

## Retraction

# Retracted: Estimation and Analysis of Sports Energy Consumption Based on Gait Tactile Parameters

### Discrete Dynamics in Nature and Society

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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] W. Yan, Z. Jian-Cheng, and L. Bi-Tao, "Estimation and Analysis of Sports Energy Consumption Based on Gait Tactile Parameters," *Discrete Dynamics in Nature and Society*, vol. 2021, Article ID 7778605, 10 pages, 2021.

## Research Article

# Estimation and Analysis of Sports Energy Consumption Based on Gait Tactile Parameters

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The morbidity of obesity and related metabolic syndrome is on the rise, which may be related to the decrease of physical activity. Therefore, keeping energy balance is the basic premise to prevent multiple metabolic syndromes, and the research on the composition and application of energy consumption has become a hot spot. The combination of expectation-maximization algorithm and MapReduce computing model realizes the migration of traditional algorithm to “cloud computing” platform. The physical fitness evaluation algorithm based on collaborative filtering is constructed, and a gait tactile recognition algorithm is proposed by feature selection based on the MEMS sensor. Finally, the algorithm is tested, and a conclusion is drawn. This algorithm is effective in monitoring and recognizing human gait. With the increase of weightlessness characteristics, the sensitivity of detection remains unchanged, and the specificity will increase. In a word, it is scientific and effective. Thus, the reference for establishing the index system of tactile biomechanical parameters of adolescent gait and studying the low-cost and portable energy measurement method of multiparameter indexes is provided.

## 1. Introduction

Gait tactile feature information includes time information consisting of periodic parameters such as support phase and swing phase. Space information consists of parameters such as step length, step width, step frequency (step speed), and step angle. Dynamic information consists of parameters such as ground support reaction force, horizontal shear force, plantar pressure distribution, and parameters such as joint swing information and acceleration of human gravity center (Daryabor et al.) [1]. From the perspective of completeness, repeatability, and uniqueness, the temporal information, spatial information, and dynamic information of gait tactile characteristics are far superior to body acceleration information in representing energy consumption characteristics of motion (Wang et al.) [2]. Although China has made great achievements in school physical education since the founding of the People's Republic of China, with the

development of The Times and social progress, there are still some outstanding problems to be solved between the work practice of school physical education, the physical fitness level of teenagers, and the physical exercise behavior. It is necessary to further strengthen the reform of school physical education and extracurricular activities and strengthen the support of science and technology. Therefore, it is very necessary to develop sports fitness methods suitable for teenagers. This requires strengthening the key technologies of adolescent health education intervention and sports intervention. It is an important problem to establish a comprehensive evaluation method system of teenagers' physical health and ensure the safety of teenagers' participation in sports activities. To evaluate the energy consumption of youth sports can better develop appropriate sports training activities for youth and take better monitoring of their sports while exercising healthily, so as to prevent their injuries and excessive fatigue.

The combination of expectation-maximization algorithm and MapReduce computing model achieves the migration of traditional algorithms to “cloud computing” platform. The fitness evaluation algorithm based on collaborative filtering is constructed, the feature selection based on the MEMS sensor is carried out, and the gait tactile recognition algorithm is proposed. The waist acceleration data coefficients were extracted and classified when walking, running, and going up and down stairs.

Based on the biomechanical gait tactile parameters, the gait frequency value is obtained, the exercise energy metabolism rate of adolescents in junior high school is accurately estimated, and the model of adolescent gait frequency and other body parameters such as BMI index, age, and gender on exercise energy metabolism rate per unit weight is innovative. At present, some famous sports brands are gradually putting the research focus on the combination of sports shoes and energy consumption evaluation, so the introduction of gait tactile parameters is a novel and worthwhile step, and it also has a good impact on the independent research and development of some future games and sports combined games and the promotion of adolescent health sports.

In conclusion, MEMS sensors can be used to accurately identify human behavior. The innovative conclusions of this paper include the following: (1) Improve the accuracy of dynamic recognition. (2) For the state capture of target falling, it has high judgment characteristics. (3) Without reducing the measurement accuracy, this paper effectively solves various factors affecting the measurement accuracy and effectively improves the specificity of the algorithm. With the increase of weight loss characteristics, the detection sensitivity remained unchanged, and the specificity increased. (4) Provide a reference for establishing the index system of adolescent gait tactile biomechanical parameters and studying the low-cost portable energy measurement method of multiparameter indexes.

The estimation of sports energy consumption is based on gait tactile parameters, which mainly consists of three parts. The first part introduces the related experimental status of sports energy consumption assessment, which provides the theoretical basis for the following. In the second part, expectation-maximization algorithm, fitness evaluation algorithm based on collaborative filtering, and gait tactile recognition algorithm are proposed. The characteristics, principles, and implementation process of the algorithm are described. The third part tests the gait tactile recognition algorithm and draws the experimental conclusion.

## 2. Related Work

Personal daily physical activity evaluation is a very classic link in the field of health management and biomedical engineering. Xu et al. used a one-dimensional accelerometer worn at the waist to measure the acceleration in the vertical direction and integrated the acceleration curve in the time domain. It was found that, under laboratory conditions, the output value of the accelerometer had a

good correlation with the consumption of oxygen (Xu et al.) [3]. Li et al. found that the correlation coefficient between the accelerometer output and the energy consumption measured by the double-labeled water method was 0.87 in a daily exercise measurement lasting 10 days (Li et al.) [4]. Li et al. tested 16 subjects with a three-dimensional portable accelerometer. It was found that there was a good linear relationship between the accelerometer output and energy consumption, and the correlation coefficient was 0.88 (Li et al.) [5]. Gomes et al. applied a support vector regression algorithm to evaluate the relationship between body acceleration signal and exercise energy consumption in walking mode. Through testing and analysis of 94 volunteers, energy consumption regression models based on body acceleration signal in walking and running states were obtained, respectively. Experiments show that the predicted value of the model had a high correlation with real energy consumption (Gomes et al.) [6]. Mcdaid et al. compared the relationship between the accelerometer and the energy consumption measured by the double-standard water method in Indian children, indicating that the relationship between the new accelerometer counts and energy consumption needed to be further studied for the smaller Asian children (Mcdaid et al.) [7]. Kang et al. conversion formulas for relations between three accelerometers and energy consumption, Puyau formula, Trost formula, and Schofield's formula of double-standard water method, were compared in a large sample of European children, and the results showed that both of them overestimated the energy consumption during exercise. However, the consistency between the Trost formula and double-standard water formula was relatively high at 24 hours (Kang et al.) [8]. But these formulas had certain defects in the application of large sample children. At present, energy research related to children is gradually warming up. Chowdhury et al. developed a portable energy consumption meter suitable for plateau movement based on a MEMS acceleration sensor (Chowdhury et al.) [9]. Namboonlue et al. used a pedometer to study the energy consumption level of the traveling time at unsynchronized downward speed, and the results showed that the energy consumption per unit body weight increased with the fast speed, faster step frequency, and longer stride (Namboonlue et al.) [10]. Sawyer et al. conducted systematic modeling of energy consumption in the walking process and established a nonlinear motion energy consumption prediction model by taking traveling speed, human weight, weight-bearing, and slope of the traveling route as independent variables and verified the effectiveness of the model through 16 sample tests (Sawyer et al.) [11].

Although sports energy consumption book based on body acceleration information is still a research hotspot since the 1960s and sports energy monitor and pedometer based on various principles have been developed, the results have not really become the productivity to guide the general public to keep fit scientifically and maintain a healthy life. Research findings are being used more as sampling tools or at the top end of the population, not really benefiting the general public.

### 3. Japanese Motion Energy Consumption Algorithms Based on Tactile Parameters of Gait

*3.1. Expectation-Maximization Algorithm.* Kinematics is simpler than dynamics. Kinematics only focuses on the motion of the object and does not need to consider what kind of action the object will lead to change. Dynamics is to study what kind of action the object will produce a certain movement, that is, to study the change of the motion state of the object and the reasons for the change. Normally, objects are subject to force to change their motion patterns. Newton's second law of motion is to study this situation, so the basis of dynamics research is Newton's second law of motion. When dynamic and kinematic model generation method [10] is applied to gait recognition, it is necessary to know the external pressure, speed, and time of gait recognition. It is more complex for gait recognition and seldom used in gait control of the snake-like robot. Because neurons are organized and linked by a large number of small nerve microunits, the complexity of the human brain depends on the complexity of these links. Neuronal links reflect many unique features of human brain function. It is precisely because of this writing neural tree that the human brain has the highly self-organizing learning ability of memory, storage, emotion, calculation, and so on. When dealing with complex information problems, neural links need to consider multiple models at the same time. The model training dimensions of the algorithm are different. Because pedestrian rerecognition mainly extracts static features, the model training still stays on the two-dimensional image. In addition to static features, gait recognition also needs to extract dynamic features, so 3D video training is needed, which is more difficult and has a relatively high threshold. When people focus on the neuron research of the complex mechanism of the human brain, they often digitize these unit neuron tissues and then link them to form a highly linear dynamic system. The neuronal complexity of the human brain is highly similar to the functional system of digital link. The dynamic behavior of the neural network is very complex, so the neural network model control method is not widely used in the snake-like search and rescue robot.

Therefore, the gait tactile sensing method is optimized on the basis of predecessors' achievements, and physical fitness needs to be understood in both broad and narrow senses. Generally speaking, it refers to the related elements of the human body's reserved physical ability in order to satisfy its needs, which is the embodiment of human basic motor ability and the systematic response of organ function in the process of movement. In a narrow sense, it is the collection of special forces and other sports qualities that are related to sports (Cappellotto et al.) [12]. The research of sports energy estimation is mainly carried out by mining the existing literature data, using the expectation-maximization algorithm, which will be described in detail below. In order to realize the maximum likelihood estimation in mathematics, the likelihood function needs to be defined first:

$$\text{lik}(\theta) = f_D(x_1, \dots, x_n | \theta). \quad (1)$$

To obtain maximum likelihood estimation is to find an appropriate parameter  $\theta^*$  in a given observation set  $X$  to maximize the likelihood estimates of the observation set:

$$\theta^* = \operatorname{argmax}_{\theta} \Pr(X = x; \theta). \quad (2)$$

For example, in this case, the ball may fall into box a and box b after being released, and our goal is to build a model to predict which box the ball will fall into. For complex enough measurements, see Figure 1.

This is bound to produce an extremely accurate model. However, it will take a long time and energy to construct such a model. With the statistical model, Bernoulli random variable  $Y$  and parameter  $P$  can be simulated in this game, and variable  $X$  is defined. The statistical results of a group of tests are recorded.  $X$  is determined by  $Y$ , so the observation of  $X$  can be regarded as the observation of  $Y$ . Maximum likelihood estimation based on simple Bernoulli model is calculated relatively simple, as shown in Figure 2, which is a model with higher complexity. It is assumed that only the final falling result is observed, but the actual falling path cannot be observed. In this model, we have three cups and three triangles. After the beginning, there are four paths for the ball, of which one or two paths lead to the B bucket.

In this model, it is still assumed that each triangle satisfies Bernoulli's random condition, so the random variable is defined as  $0 = \langle P_0, P_1, P_2 \rangle$ , which represents the probability of the ball falling to the right at the upper, left, and right triangles, respectively. Define the value of variable  $X$  in  $\{a, b, c\}$  to indicate where the final ball falls. Variable  $Y$  takes a value in  $\{0, 1, 2, 3\}$  to indicate the path of the ball. Now the condition is that the route cannot be observed directly, and the problem is that, of two sets,  $X$  and  $Y$ , only one set can be observed directly.  $Y$  is a latent variable, which describes a potential model. This kind of algorithm is very useful in word processing, such as parsing number, voice tag, and word alignment. In the aspect of control, because people have many kinds of movement modes, the corresponding control laws of different movement modes are different. And because the specific motion is different, the hardware design of the whole human motion control system is also different, so the comparative control rules do not refer to the generalized control mode but refer to the necessary step of all control laws, that is, the control of joint rotation. This has a great influence on the establishment of control rules and the design of hardware system.

*3.2. Fitness Evaluation Algorithm Based on Collaborative Filtering.* The technical principle is based on the related theories of ACSM on sports health promotion (Chowdhury et al.) [13]. The association rule algorithm uses the Apriori algorithm to query all itemsets whose support is greater than the minimum support. These itemsets are called frequency sets, and the frequency sets containing  $K$  items are called  $k$ -itemsets. The integration value generated by the initial frequency is used as the final result value. In the first step of

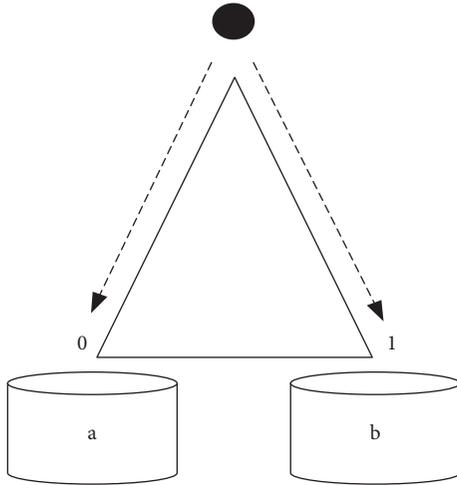


FIGURE 1: A simple experimental model.

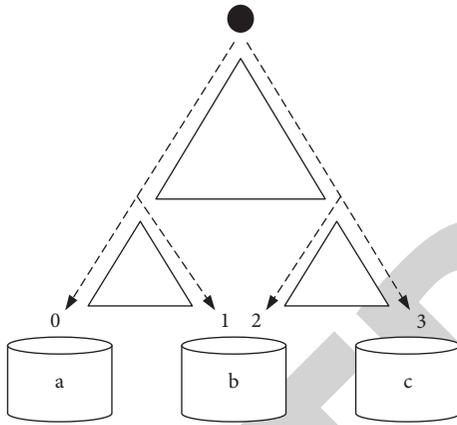


FIGURE 2: A complex experimental model.

the Apriori algorithm, the recursive method is used. The formula is expressed as follows:

$$L_1 = \{l \text{ arg } e1 - \text{itemsets}\}; // \quad (3)$$

Generate a frequent itemset L1:

$$\text{for } (k = 2; L_{k-1} \neq 0; k++) \text{do} // \quad (4)$$

The loop generates 2 itemsets multiple times, A—until some  $r$  makes  $L_r$  empty. Step 2 algorithm: assume that only one item is considered on the right side of the rule if a frequency set is given

$$Y = I_1, I_2, I_3, \dots, I_k, \quad k \geq 2, I_j \in I. \quad (5)$$

The rule contains only the items in set  $\{I_1, I_2, I_3, \dots, I_k\}$ , with a maximum of  $k$  rules. This rule is like  $I_1, I_2, I_3, \dots, I_{i-1}, I_{i+1}, I_k \rightarrow I_i$ . It is necessary to give a result value with greater confidence than the preset value. Wellness is not only the absence of disease and muscular development but also a state of “physical and mental harmony” in which the internal and external body, including organs, physical strength, behavior, and moral awareness, conform to people’s daily life, study, work, leisure, and

entertainment. Among them, as shown in Figure 3, good physical fitness is one of the most important signs of physical health. Corresponding to physical fitness is the concept of physical fitness proposed by ACSM of the United States. In contrast, physical fitness is more broadly related to physical fitness. Related health fitness management studies also show that health fitness management can identify the causes of poor or declining health fitness through tests and medical examinations, then formulate the corresponding exercise prescription and supervise the implementation of exercise prescription through scientific and effective health fitness management system, and effectively improve the health fitness status of the relevant population (Hlophe et al.) [14].

In the evaluation of physical fitness management effect, about 4–6 weeks of exercise intervention should be timely evaluated to confirm the effect of the intervention, and the intervention program should be adjusted according to the evaluation of the effect so as to achieve better results in the subsequent intervention and management.

**3.3. Feature Selection.** Under the standard function, feature selection is to select the subdimension set from the multidimensional features, and the selected subset must be optimal. The basic idea is to fuse all the dimensionality reduction results, select the efficient feature selection algorithm for sampling, and then obtain the efficient features on the subsample set. In terms of feature selection, attention should be paid to the formulation of search strategies and criteria (Miller et al.) [15]. Then, according to the selection strategy and criteria, the subset is evaluated, and the evaluation results are compared with the stop criteria. If the evaluation results are better than the selected criteria, stop. If the selected result is not better than the current standard, continue. Finally, the search strategy in this process is given. The general search process is shown in Figure 4.

Select a feature subset containing all important information from the initial feature set. If there is no domain knowledge as a priori hypothesis, you have to traverse all possible subsets and may encounter combinatorial explosion. Generate a “candidate subset” and evaluate it, generate the next candidate subset based on the evaluation results, and repeat the above operations until a better candidate subset cannot be found. Subset search: greedy search reduces computation and looks for local optimization rather than global optimization. Forward search: a strategy that treats each feature as a candidate subset and gradually adds related features. Backward search: a strategy that starts from the complete feature set and gradually reduces the strategy of irrelevant features. Two-way search: a strategy that combines forward and backward search, adds selected relevant features in each round, and reduces irrelevant features at the same time.

**3.4. Gait Tactile Recognition Algorithm.** In the whole process of gait operation, the SVM classifier is used for classification. Besides running, the recognition rate of walking and stairs

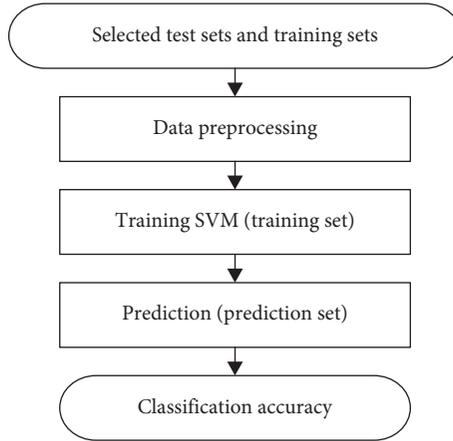


FIGURE 3: Algorithm flowchart.

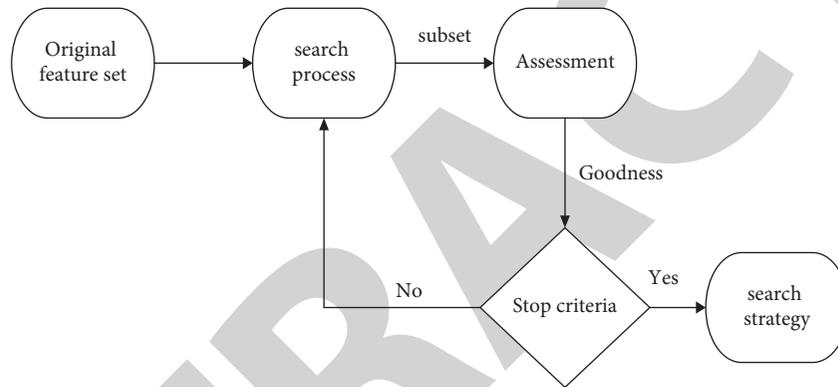


FIGURE 4: The general process of feature selection.

going up and down is less than 90%. In the following section, the height change of the human body will be measured by a barometer.

Add a barometer to the current equipment, which is selected to use BMP280, whose relative accuracy is  $\pm 1$  m. After consulting the data, it can be seen that the height, generally the floor size of residential buildings and shops, is more than 2.8 m. The time is often more than 12 seconds. By calculating the change of barometer in 12 seconds, the height change value can be obtained when  $|\Delta h| > 2m$ . And the low-pass filter is transplanted into embedded devices using C code (Figure 5). The filter model is shown in formula (1), and the values of  $\vec{a}$  and  $\vec{b}$  in the previous chapter are determined as shown in formulas (2) and (3), respectively. The filter is of second order.

$$y[n] = \sum_{k=1}^N a_k * y[n-k] - \sum_{k=0}^N b_k * x[n-k], \tag{6}$$

$$\vec{a} = \{1.0000, 0.4602\},$$

$$\vec{b} = \{0.7301, 0.7301\}.$$

The implementation process of the filter is shown in Figure 6.

#### 4. Testing and Application of Gait Tactile Recognition Algorithm

4.1. *Experimental Parameters and Flowchart.* The test chooses the function provided by the LibSVM toolbox to recognize features on M. Since SVM is a binary classifier, a pair of other methods is used to realize multiclass classification. The four behaviors of walking, running, climbing stairs, and descending stairs need to be recognized, so the four two-class classifiers need to be constructed when training the  $i$ -th classifier. In the previous validation, the basic characteristics of gait have been determined. Select 500 features of the current behavior and 500 features. The flowchart of the algorithm is shown in Figure 7.

The fastest optimization method to optimize the memory to improve the final measurement accuracy is to optimize the penalty parameter C and kernel function parameter  $g$  within a certain range. By selecting the appropriate step size, you need to adjust the grid point detection setting to the highest combination parameter. Cross validation is adopted in the verification method in this paper, and the parameters of this method are optimized, which can effectively prevent the training from overlapping

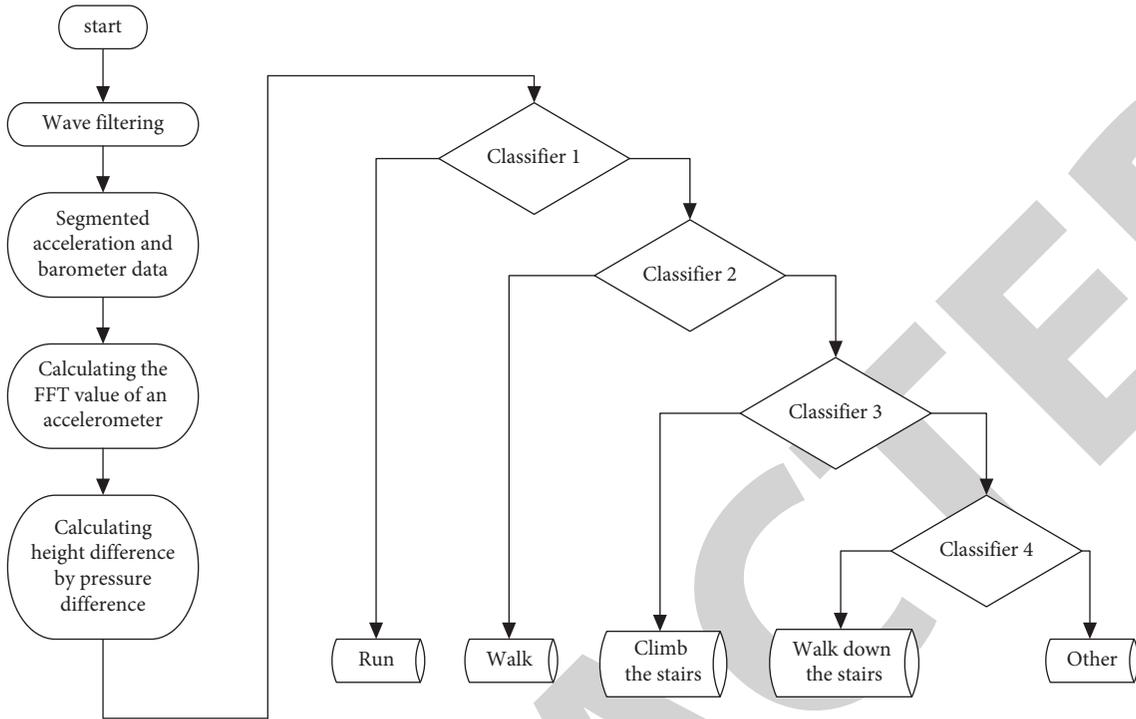


FIGURE 5: Gait recognition flowchart.

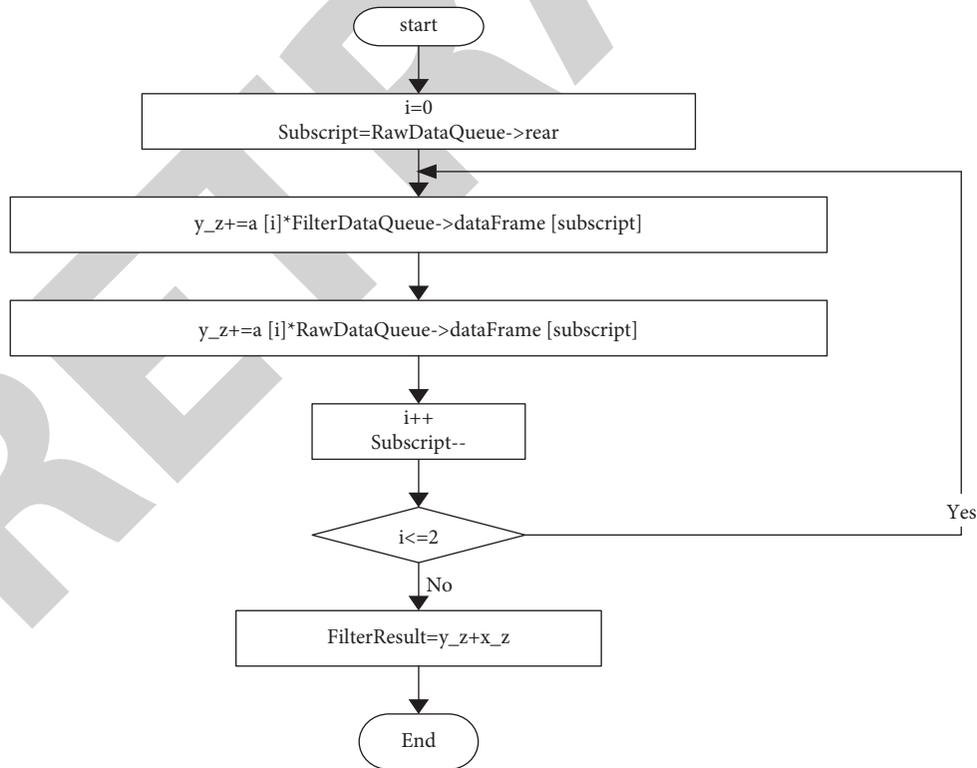


FIGURE 6: Filter implementation flowchart.

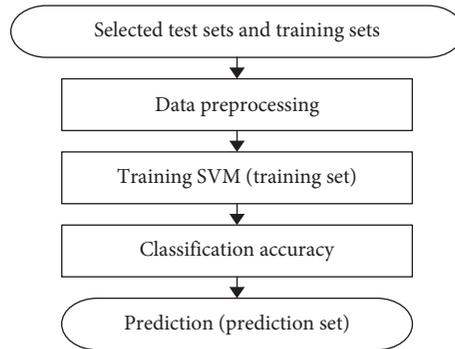


FIGURE 7: Algorithm flowchart.

too much so as to obtain a good classification effect. The basic idea of cross validation parameter optimization is to group the original data from some angles. Some of the data are used as the training set of the model, and the other data are used as the test set of the model.

**4.2. Test Result.** The researchers were asked to wear test equipment at the waist to record four gait patterns of walking, running, and going up and down stairs, each lasting 300 seconds. After statistical deletion, the six participants were between 21 and 60 years old, 150 cm to 181 cm tall, and 45 kg to 75 kg in weight. The final gait recognition results are shown in Table 1, indicating that the recognition accuracy has been improved to a certain extent. The data source of this paper is the waist-wearing test equipment records. The results are shown in Table 2.

The wearing method of the equipment and the choice of the experimental subjects are the same as in the previous section. As can be seen from Figure 8, the error of step counting between ascending stairs and descending stairs is slightly larger, but both are less than 2%. The accuracy of step counting products has been improved to a certain extent. However, compared with walking and running, the accuracy of walking up and down stairs is lower.

If the fall judgment algorithm above is used, the fall judgment behavior will be determined as a fall. Acceleration and gyroscope data waveforms are obtained when the device flips in the hand and actually falls back (Figure 9).

By observing the sensor curve and the actual fall curve of the hand flip scene, the acceleration data of the hand flip are not known to be weightless. Therefore,  $accx\_postue$  and  $gyrm\_angle$  are the fall characteristics. Figure 9 shows that, besides the weightlessness characteristics of the fall process, the weightlessness state is reflected in the sensor data. For a period of time, the weightlessness degree of the

body can be calculated. The maximum and minimum values of the parameter threshold of the drop value can be seen in Figure 9. The threshold of impact force is 3.1, the threshold of velocity is 5.2 m/s, the threshold of posture is  $30^\circ$ , and the threshold of flip angle is  $80^\circ$ . The weightlessness feature is added as one of the fall features. According to the different directions of falls, falls can be divided into four types: forward fall, backward fall, left fall, and right fall. In order to avoid injuries to the experimenters, all the experiments are carried out on the cushion. Compared with the actual landing, the impact strength will be reduced due to the slowing down of the cushion surface. But its inclination and attitude control will be the same. Therefore, this study can accurately evaluate the test. In addition, this paper also conducted a daily test. The tested personnel need to complete different daily activities, such as standing, walking, cycling, sitting for a long time, and climbing stairs. Finally, lie down, and each tester completes 20 times for each behavior, a total of 6 testers. Then, the algorithm identification is carried out for the tested personnel, the test error and measurement sensitivity are counted, and the extracted features are compared with the traditional features. Finally, it is found that the algorithm will not reduce the detection accuracy of falling targets after adding weightlessness characteristic parameters, which increases the reliability of the algorithm. At the same time, it shows that the algorithm in this paper has a reliable practical value.

In conclusion, MEMS sensors are used to accurately identify human behavior. One of the innovative conclusions of this paper is to improve the accuracy of dynamic recognition. For the state capture of target falling, it has very high judgment characteristics. This has a very important reference value for the study of human turnover shape in weightlessness. Therefore, the research of this paper effectively improves the specificity of the algorithm without reducing the research of weightlessness determination.

TABLE 1: Specific sensitivity processing of the algorithm.

	Impact force + attitude + speed	Impact + attitude + speed + angle	Impact + attitude + velocity + angle + weightlessness characteristics
Sensitivity (%)	100.00	100.00	100.00
The old man walks	100.00	100.00	100.00
The old man runs	100.00	100.00	100.00
The old man goes up the stairs	100.00	100.00	100.00
The old man goes down the stairs	100.00	100.00	100.00
The old man is sitting at the station	100.00	100.00	100.00
The old man lies in the bed	100.00	100.00	100.00
The young man walks	100.00	100.00	100.00
Young people run	100.00	100.00	100.00
Young people go up the stairs	100.00	100.00	100.00
Young people go down the stairs	100.00	100.00	100.00
The young man is sitting at the station	100.00	100.00	100.00
The young man lies in the bed	100.00	100.00	100.00
Young people jump	100.00	100.00	100.00
Take the equipment out of the waist	86.10	89.60	100.00
Wearing equipment at the waist	100.00	100.00	100.00
Put the equipment on the table	76.90	91.20	99.10
Play on the hand	72.50	78.70	92.50
Average specificity (%)	96.21	97.62	99.50

TABLE 2: Test result set table.

Experimenter	A flat walk (second)	A flat run (second)	Up the stairs (second)	Down the stairs (second)
Female 1	289	300	292	287
Female 2	291	297	289	289
Female 3	276	299	281	292
Male 1	287	298	288	291
Male 2	288	299	283	291
Male 3	289	296	290	291
Average recognition rate	95.56%	99.39%	95.72%	96.72%

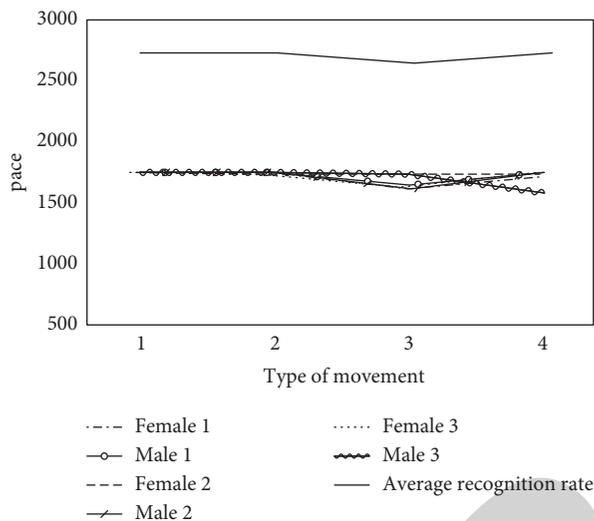


FIGURE 8: Step algorithm final test performance.

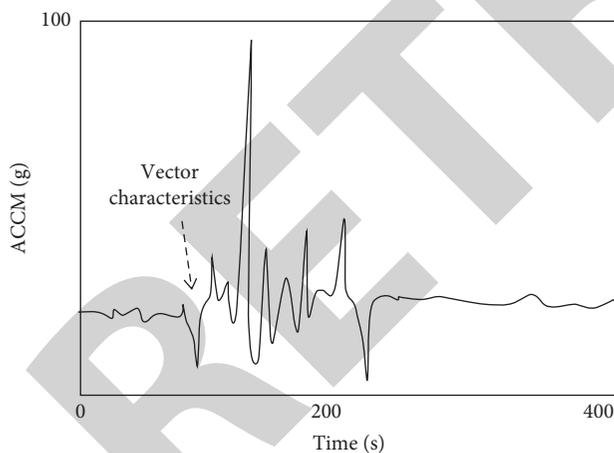


FIGURE 9: Data waveform.

## 5. Conclusion

Through the Hadoop framework algorithm, the expected maximum algorithm is effectively combined with the MapReduce model and migrated to the “cloud computing” platform to realize the theoretical model of large-scale data operation in order to improve the recognition efficiency of dynamic classification. At the same time, combined with the gait tactile recognition algorithm, it is verified. The results show that the proposed algorithm can effectively supervise

various algorithms. Because of the change of target weight caused by weight loss, the detection sensitivity of this paper is particularly important. With the increase of data specificity, the measurement of human turnover under the characteristics of weightlessness becomes more and more complex. Without reducing the measurement accuracy, this paper effectively studies various factors affecting the measurement accuracy, which effectively improves the specificity of the algorithm. Through simulation, the algorithm in this paper is of great practical application value. However, due to the further optimization of the collected data, some of the collected data are not complete, especially in the case of rolling and swinging. In future research, the experiment of this paper needs to add more data for research.

## Data Availability

The experimental 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 regarding this work.

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