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Trajectory Method for Defense Human Motion Posture Based on Nano-Sensor

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HIGHLIGHTS

- Construct a motion trajectory description model using the collected data.
- Using the gravitational model to determine the attraction and repulsion of the defending human.
- We propose nano-sensor-based defense human motion posture trajectory method.

Abstract: Nano-sensor can directly monitor human motion, and transmit the data to the monitoring center through the micro-nano interface, which can be analyzed and processed based on real-time monitoring data under the premise of execution capability. Due to the defense human motion posture trajectory data containing rapidly changing angular velocity and acceleration, it is difficult to perform fine localization and analysis during rapid motion. Therefore, a trajectory method for defense human motion posture based on nano-sensor is proposed. First, nano-sensor monitoring nodes are arranged to set up the defense data mining process and initially obtain the defense human motion posture trajectory data. Second, the collected data are used to build a trajectory description model to match the trajectory states under different virtual forces. Finally, according to the trajectory state conversion of human running trajectory coordinate system, using the gravitational model to determine the attraction and repulsion of the defending human, to achieve the deep mining of defense posture data. The results show that the proposed method can classify the five defense poses more accurately than other traditional methods, and the accuracy of defensive posture recognition is high. It can truly restore the execution of tactics, arrange the offensive and defense positions of personnel, and better design the defense and offensive strategies of personnel.

Keywords: Trajectory; Defense posture; Human motion posture; Nano-sensor; Data mining.

INTRODUCTION

With the continuous development of nanotechnology, a variety of new Nano-devices such as Nano-antennas and Nano-batteries, as well as Nano-processors and storage have been generated, the most widely used of which are nano-sensors and actuators. New nanomaterials, at this stage, can create components with sizes between 1 nm and several hundred nm, which directly perform the tasks of sensing and processing as well as actuation [1]. Nano-sensor not only changes the size of the original sensors, but also generate new functions in the detection of properties, i.e., they allow the measurement of events at the nanometer scale using the properties of nanomaterials and nanoparticles. Nano-sensor is designed with multiple acquisition nodes to detect, chemicals below one part per billion, and the presence of multiple viral and bacterial infectious agents [2-3]. Its application in data identification and mining enables targeted and rapid localization of data and accomplishes full-time trajectory. Data mining of the motion trajectory of defense human motion posture can realistically restore the execution of tactics, arrange the offensive and defense positions of personnel, and better design personnel defense and attack strategies. Therefore, it is of great research value to study the data mining algorithm of the motion trajectory of defense human motion posture.

For the important research topic of motion trajectory data mining, Huang H, Deng R [4] proposed a motion trajectory data mining algorithm based on image recognition, combining data mining techniques to obtain effective data from massive video and image data, using mathematical statistics and data mining techniques for data processing, and scientific analysis of motion race technology with the support of ergonomics. Based on machine learning algorithms, image analysis and image feature recognition processing are combined with image recognition technology to realize real-time trajectory of athletes' dynamic features, to achieve deep data mining. However, the algorithm is too complicated, which leads to the rise of time-consuming motion trajectory data mining and the practical application effect is not good. Wang J [5] presented a data mining algorithm for large sports matches based on an online data migration model. Based on the online data migration model, a system model is developed to handle the applications of sending nodes, relay nodes and receiving nodes in the matching network, and an online distributed cost optimization control strategy is proposed to be responsible for the operation and processing of the applications in the communication system. This control strategy achieves the optimization of the target system overhead infinitely close to the theoretical optimum while ensuring the stability of the application queue, which is utilized to achieve the mining of sports match data. In practical applications, it is found that this algorithm suffers from poor quality of defense pose classification, which makes it difficult to achieve the expected research goals. Zhang S, Mao H [6] propose a motion data mining algorithm with XGBoost algorithm and design a mobile processor performance data mining framework MobilePerfMiner, which uses hardware counters and iteratively uses the XGBoost algorithm to construct performance models, rank the importance of micro-architectural events for big data tasks, and reduce the performance big data dimension to optimize the big data mining algorithm based on the described performance characteristics, and use the optimized algorithm to implement motion trajectory data mining. However, the algorithm suffers from the problem of low defense pose recognition rate, and the practical application is not good. Yin Z, Cui W [7] proposed a motion data mining algorithm based on the discrete Morse principle, which combines data mining with discrete Morse theory, and applies the concept of critical point in discrete Morse theory to optimize the grid clustering process to obtain clustering results based on the theorem that the cell complex reaches optimality when it has the minimum possible critical point, to complete the mining of motion data. In the experimental test, it is found that this algorithm has the problem of low search completion rate and accuracy rate, and the practical application is not good. Ju and coauthors [8] proposed a motion data mining method based on ID3 algorithm. The application steps and data processing process of the traditional ID3 algorithm are analyzed, the attribute missing and overfitting problems are elucidated, the direction for the subsequent algorithm optimization is provided, and an ID3 optimization algorithm based on -nearest neighbors is designed, which selects the values similar to -nearest neighbors to fill the missing values, and the sports competition sports data are mined using this advanced algorithm to realize sports data mining. However, the data mining results of this algorithm have the problem of low search completion rate and search accuracy rate, and there are still some differences with the ideal application effect. Sun Y and coauthors [9] proposed a novel 3D human motion pose detection method. Nano sensors capture human EMG signals, de-noised by blind source separation. Time-domain and frequency-domain features are extracted. Multi-agent deep reinforcement learning model outputs 3D local pose. However, Challenging for ordinary sensors to capture subtle pose changes accurately. Relies on Nano sensors and complex multi-agent deep reinforcement learning model, potentially increasing cost and computational requirements.

However, the application of the above algorithms to defense human motion posture trajectory data mining has the problems of poor quality of defense posture classification, low accuracy of defense posture, low recall and precision, and long mining time. Therefore, a new nano-sensor-based defense human motion posture trajectory data mining method is designed as a research objective to solve the problems of the above methods, and the main contributions of this paper are as follows:(1) The use of nano-sensor in the collection of defense human motion posture trajectory data to address the problem of traditional methods to capture the rapidly changing angular velocity and acceleration. (2)Convert the human running trajectory coordinate system, corresponding to the attractive and repulsive forces of the defending human, and mine the defense posture data to ensure the quality of data mining with the transformation of defense strategy, routes and tactical switching. (3) Different data sets are applied to demonstrate that the proposed nano-sensor-based defense human motion posture trajectory data mining of the proposed method can quickly and accurately mine defense human motion posture trajectory data

METHODOLOGY

Nano-sensor-based preliminary data acquisition

Nano-sensor nodes are small in size and can store limited energy. Therefore, in the process of data mining, it is necessary to use a simple pulse communication mechanism, namely femtosecond pulse transmission channel [10].

A modulation scheme to control the switch is put into the nano-sensor to extend the switch keying TS-OOK, where each node sends one bit in a time interval [11-12]. A femtosecond pulse sent represents the transmission bit "1", that is, the high bit; By keeping silent, the transmission bit "0", that is, the low bit, and the low bit conflict does not have a negative impact [13], as shown in Figure 1.

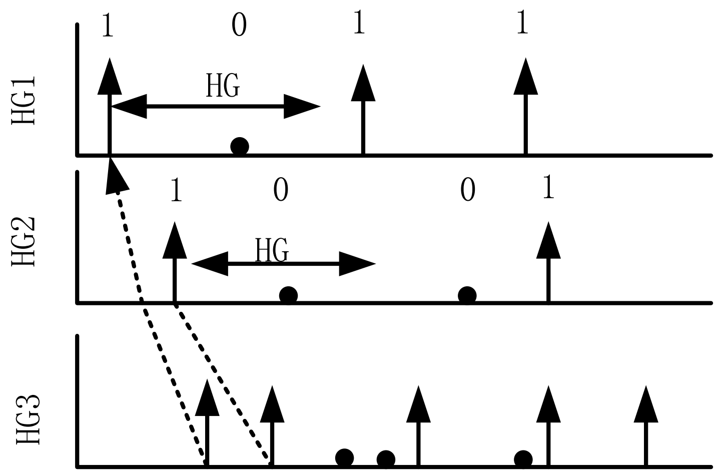


Figure 1. The data acquisition process of nano-sensor

It can be seen from the analysis of Figure 1 that the arrow represents the high position and the dot represents the low position. In this paper, three nano-sensors are used to collect the motion trajectory data of the defense human motion posture. These three nano-sensors are represented by HG1, HG2 and HG3, respectively. The data transmission process of HG1 nano-sensor is from high position to low position to high position to high position. The data transmission process of HG2, a nano-sensor, is from high position to low position to low position to high position, while HG3 is responsible for integrating the first two sensors and taking the collected data as the basis for subsequent data mining.

Nano-sensor [14-15] shows a gradual decline in data mining and transmission. The first nano-sensor transmits the symbol sequence, namely HG1-1011, and the second sensor is HG2-1001.

The time interval between two adjacent bits is M_z, and the pulse duration is M_x, which shall meet the following requirements:

$$M_z \geq M_x \tag{1}$$

where M_z is a fixed value. On this basis, simple channel access mining is implemented to generate human motion posture trajectory mining factors

$$\lambda = \frac{M_z}{M_x} \tag{2}$$

where λ is the mining factor and the ratio of M_z and M_x.

The signal generated by the motion is Gaussian pulse [16]. The Gaussian pulse with a peak power of several μW is established, and the equivalent energy consumption is εJ (10-18J). The data mining function of the nano-sensor is established as follows:

$$\gamma(\chi) = \frac{\alpha_1}{\sqrt{2\pi\eta'}} \exp\left(-\frac{(\chi-\mu)^2}{2\eta'^2}\right) \tag{3}$$

where γ is pulse; $\gamma(\chi)$ is the mining function; α_1 is the pulse amplitude; η' and μ are Gaussian pulse variance and center point.

The main frequency of Gaussian pulse power spectral density is in the THZ frequency band [17], and its derivative is calculated according to the time series as follows:

$$\varepsilon_\mu(m) = \alpha_0^2 \exp\left(-(2\pi\eta' m)^2\right) \tag{4}$$

where m is the frequency of the transmitted signal. The interval time in the nano-sensor nodes is the same. Through the collision of consecutive adjacent bits, the motion trajectory of the defense human is mined [18].

Construction of motion trajectory description model

The collected data are used to build a model for describing the motion trajectory, to analyze the motion trajectory of the defense human motion posture from the kinematic point of view, to define it by geometric properties, and describe the change law of the motion posture trajectory. It is possible to comply with the kinematic principles, but also to take into account the relationship between the force and speed of human defense, so that the data of the trajectory of the motion can be mined. Based on the human motion dynamics model, as shown in Figure 2.

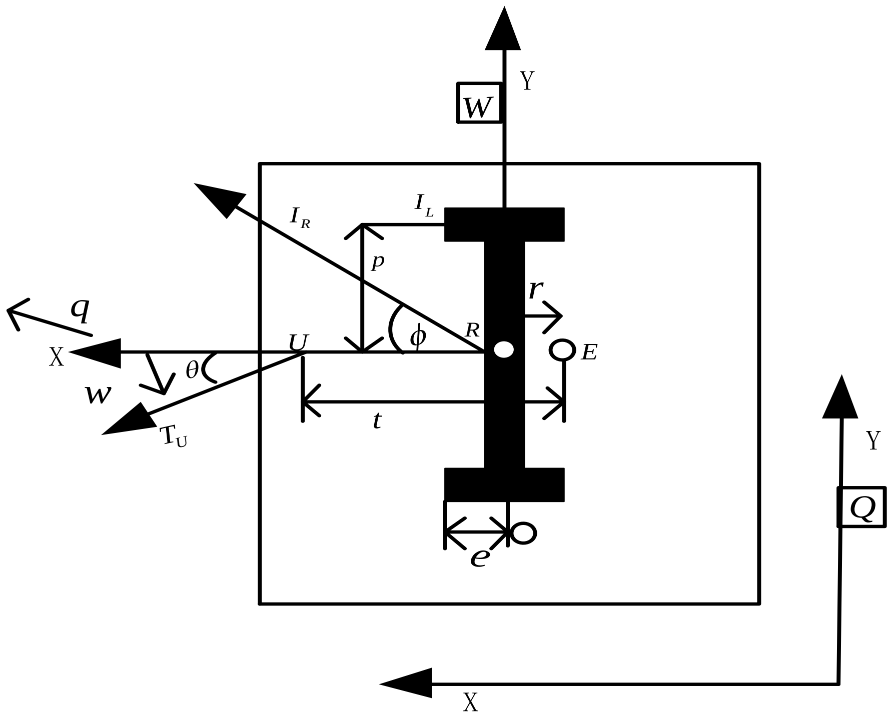


Figure 2. Structure of motion dynamics model

According to Figure 2, Q coordinate system is the global coordinate system, and W is the human kinematics coordinate system. E is the center of gravity of the human. R is the support center of the human.

T_U is the resultant force of the virtual force. U is the acting point of virtual force. q is the linear velocity of the X axis in the W coordinate system. w is the angular velocity of human motion. e is the maximum support point distance of the human. I_R is the linear velocity of the human body moving to the right. I_L is the linear velocity of the human body moving to the left. p is the di-posture from the human to the global coordinate system. t is the distance from the center of gravity of the human to the virtual force acting point U ; r is the distance from the center of gravity of the human to the support center point R .The included angle between the virtual force T_U and the X axis in the human coordinate system W is θ;The included angle between the global coordinate system Q and the X axis in the human coordinate system W is ϕ. Based on this, a motion trajectory description model is constructed to analyze the motion trajectory of defending human motion posture from the perspective of kinematics. Under the action of virtual force, the applied dynamic equation is

$$\begin{cases} \sum T = iU \\ \sum i = O_E \Omega \end{cases} \tag{5}$$

where Ω is the dynamic guidance parameter. T is the module of T_U . i is the weight of the human. O is the inertia of rotation about the vertical axis Y. O_E is the inertia generated under the action of the center of gravity of the human. From this, we can get

$$\begin{cases} \left(O_A + ir^2\right)w - 2irqw + \dfrac{2sp^2}{e}w = T\left(t-r\right)\sin\theta \\ iq + irw^2 + \dfrac{2s}{e}q = T\cos\theta \end{cases} \tag{6}$$

where O_A is the energy generated by rotational inertia. s is the friction coefficient of the motion in the defense trajectory of the human.

Set the r value to zero or small enough to obtain the relationship between body weight and inertia energy as follows:

$$d = \frac{i}{O_A} \tag{7}$$

where d is the ratio of the two. By simplifying formula (7), the linear differential equation is obtained as follows:

$$\begin{cases} q = \dfrac{1}{ie}\left(-2sq\right) + \dfrac{1}{i}T\cos\theta \\ w = \dfrac{p^2}{ie}\left(-2sdw\right) + \dfrac{1}{i}Tdt\sin\theta \end{cases} \tag{8}$$

The human defense state space function is obtained

$$\begin{cases} J = \left(q, w\right)^S \\ g = \left(T\cos\theta, T\sin\theta\right)^S \end{cases} \tag{9}$$

where S represents the defense state of human; g is the spacing coefficient; J is the human defense posture matrix

$$J = \begin{bmatrix} \dfrac{-2s}{ie} & 0 \\ 0 & \dfrac{-2sp^2}{eO_A} \end{bmatrix} J + \begin{bmatrix} \dfrac{1}{i} & 0 \\ 0 & \dfrac{t}{O_A} \end{bmatrix} \begin{bmatrix} T\cos\theta \\ T\sin\theta \end{bmatrix} \tag{10}$$

Through the motion under the action of virtual force, the defense state space equation is deduced as follows:

$$f\left(J\right) = UJ + Gg \tag{11}$$

where G is the spatial coefficient matrix. According to the trajectory state of human defense motion, nano-sensors are introduced to mine its data, and a regular mining process is set.

Defense posture using trajectory coordinate system transformation

According to the motion trajectory description model and the trajectory state transformation of the human motion trajectory coordinate system, the gravity model is used to determine the attraction and repulsion of the defense human, to realize the deep mining of defense posture data.

Set h as the target point of human defense. j is the motion trajectory point of the opponent in the process of defense. The attraction of target points h to the best trajectory of human defense is T_h .The repulsive force of the opponent's trajectory points to defense is T_j .

If there is more than one target point h , there will be more than one attraction is T_{hf} . $f = 1, 2, 3...$ If there are multiple opposing occupation trajectory points, then there will be multiple repulsive gravitational forces are T_{jl} . $l = 1, 2, 3...$

$$T_U = \sum T_{hf} + \sum T_{jl} \tag{12}$$

The magnitude of the attractive force T_{hf} and repulsive force T_{jl} can be obtained by drawing on the universal gravity model [19-20]

$$T = K \frac{iv}{e^2} \tag{13}$$

where in the model of gravity, K is the gravitational constant .The magnitude of the gravitational force on two antagonistic bodies is proportional to the product of their own weights, where v is the weight of the antagonist.

Trajectory data mining by virtual forces [21-22], when the human motion trajectory changes, T_{hf} and T_{jl} will also change, firstly, T_{hf} is defined as follows.

$$\begin{cases} T_{hf} = B, c_{hf} > c_0 \\ T_{hf} = K, 0 < c_{hf} \le c_0 \\ T_{hf} = 0, c_{hf} = 0 \end{cases} \tag{14}$$

where c_{hf} is expressed as the distance between the target point and the initial position of the human. c_0 is a fixed distance.

When $c_{hf} > c_0$, it means that the distance is far, and at this time the attraction of the target point is a constant c . When $0 < c_{hf} \le c$, it means that the farther the target point is, the greater its attraction. When $c_{hf} = 0$, it means that the body reaches the target point and the attraction is 0.

Then, define T_{jl} as follows:

$$T_{jl} = K, c_{jl} > 0 \tag{15}$$

where c_{jl} is the distance between the opponent's personnel and the defense point. The closer the defender is to the opponent, the greater the repulsive force it generates.

Performing data mining of defense human motion trajectories can be calculated by differential solution equations, with velocity w and pinch angle ϕ as unknown parameters.

Set the human to start defending at time n as follows:

$$\begin{cases} w_0(n) = w(n-1) \\ \phi_0(n) = \phi_0(n-1) \\ \phi_0(n) = w_0(n) = w(n-1) = \phi_0(n-1) \end{cases} \tag{16}$$

where ϕ_0 and w_0 are the initial states of the human defense. The virtual force analysis of the human defense above enables the data recording for its defense posture path and obstacle avoidance route.

Through the action of the virtual force T_U , a combined force artifact can be formed in the nano-sensor, and then decomposed and transformed with a split force to mine the defense posture data for analysis. The method process of this paper is shown in Figure 3.

EXPERIMENTAL RESULTS AND ANALYSIS

Experimental environment and Data sets

In the experiment, CPU is i7-8700, memory is 32G, program language is Python 3.6, storage hard disk is SAS model, the number of expandable hard disks is 6, configuration of 542MB Flash array controller. The simulation software is MATLAB 7.2.

Wyscout data set: This dataset describes the details of each ball handling event in multiple one-game matches. The dataset provides a comprehensive description of various sports matches, including tennis, golf, ice hockey, beach volleyball, baseball, handball, basketball, football, volleyball, badminton, softball, cricket, shuttlecock, table tennis, and billiards. Specifically, third-party data companies manually mark each ball handling event from the game footage, such as passes, shots, disposals, scrums, etc., and record the player, time, location (coordinates on the pitch), and other details of the event (e.g., left or right foot used, success or failure). Statistically, Wyscout's data covers 1,941 games, about 3 million events, involving 4,299 players.

YouTube-8M data set: YouTube-8M is a large-scale annotated video dataset comprising over 6 million YouTube video IDs, featuring a diverse range of over 3,800 visual entity labels, including basketball, football, baseball, and rugby. It is equipped with billions of frames and audio clips of pre-computed audiovisual features designed to fit on a single hard drive. Basketball-related video material is retrieved from this dataset, and all video material is consolidated into a new dataset as a way to ensure the smooth execution of subsequent experiments. In the experimental process, the YouTube-8M data set is used as the main dataset, and the defense human motion posture trajectory data mining method is trained according to the preset training groups, while the subsequent experiments are completed using the two datasets to obtain the relevant experimental results.

Nano-sensor data set: This paper uses nano-sensors to collect defensive human posture and motion trajectory data for basketball and football matches. The implementation steps are as follows: (1) Before implanting or wearing the sensors, the subject is physically tested and his/her physical health is assessed to ensure that the installation of the nano-sensors will not cause any serious impact on his/her health. (2) Nano-sensors are installed at different parts of the subject's body as per requirement. For instance, sensors can be installed in muscles, bones, joints, and other areas to obtain more accurate data. (3) Before the data acquisition process, the sensors need to be calibrated and configured to ensure accurate measurements of human posture and motion information. (4) Data can be collected through wearable devices or wireless transmission methods. During the data acquisition process, the subjects should maintain normal activities and movement states while following the instructions of the operators.(5) The data collected by the sensors can be stored in internal storage devices such as chip memory or flash cards. The data can also be transferred to external data processing systems through methods like Bluetooth or Wi-Fi. (6) The results can be fed back to the operators through external devices such as computers, smartphones, or tablets.

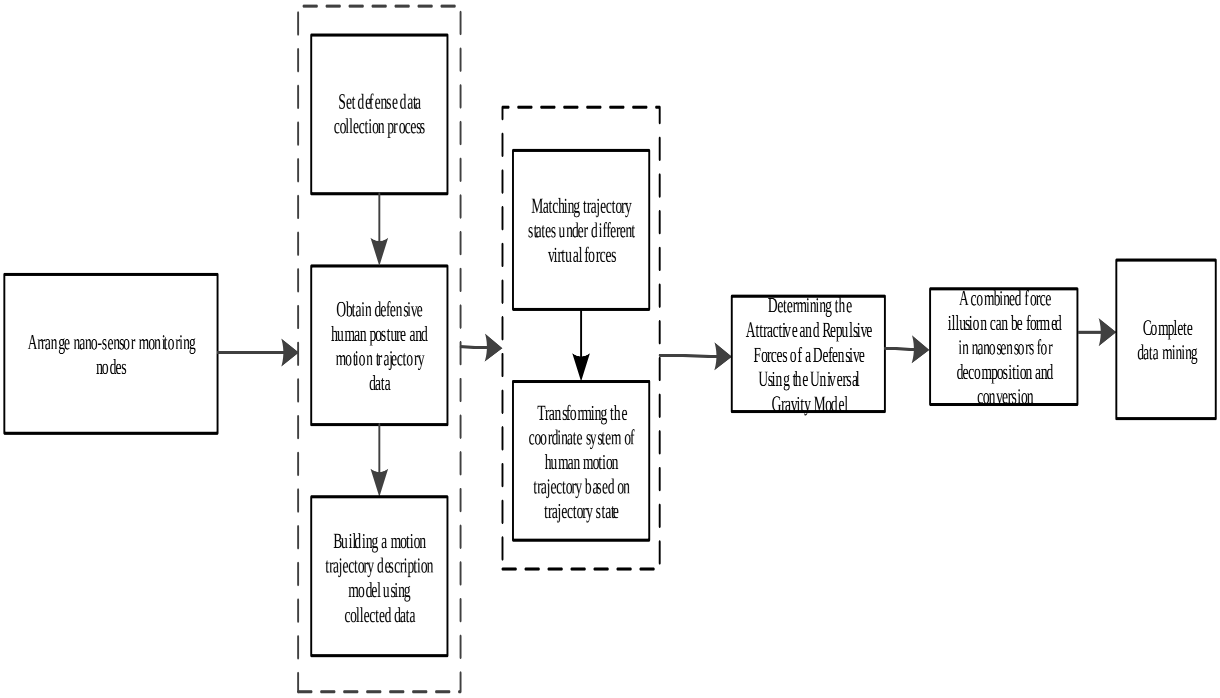


Figure 3. The method process of this paper

After the dataset is configured, it is divided into two parts: a training set and a test set. The Wyscout public dataset includes 800 images as the training set and 200 images as the test set. The YouTube-8M dataset consists of 4600 images for training and 400 images for testing. The nano-sensor dataset includes 1840 images for training and 160 images for experimentation. This subset of data serves as the experimental foundation, and the experimental process is conducted using both datasets. Data filtering and cleansing procedures are applied to the datasets. In the processing of posture and motion trajectory data, interpolation methods such as linear interpolation or spline interpolation are commonly employed to handle missing values. In human posture and motion trajectory data, outliers typically represent unreasonable or erroneous data. Statistical methods are used to remove outlier data for data filtering and cleansing purposes. A learning rate is 0.53, maximum simulation duration is 5s, and maximum step size is set for the experiments. During the experimental process, the defensive human posture and motion trajectory data mining method is trained using these three experimental datasets according to the designated training groups. Subsequently, the two datasets are utilized for follow-up experiments to obtain the relevant experimental results.

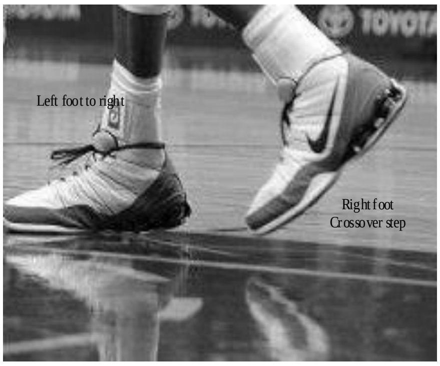
To ensure the experimental data has reliable reference value, basketball game videos from three datasets were selected as samples for mining human posture and motion trajectory data. Multiple male individuals with acceptable basketball skills were chosen as references, and their defensive postures during the games were statistically analyzed. The basketball game action features are shown in Table1.

Table 1. Basketball game action features

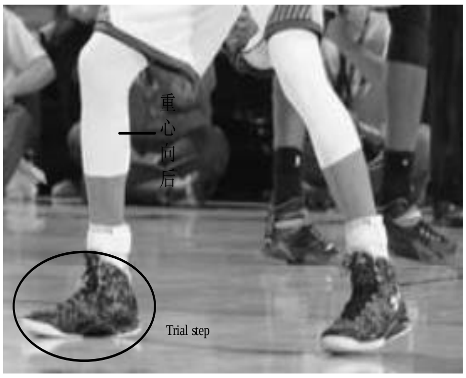
Features	Wyscout data set	YouTube-8M data set	Nano-sensor data set
Backward step	25	26	25
Crossover step	53	72	42
Trial step	13	16	25
Jump step	81	56	23
Side slide step	23	18	15

According to the contents of Table 1, five classical footsteps were selected as defense postures, which are: backward step, crossover step, trial step, jump step and side slide step. The live posture display is shown in Figure 4.

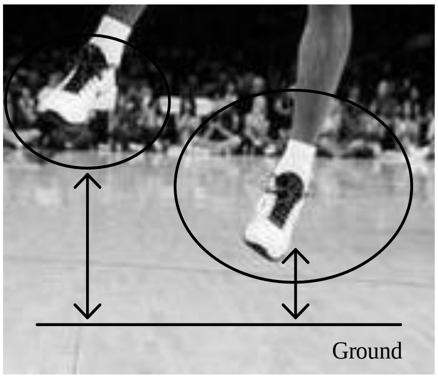
(a) Backward step



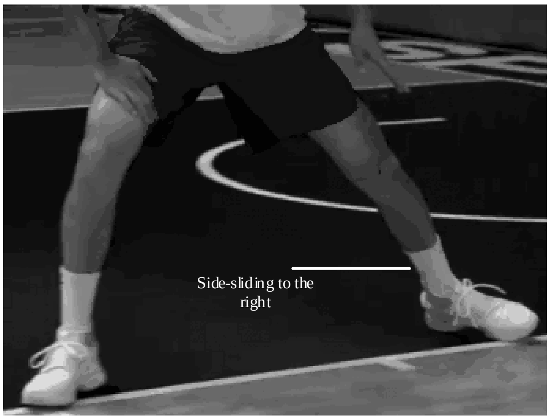
(b) Crossover step



(c) Trial step



(d) Jump step



(e) Side slide step.

Figure 4. Basketball game defense posture footwork

According to the data in Figure 4, the images in the game video were counted separately to ensure that the same defense posture could appear more than 15 times in the game. After the statistics were finished, all the above five postures met the test requirements, and the number of times was set for each posture, with 50 sets of steps for each group as the original mining data. Comparisons were made by the six groups of methods selected, respectively.

Evaluation Metrics

The result of defense posture classification: the more backward, crossover, trial and jump steps and side slide step s are identified by the classification, the better the classification is.

Defense posture recognition accuracy: To compare the accuracy of different methods more specifically, the above data sample is still used as an example to calculate the recognition accuracy by classifying the results of each posture, and the formula is

$$T_{\varsigma}=\frac{Z(A)}{F(A)}\times 100\% \tag{17}$$

where T_{ς} is the accurate recognition. $Z(A)$ is the number of correctly classified poses. $F(A)$ is the overall sample data volume.

Recall: The ratio of the relevant amount of defense human motion posture trajectory information p_i to the total amount p_j detected from the database, which is calculated by the following formula.

$$P=\frac{p_i}{p_j}\times 100\% \tag{18}$$

Precision: the percentage of the detected relevant defense human motion posture trajectory information r_i and the detected total methods r_j. The calculation formula of this index is as follows:

$$R=\frac{r_i}{r_j}\times 100\% \tag{19}$$

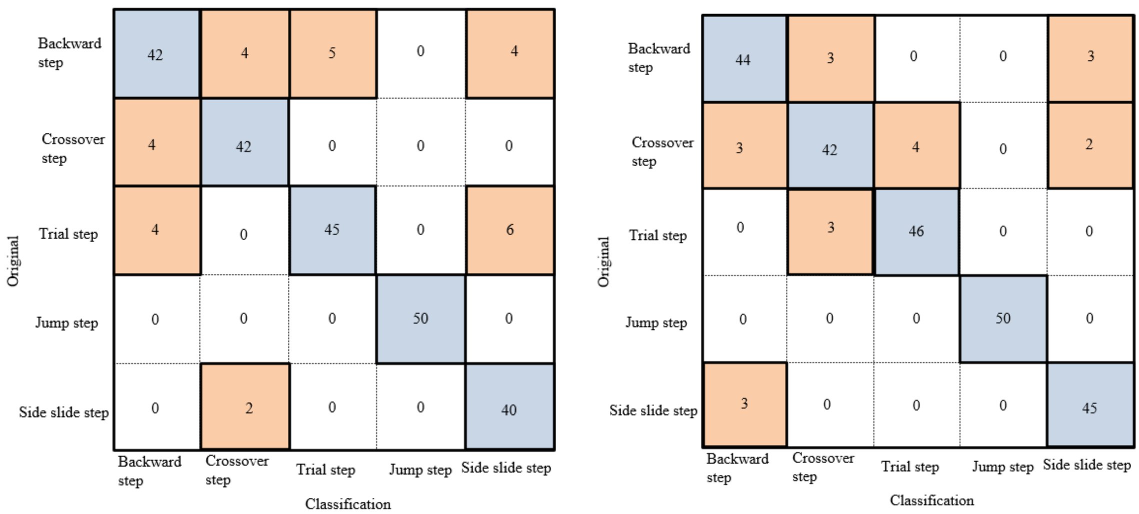
Data mining time: data mining time refers to the time consumed to complete the data mining of defense human motion posture trajectory. The calculation formula of this index is as follows:

$$T=\sum_{i=1}^{N} t_i \tag{20}$$

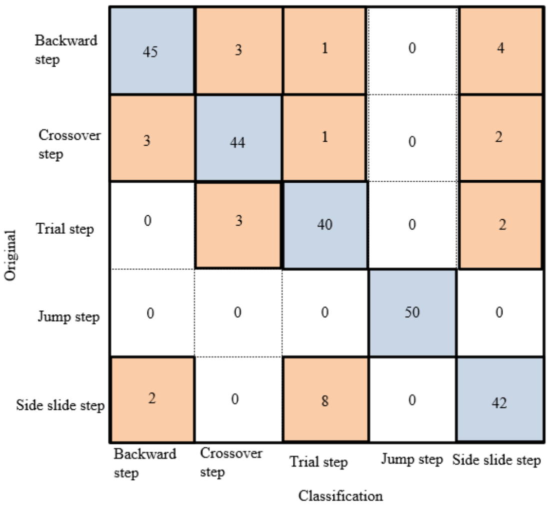
where t_i denotes the time spent for the i th defense human motion posture trajectory data mining step. N denotes the total number of steps.

RESULTS AND DISCUSSION

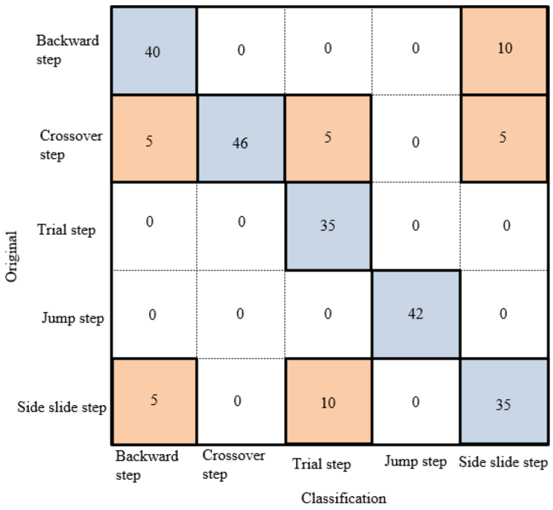
The statistical data were uploaded into the MATLAB test platform, and six groups of methods were connected in turn, while a confusion matrix was established to compare the classification results of defense posture under different methods, as shown in Figure 5.



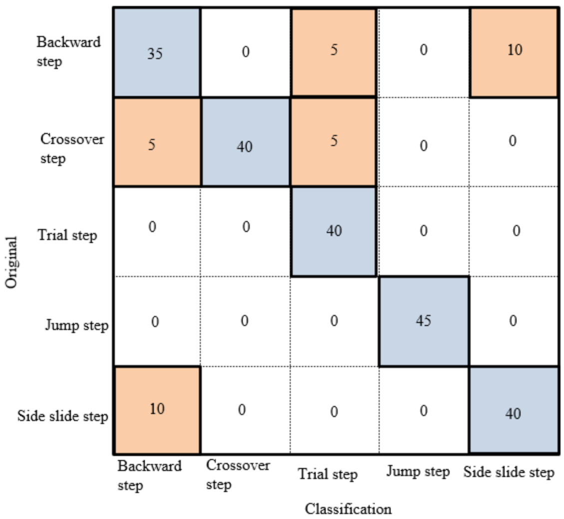
(a) ATTS[4] method (b) DMPL[5] method



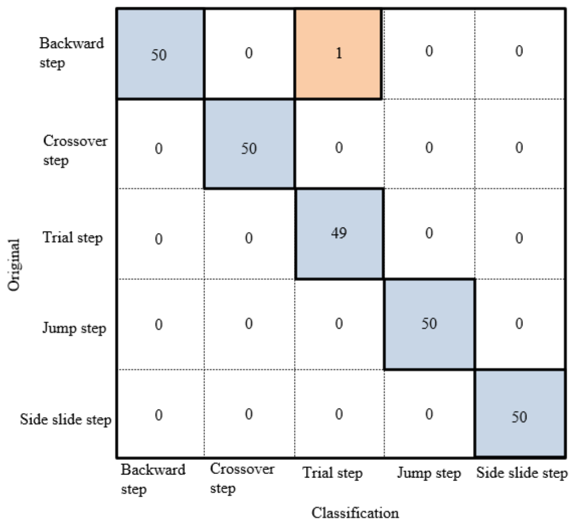
(c) OATPP[6] method



(d) DMMSD[7] method



(e) ODMM[8] method



(f) Proposed method

Figure 5. Comparison of defensive posture footwork in basketball

As seen in Figure 5, the proposed method only has confusion in the trial step and the number of groups is one, which shows a small statistical bias, while other classification data such as pose are consistent with the original data. While the methods of ATTS [4] and DMPL [5], as well as the method of OATPP [6], accomplished accurate classification only in the jump step, without the mixing of other poses, all other poses showed classification bias. In contrast, the methods of DMMSD[7] and ODMM[8] showed classification errors and a high number of misclassifications in the backward step and side sliding steps and in the trial step, and did not complete the full number in the remaining defense posture classification. The comprehensive results show that the five groups of traditional methods have the problems of missing data and classification confusion in the classification process, which lead to the inconsistency between the total number and the original number of poses, and the proposed method has no missing phenomenon and less number of classification confusion, which is more valuable for application.

According to the formula (17) for calculation, the results of defense posture recognition accuracy calculation are shown in Table 2.

Table 2. Comparison of defense posture recognition accuracy (%)

Number of experiments	ATTS[4] method	DMPL[5] method	OATPP[6] method	DMMSD[7] method	ODMM[8] method	Proposed method
10	82	84	89	83	71	98
20	84	90	84	92	90	97
30	84	92	80	84	86	99
40	90	88	75	73	82	98

50	80	90	88	77	85	99

According to Table 2, it can be observed that there are variations in the recognition accuracy among different methods. The minimum recognition accuracy of the proposed method is 97%. The method in ATTS [4] has a minimum recognition accuracy of 80%, while the method in DMPL [5] achieved a minimum recognition accuracy of 84%. For the method in OATPP [6], the minimum recognition accuracy is 75%, and DMMSD [7] is 73%, while ODMM [8] method is 71%. The recognition accuracy of the proposed method is 17% higher than that the method in ATTS [4], 13% higher than DMPL [5], 22% higher than OATPP [6], 24% higher than DMMSD [7], and 26% higher than ODMM [8]. These results demonstrate that the defensive posture recognition accuracy of the proposed method is higher, indicating favorable practical application outcomes. The reason for this is that the method uses the gravity model to determine the attraction and repulsion of the defending human as a way to achieve deep mining of the defensive posture data, which enables the data type to be determined during the data mining process, and therefore the classification accuracy of the method is high.

The recall comparison of the data mining results of the defense human motion posture trajectory is shown in Figure 6.

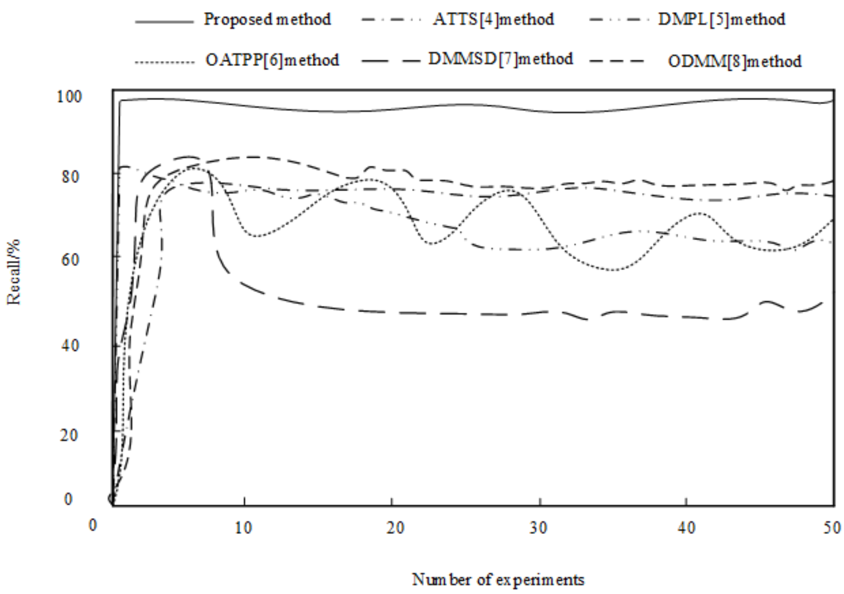


Figure 6. Comparison of recall

According to the data in Figure 6, it can be seen that with the increase in the number of experiments, the recall of the data mining results of the defense human motion posture trajectory of different methods is the highest among the six methods, that is, 97%, which is 19% higher than the method in ATTS[4], 22% higher than the method in DMPL[5], 16% higher than the method in OATPP[6], 14% higher than the method in DMMSD[7], and 12% higher than the method in ODMM[8], It shows that the data mining results of the defense human motion posture trajectory of the proposed method have higher recall and more comprehensive data mining results.

The precision comparison of the data mining results of defense human motion posture trajectory is shown in Table 3.

Table 3. Comparison of precision (%)

Number of experiments	ATTS [4] method	DMPL [5] method	OATPP [6] method	DMMSD [7] method	ODMM [8] method	Proposed method
10	68	82	83	81	91	98
20	69	86	84	83	89	96
30	78	85	75	84	86	97
40	75	87	76	75	82	98

50	74	88	71	76	84	95

According to the results in Table 3, it can be seen that with the increase in the number of experiments, the precision of the data mining results of the defense human motion posture trajectory of different methods is the highest among the six methods, that is, 98%, which is 20%, 10%, 14%, 14% and 7% higher than that of the methods in ATTS[4], DMPL[5], OATPP[6], DMMSD[7] and ODMM[8], respectively, indicating that the precision of the proposed method is the highest, the accuracy of data mining of defense human motion posture trajectory is higher. The reason is that the method uses nano-sensors to monitor the nodes to obtain the defense human posture motion trajectory data, using the gravity model to determine this to achieve the defense posture data depth mining. Therefore, the data mining results are more accurate.

The results of defense human motion posture trajectory data mining time comparison of six methods are shown in Table 4.

Table 4. Comparison of data mining time (ms)

Number of experiments	ATTS [4] method	DMPL [5] method	OATPP [6] method	DMMSD [7] method	ODMM [8] method	Proposed method
10	261	235	155	156	135	56
20	215	247	163	123	136	54
30	148	256	147	147	158	58
40	159	266	152	110	166	53
50	163	281	169	163	96	52

The results in Table 4 show that with the changing number of experiments, the mining time of different methods all show a fluctuating trend, among which the minimum value of data mining time of defense human motion posture trajectory of this method is 52ms, which is the lowest among the six methods, 96ms lower than the method of ATTS[4], 183ms lower than the method of DMPL[5], 95ms lower than the method of OATPP[6], 58ms lower than the method of DMMSD[7], and 44ms lower than the method of ODMM[8], indicating that the data mining time of this method is shorter and more efficient. The reason is that the method uses the data collected by the nano-biosensors to build a motion trajectory description model to match the trajectory state under different virtual forces, to realize the depth mining of the defensive posture data, the method execution efficiency is high and the mining time is short.

Table 5. Comparison Results of F1 score, sensitivity, ROC, MRR, DCG, NDCG, and NAE

Method	F1 Score	Sensitivity	ROC	MRR	DCG	NDCG	NAE
Proposed	0.92	0.88	0.94	0.82	0.87	0.85	0.041
ATTS[4]	0.88	0.84	0.91	0.75	0.81	0.78	0.054
DMPL[5]	0.85	0.78	0.89	0.69	0.76	0.72	0.062
OATPP[6]	0.90	0.86	0.92	0.78	0.84	0.81	0.049
DMMSD[7]	0.87	0.81	0.90	0.73	0.79	0.75	0.057
ODMM[8]	0.82	0.74	0.88	0.65	0.72	0.68	0.065

The calculation results of F1 Score, Sensitivity, Receiver Operating Characteristic (ROC), Mean Reciprocal Rank(MRR), Discounted Cumulative Gain(DCG), Normalized Discounted Cumulative Gain (NDCG) and Normalized Absolute Error (NAE) for the proposed method and other methods are shown in Table 5.The proposed method achieves an F1 score of 0.92, outperforming ATTS[4] (0.88), DMPL[5] (0.85), OATPP[6] (0.90), DMMSD[7] (0.87), and ODMM[8] (0.82). This indicates that the proposed method has the highest balance between precision and recall in classifying defensive postures. With a sensitivity score of 0.88, the proposed method performs better than ATTS [4] (0.84), DMPL [5] (0.78), OATPP [6] (0.86), DMMSD [7] (0.81), and ODMM [8] (0.74). It shows the ability of the proposed method to capture a higher proportion of positive instances for defensive postures. The proposed method achieves the highest ROC score of 0.94 compared to ATTS [4] (0.91), DMPL5] (0.89), OATPP6] (0.92), DMMSD [7] (0.90), and ODMM [8] (0.88). This indicates that the proposed method has better discrimination power in distinguishing between positive and negative instances of defensive postures. With an MRR score of 0.82, the proposed method outperforms ATTS [4] (0.75), DMPL [5] (0.69), OATPP [6] (0.78), DMMSD [7] (0.73), and ODMM [8] (0.65). It suggests that the Proposed method has a higher capability of correctly ranking the defensive postures. The proposed method achieves higher scores in both DCG (0.87) and NDCG (0.85) compared to ATTS [4] 0.81), DMPL [5] (0.76), OATPP [6] (0.84), DMMSD [7] (0.79), and ODMM [8] (0.72). This signifies the proposed method ability to accurately rank the importance of defensive postures. The proposed method exhibits the lowest NAE score of 0.041, indicating better accuracy in predicting defensive postures compared to ATTS[4] (0.054), DMPL[5] (0.062), OATPP[6] (0.049), DMMSD[7] (0.057), and ODMM[8] (0.065). In summary, the proposed method outperforms the other methods in terms of F1 score, sensitivity, ROC, MRR, DCG, NDCG, and NAE. It demonstrates a higher balance between precision and recall, improved capture of positive instances, better discrimination power, accurate ranking of defensive postures, and higher prediction accuracy. These results highlight the superiority of the proposed method in the analysis of defensive human posture motion trajectory data, with potential applications in tactical planning and sports competitions.

CONCLUSIONS

The data collection task of the nano-sensor is set, and the energy consumption index is assigned at different nodes to calculate the attractive and repulsive forces generated during human defense, and the data mining method design of the motion trajectory is completed. The results show that the proposed method only has confusion in the trial step, and the number is one group, and there is a small statistical deviation, while the classification data of other postures are consistent with the original data. The total recognition accuracy rate of defense posture is 97%, the recall of data mining results of defense motion posture trajectory is 97%, the precision rate is 98%, and the mining time of defense motion posture trajectory data is 53ms. It can achieve the goal of accurately and quickly mining the trajectory of human defense motion. With only two groups of sensors, the data collection and monitoring capabilities are limited. This may result in incomplete or biased data, as the entire target area may not be adequately covered. Lack of comprehensive coverage could potentially lead to inaccurate or incomplete mining results. In the future research will be conducted on the arrangement of the nano-sensor network to consider the problem of data compression in the network and provide new ideas for accurate mining.

Conflicts of Interest: The authors declare that there is no conflict of interest with any financial organizations regarding the material reported in this manuscript.

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