

Retraction

Retracted: Recognition and Simulation of Exercise Mode Based on Energy Consumption Model

Complexity

Received 23 January 2024; Accepted 23 January 2024; Published 24 January 2024

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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) Manipulated or compromised peer review

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] Y. Li, "Recognition and Simulation of Exercise Mode Based on Energy Consumption Model," *Complexity*, vol. 2021, Article ID 9960483, 11 pages, 2021.

Research Article

Recognition and Simulation of Exercise Mode Based on Energy Consumption Model

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Received 16 March 2021; Revised 29 March 2021; Accepted 2 April 2021; Published 13 April 2021

Academic Editor: Zhihan Lv

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Sports energy consumption is a quantitative reflection of physical exercise effect. Combined with different sports modes and students' physical characteristics, the calculation model of sports energy consumption is put forward. Firstly, the relationship between students' age, height, weight, gender, and energy consumption is analyzed by using multiple linear regression method, and a linear acceleration model is proposed by combining different exercise methods. The relationship between the integral value of acceleration and energy consumption is analyzed, and a linear integral model based on different motion modes is proposed. Based on the kinetic energy theorem, the student movement energy expenditure is estimated. This paper proposes a human movement recognition method based on hybrid features, which mostly can represent the curve of the second generation wavelet transform edge thinning, and from the edge and texture features of the optimal said human posture, the statistical characteristic of the second generation wavelet transform is subtly trained as image characteristics, learning and recognition of human movement. Then, the motion recognition algorithm is tested, which can effectively identify the common movement patterns of primary and middle school students. Finally, the linear relationship between the estimation results of the model and the calculation results of Meijer is analyzed. The analysis results show that the linear acceleration model proposed in this paper can estimate the energy consumption of primary and middle school students' motion relatively accurately.

1. Introduction

The acquisition of motion data needs to be based on the data acquisition system. Traditional physical exercise is lacking relevant hardware foundation and conditions; people can only use stopwatch, ruler, and other tools to record the exercise data. The motion data collected in this way are not only of single type, but also of large error and could not accurately reflect the motion situation. With the rapid development of electronic products, wearable devices can help people record all kinds of exercise data anytime and anywhere. These data describe the movement of individuals over time, objectively reflect the movement state of the human body, and reflect the spatiotemporal movement trajectory of individuals [1, 2]. Through the analysis of these data, we can get the information of motion mode, motion posture, etc. The quality of exercise is directly related to different exercise

modes, which determine the amount of energy consumption and have different exercise effects [3, 4]. Therefore, a comprehensive analysis of primary and middle school students' exercise mode is helpful to understand the actual effect of exercise and make reasonable evaluation of students' exercise energy consumption.

Through further processing of sports data, we can also get valuable information such as energy consumption in sports. Energy consumption is the quantitative reflection of sports quality and the objective basis for analyzing the sports quality of primary and middle school students. Using these information, we can scientifically arrange the exercise plan and provide students with reasonable sports evaluation or suggestions, so as to achieve the purpose of strengthening physical fitness. The advanced stage of human motion analysis is motion recognition, which is also an indispensable part. Analysis of human motion recognition can be

applied in many aspects: sports identification can be used for sports video automatic analysis and evaluation, and providing scientific and intuitive auxiliary analysis method is used to create personalized training system, put forward better tactics for coaches to provide good advice, and quicken the process of digital sports training. It can also provide real-time information such as automatic explanation of match conditions and commentary for the broadcast of sports matches. Motion recognition can provide constraints for motion tracking, enhance the robustness and accuracy of motion capture, and provide a basis for subsequent behavior understanding.

This paper will use the method of multiple linear regression to analyze the relationship between students' age, height, weight and gender and energy consumption and put forward a reasonable sports energy consumption model combined with different sports ways, in order to estimate the actual energy consumption of primary and middle school students in the process of sports. This paper analyzes the change characteristics of heart rate and energy consumption in normal college students' exercise and fitness running after class, constructs the regression equation of heart rate monitoring and energy consumption, monitors the exercise effect of college students' exercise and fitness running after class, and provides some theoretical basis for the monitoring of energy consumption in college students' physical activities in China. Manpower and material resources will be organized to carry out computer simulation test and field test on the motion data acquisition system to verify the performance of the system; then the accuracy of the motion pattern recognition algorithm is tested. Finally, the linear regression method is used to analyze the energy consumption model and verify the accuracy of the model.

2. Related Work

Energy consumption in human sports is a true reflection of various sports activities, and objective, accurate, and highly repeatable energy consumption measurement method is the key to study various sports [5, 6]. Accurate measurement of energy consumption, especially of physical activity, and understanding of college students' physical activity level are of great significance to guide college students' scientific exercise and formulate the recommended standard of sports load with a definite object in mind. In order to scientifically and accurately evaluate the energy consumption of human body exercise, researchers have used various methods for decades, trying to reveal the relationship between the amount of exercise, exercise intensity, and exercise efficiency and human health from different angles. Commonly used energy consumption measurement methods include questionnaire survey method [7], double standard water method [8], indirect calorimetry method [9], heart rate monitoring method [10], and motion sensor method [11]. Double standard water method calculates energy expenditure by making the subjects take two nonradioactive water portions labeled with two isotopes and detecting the difference in the elimination rate of the two isotopes in the subjects' body after a period of metabolism. This method is considered as

the "gold standard" for the determination of energy consumption due to its high accuracy and wide application range [12]. Indirect calorimetry [13] allows the subject to wear a breathing mask and calculates the energy consumption by analyzing the amount of oxygen consumption and carbon dioxide production of the subject. This method has been widely used in the measurement of energy metabolism in quiet and active state. However, due to the high price of the test instrument and the discomfort caused by wearing the mask, this method cannot be applied to the measurement of large sample. In general, this method is feasible in the application of heart rate monitors, motion sensors, and other effectiveness studies, but it is not very practical in the detection of routine life energy consumption and daily training. In order to develop a simple and low cost energy consumption measuring technology, a lot of research has showed the feasibility of the method of heart rate monitoring [13]; heart rate method provides a continuous physical activity of the total energy consumption, indirect and objective standard of measuring; at the same time, the heart rate measurement is relatively cheap, simple, and practical, with no damage and can be used for a variety of studies. Subjects are also easy to accept, easy for test operation.

For primary and middle school students, the most important exercise indicator is energy consumption. A sports data collector is worn on the user's upper arm with an arm band, and various sports data are acquired through a series of sensors, and then the energy consumption of sports is calculated comprehensively [14]. In the laboratory environment, human energy consumption in sports is measured by recording the exercise heart rate, and it is proved that there is a linear relationship between the exercise data collected by the accelerometer and the energy consumption [15]. The sports energy consumption detection system based on volume domain network is designed, which includes a complete sports energy consumption detection terminal and integrates multiple modules such as main control, communication, and data transmission [16]. In addition, the calculation of energy consumption of walking and daily physical activities [17] was done. These studies required harsh experimental conditions; for example, skin temperature and current were measured [18], so they could not be widely promoted. Moreover, the analysis subjects of these studies were all adults, and the results are not entirely applicable to primary and middle school students. The effect of physical exercise is closely related to the way you exercise. At present, there are also some studies on movement pattern recognition. For example, motion capture and analysis system, which combines motion mechanics and biological principles, strives to accurately restore human motion posture [19]. A hidden conditional random field object recognition model based on maximum boundary value was proposed, and a large number of global and local features were combined to distinguish different actions [20]. A computer-aided motion system based on 3D human motion simulation and video analysis was developed, which realized the extraction of moving human body based on dynamic background construction for gymnastics, track and field,

weightlifting, and other events, and could accurately identify different motion modes [21]. At present, the methods of human motion recognition are mainly divided into three categories: learning-based human motion recognition, model-based human motion recognition and performance-based human motion recognition. Roughly speaking, human motion recognition can be divided into model method and model-free method according to the overall framework adopted [22]. The model-based method establishes a human body model to match the human body in the image and establishes a likelihood function of whether the matching is accurate or not according to certain conditions, so as to find the state space closest to the real condition. The method is also called the top-down method. The model-free method, on the other hand, selects the optimal parameters through statistical learning of the sample images or motion features in the training database, and then identifies the human movements in the test samples according to a certain pattern or mapping relationship [23]. In the aspect of gait recognition has achieved a good effect and can identify the identity of people through the different gait; a dynamic Bayesian network based on primitive features is used to realize the natural action recognition of nonspecific people [24]. It mainly focuses on extracting human motion postures from videos to generate human animation, and marks should be pasted on the key points of the human body [25]. It has achieved fruitful results in the aspects of model-based human motion tracking, learning-based human motion tracking, and recognition and motion capture data processing [26–30]. Generally speaking, these studies or products only focus on objectively depicting and presenting the sports mode, and their purpose is to help professional athletes to correct their sports posture and improve their performance in competition. The sports items targeted at are not consistent with the actual teaching of primary and middle schools and are not convenient for primary and middle school students to use. Moreover, these results do not establish a mathematical model between exercise pattern and energy consumption, which is not conducive to subsequent research [31, 32]. Therefore, it is of great significance to study the common exercise mode of primary and middle school students and correctly identify different exercise modes for in-depth understanding of the exercise situation of primary and middle school students.

The above studies indicate that cost-benefit analysis is a method to evaluate the results and costs of various health

intervention programs and provides decision makers with the basis of intervention programs in the form of cost-benefit ratio. There are many ways to intervene in exercise, and from an economic point of view we would advise policy makers to choose the intervention with a higher price. To date, few studies have been conducted in adults to evaluate the cost-effectiveness of walking interventions to increase physical activity levels and improve health. The lack of cost-benefit analysis of exercise interventions highlights the lack of cost-effectiveness in the design of interventions by researchers. The consciousness of benefit evaluation lacks the concept of “obtaining the maximum benefit with the minimum cost.” Therefore, the main purpose of this study is to measure and study the characteristics of sports energy consumption of Chinese people, establish a prediction formula for field sports energy consumption, and construct sports guidance suggestions supported by scientific evidence.

3. Research on Identification of Exercise Pattern Based on Energy Consumption of Exercise

Sports energy consumption is the objective and quantitative reflection of sports effects. We study the energy consumption of primary and middle school students in sports on the basis of sports data acquisition system and movement mode recognition algorithm and put forward the calculation model of energy consumption.

3.1. Assessment Based on Exercise Energy Expenditure. This paper studies three common basic movements in primary and middle school physical exercise, namely walking, running, and jumping. According to the relevant background theory of sports biomechanics, the analysis objects in this paper are firstly divided into specific sections, and the structure is shown in Figure 1.

Collected by triaxial acceleration sensor is the X, Y, Z three axis acceleration component. There is a linear relationship between movement energy expenditure and acceleration, so at the initial stage of the study, using energy consumption calculation of acceleration as the primary data research, namely the relationship between the acceleration and the energy consumption, available formula is expressed as

$$\text{exercise energy consumption} = c \times \text{combined acceleration of motion} + d, \quad (1)$$

where c and d are the coefficients related to individual body parameters, which can be obtained by computer linear regression analysis. However, in the research process, the author found that such form was too simple, and due to the difference in physical quality, it was difficult to obtain satisfactory results for the estimation of c . In addition, because the acceleration changes so dramatically during running, it is

difficult to find an accurate d value compared with a relatively gentle movement such as walking. Horizontal direction of the energy consumption model of energy consumption and the vertical direction is different, if the acceleration as the original data of energy consumption study is likely to cause small calculation, because the human body movement to overcome gravity in the vertical direction

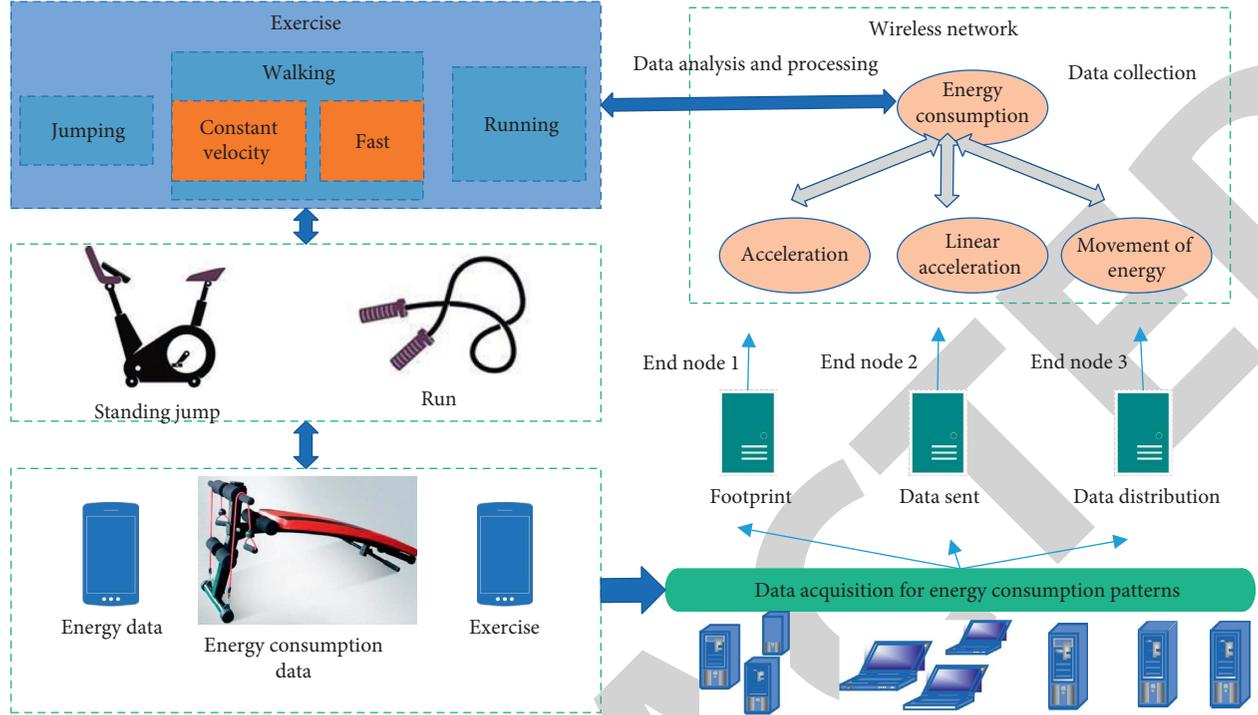


FIGURE 1: Exercise data collection of energy consumption pattern.

when doing work, due to the horizontal direction of energy consumption model of energy consumption and the vertical direction, is different.

$$EE(t) = c_1 \times J(t) + d_1 \times W(t) + e. \quad (2)$$

J represents the motion starting point measurement parameter and W represents the motion speed or frequency.

Table 1 shows the results of step-by-step multiple linear regression analysis of motion data at constant speed using Excel.

Similar to the linear acceleration model, the form of the linear integration model is also a function type; the difference is that its independent variable is the integral value of the absolute value of acceleration. Some studies show that there is a linear relationship between the integral value of the absolute value of acceleration and the energy consumption of motion, which can be used to estimate the energy consumption of motion.

$$UA = \int_{t=0}^T |c_x| d_t. \quad (3)$$

Then, within the time $[[0, T]$, the UA model of the integral value of the total added velocity can be expressed as

$$EE(t) = c_2 \times UA(t) + d_2. \quad (4)$$

For each type of exercise, the model gives two formulas for boys and girls. Same as the linear acceleration model, this model also combines fast walking and slow running to analyze the energy consumption of motion. The linear analysis process is also similar to that of the linear acceleration model. Let the average acceleration of the

TABLE 1: Linear regression analysis (I).

| | Parameter | Standard error | p | r |
|-----------|--------------|----------------|---------|-----------|
| Intercept | -0.005257836 | 0.002548934 | 0.04642 | 0.8769369 |
| a1 | 0.006421354 | 0.000318887 | 0.02751 | 0.8456437 |
| b2 | 0.013422844 | 0.000429972 | 0.02558 | 0.9346712 |

p represents the linear regression parameter, r represents the linear regression energy consumption coefficient, and a1 and b2 represent the body correlation coefficients of human movement.

acceleration phase of motion be UA . Due to the great individual differences in physical exercise, the duration of the acceleration phase is also different. In order to ensure the validity of the data, the data of 4 seconds after the start of the exercise timing is used to calculate UA . From the fifth second, the motion state is considered to be stable. The motion data of the middle five seconds are omitted to prevent the overlapping of acceleration stage and stability stage caused by individual differences. Assuming that the motion is stable, the energy consumption value is calculated.

To study the energy metabolism of physical activities, we should focus not only on how much energy is consumed by each activity (kcal) but also on what substances are used to provide energy during the activity and how they are used. As we all know, there are three main energy sources that provide the body with energy: carbohydrates, fats, and proteins. The proportion of protein in exercise energy supply is very small, and the main energy supply substances are carbohydrate and fat, which provide energy for exercise through sugar oxidation and fat oxidation, respectively. Therefore, the process of exercise is not only the process of burning calories, but also the process of using sugar and lipid

energy substances. It is of great significance for obese people and people with abnormal blood sugar and blood lipids to develop targeted exercise intervention programs to understand what kind of exercise mode is beneficial to mobilize fat and promote fat metabolism and what kind of exercise mode is more beneficial to consume sugar and promote sugar metabolism.

To make a brief summary of the method of movement mode identification, we have the following steps.

Step 1: collect data, filter processing to eliminate noise.

Step 2: Analyze the data and movement time within 1 second at the end of the data segment. If the average combined acceleration at the end of 1 second is approximately equal to 1 second and the motion duration is no more than 10 seconds, it is identified as a jump. Otherwise it is walking or running.

Step 3 (a): If the second step is identified as a jump, the data of 3 seconds before the start of the movement is analyzed, and the data consistent with the characteristics of running is the long jump. Otherwise, it is the standing long jump.

Step 3 (b): If the second step identifies the movement mode of nonjumping, then calculate the step frequency first. Those whose stride frequency is less than 110 steps per minute are identified as slow walking, those whose stride frequency is more than 150 steps per minute are identified as fast running, and those whose stride frequency is between 110 and 150 steps per minute are identified as the next step.

Step 4: If the third step is judged to be slow running or fast walking, three values of the amplitude area of the acceleration signal, the tilt angle of the body during the movement, and the difference rate of the average acceleration in the acceleration stage and the stable stage are respectively calculated, and the three results are voted on. The one who gets more votes will be the final output result. Figure 2 is the flow chart of the motion pattern recognition algorithm, from which we can intuitively see the algorithm flow.

3.2. Feature Extraction of Exercise Pattern under Energy Consumption Model. By the curve of the second generation, wavelet transform characteristics of decomposition coefficient can be seen such that the curve wavelet transform has the characteristics of multiscale and multiple directions; the curve of the wavelet decomposition coefficient from the lowest to the highest scale is a process from coarse to fine, step by step carefully, several scales in the middle of the subdivision angle, and the direction of the subblock coefficient of a layer represents the direction of the energy scale, so the coefficient of each small piece completely can represent the characteristic of the direction. In order to take advantage of the multiscale and multidirection features of the second generation of curvilinear wave transform, which can accurately express the image direction and detail information, the block-based statistical features of the second generation of curvilinear wave transform are extracted as

edge features. And in order to capture the image of the overall and local texture information, we use the curve of the second generation wavelet transform to extract the low-frequency subband coefficients of texture information, the curve of the second generation wavelet transform binary low-frequency subband coefficients of block profile control points, and the calculation of molecular block profile control cooccurrence matrix; here with the help of the concept of gray level cooccurrence matrix to calculate the image transform domain subband coefficients of cooccurrence matrix and seeking the cooccurrence matrix texture statistics, the texture statistical order of magnitude is as the texture feature vector. Compared with the original image, it is easier to extract compact and representative texture information because the coefficients of the low-frequency subbands of the second generation of curvilinear wave transform can sparsely represent the approximate information of the image. And the image edge information and texture information as the image features are called the mixed feature.

The summary diagram of feature extraction method is shown in Figure 3. The first row of Figure 3 is a human motion sample image, and the first column of the second row is a reconstructed image of the lowest frequency subband coefficient of the second generation of curvilinear wave transform. It can be seen that the coefficient of the lowest frequency subband represents the approximate information of the original image and is an approximation to the original image. The second line of the second and the fifth columns was times of curve of the second generation wavelet transform rough and refined, the reconstructed image of a child with coefficient of it can be seen that times of coarse and fine layers said a subband coefficients of the edge on one of the direction information of source image, and the more the outer layer of the subband for fine image edge. In this way, the coefficients on different scales represent the edges of the image with different degree of fineness. Therefore, the edge features of the image can be extracted from the coefficients of each layer subband of the second generation of curvilinear wave transform.

Longitudinal movement behaviors of the target include quasibalanced gliding and constant angle of attack jumping. Recognition refers to the labeling of the two longitudinal behaviors respectively, and the corresponding movement behaviors can be obtained by classifying and identifying the labels according to the corresponding movement characteristics of each behavior. After the classification algorithm is defined, it is necessary to design the classifier and analyze the results to determine the longitudinal motion behavior recognition method, including the following four steps:

- (1) Screen the preprocessed data to obtain the data useful for longitudinal classification.
- (2) Divide the data into two parts proportionally for training and testing.
- (3) Train the classifier with the training data and save the obtained classifier.

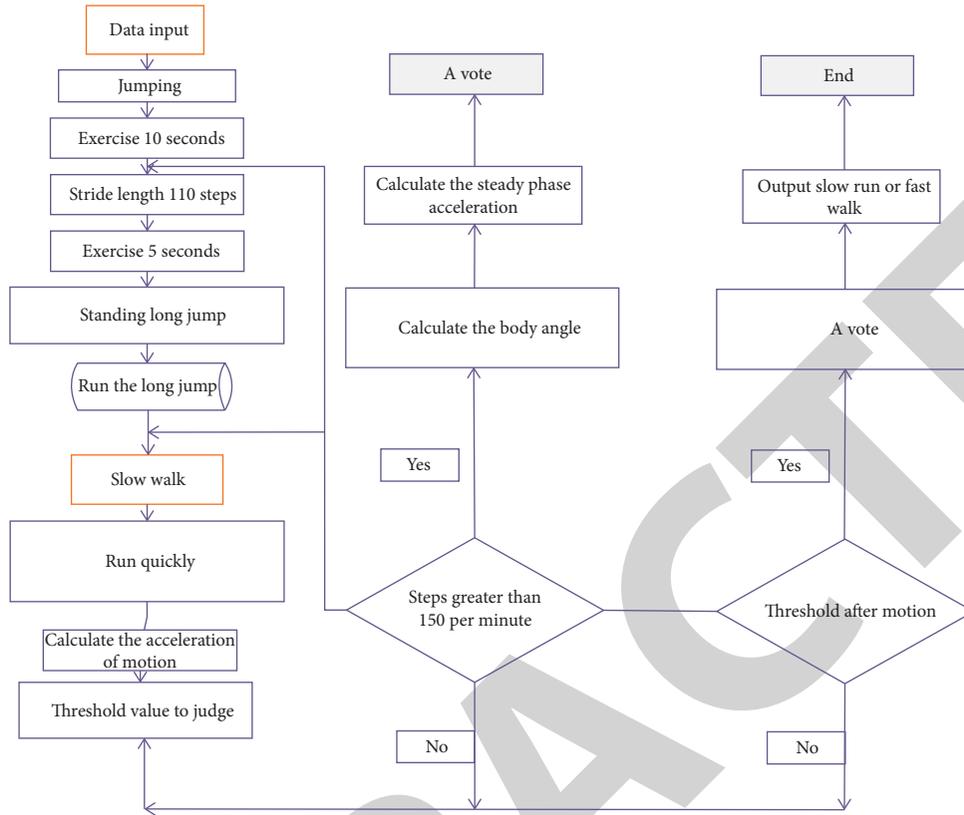


FIGURE 2: Motion pattern recognition algorithm flow chart.

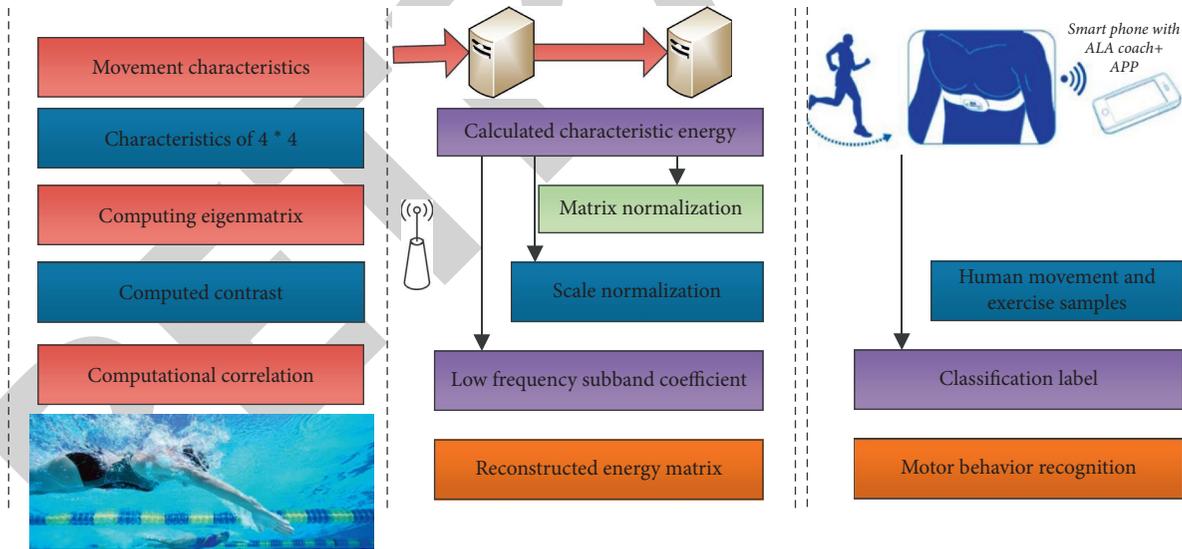


FIGURE 3: Motion and exercise recognition feature extraction method.

- (4) Test the saved classifier with the test data, and analyze the classification results to get the identification methods of different movement behaviors.

However, for attributes with a large number of values, especially some continuous values, the increase of information gain will easily lead to overfitting, and the importance of features will decrease with the increase of their internal information. Then it is necessary to consider the information gain rate at the same time, which is a kind of

compensation measure to solve the problem of information gain. After data set D has experienced the division of feature S , its generalized splitting information is measured as

$$S(D, S) = \sum_{i=1}^n \left(\frac{|D_i|}{|D|} * \log_2 \frac{|D_i|}{|D|} \right). \quad (5)$$

The role of individualized goals and regular social support: it is not enough for pedometers to be used as a

support for walking interventions. Studies have shown that pedometers are most effective at the beginning of the intervention, and their monitoring and feedback effects begin to fade after a few months of intervention. How to change the external motivation (such as pedometer, reward) into the internal motivation to persist in exercise is an important proposition that intervention research should explore. Based on previous intervention research experience, in addition to using pedometers, we also added measures such as goal setting, regular telephone communication, and group meeting to strengthen social support, so as to strengthen the scientific understanding and motivation of the intervention subjects to exercise and improve their compliance.

However, the information gain rate also has the situation of overcompensation, so select some attributes with less information. In order to solve this problem, it is necessary to consider the size of the information gain as well as the information gain rate characteristics of the information gain of more than average and then compare their information gain rate: first of all, the only consideration for longitudinal motion behavior classification and the information gain and information gain rate according to the ranking results from large to small as shown in Table 2.

30% data (about 57,400 points) were randomly selected from all the experimental data (268 pieces) for the training of classifier, and the remaining 70% was used to test the accuracy of the generated classifier. Based on the Random Forest method and the Adaboost method, the classifier was established and the test data was used to test the classifier. The recognition accuracy was shown in Table 3.

For the identification of lateral movement behavior, the identification accuracy of Random Forest is very high. The identification accuracy of this method is close to 1 for either a single lateral maneuver or a combination maneuver, and the identification is not accurate enough only in the initialization. Adaboost method is not suitable for the identification of lateral movement behavior, and it is only accurate when the lateral movement is not maneuvering. However, the movement of the target often needs to consider the lateral movement, so this method is no longer applicable. This is because the Random Forest reduces the variance by means of the average method and is suitable for the classification with small deviation. When the training set changes very little and the predicted results are significantly different, the Random Forest will have a very good effect. However, Adaboost considers the weight of each classifier and has a high deviation, which makes it more suitable to solve a certain part of the problem; that is, it cannot fit the training set well. To sum up, the Random Forest method is adopted for the recognition of all lateral motion behaviors. For the lateral initialization problem, the initial conditions can be assumed to be known to solve it.

4. Results Analysis

The exercise data of 20 students (11 males and 9 females) will be taken as reference and for comparison to calculate the exercise energy consumption value respectively and then evaluate the model and analyze the result error with this

TABLE 2: Ranking of information gain/information gain rate of each feature of longitudinal motion behavior classification.

| Characteristics | h | θ | h | $\hat{\theta}$ | \hat{h} | \hat{v} | v |
|-----------------|-------|----------|-------|----------------|-----------|-----------|-------|
| Inf.Gain | 0.567 | 0.372 | 0.312 | 0.256 | 0.186 | 0.187 | 0.167 |
| Gain ratio | 0.274 | 0.183 | 0.167 | 0.134 | 0.098 | 0.087 | 0.084 |

TABLE 3: Longitudinal motion behavior recognition test results.

| Method | Recognition accuracy (%) |
|---------------|--------------------------|
| Random Forest | 96.08 |
| Adaboost | 61.38 |

value as the standard. Taking the sum of energy consumption of five jumps as the research object, the calculation results of energy consumption of six movement modes are shown in Table 4 respectively.

In the linear acceleration model, this paper divides the acceleration into two groups: horizontal (X -axis and Y -axis) and vertical (Z -axis) and takes into account the influence of individual body parameters, such as height, weight, gender, and age, on energy consumption. Through the study, the author found that the relationship between body weight and exercise energy consumption was the largest ($P < 0.05$). With the increase of body weight, under the condition of the same amount of activity, both horizontal and vertical exercise energy consumption increased respectively. Figure 4 shows the comparison between the average energy consumption of various sports of 20 students and the calculated results of Meijer formula.

It can be seen from Figure 4 that the estimated results of the three models proposed by Muwen and the calculated results of Meijer formula maintain a consistent trend of change, indicating that the model proposed in this paper can objectively reflect the real situation and trend of students' sports energy consumption. But on the whole, according to Meijer formula as the standard, the three models all underestimate students' exercise energy consumption to varying degrees.

In addition, since the run-up long jump and standing long jump are aperiodic movement modes, their movement processes are relatively complex; especially the run-up long jump combines different movements such as running and taking off, so the underestimation of the energy consumption of jumping mode may be caused by the complexity of movement movements. Figure 5 is the schematic diagram of linear analysis between the estimated results of energy consumption in various sports of 20 students and the calculated results of Meijer formula.

By comparison, according to Meijer formula, the linear acceleration model is the most accurate in estimating motion energy consumption, and its error rate is the least among the three models. With Meijer formula as the standard, the estimation error of motion energy consumption by using linear integral model and kinetic energy theorem is large. Therefore it could be used in the project follow-up work in this paper, the formula of energy consumption of linear acceleration model as a movement to replace system of the

TABLE 4: Estimation of students' energy consumption by linear acceleration model.

| Sports | Male energy expenditure (Kcal) | Girl energy expenditure (Kcal) | Total energy consumption (Kcal) |
|-------------------------------------|--------------------------------|--------------------------------|---------------------------------|
| | Mean soil standard deviation | Mean times standard deviation | Mean times standard deviation |
| 5 standing long jumps | 1.89 ± 0.46 | 1.54 ± 0.38 | 1.56 ± 0.62 |
| Running long jump S times | 6.62 ± 0.44 | 5.86 ± 0.48 | 6.39 ± 0.71 |
| Walk at a normal speed for 1 minute | 3.26 ± 0.44 | 3.21 ± 0.47 | 3.25 ± 0.78 |
| Walk briskly for 1 minute | 8.23 ± 0.52 | 7.49 ± 0.43 | 7.66 ± 0.76 |
| Run slowly for 1 minute | 9.3 ± 0.48 | 8.72 ± 0.43 | 8.79 ± 0.83 |
| Run fast for 1 minute | 10.73 ± 1.08 | 9.52 ± 1.22 | 10.38 ± 2.21 |

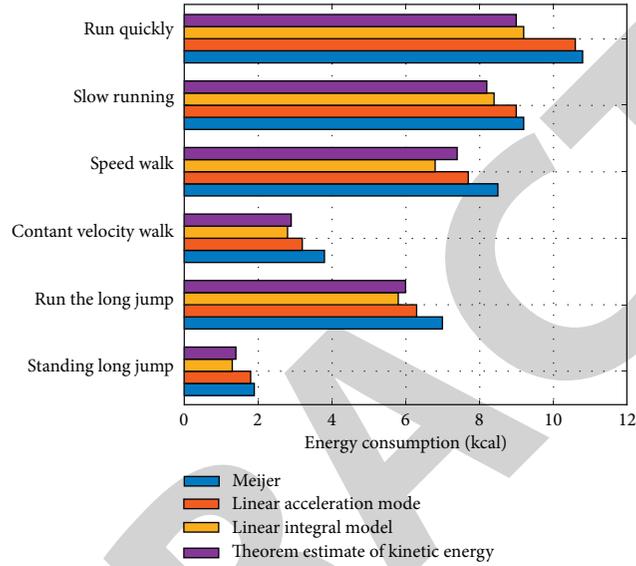


FIGURE 4: Comparison of average energy consumption calculated by different methods.

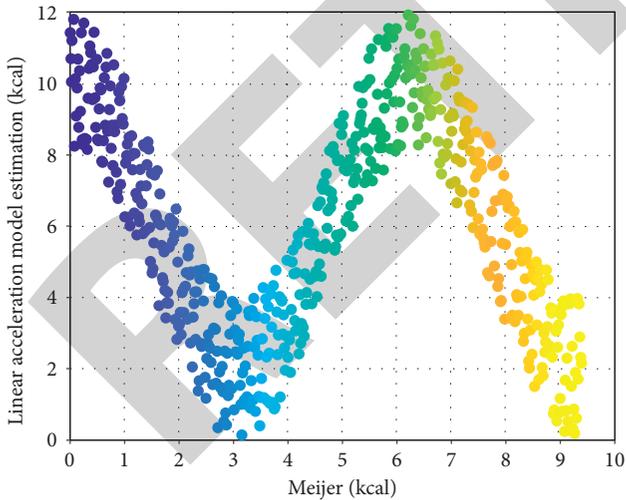


FIGURE 5: Schematic diagram of linear analysis of the estimated value of linear acceleration model and the calculated value of Meijer formula.

original formula; this model can more accurately estimate the primary and middle school students in the different movement modes of energy consumption and can be used as a reference of middle and primary school sports teaching, but there is still room for improvement.

To compare the interaction between motion behavior recognition and trajectory estimation, it is necessary to select a trajectory under the same motion condition for explanation. Under the same trajectory condition, the trajectory estimation results based on target behavior recognition are shown in Figure 6. Since the behavior recognition is carried out under ideal environment, only the estimation results about the motion parameters are given here and compared with the standard data.

From Figure 6, based on the height of the movement behavior recognition, speed, elevation angle, and trajectory angle motion parameters estimation errors are within a reasonable scope; it basically can reconstruct real motion trajectory of the target, in the case of motion behavior being identified accurately; classification of the estimated trajectory can be reasonable approximation target trajectory; that is, identifying the parameters of the longitudinal and lateral movement behavior (used for identification of aerodynamic force, the movements of target is obtained) can be effectively applied to the trajectory estimation.

In order to select the appropriate classification parameters, the “K-fold” cross-validation method was adopted with an accuracy of 94.59%, and the results were shown in Figure 7.

Figure 7 shows the visualization results of statistical feature extraction of Jack from the motion video mentioned

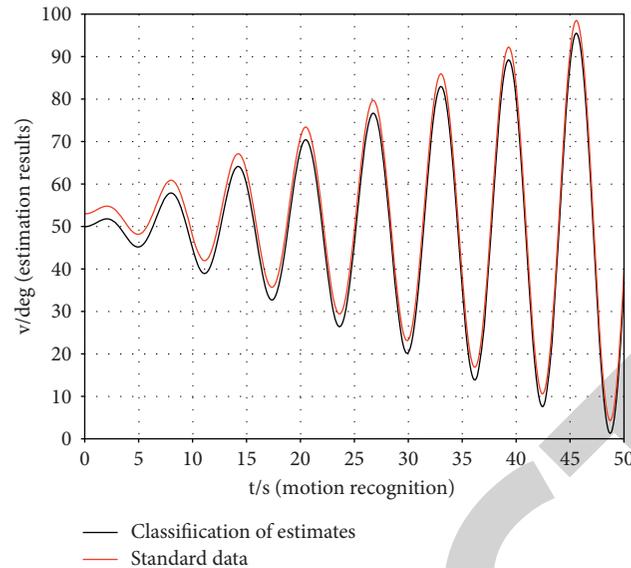


FIGURE 6: Ballistic estimation results under the condition of motion behavior recognition.

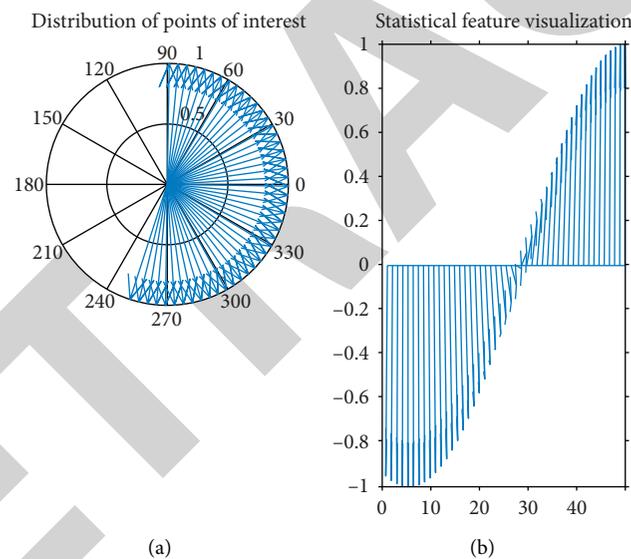


FIGURE 7: Statistical characteristics of action Jack.

above. (a) Distribution of space-time interest points of action Jack in polar coordinates, from which the information of angle and radius can be seen. (b) Characteristics obtained after statistical analysis.

5. Conclusion

In this paper, a complete motion recognition algorithm is designed. First of all, the author analyzes the movement characteristics of three common movement modes of primary and middle school students and extracts the data characteristics of different movements, including step number, step frequency, movement time, and acceleration. Then the motion recognition algorithm and motion energy consumption model are proposed by processing

and analyzing the data. The algorithm can be well combined with the existing results to improve the existing system. Through the test, the motion pattern recognition algorithm proposed in this paper can identify the common motion patterns in primary and secondary schools more accurately and achieve the desired effect. According to the related theoretical results, the linear regression analysis of the motion data is carried out, and the linear acceleration model and the kinetic energy theorem estimation model are proposed, among which the acceleration model is the most accurate. Based on the linear integral model, although there are some errors, the results can reflect the overall situation and trend of primary and secondary school students' movement and achieve the desired effect.

Data Availability

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

Conflicts of Interest

The author declares that they have no known conflicts of interest or personal relationships that could have appeared to influence the work reported in this paper.

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