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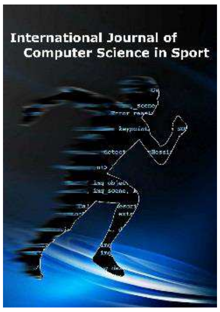

Spin measurement system for table tennis balls based on asynchronous non-high-speed cameras

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Abstract

The spin of the ball plays a crucial role in table tennis tactics. However, it has rarely been measured and reported for the broadcast audience to better understand table tennis matches. This paper introduces a system designed to measure the spin of a table tennis ball without using electrically synchronized shutters or high-speed cameras. The system employs multiple unsynchronized cameras to detect the logos printed on the ball and estimates its three-dimensional translational motion to determine the spin rate (rotational velocity expressed in the revolutions per unit time) and spin axis (imaginary line around which the ball rotates). An experimental analysis indicated median errors of 0.78 rps and 12.5° in spin rate and axis, respectively. Additionally, the system exhibited sufficient resolution to analyze the spin rate and axis of a service ball in table tennis, distinguishing between spin axes that differ by 30° with 95.8% confidence. The developed system was used in the Japanese T-League to report the spin of several services after the live streaming of matches. The developed system successfully measured the spins of 92.1% of the served balls, confirming that the system has sufficient capability to feedback spin data immediately after a match.

KEYWORDS: TABLE TENNIS, BALL SPIN, TRAJECTORY, COMPUTER VISION, UNSYNCHRONIZED CAMERA

Introduction

The spin rate of a ball, rotational velocity of the ball expressed in revolutions per unit of time, is crucial for comprehending tactics and techniques in numerous sports. For instance, the spin of the ball significantly influences its trajectory in a baseball game, and the pitcher's control over the ball's spin is instrumental in making the ball's trajectory less predictable to the batter. Nagami et al. (2011) analyzed the trajectory of high-speed pitches delivered by college-level pitchers. They determined that pitchers who achieved the highest strikeout rates in collegiate baseball leagues exhibited the highest ratio of rotational to translational velocities of the ball. Additionally, the spin rate is significant for hitters as well because a strong backspin on the ball results in an upward lift and increases the distance traveled by the ball. The spin rates of both pitched and batted balls in Major League Baseball, the premier professional baseball league of the United States, have been measured for comprehensive performance analysis. Similar to baseball, the spin rate of the ball is a critical factor that influences shot distance in golf (TrackMan, n.d.-a). Herein, as the spin rate of a ball affects its bounce after being dropped, backspin is occasionally applied to ensure precise ball placement, particularly over shorter distances. To achieve optimal ball spin under various conditions, the correlation between the mechanical properties of golf clubs and ball spin is being increasingly researched (Monk, Davis, Strangwood, & Otto, 2004; Moriyama, Yamaguchi, Yabu, & Tsunoda, 2004). Professional golf tours in the United States measure the spin of each shot and publish average values (TrackMan, n.d.-b). In tennis, although the emphasis is placed on the translational velocity of the ball, the spin of the ball is a crucial factor that influences both the trajectory and the variations in the post-bounce trajectory of the ball. Goodwill, Douglas, Miller, and Haake (2010) demonstrated the impact of the string stiffness of a tennis racket on ball spin. Sakurai, Reid, and Elliott (2013) measured the spin of three types of serves performed by seven elite male players and provided a quantitative analysis of the spin for each type. Furthermore, an ATP Tour measures the spin of all shots and publishes the average spin rate of the forehands and backhands for each match (Infosys, 2017). These reports imply that ball spin is employed in numerous sports to comprehend or analyze gameplay.

Similarly, the spin of the ball is a tactically and technically important element of table tennis. Geske~~,~~ and Mueller (2010) reported that handling a spinning ball in table tennis is more challenging than in other racket sports as the spin of the ball significantly alters its trajectory following its impact with a racket. This can be attributed to the exceedingly lightweight of the ball, which exhibits a high coefficient of friction when struck by the rubber side of a table tennis racket. Consequently, the frictional force substantially influences the post-impact trajectory of the ball. Numerous table tennis players capitalize on this characteristic and manipulate the spin of the ball during service to induce errors in their opponents. Lodziak (2020) observed that a combination of backspin, topspin, sidespin, and no spin or extremely low spin is required to enhance the variability of serves. Furthermore, certain techniques exist that not only control the spin but also render it challenging to discern the spin from the hitting motion. Iino, Tamaki, Inaba, Yamada, and Yoshida (2021) reported that elite players possess superior skills in delivering services with indiscernible spins, in contrast to collegiate players. If the receivers cannot accurately discern the spin on the service, they may struggle to return the ball successfully to the opponent's court or the ball may be returned in a manner that makes it susceptible to a powerful hit by the opponent.

Despite the significant role of ball spin in table tennis, only a few studies have measured ball spin during actual matches. Huan, Zhifeng, Shaofa, and Enting (1992) assessed the spin rate of three different types of strokes executed by 24 players on the Chinese National Team and the National Youth Team. Lee and Xie (2004) quantified the spin rate of backspin and sidespin services executed by five Singaporean players. Iizuka et al. (2010) measured the spin of the services of six top-level Japanese junior players. However, these studies evaluated the spin characteristics of balls launched in controlled laboratory settings devoid of opponents rather than during live gameplay. Yoshida, Yamada, Tamaki, Naito, and Kaga (2014) measured the spin rate of service balls in eight men's and eight women's singles matches. The results indicated that the most frequent spin rate for men's services was between 50 and 60 rps, whereas that for women's services ranged from 40 to 50 rps. They focused on measuring the spin of the ball during a match, specifically the spin rate, without considering the spin axis, imaginary line around which the ball rotates.

To the best of our knowledge, no studies have reported instances of ball spin measurements during a game of table tennis because of the challenges involved. The simplest method involves manual measurement, as reported by Yoshida et al. (2014). The surface of a table tennis ball bears an imprint of the manufacturer and/or professional league logo (Figure 1). The spin rate can be determined by capturing images using a high-speed camera and measuring the time taken by the logo to complete a single rotation. However, the spin-axis measurement in this method is time-consuming. Moreover, manual measurement of the ball spin is challenging for several samples. To address this challenge, numerous approaches have been proposed for the automated assessment of ball spin using computer vision technology, which often requires high-speed cameras (Furuno, Kobayashi, Okubo, & Kurihara, 2009; Jinji & Sakurai, 2006; Kadowaki, Kobayashi, & Watanabe, 2006; Liu, Hayakawa, & Nakashima; Shum & Komura, 2005; Szep, 2011; Tamaki, Sugino, & Yamamoto, 2004; Tamaki, Ushiyama, Raytchev, & Kaneda, 2011; Tamaki, Wang, Raytchev, Kaneda, & Ushiyama, 2012). However, employing high-speed cameras entails several issues, such as expensive equipment, substantial data volume, and prolonged computational time. This implies that high-speed cameras are impractical for the measuring ball spin in a short period of time. Moreover, several measurement methods quantify the spin by adding a mark to the ball's surface rather than using the logo imprinted on the ball (Furuno et al., 2009; Jinji & Sakurai, 2006; Kadowaki et al., 2006; Liu et al., 2012; Shum & Komura, 2005; Szep, 2011; Tamaki et al., 2004; 2011; 2012). Since table tennis players may utilize ball marks to identify spin, the method of adding marks to the ball is inappropriate as a method of measuring ball spin during a game in table tennis.

Several studies detected the logo and measured the spin even when the ball remained intact. Zhang, Xiong, Zhao, and Wang (2015) estimated the three-dimensional (3D) pose of a ball using the logo information and calculated its spin based on the 3D pose in successive frames. Although the official ball can be utilized as is in this method, the analysis assumed that the ball does not undergo any rotation between consecutive frames; in other words, the method relies on the assumption that a high-speed camera is used. Moreover, the method assumed the printing of only one symbol on the ball, whereas two different logos may be printed on actual balls. Tamaki, Saito, and Yoshida (2015) measured the spin of an intact ball without using a high-speed camera; however, their method required the electrical synchronization of the camera shutter. This poses a technical challenge in terms of establishing a cable setup for transmitting synchronized signals over long distances without introducing delays. Furthermore, their method assumed that only one mark was printed on the ball. Other methods utilize motion blur (Boracchi, Caglioti, & Giusti, 2009), whereas certain approaches measure the rotation solely based on the ball trajectory (Su, Fang, Xu, & Tan, 2013). These methods are highly sensitive to errors in ball position measurement, rendering stable spin measurement a complex task. In summary, numerous technical obstacles exist in measuring the ball spin, which likely account for the limited number of measurements conducted to date.

Figure 1. Example of a table tennis ball with two logos printed on it: the T-League logo and the logo of the manufacturing company.

In this study, we developed a novel system for measuring the ball spin by eliminating the need for a high-speed camera and the electrical synchronization of cameras. The developed system was specifically designed to quantify ball spin in T-League matches, the professional table tennis league of Japan. Furthermore, the performance of the system was evaluated based on actual match data. The paper presents a comprehensive description of the proposed methodology and the performed experiments that assessed the accuracy of the developed system.

Developed Spin Measurement System

Figure 2 illustrates the system configuration and flowchart, comprising an operational computer, several ball-tracking computers, and a single computer for calculation. Each computer performs specific tasks, such as initiating and terminating ball tracking, tracking the ball based on images captured by a camera, and computing the trajectory and spin of the ball based on the data collected by ball-tracking computers. Each dedicated tracking computer is connected to a single camera. The ball-tracking process concludes when the operator signals the end of the rally, and the rally data are placed in a queue awaiting the computation of the ball's trajectory and spin; a computer executes a program to monitor this queue. If a rally lacks complete measurements, the trajectory of the ball is calculated for all shots to determine the spin of the served ball. The proposed system performs six primary tasks, namely, camera calibration, ball tracking, temporal offset calculation, trajectory reconstruction, logo detection, and ball spin calculation.

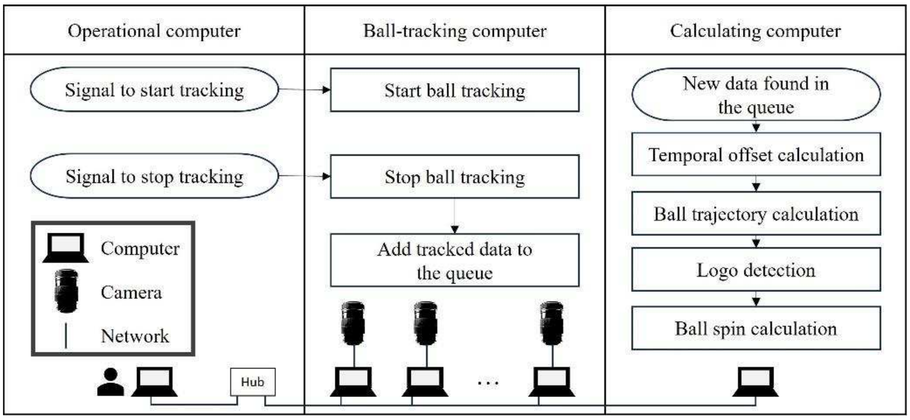


Figure 2. Configuration of the developed system and the flowchart of measuring the ball spin.

Camera Calibration

In traditional 3D measurements, camera parameters are typically computed using the direct linear transformation (DLT) method (Hartley & Zisserman, 2003, pp.178-181). However, this method requires a minimum of six control points encircling the measurement area. As gaining access to a playing area may be impossible in real-life scenarios, the only available control points are the four corners of the table tennis table and the end points of the net assembly. The height of the net assembly is 0.1525 m. This means that the four corners of the table tennis table and the end points of the net assembly cannot enclose the measurement area and are not suitable control points for calculating the camera parameters by DLT method. Thus, the developed system calculated camera parameters using the method proposed by Suzuki, Takenaka, Enomoto, and Tauchi (2016). According to their approach, the camera parameters can be estimated when a minimum of three points with known real coordinates (control points) are visible in the image. In this system, camera parameters were calculated by the method of Suzuki et al. (2016) using the four corners of the table tennis table and two end points of the net assembly as control points. Although their method is versatile and applicable to various situations, a drawback exists: if the initial camera position values are inaccurate, the optimization may be ineffective. Therefore, we employed a rangefinder to ascertain the position of the camera within a coordinate system established on a table-tennis table to achieve precise initial values, thereby enhancing calibration stability and accuracy.

Ball Tracking

The AdaBoost algorithm, which performs adaptive boosting, combines weaker classifiers to formulate a single, accurate, and precise classifier (Freund & Schapire, 1997). AdaBoost is readily accessible through OpenCV, a computer vision library (OpenCV, 2023), and has been extensively applied to object detection and identification. The rationale for selecting this conventional algorithm rather than the commonly employed deep learning-based methods for general object recognition lies in its ability to achieve ball detection with substantial performance and significantly reduced computation time. Moreover, as table tennis balls are spherical and exhibit minimal changes in appearance at various angles, high probability detection can be achieved without using intricate deep-learning algorithms.

We employed a region of interest (ROI) in ball tracking to reduce false positives and processing time. In the context of object detection, we addressed the classic trade-off between detection recall and false-positive rates. Our challenge was to minimize false positives while maintaining a high detection rate, particularly when detecting table tennis balls that minimally vary in appearance across multiple postures. Adaptive ROI settings were effectively employed to address this issue. The initial ROI in the proposed system encompassed the entire table-tennis table until a consistent ball-detection pattern emerged. Once this occurred, the ROI was narrowed based on the ball movement, as illustrated in Figure 3. This strategy excluded objects such as players' hands and faces, which often led to false positives. Furthermore, the implementation of a smaller ROI contributed to enhanced computational efficiency. Ball tracking provided data on the position of the ball in image coordinates and the image itself. The image captured the area surrounding the ball and enabled logo detection.

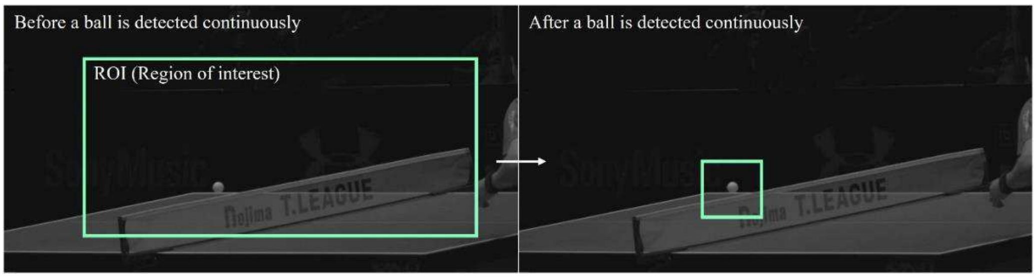


Figure 3. Example of the region of interest (ROI) when detecting the table tennis ball. The larger left ROI is set until consecutive balls are detected, and the smaller right ROI is set after detecting consecutive balls.

Temporal Offset Calculation

Temporal Offset

In this paper, temporal offset refers to the discrepancy in shutter timing across distinct cameras. When employing cameras lacking shutter synchronization, one camera shutter is not released concurrently with the other. However, if multiple cameras capture images at the same frame rate, the discrepancy in shutter timing remains constant.

Calculating the Temporal Offset

The temporal offset between cameras was calculated based on the ball's position data. We began by reconstructing the trajectory of the ball in each image using cubic splines. This reconstruction occurred only when the position of the ball was consistently recorded. A spline curve is a mathematical function, with time and position as the independent and dependent variables, respectively. This facilitates the determination of the position of the ball at any given time from the perspective of each camera. However, owing to unsynchronized shutters, the ball's position cannot be calculated at the same instance even if the same value is input into the spline curve for each camera. The larger the temporal offset, the greater the error in calculating the position of the ball. This error affects the accuracy of determining the 3D position of the ball. To assess this accuracy, we used the reprojection error as a guide (Hartley & Zisserman, 2003, pp.180-181). The sum of these reprojection errors is typically used as a cost function when optimizing the camera parameters computed by DLT (Hartley & Zisserman, 2003, p.181). However, when all reprojection errors are summed, the calculation results may be strongly influenced by outliers, making the calculation results unstable. Polynomial expressions including splines often fail to accurately represent abrupt motion changes, such as ball bounces. Therefore, using the median value addressed this issue and enabled the identification of a stable and optimal solution. In this method, we employed a fixed-step approach to maintain a consistent level of accuracy within a specific range and avoid local minima. The initial value of the temporal offset in the optimization calculation was set to 0 because the system assumed that the timing of the start of the recording was synchronized across all cameras.

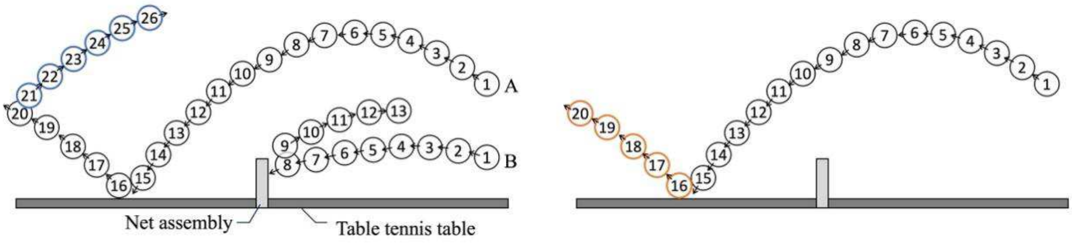
Although the aforementioned method is based on the method proposed by Tamaki and Saito (2015), certain differences exist. The method developed by Tamaki and Saito (2015) computes both temporal offsets and camera parameters simultaneously, and their approach is time-consuming as it involves two optimization calculations. Moreover, as temporal differences between cameras may change slightly over time, they must be calculated as frequently as possible. In our system, the camera parameters were first calculated, which were then used to determine the temporal offset between the cameras; this facilitated rapid calculation of the temporal offsets. Another advantage was the computation efficiency of determining the temporal offsets in each rally.

Trajectory Reconstruction

Reconstructing trajectories that undergo abrupt changes is difficult. In the proposed system, we created multiple trajectory models to depict an entire rally and classified them based on shots and bounces.

Detecting the Starting Point of the Trajectory

In the first step, we determined the instant when the ball entered the table-tennis table and its direction of travel at that moment. As this analysis did not consider the trajectory of the toss preceding the service, we identified the moment when the ball first entered the table and considered that as the starting point of the trajectory. The entry point onto the table occurred after the ball was served, and the direction of the ball's travel at that moment corresponded to the direction of the service.



(a) Shots detection (b) Bouncing detection

Figure 4. Trajectory reconstruction. (a) Black circles indicate the ball before shot and blue circles indicate the ball after shot. Since trajectory A reverses traveling direction between 20 and 21, it is considered that a shot occurred between 20 and 21. Although trajectory B has a reversal in traveling direction between 8 and 9, it is not considered a shot because it occurs close to the net. (b) Black circles indicate the ball before bouncing and orange circles indicate the ball after bouncing. The traveling direction of the ball reversed from downward to upward between 15 and 16. In addition, the traveling direction after the reversal is consistently upward. Therefore, we considered a bounce occurred between 15 and 16.

Detecting Shots and Bounces

We detected the moment when the shots occurred after the service (Figure 4(a)). Typically, a ball either changes its direction of movement when it is hit. Initially, we identified the point at which the velocity of the ball changed along the sideline. The distance between the ball and net was calculated at the point where the change in direction was detected. In general, the collision of the ball with the net follows a path similar to that of a shot. Although a player can hit a ball close to the net before it bounces in tennis, this action is prohibited in table tennis. Consequently, if the distance between the ball and net is less than 0.1 m during the change in direction, it qualifies as a collision between the ball and net. Note that the threshold value of 0.1 m for the distance to the net is only an empirically determined value used in this study, and the optimum value varies depending on the shooting conditions.

We determined bouncing by identifying the point where the vertical velocity of the ball changed direction or undergoes an abrupt shift (Figure 4(b)). However, the vertical speed is typically low when the ball moves horizontally, resulting in measurement errors that can induce uncertain motions in the vertical direction. To address this, the bouncing was determined by considering only that motion which consistently moved in the same direction across four frames and exceeded a certain threshold. When colliding with the corner of a table tennis table, the direction of travel may not be reversed. In the developed system, a bounce is also considered to have occurred when the vertical velocity component is greater than 1 m/s and the absolute value of the vertical velocity changes by more than 70% instantaneously. Note that the 4 frames used for judging consistent movement and 70% used for judging abrupt shift are only empirically determined values in this study, and the optimal values vary depending on the shooting conditions.

Reconstructing Trajectories

The system generated multiple models to represent the entire rally by separating them at moments of shots or bounces. Trajectories without shots or bounces were represented using quadratic polynomials. To enhance stability, the random sample consensus (RANSAC) method (Fischler & Bolles, 1981) was employed because a few measured ball positions exhibited significant errors. Finally, we identified the starting and ending points of the reconstructed ball trajectory. The trajectories were extended to locate the point where they were closest to other trajectories, designating the point immediately before as the end of the previous trajectory and that immediately after as the start of the subsequent trajectory.

Logo Detection

The trajectory of the ball was selected for logo detection by segmenting the trajectory within a single shot into two or three shorter sub-trajectories. We measured the spin of the ball after the first bounce for services and before the first bounce for shots following the services. Consequently, a trajectory was selected from the multiple shorter sub-trajectories constituting the shot, ensuring it passed over the net. Only the ball used in calculating this trajectory was employed for logo detection. The image of the ball corresponding to the selected trajectory was the target of logo detection.

The detection of the logos on the ball was accomplished using YOLOv3 (Redmon & Farhadi, 2018), a neural network-based algorithm known for its excellent object detection capabilities. This method facilitated the simultaneous detection of logos and the identification of logo types. Typically, YOLOv3 outputs a rectangular area containing an object as the detection result. The developed system considered the center of the rectangular area as the logo location. Previously, researchers have estimated the logo region via frame differentiation during spin measurements in official balls (Zhang et al., 2015; Tamaki et al., 2015); however, frame differentiation cannot distinguish between multiple logos. As the official balls used in the T-League comprise two distinct logos (Figure 1), we selected YOLOv3 to address scenarios involving multiple logos on a ball.

Spin Calculation

The spin of the ball was calculated using the positions of the ball and logo. As the proposed system does not rely on high-speed cameras, the ball may complete more than one revolution within adjacent frames during rapid rotations. Consequently, relying solely on the position of the logo does not provide a clear spin measurement. The trajectory of the ball can be a promising indicator for solving this problem.

Calculating the 3D Position of Logos

Considering $\boldsymbol{c} = (c_x, c_y)$ as the center of the ball in pixels in an image, $\boldsymbol{m} = (m_x, m_y)$ as the position of the logo in pixels in an image, r as the radius of the ball in pixels in an image, $\boldsymbol{M'} = (M'_x, M'_y, M'_z)$ as the center of the ball in 3D coordinate system, M'_x and M'_y are calculated by Equation 1 and 2. Note that the coordinates calculated by these formula are not the coordinate system set up on the table tennis table as described in the Camera Calibration section, but a coordinate system with the center of the table tennis ball as the origin. Since a table tennis ball is a sphere, the coordinates of the logo drawn on its spherical surface satisfy the equation of a sphere. Calculate M'_z by substituting the xy coordinates of the logo into the equation for the sphere and solving the equation for the z coordinate (Equation 3). Finally, each coordinate value is normalized to the ratio of the radius of the ball on the image r and multiplied by the transpose of the camera rotation matrix $\boldsymbol{R^T}$ to obtain the 3D coordinates of the logo $\boldsymbol{M}$ (Equation 4).

$$M'_x = m_x - c_x \tag{1}$$

$$M'_y = m_y - c_y \tag{2}$$

$$M'_z = -\sqrt{r^2 - \left((m_x - c_X)^2 + \left(m_y - c_y\right)^2\right)} \tag{3}$$

$$\boldsymbol{M} = \boldsymbol{R}^{\mathrm{T}} \begin{bmatrix} M'_x/r \\ M'_y/r \\ M'_z/r \end{bmatrix} \tag{4}$$

Here, $\boldsymbol{M}$ denotes the coordinate in the coordinate system, with the center of the ball as the origin and the radius of the ball as 1; the coordinate axis is shared with the world coordinate system established on the table-tennis table. The radius of the ball is found by examining its outline in an image. However, its accuracy may vary depending on the background and lighting conditions of the ball. To address this issue, the proposed system projected a 3D model of a ball composed of 171 point clouds onto an image. The farthest distance between these projected points and the center of the ball was measured, which was then used as the radius of the ball.

Spin Axis Calculation

To determine the rotation axis, we began by reconstructing a planar model based on the 3D coordinates of the logo. Initially, outliers were eliminated from the logo positions using the RANSAC method, and the least-squares plane was computed using all data points, excluding outliers. The normal vector of the reconstructed plane was considered the spin axis.

In general, preliminary processing is necessary before calculating the planar model of a ball with two different logos. The official T-League ball displayed two distinct logos positioned symmetrically around the center of the ball. Consequently, the system employed a method in which the position of one logo enabled the determination of the position of the other logo; the spin axis was derived from the information provided by both logos. However, this method is viable only if the position of one logo can be deduced from that of another. A more adaptable solution involves extracting two planes from the two logos and computing the average of the obtained normal vectors.

Spin Rate Calculation

Initially, we calculated the candidate values for the rotation angle of the logo. This angle was determined based on the rotation angles of the two logos captured from the same viewpoint at different times as the cameras were not synchronized. However, the lack of high-speed cameras rendered the determination of the direction (clockwise or counterclockwise) and number of rotations between two different frames challenging (Figure 5). Based on previous studies (Huan et al., 1992; Iizuka et al., 2010; Lee & Xie, 2004; Yoshida et al., 2014), the maximum spin rate of a table tennis ball is approximately 150 rps and is unlikely to exceed 200 rps. If the time between frames where the rotation angle is measured is set to Δt, the maximum candidate value for the number of rotations between consecutive frames is $200 \cdot \Delta t$. Assuming that the camera captures frames at 120 fps and the logo is detected in consecutive frames, two candidate values exist for the number of revolutions. When multiplied by 2 (for the direction of rotation), the total number of candidate values for the angle of rotation becomes 4 (Figure 5). In summary, although the rotation angle could not be precisely calculated from the logo position data, the candidate values for the angle were successfully determined.

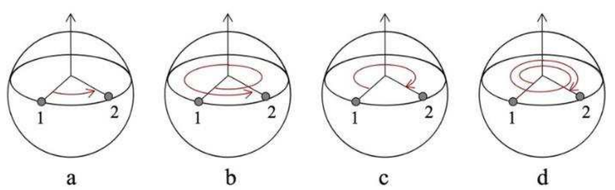


Figure 5. Candidate values of the rotation angle. The gray circles in the figure indicate the location of the logo, and the numbers indicate the frame number. Even when the logo is detected in consecutive frames, the spin direction and the number of revolutions cannot be determined. Therefore, the spin rate of the ball cannot be uniquely identified.

Finally, we determined the correct spin rate from the candidate values of the rotation angle by analyzing the 3D path of the motion of the ball. Considering the mass of the ball (kg) as m, radius (m) as r, gravitational acceleration (m/s^2) as $\boldsymbol{g}$, position of the ball (m) as $\boldsymbol{x}$, velocity of the ball (m/s) as $\dot{\boldsymbol{x}}$, the norm of velocity vector as $|\dot{\boldsymbol{x}}|$, acceleration of the ball (m/s^2) as $\ddot{\boldsymbol{x}}$, angular velocity of the ball (rad/sec) as $\boldsymbol{\omega}$, air density (kg/m^3) as ρ, drag coefficient as C_D, and lift coefficient as C_M, the movement of the ball follows the equation as indicated below.

$$\ddot{\boldsymbol{x}} = \frac{1}{m}(F_G + F_D + F_L) \tag{5}$$
$$F_G = m\boldsymbol{g} \tag{6}$$
$$F_D = -\frac{1}{2}C_D\pi r^2\rho|\dot{\boldsymbol{x}}|\dot{\boldsymbol{x}} \tag{7}$$
$$F_L = \frac{4}{3}C_M\pi r^3\rho\boldsymbol{\omega} \times \dot{\boldsymbol{x}} \tag{8}$$

Here, F_G denotes gravity, F_D indicates the air resistance, and F_L represents the lift created by the spin of the ball. When measuring the state of the ball's motion at a particular point, its subsequent trajectory can also be computed. With the data collected thus far, several possible paths were calculated for the ball based on different rotation angles. Considering that the trajectory of a table tennis ball changes significantly with spin, calculating the trajectory using an incorrect spin rate results in a substantial deviation from the actual trajectory. Therefore, the correct spin rate was the candidate value that generated the trajectory closest to the trajectory that has been measured with the system (Figure 6).

A more precise spin rate was further determined. Typically, a low spin rate results in a small angle of rotation between two frames. In such instances, the rotation angle within a single frame becomes minimal and errors in measuring the position of the logo become more significant. To minimize the margin of error in the spin rate calculations, we iteratively updated the spin rate by using extensive time intervals between frames to calculate the rotation angle. During this process, we selected the candidate spin rate that was most closely aligned with the initially calculated spin rate. The iterative process was continued until either the time interval or rotation angle reached a predetermined upper limit, thereby substantially enhancing the accuracy of spin rate calculations. In this study, the upper limit was set until the rotational angle reaches 360 degrees or until the rotational interval reaches 30 ms if the time elapsed before the rotational angle reaches 360 degrees is less than 30 ms.

The aforementioned method for measuring the spin was based on that reported by Tamaki et al. (2015); however, several important differences existed. The proposed system was designed to handle cases with two different logos printed on the ball, whereas the conventional method assumes that only one logo is printed. Additionally, our system introduced the novel concept of iterative spin-rate updating, without which the accuracy of the calculations for low spin rates may be compromised. In summary, the developed system incorporated various technological advancements, enabling the measurement of ball spin at actual match venues using asynchronous non-high-speed cameras.

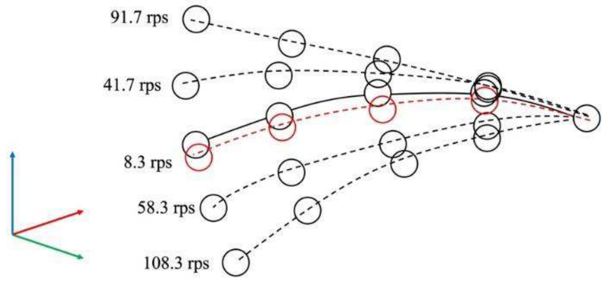


Figure 6. Selecting the correct spin rate. The solid line indicates the trajectory of the ball measured by the system, the dotted lines show the trajectories generated based on candidate values of spin rate, and the red dotted line shows the trajectory corresponding to the selected spin rate. The candidate value that generates the closest trajectory to the measured trajectory is selected as the correct rotation speed.

Laboratory Experiment

We performed experiments to assess the accuracy of the proposed system in measuring the spin rate and axis. This section presents an analysis of the utility of the system based on experimental findings and measurement accuracy.

Data Collection

The experimental trial involved four table tennis games played by three students at a university gymnasium. Three cameras (Grasshopper3; Teledyne FLIR) with unsynchronized shutters were used to capture the images; the resolution and frame rate were 1920×1080 pixels and 150 fps, respectively. Only the gymnasium light was used during the trial. In addition to using cameras with unsynchronized shutters, the same trial was recorded using a high-speed camera (HAS-U2 by DITECT) positioned adjacent to the table-tennis table with its optical axis aligned parallel to the end line of the table. The resolution and frame rate of the high-speed camera were 640×480 pixels and 1000 fps, respectively.

Among the trials, we selected 58 rallies captured by the high-speed camera, wherein the logos were visible. The spin of the service ball was measured using both the developed system and a high-speed camera, and the results were compared. In the case of the measurements obtained via the high-speed camera, the ball's center, radius, and logo positions were manually digitized in the images. The spin axis was determined using the algorithm explained in Section Spin Calculation, and the spin rate was calculated based on the rotation angle between two frames considered as far apart in time as possible. We focused on measuring the spin of only the service ball because the proposed system was designed for this specific purpose.

Statistical Analysis

Prior to the statistical analysis, the Shapiro-Wilk test was performed, which negated the normality of the distribution of errors in spin rate and in the spin axis. Therefore, the median was used as the representative value of the error distribution and the interquartile range was used as the measure of variability.

Monte Carlo simulations were performed to quantitatively evaluate the impact of the error distribution of the measured spin axis on the tactical analysis of table tennis. Figure 7 illustrates the categorization of spin axes in table tennis services. Typically, the spin direction in table tennis can be primarily categorized into four: backspin, topspin, and two variations of sidespin (Geske & Mueller, 2010; Lodziak, 2020), with certain intermediate spin states between them (Geske & Mueller, 2010), resulting in eight distinct spin rotations (Figure 78 (a)). Although these eight spin rotations form the foundation of table tennis, certain players further subdivide the spin direction. Iizuka et al. (2010) reported instances where a player executed side-backspins with "strong side" and "strong back" as distinct services, indicating that the spin direction was divided into three equal parts rather than into two (Figure 78 (b)). Therefore, the ability to accurately identify eight distinct spin axes or two services with spin axes that differ by 45° is the minimum requirement for spin analysis. If two services with spin axes differing by 30° can be correctly identified, the resolution can be considered capable of analyzing finer details. To assess this, Monte Carlo simulations were conducted to introduce errors based on the empirically observed distribution of two randomly generated spin axes differing by 30°. The number of trials was set at 10,000.

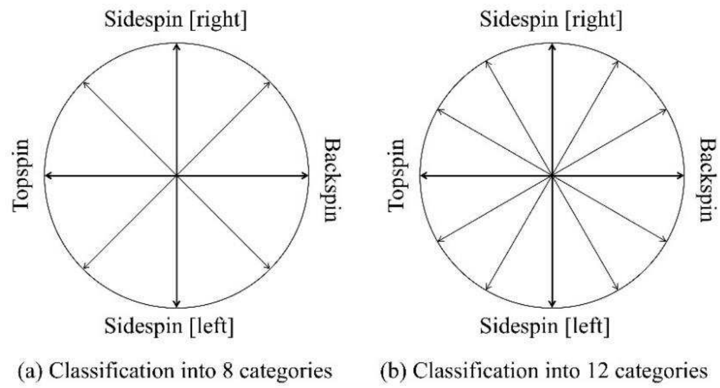


Figure 7. Categorization of spin axes in table tennis services. The ball spins clockwise when viewed from the starting point of the spin axis.

Results

Figure 8 depicts the frequency distribution of the difference between the values measured using the developed system and the high-speed camera. The median errors for the spin rate and axis were 0.78 rps and 12.5°, with interquartile ranges of 0.94 rps and 10.9°, respectively.

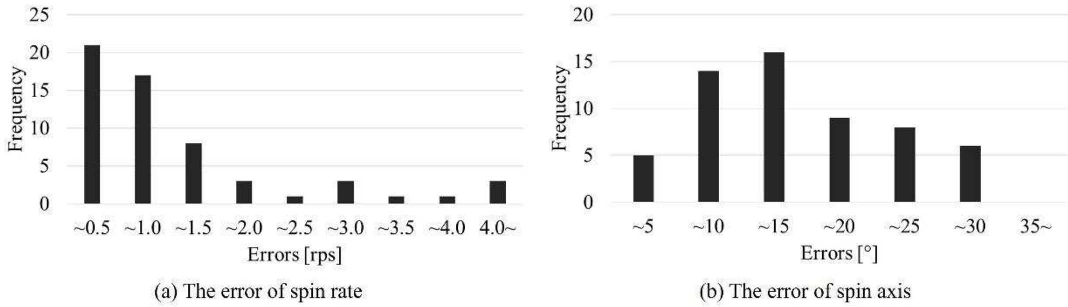


Figure 8. Frequency distribution of the difference between the values measured using the developed system and the high-speed camera.

Discussion

Previously, Zhang et al. (2015) assessed the magnitude of a measurement error solely based on its absolute value. However, this evaluation was subjective and insufficient for determining the effectiveness of the system. In this study, the precision of the measurement system was assessed in terms of its capacity to analyze the tactics employed by table tennis players, who often vary the spin rate and axis rather than employing the same spin during service. As the spin of the served ball is the foundation for table tennis tactics, its accurate measurement can be a valuable tool for analyzing players' tactics.

In general, the spin rate error is sufficiently small to analyze the tactics and skills of table tennis players. Iizuka et al. (2010) measured the spin of balls served by elite junior players, wherein the same services with balls were hit with different spin rates ranging from 3.7 rps to 9.3 rps, which accounted for 7% to 19% variation. Based on this finding, we inferred that table tennis players may not consider a difference of approximately 10 rps as a "different spin." The median measurement error of the developed system was only 0.78 rps, which was significantly smaller than the variation in spin rate observed among table tennis players' serves. Therefore, the spin rate resolution of this system was deemed sufficient to analyze players' performance.

The performed experiments indicated that the spin axis can be practically measured. The magnitude of the measurement error observed in the experiment is difficult to assess subjectively. Therefore, this study used Monte Carlo simulations to evaluate the extent to which this error affects the discrimination of the type of rotation. Results of a Monte Carlo simulation of 10000 trials, the probabilities of correctly identifying the relationships among the 8 and 12 different rotation directions were 99.4% and 95.8%, respectively. In conclusion, the ability of the system to measure the spin axis demonstrated a practical resolution suitable for an in-depth analysis of the rotation direction.

Spin Measurement in T-League

The proposed system was used to measure the spin of the service ball immediately after a rally in T-League matches. The collected data were utilized for live match commentary on Hikari TV and the dTV Channel by NTT Plala Inc. This section presents an analysis of the performance of the system with respect to calculation speed using a case study.

Data Collection

Four Teledyne FLIR Grasshopper cameras with independently operating shutters were employed for capturing images. The resolution and frame rate were set to 1920 × 1080 pixels and 150 fps, respectively. Table 1 summarizes the detailed computer specifications. All computers were connected using a wired local area network at a transfer rate of 1 Gbps.

Table 1. Detailed specifications of the computers used in the experiment.

	Operational computer	Ball-tracking computer	Calculating computer
OS	Windows 10 Pro	Windows 10 Pro	Windows 10 Pro
CPU	Intel Core i7-8750H 2.21GHz	Intel Core i7-9700 3.0GHz	Intel Core i7-8750H 2.21GHz
GPU	GeForce GTX 1050	GeForce RTX 2060	GeForce GTX 1050
Memory	16GB	32GB	16GB

We measured 242 rallies during four T-League matches. During each rally, we recorded the time when the operator began and finished tracking the ball along with the time when the calculation of the trajectory of all shots and the service spin was completed. Subsequently, two key time intervals were calculated: the in-play time (tracking end time−tracking start time) and the calculation time (calculation end time−tracking end time).

Statistical Analysis

The percentage of correctly measured spin was calculated. The success or failure of the measurement results was determined visually at a later date based on the image of the ball taken and the time information. The conditions for successful measurement were that the tilt of the axis of spin did not deviate significantly from the visually identified spin axis, and that the correct candidate value was selected from the candidate values of spin speed. This is a case study of the actual use of this system. Since no measurements were made using a high-speed camera, it is not possible to precisely evaluate the results and errors of the spin measurements. Therefore, as described above, the evaluation was limited to the extent that if the spin was measured to be different enough to be detected visually, it was a failure; otherwise, it was a success.

The time required to calculate the trajectory increased with the in-play time. A first-order regression model was employed, with the in-play time and computation time as the independent and dependent variables, respectively, to ascertain the variations in computation time with the changes in in-play time. The ball tracking was performed in real-time, and the calculated time did not encompass the time required for ball tracking.

Results

The developed system successfully measured the spins of 92.1% (223 / 242) of the served balls. Figure 9 illustrates the scatter plots indicating the correlation between the in-play time and computation time. Considering the in-play time (Δplay) and computation time (Δcalc) in seconds, the first-order regression was derived as $\Delta play = 0.51\Delta calc + 4.3$ The system calculated the ball spin during the rally and immediately after the rally ended, contributing to the match commentary.

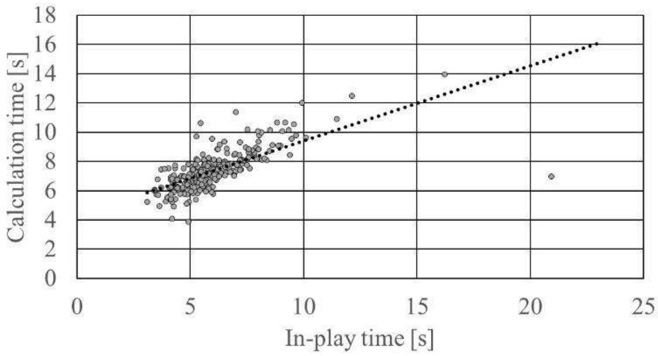


Figure 9. Correlation between in-play time and calculation time. The dotted line denotes the regression line calculated with the in-play time and calculation time as the independent and dependent variables, respectively.

Discussion

The study findings confirmed that the system can measure ball spin in a short time. The increase in calculation time with the increased in-play time was only 51%, indicating that the calculation time remained relatively stable even during extended rallies. As numerous table tennis matches conclude with rallies spanning only five or six hits (Tamaki & Yoshida, 2020), the proportion of in-play time to the overall match duration is not substantial. This indicates that the calculation time remains sufficiently short to use the calculation results immediately after the rally. Notably, all calculations were completed immediately after the match, further confirming these findings.

Improving the logo-detection time could enhance the real-time system performance. In the obtained first-order regression equation, we introduced a constant term of 4.3 s into the calculation time, independent of in-play time. The spin measurement of the served ball remained unaffected by the in-play time and corresponded to the constant term in the aforementioned first-order regression equation. Most of the computational time required to calculate the spin was used for logo detection. Therefore, real-time logo detection can substantially improve the entire measurement process. The challenge lies in both the performance of the graphics processing unit (GPU) and the employed logo-detection algorithm. Real-time logo detection can be achieved by enhancing the GPU computational power or accelerating object detection algorithms. In the future, we intend to use the system for real-time logo detection and completing the spin measurement immediately after the serve.

Conclusion

In this study, we developed a system to measure the ball spin immediately after a rally. Unlike conventional systems that use cameras with electrically synchronized shutters or high-speed cameras, our approach prioritized accessibility at match locations and employed multiple unsynchronized cameras to detect the logos printed on the ball. Experiments performed at a university gymnasium confirmed that the developed system had a median error for the spin rate and axis were ~~of~~ 0.78 rps and 12.5°, with interquartile ranges of 0.94 rps and 10.9°, respectively. The error in the spin rate is small compared to the intentional variations by table tennis players. We analyzed the effect of rotation axis error on the identification of rotational axes and found that the probability of identifying two kinds of spin with 30° different spin axes was 95.8%. The results indicated that the system can analyze players' tactics with sufficient precision. Analysis of the measurements from T-League matches further demonstrated the system has sufficient capability to provide immediate feedback on spin data.

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