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Prediction Method of Standing Long Jump Performance Based on Key Frame Recognition and Elastic Network

Bingkun Jiang[1], Haicheng Qu[1], Xianming Liu[1], Lin Yang[1*]

[1]*Information Support Force Engineering University, Chongqing, China*
**Corresponding Author. Email: 599965723@qq.com*

Abstract. Aiming at the problems of low efficiency and large errors in traditional standing long jump measurement, this paper proposes a performance prediction method based on key frame recognition and elastic network. Using AI human pose estimation data, we establish a key frame detection algorithm to identify take-off and landing moments accurately. A dual-model fusion framework combining physical calculation and elastic network regression is constructed to realize performance prediction. Meanwhile, personalized training effect is evaluated via Bootstrap resampling. Experiments show that the model's relative error is only 3.04%, and the prediction for athletes is reliable. It provides an intelligent and quantitative tool for student physical health monitoring and scientific training.

Keywords: Standing long jump, Key frame recognition, Elastic network, Performance prediction

1. Introduction

Standing long jump is a key test item in the National Student Physical Health Standard.It is an important indicator to measure adolescents' lower limb explosive power and physical coordination [1].Traditional measurement for standing long jump mainly relies on manual judgment and tape measurement.These old methods have many obvious problems in real tests.They work slowly and cannot meet large-scale physical health monitoring [2]. The judgment of take-off and landing moments is too subjective and easily affected by people.In addition, the measurement error is usually large and unstable, which reduces the accuracy of results [3]. In recent years, AI human pose estimation technology develops fast and becomes widely used in sports analysis.This technology can capture 33 key joint coordinates of human body in real time by using ordinary cameras [4]. It provides a new and practical way for quantitative analysis and intelligent evaluation of sports movements.However, most studies at home and now only focus on action recognition or simple distance measurement.They do not build a complete and systematic model for the whole process [5]. Some studies can recognize key frames but cannot predict scores.Some can predict scores but cannot analyze influencing factors or give training suggestions.Few systems combine key frame detection, factor analysis, score prediction and personalized training together.To fill these gaps, this paper takes standing long jump as the research object.We use real coordinate data of human key points to build several models.First, we build an automatic key frame recognition model to find exact take-off and landing moments.Then we establish a flight motion model based on biomechanical rules to describe

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body movement in the air.We also use elastic network regression to combine physical fitness indicators and kinematic indicators to build a score prediction model.In addition, we use the Bootstrap resampling method to finish personalized training effect prediction under small sample conditions.This study aims to solve core difficulties in intelligent evaluation of standing long jump.It provides an automatic and high-precision quantitative method for student physical health monitoring.At the same time, it offers theoretical support and technical reference for scientific and personalized training in physical education.

2. Data and research methods

The data in this paper come from coordinate sequences of 33 human key points in standing long jump videos. These raw data have many invalid frames with all-zero coordinates and strong noise interference. We must carry out standardized preprocessing to ensure the quality of the later analysis. First, we build a standard coordinate system for video frames. We set the origin at the top-left corner of the image. We use t to represent the frame time. The time interval between two frames Δt is 1/30 second. These settings lay a solid coordinate foundation for the following kinematic calculations. For abnormal frames with all-zero values, we use linear interpolation to repair the incomplete data. The repair formula is:

$$P_i(t_k) = P_i(t_{k-1}) + \frac{P_i(t_{k+1}) - P_i(t_{k-1})}{t_{k+1} - t_{k-1}} (t_k - t_{k-1}) \tag{1}$$

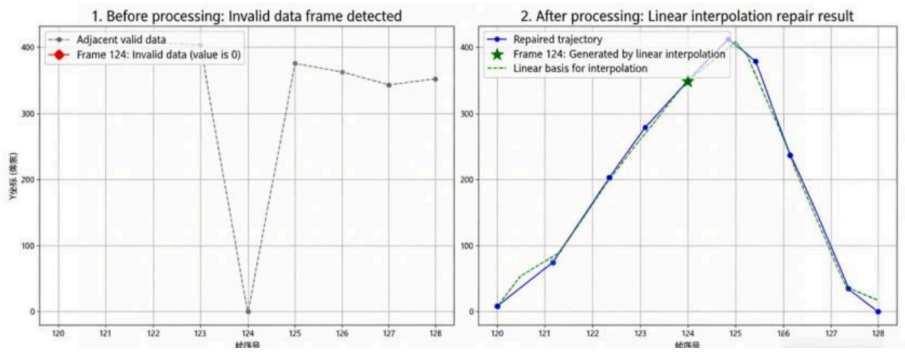


Figure 1. Effect comparison of linear interpolation for repairing invalid data frames

This method can effectively fill the missing parts in data. It keeps the continuity of the whole movement trajectory. The comparison of repair effects is shown in Figure 1. The research methods in this paper integrate many interdisciplinary technologies. We use Savitzky-Golay filter to remove noise from the center-of-gravity trajectory. We calculate the body center of gravity by the human body segmentation weighting method. We use Spearman correlation analysis to find out the key factors that affect the final scores. We build an elastic network regression model to predict standing long jump results accurately. We also combine Bootstrap resampling method to deal with statistical problems in small sample situations. The whole research process follows the standard steps: data preprocessing, model construction, solution verification, application and promotion. It takes into account both biomechanical rationality and statistical modeling accuracy. Table 1 shows the explanation of core symbols. The unified symbol system make the model derivation and result analysis more standardized and clearer.

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Table 1. Nomenclature

Symbol	Description	Unit
t	Video frame sequence time	frame
Δt	Time interval between consecutive frames, Δt=1/30 s	second
$P_i(t)$	Pixel coordinate of the i-th joint at frame t	pixel
Cx(t),Cy(t)	Horizontal and vertical coordinates of body center of mass	pixel
t_c,t_{to},t_a,t_l	Crouch bottom, take-off, apex, landing moment	frame
t_f	Flight time	frame
θ_{to}	Take-off angle	degree
θ_{tr}	Trunk forward inclination	degree
v_h	Horizontal take-off velocity	pixel/s
h_c	Crouch depth	pixel
hj	Jump height	pixel

3. Key frame recognition and motion modeling

Key frame recognition is the core basis for analyzing standing long jump movements and calculating scores.This paper design a four-stage time recognition algorithm based on center-of-gravity trajectory and foot key-point changes.It can automatically judge key moments such as take-off and landing.We calculate human body center of gravity by seven-segment weighting method, it fully consider the mass ratio of each body part.The calculation formulas are:

$$C_x(t) = \frac{\sum_{i=1}^{7} w_i \cdot x_i(t)}{\sum_{i=1}^{7} w_i}, C_y(t) = \frac{\sum_{i=1}^{7} w_i \cdot y_i(t)}{\sum_{i=1}^{7} w_i} \quad (2)$$

The body segment mass weight distribution are shown in Table 2. The trunk accounts for 49.7%, it is the dominant part of center of gravity.

Table 2. Segment mass weight distribution of the human body (based on anthropometric research)

Body Segment	Keypoint Set	Mass Weight wi	Percentage (%)
Head	{0, 7, 8}	0.081	8.1
Trunk	{11, 12, 23, 24}	0.497	49.7
Thighs	{23, 24, 25, 26}	0.2	20
Shanks	{25, 26, 27, 28}	0.092	9.2
Feet	{27, 28, 31, 32}	0.028	2.8
Upper arms	{11, 12, 13, 14}	0.054	5.4
Forearms	{13, 14, 15, 16}	0.048	4.8

This calculation method can truly reflect the real center position of human body.We use Savitzky-Golay filter to process vertical coordinates of center of gravity.Then we recognize the highest point, lowest squat point, take-off time and landing time in order.The vertical trajectory of center of gravity for Athlete 1 are shown in Figure 2.

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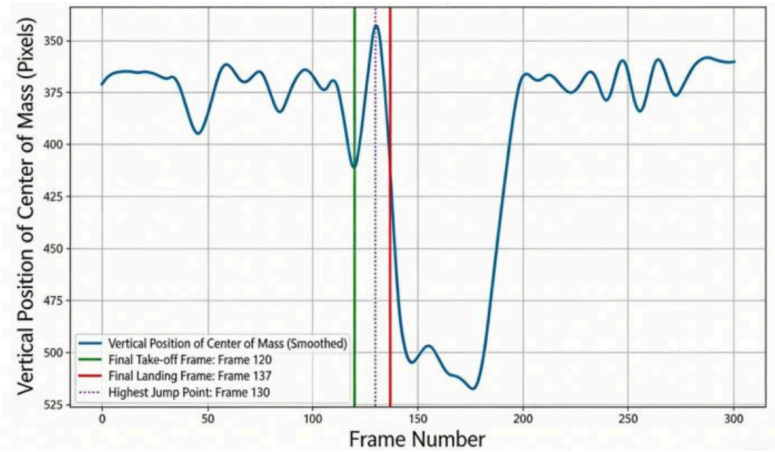


Figure 2. Vertical movement trajectory of athlete 1's center of mass

The algorithm can clearly capture the full cycle characteristics of the movement.During the flight phase, the body center of gravity follow projectile motion rules.The vertical uniformly accelerated motion formula is:

$$C_y(t) = \frac{1}{2} g_{pix}(t - t_{takeoff})^2 + v_{y0}(t - t_{takeoff}) + C_y(t_{takeoff}) \tag{3}$$

We also build attitude quantification models such as knee joint angle, forward extension distance and trunk forward inclination.They can describe the flight process accurately in mathematics.Through model verification, we calibrate pixel-centimeter scale with Athlete 1 data.The relative prediction error of Athlete 2 is only 3.04%, as shown in Table 3.It prove the high accuracy and reliability of key frame recognition and motion modeling.

Table 3. Model validation results

Athlete	Pixel Distance	Actual Performance (cm)	Predicted Performance (cm)	Relative Error (%)
Athlete 1	473	158	158.0*	0
Athlete 2	354.94	115	118.5	3.04

4. Construction of performance prediction model

This paper build a dual-model fusion prediction framework with physical measurement and elastic network regression.It base on key frame recognition and kinematic indicators extraction.It solve the problem of big prediction bias in single model.The physical model calculate score directly by pixel-centimeter conversion.The formula is:

$$\hat{y}_{phy} = \frac{d_{pix}}{k_{scale}} \tag{4}$$

This model do not need complex feature engineering.It directly reflect the real distance of the jump.The statistical model use elastic network regression.It combine advantages of L1 and L2 regularization.It solve the problem of multicollinearity in features.The objective function is:

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$$min_{\beta}\left\{\frac{1}{2n}\left\|y-X\beta\right\|_2^2+\alpha\left[(1-\rho)\frac{1}{2}\left\|\beta\right\|_2^2+\rho\left\|\beta\right\|_1\right]\right\} \tag{5}$$

We use 5-fold cross-validation to get optimal hyperparameters α*=0.1096 and ρ*=0.50.Model verification result are shown in Figure 3

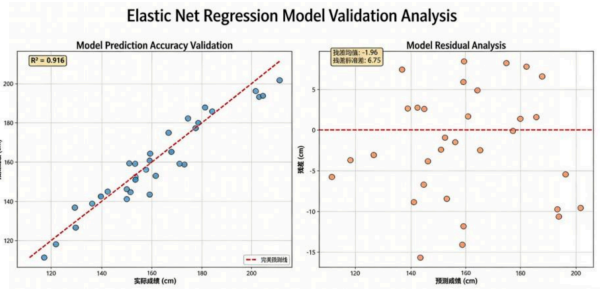


Figure 3. Elastic Net Regression Model Validation Analysis

The predicted values fit well with actual values.Residuals have no systematic deviation and the reliability is good.We use Spearman correlation analysis to select core features.The correlation between physical fitness indicators and scores are shown in Table 4 .

Table 4. Correlation analysis between physical fitness indicators and performance (top 3)

Physical Fitness Indicator	Correlation Coefficient (rs)	p-value	Significance
Physical Fitness Score	0.91	< 0.001	***
Fat Control Mass (kg)	-0.87	< 0.001	***
Body Weight (kg)	0.79	< 0.001	***

Body score, fat control and body weight are the most important factors.Trunk forward inclination is the only significant technical indicator.Finally, we use weighted fusion strategy to combine two models.The fusion formula is:

$$\hat{y}final = wphy \cdot \hat{y}phy + wstat \cdot \hat{y}_{stat} \tag{6}$$

We set weight 0.4 for physical model and 0.6 for statistical model.It give full play to the multi-feature fusion advantage of statistical model.It improve the robustness of the final prediction results.

5. Result analysis and model evaluation

This paper's model are verified by practical analysis and tests.It realize accurate prediction of standing long jump results and personalized training effect evaluation.The dual-model fusion prediction show that the 6-year-old Athlete 11 get a score of 121.9 cm.The prediction interval is [114.0,127.1] cm.It reach the excellent level for 6-year-old boys.Small-sample analysis based on Bootstrap resampling show that after 8 weeks of personalized training.The trunk forward inclination, horizontal take-off speed and flight time of Athlete 11 increase by 5.5%, 20.4% and 13.9% respectively.The score can reach 131.5 cm.The overall prediction confidence is 77.8%.The staged training effect are shown in Table 5.It follow the exponential curve rule of motor skill learning.Sensitivity analysis results are shown in Table 6.

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Table 5. Prediction of phased training effects

Training Stage	Progress P(t)	Predicted Performance (cm)	Cumulative Improvement (cm)	Improvement Rate (%)
Before Training	0	121.9	0	0
After 2 Weeks	0.3	125.7	3.8	3.1
After 4 Weeks	0.5	128.3	6.4	5.2
After 8 Weeks	0.75	131.5	9.6	7.9

Table 6. Sensitivity analysis results of key parameters

Parameter Name	Variation Range	Performance Change (cm)	Sensitivity (%)	Sensitivity Level
Kinematics-performance Correlation Coefficient	[0.55, 0.95]	[128.9, 134.0]	4.28	Medium-sensitive
Age Adjustment Coefficient	[0.60, 0.90]	[129.6, 133.4]	3.81	Medium-sensitive
Learning Rate Parameter	[0.123, 0.223]	[126.9, 129.5]	3.05	Medium-sensitive
Take-off Speed Weight	[0.30, 0.50]	[130.8, 132.2]	2.93	Medium-sensitive

The sensitivity of key parameters of the model are all lower than 5%.There are no high-sensitive parameters.The robustness index reach 1.0.It verify the practical stability of the model.The model in this paper have many advantages.It have high automation, multi-model fusion and strong personalized analysis ability.It can be extended to jumping events such as high jump and triple jump.But it also have some disadvantages.The sample size is limited.It rely too much on equipment.The adaptability for young-age groups are not enough.Overall, this model realize the whole intelligent analysis process of standing long jump.It cover movement recognition, score prediction and training optimization.It provide an efficient and accurate technical tool for intelligent monitoring and scientific training of students' physical health.

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