

第一页为封面页

参赛学生姓名： 陈展涛、陈曦、卢添城

中学： 中山市小榄中学

省份： 广东省

国家/地区： 中国

指导老师姓名： 方劲、胡学军

指导老师单位： 中山市小榄中学

论文题目： HPR-DATS: A Data-Driven Darts
Training Assisted System based on Skeleton
Analysis and Machine Learning

A Data-Driven Assisted Darts Training System based on Skeleton Analysis and Machine Learning

Zhantao Chen¹, Xi Chen¹ and Tiancheng Lu¹

¹Xiaoping Technology Innovation Lab, Zhongshan Xiaolan Senior High School, Guangdong, 528415, China

ABSTRACT

Previous research on darts was limited to capturing the movements of dart players, and no systematic auxiliary evaluation of players was established. In this study, a data-driven assisted darts training system is developed based on kinematic analysis and machine learning. In the first part of this study, the study explores the four factors that affect dart scoring. From these four factors, it extends to 12 static features and 6 dynamic features of dart throwing movements, making the evaluation criteria of dart sports digital and quantifiable. Moreover, this study establishes a GDA model by collecting 1,048 dart throwing data from professional athletes and 1,348 non-professional athletes. The established GDA model is used to verify the effectiveness of 18 dart throwing action features and established a solid feature foundation. In the second part of the study, based on the analysis of human kinematics, this study uses machine learning to establish a best dart throwing curve model, so that dart players have an intuitive learning object for dart movements. Based on the 18 features of the first part, the study establishes a set of athlete recommendation models based on z-score scoring standards, which can provide personalized and professional guidance programs for athletes. With the help of this system, athletes can adjust their movements during the training process, thereby enhancing the scientific basis of darts and improving the overall training effect.

KEYWORDS

Dart training, Human pose recognition, Dart throwing force assessment, Stability analysis, Release timing analysis, Trajectory fitting

Contents

1	Introduction	3
2	Literature Review	3
3	Methodology	4
3.1	Factors of Dart-Throwing Accuracy	5
3.1.1	Three-Link Kinematic Model	5
3.1.2	Speed of Throwing Darts	6
3.1.3	Body Stability	6
3.1.4	The Angle of The Action	7
3.2	Methods for Collecting Data.	8
3.2.1	Selection of Data Collection Equipment	8
3.2.2	Construction of Data Acquisition Software	8
3.3	Data Collection and Preprocessing	11
3.3.1	Data Collection	12
3.3.2	Data Preprocessing	13
3.3.3	Dart-to-Bullseye Distance Measurement Method	13
3.4	Use GDA to verify the effectiveness of 18 features	17
3.4.1	Two-class Gaussian Discriminant Model	17
3.5	Trajectory Fitting Method for Dart Throws	19
3.5.1	Selection of Optimal Dart-Throwing Trajectories	20
3.5.2	Fitting of Throwing Trajectory	20
3.6	Guidance and Recommendations for Athletes	23
3.6.1	Selection of Optimal Throwing Trajectories	23
3.6.2	Recommendation Model	23
4	Result	23
4.1	Accuracy of Dart-to-Bullseye Distance Detection	25
4.2	Result of GDA Model	25
4.3	Shap Value Analysis Results of 18 Motion Features	26
4.4	Trajectory Fitting Results and Performance Evaluation	27
4.5	Evaluation of the Personalized Training Recommendation System	28
5	Discussion	30
6	Conclusion	30
7	Project Outcome	31

1. Introduction

With the implementation of the national fitness strategy [1], sports scientific research has received more and more attention. In recent years, the focus of sports has expanded from traditional physical training to movement mechanics, technique assessment, and sports injury prevention. The development of motion capture and gesture recognition technology has provided valuable tools for these efforts[2], allowing sports performance to be recorded and analyzed in a more objective and quantitative way.

Computer-based human movement recognition and analysis systems are increasingly used in sports training and have been verified by many scholars. Practical applications include motion assistance systems relying on technologies such as video observation[3], template matching[4] and wearable sensors[5]. For example, video-based observation methods are widely used in sports training and rehabilitation, with coaches analyzing slow-motion replays to identify performance details. Although useful, these methods are limited by subjectivity, reliance on observer experience, and the lack of standardized evaluation metrics.

Darts, a precision target-based sport, exemplifies the potential of such a system. Darts originated in medieval England as a military exercise and later evolved into an entertainment and competitive sport governed by international organizations such as the Professional Darts Corporation (PDC) and the World Darts Federation (WDF). In China, darts has gained increasing recognition since it was officially included in the national sports program in 1999 and was recently included in the education curriculum[6]. The establishment of darts associations and school-level training activities further promoted its development, transforming the sport from leisure and entertainment into an organized and educational sport.

However, there are two shortcomings in current research on dart sports. The first is that the factors that affect dart players' scores have not been determined from kinematic characteristics, and the influencing factors have been numerically quantified and their validity verified. Second, existing training methods mainly rely on video observation technology, template matching technology and wearable technology. These technologies mainly rely on the experience of professional coaches, making the guidance and suggestions given subjectivity affected by humans, and fail to perform personalized analysis of athletes and establish standard evaluation indicators.

To address these deficiencies, the objective of this study is to establish a darts player auxiliary training system that uses data-driven methods based on human kinematics and machine learning. The objective is divided into two parts. The first is to establish a complete set of feature engineering. This study explores the scoring factors influencing darts and provides a complete and accurate analysis of the sport. Then, key indicator features that can quantify the darts throwing process are established. These features can reflect the characteristics of the quality of darts movements and are used for the establishment of an auxiliary training system for darts players. Secondly, improve the existing athlete training assistance system and make up for the subjective and empirical problems existing in the current system. Establish a new type of darts action training improvement method that can achieve automation, standardization and personalization. This makes the training of darts players more scientific and encourages them to improve their performance.

2. Literature Review

Darts originated in medieval England, where soldiers initially inserted short arrows into wooden boards of wine barrels for training purposes. Over time, this practice gradually evolved into a recreational activity. By the end of the 19th century, darts had become an important part of British tavern culture. In the early 20th century, with the introduction of sisal dartboards and the standardization of the "1-20" dartboard layout, the rules governing the sport of darts became increasingly formalized. The establishment of the British Darts Organisation (BDO) in 1973 and the World Darts Federation (WDF) in 1974 laid the groundwork for the international development of the sport. Since the 1990s, the rise of the Professional Darts Corporation (PDC) has contributed to the transformation of darts from a recreational activity into a professional competitive sport[7]. Today, darts is widely practiced in Europe, North America, Asia, and other regions. With the increasing diversity of sports events and activities, darts classes have been incorporated into physical education curricula for primary and

secondary school students[6]. As a result, an increasing number of experts have conducted research into the biomechanics and techniques of dart throwing.

Huang (2024) et al. used an optical motion capture system to compare the differences in throwing mechanics between professional and intermediate players at different target positions (high, medium and low targets), and found that intermediate players had significant changes in shoulder internal rotation speed and elbow rotation speed, while the professional group was relatively stable. In addition, it was found that when the accuracy requirements were high or when using light darts, the elbow pronation angle was larger and the wrist palm flexion velocity was higher[8]. Letournel (2025) studied the use of Xsens wearable IMU system to monitor the opponent, forearm, upper arm and shoulder in real time, collect data such as angular velocity and acceleration, and analyze the differences in action patterns and performance between the main hand and the non-main hand (lateralized lateralization), providing empirical support for action control and training intervention[5]. Wolfe (2006) et al. showed that the proximal carpal arrangement remains relatively stationary in dart movement, forming a stable support platform; this biomechanical structure is of fundamental significance for understanding the wrist movement control mechanism.[9]

Predecessors used biomechanical and kinetic analysis methods to point out the key factors in dart movement. It shows that factors such as hand joint movement trajectory, body stability, and throwing speed are crucial to throwing performance, which provides a solid theoretical basis for subsequent research.

However, previous research methods still have certain limitations in dart sports: on the one hand, in feature engineering, previous research focused on a certain problem in dart sports, and lacked analysis of interrelations among performance factors and failed to propose a quantitative evaluation framework. And in terms of data collection, most of them use optical cameras to shoot athletes, and the data obtained have large errors, making it impossible to obtain accurate data on athletes throwing darts. There are also studies using human body wearable devices to collect action data from athletes, but this collection method also affects the results of dart players' throwing.

On the other hand, there are limitations in the methods of darts training and coaching. The first is that traditional dart player training relies on image observation methods. This is done manually by the darts coach to analyze the darts players, and is greatly affected by the experience and ability of the darts coach. Second, in traditional training methods, the features of movements cannot be quantified, precise errors can be given, and it cannot intuitively show in which direction the athletes' movements need to be adjusted, and how much movement adjustment can achieve a higher score. Usually just some vague reminder. Third, some studies use template matching for training, but template matching usually only adapts templates to most people and cannot perform personalized analysis for individuals.

In general, this study was carried out from two aspects: the limitations of dart movement characteristics and the shortcomings of training methods. The purpose of the research is to build a data-driven dart player assistance system based on skeleton analysis and machine learning.

3. Methodology

The purpose of this research is to improve the limitations of dart movement characteristics and training methods, and build a data-driven dart player assistance system based on skeleton analysis and machine learning. In the first part, this study will explore the factors that affect dart players' scores, obtain comprehensive and complete dart characteristics, and establish a feature engineering for dart sports. And a set of high-precision dart motion data sets were constructed through the kinect2.0 human posture sensor. This data set was used to verify the effectiveness of dart features, and also provided a data basis for the improvement of dart player training methods. In the second part, this research will use a data-driven approach, combining kinematics and machine learning methods to construct a set of training methods that can help dart players improve their performance. Among them, one is to fit the athletes' personalized optimal dart throwing trajectories, which allows dart players to match their own movements and target movements, find the differences between them, and thereby improve their performance. The second is to use the dart motion characteristics obtained in the first part to analyze the errors in the athletes' movements through z-scores, and to give personalized improvement suggestions for these errors, so that the athletes can understand their own shortcomings. This research will establish an automated, standardized, and personalized training system for athletes,

thereby providing scientific basis and technical support for athlete training. The overall idea of this research is shown in Figure1.

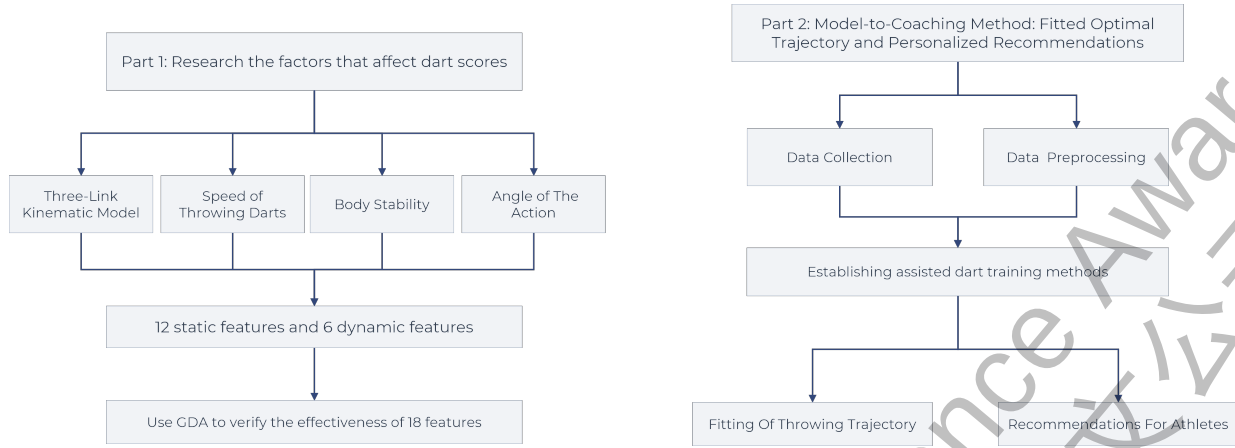


Figure 1. Methodology Flow Chart

3.1. Factors of Dart-Throwing Accuracy

In the first part of the research, it is necessary to determine the scoring factors that affect the dart movement, quantify the scoring factors, and establish feature engineering for the dart movement. To this end, this study reviewed a large number of literature and materials in related fields, and conducted in-depth research based on the practical experience of professional darts coaches. Through this process, the study summarized several important factors that have a decisive influence on throwing performance, including the three-link kinematic model, the speed of throwing darts, body stability and action angle.

3.1.1. Three-Link Kinematic Model

The Three-Link Kinematic Model, as shown in Fig.2, is a crucial action model in the darts movement. In the technical analysis of dart throwing, the throwing arm is often abstracted into a three-link mechanism to use mechanical kinematics principles to model and explain the movement[10].

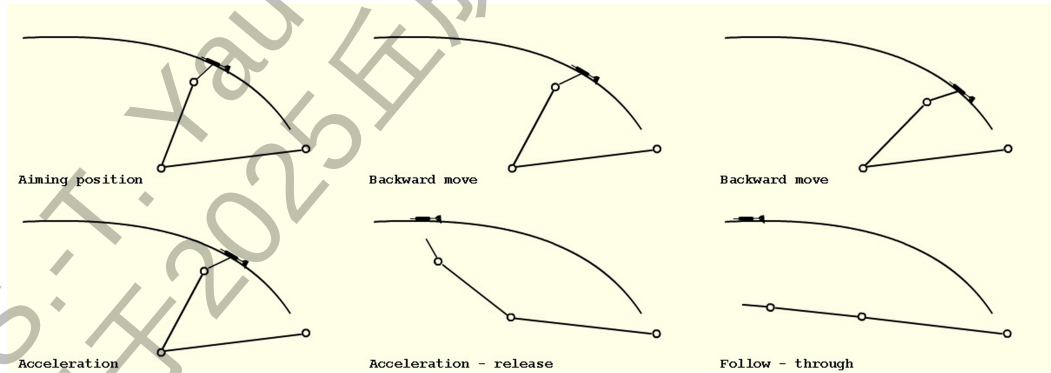


Figure 2. The Three-Link Kinematic Model

The three-link kinematic model consists of three parts: the upper arm, forearm and hand. The shoulder joint is the fixed point, and the elbow joint and wrist joint are two hinges respectively. During the throwing process, the shoulders are usually relatively stable, serving as a support and reference point throughout the motion. When the arm swings backward, the elbow joint should remain relatively fixed to ensure the stability of the throwing action; only when the arm swings forward and the dart accelerates, the elbow joint will rise with the trend, extending the acceleration path of the dart, improving the guidance of the action, and thereby improving the accuracy of throwing. Through the

coordination of the three-link mechanism, the throwing arm can achieve efficient power transmission, allowing the dart to obtain stable and controllable speed and direction[11].

Based on the three-link kinematic model theory, the research quantifies the joint motion of the throwing arm and selects key motion indicators for time series curve analysis. Specifically, it is divided into shoulder joint, elbow joint and wrist joint. The variation curve of shoulder joint pitch angle over time reflects the movement pattern of the shoulder throughout the throwing motion, thereby validating its role as a proximal stable fulcrum in the three-link system. The curve of the elbow joint bending angle changing with time reveals the complete dynamic process of the elbow joint from flexion to extension and finally release, highlighting its power transmission and acceleration function as an intermediate link. Finally, the curve of the wrist extension angle changing with time is used to examine whether the wrist is unstable at the moment of release. The reverse control of the wrist helps to accelerate and control the throwing direction.

3.1.2. Speed of Throwing Darts

In dart throwing, the throwing speed of the player is one of the key factors affecting the throwing effect. The entire movement should reflect the coherence and controllability of rapid delivery. Usually, from the back swing of the arm to the release, the speed passes through the shoulder joint, elbow joint and wrist joint in sequence. The shoulder provides the overall driving force as the initial force, and then the force gradually transitions to the elbow and reaches a peak at the wrist.

This gradual power transmission method helps ensure the stability and coordination of movement, allowing the dart to obtain the ideal initial speed and direction at the moment of release, thereby improving the accuracy of throwing. At the moment when the dart takes off, the rapid "shaking" or "swinging" of the wrist joint can further give the dart additional acceleration, which not only increases the speed of the dart, but also enhances the stability of the flight process. Especially for skilled players, correct and effective use of the wrist can significantly improve the hit rate of darts. However, if there is a lack of precise control of wrist movements, it may cause throwing deviations. Therefore, its training and application need to be individualized and gradual[12].

Based on these theories, this study established a dynamic indicator of the speed versus time curve and a static indicator of the moment when the dart was released. This helps us learn the force patterns of accelerating, decelerating, and releasing torque. Fig.3 is the speed versus time curve.

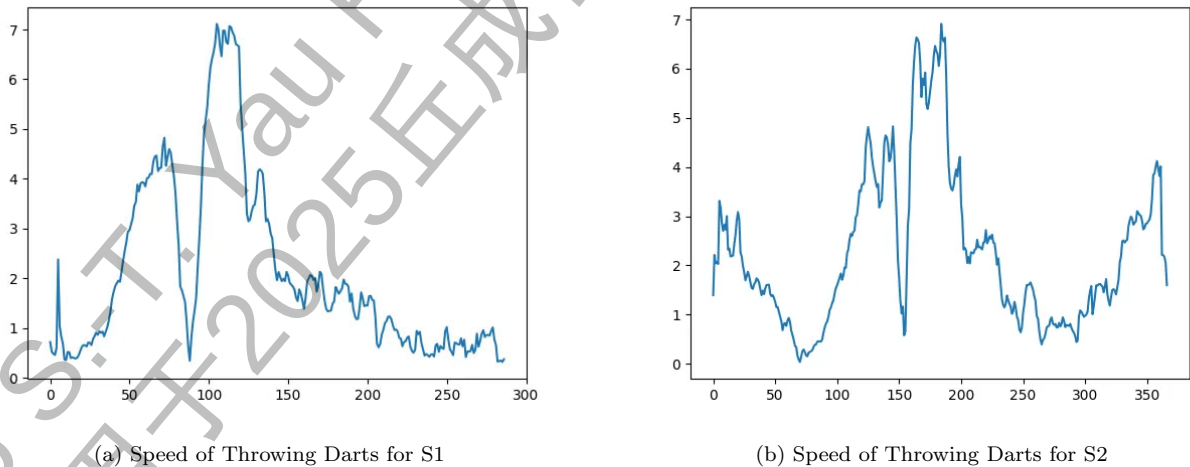


Figure 3. Speed of Throwing Darts.

3.1.3. Body Stability

In the sport of darts throwing, movement stability is a core factor affecting performance and performance. First of all, from a kinematic perspective, stable joint motion patterns (especially the coordination of shoulders, elbows, and wrists) can ensure the repeatability of hand trajectories, thereby reducing unnecessary energy loss and improving throwing accuracy[12]. The study found that high-

level players showed consistent joint angular velocities and trajectories across multiple throws, while low-level players were more prone to fluctuations in shoulder and elbow joint control[8].

Based on these theories, this study established a series of quantitative indicators. Including grip stability, head stability, trunk core stability and footstep stability. Grip stability reflects whether the dart remains stable in the hand, and large fluctuations indicate unstable grip. Head stability evaluates whether the head remains stable and whether the eyesight moves during the throw. Core stability measures the stability of the body's core throughout the throwing process. Finally, foot stability assesses whether the lower body maintains a correct and stable posture to support overall movement.

3.1.4. The Angle of The Action

During dart throwing, joint angles are an important factor in determining the accuracy and stability of the throwing. First of all, the angle changes of the shoulders, elbows, wrists and other joints determine the trajectory of the hands and darts. Studies have shown that high-level throwers can maintain relatively stable and repeatable angle control during the elbow joint flexion and wrist dorsiflexion, thereby achieving a more accurate throwing trajectory[8].

Secondly, the angle selection of the moment of release directly affects the speed and direction of the dart. For example, the extension angle of the elbow joint and the palm flexion velocity of the wrist are closely related to the release speed of the dart, and a slight difference in the release angle can lead to a significant deviation of the landing point[12]. Therefore, the action angle not only determines the directionality of the power output, but also affects the stability and final landing point of the dart flight.

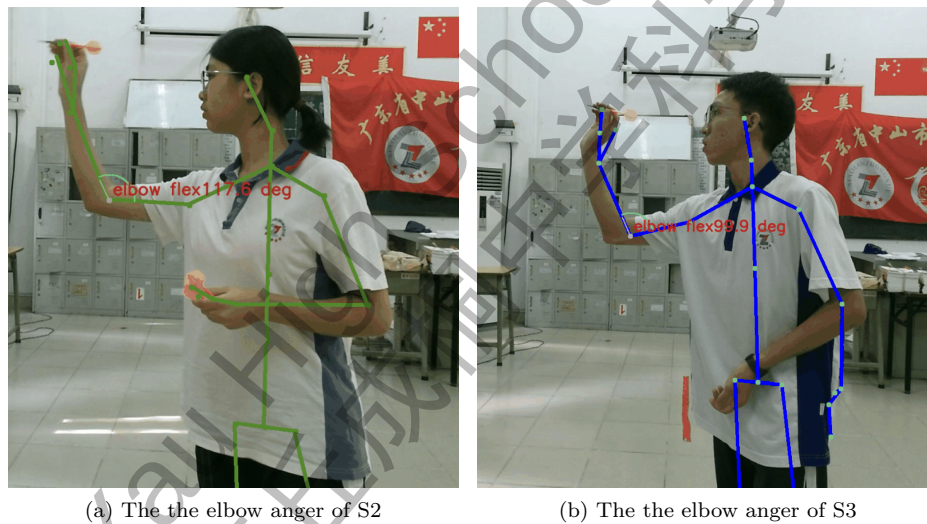


Figure 4. The Elbow Joint Angle of The Action.

Finally, action angles also play an important role in different throwing strategies. Expert throwers often compensate for action timing errors by adjusting the angular acceleration of the elbow and wrist, thereby maintaining a high hit rate in high frequency throws[13].

Based on these theories, the study defines the following quantitative indicators. The instantaneous shoulder joint pitch angle at release characterizes the elevation of the upper arm, which directly affects the release trajectory of the dart. The instantaneous elbow joint flexion angle at release reflects the degree of extension of the forearm, where excessive or insufficient values may impair throwing efficiency. The instantaneous wrist extension angle at release describes wrist motion at the moment of release, influencing both the release speed and directional control of the dart. The instantaneous trunk yaw angle around the vertical axis at release evaluates whether the torso rotates in synchrony with the throwing arm. In addition, the time-varying curve of trunk rotation about the vertical axis serves as an indicator of core stability and the underlying force generation pattern. The instantaneous angle between hand speed direction and the target direction at release quantifies the alignment between the release motion and the intended target. Finally, the time-varying curve of the hand-to-bullseye angle assesses whether the throwing trajectory remains accurately aligned with the dartboard center

or shows deviations. For example, the instantaneous elbow joint flexion angle at release is shown in Fig.4

In general, through literature surveys and inquiries of professional dart coaches, this paper summarizes four factors that influence dart throwing, and the study establishes 12 static indicators as shown in Table. 1 and 6 dynamic indicators as shown in Table. 2.

3.2. Methods for Collecting Data.

The study uses Kinect 2.0 human posture recognition sensor and a dart target image acquisition device as hardware system. In software systems, the study designs based on python program. It can also synchronize the athlete's throwing video and dart landing position information, thereby realizing the linkage analysis of scores and action postures. And a data foundation was established for subsequent athlete assisted training systems.

3.2.1. Selection of Data Collection Equipment

Kinect is the XBOX360 somatosensory peripheral device officially announced by Microsoft on June 2, 2009. Kinect completely subverts the single operation of the game, making the concept of human-computer interaction more thoroughly. It is a 3D somatosensory camera, and it also imports functions such as instant dynamic capture, image recognition, microphone input, voice recognition, and community interaction, as shown in Fig. 5.



Figure 5. Kinect 2.0-based human pose recognition sensor

The Kinect 2.0 sensor integrates multiple hardware modules, including a color camera capable of capturing 1920×1080 RGB images, an infrared camera for acquiring video images within its field of view, and a depth camera that analyzes infrared signals to generate depth maps of human subjects and surrounding objects. Owing to these features, Kinect has been widely applied in research areas such as medicine, biomechanics, robotics, meteorology, and optical control. In the study, Kinect 2.0 was primarily employed to acquire both high-resolution color images and human joint data, enabling accurate posture detection and motion analysis of dart athletes.

Kinect has a wide range of applications in the field of scientific research, covering medicine, biomechanics, robotics, meteorological, and optical control. In the study, the study mainly uses kinect2.0 to obtain color image data and human joint node data to realize posture detection of dart athletes.

To obtain dart landing data, the study was configured with a 1080p HD camera based on CMOS sensor. Considering avoiding interference with athlete throwing movements, the camera is installed under the dart machine for shooting. In order to achieve subsequent image geometric correction, a 9×6 checkerboard calibration plate was pasted under the dart target to facilitate perspective transformation and precise correction of the target image, as shown in Fig. 6.

3.2.2. Construction of Data Acquisition Software

In terms of the connection between Kinect2.0 hardware and information systems, the study introduced the PyKinect open source library as an intermediate bridge to open up the technical interface between the sensor layer and the application layer. The software systems is shown in Fig.7. With this

Table 1. Twelve feature of dart throwing at the release

Category	feature	Formula
Motion Speed and Direction	Release speed (hand linear velocity at release)	$\ \mathbf{p}_{\text{hand}}(t) - \mathbf{p}_{\text{hand}}(t-1)\ \cdot FPS$
	Release alignment angle (hand velocity vs. target)	$\theta(a, b) = \arccos\left(\frac{a \cdot b}{\ a\ \ b\ }\right)$
Grip Stability	Mean grip distance	$\frac{1}{T} \sum_{t=1}^T d_t, \quad d_t = \ \mathbf{p}_t^{(\text{THUMB_R})} - \mathbf{p}_t^{(\text{HANDTIP_R})}\ $
	Grip distance variability (standard deviation)	$\sqrt{\frac{1}{T} \sum_{t=1}^T (d_t - \bar{d})^2}$
Body Stability	Head stability (± 5 frames)	$\frac{1}{ S -1} \sum_{t \in S} \ \mathbf{q}_t - \mathbf{q}_{t-1}\ , \quad S = \{r-5, \dots, r+5\}$
	Trunk stability (± 5 frames)	$\frac{1}{ S -1} \sum_{t \in S} \ \mathbf{q}_t - \mathbf{q}_{t-1}\ , \quad S = \{r-5, \dots, r+5\}$
	Ankle stability (± 5 frames)	$\frac{1}{ S -1} \sum_{t \in S} \ \mathbf{q}_t - \mathbf{q}_{t-1}\ , \quad S = \{r-5, \dots, r+5\}$
Motion Angles	Shoulder pitch angle at release	$\theta = \arccos\left(\frac{a \cdot b}{\ a\ \ b\ }\right)$
	Elbow flexion angle at release	$\theta = \arccos\left(\frac{a \cdot b}{\ a\ \ b\ }\right)$
	Wrist extension angle at release	$\theta = \arccos\left(\frac{a \cdot b}{\ a\ \ b\ }\right)$
	Trunk yaw angle at release	$\theta = \arccos\left(\frac{a \cdot b}{\ a\ \ b\ }\right)$
Release phase percent	Proportion of the throwing cycle elapsed at the release frame (0-100%)	$\frac{r_{idx}}{T} \times 100$

Table 2. Six dynamic feature of dart throwing

feature	Formula
shoulder pitch	$f_i^{\text{hand_speed}} = \ \mathbf{v}_i\ = \left\ \frac{\mathbf{p}_i^{(\text{HANDTIP_R})} - \mathbf{p}_{i-1}^{(\text{HANDTIP_R})}}{\Delta t} \right\ $
elbow flexion	$\mathbf{v}_t = \frac{\mathbf{p}_t^{(\text{HANDTIP_R})} - \mathbf{p}_{t-1}^{(\text{HANDTIP_R})}}{\Delta t}, \quad \mathbf{z} = (0, 0, 1)$ $\theta_i^{\text{hand_to_bull}} = \arccos\left(\frac{\mathbf{v}_i \cdot \mathbf{z}}{\ \mathbf{v}_i\ \ \mathbf{z}\ }\right)$
wrist extension	$\mathbf{u}_i = \mathbf{p}_i^{(\text{ELBOW_R})} - \mathbf{p}_i^{(\text{SHOULDER_R})}$ $\mathbf{s_to_sp}_i = \mathbf{p}_i^{(\text{SPINE_SHOULDER})} - \mathbf{p}_i^{(\text{SHOULDER_R})}, \quad (\mathbf{s_to_sp}_i)_x = 0$ $\theta_i^{\text{shoulder_pitch}} = \arccos\left(\frac{\mathbf{u}_i \cdot \mathbf{s_to_sp}_i}{\ \mathbf{u}_i\ \ \mathbf{s_to_sp}_i\ }\right)$
hand speed	$\mathbf{u}_i = \mathbf{p}_i^{(\text{ELBOW_R})} - \mathbf{p}_i^{(\text{SHOULDER_R})}, \quad \mathbf{f}_i = \mathbf{p}_i^{(\text{WRIST_R})} - \mathbf{p}_i^{(\text{ELBOW_R})}$ $\theta_i^{\text{elbow_flex}} = \arccos\left(\frac{\mathbf{u}_i \cdot \mathbf{f}_i}{\ \mathbf{u}_i\ \ \mathbf{f}_i\ }\right)$ $\text{elbow_flexion}(\tau) = \text{CubicSpline}(t^{ms}, \theta_i^{\text{elbow_flex}})(\tau)$
hand to bull angle	$\mathbf{f}_i = \mathbf{p}_i^{(\text{WRIST_R})} - \mathbf{p}_i^{(\text{ELBOW_R})}, \quad \mathbf{h}_i = \mathbf{p}_i^{(\text{HAND_R})} - \mathbf{p}_i^{(\text{WRIST_R})}$ $\theta_i^{\text{wrist_ext}} = \arccos\left(\frac{\mathbf{h}_i \cdot \mathbf{f}_i}{\ \mathbf{h}_i\ \ \mathbf{f}_i\ }\right)$
trunk yaw	$\mathbf{t}_i = \mathbf{p}_i^{(\text{SPINE_SHOULDER})} - \mathbf{p}_i^{(\text{SPINE_BASE})}, \quad \mathbf{t}_i^{xz} = (t_x, 0, t_z), \quad \mathbf{z} = (0, 0, 1)$ $\theta_i^{\text{trunk_yaw}} = \arccos\left(\frac{\mathbf{t}_i^{xz} \cdot \mathbf{z}}{\ \mathbf{t}_i^{xz}\ \ \mathbf{z}\ }\right) \cdot \text{sign}(t_{i,x}^{xz} + \varepsilon)$



Figure 6. Dart image acquisition equipment and the data acquisition scene

design, real-time collection, transmission and processing of motion data are realized, which not only reduces the coupling between hardware and software, but also provides a stable and scalable operating environment for subsequent data management and analysis.



Figure 7. The Software Systems for Data Collection

3.3. Data Collection and Preprocessing

Data acquisition and preprocessing are a crucial part of scientific research, and data is the cornerstone of artificial intelligence research.

During the entire data collection process, our collection objects were students from Zhongshan Xiaolan Middle School, and they were conducted in the school's dart training room. We run the

acquisition system built in the previous article in our laptop, and use the USB interface to connect the kinect2.0 device and the high-definition camera.

In the process of data processing, the study uses a combination of manual processing and automatic processing to process video and image data using the opencv-python library, and enhance and propose images information, which is conducive to the establishment of subsequent machine learning models.

3.3.1. Data Collection

The data for the study are from the student group of Xiaolan Middle School in Zhongshan City, Guangdong Province, including four professional dart athletes from the dart team and three ordinary students, as shown in table 3. By systematically collecting the movement process of the subjects, the study obtains a large amount of original data with research value.

Table 3. Participant information and data collection summary

Category	Subject	Gender	Height	Weight	Arm Span	Num.
Professional athletes	S1	Female	170 cm	58 kg	165 cm	237
	S2	Female	168 cm	57 kg	170 cm	251
	S3	Male	168 cm	55 kg	172 cm	255
	S4	Male	175 cm	70 kg	180 cm	305
	S5	Male	176 cm	55 kg	173 cm	696
Non-professional athletes	S6	Male	173 cm	55 kg	165 cm	430
	S7	Male	170 cm	60 kg	168 cm	222

These data not only cover the normative and stable characteristics of professional athletes in throwing movements, but also reflect the movement patterns of ordinary students under non-professional training conditions, providing a solid data basis for subsequent comparative analysis and model construction.

To ensure the high-definition image quality and depth information accuracy of the collected data, this article uses Kinect human posture sensor to record the movements of dart athletes during throwing. In terms of data types, the system mainly collects color high-definition video data during athlete throwing, and also obtains information on each node. Specifically, each frame of the image contains 25 skeletal joint nodes, and each joint node comes with three-dimensional spatial coordinates (x, y, z), as shown in Fig. 8.

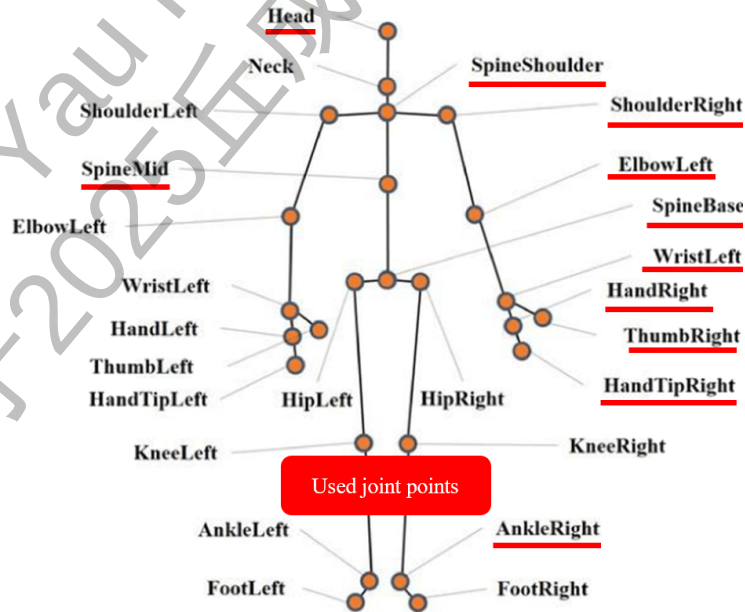


Figure 8. 25 skeletal joint points[14]

In order to achieve the quantitative analysis of the throwing action of dart athletes, the data of

the athlete's throwing process are collected, and the relevant data of the dartboard are collected, as shown in Fig. 9. By obtaining target data, the distance between the dart landing point and the target center can be accurately calculated, thereby providing objective evaluation indicators for the athlete's throwing action. This indicator can not only be used as a direct measure of throwing accuracy, but also can establish a unified reference for subsequent action feature extraction and performance analysis.

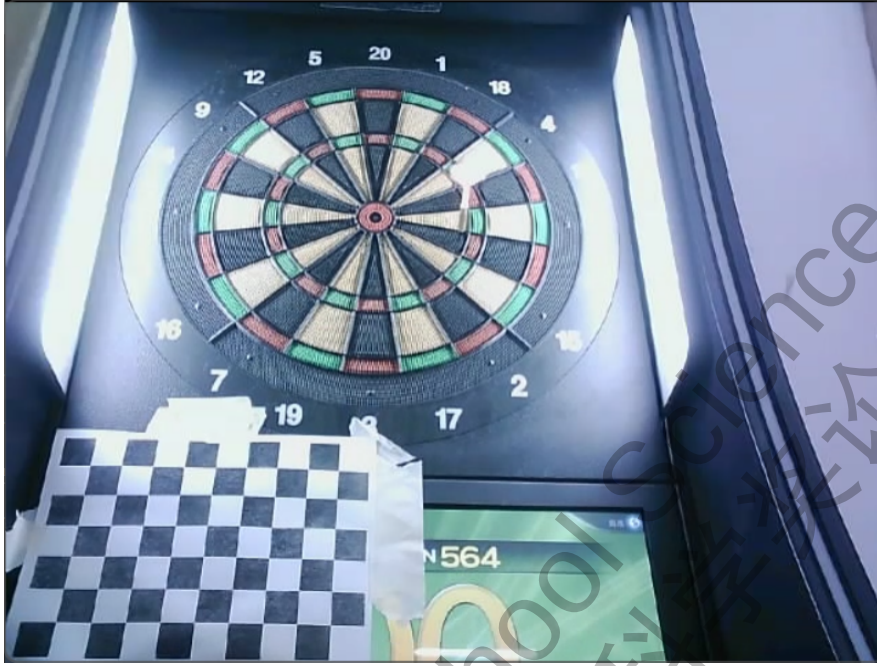


Figure 9. Dart image example

3.3.2. Data Preprocessing

Data processing is an important part of scientific experiments. Through reasonable data processing, some abnormal data can be filtered out to ensure the accuracy of the data and the effectiveness of the experiment.

In the manual processing stage, the study first classified the data, which is divided into professional athlete data and non-professional data. We filtered out data that were unclear, incomplete, obstructed in the middle and there were unrelated personnel entering during the shooting process. We conducted a comprehensive screening of the integrity of the data.

During the collection of dart-throwing motions, variations in the duration of each throw among athletes lead to inconsistencies in the number of acquired skeletal joints points frames. Such discrepancies in frame counts adversely affect subsequent motion comparison, temporal feature extraction, and model training. To address this issue, the study employs cubic spline interpolation to perform time-domain resampling and completion of the joints points trajectories for each throwing motion.

Specifically, the joint point sequences collected during each throw were first normalized to a fixed temporal length (120 frames in the study). On this basis, cubic spline interpolation was applied separately to the three-dimensional coordinates of each joint points to generate trajectory sequences of equal length. This approach not only ensures smooth transitions while preserving the original variation trends in the data, but also effectively retains the temporal characteristics of the motion, thereby providing a consistent and reliable data foundation for subsequent analysis and modeling.

3.3.3. Dart-to-Bullseye Distance Measurement Method

Since the camera needs to avoid interference with the athlete's normal throwing movements during installation, the shooting angle cannot face the surface of the dart machine, so the collected images have obvious tilt and perspective distortions. If not corrected, the dart landing points will deviate between the image coordinate system and the actual physical coordinate system, thereby affecting the accuracy of landing point detection.

To solve this problem, the study pasted a chessboard calibration plate to the surface of the dart machine before the experiment began, and obtained the camera's internal and external parameters and distortion coefficients through the camera calibration process. In the image processing stage, the obtained calibration parameters are used to perform inverse projection operations on the original image, eliminating the distortion and perspective effects, thereby realizing geometric restoration of the image.

Algorithm 1: Dart tip detection and distance to bullseye (short)

Input: Video $\mathcal{V}$; chessboard (9×6); bin. threshold T ; resample N

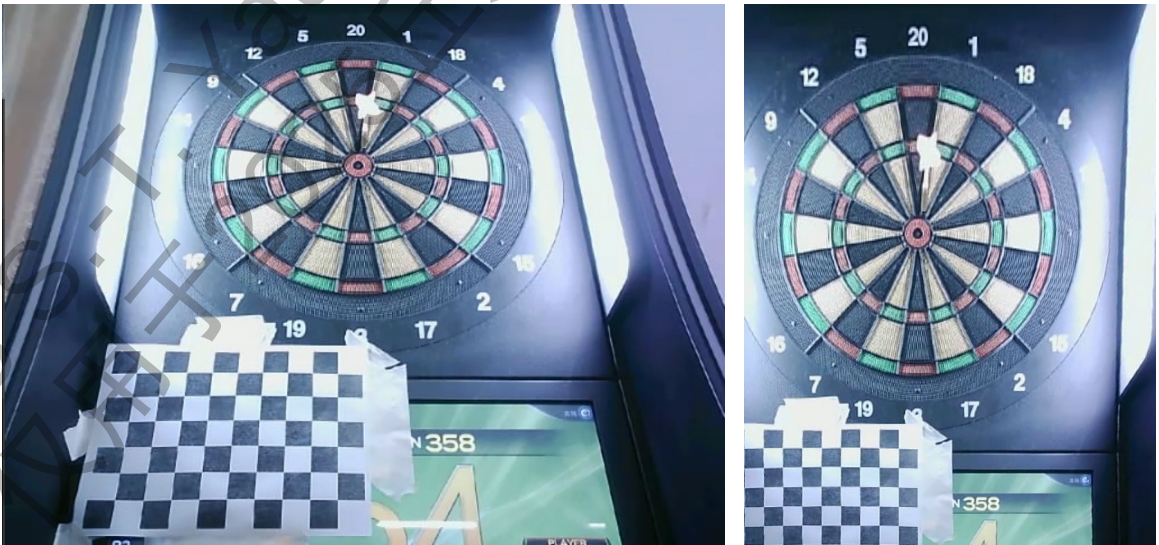
Output: Tip $\mathbf{p}_{tip}$, center $\mathbf{c}$, distance d

- 1 Read final frame $\mathbf{I}_2$ and a pre-final $\mathbf{I}_1$ from $\mathcal{V}$;
 - 2 **for** $\mathbf{I} \in \{\mathbf{I}_1, \mathbf{I}_2\}$:
 - 3 $\lfloor$ if chessboard found $\Rightarrow$ warpPerspective to canvas;
 - 4 Denote rectified $\mathbf{F}_1, \mathbf{F}_2$;
 - 5 Detect bullseye on $\mathbf{F}_1$ via HSV(red+black) + morphology $\Rightarrow$ best circle center $\mathbf{c}$; if fail $\Rightarrow$ HoughCircles + black-fill check;
 - 6 Crop square ROI around $\mathbf{c}$ from $\mathbf{F}_1, \mathbf{F}_2$; $\mathbf{D} \leftarrow |\text{blur}(\mathbf{R}_2) - \text{blur}(\mathbf{R}_1)|$; percentile bandpass $\Rightarrow$ binary mask $\mathbf{M} = (\mathbf{D} \geq T)$;
 - 7 Extract largest contour $\mathcal{C}$; PCA axis $\mathbf{v}$, centroid $\bar{\mathbf{x}}$; Resample $\mathcal{C}$ to N points, smooth, compute curvature κ_i ; Score outer candidates $s_i = \kappa_i \cdot (1 + w[(\mathbf{p}_i - \bar{\mathbf{x}}) \cdot \mathbf{v}]_+)$; **if** $\max s_i$ *invalid* **then**
 - 8 (i) skeleton endpoints farthest from $\bar{\mathbf{x}}$; **else**
 - 9 $\lfloor$ (ii) farthest contour point from $\bar{\mathbf{x}}$;
 - 10 Pick best $\mathbf{p}_{tip}^{(roi)}$ and refine locally;
 - 11 Restore to full image: $\mathbf{p}_{tip} = \mathbf{p}_{tip}^{(roi)} + (x_0, y_0)$; $d = \|\mathbf{p}_{tip} - \mathbf{c}\|_2$; **return** $(\mathbf{p}_{tip}, \mathbf{c}, d)$.
-

For the dart plane (i.e., the checkerboard calibration plane), a homography transformation matrix H between the world coordinate system and the image coordinate system can be established, and the relationship is as follows:

$$s \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = H \begin{bmatrix} X \\ Y \\ 1 \end{bmatrix} \quad (1)$$

where (X, Y) represents the real physical coordinates on the dart plane, (u, v) represents the corresponding image coordinates, and s is the scale factor. By calculating and obtaining the inverse matrix of H , the image obtained by tilting can be remapped into an ideal orthogonal projection image. The image comparison before and after correction is shown in Fig. 10.



(a) Before calibration and cropping

(b) After calibration and cropping

Figure 10. Dartboard images before(a)/after(b) chessboard-based correction and cropping.

After the perspective correction is completed, the restored image is equivalent to the result collected from the camera's position facing the dart machine. This not only ensures the one-to-one correspondence between the image coordinates and physical coordinates of the dart, but also lays a reliable geometric foundation for subsequent landing detection and accuracy evaluation.

To achieve high-precision recognition of the distance between the dart landing point and the bulls-eye, the study develops a set of image processing and object recognition algorithms based on OpenCV. The process of identifying darts is shown in Fig.11 and the algorithm1.

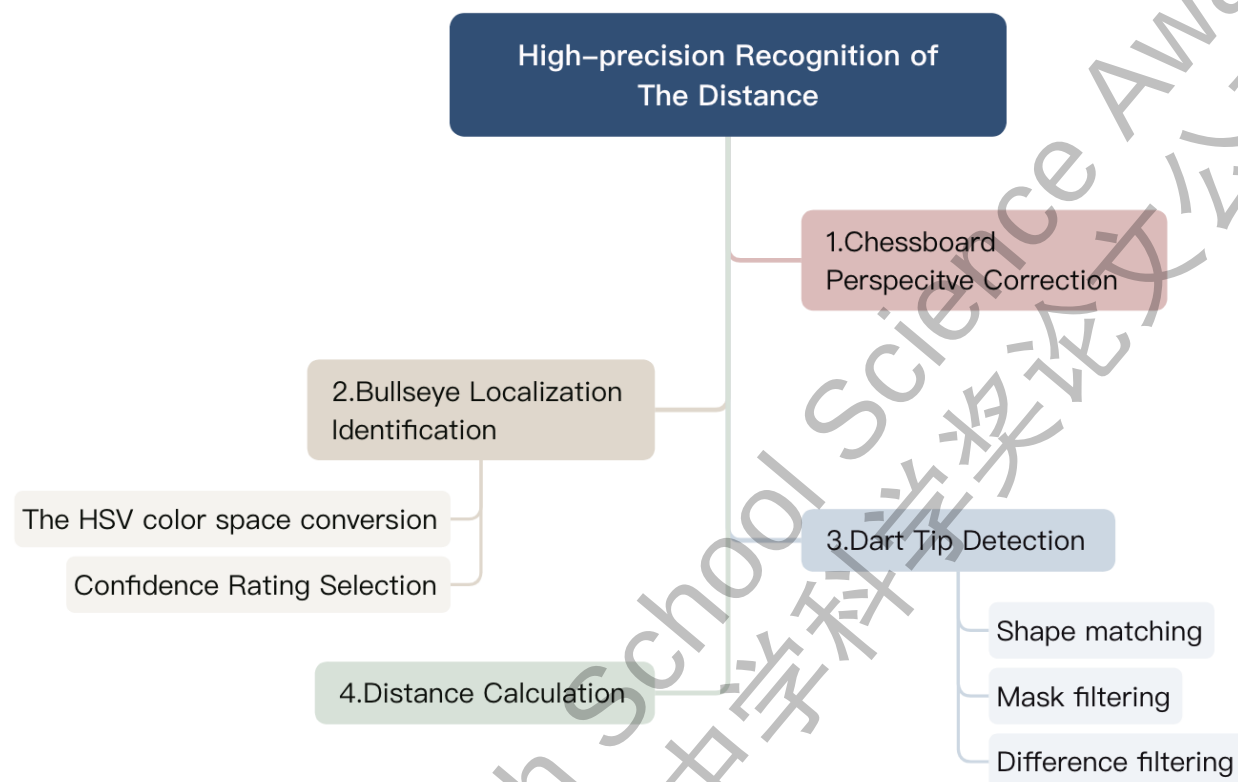


Figure 11. Distance measurement flow chart

The image data are first corrected using a chessboard calibration method. After completing the perspective correction of dartboard images, the system compares the final frame of the throwing video with the 18th frame captured before and after the dart is released, thereby filtering out redundant information. This process facilitates the accurate identification of the dart.

For bullseye localization, the algorithm first utilizes the HSV color space to extract the red outer ring and the black inner region from the geometrically corrected image. Candidate regions that do not meet the requirements are discarded by filtering based on the area and circularity of the red ring. The minimum enclosing circle of the red ring is then used to determine the candidate center and radius. Subsequently, the proportion of black pixels in the inner region is calculated for verification, thereby ensuring the accuracy of bullseye detection. When multiple candidate regions are obtained, the algorithm assigns scores according to circularity, area, proportion of inner black pixels, and proximity to the image center, selecting the highest-scoring region as the final bullseye position. If red ring detection fails, the method falls back to Hough circle detection for small circle identification, combined with inner black ratio verification to confirm the bullseye position, as shown in Fig.12.

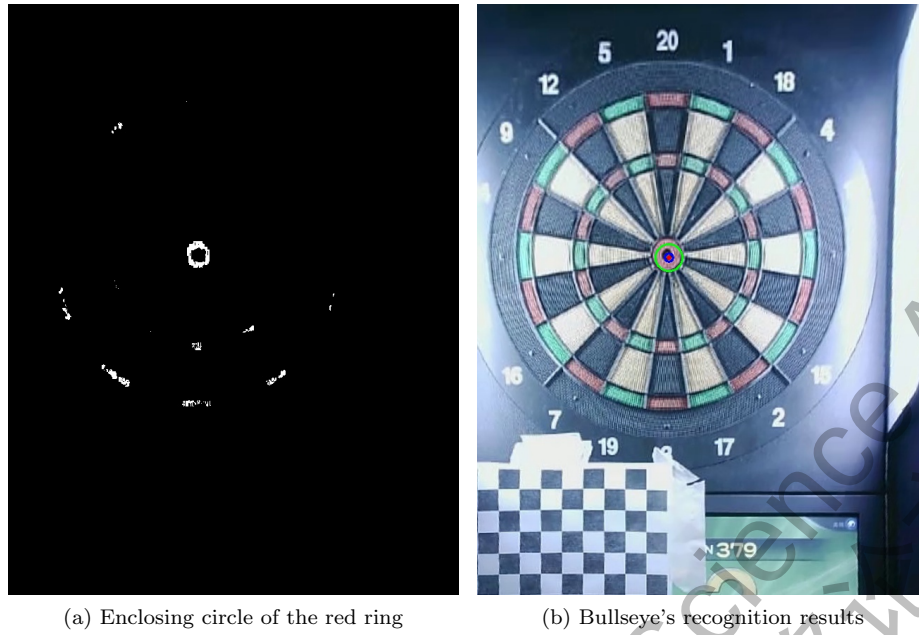


Figure 12. (a) is the Enclosing circle of the red ring obtained through the color mask, and (b) is the result of bull's eye recognition.

For dart tip detection, the system applies frame differencing between two selected images, followed by blurring, normalization, threshold segmentation, and morphological operations to generate a mask containing only the dart. The largest external contour is extracted from the mask, and its contour points are resampled with equal arc length and smoothed. Principal component analysis is then employed to calculate the orientation of the contour's major axis, after which the curvature and outward projection intensity of each contour point are computed. Among the outer contour points and convex hull points, the most probable tip position is determined through a comprehensive scoring process, which is shown in Fig. 13. If this procedure fails, a skeletonization algorithm is applied to identify the endpoint farthest from the contour centroid as the candidate tip; if this also fails, the point on the external contour most distant from the centroid is directly selected as the dart tip.

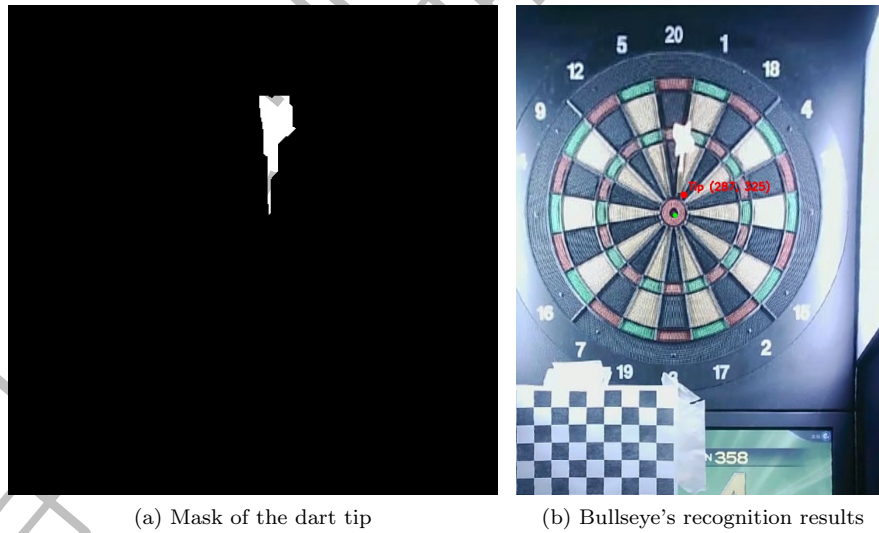


Figure 13. (a) is the Mask of the dart tip obtained through frame differencing, and (b) is the result of dart tip recognition.

Finally, map the position of the dart tip in the local coordinate system back to the global image coordinate system. Then, the Euclidean distance between the detected dart tip and the identified bullseye is calculated to obtain a final measure of dart landing.

3.4. Use GDA to verify the effectiveness of 18 features

In order to verify the effectiveness of the 18 features, this study used the Gaussian discriminant model and shap Value methods for verification. The reason why this article uses the Gaussian distribution is because the score distribution of dart players conforms to the Gaussian distribution, as shown in the Fig.14. Using the Gaussian discriminant model can determine whether the 18 features can distinguish professional athletes from non-professional athletes. If the dart action can be successfully distinguished whether the dart action is correct or not, it proves that these 18 features are effective. This study also used shap value verification. Shap value can determine the impact of each feature on the scoring factors, thereby determining which dart movement features should be emphasized. Next is the specific experimental method.

Motion data were acquired using a Kinect 2.0 body posture sensor from both professional and non-professional dart players. Following data acquisition, preprocessing was performed by resampling the joint trajectories to 120 frames via cubic spline interpolation within a temporal window of ± 250 ms around the release instant, identified by peak hand velocity. From the normalized trajectories, 18 biomechanical features were extracted. These features were subsequently used to train a Gaussian Discriminant Analysis (GDA) model. Once trained, the model enabled automatic scoring of new motion data by computing the same set of features and evaluating them against the learned discriminant function.

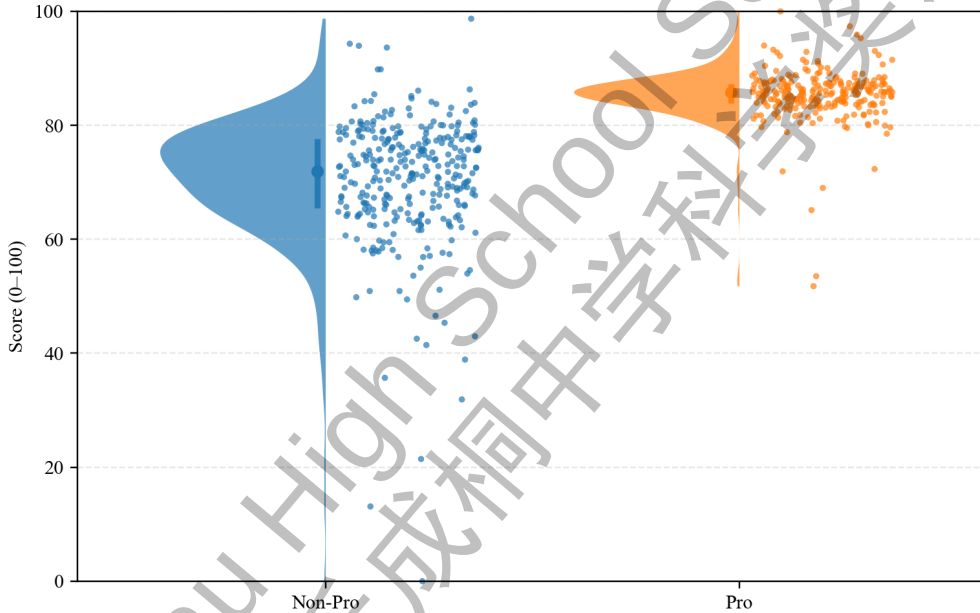


Figure 14. Distribution of shooting data

3.4.1. Two-class Gaussian Discriminant Model

When using the Gaussian classification model for verification, this study first extracted 18 characteristic sports features of professional athletes and non-professional athletes, converted these 18 features into 18-dimensional vectors, and then input the vector into the Gaussian model. Gaussian fitting was performed on professional athletes and non-professional athletes respectively. The fitting results were two types of distribution probabilities. The model judgment method is to bring the data into the two Gaussian models that have been fitted, subtract the probabilities of the two models, and use the obtained values to determine which type the data belongs to. If the obtained value can successfully distinguish the type of data, it means that the Gaussian discriminant model is effective, further indicating that these 18 features can effectively represent the characteristics of the dart throwing action. The training process of the Gaussian discriminant model is shown in the algorithm2.

Algorithm 2: GDA-based scoring for dart-throwing motion

Input : Professional set $X_p = \{x_i\}_{i=1}^{N_p}$, Non-professional set $X_n = \{x_i\}_{i=1}^{N_n}$, regularizer $\epsilon > 0$, feature dim $d=18$, (optional) priors π_p, π_n , new sample $x^{(\text{new})}$

Output: Predicted label $\hat{y} \in \{\text{pro}, \text{non}\}$, calibrated score $s_{0-100} \in [0, 100]$

```
1 Stage A: Train GDA;
2 for  $c \in \{p, n\}$  do
3    $\mu_c \leftarrow \frac{1}{N_c} \sum_{i \in c} x_i$ ;
4    $\Sigma_c \leftarrow \text{cov}(X_c) + \epsilon I$ ; // diagonal regularization
5 end for Optional
6  $\pi_c \leftarrow \frac{N_c}{N_p + N_n}$ ;
7 Stage B: Calibrate raw margin on train set;
8  $S_{\text{train}} \leftarrow \emptyset$ ;
9 foreach  $x \in X_p \cup X_n$  do
10  for  $c \in \{p, n\}$  do
11     $\ell_c(x) \leftarrow -\frac{1}{2}[(x - \mu_c)^\top \Sigma_c^{-1}(x - \mu_c) + \log \det \Sigma_c + d \log(2\pi)]$ ;
12  end for
13   $m(x) \leftarrow \ell_p(x) - \ell_n(x)$ ; // discriminant margin
14  Append  $m(x)$  to  $S_{\text{train}}$ ;
15 end foreach
16 Compute  $m_{\min}, m_{\max}$  from  $S_{\text{train}}$  ;
17 Stage C: Inference for  $x^{(\text{new})}$ ;
18 for  $c \in \{p, n\}$  do
19    $\ell_c \leftarrow -\frac{1}{2}[(x^{(\text{new})} - \mu_c)^\top \Sigma_c^{-1}(x^{(\text{new})} - \mu_c) + \log \det \Sigma_c + d \log(2\pi)]$ ;
20 end for
21  $m \leftarrow \ell_p - \ell_n$ ; // raw discriminant score
22  $\hat{y} \leftarrow \arg \max\{\ell_p, \ell_n\}$ ;
23 Stage D: Map margin to  $[0, 100]$ ;
24  $s_{0-100} \leftarrow \text{clip}\left(100 \times \frac{m - m_{\min}}{m_{\max} - m_{\min}}, 0, 100\right)$ ;
25 return  $(\hat{y}, s_{0-100})$ ;
```

For the set of professional samples $X_p = \{x_i\}_{i=1}^{N_p}$ and non-professional samples $X_n = \{x_i\}_{i=1}^{N_n}$, an 18-dimensional multivariate Gaussian distribution was fitted for each class:

$$\mu_c = \frac{1}{N_c} \sum_{i \in c} x_i, \quad \Sigma_c = \text{cov}(X_c) + \epsilon I, \quad c \in \{p, n\}. \quad (2)$$

where $\epsilon = 10^{-6}$ is a diagonal regularization term introduced to ensure the invertibility of the covariance matrix Σ_c and to improve numerical stability. Each feature vector $x \in \mathbb{R}^{18}$ consisted of 18 indicators, including throwing velocity, joint angles, and stability metrics.

Log-likelihood: The log-likelihood of any sample x under class c was computed as

$$\log p_c(x) = -\frac{1}{2}[(x - \mu_c)^\top \Sigma_c^{-1}(x - \mu_c) + \log \det \Sigma_c + d \log(2\pi)] \quad (3)$$

where $d = 18$ denotes the feature dimension.

The discriminant function was defined using the log-likelihood difference:

$$\text{score}(x) = \log p_p(x) - \log p_n(x) \quad (4)$$

Finally, the scores in this article are mapped to 0 to 100 by using the method of max-min.

In short, this study is based on the joint point action data obtained through the Kinect 2.0 sensor,

and based on four factors that affect the dart score: the link model, the throwing speed of the dart, the angle and stability of the dart when throwing, 18 biomechanical features were extracted and a Gaussian discriminant analysis model was trained. The results of the Gaussian discriminant model were used to verify the effectiveness of the four factors that affect the dart score and the 18 extracted features.

3.5. Trajectory Fitting Method for Dart Throws

After completing the validity verification of the four factors that affect the dart score and the 18 extracted features. The second part of this research has begun, establishing a data-driven darts sports auxiliary training system based on skeleton analysis and machine learning. Traditionally, darts players have relied primarily on the experience and demonstration of coaches for technical guidance. However, this approach makes it difficult for coaches to clearly communicate their intentions, and athletes often have considerable challenges in fully mastering the basic elements of the technique. Moreover, many training standards are determined by the personal characteristics of the coach rather than the personal characteristics of the athlete. Therefore, personalized training guidelines that are developed based on the athlete's own performance data and adapted to increasing skill levels will greatly increase training efficiency. To this end, this study uses a large number of dart motion recording data sets to conduct trajectory fitting experiments, aiming to obtain personalized optimal trajectories. To achieve this goal, this study first proposes to identify a high-quality subset of throwing trajectories from athletes' historical data. The selection of these superior trajectories is based on a weighting scheme that combines trajectory stability and the distance between the dart's landing point and the target. Weighted fitting and coordinate translation are then applied to obtain an initial fitted trajectory, which is subsequently refined using a minimum jerk model to produce the final optimal trajectory. As athletes' skills improve, the quality of data collected is expected to improve, allowing for further refinement of optimal trajectories. The framework is shown in the Fig.15.

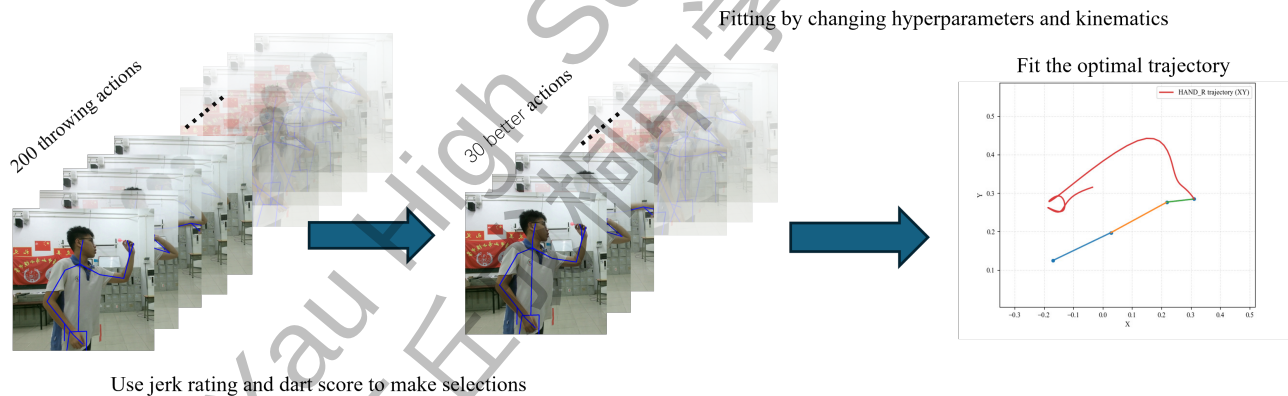


Figure 15. Flow chart of optimal trajectory fitting

To achieve this objective, the study first proposes identifying high-quality subsets of throwing trajectories from the athlete's historical data. The selection of these superior trajectories is based on a weighting scheme that incorporates both trajectory stability and the distance between the dart landing point and the target. Weighted fitting and coordinate translation are then applied to obtain an initial fitted trajectory, which is subsequently refined using a minimum-jerk model to produce the final optimal trajectory. As the athlete's skill improves, the quality of the collected data is also expected to increase, thereby enabling further refinement of the optimal trajectory.

It should be emphasized that the ultimate goal of dart training is to achieve precise control such that the dart lands exactly on the intended target. However, in this experiment, for reasons of feasibility and optimization of the experimental protocol, athletes were instructed to aim specifically at the bullseye. The experiment was therefore conducted under this assumption.

3.5.1. Selection of Optimal Dart-Throwing Trajectories

The research needs to use reasonable methods to filter out the 200 latest historical throwing data and select higher quality trajectories from them.

In terms of selection method, the selection algorithm of this study can combine the distance between the dart's landing point and the dart's bull's-eye to select a better throwing trajectory with high scores and throwing action. Specifically, this study first performed data standardization operations. Select the manual speed peak positioning of the release frame, intercept the 250ms clips before and after the release, and resample to a fixed length of 120 frames after cubic spline interpolation. Only the 6 joints of the right arm (shoulder, elbow, wrist, hand, fingertips, thumb) are retained and samples with off-target abnormalities are eliminated. In terms of judging the quality of an action, the "goodness" of each sample is weighted w . This weight contains information about the distance from the dart to the bullseye and information about the stability of the action. The specific calculation formula is as follows:

$$w = \frac{\exp(-a \cdot \text{distance})}{\sqrt{1 + b \cdot \text{jerk}}} \quad (5)$$

$$\text{jerk} = \sum_k \|\Delta^3 \mathbf{h}_k\|_2^2,$$

where the distance between the dart landing point and the bullseye and the jerk is defined as the sum of squared third-order derivatives of the hand trajectory, which serves as a quantitative measures of motion smoothness. A smaller distance corresponds to a higher weight. A lower jerk value indicates smoother motion and is therefore assigned a higher weight.

Parameters:

$$a = 0.25 \quad b = 1 \times 10^{-4}, \quad (6)$$

where b is used to control the penalty strength of jerk. Finally, the weight w is selected from the first 30 best curves in order from large to small.

3.5.2. Fitting of Throwing Trajectory

In optimal curve fitting, the study uses minimum-jerk fitting, a kinematic smoothing method derived from human motion control theory. Natural human movements (such as stretching and throwing) tend to follow the minimum jerk principle[15]. And our optimal curve fitting process is shown in the algorithm3.

In the updated weighting scheme, a two-stage strategy was employed. In the first stage, a preliminary ranking of all trajectories was performed by assigning weights that jointly considered throwing accuracy and motion smoothness. Specifically, each sample's weight was defined as

$$w_i(a) = \frac{\exp(-a d_i)}{\sqrt{1 + b \cdot J_i}}, \quad i \in \mathcal{S}, \quad (7)$$

where d_i denotes the dart-bullseye distance of sample i , J_i is the hand jerk cost, and $b > 0$ is a scaling factor. In this formulation, throws landing closer to the target (d_i small) and exhibiting smoother kinematics (J_i small) are assigned larger weights. The jerk cost J_i is explicitly computed as

$$J_i = \sum_t \|\Delta^3 \mathbf{p}_t^{(\text{HAND})}\|^2, \quad (8)$$

where $\Delta^3 \mathbf{p}_t^{(\text{HAND})}$ is the third-order finite difference of the hand trajectory at frame t . The top- K trajectories were then selected based on (7).

In the second stage, rather than using a fixed parameter, the weighting parameter a was treated as a tunable hyperparameter and optimized directly on the fixed top- K set. The objective was to

Algorithm 3: Optimal Throwing Trajectory Fitting

Input: RawTrials = {trial₁, ..., trial_M}; PRE_MS= 250, POST_MS= 250, N=120, K=30;
 $a_0=0.25$, $b=10^{-4}$, $\lambda>0$; JointsUsed=[Shoulder_R, Elbow_R, Wrist_R, Hand_R,
 HandTip_R, Thumb_R], TrunkJoint=SpineShoulder.

Output: $\mathcal{A}^*$ (smoothed reference), a^* (optimized weight).

// Stage 0: preprocess all trials

```

1  $S \leftarrow []$ 
2 foreach  $trial \in RawTrials$  do
3    $r \leftarrow \text{locate\_release\_by\_manual\_speed\_peak}(trial)$ 
4    $seg \leftarrow \text{clip\_window}(trial, \text{center} = r, \text{pre\_ms} = \text{PRE\_MS}, \text{post\_ms} = \text{POST\_MS})$ 
5    $A \leftarrow seg.positions[JointsUsed]$ ;  $t \leftarrow seg.positions[TrunkJoint]$ 
6    $\hat{A} \leftarrow \text{cubic\_spline\_resample}(A, N)$ ;
7    $\hat{t} \leftarrow \text{cubic\_spline\_resample}(t, N)$ 
8   if  $is\_off\_target(seg.meta)$  then
9     continue
10   $d \leftarrow seg.meta.dart\_to\_bull\_distance$ ;
11   $J \leftarrow \sum_t \|\Delta^3 \mathbf{p}_t^{(HAND)}\|^2$ ;
12  append  $(\hat{A}, \hat{t}, d, J)$  to  $S$ 

```

// Stage 1: initial ranking with fixed a_0

```

13 foreach  $(\hat{A}^{(i)}, \hat{t}^{(i)}, d_i, J_i) \in S$  do
14    $w_i \leftarrow \exp(-a_0 d_i) / \sqrt{1 + b J_i}$ 
15 Sort  $S$  by  $w_i$  (desc);  $S_K \leftarrow$  first  $K$  items
  // Stage 2: learn  $a$  on Top- $K$  and build template

```

```

16 foreach  $(\hat{A}^{(i)}, \hat{t}^{(i)}, d_i, J_i) \in S_K$  do
17    $\tilde{w}_i(a) \leftarrow \exp(-a d_i) / \sqrt{1 + b J_i}$ 
18 Normalize  $\{\tilde{w}_i(a)\}$  so that  $\sum_i \tilde{w}_i(a) = 1$ 
19  $\bar{A} \leftarrow \sum_{i \in S_K} \tilde{w}_i(a) \hat{A}^{(i)}$ ;  $\bar{t} \leftarrow \sum_{i \in S_K} \tilde{w}_i(a) \hat{t}^{(i)}$ 
20  $\bar{\delta} \leftarrow \sum_{i \in S_K} \tilde{w}_i(a) (\hat{A}_{\cdot, \text{shoulder}}^{(i)} - \bar{t})$ 
21  $\tilde{A}(a)_{k,j} \leftarrow \bar{A}_{k,j} + (\bar{t}_k + \bar{\delta}_k - \bar{A}_{k, \text{shoulder}})$ 
22  $a^* \leftarrow \arg \min_a \sum_{i \in S_K} \text{MSE}(\tilde{A}(a), \hat{A}^{(i)})$ 
23 Set  $\tilde{A} \leftarrow \tilde{A}(a^*)$ 

```

// Stage 3: minimum-jerk smoothing

```

24 Form  $D_3$  (third-order difference); solve along time

```

$$(I_N + \lambda D_3^\top D_3) \mathcal{A}^* = \tilde{A}$$

for each joint $j=0..5$ and coordinate $c=0..2$ (banded SPD solver)

```

25 return  $\mathcal{A}^*, a^*$ 

```

minimize the total mean squared error (MSE) between the weighted template curve and the selected trajectories,

$$a^* = \arg \min_a \sum_{i \in \mathcal{S}} \text{MSE}(Q(a), \hat{\mathcal{A}}^{(i)}), \quad (9)$$

where $Q(a)$ denotes the weighted template trajectory constructed using weights $\{w_i(a)\}$.

This two-stage weighting process integrates accuracy and naturalness while allowing data-driven adjustment of the weighting parameter, resulting in a more robust and physiologically meaningful reference trajectory.

The weighted averaging process was applied to obtain representative trajectories of the right arm and trunk. Specifically, the weighted mean trajectory of the six right-arm points was computed as

$$\bar{\mathcal{A}} = \sum_{i \in \mathcal{S}} w_i(a^*) \hat{\mathcal{A}}^{(i)} \in \mathbb{R}^{N \times 6 \times 3}, \quad (10)$$

while the weighted mean trajectory of the SpineShoulder point was $\bar{\mathbf{t}} = \sum_{i \in \mathcal{S}} w_i(a^*) \hat{\mathbf{t}}^{(i)} \in \mathbb{R}^{N \times 3}$. To account for the relative displacement between the shoulder and SpineShoulder, the weighted mean offset was defined as

$$\bar{\delta} = \sum_{i \in \mathcal{S}} w_i(a^*) \left(\hat{\mathcal{A}}_{\cdot, \text{shoulder}}^{(i)} - \hat{\mathbf{t}}^{(i)} \right). \quad (11)$$

To prevent drift of the averaged shoulder position, each frame k was translated such that

$$\tilde{\mathcal{A}}_{k,j} = \bar{\mathcal{A}}_{k,j} + \left(\bar{\mathbf{t}}_k + \bar{\delta}_k - \bar{\mathcal{A}}_{k, \text{shoulder}} \right), \quad j = 1, \dots, 6, \quad (12)$$

thereby ensuring that the averaged shoulder position follows the SpineShoulder trajectory with the mean offset. This alignment guarantees that the shoulder consistently follows SpineShoulder motion throughout the trajectory.

Subsequently, minimum-jerk smoothing was applied to the aligned trajectory $\tilde{\mathcal{A}}$ to obtain the refined curve $\mathcal{A}^*$. The optimization was formulated as

$$\mathcal{A}^* = \arg \min_{\mathcal{A}} \frac{1}{2} \|\mathcal{A} - \tilde{\mathcal{A}}\|_F^2 + \frac{\lambda}{2} \|D_3 \mathcal{A}\|_F^2, \quad (13)$$

where the first term keeps the final trajectory close to the weighted, trunk-aligned mean $\tilde{\mathcal{A}}$, and the second term penalizes the third-order finite difference (jerk) along the temporal axis to enforce smoothness, with $\lambda > 0$ the smoothing weight. The associated normal equations are

$$(I_N + \lambda D_3^\top D_3) \mathcal{A}^* = \tilde{\mathcal{A}}, \quad (14)$$

with I_N the $N \times N$ identity. The left-multiplication acts along the time dimension and is broadcast over the 6×3 channels, so the resulting symmetric positive-definite banded system can be solved efficiently (e.g., via Cholesky factorization) to yield $\mathcal{A}^* \in \mathbb{R}^{N \times 6 \times 3}$.

In summary, the 30 most accurate and stable trajectories were first selected from the recent 200 movements. The form of changing the hyperparameter a will be used to fit the trajectory with the smallest MSE of the 30 better trajectories, and further refined using minimum jerk optimization to enhance smoothness. The resulting trajectory not only reflects the athlete's individual movement pattern, but also retains a natural and physiologically reasonable form, thereby providing a more effective imitation learning reference for darts players and ultimately promoting performance improvement.

3.6. Guidance and Recommendations for Athletes

To achieve scientific evaluation and provide personalized feedback for dart-throwing performance, the study designed a function-driven assessment framework. Motion data were first collected from the target athletes. After selecting the 30 most representative throwing actions from the 200 newest actions, the data were preprocessed and 18 fundamental kinematic features were extracted, which were then used to design and train the evaluation model. Once trained, the model was capable of assessing athletes' throwing actions and providing targeted feedback. Furthermore, subsequent motion data from athletes were continuously updated into the database and incorporated into the refinement of the evaluation model. Through this iterative optimization, the model adapts in parallel with the athlete's skill development, thereby ensuring progressive improvements in both evaluation accuracy and training efficiency.

3.6.1. Selection of Optimal Throwing Trajectories

In selecting the most representative dart-throwing actions, the distance between the dart landing point and the bullseye was adopted as the primary evaluation criterion. Initially, unreasonable actions were manually excluded. Subsequently, the landing distances were automatically computed and ranked in ascending order. From the most recent 200 throws, the top 30 actions with the smallest landing distances were selected as the representative high-quality samples.

3.6.2. Recommendation Model

In constructing the recommendation model, this study uses the mean and standard deviation of each key feature to evaluate whether an athlete's movement is standard, and to calculate the deviation between the athlete's movement and the optimal movement. If the deviation is large, corresponding improvement suggestions are provided.

During the evaluation of a new motion, the same 18 features were computed. The deviation between the new action and the high-quality reference distribution was then quantified using the z-score. Based on the magnitude of the z-score, tailored recommendations were provided to guide the athlete in correcting and refining their technique. The whole process is shown in algorithm4.

For a new sample feature of the motion, denoted as $x_j^{(new)}$, the z-score was computed as

$$z_j = \frac{x_j^{(new)} - \mu_j}{\sigma_j + \varepsilon} \quad (15)$$

where ε is a small positive constant introduced to prevent division by zero.

Based on the absolute magnitude of z_j , performance was categorized into three levels:

- $|z_j| \leq 1.0$: acceptable;
- $1.0 < |z_j| \leq 2.0$: slight deviation;
- $|z_j| > 2.0$: significant deviation.

In summary, the most recent 200 motion records of each athlete were analyzed, from which 30 high-quality dart-throwing actions were selected. For these actions, 18 motion features were extracted, and the mean and standard deviation of each feature were computed to serve as reference values. New actions were then evaluated by calculating the deviations of their features from these references. Finally, based on the magnitude of these deviations, appropriate recommendations were provided for each feature.

4. Result

After two parts of the systematic research methodology, this experiment realized the exploration of the factors that affect dart scores, and successfully established the static characteristics of 12 dart movements and the dynamic characteristics of 6 dart movements. Then, by establishing dart player

Algorithm 4: Baseline-guided recommendation via z-score (BRZ)

Input: Recent motion records $R = \{r_i\}_{i=1}^M$; feature extractor $\Phi(\cdot) \rightarrow \mathbb{R}^{18}$; hit-distance $d(r_i)$ or quality score; K : number of high-quality motions; ε : small constant; thresholds $T = \{1.0, 2.0\}$.

Output: Per-feature verdicts and suggestions S , and overall verdict.

```
1 Step 0. Candidate selection
2 Initialize candidate pool  $C \leftarrow \emptyset$ ;
3 foreach record  $r_i \in R$  do
4   if  $r_i$  is valid then
5      $x_i \leftarrow \Phi(r_i)$ ;
6      $q_i \leftarrow$  quality from  $d(r_i)$ ;
7      $C \leftarrow C \cup \{(r_i, x_i, q_i)\}$ ;
8 Filter  $C$  with IQR on  $q_i$ ;
9  $H \leftarrow$  top- $K$  instances from  $C$  by  $q_i$ ; // high-quality set
10 Step 1. Baseline distribution
11 for  $j = 1$  to 18 do
12    $\mu_j \leftarrow \text{mean}(\{x_j \mid (\cdot, x, \cdot) \in H\})$ ;
13    $\sigma_j \leftarrow \text{std}(\{x_j \mid (\cdot, x, \cdot) \in H\})$ ;
14 Step 2. New motion evaluation
15  $x^{(\text{new})} \leftarrow \Phi(r_{\text{new}})$ ;
16 for  $j = 1$  to 18 do
17    $z_j \leftarrow \frac{x_j^{(\text{new})} - \mu_j}{\sigma_j + \varepsilon}$ ;
18 Step 3. Per-feature grading
19  $S \leftarrow \emptyset$ ;
20 for  $j = 1$  to 18 do
21   if  $|z_j| \leq 1.0$  then
22      $\text{verdict}_j \leftarrow$  "acceptable";
23      $\text{suggestion}_j \leftarrow$  "keep current technique";
24   else if  $|z_j| \leq 2.0$  then
25      $\text{verdict}_j \leftarrow$  "slight deviation";
26      $\text{suggestion}_j \leftarrow$  small adjustment for feature  $j$ ;
27   else
28      $\text{verdict}_j \leftarrow$  "significant deviation";
29      $\text{suggestion}_j \leftarrow$  strong correction for feature  $j$ ;
30  $S \leftarrow S \cup \{(j, z_j, \text{verdict}_j, \text{suggestion}_j)\}$ ;
```

shooting hardware based on kinect2.0 and using the pyKinect library in Python, the shooting software was established, achieving the shooting of 1048 videos of 4 professional athletes and 1348 videos of 3 non-professional athletes. Next, based on the data, the GDA model and the shap value method are trained to verify the effectiveness of the 18 features. In the second part, this experiment established a machine learning model by extracting 18 dart movement features verified in the first part based on the data captured from professional and non-professional dart players, and implemented a data-driven dart player auxiliary training system based on bone analysis and machine learning. One is to fit the best throwing trajectory for the dart movement, and the other is to generate personalized suggestions for movement improvement. Used together, these two methods can help significantly improve athletes' performance and realize the automation, standardization and personalization of darts training.

4.1. Accuracy of Dart-to-Bullseye Distance Detection

In the measurement of the distance between the dart and the bullseye, the study achieved promising results. Across 2,396 test samples, the experiment yielded a Pearson correlation coefficient of 0.917 and a mean absolute error (MAE) as low as 7.77, as illustrated in the Fig.16. These findings demonstrate that the dart image processing and recognition algorithm developed in this work can accurately detect both the dart and the bullseye, thereby enabling precise distance measurement.

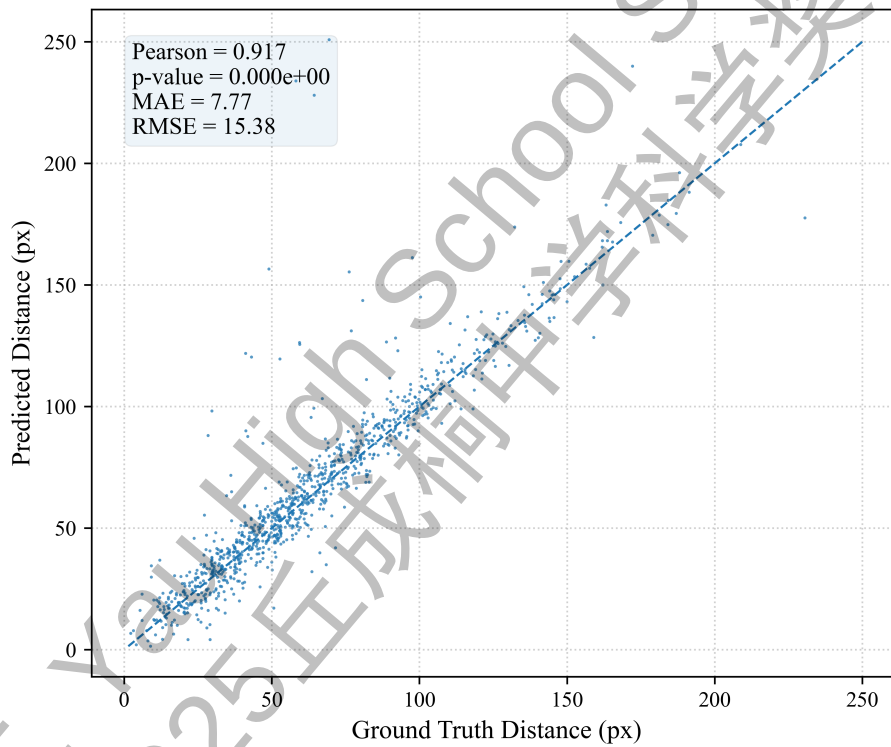


Figure 16. The result of Distance measurement

4.2. Result of GDA Model

In the process of verification using the GDA model, this study fits Gaussian models to the sports data of professional athletes and non-professional athletes respectively. By comparing the results of the two models to distinguish the types of data, the results show that the model can effectively determine the type of dart player, which also proves that the 18 features of dart movement can well represent the quality of dart movement, and has established a complete feature engineering for dart movement. Regarding the score limits for distinguishing the two athletes, this experiment verified various value limits and found that when 78.2 is used as the threshold, the model has the highest accuracy in distinguishing the two athletes, reaching an accuracy of 90.6%, as shown in Figure 17.

During the verification process, we used the model to evaluate each athlete, and averaged the results of each athlete's 10 action evaluations. The table below4 shows the evaluation results produced by applying the scoring model to each athlete. The evaluation results verified the accuracy of the model in distinguishing professional athletes from non-professional athletes, and also verified the effectiveness of 18 dart throwing action features.

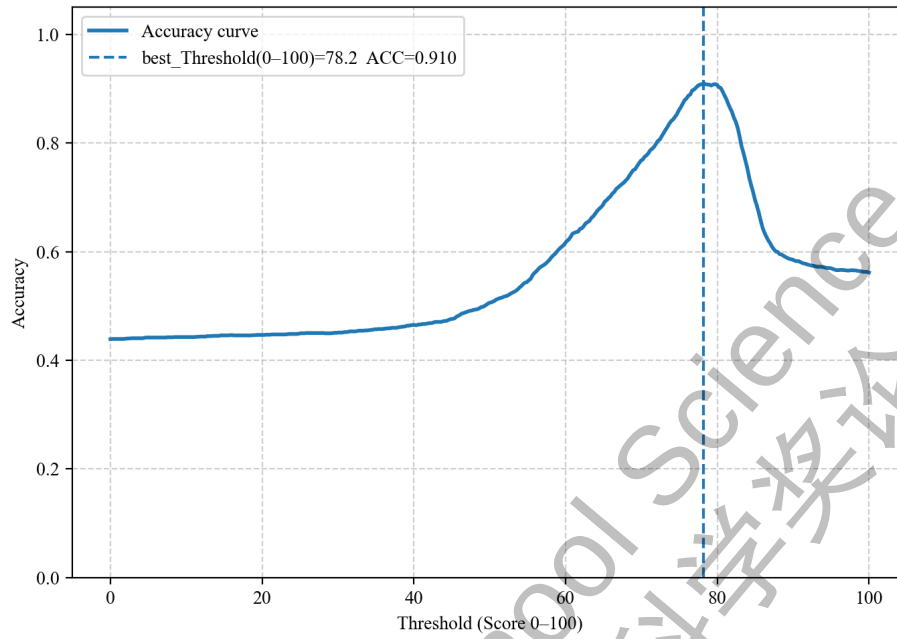


Figure 17. Accuracy of the dart action scoring model.

Table 4. Results of the scoring model(use 78.2 as the threshold)

Category	Participant	score	result
Professional athletes	S1	80.202	good
	S2	83.889	good
	S3	79.433	good
	S4	81.280	good
Non-professional athletes	S5	75.966	bad
	S6	59.965	bad
	S7	67.221	bad

4.3. Shap Value Analysis Results of 18 Motion Features

In this study, based on the GDA model analysis, 18 dart throwing characteristics were analyzed using the shap value method. The SHAP analysis is shown in Figure18. By performing shap value analysis on 18 dart throwing features, we can explore the importance proportion of the 18 features that affect dart scoring. Shap value results show that **release speed**, **release alignment angle** and **trunk yaw** are the most influential motion features for motion quality. This result is consistent with previous biomechanical studies that have highlighted throwing speed, alignment control and trunk stability as decisive determinants of dart performance

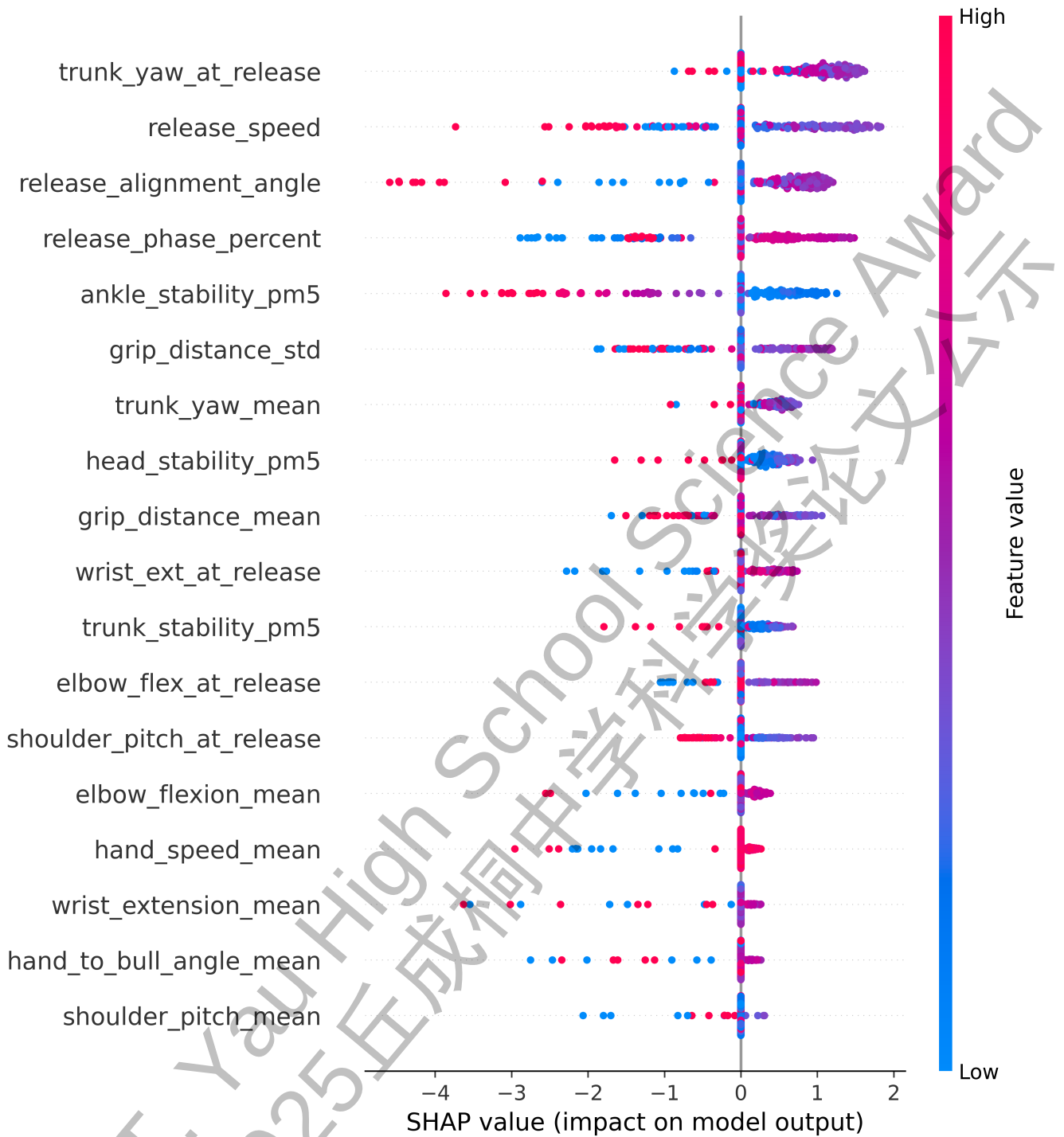


Figure 18. 18 feature analysis figures of GDA model

4.4. Trajectory Fitting Results and Performance Evaluation

In the second part of this study, in order to establish a data-driven auxiliary training system for dart players based on bone analysis and machine learning, this study carried out personalized optimal trajectory fitting for athletes. By selecting 30 high-quality throwing movements from the athlete's recent 200 throwing attempts, and using the minimum acceleration fitting method, the optimal throwing movement of athlete S3 was successfully derived. The obtained fitting trajectory is as shown in the corresponding figure19 shown.

It can be observed that in the fitted throwing trajectory, the athlete's shoulder remains relatively stable. During the backward swing of the arm, the elbow joint is maintained in a relatively fixed

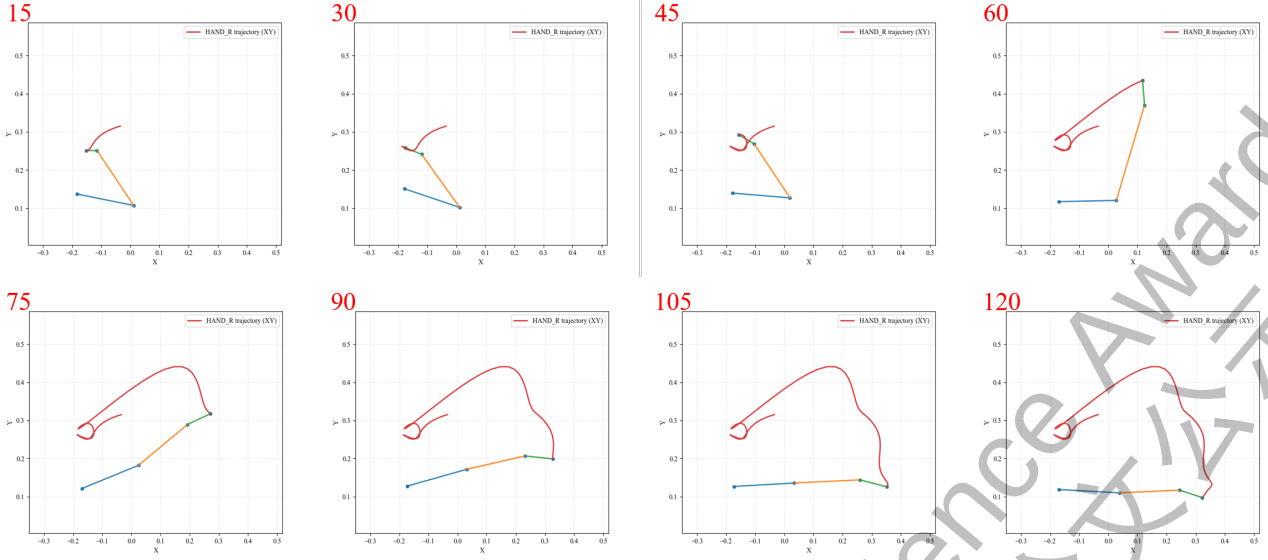


Figure 19. Fitted optimal throwing trajectory for athlete He Zhihong.

position to ensure the stability of the throwing motion. It is only during the forward swing and dart acceleration phase that the elbow joint rises in response to the need for extending the acceleration path. This behavior is in full accordance with the principles of the three-link kinematic model.

In terms of stability, the throwing trajectory exhibits a smooth and continuous profile. Apart from the forward and backward arm swings observed during the dart preparation phase—which are characteristic of the aiming process in dart throwing—no excessive tremors or unnecessary fluctuations are present. This indicates that the trajectory also satisfies the stability requirements of effective dart-throwing motion.

Through analysis of the three-link kinematic structure and motion stability within the optimal throwing trajectory, the effectiveness and success of the optimal dart-throwing trajectory fitting method are substantiated.

4.5. Evaluation of the Personalized Training Recommendation System

In the final stage of the experiment, to further support athletic training and assist athletes in optimizing their movements, a recommendation model was successfully established based on 18 extracted kinematic features. This model provides personalized guidance by generating intuitive, conversational-style suggestions, offering athletes with meaningful and actionable feedback. An example of the athlete-specific guidance generated by the system is presented. A suboptimal dart-throwing motion, as shown in Fig. 20, from a non-professional athlete was input into the model, which subsequently returned a set of targeted recommendations for movement improvement.

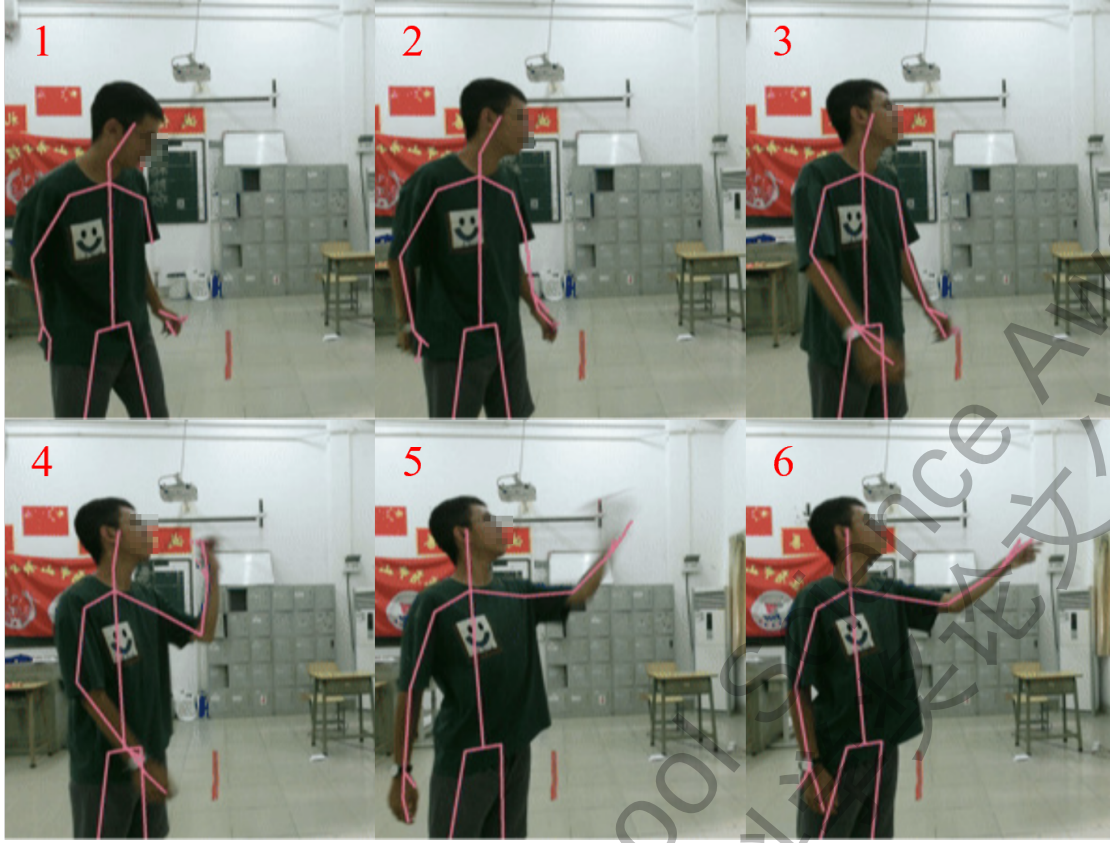


Figure 20. One of Not-standard action from S6

- (1) Abnormal elbow behavior in the three-link mechanism ($|z|_{\max} = 9.72$): During the backward swing, the elbow should remain largely stationary. It should rise naturally only at a specific point during the forward swing and acceleration phase, enabling a fully extended, linear release.
- (2) Significant deviation in trunk stability during motion ($|z|_{\max} = 8.11$): Emphasize consistency training for movements within the 100 ms prior to release.
- (3) Irregular acceleration curve ($|z|_{\max} = 6.18$): Maintain a continuous and uniform acceleration rhythm; avoid the “pause-re-accelerate” pattern.
- (4) Excessive release velocity ($z = 5.94$): Reduce the amplitude of the backswing, keep the motion relaxed, and ensure that the speed results from steady acceleration rather than abrupt force.
- (5) Insufficient trunk stability at the release moment ($z = 5.82$): Engage the core, minimize body sway, and keep the center of gravity stable over the supporting foot.
- (6) Inadequate head stability at release ($z = 1.53$): Maintain steady gaze on the target; avoid nodding or lateral movement to preserve a consistent visual axis before and after release.
- (7) Deviation in aiming angle ($z = 1.52$): Ensure a straight release path with minimal wrist supination or pronation.
- (8) Forward shoulder rotation at release ($z = 1.11$): Stabilize the shoulder angle to serve as a consistent support point throughout the motion.
- (9) Premature release ($z = -1.54$): Complete stable acceleration before finger release. Use verbal timing cues such as “pull-hold-release” to reinforce rhythm.
- (10) Abnormal elbow extension at the moment of release ($z = -2.63$): Ensure full extension of the elbow during the release phase.

These recommendations comprehensively integrate multiple dimensions of analysis-including the three-link kinematic structure, motion stability, throwing speed, and joint angles-resulting in well-rounded and rational feedback for the athlete. Moreover, the suggestions are articulated in an intuitive and accessible manner, making them both accurate and actionable. The model-generated guidance has been positively recognized by professional dart coach for its clarity and practical value.

5. Discussion

The experimental results of the study show that this study explored four factors that affect dart scores, namely the three-link kinematic model, the speed of dart throwing, the athlete's body stability and the angle of dart throwing, and summarized 18 quantifiable dart movement characteristics. Through the GDA model verification and shap value verification established with a large amount of data, the effectiveness of the 18 features was proved, and a feature basis was established for dart movement. In the second part, this research successfully established a data-driven auxiliary training system for dart players based on bone analysis and machine learning. Two auxiliary training methods, optimal trajectory fitting and personalized recommendation, are implemented. Together, these training methods enable accurate analysis of dart throwing motion and provide athletes with scientifically based feedback.

However, although this experiment has established a relatively complete feature engineering for the sport of darts and verified these features, these features are not comprehensive. The features are only based on human kinematics and do not take into account the environmental factors and psychological factors of dart players. These factors will also have a greater impact on athletes.

The optimal trajectory fitting model can derive personalized throwing motions and can be gradually improved as the athlete improves. However, this model has certain limitations. Specifically, it currently only supports trajectory fitting for fixed targets (i.e. bullseyes), whereas players typically aim at various designated areas on the dart board. Furthermore, the model lacks sensitivity to fine-grained motion details and requires high-quality input data for reliable performance. Moreover, displaying the optimal curve through a two-dimensional throwing process cannot allow dart players to intuitively understand the action. In the future, we hope to combine the augmented reality technology (AR) to establish a three-dimensional visualization of the optimal curve fitting to facilitate dart players to understand the action and improve the training effect.

The recommendation model provides personalized, data-driven feedback that is both scientifically based and easy for athletes to understand. By integrating specific biomechanical indicators, the system can help athletes identify and correct specific movement deficiencies. However, the types of feedback suggestions are still limited, and the language expression of guidance is relatively uniform. In future work, this research aims to integrate large language models to enhance the richness and adaptability of recommendation outputs.

In future work, this study aims to address the identified limitations and further enhance the functionality of the system. Specifically, the research plans to extend the trajectory fitting model to support user-defined positions of the entire dartboard, rather than just the bullseye, and use AR technology for visualization. Finally, the study envisions combining recommendation models with large-scale language models to achieve more accurate, diverse, and context-aware feedback, thereby further improving system adaptability and user experience.

6. Conclusion

In summary, this study explores the four factors that affect dart scores, and summarizes 18 quantifiable dart motion features. Through GDA model verification and shap value verification, the effectiveness of the 18 features was proved, and a feature basis was established for dart motion. In the second part, this research successfully established a data-driven auxiliary training system for dart players based on bone analysis and machine learning. Two auxiliary training methods, optimal trajectory fitting and personalized recommendation, are implemented. Together, these training methods enable accurate analysis of dart throwing motion and provide athletes with scientifically based feedback.

In the first part of the study, the study explored four factors that affect dart scoring, namely the three-link kinematic model, the speed of dart throwing, the player's body stability and the angle of dart throwing, and summarized 18 quantifiable dart movement characteristics.

Subsequently, in the construction of the data set, this study used kinect2.0-based shooting equipment and python to write data shooting software, and collected 1048 data of professional athletes and 1348 data of non-professional athletes. Based on the data processing method of chessboard calibration, the study used OpenCV to implement a computer vision algorithm to automatically calculate the distance between the dart landing point and the bullseye. The experiment yielded a Pearson

correlation coefficient of 0.917 and a mean absolute error (MAE) as low as 7.77. The identification system has high accuracy and reliability. Finally, a data set was constructed for factor validation and improved dart training methods.

Next is the verification of 18 dart movement characteristics. In order to verify the effectiveness of the 18 features, this study used the Gaussian discriminant model and shap Value methods for verification. Use 18 features to train the Gaussian discriminant model. If the Gaussian discriminant model can successfully distinguish whether the dart action is correct or not, it proves that these 18 features are effective. This study also used shap value verification. Shap value can determine the impact of each feature on the scoring factors, thereby determining which dart movement features should be emphasized. The results of the study partly show that the dart motion feature engineering established in this study is effective.

In the second part of the research, this study successfully established a data-driven dart player auxiliary training system based on bone analysis and machine learning. The auxiliary training system consists of two parts, namely the fitting of the optimal throwing trajectory of dart motion and the personalized recommendation model for dart players.

In terms of fitting the optimal throwing trajectory of darts, this study first selected the 30 most accurate and stable trajectories from the recent 200 movements. Using the form of changing the hyperparameter a , the trajectory with the smallest MSE of the 30 better trajectories was fitted, and further refined using minimum jerk optimization to enhance smoothness. The resulting trajectory not only reflects the athlete's individual movement pattern, but also retains a natural and physiologically reasonable form, thereby providing a more effective imitation learning reference for darts players and ultimately promoting performance improvement. As for the personalized recommendation model for dart players, this study uses the 18 motion features in the first part to determine the quality of the action by calculating the z-score score. Appropriate recommendations are provided for each feature based on the z-score score. This makes the suggestions given by the suggestion model automated, standardized, and personalized, establishing a scientific training system for darts players.

In future work, this study aims to address the identified limitations and further enhance the functionality of the system. Specifically, the research plans to extend the trajectory fitting model to support user-defined positions of the entire dartboard, rather than just the bullseye, and use AR technology for visualization. Finally, the study envisions combining recommendation models with large-scale language models to achieve more accurate, diverse, and context-aware feedback, thereby further improving system adaptability and user experience.

7. Project Outcome

Under the guidance of both the HPR-DATS system and professional darts coaches, the Zhongshan Xiaolan Senior High School darts team achieved remarkable success in the 2025 Guangdong Provincial Darts Championship for Primary and Secondary Schools. The eight team members demonstrated composure, determination, and resilience in the face of strong opponents, ultimately securing 2 championships, 2 runner-up titles, 3 third-place finishes, and several individual top-six rankings, which is shown in Fig.21 and Fig.22. The team was further awarded the first prize in the overall team standings for the senior high school division[16]. The effectiveness of HPR-DATS in supporting training was fully recognized and affirmed by the professional coaches.



Figure 21. Dart team winning



Figure 22. Dart team member

References

- [1] 国务院. 国务院关于印发全民健身计划(2021—2025年)的通知. https://www.gov.cn/zhengce/content/2021-08/03/content_5629218.htm, June 2021.
- [2] R. Tian. Action recognition technology for professional basketball game training based on ssd and 3d convolution. *Journal of Computational Methods in Sciences and Engineering*, 2025.
- [3] Sian Barris and Chris Button. A review of vision-based motion analysis in sport. *Sports medicine*, 38(12):1025–1043, 2008.
- [4] A.F. Bobick and J.W. Davis. The recognition of human movement using temporal templates. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 23(3):257–267, 2001.
- [5] Anna Letournel, Joana Carvoeiro, João Elias, Daniel Lopes, and Hugo Alexandre Ferreira. Wearable sensor analysis of movement biomechanics and lateralization in dart throwing. *Sensors*, 25(9):2862, 2025.
- [6] 国家体育总局. 飞镖运动进校园、进社区. <https://www.sport.gov.cn/n20001280/n20067626/n20067766/c27861111/content.html>, June 2024.
- [7] Leon Davis. "stand up if you love the darts!" – understanding the key catalysts responsible for the rapid transformation of professional darts corporation (pdc) darts during the 2000s. *Sport in History*, 44:1–28, February 2023.
- [8] T. Y. Huang, J. Hamill, H. Yang, and W. T. Tang. Upper-limb joint kinematics analysis of accuracy dart throwing at different vertical targets between different level dart players. *Journal of Human Sport and Exercise*, 19(3):722–736, 2024.
- [9] S. W. Wolfe, J. J. Crisco, C. M. Orr, and M. W. Marzke. The dart-throwing motion of the wrist: is it unique to humans? *The Journal of Hand Surgery*, 31(9):1429–1437, 2006.
- [10] SH HosseiniZarch, S Arsham, SF Tabatabaei Ghomshe, and MH Honarvar. Identifying control structure of multi-joint coordination in dart throwing: the effect of distance constraint. *Pedagogics, psychology, medical-biological problems of physical training and sports*, (6):267–281, 2019.
- [11] S. A. Mousavi, M. Shahbazi, E. Arabameri, and E. Shirzad. The effect of virtual reality training on learning and kinematics characteristics of dart throwing. *International Journal of School Health*, 6(1):1–7, 2019.
- [12] R. Yoshida, M. Kurematsu, and J. Hakura. Darts training system based on skeleton estimation. In *International Workshop on Advanced Imaging Technology (IWAIT) 2025*, pages 334–339. SPIE, feb 2025.
- [13] B. N. Tran, S. Yano, and T. Kondo. Coordination of human movements resulting in motor strategies exploited by skilled players during a throwing task. *PLOS ONE*, 14(10):e0223837, 2019.
- [14] Esmaeel Khaleghi, Hadi Soltanizadeh, Masoume Gholizade, Farhad Azadi, Mohammad Zahraei, and Mohammad Rahmanimanesh. Detection of gait disorders in people with a walking disability. *Multimedia Tools and Applications*, 81, 08 2022.
- [15] Tamar Flash and Neville Hogan. The coordination of arm movements: an experimentally confirmed mathematical model. *Journal of Neuroscience*, 5(7):1688–1703, 1985.
- [16] 中山市小榄中学 (中山市外国语学校). 蝉联省赛一等奖! | 三载飞镖逐梦, 榄中再续辉煌. <https://wgw.weixiao100.com.cn/custom/wgw/content?templateType=3&menuid=893&detailid=2836558&schoolCode=1917362-9>, May 2025.

此页开始为致谢页

致谢

本研究在中山市小榄中学（中山市外国语学校）正式开设的飞镖课程与省级飞镖协会支持的训练体系中开展。我们在此谨向信息技术教师方劲老师（项目主要导师）与体育教师胡学军老师致以诚挚感谢：方老师在研究问题界定、方法路线搭建、实验流程规范、数据处理与论文结构等方面提供了系统性、无偿的学术指导；胡老师在飞镖专项技术、训练组织、样本协调与安全把关方面给予了专业支持与无偿指导。项目由我们团队自主实施，老师们不参与具体的数据采集、编程实现与统计计算；除训练时段教练在不干扰投掷的前提下配合口令与秩序外，项目无任何第三方有偿协助。

选题源于学校规范化飞镖课程与胡学军老师提出的“训练科学化”需求。我们据此确立使用Kinect2.0姿态识别结合运动学与机器学习的技术路线，在方劲老师把关下完成专业 1053 组与非专业 1351 组投掷数据的采集与标注。推进过程中，我们依次解决三类关键难题：

首先，飞镖投掷受多因素耦合影响且权重不一，我们分别进行了文献检索和专业教练访谈，结合运动学判据构建候选指标体系，最终筛定 18 项可量化特征，用于刻画上肢链条协同、躯干稳定、出手节律与落点表现等核心维度；其次，在不影响投掷的前提下获取精确落点距离。我们将高清摄像头布置于靶面下方安全角度，采用棋盘格标定与平面单应性将斜视图矫正为正视图，自动识别飞镖落点并计算与靶心的距离，从而在保证训练流畅的同时获得满足精度要求的距离数据。

在分工方面，陈展涛负责总体统筹与核心代码实现，主导实验方案设计、特征工程、模型训练与结果汇总，并完成论文主要的撰写；陈曦承担数据记录与清洗、可视化图表制作与结果解读撰写；卢添城协助采集与标注，系统检索并整理飞镖/投

掷运动学与姿态识别文献，撰写相关工作与附录，并维护实验与版本台账。方劲老师定期组织组会与阶段性评审，审阅并修改研究框架、数据治理与学术表达；胡学军老师核实动作判据、训练流程与样本分层口径，并就结果如何转化为训练实践提出建议。论文终稿由学生集体完成，教师提供的是无偿的学术与实践把关。

我们由衷感谢学校“小平科技创新实验室”和校飞镖队提供的设备与场地保障，感谢校队教练在不影响训练的前提下协助口令与秩序维护，感谢所有参与采集的运动员与同学的耐心配合与宝贵反馈。

参赛学生简历

陈展涛

中山市小榄中学“小平科技创新实验室”核心成员，高二时已完成信息系统前后端全栈开发与人工智能方向的系统学习，能够自主搭建信息系统，改良神经网络结构并进行参数优化实验，具备扎实的技术基础，同时有一定的学术研究基础，会使用Latex撰写论文。

陈展涛的科研项目“HPR-DATS-基于”曾于教育部教育技术与资源发展中心举办的全国师生素养提升实践活动（第二十五届学生活动）获全国“创新之星”称号，以及广东省教育厅主办的2024年粤澳学生信息科技创新大赛一等奖。该项目助力我校飞镖队在省锦标赛中摘得多个冠军。

陈曦

中山市小榄中学“小平科技创新实验室”核心成员，高二时深入钻研人工智能与网络安全领域。针对物联网环境下的网络入侵难题，独立设计并开发了“基于卷积神经网络多特征融合的物联网网络入侵深度检测系统”。通过分析CICIDS2018数据集，优化数据清洗与特征融合策略，构建CNN模型实现高精度入侵识别，并利用Flask和Vue3搭建前后端系统，结合Scapy库实时捕获流量数据。该项目在第40届广东省青少年科技创新大赛中获一等奖，在2025年粤港澳学生科技创新大赛中获省一等奖。高一时参与的项目《基于CNN算法人群密度预测在校园管理的应用》在中国国际大学生创新大赛（2024）广东省分赛（萌芽赛道）中获优胜奖。

卢添城

中山市小榄中学“小平科技创新实验室”主要成员，高二时完成人工智能的相关学习，并完成了科研项目“深度学习与本地大模型（LLM）支持下的中医舌诊AI系统”于2025年粤港澳学生科技创新大赛中获省二等奖，第二十二届中山市青少年科技创新大赛一等奖。

指导老师简历

方劲，中共党员，中山市小榄中学高中信息技术一级教师，计算机科学与技术硕士研究生，全国中小学实验教学能手，广东省基础教育教研体系建设高中信息技术学科教研项目（中山）成员，广东省十佳科技优秀辅导员，广东省科技劳动实践优秀指导教师，中山市优秀教师，中山市中小学人工智能教育教师培养计划项目指导团队成员。曾主持（参与）国家级课题1项，省级课题3项，市级课题6项，发表计算机SCI1篇，国际会议EI论文2篇，发表教育类论文国家级论文3篇，省级论文5篇，拥有2项发明专利，1项软件著作权，编写出版教材《人工智能教育》并通过审定。方劲老师长期致力于高中阶段人工智能教育，指导学生在科技创新领域获各级奖项200余项，其中国家级奖项8项（国一3人次），省级30余人次（省一13人次）。

胡学军，男，1974年出生，中共党员，中山市小榄中学体育与健康高级教师，教龄27年，毕业于华中师范大学体育系体育教育专业，教育硕士；中山市教育学会第六届中小学体育与健康教育专业委员会理事，中山市教科研专家库成员，中山市教师发展中心客座讲师和新教师培训导师，广东省肖建忠名师工作室网络学员；被评为中山市高中体育与健康学科带头人、中山市教学质量综合评价先进教师、中山市骨干教师、中山市优秀教师、中山市第四届“三名”工作室优秀学员、广东省飞镖优秀教练员、中山市足球（田径、篮球）优秀教练员、小榄镇体育学科带头人、小榄镇教学能手等。主持国家级、省级课题各1项，参与省级课题1项、市级课题2项；主持课题《关于学校课余训练、体育教学、群体活动协调性发展的实验性研究》获国家体育科研成果二等奖；研究项目《高考体育术科训练的实效性研究》获中山市科研成果一等奖；主编体育专著2部、参编1部；13篇论文在省级以上刊物发表，16篇论文获国家、省、市级以上一、二等奖。教学课程资源获广东省优秀奖项；指导青年教师获中山市教学比赛一等奖，教学技能大赛一等奖；指导校飞镖队连续3年获广东省飞镖锦标赛一等奖，其中2年蝉联冠军；指导校足球队

获中山市高中足球联赛一等奖3次；指导田径队获中山市高中组团体总分亚军；指导篮球队获中山市季军；所带体育队参加高考成绩优异，为各本、专科院校输送大批优秀体育人才。

2025 S.-T. Yau High School Science Award
仅用于2025丘成桐中学科学奖论文公示