Data Acquisition Method of Human Injury in Sports Based on Internet of Things

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Abstract. Traditional data acquisition methods usually collect and upload data at a fixed time interval, which is easy to generate a large number of redundant data, leading to large acquisition errors. To solve this problem, this study designed a new method of human injury data collection in sports based on the Internet of things. First of all, select the strong representative features such as the mean value and peak mean value of human injury data, and detect the human motion state according to the resultant acceleration, signal intensity region and tilt angle. Then, set up multiple sensors. Capture multi angle information of human motion data. Finally, using the adaptive strategy, the ratio of the residual energy and the total energy of the Internet of Things collection node is used to characterize the overall energy state of the node, reduce data redundancy, and then send the data to the data sink node through wireless transmission to confirm the current human motion injury state. Test results show that the average acquisition error of this method is relatively small, and it can collect human injury data more accurately in long-term sports.

Keywords: Internet of things · Athletic sports · Human body injury · Data collection · Movement characteristics · Adaptive acquisition

1 Introduction

Good health not only helps us to maintain a positive and optimistic mood and attitude towards life, but also helps to enhance happiness and self-confidence. Having a strong physique is the fundamental guarantee for our study, work and life. At present, regular sports have been proved to be helpful in slowing down and preventing the development of chronic diseases, and have important significance in sub-health intervention and promoting human health. But in sports, we need to follow a certain scientific way, otherwise, it will not only be difficult to achieve the purpose of strengthening the body and curing diseases, but even counterproductive, causing secondary damage to the body.

In sports, it is necessary to monitor the sports state of athletes, and understand the exercise situation of sports participants according to their state, including whether the action category is correct, the number of actions, the amount of exercise and the period

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are appropriate. In this process, it is an important link to collect and analyze the injury data of sports participants, which can help people track their own health at the sports fitness level [1].

At present, the wireless body area network (WBAN) composed of multi-sensor is usually used to assist instructors to monitor the movement of sports participants, determine the movement status of participants by collecting human injury data, and make timely corrections and guidance, adjust their exercise intensity in a timely manner, give early warning to individual sports fatigue, and give an alarm at the first time when abnormal conditions occur in the participants' bodies, The medical staff shall be informed to carry out timely rescue and realize continuous dynamic monitoring of important parts of the human body [2].

On the basis of traditional research, this paper proposes a method of collecting human injury data in sports based on the Internet of Things, which makes it possible to monitor user oriented sports, and makes it easier for people to obtain professional sports guidance when participating in sports exercises, so as to improve the professionalism of sports and exercise participants, effectively avoid the occurrence of sports injuries, and improve the effect of sports exercises.

2 Analysis of Human Motion Characteristics

The movements of the lower limbs of the human body are achieved by driving the bones through the relevant skeletal muscles to complete the rotation of the corresponding joints. The main muscles of the lower limbs are the hip muscles, thigh muscles, calf muscles and foot muscles. The human body has different exclusive characteristics in different movement modes such as standing, walking, and running. The travel speed, ups and downs of the center of gravity, height and posture in different movement modes will all affect the gait of the movement. A general multi-sensor human posture data acquisition system needs to configure 11 sensors, which are located in 11 parts of the human body's head, upper arm, lower arm, chest, abdomen, thigh and calf, and the sensor binding position is between the two joints on body parts. However, due to the large number of sensors used in this process, the system has high requirements for data aggregation and fusion, which easily leads to low effective recognition rate of the final information.

In order to improve the operation and recognition efficiency of the system, the sensor nodes of the head, chest and lower arm are removed in this paper, because the pose data of the head and lower arm have little impact on the pose recognition, which is relatively redundant. The motion of the chest and abdomen are basically similar, so one is taken as the node. When the human body remains standing, there is no obvious movement sign except for the normal natural weak shaking of the human body. The characteristic data with strong representativeness such as the mean value, peak mean value, standard deviation, covariance and skewness of the data are selected as the characteristic values of motion pattern recognition.

The standard deviation of human injury data in sports is calculated as follows:

$$\varepsilon = \sqrt{\frac{1}{u}\sum_{i=1}^{u}\left(A_i - \overline{A}\right)^2} \tag{1}$$

In formula (1), ε is the standard deviation; u is the number of data samples; i is the data serial number; A_i is the data sample; $\overline{A}$ is the mean. The standard deviation reflects the volatility of the action range. The standard deviation can reflect the range of human motion in sports. The larger the range of motion, the greater the standard deviation. The smaller the range of motion, the smaller the standard deviation.

Seven sensors were used in the study, which were bound to seven parts of the human body, including the left upper arm, right upper arm, abdomen, left thigh, left calf, right thigh and right calf. The coordinate system that specifies the initial binding position of each sensor is consistent, the X axis points to the left side of the human body, the Y axis points to the top of the human body, and the Z axis points to the front of the human body [3]. Because the muscles of the lower limbs need to maintain the balance of the human body, stand stably, and walk frequently, they are more developed and powerful than the muscles of the upper limbs of the human body. The complete time from the heel of a lower extremity touching the ground to the heel of the lower extremity touching the ground again is the gait cycle. In this time period, the gait cycle can be effectively divided into a support period and a swing period according to whether the foot of the lower limb touches the bottom. Covariance is often used to calculate and evaluate the overall error between two sets of variables. Therefore, calculate the covariance difference between the acceleration and angular velocity at the upper and lower limbs of the human body, and identify the motion state according to the calculation results. The covariance is calculated as follows:

$$c = \frac{\sum_{i=1}^{u} \left(b_i - \overline{b}\right)(\gamma_i - \overline{\gamma})}{u - 1} \tag{2}$$

In formula (2), c is covariance; b_i and $\overline{b}$ represent acceleration samples and combined values; γ_i and $\overline{\gamma}$ represent the sum of angular velocity samples. The covariance feature of the standard matrix of the static attitude is roughly distributed between 0.09 and 0.011, and the variance feature of the standard matrix of the moving attitude is highly distinguishable from the static attitude. Therefore, the static attitude and the moving attitude can be distinguished by this feature. The data point distribution dispersion, peak valley value difference and numerical point distribution ratio have characteristics similar to acceleration. The respective kurtosis of the data represents the slope of the data fluctuation peak, which can reflect the maximum amplitude of human movement. The calculation formula is:

$$\varphi = \frac{\sum_{i=1}^{u} \left(A_i - \overline{A}\right)^4 h}{u\varepsilon^4} \tag{3}$$

In formula (3), φ is the kurtosis; h is the sample interval of the data. Different from the slow walking mode, the running speed in the running mode is faster, and the frequency of changes in the center of gravity of the human body increases. It is necessary to increase the frequency, speed up, and increase the range of motion and elbow curvature to maintain the stability of the human body. The phase division of the gait cycle presents periodic changes in time and space [4]. And according to the phase change of the corresponding gait cycle, the data characteristics of the surface EMG signal of the lower limbs of the human body also have corresponding periodic changes, and at the same time have a high correlation with the gait cycle.

3 Motion State Description

In order to describe the motion state of human body, it is necessary to introduce several motion features, including acceleration, signal intensity region and inclination angle. The principle of the accelerometer is to calculate the acceleration value of the block at this moment through the force generated by the inertia of a block in motion. The accelerometer can not only measure the acceleration of the block, but also the gravity value of the block. The resultant acceleration represents the arithmetic square root of the vector sum of squares of triaxial accelerations in space. The calculation formula of resultant acceleration $v(t)$ at time t is as follows:

$$v(t) = \sqrt{v_x^2(t) + v_y^2(t) + v_z^2(t)} \tag{4}$$

In formula (4), $v_x(t)$, $v_y(t)$, $v_z(t)$ represents the output value of the acceleration sensor in the three directions of X, Y, and Z, respectively. $v(t)$ is a general description of the acceleration value changes in all directions, which can reflect the intensity of the human body's motion state.

Compared with the standing state, when the human body is in the slow walking state, the acceleration in the X, Y and Z directions increases with the increase of the swing arm speed and frequency. The resultant acceleration fluctuates between 5.285–17.391 m/s2. The angular velocity changes with the action amplitude and the curvature of the axis joint, the peak valley value difference increases, and the resultant angular velocity fluctuates between 0.125–2.847 rad / s.

Due to the abnormal jitter in the movement process and the influence of the measurement environment, it is inevitable to produce noise. The frequency of human motion is generally concentrated in 0-20Hz, and the change is more obvious in 0-5Hz, and the frequency of noise is certainly greater than this frequency. Therefore, low-pass filter can be selected to suppress noise [5].

When a fall occurs, the change of the $v(t)$ curve increases significantly, so the fall behavior can be preliminarily judged by setting the threshold value of the resultant acceleration. The SMV curve changes of falls are similar to those of strenuous exercise and running. This paper uses a 4th-order Butterworth low-pass filter to denoise the triaxial acceleration and triaxial angular velocity data. Filter parameters: the pass-band cut-off frequency is 20 Hz, the stop-band cut-off frequency is 23.5 Hz; the minimum pass-band attenuation is 3 dB; the stop-band maximum attenuation is 20 dB. Use the signal strength area to make up for the lack of $v(t)$-curve threshold detection. The signal strength area W can be used to analyze the amplitude of dynamic motion, and its expression is:

$$W = \frac{1}{t}\left(\int_0^1 |v_x(t)|dt + \int_0^1 \left|v_y(t)\right|dt + \int_0^1 |v_z(t)|dt\right) \tag{5}$$

For some movements, the limbs always move in the horizontal plane during the movement, so the average acceleration along the axis of the limb direction is always near zero. For other movements, the limbs always move in the vertical plane, so the average acceleration along the axis of the limb direction is around 1g. Because there are some similarities in the behavior of human activities, such as the acceleration changes of falling and rapid sitting are relatively similar, the tilt angle is used to judge the posture. The inclination angle represents the angle between the body and the vertical direction, and the formula is:

$$\beta = ar\cos\left(\frac{l(t)}{g}\right)\left(\frac{180}{\pi}\right) \tag{6}$$

In formula (6), β is the inclination angle; $l(t)$ is the height of the body torso; g is the acceleration of gravity. In the whole process of falling, the human body will be in different states over time during the fall, and the change of the posture of the human body from 0° to 90° during the fall process can be reflected by the inclination angle. In the static state, the three-axis angular velocity data should be zero, the X, Y axis acceleration should be zero, and the Z axis acceleration should be + 1g or -1g, but the data measured by the sensor will drift during the actual measurement process. Data to compensate. After compensation, the acceleration measurement value of the sensor is stable at 0.001g, and the angular velocity measurement value is stable at 0.05°/s, which corrects the error.

4 Multi-sensor Data Fusion in Human Motion

The motion data collected by the sensor will be uniformly encrypted and stored in the database, and the identification result is only the motion status information and the number of the safety device worn. Therefore, it can effectively avoid adverse effects caused by personal data leakage [6].

Before entering the designated area, the person being tested should enter personal characteristic information, that is, personal movement characteristic data, so as to ensure that all safety device wearers can be accurately identified. The terminal locations in the area are similar, and the collected environmental parameters have strong coupling, that is, there is a spatial correlation between the sensing data of each terminal in the monitoring area. The time synchronization server is the timing center of the system, which can provide millisecond-level time synchronization for all distributed positioning devices. The sensing data of a single collection terminal can form a time series, and through the analysis of the time series, it can be found that the sensing data within a certain period of time has a strong temporal correlation [7]. Each pressure sensor can actually provide complementary information. That is to say, each sensor in complementary fusion captures different aspects of the monitored object, which is used to improve the accuracy and reliability of the system. Therefore, the sensing data collected by the terminals in the adjacent monitoring area have strong spatial and temporal correlation. The data fusion process is shown in Fig. 1.

The time synchronization server is equipped with a microcontroller and a RF transceiver, which periodically broadcasts the relative time value to all distributed positioning devices in the space field through wireless communication. Each distributed position device maintains time synchronization with the time synchronization server,

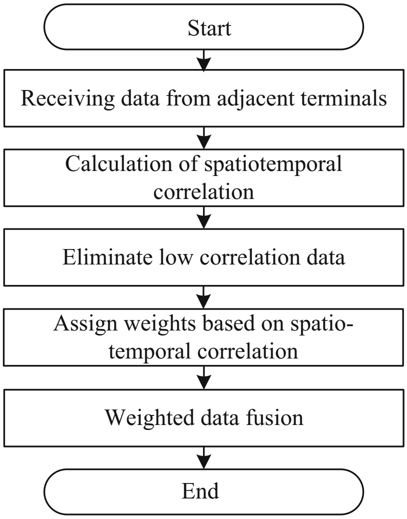

Fig. 1. Schematic diagram of isomorphic data fusion

thereby realizing time synchronization between all distributed positioning devices [8]. Firstly, the dynamic time planning distance method is used to calculate the spatial distance of terminal data at each time point in a period of time. In the window time, the time data series of terminals E_1 and E_2 are $\zeta(E_1)$ and $\zeta(E_2)$ respectively, and the distance D between terminal perceived data is expressed as:

$$D=f[\zeta(E_1), \zeta(E_2)] + \min f\left[\zeta'(E_1), \zeta'(E_2)\right] \tag{7}$$

In formula (7), f is the Euclidean distance between the corresponding data points in the sequence; ζ' is the sequence of the previous data sampling period. The main function of the time synchronization server is to send time information regularly to ensure the time synchronization of the entire network. The distance between data points is calculated recursively. By calculating the distance of each terminal data, the median absolute dispersion method is used to set the correlation threshold, and the low correlation terminal data exceeding the threshold will not participate in this data fusion.

Generally, for statistical data, the number of digits is reserved to 6 significant digits at most. Therefore, for the data extracted by different sensors, the data digits are unified respectively to avoid the error impact on the subsequent eigenvalue extraction. Take the median of the calculated space-time distance and calculate the absolute difference with each distance, and then take the median of all the obtained absolute values as MAD. Calculate the correlation degree between the terminal data according to the calculated dynamic time planning distance, and use the exponential function to quantify the spatio-temporal correlation degree between the terminal data, which is expressed as:

$$R = e^{-\frac{D^2}{2}} \tag{8}$$

In formula (8), R is the spatiotemporal correlation degree; e is an exponential function. The weight is allocated according to the strength of the correlation degree, wherein the higher the correlation degree between the terminal perception data, the greater the allocated weight. According to the size of the weights, weighted data fusion is performed on the currently collected sensing data to achieve the purpose of improving the accuracy of the sensing data.

In order to directly import relevant data into MATLAB for eigenvalue calculation, the sensor category name and time node information are eliminated, and only the human motion dynamic data detected by the sensor is retained. Even if the information provided by multiple pressure sensors is used, it is still unable to obtain gait spatial measures such as stride length and pace. When multiple kinds of sensor signals are needed to obtain information that cannot be obtained by observing these signals independently, collaborative fusion plays a role. According to the assigned weights, the isomorphic perceptual data with strong spatial-temporal correlation is weighted for data fusion, and the fusion results will be reported to the server as the final measured data value of the terminal.

5 Establishing a Sports Injury Data Collection Model Based on the Internet of Things

The above contents analyze the human motion characteristics, describe the motion state, and implement the fusion of multi-sensor data in the human motion process. On this basis, take the fused multi-sensor data as the basic data, and establish the sports injury data acquisition model based on the Internet of Things.

Large-scale data acquisition and transmission requires the acquisition system to support long-distance communication and support a large number of sensor nodes to work at the same time. The data acquisition model proposed in this paper is shown in Fig. 2.

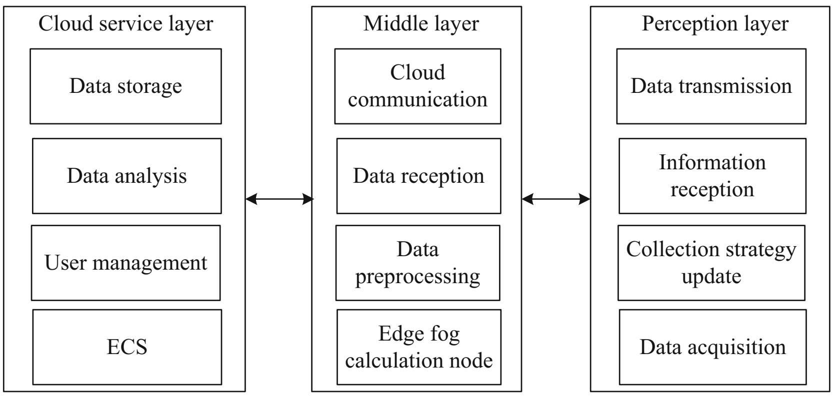

Fig. 2. Sports injury data collection model

Collection setting is a necessary configuration module for data collection, mainly an interface management module that needs to be configured for a collection task. In this part, the interface design of configurable collection, analysis and conversion will be realized. It includes task ID, DTU enable, acquisition command, acquisition cycle, task mode, matching rules, data segmentation, data conversion, filtering rules, incremental threshold, maximum and minimum value (optional), adaptive switch, etc. The data acquisition of human sports injury is located in the perception layer, and the adaptive adjustment of data acquisition interval is completed according to the set adaptive acquisition strategy.

In traditional data collection methods, data are generally collected at fixed time intervals and uploaded. The data interaction is carried out in the CBI mode, and all the information in the system interface will be saved through the configuration file, which is logically the corresponding relationship between nodes and sub-nodes [9]. The fixed acquisition interval requires consideration of energy consumption and data sensitivity. When the human body motion is in a stable state, performing data collection at fixed intervals will generate a large amount of redundant data and waste energy. When sports are in a state of rapid change, if the set collection time interval is too large, it will inevitably lead to less data collected. The information display method of each check box in the configuration interface is the node name and the node field name consists of two important parts. The precondition for data transmission is to establish a connection between the two parties. This part is transmitted using the TCP protocol, and the data transmission is performed by establishing a socket channel.

When the acquisition system adopts fixed interval for data acquisition, there will be problems if the acquisition interval is set too short or too long. Therefore, the acquisition system needs to be able to reasonably set the acquisition frequency according to the demand, so as to maximize the contradiction between data perception and energy consumption [10]. In this paper, an adaptive strategy is proposed to select the ratio of residual energy and total energy of nodes to represent the overall energy state of nodes. After initializing the acquisition, start to adjust the acquisition interval. When the collected data changes frequently, the collection interval will be dynamically reduced. Assuming that the value of the data currently collected by the system is Z_0 and Z is the data reference threshold, there are:

$$Z = \begin{cases} Z_{\min}, Z_0 < Z_{\min} \\ Z_{\max}, Z_0 > Z_{\max} \end{cases} \tag{9}$$

In formula (9), $Z_{\min}$ and $Z_{\max}$ are the minimum and maximum thresholds of sports injury data, respectively. After obtaining the reference threshold, it is necessary to calculate the degree of deviation of the data. At this time, the following method is used to calculate:

$$\begin{cases} \eta_1 = |Z_0 - Z| \\ \eta_2 = Z_{\max} - Z_{\min} \end{cases} \tag{10}$$

In Eq. (10), η_1 is the difference between the collected data and the reference threshold; η_2 is the difference between the maximum threshold and the minimum threshold. On this basis, the adaptive acquisition strategy can be expressed as:

$$\kappa = \begin{cases} \kappa_0\left(1 - \frac{\eta_1}{\eta_2}\right)\left(1 - \frac{\delta}{\delta_0}\right), \eta_1 \leq \eta_2 \\ \kappa_{\min}, \eta_1 > \eta_2 \end{cases} \tag{11}$$

In formula (11), κ represents the updated acquisition interval; κ_0 and $\kappa_{\min}$ represent the initial acquisition interval and the set minimum motion injury data acquisition interval, respectively; δ and δ_0 represent the current state and initial energy of the acquisition node, respectively. The entire transmission process includes initializing the connection of the device, obtaining the mac address for data MD5 verification, obtaining the node data of the configuration file, establishing the channel and authenticating, and waiting for the data packet to be sent. When the data is in a normal state, the system tends not to update the collection interval, but uses the initial collection interval for data collection; when the data fluctuation exceeds the normal range, the system needs to update the collection interval. After the transmission channel is established, the gateway sends a collection command to the gateway through the Modbus TCP protocol. After receiving the collection command, the collection end will immediately feed back the information data stream. After the gateway receives the data, the data will be analyzed, matched and filtered. Operation, and send the collection result package to the cloud. Data needs to be formatted and preprocessed after collection.

In the txt text file, in addition to the real-time sensor data in the X, Y and Z directions, the data information collected by the sensor also includes the category annotation and coordinate axis annotation of each sensor. In addition, the digital digits recorded and saved by each category of data are lack of consistency, so it is necessary to sort out all data contents according to categories. Considering the extreme situation that the data deviates too much, and when the new acquisition cycle calculated is less than the sleep time supported by the hardware, this acquisition interval will be set as the minimum acquisition interval. Control the relevant sensors and obtain the readings of the equipment to obtain the data of the motion state; Send data to the data convergence node by wireless way; Receive the information of the data convergence node to confirm the current motion state. Before data analysis, it is necessary to import the contents of txt file recording motion data into the Excel table of Office, and classify the contents and set the digits of the imported information.

6 Experimental Studies

In order to verify the practical application effect of the data collection method of human injury in sports based on the Internet of Things, a comparative experiment was designed to compare the method in this paper with the traditional data collection method based on association rule algorithm and the data collection method based on edge computing.

6.1 Experiment Preparation

The data processing program in this paper is based on the GUI module in MATLAB as the development platform, and the upper computer software system is built. In the experimental test, 10 volunteers (aged 25–45 years old, height 160cm-180cm, 5 males and 5 females) were invited to conduct sports data collection experiments.

The acquisition experiment requires the subjects to perform the data acquisition experiment of the exercise process in a state of no muscle fatigue and a good mental state. The purpose of the action counting and cycle calculation experiments is to verify the accuracy of data collection. For this experiment, the objectiveness of the experimental results is largely affected by the number of trials. Especially for action counting, the validity of the analysis method can only be demonstrated if the results are still accurate when the number of times is sufficient. The experiment set the data collection time as 60 min, and repeated 50 movements during this time. This value is higher than the number of times required for a single exercise, which can verify the accuracy of the method.

During the experiment, in addition to using sensors to collect and record motion data, a stopwatch was also used to time the cycle of each action as the actual standard.

6.2 Results and Analysis

For the movement of limbs rotating around joints, the sensitive axis is generally angular velocity, while for the vertical movement of limbs such as shoulder pushing and heel lifting, the sensitive axis is acceleration. Therefore, the angular velocity and acceleration of motion are selected as the collected data for the experiment.

Due to the different structure of the crowd and the different physical characteristics of individual pedestrians, the statistical distribution of stride length and stride frequency is often relatively discrete, because for individual pedestrians, the size of their stride length is largely subject to their physical characteristics. In motion, the amplitude and frequency of motion fluctuations fluctuate in varying degrees with the intensity of motion changes. Therefore, it is of practical significance to select stride and stride frequency data to analyze the effect of injury data collection.

The average error of data acquisition is obtained by comparing the motion data acquisition value with the actual value. In the 60 min test time, the results of motion angular velocity, acceleration, stride and step frequency data acquisition error obtained by different methods are shown in Table 1, 2, 3 and 4.

In the angular velocity data acquisition, the average acquisition error of the human injury data acquisition method in sports based on the Internet of things designed in this paper is 2.34%, which is 1.32% and 2.11% lower than the comparison acquisition method based on association rule algorithm and edge calculation.

In the sports acceleration data acquisition, the average acquisition error of the human injury data acquisition method in sports based on the Internet of things designed in this paper is 2.02%, which is 1.81% and 2.45% lower than the comparison acquisition method based on association rule algorithm and edge calculation.

In the movement stride data acquisition, the average acquisition error of the human injury data acquisition method in sports based on the Internet of things designed in this paper is 2.17%, which is 1.49% and 1.95% lower than the comparison acquisition method based on association rule algorithm and edge calculation.

In the step frequency data acquisition, the average acquisition error of the human injury data acquisition method in sports based on the Internet of things designed in this paper is 2.27%, which is 1.00% and 1.64% lower than the comparison acquisition method

Table 1. Motion angular velocity data acquisition error (%)

Acquisition time (min)	Data collection method of human body injury in sports based on Internet of Things	Data collection method of human body injury in sports based on association rule algorithm	Data collection method of human body injury in sports based on edge computing
5	1.84	3.59	4.16
10	1.91	3.66	5.52
15	2.55	3.45	3.46
20	2.60	3.14	5.36
25	2.52	4.57	4.95
30	1.86	2.31	3.85
35	2.78	3.68	5.47
40	2.25	4.52	4.52
45	2.54	5.26	5.58
50	2.82	3.23	3.36
55	1.96	2.65	3.49
60	2.43	3.88	3.63

Table 2. Motion acceleration data acquisition error (%)

Acquisition time (min)	Data collection method of human body injury in sports based on Internet of Things	Data collection method of human body injury in sports based on association rule algorithm	Data collection method of human body injury in sports based on edge computing
5	1.34	4.43	4.26
10	1.61	3.16	5.28
15	2.25	4.05	5.59
20	1.92	2.52	4.96
25	1.83	3.28	3.37
30	2.76	5.86	3.41
35	2.65	3.93	4.86
40	2.78	4.61	5.50
45	2.09	3.34	4.29
50	1.66	3.57	3.63
55	1.52	3.72	4.14
60	1.84	3.45	4.35

Table 3. Movement stride data collection error (%)

Acquisition time (min)	Data collection method of human body injury in sports based on Internet of Things	Data collection method of human body injury in sports based on association rule algorithm	Data collection method of human body injury in sports based on edge computing
5	2.54	3.16	3.26
10	2.41	3.25	3.48
15	2.95	3.48	4.47
20	1.82	3.96	2.95
25	1.66	2.52	3.63
30	1.43	2.74	4.48
35	1.72	4.96	5.96
40	1.55	4.35	4.58
45	2.28	3.35	4.47
50	2.36	3.48	5.11
55	2.43	4.62	3.35
60	2.84	4.08	3.68

Table 4. Movement cadence data collection error (%)

Acquisition time (min)	Data collection method of human body injury in sports based on Internet of Things	Data collection method of human body injury in sports based on association rule algorithm	Data collection method of human body injury in sports based on edge computing
5	2.66	2.48	2.86
10	1.85	2.62	3.74
15	1.44	3.59	4.98
20	2.57	4.47	5.61
25	2.61	2.58	2.95
30	2.75	2.63	2.90
35	2.48	3.12	3.39
40	1.82	3.15	3.65
45	1.96	2.41	4.58
50	2.53	4.86	4.46
55	2.34	3.59	4.73
60	2.28	3.75	3.12

based on association rule algorithm and edge calculation. The data acquisition interval of the design method in this paper will be adjusted adaptively with the deviation of the collected data and the change of energy. Therefore, the average error of the acquisition is relatively small, and the data acquisition of human injury can be realized more accurately in long-term sports.

7 Conclusion

In sports training, it is necessary to monitor the movement state of the athlete. A network composed of multi-sensors can assist the instructor to monitor the body movements of the sports participants, and by collecting the data of the human body injury, it is possible to know whether the number and cycle of the athlete's movements are appropriate.

In the traditional data collection method, data is generally collected and uploaded at fixed time intervals, which will generate a large amount of redundant data and cause a waste of energy. Aiming at this problem, this paper designs a data collection method for human injury in sports based on the Internet of Things. After the acquisition is initialized, the adjustment of the acquisition interval begins. When the collected data changes frequently, the collection interval will be dynamically reduced. Control the relevant sensors and obtain the readings of the equipment to obtain the motion data, and send the data to the data aggregation node wirelessly to collect the current motion state data. The average error of the collector in this paper is relatively small, which can achieve accurate collection of long-term motion data.

Although the method designed in this paper improves the ability of environmental perception, the overall energy consumption of the proposed strategy is still large in the case of drastic changes in the environment. Therefore, the next step is to study a more reasonable node sleep strategy to further reduce the energy consumption of data collection.

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