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Article

Optimization of alpine skiing turning techniques based on biomechanics

Changfeng Li[1], Jiandong Wang[1], Bing Zhou[1], Baoku Sui[2,*]

[1] Department of Physical Education and Research, the Tourism College, Changchun University, Changchun 130607, China
[2] Ice and Snow Sports Institute, Capital University of Physical Education and Sports, Beijing 100191, China
[*] **Corresponding author:** Baoku Sui, suibaoku2024@163.com

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Abstract: Alpine skiing turning technique requires high coordination of movements, but the existing training methods lack in-depth analysis of biomechanical characteristics. Athletes are prone to injuries during training. Technical optimization mainly relies on summarizing experience and lacks a precise quantitative basis. This paper aims to systematically analyze and optimize alpine skiing turning techniques from a biomechanical perspective, build a scientific action model and data analysis system, realize quantitative evaluation of technical movements, improve training safety and technical level, and provide scientific guidance for athletes. The study uses motion capture equipment to record three-dimensional motion trajectories and pressure sensors to collect mechanical data. By building an analysis model based on biomechanics, key features such as joint angles and torque changes are extracted, and an optimization scheme is designed in combination with a nonlinear multi-objective optimization algorithm. Based on these models and algorithms, a real-time feedback system is developed to provide personalized training suggestions to support athletes in adjusting movements and improving their technical level. The experimental results show that compared with the traditional training method, the coordination and balance of the optimized training model are improved by about 23.6% and 13.6% respectively, the action efficiency is improved by about 26.9%, and the risk of injury is reduced by more than 20%. In addition, the results of the model generalization ability test also show that the optimized training method has the characteristics of adapting to different groups. This shows that the optimized training method can significantly improve movement coordination and efficiency while reducing the risk of sports injuries, providing a new path for the scientific training of alpine skiing.

Keywords: alpine skiing technique; biomechanical analysis; motion capture; nonlinear optimization; real-time feedback system

1. Introduction

Alpine skiing is a sport that combines speed and technology, in which turning technology, as a core skill, directly affects the performance and safety of skiers. During skiing, athletes need to coordinate lower limb joints, core muscles and upper limb movements, while adapting to complex terrain and rapidly changing environments. In this high-intensity sport, reasonable technical movements can not only improve speed and stability, but also effectively reduce the risk of injury. However, the current training and technical research of alpine skiing mainly relies on coaching experience and lacks quantitative analysis of biomechanical characteristics. This training method is difficult to systematically capture the core elements of technical movements, resulting in limited technical optimization effects. In addition, due to the lack of scientific movement monitoring and evaluation mechanisms, athletes are prone to sports injuries during high-repetitive and high-intensity training. Therefore, how to deeply analyze the biomechanical characteristics of alpine skiing turning techniques through scientific means and build a systematic optimization solution is a problem that needs to be studied at present.

This paper constructs an analysis model based on biomechanics, integrates motion capture equipment and multimodal sensors, and extracts key information on joint angles, torque changes, and pressure distribution in alpine skiing. The study combines nonlinear multi-objective optimization algorithms to design optimization schemes, and puts forward improvement suggestions focusing on the dynamic balance and mechanical coordination issues during ski turns. In addition, a personalized training system is developed based on real-time data feedback technology to achieve accurate monitoring and real-time adjustment of movement performance.

The innovation of this paper is to design a multidisciplinary fusion method that combines biomechanics, motion capture and computer modeling technology to fill the gap in the lack of movement quantification and optimization solutions in traditional training methods. Through data verification of athletes' actual training, the study improved the stability and efficiency of technical movements, reduced the risk of sports injuries, and provided new ideas for the scientific and precise training of alpine skiing.

2. Related work

For the optimization of alpine skiing turning techniques, existing studies have explored from multiple angles. Some studies have used three-dimensional kinematic analysis methods based on motion capture technology to obtain changes in athletes' body postures and analyze the dynamic trajectory and speed characteristics of skiing movements [1]. However, these studies are limited to surface motion trajectory analysis and lack in-depth mechanical data analysis. Another type of research uses ground reaction force sensors to obtain the mechanical characteristics of skiing movements [2,3], but fails to effectively combine the details of the movements and it is difficult to build an overall technical optimization framework. In addition, there are studies that use electromyographic signals to analyze muscle activation patterns [4,5], but due to the complexity of the sports environment, this type of method is limited in its application in skiing. The introduction of deep learning and nonlinear optimization technology has provided new ideas for biomechanical research [6], but in the field of alpine skiing, there are still few practical application cases of these methods. To solve the above problems, this paper adopts a method that combines nonlinear multi-objective optimization algorithm [7] with motion capture technology [8] to systematically analyze the core biomechanical characteristics of alpine skiing turning technology from three aspects: motion trajectory, mechanical properties and muscle coordination, and designs targeted optimization schemes to provide quantitative basis for athletes' technical improvement.

In recent years, scholars have studied the biomechanical framework from different angles and methods. Among them, Li M used the novel SFO-MCNN (synergistic fibroblast-optimized malleable convolutional neural network) method and combined it with a biomechanical framework to analyze student movements and found that the algorithm achieved the highest evaluation results in improving average skill performance, physical fitness, student happiness, and physical education teaching efficiency [9]. Jasper Verheul et al. discussed the unique aspects and challenges of measuring biomechanical loads at different levels in laboratory and field settings, helping sports scientists and practitioners to think critically about the value and limitations of biomechanical load metrics. He continued to explore new measurement methods to gain a deeper understanding of the biomechanical load-response pathways that occur in the field [10]. Lloyd D explored the application of biomechanics in identifying the causes of musculoskeletal tissue injury and degeneration, and evaluated how biomechanics can be used to develop training programs aimed at maintaining or restoring tissue health. His research found that the quality and effectiveness of biofeedback technology can be improved by combining personalized neuromusculoskeletal models with real-time motion capture and medical imaging [11]. Gerwyn T.G. Hughes et al. introduced the application of technologies such as inertial measurement units (IMUs) to measure human motion and inertial forces during movement in the field of sports biomechanics, emphasizing the cost-effectiveness and portability of these technologies, but requiring extensive independent testing to establish their validity and reliability [12]. In teaching, Liu Y et al. used Internet big data analysis to implement a personalized IRDC (Internet + retrieval literature + big data + cloud) teaching model to address the problems of single teaching methods in sports biomechanics education. The results showed that this model can give full play to the advantages of big data teaching, improve teaching pertinence, and improve students' academic performance and comprehensive quality [13]. In the analysis of athletes' force points, Jasper Verheul et al. recorded athletes' whole-body kinematics and ground reaction forces (GRF) using a three-dimensional motion capture system and a force measurement platform, and used a direct mechanical method to estimate GRF from the acceleration of various parts of the body. The results showed that the accuracy of the estimation was affected by the type of movement and the number of body segments, and was not suitable for evaluating the whole-body biomechanical load in different dynamic and high-intensity activities [14]. Xavier Gasparuttoa et al. [15] compared two biomechanical models with different trunk and shoulder characteristics to evaluate the effects of these characteristics on the kinematics and dynamics of pitchers and found that different characteristics had significant effects on the kinematics and dynamics of pitchers. Although these biomechanical studies cannot be directly applied to the turning techniques of alpine skiing, they provide a certain reference for the use of the algorithms and techniques in this paper. This paper can integrate the relationship between motion trajectory, mechanical characteristics and muscle activity to comprehensively analyze the key biomechanical elements of turning techniques.

In the study of optimization strategies for alpine skiing turning techniques, many studies have used different methods to improve movements and efficiency. Cai C et al. established a trajectory optimization model for super-G skiers based on optimal control theory, used pseudo-spectral method to solve the multi-stage nonlinear optimal control problem, obtained the time-optimal trajectory, and verified the effectiveness and rationality of the model through simulation [16]. Based on the assumption that the forces and moments acting on skiers during a turn are approximately balanced, Komissarov [17] analyzed the model of pure carving turns in alpine skiing and snowboarding and found that pure carving is only feasible on slopes with a small slope gradient, and the critical slope gradient range is 8°–20°. However, the upper speed and slope limits set by the model are too strict. Legotin S D et al. used numerical modeling methods to study the motion of the skier-snowboard mechanical system during carving turns and obtained dimensionless parameter system equations that describe the skier's speed and trajectory, the relative angle between the body and the snowboard and the slope [18]. Jo H D compared and analyzed the kinematic variables of short turns of 12 skiers (6 skilled and 6 unskilled) and found that skilled skiers had a larger shoulder twist angle at the beginning of the turn, a higher pole check angle at the end, and a more rightward center of gravity horizontal displacement. Skilled skiers can better control the center of gravity displacement, trajectory, speed, edge angle, and lower limb joint angle when turning. Studies have shown that the upper body should be inclined to the side holding the pole, the edge angle should be increased when turning, and the arm should be swung in the direction of the forearm vector when checking the pole [19,20]. In addition, Deva E et al. systematically reviewed relevant literature and analyzed the effects of ground reaction force on specific stages of ski turns. They found that the ground reaction force reaches its peak during the control phase of the turn, with greater force on the outer foot and greater force on the steeper the slope [21]. Kim J N used an inertial measurement unit to measure the three-dimensional angles of the ankle, knee, and hip joints of 14 ski coaches during basic long turns, long carved turns, basic short turns, and short carved turns. He found that the angles of the lower limb joints in the medial and lateral axes and the vertical axis were significantly different during long turns and carved turns, and short turns required more complex lower limb joint movements than long turns [22]. These studies explain the turning problem of alpine skiing to a certain extent and propose solutions, but most of these studies have deficiencies in data collection, environmental adaptability and algorithm efficiency. This paper combines nonlinear multi-objective optimization algorithms with biomechanical analysis to systematically analyze the details of movements and mechanical characteristics, improve turning techniques and enhance training effectiveness.

3. Biomechanical analysis and optimization model construction

3.1. Movement collection and data processing

The application scenarios of the biomechanical analysis model are mainly the consistency analysis between the joint angle and the movement trajectory when skiing turns, the force balance assessment and the improvement of movement efficiency. Through detailed three-dimensional kinematic analysis of each athlete's movements, a detailed movement assessment report can be provided to the athlete at the beginning of training, and after each training session, combined with real-time data feedback, optimization suggestions for the athlete's technical movements are made to ensure the accurate achievement of each training goal. The three-dimensional trajectory of alpine skiing turns was acquired using the Vicon motion capture system [23,24]. Sixteen high-precision infrared cameras were set up in the experimental site to construct a three-dimensional space covering the complete skiing trajectory. The relative positions between the cameras were strictly calibrated, and the DLT (Direct Linear Transform) algorithm was used to correct the camera parameters and construct a global coordinate system. The data sampling frequency is set to 250 Hz to ensure that the details of high-speed movements are captured without loss. The key points of the skier's body are marked with passive reflective markers, covering the key points of the main joints and the center of gravity. The infrared reflection signal captured by the camera calculates the three-dimensional coordinates of the markers through the principle of triangulation positioning to form a continuous trajectory of joint movement.

In order to obtain the pressure distribution on the bottom of the ski boot and the moving path of the center of gravity, the experiment used a Tekscan flexible pressure sensor array [25]. The sensor is placed on the bottom of the ski boot and records the contact pressure of different areas during the sliding process. The sampling frequency is 100 Hz and is synchronized with the trajectory data. The sensor data is converted into pressure values through voltage signals, and the dynamic change path of the center of gravity position is calculated in combination with the mechanical model. The real-time calculation formula of the center of gravity is:

$$C_x = \frac{\sum_{i=1}^{N} F_i \times x_i}{\sum_{i=1}^{N} F_i}, C_y = \frac{\sum_{i=1}^{N} F_i \times y_i}{\sum_{i=1}^{N} F_i} \tag{1}$$

Among them, F_i represents the pressure value recorded by the ith unit of the sensor, x_i and y_i are the horizontal and vertical coordinate positions of the unit respectively, and N is the total number of sensor units.

Motion acquisition and sensor data are synchronized through external trigger signals. The motion capture system and the pressure sensor system set a unified trigger time point to ensure the consistency of different data sources on the time axis.

In order to reduce random errors and high-frequency noise in the data, all collected data are processed using a Butterworth low-pass filter [26]. The filter order was set to 4, the cutoff frequency was set to 6 Hz, and the smoothness of the filtered signal was verified by visual inspection and spectrum analysis. The core equation of the low-pass filtering process is:

$$y[n] = b_0 x[n] + b_1 x[n-1] + \cdots + b_M x[n-M] - a_1 y[n-1] - \cdots - a_N y[n-N] \tag{2}$$

Among them, $x[n]$ is the original signal, $y[n]$ is the filtered signal, $\mathrm{b_M}$ and $\mathrm{a_N}$ are the transfer function coefficients of the filter, which are calculated by the preset cutoff frequency.

All collected and processed data are standardized, and the Z-score normalization method is used to make the data distribution between different skiers comparable. The standardization formula is as follows:

$$Z = \frac{X - \mu}{\sigma} \tag{3}$$

Among them, X is the original data, μ is the data mean, and σ is the data standard deviation. The standardized data is used for biomechanical feature extraction and optimization modeling.

3.2. Extraction of action biomechanical features

The action biomechanical features are completed through the whole-body skeletal-muscle dynamics model based on OpenSim [27]. The model construction involves the parametric description of the complete joint chain, and the flexion, extension and rotation angles of the key joints of the skier in the turning action are selected as the main feature variables. The optimization model not only analyzes the static movement characteristics of athletes, but also focuses on the dynamic changes during the turning process. The model can calculate the changes in joint torque and shear force in real time, and analyze the impact of force fluctuations on athletes' movements during sharp turns or high-speed sliding. The extraction of these dynamic features helps to more accurately evaluate the effect of technical optimization. When evaluating the changes in the biomechanical characteristics of athletes, the changes in joint angles are calculated by inverse kinematics, and the changes in shear force of the knee and hip joints are analyzed using the torque inversion method, and the force conditions of athletes in different turning situations are recorded in real time. By comparing the data before and after optimization, the changes in technical coordination and force balance during training are clearly shown, so as to fully capture the technical performance of athletes during the turning process. In addition, due to differences in physiological structure, male and female athletes have different force patterns, joint angles and muscle coordination when turning. The model adjusts the optimization goals according to the gender of the athlete. For example, the optimization goals of the knee and hip joints will be adjusted according to gender differences, thereby achieving more accurate personalized training. As shown in **Figure 1**, the input data is driven by the three-dimensional motion trajectory collected by the Vicon system, the joint angles are calculated by inverse kinematics, and the objective function is to minimize the square error between the marker point and the model predicted position.

Figure 1. Distribution of joint torque and shear force.

The characteristics of joint angle change are extracted by interval integration method:

$$\theta(t) = \arctan(\frac{y_2(t) - y_1(t)}{x_2(t) - x_1(t)}) \tag{4}$$

In the formula, $\theta(t)$ represents the angle of a joint, and (x_1, y_1) and (x_2, y_2) are the instantaneous positions of the bone endpoints connected by the joint.

The moment analysis uses joint dynamics inversion to calculate the shear force and moment of the knee and hip joints. In this process, the inverse solution based on the Newton-Euler dynamics equation is:

$$\tau = J^T F_{\text{ext}} + I\ddot{\theta} \quad (5)$$

Among them, τ is the joint torque, J is the Jacobian matrix, F_{ext} is the external force vector, and $\ddot{\theta}$ is the angular acceleration. The shear force is calculated by decomposing the projection of the ground reaction force on the joint surface. During the analysis, the maximum values of the torque and shear force are quantified by the peak extraction method. When extracting joint angle and torque changes, the inverse kinematics method is used to calculate the joint angle through the three-dimensional coordinate data obtained by the motion capture system. To ensure the accuracy of the extraction, the least squares method is used to optimize the square error between the marker point and the predicted position. In addition, the torque is reversely solved by combining the Newton-Euler equation to accurately evaluate the force characteristics of the knee and hip joints and monitor the changes in technical movements in real time.

Three-dimensional kinematic analysis is used to quantify the deviation between the skier's motion trajectory and the target sliding path. Taking the sliding path as the reference curve, the error is calculated by the Euclidean distance from the point to the curve:

$$d_i = \min_j \parallel P_i - C_j \parallel \quad (6)$$

Among them, P_i is the point on the actual trajectory of the skier, and C_j is the set of points on the target curve. The mean and standard deviation of all point errors are used as evaluation indicators of path deviation.

The movement coordination analysis is combined with pressure distribution data to evaluate the balance of left and right foot pressure and the stability of the center pressure trajectory. The stability of the pressure trajectory is calculated by the sliding window method. The discretization smoothing index of the trajectory is defined by the mean squared error (MSE):

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(P_i - \overline{P})^2 \quad (7)$$

In the formula, P_i is the discrete point on the trajectory, $\overline{P}$ is the center point of the trajectory, and N is the total number of discrete points.

After the feature extraction results are standardized, they are input into the optimization model and feedback system to achieve action optimization and suggestion generation.

3.3. Action optimization model construction

During the model building process, the optimization algorithm makes personalized parameter adjustments based on each athlete's biomechanical data (joint angle range, force distribution, etc.). During the genetic algorithm solution process, the model automatically adjusts the weight of the objective function based on the athlete's historical data and the deviation of the current action, ensuring that each athlete's training program can maximize its physiological characteristics and technical level, thereby achieving the best optimization effect. The optimization paths for beginners and professional athletes are different. The system will gradually adjust the optimization goals based on their technical foundation to ensure that each athlete can effectively improve their technical level under the premise of safety.

The core of the motion optimization model is nonlinear multi-objective optimization. Taking the knee joint shear force, impact force change rate and motion efficiency as optimization targets, a multi-objective function is constructed and solved through genetic algorithm. The expression of the optimization function is:

$$\min F(x) = [f_1(x), f_2(x), -f_3(x)] \tag{8}$$

Among them, $f_1(x)$ represents the knee joint shear force change rate, $f_2(x)$ represents the knee joint impact force change rate, and $f_3(x)$ represents the action efficiency. In order to balance the weights of different objectives, the objective function uses the normalized value as input, and the weight is dynamically adjusted by the weighted sum method.

The knee joint shear force change rate is calculated by the following formula:

$$f_1(x) = \frac{\Delta F_{\text{shear}}}{\Delta t} \tag{9}$$

In the formula, ΔF_{shear} is the change in shear force and Δt is the time interval. This indicator is used to quantify the change in dynamic load caused by the action on the joint. The calculation of the impact force change rate is based on the peak ground reaction force:

$$f_2(x) = \frac{F_{\text{impact}}^{\max} - F_{\text{impact}}^{\min}}{T_{\text{impact}}} \tag{10}$$

In the formula, $F_{\text{impact}}^{\max}$ and $F_{\text{impact}}^{\min}$ are the maximum and minimum values of the impact force, respectively, and T_{impact} is the duration of the impact force. This indicator is used to describe the stability of the action and the degree of impact on the key.

The action efficiency is quantitatively quantified by the sliding path matching degree, and is calculated by the distance between the actual action trajectory and the target path:

$$f_3(x) = 1 - \frac{\sum_{i=1}^{N} d_i}{N} \tag{11}$$

Among them, d_i is the deviation value of the ith point, and N is the total number of discrete points. During the optimization process, the improvement of path matching directly reflects the improvement of action efficiency. As shown in **Figure 2**, the comparison of shear force and impact force before and after optimization in the experiment is shown. The red curve represents the force before optimization, and the green curve represents the force after optimization. By comparing the two, it can be observed that both shear and impact forces are reduced after optimization. The improvement in force behavior (i.e., lower peaks and reduced vibrations) demonstrates the effectiveness of the optimization process in minimizing joint loads during skiing movements.

Figure 2. Comparison of shear force and impact force change rate before and after optimization.

The variables input into the optimization model include joint angle range, time distribution of force during the action, and dynamic changes. The joint angle range is limited to the range allowed by the skiing technical specifications to ensure the feasibility and safety of the optimized action. Random generation is used for variable initialization, and variable update is completed by NSGA-II (Nondominated Sorting Genetic Algorithm II) algorithm [28]. The convergence of the objective function is achieved through population iteration. The genetic algorithm uses non-dominated sorting as the selection criterion, and the crossover probability and mutation probability are set to 0.9 and 0.1 respectively to enhance the diversity of solutions. The fitness function directly corresponds to the objective function value and is defined by the following formula:

$$\text{Fitness}(x) = \frac{1}{1 + \sum_{i=1}^{3} w_i f_i(x)} \tag{12}$$

w_i is a weight factor, which is dynamically adjusted during the optimization process to improve the global search capability of the solution. Multi-objective optimization uses the Pareto front sorting method to obtain a set of solutions that are balanced among the objectives.

The model output is verified experimentally to evaluate its effectiveness. The output action parameters significantly improve the action efficiency while reducing the change rate of knee joint shear force and impact force. The optimized action is provided to athletes through the real-time feedback system for training suggestion generation.

3.4. Real-Time feedback system design

The design of the real-time feedback system is based on embedded sensor modules [29] and Bluetooth data transmission technology to achieve efficient data collection and real-time feedback. The system monitors the athlete's movement characteristics in real time and generates personalized adjustment suggestions based on real-time data. When processing data, the system will dynamically adjust based on the athlete's personalized parameters and provide targeted technical improvement suggestions. The system's response time is controlled within 1 second to ensure that athletes can get immediate feedback during training, so that they can get accurate guidance at every stage of training. To ensure the real-time and processing speed of data, the system uses efficient data compression and transmission technology, and optimizes the response time of the feedback system. The data transmission frequency is set to 250 Hz to ensure that all key movements during skiing can be processed in a timely manner. The system also uses parallel computing technology to optimize the data processing process, minimize delays, and ensure accurate and timely feedback during high-intensity training. When athletes are doing alpine skiing training, the sensor modules they wear transmit the collected motion trajectory and mechanical data to smart devices in real time via Bluetooth for further processing and analysis. Under different ski resort conditions, the system will adjust training suggestions based on real-time collected ski trail information. For example, on steep slopes, the system will increase monitoring of knee joint loads and adjust movement suggestions accordingly to ensure athlete safety and training effectiveness. The sensors used in the system include the Vicon motion capture system and the Tekscan flexible pressure sensor. The Vicon motion capture system is mainly used to record the three-dimensional motion trajectory of the skier, and the Tekscan flexible pressure sensor is used to collect pressure distribution and center of gravity movement path. The selection of sensor modules takes into account the requirements of high accuracy, real-time performance and low latency to ensure rapid response to dynamic changes. The data transmission and processing flow of the system is shown in **Figure 3**:

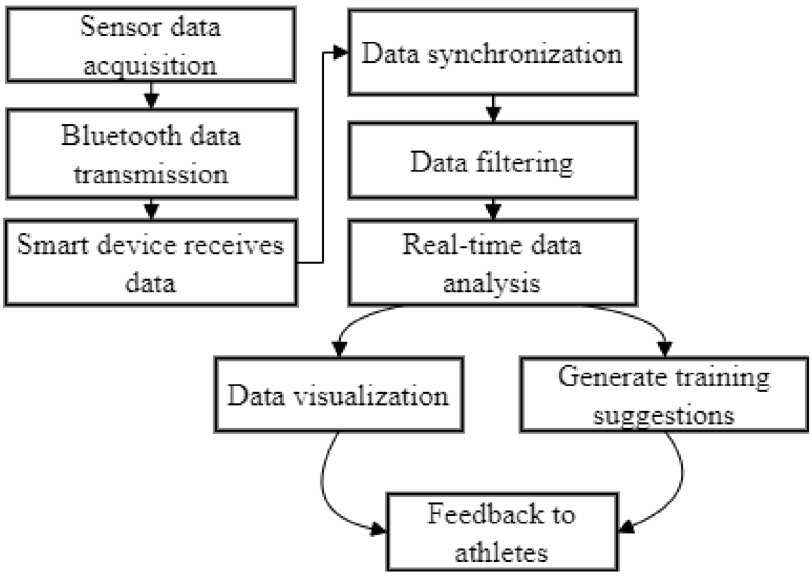

Figure 3. Data transmission and processing flow chart.

Sensor data is transmitted to smart devices via Bluetooth modules. The key to this process is to ensure the stability and real-time performance of data transmission. The optimized Bluetooth protocol is used during the transmission process to minimize data loss and delay, ensuring that athletes receive timely and accurate feedback during training. The frequency of data transmission is maintained at 250Hz to meet the rapid response requirements of alpine skiing turns. The motion data and mechanical data collected by the sensor are synchronously processed through an embedded algorithm to ensure the time consistency between the data sources.

After the data is transmitted to the smart device, the system uses a Python-based visualization interface to display and feedback the data in real time [30]. Python's Matplotlib and PyQt frameworks are used to develop the graphical interface, where Matplotlib is responsible for generating various charts, and PyQt is used for the layout of the interface and the implementation of interactive functions. Data visualization includes joint angle change curves, torque change curves, deviation diagrams between the sliding path and the target path, etc. For each key action indicator, the system sets a threshold and compares it with real-time data to provide real-time feedback. For example, when the knee angle exceeds the preset safety range, the system can prompt the athlete with a red warning box on the interface. When the matching degree between the sliding path and the target path is lower than the standard value, the system can provide corresponding adjustment suggestions.

The real-time feedback system also has a personalized training suggestion generation module. The training suggestion generation module relies on a personalized data matching model to automatically generate accurate improvement suggestions by analyzing the differences between the athlete's current movements and the optimization model. This module analyzes the athlete's technical deviations based on the comparison of the athlete's real-time data and historical data, and automatically generates targeted action adjustment suggestions. The suggestions include action angle, force distribution, center of gravity position, etc., and are displayed in the form of charts or text through a visual interface, which is convenient for athletes to quickly understand and adjust. The system response time is strictly controlled within seconds, ensuring that athletes can get timely feedback after each action and optimize the training effect.

To ensure the stability and efficiency of the system, the system's computing load and resource management are considered throughout the design process. When processing data, the embedded processing unit is responsible for quickly processing and filtering out redundant data, while performing real-time synchronization and feedback. All charts and suggestion generation modules are calculated by the smart device side, using Python's multi-threading mechanism to optimize the parallel operation of the graphical interface and data processing to avoid interface freezes or delays caused by calculation overload.

The system design not only focuses on real-time and accuracy, but also takes into account the user's operational convenience. The interface design is simple and intuitive, and athletes can quickly access feedback content and suggestions through touch screen, voice or gesture. In order to enhance the athlete's sense of participation and interactivity, the system also supports athletes to customize training goals and feedback thresholds to meet the needs of athletes of different levels.

4. Experimental data and technical evaluation

4.1. Experimental data collection plan

Data collection is carried out by combining a ski simulator with an actual ski resort environment to simulate the action characteristics under different turning radii and slope conditions. In the simulator, a variety of turning radii (small, medium, and large) and slopes (10 degrees, 20 degrees, and 30 degrees) are set. Under each condition, the athlete completes the turning action, and the sensor records data such as the knee joint angle, hip joint angle, center of gravity position, and torque distribution. The simulator's sensors synchronously collect the motion trajectory and biomechanical data of each turn. During the data collection phase, the influence of external variables (weather, slope, etc.) in the skiing environment was controlled. To this end, the experiment set up a unified skiing venue and climate conditions to ensure the consistency and comparability of the data. In addition, the same type of skiing equipment and sensors were used during the data collection process to ensure that the experimental conditions of different athletes were as similar as possible, reducing the interference of external factors on the experimental results.

During the actual ski field test phase, the motion trajectory is obtained through the motion capture system, and the mechanical data of the contact point is collected using the pressure sensor. Data collection covers different turning radii and slope conditions to ensure the uniformity and representativeness of the data.

During each turning action, the athlete's joint angle, force change and other data are sampled at high frequency and transmitted to the computing system in real time for processing. The data is cleaned by filtering and interpolation methods to ensure the accuracy of the data. In addition, during the experiment, the athletes' fatigue status was regularly assessed (using heart rate monitoring equipment) to ensure a reasonable distribution of training intensity and avoid excessive physiological burden caused by overtraining.

4.2. Experimental equipment information

The equipment used in the experiment mainly includes motion capture system, pressure sensing system and computing analysis platform. The equipment information is shown in **Table 1**.

Table 1. Experimental equipment information.

Equipment Name	Model	Key Parameters
Motion Capture Device	Vicon System	Sampling Rate: 200 Hz, Accuracy: mm-level
Pressure Sensing Device	Tekscan System	Sampling Rate: 100 Hz, Accuracy: mm-level
Computing Devices	MATLAB, OpenSim	MATLAB: Data Analysis and Processing; OpenSim: Modeling and Simulation

The Vicon motion capture system provides high-precision three-dimensional trajectory data of skiing movements, so that the details of the movements can be accurately reflected. In the actual data collection process, the system can provide detailed spatial coordinate data for each turning action, helping to analyze the athlete's posture changes and joint angles during the turning process. Through accurate motion trajectory acquisition, the Vicon system can efficiently support subsequent biomechanical feature extraction and model optimization. The sole force data provided by the Tekscan pressure sensing system can effectively reflect the mechanical changes of athletes when turning. The device comprehensively records the pressure distribution of the sole of the foot in contact with the ground through a network of sole pressure sensors and provides real-time mechanical feedback.

The computing platform composed of MATLAB and OpenSim software is the core of the entire experimental data processing and analysis. MATLAB provides powerful computing power for preliminary data cleaning and processing, filtering and analyzing the raw data collected from the Vicon and Tekscan systems. OpenSim builds a biomechanical model of the athlete based on the motion data provided by MATLAB, further simulates skiing movements, and calculates the torque changes and force characteristics of the joints. This analysis process provides a scientific basis for optimizing action design and generating personalized training suggestions, thus improving training results and the technical level of athletes.

Overall, the combination of the Vicon system, Tekscan pressure sensing system, and MATLAB and OpenSim platforms can efficiently and accurately collect, process, and analyze various biomechanical data of skiing actions, ensuring the accuracy of the experiment and the reliability of the experimental results.

4.3. Technical evaluation indicators

In order to comprehensively evaluate the optimization effect of alpine skiing turning technique, this paper adopts four main technical evaluation indicators: movement coordination, force balance, movement efficiency and injury risk. These indicators can accurately reflect the biomechanical characteristics of athletes during the turning process.

Movement coordination mainly evaluates the consistency between joint angles and sliding trajectories. In alpine skiing, the athlete's movement coordination directly affects the smoothness and stability of turns. This indicator measures the accuracy of technical execution by comparing the relative consistency of joint angle changes and sliding trajectories. The definition formula is as follows:

$$\mathrm{C} = \frac{\sum_{i=1}^{n} |\theta_i - \theta_{\mathrm{optimal},i}|}{n} \tag{13}$$

Among them, θiAmong them, θ_i is the joint angle at the i moment, $\theta_{\mathrm{optimal},i}$ is the joint angle at the ideal moment, and n is the number of sampling points. The lower the index value, the closer the athlete's joint angle and turning trajectory are to the ideal state, indicating that the movement coordination is better.

The force balance reflects the symmetry of the athlete's weight distribution and the stability of the movement. The pressure distribution data provided by the pressure sensing system can be used to calculate the pressure ratio of the left and right feet. The calculation formula is:

$$F_{\text{balance}} = \frac{P_{\text{right}}}{P_{\text{left}}} \tag{14}$$

Among them, P_{right} and P_{left} are the pressure values of the right foot and the left foot respectively. If the pressure ratio is close to 1, it means that the athlete can evenly distribute the weight during the turn, maintain a good force balance, and reduce the instability during the sliding process.

Movement efficiency mainly reflects the speed and accuracy of the athlete's movement during the turn. The calculation formula is as follows:

$$E = \frac{v}{\Delta d} \tag{15}$$

In the formula, v is the athlete's skating speed, and Δd is the deviation of the skating trajectory, which is usually calculated by a motion capture system. The ratio of speed to trajectory deviation can evaluate whether the athlete can complete the turning action at the optimal speed while maintaining a small trajectory deviation, indicating the athlete's smoothness and technical stability in the turn.

The injury risk assessment measures the peak force and impact force change rate of the knee joint during a turn, with the goal of predicting the likelihood of a skier getting injured during a turn. The knee joint is the part that is most stressed and prone to injury during skiing. When turning at high speed, the external force on the joint increases significantly. The calculation formula for the injury risk index is:

$$R_{\text{injury}} = \frac{F_{\text{peak}}}{\Delta F} \tag{16}$$

Among them, F_{peak} is the maximum peak value of the force on the knee joint, and ΔF is the force change rate (the change in the force on the knee joint per unit time). The injury risk index can reveal whether the pressure on the knee joint exceeds the safety threshold during high-intensity turns and infer the risk of injury to athletes. High peak values and large force change rates usually indicate a higher risk of injury, so this indicator is very important for preventing athletes from getting injured.

The four evaluation indicators measure the optimization effect of athletes' turning techniques from different angles. By evaluating the coordination of movements, force balance, movement efficiency and injury risk, it can fully understand the changes in training effects, so as to adjust the training program to reduce the risk of injury and optimize technical execution.

5. Experimental results and analysis

5.1. Comparative experiment: Comparison of the effects of traditional training and optimized training

In order to evaluate the application effect of the biomechanics-based optimized training model in alpine skiing turning technology, 20 athletes with similar skiing levels (half male and half female) were invited to participate in the experiment and divided them into an experimental group and a control group. The experimental group (10 people, half male and half female) used the optimization model for training, and the control group (10 people, half male and half female) used the traditional training method. After three months of training, the two groups of athletes were evaluated for four key indicators: movement coordination, force balance, movement efficiency, and injury risk.

The comparative experimental results are shown in **Figure 4**. The evaluation results of the movement coordination index show that the experimental group showed higher movement consistency during the turning process. By calculating the consistency between joint angle and sliding trajectory, the average coordination score of the experimental group was 0.89, while that of the control group was 0.72, and the movement coordination of the experimental group improved by about 23.6%. This shows that through optimized training, athletes can more accurately control the matching of joint angle and sliding trajectory, and improve the fluency and accuracy of turns. In terms of force balance, the average left-right foot pressure ratio of the experimental group was 1.02, while that of the control group was 1.18. The force balance improved by about 13.6%, indicating that optimized training helps athletes achieve a more even distribution of weight during turns and reduces the instability caused by excessive force on one side of the foot. The evaluation results of movement efficiency showed that the ratio of sliding speed to trajectory deviation was 8.5 in the experimental group, while it was 6.7 in the control group. The experimental group's movement efficiency increased by about 26.9%, indicating that optimized training can effectively improve athletes' ability to increase their sliding speed while ensuring trajectory accuracy. Higher efficiency means that athletes can complete higher-quality turns with less energy consumption, which has a positive impact on improving overall skiing performance. Injury risk assessment is performed through the peak force of the knee joint and the rate of change of impact force. In terms of the peak force of the knee joint, the average value of the experimental group was 320 N, which was 20% lower than the 400 N of the control group. For the impact force change rate, the average value of the experimental group was 2.4 N/ms, which was about 22.6% lower than the 3.1 N/ms of the control group. This shows that optimized training can effectively reduce the burden on the knee joint and reduce the risk of injury to athletes when turning.

The comparison results show that the optimized training method based on biomechanics can significantly improve the technical level of alpine skiers and effectively reduce the risk of injury compared with the traditional training method. The optimized training program provides more accurate training guidance for skiers by adjusting the coordination of movements, force balance and improving movement efficiency. Through the quantitative analysis of these evaluation indicators, athletes can adjust their training strategies in real time, improve training effects and ensure the safety of the training process.

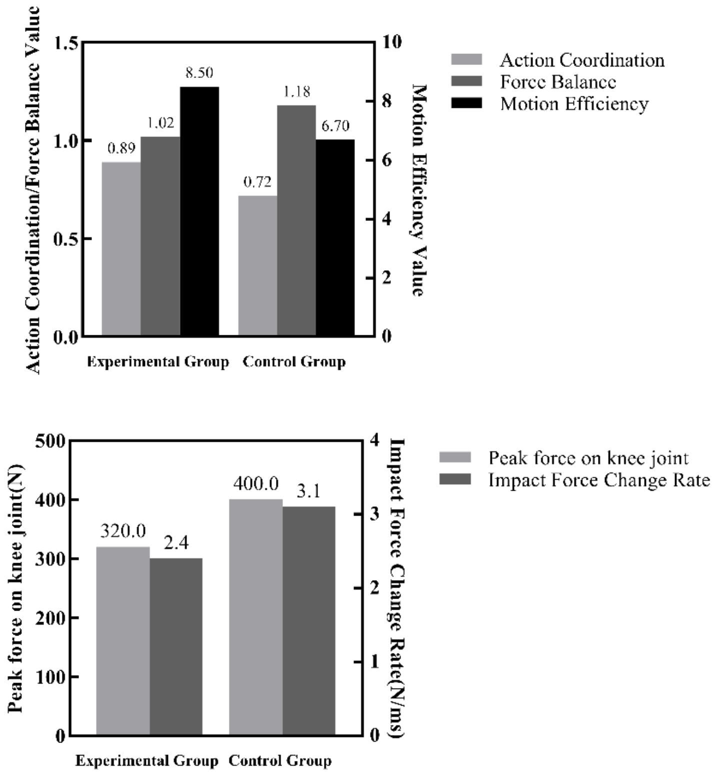

Figure 4. Comparison of different technical indicators between traditional training and optimized training groups.

5.2. Model generalization ability test

In order to further evaluate the generalization ability of the biomechanical optimization training model in groups with different technical levels, the experiment invited 5 beginners and 5 professional skiers. The experimental design is divided into two stages: before training, the athletes' biomechanical indicators were tested before optimization training; after a certain period of optimization training, the same athletes were tested again to evaluate the impact and adaptability of the training model on their technical level.

The results of the experimental test are shown in **Figure 5**. In the test phase before optimization training, the beginner group had a movement coordination score of 0.62, a force balance of 1.30, a movement efficiency of 5.8, a knee joint force peak of 440 N, and an impact force change rate of 3.5 N/ms. In contrast, professional skiers had a higher coordination score of 0.85, a force balance of 1.05, a movement efficiency of 9.2, a knee force peak of 380 N, and an impact force change rate of 3.0 N/ms. There are obvious differences between beginners and professional skiers in these indicators, reflecting the impact of technical level on skiing performance and biomechanical characteristics. After the optimized training, the performance of both groups of athletes improved significantly. The beginners' movement coordination improved to 0.80, force balance improved to 1.10, movement efficiency increased to 7.4, the peak force of the knee joint decreased to 400 N, and the impact force change rate decreased to 3.0 N/ms. The professional skiers' coordination improved to 0.92, force balance improved to 1.00, movement efficiency increased to 9.9, knee joint force peak decreased to 360 N, and impact force change rate decreased to 2.7 N/ms. Through optimized training, the beginners' coordination improved by about 29%, force balance improved by about 15.4%, movement efficiency improved by about 27.6%, knee joint force peak decreased by about 9.1%, and impact force change rate decreased by about 14.3%. For the professional skier group, movement coordination improved by about 8.2%, force balance improved by about 4.8%, movement efficiency improved by about 7.6%, peak force on the knee joint decreased by about 5.3%, and the impact force change rate decreased by about 10%.

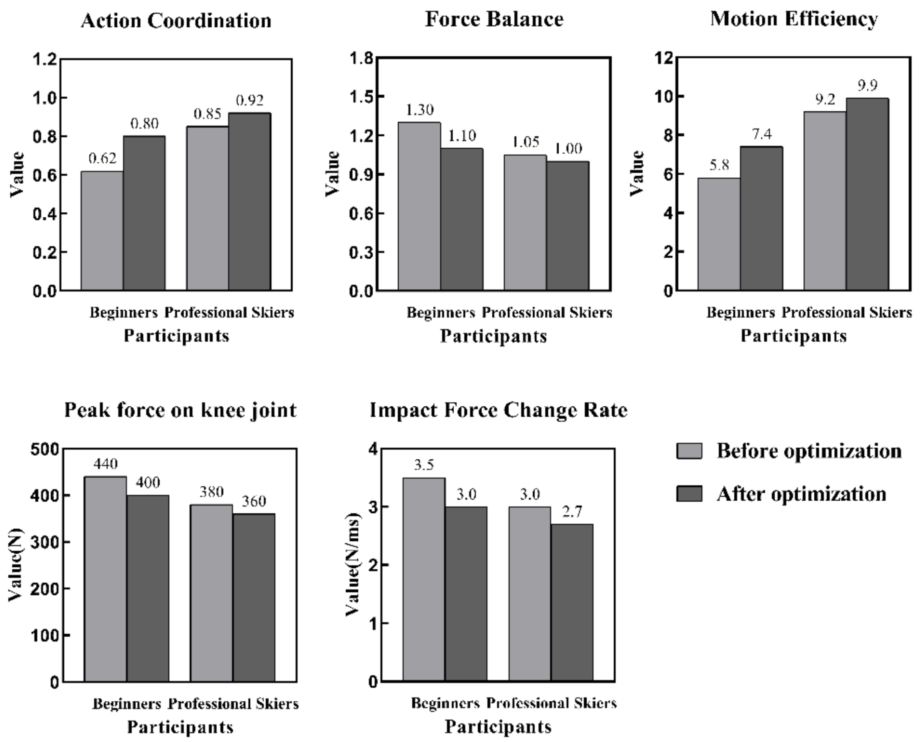

Figure 5. Comparison of various indicators between beginners and professional skiers before and after optimization training.

From the experimental results, it can be concluded that the optimization training model has a strong generalization ability among athletes of different levels and can effectively improve various technical indicators, especially for beginners. Although the improvement of professional skiers is relatively small, the overall training effect still exists. The experimental results verify the wide adaptability of the optimization training model in diverse groups and demonstrate its potential in technical optimization and injury prevention in practical applications.

6. Conclusions

Based on the biomechanical research on the optimization of alpine skiing turning technology, this paper designs a comprehensive method that integrates motion capture, mechanical data analysis and nonlinear multi-objective optimization algorithm, which provides an innovative path for the quantitative analysis and optimization of skiing technology. The study constructed a biomechanical analysis model, extracted key features, designed a personalized action optimization plan and a real-time feedback system, and significantly improved the coordination of movements, force balance, and efficiency of movements. The optimization model studied has achieved remarkable results in optimizing joint angles and shear forces through a nonlinear multi-objective optimization algorithm. In a comparative experiment between beginners and professional skiers, the model can customize training plans based on individual differences and improve athletes' movement coordination and center of gravity stability. The experimental results showed that the optimization training achieved significant results in both the beginner and professional skier groups, with movement coordination improved by 29% and 8.2% respectively. The movement efficiency was improved by 27.6% and 7.6% respectively, and the main indicators of injury risk such as peak force on the knee joint and impact force change rate were reduced, verifying the wide applicability and technical advantages of the model in groups with different technical levels. The study not only has guiding significance for the technical optimization of skiing, but also provides a scientific basis for reducing the risk of training-related injuries. However, this study still has some limitations, mainly reflected in the relatively small sample size of the experiment and the lack of diversity in environmental conditions, which affects the generalization performance of the model in more complex skiing scenes, and the performance of the model in complex vision, statistical logic and other environments still needs to be further verified. Future research can further expand the scope of the experiment to cover more fitness athlete groups and different environmental conditions while considering testing under a wider range of environmental conditions and combining equipment with the psychological state of athletes to improve the universality of the model. In addition, it is planned to combine advanced sensing technology with artificial intelligence algorithms to explore the cross-domain application of biomechanical analysis in other sports and promote the development of precision training and personalized sports science.

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