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Retraction

Retracted: Intelligent Running Posture Detection Based on Artificial Intelligence Combined with Sensor

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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

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

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

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

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

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

References

[1] Z. Lai, M. Wang, L. Wang, and Y. Zhou, "Intelligent Running Posture Detection Based on Artificial Intelligence Combined with Sensor," *Journal of Sensors*, vol. 2022, Article ID 6746260, 7 pages, 2022.

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Research Article

Intelligent Running Posture Detection Based on Artificial Intelligence Combined with Sensor

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In order to avoid injuries caused by incorrect running posture to a greater extent and reduce the impact on athletes' performance and physical health, on the basis of artificial intelligence sensors, the author studies the accurate detection of intelligent running motion posture. Using artificial intelligence sensors, an adaptive error quaternion unscented Kalman filter (DAUKF) algorithm is designed. The attitude analysis and recognition system based on the inertial measurement unit can not only measure the motion information of human body but also obtain the motion characteristic data and movement state of the human body through the analysis of posture data. Use the error quaternion and gyroscope drift error to establish the equation of state, the measurement values of the accelerometer and magnetometer are used to establish the observation equation, and the fading memory method is introduced to adaptively adjust the observation noise covariance, so as to reduce the interference of the system itself and the environment on attitude detection. Experimental results show that the proposed method improves the attitude detection accuracy, effectively suppresses the influence of drift error and dynamic observation noise, and provides a foot attitude detection scheme suitable for long-distance running.

1. Introduction

As an aerobic fitness exercise, running is becoming more and more popular. Running can not only exercise cardiopulmonary function and enhance muscle strength, but also continuous and effective jogging can also play a role in reducing fat and losing weight. But according to scientific surveys, 70% of runners run incorrectly, and wrong running posture not only fails to achieve the ideal fitness and shaping effect but also may bring unexpected damage to the body [1]. At present, in terms of fitness running, the common method to judge whether the running posture is standard is to draw conclusions with the help of direct observation of personal trainers or other professional instructors, and this method has many limitations, in order to provide more comprehensive and convenient running posture guidance to more runners. In many long-distance running sports, injuries caused by incorrect starting posture of athletes are extremely common, which has a great impact on the performance and physical health of athletes. With the rapid improvement of sports science and technology and the use of scientific technology to analyze the starting posture of long-distance runners, improve the skills of distance runners, and avoid unnecessary injuries to athletes to the greatest extent possible, it has become the main task to be solved urgently in the field of long-distance running training. Applying 3D image analysis technology to the training of middle and long distance runners, it has gradually become a widely used core technology. The human body recognition process is shown in Figure 1. The processor and the memory matches the processor, and the processor can process the bone point location coordinates stored in the memory, according to the actual situation of the data, calculate the changes of one or more individuals, select the value of the location coordinate parameters, judge the activity status of the activity status according to the selected characteristics, and complete the identification of one or more human activities in human-computer interaction. Three-dimensional image analysis technology has a positive role in promoting the analysis of the accuracy, coordination, and effectiveness of athletes' technical movements. However, when using the traditional three-dimensional image analysis method to correct the

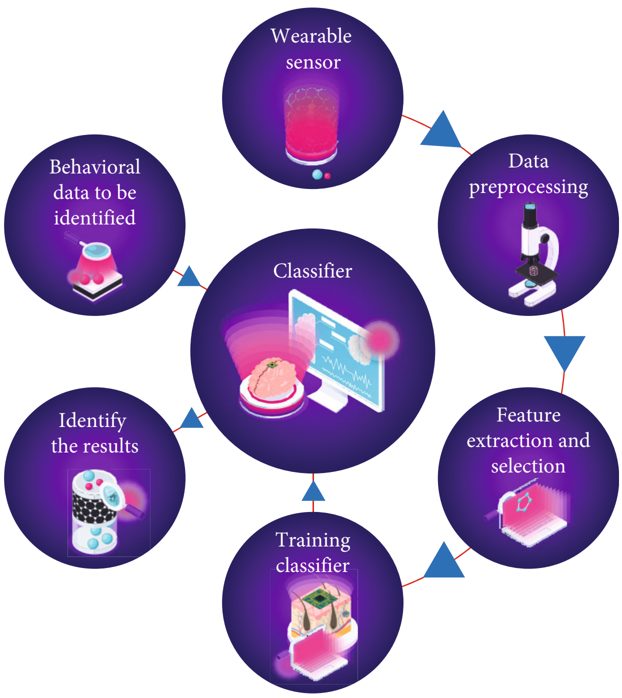

Figure 1: Human activity recognition framework.

starting posture of long-distance runners, the reasonable matching threshold of the starting posture of long-distance runners cannot be given, which makes the implementation of the starting posture correction of long-distance runners into a bottleneck, and it has attracted the attention of many experts and scholars [2]. At present, there are many studies on the starting posture of long-distance runners based on image analysis, and some relative studies have also yielded certain results. The attitude angle calculation module is the core module of the system, its main content is the attitude calculation algorithm, and the purpose of attitude analysis and recognition is to establish the relationship between multiple nodes; so, it is very important to obtain the attitude angle of each joint node. Important. Taking into account the performance of the embedded software and hardware systems and inertial sensor components of this system, the attitude calculation algorithm used in this system is the gradient descent algorithm. The development of artificial intelligence sensors is increasingly integrated and precise, supplemented by the combination of Internet of Things technology and Internet 5G communication technology, including the cooperation between a variety of artificial intelligence devices, sensor hardware, and control software, which can realize the real-time and reliability of dynamic data and information control. The application of artificial intelligence sensors in different industries will greatly innovate the traditional manufacturing, living, and living methods, improve the economic benefits of industry and agriculture, and meet the diversified information technology needs of social development. The data of the nine-axis sensors is fused by the gradient descent algorithm, and each sensor has complementary advantages and overcomes the disadvantages of a single sensor, making it suitable for the hardware system of the system and then obtaining a more accurate attitude angle solution [3]. UKF combines unscented transformation and standard Kalman filter, which is approximated based on the statistical characteristics of state quantities, compared with EKF, to a certain extent, and it avoids the linearization of the EKF algorithm, the complicated calculation process of the Jacobian matrix, and the possible filter divergence.

This paper studies the accurate detection of intelligent running posture based on AI sensors. An adaptive error quaternionic trace Kalman filter (DAUKF) algorithm is designed. The equation of state is established using the error quaternion and the gyroscope drift error and the observation equation using the accelerometer and magnetometer, introducing the fading memory method to adaptively adjust the observation noise covariance to reduce the interference of the system itself and the environment to the attitude detection.

2. Literature Review

For this research question, Luz et al. proposed an image analysis based on an improved Gaussian mixture model, a method of correcting the starting posture of long-distance runners. The method first establishes the connection between the regional pixels and generates a Gaussian model of the starting posture image of the long-distance runner and the target foreground detection of the athlete's starting posture, and based on this, the starting posture correction of the long-distance runners was completed. This method is simpler; however, there is a problem of method limitations [4]. Jafarnezhadgero et al. focused on an array-based image analysis method to correct the starting posture of long-distance runners. The method first uses bilateral filters to denoise the images of athletes' starting postures and eliminates unstructured background disturbances in sparse components, and based on this, the starting posture correction of long-distance runners under image analysis is completed. The correction time complexity of this method is low, but there is a problem of poor image matching stability [5]. Zhang et al. proposed a method for correcting the starting posture of long-distance runners based on image analysis based on specific feature recognition. The method firstly locates the starting posture of long-distance runners, obtains the starting posture feature matching threshold of long-distance runners, and completes the starting posture correction of long-distance runners based on image analysis. This method has high pose correction accuracy, but the image correction process is cumbersome and time-consuming [6]. Taddei et al. stated that the main methods of motion gesture recognition today are as follows: human activity recognition by analyzing images and recognition using inertial sensors. Image recognition generally first collects video or image information and then processes, trains, and classifies different pose images according to image recognition algorithms such as neural networks [7]. Hyon et al. proposed that in order to improve the accuracy of gesture recognition, the image recognition method requires multisource features and improved image clarity to obtain high-quality and large-scale image data, and this results in poor real-time recognition. Besides, the precision requirements for equipment also make identification expensive, the identification of

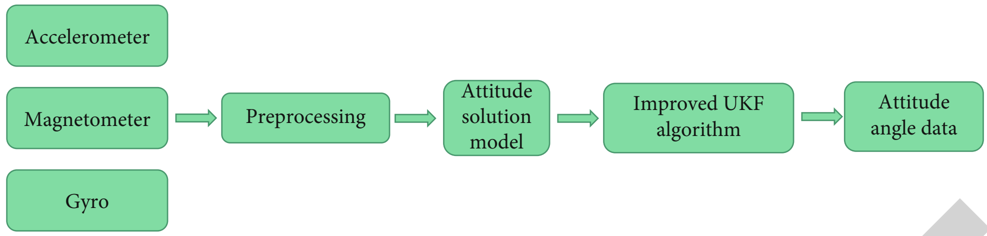

FIGURE 2: Flowchart of the posture detection algorithm.

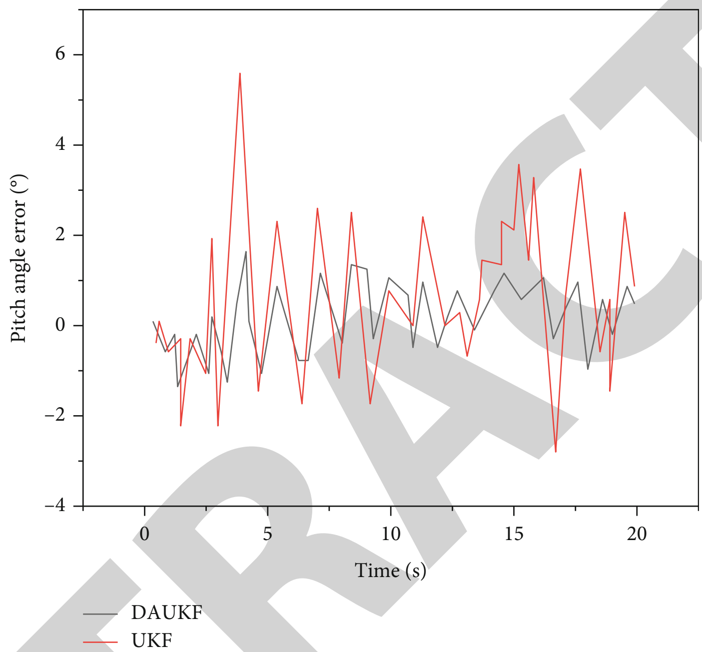

FIGURE 3: Comparison curve of angle error using DAUKF.

environmental locations and equipment deployment conditions strictly limits the flexibility of identification, and it increases the difficulty of detection and recognition [8]. Prawiro et al. stated that compared with this, attitude detection based on inertial sensors effectively improves the limitations of image recognition methods; due to the improvement of sensor design and manufacturing technology, with the advantages of high precision, high sensitivity, and small size, wearable devices have become electronic products for mass consumption; after the integration of wireless communication technology, it is more widely used in sports health, rehabilitation therapy, competitive entertainment, etc. [9]. Ding and others believe that as a long-term or even lifelong exercise, the best state is that each runner can choose the most comfortable and appropriate running posture according to his own characteristics. The basic way to protect yourself from injury is to constantly summarize your running posture, and then improve your running skills and efficiency. Through gradual adjustment and improvement, cultivate good long-distance running habits, and then benefit from comfortable and efficient running [10]. Chen and Li stated that the technology for motion posture detection of smart wearable devices is not yet mature, and only some devices have the function of detecting foot posture. Therefore, it is effective to detect the posture of the foot during running, and it will become one of the important applications of smart wear in the field of sports health in the future. According to the key running method, for novice long-distance runners, developing wrong running habits can easily cause different degrees of sports injuries to the body [11]. Zhang et al. believe that traditional high-precision gait analysis and detection methods often require the help of optical and pressure sensors; therefore, it is mostly used for rehabilitation treatment, even if it is made into a portable detection device, the cost is high, and it is not suitable for outdoor sports. Due to its small size, low cost, and good flexibility, MEMS inertial sensors are currently mainly used for foot posture detection [12]. Zhang et al. stated that due to the characteristics of the sensor itself, the system noise used to detect the attitude and the environment, and the interference to the measurement will lead to a decrease in the detection accuracy. Different from general posture detection, foot posture detection suitable for long-distance running will encounter more external forces; so, the algorithm needs to be adaptively adjusted for certain periodically changing foot postures [13]. Wu et al. stated the following: such as that a

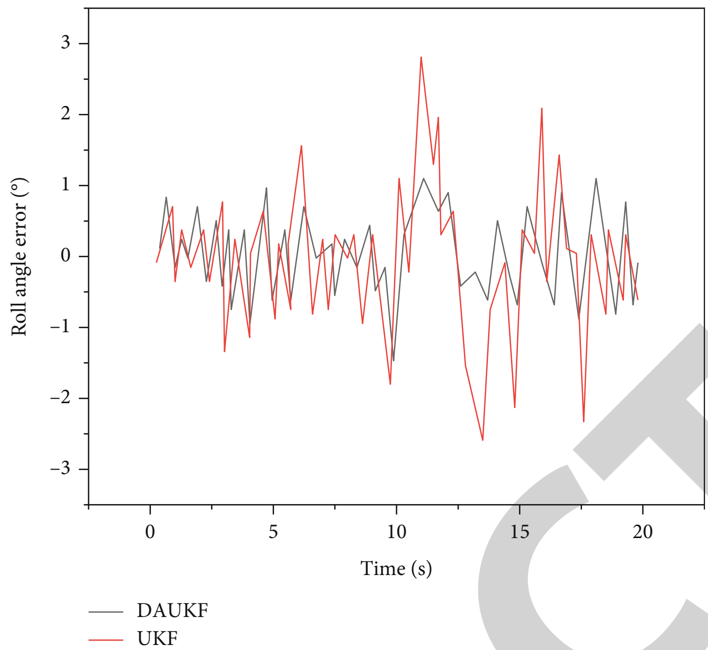

FIGURE 4: Comparison curve of angle error using UKF.

TABLE 1: Comparison results between DAUKF and UKF.

Algorithm type	Angle error	Max/ (°)	Average/ (°)	Standard deviation/(°)
UKF	Roll angle	2.88	-0.04	0.90
UKF	Pitch angle	5.62	0.42	1.50
DAUKF	Roll angle	1.56	0.10	0.50
DAUKF	Pitch angle	1.60	0.19	0.69

variety of intelligent sensor as artificial intelligence information collection identify the transmission of the most important link, its equivalent to the heart of the Internet of things, through the combination of intelligent sensor, control system, and control chip, can realize the real-time monitoring of dynamic information in the environment, and complete industry intelligent equipment automation control and management of [14].

Based on the current research, this paper studies the accurate detection of intelligent running posture based on AI sensors. An adaptive error quaternionic trace Kalman filter (DAUKF) algorithm is designed. The equation of state is established using the error quaternion and the gyroscope drift error and the observation equation using the accelerometer and magnetometer, introducing the fading memory method to adaptively adjust the observation noise covariance to reduce the interference of the system itself and the environment to the attitude detection.

3. Methods

UKF combines unscented transformation and standard Kalman filter, which is approximated based on the statistical characteristics of state quantities; compared with EKF, to a certain extent, it avoids the linearization of the EKF algorithm, the complicated calculation process of the Jacobian matrix, and the possible filter divergence. Generally, the selection of the initial value of the UKF algorithm in the actual process will affect the filtering effect, the noise in the actual observation process will lead to a decrease in the filtering accuracy, and the problem of in-model error cannot be solved ideally by scaling the covariance [15, 16]. The initial state quantity is set to the mean value $\hat{x}_0$ of the state quantity, and the covariance is set to P_0 as shown in Equation (1):

$$P_0 = E\left[(x_0 - \hat{x})(x_o - \hat{x})^T\right]. \tag{1}$$

These are specific steps of the improved adaptive UKF algorithm:

(1) Unscented transformation: the essence of the unscented transformation is that the probability distribution approximates the nonlinear function in the system, and the sigma point set is obtained according to a selection rule and ensures that the mean and variance of the selected point set are equal to the original distribution [17]. The author adopts the selection rule of symmetrical sampling, and the specific steps are as follows: sigma point sampling is shown in Equation (2):

$$X_k = \begin{pmatrix} \bar{x}_k \\ \bar{x}_k - \sqrt{(n+\lambda)P_k} \\ \bar{x}_k + \sqrt{(n+\lambda)P_k} \end{pmatrix}^T. \tag{2}$$

Table 2: 4 groups of experimental control results.

Test group	Group 1	Group 2	Group 3	Group 4
Landing method	Forefoot	Forefoot	Heel	Back heel eversion
Angle/(°)	5 ~ 25	30~50	5 ~ 25	30~50
Recognition rate/%	85.7	84.1	87.9	93.6

In the formula, $\bar{x}_k$ is the mean value of the state quantity at time k, and P_k is the variance matrix at time k.

The weight calculation is shown in Equation (3):

$$\begin{cases} W_i^m = \dfrac{\lambda}{n-\lambda}, i = 0, \\ W_i^c = \dfrac{\lambda}{n+\lambda} + \left(1 - \alpha^2 + \beta^2\right), i = 0, \\ W_i^m = W_i^c = \dfrac{\lambda}{2(n+\lambda)}, i = 1, 2, \cdots, 2n. \end{cases} \quad (3)$$

After the weighted calculation of the sigma point after the unscented transformation, the state prediction and covariance matrix at the next moment are obtained, as shown in Equation (4):

$$\begin{cases} \hat{x}_{k+1,k} = \sum_{i=0}^{2n} W_i^m x_{i,k+1,k}, \\ P_{k+1,k} = \sum_{i=0}^{2n} W_i^c (x_{i,k+1,k} - \hat{x}_{k+1,k}) \cdot (x_{i,k+1,k} - \hat{x}_{k+1,k})^T + V_k. \end{cases} \quad (4)$$

(2) Using the weights to calculate the observed value estimate as shown in Equation (5):

$$\hat{z}_{k+1,k} = \sum_{i=0}^{2n} W_i^m z_{i,k+1,k}. \quad (5)$$

(3) Adaptively adjust the observation noise covariance matrix

The noise inside the system depends on the sensor itself and is relatively stable. Due to the influence of the external environment, the observation noise is prone to changes that are difficult to estimate. In order to prevent the error change that occurs when the observation is introduced, the author introduces the idea of fading memory, changes the weight according to the distance from the noise to be observed, and adaptively adjusts the observation covariance matrix [9]. Therefore, it is assumed that the weight sequence when calculating the observation error covariance is as shown in Equation (6):

$$\sum_{i=1}^{k} \beta_i = 1, \beta_{i-1} = \beta_i b, 0 < b < 1. \quad (6)$$

The recursive calculation of the equal-scale summation formula and the weight sequence is shown in Equation (7):

$$\hat{R}_k = (I - \beta_{k-1})\hat{R}_{k-1} + \frac{1}{2}\beta_{k-1}(z_k - z_{k-1})^2. \quad (7)$$

In Equations (6) and 7, β is the weight of the corresponding time, and b is the fading memory factor. The larger b is, the greater the weight of $\hat{R}_{k-1}$ at the previous moment in the calculation. According to the nonstationary state of observation noise in a certain range during long-distance running, the value range of the fade-out memory factor needs to be obtained through actual measurement [18–20]. Update the prediction covariance matrix and the observation covariance matrix as shown in Equation (8):

$$\begin{cases} P_{x_{k+1},z_{k+1}} = \sum_{i=0}^{2n} W_i^c (x_{i,k+1,k} - \hat{x}_{k+1,k}) \cdot (z_{i,k+1,k} - \hat{z}_{k+1,k})^T, \\ P_{z_{k+1}} = \sum_{i=0}^{2n} W_i^c (z_{i,k+1,k} - \hat{z}_{k+1,k}) \cdot (z_{i,k+1,k} - \hat{z}_{k+1,k})^T + \hat{R}_{k+1}. \end{cases} \quad (8)$$

The updated Kalman gain matrix is shown in Equation (9):

$$K_{k+1} = P_{x_{k+1},z_{k+1}} P_{z_{k+1}}^{-1}. \quad (9)$$

The updated state value and state variance matrix are shown in Equation (10):

$$\begin{cases} \hat{x}_{k+1} = \hat{x}_{k+1,k} + K_{k+1}(z_{k+1} - \hat{z}_{k+1,k})^T, \\ P_{k+1} = P_{k+1,k} - K_{k+1} P_{z_{k+1}} K_{k+1}^T. \end{cases} \quad (10)$$

4. Results and Analysis

The flow of the pose estimation algorithm is shown in Figure 2.

In the experiment, the Arduino UNO development board was selected, the MPU9250 was used as the sensor to collect the nine-axis attitude data, and the serial port was used to transfer the data to the MATLAB 2018b platform for simulation experiments [21]. The sensor module is placed in the front of the foot, and the error analysis is carried out by simulating the stepping and lifting of the foot during running, and selecting a 20 s time from a 5 min continuous process [22]. Comparing the DAUKF proposed by the author with the general UKF algorithm, as shown in Figures 3, 4 and Table 1, when the DAUKF algorithm is used to solve the attitude, the error fluctuation of the roll angle and pitch angle is smaller than that of using the UKF algorithm directly. Therefore, it has a better recognition effect for the wrong posture of the foot during long-distance running [23, 24].

The valgus angle refers to the rotation angle of the foot from the beginning of the ground contact to the pedaling off the ground, the landing method is the contact method of the foot and the ground, and all are important indicators for judging running foot posture. As shown in Table 2, 4 groups of controls were set up in the experiment, and group 1 mainly completed the landing on the ball of the foot (forefoot) according to the key running method and kept the valgus angle controlled within the normal range (5° ~250). The remaining 3 groups were changes to the first group's valgus angle, landing method, and both [25, 26]. Through quantitative analysis of the roll angle and pitch angle of the foot after the foot begins to touch the ground and leaves the ground, it is determined whether the landing method and valgus angle of the foot posture are abnormal. Using the change of the pitch angle, the swing of the foot from touching the ground to flying during the movement can be described more accurately, one full swing cycle to touchdown. Each group of experiments was conducted for 5 minutes, and the roll and pitch angles of each group were changed according to the swing cycle to analyze whether they exceeded the recommended range of the key running method and then put forward appropriate suggestions for improving foot posture [27].

The experimental results are shown in Table 2, using the DAUKF algorithm can achieve a better recognition rate for bad foot postures. When the valgus angle exceeds a reasonable range, the recognition rate can reach 84.1%, and when the landing method is incorrect, the recognition rate can reach 87.9%, and when both are unreasonable, the recognition rate reaches 93.6%.

5. Conclusion

This paper proposes the attitude analysis and recognition system based on inertial measurement unit, and it can not only measure the motion information of the human body but also obtain the motion characteristic data and motion state of the human body by analyzing the posture data. The research on attitude analysis and recognition system has high scientific theoretical significance, commercial value, military value, and social value, such as stage performance, rehabilitation medical treatment, special effects production, game interaction, and sports training, and the market potential is huge. Based on the artificial intelligence inertial measurement technology, the author designs a human body posture analysis and recognition system. Through this system, the human body motion information is collected and analyzed and recognized, and the algorithm of posture calculation and recognition is studied and realized. First of all, for the inaccurate solution result caused by the inconsistency between the output of a single inertial sensor and the real value, a feasible calibration scheme is applied; then, according to the characteristics of the system, an attitude calculation algorithm based on the gradient descent algorithm is designed to minimize the influence of system noise and estimation error, an attitude analysis and recognition method based on attitude angle is proposed, and the feasibility and performance of the system are also verified by experiments. This method improves the attitude detection accuracy, effectively suppresses the influence of drift error and dynamic observation noise, and provides a foot attitude detection scheme suitable for long-distance running.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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