Gesture interactive recognition method of moving equipment based on virtual reality technology

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Abstract: The existing interactive recognition methods for gesture recognition of moving equipment have poor recognition effect and low recognition accuracy, which lead to some limitations of gesture interactive recognition. Therefore, a gesture interactive recognition method for moving equipment based on virtual reality technology is proposed. Firstly, we collect and divide the hand gesture features of sports equipment, analyse the common hand gesture categories of sports equipment, and use virtual reality technology to pre-process the hand gesture interactive recognition data of sports equipment. After pre-processing, we complete the hand gesture interactive recognition of sports equipment based on virtual reality technology. The experimental results show that the accuracy of gesture recognition is more than 95%, and that of complex gesture recognition is more than 93%. Compared with the existing gesture recognition methods, this method has higher effectiveness and recognition accuracy, which fully meets the research requirements.

Keywords: virtual reality; sports equipment; gesture interaction; gesture recognition.

Reference to this paper should be made as follows: Shen, Y. (2023) 'Gesture interactive recognition method of moving equipment based on virtual reality technology', *Int. J. Product Development*, Vol. 27, Nos. 1/2, pp.15–27.

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1 Introduction

In computer science, gesture interaction recognition is a mathematical algorithm used for gesture recognition (Aslam and Samreen, 2020). Gesture interaction recognition is derived from the movement of various parts of the human body, but usually refers to the movement of the face and hands. Users can use simple gestures to control or interact with the device in such a way that the computer can understand the human behaviour. The gesture interaction recognition method has received increasing attention in the current design of sports watches and other related devices. It can accurately recognise human motion behaviours and gesture movements. At present, the research on gesture interaction recognition of sports devices mainly focuses on the field of computer vision, and gesture action recognition based on wearable sports devices has gradually become a hot content of current research. However, the accuracy of gesture recognition is not high enough to meet the user's demand for the recognition effect of wearable sports devices.

In Li et al. (2020), a gesture recognition system based on smart phone is proposed. Nexmon firmware is used to obtain 256 CSI subcarriers from the bottom layer of smart phone in 80 MHz bandwidth and IEEE 802.11ac mode. Cross correlation method is used to fuse the extracted CSI features in time domain and frequency domain, and then the improved DTW algorithm is used to classify and recognise gestures, but the recognition accuracy is not high. In Zhang et al. (2019), a real-time gesture recognition model based on surface EMG signal is proposed. The sEMG signal is extracted, and the sliding window method is used to extract the data features. A gesture recognition model based on training set is established, and the neural network is used for gesture recognition. This model effectively realises the real-time gesture recognition, but the recognition effect of this model is poor. Du et al. (2020) proposed a real-time gesture recognition method based on heartbeat signal. Two way long-term and short-term memory (BILSTM) network is used to learn HR features, and Convolution Neural Network (CNN) is used to learn finite element features. However, this recognition method can only recognise facial emotions, which can achieve real-time gesture recognition to a certain extent, but the overall real-time gesture recognition needs to be further optimised. However, the above three methods still have the problems of poor differentiation effect and low recognition accuracy, which leads to the limitation of gesture recognition.

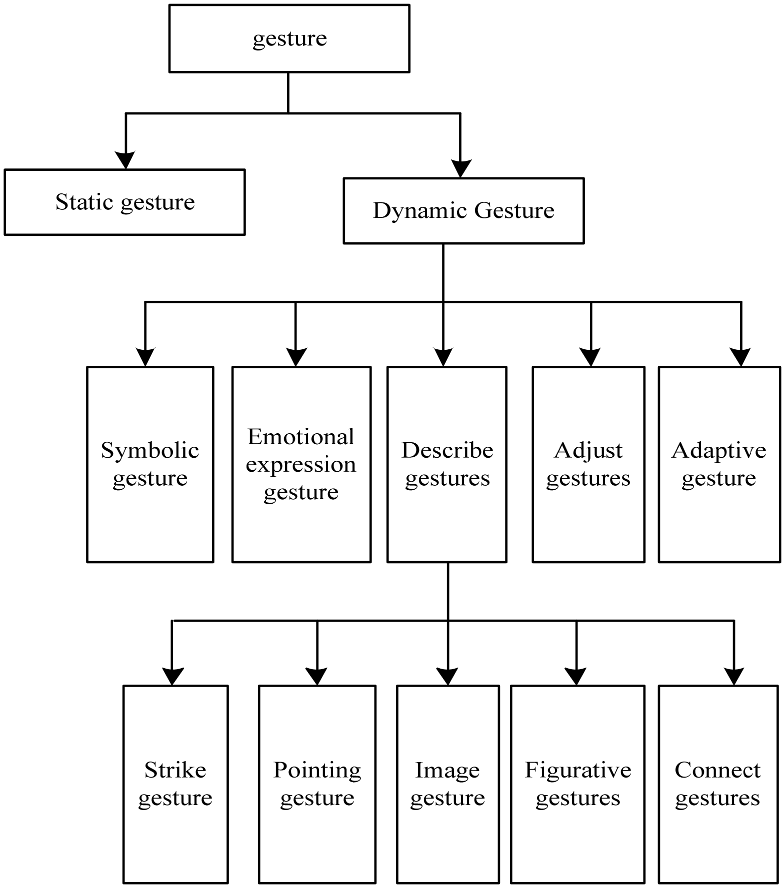
In view of the above problems, this paper proposes a gesture recognition method based on virtual reality technology for sports equipment.

2 Motion device gesture interaction recognition method

2.1 Motion device gesture feature categories

In the process of performing gesture interaction recognition of motion devices, data acquisition and display processing are mainly performed through virtual reality and graphics and other related technologies. Based on the data acquisition and display images, accurate recognition and effective analysis of the dynamic changes in human limbs is carried out, due to the rapid and complex changes in human hand movements. Therefore, in the process of recognition, it is first necessary to transform the gesture recognition command, so as to realise the data processing of gesture motion interaction information. In order to effectively guarantee the gesture recognition effect of sports equipment, it is necessary to further analyse the trajectory of sports gesture changes and interaction characteristics, and to divide the common gesture categories based on the gesture characteristics data collection results, so as to effectively improve the accuracy and interaction performance of gesture interaction recognition. Combined with virtual reality technology, the categories of motion gesture features are divided as shown in Figure 1.

Figure 1 Classification of motion gesture characteristics



The motion gesture feature classification based on Figure 1 is modelled to determine the gesture changes (Hasanudin et al., 2021). Based on the existing gesture feature modelling method, the feature structure, boundary, feature vector and other relevant parameters of the recognition image are collected and the gesture interaction recognition is performed with the hand image change and motion trajectory as Martinez-Gonzalez et al. (2020). Suitable gesture feature recognition models are selected according to the application requirements, as shown in Figure 2.

The hand gesture feature recognition model in Figure 2 can recognise the trend of hand external morphological changes through virtual reality technology, which has the advantages of simple operation, small computation, fast computing speed and real-time detection (Javan et al., 2020). Usually, the recognition of motion devices can be more limited due to the diverse gesture changes (Schffer et al., 2021). Based on this, the 3D gesture modelling of the gesture interaction image is further combined with virtual reality technology to ensure the spatial dimension of the image, extract the gesture change detection parameters, and pre-process the extracted feature vectors for trajectory similarity calculation, as shown in Figure 3.

Figure 2 Hand gesture feature recognition model

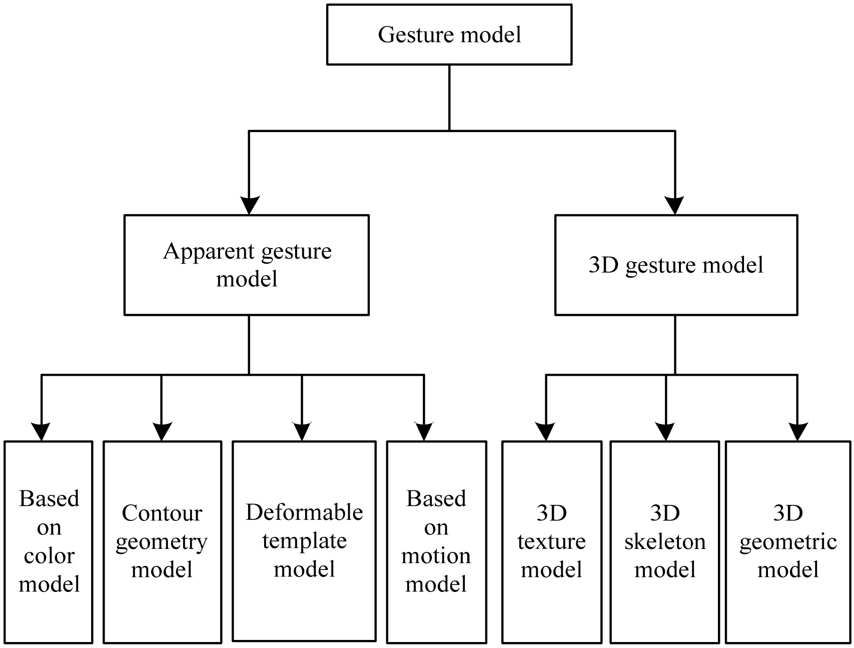
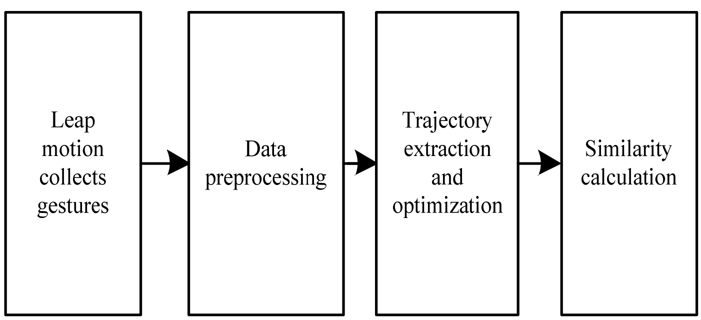


Figure 3 Gesture trajectory recognition process



The gesture trajectory recognition process based on Figure 3 further optimises the gesture interaction recognition method by detecting the gesture change trend through sensors and capturing the gesture images to obtain the information of fingertip position, finger centre position, fingertip speed and other related parameters to achieve the capture of finger movement and change features (Wan et al., 2021). On this basis, the gesture feature vector information is normalised, and the specific information is shown in Table 1.

Table 1 Gesture feature vector information

Attribute	*Significance*
tip position	Fingertip coordinates
tip velocity	Fingertip speed

Since the gesture recognition of motion devices is somewhat random and contains many abnormal data, data cleaning is required and the validity of the cleaned gesture feature change trajectory is judged. In this way, the smoothness of the image is ensured (Balducci et al., 2020).

2.2 Motion device gesture motion trajectory recognition algorithm

In the study of gesture images, first of all, a comprehensive acquisition and segmentation of gesture images is required. The length of the five fingers from the centre outward is set to 0 to obtain the new dynamic feature values of the gesture and normalise them (Wang et al., 2019). In the gesture recognition process, the acquisition rate of feature information is r, the common feature is z and the gesture feature acquisition and detection times are t_1 and t_2, respectively, then the numerical algorithm for the simulation specification of gesture recognition is

$$L = \bigcup z * \lim_{0 \to \infty} \frac{t_1 - t_2}{2r} \tag{1}$$

After the specification of the values of gesture recognition, the virtual reality processing platform for gesture recognition needs to be optimised for simulation modelling of gesture feature images of sports equipment using the principle of inverse distance weight calculation. If the weight value is x and the discrete value is n, the standard display algorithm for the gesture space of the motion device is

$$L(1+x)^n = \text{rule} : L\left[1 + \frac{x}{1!} + \frac{2(n-1)x^2}{2!} + \ldots + \frac{n(n-1)x^n}{n!}\right] \tag{2}$$

The interface interaction mode is improved and optimised in the virtual environment, mainly combined with visual perception technology for virtual display. w denotes privileged value stability information, h denotes the image transformation data weights in the 3D virtual simulation platform, and u is the pixel resolution of the virtual platform display image (Yang et al., 2021). q denotes the highest inverse distance coefficient of the 3D image in the platform interface. h denotes the inventory in the virtual display process visual colour difference, and z_i denotes the bracketing difference of the virtual display. Then, the discrete equation of the collected data scale code is

$$\varpi = \sum \sum \left[\frac{1}{2w} \lim_{0 \to \infty} L(1+x)^n - h\right]^2 - u * (q + z_i) \tag{3}$$

On the basis of the above, the gesture interaction interface of the motion device is displayed and processed, and the feature image interference cleaning is carried out in combination with virtual reality technology. It is assumed that n factors interfere in the process of gesture recognition, and the interference degree can be written as $x_i\,(i = 1, 2, 3, \ldots, n)$, if the interference mixture value of image recognition is $s_i\,(i = 1, 2, 3, \ldots, n)$, then the anti-disturbance algorithm of gesture recognition can be written as

$$x = \varpi \sum \sum s_i + x_i \tag{4}$$

Scaling and shifting of gesture feature change data is performed based on the above calculation results. Hand gesture state attributes are used for fast recognition of hand images so as to effectively characterise each pixel of digital images, and image pixel matching is performed after obtaining image feature frames. The dynamic gesture similarity is calculated by judging the dynamic gesture digital image noise data. The specific formula is

$$P = \mathrm{x}\sum_{n=1}^{m} \omega_n f_n(x) \tag{5}$$

In the above equation m is the gesture change information. X it's the increment of motion. ω_n is the weight. $f_n(x)$ is the time series. Further, HMM gesture recognition and probabilistic model analysis are used to describe the transformation of gesture change characteristics in different states. If the initial state is $\lambda = (x, O, a, B, \pi)$. Then, the gesture change trajectory under different time changes is $\lambda = (\pi, A, B)$. Based on this, the motion trajectories are further compared in the 3D gesture space, and the similarity effects of the *X*-axis, *Y*-axis and *Z*-axis data changes are analysed to calculate the gesture weighting parameters with the following equations:

$$d_{ab} = P\sqrt{\lambda(x_a - x_b)^2 + \gamma(y_a - y_b)^2 + \delta(z_a - z_b)^2} \tag{6}$$

Within the effective threshold range of gesture feature classification samples, the sample size is calculated by the following equation:

$$D_{TP_{k1\leqslant k\in L}} = \sum_{i=1}^{N} \sqrt{(x_i(t) - x_i(p))^2 + (y_i(t) - y_i(p))^2 + (z_i(t) - z_i(p))^2} \tag{7}$$

In the above equation t represents the total calculation time. p indicates the peak value of velocity wave. On this basis, the effective threshold of gesture feature classification samples is calculated, and the formula is as follows:

$$Ed = \frac{1}{L}\sum_{k=1}^{L} D_{TP_k} d_{ab} \tag{8}$$

Based on this, the different gesture features are further segmented so as to effectively reduce the recognition difficulties. The following non-linear mapping function is obtained.

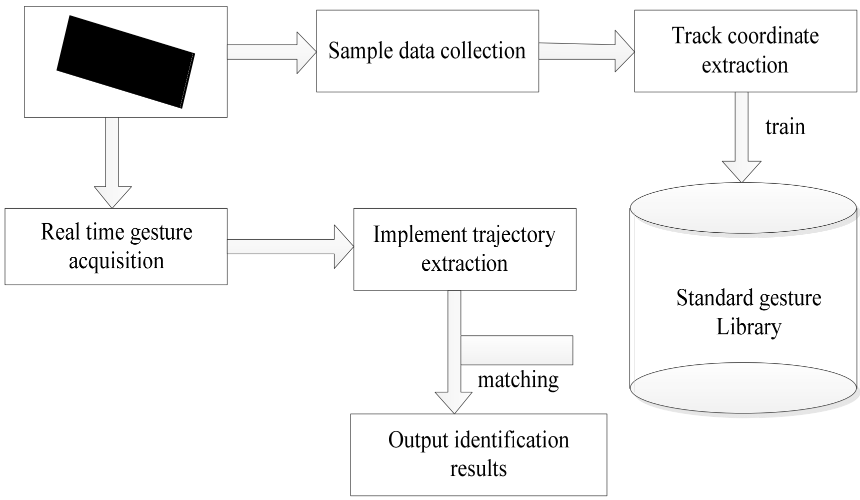
$$y = \exp Ed\left[-(W_i - X)^t (W_i - X)/2a^2\right] \tag{9}$$

where W_i denotes the privilege value and a denotes the image segmentation threshold. Based on the above algorithm, trajectory recognition and image denoising can effectively guarantee the gesture recognition effect and improve the recognition accuracy.

2.3 Implementation of interactive recognition of motion devices

The key of interactive recognition of moving devices is to obtain and judge the starting and ending position of gesture motion trajectory, which is used as the recognition threshold. To guarantee the transformation of gesture change data acquisition at the starting point, the gesture recognition process is optimised through gesture training. The specific steps are shown in Figure 4.

Figure 4 Gesture recognition training process



Based on the above training process, the gesture data feature acquisition recognition is performed to read the accelerated data of gesture changes during the motion process. The solution process is as follows: when the motion device is at rest the output value is $\vec{a}_o = \begin{bmatrix} 0 & 0 & g \end{bmatrix}$

where g denotes the acquisition data, the motion device measurement value in the motion state is set to: $\vec{a}_t = \begin{bmatrix} a_x & a_y & a_z \end{bmatrix}$, and the gesture change posture angle is calculated as follows:

$$\theta = \text{arc}\,\text{y}\sin \vec{a}_o - \vec{a}_t \tag{10}$$

The trajectory of the change is as follows:

$$\gamma = \arcsin\left(\frac{a_y}{g\cos\theta}\right) \tag{11}$$

Based on the change trajectory, the gesture change information $\vec{m}_t = \begin{bmatrix} m_x & m_y & m_z \end{bmatrix}$ is obtained, which is further calculated to obtain

$$\psi = \arctan\frac{m_y\cos\gamma + m_z\sin\gamma}{m_x\cos\theta + m_y\sin\theta\sin\gamma - m_z\cos\theta\sin\gamma} \tag{12}$$

Based on the above algorithm, the gesture motion coordinates are further displayed interactively. In order to facilitate gesture interactive recognition processing and effectively reduce the amount of computation, it is necessary to further segment the recognition image and detect the gesture. Based on the gesture shape and colour for feature description, the recognition parameters are processed for specification, and the specific hand detection indexes are shown in Table 2.

Table 2 Hand posture self-adaptive change detection index

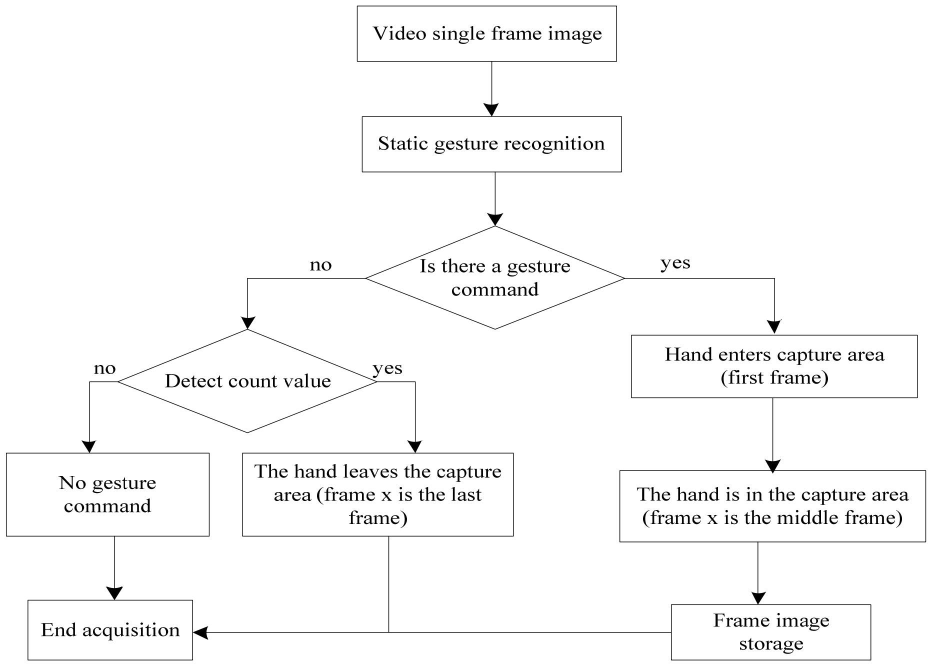
Method	*Advantage*	*Detection rate*	*Detection speed*
shape	Good robustness to skin colour and light changes	higher	The amount of calculation is large and the calculation speed is slow
skin colour	The method is simple and not affected by the change of gesture shape.	The detection rate is related to the complexity of the background and the skin colour of the background	The calculation is less and the speed is faster
Combination of shape and skin colour	This method improves the robustness of hand detection.	The detection rate is improved	The amount of calculation is reduced
Optical flow method	Comprehensive scenario information is available	higher	High computational complexity and fast detection
Inter frame difference method	This method is simple and easy to implement.	Low precision of moving target detection	Less calculation and faster detection
Background difference method	This method is simple and easy to implement	The method can detect moving objects completely	Less calculation and faster detection

In the case of finger immobility, the coordinate position of the finger is unchanged and further in the case of Euclidean distance of 60, tracking detection and feature recognition are performed for the change of hand adaption. The specific recognition steps are shown in Figure 5.

The optimised gesture interaction recognition steps for motion devices in Figure 5 can quickly and accurately identify rapid research target gesture changes in complex environments to fully meet research requirements.

Based on virtual reality technology, a gesture recognition method in mobile devices is proposed. Firstly, the characteristics of gesture of sports equipment are collected and divided, and the classification of common sports equipment gesture is analysed. The recognition data of gesture interaction of sports equipment is pre-processed by virtual reality technology. On this basis, the virtual reality technology is used to recognise the motion equipment gesture.

Figure 5 Optimisation of gesture interaction recognition steps



3 Testing experiments

3.1 Experimental protocol

In this paper, by Strictly Standardising the experimental parameters, under the same experimental environment, the simulation experiment is designed and compared with the traditional method, which improves the accuracy and reliability of the simulation experiment. In order to verify the practical application effect of gesture recognition method for sports equipment based on virtual reality technology, a 64 bit processor, 8GB memory and $D \times 11$ graphics card are selected as the experimental test environment. In order to improve the accuracy of the experimental results, the method in this paper is compared with the methods in Li et al. (2020); Zhang et al. (2019) and Du et al. (2020)

3.2 Experimental data

In order to verify the accuracy of the experiment, after several iterations, the effective parameters are obtained. The processor of the parameters needs 64 bits, and the built-in sb3.0 bus. In order to ensure the smooth progress of the experiment and provide convenient conditions for the subsequent experimental data collection, the specific experimental configuration parameters are shown in Table 3.

Table 3 Experimental equipment and parameter configuration

Parameter	*Index*
CPU	IntelCore
processor	64 bit
Graphics card	NAIDIA
built-in	USB3.0 bus
OS	WIN8.1

3.3 Performance indicators

Based on the above experimental environment and experimental preparation data, 16 gestures are tested and the performance test indexes are set as gesture detection and recognition, acceleration, posture angle and gesture interaction recognition effect. In the course of the experiment, each gesture should be executed coherently. Based on this, the custom interaction gesture changes in a short time range are processed for data sample training as shown in Table 4.

Table 4 Interactive gesture changes for data training samples

Custom	*Gesture*
Circular motion	Put up a finger in a circular motion
move	Put up two fingers and move in the palm of the hand
rotate	Put up three fingers to form the palm plane and start to rotate
To contract or expand	Erect four fingers to contract or expand
Shake left and right	Raise five fingers and wave, shake left and right
Shaking back and forth	Put up five fingers and shake them back and forth
merge	Five fingers merging

3.4 Testing and analysis of performance indicators

Based on the contents of Table 4, 70 groups of gesture data were randomly selected for comparative detection. Analyse the gesture recognition effect of the traditional method and the method in this paper, and the specific detection results are shown in Table 5.

Table 5 Experimental results of hand gesture detection and recognition

Category	*Traditional method*		*Method of this paper*	
	V gesture	*0 gesture*	*V gesture*	*0 gesture*
Number of tests	50	50	75	81
Number of tests	50	48	86	94
Detection rate	80%	76%	97.2%	96.4%
Number of identifications	50	49	89	92
Recognition rate	70%	88%	97.6%	95.4%

Based on the comparison data in the above table, it can be seen that the gesture recognition accuracy of this paper's method is above 95% compared to the accuracy of the traditionally proposed gesture recognition method. The accuracy is significantly higher. In order to further test the influence of this method on the recognition of attitude change acceleration and attitude angle data, the motion gesture acceleration is tested. The specific test results are shown in Figures 6 and 7.

Figure 6 Motion gesture acceleration data

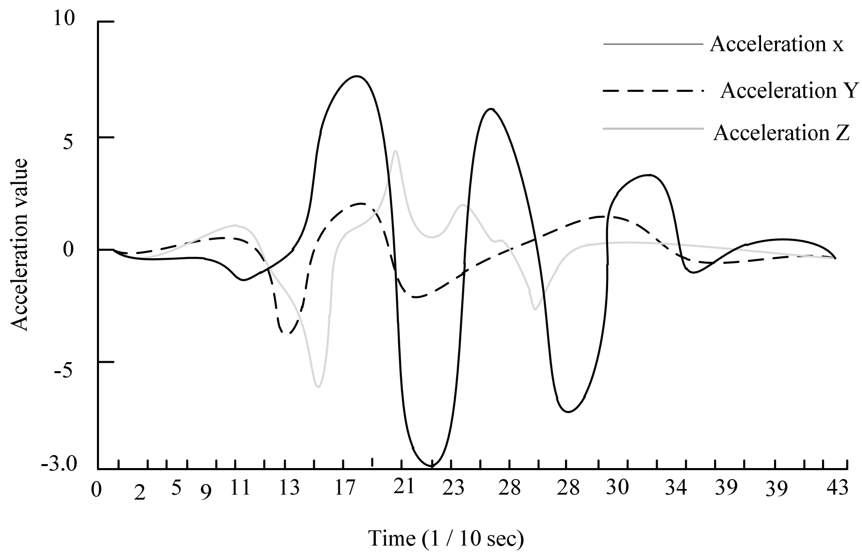
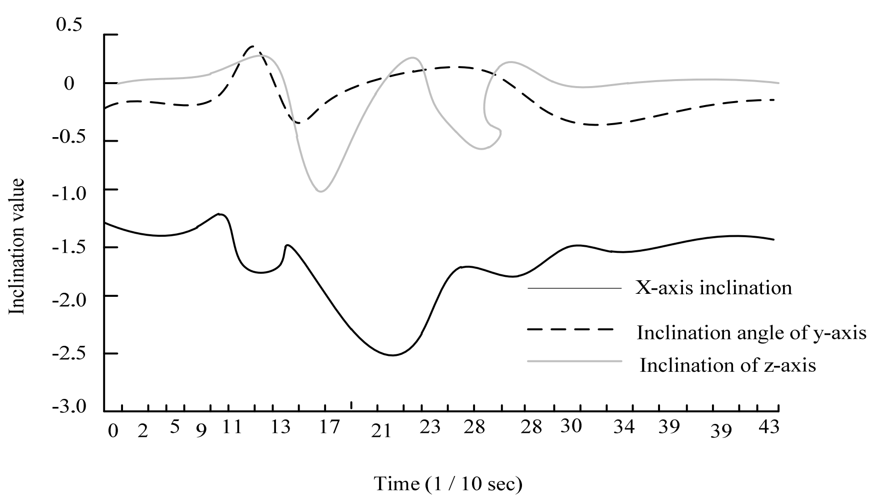
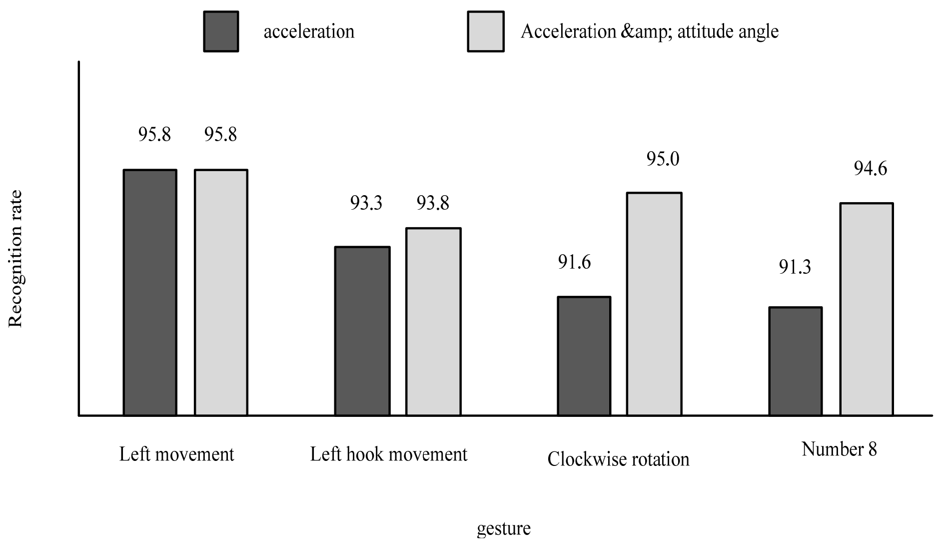


Figure 7 Motion gesture posture angle data



The experimental results above show that the method in this paper is effective in detecting the recognition of gesture change acceleration and the effect of gesture posture angle data recognition. It can be better for accurate recognition of rapid gesture change situations in complex environments. Furthermore, the gesture interaction recognition effects of the two methods in different environments and different time points are compared and analysed. The comparison results are shown in Figure 8.

Figure 8 Gesture interaction recognition effect comparison



From the above experimental comparison results, it can be seen that when the action is relatively simple, the recognition effect of the two data recognition methods is basically the same. However, in complex environments or in the process of carrying out complex gestures recognition, the recognition accuracy of the method in this paper is basically above 93%, and the recognition accuracy is significantly higher, which can better meet the research requirements.

4 Conclusion

The existing interactive gesture recognition methods have some limitations due to their poor recognition effect and low recognition accuracy. Therefore, a gesture recognition algorithm based on virtual reality technology is proposed. Firstly, this paper collects and divides the gesture features of sports equipment, analyses the gesture classification of common sports equipment and uses virtual reality technology to pre-process the gesture recognition data of sports equipment. Based on the model, the gesture recognition of sports equipment is realised by using virtual reality technology. The accuracy of this method for gesture recognition is more than 95%, and for complex gesture recognition is more than 93%. The recognition accuracy is high, which fully meets the needs of research. In the future, angular velocity will become a feature parameter for further study of gesture recognition.

Acknowledgement

This work was supported by Anhui Provincial Support plan for outstanding young talents in Colleges and Universities no. gxyqZD2018138.

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