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Multi-surface Tennis Performance and Training: The Application of Deep Learning in Performance Analysis and Player Development

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Abstract. With the development of data-driven sports and artificial intelligence, computer vision and deep learning technology are now being used in new ways for tennis performance analysis and athlete training. Hard courts, clay courts, and grass courts are all different in terms of technology, tactics and physical demands; thus, many-surface-capable players are required at present. However, the previous method of tennis performance analysis was based on manual observation and statistical collection; thus, it suffered from human error, missing data, and slow feedback. Review of existing research on court-surface effects, traditional tennis data collection, and the application of deep learning and computer vision in tennis analysis. Explore applications of artificial intelligence in supporting the collection of match data, cross-surface tactical analysis, and personalised player training. Deep learning can be used to collect all-round, unbiased performance data on the players through coaches, identify any deficiencies in their game, and set up customised training plans. Complex visual environments, data integration, equipment costs and the interpretation of non-visual performance factors are also problems. In the future, research will integrate computer vision and wearable/physiological data to build lightweight AI systems for more accessible tennis training applications.

Keywords: tennis performance, multi-surface training, player development, deep learning

1. Introduction

With the development of professional tennis and sports science, data-driven performance analysis in the training and competition preparation of athletes has gradually been implemented. Both players' skills and health are factors that affect their tennis ability; other reasons also change this [1]. The three main court surfaces are hard, clay and grass courts; they have different ball speeds, bounce heights, friction, player movement and rally durations, and thus different technical, tactical and physical requirements [2]. Hard courts are relatively stable playing surfaces, generally have a strong serve and aggressive baseline play, and the rally pattern is usually relatively even. Clay courts are generally slower for the ball and result in longer rallies; therefore, more stamina, lateral movement and patience in building points are needed. Grass courts generally have a quicker and lower bounce, thus requiring faster reaction speeds and more effective serving to build up a point quickly [2].

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The above reasons are even more prominent in the case of international tennis, as players need to play on various kinds of courts during the off-season. Therefore, professional players also need to be able to adapt well to changes in the court environment at present. However, the availability of all kinds of training environments is not uniform. Traditionally, tennis training and competition in China have focused more heavily on hard courts, and opportunities for systematic training and long-term performance data collection in clay and grass courts are relatively scarce [3]. Thus, the players will be unable to learn about and practise adaptation in various circumstances. At the same time, the coach can collect data on how players' movements, rally strategies and shot selection change in different Areas and under different conditions. With the growth of the demand for objective, continuous and comparable performance data, the defects of the traditional method of tennis analysis have gradually been revealed, and now a more systematic and technology-supported system for performance assessment is needed.

2. Literature review

2.1. Effect of different court surfaces on tennis performance

Previous studies have all pointed out that the court surface is relatively far from the athlete. Different Surfaces have different friction, ball rebound and ball speed, so they will have different trajectories for the ball, and thus players' movement, shots and tactics will also change. Cross-examined the horizontal and vertical speed characteristics of tennis courts to show that differences in the coefficient of sliding friction and ball-surface interaction significantly affect the speed and behaviour of the ball after bouncing [4]. The above physical differences offer some support for learning why one needs to change one's technique and tactics based on the circumstances of the game.

Empirical studies of professional competitions have also shown different match characteristics on different court surfaces. Doğan and others analysed 1,004 singles matches from the 2019 Australian Open, French Open, Wimbledon and US Open, and compared indicators such as aces, double faults, first- and second-serve performance, break points, winners, unforced errors, total points won, fastest serve and match duration on hard, clay and grass courts. Based on the above research results, match statistics differ across various court surfaces, and thus different patterns of competition are exhibited under different surface conditions [5].

The physical requirements for tennis players also vary depending on the type of court. Pluim et al. conducted a systematic review and meta-analysis of the evidence from 64 studies and quantitatively analysed 42 studies to examine match duration, on-court movement and stroke performance on hard, clay and grass courts. The results show that the type of court is one of the reasons for changes in the physical requirements of tennis, and different surfaces require different movements, rallies and levels of exertion [6].

These results have some applications for player training. Training is generally held in a single place, so players do not have many opportunities to learn all-weather technical and tactical skills. Limited exposure to clay courts may reduce the opportunity for adaptation in a longer rally to increased movement requirements and a different ball-bounce characteristic. In light of the competition from abroad, the problem has become even more serious, and all-around performance is now required. Hard courts make up a significant proportion of the tennis training facilities in China, and therefore, organised exposure to clay and grass courts is relatively limited. However, most of the previous research has only focused on identifying differences in performance and physical demands across surfaces, and relatively little attention has been paid to how to systematically recognise these differences through continuous performance data and apply them to personalised, cross-surface training plans. It offers a good basis for further research in the area of objective and technology-assisted approaches to multi-surface tennis training.

2.2. Limitations of traditional tennis data collection

In the past, tennis ability assessments have mainly relied on subjective observation and off-court data, etc. Coaches and performance analysts usually observe players during practice and games to collect data manually on serving efficiency, rally length, stroke selection, ball-landing position, movement pattern and tactical choices, etc. Field measurements have also been carried out to collect all kinds of physical data on the various court surfaces, such as ball speed and rebound characteristics. The above ways of inquiry have offered some reference points for research on tennis performance and are still widely used in practice.

Manual Data Collection also has some serious defects. First, there may be errors in the collected data due to human observation and judgement. Tennis has a high-speed ball, frequent changes in player positions and many different stroke paths, so it is challenging for observers to record all these events consistently. Irregular strokes, low-angle shots, rapid changes in direction, and other short-duration actions may be missed or recorded differently by different observers. Second, the Quantity and range of information that can be collected manually are relatively small. Most human observers focus on certain performance indicators, and continuous data on ball trajectories, player movements and small-scale technical changes are difficult to collect comprehensively [7].

Another deficiency is that the old-style data collection is inefficient and slow. Detailed manual recording is time-consuming and labour-intensive; thus, it is impractical to do so for a large number of matches and players [7]. Often, the data are organised and analysed only after a training session or a game has been played; thus, timely feedback for adjustment of future training is not possible. Individual observers also have some variability and cannot collect standardised data for all matches, training environments, and court surfaces. Therefore, although the traditional methods are still useful in practice, their deficiencies in accuracy, completeness, efficiency and timeliness mean that they are less suitable for building continuous and comparable datasets of multi-surface tennis performance analysis. Therefore, the demand for automatic and technology-assisted means of analysing tennis performance has been rising.

2.3. Deep learning and computer vision in tennis analysis

With the development of artificial intelligence, deep learning and computer vision have provided new paths to address some of the deficiencies in traditional tennis performance analysis. Computer Vision systems can automatically detect and track players, tennis balls and movement trajectories in match or training videos to collect performance data at a large scale with less reliance on manual observation. The above technologies can provide more continuous and standardised data on the movement of the ball, position of players, stroke patterns, etc., and offer a new way of objective performance evaluation and data-driven training.

Recently, some new technology has also begun to be used in tennis training. Liu and others have explored AI-driven coaching systems, virtual reality training environments, wearable sensors, etc., for young tennis players in China [8]. Based on the above results, AI-powered coaching systems, VR training environments and wearable sensors were all significantly related to the acquisition of technical skills, providing additional sources of performance data and feedback for player development through technology-supported training. This paper has only investigated the

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connection between new-age technology and training results; the technical features of some computer vision algorithms have not been studied.

Different algorithms can be used for different analysis tasks in computer vision-based tennis analysis. CenterNet is a type of keypoint-based object detection method that finds the centre point of an object to locate it; therefore, it can be used to find corresponding objects in video frames [9]. DBSCAN is a density-based clustering algorithm that can find clusters of irregular shapes and separate noise points; thus, it is suitable for the analysis of space or trajectory data. Now, many applications of computer vision are used in the analysis of sports videos, such as detecting players and balls and tracking the trajectory of a ball [10]. Tennis ball tracking is still difficult because the ball is small, moves at high speed, and may appear blurred or partially out of view in consecutive frames [11]. Therefore, the efficiency of visual detection and tracking methods will differ under various conditions, such as different object sizes, motion blur, occlusion, light conditions, and complexities in the matching environment. The above problems show that one or more of the computer-vision approaches are not suitable for real tennis scenarios.

Although automated visual analysis has some advantages, most of the previous research has not explored how to use computer vision data for organised comparisons of players' performance on different court surfaces. Most of the previous research has focused on the technical capabilities of detection algorithms or the general advantages of technology-assisted training. Less attention has been paid to connecting the automatically collected visual data with surface-specific technical, tactical and physical features. Therefore, more studies are needed to investigate how to apply AI-based visual analysis for cross-surface performance evaluation and provide personalised tennis training based on objective data.

3. Applications of deep learning in tennis training

3.1. Automatic matching data collection

One of the first applications of deep learning to tennis is in automatic collection of match and training data. Computer vision systems can recognise and track the tennis ball and players in video to obtain various performance data on the court, such as serve speed, rally length, aces, double faults, break points, ball landing positions, and movement trajectories. Automatic data collection can handle a large amount of information in a short time compared to manual recording, and at the same time, it reduces the workload and subjectivity of human observation. Visual Tracking can be used to continuously collect data throughout the game instead of at specific moments. It can help coaches gain a fuller view of how players perform and build a uniform set of data for all matches, players and courts [11].

The other is that the results will be released sooner. Automatically recognise the paths of balls and players to show or record related performance indicators in real time during a game. For example, the distribution of the landing positions of the balls can be used to assess shot consistency and tactical tendencies, and movement trajectories can offer information on court coverage and positioning [12]. Automatically track the position of the ball without bias and help the linesman and other officials line the game accurately. In other words, one can gather a large amount of standardised data to observe changes in a person's performance over time rather than observing them individually. Help provide support for evidence-based decision-making and reduce reliance on subjective judgment of players' strengths and weaknesses.

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3.2. Tactical analysis of different court surfaces

Different surfaces of the tennis courts will affect the players' movement and technique at different times. Hard courts, clay courts and grass courts all have different characteristics of ball speed, bounce height, friction and player movement. For example, clay courts generally have slower rallies and require players to engage in extended exchanges, whereas grass courts are relatively fast with low bounces, and quick reactions and good use of short points are needed. Therefore, a player who performs well on one kind of court may not be equally skilled in terms of technique and tactics on other surfaces. Therefore, under all circumstances in court, a deficiency of the players will be revealed and improved upon.

The situation in China is relatively serious, and many players are training at hard-court training centres for the Olympics. Too much emphasis has been placed on one kind of surface; thus, the players have formed an all-too-uniform set of technical habits and lack adaptability in various playing environments. Players will have some difficulties in movement, endurance for a long rally, serving and returning strategies, and tactical changes when playing on clay or grass courts. These differences cannot always be observed in the game after the match.

Deep learning technology can offer a more organised way to study the above differences. Continuously accumulate match and training data from players performing on hard, clay and grass courts to compare changes in technical ability, movement patterns, rally characteristics and tactical choices under different surface conditions via AI-based systems. For example, the system can recognise the different rally durations, movement distances, recovery times, shot selections and court positions on different surfaces. The above comparisons can identify particular deficiencies that may arise from prolonged training on a single-court surface.

3.3. Personalised player development

Deep learning can also be applied to individualised training plans for players based on a larger body of data [13]. The previous way of teaching was based on the teacher's own experience and observation, so any minor changes in the students' movement or study habits went unnoticed. It will be difficult to determine the specific reasons for the performance gap among the court surfaces. Automated visual analysis can collect more specific data on how players move and perform all sorts of techniques, such as changes in body and racket movement, footwork, court position, where the ball lands, modifications to movement patterns under different circumstances, etc.

Given the above indicators and data on court features and past match results, a data-driven system can build a personal performance model for each player. For instance, the system can recognise that a player's performance has dropped on clay because of a lack of lateral movement, reduced stamina in long rallies, or a change in shot selection. The quality of play in the faster court will also be reflected in quicker responses, more efficient serves, advantageous positions after returns, and so on. Coaches do not use a single training plan for all players; instead, according to the differences among the players, they can strengthen specific strengths or address deficiencies in the players' performance at different times or under different circumstances.

4. Conclusion

Deep learning and computer vision are used in this paper to study tennis performance analysis and multi-surface player training. Hard, clay and grass courts have different technical, tactical and physical requirements according to the research results, and traditional manual data collection has shortcomings in accuracy, efficiency, data volume and timeliness. Deep learning can collect more objective and continuous data by automatically tracking the path of balls and players, shot patterns, etc. Based on the above data, compare the performance of all surfaces and help coaches determine what training adjustments need to be made for individual players.

This study also has some deficiencies. Firstly, it is based on a summary of existing studies rather than new experimental data, so the proposed application of AI in cross-surface training still needs to be verified empirically. Second, computer vision systems are also subject to problems such as lighting variations, motion blur, occlusion, different camera positions, etc. Visual data cannot show all the psychological, physiological and recovery factors either. Thus, AI will be employed to offer decision support and not substitute for professional coaching.

Future research can take the actual player data from several courts to carry out an extended study on the efficacy of AI-aided training. Computer vision is used with wearable sensors and other physiological data to build an all-weather performance observation system. At the same time, light-weight and low-cost AI models should be developed to enhance the accessibility of intelligent tennis analysis for young people and grassroots training in China.

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