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Physics-Informed Dual-View YOLO Framework for Tennis Ball Trajectory Prediction

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Abstract

The flight behavior of spinning tennis balls constitutes a nonlinear aerodynamic system governed by the coupling among translational motion, rotational dynamics, gravity, and aerodynamic forces. Conventional trajectory prediction methods often rely on simplified projectile assumptions and therefore fail to accurately reconstruct spin-induced nonlinear trajectory evolution under realistic high-speed sports conditions. To address this limitation, this study proposes a physics-informed tennis trajectory reconstruction framework integrating synchronized dual-view motion acquisition, YOLO-based object localization, three-dimensional kinematic reconstruction, and Magnus-effect-informed aerodynamic simulation. Side-view and top-view observations are utilized to estimate key motion parameters, including initial velocity, elevation angle, and lateral motion angle, which are subsequently incorporated into a nonlinear aerodynamic trajectory model considering gravity, drag, and spin-induced lift forces.

Experiments were conducted using 40 tennis strokes collected under daytime and nighttime conditions on a red clay court with physically measured landing-point references. The results demonstrate that incorporating Magnus-effect coupling substantially improves longitudinal trajectory reconstruction accuracy. Specifically, the Z-axis mean absolute error decreased from 2.49 m to 1.08 m, while the overall RMSE decreased from 2.82 m to 1.52 m compared with the non-Magnus model. Spatial deviation analysis further revealed reduced systematic prediction bias and improved trajectory stability under varying illumination conditions. The proposed framework establishes a coupled visual–physical paradigm for nonlinear sports trajectory reconstruction by integrating deep learning–based motion acquisition with physics-informed aerodynamic modeling. The study contributes toward physically consistent

landing-point prediction, intelligent sports analytics, and high-fidelity trajectory simulation in high-speed sports environments.

Keywords: Magnus Effect, Aerodynamic Simulation, 3D Spatial Reconstruction, Computer Vision in Sports, Physics-Based Sports Simulation, Multi-View Vision System

1. Introduction

The flight dynamics of spinning sports balls constitute a complex nonlinear physical system governed by the coupled interaction of gravitational acceleration, aerodynamic drag, and rotationally induced lift forces. In racket sports such as tennis, the trajectory evolution of a ball is highly sensitive to initial velocity, launch angle, spin rate, and environmental perturbations, leading to substantial variations in spatial motion and landing behavior[1-6]. Small perturbations in impact conditions may therefore produce considerable divergence in trajectory evolution due to nonlinear aerodynamic coupling. Among these factors, the Magnus effect plays a particularly critical role by generating spin-dependent lift forces that alter both the vertical and lateral characteristics of the ball trajectory. Consequently, accurately modeling the flight behavior of spinning tennis balls remains a challenging problem in nonlinear dynamics, sports physics, and physics-informed trajectory prediction.

Recent advances in computer vision and deep learning have substantially improved the capability of high-speed object detection and motion tracking in dynamic sports environments. Vision-based systems employing convolutional neural networks (CNNs) and YOLO architectures have demonstrated strong performance in detecting small and rapidly moving objects under challenging conditions such as motion blur, occlusion, and variable illumination[7, 8]. These developments have facilitated the emergence of intelligent sports analytics systems for performance evaluation, tactical analysis, and motion reconstruction. However, most existing studies primarily emphasize object localization and geometric trajectory estimation from a data-driven perspective, while the underlying nonlinear physical mechanisms governing spinning ball motion are often simplified or neglected[9, 10].

Traditional trajectory prediction approaches frequently rely on idealized projectile assumptions or gravity-dominant parabolic models that do not adequately account for spin-dependent aerodynamic interactions[11, 12]. Although several studies have investigated the Magnus effect in spinning ball systems, most existing frameworks either employ simplified analytical approximations or lack integration with real-time visual motion acquisition[13-15]. In practical tennis scenarios, the trajectory of a spinning ball is simultaneously influenced by translational velocity, rotational velocity, aerodynamic drag, and lift-force coupling, forming a highly dynamic system characterized by nonlinear trajectory deviation and sensitivity to initial conditions. Existing single-view vision systems are also limited in reconstructing three-dimensional spatial motion, particularly under high-speed racket–ball interaction conditions where motion blur and occlusion frequently occur[16-19]. Existing trajectory simulation systems typically account only for gravity and aerodynamic drag while neglecting rotational dynamics, which significantly limits the precision of

trajectory prediction and impact localization.

To address these limitations, this study proposes a coupled visual–physical framework that integrates dual-view video analysis, deep learning–based object localization, and physics-informed trajectory simulation incorporating the Magnus effect. Rather than treating visual detection as an isolated task, the proposed framework employs computer vision as a parameterization mechanism for nonlinear trajectory modeling. A synchronized dual-camera configuration consisting of top-view and side-view perspectives is utilized to estimate impact-related kinematic variables, including initial velocity, elevation angle, and lateral deviation angle. These variables are subsequently incorporated into a physics-based simulation model governed by gravitational, drag, and spin-induced aerodynamic forces. The rotationally induced lift behavior associated with the Magnus effect is represented as a coupled force interaction: $\vec{F}m \propto \vec{\omega} \times \vec{v}$. Where the Magnus force is jointly determined by the angular velocity vector and translational velocity vector of the ball. This coupling mechanism introduces nonlinear perturbations into the trajectory evolution process, resulting in substantial deviations from conventional parabolic motion assumptions.

To overcome these challenges, this study proposes a novel system architecture that integrates dual-view video analysis, deep learning–based object detection, and physics-informed trajectory simulation incorporating the Magnus effect. Specifically, the YOLO framework is employed to track tennis balls with enhanced robustness under varying lighting conditions and motion blur[17-21]. First, the integration of YOLO-based detection enhances object localization stability under high-speed motion and variable illumination conditions. Second, the incorporation of spin-dependent aerodynamic modeling enables more physically consistent trajectory evolution and landing-point prediction. Third, the dual-view reconstruction mechanism improves the estimation of spatial motion parameters by integrating lateral and vertical kinematic observations into a unified three-dimensional representation. Experimental validation was conducted using synchronized 60 FPS recordings collected under both daytime and nighttime environments, with comparative analyses performed between Magnus-effect and non-Magnus-effect simulations to evaluate the influence of nonlinear aerodynamic coupling on trajectory prediction accuracy.

This study contributes a cross-disciplinary framework integrating nonlinear dynamics, computer vision, and sports physics for intelligent trajectory analysis in racket sports. By coupling data-driven visual motion acquisition with physics-informed aerodynamic simulation, the proposed system establishes a unified paradigm for analyzing spin-dependent trajectory evolution in high-speed sports environments. The framework not only improves landing-point prediction accuracy but also provides a methodological foundation for future research involving nonlinear motion

reconstruction, virtual–physical sports integration, and intelligent sports dynamics modeling. The primary contributions of this study are summarized as follows:

(1) A dual-view visual motion acquisition framework integrating synchronized top-view and side-view observations is proposed for reconstructing the three-dimensional spatial evolution of high-speed tennis ball trajectories.
(2) A physics-informed nonlinear trajectory model incorporating Magnus-effect-induced aerodynamic coupling is developed to simulate spin-dependent lift behavior and trajectory deviation beyond conventional parabolic assumptions.
(3) A coupled visual–physical prediction architecture integrating YOLO-based object localization, kinematic parameter extraction, and aerodynamic force simulation is established for intelligent landing-point prediction and nonlinear sports trajectory analysis.
(4) A comparative experimental analysis under different environmental lighting conditions and aerodynamic modeling settings is conducted to investigate the influence of spin-induced nonlinear perturbations on prediction accuracy and trajectory stability.

The remainder of this paper is organized as follows. Section 2 reviews related work on sports vision systems, aerodynamic modeling, and trajectory reconstruction. Section 3 presents the proposed dual-view physics-informed framework and nonlinear trajectory modeling method. Section 4 reports the experimental results and performance evaluation. Finally, Section 5 concludes the paper.

2. Related Work

The analysis of high-speed ball motion in racket sports has become an important topic in computer vision, nonlinear dynamics, and sports physics. Accurate tennis trajectory reconstruction requires both reliable visual localization and physically consistent modeling of aerodynamic and spin-induced motion. Earlier studies mainly relied on traditional image processing methods such as color segmentation and contour extraction, while recent advances in deep learning, particularly CNN- and YOLO-based architectures, have significantly improved the detection and tracking of fast-moving objects. Trajectory prediction research has also evolved from simplified parabolic approximations toward physics-informed models incorporating aerodynamic drag and rotational effects. Among these factors, the Magnus effect plays a critical role in nonlinear trajectory deviation. In addition, multi-camera systems and three-dimensional coordinate fusion methods have been increasingly adopted to improve spatial reconstruction accuracy in high-speed sports scenarios.

Accordingly, the related literature can be categorized into three major dimensions

associated with the present study. Section 2.1 reviews vision-based motion detection and trajectory tracking methods for high-speed sports analysis. Section 2.2 discusses nonlinear aerodynamic modeling of spinning ball trajectories, with particular emphasis on Magnus-effect-induced dynamics. Section 2.3 introduces multi-view spatial reconstruction and three-dimensional motion analysis methods for high-speed trajectory estimation.

2.1 Vision-Based Motion Detection and Trajectory Tracking

In sports video analysis, accurately detecting and tracking fast-moving objects such as tennis balls remains a fundamental challenge for motion reconstruction and trajectory estimation. Earlier studies primarily relied on traditional image processing techniques, particularly foreground–background segmentation and HSV-based color thresholding[11, 22]. These approaches isolate moving foreground regions from static backgrounds and identify target objects based on predefined color distributions. Although computationally efficient and relatively simple to implement, such methods are highly sensitive to illumination variation, background complexity, occlusion, and motion blur—conditions frequently encountered in high-speed racket sports environments. These limitations often reduce localization stability and subsequently affect the accuracy of kinematic parameter estimation and trajectory reconstruction. Figure 1 illustrates a conventional HSV-based tennis ball detection pipeline consisting of image acquisition, color-space transformation, foreground masking, color filtering, and object localization. While this framework enables rapid object extraction, its detection performance often deteriorates under visually dynamic conditions, resulting in unstable spatial tracking and reduced reliability for subsequent motion analysis and trajectory prediction.



Figure 1. Conventional HSV-based framework for visual localization and trajectory-related motion extraction.

The framework employs color-space transformation and foreground segmentation to

identify tennis ball motion from video sequences. However, the approach remains highly susceptible to illumination fluctuation, motion blur, and background interference, often leading to unstable spatial localization and reduced reliability in high-speed trajectory reconstruction.

To overcome the limitations of traditional image-processing methods, recent studies have increasingly adopted Convolutional Neural Networks (CNNs) for high-speed motion detection and trajectory-related object localization[23, 24]. Compared with conventional handcrafted feature extraction approaches, CNN-based models are capable of learning hierarchical spatial representations directly from raw image data, enabling more robust detection under complex environmental conditions such as motion blur, background interference, occlusion, and illumination variation[20, 21, 25]. This improvement is particularly important in racket sports scenarios, where unstable object localization may significantly affect subsequent kinematic estimation and trajectory reconstruction. As illustrated in Figure 2, a typical CNN framework employs convolutional operations, nonlinear activation mechanisms, and hierarchical feature aggregation to construct deep spatial representations of target motion. These representations are subsequently utilized for object localization and classification tasks. Owing to their strong feature-learning capability and generalization performance, CNN-based motion detection frameworks have become increasingly important in real-time sports tracking and high-speed trajectory analysis systems.

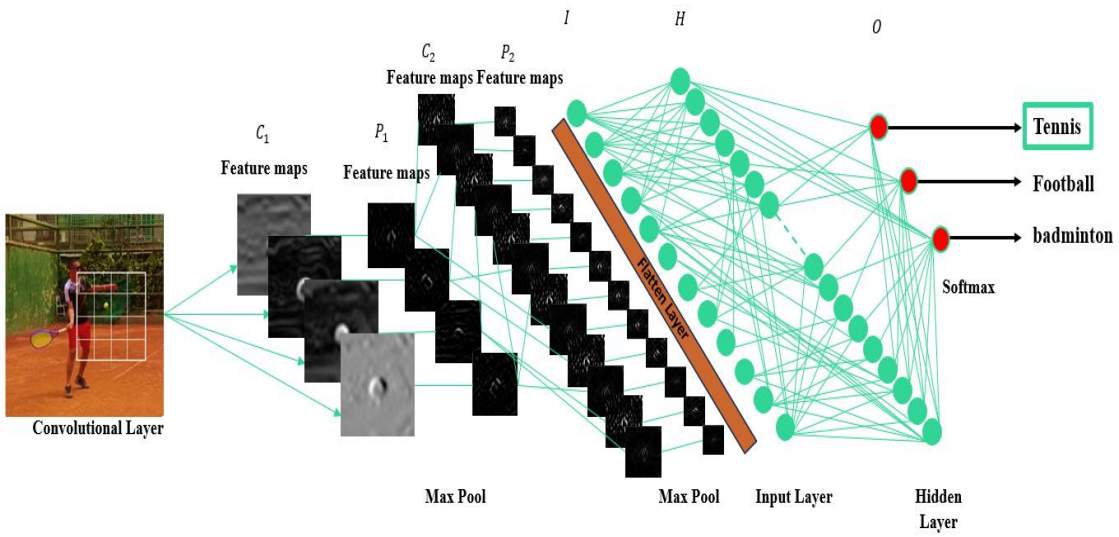


Figure 2. CNN-based framework for high-speed tennis ball motion localization. *The figure illustrates a representative CNN workflow for extracting hierarchical spatial features from tennis motion imagery through convolutional operations and nonlinear*

feature transformation. The learned feature representations are subsequently utilized for object localization and motion-related classification, enabling more robust tracking performance under dynamic sports environments.

Building upon CNN-based motion detection frameworks, end-to-end architectures such as YOLO (You Only Look Once) have become widely adopted for real-time tracking and localization of high-speed objects in sports video analysis[6, 26]. Compared with traditional multi-stage detection methods, YOLO-based frameworks provide improved computational efficiency and spatial localization stability, enabling reliable tracking of small and rapidly moving targets such as tennis balls under dynamic environmental conditions[27, 28]. This capability is particularly important for trajectory-related applications, where inaccurate object localization may directly influence kinematic parameter estimation and subsequent physical trajectory modeling[1, 29]. Figure 3 illustrates the general YOLO-based motion localization process. The framework performs simultaneous object localization and classification through an end-to-end prediction mechanism, enabling stable real-time tracking under conditions involving rapid motion, partial occlusion, and motion blur. Owing to its robustness and temporal consistency, YOLO has become an important visual acquisition mechanism in high-speed sports trajectory analysis systems.

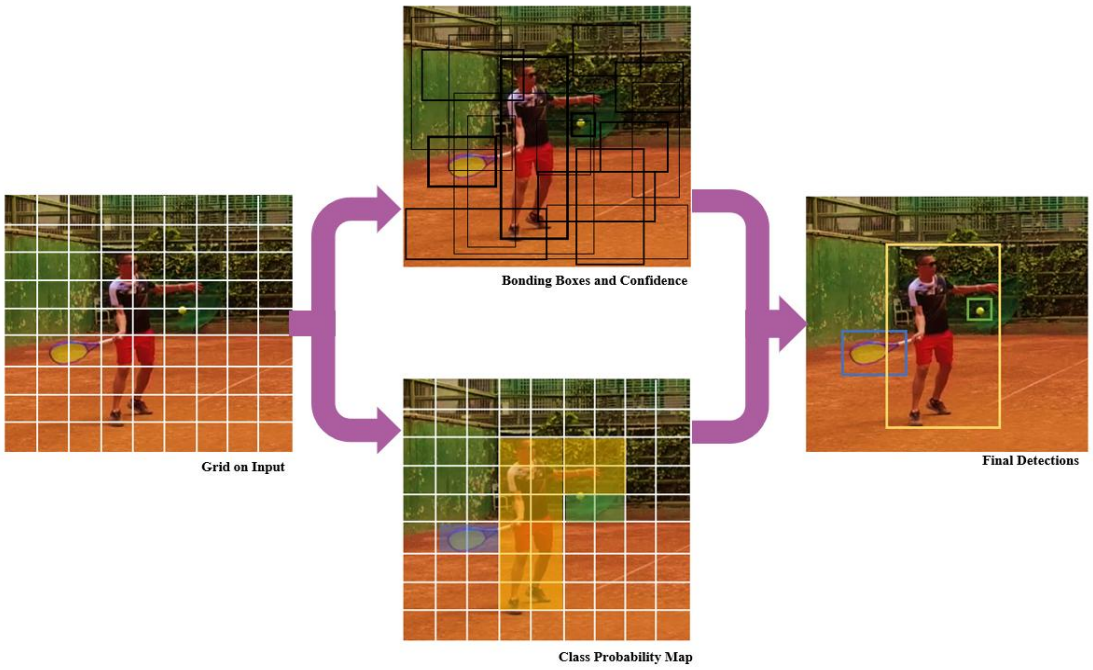


Figure 3. YOLO-based framework for high-speed motion localization and trajectory-related object tracking.

The figure illustrates the end-to-end localization process of the YOLO framework for

detecting fast-moving tennis balls in dynamic sports environments. The architecture enables stable spatial tracking and real-time motion localization under conditions involving rapid motion, occlusion, and motion blur.

In this study, the YOLO framework is employed as a visual motion localization mechanism integrated with synchronized dual-view video acquisition at 60 FPS. The proposed configuration improves the spatial consistency of tennis ball tracking during high-speed racket–ball interaction, thereby enabling more reliable estimation of kinematic variables, including initial velocity, launch angle, and lateral displacement. These motion parameters subsequently provide essential inputs for nonlinear aerodynamic trajectory modeling and Magnus-effect-informed trajectory simulation.

2.2 Nonlinear Aerodynamic Modeling of Spinning Ball Trajectories

The Magnus effect represents a nonlinear aerodynamic phenomenon generated by the interaction between translational motion and rotational velocity in a fluid medium. When a spinning ball travels through air, asymmetric airflow distribution around the ball surface produces a pressure imbalance that generates a spin-dependent lift force perpendicular to the direction of motion[17-19]. This coupled aerodynamic interaction substantially alters the trajectory evolution of the ball and introduces nonlinear deviations from idealized projectile motion. In racket sports such as tennis, the influence of the Magnus effect becomes particularly significant under high-speed and high-spin conditions, where small variations in rotational velocity may lead to considerable differences in flight behavior and landing position[30-32].

Numerous studies have investigated the aerodynamic influence of spin on sports ball trajectories. Mehta and Pallis experimentally demonstrated that tennis ball spin induces substantial aerodynamic deviation through wind tunnel analysis[16], while Robinson and Robinson modeled the curvature behavior of spinning tennis serves under different environmental conditions[33]. These studies collectively highlight the importance of incorporating rotationally induced aerodynamic forces into trajectory prediction systems. Nevertheless, many existing trajectory models still rely primarily on gravity-driven or drag-dominant projectile approximations, while the nonlinear coupling between translational velocity and spin-induced lift forces remains insufficiently modeled under realistic sports conditions[10].

To address this limitation, the present study incorporates Magnus-effect-informed aerodynamic modeling into a physics-informed trajectory reconstruction framework for high-speed tennis motion analysis. Rather than relying solely on geometric extrapolation, the proposed approach integrates visual motion acquisition with nonlinear aerodynamic simulation to reconstruct more physically consistent ball

trajectories. Figure 4 illustrates the influence of Magnus-effect-induced aerodynamic coupling on tennis ball trajectory evolution. Compared with conventional parabolic motion assumptions, the Magnus-informed trajectory exhibits substantial deviations in flight behavior, demonstrating the critical role of spin-dependent nonlinear forces in high-speed sports trajectory dynamics.

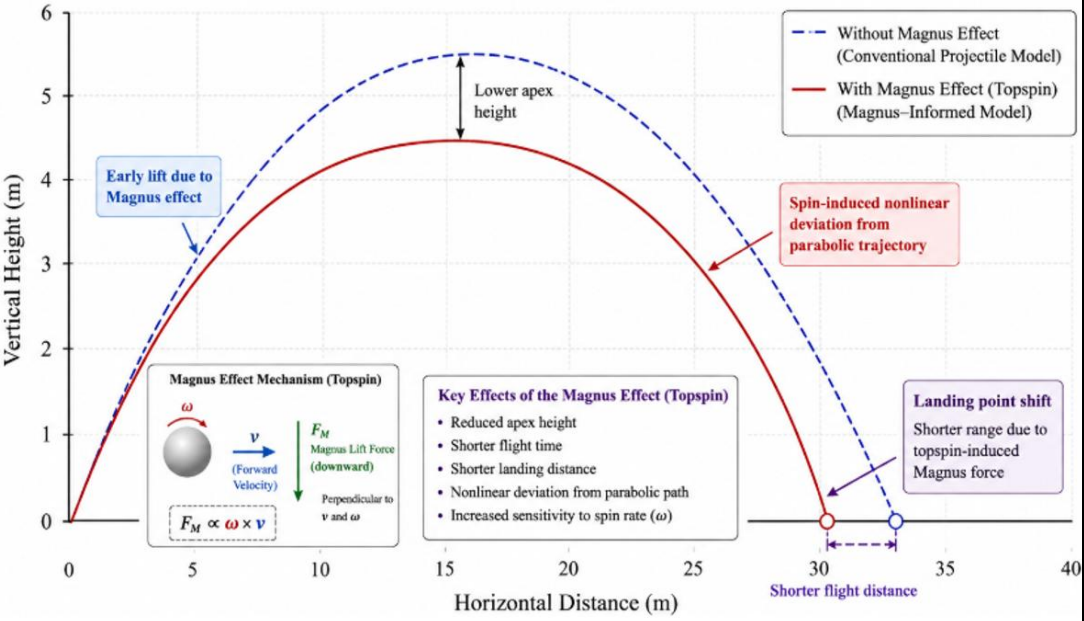


Figure 4. Nonlinear trajectory evolution under Magnus-effect-induced aerodynamic coupling.

he blue dashed curve represents the conventional projectile model considering gravity and drag only, while the red solid curve represents the Magnus-informed model with topspin. The Magnus effect generates a downward lift force, leading to a lower apex height, nonlinear trajectory deviation, and a shorter landing distance.

2.3 Multi-View Spatial Reconstruction for High-Speed Motion Analysis

Accurate reconstruction of three-dimensional (3D) spatial coordinates is fundamental to sports motion analysis and trajectory simulation systems[34-37]. I In high-speed racket sports such as tennis, relying on a single camera view often results in insufficient spatial coverage, motion blur, and partial occlusion, thereby limiting the reliability of motion reconstruction and kinematic estimation. Consequently, multi-camera configurations have become an effective approach for capturing complete three-dimensional motion information in dynamic sports environments, enabling improved spatial localization and trajectory reconstruction accuracy[38-40]. As illustrated in Figure 5(A), synchronized side-view and top-view observations provide complementary motion information for two-dimensional trajectory tracking under

different projection planes.

Previous studies have investigated dual-view camera architectures using geometric calibration, affine transformation, and triangulation techniques for motion reconstruction. Multi-camera systems have been widely applied in 3D trajectory estimation and high-speed motion analysis across various sports domains. For example, Kim et al. Employed a dual-camera configuration combined with radar sensing to achieve three-dimensional localization and velocity estimation in baseball[41]. While Wang et al. Implemented a depth-enhanced dual-view framework for reconstructing basketball shooting trajectories[42]. These studies collectively demonstrate the adaptability and effectiveness of multi-view systems for capturing small and rapidly moving objects in dynamic sports environments. Lai et al. Further proposed a side-view and top-view tennis trajectory analysis system capable of reconstructing three-dimensional ball motion; however, the framework relied primarily on HSV-based object segmentation and did not incorporate spin-dependent aerodynamic modeling such as the Magnus effect, thereby limiting the physical realism and predictive consistency of the reconstructed trajectories[10].

The present study advances previous research by integrating YOLO-based motion localization with a synchronized dual fixed-camera framework for high-speed tennis trajectory reconstruction. As shown in Figure 5(B), the side-view camera captures motion evolution within the X–Z plane, enabling estimation of elevation angle and vertical velocity, while the top-view camera records trajectory displacement within the X–Y plane for calculating lateral motion and horizontal velocity components. Through synchronized frame correspondence and triangulation-based spatial reconstruction, the proposed framework estimates three-dimensional ball coordinates for each time step. This non-intrusive configuration requires no active markers or external sensing devices and is therefore highly suitable for outdoor and field-based sports applications.

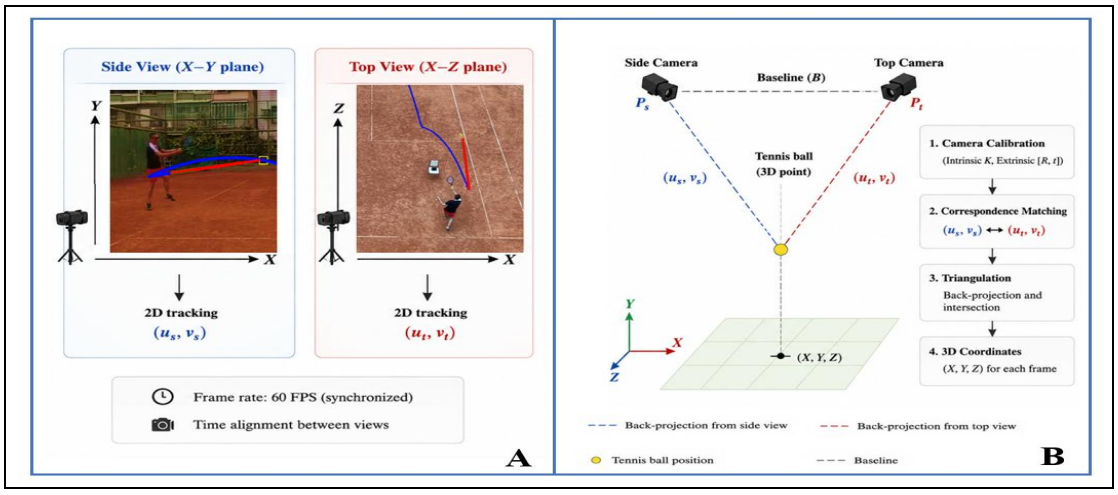


Figure 5. Multi-view motion tracking and three-dimensional spatial reconstruction framework for high-speed tennis trajectory analysis.
The figure illustrates the proposed dual-camera framework for synchronized tennis ball tracking and 3D spatial reconstruction. Side-view and top-view observations are utilized for two-dimensional trajectory acquisition, while triangulation and frame correspondence are employed to reconstruct three-dimensional ball coordinates for trajectory analysis and aerodynamic simulation.

The reconstructed three-dimensional motion data are integrated with a Magnus-effect-informed aerodynamic model to simulate spin-induced nonlinear trajectory evolution. Compared with previous approaches relying solely on geometric extrapolation or simplified projectile assumptions, the proposed hybrid visual–dynamic framework provides improved physical realism and enhanced landing-point prediction accuracy. The framework therefore establishes a coupled multi-view motion reconstruction paradigm for intelligent sports trajectory analysis and physics-informed motion simulation.

3. Method

This chapter presents the proposed physics-informed framework for high-speed tennis trajectory reconstruction and landing-point estimation through the integration of multi-view motion acquisition, deep learning–based visual localization, and nonlinear aerodynamic simulation. Unlike conventional approaches relying on simplified parabolic assumptions, the proposed system incorporates three-dimensional spatial reconstruction and Magnus-effect-induced aerodynamic coupling to model spin-dependent trajectory evolution under realistic sports conditions.

The remainder of this chapter is organized as follows. Section 3.1 introduces the overall framework architecture and computational workflow. Section 3.2 describes the synchronized dual-camera configuration and motion acquisition protocol. Sections 3.3 and 3.4 present the YOLO-based motion localization method and impact-frame identification procedure, respectively. Section 3.5 details the estimation of kinematic and spatial motion parameters, while Section 3.6 explains the nonlinear trajectory simulation process incorporating Magnus-effect-informed aerodynamic modeling.

3.1 System Overview

The proposed framework reconstructs high-speed tennis ball trajectories through the integration of multi-view motion acquisition, deep learning–based visual localization, and physics-informed aerodynamic simulation. Rather than relying solely on geometric extrapolation or simplified projectile assumptions, the system

incorporates spin-dependent nonlinear aerodynamic modeling to estimate realistic trajectory evolution and landing behavior under dynamic sports conditions. The framework consists of several coordinated modules, including synchronized dual-view video acquisition, YOLO-based motion localization, impact-frame identification, spatial motion parameter estimation, and Magnus-effect-informed trajectory simulation.

As illustrated in Figure 6, the reconstruction process begins with synchronized video acquisition from two fixed viewpoints: a side-view camera capturing motion within the X–Z plane and a top-view camera observing displacement within the X–Y plane. These complementary observations provide spatial information required for three-dimensional motion reconstruction. The acquired video sequences are subsequently processed using a YOLO-based visual localization framework to detect tennis ball positions across consecutive frames. Following impact-frame identification, the system estimates key kinematic and spatial parameters, including elevation angle, vertical displacement, horizontal velocity, and lateral motion deviation.

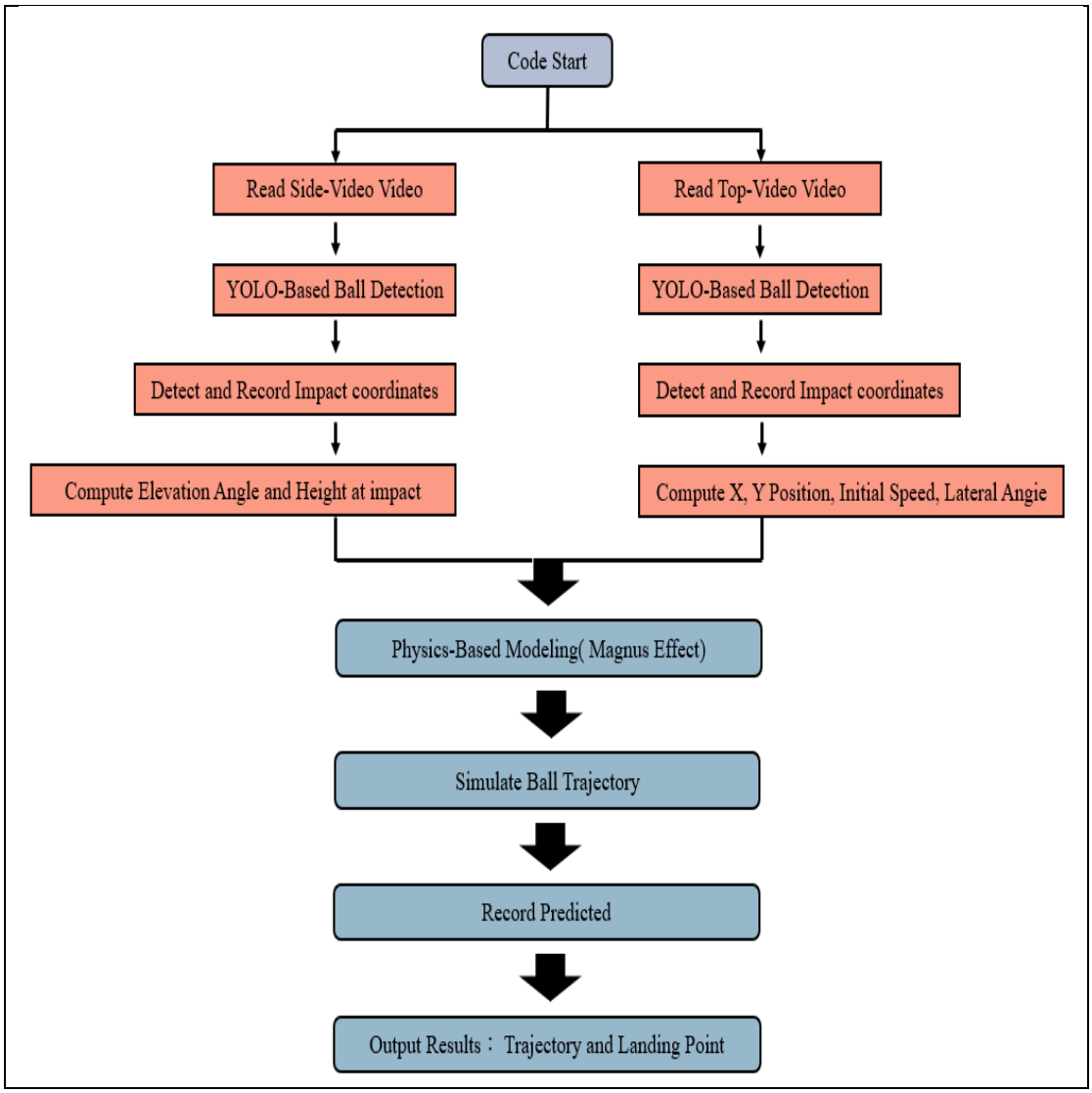


Figure 6. Coupled visual–physical framework for high-speed tennis trajectory reconstruction and aerodynamic simulation.
The framework integrates synchronized dual-view motion acquisition, YOLO-based visual localization, spatial motion parameter estimation, and Magnus-effect-informed nonlinear aerodynamic modeling for three-dimensional trajectory reconstruction and landing-point estimation.

The extracted motion parameters are then incorporated into a physics-informed simulation module governed by gravitational, drag, and Magnus-effect-induced aerodynamic forces. Through nonlinear aerodynamic trajectory modeling, the system reconstructs spin-dependent flight evolution and predicts landing positions under realistic motion conditions. The reconstructed trajectories and landing-point estimations are subsequently visualized and stored for further motion analysis. Owing to its modular architecture and non-intrusive sensing configuration, the proposed framework provides strong adaptability for high-speed sports trajectory reconstruction and physics-informed motion analysis applications.

3.2 Dual-Camera Configuration and Data Acquisition

To acquire synchronized multi-view motion data for three-dimensional trajectory reconstruction, this study employed an Osmo Action camera and a drone-mounted 4K camera to record tennis strokes from side-view and top-view perspectives, respectively. The side-view camera recorded video at 1080P resolution and 60 frames per second (FPS), while the aerial camera captured 2160P (4K) video at 60 FPS, ensuring temporal synchronization and sufficient spatial resolution for high-speed motion analysis. The side-view camera was mounted on a tripod at a height of approximately 1.39 m and positioned 3.28 m from the doubles sideline and 3.13 m behind the baseline on the right side of the court. This configuration provided a stable lateral observation angle for capturing racket–ball interaction, elevation angle, and vertical trajectory evolution. The drone-mounted top-view camera hovered approximately 12 m above the court and 4.5 m behind the baseline, enabling wide-area observation of horizontal displacement and lateral trajectory evolution during ball flight.

Both video streams were recorded simultaneously under consistent environmental conditions to minimize temporal misalignment and spatial inconsistency between viewpoints. The synchronized recordings served as the primary data source for YOLO-based motion localization, spatial parameter estimation, and nonlinear aerodynamic trajectory reconstruction in subsequent processing stages. The experiments were conducted on a red clay tennis court at National Kaohsiung University of Science and Technology (NKUST), Kaohsiung, Taiwan. To ensure acquisition stability and

operational safety, the experimental procedure was coordinated by five personnel responsible for drone operation, side-view recording, experimental supervision, ball serving, and stroke execution. The overall spatial arrangement and personnel configuration are illustrated in Figure 7.

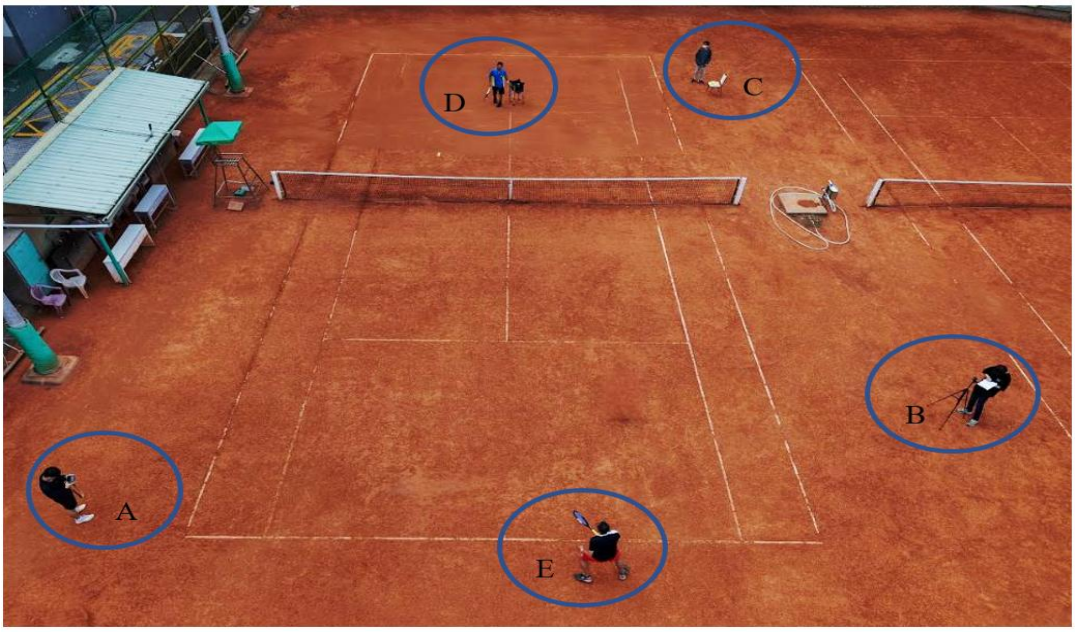


Figure 7. Experimental environment and personnel configuration.
This figure illustrates the spatial arrangement of personnel during the video data collection process. Five roles were assigned in the experimental setup: A represents the drone operator, B is the camera operator, C is the experiment supervisor, D is the server, and E is the hitter.

The synchronized multi-view acquisition framework established in this study provides complementary spatial observations for subsequent motion localization and three-dimensional trajectory reconstruction. By combining side-view and top-view motion information, the proposed system improves spatial consistency and enables more reliable estimation of kinematic parameters under high-speed sports conditions.

3.3 YOLO-Based Tennis Ball Detection

The proposed framework employs YOLOv8 as the primary visual motion localization mechanism for detecting high-speed tennis ball trajectories across consecutive video frames. YOLOv8 adopts an end-to-end detection strategy that enables simultaneous object localization and classification with high computational efficiency and spatial consistency. Compared with earlier detection frameworks, YOLOv8 provides improved localization robustness under conditions involving motion

blur, rapid displacement, partial occlusion, and illumination variation, which are commonly encountered in high-speed racket sports environments.

To improve localization precision for small and fast-moving objects, the framework incorporates multiscale feature extraction and optimized bounding-box regression mechanisms. In particular, the integration of Distribution Focal Loss enhances spatial localization granularity and improves detection stability during rapid ball motion. These characteristics are particularly important for subsequent kinematic parameter estimation and three-dimensional trajectory reconstruction, where localization errors may directly influence aerodynamic simulation accuracy. Figure 8 illustrates the conceptual workflow of the YOLO-based motion localization framework employed in this study. The model performs hierarchical feature extraction, spatial motion representation learning, and object localization to identify tennis ball positions across synchronized video sequences for subsequent trajectory analysis.

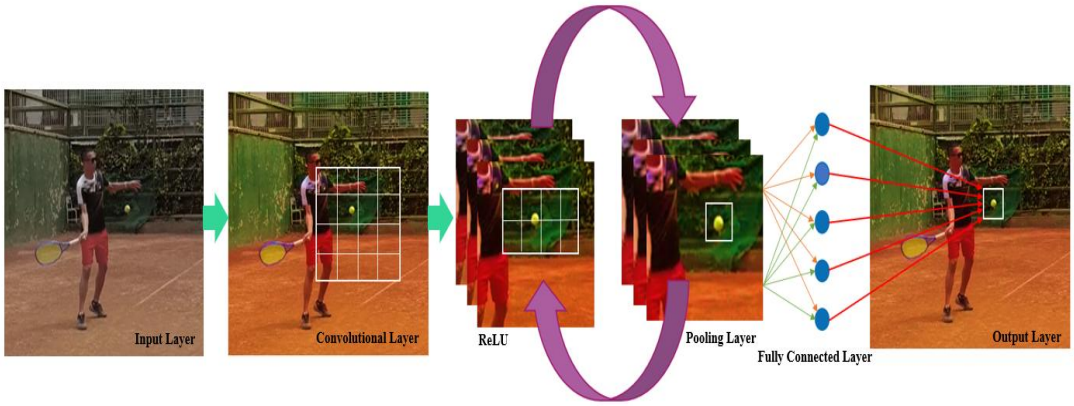


Figure 8. Conceptual workflow of the YOLO-based visual motion localization framework for high-speed tennis trajectory analysis.
The framework performs hierarchical feature extraction and spatial localization across synchronized video frames to identify tennis ball positions under dynamic sports conditions. The extracted motion information is subsequently utilized for kinematic parameter estimation and trajectory reconstruction.

In this study, YOLOv8 is employed as the primary visual localization framework for detecting tennis ball positions across synchronized video frames. To ensure reliable spatial localization under high-speed motion conditions, the framework incorporates confidence-based prediction filtering and Non-Maximum Suppression (NMS) to eliminate redundant detections. The confidence score associated with each predicted bounding box is formulated in Equation (1), while the suppression criterion used for overlapping predictions is defined in Equation (2). By retaining only the highest-confidence spatial prediction, the framework improves localization stability and

reduces duplicate detections during rapid ball motion.

The Intersection over Union (IoU) metric is adopted to evaluate spatial overlap consistency between predicted and ground-truth bounding boxes. The intersection-area computation and IoU ratio are defined in Equations (3) and (4), respectively. Since tennis balls occupy relatively small image regions and frequently exhibit motion blur during high-speed flight, a spatial containment constraint is additionally introduced to complement IoU-based matching. Specifically, a predicted bounding box (P) is considered a valid localization result when it is fully enclosed within the corresponding ground-truth region (G), as defined in Equation (5). This strategy improves localization robustness and enhances the reliability of subsequent kinematic parameter estimation and trajectory reconstruction.

$$Confidence = Pr(Object) \times IoUU_{truth,pred} \tag{1}$$

$$keep_{\mathrm{i}} = IoU(box_i, box_j) < \tau \tag{2}$$

$$Area(A \cap B) = max(0, min(x_2^A, x_2^B) - max(x_1^A, x_1^B)) \tag{3}$$

$$\cdot\, max(0, min(y_2^A, y_2^B y) - max(y_1^A, y_1^B\ ))$$

$$IoU = \frac{Area(A \cap B)}{Area(A) + Area(B) - Area(A \cap B)} \tag{4}$$

$$P \subseteq G \Leftrightarrow (x_1^P \geq x_1^G) \wedge (y_1^P \geq y_1^G) \wedge (x_2^P \leq x_2^G\ ) \wedge (y_2^P \leq y_2^G) \tag{5}$$

Through the integration of confidence-based filtering, IoU evaluation, and spatial containment constraints, the proposed localization framework improves the stability and precision of tennis ball detection under high-speed motion conditions. The resulting spatial localization information provides reliable input for subsequent kinematic parameter estimation and three-dimensional trajectory reconstruction, thereby supporting the physics-informed aerodynamic simulation framework developed in this study.

3.4 Impact Frame Identification

To estimate critical kinematic parameters such as initial velocity, elevation angle, and lateral motion deviation, the proposed framework first identifies the temporal location corresponding to racket–ball interaction, referred to as the impact frame. This temporal localization process serves as a critical reference point for subsequent motion parameter estimation and nonlinear trajectory reconstruction.

The impact frame is determined by analyzing the temporal evolution of tennis ball motion extracted from YOLOv8-based spatial localization results. During racket–ball interaction, the ball typically undergoes a rapid transition in motion direction and

velocity distribution, producing an observable discontinuity in trajectory evolution. Accordingly, the proposed framework identifies the impact event by detecting abrupt directional transitions and angular variation between consecutive trajectory segments across synchronized video frames.

As illustrated in Figure 9, the incoming trajectory prior to racket contact is represented by the blue motion path, whereas the outgoing trajectory following impact is indicated by the red motion path. The transition point between these motion segments corresponds to the estimated impact frame. Under the synchronized 60 FPS acquisition configuration employed in this study, the trajectory transition can be reliably localized within a short temporal interval, thereby improving the consistency of subsequent kinematic estimation and aerodynamic trajectory simulation.

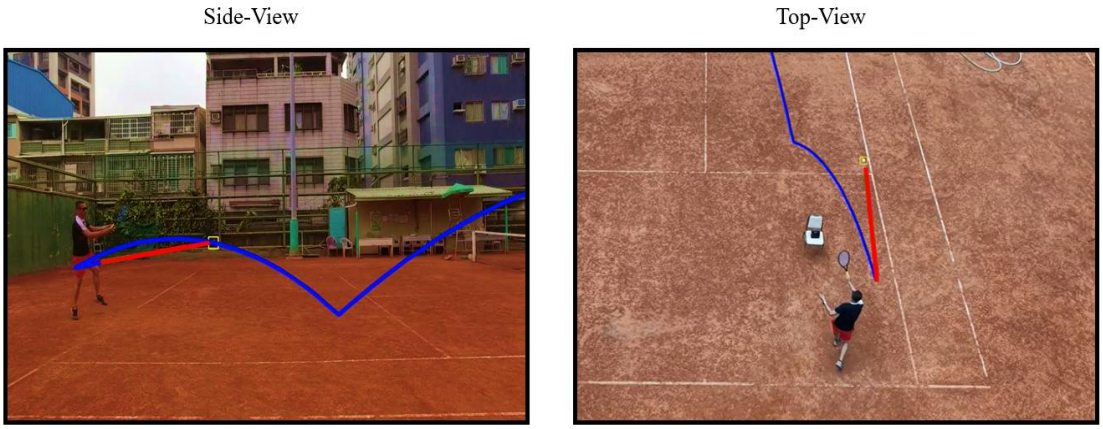


Figure 9. Visual demonstration of automatic impact-frame identification under side-view and top-view motion observations.
The incoming trajectory prior to racket–ball interaction is represented by the blue motion path, while the outgoing trajectory following impact is indicated by the red motion path. The transition point between the two trajectory segments is identified as the estimated impact frame for subsequent kinematic parameter estimation and trajectory reconstruction.

3.5 Kinematic and Spatial Parameter Estimation

Following impact-frame localization, the proposed framework estimates a set of kinematic and spatial motion parameters required for nonlinear trajectory reconstruction and aerodynamic simulation. These parameters include initial velocity, elevation angle, and lateral motion direction, which collectively define the initial conditions governing subsequent trajectory evolution. The parameters are estimated from synchronized dual-view motion observations and reconstructed spatial displacement information obtained from YOLO-based localization results.

3.5.1 Initial Velocity Reconstruction

Initial velocity is one of the most critical kinematic parameters governing tennis ball trajectory evolution. In physics-informed aerodynamic simulation, the reconstructed initial velocity directly affects subsequent drag-force computation, Magnus-effect-induced motion behavior, and landing-point estimation. Therefore, accurate estimation of the ball velocity immediately following racket–ball interaction is essential for reliable nonlinear trajectory reconstruction.

To estimate the initial velocity, the proposed framework utilizes synchronized consecutive frames captured immediately after the identified impact frame. As illustrated in Figure 10, the displacement of the tennis ball between the impact frame (Frame A) and the subsequent post-impact frame (Frame B) is reconstructed from YOLO-based spatial localization results. The yellow bounding boxes indicate the detected ball position in each frame, while the displacement vector represents the motion transition occurring within the short temporal interval between consecutive frames.

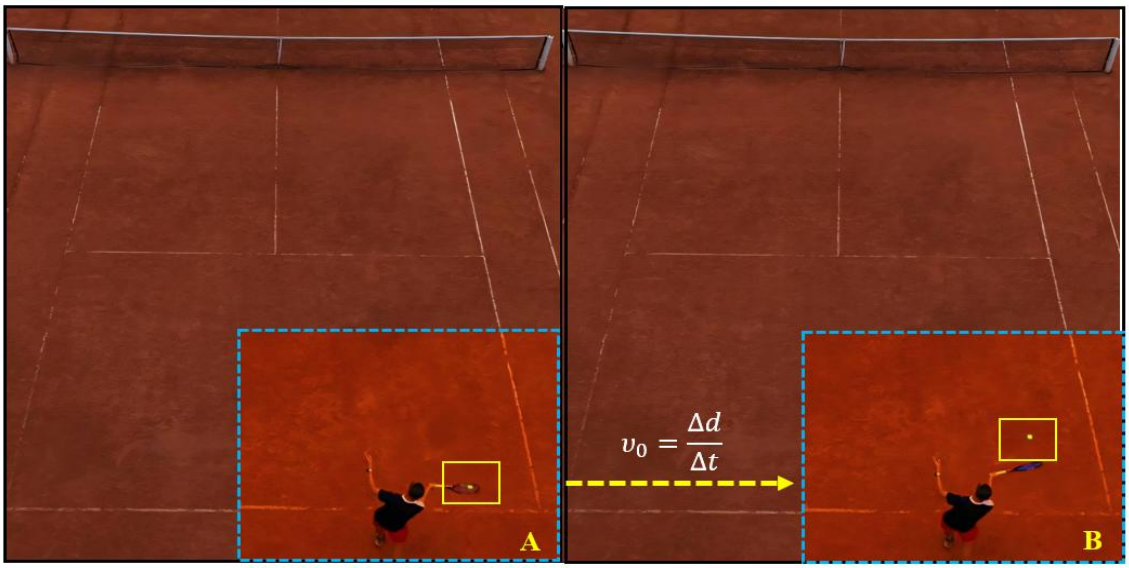


Figure 10. Temporal displacement reconstruction for initial velocity estimation using synchronized consecutive frames.

The impact frame (A) and the subsequent post-impact frame (B) are utilized to reconstruct short-term tennis ball displacement immediately following racket–ball interaction. The tennis ball positions detected by the YOLO-based localization framework are enclosed within yellow bounding boxes, while the displacement vector illustrates the frame-to-frame motion transition used for initial velocity reconstruction.

As shown in Figure 10, the frame-to-frame displacement reconstruction provides

a direct representation of short-term ball motion immediately after racket contact. The reconstructed initial velocity subsequently serves as a key initial condition for the nonlinear aerodynamic trajectory simulation developed in this study, enabling Magnus-effect-informed trajectory evolution and physically consistent landing-point estimation under realistic high-speed sports conditions.

The initial velocity is computed using the displacement–time relationship (6), where v_0 denotes the reconstructed initial velocity, Δd represents the spatial displacement of the tennis ball between two consecutive synchronized frames, and Δt the temporal interval between frames. Under the 60 FPS acquisition configuration adopted in this study, the temporal interval is defined as (7). To account for three-dimensional motion evolution, the spatial displacement is reconstructed using Euclidean distance estimation (8), where (x_1, y_1, z_1) and (x_2, y_2, z_2) denote the reconstructed three-dimensional coordinates of the tennis ball obtained from synchronized multi-view spatial observations.

$$v_0 = \frac{\Delta d}{\Delta t} \tag{6}$$

$$\Delta t = \frac{1}{60}\ s \tag{7}$$

$$\Delta d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2} \tag{8}$$

The frame-to-frame displacement reconstruction provides a direct representation of short-term ball motion immediately after racket contact. The reconstructed initial velocity subsequently serves as a key initial condition for the nonlinear aerodynamic trajectory simulation developed in this study, enabling Magnus-effect-informed trajectory evolution and physically consistent landing-point estimation under realistic high-speed sports conditions.

3.5.2 Elevation Angle Estimation

The elevation angle represents a critical kinematic parameter governing the vertical evolution of tennis ball trajectories. In physics-informed aerodynamic simulation, the elevation angle directly influences trajectory curvature, apex height, flight duration, and the interaction between gravitational and Magnus-effect-induced aerodynamic forces. Accurate estimation of the launch elevation angle is therefore essential for realistic nonlinear trajectory reconstruction.

In the proposed framework, the elevation angle is estimated using synchronized side-view motion observations obtained immediately following racket–ball interaction. As illustrated in Figure 11, the side-view camera captures the vertical displacement of the tennis ball relative to the horizontal motion direction. The detected ball positions are first reconstructed from consecutive frames using YOLO-based spatial localization,

after which the vertical displacement ΔY and horizontal displacement ΔX are computed within the side-view projection plane. The elevation angle is subsequently estimated using the geometric relationship between vertical and horizontal displacement components (9), where θ denotes the reconstructed elevation angle, ΔY represents the vertical displacement of the tennis ball, and ΔX corresponds to the horizontal displacement observed from the side-view projection.

$$\theta = \tan^{-1}\left(\frac{\Delta Y}{\Delta X}\right) \tag{9}$$

As shown in Figure 11, the reconstructed velocity vector v_0 forms an angular relationship with the horizontal reference plane immediately after racket–ball interaction. The estimated elevation angle therefore provides an important initial directional condition for subsequent three-dimensional trajectory reconstruction and nonlinear aerodynamic simulation. The reconstructed elevation angle is subsequently integrated with initial velocity and spatial motion parameters to establish the initial conditions required for Magnus-effect-informed trajectory evolution and landing-point estimation under realistic high-speed sports conditions.



Figure 11. Geometric illustration of elevation angle estimation from side-view.
This figure illustrates the geometric configuration used for estimating the elevation angle from the side-view.

3.5.3 Lateral Motion Angle Estimation

The lateral motion angle represents the horizontal directional component governing tennis ball trajectory evolution within the court plane. In aerodynamic trajectory simulation, this parameter plays an important role in determining lateral

displacement behavior, directional deviation, and spin-induced horizontal trajectory evolution. Accurate estimation of the lateral motion angle is therefore essential for realistic three-dimensional trajectory reconstruction and landing-point prediction.

In the proposed framework, the lateral motion angle is estimated using synchronized top-view motion observations obtained immediately following racket–ball interaction. As illustrated in Figure 12, the top-view camera captures the horizontal displacement of the tennis ball relative to the forward motion axis of the court. The YOLO-based localization framework first identifies the tennis ball position across consecutive synchronized frames, after which the horizontal displacement components are reconstructed within the top-view projection plane.



Figure 12. Geometric illustration of lateral deviation angle from top-view.
Gray dashed line: Ball field forward axis (Z-axis). Blue vector: Initial velocity vector of the ball's motion after impact. Red arc: Angle between the ball's direction of motion and the forward axis, defined as the horizontal deflection angle.

The lateral motion angle is computed from the geometric relationship between the reconstructed displacement vector and the forward court axis (10), where ϕ denotes the reconstructed lateral motion angle, ΔX represents the lateral displacement component, and ΔZ corresponds to the forward displacement component observed

from the top-view projection plane.

$$\phi = \tan^{-1}\left(\frac{\Delta Y}{\Delta X}\right) \tag{10}$$

The reconstructed initial velocity vector v_0 forms an angular deviation relative to the forward motion axis immediately following racket–ball interaction. The resulting lateral motion angle therefore provides an important directional parameter for modeling horizontal trajectory evolution and spin-dependent aerodynamic deviation during ball flight. The reconstructed lateral motion angle is subsequently integrated with initial velocity and elevation angle parameters to establish the complete three-dimensional initial conditions required for Magnus-effect-informed nonlinear trajectory simulation and physically consistent landing-point estimation.

3.5.4 Three-Dimensional Initial Velocity Vector Reconstruction

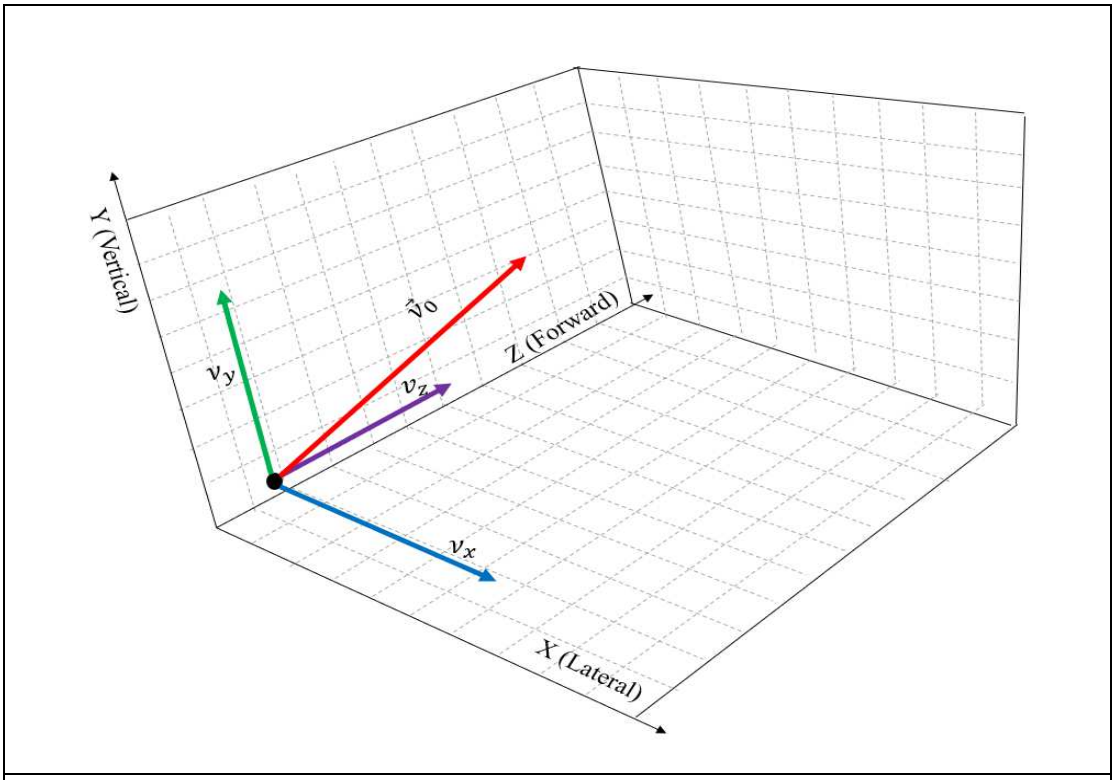
Based on the kinematic parameters reconstructed in Sections 3.5.1– 3.5.3, including the initial velocity magnitude v_0, elevation angle θ, and lateral motion angle ϕ, the proposed framework reconstructs the three-dimensional initial velocity vector immediately following racket–ball interaction. This vector formulation establishes the initial motion condition governing subsequent nonlinear trajectory evolution and aerodynamic simulation.

As illustrated in Figure 13, the reconstructed initial velocity vector is represented within a court-fixed three-dimensional coordinate system composed of lateral(X), vertical(Y), and forward(Z) motion axes. The total initial velocity vector is decomposed into three orthogonal motion components (11), where v_x, v_y and v_z denote the lateral, vertical, and forward velocity components, respectively. Using the reconstructed elevation angle and lateral motion angle, the velocity components are formulated as (12).

$$\phi = \tan^{-1}\left(\frac{\Delta Y}{\Delta X}\right) \tag{11}$$

$$\begin{aligned} v_x &= v_0 \cos\theta \, sin\phi \\ v_y &= v_0 \sin\theta \\ v_z &= v_0 \cos\theta \, cos\phi \end{aligned} \tag{12}$$

As shown in Figure 13, the red vector represents the reconstructed total initial velocity immediately after impact, while the blue, green, and purple vectors correspond to the lateral, vertical, and forward motion components within the court-fixed coordinate system. Through this vector decomposition process, the proposed framework reconstructs the initial directional state of the tennis ball in three-dimensional space.



igure 13. Three-dimensional initial velocity vector reconstruction in the court-fixed coordinate system.

The figure illustrates the decomposition of the reconstructed initial velocity vector into lateral(v_x), vertical(v_y), and forward(v_z) motion components within the court-fixed coordinate system. The reconstructed three-dimensional velocity vector defines the initial directional condition for subsequent nonlinear aerodynamic trajectory simulation and Magnus-effect-informed motion evolution.

The reconstructed three-dimensional velocity vector subsequently serves as the primary initial condition for the nonlinear aerodynamic simulation framework developed in this study. By integrating velocity magnitude and directional motion components, the proposed framework enables Magnus-effect-informed trajectory evolution and physically consistent landing-point reconstruction under realistic high-speed sports conditions.

3.6 Aerodynamic Trajectory Simulation with Magnus Effect

Following reconstruction of the three-dimensional initial velocity vector, the proposed framework performs aerodynamic trajectory simulation to model the subsequent flight behavior of the tennis ball under realistic high-speed motion conditions. Unlike conventional projectile models that consider only gravitational acceleration, the present study incorporates both aerodynamic drag and Magnus-effect-induced lift forces to achieve physically consistent trajectory evolution and landing-

point prediction.

As illustrated in Figure 14, the motion of a spinning tennis ball is governed by the interaction among three principal physical components: the initial velocity vector $\vec{v}$, aerodynamic drag force $\vec{F}_d$, and Magnus force $\vec{F}_m$. The drag force acts in the direction opposite to the ball's motion and gradually reduces translational velocity during flight. In contrast, the Magnus force arises from the interaction between ball rotation and surrounding airflow, generating an aerodynamic lift component that produces lateral or vertical trajectory deviation.

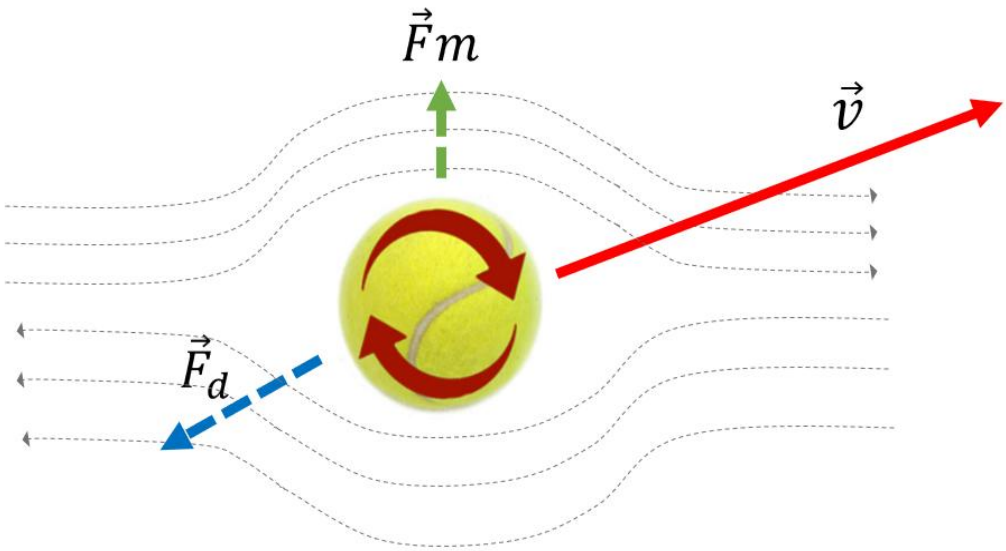


Figure 14. Aerodynamic force interactions acting on a spinning tennis ball during trajectory evolution.
The figure illustrates the interaction between ball velocity, aerodynamic drag, and Magnus force during spinning-ball flight. The combined aerodynamic effects produce nonlinear trajectory deviation during ball motion.

The Magnus force is modeled as proportional to the vector cross product between angular velocity and translational velocity (13), where $\vec{\omega}$ denotes the angular velocity vector associated with ball spin, and $\vec{v}$ represents the translational velocity vector of the tennis ball. The resulting aerodynamic force direction is perpendicular to both the spin axis and motion direction, thereby introducing nonlinear trajectory deviation during flight. To account for aerodynamic resistance, the drag force is modeled as (14), where c_d denotes the aerodynamic drag coefficient and $\|\vec{v}\|$ represents the magnitude of the translational velocity vector. The drag force continuously dissipates kinetic energy throughout the flight process and influences both trajectory curvature and landing distance.

$$\vec{F}_m \propto \vec{\omega} \times \vec{v} \tag{13}$$

$$\vec{F}_d = -c_d \|\vec{v}\| \vec{v} \tag{14}$$

By integrating gravitational acceleration, aerodynamic drag, and Magnus-effect-induced lift into a unified motion framework, the proposed simulation model reconstructs the nonlinear flight evolution of spinning tennis balls under realistic sports conditions. The reconstructed trajectory is subsequently utilized for landing-point prediction and three-dimensional motion visualization, thereby enabling physically informed sports trajectory analysis and virtual–physical trajectory integration.

4. Experiments and Results

To evaluate the physical consistency and predictive robustness of the proposed nonlinear trajectory reconstruction framework, a controlled experimental dataset comprising 40 tennis strokes was collected under realistic court conditions. The dataset was equally distributed across daytime and nighttime environments to investigate the influence of environmental illumination on visual motion localization and aerodynamic trajectory reconstruction. Each stroke was synchronously recorded using a dual-view acquisition framework consisting of a top-view aerial camera and a side-view court-level camera. Both cameras operated at 60 frames per second (FPS) to ensure sufficient temporal resolution for high-speed motion analysis and frame-level trajectory reconstruction.

Unlike conventional trajectory evaluation approaches relying solely on post-hoc video annotation, the present study employed a red clay tennis court to obtain physically observable landing-point ground truth. After each stroke, the actual landing position of the tennis ball was directly identified from the clay-surface impact mark and subsequently measured using a standard tape measure to establish spatial reference coordinates. This measurement strategy reduced annotation ambiguity and provided physically validated spatial observations for evaluating nonlinear trajectory evolution and landing-point reconstruction accuracy.

The coordinate system adopted in this study defined the origin at the intersection between the right doubles sideline and the baseline corner from the server's perspective. The X-axis represented lateral court displacement, whereas the Z-axis corresponded to longitudinal forward displacement along the court surface. Through the integration of synchronized multi-view motion acquisition and physically measured landing references, the proposed experimental framework establishes a reliable validation environment for assessing aerodynamic trajectory reconstruction, Magnus-effect-induced nonlinear deviation, and physics-informed landing-point prediction under realistic high-speed sports conditions.

4.1 Comparative Trajectory Reconstruction Analysis

To investigate the influence of spin-induced aerodynamic modeling on landing-point reconstruction performance, comparative trajectory simulations were conducted under two different physical modeling conditions: (1) aerodynamic trajectory reconstruction incorporating the Magnus effect and (2) conventional projectile-based trajectory reconstruction without Magnus-effect coupling. Prediction performance was evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) based on the spatial discrepancy between predicted landing positions and physically measured ground-truth coordinates. The quantitative comparison results are

summarized in Table 1.

As shown in Table 1, the incorporation of the Magnus effect substantially improved longitudinal trajectory reconstruction accuracy. Under the Magnus-effect-enabled condition, the Z-axis MAE decreased from 2.49 m to 1.08 m, while the corresponding RMSE decreased from 2.74 m to 1.34 m. Similarly, the total landing-point MAE decreased from 2.57 m to 1.32 m, accompanied by a reduction in RMSE from 2.82 m to 1.52 m. These findings indicate that spin-induced aerodynamic forces play a critical role in governing forward trajectory evolution and depth-related curvature during tennis ball flight.

In contrast, the X-axis reconstruction error exhibited comparatively minor variation between the two modeling conditions. The lateral MAE changed only slightly from 0.55 m to 0.57 m, while the RMSE varied from 0.66 m to 0.72 m. This observation suggests that the Magnus effect primarily influences longitudinal aerodynamic trajectory evolution rather than lateral displacement behavior under the current experimental configuration. From a physical perspective, the dominant contribution of the Magnus effect is associated with trajectory curvature and depth evolution along the flight direction, whereas lateral motion remains comparatively less sensitive to spin-induced aerodynamic coupling.

Table 1. MAE and RMSE of landing-point reconstruction under different aerodynamic modeling conditions.

	With Magnus Effect			Without Magnus Effect		
	X error	Z error	Total error	X error	Z error	Total error
MAE	0.57	1.08	1.32	0.55	2.49	2.57
RMSE	0.72	1.34	1.52	0.66	2.74	2.82

All values are expressed in meters (m)

The distributional characteristics of the reconstruction errors are further illustrated in Figure 15. Compared with the conventional non-Magnus model, the Magnus-effect-enabled framework exhibits both reduced median error and narrower error dispersion. The tighter interquartile range observed in the Magnus-based reconstruction indicates improved trajectory stability and greater physical consistency during nonlinear aerodynamic evolution. In contrast, the broader distribution observed in the non-Magnus condition suggests that simplified gravity-based projectile assumptions are insufficient for accurately reconstructing realistic spinning-ball motion under high-speed sports conditions.

The comparative results demonstrate that incorporating spin-dependent aerodynamic coupling substantially enhances the physical realism and reliability of

tennis trajectory reconstruction. By integrating Magnus-effect-informed motion dynamics with synchronized multi-view spatial reconstruction, the proposed framework achieves more stable nonlinear trajectory evolution and improved landing-point prediction consistency under realistic experimental environments.

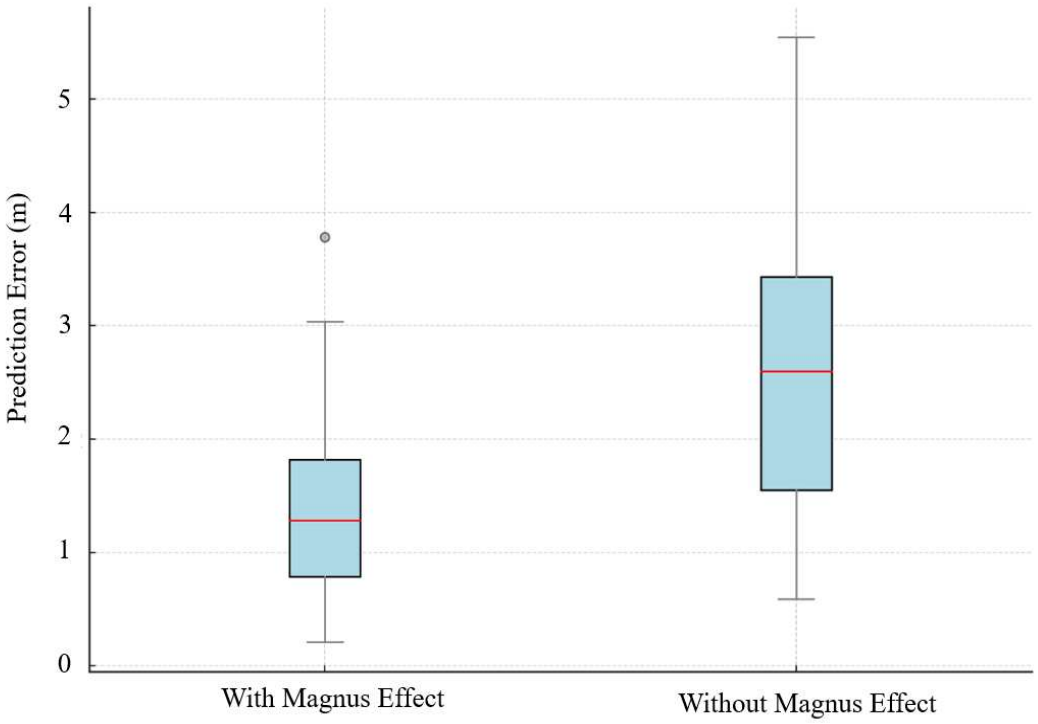


Figure 15. Distributional comparison of landing-point reconstruction errors under different aerodynamic modeling conditions.

The figure compares the distribution of landing-point reconstruction errors between trajectory simulations performed with and without Magnus-effect coupling. The Magnus-effect-enabled model exhibits reduced median error and narrower error dispersion, indicating improved trajectory stability and enhanced physical consistency during nonlinear aerodynamic trajectory evolution.

4.2 Aerodynamic and Environmental Effects on Landing-Point Reconstruction

To further investigate the influence of aerodynamic modeling and environmental illumination on landing-point reconstruction performance, both statistical regression analysis and spatial deviation analysis were conducted. The regression results are summarized in Table 2, while the spatial distribution of reconstruction deviations under different aerodynamic and lighting conditions is illustrated in Figure 16.

As shown in Figure 16, the simulations performed without Magnus-effect coupling exhibit a clear downward deviation along the longitudinal (ΔZ) direction under both daytime and nighttime conditions. Most non-Magnus predictions are distributed below

the ground-truth origin, indicating systematic underestimation of forward trajectory evolution and insufficient modeling of depth-related trajectory curvature. This observation suggests that conventional gravity-based projectile assumptions are inadequate for accurately reconstructing spinning-ball motion under realistic high-speed sports conditions.

In contrast, the Magnus-effect-enabled simulations exhibit distributions that are more concentrated around the actual landing position, with smaller confidence regions and reduced spatial dispersion. These results indicate improved trajectory stability and enhanced physical consistency during aerodynamic trajectory reconstruction. From a nonlinear dynamics perspective, incorporating Magnus-effect coupling enables the model to better capture spin-induced lift and nonlinear flight evolution throughout the ball trajectory. Furthermore, the confidence ellipses in Figure 16 show that the non-Magnus models exhibit larger reconstruction variance and stronger directional bias, particularly along the longitudinal axis. By comparison, the Magnus-based models maintain more compact and symmetric spatial distributions under both lighting conditions. Overall, these findings demonstrate that physically informed aerodynamic modeling substantially improves the stability, realism, and reliability of landing-point reconstruction in high-speed tennis trajectory simulation.

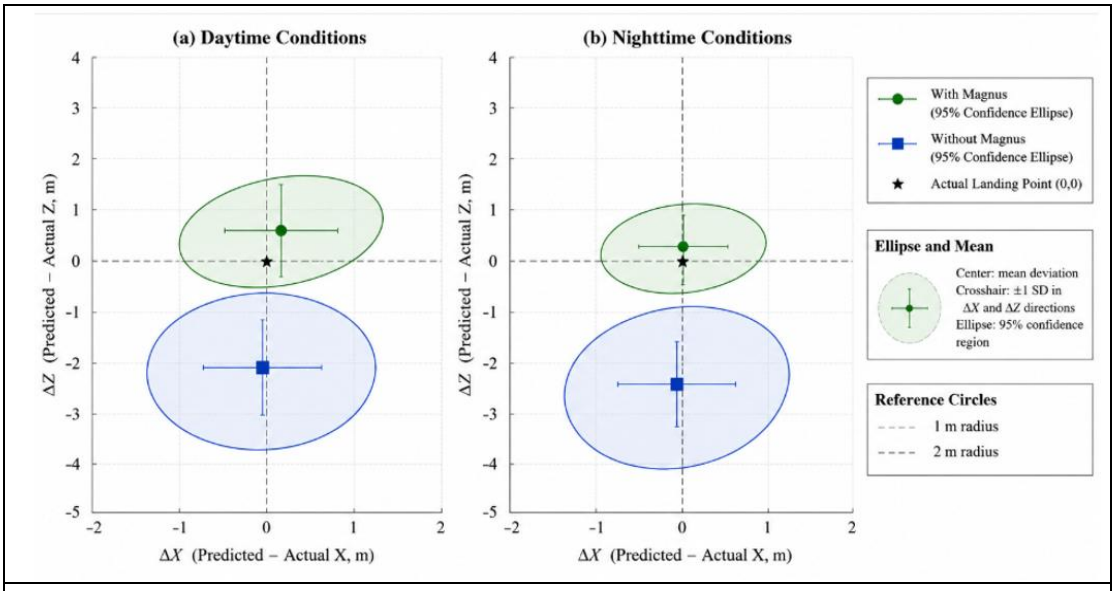


Figure 16. Spatial distribution of landing-point reconstruction deviations under daytime and nighttime conditions.

Each subplot summarizes the deviation between predicted and physically measured landing positions in the horizontal (ΔX) and longitudinal (ΔZ) directions. Green markers represent results with Magnus-effect modeling, while blue markers represent results without Magnus-effect modeling. The filled markers indicate the mean deviation, and the solid ellipses represent the 95% confidence regions of the deviation

distribution. Crosshairs denote ±1 standard deviation in both ΔX and ΔZ directions. Dashed circles indicate radial error bounds of 1 m and 2 m from the actual landing point at the origin (0,0). Ellipses closer to the origin and with smaller areas indicate higher reconstruction accuracy and stability.

The regression analysis presented in Table 2 further supports these observations. For lateral reconstruction errors along the X-axis, the regression model yielded relatively low explanatory power (R^2=0.09), indicating that aerodynamic modeling and environmental illumination exert limited influence on lateral displacement reconstruction under the current experimental configuration. The Magnus effect was not statistically significant for X-axis reconstruction error (p=0.80), suggesting that spin-induced aerodynamic coupling primarily affects longitudinal trajectory evolution rather than lateral motion deviation. However, nighttime recording conditions significantly reduced X-axis reconstruction error (p=0.01). This improvement is likely attributable to enhanced foreground–background contrast under artificial illumination, which improves object localization stability in aerial-view motion acquisition. In contrast, daytime aerial recordings are more susceptible to environmental reflections and illumination variability, potentially reducing localization consistency for small high-speed objects.

For longitudinal reconstruction errors along the Z-axis, the regression model achieved substantially higher explanatory power (R^2=0.33). Most importantly, the inclusion of Magnus-effect coupling significantly reduced Z-axis reconstruction error (p<0.001). This result confirms that spin-induced aerodynamic lift plays a dominant role in governing forward trajectory curvature and depth-related landing evolution during tennis ball flight. The day/night variable was not statistically significant for Z-axis reconstruction (p=0.40), indicating that the side-view acquisition environment remained comparatively stable across illumination conditions.

The combined statistical and spatial analyses demonstrate that Magnus-effect-informed aerodynamic modeling substantially improves longitudinal trajectory reconstruction consistency and reduces systematic landing-point bias under realistic high-speed sports conditions. The findings further indicate that physically informed trajectory evolution models are essential for accurately reconstructing spinning-ball motion beyond simplified gravity-based projectile assumptions.

Table 2. Regression analysis of aerodynamic and environmental effects on landing-point reconstruction errors

View	Variable	Coefficient	p-value	R-squared
Top View (X-axis)	Intercept	0.67	0	0.09

	Magnus Effect	0.02	0.8	
	Time of Day (Night)	-0.24	0.01	
Side View (Z-axis)	Intercept	2.58	0	0.33
	Magnus Effect	-1.4	0	
	Time of Day (Night)	-0.18	0.4	

$p < 0.05$ indicates statistical significance. All errors are measured in meters.

5. Conclusion

This study proposed a physics-informed tennis trajectory reconstruction framework integrating synchronized dual-view motion acquisition, YOLO-based object detection, three-dimensional kinematic reconstruction, and aerodynamic trajectory simulation incorporating the Magnus effect. Through synchronized top-view and side-view observations, the proposed system reconstructed key motion parameters and simulated nonlinear tennis ball trajectories under realistic high-speed sports conditions.

The experimental results demonstrated that incorporating Magnus-effect-informed aerodynamic modeling substantially improved landing-point reconstruction accuracy and trajectory stability. Comparative analyses showed significant reductions in longitudinal reconstruction error and systematic depth-related prediction bias under Magnus-effect-enabled conditions. These findings confirm that spin-induced aerodynamic forces play a critical role in governing nonlinear tennis trajectory evolution and that simplified gravity-based projectile models are insufficient for accurately reconstructing realistic spinning-ball motion.

The proposed framework establishes an effective integration between computer vision and nonlinear aerodynamic modeling for intelligent sports trajectory analysis. By combining multi-view spatial reconstruction with physics-informed motion simulation, this study advances toward physically consistent landing-point prediction and high-fidelity sports trajectory reconstruction.

Nevertheless, several limitations remain. The current framework does not directly estimate real-time spin magnitude or airflow turbulence, which may further influence trajectory evolution under real-world conditions. Future research may incorporate physics-informed learning models and adaptive aerodynamic parameter estimation to improve nonlinear trajectory reconstruction and intelligent sports simulation capabilities.

Declarations

Ethics approval and consent to participate

The study was approved by the Institutional Review Board of Kaohsiung Medical University Hospital, Kaohsiung, Taiwan (KMUHIRB) (approval code: KMUHIRB-E(I)-20220234; approval date: 27 September 2023). Written informed consent was obtained from all participants prior to their participation in the study.

Consent for publication

Written informed consent for publication of the identifiable images presented in Figures 1, 3, 8, 9, 10, and 11 was obtained from the corresponding author, who is the individual depicted in these figures. The corresponding author has reviewed and approved the publication of these images in this manuscript.

Availability of data and materials

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

Competing Interests

The authors declare that they have no competing interests.

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Authors' contributions

Conceptualization: W.-T.L. and H.-C.H.; methodology: W.-T.L. and H.-C.H.; software: K.G.L. and K.W.L.; validation: H.-C.H.; formal analysis: K.G.L.; investigation: W.-T.L. and H.-C.H.; resources: K.W.L.; data curation: K.G.L.; writing—original draft preparation: W.-T.L. and H.-C.H.; writing—review & editing: W.-T.L.; visualization: K.G.L.; supervision: K.W.L.; project administration: K.W.L.; funding acquisition: W.T.L. All authors have read and approved the final manuscript.

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