USING TRACKING TECHNOLOGY TO ESTIMATE BALL SPIN IN TENNIS

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The purpose of this study was to examine the ability of a physical model to estimate the spin of trajectories measured by a multi-camera ball tracking system. Ball spin rates and spin axis estimated from theoretical ball trajectory models were assessed for their accuracy against high-speed vision (the ground truth). A trajectory model applied to ball tracking data was able to estimate ball spin axis direction with high accuracy and ball spin rates with an RMSE of 219.43 RPM. With tracking technology now common place during professional level tennis matches, the use of a trajectory model provides a non-invasive method to accurately estimate the spin imparted when hitting.

KEY WORDS: Validation, Hawk-Eye, computer vision, tennis performance

INTRODUCTION: Tennis players impart varying amounts of spin when hitting to alter a balls trajectory, which may have performance and injury implications (Abrams, Harris, Andriacchi, & Safran, 2014; Mecheri, Rioult, Mantel, Kauffmann, & Benguigui, 2016). However, at present there are few practical measures that can be implemented during match play to provide an accurate estimate of ball spin, limiting the ability to further investigate these concepts.

Ball spin rates in tennis have previously been measured from high-speed vision collected during matchplay, by tracking the balls logo across frames to measure ball revolutions (Goodwill, Capel-Davies, Haake, & Miller, 2007; Kelley, 2011). This requires the ball's logo to be in view of the camera which is not always the case and requires high-speed vision to be collected from specific perspectives which can be labour intensive. These challenges may be overcome if ball spin can be accurately estimated from ball tracking data routinely collected during matchplay.

Multi-camera ball tracking technology is now common place during professional level matches to assist in adjudication by allowing players to challenge line calls. A physical model has previously been applied to ball tracking data in tennis to measure the lift coefficient (C_L) of serves, providing a proxy for ball spin (Mecheri, et al., 2016). However, measures of spin in revolutions over time (i.e., revolutions per minute (RPM)) are more commonly used by players, coaches and commentators and thus may be more easily interpreted. Therefore, the aim of this study was to assess if ball spin rate (RPM) and spin axis direction (topspin, backspin, sidespin) could be accurately estimated by applying a ball trajectory model to ball tracking data.

METHODS: A ball machine was setup to project tennis balls with varying spin rates (-4392 to 3400 RPM) and spin axis directions (topspin, backspin, sidespin) down the middle of a tennis court. A single high-speed camera (250 frames/s, shutter speed 1/5600s) positioned side on to or above the balls trajectory and an 8-camera Hawk-Eye system (Hawk-Eye Innovations Ltd, Basingstoke, UK) concurrently captured each ball projected. A trial was valid if the intersection of equator lines drawn on each ball became the spin axis, which was perpendicular to the viewing axis of the camera (i.e., spin in only one dimension). For valid trials (n = 165), ball spin was calculated from high-speed vision by measuring the angle of a point on the ball relative to the intersection of equator lines. Three consecutive frames of vision immediately post-impact with the ball in full camera view (full frame) were digitised using Tracker Video analysis software (version 4.9.8, open source physics, https://physlets.org/tracker/).

Initial ball trajectory parameters measured by Hawk-Eye (measured trajectory) were used to simulate the two-dimensional trajectory of a ball using a theoretical model (modelled trajectory). The theoretical model incorporated the gravitational and aerodynamic forces acting on a ball through flight, and assumed the ball was launched with pure topspin, backspin or sidespin, thus having motion in only two dimensions. This model was initially solved using known spin from high-speed vision to determine a trajectory's drag coefficient (C_D) and C_L, which were subsequently used as model inputs to estimate spin.

The C_D and C_L for a given trajectory were determined based on methods used by Cross and Lindsey (2014), where ball tracking data was substituted for high-speed vision. Error between a modelled and measured ball trajectory was minimised to find the C_D and C_L of a given trial. This was done using "Nelder-Mead" and "L-BFGS-B" optimiser methods from the "optim" package and the "nmbk" optimiser, part of the "dfoptim" package in R (R Core Team, 2017). Ball spin rate (RPM) and spin axis direction were subsequently estimated by modelling a balls trajectory from launch to landing using observed C_D and C_L. Variation in C_D was found for a given spin parameter (Sp = ball radius x ball spin / ball velocity), thus, aforementioned optimisers were used to find the combination of spin and C_D resulting in the smallest error between a modelled and measured trajectory at landing, with this value taken as the trials spin rate. Modelled trajectories can be altered by varying the C_L, while the optimiser and variables included in the error minimised at landing can affect the estimated ball spin rate. Therefore, different combinations of C_L calculation, optimiser method and error were tested for their accuracy to estimate spin rate and direction.

Spin estimates were compared to spin rates measured from high-speed vision (the ground truth) using a Bland-Altman analysis, root mean square error (RMSE) and paired t-tests. All spin rates were analysed as absolute values to focus on the magnitude of topspin and backspin trials. Median percentage error was also calculated overall and within spin ranges, both reported with 95% confidence intervals (CI) for the median error using 1,000 bootstrap resamples.

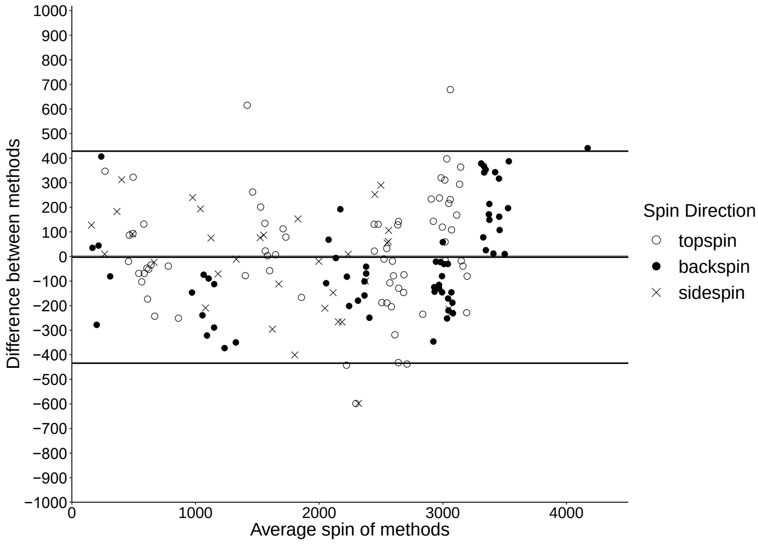
RESULTS: The "L-BFGS-B" optimiser was poor at predicting spin, consistently outperformed by Nelder-Mead optimisers. Models estimated spin with the highest accuracy when the error minimised at landing included velocity components, rather than ball height alone or in combination with landing angle. There was similar performance across numerous ball trajectory models using a Nelder-Mead optimiser, however only results from the top performing model are emphasised below.

The most accurate spin estimates were produced when using the "nmbk" optimiser, lift coefficient calculation of $C_L = 0.505 \times Sp$ and by minimising the error in ball height and velocity components at landing. Ball spin was predicted by the trajectory model with an RMSE of 219.43 RPM and mean bias of -2.86 ± 220.08 RPM, median percentage error of the method is presented in table 1. The error relative to the standard deviation in spin means that the typical error is 5 times lower in magnitude than the typical difference in spin between a randomly selected pair of trials in the sample, suggesting that the error is low enough to be practically useful. Additionally, the spin axis for >99% of trials was correctly classified.

Table 1 Median percentage error of spin estimates

	Number of trials	Median % error (95% CI)
Overall (all trials)	165	7.29 (6.12, 8.79)
0 – 1500 RPM	44	18.79 (12.03, 23.99)
1500 – 3000 RPM	82	5.34 (3.45, 5.92)
>3000 RPM	39	6.13 (3.52, 8.35)

Figure 1 Bland-Altman plot for actual spin rates compared to estimates from the ball trajectory model



DISCUSSION: Given the range of spin rates validated in the current study (i.e., -4392 to 3400 RPM), the use of this method would appear best suited for groundstrokes and serves imparted with lower levels of spin (i.e., flat serves). Groundstroke spin rates have been measured at <4,000 RPM, while serve spin rates have approximated 5,000 RPM during matchplay (Goodwill, et al., 2007; Kelley, 2011). Thus, the accuracy of this method for strokes characterised by higher spin rates, outside of the range validated, is unknown. This is relevant as there is some evidence from other sports suggesting that C_L may level off as Sp increases (Goff and Carre, 2009; Nathan, 2008), in turn, affecting the computation of spin.

Compared to spin estimated from tracking technology in other sports (i.e., baseball) (Matsuo, Nakamoto, & Kageyama, 2017; Nathan, Kensrud, Smith, & Lang, 2014), the estimates in the current study contained higher error. Nathan et al. (2014) found an RMSE of 35 RPM when validating TrackMan spin rates against high-speed vision. This higher accuracy could be due to differences in tracking technology. Hawk-Eye is a multi-camera tracking system sampling at 50-60Hz, while Trackman utilises Doppler radar technology sampling at 48,000 Hz. While the higher accuracy of TrackMan would be appealing, Hawk-Eye is now common place in tennis for officiating and broadcast purposes. Additionally, the accuracy of the method presented in the current study is likely sufficient for large scale investigations into the effect of spin on player performance and other aspects of the game.

Historically, applied research in tennis has focused on ball velocity and/or accuracy as its outcome measures (Whiteside and Reid, 2017). The direct influence of ball spin on these outcomes has largely been overlooked, which is unfortunate given the practical significance attached to the use of spin by coaches in teaching stroke production (Elliott, Reid, & Miguel, 2009). The introduction of a valid and non-invasive spin measure provides the opportunity for researchers to not only investigate the relationship between ball spin and performance but also musculoskeletal injury. The link to musculoskeletal injury, especially of the upper limb, seems intuitive given that ball spin is largely a product of the speed and trajectory of the player's racquet swing (Choppin, Goodwill, Haake, & Miller, 2007).

Hawk-Eye does not provide original ball coordinate data, rather a third-degree polynomial which may have affected the accuracy of variables derived and used to estimate spin. Additionally, despite tennis ball mass and diameter being found to vary (Cross and Lindsey, 2014), along with air density these were held constant across all trials when modelling a balls trajectory as it is not practical to measure these variables during matches. Both limitations may have affected the accuracy of spin estimates.

CONCLUSION: At present, there is no published method to estimate ball spin from computer vision outputs of ball position in tennis. Our proposed method offers one such solution, with the prospect of being able to measure spin with error rates of 219.43 RPM. As with other technologies used to appraise components of player behaviour (such as radar gun measurement of ball speed), it is important for coaches to be mindful of these measurement errors when evaluating whether observed effects in hitting performance are real.

REFERENCES:

Abrams, G.D., Harris, A.H., Andriacchi, T.P., & Safran, M.R. (2014). Biomechanical analysis of three tennis serve types using a markerless system. *British Journal of Sports Medicine,* 48(4), 339-342. Choppin, S.B., Goodwill, S., Haake, S., & Miller, S. (2007). 3D player testing results from the Wimbledon Qualifying Tournament. In S. Miller & J. Capel-Davies (Eds.), *Tennis Science and Technology 3* (pp 341- 348). London: International Tennis Federation.

Cross, R., & Lindsey, C. (2014). Measurements of drag and lift on tennis balls in flight. *Sports Engineering*, 17(2), 89-96.

Elliott, B., Reid, M., & Miguel, C. (2009). *Technique Development in Tennis Stroke Production.* London: International Tennis Federation.

Goff, J.E., Carre, M.J. (2009). Trajectory analysis of a soccer ball. *American Journal of Physics,* 77(11), 1020-1027.

Goodwill, S., Capel-Davies, J., Haake, S., & Miller, S. (2007). Ball spin generation by elite players during match play. In S. Miller & J. Capel-Davies (Eds.), *Tennis Science and Technology 3* (pp 349-356). London: International Tennis Federation.

Kelley, J. (2011). *Measuring ball spin rates in match play tennis* (Doctor of Philosophy). Sheffield Hallam University.

Matsuo, T., Nakamoto, H., & Kageyama, M. (2017). *Comparison of Properties of a Pitched-Ball Rotation Measured by Three Different Methods.* Conference of the International Society of Biomechanics in Sport, Cologne, Germany.

Mecheri, S., Rioult, F., Mantel, B., Kauffmann, F., & Benguigui, N. (2016). The serve impact in tennis: First large-scale study of big Hawk-Eye data. *Statistical Analysis and Data Mining,* 9(5), 310-325.

Nathan, A.M. (2008). The effect of spin on the flight of a baseball. *American Journal of Physics,* 76(2), 119-124.

Nathan, A.M., Kensrud, J., Smith, L., & Lang, E. (2014). Testing TrackMan: Just How Well Does TrackMan Work? Retrieved Date Accessed, 2018, from https://www.baseballprospectus.com/news/article/23202/testing-trackman-just-how-well-does-trackman-work/.

Whiteside, D., & Reid, M. (2017). Spatial characteristics of professional tennis serves with implications for serving aces: A machine learning approach. *Journal of Sports Sciences, 35*(7), 648-654.