=1}^{N} \sum \sum_{t=1}^{T-1} \sum_{\log}} \sum_{t=1}^{T-1 \sum_{i i_{t+1}}} \log. \tag{12}$$

Similarly, using the Lagrange multiplier method with constraint $\sum_{j=1}^{N} a_{ij} = 1$, one can find

$$a_{ij} = \frac{\sum_{i=1}^{T-1} P\left(O, i_t = i, i_{t+1} = j | \bar{\lambda}\right)}{\sum_{t=1}^{T-1} O, i_t = i | \bar{\lambda}}. \tag{13}$$

To find the parameter B, the third term of equation (3.16) can be written as

$$\sum_{I}^{\bar{\sum} \sum_{j=1}^{N} \sum_{j} (o_t) \left(O, i_t = j | \bar{\lambda}\right) \sum_{t=1}^{T} \sum_{\log}} \left(\sum_{i=1}^{T \sum_{i=1}^{T} \sum_{i_t (o_t)}} \log \right). \tag{14}$$

The constraint is $\sum_{k=1}^{M} b_j(k) = 1$. Note that the partial derivative of $o_t = v_k$ with respect to $b_j(o_i)$ is not 0 only at $b_j(k)$, denoted by $I(o_t = v_k)$. Find the

$$b_j(k) = \frac{\sum_{t=1}^{T} P\left(O, i_t = j | \bar{\lambda}\right) I(o_t = v_k)}{\sum_{t=1}^{T} P\left(O, i_t = j | \bar{\lambda}\right)}. \tag{15}$$

4.2. Improved HMM-Based Badminton Action Recognition. Due to the temporal nature of badminton actions, the stroke actions can be modeled by a probabilistic model about temporal sequence.

The algorithm of equations (13)–(15) is modified by setting the sequence of M observations as $O^{(m)}$, $m = 1, 2, \ldots, M$, p_m.

$$\begin{aligned}
\overline{\pi_i} &= \sum_{m=1}^{M} \frac{\alpha_1^{(m)}(i) \beta_1^{(m)}(i)}{P\left(O^{(m)} | \lambda\right)}, \\
\overline{a_{ij}} &= \frac{\sum_{m=1}^{M} P_m \sum_{i=1}^{T_m - 1} \alpha_t^{(m)}(i) a_{ij} b_j\left(\mathbf{O}_{t+1}^{(m)}\right) \beta_{t+1}^{(m)}(j)}{\sum_{m=1}^{M} P_m \sum_{i=1}^{T_m} \alpha_t^{(m)}(i) \beta_t^{(m)}(j)}, \\
\overline{b_j(k)} &= \frac{\sum_{m=1}^{M} P_m \sum_{t=1}^{T_m - 1} \alpha_t^{(m)}(i) \beta_1^{(m)}(j) I(o_t, v_k)}{\sum_{m=1}^{M} P_m \sum_{t=1}^{T_m} \alpha_t^{(m)}(i) \beta_t^{(m)}(j)}.
\end{aligned} \tag{16}$$

5. Testing Effectiveness

The HMM's beginning probability, transfer probability, and observation probability all include crucial information for determining the model's size, including the observation set size and the number of states, and the input of the model, i.e., the length of the observation sequence, is also a decisive factor for the accuracy of the model recognition. In this paper, by dynamically adjusting three important parameters of observation set size, the number of states, and observation sequence length, we build and train HMM, and perform recognition, and get the average recognition rate under the corresponding parameter models.

As shown in Figure 1, the 3-dimensional variation plot of the corresponding recognition rate is obtained by adjusting the observation sequence length and the number of states for the case of an observation set size of 32. By comparing and adjusting the three important parameters of the HMM, the highest recognition rate of 94% is finally obtained with the number of states of 9, the length of observation sequence of 10, and the size of observation set of 32.

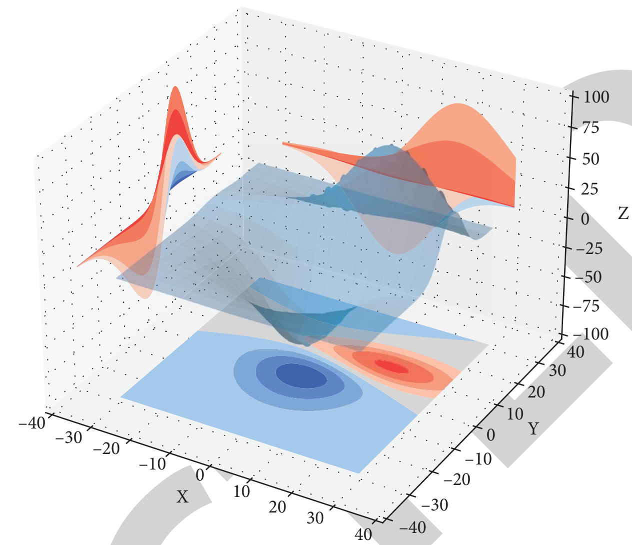

Figure 1: Recognition rate of different HMM parameters.

5.1. Recognition Effect. For the data segmentation technique of hitting action extraction in data preprocessing algorithm, three different segmentation methods are compared, and the preprocessing algorithm with higher recognition rate is selected.

Method 1: sliding window segmentation based on hitting moments. For each hitting point, the peak of the hitting moment is detected, and fifty sample points before and after the hitting moments are used as the hitting action features.

Method 2: sliding window segmentation based on extreme values. A sliding window with a window width of 100 is used to detect and reset the extreme values, and each extreme value is generated corresponding to the extraction of one hitting action [25].

Method 3: window segmentation depending on events. The starting and finishing instant points for window segmentation are determined by sensing two occurrences of the player starting and hitting.

5.1.1. Experimental Method. The single variable principle is used, i.e., the above three different hitting action extraction algorithms are used, other data processing, training, and recognition are kept the same. The same sample data are used for the HMM model training and the same test data are used for the recognition of ten hitting actions.

5.1.2. Experimental Results. As shown in Figure 2, the three different bar colors represent the three different hitting action extraction methods, the horizontal axis represents the ten different hitting actions, and the vertical axis represents the recognition rate of each hitting action. It can be seen that method 1 has a slightly higher recognition rate of the batting motion.

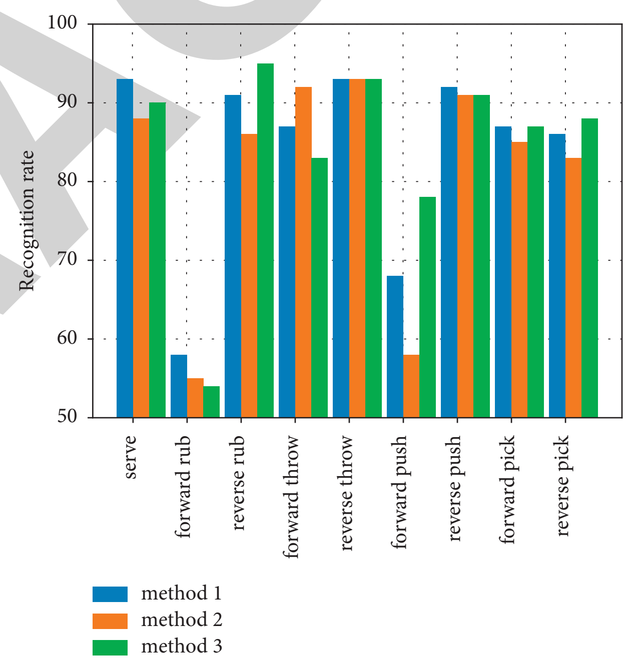

Figure 2: HMM action recognition rate of different preprocessing algorithms.

5.1.3. Experimental Conclusion. Method I has a higher recognition rate compared with Method II and Method III, so this paper uses Method I to extract the hitting action, i.e., the peak detection of the hitting moment for each hitting point and fifty sample points before and after the hitting moment as the hitting action features.

5.2. Experiment of Action Recognition Based on Different Model Algorithms. **Experimental purpose:** to compare different algorithms for training and recognition of models and select the model algorithm with the higher recognition rate as the method in this paper.

Method 1: training and recognition based on SVM. The algorithm model of the support vector machine is used for ten kinds of batting actions.

Method 2: training and recognition of traditional HMM. The model is trained by the traditional Baum-Welch algorithm.

For recognition, the posterior probability of each batting motion model is calculated and compared.

Method 3: improved HMM training and recognition. The improved Baum-Welch algorithm is used for model training, and the posterior probabilities of each hitting action model are calculated and compared for recognition.

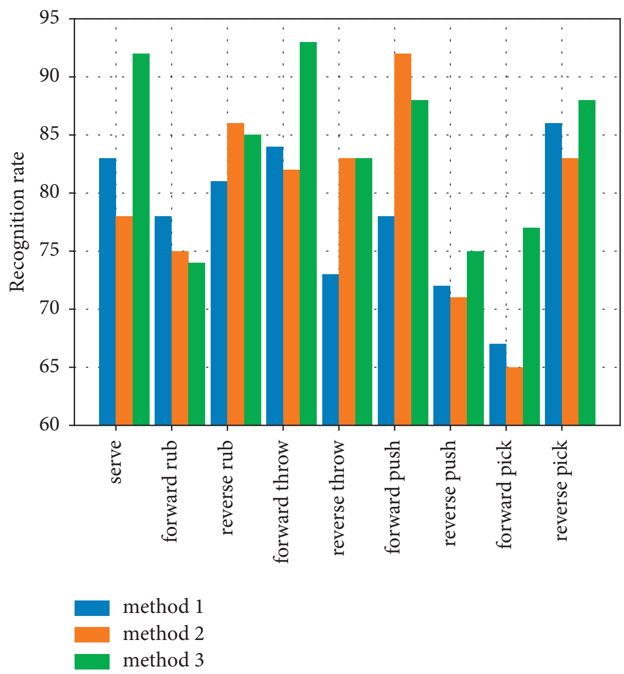

Figure 3: Action recognition rate of the different model algorithms.

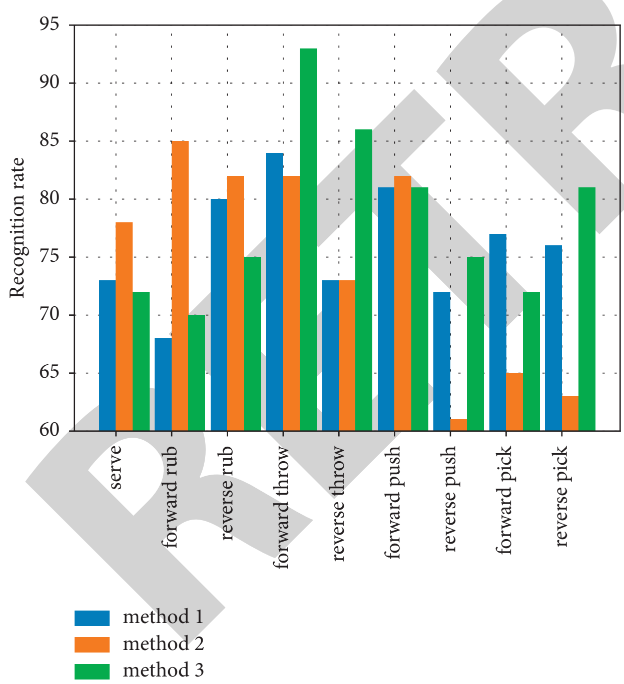

Figure 4: Recognition rate of the same and different athletes' movements.

5.2.1. Experimental Method. The single variable principle is used, i.e., the three different algorithmic models mentioned above are used for training and recognition of ten batting actions. The training data and sample data remain unchanged, and the other data processing methods remain unchanged.

5.2.2. Experimental Results. As shown in Figure 3, the three different bar colors represent the above three different algorithm models, the horizontal axis represents the ten different batting actions, and the vertical axis represents the recognition rate of each batting action. It can be seen that Method 3 has a slightly higher recognition rate of the batting motion.

5.2.3. Experimental Conclusion. Method 3 has higher recognition rate compared with Method 1 and Method 2, so this paper uses Method 3 for stroke action model building, training, and recognition to carry out, i.e., ten different badminton strokes are recognized by using improved HMM, and the average recognition rate based on the same player is up to 97.3%.

5.3. Experiment of Action Recognition Based on the Same and Different Athletes. **Experiment purpose:** to investigate the effect of the same and different athletes on the recognition rate of the system.

Method 1: same athlete, i.e., both training data and test data are from the same athlete.

Method 2: different athletes, i.e., both training data and test data are composed of a mixture of different types of athletes.

5.3.1. Experimental Method. Using the single variable principle, i.e., using the above two different sample data sources, the system recognition rate is tested using the badminton stroke recognition algorithm in this paper.

5.3.2. Experimental Results. As shown in Figure 4, the two different bar colors represent the above two different data sources, the horizontal axis represents ten dissimilar stroke actions, and the vertical axis represents the recognition rate of each stroke action.

6. Conclusion

This paper presents two Baum-Welch training algorithm improvement schemes for the HMM-based badminton action recognition algorithm, as well as experimental analysis of the recognition rate of the two improvement schemes; and the effect of HMM model parameters on the recognition rate of badminton action. To examine the system, this paper uses dynamic model parameter adjustment. To investigate the value of the model parameters that cause the system to have the highest recognition rate, an experimental strategy of dynamically altering the model parameters to examine the recognition rate of the system has been adopted. For the design and implementation of badminton technical characteristics statistics and pace training system, it is mentioned that the error analysis of the score and error judging algorithm and the pace reduction algorithm is carried out in the technical statistics function module, and the relative error of this function is actually measured and calculated.

Data Availability

The datasets used during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] Y. Wang, "Real-time collection method of athletes' abnormal training data based on machine learning," *Mobile Information Systems*, vol. 2021, Article ID 9938605, 11 pages, 2021.

[2] C. Cong and D. Fu, "An AI based research on optimization of university sports information service," *Journal of Intelligent and Fuzzy Systems*, vol. 40, no. 2, pp. 3313–3324, 2021.

[3] Z. Ghahramani, "Probabilistic machine learning and artificial intelligence," *Nature*, vol. 521, no. 7553, pp. 452–459, 2015.

[4] Z. M. Yaseen, A. El-Shafie, O. Jaafar, H. A. Afan, and K. N. Sayl, "Artificial intelligence based models for stream-flow forecasting: 2000-2015," *Journal of Hydrology*, vol. 530, pp. 829–844, 2015.

[5] V. Nourani, A. Hosseini Baghanam, J. Adamowski, and O. Kisi, "Applications of hybrid wavelet-Artificial Intelligence models in hydrology: a review," *Journal of Hydrology*, vol. 514, pp. 358–377, 2014.

[6] P. An, Z. Wang, and C. Zhang, "Ensemble unsupervised autoencoders and Gaussian mixture model for cyberattack detection," *Information Processing & Management*, vol. 59, no. 2, Article ID 102844, 2022.

[7] C. Chao, "Footwork teaching of college badminton elective course," in *Proceedings of the 3rd International Conference on Science and Social Research (ICSSR 2014*, pp. 281–283, atlantis press, Tianjin, China, June 2014.

[8] K.-C. Lin, C.-W. Wei, C.-L. Lai, I.-L. Cheng, and N.-S. Chen, "Development of a badminton teaching system with wearable technology for improving students' badminton doubles skills," *Educational Technology Research & Development*, vol. 69, no. 2, pp. 945–969, 2021.

[9] K.-P. Kuo, H.-H. Tsai, C.-Y. Lin, and W.-T. Wu, "Verification and evaluation of a visual reaction system for badminton training," *Sensors*, vol. 20, no. 23, p. 6808, 2020.

[10] T. Hülsdünker, H. K. Strüder, and A. Mierau, "Visual but not motor processes predict simple visuomotor reaction time of badminton players," *European Journal of Sport Science*, vol. 18, no. 2, pp. 190–200, 2018.

[11] M. G. Kibria, K. Nguyen, G. P. Villardi, O. Zhao, K. Ishizu, and F. Kojima, "Big data analytics, machine learning, and artificial intelligence in next-generation wireless networks," *IEEE Access*, vol. 6, pp. 32328–32338, 2018.

[12] X. Xiang, Q. Li, S. Khan, and O. I. Khalaf, "Urban water resource management for sustainable environment planning using artificial intelligence techniques," *Environmental Impact Assessment Review*, vol. 86, Article ID 106515, 2021.

[13] G. Hessler and K.-H. Baringhaus, "Artificial intelligence in drug design," *Molecules*, vol. 23, no. 10, p. 2520, 2018.

[14] Z. Wang and R. S. Srinivasan, "A review of artificial intelligence based building energy use prediction: contrasting the capabilities of single and ensemble prediction models," *Renewable and Sustainable Energy Reviews*, vol. 75, pp. 796–808, 2017.

[15] A. Klein, S. Falkner, S. Bartels, P. Hennig, and F. Hutter, "Fast bayesian optimization of machine learning hyperparameters on large datasets," in *Proceedings of the Artificial Intelligence and Statistics*, pp. 528–536, PMLR, Fort Lauderdale, FL, USA, April 2017.

[16] M. Feurer and F. Hutter, "Hyperparameter optimization," in *Automated Machine Learning*, pp. 3–33, Springer, Berlin, Germany, 2019.

[17] H. Zeng and Y. Xiao, "A study on badminton teaching and training methods in vocational colleges," *Journal of Human Movement Science*, vol. 2, no. 3, pp. 81–84, 2021.

[18] B. Xu, "The role of physical training in badminton teaching," in *Proceedings of the 2nd International Conference on Civil, Materials and Environmental Sciences*, pp. 285–287, Atlantis Press, London, UK, April 2015.

[19] J. Pei, K. Zhong, M. A. Jan, and J. Li, "Personalized federated learning framework for network traffic anomaly detection," *Computer Networks*, vol. 209, Article ID 108906, 2022.

[20] B. Huijgen, I. Faber, and M. Elferink-Gemser, "Assessing cognitive performance in badminton players: a reproducibility and validity study," *Journal of Human Kinetics*, vol. 55, no. 1, pp. 149–159, 2017.

[21] Q. Li and H. Ding, "Construction of the structural equation model of badminton players' variable direction ability and its enlightenment to sports training," *Annals of Palliative Medicine*, vol. 10, no. 4, pp. 4623–4631, 2021.

[22] S. Dube, S. Mungal, and M. Kulkarni, "Simple visual reaction time in badminton players: a comparative study," *National Journal of Physiology, Pharmacy and Pharmacology*, vol. 5, no. 1, pp. 18–20, 2015.

[23] M. Bhabhor, K. Vidja, G. Dubal, M. Padalia, and V. Joshi, "A comparative study of visual reaction time in badminton players and healthy controls," *Indian Journal of Applied-Basic Medical Sciences*, vol. 15, no. 20, pp. 76–82, 2013.

[24] S. Dane, F. Hazar, and Ü. Tan, "Correlations between eye-hand reaction time and power of various muscles in badminton players," *International Journal of Neuroscience*, vol. 118, no. 3, pp. 349–354, 2008.

[25] H. El-Gizawy and A. Akl, "Relationship between reaction time and deception type during smash in badminton," *Journal of Sports Research*, vol. 1, no. 3, pp. 49–56, 2014.