Journal of Human Kinetics volume xx/xxxx, x–x DOI: 10.5114/jhk/221547
Section I – Kinesiology

Computer Vision-Based Analysis of Tennis Contact Point Characteristics for Performance Evaluation

by

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Precise timing of ball-racket contact is a critical determinant of stroke performance in tennis, yet few studies have objectively quantified this variable across different players' groups. This study developed and validated a hybrid vision-based framework combining K-nearest neighbors (KNN) background subtraction with Hue-Saturation-Value (HSV) color segmentation to analyze the spatial relationship between the contact point and the apex of the ball's trajectory. Twelve participants were recruited and stratified by skill level and gender, each performing 30 forehand and 30 backhand strokes, yielding 720 stroke events. Contact point overlap ratios and vertical height distributions were extracted, and two-way ANOVA was used to examine main and interaction effects. Results indicated a significant effect of the skill level, with top-level players demonstrating higher overlap ratios and reduced vertical deviations compared to average-level players ($p < 0.001$, partial $\eta^2 = 0.386$). Gender differences were negligible among top-level players but pronounced in the average-level group, particularly for backhand strokes ($p < 0.001$). These findings highlight the skill level as the dominant factor influencing contact point precision, while gender disparities emerge primarily among less experienced athletes. The proposed computer vision approach offers a low-cost and scalable tool for objective stroke assessment and has potential applications in individualized training feedback and performance monitoring.

Keywords: *computer vision; tennis ball tracking; background subtraction; color segmentation; KNN background modeling*

Introduction

Sportstech, commonly referred to as sports technology, is an increasingly expanding sector that merges the realms of athletics and technology to elevate athletic performance, enhance training techniques, and offer fans new and creative methods to engage with their beloved sports (Gulhane, 2014; Petrović et al., 2015; Ratten, 2019). This sector includes a diverse array of technologies, such as wearables, analytics, virtual reality, and artificial intelligence, all focused on transforming how sports are played, coached, and experienced (Barbosa, 2018; Nadikattu, 2020; Ratten, 2020; Ráthonyi et al., 2018). In recent years, tennis has seen a number of innovations that helped to improve referee decision-making and enhance players' performance, including the eagle-eye line penalty system and telemetry sensors (Benítez et al., 2019a, 2019b; Leveaux, 2010; Neville andSalmon, 2016). Processing and analyzing large amounts of data in tennis using artificial intelligence algorithms can help identify and predict players' movements and actions, predict future positions, speeds, and the spin of shots, and recognize racket movements (swings) (AlShami et al., 2023; Jhamb and Greer, 2024; Liu and Sun, 2022). All of this can help coaches evaluate players' performance, focus on strengths and weaknesses, and potentially help coaches make more informed decisions during tennis matches. However, the practical implementation of visual communication

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tools in training environments remains underexplored, especially in terms of usability and feedback precision for both players and coaches.

Tennis is a highly technical sport that requires a combination of physical ability and strategic thinking. Learning skills in tennis is not an easy task and skills are usually enhanced through coaching. A key skill in tennis is the ability to effectively utilize both the forehand and backhand strokes (Yu and Huang, 2025). A player's advantage in the drive emphasizes the contact point, and the higher up the volley stroke, the more advantageous the player can be, but this is not an easy skill to learn (Abdullah et al., 2023; Blackwell and Knudson, 2005; Koronas and Koutlianos, 2021; Wang et al., 2010). Although all tennis players must master these two strokes to some degree, there can be a wide variation in ability among players. This can be attributed to a number of factors, including an individual's physical characteristics, the level of training and proficiency. The forehand is generally considered to be the more powerful and dominant shot in tennis. It allows the player to generate more power and control over the ball, making it a valuable weapon in competitive play. A player with a strong forehand is often able to take control of the game and force the opponent into a defensive position. In contrast, the backhand is often considered a more difficult shot to master (Landlinger et al., 2010; Rota et al., 2012; Sawali, 2018). It requires more precise timing and technique, as well as the ability to generate power and consistency from less natural positions. The difference between a player's forehand and backhand strokes can have a significant impact on their overall performance on the tennis court. Players who excel in both areas of the game are able to maintain a balanced and varied game and thus have a competitive advantage over opponents who are weaker in one area.

In the sport of tennis, the characteristics of a player's contact point are critical to their performance on the court. While coaches play an important role in developing players' skills and techniques, there is a need for more scientific methods to accurately understand and improve contact point characteristics. Taking advantage of computer vision techniques, especially foreground/background segmentation and color segmentation, coaches and players can gain a deeper understanding of the nuances of the point of impact and acquire information about the characteristics of the contact point of impact (Huang, 2022; Naik et al., 2022; Peng and Tang, 2022). Foreground/background segmentation is a low-cost computer vision technique that separates the foreground (e.g., players and tennis balls) from the background (a tennis court) (Brissman et al., 2021; Pechini, 1967; Tsai et al., 2012). This segmentation is essential for accurately analyzing players’ shot characteristics. The background subtraction algorithm is a technique commonly used in image processing and computer vision, which is able to cut out moving objects from image sequences to achieve the effect of tracking objects, and can be applied to track moving tennis balls in the image in this way (Zhang, 2024; Zhang, 2021). By utilizing this technology, players can better understand where they hit the ball in relation to the position of the ball on the court, allowing them to make more accurate hitting and training decisions. In addition, coaches can use this information to develop training programs and provide targeted feedback to players to further improve their overall performance on the court. Color segmentation is another valuable tool in the field of tennis analytics, as it helps differentiate between elements on the court based on their color (Hu, 2023; Jhamb and Greer, 2024; Yan andXin, 2021). The technique can be used to track the movement of the tennis ball in real time, allowing players to adjust their shots accordingly (Gong and Wang, 2021; Wu and Xiao, 2022). By incorporating color segmentation into the training routine, players can gain a more granular understanding of the shot placement and improve their overall accuracy and consistency on the court.

For tennis ball tracking, background subtraction and color filtering are commonly used methods for extracting foreground objects (Huang, 2022; Tang and Huo, 2021). The K-Nearest Neighbors (KNN) algorithm, a non-parametric classification method, is known for its robustness in handling dynamic scenes, and can be used to separate foreground objects with high precision (Gu et al., 2019; Sadrabadi et al., 2020; Singh, 2018). Background subtraction is a fundamental technique for moving object detection that works by modeling the background and distinguishing static elements from moving objects. Among the most widely used methods are the Gaussian

Mixture Model (GMM) and KNN-based background modeling. Unlike the GMM, KNN background modeling adapts better to local variations in lighting and motion, making it more suitable for sports environments. KNN modeling utilizes a history buffer of pixel values and classifies a pixel as part of the background if it is similar to its K-nearest neighbors (Gao et al., 2007; Lou et al., 2023). This method is particularly effective in handling dynamic backgrounds and varying lighting conditions. In tennis ball tracking, KNN background subtraction helps eliminate court lines, shadows, and other non-target moving objects, thereby improving detection accuracy (Gong and Wang, 2021; Tang et al., 2024; Wang et al., 2021). Although KNN modeling is primarily used for classification and pattern recognition, it can also be applied in image processing for foreground extraction. The KNN-based background subtraction algorithm dynamically updates the background model and isolates moving objects. The extracted foreground objects serve as preliminary candidate regions for the tennis ball's trajectory, which can then be refined using additional image processing techniques, such as contour detection and morphological operations (Huang, 2022; Lu and Zhai, 2020). Although KNN modeling provides motion-based segmentation, combining it with color-based filtering further enhances detection precision. Color filtering is a widely used object detection technique that relies on the color characteristics of an object. Common approaches include RGB threshold filtering, HSV color space conversion, and Lab color filtering. Among these, HSV color space filtering is preferred because it separates brightness (V) from color information (H, S), allowing robust detection of tennis balls under varying lighting conditions (Tu et al., 2010; Wang et al., 2004). Studies have shown that filtering based on HSV values can effectively remove background noise while preserving only the yellow or green region characteristics of the tennis ball (Archana andKalaiselvi Geetha, 2016; Tu et al., 2010). The HSV model's separation of chromaticity and luminance makes it highly resilient to illumination changes, a common challenge in outdoor tennis environments. This robustness makes HSV an ideal color model for outdoor sports analysis.

In this study, a hybrid approach was adopted, combining HSV filtering with KNN background subtraction through a logical AND operation to enhance the precision of tennis ball detection. This integrated framework allowed accurate extraction of tennis ball trajectories, enabling subsequent analysis of bounce points, impact points, and peak trajectory positions. These trajectory-based features provided objective metrics for stroke optimization and served as foundational indicators for evaluating technical consistency across different skill levels. Building on this framework, the study aimed to address three key research questions: whether the skill level would influence the precision of the contact point relative to the ball's apex during forehand and backhand strokes, whether gender differences would exist in contact point precision, and whether an interaction between the skill level and gender would affect stroke timing and consistency.

Methods

This study employed a vision-based measurement framework to analyze the contact point characteristics of tennis strokes. The framework integrated object recognition and trajectory analysis techniques to quantify key spatiotemporal indicators of stroke execution. Figure 1 illustrates the overall experimental design, which consisted of five main components: (1) participants' recruitment and grouping, (2) field and camera setup, (3) measurement system architecture, (4) tennis ball tracking method, and (5) data normalization and visualization procedures. These components collectively ensured a systematic approach to capturing, processing, and analyzing stroke-related data for subsequent statistical evaluation.

Participants

In order to validate the analysis of stroke contact points for this study, the participants were 3 men and 3 women top players and 3 men and 3 women average players, resulting in four groups of three players, totaling twelve participants. For the purpose of this study, a top player was defined as a player who had participated in an ITF, ATP or WTA tournament. An average player was defined as a player who had participated in minor or regional tournaments only. This classification allowed us to investigate performance differences associated with competition experience.

Demographic information of the participants is shown in Table 1. This study was approved by the Institutional Review Board of the Kaohsiung Medical University Hospital, Kaohsiung, Taiwan (approval code: KMUHIRB-E(I)-20220234; approval date: 27 September 2023). Written informed consent was obtained from all players prior to participation.

Although the sample size comprised only twelve participants, this design aligns with exploratory studies in sports biomechanics where elite and sub-elite groups are difficult to recruit (Landlinger et al., 2010; Rota et al., 2012). Each participant contributed 30 forehand and 30 backhand strokes, yielding a total of 720 stroke observations, which provided sufficient data density for reliable two-way ANOVA analysis (Abdullah et al., 2023). Moreover, the distinct skill-level stratification (ITF/ATP/WTA vs. regional players) ensured clear group contrasts, compensating in part for the limited number of participants. Future studies should aim to expand the sample size to enhance generalizability.

Field Environment Setup

Experiments were conducted using a GoPro HERO10 Black, recording at a focal length of linear x 1.0 (19 mm) and using an image quality of 1080 p at a frame rate of 30 fps. The camera was set up at a distance of 2.45 m from the closest sideline, and 5 m from the base line. The forehand shot was set to the right side, while the backhand shot was set to the left side. The setup was fixed for all footage, as shown in Figure 2.

Measurement System Modules

The system read the forehand and backhand clips of each player, tracked the tennis balls by background subtraction and HSV color segmentation, and then found the key points one by one and recorded their pixel coordinates. After reading the video, the interfering data were ignored and normalized, and finally the distribution and box plots were drawn for subsequent data analysis. To improve interpretability, the system also provided visualized video frames highlighting the trajectory and key impact points, as illustrated in Figure 3. In order to enhance the perceptual clarity and facilitate the understanding of the three salient features related to the tennis ball flight process in this study, we adopted the visual presentation in the form of computer visual clips. The purpose of including these computer visual clips was to provide a detailed and clear presentation to facilitate the understanding of the intricacies of the phenomena under study.

Tennis Ball Tracking Method

In this study, a vision-based tracking method was implemented to analyze the trajectory of a tennis ball using a combination of background subtraction and color segmentation techniques. The system employed the K-Nearest Neighbors (KNN) background subtraction model, which effectively isolated moving objects from the background. To ensure a structured representation of the algorithm, a Python-style pseudocode is presented in Table 2, outlining the essential steps in the image processing workflow.

Pseudocode Description

The pseudocode in Table 2 illustrates the core operations involved in detecting and tracking the tennis ball from video frames. The workflow consisted of the following major steps. First, the system initialized a background subtraction model using the $cv2.createBackgroundSubtractorKNN(\,)$ function from OpenCV. This model was continuously updated to distinguish moving objects from static backgrounds. Next, color segmentation was used to enhance detection accuracy. The HSV color filter was applied via $FilterHSV(fm)$, this combined mask effectively excluded noise and preserved only regions satisfying both motion and color characteristics of tennis balls. Then, binary masking and object isolation were performed. The resulting binary mask (bs) from background subtraction was combined with the HSV filter mask (hsv) using a logical AND operation ($new\_fm = bs\ AND\ hsv$). This step removed irrelevant objects, retaining only candidate regions that matched the expected motion and color properties of a tennis ball. Afterwards, trajectory recording was completed. When the ball was detected in a frame, its coordinates were stored in the list $tennis\_p[count]$, allowing the system to track its movement. When no ball was found and the previous frame did not contain a detection event, a new round of tracking began ($count = count + 1$). Three key points were extracted per trajectory: the ground point (maximum Y), the highest point (minimum Y), and the contact point (maximum X). The contact point ($contact\_p$) was considered the maximum X-coordinate corresponding to the ball's furthest horizontal position before interaction with the player. Finally, normalization and visualization were performed. The extracted key points were normalized using $Normalize(ground\_p, highest\_p, contact\_p)$ and their trajectories were visualized with $DrawPlots(ground\_p, highest\_p, contact\_p)$.

Data Normalization and Draw Plots

After the video was fully processed and all key points were obtained, data normalization was performed. Trajectories containing detection errors or missing points were excluded prior to normalization. The normalization procedure consisted of three steps. First, all ground points were translated to the origin (0, 0). Second, the highest and contact points were translated by the same offset applied to the ground points. Third, pixel units were converted into distance units.

Since absolute distance accuracy was not achievable with a single-camera setup, the length of visible sideline segments was averaged and used as a scaling reference, as shown in Table 3.

Statistical Analysis

All statistical analyses were conducted to examine the effects of two factors—the skill level (two levels: top-level and average-level) and gender (male and female)—on stroke execution characteristics, particularly the vertical deviation between the contact point and the apex of the ball's trajectory. This dependent variable is widely recognized as an indicator of stroke timing and spatial precision in racket sports (Koronas andKoutlianos, 2021; Landlinger et al., 2010). A two-way analysis of variance (ANOVA) was employed to evaluate (1) the main effect of the skill level, (2) the main effect of gender, and (3) the interaction effect between the skill level and gender. Such factorial designs are frequently used in sports biomechanics studies to explore performance differences across multiple factors (Blackwell andKnudson, 2005; Rota et al., 2012).

Prior to conducting the ANOVA, the assumptions of normality and homogeneity of variances were verified using the Shapiro-Wilk and Levene's tests, respectively, following standard procedures in motor performance research (Abdullah et al., 2023). Effect sizes were reported as partial eta squared (η^2), with interpretation thresholds of 0.01 (small), 0.06 (medium), and 0.14 (large) according to Cohen's guidelines (Cohen, 2013). Where significant main or interaction effects were observed, Bonferroni-adjusted pairwise comparisons were performed to control for Type I error (Gao et al., 2007). Statistical significance was set at $p < 0.05$, and all computations were conducted using SPSS Statistics (version 28, IBM Corp., Armonk, NY, USA).

Results

In this study, the computer vision system was used to understand different stroke characteristics of tennis players, and to verify differences in forehand and backhand execution. The system also examined stroke execution patterns showing that top-level players demonstrated superior timing and spatial consistency in both forehand and backhand strokes.

Contact Point and the Apex Overlap

To evaluate stroke timing precision, the spatial overlap between the contact point and the apex of the ball's trajectory was calculated, expressed as the overlap ratio (%). This measure served as an indicator of the players' ability to strike the ball at its optimal vertical position during both forehand and backhand strokes. The descriptive results for each group are summarized in Table 4.

Top-level players demonstrated markedly higher overlap ratios across both stroke types. In forehand strokes, both male and female top-level players achieved overlap ratios exceeding 95%, while their backhand overlaps remained above 85% (men: 91.7%; women: 85%). In contrast, average-level players exhibited substantially lower ratios, particularly in backhand execution, where female participants recorded no overlap and male participants only 1.7%. Average-level forehand overlaps were also lower, with men reaching the value of 28.3% and women reaching the value of 21.7%.

These findings highlight a pronounced skill-related disparity in temporal-spatial coordination. Elite players consistently executed strokes near the apex, reflecting refined anticipatory control and technical stability, whereas average-level players displayed greater variability and missed the optimal impact zone more frequently. Gender differences were minimal within the top-level group but became more apparent among average-level participants, particularly in backhand execution.

Contact Point Height Distribution

The vertical distribution of contact point heights was analyzed to compare stroke execution across skill levels and genders. Figure 4 presents boxplot comparisons for forehand and backhand strokes among the four participant groups.

For forehand strokes, top-level women recorded the highest median contact point height at 1.45 m, exceeding the 1.25 m observed in top-level men. Both groups demonstrated narrow interquartile ranges (IQRs of 0.10–0.15 m), indicating consistent timing and spatial control. In comparison, average-level men achieved a median height of 1.25 m, higher than the 1.00 m observed in average-level women. However, the average-level groups exhibited broader IQRs, with average-level women showing the widest variability (0.80–1.30 m), reflecting inconsistent striking positions. For backhand strokes, top-level women again demonstrated the highest median at 1.45 m, slightly higher than the 1.25 m of top-level men, with both groups maintaining relatively narrow IQRs (0.10–0.15 m). Average-level men displayed a median of 1.20 m, whereas average-level women had the lowest median at 1.00 m and the broadest IQR (0.80–1.20 m), indicating the greatest inconsistency in backhand execution among all groups.

Overall, the skill level exerted a stronger influence than gender on contact point height. Top-level players consistently achieved higher and more stable impact positions, while average-level players, particularly women, displayed lower contact points and greater variability.

Two-Way ANOVA Results

A two-way ANOVA was performed to evaluate the effects of the skill level (top-level vs. average-level) and gender (male vs. female) on the vertical deviation between the contact point and the ball's apex. The analysis examined the main effects of the skill level and gender, as well as their interaction (Table 4).

The results revealed a significant main effect of the skill level ($F(1, 716) = 449.838$, $p < 0.001$, partial $\eta^2 = 0.386$), indicating a large effect size. Top-level players demonstrated substantially smaller deviations from the apex compared to average-level players, reflecting superior timing precision and technical consistency. A significant main effect of gender was also observed ($F(1, 716) = 50.636$, $p < 0.001$, partial $\eta^2 = 0.066$). Male participants, on average, achieved closer contact points to the apex than female participants, suggesting better temporal alignment during stroke execution.

Furthermore, a significant interaction effect between the skill level and gender was identified ($F(1, 716) = 39.819$, $p < 0.001$, partial $\eta^2 = 0.053$). As illustrated in Figure 5, gender differences were minimal among top-level players, where both male and female participants exhibited similarly small deviations. In contrast, gender disparities became pronounced in the average-level group, with female participants showing considerably greater deviations than their male counterparts.

Post hoc comparisons revealed that skill level differences were more pronounced among female($\eta^2 = 0.346$) than male participants ($\eta^2 = 0.134$), underscoring that skill acquisition exerted a dominant influence on stroke precision, particularly in lower-skilled female athletes.

Table 1. The participants' demographic information.

Group	Year of birth	Body height (cm)	Body mass (kg)	Tennis training experience (years)
Top players men (1)	1993	180	73	15
Top players men (2)	1989	176	75	18
Top players men (3)	1987	184	80	20
Top players women (1)	1997	172	62	15
Top players women (2)	1995	174	74	16
Top players women (3)	1989	161	58	19
Average players men (1)	1996	177	76	10
Average players men (2)	1993	170	58	12
Average players men (3)	1997	178	69	10
Average players women (1)	1996	155	50	11
Average players women (2)	1997	160	41	12
Average players women (3)	1992	158	53	14

Table 2. The system's pseudocode (Python Style).

```
knn ← cv2.createBackgroundSubtractorKNN()
# creating KNN model for Background Subtraction

set tennis_p to empty list
set count to 0
while (video is not finish):
fm←video read 1 frame

# Tracking the tennis ball
bs←knn.apply(fm) # Background Subtraction to get moving objects.
hsv←FilterHSV(fm) # HSV color segmentation to get tennis-like color objects.
new_fm←bs AND hsv
# The frame is black if don't have tennis after AND operation.

if (find the tennis ball from this frame):
tennis_p[count].append(get tennis' coordinate in image)
# Record this ball round's tennis trajectory.
elif (can't find tennis ball from this frame, and last frame haven't run this section):
# only run ONCE in each ball round start
set tennis_p[count] to empty list
count←count+1

set ground_p, highest_p, contact_p to empty lists
for i in range(count):
set ground, highest, contact to 0
for j in range(len(tennis_p[count])):
# Origin point is at left-top corner in image's coordinate.
ground←find max Y in tennis_p[count] list
if (ground was already found):
highest←find min Y in tennis_p[count] list
contact←find max X in tennis_p[count] list
ground_p.append(ground)
highest_p.append(highest)
contact_p.append(contact)

Normalize(ground_p, highest_p, contact_p)
DrawPlots(ground_p, highest_p, contact_p)
```

Table 3. Formula chart.

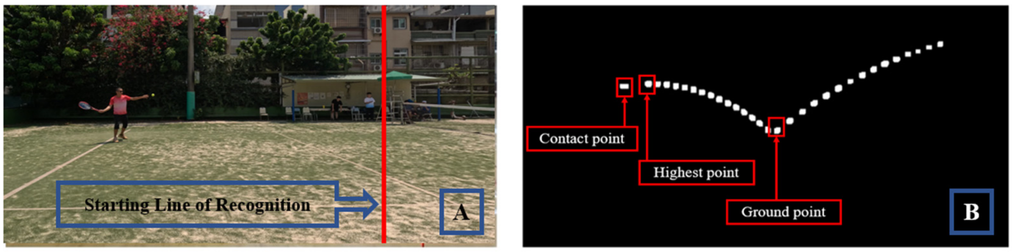
$$1\ pixel = \frac{\sum_{i=1}^{n} \frac{5.5\ meters}{x_i}}{n} \quad \begin{cases} n = 4\ sidelines (2\ singles, 2\ doubles) \\ x_i\ is\ the\ pixel\ length\ of\ the\ sidelines\ in\ image \end{cases}$$

Table 4. Overlap ratios by group and stroke type.

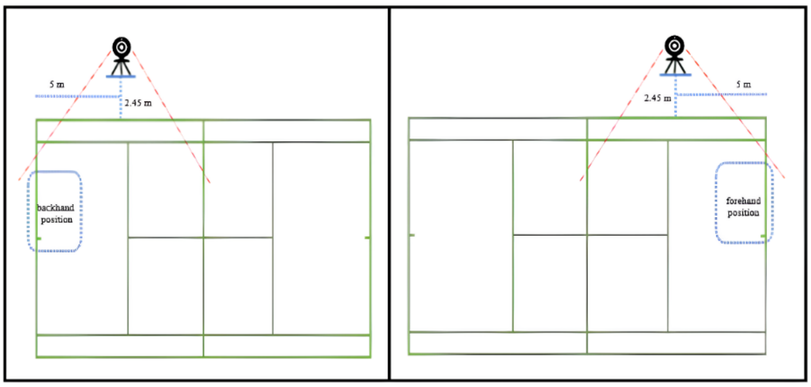
Player Group	Forehand Overlap (%)	Backhand Overlap (%)
Top Men	95	91.7
Top Women	95	85
Average Men	28.3	1.7
Average Women	21.7	0

Table 5. Two-way ANOVA summary.

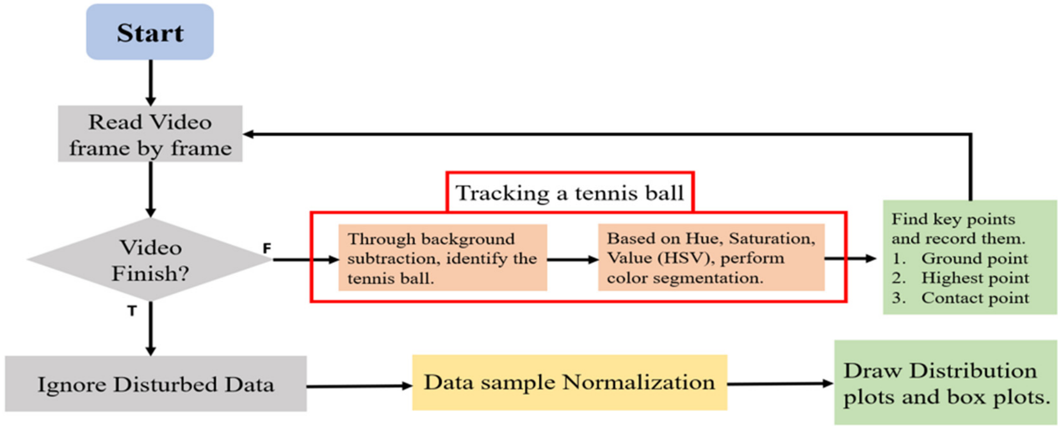
	Source	F-value	*p*-value	Partial η^2
1	Skill Level	449.838	< 0.001	0.386
2	Gender	50.636	< 0.001	0.066
3	Skill × Gender	39.819	< 0.001	0.053
4	Error	-	-	-



Figures 1. Measurement framework for object recognition. A recognizable starting line is clearly visible in the red block (A). The tennis ball flies over the starting line and begins to track. Area (B) captures the trajectory of the tennis ball as it travels in order to capture the three key points.

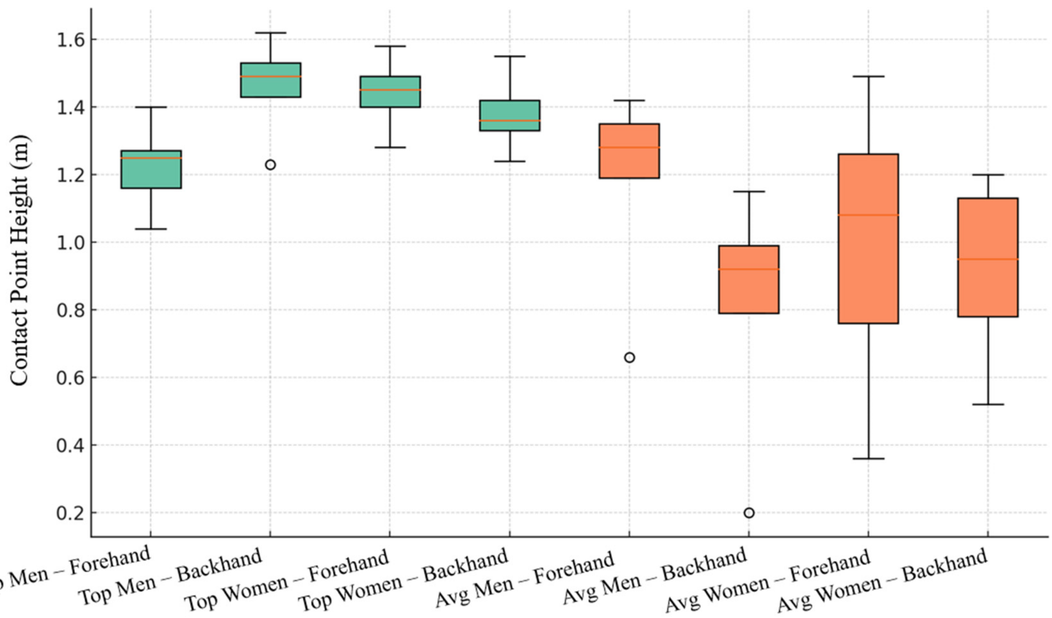


Figures 2. Schematic of the court environment setup.



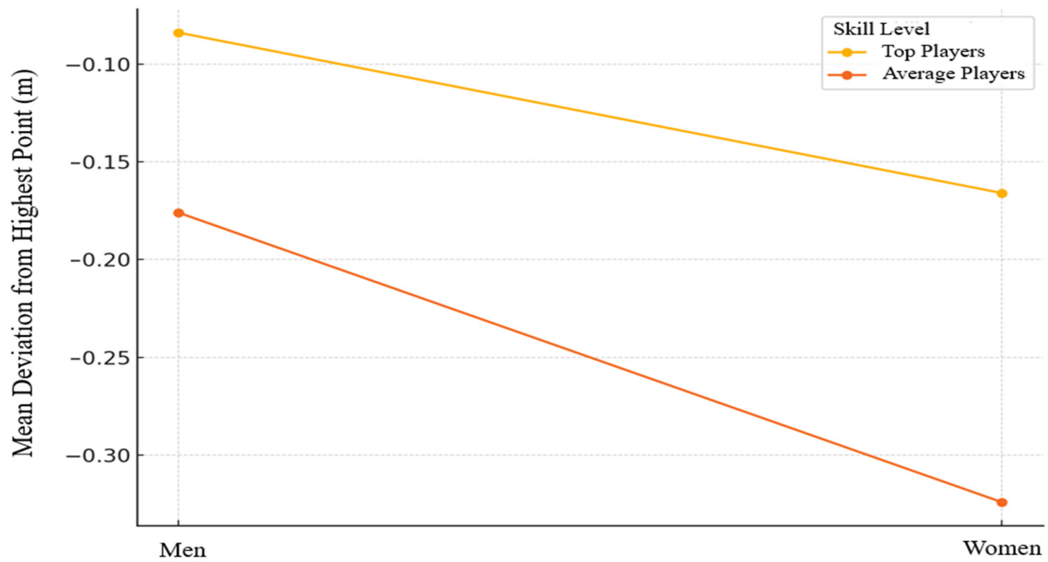
Figures 3. System flow for this study. The blue block system captures the three key points of the stroking process.

Ground point: the point at which the tennis ball touched the ground; highest point: the highest position of the ball reached after the rebound; contact point: the point at which the player's racket hit the ball



Figures 4. Boxplot of contact point heights by group and the stroke type across eight players' subgroups (Top/Avg × Gender × Stroke). Top-level players are represented in green; average-level players in orange. The boxes indicate the interquartile range (Q1–Q3), with horizontal lines marking the median. Whiskers represent the full range of contact heights.

Avg: average



Figures 5. Interaction plot illustrating the estimated mean deviation between the contact point and the ball's apex, categorized by gender and the skill level. The vertical axis represents the average vertical distance from the contact point to the highest point in meters.

Discussion

The present study aimed to examine how the skill level and gender influenced stroke precision, quantified by the vertical deviation between the contact point and the ball's apex during both forehand and backhand executions. These findings align with previous research highlighting the impact of playing experience on stroke mechanics and timing precision (Choi et al., 2026). The two-way ANOVA results revealed that the skill level exerted the strongest effect on stroke accuracy, with top-level players consistently achieving smaller deviations and higher overlap ratios compared to average-level players. Notably, gender-related differences were minimal among elite players but became pronounced in the average-level group, where female participants exhibited lower contact point heights and greater variability than their male counterparts. Furthermore, while both forehand and backhand strokes displayed skill-related disparities, backhand performance appeared more sensitive to variations in both gender and skill, suggesting that this stroke requires more refined timing and coordination.

These findings align with previous research highlighting the impact of playing experience on stroke mechanics and timing precision. Landlinger et al. (2010) reported that elite tennis players demonstrated more consistent forehand contact positions and superior timing compared to intermediate players, supporting the current observation that the skill level is a primary determinant of contact point precision. Similarly, Rota et al. (2012) emphasized the role of muscle coordination in generating forehand drive velocity, which may underlie the reduced deviation observed among top-level participants in our study. Although gender differences in tennis performance are often attributed to anthropometric and strength related factors, our findings suggest that experience and technical training mitigate these disparities, particularly in elite athletes. The integration of a hybrid KNN-HSV computer vision framework in the present study further extends prior work by providing an automated and objective method for quantifying these spatiotemporal characteristics with high precision.

The pronounced influence of the skill level over gender may reflect superior anticipatory control and visuomotor coordination developed through extensive competitive experience (Deghaies et al., 2026). Elite players have been shown to anticipate ball trajectories more effectively and adjust stroke timing with minimal variability (Farrow and Abernethy, 2003; Müller and Abernethy, 2012). This capacity likely enables top-level players to achieve consistent contact near the apex regardless of gender. From a practical standpoint, these insights underscore the potential for applying vision-based analytics in coaching settings. By pinpointing deviations in contact point height and overlap, coaches can deliver data-driven feedback to refine timing, particularly for novice female players who exhibited the greatest variability in this study. Additionally, the clear differences in backhand performance suggest that training programs should prioritize backhand-specific drills and visual feedback mechanisms to enhance stroke stability and precision.

Limitations

This study has several limitations that should be acknowledged. First, the sample size was relatively small, consisting of twelve participants divided into four groups by skill level and gender. Although each player contributed a large number of stroke events, which contributed to data density, the small group sizes may limit the generalizability of the findings to broader tennis populations. Second, the participants were recruited exclusively from elite and regional competitive levels, which may not fully represent recreational players or athletes from other developmental stages. Third, the data were collected under controlled indoor conditions using a single-camera setup, which does not account for variability in outdoor lighting, court surfaces, or match play scenarios. Finally, the analysis relied on two-dimensional KNN-HSV processing; thus, potential three-dimensional kinematic factors (e.g., body rotation or depth of the contact point) were not captured.

Future research should address these limitations by incorporating larger and more diverse samples, including players from different competitive levels and age groups. Expanding the measurement framework to multi-camera or three-dimensional motion capture systems would enhance the ecological validity of the results and allow more comprehensive assessment of stroke mechanics. Moreover, testing the framework under actual match conditions and exploring additional performance variables, such as ball speed, spin, and psychological factors, could further strengthen its practical application in tennis training and coaching.

Conclusions

This study investigated the combined effects of the skill level and gender on stroke precision, focusing on the vertical relationship between the contact point and the apex of the ball's trajectory. Utilizing a hybrid KNN-HSV vision framework, the results demonstrated that the skill level was the dominant factor influencing contact point accuracy. Top-level players consistently achieved smaller deviations and more stable contact heights compared to average-level players. Gender differences were negligible among elite players but became more pronounced within the average-level group, particularly during backhand strokes.

These findings highlight the potential of vision-based motion analysis as an objective tool for tennis training and performance evaluation. By quantifying spatiotemporal metrics such as the overlap ratio and contact point height distribution, coaches can provide targeted feedback to improve stroke timing, especially for novice female athletes who exhibited the greatest variability. Future research should validate this framework in larger and more diverse cohorts, incorporate three-dimensional or multi-camera tracking to capture full kinematics, and explore its integration into real-time feedback systems during competitive play.

Author 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 agreed to the published version of the manuscript.

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Funding Information: This research was funded by the National Science and Technology Council (NSTC), Taiwan, grant number 114-2637-H-992-002-, and the Ministry of Education (MOE) Teaching Practice Research Program, Taiwan, grant number: MOE-114-TPRGE-0053-045Y1.

Institutional Review Board Statement: The study was approved by the Institutional Review Board of the **Kaohsiung Medical University Hospital, Kaohsiung, Taiwan (KMUHIRB)** (approval code: **KMUHIRB-E(I)-20220234; approval date: 27 September 2023**).

Informed Consent: Informed consent was obtained from all participants included in the study.

Conflicts of Interest: The authors declare no conflict of interest.

Acknowledgements: The authors would like to thank all participants and supporting staff for their assistance during the study.

Received: 10 April 2025

Accepted: 07 May 2026

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