Hindawi
Security and Communication Networks
Volume 2023, Article ID 9845741, 1 page
https://doi.org/10.1155/2023/9845741

Retraction

Retracted: Action Recognition and Application of Table Tennis Training Based on IOT Perception

Security and Communication Networks

Received 26 December 2023; Accepted 26 December 2023; Published 29 December 2023

This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret 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 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] Z. Zhang, "Action Recognition and Application of Table Tennis Training Based on IOT Perception," *Security and Communication Networks*, vol. 2023, Article ID 8911564, 11 pages, 2022.

Hindawi
Security and Communication Networks
Volume 2022, Article ID 8911564, 11 pages
https://doi.org/10.1155/2022/8911564

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Research Article

Action Recognition and Application of Table Tennis Training Based on IOT Perception

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Received 8 July 2022; Revised 28 July 2022; Accepted 11 August 2022; Published 31 August 2022

Academic Editor: Hangjun Che

As the national sport of our country, table tennis focuses on continuous innovation and development. Table tennis is a high-quality sport characterized by fast movement and great flexibility. Unlike other human behaviors, identifying ping pong shots is idiosyncratic and difficult. Table tennis training is extremely important, and correct training can make athletes progress. In this paper, based on the perception of the Internet of Things, the action recognition and application of table tennis training actions are carried out, and the following conclusions are drawn: (1) the training movements of table tennis are relatively complex, which has a great challenge to the action recognition technology. The action recognition technology based on IoT perception can efficiently identify table tennis training actions. (2) Analyze and study the action recognition algorithm based on IoT perception, and propose a higher recognition accuracy and more stable algorithm DTW. (3) Comparing the accuracy, loss rate, and time impact between the algorithm in this paper and the traditional recognition algorithm, it is concluded that the algorithm proposed in this paper has higher accuracy and lower loss rate than the traditional algorithm. And with good stability, it is not affected by the environment and time. The algorithm in this paper is an algorithm with better performance and more worthy of use.

1. Introduction

In today's era of rapid network and rapid progress in computer technology, the Internet of Things has been further developed and gradually integrated into our lives, bringing great convenience to our lives. However, the computing power of today's computers is very weak and cannot provide faster computing power to the perception layer. The perception layer network applied to information perception has potential security threats. Biometrics can add absolute features that improve security. By analyzing its safety and looking for evidence to prove it, it is proved that the protocol has high reliability and practicability [1]. IoT is supported at the core of the network, with RFID, GPS, sensors, and laser scanners as part of signal detection and collection, network layer and taskbar, network layer, and receiver layer. The application of the Internet of Things can realize the connection between things and people and things and things, so the Internet of Things is also called the new trend of the information industry. What we need to do now is to combine practical experience, examine the environmental security system from the perspective of the Internet of Things, improve the key technologies of the Internet of Things reform system, and ensure the safe operation and healthy development of the Internet of Things [2]. A typical Internet of Things (IOT) connects all commodities with the Internet through sensing devices such as radio frequency identification (RFID) to realize intelligent identification and management of things in a specific area. The Internet of Things covers all aspects of daily life: wireless Internet access, Internet of Things video phones, and automatic gas detection are all applications of the Internet of Things. Despite the wide range of IoT applications, most people still know very little about the new technology behind it. So, this article attempts to provide readers with an opportunity to explore this mystery. By citing a large number of practical application examples of communication technologies in the Internet of Things, it fully reflects the key role played by the Internet of Things [3]. As the variety and number of devices increases, so does the amount of information on the Internet

(IoT). They do not just increase the amount of information on the web. But it also affects the transmission and processing speed on the Internet. However, the device discovery layer consolidates the data as soon as it is collected. This not only saves a large part of the area, but also shortens the processing time and realizes real-time performance. Based on this idea, this paper proposes a node discovery mapping algorithm to find connections between nodes. Exchange information, collaborate, and reduce network load between screen detection devices and improve real-time performance [4]. The Internet of Things provides us with the most intelligent calculation method, which can help us calculate what we want to know very easily and conveniently. And fully integrated into our lives, the indispensable devices in our lives such as mobile phones and computers are related to big data, but it is precisely because of this that our security is also threatened, and our personal information may be exposed out. Whether we inadvertently browse files under the line of sight of cameras or shoot confidential files with mobile phones by internal ghosts, our privacy will be invaded by big data and leaked out. Although optical-based recognition technology reduces this risk, it still cannot fundamentally solve the problem [5]. For a long time, in motor theory, it was believed that the success of any motor test with complex coordination depends first on technical and tactical training, and gradually increases (depending on age criteria) of functional task complexity. In this regard, there is still considerable potential in table tennis examinations: improving the quality of technical and tactical training, including on a large scale, perfecting the teaching control system, and turning it into a long-term reference point at all stages. Training; organize a motivational system to increase and maintain the group participating in this test to increase motivation for cognitive motor activity. This potential should be capitalized. For table tennis, improving the quality of technical and tactical training and increasing the number of participants can be ensured by: improving the content, coherence, and methodology of technical and tactical training; improving the teaching control system; and turning it into a long-term reference for all stages of training point [6]. Due to the world situation, sports and health issues are very important, we have noticed that the interest in table tennis is on the rise as a high-profile sport. Table tennis is one of the favorite sports of students. It helps develop the following skills: accuracy, speed and reflexes, explosiveness, rhythmic operational thinking, concentration, and coordination. Table tennis is recommended as the most promising sport with health benefits [7]. Before the start of the table tennis league, the athletes participating in the experiment were asked to randomly take a balance test, which was to study whether the balance of men and women was different and whether it would affect the SEBT. We tested 8 athletes in the experiment and recorded their consumption at intervals. As a result, the reach distance shows a decrease as the training progresses in all directions. Female table tennis players exhibit poorer dynamic postural control compared to male table tennis players [8]. A table tennis posture training apparatus and its use method guide and improve table tennis players' forehand, backhand, and other hitting actions by forcing the hand to hit the ball on the correct trajectory. The equipment includes a waist belt and chest strap, or a wide waist belt, to position the vertical rigid bar support where the training guide is mounted. The training guide consists of one or two plates that can be adjusted at 6 degrees of freedom via a specially designed gimbal. There are two gimbal joints between the guide plate and the vertical pole brackets strapped to the player's torso. Players can adjust the position, direction, and angle of the guide plate according to their needs through two universal joints. Torso-mounted table tennis training device significantly improves paddle trajectory by guiding hands to return the ball to opposing players bouncing off the table [9]. Multi-ball training is an emerging method of finding immortals, combined with an innovation of Chinese table tennis technology. Combined with mathematical statistics, expert interviews, and other research methods, the multi-ball method and the single-ball method were compared in the same training content and in the same time unit and heart rate recovery (heart rate after 3 minutes of rest after exercise), to evaluate training volume and training effect by comparing and analyzing data [10]. Action representation and modeling play an important role in recognizing random action. But due to variability related to actors, camera viewpoints, durations, etc., explicit segmentation and labeling of motion are not trivial. So our training uses histogram training and can capture the movement and trajectory of athletes, while for video, a fixed value representation is required called a "Super Motion Vector" (SMV). [11]. It is extremely simple for us humans to do an action, but it is very difficult for a computer to recognize an action. Mobile cameras that shoot broadcast-quality video make this more difficult. Our main research action is in the media sector. That is, atypical graphics have a resolution. It can be demonstrated with the following video of table tennis movements. Take a method of decomposing the problem into three subproblems. The table tennis player data is first tracking the action, then generates an image to make a rough estimate of the position of the action. Action recognition systems use the stabilization results given by the stabilization process to classify actions using motion and pose features. A more advanced algorithm is proposed, which can help us solve problems that cannot be solved currently. Consistency of the template library is addressed by iteratively selecting templates to better fit the training data [12]. As one of the leading technologies of human-computer interaction, action knowledge is one of the hotspots in pattern recognition research. An accelerometer is a smart sensor. It is characterized by low power consumption, small size, low cost, and wide application. The acceleration of the cognitive activity detection process is currently divided into three levels: feature extraction, feature selection, and recognition algorithms. We propose a 3D accelerometer signal recognition algorithm that can identify various types of collisions based on the movements of tennis players on footnote maps. Data were collected with associated heart rate monitors and table tennis movements. The default acceleration threshold is similar to the fixed threshold and key features of character design and action length [13]. Whether it is possible to recognize different actions and distinguish them accurately is very important. Now we are mainly confused whether the action recognition is affected by the direction of the recognized action. We can use the adaptive action paradigm to discern visual processes for specific actions and orientations. Under different conditions, the people conducting the experiments are used to moving back and forth and high fives. The participants then classified the ambiguous movement's action or direction of movement [14]. Computers can recognize human gestures through human-computer interaction systems like an Xbox camera. They recognize simple movements, but they do not have powerful advanced algorithms for more difficult identification. We need a robust body action recognition method that relies on DTW and use the best position between two points to identify the action. [15].

2. About Table Tennis Training and IoT Perception Action Recognition

2.1. About Table Tennis. The standardization of table tennis begins with the establishment of the ITTF constitution and competition rules, which is also a sign that table tennis has shifted from a folk sport to a competitive event. The establishment of the ITTF in 1926 made the table tennis competition gradually improved and standardized, and also greatly improved the viewing and fun of the project. Table tennis can not only develop athletes' speed, strength, agility, endurance, and other qualities, but also exercise courage, wit, courage, tenacity, and other psychological qualities, and comprehensively promote the physical health of athletes.

2.2. Table Tennis Training and Action Analysis. (1) Special strength training can be divided into three parts: upper body exercise, lower body exercise, and waist exercise. Core strength training is comprehensive and can be enhanced by back throwing medicine balls, standing long jumps, sit-ups, and planks. (2) Speed training needs to be combined with strength training when performing fast training. And according to the athlete's own characteristics to carry out training. You can use the table as the boundary to perform left and right footwork exercises, left and right jumping exercises, cross-step movement exercises, long and short ball movement exercises, and push-side throw exercises. (3) Endurance training quality includes general endurance and special endurance. We usually do it in part after training. We can train athletes for long-distance running, or we can also allow athletes to carry out uninterrupted spiking training, so as to further exercise the endurance of players. and physical strength. (4) Agility training. Agility training mainly trains the reflexes of the players. The stronger the reflexes of the players, the more difficult the balls can be caught. We can send the ping-pong balls in the direction we cannot figure out, and let the players catch the ping-pong balls. The ball, and then exercise the player's reflexes and agility.

Table tennis training content is shown in Figure 1.

2.3. IoT Perception Technology. The field of IoT detection technology mainly includes RFID receiving technology, sensor technology, two-dimensional code identification technology, and biometric identification technology (1) Radio frequency identification technology, which is a noncontact automatic identification technology that uses radio waves to automatically contact and instantly identify objects. (2) Sensor technology, as an artificial IoT technology, IoT sensors are mainly responsible for retrieving the "audio" content of objects. Sensors collect and retrieve information from information sources and process, modify, and identify the received information according to defined rules. A sensor is the input to a measurement system and usually consists of a sensor and a sensor that converts the input variable into a measurable signal. (3) Two-dimensional code identification technology. Today, the use of two-dimensional identification technology is becoming more and more popular in daily life, and it has become a simple, fast, and convenient practical identification. Black and white images are defined in horizontal and vertical plane orientations using 2D copies of multiple geometric shapes, based on specified data and information disclosure, and are automatically recognized and read by images from light-duty or scanning devices. (4) Biometric recognition technology. With the development of artificial intelligence, biological and statistical analysis methods such as facial expression analysis, speech recognition, eye measurement, and motion control are becoming more and more popular and widely used in this field. Biometrics replaces technologies designed to calculate the value and identity of human-recognized information based on physical characteristics or techniques of the human body.

The identification technology based on IoT perception is shown in Figure 2.

2.4. Action Recognition. Training Action Recognition Human Behavior for Table Tennis is essentially about recognizing human behavior. At this stage, researchers at home and abroad are developing more methods for table tennis ball recognition, and the use of human activity analysis has been widely used in recent years. Human discovery methods can be divided into deep knowledge and advanced traditional artificial methods. This classic approach provides a solid theoretical basis for further research into human factual analysis in tennis matches. Initially, traditional recognition of human behavior relied heavily on knowledge of objects and classifications. Artistically designed functions are used to capture different spatiotemporal motions in movies, but manually extracting functions is time-consuming and laborious, and complex to retrieve quickly from the data.

3. Action Recognition Algorithm for Table Tennis Training Based on IoT Perception

3.1. Wi-Fi-Based Perceptual Recognition Technology. We use channel state information (CSI), an information that accurately describes the channel material, for perception and

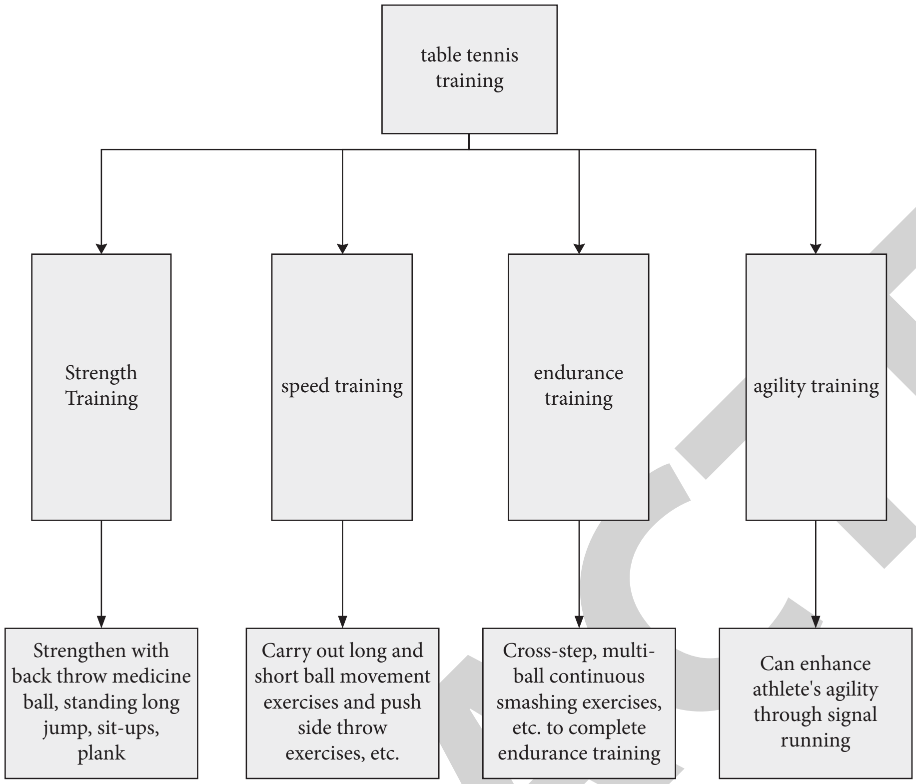

Figure 1: Table tennis training content.

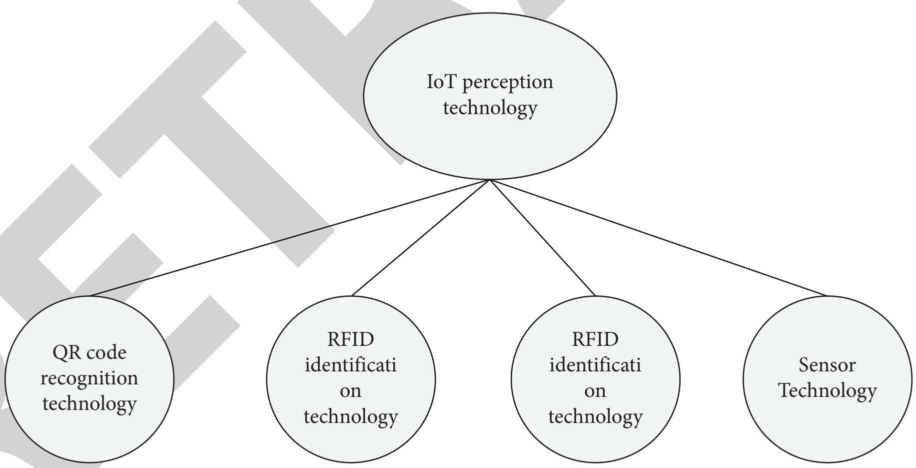

Figure 2: IoT perception and recognition technology.

action recognition. The key is to be able to describe the same signal propagation as the receiver, technology breaks the criteria down into several equations. If there are m, n antennas at the beginning and end, respectively, then it can be expressed by the following formula:

$$\begin{bmatrix} H_{11} & \dots & H_{1,j} \\ \vdots & \vdots & \vdots \\ H_{i1} & \vdots & H_{i,j} \end{bmatrix}, \quad i \in [1, mn], \quad j \in [1, N]. \tag{1}$$

The meaning of $H_{i,j}$ can be called the CSI value.

The received signal of the MIMO system can be expressed as

$$Y_i = H_i X_i + N_i, \quad i = 1, 2, \dots. \tag{2}$$

The meanings of $|R_j|$ and θ_j are the phase positions on the j-th path, the meaning of p is the total number of propagation paths, and the value of S represents the received signal. The larger the value of S, the stronger the received signal.

Calculating it gives

$$H = [H(f_1), H(f_2), \ldots, H(f_N)],\quad N = 1, 2, 3, \ldots, \tag{3}$$

$$H(f_k) = \left|H(f_k)\right|^{e^{j\angle H(f_k)}}, \quad k \in [1, N]. \tag{4}$$

The name of N is called the number of subcarriers, and $H(f_k)$ is the CSI value. CSI has less random noise and is more suitable for sensory research than the data from the first period.

3.2. RFID-Based Perception and Identification Technology

3.2.1. Phase. Phase is a periodic function whose period is $0 - 2\pi$ and can be calculated as:

$$\varphi = 2\pi\left(\frac{2d}{\lambda}\right)\mathrm{mod}\,(2\pi). \tag{5}$$

Due to the influence of the RFID hardware characteristics, the identified position will produce differences and offsets, we call it φ_n, and at the same time, due to the multipath effect, the identified phases will also have differences and offsets, we call it φ_e, so φ can be expressed as follows:

$$\varphi = \left(\frac{2\pi \cdot 2d}{\lambda} + \varphi_n + \varphi_e\right)\mathrm{mod}\,(2\pi). \tag{6}$$

3.2.2. Signal Acceptance Strength. In RF-based scanning analysis techniques, RSSI is very easy to measure, so the received signal strength is the first to be studied and applied by experts. As the radio signal increases, the signal strength decreases with the length, which means that there is a certain correlation between signal strength and range. The signal strength of RSS during transmission can be represented by the following formula:

$$p_r = p_t \mathrm{T} G_r^2 G_t^2 \left(\frac{\lambda}{4\pi d}\right)^4. \tag{7}$$

The meaning of p_t in the formula is the strength of the transmitted signal, the meaning of G_r and G_t is the consumption of the signal by the circuit when the signal is sent, the meaning of T is the consumption during the transmission process, the larger the value of p_t, and the stronger the strength of the signal.

Combined with the formula, the final RSSI calculation formula can be obtained:

$$\mathrm{RSS} = 10\lg\left(\frac{P_r}{1mW}\mathrm{T}G_r^2 G_t^2\left(\frac{\lambda}{4\pi d}\right)\right). \tag{8}$$

3.2.3. Doppler Shift. The meaning of Doppler shift refers to the frequency shift of transmission and reception. We let the velocity of an object be v, the angle of antenna motion be a, and the Doppler frequency shift can be expressed by the following formula:

$$\Delta f = \frac{2v}{\lambda}\cos(a). \tag{9}$$

3.3. Label Reflection Model. The signal received by the reader can be simply divided into the reflected signal with the tag and the reflected signal without the tag. Since the reflected signal without the tag is not affected by any tag, that is why it is developed from the RFID automatic recall scanner for commercial use of RFID technology is now widely used in tracking and analysis systems as people move between tags, stages, and RSSI changes, but these changes are severely affected by the lack of visibility in these areas. Therefore, this method is used to study hand movements, and the influence of the circuit on the RF signal is much smaller than that of human movements.

3.3.1. Phase Signal. What the receiver receives is the result of the accumulation of multiple signals, so the actual received signal S can be calculated as:

$$S = \sum_{j=1}^{P}\left|R_j\right|e^{-i\theta_j}. \tag{10}$$

Then we can get the value of S_{RSSI}:

$$S_{\mathrm{RSSI}} = 10\,\log_2 S^2. \tag{11}$$

Phase φ is calculated using the following equation:

$$\varphi = \frac{2\pi \cdot 2d}{\lambda}\mathrm{mod}\,(2\pi). \tag{12}$$

In real use, it will definitely be interfered by RFID hardware, the identified position will produce differences and offsets, we call it φ_n, and at the same time, due to the multipath effect, the identified phases will also have differences and offsets, we call it φ_e, so φ can be expressed as:

$$\varphi = \left(\frac{2\pi \cdot 2d}{\lambda} + \varphi_h + \varphi_e\right)\mathrm{mod}\,(2\pi). \tag{13}$$

Using the period difference can effectively reduce the phase error and improve the accurate period performance.

3.3.2. The Influence of Hand Movement on the Label. When the hand crosses the tag, the tag receives a tag representing the movement of the hand, marking the two tags S_r and S_f so that the actual received signal S_a can be seen:

$$S_a = S_r + S_f. \tag{14}$$

3.4. Phase Preprocessing

3.4.1. Phase Unwrapping. The raw phase signal is a periodic function, its range is $0 - 2\pi$rad, and it has a chance to vary. $\Delta N_{t,1} = N_{t,i+1} - N_{t,i}$ can be calculated using the following formula:

$$\Delta N_{t,i} = \begin{cases} 0, & \left|\varphi_{t,i+1} - \varphi_{t,i}\right| < \pi, \\ -2\pi, & \pi \le \varphi_{t,i+1} - \varphi_{t,i} \le 2\pi, \\ 2\pi, & -2\pi \le \varphi_{t,i+1} - \varphi_{t,i} \le -\pi. \end{cases} \tag{15}$$

The meaning of φ_i is the phase vector value of the collected original letter signal t, $\varphi_i = [\varphi_{t,1}, \varphi_{t,2}, \ldots, \varphi_{t,n}]$, $t = 1, 2, \ldots, 9$, $(t_i, \varphi_{t,i})$ and $(t_{i+1}, \varphi_{t,i+1})$ the meanings of Z and X are the phase values of two continuous times.

Then the value of $N_{t,i}$ can be calculated by the following formula:

$$N_{t,i} = \sum_{j=1}^{i-1} \Delta N_{t,j}, \quad i = 1, 2, 3, \ldots, n. \tag{16}$$

3.4.2. Phase Normalization. Find the average of 9 pistons in a fixed position. When processing the data from the next step, the component values for each label are subtracted from the standard mean.

The acquired phase matrix can be expressed as:

$$\varphi_{m\times n} = \begin{bmatrix} \varphi_{1,1} & \cdots & \varphi_{1,n} \\ \vdots & \ddots & \vdots \\ \varphi_{m,1} & \cdots & \varphi_{m,n} \end{bmatrix}. \tag{17}$$

The meaning of m, n is the number of labels and the number of collection points, respectively. Calculate the mean of the rest state for each label:

$$\overline{\varphi_m} = \frac{\sum_{i=1}^{n} \varphi_{m,i}}{n}, m = 1, 2, \ldots, 9. \tag{18}$$

Typical results are obtained by subtracting the average phase balance value from the appropriate signal to read each phase.

3.4.3. Calculate the Boundaries of Each Label. For the length of the sliding window L we use to express, the amplitude value and frequency of the i-th window can be expressed as:

$$A_i = \sum_{k=1}^{L} \left|\phi_{i,k}\right|, \tag{19}$$

and

$$F_i = \sum_{k=1}^{L} \left|\phi_{i,k} - \phi_{i,k-1}\right|. \tag{20}$$

In the formula, the meaning of $\phi_{i,k}$ is the i-th data point of the k-th sliding window.

The formula for calculating the difference function G is as follows:

$$G(i) = C_A\left|A_{i+1} - A_i\right| + C_F\left|F_{i+1} - F_i\right|. \tag{21}$$

3.5. DTW Algorithm. The DTW algorithm is an algorithm used to calculate the similarity of different datasets. Based on two independent sequences, the DTW algorithm can calculate the similarity of the two sequences, and can also combine DTW to verify and verify the two sequences. The basic idea behind the algorithm is to pick a point in one row and look for a point in another row to find the best path.

The specific calculation method is as follows: $X = (x_1, x_2, \cdots, x_n)$ and $Y = (y_1, y_2, \cdots, y_n)$ are two permutations, their length is m, n, and the DTW algorithm can calculate its minimum value., the mapping cost of X, Y can be calculated as:

$$d_{ij} = \left\|x_i - y_i\right\|. \tag{22}$$

The meaning of d_{ij} in the formula is the Euclidean distance between two points. According to the above formula, the DTW distance between the two sequences can be expressed as:

$$\mathrm{DTW}(X, Y) = \min \sum d_W, w \in (1, 2, 3 \cdots, k). \tag{23}$$

DTW is a good tool for comparing differences, the difference between X and Y can be calculated very well with the above classification formula.

3.6. Action Recognition. The RF-AH system uses the DTW algorithm to calculate the total distance between the known pattern and the pattern model and uses the minimum accumulation formula as the operation to display the corresponding minimum distance.

Step 1:

$$D_t(i, j) = \mathrm{Dist}_t(i, j) + \min\left[D_t(i, j-1), D_t(i-1, j), D_t(i-1, j-1)\right]. \tag{24}$$

Step 2:

$$\xi = \arg\min(D_t), t = 1, 2, \cdots, 9. \tag{25}$$

The meaning of t in the formula is the serial number of the template action sample.

4. Experiments Related to Action Recognition of Table Tennis Training Based on IoT Perception

In order to further explore the application and role of IoT perception in action recognition for table tennis training, we conducted a series of experimental research and analysis on the IoT perception action recognition algorithm, so as to see the difference between the algorithms more directly and clearly and advantages and disadvantages.

4.1. Table Tennis Action Experiment. The skills and techniques of sports are the keys to judge whether an athlete is good or not. Table tennis is not as simple as it seems. It contains many technical movements, which cannot be done without professional training. There are many kinds of catching movements in, here we mentioned eight kinds of catching movements such as forehand attack, forehand pull, backhand pick, and so on.

In the experiment, we recruited 12 table tennis players, half male and half male. We perform action recognition on these athletes, and the specific recognition data are shown in Table 1.

4.2. Identify Performance Evaluation Indicators. Accuracy, recall, precision, and $F1$ scales are commonly used to evaluate the performance of evaluation tasks. For binary classification activities, the origin is described as follows: In binary classification activities, rows represent actual sample categories, and columns represent suggested categories. TP number is used correctly in positive samples. FP was the quantity of false positive samples; the quantity of TN in negative film is marked correctly; there are also some examples that are wrongly predicted as negative. The details are shown in Table 2.

4.3. Algorithm Improvement Comparison

4.3.1. Algorithm Segmentation Improvement. Careful segmentation of actions is crucial for future recognition, so we improved the DTW method, and then conducted a comparative test before and after the algorithm improvement: 5 athletes were selected. Before the algorithm improvement, the accuracy rate was not high, but after the improvement, the accuracy has significantly improved. The specific experimental results are shown in Figure 3.

From the data shown in Figure 3, we can know before the refinement of the algorithm in this paper, the accuracy of the algorithm's operational research analysis was very low and did not produce the expected results. After the algorithm is split and upgraded, the analysis accuracy of the algorithm operation is significantly improved, and the detection accuracy is significantly improved. From this, it can be concluded that our improved algorithm is efficient and can make the system more accurate.

4.3.2. Action Segmentation Performance. Due to the repetitive nature of bodyweight exercise, segmenting a group of actions and segmenting a phase profile containing a complete single action is necessary for correct identification. So use the number of correctly detected actions/the number of actual actions to represent the segmentation accuracy. Analysis of the system action segmentation performance

Table 1: Number of effective samples corresponding to each ping-pong action.

Action category	Male sample	Female sample	Total sample
Forehand attack	142	136	278
Forehand pull	144	142	286
Forehand rub	143	145	288
Forehand pick	140	139	279
Backhand stroke	148	141	289
Backhand pull	145	143	288
Backhand rubbing	143	137	280
Backhand spinning ball	142	145	287
Total	1147	1128	2275

Table 2: Confusion matrix of two classifications.

Category	Positive	Negative
Positive	TP	FN
Negative	FP	TN

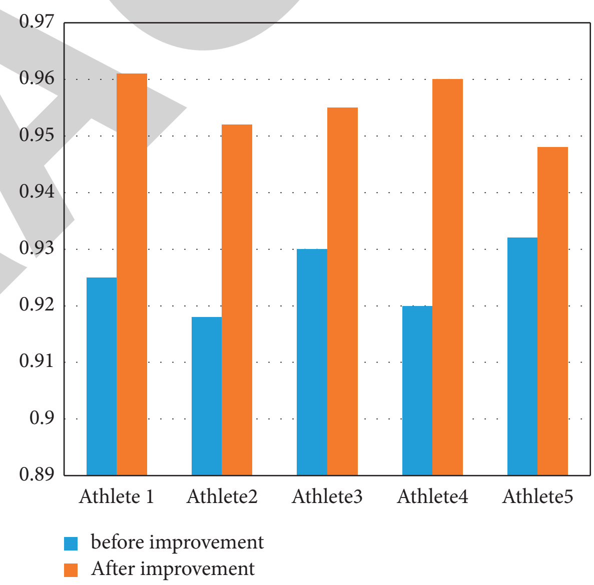

Figure 3: Algorithm improvement comparison.

shows that the reduction of segmentation accuracy is due to the fact that athletes may take a short rest when they are halfway through the exercise, resulting in one action being divided into two actions. The segmentation accuracy of different actions is shown in Figure 4.

4.4. Ping-Pong Action Recognition Results and Analysis

4.4.1. Confusion Matrix Experimental Analysis. The signal features are obtained by the method of signal analysis, and the action samples are identified by the DTW algorithm. Of all the functional samples obtained, 30% were randomly selected as testing kits, and the remaining 70% were used as training kits. The DTW method, validated and analyzed, attempts to obtain a mixture matrix of all test samples, where

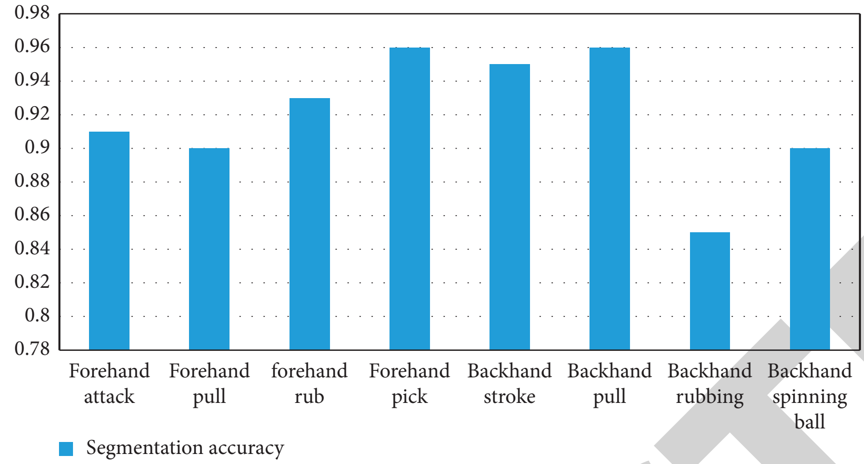

Figure 4: Action segmentation accuracy.

Table 3: DTW prediction confusion matrix.

	Forehand attack	Forehand pull	Forehand rub	Forehand pick	Backhand stroke	Backhand pull	Backhand rub	Backhand pick
Forehand attack	82	1	0	0	0	0	0	0
Forehand pull	0	85	0	0	0	1	0	0
Forehand rub	0	0	87	0	0	0	0	0
Forehand pick	0	0	0	84	0	0	0	0
Backhand stroke	0	0	0	0	85	1	0	1
Backhand pull	0	0	0	0	0	86	0	0
Backhand rubbing	0	0	0	0	0	0	84	0
Backhand spinning ball	0	0	0	0	0	0	0	86

Table 4: Performance evaluation results of different sensors.

	Acc	Gyro	Mag	Acc-gyro	Acc-mag	Gyro-mag	A-G-M
Accuracy(%)	92.53	88.29	92.83	96.78	96.83	96.49	97.41
Precision(%)	92.67	88.28	93.01	96.97	96.85	96.54	96.43
Recall(%)	92.54	88.34	92.84	96.80	95.83	96.49	97.42
$F1$-score(%)	92.51	88.28	92.85	96.78	96.83	96.50	96.42

each row is the current activity category, each column is the expected sample activity category, and records a sequence vector for the specified category. The sum of the order vector values represents the number of samples needed. The test sample matrix is shown in Table 3.

It can be seen from the error table (Table 3) that the different functions of table tennis skills can be correctly identified on the whole. Different skill activities have different recognition requirements, and some recognition results are very good.

4.4.2. Performance Evaluation of Different Sensors. In order to evaluate the performance of various sensors in analyzing table tennis activities, this paper conducts experiments on the detection effects of various sensors based on the DTW algorithm and uses indicators such as accuracy, precision, recall, and $F1$ to evaluate. Among them, Acc only uses a speed sensor, Gyro only uses a gyro sensor, Mag only uses a magnetic field sensor, Acc-Gyro only uses a speed sensor, and Accro Gyro only uses a speed sensor. Gyro sensor and Acc-Mag are meant to go hand in hand. For magnetic field sensors, Gyro-Mag demonstrated the use of both gyroscopes and magnetic field sensors, and AGM demonstrated the use of three types of sensors simultaneously. The test results are shown in Table 4.

According to the data in Table 4, in general, more sensors can achieve better performance in capturing ping-pong movements. However, using all three sensors at the same time scored higher than otherwise.

4.5. Influence of Multipath Effect. RFID tags also affect the environment. Due to the existence of multilayer tags, if there are any interfering objects near the RFID system, the tags will jump and scatter, causing signal interference. Experimental and comparative data were collected in the same indoor environment with chairs and shelves placed around

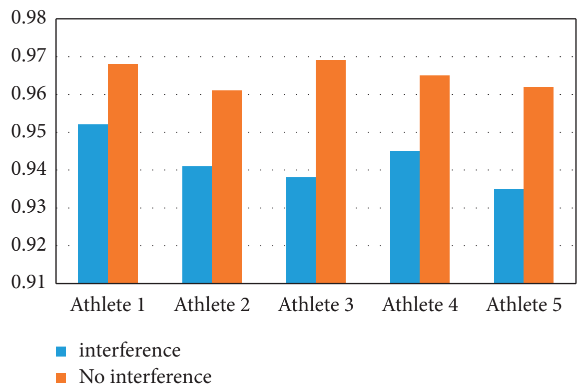

Figure 5: System accuracy with and without interference.

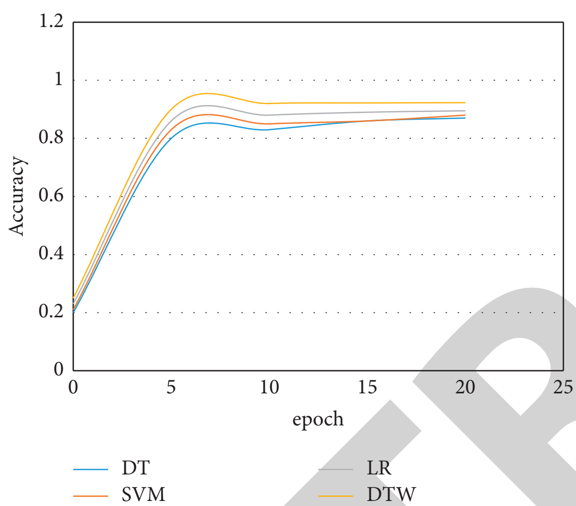

Figure 6: The accuracy of identifying similar actions.

the system. According to the systematic method proposed in this chapter, the signals of both cases are processed identically, and the experimental results are obtained. It can be seen that the system is basically unaffected, and the diagnosis and detection speed is slightly slower, indicating that the system is strong. The result is shown in Figure 5.

4.6. Recognition Experiment of Similar Actions. In order to analyze and study the recognition performance of the DTW in similar actions, this experiment compares other traditional algorithms of this algorithm in the recognition of similar actions. The ability to recognize similar actions. From the experimental data, we can know that the algorithm in this paper has better recognition ability for similar actions than other traditional algorithms. The accuracy of the algorithm in the specific experiment is shown in Figure 6.

We can know from Figure 6 of this paper that in the identification of similar actions, the algorithm in this paper has higher accuracy than other algorithms and can be stabilized, so it can be concluded that the algorithm in this paper recognizes similar actions. Compared with other

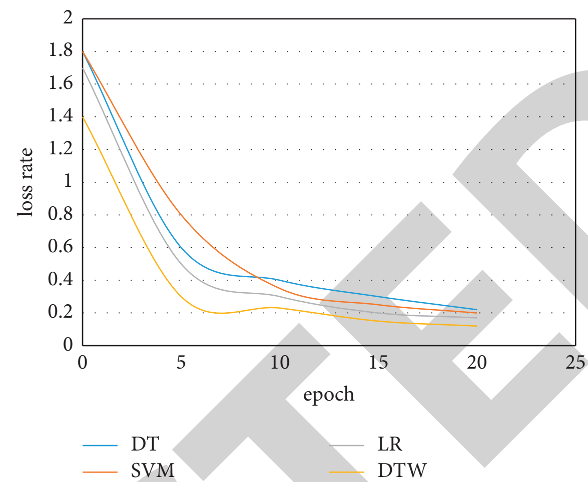

Figure 7: Loss rate for identifying similar actions.

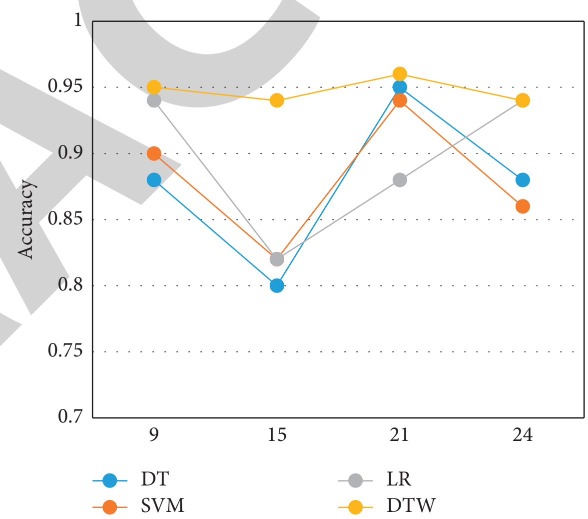

Figure 8: The accuracy of the algorithm at different times.

traditional algorithms, it has better recognition ability and has more outstanding performance.

The specific algorithm identification loss rate data in the experimental results are shown in Figure 7.

4.7. Impact on the System at Different times. To verify whether the robustness of the algorithm will be affected by time, including the impact of time on each algorithm, samples were collected in three different time periods, namely, nine o'clock, fifteen o'clock, and twenty-one o'clock. The recognition accuracy rate of each algorithm in three time periods is obtained, and the recognition accuracy rate of each algorithm in three time periods is obtained, so as to compare the time effect of the algorithm. The specific experimental result data are shown in Figure 8.

It can be seen from Figure 8 that the accuracy of the algorithm in this paper (DTW) does not change much and is relatively stable at different times, while other traditional

Table 5: Performance evaluation indicators.

Mode	Accuracy(%)	Precision(%)	Recall(%)	$F1$-score(%)	time(ms)
DT	93.93	93.96	91.93	93.93	0.379
SVM	92.97	93.27	92.99	93.03	0.143
LR	94.68	95.72	95.69	94.69	0.093
DTW	95.41	96.43	97.42	96.42	0.028

algorithms affect the cycle and the accuracy also changes accordingly. Its impact is relatively large. The experimental results confirm that the time has no effect on the algorithm in the paper, and the effect is better than the traditional algorithm, and the stability of the algorithm is highlighted in this paper.

According to Figure 8, it can be known that the accuracy of DTW in identifying actions in different time periods does not change much and is relatively stable, while other traditional algorithms are affected by the time period, the accuracy becomes fluctuating, and the impact is relatively large. The experimental results prove that the algorithm in this paper is not affected by time, and it performs quite well compared to the traditional algorithm, which highlights the stability of the algorithm in this paper.

4.8. Comparative Test of Performance Evaluation Indicators. The DTW diagnostic algorithm integrates three main classifiers, decision tree, auxiliary vector engine, and transport regression. This paper provides a comparative analysis of the recognition performance using the basic ping-pong algorithm. In addition to evaluating performance, accuracy, precision, retention, and $F1$ scale, this paper compares the average response time of each algorithm to evaluate sample sampling performance. Experimental data are shown in Table 5.

It can be seen from Table 5 that the algorithm in this paper is superior to other traditional algorithms in the four performance evaluation indicators of accuracy, precision, recall, and $F1$ metric. This fully proves that the algorithm in this paper has more powerful performance and higher accuracy than other algorithms and is more stable than other algorithms. It is a better and more worthwhile algorithm.

Overall, we know from the table that the performance indicators of the DTW method are better than other class classifications except for the time efficiency, and the average DTW prediction time is less than the base class prediction time. Among the individual-based classifiers, decision trees and organizational regression make good use of time, and the average prediction time is much shorter than that of support vector machines.

5. Conclusion

With the rapid development of IoT technology, many IoT devices appear in our daily life and are used in various fields. As a key technology of human-computer communication, the recognition of human behavior is the key to research in many fields. Table tennis is fast, complex, and similar in structure, so it is difficult to accurately judge the movements of players. There are many traditional methods of identifying events. This recognition method relies on relatively complex vision, but has obvious shortcomings such as limited analysis range and high light output; operational knowledge based on inertial sensors can fill the gaps in vision technology. The identification method based on wireless signal is relatively new, but the development is not advanced enough, and the identification effect is not perfect. With IoT detection capabilities, activity can be identified accurately and efficiently. As an IoT discovery technology, RFID has become a research object due to its low cost, high precision, flexibility, and high stability. With the advancement of technology, the perception recognition technology of IoT is the best way to identify the future business.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work.

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