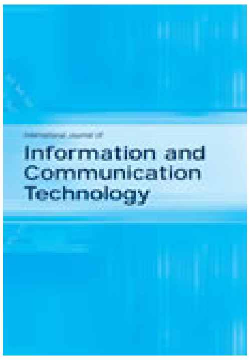

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Measurement and evaluation of linear motion parameters of ice and snow athletes based on acceleration sensors

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Abstract: With the popularisation and development of ice and snow sports, the measurement and evaluation of athletes' sports parameters are of great significance in improving their competitive level and avoiding sports injuries. This article proposes a linear motion parameter measurement and evaluation method for ice and snow athletes based on acceleration sensors. This method collects real-time acceleration data during exercise by wearing acceleration sensors, and uses data fusion and filtering techniques to extract linear acceleration and velocity changes of athletes. Furthermore, the Kalman filtering algorithm is used to optimise the noisy data in order to improve its accuracy and stability, and used support vector machine (SVM) algorithm to classify and evaluate the athletes' motion state. The experimental results show that this method can accurately measure the linear motion parameters of ice and snow athletes, efficiently evaluate their sports status.

Keywords: acceleration sensor; linear motion parameters; exercise assessment; Kalman filter; support vector machine; SVM.

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1 Introduction

Ice and snow sports, as a highly technical and challenging sport, not only require athletes to possess excellent physical fitness and skills, but also require precise sports data support to improve training efficiency and competitive performance. With the advancement of technology, sports data analysis has become one of the important tools in athlete training. Traditional sports assessment methods often rely on manual observation or the use of simple timing devices, which are not only limited by the accuracy and real-time nature of the assessment, but also susceptible to human factors. Therefore, researchers are increasingly inclined to use high-precision sensor technology to achieve precise measurement and evaluation of athletes' athletic performance.

As a modern motion monitoring tool, acceleration sensors are widely used in data collection and motion evaluation of various sports projects due to their high sensitivity, low cost, and portability (Troiano et al., 2014). Acceleration sensors can capture real-time changes in the acceleration of athletes during their movements, and then calculate relevant motion parameters such as speed, displacement, and acceleration. These data provide valuable information for athletes' performance (Freedson et al., 2005). Especially in ice and snow sports, due to the complex sports environment and high-intensity training requirements, accurate measurement of sports parameters is particularly important. By effectively accelerating sensor collection and data processing methods, more targeted training feedback can be provided to athletes, avoiding sports injuries and improving their competitive level.

However, although acceleration sensors can provide rich motion data, extracting effective information from large amounts of data and conducting real-time and accurate evaluations remains a challenge. In recent years, scholars have proposed some motion evaluation methods that combine sensor data to address this issue. Among them, Kalman Filter algorithm and machine learning technology have become important research directions. The Kalman filter can effectively remove noise from sensor data and improve data accuracy; Machine learning algorithms, especially classification models such as support vector machines (SVMs), can intelligently evaluate the movement status of athletes.

In recent years, with the advancement of sensor technology, athletes' performance evaluation has gradually relied on modern devices such as acceleration sensors. Many studies have attempted to apply acceleration sensors to monitor athletes' training and competitive status. For example, Jarchi et al. (2018) proposed a gait analysis method based on acceleration sensors, which accurately recognises and classifies human motion posture through acceleration data, providing theoretical support for gait optimisation. Rana and Mittal (2020) used the Kalman filter algorithm to optimise the speed and displacement estimation of athletes, thereby improving the accuracy and stability of motion parameters. Qiu et al. (2022) further applied acceleration sensors to real-time state monitoring of skiing and proposed an evaluation system that combines acceleration data and kinematic models, effectively reflecting the performance of athletes during skiing. Similarly, Liu et al. (2020) proposed a multidimensional motion evaluation method based on acceleration sensors, combined with Kalman filtering and clustering analysis, for dynamic monitoring of runners. Guo et al. (2024) studied the application of SVM for classifying acceleration sensor data, successfully identifying different movement states of skiers and providing real-time feedback for athlete training.

In addition, Lu et al. (2021) used acceleration sensors to monitor the speed and displacement of ice skaters, combined with machine learning algorithms for data analysis, and proposed a new athlete evaluation system. Wilk et al. (2020) studied the application of acceleration sensors in ice and snow sports, proposed a real-time motion state evaluation method based on sensor data fusion, and successfully applied it to skiing training. Waqar et al. (2021) further extended the combination of Kalman filtering and acceleration sensors, studied the linear motion parameters of athletes, and proposed an optimised data processing algorithm to improve the accuracy of athlete motion evaluation. Zwölfer et al. (2023) proposed a new motion posture recognition method by combining acceleration sensors with deep learning technology, which was successfully applied to motion analysis of ice and snow sports, providing a more accurate evaluation method. Mendes et al. (2016) studied multi-sensor fusion technology, which combined acceleration sensors and visual information to achieve comprehensive performance evaluation of ice and snow athletes, and improved the accuracy and real-time performance of the evaluation system based on this.

In summary, although existing research has provided multiple methods for athletes' training and assessment of their athletic performance, most studies still rely on single sensor data or relatively simple data processing techniques. How to combine acceleration sensor data and kinematic models to enhance the intelligence, real-time performance, and accuracy of evaluation systems remains one of the current research challenges. On the basis of previous work, this article proposes a new linear motion parameter measurement and evaluation method for ice and snow athletes based on acceleration sensors. By combining Kalman filtering and SVM algorithms, the accuracy and real-time performance of athlete motion state evaluation are optimised, further enhancing the scientific and personalised nature of ice and snow sports training.

The main contributions of this article are as follows:

1 Proposed a method for measuring and evaluating linear motion parameters of ice and snow athletes based on acceleration sensors: This study is the first to apply acceleration sensors to real-time monitoring of the motion status of ice and snow athletes. Combined with kinematic models, the linear motion parameters of athletes, such as speed, acceleration, and displacement, are accurately calculated through sensor data, providing quantitative support for athletes' performance.

2 Using Kalman filtering algorithm to optimise data processing: In order to improve the accuracy and stability of data collected by acceleration sensors, this paper introduces the Kalman filtering algorithm, which can effectively remove noise from sensor data, optimise motion parameter estimation, and enhance the accuracy of athlete state evaluation. This method has higher accuracy and robustness compared to traditional smoothing methods.

3 Combining SVM for intelligent classification of athlete states: In the evaluation of sports states, this paper adopts SVM algorithm to classify and evaluate the real-time sports state of athletes. SVM successfully distinguishes different motion states by constructing hyperplanes in high-dimensional space, achieving intelligent evaluation of the performance of ice and snow athletes.

2 Relevant technologies

2.1 Acceleration sensor

An acceleration sensor is an electronic instrument designed to detect and measure an object's acceleration in 3D space. It provides important information about the motion state of an object by detecting changes in acceleration in various directions (Riaboff et al., 2022). In motion analysis, acceleration sensors are widely used to measure physical parameters such as linear acceleration, velocity, and displacement of objects. The working principle of acceleration sensors is based on Newton's second law, which describes the connection between an object's acceleration and the force applied to it. The basic equation is as follows:

$$F = m \cdot a \tag{1}$$

where, F is the force acting on the object, m is the mass of the object, and a is the acceleration of the object. By measuring acceleration and combining it with mass information, the force acting on an object can be calculated. However, modern acceleration sensors do not directly measure force, but indirectly obtain acceleration by measuring the displacement of a mass block in a specific direction.

In acceleration sensors, common working principles include piezoelectric, microelectromechanical systems (MEMS), and capacitive. Taking MEMS acceleration sensors as an example, their working principle is based on displacement of micro mechanical structures (Grouios et al., 2022). The core structure of an acceleration sensor usually consists of a mass block and a pair of capacitor plates. When the sensor experiences acceleration, the mass block will undergo a small displacement relative to the housing, causing a change in the capacitance value. By measuring the change in capacitance, the acceleration of an object can be calculated.

Assuming that the output signal of the acceleration sensor is the change in capacitance ΔC, the relationship between this change and the acceleration of the object a_x can be expressed as:

$$\Delta C = k \cdot a_x \tag{2}$$

where k is the sensitivity coefficient of the sensor, and a_x is the acceleration measured by the sensor. By calibrating the sensor, the coefficient k can be obtained, thereby achieving accurate measurement of acceleration.

For data processing in practical applications, it is usually necessary to convert acceleration data into velocity and displacement. Assuming the acceleration measured within time t is $a(t)$ the velocity $v(t)$ and displacement $x(t)$ can be obtained by integrating the acceleration, and their mathematical expressions are as follows:

$$v(t) = \int a(t)dt + v_0 \tag{3}$$

$$x(t) = \int v(t)dt + x_0 \tag{4}$$

where v_0 and x_0 are the initial velocity and initial position, respectively. If the acceleration is assumed to be constant, the calculation of velocity and displacement can be simplified as a linear function. For acceleration data in practical applications, the acceleration usually changes over time, so it is necessary to solve it through numerical integration and other methods.

Due to the influence of noise on the data collected by acceleration sensors, it is necessary to process the raw acceleration data in practical applications to improve its accuracy. Common processing methods include low-pass filtering, Kalman filtering, etc. The Kalman filter is a recursive method that enhances measurement accuracy and reduces noise by dynamically modelling and estimating acceleration data states. Assuming that the observed value of acceleration data $a(t)$ after noise interference is $y(t)$, the Kalman filter uses the optimal estimation equation:

$$\hat{x}(t) = \hat{x}(t-1) + K \cdot \left(y(t) - \hat{x}(t-1) \right) \tag{5}$$

where $\hat{x}(t)$ is the estimated value of the current acceleration, K is the filtering gain, indicating the degree of dependence of the current estimated value on past data, $\hat{x}(t-1)$ is the estimated value at the previous time, and $y(t)$ is the current observation value. Kalman filtering can effectively remove noise while maintaining estimation accuracy.

Therefore, acceleration sensors can not only capture athletes' acceleration in real time, but also need to use mathematical models and data processing methods to effectively analyse and evaluate the collected data, and then calculate athletes' speed, displacement, and motion status. These precise motion parameters have important application value for athletes' training, competition, and injury prevention.

2.2 Kalman filtering

The Kalman filter is a recursive method that estimates a system's state using a sequence of observational data (Khodarahmi and Maihami, 2023). It was first proposed by Swiss mathematician Rudolf Kalman in 1960 and is widely used in fields such as navigation, control systems, and signal processing. As shown in Figure 1, the core idea of Kalman filtering is to establish a linear relationship between system state and observation, and to obtain the optimal estimate of system state through iterative updates by combining measurement data and prediction models. Kalman filtering can not only estimate the state of dynamic systems, but also effectively handle observation data with noise (Urrea and Agramonte, 2021).

The basic principle of Kalman filtering is based on Bayesian estimation theory, which minimises the mean square error of estimation under given observation conditions. Let the state of the system be a vector x_k, which is affected by the control input and random noise at every moment k. The dynamic model of the system's state can be represented as:

$$x_k = F_k x_{k-1} + B_k u_k + w_k \tag{6}$$

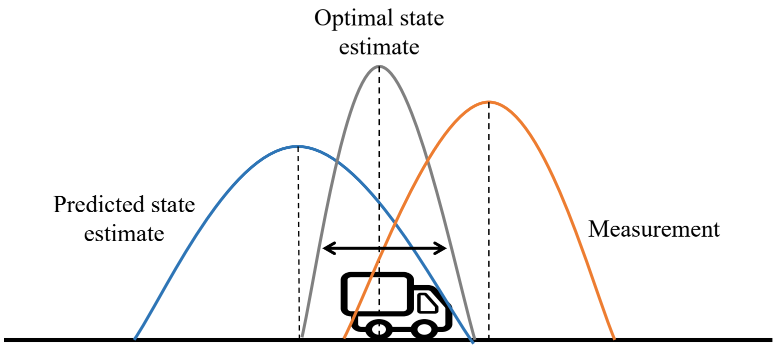
where F_k is the state transition matrix, B_k is the control input matrix, u_k is the control input, and w_k is the process noise

The observation model of the system describes how to obtain observation data from the system's state. Usually, there is a linear relationship between observed values and system state x_k, which includes observation noise. The observation equation can be expressed as:

$$z_k = H_k x_k + v_k \tag{7}$$

where H_k is the observation matrix, v_k is the observation noise, assuming its mean is zero and covariance is R_k.

Figure 1 Structure of Kalman filtering (see online version for colours)



The Kalman filter recursively estimates the system state through prediction and updating. Kalman filtering has significant advantages in many applications, especially when dealing with signals with noise. It can balance between the system model and the observed data, gradually approaching the optimal system state estimation through recursive updates.

2.3 Support vector machine

SVM is a supervised algorithm rooted in statistical learning theory, commonly applied in classification and regression tasks (Roy and Chakraborty, 2023). As shown in Figure 2, the core idea of SVM is to find an optimal hyperplane that can correctly separate data points of different categories while ensuring the maximum interval between categories. This algorithm is well-suited for high-dimensional, linearly inseparable data. By applying kernel tricks, it maps the data to a higher-dimensional space where linear separability becomes possible (Kok et al., 2021).

The basic task of SVM is to partition sample data into different categories through a hyperplane. For a given sample dataset 1, where 2 is the feature vector of the sample and 3 is the class label, the aim of SVM is to identify a hyperplane that maximally separates the two data classes. Assuming the hyperplane equation is:

$$w^T x + b = 0 \tag{8}$$

where w is the normal vector of the hyperplane, and b is the bias. In order to maximise the classification interval between two types of samples, SVM solves the optimal hyperplane such that the support vectors on both sides of the hyperplane are farthest from the hyperplane.

The objective of a SVM is to maximise the margin between two sample classes, that is, the distance between sample points and the hyperplane. For the hyperplane equation, its distance S can be expressed by the following equation:

$$S = \frac{1}{\| w \|} \tag{9}$$

Therefore, maximising the interval is equivalent to minimising $\| w \|$. In order to satisfy the classification constraint that positive and negative class samples are located on both sides of the hyperplane and at least 1 away from the hyperplane, we need to optimise the following objective function:

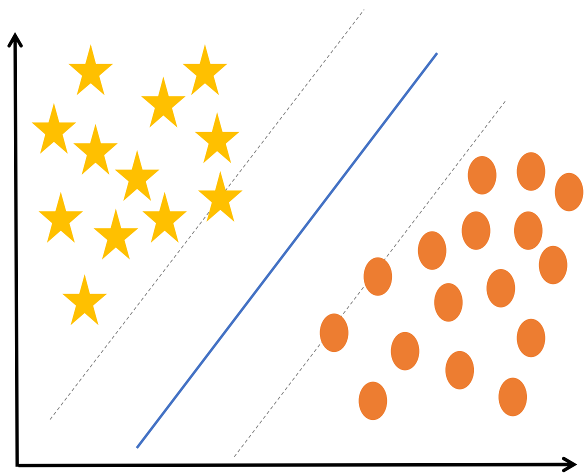
$$\min_{w,b} \frac{1}{2} \| w \|^2 \tag{10}$$

Meanwhile, the constraint conditions are:

$$y_i \left(w^T x_i + b \right) \geq 1 \tag{11}$$

where y_i is the label of the sample x_i and x_i is the feature of the sample. This constraint ensures that all samples are correctly classified and that each sample maintains at least a certain distance from the hyperplane.

Figure 2 Structure of SVM (see online version for colours)



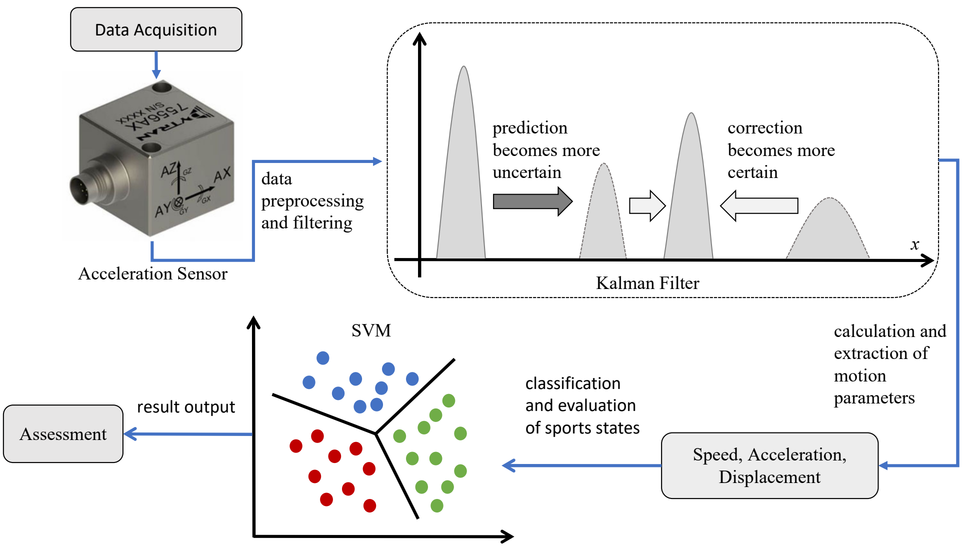
In SVM, the final decision boundary is determined by the hyperplane that maximises the interval, and the sample points that determine this hyperplane are called support vectors. Support vectors are the data points nearest to the hyperplane, essential for defining the decision boundary's position and orientation. Other non support vectors have a relatively small impact on the hyperplane and therefore do not play a direct role in determining the optimal classification boundary.

In summary, SVMs can find the optimal decision boundary in high-dimensional space by maximising the classification interval, and are suitable for both linearly separable and linearly inseparable problems. Its strong generalisation ability, robustness, and ability to handle nonlinear problems through kernel functions have achieved significant results in many practical applications.

3 Measurement and evaluation method of linear motion parameters for ice and snow athletes based on acceleration sensors

The method proposed in this article for measuring and evaluating linear motion parameters of ice and snow athletes based on acceleration sensors, combined with acceleration sensor data, Kalman filtering algorithm, and SVM classification algorithm, can obtain key motion parameters such as linear acceleration, velocity, and displacement of athletes in real time, and classify and evaluate their motion status. The model framework diagram is shown in Figure 3.

Figure 3 Method framework diagram (see online version for colours)



3.1 Accelerate sensor data acquisition and preprocessing

Firstly, by wearing acceleration sensors on key areas of athletes such as the chest, waist, legs, etc., real-time three-dimensional acceleration data during ice and snow sports can be collected. Acceleration data is usually represented as $a(t) = [a_x(t), a_y(t), a_z(t)]^T$, where $a_x(t)$, $a_y(t)$, $a_z(t)$ represents the acceleration components in the three coordinate axis directions.

The linear acceleration of athletes can be obtained by synthesising acceleration data:

$$a_{linear}(t) = \sqrt{a_x(t)^2, a_y(t)^2, a_z(t)^2} \tag{12}$$

This step provides raw acceleration data for subsequent motion parameter calculations, but the actual collected acceleration data is often affected by sensor errors, environmental interference, and other factors, so noise filtering is required.

3.2 Data fusion and Kalman filtering

To enhance data accuracy and stability, this article applies the Kalman filtering algorithm to refine the collected acceleration data. Kalman filter is a recursive optimal estimation algorithm that can reduce the impact of noise on motion parameter estimation by fusing observed and predicted values. Set the state vector of acceleration data to $x(t) = [v_x(t), v_y(t), v_z(t)]^T$, where $v_x(t)$, $v_y(t)$, $v_z(t)$ represents the components of velocity in the x, y, and z directions. According to the kinematic model, the relationship between velocity and acceleration is:

$$v(t) = v(t-1) + a(t)\Delta t \tag{13}$$

where $v(t-1)$ is the velocity estimate at the previous time, $a(t)$ is the acceleration at the current time, and Δt is the time interval.

The optimisation process of Kalman filter is predicted and updated through the following formula:

In the prediction step, the Kalman filter utilises the state estimation and control input from the previous moment to predict the current state and predicted covariance. The predicted state estimate is:

$$\hat{x}_{\overline{k}} = F_k \hat{x}_{k-1} + B_k u_k \tag{14}$$

where $\hat{x}_{\overline{k}}$ is the predicted value for the current state.

The covariance matrix $P_{\overline{k}}$ for prediction is:

$$P_{\overline{k}} = F_k P_{k-1} F_k^T + Q_k \tag{15}$$

where $P_{\overline{k}}$ is the covariance matrix of prediction error, P_{k-1} is the covariance matrix of the previous time, and Q_k is the covariance of process noise.

In the update step, the Kalman filter combines the actual observed values z_k and the predicted state estimate to correct the state estimate. Firstly, calculate the observation residual:

$$y_k = z_k - H_k \hat{x}_{\overline{k}} \tag{16}$$

where y_k is the measurement residual.

Then, calculate the Kalman gain matrix K_k, which determines the weighting relationship between prediction and observation:

$$K_k = P_{\overline{k}} H_k^T \left(HkP_{\overline{k}} H_k^T + R_k \right)^{-1} \tag{17}$$

The Kalman gain adjusts state estimation by considering the difference between observed and predicted values.

Next, update the state estimation:

$$\hat{x}_k = \hat{x}_{\overline{k}} + K_k y_k \tag{18}$$

Finally, update the covariance matrix:

$$P_k = \left(I - K_k H_k \right) P_{\overline{k}} \tag{19}$$

where P_k is the updated estimation error covariance matrix, and I is the identity matrix. Optimise acceleration and velocity through Kalman filtering, remove noise, and improve data accuracy.

3.3 Deduction of linear motion parameters

After optimising acceleration and velocity, we can further derive linear motion parameters such as instantaneous velocity, acceleration, and displacement of athletes. Specifically, instantaneous velocity can be obtained by integrating acceleration:

$$v_x(t) = \int_0^t a_x(t)dt \tag{20}$$

$$v_y(t) = \int_0^t a_y(t)dt \tag{21}$$

$$v_z(t) = \int_0^t a_z(t)dt \tag{22}$$

Displacement can be obtained by integrating the velocity again:

$$d_x(t) = \int_0^t v_x(t)dt \tag{23}$$

$$d_y(t) = \int_0^t v_y(t)dt \tag{24}$$

$$d_z(t) = \int_0^t v_z(t)dt \tag{25}$$

The instantaneous velocity and displacement derived from these formulas can accurately reflect the dynamic performance of athletes in ice and snow sports.

3.4 SVM classification and evaluation

Once the athlete's motion parameters, such as acceleration, velocity, and displacement, are obtained, the next step is to classify and assess the athlete's motion state in real time. Therefore, this article adopts the SVM algorithm for classification. SVM distinguishes different motion states such as acceleration, deceleration, and uniform speed by constructing hyperplanes in high-dimensional space.

The training process learns classification boundaries by using historical motion data (including velocity, acceleration, and other information) as the training set. During the testing phase, SVM utilises a trained classification model to evaluate real-time motion data and output the current motion state of the athlete. The classification model of SVM can be expressed as:

$$f(x) = \sum_{i \in S} \alpha_i y_i K(x_i, x) + b \tag{26}$$

where x_i is the training sample, y_i is the label (motion state), α_i is the Lagrange multiplier, $K(x_i, x)$ is the kernel function, and b is the bias term. Through the classification results of

SVMs, we can provide real-time evaluation of athletes' athletic performance, helping coaches and athletes adjust their training strategies.

Based on the classification results of SVM and the derived motion parameters, this method can evaluate the athlete's motion status in real time, such as acceleration, uniform speed, deceleration, etc., and provide dynamic feedback. This real-time feedback can provide valuable performance information for coaches and athletes, helping to adjust training plans and strategies and improve training effectiveness.

The linear motion parameter measurement and evaluation method for ice and snow athletes based on acceleration sensors proposed in this article can accurately measure the linear motion parameters of athletes and evaluate their motion status in real time through steps such as acceleration data acquisition, Kalman filter optimisation, kinematic derivation, and SVM classification. Through the comprehensive application of these technologies, the method proposed in this article not only improves the accuracy of athletes' performance analysis, but also provides strong technical support for evaluating their sports status during training and competitions.

4 Experiment

To validate the effectiveness of the linear motion parameter measurement and evaluation method for ice and snow athletes based on acceleration sensors proposed in this article, multiple comparative experiments were designed and evaluated using publicly available datasets. Common evaluation indicators were used to compare different models.

4.1 Dataset

This article uses a publicly available dataset - Skiing and Snowboarding Activity Dataset, which contains data on various skiing and snowboarding activities and is suitable for evaluating the exercise status and measuring exercise parameters of ice and snow athletes. The dataset is collected through various sensors worn on athletes, recording multi-dimensional sensor data including acceleration, angular velocity, displacement, GPS coordinates, and more. Specifically, acceleration data includes acceleration components in three axes, as well as rotation information provided by the gyroscope. Each activity of athletes is labelled as a different category, such as regular skiing, fast downhill, jumping, etc. The timestamp of the dataset is consistent with the sensor data, which can accurately reflect the athlete's movement trajectory and state changes. In addition, the dataset also includes labels for classification tasks, facilitating the recognition and evaluation of motion states. There are multiple athletes' exercise records in the dataset under different environmental conditions, which are suitable for the validation of exercise parameter calculation and exercise state classification tasks in this study.

4.2 Evaluation

In order to comprehensively evaluate the athlete sports parameter measurement and evaluation method proposed in this article, we adopted the following common evaluation indicators:

- Accuracy: it represents the ratio of correctly classified samples to the total number of samples, commonly used in classification tasks.

$$Accuracy = \frac{Correctly\ classified\ samples}{Total\ samples} \tag{27}$$

- Precision: it calculates the ratio of actual positives among the samples predicted as positive by the model, making it suitable for imbalanced datasets.

$$Precision = \frac{TP}{TP + FP} \tag{28}$$

where *TP* represents true positive and *FP* represents false positive.

- Recall: it indicates the ratio of actual positives among the samples predicted as positive by the model.

$$Recall = \frac{TP}{TP + FN} \tag{29}$$

where *TP* represents true positive and *FN* represents false negative.

- F1 Score: the harmonic mean of precision and recall, used to evaluate a model's performance comprehensively.

$$F1\text{-}Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{30}$$

- RMSE: used to evaluate the prediction accuracy of motion parameters such as velocity, acceleration, and displacement, especially suitable for regression problems.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2} \tag{31}$$

where y_i is the true value, $\hat{y}_i$ is the predicted value, and *N* is the sample size.

4.3 Comparison of experimental results

To assess the effectiveness of the method presented in this article, we conducted comparative experiments with several other common models, including the following:

Model 1 Classic acceleration integration method: by simply integrating acceleration data to calculate the speed and displacement of athletes, without considering noise and data optimisation.

Model 2 Acceleration data and Kalman filter optimisation method: only Kalman filter is used to optimise acceleration data, without considering the classification of athletes' motion states.

Model 3 SVM classification method: use SVMs to classify the movement state of athletes, and train and classify them using acceleration and velocity data.

Model 4 The acceleration sensor + Kalman filter + SVM classification method proposed in this article: the complete method proposed in this article optimises acceleration data through Kalman filtering and evaluates classification through SVM.

Table 1 Model comparison experiment results

Method	*Accuracy*	*Precision*	*Recall*	*F1 Score*	*RMSE (speed)*	*RMSE (acceleration)*
Classical acceleration integration method	0.82	0.84	0.80	0.82	0.03	0.05
Acceleration data and Kalman filter optimisation method	0.85	0.85	0.83	0.84	0.02	0.04
SVM classification method	0.88	0.87	0.85	0.86	0.02	0.03
Acceleration sensor+ Kalman filter + SVM classification method	0.92	0.90	0.89	0.89	0.01	0.02

Figure 4 Comparison results of accuracy, precision, recall, and F1 Score (see online version for colours)

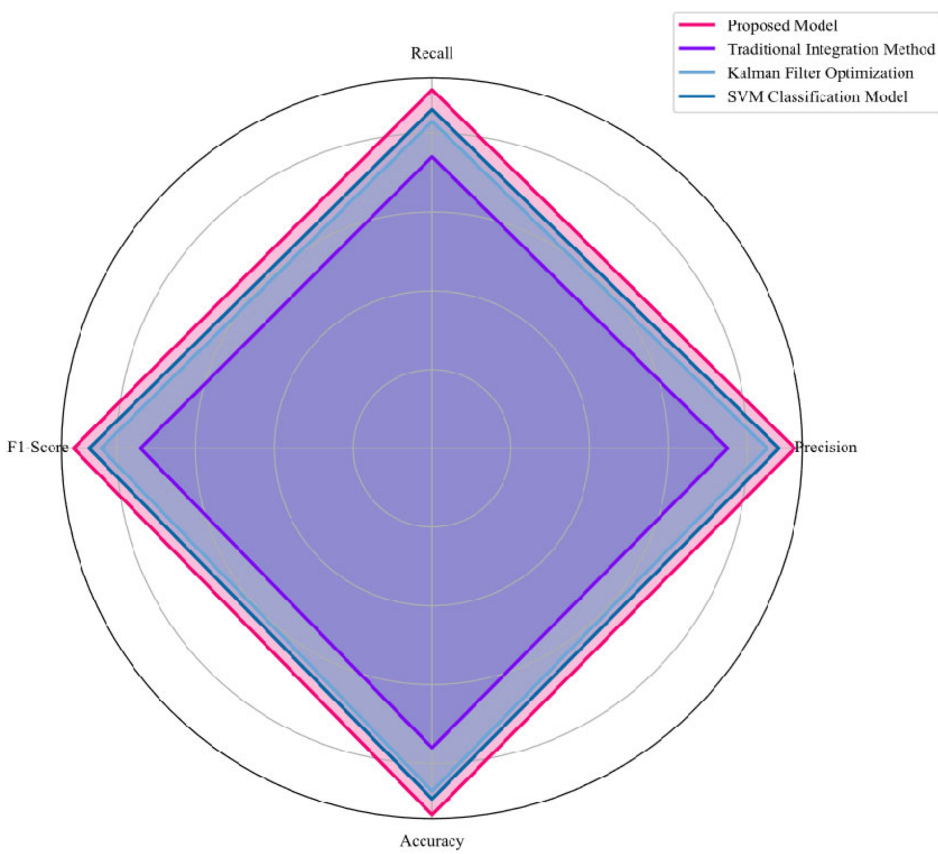
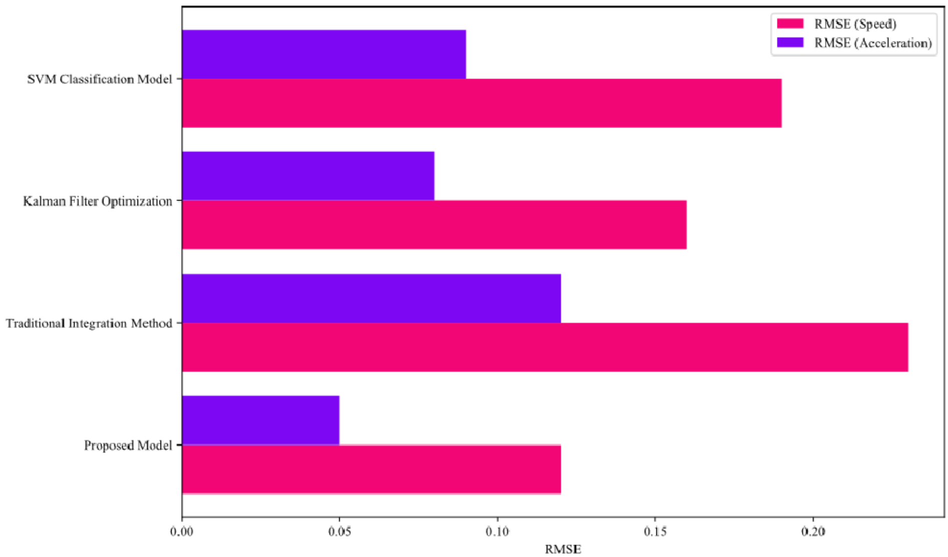


Table 1 shows the experimental results, Figure 1 compares the accuracy, precision, recall, and F1 Score, and Figure 2 compares the RMSE of velocity and acceleration.

Figure 5 Comparison results of RMSE of velocity and acceleration (see online version for colours)



5 Conclusions

This article proposes a linear motion parameter measurement and evaluation method for ice and snow athletes based on acceleration sensors, aiming to accurately estimate the key motion parameters of athletes during ice and snow sports through real-time collection and processing of acceleration data. Combined with motion state classification and evaluation techniques, it provides strong support for the analysis of sports performance in training and competitions. To this end, this article uses acceleration sensors for data acquisition, optimises noise processing through Kalman filtering algorithm, and uses SVM algorithm to classify and evaluate athletes' motion status. The experimental results indicate that the method suggested in this paper can significantly improve the measurement accuracy of linear motion parameters compared to traditional acceleration integration method and simple Kalman filter optimisation method, especially in the estimation of velocity, acceleration and displacement, with lower RMSE values and significantly improved accuracy. Compared with other common methods, this method has shown strong advantages in accuracy, precision, and recall of motion state assessment. The successful application of this method provides a new technical path for real-time monitoring and dynamic performance analysis of ice and snow athletes, and has high practical value. Future research can further explore more accurate sensor fusion technologies, introduce deep learning models, and optimise kinematic modelling for specific ice and snow sports events, thereby further enhancing the intelligence level of athlete sports state evaluation.

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Declarations

All authors declare that they have no conflicts of interest.

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