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An application of clustering to classify movement patterns in men's professional grand slam hard court tennis

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ABSTRACT

The movement cycles from Australian Open player tracking data were analysed using the Lloyd k-means clustering algorithm to classify movement patterns that exist in men's grand-slam tennis. The elbow criterion method identified six movement patterns, and the k-means model allocated each movement cycle into one of these discrete groups. A description of each movement pattern is presented, outlining three inner range and three end range movement patterns, which are distinguishable by distance, direction, time pressure, and starting location. These findings provide objective details for coaches and athletes to understand tennis movement, overcoming vague descriptions of the inner range and end range in tennis vernacular. The amalgam of distance, direction, and time pressure demands that categorise the six movement patterns can enhance the specificity of training drill design and movement evaluation. Furthermore, evaluating the movement patterns a player typically elicits during match-play can inform typical load exposure and be useful in load monitoring practices. Additionally, understanding the prevalence of movement patterns in a typical match may help understand the strategic approaches players use during match-play.

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Movement analysis; Hawkeye; data science

1. Introduction

The evaluation of elite-level movement in world-class tennis has been researched extensively in the last decade (Giles & Reid, 2021; Giles et al., 2018, 2021; Kovalchik & Reid, 2017; T. Pereira et al., 2017; Pluim et al., 2023; Roetert et al., 2003; Whiteside & Reid, 2017). Although tennis requires cyclical repetitions of smaller movement repeatedly within a match (generally termed a "movement cycle") (Margi, 2020), most literature has centred on match aggregates of distance, speed, and acceleration (Pluim et al., 2023). This approach is useful in understanding the overarching load and physical requirements of playing elite professional tennis. However, investigations of scenario based aspects of the movement cycle, such as time pressure, court

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positioning, or direction of movement are lacking. Indeed, several studies that have investigated the movement cycle also report findings ascertaining to distance demands only, with some enriched context of footwork patterns highlighted (Armstrong et al., 2024; Filipcic et al., 2021; Hughes & Meyers, 2005; Pluim et al., 2023; Roetert et al., 2003). In this sense, movement cycle literature provides little more than a fraction of insight into the multi-directional, high intensity, and complex tactical nature of tennis movement cycles, despite the availability of information to describe deeper details (Kovacs, 2007, 2009). As a result, coaches often use tennis vernacular of inner range or end range to describe movement distances, but no clear definition of these movement patterns exists.

With limited published data examining the movement cycle in detail, coaches heavily rely on their expert opinion to evaluate movement in match-play and how players move during points. When interviewed, experienced professional coaches report that elite movers utilise one of the following three match-play qualities; 1) being fast, 2) being efficient, or 3) high levels of tactical awareness (Giles et al., 2018). Being fast outlines pure physical ability, whereas efficiency and tactical awareness imply moving in response to stimuli, which is a fundamental aspect of the perception-action coupling that characterises interceptive sports such as tennis (Le Runigo et al., 2005). These qualities aim to reduce the time taken to move to a desired location, and limited research leaves a significant knowledge gap in tennis movement literature outlining these scenarios. Considering movement as a function of time also provides detail into the oscillation between maximal and sub-maximal efforts that occur during match-play. Recently, Mlakar and Kovalchik (Mlakar & Kovalchik, 2020) reported the use of time to net (i.e. how long the ball takes to leave the hitting players racket and cross the net to the opponents side of the court) to quantify time pressure in tennis match-play. This measure of time pressure informs the temporal demands placed on athletes during each shot and can be useful to detail this context in the movement cycle.

Another key feature of tennis play, which is also related to the temporal demands imposed on players, is court positioning. While some attempts have been made to incorporate court positioning into point prediction models (Carvalho et al., 2013; van Meurs et al., 2021), the interplay between court positioning and movement is poorly understood beyond the suggestion that where players "stand" on court generally determines the next direction of their travel (Carvalho et al., 2013; van Meurs et al., 2021). The examination of movement direction in tennis has been scarce though, with only one report outlining 70% of movement being lateral, 20% as forwards, and <10% as backwards (Kovacs, 2009; Weber et al., 2007). Tennis movement is rarely perfectly perpendicular or parallel to the net, a shortcoming conceded by the previously mentioned authors. The addition of player location alongside more direction categories will improve the information available regarding tennis movement cycles within given contexts of a match, giving coaches specific and context-rich information about movement cycles in certain match-play scenarios.

In tennis, there are four Grand Slam events which are unique in the sense that the large majority of the best players in the world come together to compete. Lower level tournaments may have several top-tier players competing, but the pool of talent is strongest in major Grand Slam events, bringing about the highest level of competition the game has to offer. Two of the four Grand Slams are played on hard court surfaces, with one on grass and one on clay. Men play best-of-five sets in Grand Slam events further adding to the uniqueness of these occasions. A Grand Slam event is most likely to provide the best quality information given the calibre of players that enter, and that competition is at its peak in these events.

Hawk-Eye (a markerless motion capture system; Hawk-Eye Innovations Ltd, Basingstoke, UK) are employed in Grand Slam events providing tournament owners with player and ball tracking data. The recent evolution of data availability and computer science technology has led to several detailed and complex analyses in tennis using Hawk-Eye data, providing a richer context of match-play (Giles & Reid, 2021; Giles et al., 2020, 2021; van Meurs et al., 2021; Wei et al., 2015, 2016). Machine learning approaches have been utilised in identifying a shot dictionary (Kovalchik & Reid, 2018) and also to identify different movement styles for change of direction during professional tennis matches (Giles et al., 2020, 2021). Prior to these advancements, evaluation of shot types and change of direction detail was either manual or rudimentary, much like the current state of movement cycle demands. In this way, a data-driven analysis of the temporal, directional and positional characteristics of common movement cycles in professional tennis is overdue. Therefore, the aim of this research was to investigate the typical movement patterns that capture the breadth of movement cycles for men at the Australian Open Grand Slam event.

2. Methods

2.1. Participants

All main draw Australian Open male participants from either 2021 or 2022 were considered for this study. A total of 128 males are entered each year with 169 individual males entering between 2021 and 2022. Consent for data collection and analysis during the Australian Open was obtained on entry into the tournament. An institutional research ethics committee provided ethical approval for the study (2022/ET000216).

2.2. Data collection and analysis

Participants competed in live match-play as part of the Australian Open Grand Slam tournament. The nature of tennis match-play sees participants complete several movement cycles per point, as per the definition provided by Margi (Margi, 2020), which were captured from every match and utilised in this investigation. Hawk-Eye technology was used to track the player and ball coordinates during match-play. Hawk-Eye uses a 10-camera system to track player and ball coordinates during Australian Open tennis matches with a mean error of 2.6 mm for ball tracking (Innovations). The player tracking component describes the X Y positional coordinates of each player, and the ball tracking describes the X Y Z positional coordinates of the ball during live points. The split-step action is not directly measured in the player tracking data, so opposition racket-ball impact time was used to infer it instead, due to the close timing of the split-step and opposition hitting times (Mecheri et al., 2019). The rally end was determined by the time of the last shot taken in the rally. The serve cycle and last half cycle were removed from the analysis to only include full movement cycles, as detailed in the previous work

(Armstrong et al., 2024). These data are then processed post-match using a Butterworth low-pass filter. The processed data were checked for errors consistent with tracking drop out, generally resulting from a player moving outside the Hawk-Eye camera calibration volume during match-play. Where an error was identified during a movement cycle, that movement cycle was removed from the analysis. This resulted in 1746 movement cycles being removed and leaving 116,080 movement cycles being utilised in this study.

Several features were available for consideration in this study. To narrow the available features to those which provide meaningful context to match-play and could influence the different movements during match-play, experts in tennis movement performance were engaged. This resulted in four features being utilised in the final analysis, which were distance to the ball, recovery distance, direction of travel to the ball (i.e. forwards, left, right, etc. by measure of degrees; termed direction), and time pressure as defined by Mlakar and Kovalchik (Mlakar & Kovalchik, 2020). Data were normalised by z-scores prior to clustering; however, direction was numerically categorised in 45-degree thresholds, where movement straight-left and straight-right were identical, movement forward-left and forward-right were identical, movement back-left and back-right were identical, movement straight-forward was unique, and movement straight-backward was unique. This was done to ensure the handedness of a player did not influence the directionality to the left or right of the court. The elbow criterion method was utilised to determine the most appropriate number of movement patterns (Yuan & Yang, 2019). The elbow criterion method uses the square of the distance between the sample points in each cluster and the cluster centroid and returns a sum of squared errors (SSE) value for a range of different cluster values (K) (Yuan & Yang, 2019). The plot of K by SSE should show a steep decline in SSE as the true number of clusters is approached, resulting in a slow decline in SSE thereafter (Yuan & Yang, 2019). The Lloyd k-means clustering algorithm was used to group the movement cycles of men's professional grand-slam tennis into categorised movement patterns. For interpretation of the movement pattern results, further analysis included investigation of the distribution of all variables in each movement pattern. For practicality, and to simplify interpretation, each movement pattern was labelled in accordance with its centroid information and upon consulting exemplar vision. Further descriptions of each movement pattern were provided by expert tennis coaches and movement specialists. All the analyses were performed using the Python programming language (Python version 3.11.0 [24 October 2022]).

3. Results

The elbow criterion method determined the most appropriate number of clusters as six and, therefore, six movement patterns were identified to outline the most common movement cycles that exist in men's professional grand-slam tennis played on hard courts. Table 1 provides details including how often each movement pattern occurs in a match (as a percentage), centroid values for variables used in the clustering algorithm with the addition of the mean split step locations from the centre of the net, a description of the movement pattern, and common characteristics as described by professional tennis coaches. The description of each movement pattern is outlined by directionality, tennis vernacular of movement distances and a traffic light colour system representing temporal difficulty (green being easy, amber as moderate and red as hard). The descriptions are as

Table 1. Movement pattern centroid information with additional information including labels and coach descriptions of each movement pattern. Backward inner range green (BIRG), forward inner range green (FIRG), lateral inner range amber (LIRA), multi-directional end range amber (MERA), multi-directional extended range green (MERG), lateral end range red (LERR).

Movement pattern	Percentage per match	Split Step Width	Split step depth	Distance to ball	Distance recovering	Time pressure	Dominant direction	Label	Description
1	29.92 ± 2.36%	0.37 m left of centre	0.24 m behind baseline	2.25 m	1.78 m	0.49s	Back Left	BIRG	Low time pressure, stepping backwards into shot. Typically pushed back off baseline. Generally within 1-2 steps.
2	8.75 ± 1.79%	0.66 m left of centre	1.08 m behind baseline	2.56 m	2.56 m	0.58s	Forward Left	FIRG	Low time pressure, stepping forwards into shot. Moving into the court hitting aggressively, generally within 1-2 steps
3	30.20 ± 2.68%	0.33 m left of centre	1.76 m behind baseline	2.40 m	1.79 m	0.46s	Left, Right	LIRA	Lateral movement around/behind the baseline with shuffling steps. Fast incoming ball producing time pressure. Often short distance movements.
4	14.64 ± 2.06%	0.14 m left of centre	0.81 m behind baseline	4.24 m	2.14 m	0.61s	Left, Right	MERA	Moderate time pressure with shuffling footwork. Most commonly lateral but cases of multi-directional movement. Generally well balanced with time to execute stroke, often behind the baseline.
5	3.11 ± 0.93%	0.12 m left of centre	On the baseline	6.74 m	3.27 m	0.96s	Forward, Forward Left	MERG	Low time pressure with longer distances. Often moving up towards the net but some multi-directional movements included. Usually 5+ steps with shuffling or striding footwork
6	13.46 ± 2.39%	0.16 m left of centre	1.39 m behind baseline	3.70 m	3.91 m	0.44s	Right, Left	LERR	High time pressure with hard lateral movement deep off the baseline from lunging strides. Generally associated with a hard change of direction recovering central to the midline.

follows: movement pattern 1 ($n = 32934$) – Backward inner range green (BIRG); movement pattern 2 ($n = 10351$) – Forward inner range green (FIRG); movement pattern 3 ($n = 36465$) – Lateral inner range amber (LIRA); movement pattern 4 ($n = 17497$) – Multi-directional end range amber (MERA); movement pattern 5 ($n = 3507$) – Multi-directional extended range green (MERG); and movement pattern 6 ($n = 15326$) – Lateral end range red (LERR). Figure 1 provides a visual representation of each movement pattern showing opponent hitting locations, ball bounce locations, player split-step locations, and the initial direction of the movement pattern. All movement patterns show an inferred split step location slightly left of the centreline, with FIRG the furthest left

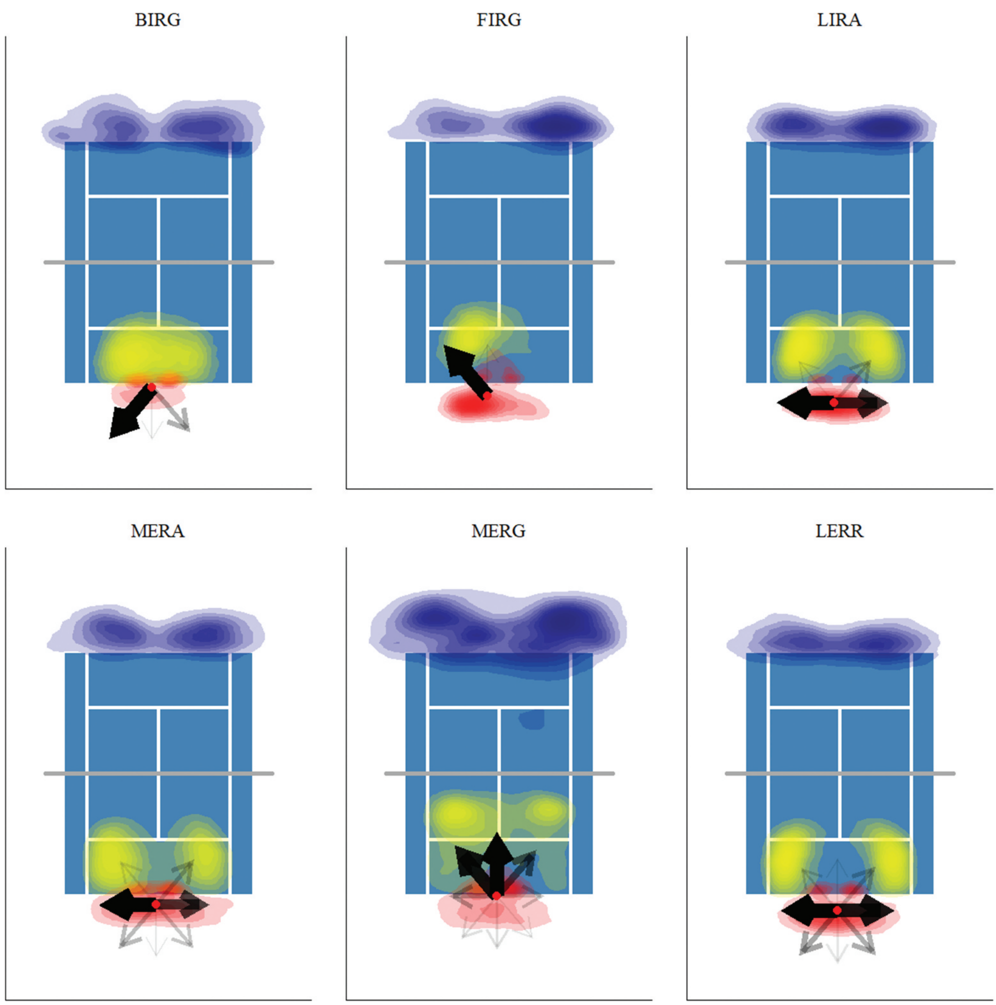

Figure 1. On court movement pattern visual representation. Navy blue represents opponent hitting location density, yellow represents incoming ball bounce location density, red represents player split-step proxy location density with the red circle displaying the mean location, and the arrow density and size representing the proportion of movement to the ball (thicker and darker showing more frequency). Backward inner range green (BIRG); forward inner range green (FIRG); lateral inner range amber (LIRA); multi-directional end range amber (MERA); multi-directional extended range green (MERG); and lateral end range red (LERR).

(0.66 m left of centre) and MERG the closest to centre (0.12 m left of centre). FIRG, LIRA, and LERR are the furthest from the baseline at ≥1 m behind and BIRG the closest to the baseline virtually on top of the line. BIRG has the shortest distance to the ball with a centroid value of 2.25 m, whereas MERG has the furthest distance at 6.75 m. Alongside the shortest distance to the ball, BIRG also has the shortest recovery distance (1.78 m), whereas LERR has the longest recovery distance (3.91 m). Time pressure was highest in LERR, with a time to net of 0.44s and lowest in MERG with a time to net of 0.96s.

When investigating the distribution of values for each variable in each movement pattern, several similarities and differences were observed. This analysis is illustrated in Figure 2 which shows larger variation in distance demands for MERG and LERR compared to the others. Time pressure is discernibly lower and more variable in MERG, with all other movement patterns appearing to have more consistent time pressure distributions. Speed shows larger magnitudes and variance when players were required to cover more court (travel longer distances). Figure 3 contrasts the frequency of direction of travel in each movement pattern. BIRG contains only backward motions, dominated by backward-left movement (45%). FIRG contains only forward motion, with ~ 63% of movement forward-left. LIRA consists of mainly direct lateral motion, accounting for >90% of movement and <10% forward-right. MERA is mostly directly lateral (~75%) and notably more often to the left, but somewhat multi-directional. MERG is also mostly forward (~75%) with ~ 15% of movement directly lateral and ~ 10% of

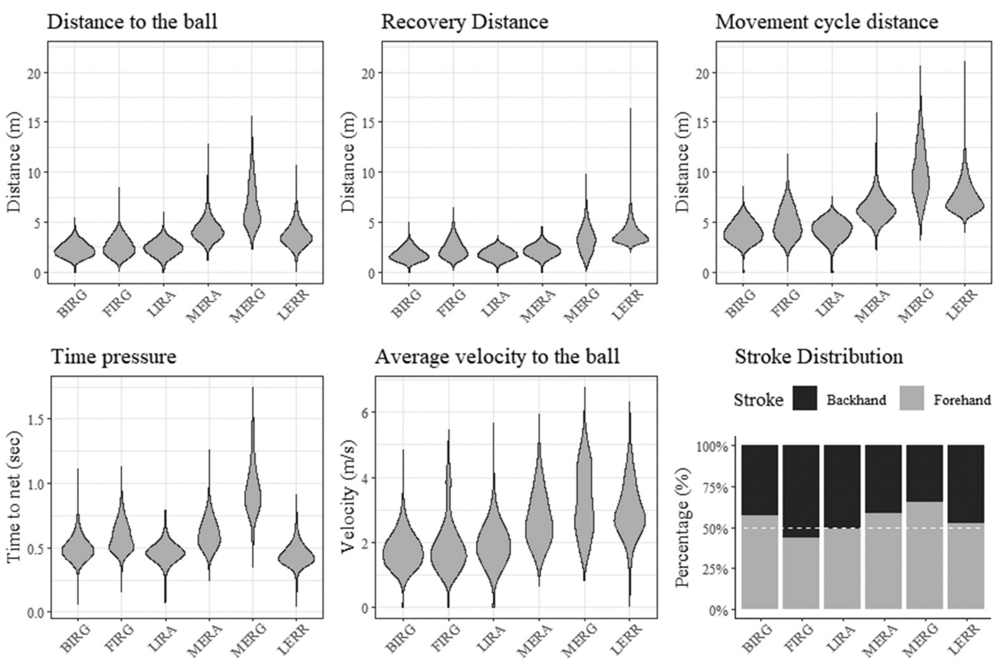

Figure 2. Comparison of variable distributions per movement pattern, including forehand and backhand stroke ratio. Movement pattern 1 – backward inner range green (BIRG); movement pattern 2 – forward inner range green (FIRG); movement pattern 3 – lateral inner range amber (LIRA); movement pattern 4 – multi-directional end range amber (MERA); movement pattern 5 – multi-directional extended range green (MERG); and movement pattern 6 – lateral end range red (LERR).

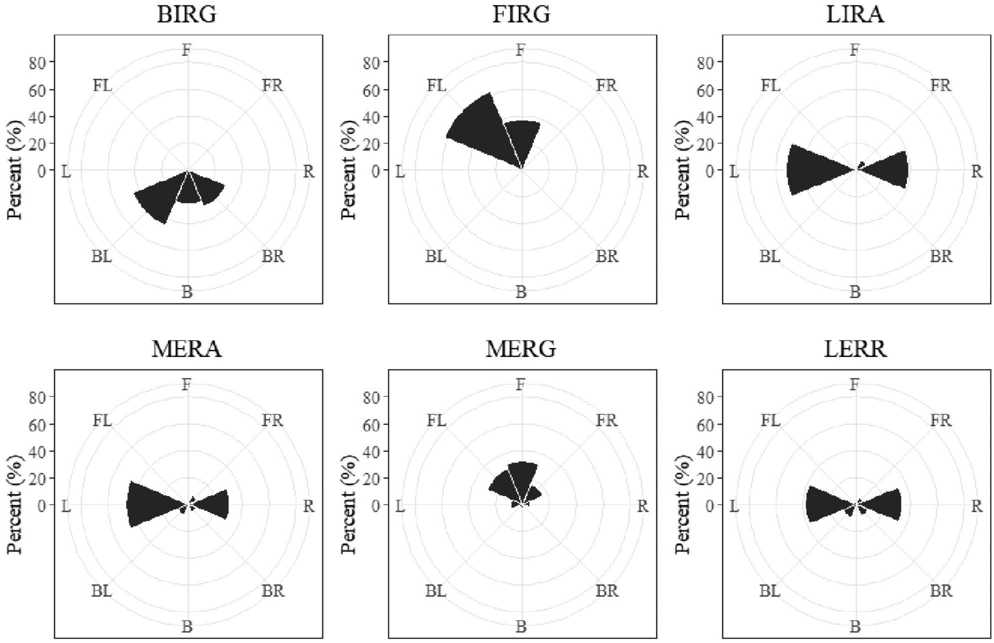

Figure 3. Relative distribution of movement direction to the ball per movement pattern. Backward inner range green (BIRG); forward inner range green (FIRG); lateral inner range amber (LIRA); multi-directional end range amber (MERA); multi-directional extended range green (MERG); and lateral end range red (LERR).

movement containing a backward motion, being the most multi-directional movement pattern. LERR is dominated by directly lateral movement (71%), and to a lesser extent, backward-left and backward-right motion (10% and 9% respectively).

4. Discussion

The purpose of this study was to provide a data-driven analysis of the temporal, directional and positional characteristics of common movement cycles in professional tennis. A k-means clustering approach classified six discrete movement patterns, varying in distance, speed, time pressure and direction. These results detail the most common movement cycles during men's professional hard court match-play, providing context which is missing in historical tennis movement analysis (Galé-Ansodi et al., 2017a, 2017b, 2018; Giles & Reid, 2021; Hoppe et al., 2014, 2016, 2020; Kovacs, 2009; Kovalchik & Reid, 2017; L. Pereira et al., 2015, 2016; T. Pereira et al., 2017; Roetert et al., 2003).

A novel aspect of this investigation is the evaluation of time pressure in movement analysis. Mlakar and Kovalchik (Mlakar & Kovalchik, 2020) present time to net as a proxy for time pressure and report normative values of 0.3–0.8 s in the men's game (depending on shot type). LERR returned the highest time pressure value (i.e. lowest time to net) of 0.44s and MERG the lowest time pressure of 0.96s. Interestingly, the distribution of movement velocity appears somewhat similar between these two movement patterns. When considered in isolation, low time pressure values intuitively imply low speed of movement. However, the current results support consideration of both time pressure and distance demands together to understand the requirements of movement speed.

The limited historical information in tennis literature outline distances of <2.5 m to occur in 80% of movement cycles (Roetert et al., 2003); however, more recent work estimates the average distance to be 4.5 m (Armstrong et al., 2024). This work has manifested into tennis vernacular of coaches describing movement requirements as inner range or end range, but direction and temporal demands have not been considered holistically with these distance requirements. The results of the current investigation provide a framework for understanding movement cycle demands in men's professional tennis in an objective and context-rich manner. The movement patterns that best support the anecdotal end range description that coaches have used for decades can be broken into three distinct movement tasks. As a comparison, the LERR pattern highlights the need for lateral movement (to the left or right of the court) under high time pressure, where players are usually central but deep off the baseline. This is different from the MERG pattern, which highlights the need for linear running (towards the net) from virtually on top of the baseline. The MERG pattern has much lower time pressure but almost twice the distance required to reach the ball, which is a key consideration when training linear running for tennis match-play. Both these scenarios are considered end range, but the details from this investigation define a deeper context for coaches to train end range in a variety of different ways that present during match-play.

Interestingly, distance has often been considered separately to direction in tennis research, where historical literature describes ~ 70% of movement to occur to the left or right of the court (Weber et al., 2007). The movement patterns identified in our research provide deeper context to the scenarios a player may face when playing at the highest level of competition, where both distance and direction are considered concurrently. Of note, the biggest proportion of movement cycles fit the LIRA pattern where movement is a short distance to the left or right with high time pressure. This is described as short shuffling movements that begin deep off the baseline. Practically, mastering this movement pattern to position oneself in a premier hitting position would be useful, given the proportion of this movement pattern to present in men's professional tennis. Furthermore, BIRG (~30%) and FIRG (~8%) comprise ~ 38% of movement patterns, which are dominated by the movement of backwards-left or forwards-left directions. Again, these patterns are short in distance but are important to conquer given their prevalence in match-play. In summary, the results of this study suggest that coaches and athletes should spend a large proportion of training targeting the inner range movement patterns of LIRA, BIRG, and FIRG, as these movements present most commonly in men's professional match-play.

The distribution of each movement pattern's frequency (presented in Table 1 as Percentage per Match) provides insights into the typical movement pattern distribution of the overall playing pool of world-class tennis talent. Conducting an analysis into the distribution of movement patterns at the individual level may be useful to understand 1) a certain playing style (i.e. serve-volley playing style may be most frequented by a higher volume of MERG) or 2) a tactical evaluation of shot selection (i.e. opposition player opening hitting angles and playing wide shots, akin to LERR). It may also be useful for coaches to understand their athlete's typical distribution of movement pattern frequencies as a load monitoring strategy. Understanding the typical exposure to end range movement patterns can be used as a reference for the demand of more physically challenging movement patterns. Matches can be evaluated and compared to this reference to evaluate if a match was more or less demanding from an end range movement perspective. This can guide and facilitate recovery and nutritional practices, a concept similarly adopted in field-based team sports with total distance, high-speed running, and mechanical workloads (Buchheit & Laursen, 2022). Considering mechanical workloads are an effective way to evaluate the physical demands of tennis movement (Galé-Ansodi et al., 2017b; Kovacs, 2006, 2009), and therefore, further investigations into each movement pattern and the associated physical workloads of each would be beneficial to build on this concept and understand the loading requirements of musculoskeletal structures in each movement pattern.

Several other findings have the potential to impact current player preparation and training design. Distance clearly contrasts between movement cycles, and these differences alone warrant applied attention. For example, BIRG and MERG have a difference in distance of more than half the court width, where preparing a player to execute MERG would require they cover nearly double the distance each movement cycle compared to BIRG. However, BIRG occurs ~ 10-times more often than MERG and athletes may rehearse BIRG more frequently to prepare for the expected exposure to this movement in match-play. In this way, movement pattern analysis can be utilised to evaluate training sessions over the course of a week or training block to ensure each movement pattern is simulated adequately to prepare athletes for tournament matches. As tennis is a game of time and space (Crespo & Miley, 1998), the aforementioned interaction between distance and time pressure must surface during training. Distance of movement with appropriate time pressure can create movement demands resulting in match quality speed, acceleration, and reaction time. The representative learning design of tennis drills has a large focus on skills (Krause et al., 2018) and with the current results, movement demands can be considered more specifically to facilitate training environment transfer to match-play. For example, as hitting technique is more variable and less effective at higher velocities (Giles & Reid, 2021), creating these ecological training environments will allow coaches to evaluate, and athletes to improve, hitting technique in match-like scenarios within the training environment.

The current results also provide a benchmark for elite professional tennis movement in the men's game, allowing comparison of junior athlete ability to professional players. Senior players tend to hit the ball faster and wider than junior players (Kovalchik & Reid, 2017), where the time pressure and distance requirements may be lower in junior tennis. The movement patterns presented in the current study can inform movement assessments evaluating an athlete's ability to execute desired shots under specific constraints. This may be of particular importance for those players nearing the end of the junior pathway and transitioning into professional match-play to ensure they are able to meet these movement requirements. That being said, the direct comparison between the results of this investigation for application with junior players should be approached with caution, as the results presented are from elite male professional tennis players. Furthermore, the application to female athletes may also be limited despite the similarities presented between the sexes in previous literature (Armstrong et al., 2024; Mlakar & Kovalchik, 2020). Future research to investigate the influence of court surface and game-style on tennis movement is warranted, given the known differences in movement demands (Galé-Ansodi et al., 2017a; L. Pereira et al., 2016; Pluim et al., 2023).

5. Conclusion

This study provides reference to common movement cycles that exist in men's professional hard court Grand Slam tennis. Six movement patterns were identified, unique in distance, time pressure and direction of movement. Classifying movement in this manner provides much needed detail into the movement cycle of professional matchplay, context regarding match tactics, allows specific evaluation of movement ability in distinct movement cycles, and can improve the ecological validity of movement based training drills.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Consent statement

Consent for data collection and analysis for this study was obtained prior to each tournament at time of entry.

Ethics approval statement

The University of Western Australia research ethics committee provided ethical approval for the study (2022/ET000216).

References

Armstrong, C., Peeling, P., Murphy, A., & Reid, M. (2024). Navigating the court: A comparison of distance demands between sexes in grand slam tennis. *Journal of Sports Science & Medicine*, *3*, 1–7. https://doi.org/10.52082/jssm.2024.1

Buchheit, M., & Laursen, P. (2022). Periodization and programming for team sports. In D. French & L. T. Rhonda (Eds.), *Nsca's essentials of sport science* (pp. 43–56). Human Kinetics.

Carvalho, J., Araujo, D., Travassos, B., Esteves, P., Pessanha, L., Pereira, F., & Davids, K. (2013). Dynamics of players' relative positioning during baseline rallies in tennis. *Journal of Sports Sciences*, *31*(14), 1596–1605. https://doi.org/10.1080/02640414.2013.792944

Crespo, M., & Miley, D. (1998). *Advanced coaches manual*. International Tennis Federation (ITF Ltd).

Filipcic, A., Leskosek, B., Crespo, M., & Filipcic, T. (2021). Matchplay characteristics and performance indicators of male junior and entry professional tennis players. *International Journal of Sports Science and Coaching*, *16*(3), 768–776. https://doi.org/10.1177/1747954120988002

Galé-Ansodi, C., Castellanlo, J., & Usabiaga, O. (2018). Differences between running activity in tennis training and Match-Play. *International Journal of Performance Analysis in Sport*, *18*(5), 855–867. https://doi.org/10.1080/24748668.2018.1525679

Galé-Ansodi, C., Castellano, J., & Usabiaga, O. (2017a). Effects of different surfaces in time-motion characteristics in youth elite tennis players. *International Journal of Performance Analysis in Sport*, *16*(3), 860–870. https://doi.org/10.1080/24748668.2016.11868934

Galé-Ansodi, C., Castellano, J., & Usabiaga, O. (2017b). More acceleration and less speed to assess physical demands in female young tennis players. *International Journal of Performance Analysis in Sport*, *17*(6), 872–884. https://doi.org/10.1080/24748668.2017.1406780

Giles, B., Kovalchik, S., & Reid, M. (2020). A machine learning approach for automatic detection and classification of changes of direction from player tracking data in professional tennis. *Journal of Sports Sciences*, *38*(1), 106–113. https://doi.org/10.1080/02640414.2019.1684132

Giles, B., Peeling, P., Dawson, B., & Reid, M. (2018). How do professional tennis players move? The perceptions of coaches and strength and conditioning experts. *Journal of Sports Sciences*, *37*(7), 726–734. https://doi.org/10.1080/02640414.2018.1523034

Giles, B., Peeling, P., Kovalchik, S., & Reid, M. (2021). Differentiating movement styles in professional tennis: A machine learning and hierarchical clustering approach. *European Journal of Sports Science*, *23*(1), 44–53. https://doi.org/10.1080/17461391.2021.2006800

Giles, B., & Reid, M. (2021). Applying the brakes in tennis: How entry speed affects the movement and hitting kinematics of professional tennis players. *Journal of Sports Sciences*, *39*(3), 259–266. https://doi.org/10.1080/02640414.2020.1816287

Hoppe, M., Baumgart, C., Bornefeld, J., Sperlich, B., Freiwald, J., & Holmberg, H.-C. (2014). Running activity profile of adolescent tennis players during match play. *Pediatric Exercise Science*, *26*(3), 281–290. https://doi.org/10.1123/pes.2013-0195

Hoppe, M., Baumgart, C., & Freiwald, J. (2016). Do running activities of adolescent and adult tennis players differ during play? *International Journal of Sports Physiology & Performance*, *11*(6), 793–801. https://doi.org/10.1123/ijspp.2015-0141

Hoppe, M., Hotfiel, T., Stuckradt, A., Grim, C., Ueberschar, O., Freiwald, J., Baumgart, C., & Vattay, G. (2020). Effects of passive, active, and mixed playing strategies on external and internal loads in female tennis players. *PLOS ONE*, *15*(9), e0239463. https://doi.org/10.1371/journal.pone.0239463

Hughes, M., & Meyers, R. (2005). Movement patterns in elite men's singles tennis. *International Journal of Performance Analysis in Sport*, *5*(2), 110–134. https://doi.org/10.1080/24748668.2005.11868331

Innovations H. (Producer). *Electronic line calling technology - how it works*. https://resources.platform.pulselive.com/HawkEye/document/2016/08/15/1e6cdaa4-2b70-4975-b722-7dca82b8e546/ELC_How_it_Works.pdf

Kovacs, M. (2006). Applied physiology of tennis performance. *British Journal of Sports Medicine*, *40*(5), 381–386. https://doi.org/10.1136/bjsm.2005.023309

Kovacs, M. (2007). *Tennis training: Enhancing on-court performance*. USRSA/Racquet Tech.

Kovacs, M. (2009). Movement for tennis: The importance of lateral training. *Strength & Conditioning Journal*, *31*(4), 77–85. https://doi.org/10.1519/SSC.0b013e3181afe806

Kovalchik, S., & Reid, M. (2017). Comparing matchplay characteristics and physical demands of junior and professional tennis athletes in the era of big data. *Journal of Sports Science & Medicine*, *16*(4), 489–497.

Kovalchik, S., & Reid, M. (2018). A shot taxonomy in the Era of tracking data in professional tennis. *Journal of Sports Sciences*, *36*(18), 2096–2104. https://doi.org/10.1080/02640414.2018.1438094

Krause, L., Farrow, D., Reid, M., Buszard, T., & Pinder, R. (2018). Helping coaches apply the principles of representative learning design: Validation of a tennis specific practice assessment tool. *Journal of Sports Sciences*, *36*(11), 1277–1286. https://doi.org/10.1080/02640414.2017.1374684

Le Runigo, C., Benguigui, N., & Bardy, B. (2005). Perception-action coupling and expertise in interceptive actions. *Human Movement Science*, *24*(3), 429–445. https://doi.org/10.1016/j.humov.2005.06.008

Margi, G. (2020). *Movement cycle*. Global Agent Academy. https://www.globalagenttennis.com/en/movement-cycle/

Mecheri, S., Laffaye, G., Triolet, C., Leroy, D., Dicks, M., Choukou, M., & Benguigui, N. (2019). Relationship between Split-step timing and leg stiffness in world-class tennis players when returning fast serves. *Journal of Sports Sciences*, *37*(17), 1962–1971. https://doi.org/10.1080/02640414.2019.1609392

Mlakar, M., & Kovalchik, S. (2020). Analysing time pressure in professional tennis. *Journal of Sports Analytics*, *6*(2), 147–154. https://doi.org/10.3233/JSA-200406

Pereira, L., Freitas, V., Moura, F., Aoki, M., Loturco, I., & Nakamura, F. (2016). The activity profile of young tennis athletes playing on clay and hard courts: Preliminary data. *Journal of Human Kinetics*, *50*(1), 211–218. https://doi.org/10.1515/hukin-2015-0158

Pereira, L., Freitas, V., Moura, F., Urso, R., Loturco, I., & Nakamura, F. (2015). Match analysis and physical performance of high-level young tennis players in simulated matches: A pilot study. *Journal of Athletic Enhancement*, *4*(5). https://doi.org/10.4172/2324-9080.1000212

Pereira, T., Nakamura, F., Jesus, M., Vieira, C., Misuta, M., de Barros, R., & Moura, F. (2017). Analysis of the distances covered and technical actions performed by professional tennis players during official matches. *Journal of Sports Sciences*, *35*(4), 361–368. https://doi.org/10.1080/02640414.2016.1165858

Pluim, B., Jansen, M., Williamson, S., Berry, C., Camporesi, S., Fagher, K., Heron, N., Janse Van Rensburg, C., Moreno-Perez, V., Murray, A., O'Connor, S., de Oliveira, F., Reid, M., van Reijen, M., Saueressig, T., Schoonmade, L., Thornton, J., Webborn, N., & Arden, C. (2023). Physical demands of tennis across the different court surfaces, performance levels and sexes: A systematic review with meta-analysis. *Sports Medicine*, *53*(4), 807–836. https://doi.org/10.1007/s40279-022-01807-8

Roetert, P., Ellenbecker, T., & Chu, D. (2003). Movement in tennis. In M. Reid, A. Quinn, & M. Crespo (Eds.), *ITF strength and conditioning for tennis* (pp. 167–175). ITF Ltd.

van Meurs, E., Buszard, T., Kovalchik, S., Farrow, D., & Reid, M. (2021). Interpersonal coordination in tennis: Assessing the positional advantage index with Australian open Hawkeye data. *International Journal of Performance Analysis in Sport*, *21*(1), 22–32. https://doi.org/10.1080/24748668.2020.1843213

Weber, K., Pieper, S., & Exler, T. (2007). Characteristics and significance of running speed at the Australian open 2006 for training and injury prevention. *Medicine and Science in Tennis*, *12*(1), 14–17.

Wei, X., Lucey, P., Morgan, S., Carr, P., Reid, M., & Sridharan, S. (2015). *Predicting serves in tennis using style priors*. Association for Computing Machinery. https://doi.org/10.1145/2783258.2788598

Wei, X., Lucey, P., Morgan, S., Reid, M., & Sridharan, S. (2016). *The thin edge of the wedge: Accurately predicting shot outcomes in tennis using style and context priors*. MIT SLOAN Sports Analytics Conference, Boston, MA.

Whiteside, D., & Reid, M. (2017). External match workloads during the first week of Australian open tennis competition. *International Journal of Sports Physiology & Performance*, *12*(6), 756–763. https://doi.org/10.1123/ijspp.2016-0259

Yuan, C., & Yang, H. (2019). Research on K-Value selection method of K-Means clustering algorithm. *Multidisciplinary Scientific Journal*, *2*(2), 226–235. https://doi.org/10.3390/j2020016