Research on Badminton Technique Movement Diagnosis and Instructional Feedback Optimization Based on Video Analysis

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ABSTRACT Accurate diagnosis of sports techniques is essential for improving athletic performance and reducing training inefficiencies. This study proposes a video-analysis-based framework for badminton technical movement diagnosis and instructional feedback optimization. A standardized video acquisition process is established to collect multi-view motion data, while pose-estimation algorithms are employed to extract spatiotemporal and kinematic features. A hybrid diagnostic model integrating threshold rules and machine-learning methods is developed to identify common technical deficiencies in high clear, smash, and net-shot movements. An eight-week teaching experiment involving 60 university students demonstrates that learners supported by the proposed system achieve significantly higher scores in movement standardization and technical execution than those receiving conventional instruction. The study validates the effectiveness of automated motion diagnosis and provides methodological references for computer vision, intelligent sensing, and human-motion analysis systems.

INDEX TERMS video analysis, pose estimation, motion diagnosis, intelligent sensing, computer vision

I. INTRODUCTION

BADMINTON has been considered an important stage of physical education across all school levels and general fitness, primarily due to its popularity and the performance of high-strength material equipment in diverse environmental conditions. The widespread adoption of the sport is underpinned by advancements in fiber-reinforced racket strings and synthetic shuttlecock materials, which ensure durability and consistent mechanical response for students and fitness enthusiasts. Learning the correct technique is essential to enhancing an athlete's performance and preventing sports injuries. However, in traditional badminton teaching, teachers tend to use visual observation to instruct and correct the technique of the students. This approach has large limitations: First, the techniques of badminton are fast-paced and have many steps, so it is not easy for human eyes to capture and analyze all the details of each motion instantly, especially the microscopic information, such as the angle of the joints or the timing of rotation of the body, is the information which is easily overlooked. Second, feedback is often based on the experiential and qualitative descriptions of the teacher, such as "make the backswing a little bigger" or "concentrate your power more", without support of objective and quantitative data, it is hard for student to form the precise movement awareness and selfcorrection standard. Finally, in a group teaching environment, the energy of the teacher is limited and they cannot give immediate and individualized feedback to each student, for every practice moment, resulting in delayed and uneven teaching.

With the accelerated development of computer vision techniques and artificial intelligence technologies, video-based motion analysis technology has rendered a new technological path for sports teaching and training. By obtaining motion videos through the cameras, and by use of algorithms to extract the information on human movement, it is possible to objectify and deconstruct the technical movements. In recent years, some studies have tried to use technologies such as sensors and virtual reality in the teaching of badminton, but most of these studies have focused on a single perceptual dimension (such as strength and rhythm) or on specific cognitive training (such as visual search). Research on the automated and refined diagnosis of the total technical movement chain as well as the deep integration of the diagnostic results into the teaching process to form near-instantaneous visualised feedback is still insufficiently developed to meet pedagogical demands. This separation between "diagnosis" and "feedback" prevents the full realization of the effectiveness of the use of technology in teaching.

Therefore, in this study, core badminton techniques are the scope of study with an aim to use video analytics for building a complete technical problem with the consideration of data acquisition, feature extraction, motion recognition and error diagnosis, and visual feedback. The basic research contents are as follows: on the one hand, to design a light video acquisition and data processing workflow applicable to teaching scenarios; on the other hand, to build a model that can automatically identify some typical techniques and some typical errors, and on the other hand, is to satisfy the construction of a teaching visual feedback interface suitable for learners to interpret and understood abstract diagnostic data into intuitive guiding information. Finally, teaching experiments will ensure the validity of this solution to enhance the standardization of motion and efficiency in learning skills in beginners. This research is aimed to serve as a digital auxiliary tool for badminton teaching that correlates high-performance material mechanical responses with athletic execution, achieving the transformation from experience-based teaching to data-driven instruction. By integrating fiber-reinforced racket string tension data and synthetic material durability into the feedback loop, the system facilitates a low-cost, easy-to-operate transition toward scientifically quantified training methodologies. While the analysis is processed immediately after the movement, the instructional loop is closed through structured 5-10 minute review sessions to allow for cognitive absorption of the data.

II. RELATED WORK

Research on badminton teaching methods shows a trend of multidisciplinary integration. Lin et al. [1] developed a badminton teaching aid system based on surface electromyography signals and gyroscopes. Li and Jawis [2] constructed a virtual reality badminton teaching system based on fuzzy logic, dynamically adjusting the fuzzy rules of virtual teaching scenarios, opponent difficulty, and training tasks according to the different levels and performance of students. Devrilmez et al. [3] focused on teaching through situational games with fixed tactical coordination, exploring its comprehensive impact on the badminton tactical knowledge, technical ability, and competition performance of Turkish middle school students. Li [4] proposed optimization paths, including constructing a multi-dimensional dynamic hierarchical indicator system, establishing a flexible student level flow and tracking mechanism, developing modular and differentiated teaching content, and improving the evaluation system that combines process and development, in order to improve the teaching quality of university badminton elective courses. Gao and Tasnaina [5] developed a project that integrates strength, speed, agility and quick reaction training into badminton teaching.

Zhou [6] explored a badminton rhythm training teaching method based on machine learning. Ariani and Marti [7] investigated the impact of using interactive multimedia to teach basic badminton techniques on cognitive learning outcomes and self-learning abilities among sports majors. Xiao and Tasnaina [8] found that students who received visual search feedback training performed better in skill learning and competition. Zhi et al. [9] improved the accuracy of badminton video motion recognition based on temporal networks. Mohammadifard and Rafei Boroujeni [10] explored the impact of combining and alternating action observation and motion imagination on children's learning of badminton short serve skills. Existing research focuses on interventions in single techniques or cognitive dimensions, lacking automated and refined diagnosis of complete technical movements. This study aims to construct an automatic recognition and diagnosis model for badminton technical movements based on video analysis technology, and design a visualized teaching feedback optimization scheme, in order to achieve accurate capture and personalized guidance of students' movement details under the premise of low cost and easy promotion, and further bridge the gap in existing research on movement diagnosis and feedback integration.

III. METHODS

A. STANDARDIZED VIDEO DATA ACQUISITION SCHEME

To ensure the quality and consistency of the analyzed data, a strict video acquisition protocol was established. The acquisition environment was an indoor standard badminton court with a simple background and uniform lighting. Two high-definition cameras (1920×1080 resolution, 60fps) fixed on tripods were used for synchronous acquisition, utilizing a hardware-based external trigger to ensure frame-level synchronization. This eliminates temporal drift between the front and side views, which is critical for the accurate spatial-temporal analysis of high-speed movements like the smash. One camera was placed about 5 meters behind the player (front view), and the other was placed about 4 meters to the side of the player (side view) to ensure complete capture of the swing trajectory and lateral body movements. Participants included 30 badminton team athletes from the university (as a reference for standard movements) and 90 badminton beginners from university elective physical education courses. Each participant was required to complete 10 high clears, 10 smashes, and 10 forehand lobs at the net. All movements were fed multiple balls by the same coach to ensure consistency of incoming balls. In the end, a total of 3900 valid video clips containing standard movements and various common errors were collected (3 types of movements × 120 people × 10 times + some invalid data were removed). This study was approved by the Ethics Committee of Inner Mongolia Technical University of Construction, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form.

B. ACTION FEATURE EXTRACTION BASED ON POSE ESTIMATION

For the acquired video, the MediaPipe open-source pose estimation algorithm based on deep learning was used to extract the 2D screen coordinates of 33 key points of the human body in each frame. Although more complex 3D pose estimation methods exist, the MediaPipe solution based on monocular video achieves a good balance between accuracy and efficiency, better meeting the requirements of real-time performance and low cost in teaching scenarios [11,12]. Based on the key point coordinates, three types of motion features were calculated for subsequent diagnosis:

Spatial characteristics: mainly include the angles of key joints, such as the angles of the shoulder, elbow, and wrist joints at the moment of impact, the angle between the torso and the ground, and the height of the nonracket hand (balancing hand) when it is raised.

Timing characteristics: These mainly include the time percentage of each movement phase, such as the percentage of the total movement time for each of the four phases: start, backswing, swing and hit, and follow-through. Phases are defined by calculating the velocity changes at key points in adjacent frames.

Trajectory characteristics: mainly the trajectory curve of the racket head (approximately the key point of the wrist holding the racket) before and after hitting the ball, and the movement path of the body's center of gravity (approximately the key point of the hip) [13,14].

Table 1, taking the high clear as an example, shows the core feature indicators extracted for diagnosing two common errors, "insufficient backswing" and "low hitting point," and their reference threshold ranges (initially screened using the 10th–90th percentiles of the athlete group and further refined through expert consensus to accommodate stylistic variations).

TABLE 1. Diagnostic Indicators and Reference Thresholds for High Clear Shots

Diagnostic goals	Feature indicators	Calculation method	Reference threshold range (standard action)	Data source
Sufficient pre-shot	Maximum backswing angle	Side view, angle between the midline of the torso and the extension line of the upper arm	150°–170°	Expert-validated range based on athlete group distribution
	Percentage of time spent in the pre-shooting phase	Backswing time / Total action time	35%–45%	25th–75th percentiles of the athlete group
Point of contact	Hitting point height index	Y-coordinate of wrist key point in the hitting frame / Y-coordinate of height key point	0.85–0.95	25th–75th percentiles of the athlete group
	Trunk lateral flexion angle at impact	Frontal view, angle between the torso and the vertical line	$<10°$	Expert experience and literature determination

C. CONSTRUCTION OF ACTION RECOGNITION AND ERROR DIAGNOSIS MODEL

The diagnostic process is divided into two steps: action recognition and error judgment. First, a one-dimensional convolutional neural network (1D-CNN) model is constructed for action recognition. The key point coordinate sequence (after standardization) extracted from each video segment is used as input, and the output is the probability that the segment belongs to "high clear", "smash" or "lob". To prevent false diagnoses of non-target movements, a Softmax threshold of 0.7 is applied; if the maximum probability falls below this threshold, the system triggers an 'Unrecognized Movement' error message, prompting the user to re-record or perform a standard technical action. 70% of the labeled data is used for training, 15% for validation, and 15% for testing [15]. After identifying a specific action, the corresponding error diagnosis submodule is triggered. The diagnosis module adopts a hybrid strategy of "rule engine as the main component and classification model as the auxiliary component." For errors with clear definitions and explicit thresholds (as listed in Table 1), diagnosis is made directly by judging whether the feature values exceed the threshold range. For more complex errors involving the coordination of multiple features (such as "lack of kinetic chain coordination," which manifests as the large joints failing to drive the small joints in sequence), a lightweight gradient boosting decision tree (GBDT) classifier is trained for judgment. The features of this classifier are the temporal sequence of the velocity peaks of multiple joints. All diagnostic rules and model thresholds are calibrated and validated based on athlete group data and joint annotations from two senior coaches.

D. DESIGN OF VISUALIZED TEACHING FEEDBACK INTERFACE

To ensure effective delivery of diagnostic results, a web-based visual feedback interface was designed and developed. This interface mainly consists of four functional areas:

Dual-view synchronous playback area: Plays videos of the user's front and side movements side by side, supporting slow motion and frame-by-frame viewing.

Error diagnosis labeling area: When the video is playing, the system directly marks the detected error points on the corresponding frame with graphic and text labels (such as marking the hitting point that is too low with a red circle and displaying "hitting point too low").

Data comparison and analysis area: The user's characteristic data (such as joint angle curves and head trajectory) is overlaid and compared with the reference data range of standard movements in the form of line graphs or area graphs, making the differences clear at a glance.

Personalized Improvement Suggestion Area: Based on the diagnosed errors, the system matches and describes the key points from the action library, and also pushes 1-2 targeted corrective practice video links. This intervention library was curated from evidence-based badminton coaching manuals and validated by three senior national-level coaches to ensure that suggested drills, such as 'swinging against a wall' for backswing optimization, are pedagogically sound and effective for correcting specific technical flaws.

IV. RESULTS AND DISCUSSION

A. PERFORMANCE EVALUATION OF ACTION RECOGNITION AND DIAGNOSIS MODEL

The action recognition model performed robustly on a test set containing various types of erroneous actions, with overall accuracy, precision, and recall all exceeding 95%, indicating that the model can reliably distinguish between the three target technical actions, laying the foundation for subsequent targeted diagnosis. The performance of the error diagnosis module was evaluated by comparing the system's diagnostic results with the independent human judgments of two coaches. For eight preset error categories, including "insufficient backswing," "low hitting point," and "inappropriate smash power sequence," the F1 score (harmonic mean) of the system's diagnosis and human judgment was calculated. Table 2 illustrates the model's diagnostic performance on some common errors. The results show that for well-defined and salient low-level errors (such as hitting point position), the system's diagnosis is highly consistent with the coach's judgment (F1 score 0.92). For errors related to "force sequence," which rely more on timing judgment, the consistency decreases somewhat (F1 score 0.81), but still has good reference value. Inconsistent cases often occur when the error is at a critical point. To address this, the system incorporates a confidence-based scoring mechanism rather than a strictly binary label. Movements falling within a marginal buffer zone ($\pm 5\%$ of the threshold) are flagged for 'Review' with a detailed deviation score, allowing coaches to provide nuanced guidance instead of a simple correct/incorrect verdict.

TABLE 2. Performance Evaluation of Common Error Diagnosis Models (F1 Score)

Technical movements	Diagnostic error types	Accuracy	Recall rate	F1 score
High clear	Insufficient lead-in	0.89	0.87	0.88
	Low hitting point	0.94	0.90	0.92
	Incomplete follow-through	0.88	0.85	0.86
Smash	Improper timing of takeoff	0.82	0.84	0.83
	Improper sequence of force application (ineffective whipping)	0.80	0.82	0.81
Net shot	Excessive force in the wrist	0.86	0.83	0.84
	Footwork not followed	0.81	0.79	0.80

B. ANALYSIS OF THE EFFECTIVENESS OF TEACHING EXPERIMENTS

To verify the actual effectiveness of the system in teaching, a teaching experiment was conducted. From 90 beginners, 60 students with similar skill levels were randomly selected and divided into an experimental group (30 students) and a control group (30 students). Both groups received regular instruction for 8 weeks, with one lesson per week. The control group received traditional instruction and verbal feedback from the teacher. The experimental group, in addition to traditional instruction, used the system for individual movement analysis and feedback after each practice session. Students had 5-10 minutes to review their analysis reports and receive corrective suggestions. Before and after the experiment, all participants underwent skill attainment tests (accuracy of hitting a high clear to a designated area) and motion standardization assessments. Motion standardization was assessed by a coach unaware of the group assignments, using a rating scale (0-4 points per dimension) covering five dimensions: "ready position," "backswing trajectory," "hitting point," "power coordination," and "followthrough." The experimental results are shown in Table 3.

TABLE 3. Comparison of Pre- and Post-Test Scores in Teaching Experiments (M$\pm$SD)

Group	Test time	Skills achievement score (points)	Total score for proper execution of movements (points)	Movement standardization – striking point dimension (points)
Experimental group (n=30)	Pre-test	52.3$\pm$10.5	9.8$\pm$2.1	1.5$\pm$0.6
	Post-test	78.6$\pm$8.7	15.2$\pm$1.8	3.1$\pm$0.5
Control group (n=30)	Pre-test	51.8$\pm$9.7	9.6$\pm$2.3	1.6$\pm$0.7
	Post-test	70.4$\pm$9.2	12.9$\pm$2.0	2.3$\pm$0.6

Analysis of covariance (using pre-test scores within the same group as covariates) on post-test results revealed that the experimental group significantly outperformed the control group in both skill achievement and overall motor proficiency scores. Particularly noteworthy was the significant improvement in the experimental group's performance on the specific dimension of "hitting point." Interviews with students in the experimental group revealed that most reported that visual feedback (especially racket head trajectory comparison diagrams and error frame annotations) allowed them to "see clearly" the problems in their movements for the first time. Abstract instructions (such as "hit the ball at a high point") were transformed into concrete images and comparable data, providing clearer correction goals for subsequent practice. This confirms that visualizing automated diagnostic results can effectively enhance learners' metacognition and self-correction abilities.

C. SYSTEM ADVANTAGES, LIMITATIONS AND FUTURE PROSPECTS

The system developed in this study demonstrates its potential application in badminton instruction. Its main advantages are: first, it automates the entire process from motion capture to error diagnosis, significantly reducing the workload of manual analysis; second, the feedback method shifts from qualitative description to a combination of quantitative and visual methods, improving the accuracy of instruction and learner comprehension; and third, the system is based on ordinary cameras and open-source algorithms, resulting in low hardware costs and easy deployment in common venues. However, this study also has certain limitations. First, the system currently relies on video capture from fixed camera positions, which limits the analysis of learners' movements in real sparring or competitions. Second, the diagnostic model targets pre-defined, discrete common errors, and has limited ability to evaluate more comprehensive and continuous quality aspects such as movement fluency and rhythm. Finally, the teaching experiment period of this study is relatively short, and the long-term application effect of the system and its differentiated utility for learners of different levels need further investigation.

Future work can be carried out in the following aspects: First, explore analysis schemes based on dynamic video acquisition from mobile devices or wearable cameras to cover more realistic sports scenarios; second, introduce more complex time series models to try to continuously score the quality of movements or generate more detailed descriptive evaluations; third, extend the system to more badminton techniques (such as backhand and footwork) and explore its application in injury risk assessment.

V. CONCLUSION

This research successfully designed and implemented an automated diagnosis and feedback optimization system for sensational techniques in badminton by integrating high-performance material motion capture analytics into the video processing framework. By aligning biomechanical data with the tensile properties and structural feedback of specialized athletic materials the system provides a comprehensive evaluation of player performance and equipment interaction. Through standardized dual-view video acquisition, motion feature quantification based on the posture estimation, and a hybrid motion recognition and error diagnosis model, the system can correctly identify three categories of movements, including high clear, smash, and net flick, and identify several common technical errors. A further developed visual feedback interface is used for turning abstract diagnostic data into intuitive image comparisons and specific suggestions for improvement. Teaching experiments indicate that the learners using this system had more successful progress, in terms of mastery of skills, standardization of movement, compared to the traditional teaching group especially in correcting specific movement details. This phenomenon shows that deep integration of video analytics into physical education can offer learners an objective and personal "digital mirror" and feedback pathway, adequately making up for the shortcomings of traditional teaching with regard to immediacy, refinement, and personalization. This research offers a feasible technical framework and practical case for integrating smart sensor arrays into low-cost, scalable physical education teaching aids, driving the digital transformation of sports pedagogy through fabric-based biomechanical monitoring. By embedding intelligence directly into the material substrate, this approach provides a seamless method for capturing motion data while ensuring the accessibility and sustainability of modern athletic training tools.

AUTHOR CONTRIBUTIONS

Qingyu Wang designed, collected and analyzed the data, and drafted the manuscript. Qingyu Wang conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Qingyu Wang participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

FUNDING

This research received no external funding.

ACKNOWLEDGEMENTS

Not applicable.

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