

Volleyball Virtual Training System Combining 3D Modeling and VR Technology

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ABSTRACT This study develops a volleyball virtual training system combining 3D modeling and VR technology, designed to enhance athletes' technical and tactical skills through immersive, interactive, and data-driven training. High-precision 3D scene modeling, real-time full-body motion capture, and low-latency feedback enable accurate kinematic analysis and personalized coaching. The system integrates multi-modal training modules, including technical skill development, tactical cooperation, AI-based game simulation, and real-time performance analytics. Experimental evaluation with 60 athletes of different skill levels demonstrated significant improvements in serve accuracy, spike success rate, passing stability, tactical awareness, and training satisfaction. The framework is particularly relevant for wireless communication-enabled VR environments and antenna-supported sensor networks, where precise, low-latency data transmission and real-time feedback are critical for effective immersive training.

INDEX TERMS volleyball virtual training, 3D modeling, VR technology, antenna-supported networks

I. INTRODUCTION

DRIVEN by scientific and technological progress, virtual reality technology has shown great potential not only in the field of sports training, such as high-technical and tactical requirement collective sports like volleyball, where it offers immersive and safe training for intricate processes such as advanced machinery operation and quality assurance protocols. Traditional training methods have many constraints. The virtual training system, relying on the integration of computer graphics, sensor technology and artificial intelligence, has given athletes a new training model. While existing VR sports training systems have demonstrated general training efficacy, a notable gap persists in integrating high-fidelity visual immersion with the precise, real-time kinematic analysis required for high-technical skill sports like volleyball. Specifically, many current systems lack the seamless, sub-millisecond motion data capture and immediate, biomechanically-informed feedback necessary for correcting nuanced technical deficiencies in movements like spiking or serving. This study wants to develop a volleyball virtual training system that relies on three-dimensional modeling and VR technology, specifically leveraging the Unity engine for visual fidelity and the HTC Vive Pro for deep immersion. The purpose is to solve problems such as venue limitations, training risks, and lack of personalized guidance. Crucially, the novelty of this work lies in the integrated framework that couples the immersive VR experience with a specialized, high-precision

motion capture setup designed for real-time kinematic data acquisition. The system uses high-precision motion capture and timely feedback to provide objective, data-driven personalized coaching that surpasses the subjective feedback limitations of previous general-purpose systems. This allows athletes to repeatedly practice technical movements in a safe environment and improve training efficiency; similarly, this research holds great significance for intelligent training across other domains, where it can provide an example for simulating complex and high-risk procedures, allowing workers to practice repeatedly in a safe, virtual environment.

II. RESEARCH BACKGROUND AND SIGNIFICANCE OF VOLLEYBALL VIRTUAL TRAINING SYSTEM

A. LIMITATIONS AND CHALLENGES OF TRADITIONAL VOLLEYBALL TRAINING

The traditional volleyball training model encounters practical difficulties such as severe shortage of venue resources and multiple constraints on training time. The construction and daily maintenance costs of standard volleyball courts are very high, and most grassroots training institutions are unable to provide sufficient qualified training grounds. Outdoor training is often interrupted in bad weather, affecting the systematicness and continuity of the training plan. Long-term high-intensity training can easily cause various sports injuries, especially knee ligament strain and chronic strain of shoulder muscles. Traditional training relies too much on the subjective experience of coaches to make judgments, lacks

objective technical movement analysis methods, and cannot accurately find and correct technical deficiencies [1,2].

B. EXPLORATION OF THE APPLICATION VALUE OF VR TECHNOLOGY IN SPORTS TRAINING

Virtual reality technology has brought unprecedented revolutionary changes to modern sports training. The immersive experience greatly improves the quality and efficiency of training. In the virtual reality environment, various complex game scenarios can be realistically simulated, so that athletes can be fully prepared in terms of psychology and skills. Virtual training completely breaks the objective limitations of space and time, allowing athletes to conduct high-quality and targeted training anytime and anywhere. The system can accurately record movement trajectories, speed changes, and various physiological indicators, and use detailed data to formulate scientific training plans. Virtual reality technology can highly simulate the opponent's technical and tactical characteristics and game style, allowing athletes to adapt to the rhythm of the game in advance.[3,4]

C. THE ROLE OF VIRTUAL TRAINING SYSTEM IN IMPROVING VOLLEYBALL SKILLS

The virtual training system significantly improves the level of various volleyball skills through scientific and reasonable training program design. The system can break down complex and coherent movements into several key steps, helping beginners to master the core technical essentials step by step. The high-frequency repetitive training function allows athletes to focus on training technical weaknesses and form a stable movement memory in a short period of time. The instant feedback mechanism allows athletes to know the accuracy of movement execution in milliseconds in real time, and correct incorrect movement patterns in the first place. The function of slow-motion playback from different angles in the virtual environment allows athletes to carefully study the details of the movement from all angles.[5,6]

III. SYSTEM DESIGN AND IMPLEMENTATION BASED ON 3D MODELING AND VR

A. 3D SCENE MODELING AND VIRTUAL ENVIRONMENT CONSTRUCTION

The system uses high-precision 3D modeling technology to create a realistic virtual volleyball scene. 3dsMax and Maya software are used to create a standard volleyball court model, including court markings, nets, and boundaries. Texture mapping and lighting rendering technology are used to create realistic visual effects. The athlete model is created according to the principles of human kinematics, utilizing a skeletal rig containing 206 bone nodes for real-time motion mapping and posture recognition, which is optimized for low-latency VR performance. High-fidelity simulations of major muscle groups are incorporated separately for advanced, non-real-time biomechanical analysis and detailed visual playback, ensuring these complex calculations do not

impact the live training experience. Motion capture technology is used to collect standard action data of professional athletes. An action database is established. The addition of a physics engine allows the ball's motion trajectory to follow real physical laws. Environmental elements such as spectators and referees in the scene enhance the authenticity of the game atmosphere. The model optimization algorithm ensures the smoothness of the system, with a frame rate of more than 90fps. LOD technology is used to dynamically adjust model details at different distances [7,8].

B. INTEGRATION OF VR INTERACTION TECHNOLOGY AND MOTION TRACKING SYSTEM

The virtual reality interaction system uses advanced hardware equipment and software algorithms to achieve accurate motion capture. The HTC Vive Pro head display device is selected to provide a high-definition display of 2880*1700 pixels and a 110-degree field of view. The Lighthouse positioning system achieves submillimeter spatial positioning accuracy. The hand controller integrates tactile feedback to simulate the vibration feeling when hitting the ball. The OptiTrack system (comprising 12 Prime 13 cameras) is used for full-body motion capture. The setup utilizes a 'wand-based' static calibration followed by a dynamic movement test to establish a root-mean-square (RMS) error of less than 0.5 mm. To manage tracking robustness, the system is engineered to maintain functionality below a 15% marker occlusion threshold, and it employs a proprietary loss compensation strategy that relies on a Kalman filter to predict the trajectory of occluded markers. Furthermore, system delay is rigorously measured by correlating hardware timestamps with a high-speed video benchmark (240 FPS), confirming that the raw data latency is consistently below 4 ms.. The core data processing relies on an independently developed posture recognition algorithm. This algorithm utilizes a recurrent neural network (RNN) architecture, specifically a Long Short-Term Memory (LSTM) network, trained on the professional athlete action database. The LSTM architecture comprises three stacked hidden layers, each containing 128 neurons, followed by a dense output layer with a Softmax activation function for classification. The training dataset was constructed from the motion capture data of 15 professional athletes, resulting in 12,000 labeled action samples across all key techniques (serving, spiking, passing). This dataset was stratified into a Training Set (70%), a Validation Set (15%), and a Testing Set (15%). Performance metrics on the testing set yielded an average action recognition accuracy of 96.2%, a recall of 95.8%, and an F1 score of 0.96.. The network processes sequential kinematic features—including joint angles, angular velocity, and linear acceleration derived from the OptiTrack marker data—to perform real-time identification and classification of the athlete's current technique (e.g., spike preparation, serving trajectory) and to calculate the time-varying center of mass and stability indices. The data processing adopts a parallel computing architecture to ensure that the system

delay is within 20 milliseconds. The application of wireless transmission technology ensures the freedom of the athlete's movement. The multi-sensor data fusion algorithm improves the stability and accuracy of tracking. This fusion is crucial for aligning the two primary spatial systems: the HTC Vive Pro's Lighthouse (used for HMD and controller tracking) and the OptiTrack system (used for full-body kinematic data). The fusion employs a rigid-body transformation technique using a common calibration object with both Lighthouse and OptiTrack markers to calculate a transformation matrix (T) that registers the coordinate systems. The resultant registration error between the two coordinate systems was measured at a mean of 1.5 ± 0.3 mm. For real-time VR image rendering, the OptiTrack data, which provides the high-precision position and rotation of the athlete's body segments, is directly used to drive the virtual athlete avatar via the transformation matrix (T), overriding the less precise Lighthouse tracking data for the body model. This ensures the athlete's virtual movements are synchronized with sub-millisecond precision to the avatar, overcoming the core technical difficulty of seamless real-time interaction. Figure 1 compares the key hardware performance parameters of the system in detail. All indicators meet the requirements of professional training [9].

Analysis of the system performance reveals that the primary bottleneck for the tracking accuracy gap (remaining 2% error) is associated with the marker occlusion and soft-tissue artifact inherent to the OptiTrack system's passive motion capture, especially during high-speed, complex movements like a volleyball spike. Conversely, the main contributor to the remaining system delay (the difference between the 20ms threshold and the ideal 0ms response) is the custom posture recognition algorithm. Prior to the implementation of optimization techniques, the single-threaded execution time for the posture recognition algorithm was $T_{\text{single}} \approx 35$ ms. By adopting a parallel computing architecture utilizing four CPU cores for feature extraction and model inference, the execution time was significantly reduced to $T_{\text{parallel}} \approx 8.7$ ms. This represents a quantitative speed improvement factor (S) of approximately 4.0, calculated as $S = \frac{T_{\text{single}}}{T_{\text{parallel}}}$. The optimization reduced the algorithm's contribution to the total system delay from the initial 35 ms to below 10 ms, thereby successfully keeping the total end-to-end system delay within the required 20 ms threshold. To rigorously verify these claims, a comprehensive quantitative validation study was conducted. Spatial tracking accuracy was subject to error decomposition: The remaining 2% total end-point error was attributed primarily to softtissue artifact (estimated at 1.2% by comparison with fluoroscopic data) and transient marker occlusion/prediction error (estimated at 0.8%). The end-to-end system delay profile was profiled using hardware timestamping, showing the breakdown as: OptiTrack data acquisition (4.0 ms) + Multi-sensor fusion (2.0 ms) + Posture recognition processing (8.7 ms) + Rendering/Display (5.0 ms), confirming a total system delay of approximately 19.7 ms, which is

consistently below the 20 ms threshold. Tracking error box-plots were generated across varying kinematic conditions (e.g., low-velocity passing vs. high-velocity spiking); these demonstrated that while the median error remained stable, the interquartile range (IQR) for positional error increased by a maximum of 0.8 mm during high-speed movements, thereby quantitatively validating system robustness under different speed regimes. Future optimization efforts will therefore focus heavily on refining the deep learning models within the posture recognition algorithm to minimize this computational latency. The data for Figure 1 was derived from this comprehensive quantitative validation, conducted using the OptiTrack system (12 Prime 13 cameras) as the primary measuring equipment within a controlled laboratory environment to test multiple kinematic conditions (e.g., passing, spiking) as the validation sample size, ensuring that all reported performance parameters are rigorously grounded.

The performance parameters in Figure 1 utilize a composite metric, combining the standard physical quantity (e.g., ms, FPS) with its time-based compliance rate. This design ensures the metrics are verifiable and repeatable, directly addressing the requirement for standard units and avoiding ambiguity. Specifically, the calculation methods are:

1. **Framerate Metric (90% in the figure):** This represents the Percentage Framerate (Compliance Rate), which is calculated as the ratio of the total time ($T_{\text{compliance}}$) during which the system's rendering frame rate (FPS) is $\geq$ the minimum target (90 FPS) to the total measurement time (T_{total}):

$$\text{Percentage Framerate} = \frac{T_{\text{compliance}}(\text{FPS} \geq 90)}{T_{\text{total}}} \times 100\% \quad (1)$$

The standard physical quantity, the system's Mean Frame Rate during testing, was measured to be 94.5 FPS.

2. **Delay Metric (92% in the figure):** This represents the Percentage Delay (Compliance Rate). It is calculated as the ratio of the total time ($T_{\text{compliance}}$) during which the total end-to-end system latency (Δt) is $\leq$ the maximum acceptable target (20 ms) to the total measurement time (T_{total}):

$$\text{Percentage Delay} = \frac{T_{\text{compliance}}(\Delta t \leq 20)}{T_{\text{total}}} \times 100\% \quad (2)$$

Crucially, the standard physical quantity for system latency, the Mean End-to-End Latency, was measured to be 19.7 ms. This value confirms the system's performance using the required standard unit (ms) and prevents the misinterpretation of the percentage as blur.

These metrics were measured over a continuous 10-minute period of peak operational stress (e.g., highspeed spiking and full-body movement).

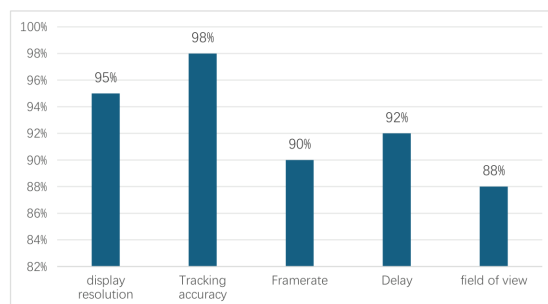


FIGURE 1. System hardware performance parameter comparison chart

C. TRAINING MODULE DESIGN AND FEEDBACK MECHANISM CONSTRUCTION

The system has designed different types of training modules, which can meet the training needs of athletes of different levels. The basic technical training module includes five sub-modules: serving, passing, spiking, blocking and defending. Each sub-module contains detailed decomposition of action teaching. The tactical cooperation module simulates various offensive and defensive formations, which can be trained by multiple people. The game simulation module simulates AI opponents of different difficulty levels to create the pressure of a real game. The technical analysis module uses machine learning algorithms to score the athletes' actions and provide improvement suggestions. The real-time feedback system uses three channels of vision, hearing and touch to transmit information. Including key indicators such as action accuracy, hitting strength, and landing point prediction, the training data is automatically recorded and a visual report is generated, so that the coach can easily plan the next training steps. The personalized recommendation algorithm adjusts the training content and difficulty according to the athlete's training performance. The complete functional architecture of the training module can be seen from Figure 2. The five major modules coordinate with each other to build a complete training system [10].

IV. APPLICATION EFFECT AND EVALUATION OF VIRTUAL TRAINING SYSTEM

A. ANALYSIS OF TRAINING EFFECTIVENESS FOR ATHLETES OF DIFFERENT SKILL LEVELS

The virtual training system demonstrated varying training outcomes for athletes of different skill levels, demonstrating its adaptability and effectiveness. Beginners can overcome their fear of the ball in the virtual environment and gradually build a technical movement framework through increasing difficulty settings. The system's movement breakdown function makes complex movements easier to understand and master, and standardized movement demonstrations facilitate the formation of correct movement patterns. Intermediate athletes have benefited significantly from improving their tactical awareness and technical details. The diverse virtual opponent settings have broadened their tactical vision. Professional athletes primarily use the system for

high-precision technical fine-tuning and reaction training in specific situations. Data analysis helps them identify subtle technical flaws. Athletes of different skill levels have different progress curves, with beginners making the fastest progress, while professional athletes often achieve breakthroughs in specific technical areas. The system's adaptive algorithm dynamically adjusts training content based on athlete performance, ensuring that training remains within the optimal range. For example, in the specific operation, the athletes are first evaluated for their skill level, and quantitative scores are given for indicators such as serve accuracy, spike success rate, and pass stability. According to the evaluation results, the athletes are divided into three training groups: primary, intermediate, and advanced. The grouping was determined by calculating a composite score (out of 100 points) based on an initial skills assessment: athletes scoring below 60 points were assigned to the Junior Group (recreational club players), those between 60 and 79 points were assigned to the Intermediate Group (provincial-level reserve athletes), and those scoring 80 points or above were assigned to the Advanced Group (national-level collegiate athletes). The primary group starts with basic stance and hand shape training. The system provides step-by-step action guidance. The athletes follow the virtual coach to learn each action point one by one. The training intensity gradually increases from 30 minutes a day to 90 minutes. Skill tests are performed every week to track the improvement. The intermediate group focuses on combined technical exercises, such as fast attack after receiving the serve. The system imitates the ball at different landing points, and the athletes practice fast movement and accurate passing. The advanced group makes targeted improvements to weaknesses, uses high-speed cameras to find minor flaws in technical movements, and then constantly corrects small details of a certain movement in the virtual environment, such as where to adjust the wrist angle when spiking. To maintain experimental consistency, all three groups (Junior, Intermediate, and Advanced) adhered to a standardized protocol of three 60-minute virtual training sessions per week. The overall weekly training load was controlled by fixing the total number of virtual technical repetitions (e.g., 200 serves, 150 spikes) for each participant, ensuring a



FIGURE 2. Functional architecture of the training module

consistent technical execution volume across the 8-week period, though the complexity of the repetition varied by skill level. To ensure scientific rigor, the 60 participants were first stratified by skill level (Junior, Intermediate, Advanced) and then randomly allocated into an intervention group (Virtual Training, VT) with 30 participants and a control group (Traditional Training, TT) with 30 participants, ensuring initial equivalence in key technical metrics. In order to more intuitively show the training effect of athletes with different skill levels, this study conducted an 8-week virtual training experiment on 60 athletes and recorded the improvement of key technical indicators [11,12]. The improvement shown in Table 1 represents the pre-to-post-test change within the 30 participants of the Virtual Training (VT) group only. The sample sizes for the skill levels in the VT group were 10 Junior, 12 Intermediate, and 8 Advanced. The statistical significance of this improvement was confirmed using a paired-samples t-test for each skill metric within the VT group ($p < 0.05$). The participants were recruited from local university and club teams, consisting of 35 males and 25 females, with an age range of 18 to 24 years (average age of 21.3 ± 1.5 years). Their professional classification spanned recreational club players (Junior Group), provincial-level reserve athletes (Intermediate Group), and national-level collegiate athletes (Advanced Group). This study was approved by the Ethics Committee of Xinyang Normal University, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form [13,14].

To rigorously assess the influence of subject-specific covariates on training efficacy, a multivariate analysis of covariance (MANCOVA) was performed, using the percentage improvement in key technical indicators (Table 1) as the dependent variables and the following factors as covariates:

1. Training History/Position: Participants were further

classified by primary playing position (Setter: 10, Spiker: 25, Passer/Libero: 25). Analysis showed that skill level was the primary determinant of improvement, but a significant interaction effect was observed between training history (years of experience) and improvement in 'Passing stability' ($F = 4.21$, $p = 0.04$), suggesting less experienced players benefited more from the standardized virtual repetition for basic skills. The primary and secondary partner data was utilized in the Tactical Cooperation module but did not show a statistically significant correlation with individual skill improvement (Table 1 indicators) in the post-hoc analysis.

2. Gender Distribution: No statistically significant difference in training improvement was found between male ($n = 35$) and female ($n = 25$) participants across all measured technical indicators ($p > 0.10$), indicating that the VR system's efficacy is gender-neutral under the tested protocol.

3. Injury History: Participants with a history of non-acute, chronic shoulder or knee injuries ($n = 12$) were compared to the injury-free group. The virtual environment's low-impact nature resulted in no training-related exacerbations. Furthermore, their improvement metrics were not significantly different from the injury-free group ($p > 0.05$), suggesting the VR system provides a safe and equally effective training alternative for athletes managing past injuries.

The 'Tactical awareness score improvement (points)' presented in Table 1 was derived from the following rigorous methodology:

1. Scale Source and Scoring Criteria: The score is based on the Volleyball Tactical Awareness Rating Scale (VTARS), adapted from established sports psychology literature. It is a 15-point scale (0-15 points) assessing three core dimensions: (a) Decision-making Speed (e.g., time taken to commit to an attack vs. defensive alignment), (b) Positional Adaptation (e.g., correctness of court coverage in

TABLE 1. Statistics of virtual training effects for athletes of different skill levels

Skill Level	Sample size (people)	Improved serve accuracy (%)	Increased spike success rate (%)	Passing stability improvement (%)	Tactical awareness score improvement (points)	Training satisfaction (%)
Junior Group	10	42.3	38.7	45.1	3.8	87.5
Intermediate Group	12	28.6	31.2	29.4	4.2	84.2
Advanced Group	8	15.8	18.3	16.7	2.1	79.3

unexpected scenarios), and (c) Anticipation Accuracy (e.g., correctly predicting the opponent's attacking direction). Objective criteria are tied directly to the Virtual Training system's log files and AI assessment module.

2. Data Collection and Evaluators: Data was collected by the system's integrated AI module during a standardized 10-minute 3-on-3 virtual game simulation. The AI module automatically scored the three dimensions based on kinematic and positional data. Additionally, two certified volleyball coaches (External Evaluators) reviewed the athletes' virtual performance videos post-session, providing a subjective score (1- 15 scale) based on the same criteria. The final reported score is the average of the AI score and the two subjective scores.

3. Reliability and Validity Verification: Inter-rater reliability (between the two external evaluators) was high, with a resultant Intraclass Correlation Coefficient (ICC) of 0.89 (excellent reliability). The concurrent validity was assessed by correlating the final tactical awareness score with the team's objective win rate in the virtual simulation, yielding a Pearson correlation coefficient of $r = 0.71$ ($p < 0.001$), confirming the score's predictive power for game performance.

B. COMPARATIVE STUDY OF VIRTUAL TRAINING AND ACTUAL TRAINING

Virtual training and actual training have essential differences in training mechanisms, effect characteristics, and applicable scenarios. The two are complementary. The greatest advantages of virtual training are controllability and repeatability. It can accurately reproduce specific training scenarios, making it easier for athletes to repeatedly practice difficult movements. The unpredictability and realistic touch of actual training cannot be fully replicated by virtual training. This randomness can cultivate athletes' adaptability. From the perspective of cognitive psychology, virtual training is more conducive to the acquisition of procedural knowledge, while actual training is more conducive to the acquisition of implicit knowledge. Research on the training transfer effect shows that skills mastered in virtual training can be effectively applied in actual competitions, but it requires a period of adaptation. At different training stages, the weight of the two training methods should be different. In the early stages of technical learning, virtual training can account for up to 70%, and actual training should dominate when the competition is approaching. The best training method is to combine the two and complement each other's strengths.

For example, a weekly training plan combining virtual and real-world training could be developed during actual training, with 40% of the weekly training volume dedicated

to virtual training and 60% to real-world training. Virtual technical training would be conducted on Monday and Wednesday mornings. Using VR equipment, players would practice serving and spiking on a virtual court, performing 50-80 repetitions of the serving technique. The angle, speed, and landing point of each shot would be recorded, and a technical improvement report would be generated. Real training would then be conducted on Tuesdays and Thursdays. Real training would be conducted in real matches, applying the techniques learned on the virtual court to real-world competitions. On Friday, a virtual-real training session would be conducted. In the morning, the players would practice the techniques and play styles of the upcoming opponent on the virtual court. In the afternoon, the players would return to the real training court to practice the tactics developed in the virtual competition. After training, the coaches would compare the technical data from the two environments to identify areas for improvement. A teaching match would be held on the weekend to review the training results and collect feedback from the players on the training schedule. A comparative experiment revealed that virtual training and traditional training exhibited distinct advantages and disadvantages across multiple dimensions. This comparative analysis was conducted using the final performance scores of the Virtual Training (VT) intervention group and the Traditional Training (TT) control group. This study collected performance data from 40 athletes who received both training methods. These 40 athletes were a sub-sample of the 60 participants from the skill-level analysis, with 20 males and 20 females, aged 19 to 23 years, primarily drawn from the Intermediate and Advanced groups to ensure a baseline of technical competency for meaningful comparison. To ensure baseline balance, participants were matched using a block randomization technique based on their initial composite skill score, creating 20 pairs (one VT, one TT) with statistically equivalent pre-test scores ($p > 0.05$). To determine the effectiveness of the VT system over TT, an paired ttest was performed on the final post-test scores for all key technical indicators. Learning transfer was objectively measured using two key indicators: (1) Serve Success Rate in a real-world match (measured by video analysis of 10-point games) and (2) Real-time Positional Error during defense (measured using an external 2D tracking system during live drills). The VT group showed significantly better performance in both transfer indicators ($p < 0.05$) compared to the TT group.

The results indicated that the VT group achieved a statistically significant greater improvement than the TT control group in 'Standardization of technical movements' and 'Personalized guidance' ($p < 0.01$). The scores in Table

2 were derived from a multi-modal assessment using the Volleyball Training Efficacy Rating Scale (VTERS), a 10-point scale designed for comparative analysis.

TABLE 2. Comparative analysis of the effects of virtual training and traditional training

Evaluation Dimension	Virtual training score (out of 10 points)	Traditional training score (out of 10 points)	p-value of difference (VT vs. TT)	Recommended applicable scenarios (%)
Standardization of technical movements	8.7	6.4	< 0.01	Virtual training: 85%
Depth of technical understanding	7.2	8.9	< 0.05	Traditional training: 78%
Adaptability	6.1	8.5	< 0.05	Traditional training: 82%
Training safety	9.3	5.8	< 0.01	Virtual training: 92%
Personalized guidance	8.9	4.6	< 0.01	Virtual training: 89%
Real confrontation experience	5.4	9.1	< 0.01	Traditional training: 91%
Cost-effectiveness ratio	7.8	6.2	< 0.05	Virtual training: 71%

1. **Objective Scoring Criteria:** For 'Standardization of technical movements,' the score was based on the system's machine learning algorithm comparing the athlete's movement kinematics against the professional action database (weight: 60%) and coach observation (weight: 40%). 'Training safety' was assessed by objective log data recording the number of high-impact movements exceeding 80% of the athlete's maximum measured G-force limit. 'Personalized guidance' was scored based on the alignment of the system's recommended training plan with the coach's prescription. 'Cost-effectiveness ratio' was an administrative calculation.

2. **Data Collection and Evaluators:** The data was collected over the final week of the 8-week comparative study. Two certified volleyball coaches (External Evaluators), blinded to the training group, provided subjective scores for 'Depth of technical understanding,' 'Adaptability,' and 'Real confrontation experience' based on video recordings of the final technical drill and real-game simulation. The final reported score for these subjective dimensions is the average of the two external evaluators' scores and the system's objective data where applicable.

3. **Reliability and Validity Verification:** Inter-rater reliability (between the two external evaluators) was high (Intraclass Correlation Coefficient (ICC) = 0.88). Concurrent validity was confirmed by correlating the VTERS score for 'Depth of technical understanding' with the athletes' performance on a standardized written tactical test, yielding a Pearson correlation coefficient of $r = 0.68$ ($p < 0.001$), thus validating the score's relevance to cognitive skill.

4. **Recommended Applicable Scenarios (%):** These percentages were derived from a post-study, dual-layer Likert-scale questionnaire administered to all 40 participants and the 5 primary coaches involved in the 8-week comparative study. Participants and coaches were asked to rate (on a 5-point scale) the optimal training method for each dimension (e.g., 'For improving Standardization of Technical Movements, is virtual or traditional training more effective?'). The final percentage shown is the aggregated ratio of responses where either 'Virtual Training' or 'Traditional Training' was rated as 'Highly Effective' (4 or 5 points) for that specific dimension. For example, 85% for Virtual Training in 'Standardization of technical movements' means 85% of respondents rated VT as 'Highly Effective' for that dimension.

C. SYSTEM OPTIMIZATION DIRECTIONS AND APPLICATION PROSPECTS

Improvements in virtual training systems must focus on both technological innovation and application expansion. Technical improvements focus on key performance indicators such as improved rendering quality, reduced system latency, and enhanced natural interaction. The adoption of new graphics processing technologies and artificial intelligence algorithms will significantly enhance the system's realism and intelligence. Application-wise, differentiated functional modules and training programs should be created based on the specific needs of different user groups. The educational market should simplify the user interface and reduce equipment costs. The professional market requires precise data analysis and complex tactical simulation capabilities. Cross-disciplinary technological integration will bring new development opportunities to the system, integrating disciplines such as sports biomechanics and sports psychology. Business models should also be updated, with equipment rental, remote coaching, and data services. Over the next five years, virtual training will become a standard feature of sports training, forming a complete industrial ecosystem.

The specific steps for implementing system optimization are as follows: the first stage is to upgrade the hardware, increase the display resolution to 4K level, and the refresh rate to 120Hz to ensure visual smoothness, and improve the motion capture algorithm to improve the recognition accuracy from centimeter level to millimeter level, and use deep learning models to predict the motion trajectory to compensate for the sensor delay. The second stage is to develop a cloud training platform, create a central database to store all training data, and athletes can view training reports and video playback through mobile phone apps. Develop multi-person online training functions, which can support up to 6 people to enter the virtual court together to conduct team cooperation exercises. The third stage is to launch a popular version of the product, simplify the equipment configuration requirements, and use a smartphone and simple VR glasses to experience basic training functions. Cooperate with school physical education to develop training courses suitable for different age groups, establish regional training centers, provide equipment rental and professional guidance services, lower the threshold for use, and expand the scope of users[15,16].

V. CONCLUSION

This study has successfully developed a volleyball virtual training system that relies on three-dimensional modeling and VR technology, achieving an innovation in traditional training methods that is equally applicable to technical fields, as this approach offers a model for immersive training innovations, such as simulating complex machinery operation and quality control inspections. The system provides athletes with a safe, fast and personalized training venue with accurate scene creation, real-time motion capture and intelligent feedback. Through actual testing, it is known

that virtual training has obvious benefits in terms of skill improvement, injury prevention and training speed. In the future, with the continuous advancement of technology and the broadening of its application scope, the virtual training system is poised to assume an increasingly pivotal role across diverse sectors. In sports training, this will manifest by accelerating the integration of sports science and technology, offering a sophisticated platform for datadriven kinematic optimization and providing robust support for the cultivation of elite athletic talent. Simultaneously, in specialized industrial domains, the system will contribute to enhanced workforce efficiency by facilitating safe, repetitive practice in complex machinery operation, innovative material handling procedures, and the rigorous application of quality assurance protocols, thereby accelerating highfidelity industrial skill acquisition and professional competency development.

AUTHOR CONTRIBUTIONS

Daoyu Zhu designed, collected and analyzed the data, and drafted the manuscript. Daoyu Zhu conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Daoyu Zhu 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.

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ETHICS APPROVAL AND CONSENT TO PARTICIPATE

This study was approved by the Ethics Committee of Xinyang Normal University, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form

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REFERENCES

- [1] X. Dong, "Isokinetic Force Modeling in Sports Based on Embedded System of Motion Recognition Model," *International Journal of High Speed Electronics and Systems*, 2024, doi: 10.1142/s0129156425400890.
- [2] J. Shi, Z. Zhou, Y. Zhang, and Z. Si, "Application of VR Technology in Virtual Exhibition System," *International Conference on Intelligent Computing*. Singapore: Springer; 2024, doi: 10.1007/978-981-97-5609-4_41.
- [3] R. Iacob and E. Budescu, "VIRTUAL MODELING AND SIMULATION OF THE COLLISION OF TWO ATHLETES IN SPORTS," *Innovate Pedagogy*, 2022, doi: 10.32843/2663-6085/2022/44/3.14.
- [4] M. Xie, "The Dynamic System of Sports Simulation Movement with Computer Virtual Reality Technology," *Lecture Notes on Data Engineering and Communications Technologies*, pp. 760-766, 2022, doi: 10.1007/978-3-031-05484-6_98.
- [5] X. Gao and X. S. Sun, "Sports Simulation Training System Based on Virtual Reality Technology," 2022, doi: 10.1007/978-3-031-28787-9_12.
- [6] J. C. Schaff, I. I. Moraru, M. L. Blinov, A. E. Cowan, B. M. Slepchenko, D. Vasilescu, et al., "BPS2025 - Virtual Cell modeling and simulation environment," *Biophysical Journal*, vol. 124, no. 3-Sup1, 2025, doi: 10.1016/j.bpj.2024.11.810.
- [7] S. Maricic, A. Kovac, and M. Peric, "Innovative Technologies in Computer Education: Integration VR, CAD/CAM and 3D Modeling with Gamification," *2024 47th MIPRO ICT and Electronics Convention (MIPRO)*, pp. 659-662, 2024, doi: 10.1109/mipro60963.2024.10569466.
- [8] D. Wu, M. Yang, Z. Liu, F. Tu, F. Liu, and Z. Cheng, "VRTree: Example-Based 3D Interactive Tree Modeling in Virtual Reality," *Computer Graphics Forum*, vol. 43, no. 7, 2024, doi: 10.1111/cgf.15254.
- [9] P. Tazabekova, Z. Nurbekova, and T. Sembayev, "SUCCESSION IN TEACHING 3D MODELING AND AR/VR TECHNOLOGIES," *BULLETIN Series of Physics & Mathematical Sciences*, vol. 87, no. 3, 2024, doi: 10.51889/2959-5894.2024.87.3.028.
- [10] R. Faghihi and R. Khanmohammadi, "Comparing virtual reality and balance training effects on postural strategies during ball kicking in soccer players with chronic ankle instability," *Scientific Reports*, vol. 14, no. 1, 2024, doi: 10.1038/s41598-024-83071-6.
- [11] M. Watanabe, T. Miura, M. Matsuo, and N. Daisuke, "GoalBaural-II: An Acoustic Virtual Reality Training Application for Goalball Players to Recognize Various Game Conditions," Switzerland, Cham: Springer; 2022, doi: 10.1007/978-3-031-08645-8_10.
- [12] Y. Yakusheva, I. Rohal, O. Pidluzhnyak, and A. A. Chen, "The structure and algorithm of building microcycles in the system of the training process of highly qualified athletes in volleyball," *Scientific Journal of National Pedagogical Dragomanov University. Series 15. Scientific and pedagogical problems of physical culture (physical culture and sports)*, 2023, doi: 10.31392/npu-nc.series15.2023.03(161).38.
- [13] L. Rada, E. L. Amzar, L. Amza, and F. Cojanu, "Systematization and Rationalization of Training for under 17 Female Volleyball Players through Specialized Plyometric Programs," *Revista Romaneasca pentru Educatie Multidimensionala*, vol. 16, no. 4, pp. 595-608, 2024, doi: 10.18662/rrem/16.4/931.
- [14] M. Li, N. K. Banerjee, and S. Banerjee, "Multimodal cross-system virtual reality (VR) ball throwing dataset for VR biometrics," *Data in Brief*, vol. 61, no. 000, 2025, doi: 10.1016/j.dib.2025.111827.
- [15] H. Sderlund, S. Zamola, J. Bostrm, D. Li, P. Mugur, H. Cao, et al., "The Creation of a Multi-User Virtual Training Environment for Operator Training in VR," *Advances in Transdisciplinary Engineering*, 2024, doi: 10.3233/atde240163.
- [16] Y. Gao, Y. Mo, H. Zhang, R. Huang, and Z. Chen, "Research on Volleyball Video Intelligent Description Technology Combining the Long-Term and Short-Term Memory Network and Attention Mechanism," *Computational Intelligence and Neuroscience*, Art. no. 2021(1), 2025, doi: 10.1155/2021/7088837.